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MARCO AURÉLIO LIMA DE QUEIROZ

BUSINESS COMPETITION DYNAMICS:
Agent-Based Modeling Simulations of Firms in Search of Economic Performance.

TESE

SÃO PAULO

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Tese apresentada à Fundação Getúlio Vargas – Escola de Administração de Empresas de São Paulo como requerimento para obtenção do título de doutor em administração de empresas

Campo de conhecimento: Estratégia Empresarial

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I dedicate this work to my wife and kids, for being.

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In several aspects, this work is also yours, dear friend. Thank you!

"Nothing is built on stone; all is built in sand.
But we must build as if the sand were stone."

Jorge Luis Borges
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RESUMO

A intenção deste trabalho é explorar dinâmicas de competição por meio de "simulação baseada em agentes". Apoiando-se em um crescente número de estudos no campo da estratégia e teoria das organizações que utilizam métodos de simulação, desenvolveu-se um modelo computacional para simular situações de competição entre empresas e observar a eficiência relativa dos métodos de busca de melhoria de desempenho teorizados. O estudo também explora possíveis explicações para a persistência de desempenho superior ou inferior das empresas, associados às condições de vantagem ou desvantagem competitiva.

Cada execução de simulação começa com a inicialização da "paisagem de adequação", que define o nível de desempenho a ser atribuído para cada possível configuração (de recursos e capacidades) que as empresas venham a adotar. Há dois modelos diferentes de paisagem de adequação disponíveis para simulação, sendo um parecido com o proposto por Kauffman, frequentemente citado e adotado por outros autores, e outro desenhado no âmbito deste trabalho, que possibilita simular mudanças de mercado (na paisagem de adequação), de natureza exógena ou endógena (em função das estratégias adotadas pelas empresas), ambas além do entendimento ou controle das empresas.

A inicialização da simulação computacional inclui também a geração aleatória de um conjunto de empresas com diferentes atributos e estados iniciais (configurações de recursos e capacidades), dentro dos parâmetros de simulação solicitados. Durante a execução da simulação, cada firma busca alcançar níveis mais elevados de desempenho, utilizando métodos (ou rotinas organizacionais) que representam, até certo ponto, os mecanismos de diferenciação e isomorfismo descritos nos campos de conhecimento da estratégia empresarial e da teoria das organizações. O modelo simula a busca por desempenho que se realiza sob condições de racionalidade limitada, informação incompleta e incerteza.

O estudo explora o comportamento das diversas variáveis representadas pelo modelo em uma variedade de cenários; apresentam-se os resultados destas simulações, discutidos à luz do que se esperaria baseado na teoria e evidências empíricas reportadas em outros trabalhos.

Dentre os resultados mais interessantes, verifica-se que:

- Os métodos de busca fazem diferença, contudo, a eficiência do método depende significativamente do contexto e, principalmente, deve-se às características, métodos de busca e escolhas realizadas pelas outras empresas com as quais uma dada empresa se relaciona;
- A persistência do desempenho superior não pode ser explicada pelos atributos individuais das firmas, neste modelo representados por sua amplitude de visão e sua capacidade de ajuste. Ao invés disto, ela é explicada pela estratégia de busca adotada, conjugada com o desdobramento das interações com outras empresas e as escolhas por estas realizadas, em situações idiossincráticas e de dependência de trajeto.

Embora os resultados deste estudo ainda requeiram validação empírica, as implicações para a prática gerencial parecem relevantes: a vantagem competitiva não é uma questão somente de posicionamento ou recursos internos da firma. Em um ambiente de constantes mudanças, com informação incompleta e incerteza, ela depende de sorte, e para além dela, do modo como as interações com outras firmas se desdobram, possibilitando que a empresa consiga sustentar um nível elevado de desempenho. Empresas que empregam estratégias de mimetismo devem buscar constantemente novas conexões para obtenção de informação sobre práticas a serem adotadas.

PALAVRAS-CHAVE

Estratégia evolucionária; teoria comportamental da firma; vantagem competitiva; simulação computacional; paisagens de adequação; modelo baseado em agentes.

ABSTRACT

The intent of this work is to explore dynamics of business competition through agent-based modeling simulations of firms searching for performance in markets configured as fitness landscapes. Building upon a growing number of studies in management science that utilizes simulation methods and analogies to Kauffman´s model of biological evolution, we developed a computer model to emulate competition and observe whether different search methods matter, under varied conditions. This study also explores potential explanations for the persistence of above and below average performances of firms under competition.

Each simulation run starts with the initialization of a fitness landscape, which defines the fitness level for each possible firm configuration. There are two different landscape models available for simulation, one that resembles the NK model proposed by Kauffman and the other, custom-developed under the scope of this project, in which we built additional functionality in order to explore potential consequences of market changes over time, due to exogenous or endogenous factors, both beyond the control of the competing firms

Next, our computer application generates a set of firms with heterogeneous attributes and initial states (or configurations for their business models), randomly assigned according to the chosen simulation parameters.

During a simulation run, each firm searches for higher levels of fitness utilizing the search methods (or organizational routines) that were designed to represent, at some extent, the isomorphic and differentiation mechanisms described by the business strategy and organizational theory literatures. The model simulates the search for performance that operates under bounded rationality, dealing with incomplete information and uncertainty.

The study examined several hypotheses through a series of simulation runs; we present the simulation outcomes obtained and discuss them in relation to what we would have expected based on theory and reported evidences from other studies in the field.

Among the most interesting outcomes, we verified that search methods matter, but that search method performance depends on the context and, most importantly, the choices of the other firms. Persistence of above average performance cannot be explained by firm specific

attributes such as vision and capacity to adjust; instead, it is due to both the search strategy adopted and the unfolding of interactions with other firms and the choices they made, in idiosyncratic and path dependence situations.

Although the outcomes of this study require empirical validation, the implications to management practice seem relevant: competitive advantage is not solely a matter of positioning neither of firm resources; it depends on the way unfolding interactions with other firms allow a company to continuously match environmental demands. Companies that rely on mimetism strategies must constantly renew and expand their information sources of recommended practices (resource configurations) in order to avoid informational traps that may lead to poor performance.

KEY WORDS

Evolutionary strategy; behaviorial theory of the firm; competitive advantage; computer simulation; fitness landscape; agent-based model.

CHARTS, FIGURES AND FRAMES

TABLES

CONTENT

1. INTRODUCTION

1.1. Context, foundations and settings of this work

The dynamics of business competition is central to the field of business strategy. Economics and organizational theories provide various competing explanations for the search mechanisms employed by firms in their struggle to survive, to solve their perceived problems and/or to pursue superior performance against others. For the strategy field, special interest relies in the understanding of why some firms consistently outperform others (Barney & Hesterly, 2006; Besanko, Dranove, Shanley, & Schaefer, 2004; Rumelt, Schendel, & Teece, 1991).

It is not a consensus that firms intentionally seek to outperform others, neither that firms have an orchestrated and sound search strategy employed by their management teams. In spite of the organizational goal and deliberateness nature of the strategy process, however, research in organizational theory describes to a high extent the search mechanisms that would account for the perceived, emerging patterns of action resulting from organizational micro-dynamics as management attempt to solve problems and improve performance (Cyert & March, 1992; Simon, 1964). Although the mechanisms (or organizational routines) most frequently reflect complex social and historical conditions, such as previous experience, path dependencies, group beliefs and learning processes, they are persistent as to provide plausible explanations for the differences in firms´ performance (Cyert & March, 1992; Nelson & Winter, 1982). The interest of the present study relies on further exploring this argument.

Many authors already utilized simulation methods to study competition under an evolutionary perspective (Anderson, 1999; Barnett & Hansen, 1996; Gavetti & Levinthal, 2000; Levinthal, 1997; Lomi & Larsen, 1996; McKelvey, 1999a; Morel & Ramanujam, 1999; Rivkin, 2000). Models simulate populations of firms searching for fitness in rugged landscapes, going beyond the use of the metaphor from biology, adopting the model created by the biologist Stuart Kauffman (1995), with few if any modifications. The appeal comes from the main concept embedded in Kauffman´s theory for the evolution of life, notably the idea of evolution as the emergence of new, unpredictable, complex adaptive patterns (and forms of life) out of simple micro-dynamics in continuous interaction with the environment. There is a growing number of scholars that consider markets and organizations as complex adaptive systems (Holland & Miller, 1991; Macy & Willer, 2002; Markose, 2005; Mitleton-Kelly, 2003; Morel & Ramanujam, 1999); on the same trend, the portrait of the strategy process turns to be one of a complex, adaptive, emergent pattern, resulting from organizational dynamics (Brown & Eisenhardt, 1998; Mintzberg, Lampel, Quinn, & Ghoshal, 2003; Teece, Pisano, & Shuen, 1997; Whittington, 2001). The attractiveness of the analogy and the use of such a model are thus justifiable.

The central argument here remains the same one stated by evolutionary economics long ago (Alchian, 1950; Nelson & Winter, 1982; Nelson, Winter, & Schuette, 1976): firms evolve over time (variation), adopting characteristics that provide or are supposed to provide better response to market demands (selection and retention). It is worth recognizing that such an "evolutionary account" is also widespread in the fields of organization theory (Aldrich, 1999; Carroll, 1997; Carroll & Harrison, 1994; Hannan & Freeman, 1977, 1984) and strategic management (Augier & Teece, 2009; Barnett & Burgelman, 1996; Lovas & Ghoshal, 2000; Schendel, 1996). The difference resides both in the way of exploring how variation, selection and retention processes work out and in the creation of higher-level order out of these micro-dynamics (Holland, 1998; Levinthal & Warglien, 1999; McKelvey, 1999b).

The current work relies on the evolutionary account, making use of the complex adaptive systems theory previously developed in the field of business strategy and adopting the theorized search mechanisms as the evolutionary engine that could provide possible explanations for why firms differ in their performance over a period in time. In order to develop such an endeavor, we have designed and built a customized platform, namely, an agent-based modeling system. This research method enables exploration and theoretical developments, while having relevant limitations that must be constantly assessed (Davis, Eisenhardt, & Bingham, 2007; Epstein & Axtell, 1996; Gilbert, 2008; Holland, 1998; Miller & Page, 2007; Prietula, Carley, & Gasser, 1998). The advice of more experienced researchers is considered as a guide:

> Having the ability to investigate new theoretical worlds (with computational techniques) obviously does not imply any kind of scientific necessity or validity – these must be earned by carefully considering the ability of the new models to help us understand and predict the questions we hold most dear. (Miller & Page, 2007, p.5)

1.2. Research objectives and potential contributions

As previously mentioned, this study has the intent of exploring issues related to the dynamics of business competition through the design and run of an agent-based modeling (ABM) system. While agent-based modeling allows open-ended explorations, we resisted the temptation to become what Macy and Willer call *"freewheeling adventurers in artificial worlds"* (2002, p. 162), and tried to "ride" into a more restricted and somewhat disciplined experimental design.

The model design and development considered the computer simulations implemented in several other studies in the fields of business strategy, management science and organizational theory. We validated the model outcomes according to existing theory in the field, but few empirical evidences where available. Some of the findings presented later provide interesting theoretical contributions to the field of business strategy, fostering additional empirical studies.

The subject of interest of this study involves the efficiency of search methods employed by firms in their struggle for better performance, under a variety of conditions such as industry stability, complexity of the business operations, availability of information about other firms´ choices etc.

Through the simulation method we investigated possible explanations for the persistence of above-average and below-average performance in hypothetical populations of firms.

Our research agenda had the following *ex-ante* research questions[1]:

I. About the search methods employed by the firms as modeled in the application:

    a. Is there a search method that explains why some firms outperform the others?

    b. What is the impact of high-changing market conditions on the relative efficiency of the search methods (observed in a.)?

[1] When we started the project we had also the interest of investigating the statistical properties of performance distribution curves for populations of competing firms. We concluded that the limitations of our model design wouldn´t allow to generate valid hypothetical distribution curves.

II. About the persistence of above and below average performers, and the existence of outliers:

   a. What causes some firms to be above and below average performers?

   b. Can simple heuristics account for sustained competitive advantage?

2. THEORETICAL FRAMEWORK

Initially we established the foundations for our project by reviewing the strategic management field, bringing selected discussions about competitive advantage. We characterize competition as the search for economic performance, supported by a large literature on both evolutionary economics and organizational theory.

Then we explored the argument that markets and organizations are complex systems, whose behaviors, as observed through macro level lens, result from micro-dynamics operating at a lower level. The organizational routines, in this case, search processes, would represent such aggregated behavior at the firm level and provide an arguable account for firm performance. The performance of the simulated sets of firms would support the discussion of the efficiency of different search strategies under varied conditions, and provide potential explanations for the persistence of above average and below average performance among competing firms.

Next, we explained why and under which boundaries and limitations we modeled the search processes of firms in analogy to Kauffman´s model of biological search, as did many other researchers in various recent works that address adaptation processes and strategic decisions.

Finally, a brief review of the current debate about the search mechanisms employed by firms and about the persistence of abnormal returns furnished the necessary context for situating our research questions within the strategic management field.

2.1. Business strategy and competitive advantage

Business strategy is the pursuit of competitive advantage; a firm has competitive advantage when it is capable of creating more economic value than its competitors do (Barney & Hesterly, 2006; Hitt, Ireland, & Hoskisson, 2005; Porter, 1996). While a variety of perspectives provide distinct definitions for the objectives that guide the strategy process (Cyert & March, 1992; Mintzberg, et al., 2003; Vasconcelos & Cirino, 2000; Whittington, 2001), the economics of strategy provide a robust orientation for the conduct of firms (Besanko, et al., 2004; Rumelt, et al., 1991).

The construct competitive advantage, however, is arguably problematic if defined simply as superior economic performance (Arend, 2003; Durand, 2002; Powell, 2001, 2003a; Powell & Lloyd, 2005); the present study´s perspective relies on the proposition that competitive advantage can be seen as both component of and resultant of superior performance, as suggested by Vasconcelos and Brito (2004). Thus, the proposed dynamics of business competition consider the following logic: firms adopt strategies and implement changes in their configurations (set of characteristics); the performance for each firm reflects such configurations; as we look for firms with superior performance, namely the "resultant competitive advantage", we will find those firms with "component competitive advantages". It is worth mentioning that the conception of our model makes hard to trace how component advantages affect resultant competitive advantage (see the section design and construction of the model for more details on it).

Some authors discuss whether one should consider above average performance as simple heuristics and persistent competitive advantage associated only with outliers (Alchian, 1950; Powell, 2003b; Wiggins & Ruefli, 2002), with market mechanisms that would make firms with abnormal returns to converge towards the mean in the long term (Jacobsen, 1988). We expect to shed new light on these issues as we run our model and analyze hypothetical populations of firms.

The present study addresses another relevant theoretical issue, which is the discussion on the sources of competitive advantage. Extensive literature about superior economic performance of a firm associates it with the exploitation of market failures, whether through:

- *Monopoly rents* derived from privileged positioning (imperfect products market) as posed by Industrial Organization theory - "IO" (Bain, 1956; Richard E. Caves, 1980; R. E. Caves & Porter, 1977; Porter, 1985);
- *Ricardian rents* derived from individual firms' resources and competences (imperfect factors market) as discussed by the Resource-Based View theory of the firm – "RBV" (Barney, 1986, 1991; Conner, 1991; E. T. Penrose, 1959; Peteraf, 1993; Wernerfelt, 1984); or

- *Schumpeterian rents*, in a world of innovation-based competition (temporary-only imperfect markets), which builds upon the work of Schumpeter (1934). The so-called Dynamic Capabilities ("DC") and other related theoretical approaches to firms´ capabilities such as "Knowledge-based view of the firm or absorptive capacity (Amit & Schoemaker, 1993; W. M. Cohen & Levinthal, 1990; Dierickx & Cool, 1989a, 1989b; Eisenhardt & Martin, 2000; Grant, 1996; Knott, 2003; Kogut & Zander, 1992; E. T. Penrose, 1959; Teece, et al., 1997).

The design of our model took these competing theories into account. The final model simulates business dynamics that better reflect the Dynamic Capabilities account (Eisenhardt & Martin, 2000; Nelson, 1991; Winter, 2003), as we based much of our definitions in several works following the traditions set by A behaviorial of the firm (Cyert & March, 1992) and the theory of evolutionary economics (Nelson & Winter, 1982).

2.2. Competition as a dynamic process of search for economic performance

The pursuit of competitive advantage is recognized by its dynamic character, although the authors provide many different arguments to explain how firms achieve superior performance: through continuous work to yield differentiated fit (Porter, 1996); because of luck or foresight to accumulate resources (Dierickx & Cool, 1989a, 1989b); due to the dynamic capabilities (Teece, et al., 1997); due to an absorptive capacity (W. M. Cohen & Levinthal, 1990); because of second order learning associated with capability monitoring (Schreyögg & Kliesch-Eberl, 2007), or other explanations (Mintzberg, Ahlstrand, & Lampel, 1998).

The perspective of strategy as essentially static, which was historically based upon the notion of economic equilibrium (Vasconcelos & Cirino, 2000) have been de-emphasized as locus of attention, and dynamics of competition prevail in strategy textbooks (Besanko, et al., 2004; Ghemawat, 2002; Hitt, et al., 2005; Mintzberg, et al., 2003).

Porter suggested that the agenda of the strategy field comprises two major issues: *"the causes of superior performance at a given period in time (termed the cross-sectional problem) and the dynamic process by which competitive positions are created (termed the longitudinal* *problem)"* (1991, p. 95). The longitudinal problem in fact has become an important stream of work in the field of business strategy many years ago (Barnett & Burgelman, 1996; Lovas & Ghoshal, 2000; Schendel, 1996).

Changes in the intellectual structure of the strategic management research field as described by Ramos-Rodriguez and Ruiz-Navarro (2004) had already identified the increasing role played by evolutionary economics during the late 1990´s, usually associated with RBV and DC theorists:

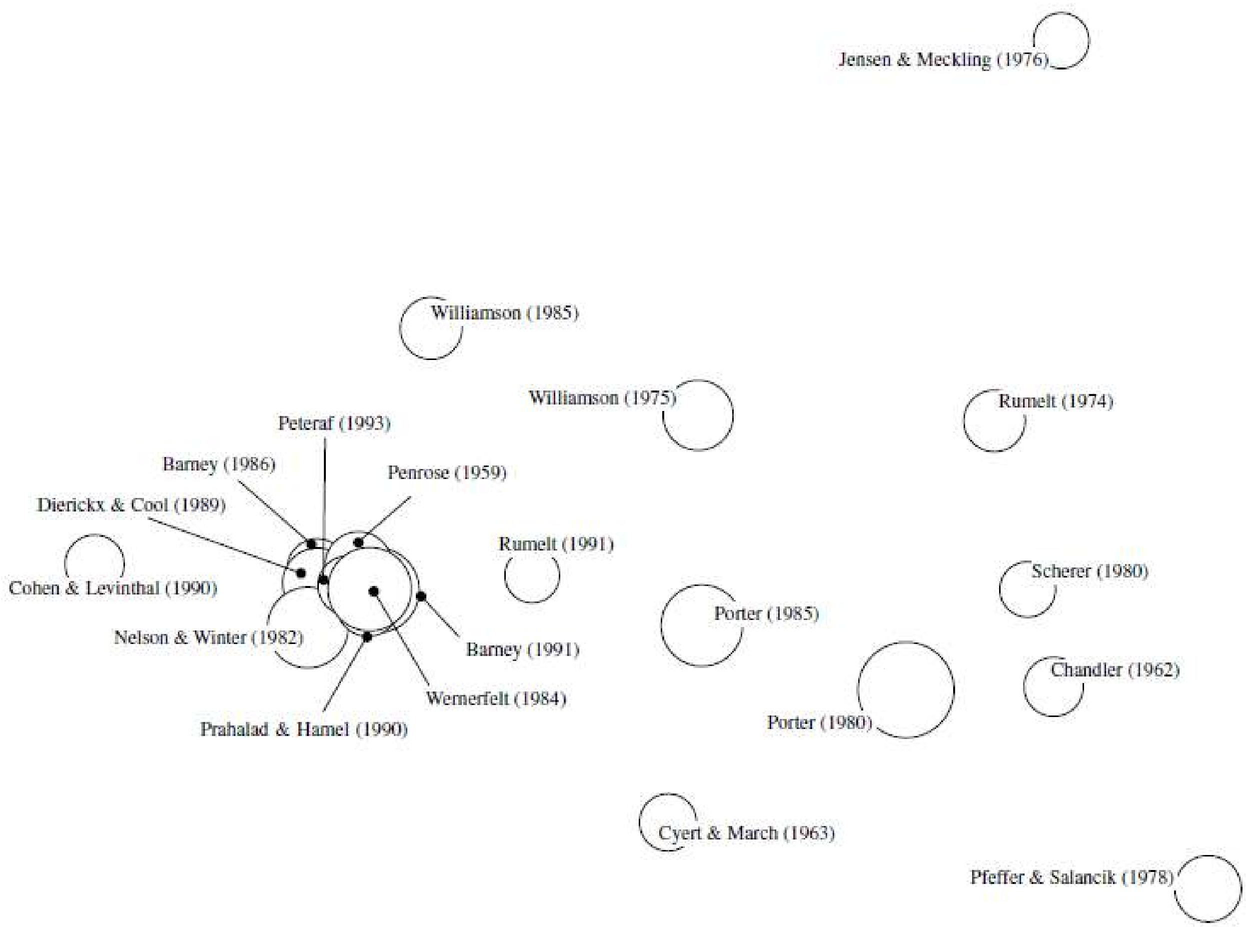


Figure 1 Intellectual structure of strategic management research: 1994-2000
Source: Ramos-rodriguez; Ruiz-Navarro, 2004 p.1000

The dynamics of business competition can be stated as follows: firms compete through variation, selection and retention of resources, capabilities and routines that can satisfy the needs of solving problems, being such process more or less intentionally driven, or environmentally determined (Levinthal, 1991). That view is reinforced by Gavetti and Levinthal in their analysis of the field of business strategy, who stated: *"[...] recent developments begin to delineate a potential unifying conceptual framework for treating the field´s defining questions – the conceptual apparatus of evolutionary economics"* (2004, p. 1309):

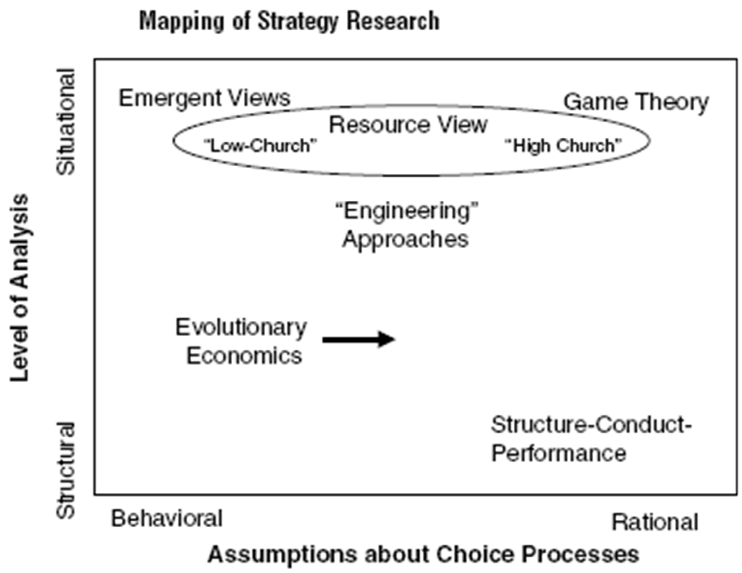


Figure 2 Mapping of Strategy Research
Source: Gavetti; Levinthal, 2004 p.1310

The present study considers these evolutionary perspectives on strategy, embedded with the behaviorial notions introduced by Cyert, March and Simon (Cyert & March, 1992; Simon, 1997). This is still considered a very promising branch of research (Dosi & Marengo, 2007). We define business competition as the evolutionary process through which firms try to change and improve their performances as they perceive problems or strive for better performance, put simply, the competition is the search for economic performance. In doing so, we adopt the same approach of several other authors utilizing simulation methods (Gavetti & Levinthal, 2000; Gavetti, Levinthal, & Rivkin, 2005; Ghemawat & Levinthal, 2008; Mezias & Glynn, 1993; Porter & Siggelkow, 2008; Repenning, 2002; Rivkin, 2000; Strang & Macy, 2001; Zott, 2003).

2.3. Markets and organizations as evolving, complex systems of adaptive agents

According to Miller and Page (2007), complexity theory in the social sciences started hundreds of years ago, with the concept of the "invisible hand" that was defined by Adam Smith: market structures would be created out of the individual action of self-interested agents, without being part of any single agent´s intention. The recognition that an observed macro level pattern may emerge out of the dynamics at a lower level is at the heart of their definition for complex systems:

> What it takes to move from an adaptive system to a complex adaptive system is an open question and one can engender endless debate. At the most basic level, the field of complex systems challenges the notion that by perfectly understanding the behavior of each component part of the system we will understand the system as a whole. (Miller & Page, 2007, p.3)

In his landmark work, "The sciences of the artificial", updated in its 3rd edition, Simon depicted three different waves of interest related to complexity. He characterizes a first wave after the 1st world war, associated with an anti-reductionist perspective (holism, gestalt). A second wave after the 2nd world war, focused on feedback mechanisms and homeostasis in complex systems (systems thinking). Finally, the current wave, centered in the investigation of the mechanisms that create and sustain complexity, the analytical tools to describe it, and in the study of chaos theory and catastrophe theory (Simon, 1996).

There is a growing interest for applying complexity theory to social sciences and provide explanation to the micro-macro relationships of a large variety of phenomena (Axelrod, 1997; Epstein & Axtell, 1996; Holland, 1998; Macy & Willer, 2002; McKelvey, 1999b; Morel & Ramanujam, 1999; Sawyer, 2001, 2005), although the interpretation of the ontological status and causation mechanisms for the emergent properties at higher levels are still controversial, as discussed by Sawyer (2001). According to him, multi agent systems ("artificial societies") engage on three distinct sociological phenomena: the model of the individual, the model of the communication language (relationships among individuals) and the observation of emergent social phenomena. The emergent properties may not be reduced to (or identified in) the individuals, and may exhibit downward causation mechanisms (from the properties to the individuals). To cope with such phenomena, Sawyer calls for a social emergentism approach, the nonreductive individualism. As Macy & Wiler suggests, agent-based modeling may help to develop a methodology "*to bridge Schumpeter´s (1909) methodological individualism and Durkheim´s rules of a nonreductionist method.*"(2002, p. 148).

Mitleton-Kelly points that there is not an unified theory of complexity, but only some common elements to be considered (Mitleton-Kelly, 2003). Burnes reviewed recent works making use of complexity theories to understand organizations and identified a variety of realms under the same umbrella, with the following common ground that we want to emphasize:

> Its proponents claim that organizations are dynamic, non-linear systems and, as such, the outcome of their actions are unpredictable but, like turbulence in gases and liquids, they are governed by a set of simple order-generating rules. (Burnes, 2005, p. 85)

The managerial expectation here is to understand the order-generating rules to possible maneuver the emergent properties of the system, such as reducing the volatility of a supply chain to improve performance, or at least tracing repetitive patterns that will provide useful information (Levy, 1994). That would be what MacLean and MacIntosh characterized as "conditioned emergence" (Macintosh & Maclean, 1999; 2003). Several authors already proposed new management techniques and approaches for dealing with enterprise dynamics and change based on the premises suggested by such theoretical perspective (Beinhocker, 1997; Brown & Eisenhardt, 1998; Lewin & Regine, 2003; McMillan, 2006; Mitleton-Kelly, 2003; Pascale, 1999).

Although attractive, it has to be considered the warning given by Burnes, McKelvey and others (references therein): to avoid the premature conversion of new ideas into normative prescriptions, and to be aware that some social scientists misuse chaos and complexity theories, applying them to organizations without adequate conceptual justification (Burnes, 2005; McKelvey, 1999b; Stacey, Griffin, & Shaw, 2000). It is also worth recognizing the limits of theorizing complex systems, by their very nature or definition (Cilliers, 2002).

With all these discussions in mind, we will turn now to explore potential applications in the fields of organizational theory and business management. To do so, a starting point is the Organization Science Journal issue specially dedicated to applications of complexity theory, "*a rich perspective for viewing many different aspects of organizations*" (Anderson, Meyer, Eisenhardt, Carley, & Pettigrew, 1999 p. 236).

Complexity theory (as presented here) is quite suitable to those researchers that build upon evolutionary economics to develop their works (Arthur, 1994; Auyang, 1998; Holland & Miller, 1991; Levinthal, 1997; Markose, 2005; Rivkin & Siggelkow, 2003). That is precisely the theoretical frame of reference upon which we built our simulation model to explore business dynamics and competitive advantage.

Agent-based modeling is one of the tools researchers employ to explore potential explanations for observed properties at a macro-level (the market or the organization) that are supposedly the outcome of dynamics at the micro-level (Arthur, 1994; Auyang, 1998; Axelrod, 1997; Holland & Miller, 1991; Macy & Willer, 2002; Sawyer, 2005). The agents, being single persons, groups or organizations, operate in a manner and in an environment under the premises postulated by complexity theory (Anderson, 1999; Arthur, 1994; Gilbert, 2008; Holland & Miller, 1991; Kimura, Pereira, & Lima, 2007; Levinthal & Warglien, 1999; Markose, 2005; Miller & Page, 2007) . Instead of having the fictional "representative agent" criticized since long in economics (Alchian, 1950), the agents in such computational representations differ from each other; they have internal states and interact with others through a web of connections; they receive and process feedback and by doing so their aggregate behavior becomes non-linear, with emergent properties under certain conditions:

> Under organized complexity, the relationships among agents are such that through various feedbacks and structural contingencies, agent variations no longer cancel one another but, rather, become reinforcing. – systems can exhibit aggregate properties that are not directly tied to agent details (Miller & Page, 2007, p.53).

A notorious agent-based modeling application in social sciences was developed as early as in 1969 by Thomas Schelling, explaining the unexpected emergent, macro-behavior of racial segregation from micro-motives of personal neighborhood preferences (Schelling, 1969). Management studies with agent-based modeling abound since then as extensively described by Gilbert (2008), Miller & Page (2007) and others mentioned before.

2.4. Adaptive agents in a fitness landscape: the NK model

One way to model the evolution of adaptive agents is to make use of the concept known as fitness landscape. Introduced by Wright (1932), it suggests that, for an interbreeding population, there is a multidimensional space in which each attribute (gene) of an organism is represented by a dimension of the space. A final dimension indicates the fitness level of the organism. Warning upfront that the representation is inadequate, Wright presents the following figure, a two-dimensional fitness landscape, for the sake of clarifying his proposition:

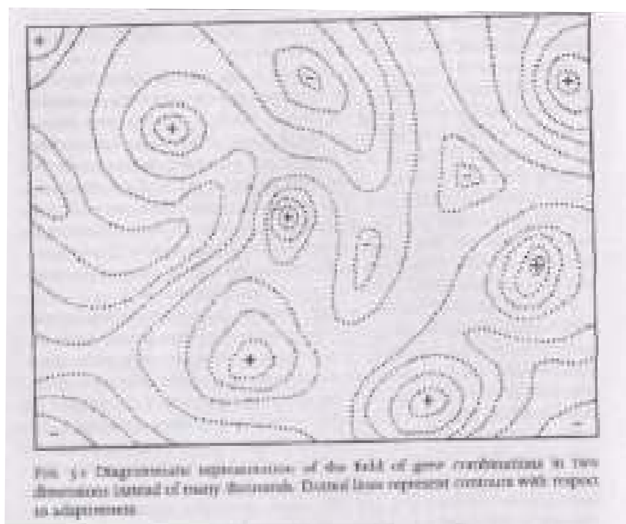


Figure 3 Original fitness landscape representation

Source:Wright, 1932, pg.358

Kauffman developed an extensive work claiming to address uncovered themes in developmental and evolutionary biology, notably the idea that simple and complex systems can exhibit powerful self-organization (Kauffman, 1993, 1995).

Among his contributions is the "NK" model, a simple - but powerful - analytic structure to represent epistatic interactions, that is, the interdependency of fitness contribution among the genes (or attributes) and to model the evolutionary process of adaptation in fitness landscapes (Levinthal, 1997). "N" would account for the number of attributes, each influenced by "K" other attributes.

The model is a rich representation for the study of evolutionary processes of various natures, with many useful implications derived from its central proposition, such as:

- The fitness landscape as a representation would become "rugged", that is, with multiple peaks and valleys as K increases. It is not clear whether a specific configuration implies being in the highest peak or just stuck in a valley; small changes in an attribute (N) might cause significant impact on the organism fitness; very similar organisms may have quite different fitness levels. It becomes unclear (even impossible to grasp) how all these interdependencies work;
- In single-peaked landscapes, when K=0, successful, incremental "adaptive walks" lead to the top ("hill climbing"), whereas in rugged landscapes, with K>2, becomes too difficult to oversee the best configuration even if the adaptive agent has the ability to look over many possible alternatives.

Many other implications derive from the model, as Kauffman´s demonstrates in his works and we explore some of those when discussing the simulation outcomes later on in this work. By now, it is worth reproducing Kauffman´s words about the potential application of his ideas in fields such as organization and management science:

> Organisms, artifacts, and organizations all evolve and coevolve on rugged, deforming, fitness landscapes. Organisms, artifacts and organizations, when complex, all face conflicting constraints. So it can be no surprise if attempts to evolve toward good compromise solutions and designs must seek peaks on rugged landscapes. (1995 , p.246)

2.5. The analogy of fitness landscapes within management science

Biological and social systems are fundamentally and qualitatively different categories of phenomena. The historicity and reflexivity found in social dynamics turn inappropriate (if not impossible) the efforts of mapping one to another, and to rely on metaphors (Introna, 2003; Macy & Willer, 2002). Therefore, the use of metaphors or analogies should be avoided as, in general, they tend to blur the nature of important issues regarding the theory of the firm, as early pointed by Penrose (1952). We take here the position of Mitleton-Kelly, who recognizes such limitations but suggests their use as transitional objects, *" [...] in the sense that they help the transition in* *our thinking when faced with new or difficult ideas or concepts.*" (Mitleton-Kelly, 2003, p. 26). She also suggests thinking more about complex behavior than complex systems.

In spite of the controversy, there is an attempt to identify unifying principles in complex adaptive systems, whether biological, physical or socio-economic (Markose, 2005; Mitchell & Taylor, 1999). In the fields of management science or business strategy, there is a growing number of works making use of fitness landscape like models to develop theoretical propositions (Ethiraj & Levinthal, 2004a, 2004b; Gavetti & Levinthal, 2000; Gavetti, et al., 2005; Ghemawat & Levinthal, 2008; Kimura, et al., 2007; Levinthal, 1997; Levinthal & Posen, 2007; Levinthal & Warglien, 1999; Porter & Siggelkow, 2008; Rivkin, 2000, 2001; Rivkin & Siggelkow, 2007; Siggelkow & Rivkin, 2008). We will refer extensively to these works later when describing our model design and the experiments we conducted.

The idea of unifying principles for complex systems is far from new, and can be traced back to von Bertalanffy (1950), as a general systems theory, or Forrester (1958, 1960), applied for management purposes. Since then, systems thinking evolved through various streams, contributing as an epistemological approach claiming to deal more properly with complex, systemic phenomena than other prevailing reductionist approaches (Georgiou, 2007).

There is still some debate around the potential distinctions complexity theory might have in relation to systems thinking, in special when considered the various schools of thought within each of these branches. Stacey, Griffin and Shaw developed a comprehensive analysis of the differences among those, but their arguments go much beyond the scope of the present work. In short, these authors defend that complexity theory, from which the model created by Kauffman would be a representation, is of a different teleology, namely Transformative, not a Formative one, as it would be the case of general systems thinking. We reproduce some of their words in this regard:

> In systems thinking, causality is primarily of the formative type taking the linear form in which the feedback process of the system causes its patterns of behavior, usually in a predictable way, but those patterns do not cause the system dynamics. The future forms to which such systems move are already given in their structure, including the boundary separating them from others. We call this Formative Teleology.(Stacey, et al., 2000 pg. 120)
>
> For Kauffman and Goodwin, interaction between the components of a system is the cause of the coherent pattern that inevitably, but completely unpredictably, emerges from that interaction when the

> system operates at the edge of chaos. The intrinsic properties of connection, interaction and relationship cause emergent coherence in the particular conditions prevailing at the edge of chaos and that emergent coherence is radically unpredictable. Efficient causality is retained as the cause of an agent's particular local response to other agents, but it is the interaction itself that operates as the transformative cause of the emergent pattern of the whole system. Furthermore, that transformative causality is circular, indeed self-referential, because self-organization causes emergent patterns in itself. (Stacey, et al., 2000 pg. 122)

The results of our simulations, as presented later in this work, illustrate the role randomness plays in creating some different or even unexpected patterns of performance (by search strategy) for the firms operating under the same settings. We can easily devise idiosyncratic and path dependent situations where past behavior and choices influence subsequent firm decisions. However, we didn´t intend to emulate in this work the learning of new organizational routines as the firms interact with the environment. In this sense, what we see is really the unfolding of what is already there – it is a formative rather than a transformative teleology according to the previous arguments. It is worth clarifying that we also made use of Kauffman´s landscape model as an analogy of the competitive landscape, but the logic of learning was not included either.

Our understanding is that what distinguishes the transformative teleology is the notion (that is not built into the model) that the emergent property of the system influences agency (firm behavior) in subsequent periods. That is what Sawyer discusses as social emergentism (2001, 2005), Giddens as structuration theory (1984) or Macy and Willer suggest in their call for the micro-macro link resolution (2002).

2.6. Theories about the search mechanisms employed by firms

The notion of bounded rationality and the recognition of the roles played by ambiguity and uncertainty in the decision-making process and related outcomes of the firms challenged the neoclassical economics assumption of firms as rational, profit maximizing agents (Alchian, 1950; Simon, 1964, 1997; Thompson, 1967).

The search mechanisms to be modeled in this study follows a large stream of work that builds upon A behavioral theory of the firm (Cyert & March, 1992), with firms having routines (or search mechanisms) to solve perceived problems or needs (Nelson & Winter, 1982), including - but not being limited to - achieving superior economic performance.

Many authors explain the way firms try to differentiate themselves in order to achieve superior economic performance. Firms search for imperfections in the products or factors markets (Barney 1986; Besanko, Dranove, Shanley, and Schaefer 2004; Porter 1985). On the other hand, there is also a large literature in organizational theory that explores why firms come to be similar one to another; the causation relies on isomorphic mechanisms that operate, with or without intentionality (DiMaggio & Powell, 1983; Oliver, 1991; Scott, 2001).

In this study both accounts were taken into consideration. In our simulations firms compete with different search methods and we analyze their relative efficiency under a variety of conditions. We counted on several previous works that applied simulation methods and created computational representations of search mechanisms such as those of Abrahamson and Fairchild (1999), Abrahamson and Rosenkopf (1997), Strang and Macy (2001), Levinthal and others (Ethiraj and Levinthal 2004a; Gavetti and Levinthal 2000; Levinthal and Warglien 1999; Rivkin 2000). As we explain later, the search methods in our model resemble those of various studies, in special that of Lant & Mezias (1992).

2.7. Persistence of above average and below average performance

As we mentioned before, the persistence of above average and below average performance is a central, controversial theme in the strategy field (Arend, 2003; Barney, 1991; Durand, 2002; Jacobsen, 1988; Knott, 2003; Porter, 1985; Powell, 2001, 2003a; Powell & Lloyd, 2005; Vasconcelos & Brito, 2004; Wiggins & Ruefli, 2002).

The simulation methods employed in this study allowed us to explore or “generate” (Epstein & Axtell, 1996) the observed phenomena of sustained above average and of sustained below average performance in competitive markets with different lens.

The conditions, as originally built into our model, set a tough challenge to firms (agents) in sustaining any kind of differentiation, as detailed later in our discussions. Even though, after running the simulations, we noticed that some firms were able to consistently outperform others, while some surprisingly failed. The simulation outcomes, we believe, contribute to the discussions of Powell and others already mentioned, and at the same time introduce somewhat new arguments on why and how firms are able to achieve superior or inferior performance.

3. METHODOLOGY

In this section we explain how the research work was organized, and we describe the approach for designing and developing the software model tied to a theoretical framework of reference that would support its internal definitions and operating routines.

We formalize the variables and relationships that drive our research program, as they constitute the foundation for the development of the computer application that we built to run our model.

Finally, we provide a preliminary clarification of the limits and limitations of our work.

3.1. Methodology for the use of simulation methods

The motivation to develop this project with simulation methods comes from works such as those of March (M. D. Cohen, March, & Olsen, 1972; March, 1991), Abrahamson (Abrahamson & Rosenkopf, 1997) and Strang and Macy (2001), in which relevant theoretical propositions came out of simulation models that exhibit both parsimony and robustness.

In fields such as economics, academic journal editors already suggest shortening papers by removing discussions since the computational approach is considered "business as usual" (Miller & Page, 2007). Specialized journals in this subject already exist, such as: "Emergence: Complexity & Organization" and "Computational and Organizational Theory". Suggested principles and "good practices" have been developed for the use of simulation methods, (Davis, et al., 2007; Gilbert, 2008; Miller & Page, 2007; Pidd, 1998; Prietula, et al., 1998). Even though, some authors consider that its value for theory development remains clouded and even controversial, requiring that researchers be quite selective about what to investigate.

The present study seems to fit properly under the recommended scope of practice with simulation methods:

> Simulation is particularly useful when the theoretical focus is longitudinal, nonlinear, or processual, or when empirical data are challenging to obtain." (Davis, et al., 2007, p. 481).

We followed the basic steps found in literature of modeling and simulation methods of research (Davis, et al., 2007; Gilbert, 2008; Law, 2007; Miller & Page, 2007; Pidd, 1998; Prietula, et al., 1998), except for the empirical validation, which we addressed only indirectly within the scope of the present work:

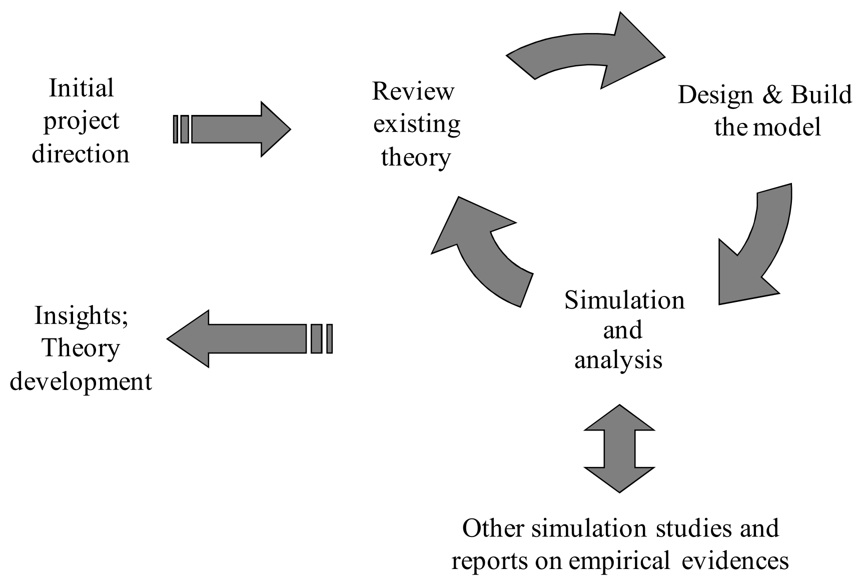


Figure 4 Methodology for the development of this work
Source: Developed by the author, based on available literature about modeling.

We defined at the very beginning of our work a research agenda around the dynamics of competition, the so-called 'longitudinal problem" of strategy (Porter, 1991). The model was initially built after extensive literature review, mainly from the journals Strategic Management Journal, Organization Science and Management Science, looking for studies making use of simulation methods to develop theoretical propositions. Several works were seminal to the initial directions taken in our study, among them: the works developed by the Santa Fe Institute, notably the "Sugarscape Model" (Epstein & Axtell, 1996) and the dynamics of cooperation represented through agent-based modeling (Axelrod, 1997).

Our initial insights directed us to the issues developed later in this work; we focused our experiments in the most promising areas, with some complimentary theory review to support the discussions. We avoided increasing the complexity of the model (for the sake of parsimony), although we made some minor adjustments (and corrections), as documented in the "Log of changes.htm" document (reproduced in the subsection: model verification and validation, and also electronically available within the system programming code).

In the following topics of this section we present our simulation model in its last version, and we comment the implications and limitations of our design choices, as far as we could realize.

3.2. Specifying the variables and relationships to be modeled

The following diagram presents the variables and relationships of our simulation model:

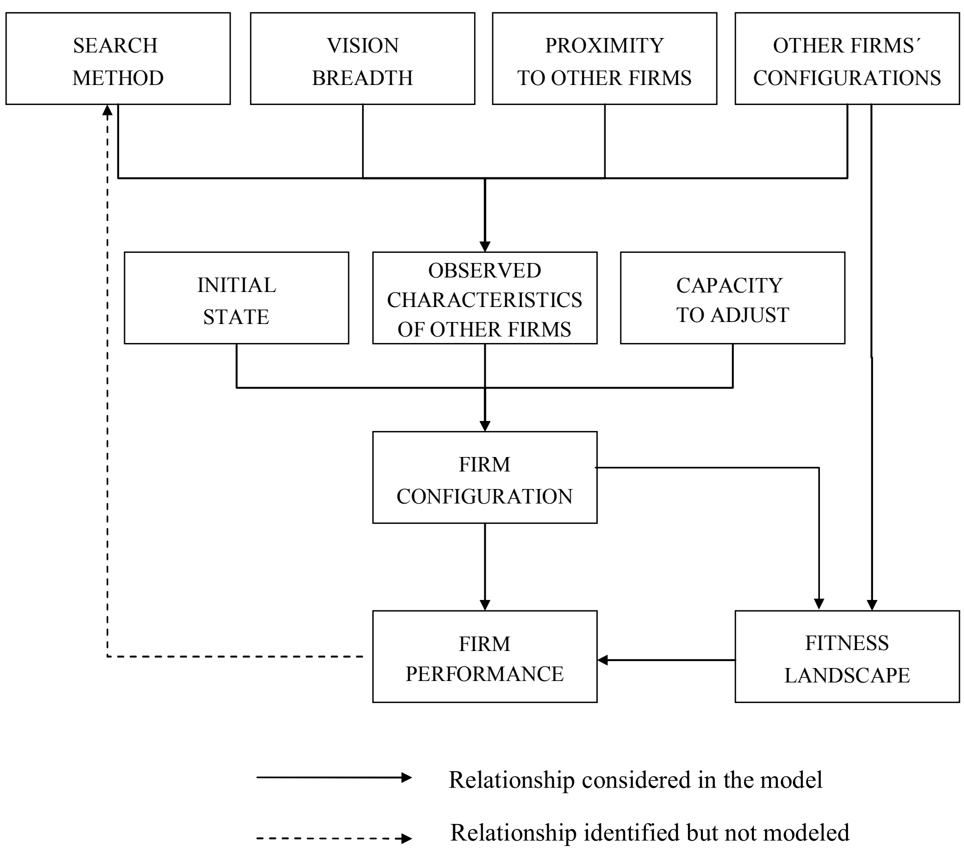


Figure 5 Variables and relationships built into the model.

We defined the variables based on both the existing theory and on developed works making use of simulation methods. By doing so, we expected to achieve some internal and external validity, following recommended practices (Davis, et al., 2007; Gilbert, 2008; Law, 2007; Prietula, et al., 1998) . We defined and operationalized all the variables as described below:

i) Search method

Definition: the logic or strategy an agent (firm) utilizes to look for improvements in its operations (Gavetti and Levinthal 2000; Rivkin 2000; Rivkin and Siggelkow 2003).

Implementation: four different search methods preliminarily configured:

i. Majority mimetism – the firm tries to improve its performance by adopting the configuration most utilized by other firms among those firms it can visualize at each specific period (round);

ii. Minority mimetism – the firm tries to improve its performance by adopting the same configuration of the leader, defined as the firm with the best fitness value among those firms it can visualize at each specific period (round); it does so with an error that can be parameterized at each different simulation;

iii. Random searching – the firm tries to improve its performance by trying new configurations at random;

iv. Market reading – the firm tries to identify what fits better to the market (by innovating), instead of looking to what and how well other firms are doing; it does so with an error that can also be parameterized for a given simulation.

The "search method" variable remains the same for the period of the simulation; it is considered a genetic endowment (Epstein & Axtell, 1996) , randomly assigned within the parameters set for the simulation (percentage of firms to be assigned to each search method). The "search method" is designed to be considered as an organizational routine - consistent (or structurally inert) for short periods of the organizational life (Cyert & March, 1992; Nelson & Winter, 1982). The search methods resemble those of various studies, in special that of Lant & Mezias (1992).

ii) Vision breadth

Definition: the number of firms that one agent can simultaneously observe in the short term in order to gather some information about the way they configure their resources (characteristics).

Implementation: the number of firms that one firm can observe at a single round during the simulation; one firm may have proximity to many firms (connections with or access to information about), but the actual number of firm observations at each round will be limited to this variable. The amount of information gathering one agent will perform depend on its "capacity to adjust" attribute.

The "vision breadth" variable is one of a genetic endowment as well as the search method (and the "capacity to adjust"). It is randomly assigned within the parameters set for the simulation (input distribution form to be utilized for random number generation and respective parameter values for the input distribution form selected). This variable is utilized in several other agent-based modeling applications, though implemented in different ways (Epstein & Axtell, 1996).

Through this variable we operationalize the notion of bounded rationality (Simon, 1997) - the firm cannot process all information that might be available through its social network – and it is aligned with other works with fitness landscapes that pose limits to information processing (Ethiraj & Levinthal, 2004a; Gavetti & Levinthal, 2000)

The "vision breadth" attribute is utilized only in the search processes of firms operating with the majority and minority mimetism methods, that require information about the configuration of other firms (random searching and market reading, as mentioned before, don´t require such information).

iii) Proximity to other firms

Definition: the list of all firms that one agent might consider to observe when searching for performance. Such set of firms would represent a variety of business conditions that explain why some firms are influential to others, such as: physical proximity (neighborhood), perception as relevant competitor, relationships at board level, business partnerships, reputation etc. Such definition allows for the accounts of isomorphic mechanisms as described in the literature of institutional theory (DiMaggio & Powell, 1983; Scott, 2001). The relevance of network connections in the search processes is at the heart of the fitness landscape model as highlighted by Gavetti and Levinthal (2000).

Implementation: pairs of firms are selected randomly at the beginning of the simulation, creating a set of firms each agent will possibly observe during the simulation run (the number of pairs depends on a simulation parameter). This approach is similar to one of the "influence matrix" operationalizations depicted by Rivkin and Siggelkow in their work (2003).

iv) Other firms´ configurations

Definition: the available information that a firm may be able to access during a simulation run of how the other firms are organizing themselves.

Implementation: see item viii – "firm configuration" variable for the details of what a specific firm configuration means.

v) Initial state

Definition: the initial configuration of the firm, assigned when the simulation is set up.

Implementation: the set up process of a simulation run assigns a random configuration to each firm, as do all other simulation studies of this kind. For more comments on the implementation: see item viii – "firm configuration".

vi) Observed characteristics of other firms

Definition: the specific information an agent can gather at a certain moment regarding the configuration of other firms. It depends on the type of information required by the "search method" of the agent, its "vision breadth", and its "capacity to adjust". An agent collects information only from the group of firms defined by "proximity of other firms".

Implementation: in each round of a simulation run, the agents have the opportunity to access information regarding other firms (if required by their respective search method). The information is limited to a pool of firms that is renewed every round, made out of the group of firms with whom the agent is connected (as defined by "proximity to other firms"). The size of the pool is limited for each agent by its "vision breadth". The amount of information about the configuration of other firms to be gathered, that is, the number of characteristics to be observed, is limited by the "capacity to adjust" of the respective agent. The definition of which characteristics to collect information about is also randomly determined for each agent, at each round.

As discussed by McKelvey (1999a), the concept of a network of connections utilized in our model is commonly utilized in agent-based models to cause "bit-flipping", that is, a change in the state of individual attributes of a certain configuration, which affects the fitness level. It is not the same sort of dynamics that network sociologists typically do, once they would look at the potential effects of centrality, structural holes etc (Burt, 1992; Padgett & Ansell, 1993)

vii) Capacity to adjust

Definition: the maximum number of characteristics in the configuration of a firm that is subject to a simultaneous change at any given moment during the simulation.

Implementation: each round a firm may search for improvements for only part of its configuration, due to the limit expressed by its "capacity to adjust". The characteristics that are subject to observation and that might be potentially changed are randomly determined at each round .

The "capacity to adjust" variable is a genetic endowment, randomly assigned within the parameters set for the simulation (input distribution form and respective parameters for this variable). The embedded notion is that firms have limits to their adaptive change process and these may vary from one to another (Cyert & March, 1992; Simon, 1997).

viii) Firm configuration

Definition: consists on a set of resources and/or capacities acquired or adopted by the firm in order to run its operations (its business model). Such a definition is broad enough as to cope with the strategy and organizational theories chosen for the present study (Barney, 1991; Cyert & March, 1992; Porter, 1996), and it is common use in management studies with simulation methods (Levinthal, 1997 and others previously mentioned).

Implementation: each firm begins a simulation run with a specific configuration, randomly assigned[2]. The configuration of a firm consists on a set of structural and flexible characteristics (or attributes), as defined by the simulation parameters. Each of the structural or flexible characteristics can assume either value "0" or "1", being the difference between these types the resilience or resistance to change. Differentiating characteristic types is one way of addressing the issue

[2] The fact that configurations are randomly assigned provides no room in our study for exploring the effect of different market structures on firm performance (Structure-Conduct-Performance paradigm as proposed in the Industrial Organization Theory).

raised by Porter & Siggelkow (2008): in fitness landscape simulation models the configuration of a firm should be treated as an activity system in which some activities may be more structurally related to others.

In our model a firm performs its search method every round, and as a result may perceive the need to change the value of a characteristic. If the observed characteristic is flexible, the firm implements the change. However, if it is structural, the firm only accumulates an observation of that value. Only after the third consecutive observation of the same value for a given characteristic a firm shall implement the change.

The characteristics may influence one another, but these interdependencies can't be directly observed or accessed by the firms during their searches (this kind of operationalization is the same one virtually all authors working with fitness landscape models utilize).

ix) Fitness landscape

We modeled two distinct landscapes in which our simulations might run.

<u>1st model: The customized landscape</u>

Definition: the set of all possible configurations that a firm might have, with the respective fitness values to be considered in each case.

Implementation: each characteristic is initially attributed a value "0" or "1", which will provide some fitness (a numeric measure) for firms holding the same characteristic value, that is, when the characteristic of the firm "matches" the landscape. The fitness contribution of each characteristic match is a random number between zero and the maximum limit defined in the simulation parameters (a different limit according to the type of characteristic). To account for the interdependence of characteristics, there is a positive or negative fitness impact assigned for various combinations of pairs of characteristics. Such combinations and their respective impacts are generated by the system according to simulation parameters (percentage of combinations; maximum limit for the impact).

Such design is similar to other landscape models, as in the work of Gavetti, Levinthal and Rivkin (2005). Our design of interdependency effects answers the critique of Porter and Siggelkow to the typical NK landscape model operationalization (2008), that is, the need of reflecting the distinctive role of key activities in a given activity system (or business model).

During the simulation, the landscape may change due to exogenous and/or endogenous causes. An exogenous change consists of changes in the value of the characteristics, with new randomly assigned fitness contributions and interdependence impacts for the combinations that involve the changed characteristic. An endogenous change consists of an increase (or reduction) in the fitness contribution associated with a specific characteristic due to the fact that too little or too many firms adopted that same attribute value. The parameters for both types of landscape change can be set at the beginning of each simulation.

2nd model: The NK model landscape

In the attempt to increase the internal validity of our model, we developed a second type of landscape in which the simulation might run, making use of the same definition and implementation of the NK model as other management studies. Our intent is to proceed with what Prietula, Carley and Gasser (1998) called "model docking", that is, an attempt to obtain convergent results utilizing two different models, in our case, two different conceptions of competitive landscape.

Definition: the multidimensional space in which every characteristic or attribute is represented by one dimension. A final dimension indicates the fitness level of the organization (Gavetti & Levinthal, 2000; Levinthal, 1997).

Implementation: we take here the detailed description in the words of Gavetti and Levinthal:

"More formally, the fitness landscape is modeled as follows. A policy is characterized as consisting of N attributes where each attribute can take on two possible values. Thus, the fitness landscape consists of 2^N possible policy choices, with the overall behavior of the organization characterized by a vector N [x_1, x_2, ..x_N] where each x_i takes on the value of 0 or 1. The contribution of a given attribute, xi, of the policy vector to the overall payoff is influenced by K other attributes.

As a result, the payoff to a particular choice, x_1, can be represented by the following expression: $f(x_i \backslash x_{i1}, x_{i2}, \ldots, x_{iK})$. The K variables with which a given element x_i interacts is specified as being the K adjacent elements (x_{i+1}, x_{i+2}, . . ., x_{i+k}). Therefore, each attribute can take on 2^{k+1} different values, depending on the value of the attribute itself (either 1 or 0) and the value of the K other attributes with which it interacts (each of these K values also taking on a value of 1 or 0). A random number drawn from the uniform distribution from zero to ,one is assigned to each of the possible $f(x_i \backslash x_{i1}, x_{i2}, \ldots, x_k)$ combination. Thus, the framework specifies the intensity of interaction effects via the parameter K but provides no restrictions on the particular functional form of the interaction effect. The overall fitness value associated with the full vector of N values, $F(x_1, x_2, \ldots, x_N)$, is simply the sum of these individual contributions divided by N: $F(x_1, x_2, \ldots, x_N) = \varepsilon_{i=1 \text{ to } N}\, f(x_I \backslash x_{i1}, x_{i2}, \ldots, x_{iK}) / N$.

To illustrate how the fitness landscape is formed, we can consider how payoffs are determined for a policy space where N, the number of dimensions, equals 10 and K equals 3. Suppose that a policy is specified by the array (1,0,0,1,1,1,0,1,0,0). The value of the first element of this array depends on the K successive elements in the array. Thus, the value of 1 in the first element of the array depends on the value of the second through fourth elements of the array. A random number, generated from a uniform distribution ranging from 0 to 1, is assigned to constitute the fitness contribution of a 1 in the first element of the array when there is a O, O, and 1 in the second, third, and fourth elements of the array, respectively. A distinct random number is assigned for the case in which there is a 1 as the second element of the array rather than a O, or any change in the third or fourth elements. This assignment is repeated for each of the N attributes of the organization, and the overall fitness for a particular organization is simply the average for the N attributes." (Gavetti & Levinthal, 2000, p.119-120)

The landscape represented by the NK model does not change during a simulation run. The following representation points to the difference in our model due to the use of the NK model (as compared to our customized landscape):

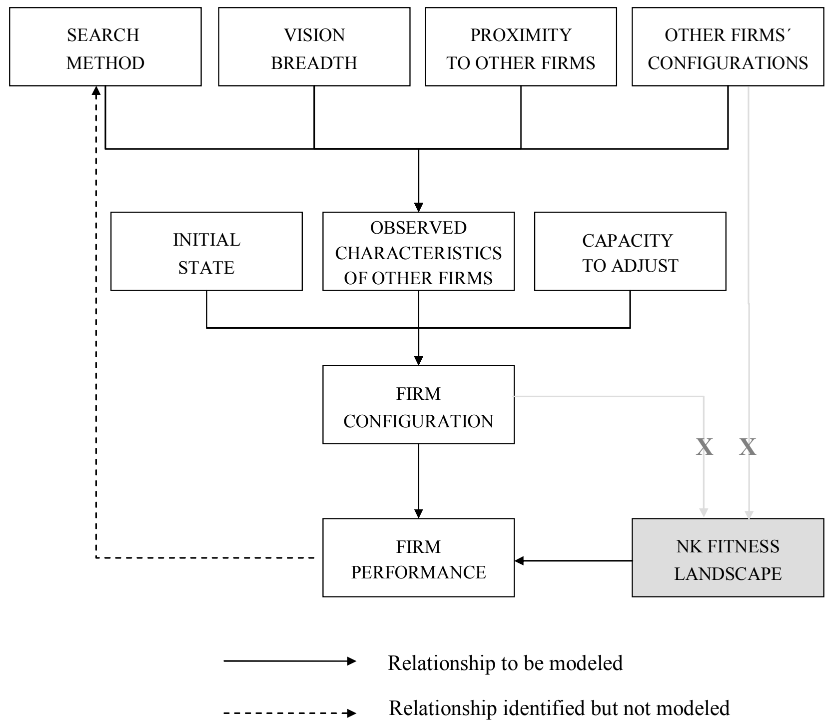


Figure 6 Variables and relationships adjusted for the NK model

x) Firm performance

Definition: it is the fitness of the organization at a given moment, due to its configuration (Gavetti & Levinthal, 2000; Levinthal, 1997; Rivkin, 2000; Siggelkow, 2002)

Implementation: the performance of a firm is the fitness level of the landscape associated with its configuration. Thus, there are two ways of calculating the fitness, depending on the landscape model.

In the NK model, as explained before, the fitness of a specific configuration is calculated as the averaged contribution of each attribute, in the range between zero and one.

In our custom model, however, the interdependency impacts may turn the highest fitness value higher than one, initially or during the course of a simulation run. To provide a better track of the relative fitness for the firms and their ability to do "hill climbing" and get to higher levels of fitness, at each round we calculate the maximum possible fitness value and divide all individual fitness scores into it.

Additional details of the variables and their relationships are available on the model specification, in the Appendix section. The way each definition was translated into an operationalization can be directly accessed within the programming code, which contains comments for all routines and procedures implemented (these comments were made available for the purpose of verification during the application development).

3.3. On the research design and its limitations

At first we make some considerations regarding the nature of our model and the use of simulation methods; then we turn to discuss identified limitations regarding its internal and external validity taking into account both the strategy and organizational theory fields.

A model, by definition, is a simplification, as a map. We hope to have built a good map for the initial research questions. In the words of Miller & Page, the model should be:

> "[…] designed to be just sufficient to tell a story that could be understood easily yet have enough substance to provide some insights into broader issues. Moving beyond the limitations of this model is going to require some compromises - namely, if we want to expand the potential for insights, we will likely need to complicate the model and, perhaps, muddy the analytic waters."(Miller & Page, 2007, p.20)

The balance between parsimony and accuracy is a judgement call, as discussed by Davis et all (2007); in order to improve the quality of our model, we relied on several other studies in the field of business strategy utilizing fitness landscapes, as mentioned in the previous subsection.

One frequent objection to computation as a research method is that the answers are "built-in" to the model, and thus one can never learn anything new from these techniques. Here we take once more the words of Miller and Page:

> "While, of course, a model can never go beyond the bounds of its initial framework, this does not imply that we cannot go beyond the bounds of our initial understanding (and in so doing allow us to develop new theoretical insights)." (2007, p.69)

We see that one way to avoid the "already built-in" objection is to design the model with parsimony, so that it becomes easy to understand how it works and what outcomes should be expected, which was exactly the first advice we quoted from Miller and Page, right above in this subsection. It is the same recommendation stressed by other authors (Macy & Willer, 2002). On the other hand, we are aware that over-simplification will lead us to what Pidd points as another thread, though this one is not exclusive of simulation methods:

> "Type Zero errors arise from inadequate attempt at problem structuring and are as liable to occur in simulation modeling as in any other management science activity." (Pidd, 1998, p.164)

Computational models may turn to be brittle, in the sense that slight changes in one area can dramatically alter their results. In this regard, we conducted robustness checks to confirm that the emerging patterns or insightful results that arose were robust for varying conditions / sets of parameters.

Special considerations about the use of simulation methods relate to randomization biases and limitations of the employed algorithms. Randomization plays an important role in our modeling; randomness can capture features like mistakes, experimentation, bounded rationality, imperfect information – all present in social systems. There is extensive literature on testing random number generators: the use of scatter plots to visualize whether potential patterns emerge, auxiliary sequences, frequency tests, serial tests, gap tests etc. We performed basic checking on algorithms already available in the development platform of our application system, Visual Basic .NET. Our testing did not identify any patterns in these programming routines. As Pidd points out, appropriate algorithms are those that, although being "pseudo-random", "*[...] are good enough to fool an observer that is ignorant of the method employed."* (1998, p.172).

We believe that we are free of the so-called set effect (special combination of random numbers) by having run several times each set of simulation parameters. As we initialized each landscape and firm configurations at every run, and the runs present quite different initial states, we believe we have also addressed the "transient effects" (potential initial bias created by the random process). Statistical techniques are applied to identify whether a "sequence effect" affect the results of the simulation (sequence in which the employed algorithm produces and combines the random numbers), but we did not make use of any special technique because our analysis from the initial simulation results didn´t indicate potential problems, neither at the micro nor at the macro levels. Other potential issues raised in the literature review were not identified during the verification and validation of our model (Law, 2007).

From a theoretical perspective, the parsimony adopted to build the model has clear drawbacks. We will comment some of them, relating to other studies with simulation methods and to some central arguments of the same schools of thought that support our work.

The model doesn´t account for second-order learning, that is, even if a firm interprets that its strategy (search method) is not working, it doesn´t change it during the course of a simulation run. We modeled such a relationship but decided not to implement it as described earlier. The reason is that we want precisely to check whether the search methods matter, and if they can help us identify sources of competitive advantage / disadvantage, instead of emulating the evolution of search methods over time. In fact, having firms with fixed, distinct search strategies throughout a whole simulation is quite usual in landscape models to evaluate their differences (Gavetti, et al., 2005; Lant & Mezias, 1992; Rivkin & Siggelkow, 2003).

One key theoretical issue in modeling is the actual duration one believes to be represented by a simulation run, that is, the meaning of "one round" – if it is a matter of days, weeks, months or years. In our case, we defined that a simulation run should last one hundred rounds, and that by doing so, we understand that we emulate competition that takes place in a period large enough as to justify above and below average performance considerations, but still within an acceptable timeframe to consider structural inertia and not to deal with the second-order learning already mentioned.

The model doesn´t consider the cost of searching, a very common issue in most studies with landscape models, although addressed with relevant contributions by others (Mezias & Glynn, 1993). It also makes no room for the discussion regarding the famous dilemma of exploration versus exploitation and the concept of ambidexterety (Andriopoulos & Lewis, 2009; Jansen, Tempelaar, van den Bosch, & Volberda, 2009; March, 1991; Rivkin & Siggelkow, 2007)

Several studies in strategy look at technological change and report evidences that different types of external change trigger different responses of the competing firms and explain the performance of the firms (Henderson & Clark, 1990; Nagarajan & Mitchell, 1998). In our model, landscape changes due to exogenous factors may be of high or low impact, although the way firms respond to change is invariably the same.

Gavetti and Rivkin discuss how search strategies change within the organizations as they get older: better knowledge of the industry allows for more rationality in their search while age is associated with the loss of plasticity (2007). Our model allows different attribute values for vision and capacity to adjust, but doesn´t consider firm aging; search method efficiencies are not directly related to the firms.

Ahuja and Katila investigate the creation of unique innovation search paths and their potential impact on competitive advantage (2004); our model considers only one elementary search method that focuses on innovation. Additional search methods would have to be created in order to deal with the issues they raised.

In the present model firms stay alive throughout the whole simulation run; while we might have dealt with entry and mortality based on other previous studies, we decided to keep it simple: firms don´t accumulate wealth (thus having slack that might alter their search strategies), don´t grow (firm size is not consider, either), they don´t acquire others, don´t form alliances neither they go out of business.

While the network of connections among firms plays a critical role in our model, network theory would surely require enhancements to our over-simplistic assumptions: structural holes and centrality positions are not potential sources of power and thus economic rents as suggested by several authors (Benjamin & Podolny, 1999; Burt, 1992; Padgett & Ansell, 1993; Podolny, Stuart, & Hannan, 1996).

One of the key factors to sustain superior economic performance is to raise barriers to imitation, either through positioning (Porter, 1985), valuable, rare, non-imitable resources and capabilities (Barney, 1986), or through some dynamic capability under the schumpeterian argument (Teece, et al., 1997). In our model, firms are able to copy others (without limitations) in the products or market factors markets. While this is clearly non-realistic, at the same time it places significant value in our simulation outcomes, as we shall see later, because we found firms that were able to sustain superior performance even in such an environment.

Rosenkopf and Nerkar provide another sample of the extent the study of search strategies evolved: moving beyond local search, firms span not only technological but also organizational boundaries (2001). Again, our model oversimplifies the search processes when confronted with the empirical evidences shown by these authors. In spite of that, we believe the model, as currently built under the scope and limits of this work, can make its contribution as presented later in this document.

The development of a simulation model is full of design decisions; every piece of code contains premises and/or assumptions about how things work: - the nature and behavior of the agents, their operating routines, the way they relate to each other, how they deal with the environment etc. We tried to present here the most relevant decisions; for sure other limitations apply.

Finally, it is salient for anyone who develops computer applications that programming steps always contain additional, detailed design decisions. We inserted comments everywhere in the programming code and we count on the .NET resources to encourage other researchers to do an on-line, structured code walkthrough and help to improve our application in a joint-effort in the near future. We would like to think this present work just as a picture out of a movie in action. For sure we can´t call our insights new theory, but what theory is not, theorizing is. (Weick, 1995).

4. DESIGN AND CONSTRUCTION OF THE MODEL

In this section we briefly present our model, its application flow and algorithms. Additional details are available in the software documentation (in the Appendix section) and in the programming code, which soon will be available for other researchers as a platform inviting for agent-based modeling system development.

It also describes the verification and validation activities considered in the scope of our work as we designed and built the model.

4.1. Platform for the development of the model

The model was custom developed in the .Net platform, with the Visual Basic language, making use of previous versions of Microsoft software that are all available for free downloading. This platform is object-oriented programming, has visual interactive simulation capability (resources) and extensive programming tools available, being one of the alternatives for the development of simulation models. (Miller & Page, 2007; Pidd, 1998).

Some agent-based modeling platforms were already available and recommended for agent-based modeling, such as NETLOGO, REPAST and SWARM (Gilbert, 2008; Robertson, 2005). We were also aware of the existence of various simulation specific developed programming languages such as SIMSCRIPT, GPSS family of computer software, CSL, SIMULA and MODSIM, as well as visual interactive modeling systems such as SIMPROCESS, Micro Saint for Windows and Stella II. We evaluated the use of those but discarded them as we had no local expertise to count on as the project moved forward.

By developing our own solution we had to face the challenge of starting from scratch but at the same time we benefited from having complete understanding (and control) of all application logic and detailed programming steps.

4.2. Model overview and high level application flow

The simulation is set up through a simulation panel that requires the definition of all parameters utilized by the model (we avoided embedding parameters in the programming code for the sake of clarity and in order to facilitate robustness checks):

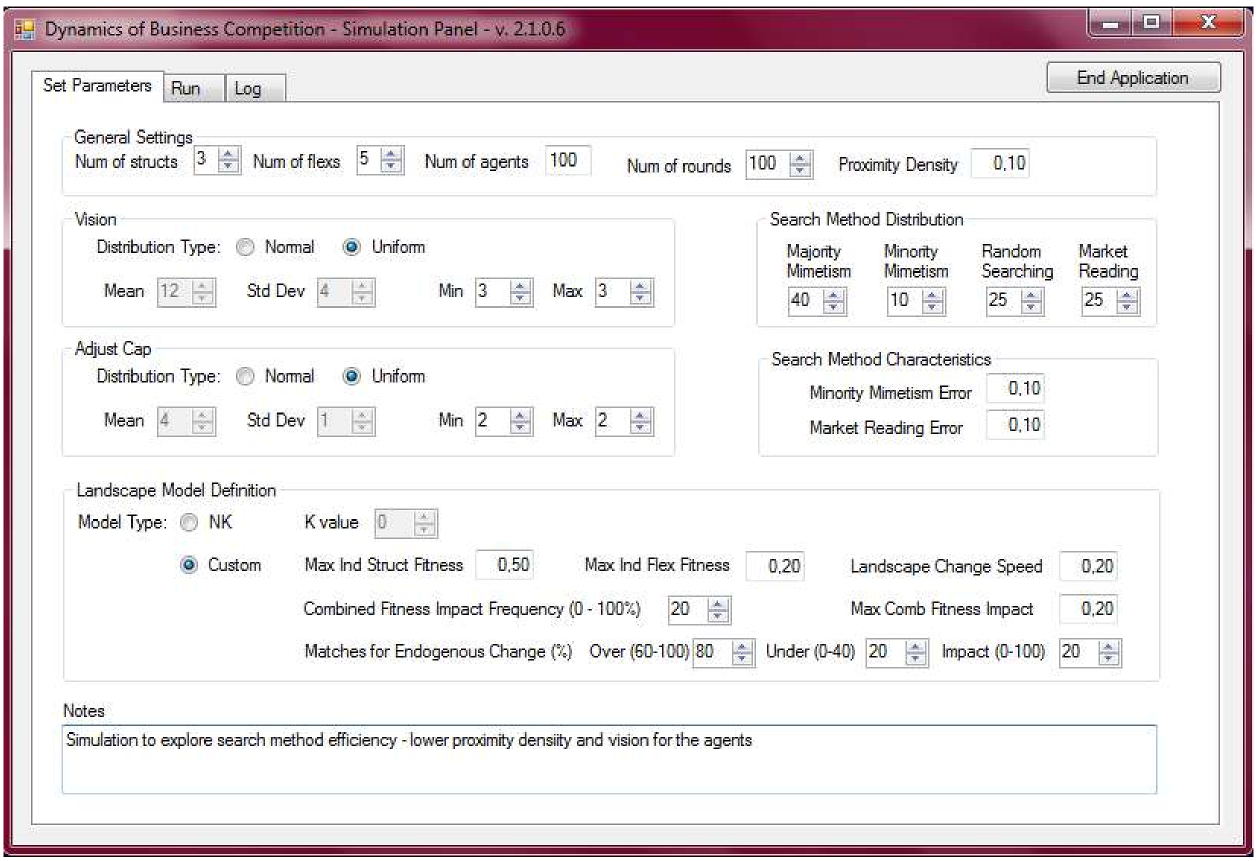


Figure 7 Simulation panel – Set parameters screen

In the sample above, the simulation considers 100 firms, each of them with 8 characteristics, 3 of the structural and 5 of the flexible types. The firms will search for performance during 100 rounds. Firms, on average, will be able to access information about 10% of the other firms (ProximityDensity parameter, which determines the amount of connections among firms).

At the population level, the firms have the following attributes:

- Uniform distribution of the Vision attribute, with minimum and maximum values equal to 3;
- Uniform distribution of the AdjustCap attribute (capacity to adjust), with minimum and maximum values equal to 2;
- The population of firms will utilize the four search methods available in the model, in the specific percentages indicated in the screen (randomly assigned to individual firms according to that proportion).

There are two parameters that regulate the expected efficiency of two search methods: for the firms assigned with the "market reading" method, their accuracy in obtaining information will be (close to) 90%; the same percentage set for the accuracy of information obtained by firms utilizing the "minority mimetism" method.

The landscape model chosen is the custom model, with the following specific parameters:

- Each structural characteristic match might yield a fitness contribution up to 0.5;
- Each flexible characteristic match might yield a fitness contribution up to 0.2;
- The interdependence of characteristics is around 20% (% of all possible combinations of two characteristics) with a potential positive or negative impact up to 0.5;
- Landscape changes due to exogenous factors: every round with 20% of probability;
- Landscape changes due to endogenous change: every round for a characteristic fitness value whenever more than 80% or less than 20% of the firms match that landscape characteristic value (0 or 1); the impact is a decrease or increase of 20%, as parameterized.

The application supports running the same simulation settings multiple times at once, and records both the summarized and detail simulation data; that is an important requirement to gain internal validity for the simulation outcomes, as we simultaneously look for consistency of these outcomes and we need to verify that the model utilizes non-patterned randomization algorithms.

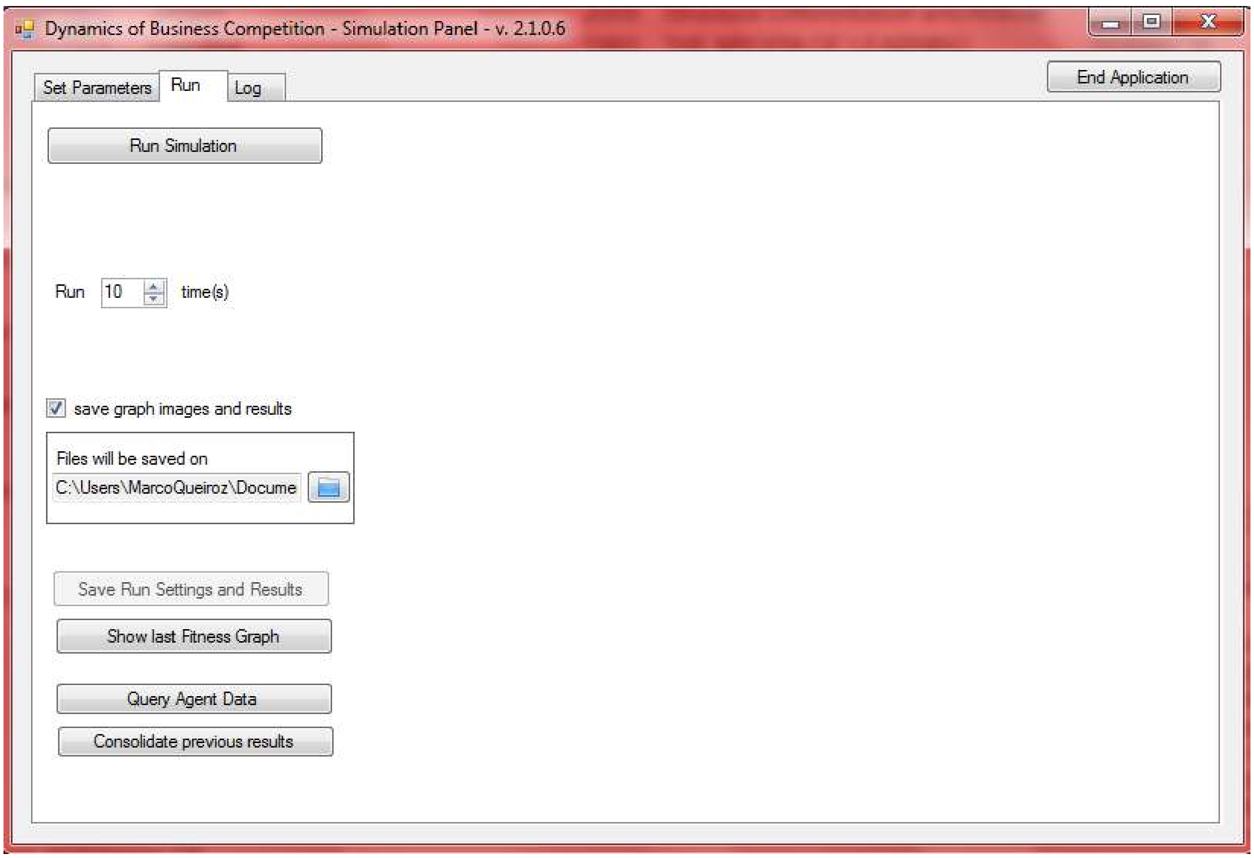


Figure 8 Simulation panel – Run screen

After defining the number of runs for the simulation parameters set, the simulation starts with the creation of the landscape:

- In the case of the custom landscape model, a landscape is created with the assignment of a value for each structural and flexible characteristic, and a fitness contribution value for each of these. Pairs of characteristics are pulled out randomly to define a "combined fitness impact" table, with corresponding fitness impacts for the "match" or "mismatch" of the respective characteristic values, also randomly generated according to the parameters set.

- In the case of the NK landscape model, the only parameter required is the K value, and the landscape is created utilizing the rules previously mentioned in this document.

The next step is the creation of the agents, with their initial states:

- For each agent, the application assigns random structural and flexible characteristic values (0´s or 1´s), a vision breadth, a capacity to adjust and a search method, all according to the defined parameters.

Then the model executes a simulation run, in which the application calls for the same routines every round:

- Each firm executes its search method once, making use of the information available at the beginning of the round (all agents move simultaneously);
- Right after all agents execute their searches, the application evaluates whether the landscape has changed (only in the case of the custom landscape model); landscape may change due to both exogenous and endogenous causes;
- Then the fitness of each agent is calculated; the results are summed up by search method, all data and all changes both in the agent and landscape characteristics or fitness values are recorded;
- The next round begins or the simulation run ends if it has reached the total number of rounds defined. In the later case, the application calculates and records information and results of the run and saves the graphical images of search method performance throughout the run. It also saves the detailed information on agent data and fitness data, by round, for that run.

The model executes all runs requested, keeping internal control of the number of sequential runs within a same simulation setting.

It is possible to visualize the simulation run during its execution through a graphical display of search method performance, as shown below:

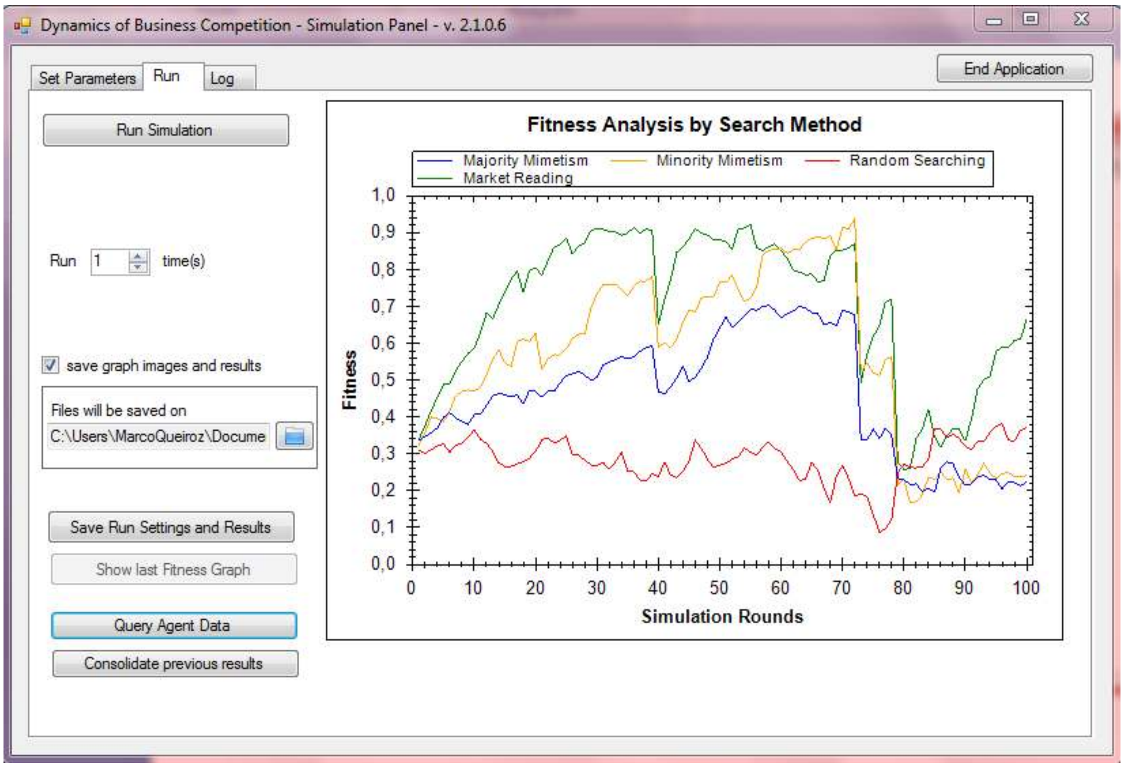


Figure 9 Simulation panel – Run screen (after the execution of a simulation run)

In the illustration above, one may want to check what caused most firms to have a significant drop of performance between the rounds 70th and 80th. A zoom feature is available on the screen to get a precise look at a round within which the drop seems to be greater:

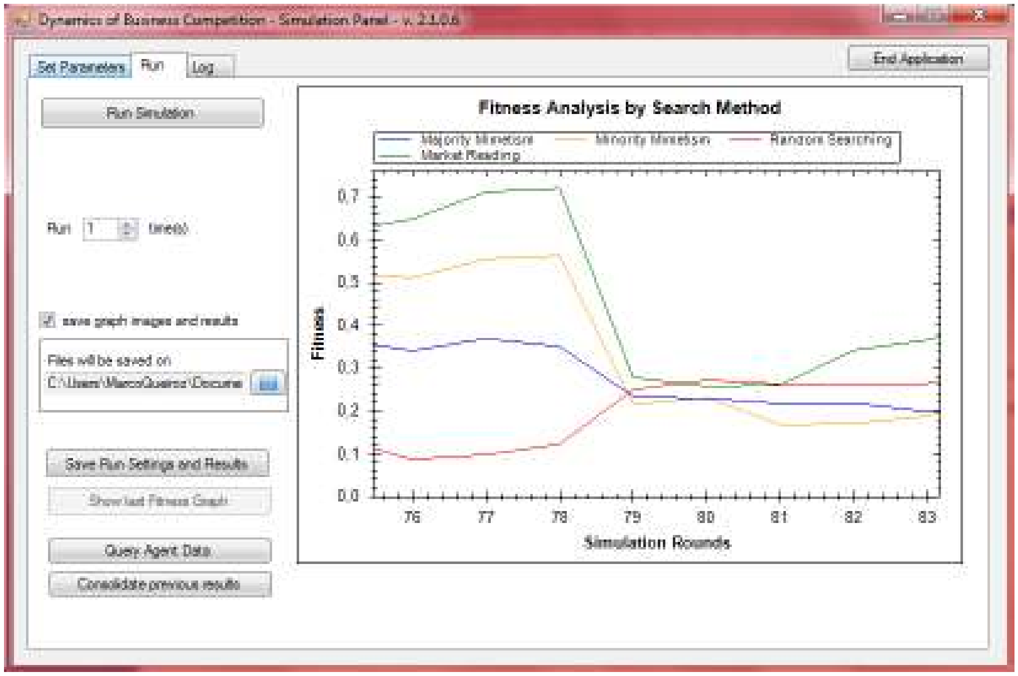


Figure 10 Simulation panel – Run screen (zoom applied to a simulation run)

One of the ways to understand what happened is to query specific agent information at that specific round, a feature made available in our custom landscape model to help us track whether the system is performing as designed, that is, for model verification purposes. We present the following detailed example we believe will help the reader get a better understanding of how our model works:

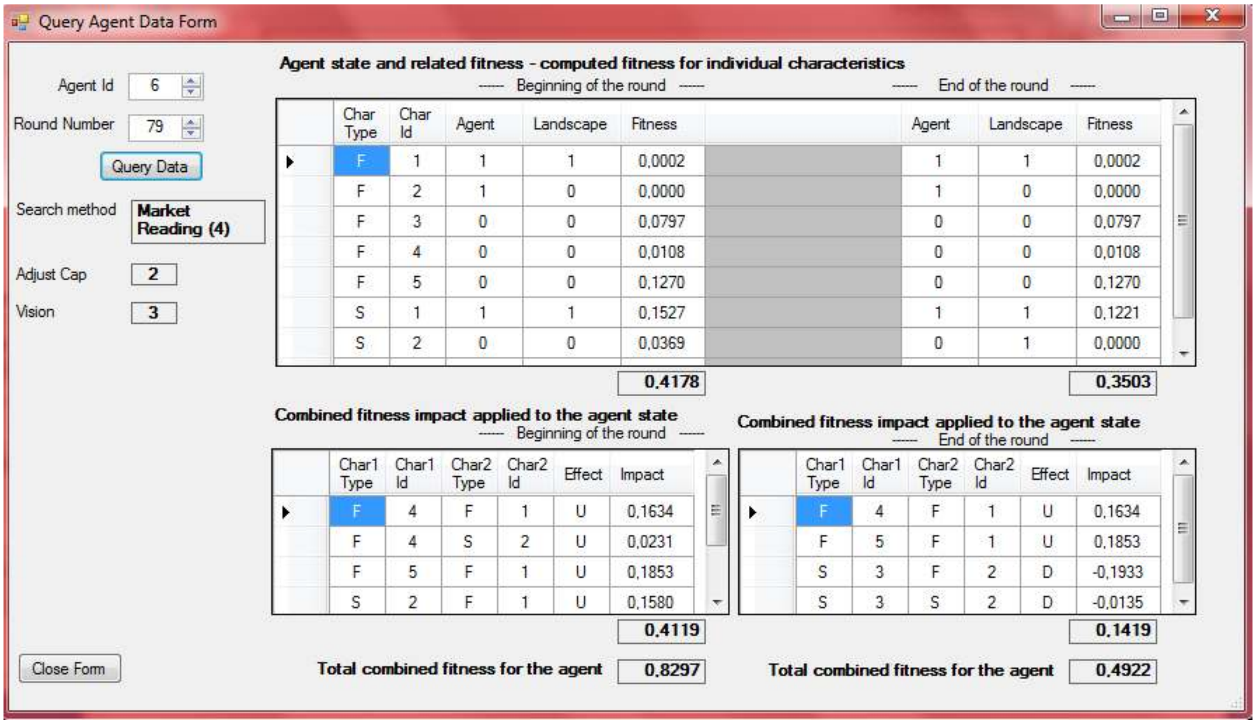


Figure 11 Query Agent Data Form – Information on specific agent and round

In the case illustrated above, agent (firm) 6 makes use of the market reading search method. It dropped significantly from one round to another, without any change in its own configuration. Two landscape changes can be identified:

- Endogenous change in structural characteristic number one (S1): following the simulation settings, when more than 80% of the agents adopt the same characteristic value at a specific round, the characteristic loses 20% of its individual fitness value. That happened in this case, and this can also be verified through queries into the system databases if necessary;
- Exogenous change in structural characteristic number two (S2): “flipping” from 0 to 1. In this case, this also affected the agent as it no longer matches this characteristic and neither is able to get the upside effects that come from the interdependency of S2 with structural characteristic number three (S3), flexible characteristics one and four (F1 and F4). Additionally, the landscape change also altered the interdependency effects as well. By the end of the round, S2 and S3 no

longer provides a bonus for alignment (upside effect), but a penalty for misalignment – which in fact applies to the firm. The screen below shows the same agent data, after scrolling the side bars in order to access the rest of the information required to support this example.

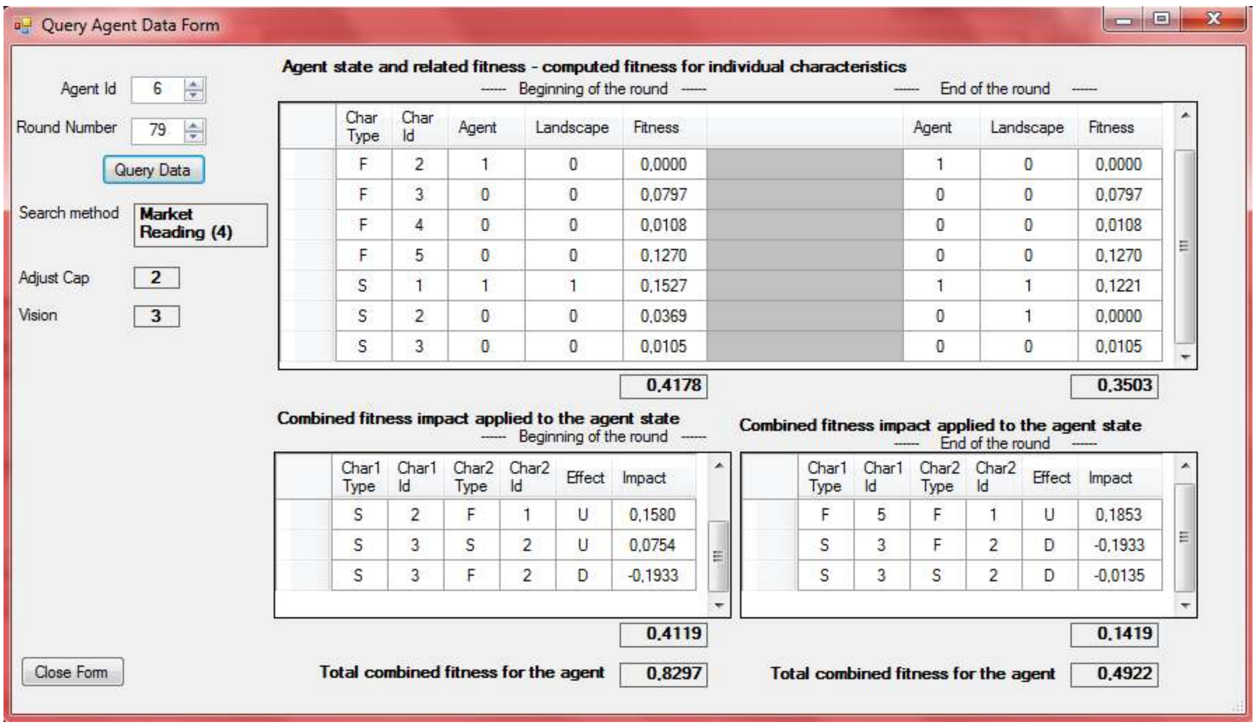


Figure 12 Query Agent Data Form – Information on specific agent and round (after scrolling)

As said before, the platform chosen for our system development provides extensive support to analyze the outcomes of our model. Easy access to the databases enables data export as desired. This is helpful to analyze a single simulation run, but not for grouping and processing detailed information for multiple runs.

To address this second requirement, we developed a consolidation function, which gathers all agent and fitness track detailed information generated in all runs of a simulation setting (originally stored under automatic generated file names agent.txt and fitness.txt). This function also provides the identification of above average and below average performance in each run, according to the number of standard deviations requested by the user. The consolidation is done into a database specifically created for this purpose, and the data can be copied directly into

Microsoft Excel spreadsheets or Minitab for statistical analysis. This is how the user interface looks like:

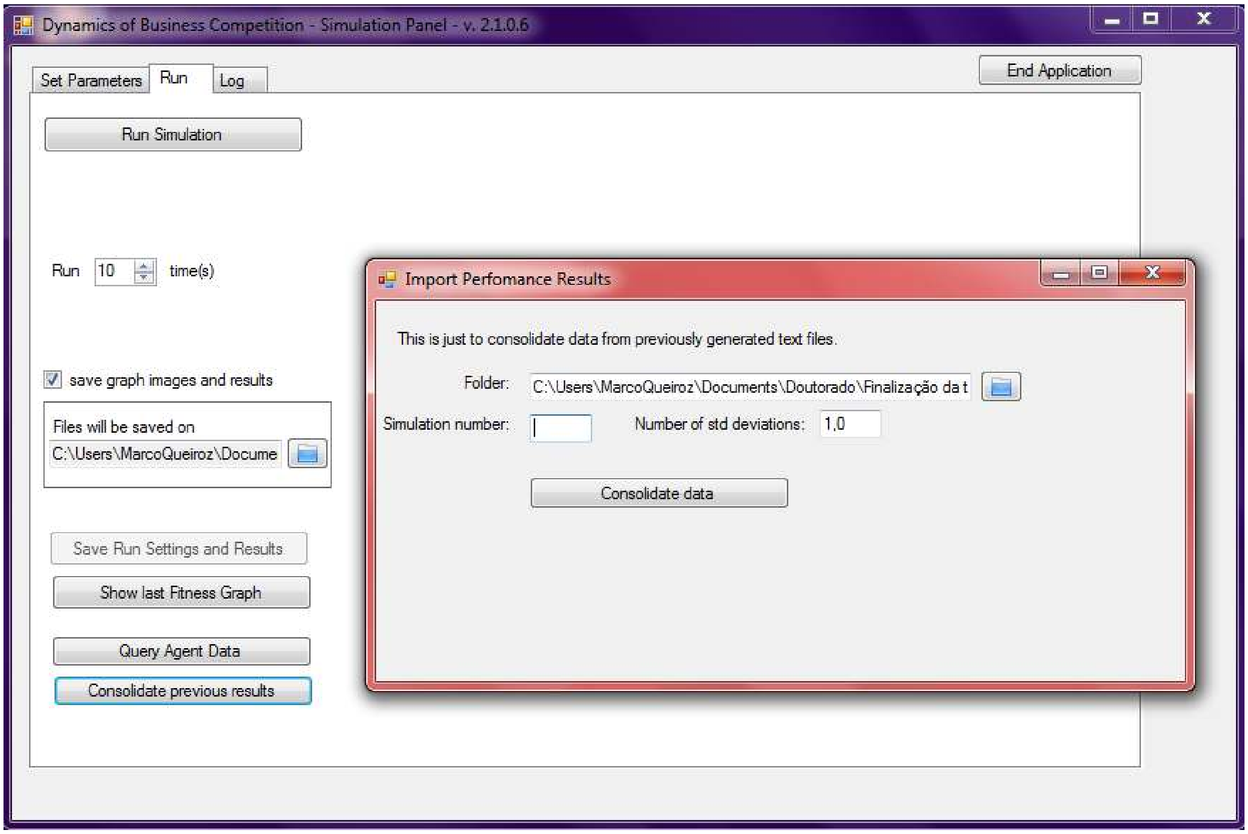


Figure 13 Consolidate previous results – data import function

4.3. Model verification and validation

A model requires both verification and validation. Verification refers to whether a model performs as the model developer and the programmer intended to, by matching the computer model against its intentional design specification. Validation aims at matching the model against its "real world" subject (Davis, et al., 2007; Gilbert, 2008; Law, 2007; North & Macal, 2007; Pidd, 1998):

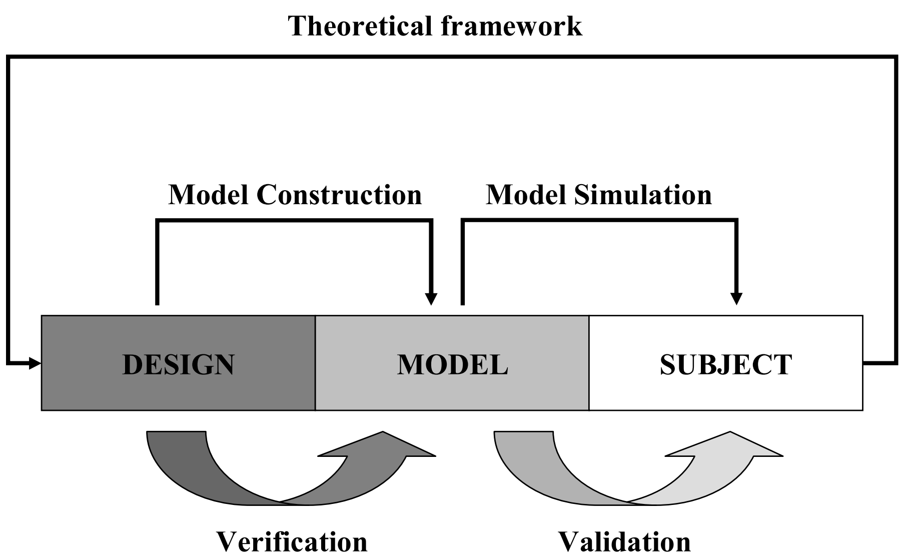


Figure 14 Model verification and validation

Source: Developed by the author.

The specifications of our model were supported by existing knowledge in the field, as demonstrated previously in this document. The technical specifications of the computer model, comprising the definition of all databases, the application flow and the outcomes were all done by the researcher, facilitated by his previous professional background with application systems development.

Commonly used programming techniques were applied to verify that the computer model performed as designed (structured code walkthroughs, structured debugging walkthroughs, unit testing). Such techniques are fully supported by already built-in capabilities of the development platform chosen (.NET has on-line walkthroughs and debugging tools).

For verification purposes, the application was designed in such a way that it keeps track of all changes in all agents and landscape states at all rounds of a simulation run. The additional tables, fields and programming logic required for such verification substantially increased the development effort, but allowed for in-depth verification of the coding and the verification of simulation results.

Indeed, we performed extensive "fine tuning" of our system. While the application development took approximately six months of intensive work (from August, 2008 to February, 2009), the review and enhancements of our model had almost eighteen months of elapsed time - from February, 2009 to September, 2010, our current software version.

The major corrections and enhancements are recorded in the system "Log of changes.htm" document, maintained inside the software platform and reproduced below:

Table 1 Dynamics of Business Competition – Log of System Changes
Updated on Sep-17-2010

Version 2.1.0.6 released on Sep-17-2010
Funcionality added:
1. Included Number of Standard deviations in "consolidate data form" function.

Version 2.1.0.5 released on Aug-20-2010
Funcionality added:
1. Auxiliary tables to support consolidation of previously generated data.

Version 2.1.0.4 released on Dec-14-2009
Funcionality added:
1. Implemented the Minority Mimetism Error concept, similar to Market Reading Error concept.

Funcionality added:
1. When processing a multi-run simulation, a tab separated text file is generated with the agent data at the end of each run.
2. When processing a multi-run simulation, a tab separated text file is generated with the agent fitness track data at the end of each run.

Version 2.1.0.3 released on Dec-03-2009
Funcionality added:
1. When processing a multi-run simulation, an html page file is generated to view the graphs, 2 by row.

Funcionality corrected:
1. When processing a simulation with multiple Runs, form data verification were done but processing continued even when data verification failed.

Version 2.1.0.2 released on Dec-02-2009
Funcionality added:
1. 3 new fields were addeed to the the Simulation Panel: Matches for Endogenous Changes Over, Under and Impact.

Funcionality modified:
1. When processing a simulation with more than 1 run, graphic file names are generated in the following template: **SIMssssRUNrrrr**, where ssss is the simulation ID and rrrr is the running id within the simulation. Example: SIM0010RUN015.jpg is the graphic for the 15th run in the simulation number 10.

Funcionality corrected:
1. Database function SettingsHaveChanged did not detected correctly changes in the Landscape related to the Market Reading Error.
2. Graphic file names were generated with time stamp missing the hours information.

Version 2.1.0.1 released on Nov-13-2009
Funcionality corrected:
1. Database function SettingsHaveChanged did not detected correctly changes in the Landscape related to the Model type and K Value.

Version 2.1 released on Nov-11-2009
Funcionality added:
1. Minor changes in information display.

Version 2.0 released on Apr-23-2009
Funcionality added
1. NK Model implemented.

Version 1.0 released on Feb-13-2009
Characteristics
1. Initial version.

The validation of a model may consider two different approaches: the “blackbox” and the “whitebox” (Pidd, 1998). The first one validates the functioning of the model by checking whether the outputs match the expected results, considering the inputs to the model. That is not possible in our case as there is no real situation to compare with. The “whitebox” approach performs extensive checking of the internal structure of the model, which was applied in our case, as demonstrated in the previous page.

As Davis et al remind us (2007), simulation methods may have adequate internal validity but probably lack external validity when they are applied to study longitudinal, nonlinear process phenomena for which empirical evidences are challenging to obtain. They state that the need of empirical data validation is contingent on such cases:

> “Our view is contingent – that is, the importance of validation should depend on the source of the simple theory that is the basis of the simulation. If this theory is based primarily on empirical evidence (e.g.,field-based case studies and empirically grounded processes), then validation is less important, because the theory already has some external validity. In contrast, if the theory is based primarily on non empirical argument (e.g., formal analytic modeling) or on evidence from distant scientific disciplines, (e.g., physics), then validation is more important.” (Davis, et al., 2007, p. 494)

That doesn´t waive us from gathering empirical evidences and improve the validation of this work, however. In fact, it is more a matter of precedence. We need first to raise some interesting insights, and then move on to the real world and find out creative ways to search for empirical evidences that would support them. That is precisely what we propose at the end of this study as next steps and future directions.

5. PLAN AND EXECUTION OF EXPERIMENTS

The computer simulations of competitive dynamics allow investigating the efficiency of search strategies and competitive advantage in a longitudinal perspective. The simplification required for modeling limits the validity of the outcomes, but at the same time provides new insights and/or raises intriguing questions regarding central issues of strategic management.

In this section we present the analysis of the simulations performed. We selected some of the outcomes and discuss their potential causes and/or implications.

The statistical analysis performed in this study was supported by the software Minitab 16. All charts and statistical tests are presented in the output form provided by the tool, with footnotes and additional comments where required.

Additional details are available in the Appendix section, as well as in the electronic version of this work, soon to be available with the full software platform and all executed simulation files.

5.1. Initial hypotheses and the planning of experiments

Our *ex-ante* research questions (presented in subsection 1.2) still drive our analysis, although the development of our simulation model revealed various promising investigation paths.

The following table summarizes the arguments that we considered when we planned the experiments. They were based on the theory review and the design specifications of our model.

This was a necessary step taken in the development of this study to delineate a manageable set of scenarios to be simulated. Additional scenarios were later included in the final test plan (as we mention later in this same section), in order to verify some of the initial premises and support our conclusions on the simulation results.

Variation on parameters (sensitivity analysis)	**Potential sources of expanation for**	
	Efficiency of search methods	**Persistence of below /above average performers**
Basic settings		
Structural characteristics Flexible characteristics	Number of characteristics turns the landscape more complex, and that may affect the relative performance of the various search methods	
Agents	No planned variations for this parameter	
Rounds	No planned variations for this parameter	
Proximity density		
% connections among firms	Mimetism strategies depend on the information of others to work	Low levels of connectivity reduce spillover of practices, thus sustaining differences
Vision		
Type (Normal or Uniform) Min - Max or Mean - STD	Mimetism strategies work better if more information is available	Different attribute values may explain above and below average performances
Capacity to adjust		
Type (Normal or Uniform) Min - Max or Mean - STD	Affects the efficency of the search methods	Different attribute values may explain above and below average performances
Search Method		
% of firms Majority mimetism % of firms Minority mimetism Reading error % of firms Random searching % of firms Market reading Reading error	Impacts the relative efficiency of search methods (mimetism depends on the strategy of others; error reading errors reduce efficiency as well)	Inefficiency of mimetism strategies under certain scenarios (explaining below average performance)
Landscape model Custom model		
CombinedImpactFrequency	Impact is associated with the number of structural and flexible characteristics	
Max struct fitness Max flex fitness Max combined impact	No planned variations for these parameters (keep a manageable number of simulation settings)	
Exogeneous change	Convergence towards fit with more stable landscapes	
Endogenous change Under / Over / Impact	Decreasing returns for most copied configurations; increasing returns for successful innovation	
NK model		
K value	NK model will be utilize to perform some "docking", that is, confirm results produced with the custom landscape model	

Frame 1 Potential areas for experimentation

Instead of going through the details that support the logic of the arguments presented in the previous table, or translate them to formal terms, we move directly into our final experiment plan with selected simulation settings, present the simulation results and our subsequent analysis, which includes regression tests and discriminant analysis that provide a proper, formal support for our findings.

Our final experiment plan comprised many sets of simulations where only few parameters were changed and we analyzed both the variations on search method efficiencies and the occurrence of above/below average performance.

We set an arbitrary baseline to allow our experiments. The baseline is represented in simulation 63, and changes in parameters to this baseline are highlighted to facilitate understanding of the proposed variations on simulation settings and the comparisons of simulation outcomes.

In the following tables we present these settings, together with explicative notes of our reasoning to select the respective parameter values or variations:

Table 2 Final test plan – Settings for simulations 57 to 62

SimulationID	57	58	59	60	61	62
Number of runs	10	10	10	10	10	10
Basic setting						
Characteristics						
structural	3	3	3	3	3	3
flexible	5	5	5	5	5	5
Agents	100	100	100	100	100	100
Rounds	100	100	100	100	100	100
Proximity density	10%	20%	30%	10%	20%	30%
Vision						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	3 - 3	3 - 3	3 - 3	10-10	10-10	10-10
Capacity to adjust						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	2 - 2	2 - 2	2 - 2	2 - 2	2 - 2	2 - 2
Search Method						
Majority mimetism	40	40	40	40	40	40
Minority mimetism	10	10	10	10	10	10
Reading error	10%	10%	10%	10%	10%	10%
Random searching	25	25	25	25	25	25
Market reading	25	25	25	25	25	25
Reading error	10%	10%	10%	10%	10%	10%
Landscape model						
Custom model	Y	Y	Y	Y	Y	Y
Combinedimpact frequency	20%	20%	20%	20%	20%	20%
Max struct fitness	0,5	0,5	0,5	0,5	0,5	0,5
Max flex fitness	0,2	0,2	0,2	0,2	0,2	0,2
Max combined impact	0,2	0,2	0,2	0,2	0,2	0,2
Landscape changespeed	0,2	0,2	0,2	0,2	0,2	0,2
Endogenous change						
Under / Over	20-80	20-80	20-80	20-80	20-80	20-80
Impact	20%	20%	20%	20%	20%	20%
NK model						
K value						

In these initial settings presented in the table above, we were willing to observe the efficiency of the search methods under different levels of information available to firms operating under the majority and minority mimetism search strategies.

Table 3 Final test plan – Settings for simulations 63 to 68

SimulationID	**63**	**64**	**65**	**66**	**67**	**68**
Number of runs	10	10	10	10	10	10
Basic setting						
Characteristics						
structural	3	3	3	3	3	3
flexible	5	5	5	5	5	5
Agents	100	100	100	100	100	100
Rounds	100	100	100	100	100	100
Proximity density	20%	20%	20%	20%	20%	20%
Vision						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	5 - 5	5 - 5	5 - 5	5 - 5	5 - 5	10 - 10
Capacity to adjust						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	2 - 2	2 - 2	2 - 2	2 - 2	2 - 2	2 - 2
Search Method						
Majority mimetism	40	25	60	60	40	40
Minority mimetism	10	25	15	10	10	10
Reading error	10%	10%	10%	10%	0%	0%
Random searching	25	25	10	20	25	25
Market reading	25	25	15	10	25	25
Reading error	10%	10%	10%	10%	10%	10%
Landscape model						
Custom model	Y	Y	Y	Y	Y	Y
Combinedimpact frequency	20%	20%	20%	20%	20%	20%
Max struct fitness	0,5	0,5	0,5	0,5	0,5	0,5
Max flex fitness	0,2	0,2	0,2	0,2	0,2	0,2
Max combined impact	0,2	0,2	0,2	0,2	0,2	0,2
Landscape changespeed	0,2	0,2	0,2	0,2	0,2	0,2
Endogenous change						
Under / Over	20-80	20-80	20-80	20-80	20-80	20-80
Impact	20%	20%	20%	20%	20%	20%
NK model						
K value						

As we can see in the above table, in the settings under analysis we changed the percentage of firms utilizing each search method. We created two specific settings where we reduced the minority mimetism reading error, a plausible theoretical scenario with interesting implications as we discuss later in this work, and we also increased the amount of information about a specific characteristic that firms utilizing search methods based on mimetism are able to gather at each round (that is, the number of firms to be observed).

The next table presents a whole set of simulations with various significant and sometimes simultaneous changes in the baseline parameters:

Table 4 Final test plan – Settings for simulations 69 to 72

SimulationID	69	70	71	72
Number of runs	10	10	10	10
Basic setting				
Characteristics				
structural	3	3	3	1
flexible	5	5	5	8
Agents	100	100	100	100
Rounds	100	100	100	100
Proximity density	20%	20%	20%	20%
Vision				
Type (Normal or Uniform)	U	U	U	U
Min - Max or Mean - STD	10 - 10	10 - 10	10 - 10	10 - 10
Capacity to adjust				
Type (Normal or Uniform)	U	U	U	U
Min - Max or Mean - STD	2 - 2	2 - 2	2 - 2	2 - 2
Search Method				
Majority mimetism	60	60	40	60
Minority mimetism	15	15	10	15
Reading error	10%	10%	0%	10%
Random searching	10	10	25	10
Market reading	15	15	25	15
Reading error	10%	10%	20%	10%
Landscape model				
Custom model	Y	Y	Y	Y
Combinedimpact frequency	20%	20%	20%	0%
Max struct fitness	0,5	0,5	0,5	0
Max flex fitness	0,2	0,2	0,2	0,2
Max combined impact	0,2	0,2	0,2	0
Landscape changespeed	0,2	0	0,2	0,4
Endogenous change				
Under / Over	20-80	20-80	20-80	20-80
Impact	20%	20%	20%	20%
NK model				
K value				

The settings for simulations 69 to 72 have an increase in the Vision parameter (compared to the baseline); we stretched the potential impact of fads / bandwagon effects with a high increase at the percentage of firms adopting the majority mimetism search method.

In one of the simulation scenarios we set exogenous change in the landscape to zero.

By simultaneously changing the reading errors associated with the minority mimetism and market reading methods in simulation 71 we stretched the challenge of innovation (in a model with practically no barriers to imitation, by design).

The last scenario emulates competition in a high-changing competitive landscape where firm configurations are easy to imitate.

Table 5 Final test plan – Settings for simulations 73 to 78

SimulationID	**73**	**74**	**75**	**76**	**77**	**78**
Number of runs	10	10	10	10	10	10
Basic setting						
Characteristics						
structural	5	5	5	3	3	5
flexible	7	7	7	5	5	7
Agents	100	100	100	100	100	100
Rounds	100	100	100	100	100	100
Proximity density	20%	20%	20%	20%	20%	20%
Vision						
Type (Normal or Uniform)	U	U	U	N	N	N
Min - Max or Mean - STD	10-10	5 - 5	5 - 5	8-2	8-2	8-2
Capacity to adjust						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	2 - 2	2 - 2	2 - 2	2 - 2	1 - 3	1 - 3
Search Method						
Majority mimetism	40	40	60	40	40	60
Minority mimetism	10	10	15	10	10	15
Reading error	10%	10%	10%	10%	10%	10%
Random searching	25	25	10	25	25	10
Market reading	25	25	15	25	25	15
Reading error	10%	10%	10%	10%	10%	10%
Landscape model						
Custom model	Y	Y	Y	Y	Y	Y
Combinedimpact frequency	20%	20%	20%	20%	20%	20%
Max struct fitness	0,5	0,5	0,5	0,5	0,5	0,5
Max flex fitness	0,2	0,2	0,2	0,2	0,2	0,2
Max combined impact	0,2	0,2	0,2	0,2	0,2	0,2
Landscape changespeed	0,2	0,2	0,2	0,2	0,2	0,2
Endogenous change						
Under / Over	20-80	20-80	20-80	20-80	20-80	20-80
Impact	20%	20%	20%	20%	20%	20%
NK model						
K value						

Simulations 73 to 78 were intended to provide comparisons with other simulation settings displayed in previous tables. Some of the variations allowed the investigation of our second area of interest: the above average and below average performance. While superior (or inferior) performance had already been identified in previous scenarios where all firms held the same values for these attributes, the settings with different Vision and AdjustCap parameter values are expected to have greater influence in the occurrence of above and below average performance. As one might have noticed, the complexity of the competitive landscape also increased due to the number of structural and flexible characteristics.

Table 6 Final test plan – Settings for simulations 79 to 84

SimulationID	**79**	**80**	**81**	**82**	**83**	**84**
Number of runs	10	10	10	10	10	10
Basic setting						
Characteristics						
structural	3	3	3	3	3	3
flexible	5	5	5	5	5	5
Agents	100	100	100	100	100	100
Rounds	100	100	100	100	100	100
Proximity density	20%	20%	20%	20%	20%	20%
Vision						
Type (Normal or Uniform)	U	U	U	U	U	N
Min - Max or Mean - STD	5 - 5	5 - 5	5 - 5	5 - 5	10 - 10	8 - 2
Capacity to adjust						
Type (Normal or Uniform)	U	U	U	U	U	U
Min - Max or Mean - STD	2 - 2	2 - 2	2 - 2	2 - 2	2 - 2	1 - 3
Search Method						
Majority mimetism	50	50	50	70	50	50
Minority mimetism	25	25	25	15	25	25
Reading error	10%	10%	10%	10%	10%	10%
Random searching	25	25	25	15	25	25
Market reading	N/A	N/A	N/A	N/A	N/A	N/A
Reading error						
Landscape model						
Custom model	N	N	N	N	N	N
Combinedimpact frequency						
Max struct fitness						
Max flex fitness						
Max combined impact						
Landscape changespeed						
Endogenous change						
Under / Over						
Impact						
NK model						
K value	0	1	2	2	3	3

Simulation settings 79 to 84 utilized the NK model. These simulations provided additional insights on how firms perform under the competitive dynamics modeled. They confirm, to some extent, the predictions of the NK model, and allowed the comparison of the customized landscape model outcomes with those of the well-known NK model (the verification procedure of "docking" our model, as mentioned before, although with limitations that derive from its own idiosyncratic design).

Table 7 Final test plan – Settings for simulations 85, 88 to 91

SimulationID	**85**	**88**	**89**	**90**	**91**
Number of runs	10	10	10	10	10
Basic setting					
Characteristics					
structural	5	3	3	3	3
flexible	8	5	5	5	5
Agents	100	100	100	100	100
Rounds	100	100	100	100	100
Proximity density	20%	20%	20%	20%	20%
Vision					
Type (Normal or Uniform)	N	U	U	U	U
Min - Max or Mean - STD	12 - 4	10-10	10-10	5 - 5	10 - 10
Capacity to adjust					
Type (Normal or Uniform)	N	U	U	U	U
Min - Max or Mean - STD	4 - 1	4 - 4	4 - 4	2 - 2	2 - 2
Search Method					
Majority mimetism	40	40	40	40	60
Minority mimetism	20	10	10	10	15
Reading error	10%	10%	10%	10%	10%
Random searching	20	25	25	25	10
Market reading	20	25	25	25	15
Reading error	10%	10%	10%	10%	10%
Landscape model					
Custom model	Y	Y	Y	Y	Y
Combinedimpact frequency	20%	20%	20%	20%	20%
Max struct fitness	0,5	0,5	0,5	0,5	0,5
Max flex fitness	0,2	0,2	0,2	0,2	0,2
Max combined impact	0,2	0,2	0,2	0,2	0,2
Landscape changespeed	0,2	0,2	0,2	0,2	0,4
Endogenous change					
Under / Over	20-80	20-80	0-100	0-100	20-80
Impact	20%	20%	0%	0%	20%
NK model					
K value					

Our last group of simulations - 85, 88 to 91 - consisted of parameter variations defined to verify if our findings were, to some extent, robust.

We stressed the differences among the firms in simulation 85. In simulations 88 e 89 we tested to validate our initial perception regarding the impact of the AdjustCap (capacity to adjust) parameter. In two scenarios we set the endogenous change off, and finally we considered a high changing environment within which companies were less flexible to change (due to the setting of structural characteristics).

All the simulation results for these scenarios are available in the Appendix section. In the next pages we present our analysis based on selected aspects of the simulation outcomes.

5.2. About the efficiency of the search methods

The opening frame of this subsection consolidates our report on the changes in parameter settings, simulation outcomes and impacts observed.

We dedicated the rest of this subsection to detail our simulation outcomes and analysis.

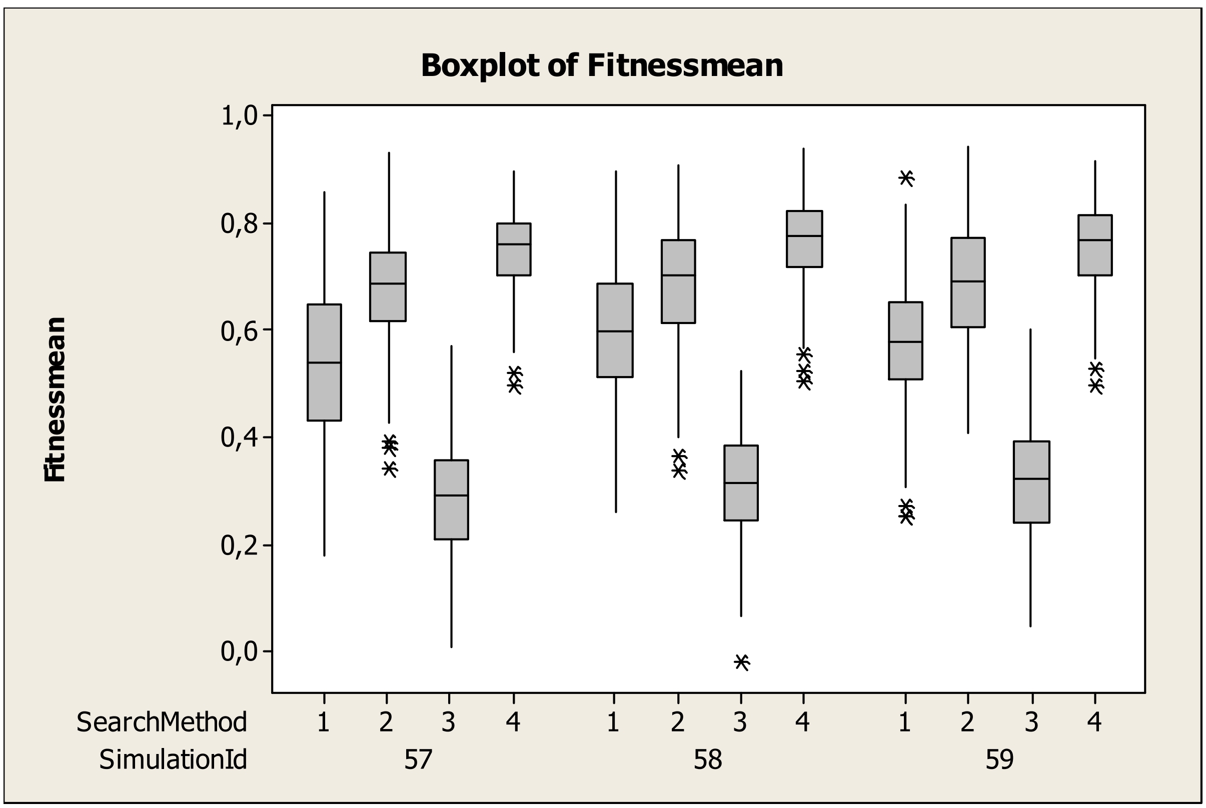
EFFICIENCY OF SEARCH METHODS

Subsection	Changes in simulation parameters	Impact detected?	Description	References (simulations)	Key considerations
5.2.1	ProximityDensity impact	Small impact	Relative performance of minority and majority mimetism methods	57-58-59 e 60-61-62	Moderate levels of contact are enough for diffusion of practices. Vision makes mimetism strategies work (on average). Under settings of low or medium connectivity among firms, informational traps may occur.
	Vision	Yes		58-61-63; 57-60; 59-62	
	Combinations of ProximityDensity/Vision	Yes		57 to 63	
5.2.2	Capacity to adjust	Yes	Impact is mediated by size of configuration and Vision.	63-74; 61-88	Mimetism methods improve as capacity to adjust gets higher in relation to number of characterisitcs (given the same landscape changespeed).
5.2.3	Search method population distribution	Yes	Relative performance of mimetism methods	63 to 66; 74-75; 81-82	Differences among settings and runs within s specific setting. Path dependence and idisyncratic effects observed. As the capacity to adjust becomes relatively lower, mimetism methods are less prone to bandwagons and traps. Strategy of others matter.
5.2.4	Search method accuracy of innovation and imitation	Yes	Relative performance of minority mimetism and market reading methods	63-67; 61-68-71	Innovation works only under low error rates as imitators are relatively fast to copy successful configurations. Excelent imitators do better than good innovators.
5.2.5	Landscape number and interdependency of characteristics	Yes	Mimetism methods are more impacted by complexity increase	61-73; 63-74; 65-75; 79-80-81	Higher levels of complexity are harder for imitators. Stability of NK model allows both methods to do "hill climbing", but some firms may get stuck under more complex landscapes
5.2.6	Frequency of exogenous change	Yes	Relative performance of mimetism methods	69-70-91	Imitators do quite well under stability (convergence towards fit). Innovators do better in turbulent environments.
5.2.7	Endogenous change	Yes	Relative performance of mimetism methods	63-90; 88-89	Imitators benefit when massive copying doen´t lead to decreasing returns of what is copied

Frame 2 Efficiency of search methods: issues and impacts identified

5.2.1. The effects of ProximityDensity and Vision

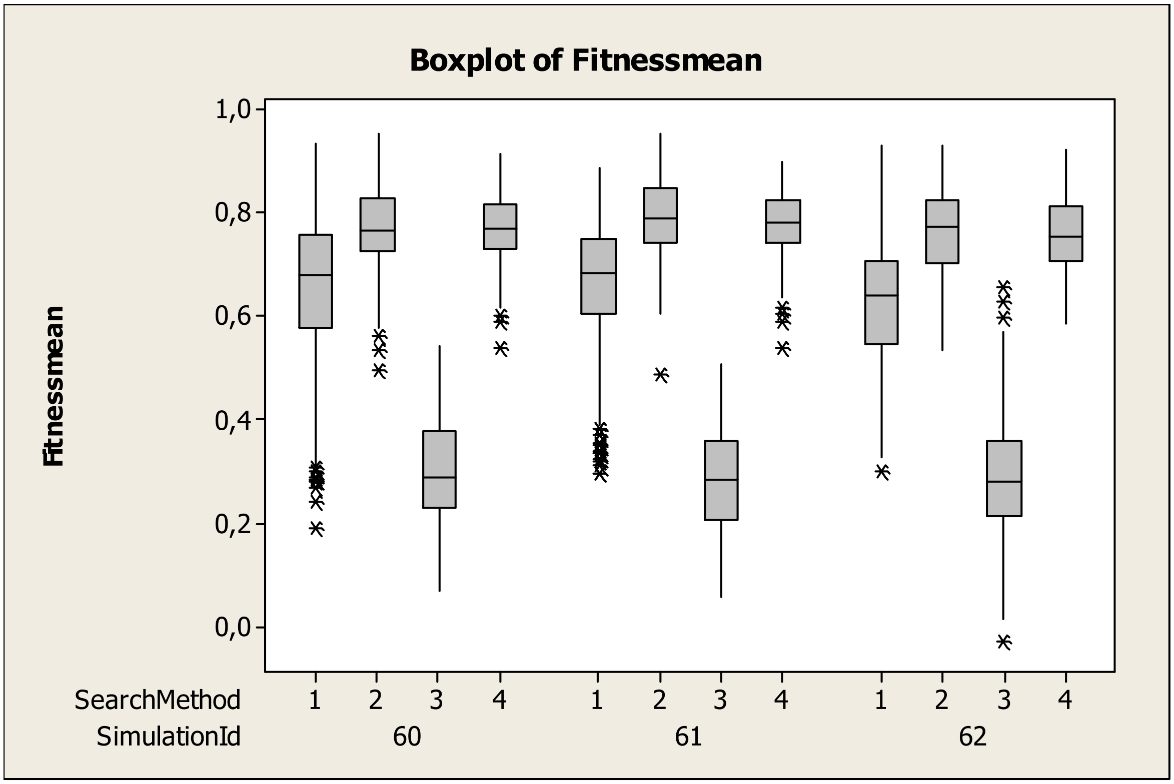
We start our analysis with simulations 57 to 62, where we could assess the relative performance of the minority and majority mimetism methods as we changed the proximity density impact and the vision parameters. As expected, we noticed an improvement in their relative performances as the parameters increase, but it is worth saying that, within the bounds of a simple model, higher connectivity works out effectively only when combined with higher ability to process information (vision breadth). Vision, in this scenario, bounded the ability of a firm to gather available information and improve its performance:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 1 Boxplot of fitness mean by search method. Simulations 57, 58 and 59

Simulation settings 57, 58 and 59 differ only in the ProximityDensity parameter, with a Vision attribute value of 3 for all firms. There is little improvement in the mimetism methods as the parameter increases.

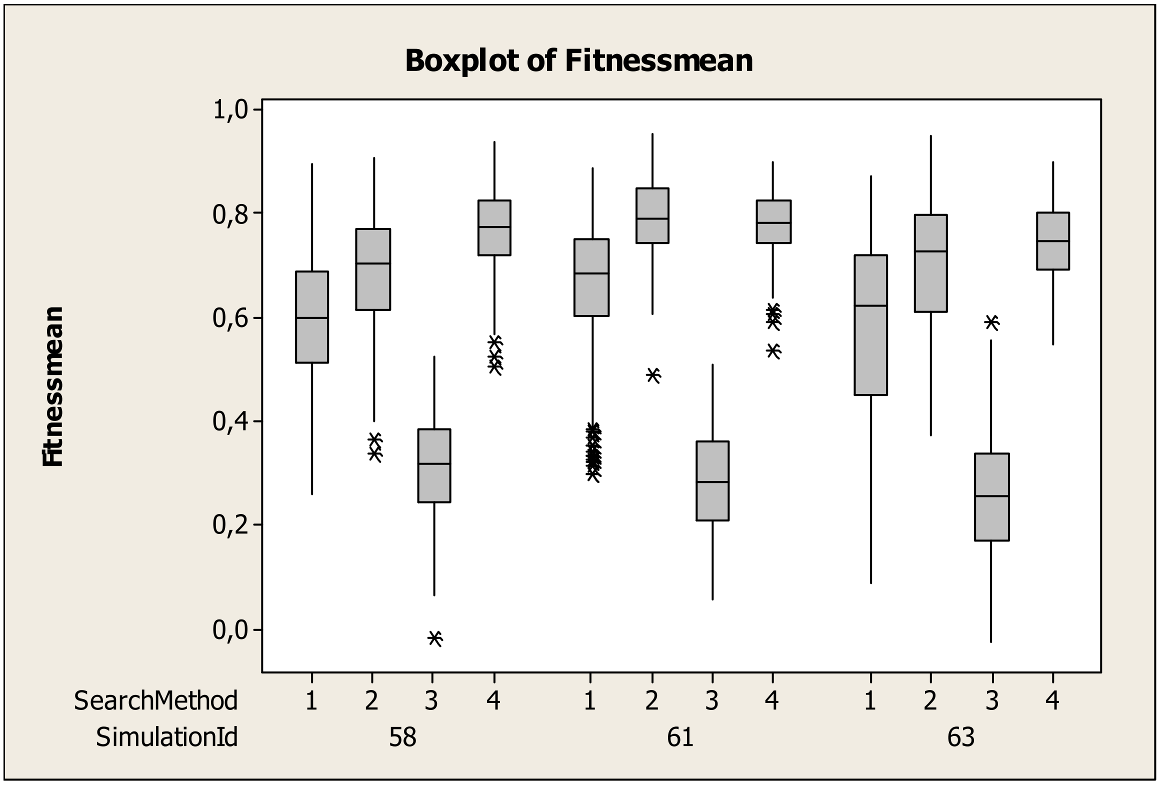


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 2 Boxplot of fitness mean by search method. Simulations 60, 61 and 62

Simulation settings 60, 61 and 62 differ from each other only in the ProximityDensity parameter, in the same way presented in the set previously shown, but in all these scenarios the Vision attribute value was set at 10 for all firms. It can be verified a significant improvement in the relative efficiency of the mimetism methods, directly associated with the Vision parameter increase. The increase in the ProximityDensity parameter makes the minority mimetism method outperform the market reading search method.

The next chart compares simulations 58 and 61 (already presented in the previous charts) with the baseline setting, for which the ProximityDensity is the same, but Vision parameter value is 5. It confirms the consistency of the effect of the Vision parameter:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Note: Simulation setting 63 is the baseline, with Vision=5. Vision is lower in simulation setting 58 (3) and higher in 61 (10). We apologize for the inconvenience of not being able to display the simulations in the sequence of the Vision parameter increase

Chart 3 Boxplot of fitness mean by search method. Simulations 58, 61 and 63

A look at the distribution curves of fitness for all firms in these simulation settings (57 to 62) allows confirming the higher diffusion of successful configurations, that is, a convergence of more firms towards higher levels of fitness[3]. That is much more a function of the Vision than of the ProximityDensity parameter, as shown in the selected descriptive statistics in the following charts:

[3] It is important to notice that all of these simulations have 25% of firms performing random search; these firms operate at lower levels of fitness and, by definition, do not converge towards fit.

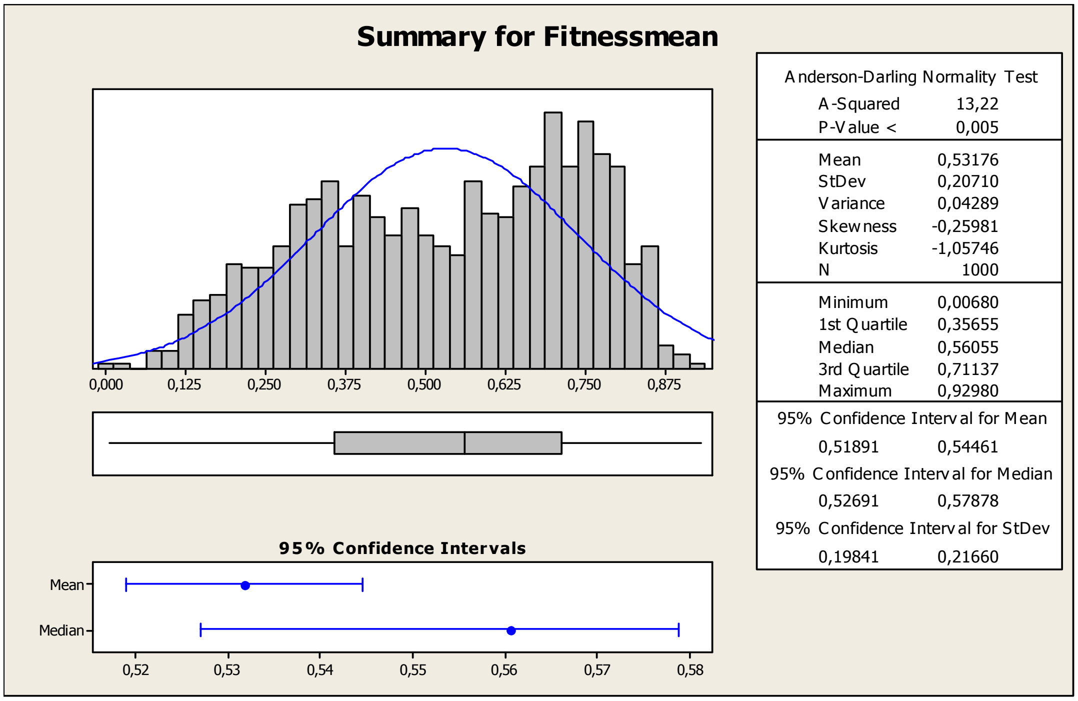


Chart 4 Graphical summary of statistics: fitness mean. Simulation 57, all runs[4]

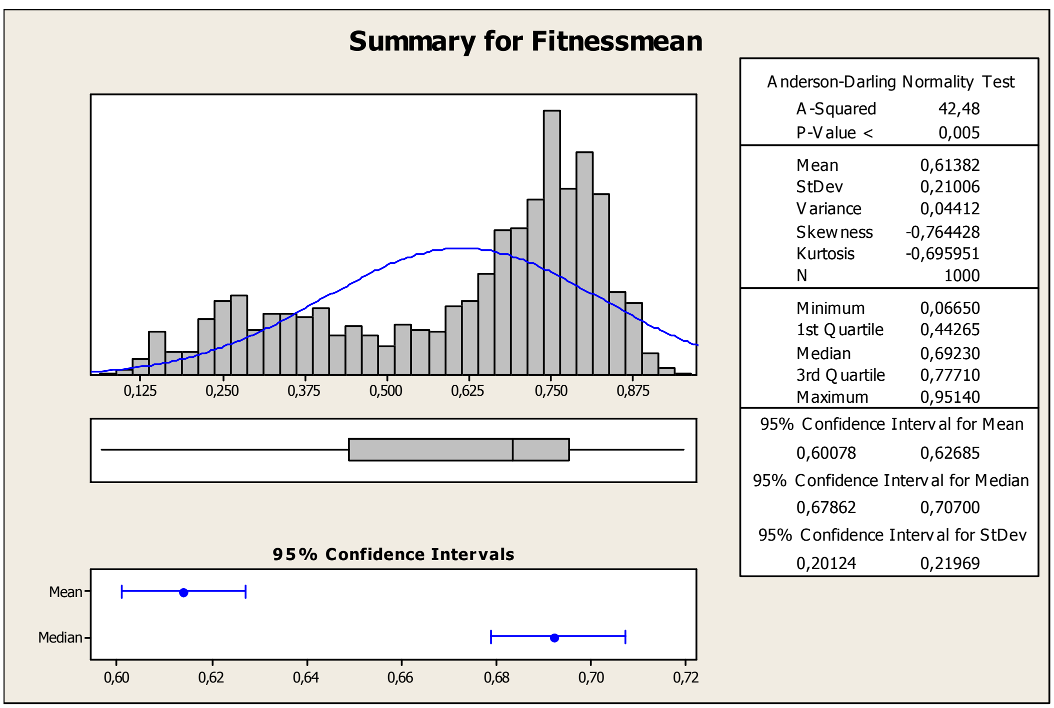


Chart 5 Graphical summary of statistics: fitness mean. Simulation 60, all runs

[4] Whenever a simulation setting is analyzed, the statistics refer to all runs executed, that is, the data is always relative to 10 executions. Descriptive statistics for all the individual runs are available in the appendix section.

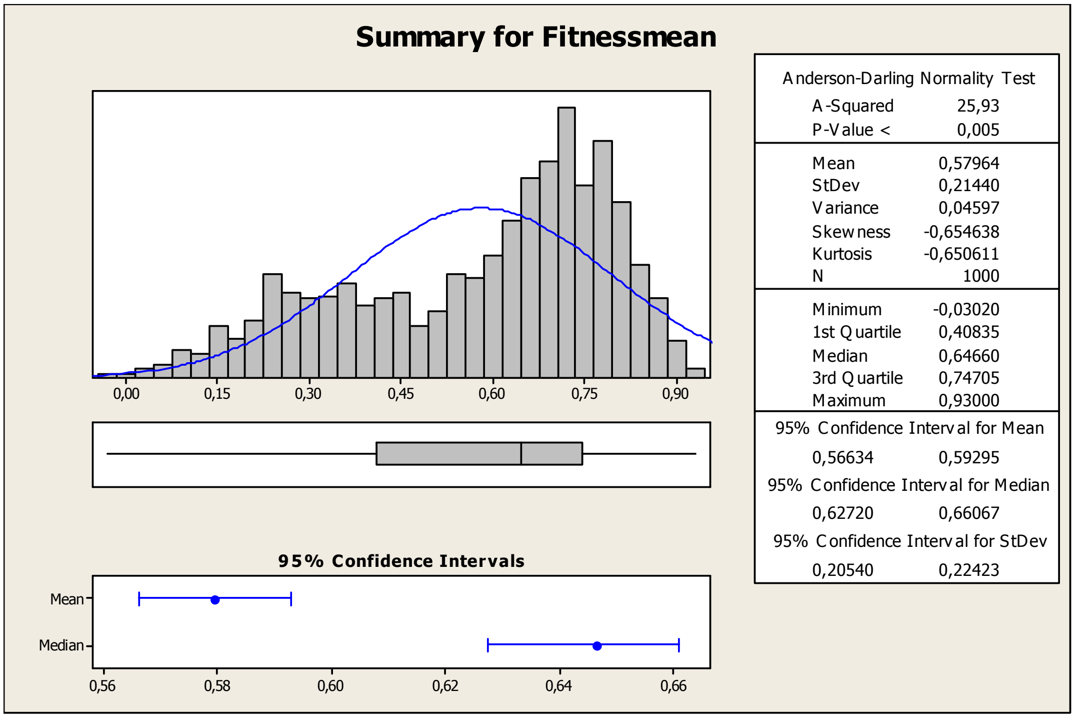


Chart 6 Graphical summary of statistics: fitness mean. Simulation 62, all runs

As discussed above, moderate levels of contact are enough to ensure diffusion of practices. However, scenarios of low (or moderate) levels of connections among firms may create traps that lead those firms with the majority mimetism search method to perform with very low levels of fitness. The following graphics illustrate this situation, for selected executions (runs) of the simulation settings:

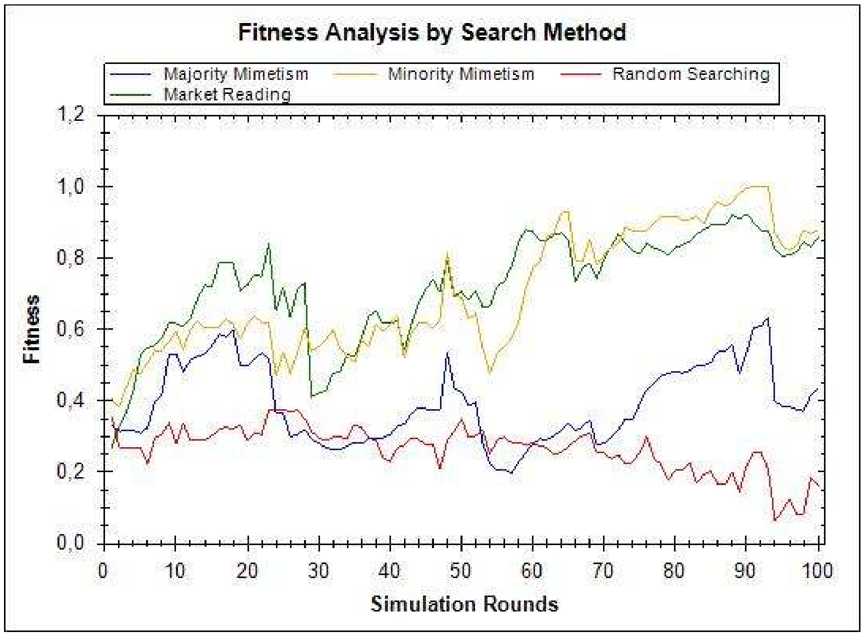


Chart 7 Evolution of fitness by search method. Simulation 60, run 3

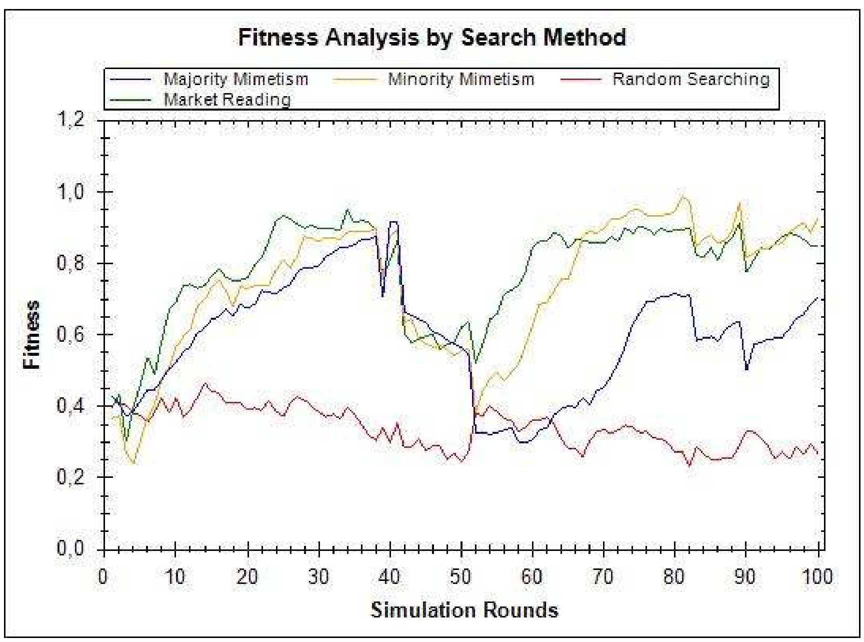


Chart 8 Evolution of fitness by search method. Simulation 60, run 4

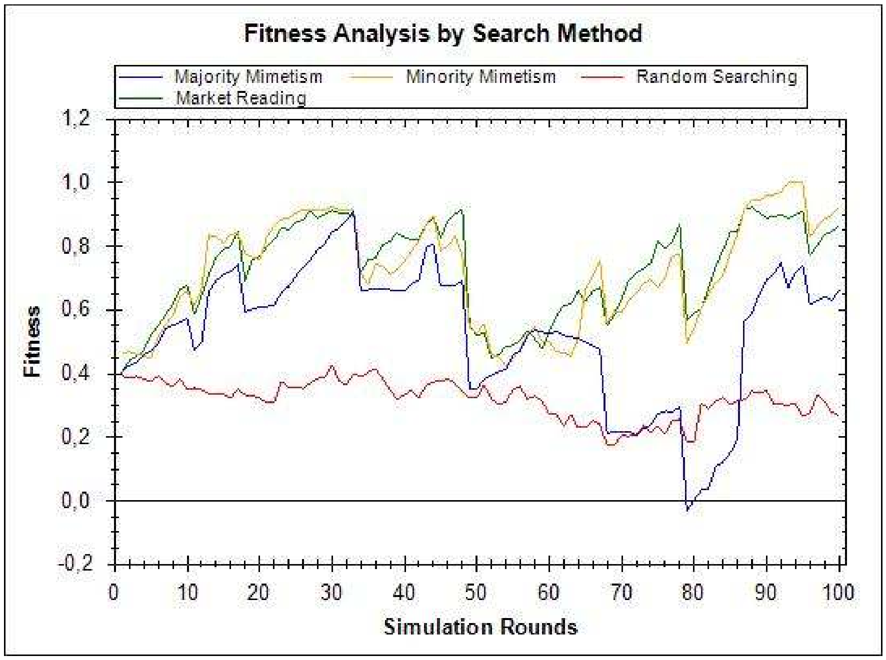


Chart 9 Evolution of fitness by search method. Simulation 60, run 6

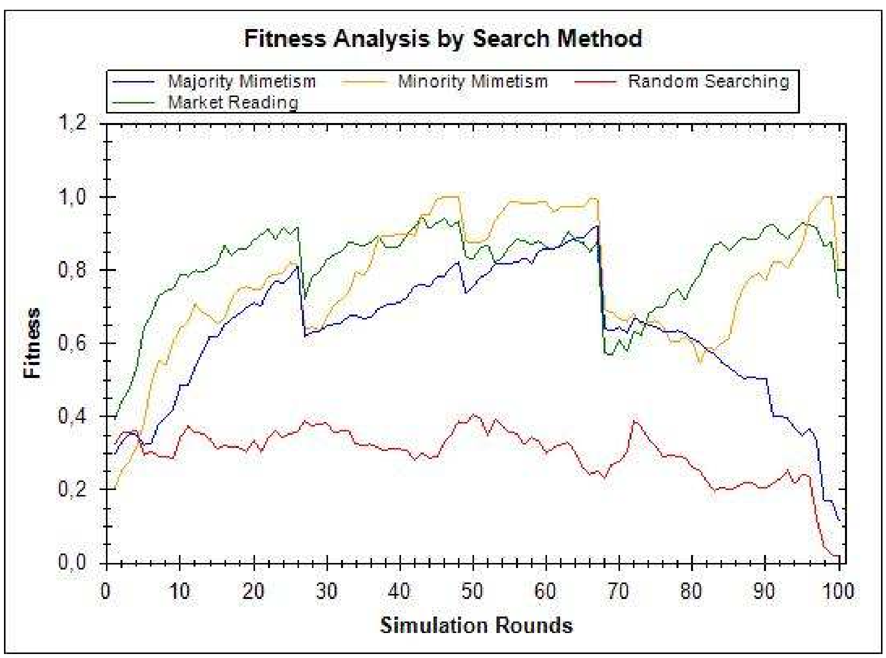


Chart 10 Evolution of fitness by search method. Simulation 61, run 3

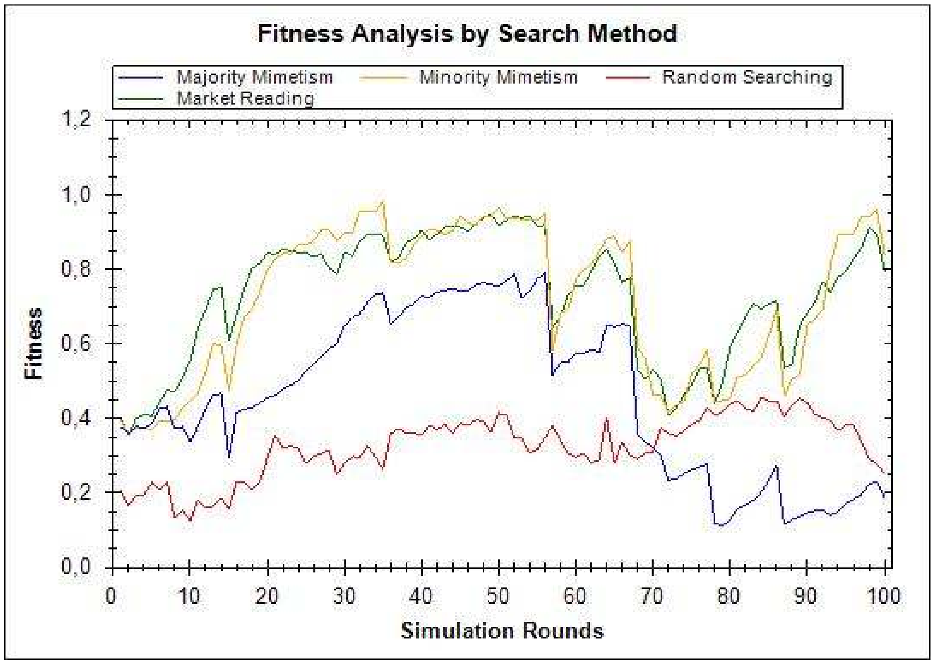


Chart 11 Evolution of fitness by search method. Simulation 61, run 7

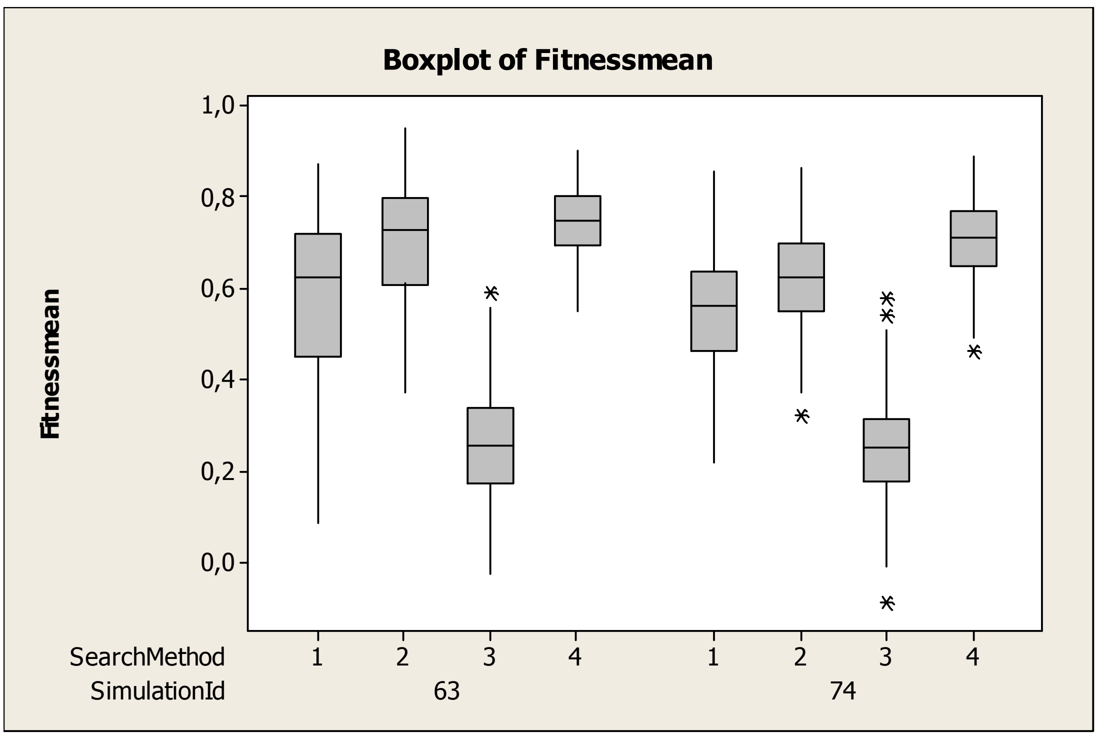
As we can see from the above charts, the firms with the majority mimetism method may face several periods (rounds) of low performance even in scenarios in which their Vision is high and the connections among firms are reasonable enough to allow diffusion of practices (information of the configurations adopted). Minority mimetism methods allow firms to achieve high levels of fitness under stability, but significant landscape changes usually cause these firms to perform at lower levels than firms with the market reading search strategy. Random searching and market reading search methods, are not sensible to the change in the two parameters analyzed (by design), and behave much the same way except for idiosyncrasies of the landscape, which differs in each run and changes due to exogenous and endogenous change along a simulation run.

In the Appendix we provide all the descriptive statistics for the various simulation settings (with the fitness value confidence intervals obtained for each search method as well as the distribution curves of fitness in each of the simulation runs). It also includes all the charts with the evolution of fitness by search method for all runs executed.

5.2.2. The effect of AdjustCap

The next parameter change that we analyzed was the capacity to adjust, or AdjustCap. This subsection addresses two conditions that mediate its influence in search method performance: the size of the configuration for a firm, and the ability to obtain information at each round (Vision).

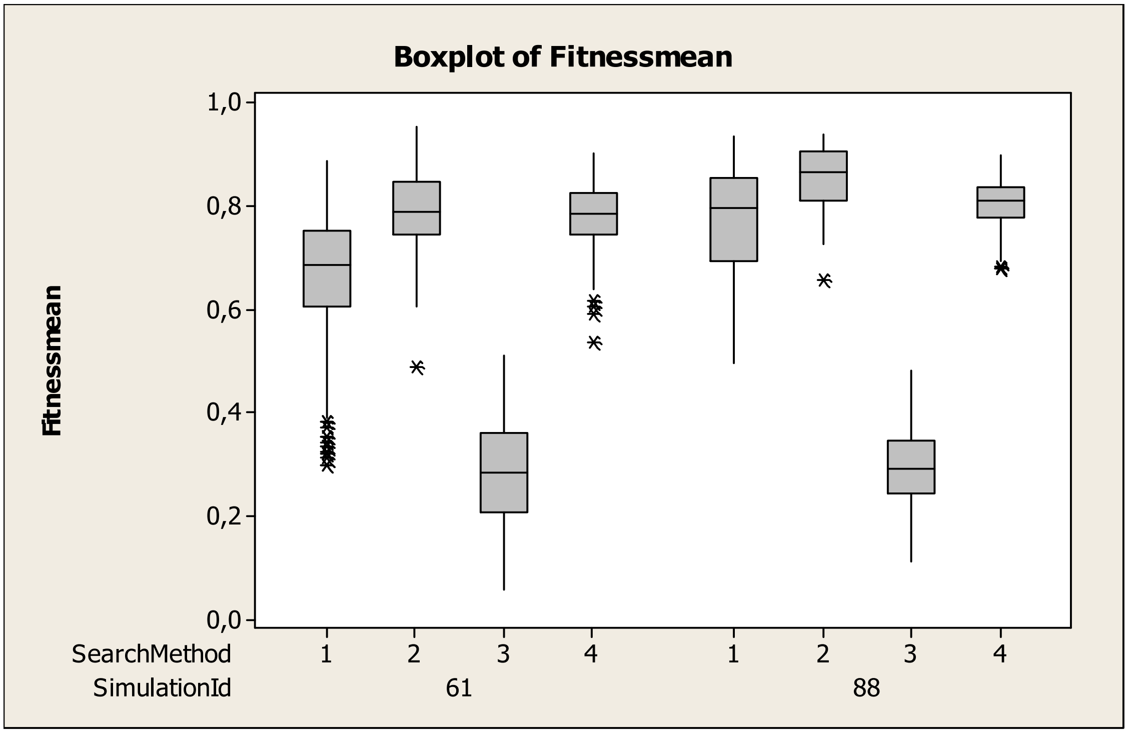
In the first case, as illustrated by the chart that follows, an increase in the complexity of the environment, more specifically in the number of structural and flexible characteristics of the simulation setting, reduces the relative efficiency of the mimetism methods:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 12 Boxplot of fitness mean by search method. Simulations 63 and 74

In the second comparison illustrated in the next chart, we evaluate an increase in the capacity to adjust, given the same landscape complexity. In this case, both mimetism methods performed better, and the minority mimetism method outperformed significantly the market reading search strategy– that is, to a large extent, due to the higher Vision parameter value utilized in both settings (as one can confirm by comparing the relative efficiencies observed in the previous chart, when both settings had a Vision parameter value of 5).



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 13 Boxplot of fitness mean by search method. Simulation 61 and 88

The following charts present the distribution curves of performance for all runs executed in simulation 88, for the population of firms and for firms aggregated by search method. It is possible to verify the superior fitness performance associated with the minority mimetism search method, for the confidence intervals of 95% utilized in our analysis:

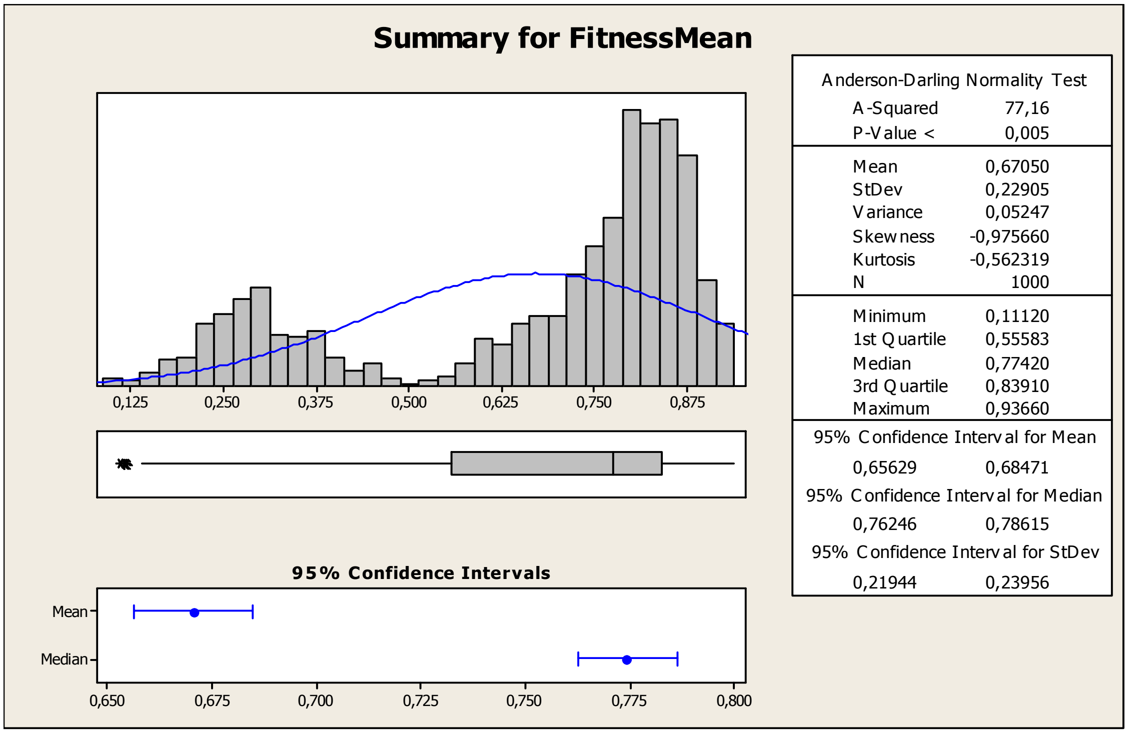


Chart 14 Graphical summary of statistics: fitness mean. Simulation 88, all runs

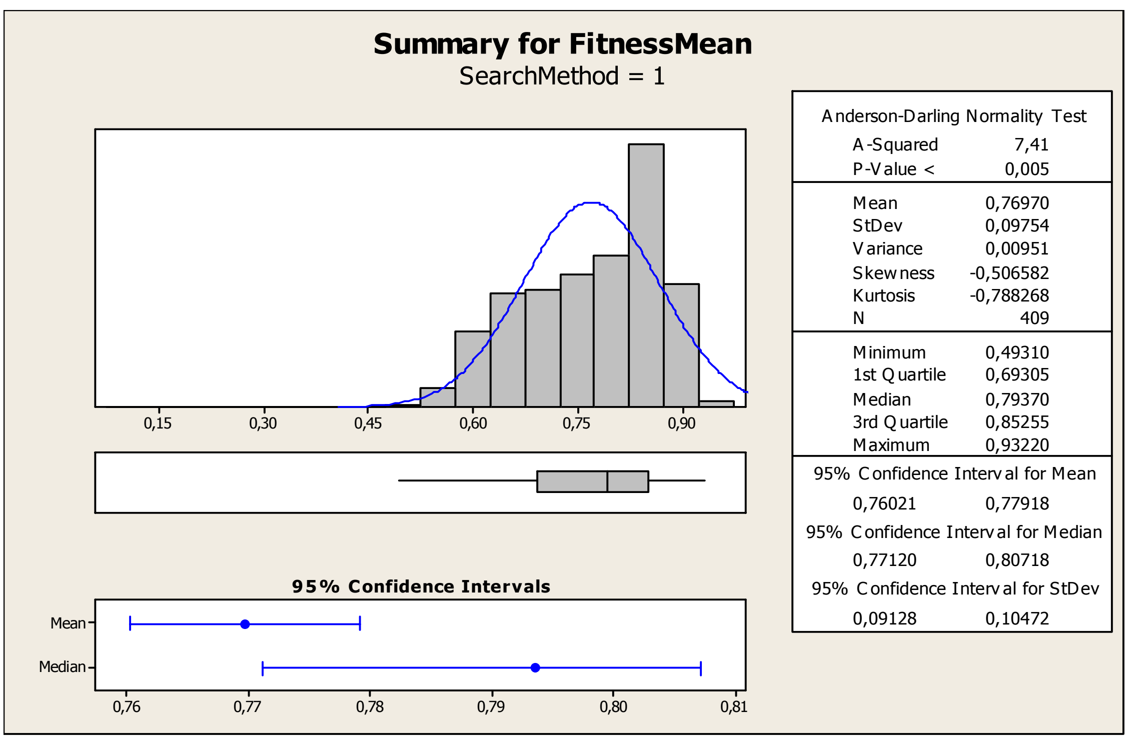


Chart 15 Graphical summary of statistics: fitness mean. Simulation 88, all runs – Majority mimetism

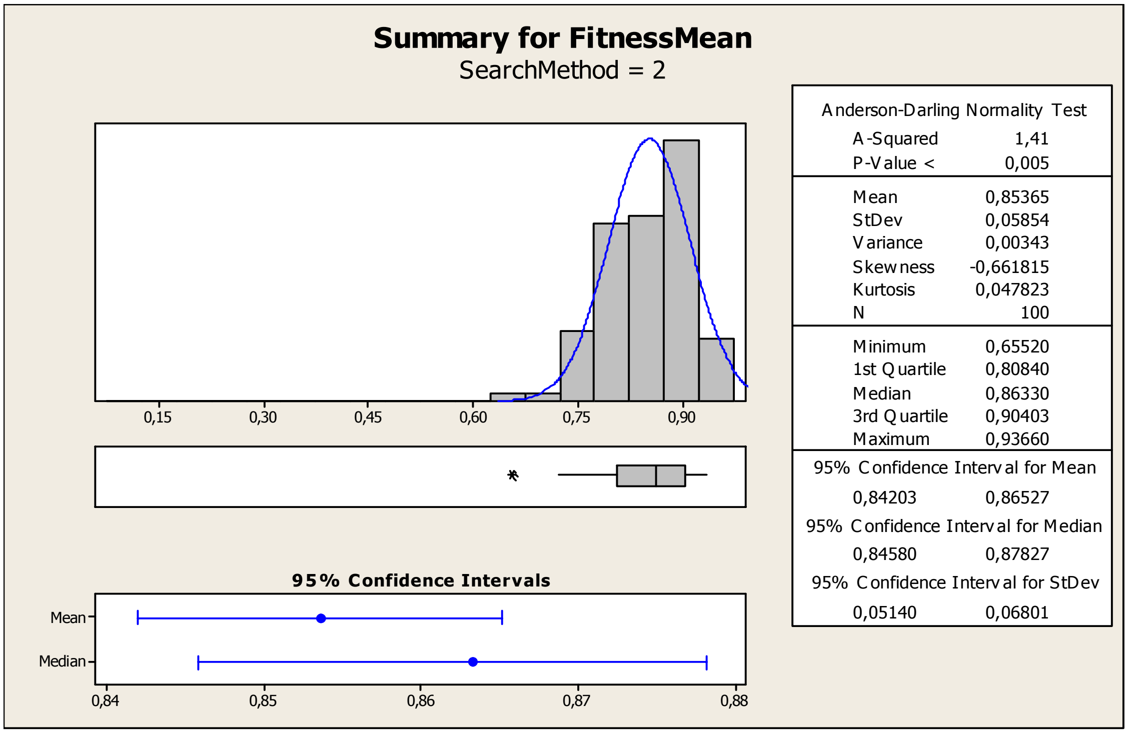


Chart 16 Graphical summary of statistics: fitness mean. Simulation 88, all runs – Minority mimetism

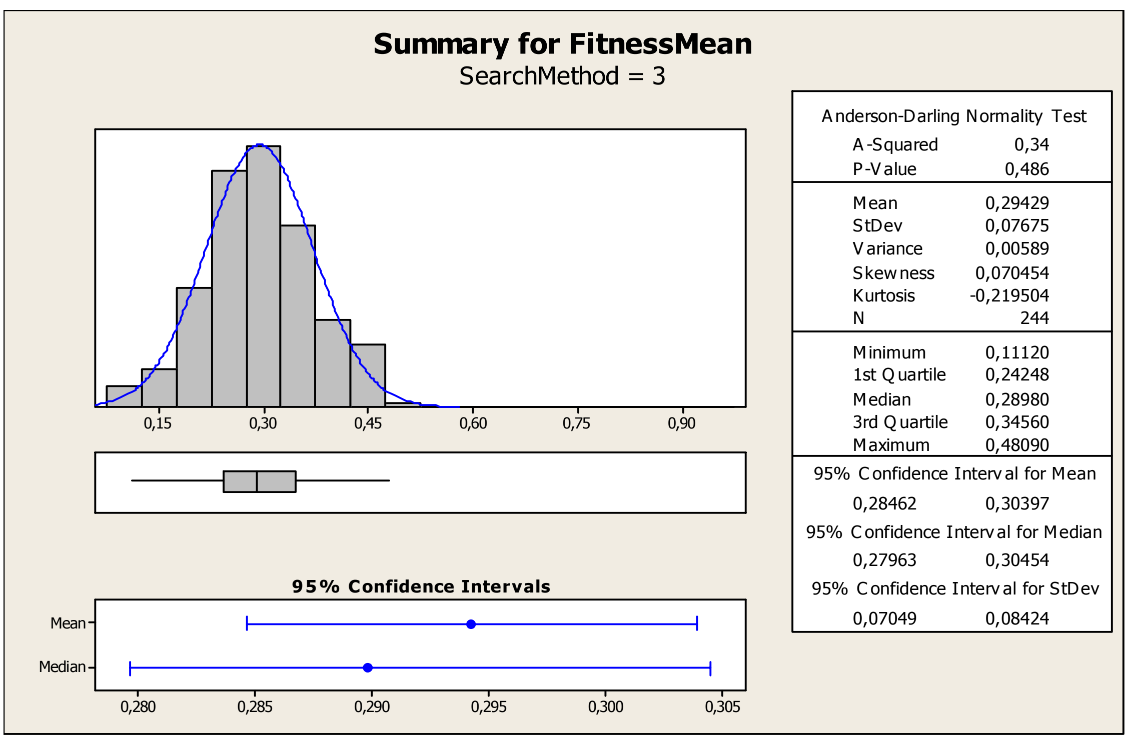


Chart 17 Graphical summary of statistics: fitness mean. Simulation 88, all runs – Random searching

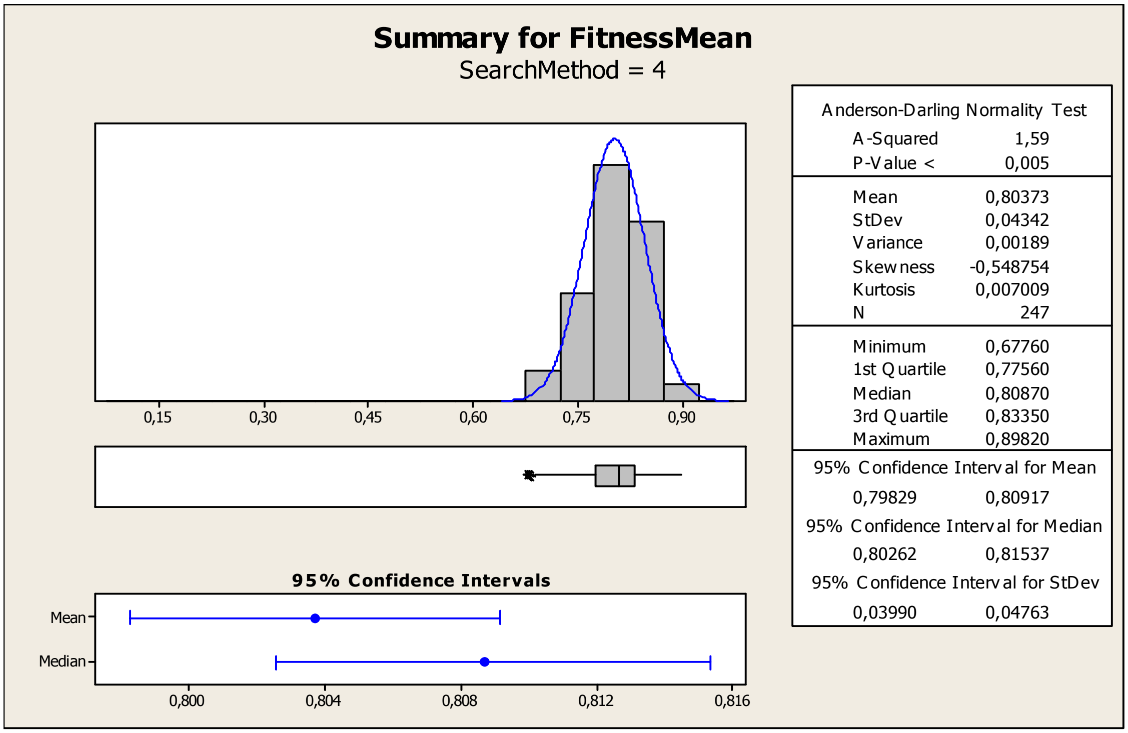


Chart 18 Graphical summary of statistics: fitness mean. Simulation 88, all runs – Market reading

The mimetism methods react quickly to severe landscape changes in such simulation setting, as it can be noticed in the simulation executions shown below:

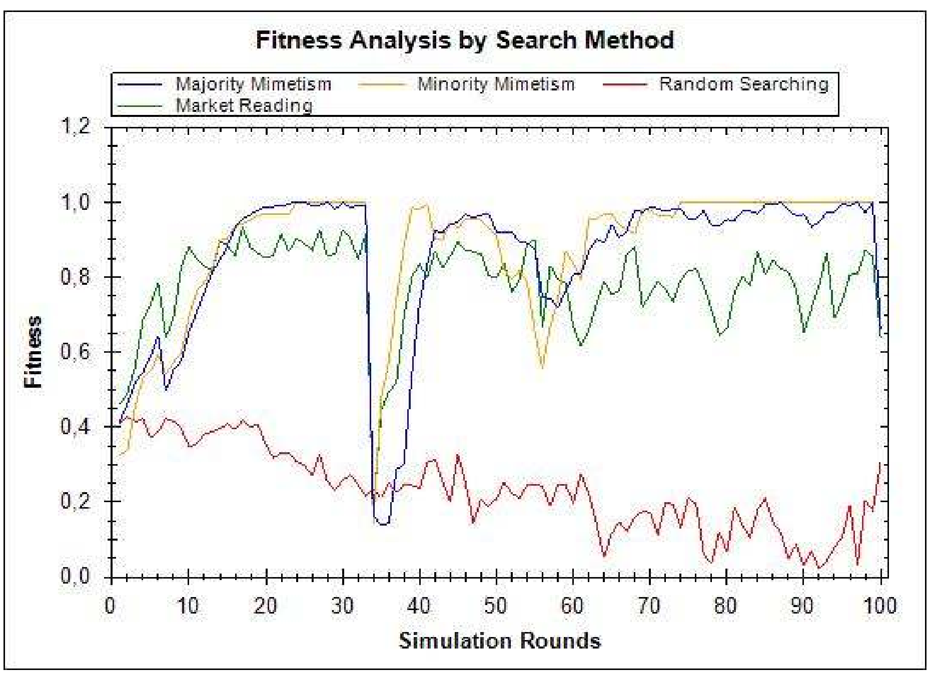


Chart 19 Evolution of fitness by search method. Simulation 88, run 6

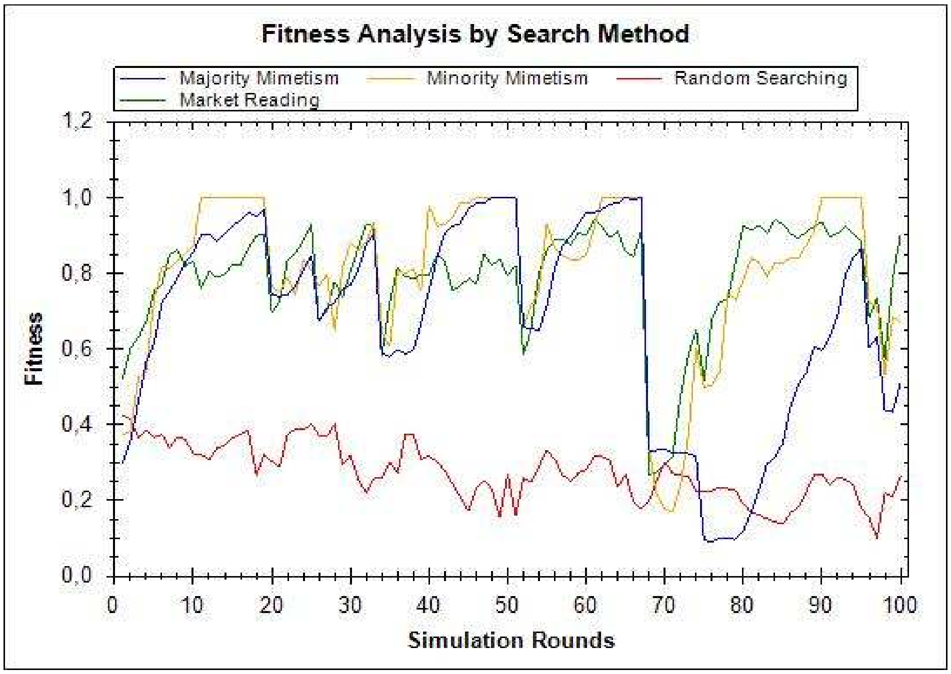


Chart 20 Evolution of fitness by search method. Simulation 88, run 9

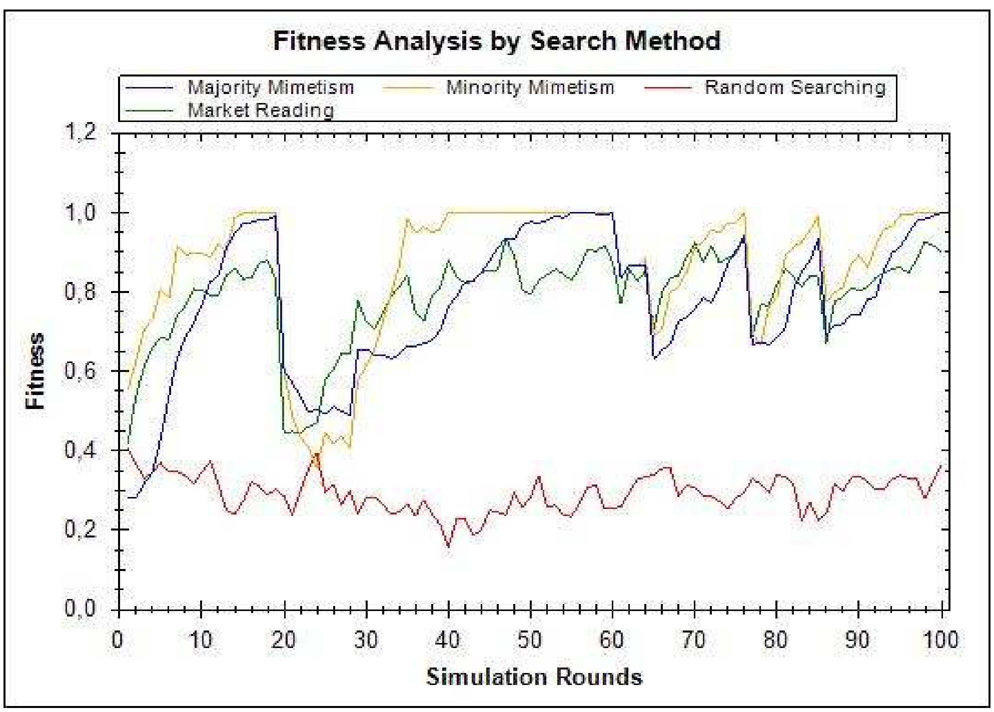
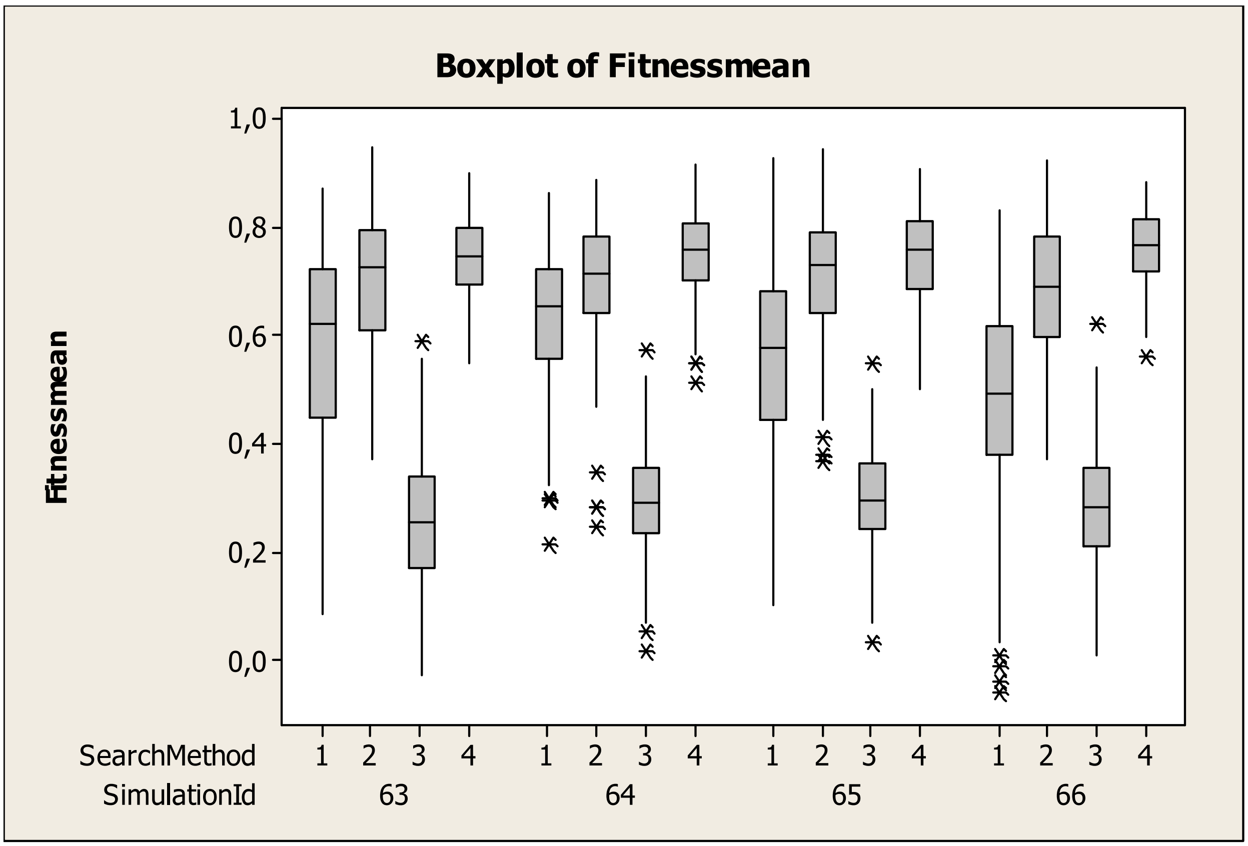


Chart 21 Evolution of fitness by search method. Simulation 88, run 10

5.2.3. The effect of search method population distribution

The relative efficiencies of the different search methods vary according to the proportion of the population utilizing each of them. The differences for some of our simulated scenarios are illustrated in the following charts:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

As we vary the proportion of firms utilizing a certain search method in the above simulations, we noticed that one of the conditions that matter for a successful search strategy is the strategy choices of others. While the performance of random search and market reading search remain practically the same, as they are not dependent on the observations of other firms[5], both the majority and minority mimetism are somewhat impacted. Simulation 66, in special,

[5] They are affected only by idiosyncratic changes in the landscape and randomized events.

introduces harder conditions for the fitness under the mimetism search processes as the simulation settings increased the risk of firms get trapped by a bandwagon effect: there are too many firms searching under the majority mimetism and increased misleading information coming from more firms running under random search. The following charts illustrate how this situation may compromise the performance of these strategies:

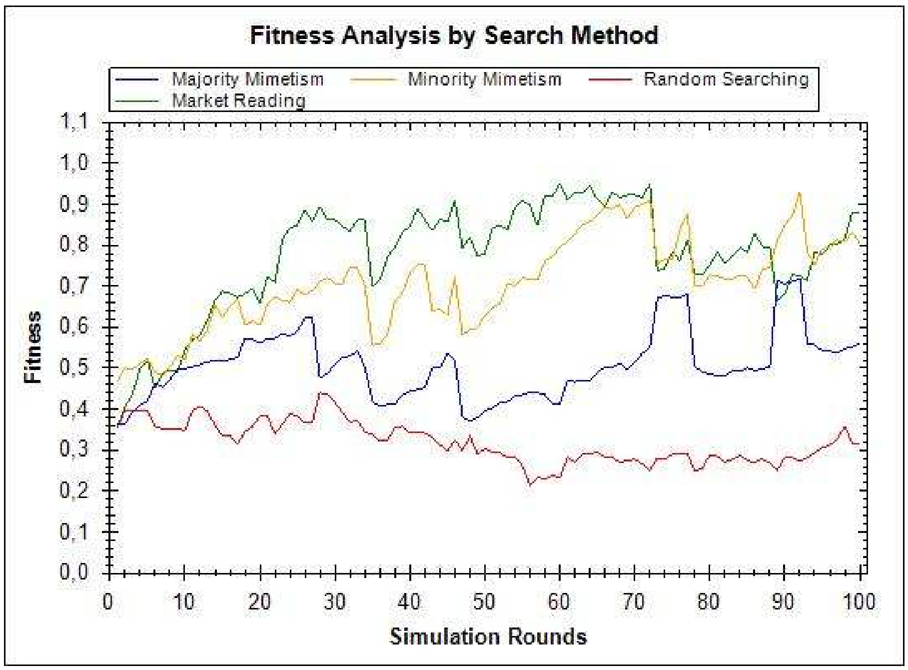


Chart 22 Evolution of fitness by search method. Simulation 66, run 1

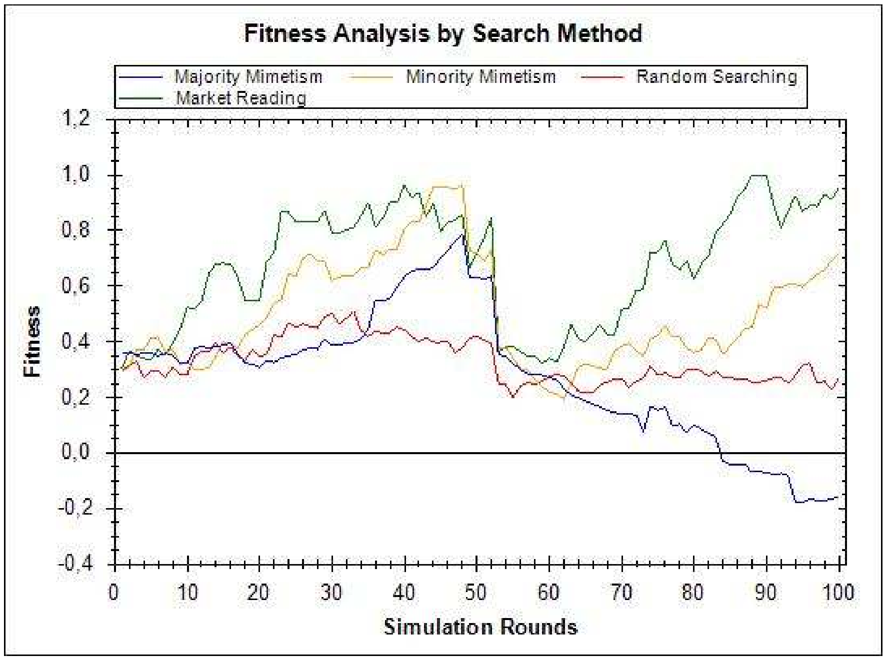


Chart 23 Evolution of fitness by search method. Simulation 66, run 6

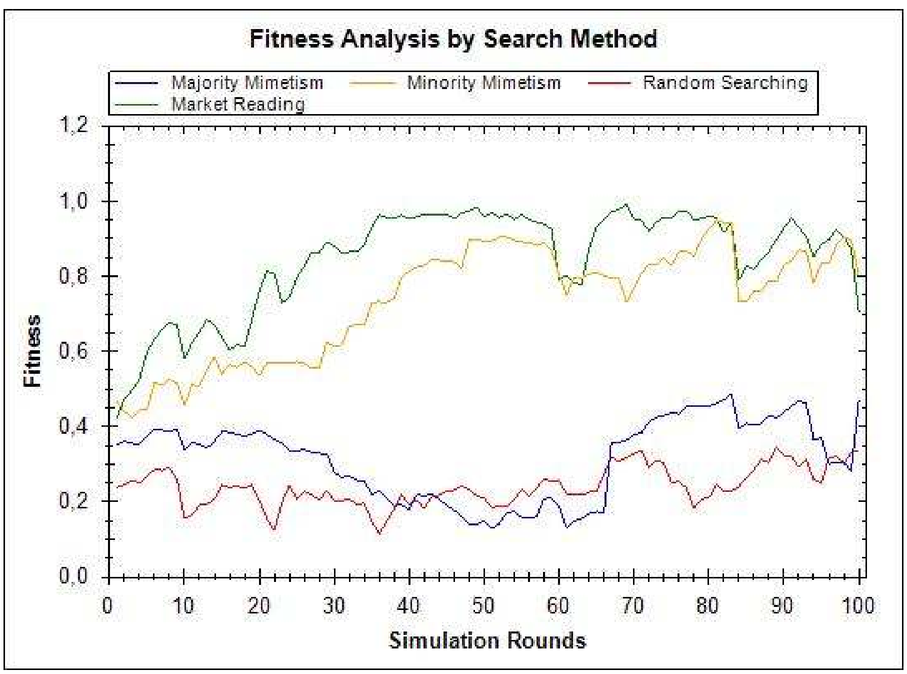
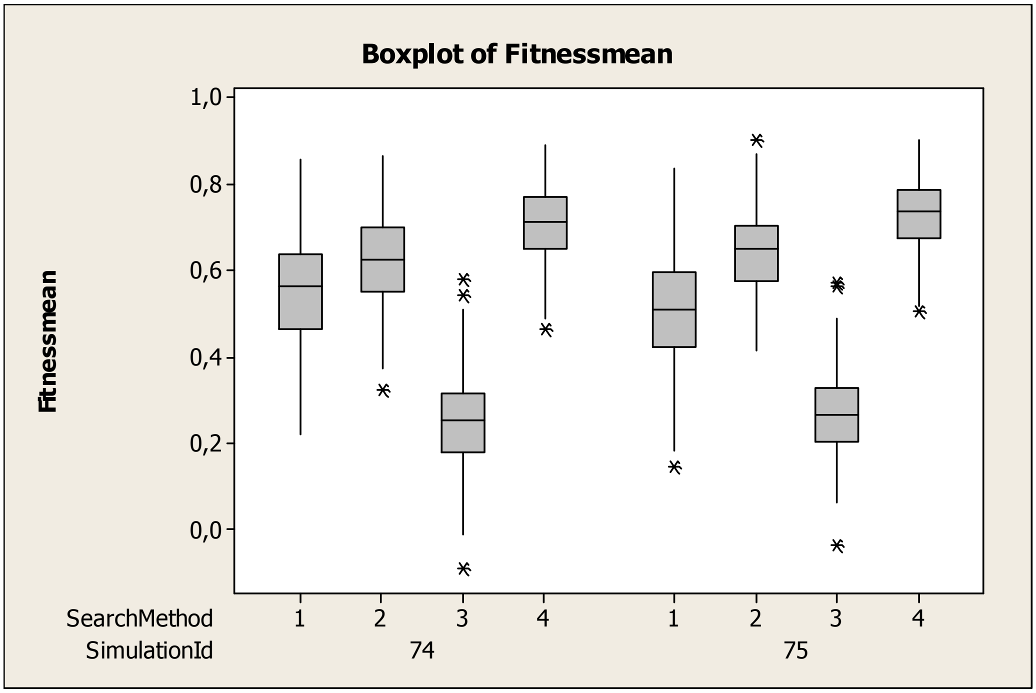


Chart 24 Evolution of fitness by search method. Simulation 66, run 10

This effect seems to be robust for the majority mimetism search method, as we change the size of the firm configurations and reduced the relative capacity to adjust for all firms:

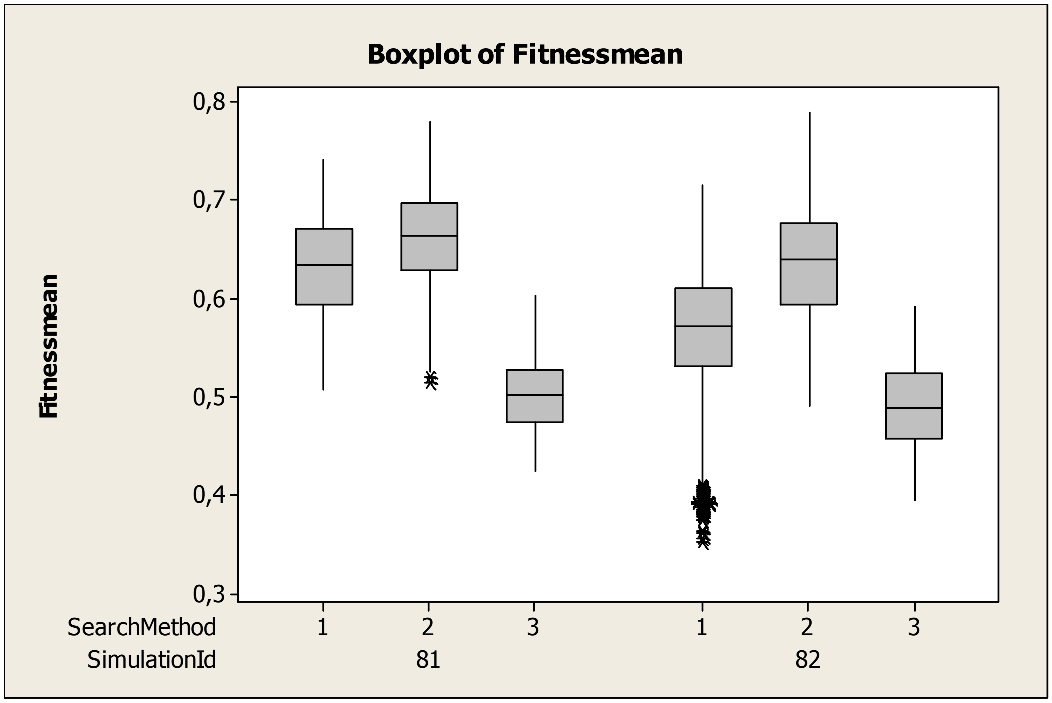


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 25 Boxplot of fitness mean. Simulations 74 and 75

In simulations 74 and 75 the complexity of the business environment is higher, as we increased the number of characteristics in the simulation settings. Because we maintained the AdjustCap parameter with the baseline value, companies were not so fast adopters of new configurations. This reduces to some extent the risks associated with the mimetic strategies. Even though, the majority mimetism method is getting worse as the number of firms utilizing this strategy increases.

We simulated similar scenarios making use of the NK landscape model. The same effect is also observed:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search

Chart 26 Boxplot of fitness mean. Simulations 81 and 82

Looking at the various executions of these simulation settings we identified two very different fitness performance tracks between them, illustrated in the following charts. We start by showing two typical runs of simulation 81, in which firms with the majority mimetism method incrementally improved performance[6]:

[6] Please note that under the NK model only search methods 1, 2 and 3 are employed.

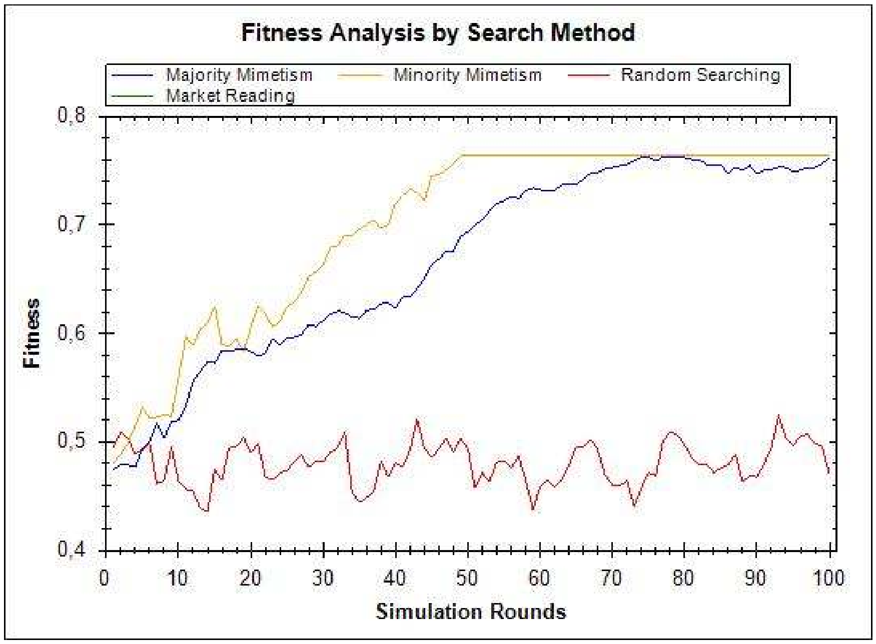


Chart 27 Evolution of fitness by search method. Simulation 81,run 3

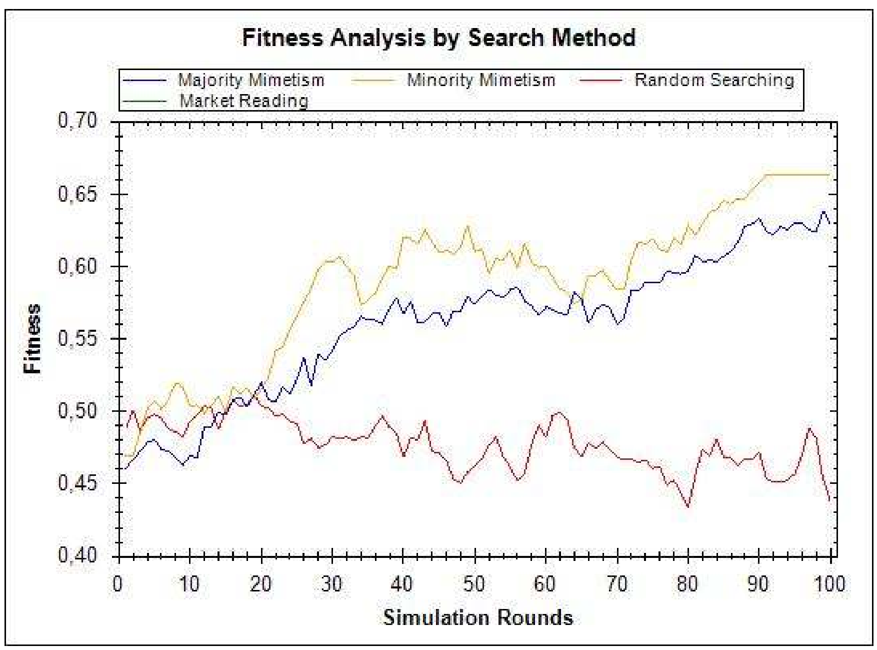


Chart 28 Evolution of fitness by search method. Simulation 81,run 4

In simulation 82, however, the majority mimetism method sometimes got trapped in self-reinforcing mechanisms that led firms to very poor performance levels, as illustrated by the following simulation executions:

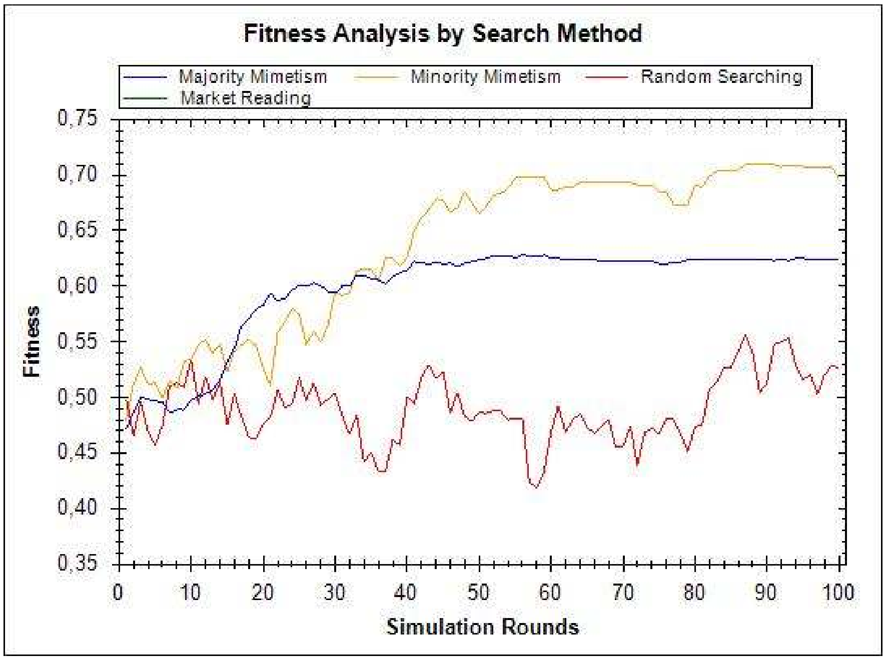


Chart 29 Evolution of fitness by search method. Simulation 82,run 3

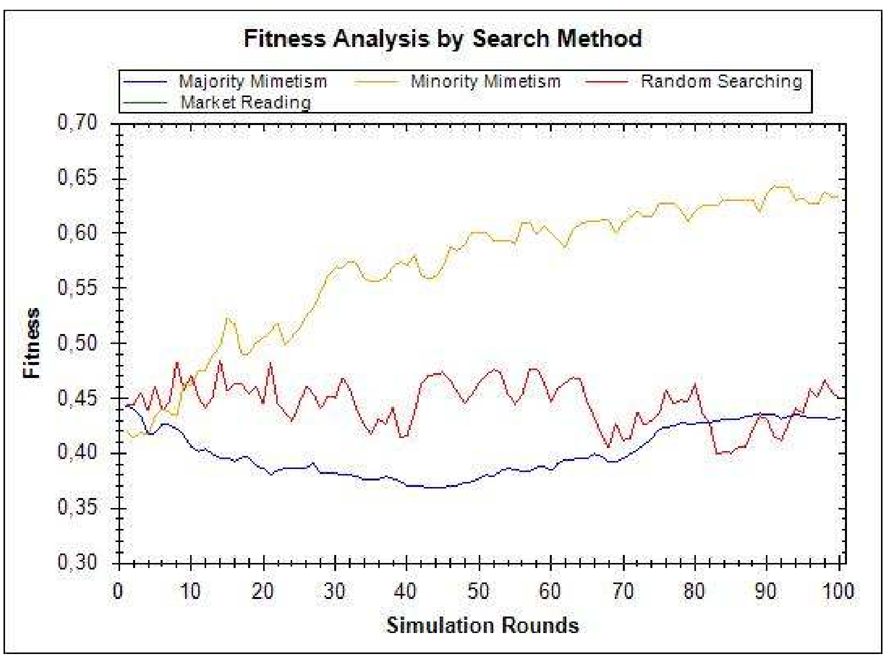


Chart 30 Evolution of fitness by search method. Simulation 82,run 5

The distribution curve of fitness for the population of firms is considerably different in the two simulation settings under analysis. While simulation 81 shows the tendency of majority mimetism firms converge towards fit, the same is not that clear in simulation 82. The kurtosis provides a good measure of this difference:

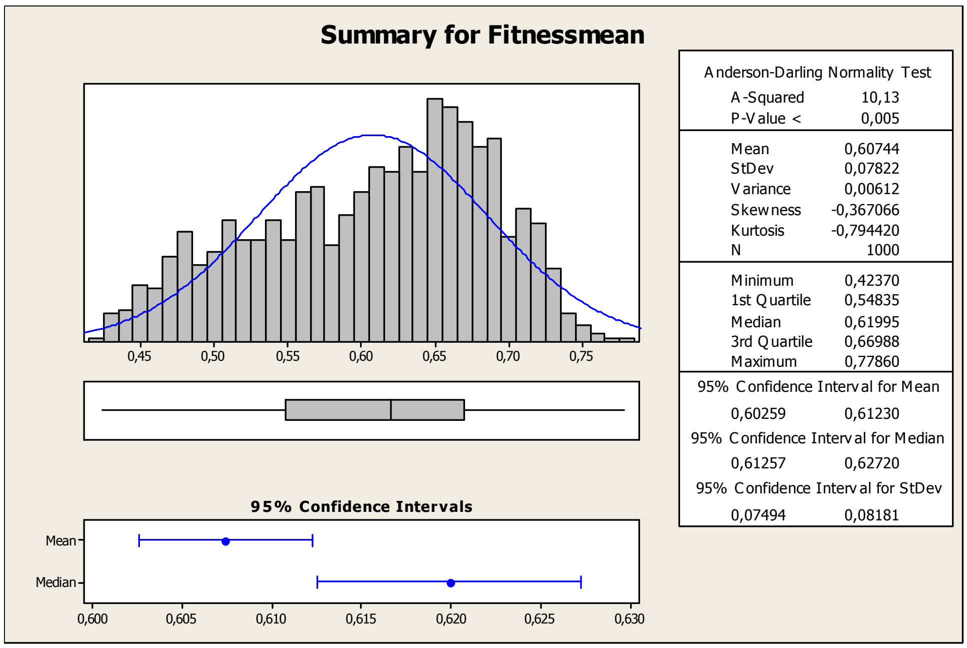


Chart 31 Graphical summary of statistics: fitness mean. Simulation 81, all runs

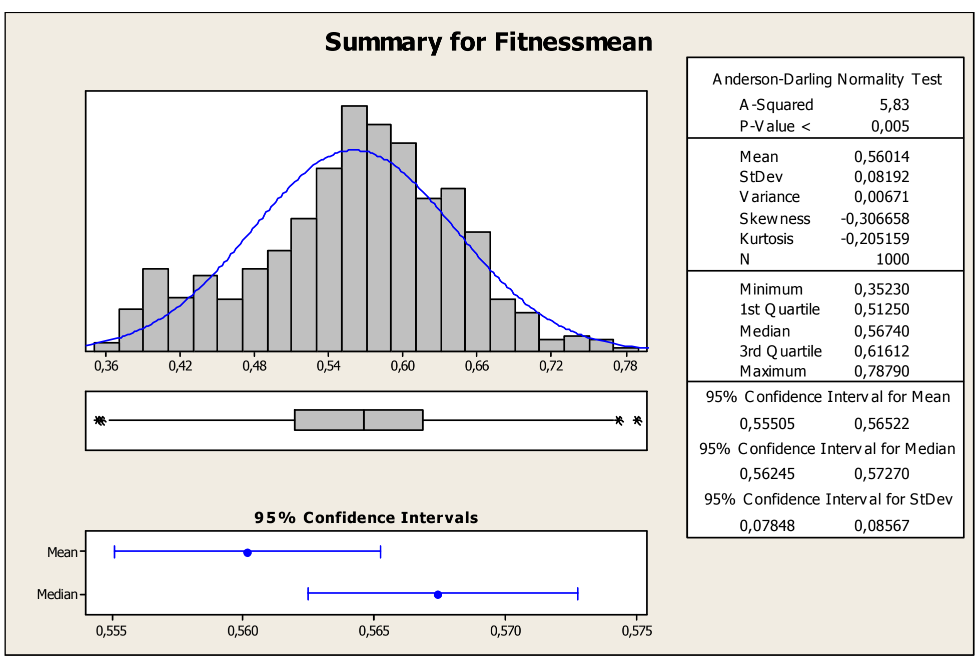
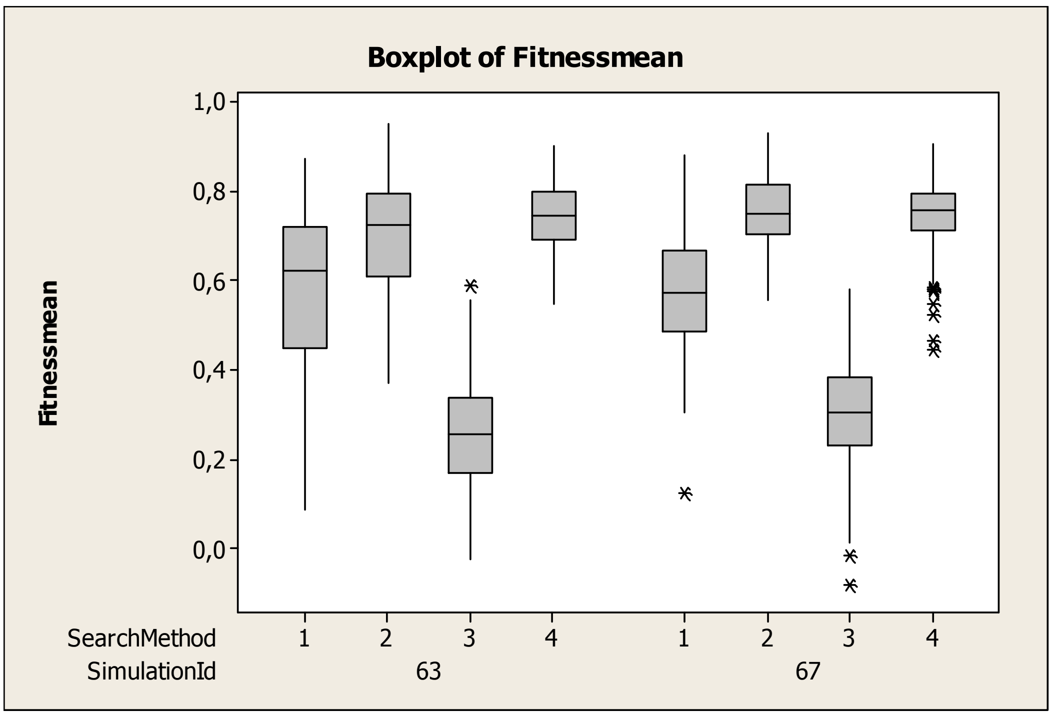


Chart 32 Graphical summary of statistics: fitness mean. Simulation 82, all runs

5.2.4. The effects of procedural accuracy in the execution of the search methods

In our experiment, we made changes in the simulation parameters in order to verify the potential impact of lack of accuracy in the market reading and the minority mimetism search methods. Starting with our baseline scenario, it is easy to verify such effect:

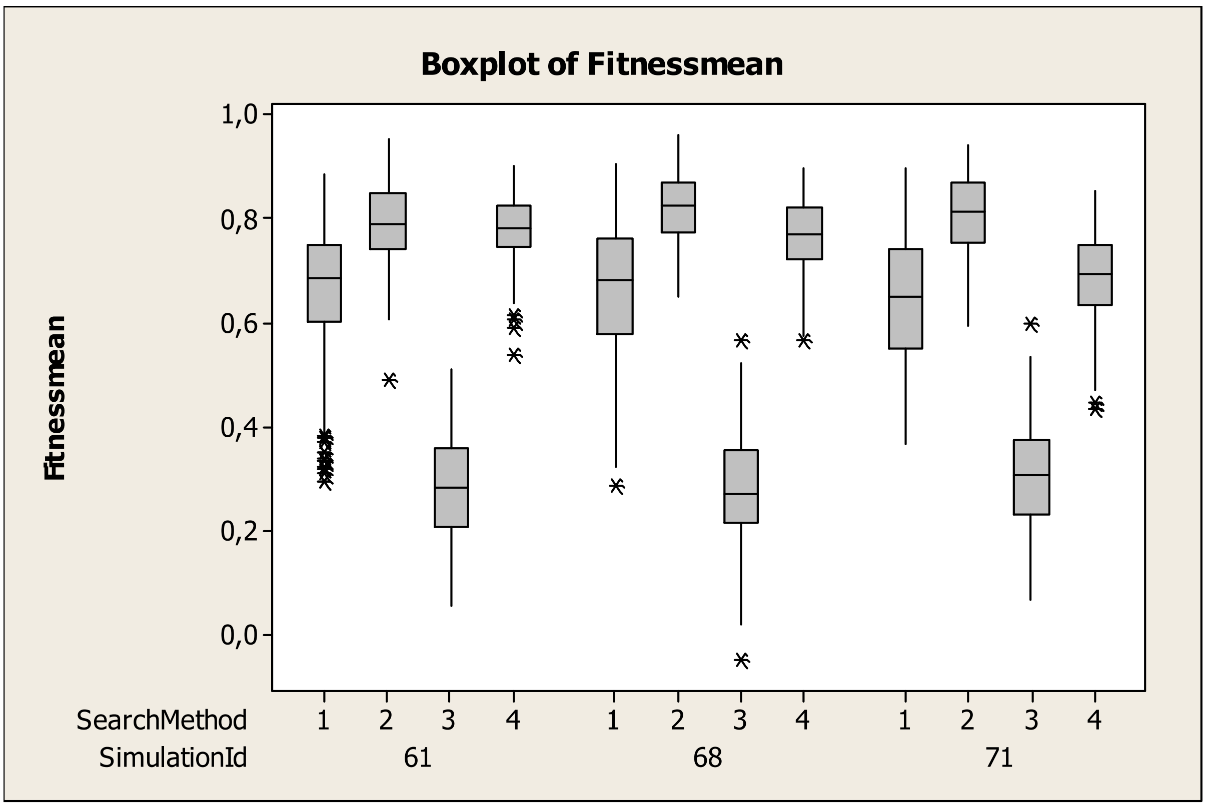


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 33 Boxplot of fitness mean by search method. Simulations 63 and 67

Under our baseline setting, simulation 63, the efficiency of the minority mimetism method is close to (but lower than) that of the market reading, with the same rates of error in performing their respective procedures (see Appendix for the confidence intervals on fitness mean for each method). However, a slight change in the minority parameter may bring its efficiency to the same level, that is, accurate imitators do as well as innovators, that have to operate with some expected error rate (in reading market needs / finding rewarding configurations).

Another stretch on the competitiveness of innovators is experimented in the scenarios where the Vision parameter is higher, that is, the ability of firms utilizing mimetism methods to process information regarding other firms´ configurations. For example, in simulation 61, both error rates are set at 10%; the results show that the fitness confidence intervals for minority mimetism and market reading overlap. In the other two scenarios, simulation 68 and 71, the market reading search method underperforms:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 34 Boxplot of fitness mean by search method. Simulations 61, 68 and 71

There are two considerations we want to make at this point. First, the “schumpeterian” process of innovation is not quite well represented in our model, as the landscape changes but not as a function (and in the direction) of the innovators efforts. Second, the factors market as designed in our model allows any firm “to acquire” any resource configuration. Thus, there is no advantage for pioneers, except for the good fitness score that an innovator might enjoy in the rounds prior to be imitated.

Under frequent landscape changes, innovators may be the first to adopt rewarding configurations; as the landscape remains stable, minority mimetism firms perform better. The explanation is that innovators, to some extent, persist on trying unsuccessful new configurations[7] – the market preferences are not changing in this simulated scenarios.

The following charts illustrate the dynamics of simulation 68, in which minority error is set to zero (excellent imitators) and market reading error is set at 10%:

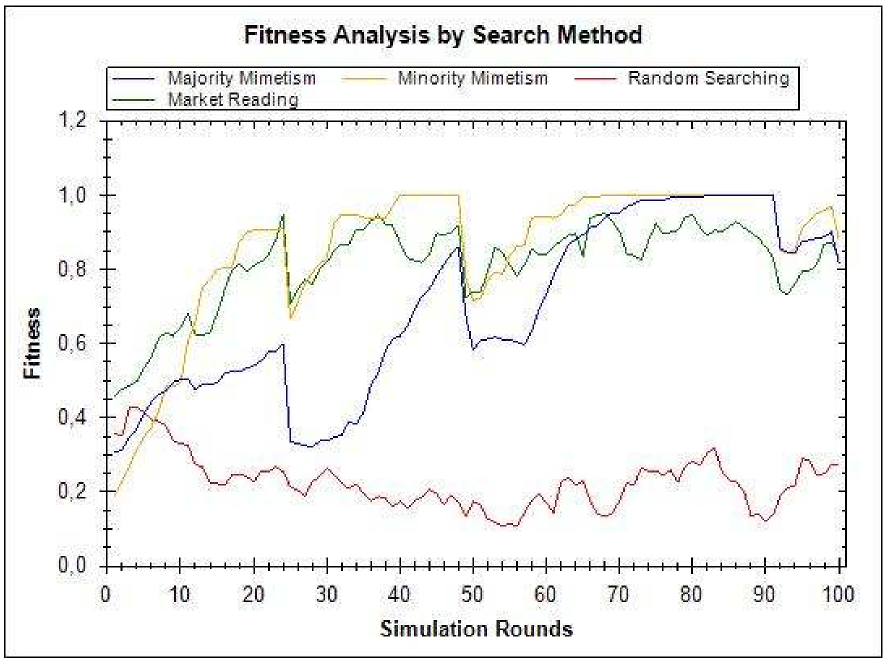


Chart 35 Evolution of fitness by search method. Simulation 68, run 3

[7] Because of the error rate parameter that is always present in the market reading routine.

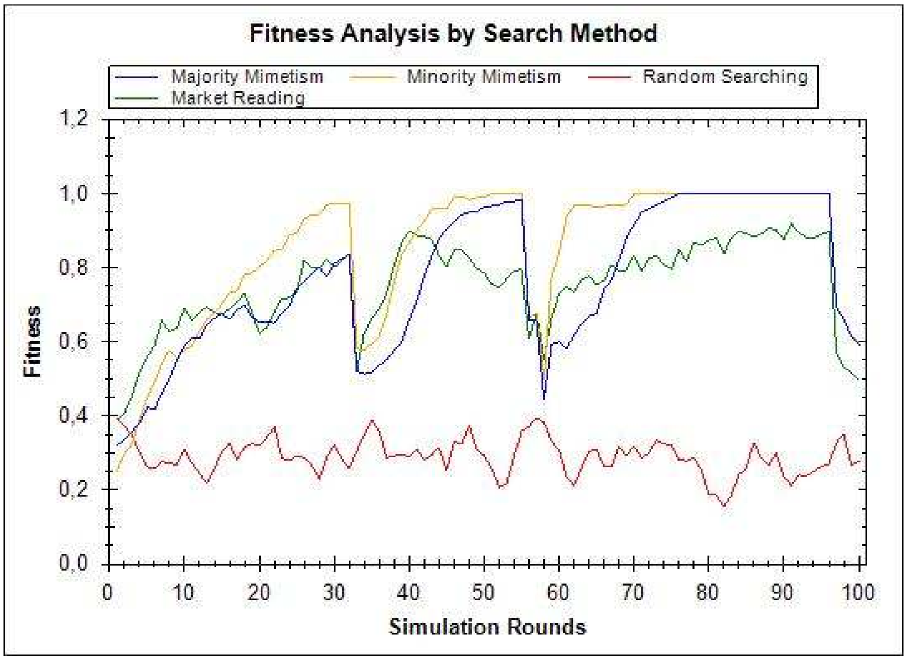


Chart 36 Evolution of fitness by search method. Simulation 68, run 5

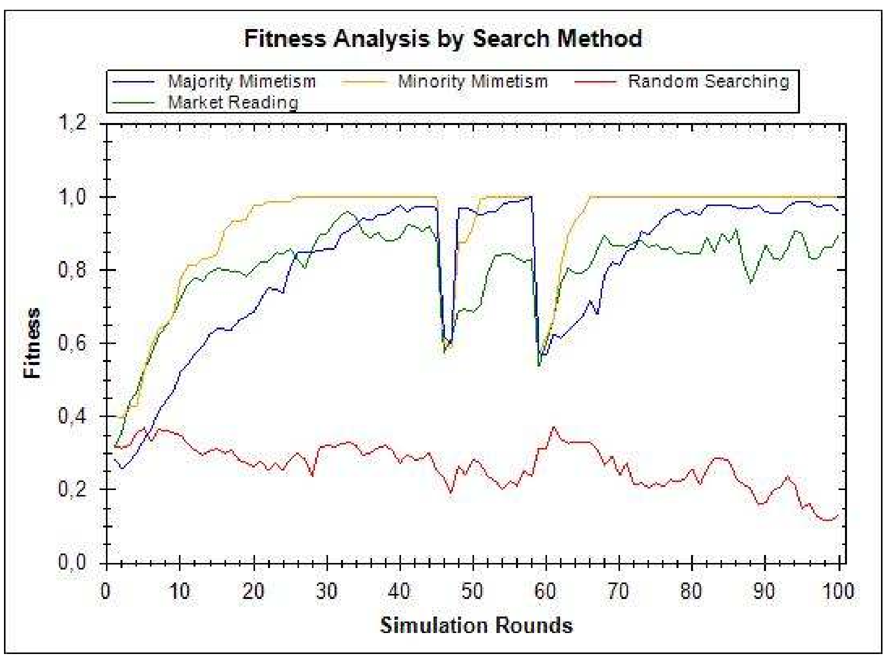
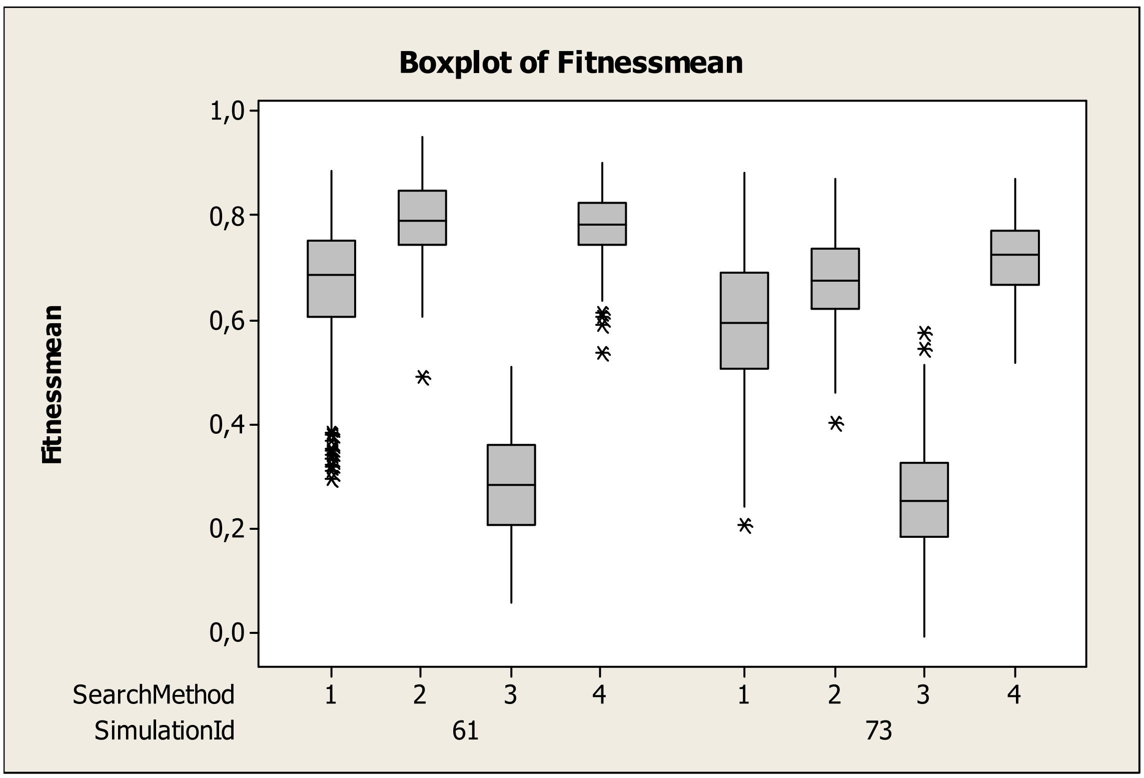


Chart 37 Evolution of fitness by search method. Simulation 68, run 9

5.2.5. Landscape complexity and its impact in search method performance

As the number of characteristics for a firm configuration increases, that is, the landscape turns to be more complex[8], the firms with mimetism strategies become less efficient in their search. This can be verified in the comparison of fitness (by search method) in the following simulation settings:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 38 Boxplot of fitness mean by search method. Simulations 61 and 73

The distribution curve of fitness for the population of firms shows that, in most cases, firms performing the minority mimetism search method were not able to converge towards high

[8] The AdjustCap parameter influences this relationship as mentioned before, in the specific section that addressed this parameter´s effect.

levels of fitness (kurtosis as a measure to indicate). The confidence intervals for fitness mean can be utilized to verify the differences of efficiency between the minority mimetism and the market reading methods:

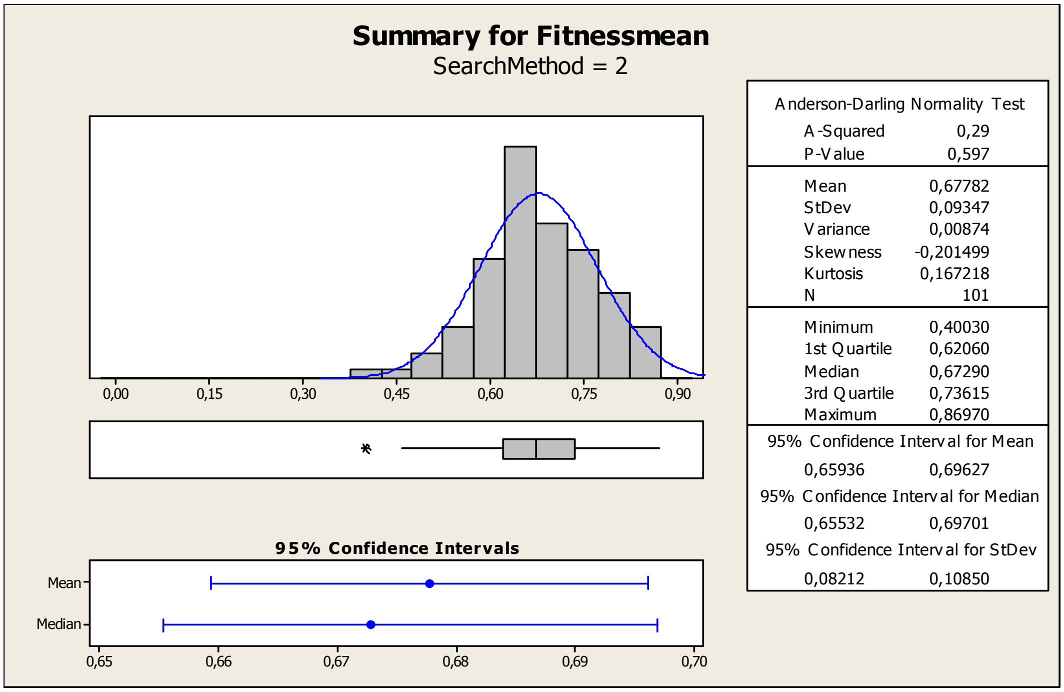


Chart 39 Graphical summary of statistics: fitness mean. Simulation 73, all runs – Minority mimetism

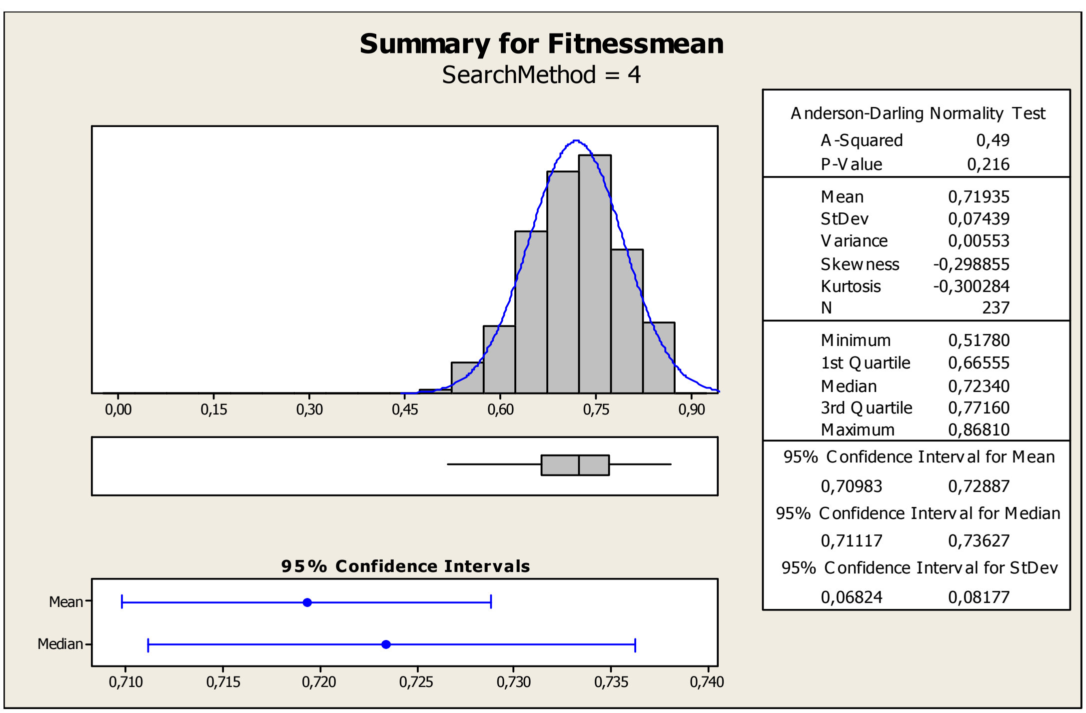
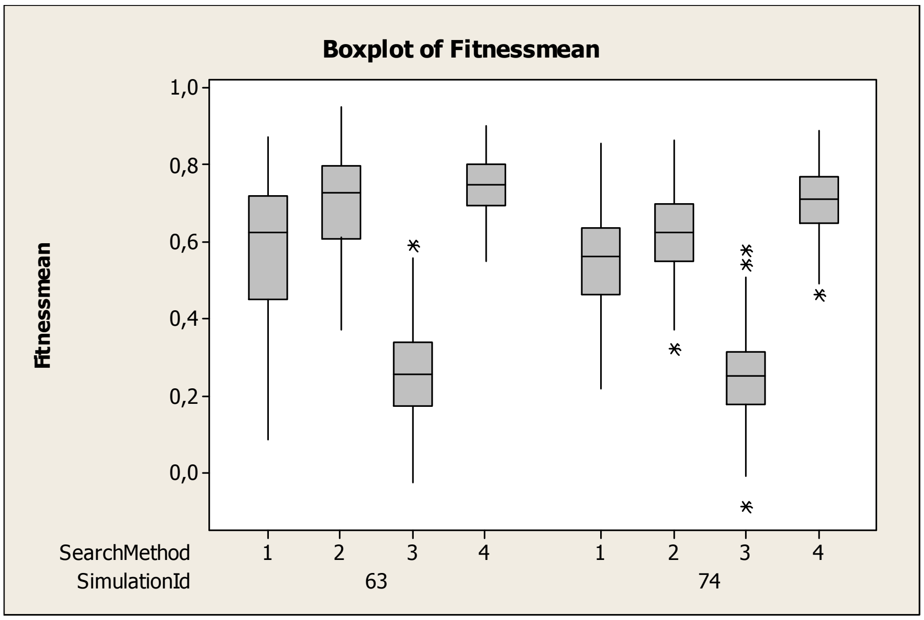


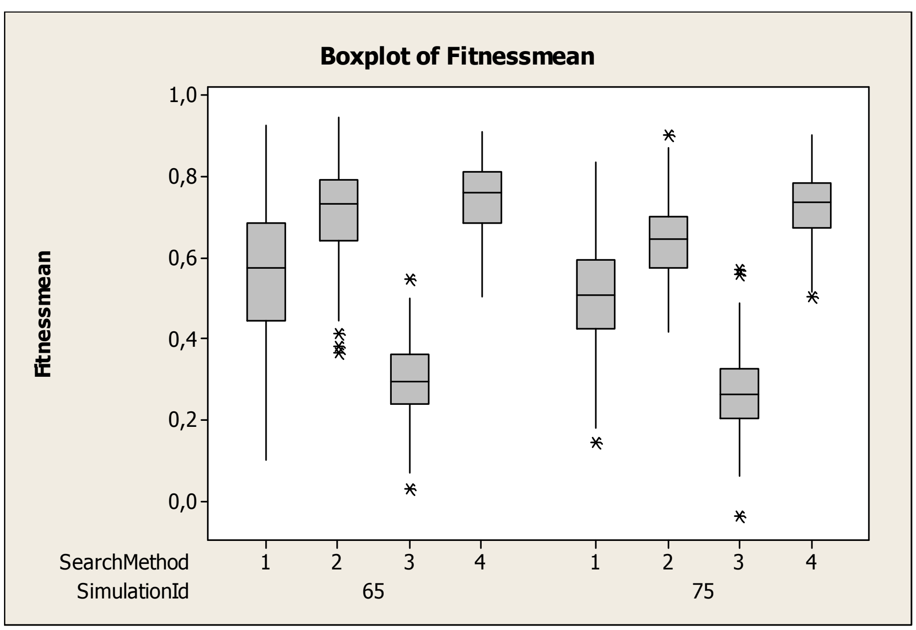
Chart 40 Graphical summary of statistics: fitness mean. Simulation 73, all runs – Market reading

The same pattern of variation in the relative efficiency is observed in the comparison of fitness mean (by search method) of other simulation settings:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 41 Boxplot of fitness mean by search method. Simulations 63 and 74

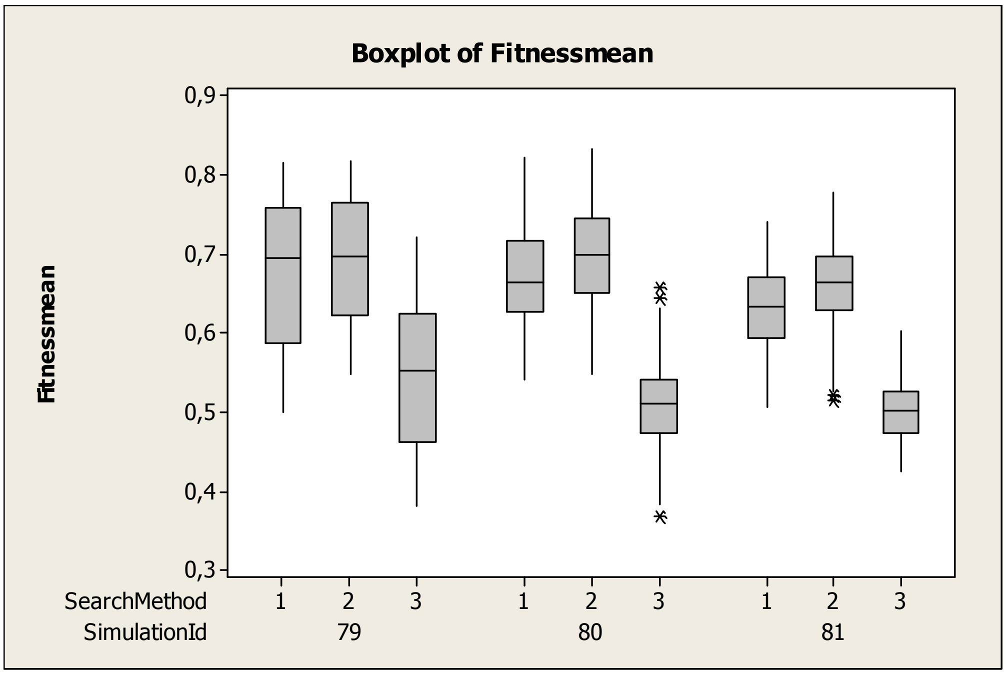


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 42 Boxplot of fitness mean by search method. Simulations 65 and 75

In the case of the NK model, our analysis gets limited because we could not design a search method that would be considerably equivalent to the market reading for our verification purposes (due to the very nature of the NK model).

Nevertheless, it is interesting to observe the simulation results as the complexity increases, that is, when "K value" is increased:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 43 Boxplot of fitness mean by search method. Simulations 79, 80 and 81

In the NK model the landscape doesn´t change over time[9], thus, firms effectively do the "hill climbing" as expected, with more or less difficulty. Exceptionally, some firms with the majority mimetism search method may get "stuck" in a plateau, what is more frequently in the case of a higher K value, as illustrated in the following sequence of simulation execution runs[10]:

[9] There is a variation, the NK(C) model, that does change over time. The effort to implement this variation, however, was beyond the limits we set for the present work.
[10] Note that under the NK model only search methods 1, 2 and 3 are employed.

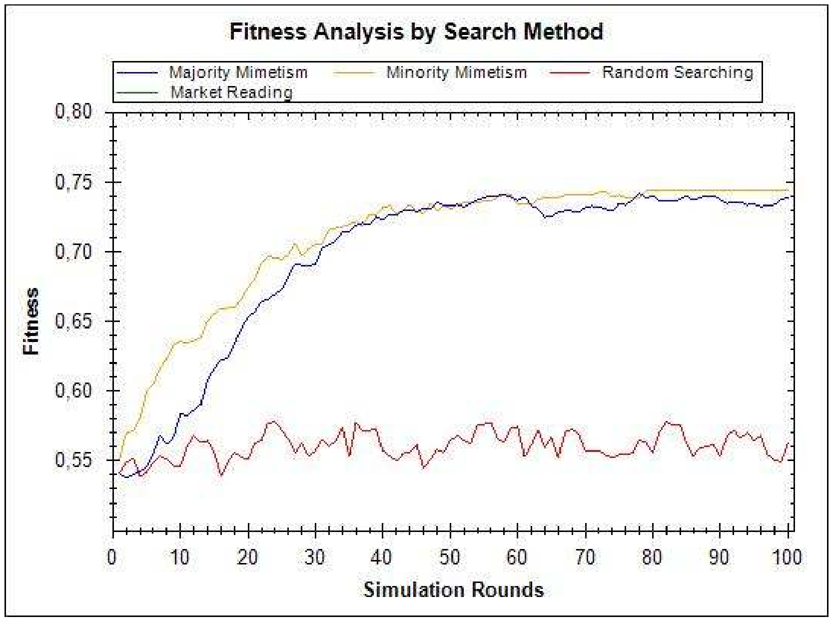


Chart 44 Evolution of fitness by search method. Simulation 79, run 2

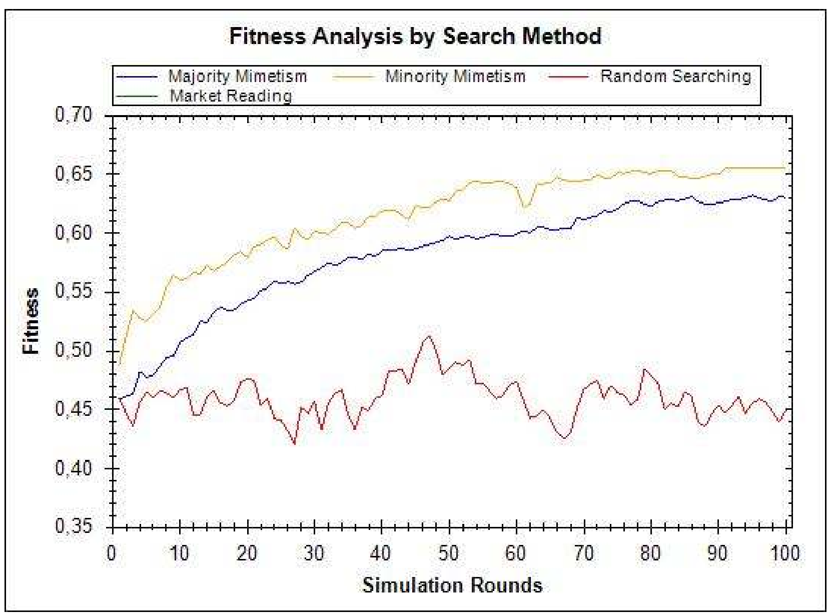


Chart 45 Evolution of fitness by search method. Simulation 79, run 10

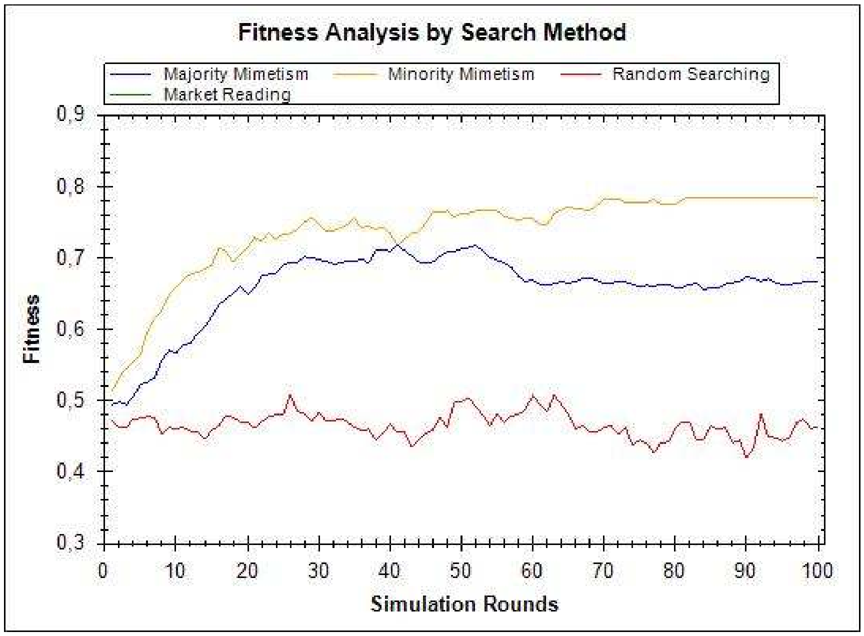


Chart 46 Evolution of fitness by search method. Simulation 80, run 1

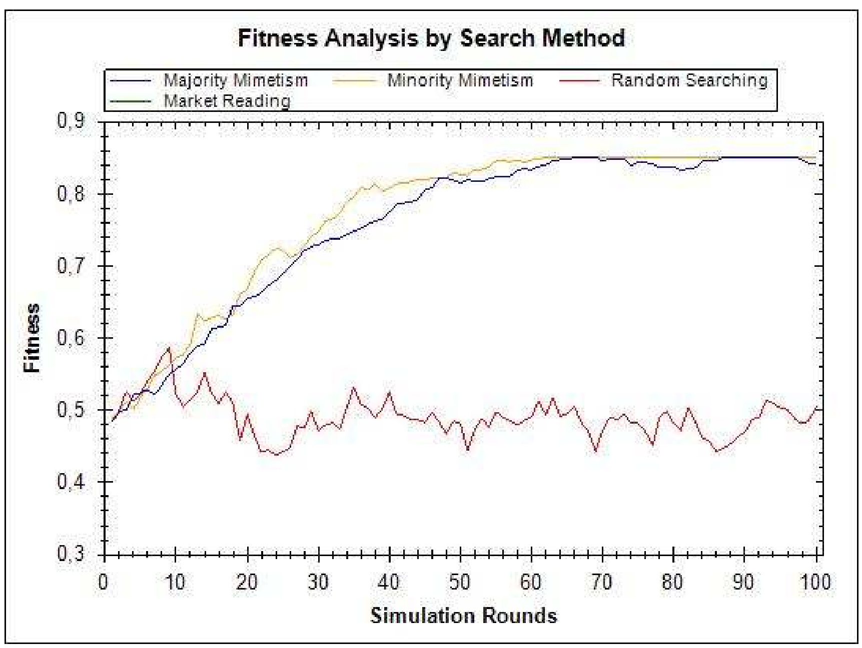


Chart 47 Evolution of fitness by search method. Simulation 80, run 4

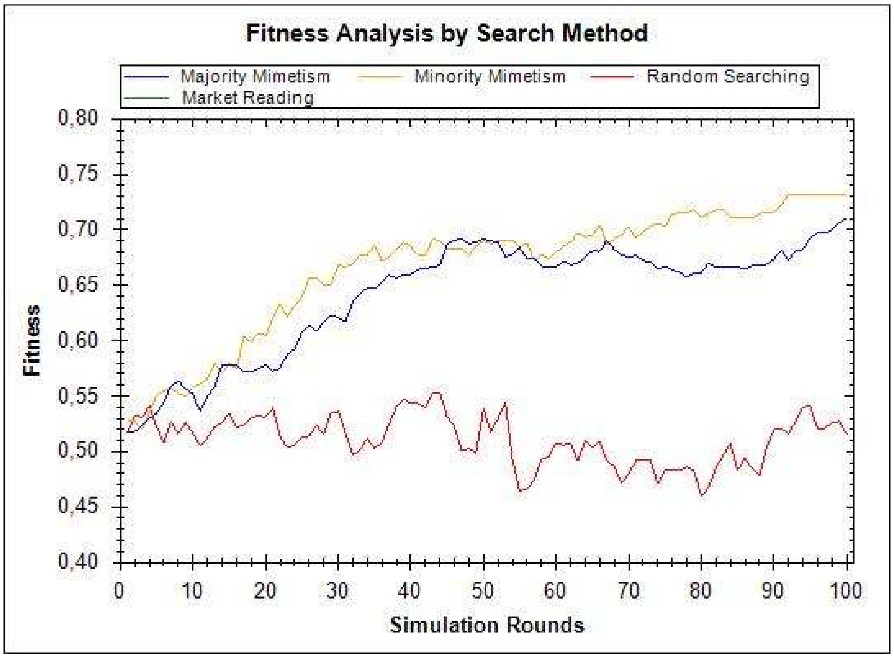


Chart 48 Evolution of fitness by search method. Simulation 81, run 9

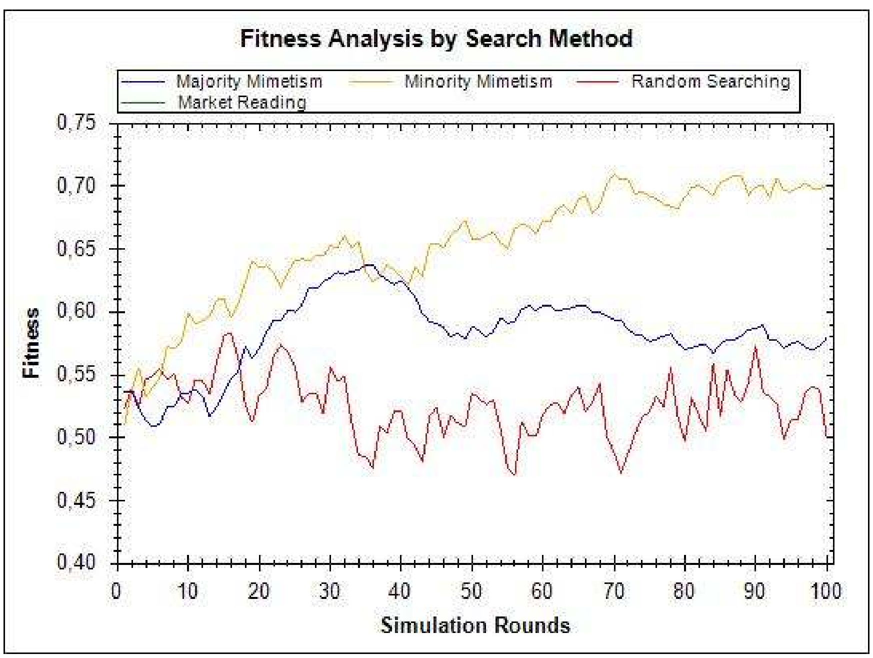
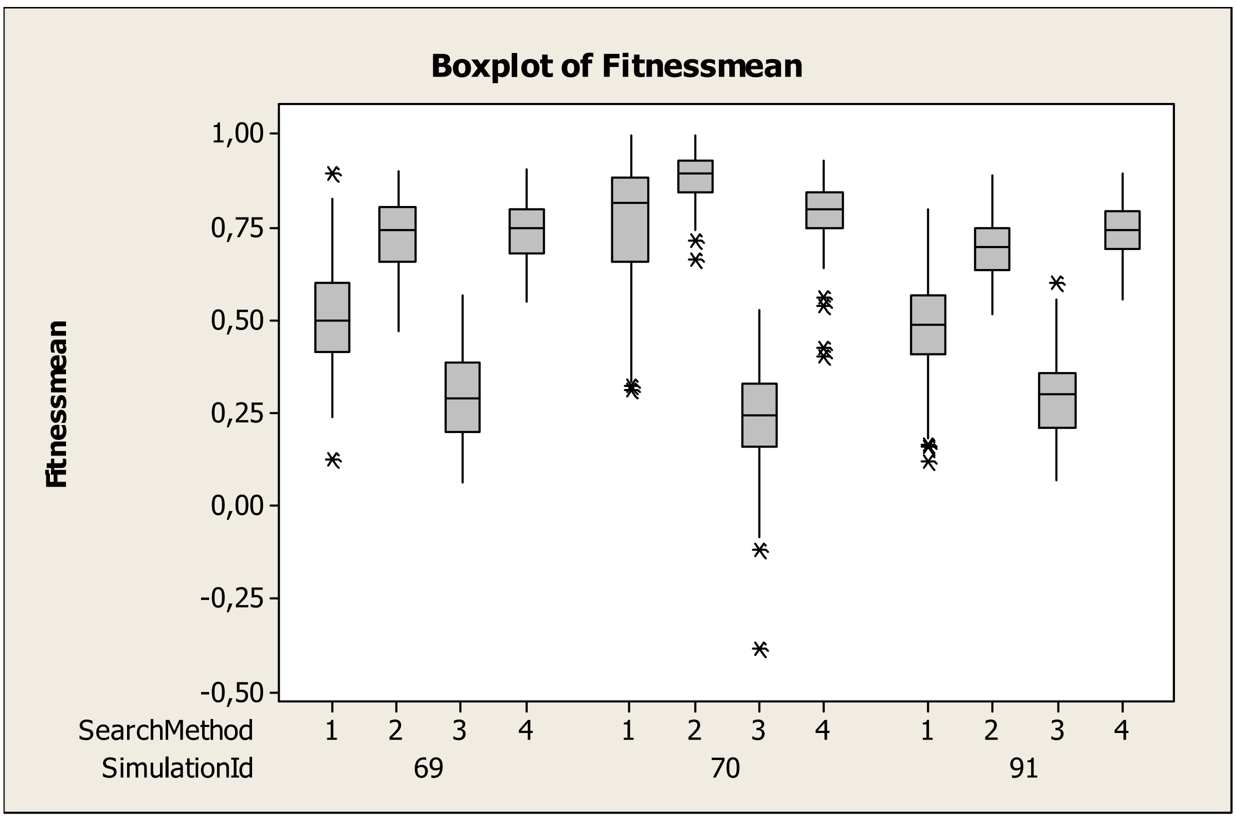


Chart 49 Evolution of fitness by search method. Simulation 81, run 10

5.2.6. Effects of landscape exogenous changes

As described before, our customized landscape model allows for two types of landscape change: due to exogenous or endogenous causation mechanisms. We first explore the effect of different rates of exogenous change, maintaining the endogenous change parameters initially considered in our simulation settings baseline.



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 50 Boxplot of fitness mean by search method. Simulations 69, 70 and 91

In simulation 70, landscape change doesn´t occur; as expected, mimetism methods perform better. The "hill climbing", with a high Vision parameter as set for all these scenarios (Vision value = 10), makes even the majority mimetism search method to outperform the market reading, as shown in these detailing charts:

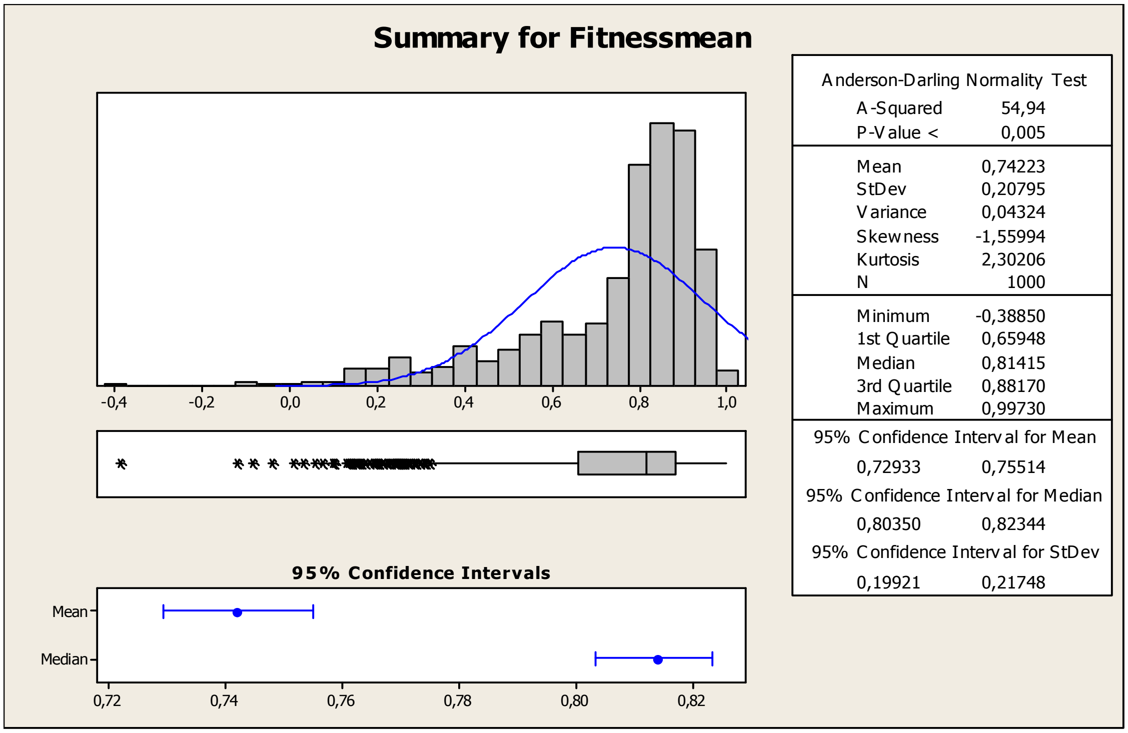


Chart 51 Graphical summary of statistics: fitness mean. Simulation 70, all runs

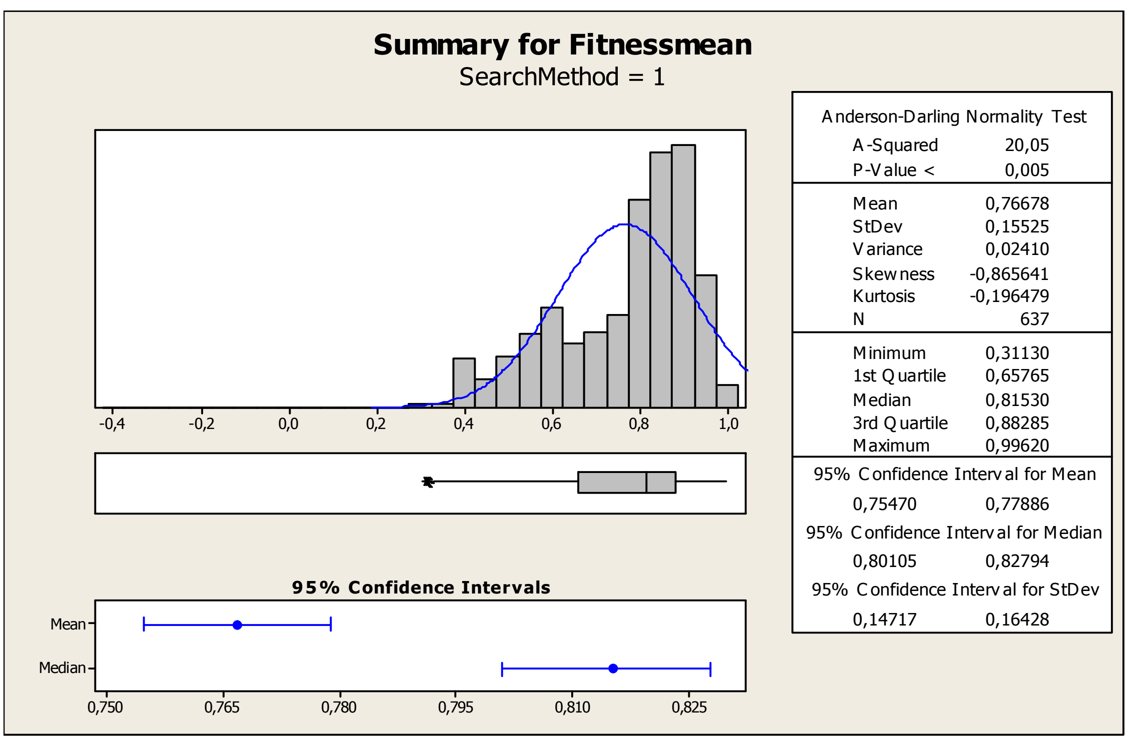


Chart 52 Graphical summary of statistics: fitness mean. Simulation 70, all runs – Majority mimetism

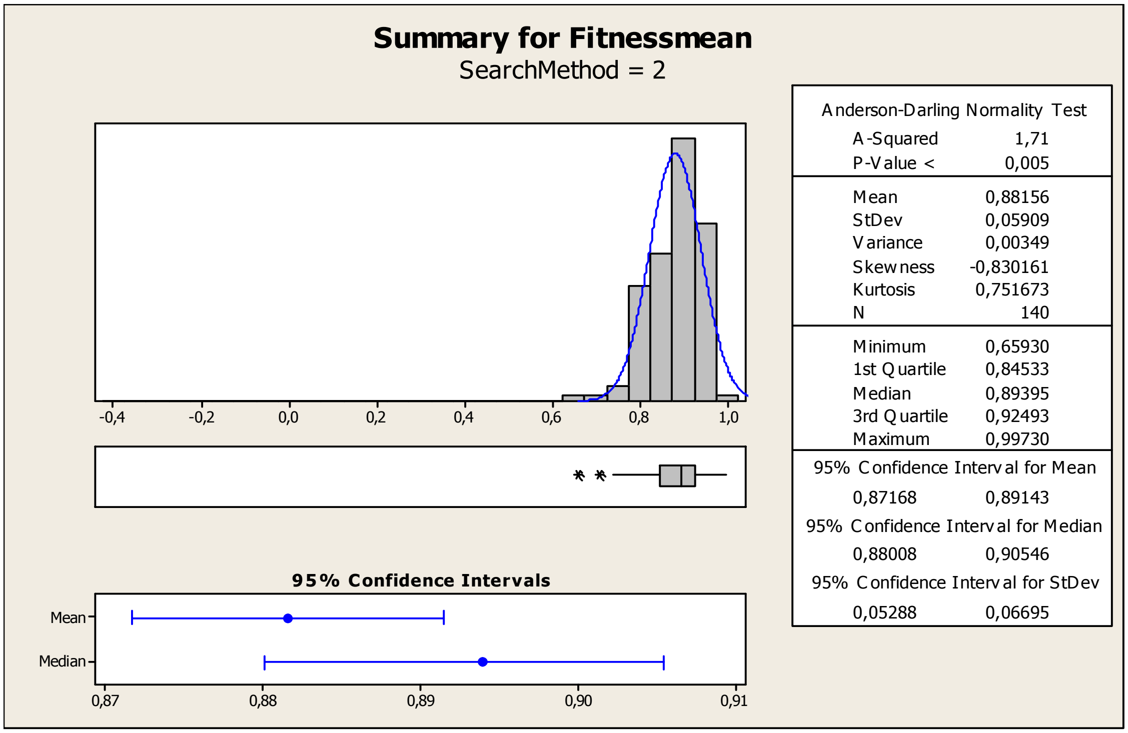


Chart 53 Graphical summary of statistics: fitness mean. Simulation 70, all runs – Minority mimetism

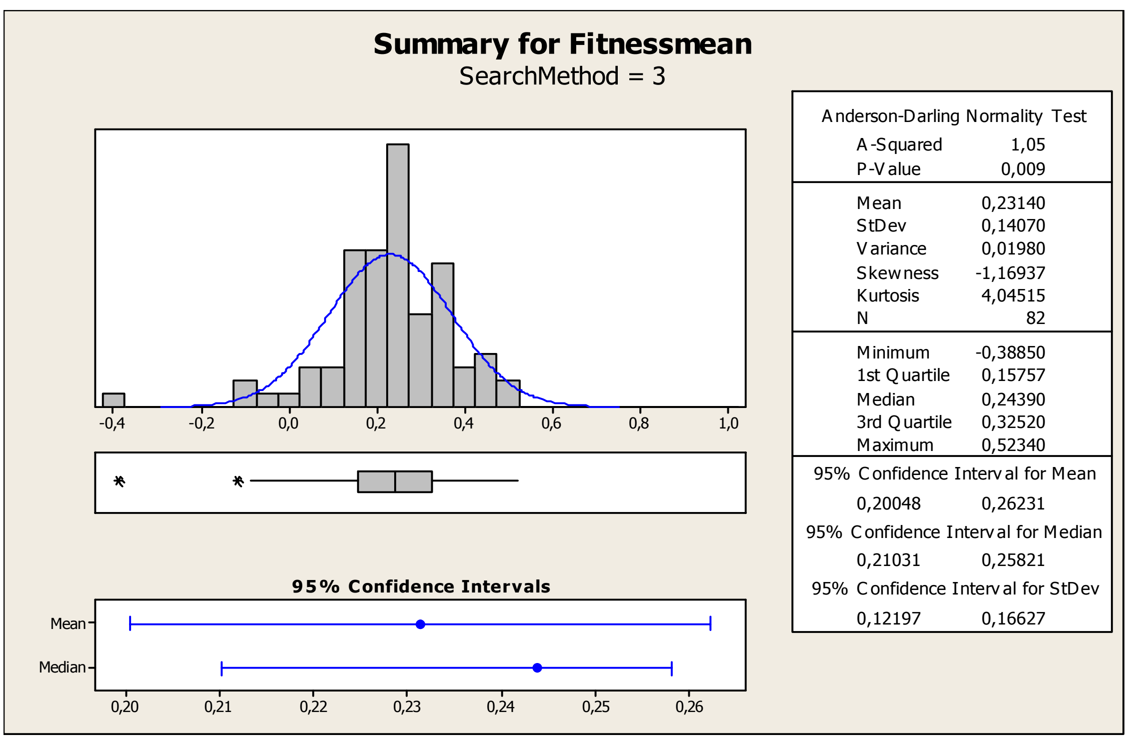


Chart 54 Graphical summary of statistics: fitness mean. Simulation 70, all runs – Random search

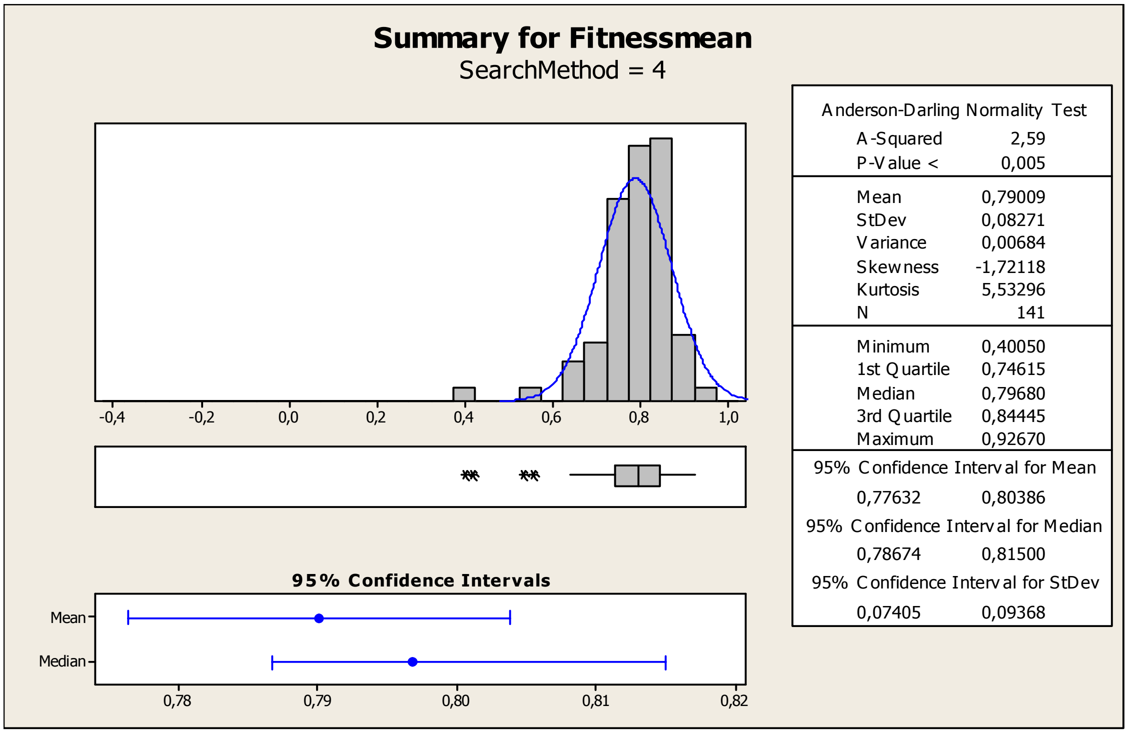


Chart 55 Graphical summary of statistics: fitness mean. Simulation 70, all runs – Market reading

The firms with the majority mimetism search method achieve, on average, a higher performance than the firms operating with the market reading search method. Nevertheless, firms searching with majority mimetism strategies also get trapped due to self-reinforcing dynamics, depending on the specific relationships each firm has. We selected two runs of this same simulation setting to illustrate the distinct outcomes:

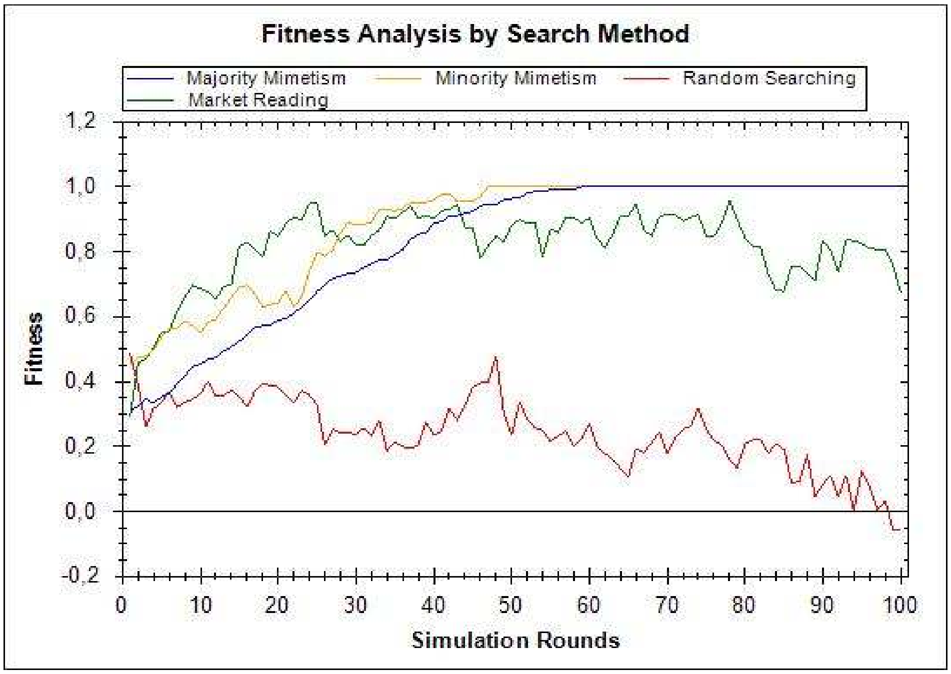


Chart 56 Evolution of fitness by search method. Simulation 70, run 7

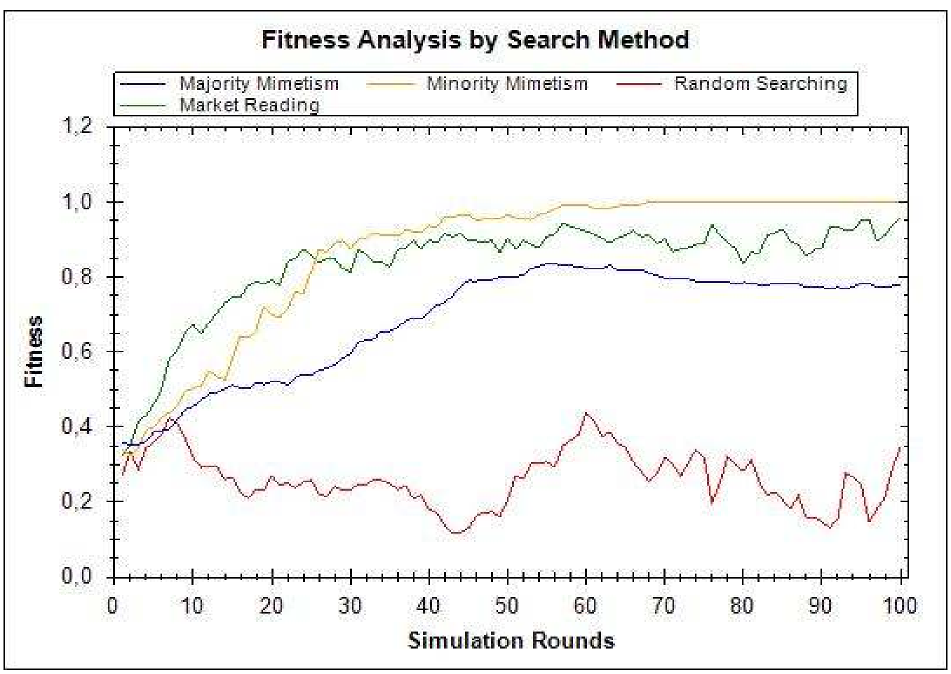


Chart 57 Evolution of fitness by search method. Simulation 70, run 9

In contrast to simulation 70, the landscape settings in simulation 91 provide a representation of “high-changing” markets. The distribution curve of fitness performance is different, as we can verify by comparing the kurtosis and skewness metrics to those of the previous simulation setting:

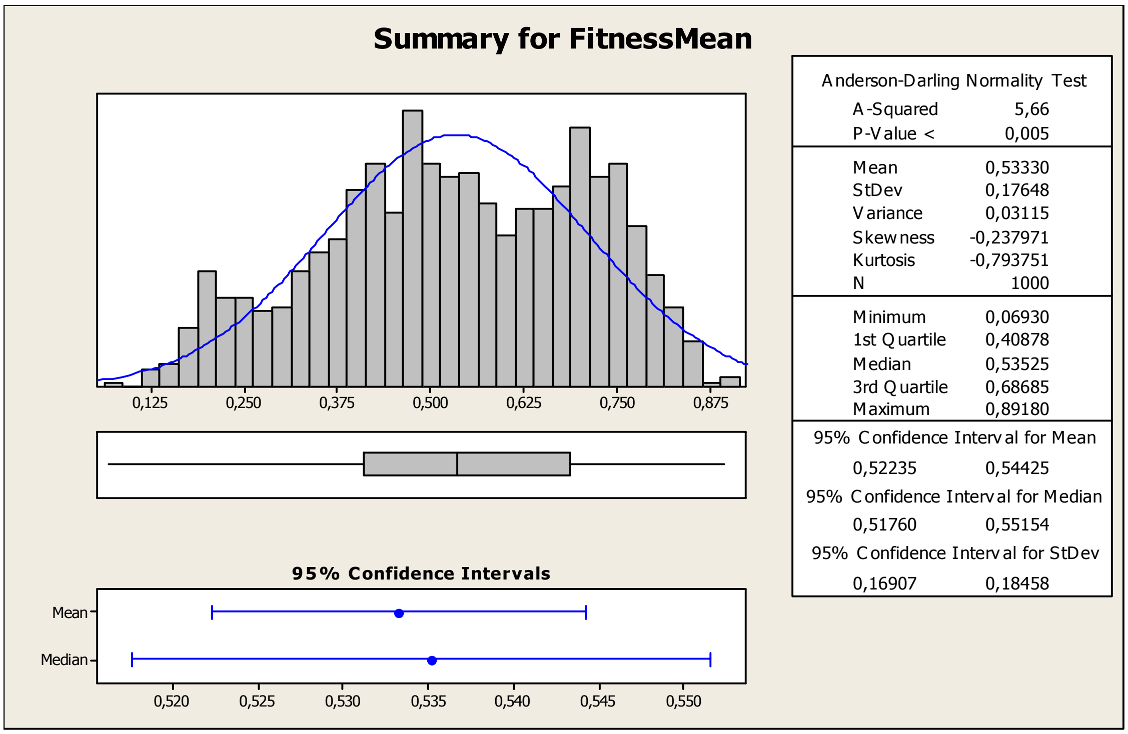


Chart 58 Graphical summary of statistics: fitness mean. Simulation 91, all runs

Such scenario rewards innovators, which are able to adopt faster to changing needs, preferences or technologies than the firms adopting mimetism strategies, as verified by the detailed statistics by search method in the following charts:

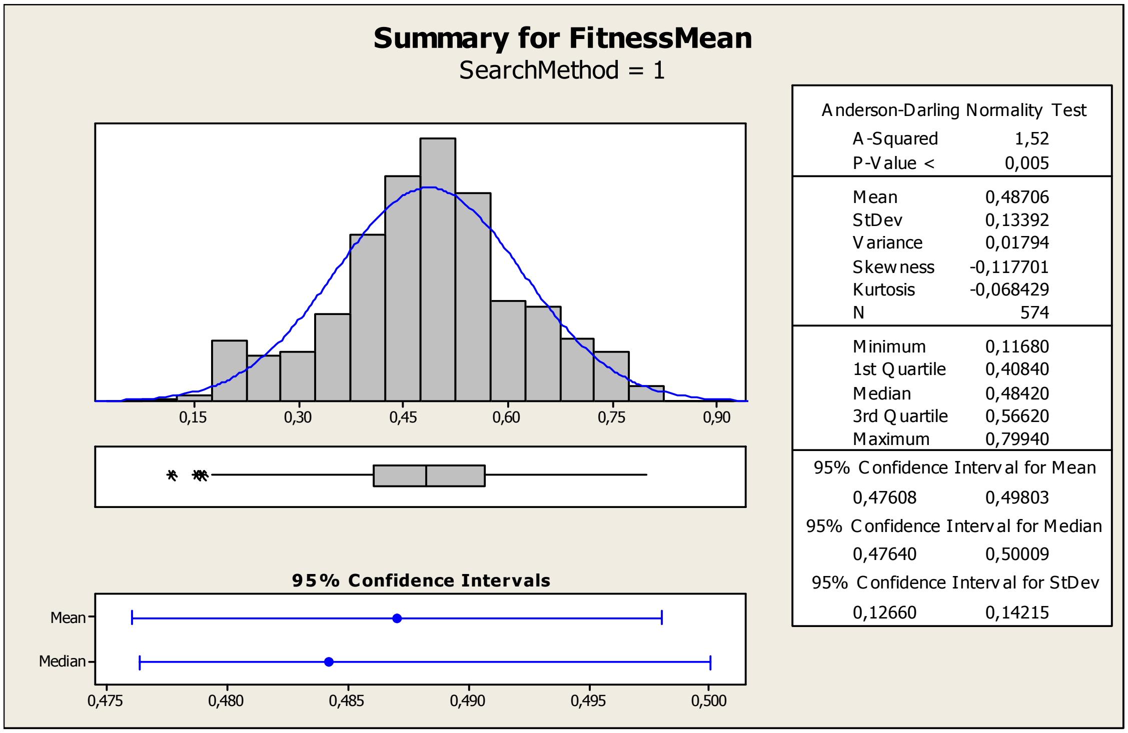


Chart 59 Graphical summary of statistics: fitness mean. Simulation 91, all runs – Majority mimetism

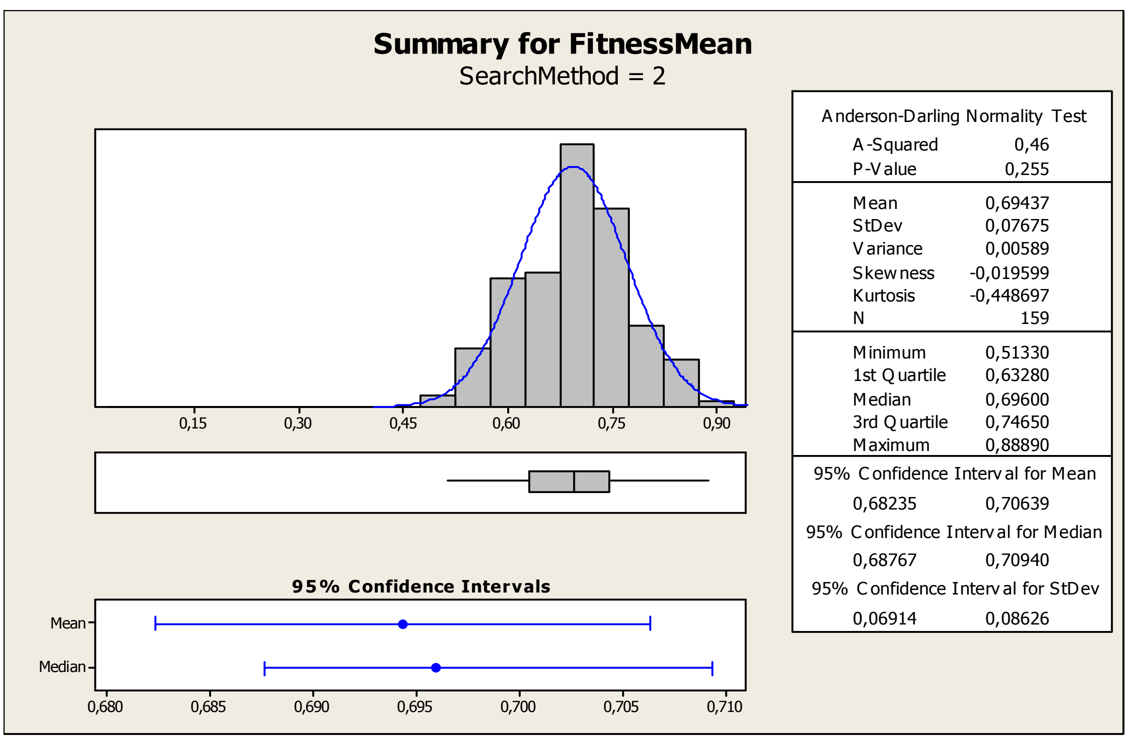


Chart 60 Graphical summary of statistics: fitness mean. Simulation 91, all runs – Minority mimetism

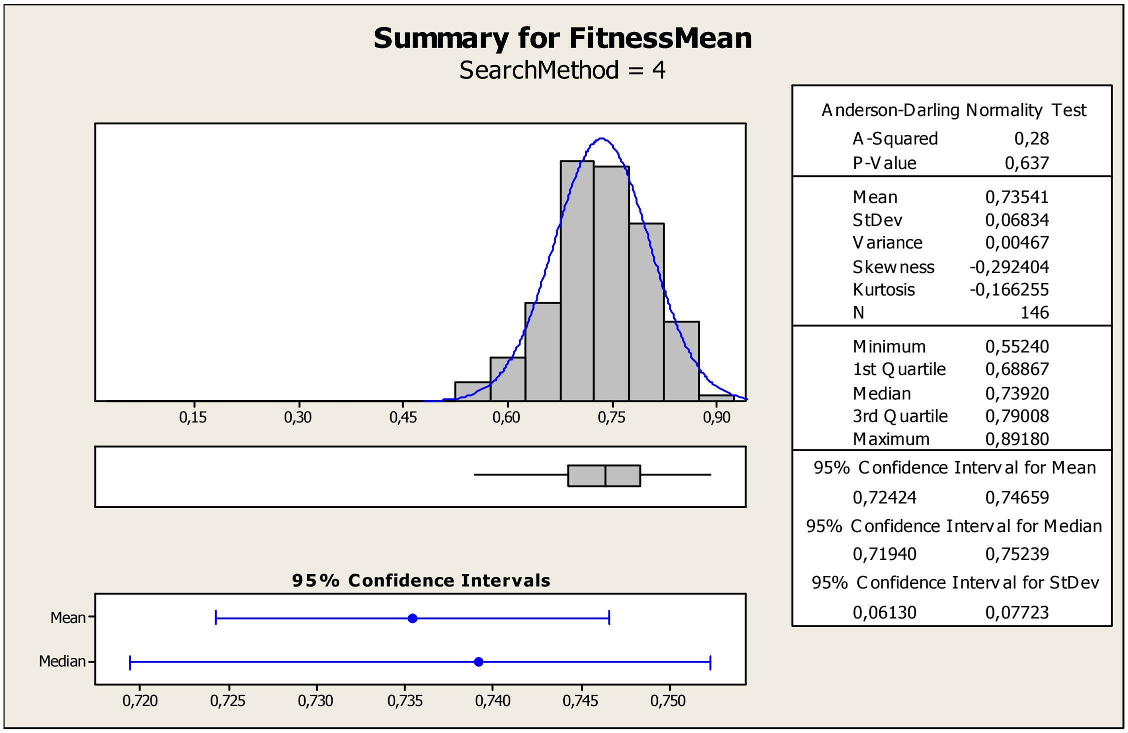


Chart 61 Graphical summary of statistics: fitness mean. Simulation 91, all runs – Random search

The following charts from selected executions illustrate the competitive dynamics:

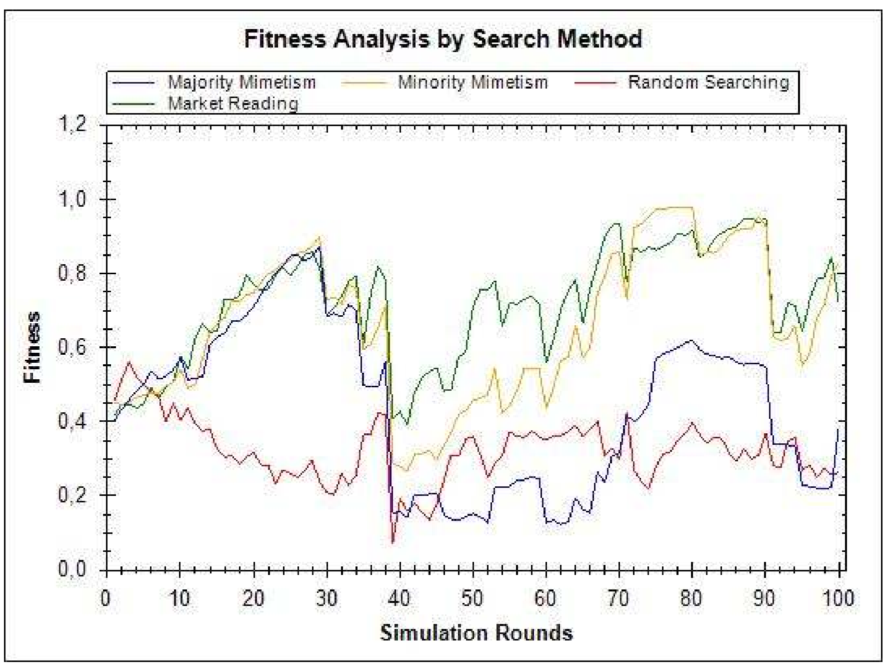


Chart 62 Evolution of fitness by search method. Simulation 91, run 1

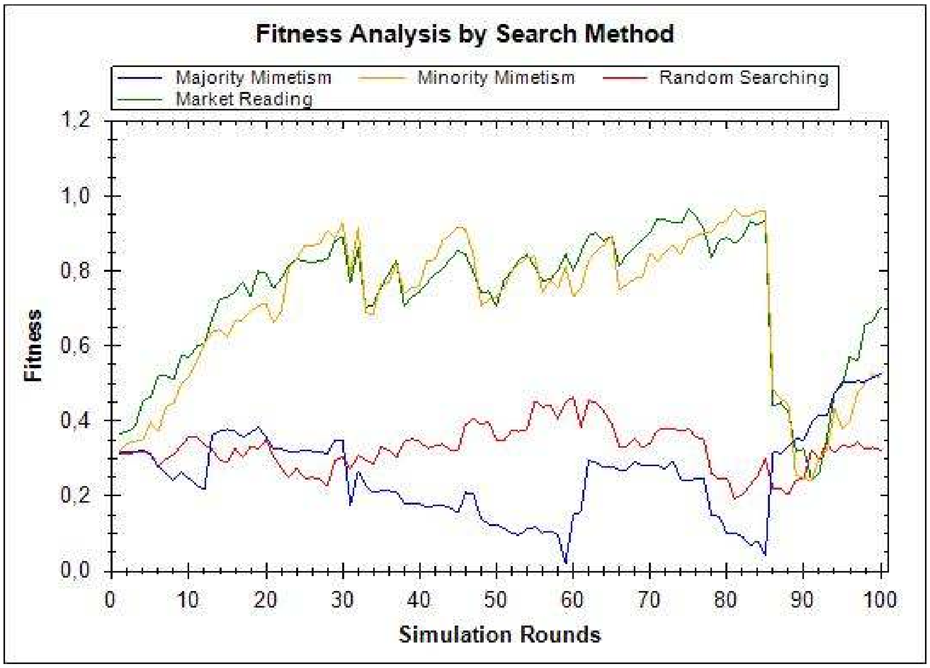


Chart 63 Evolution of fitness by search method. Simulation 91, run 6

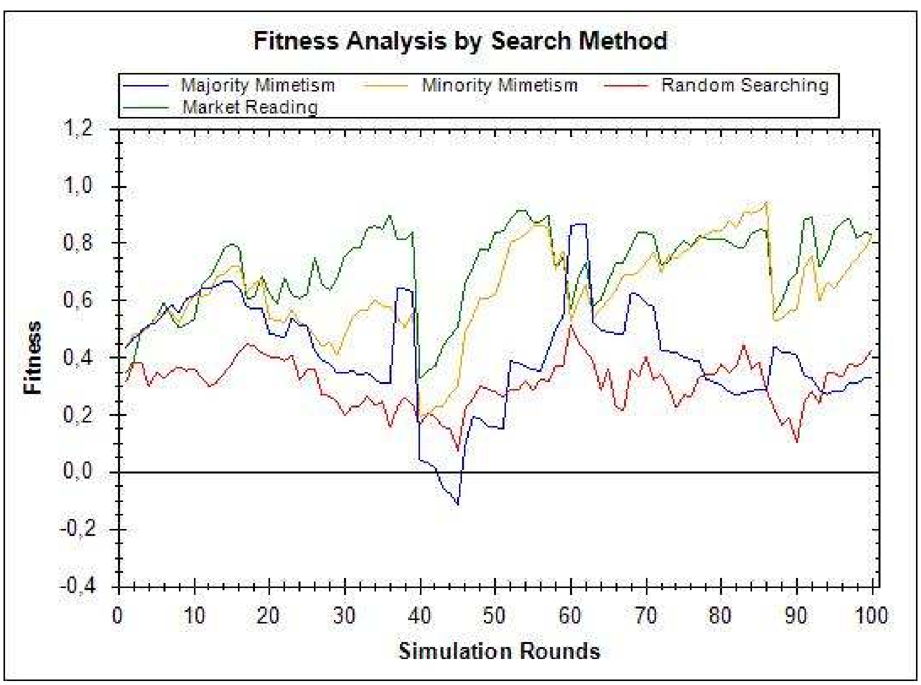
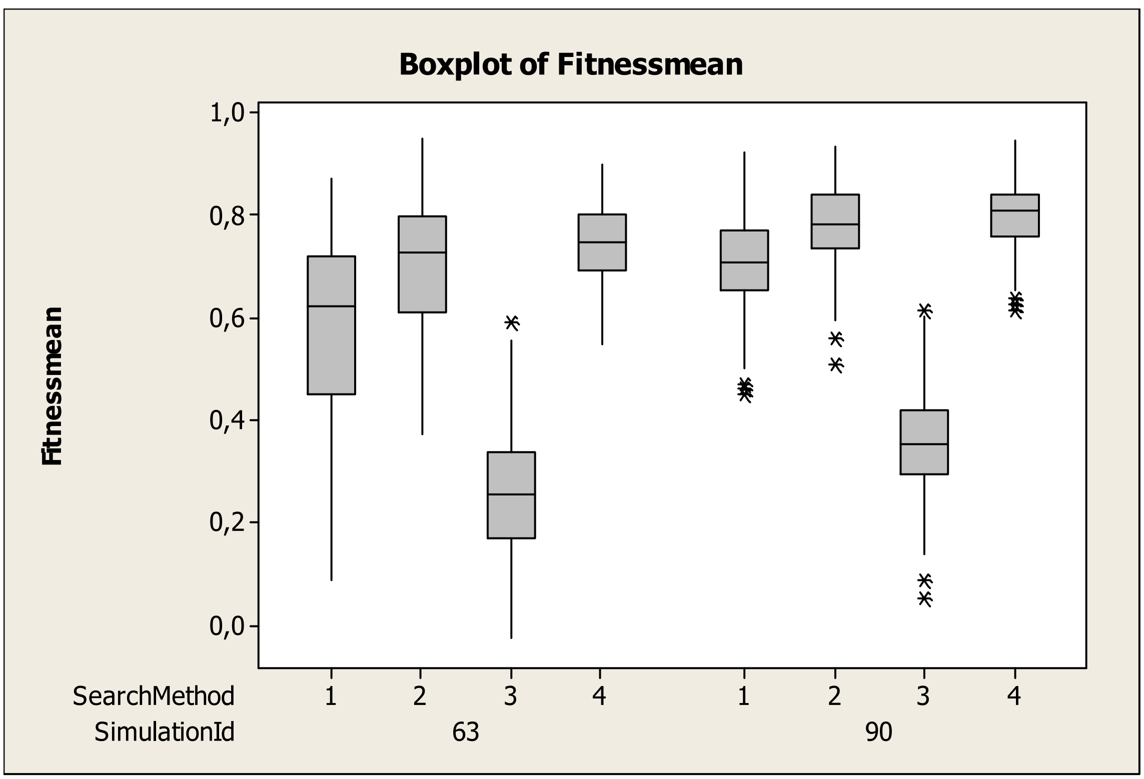


Chart 64 Evolution of fitness by search method. Simulation 91, run 8

5.2.7. Effects of landscape endogenous changes

We now turn to analyze the effects of variation in the endogenous change parameters built into our model.

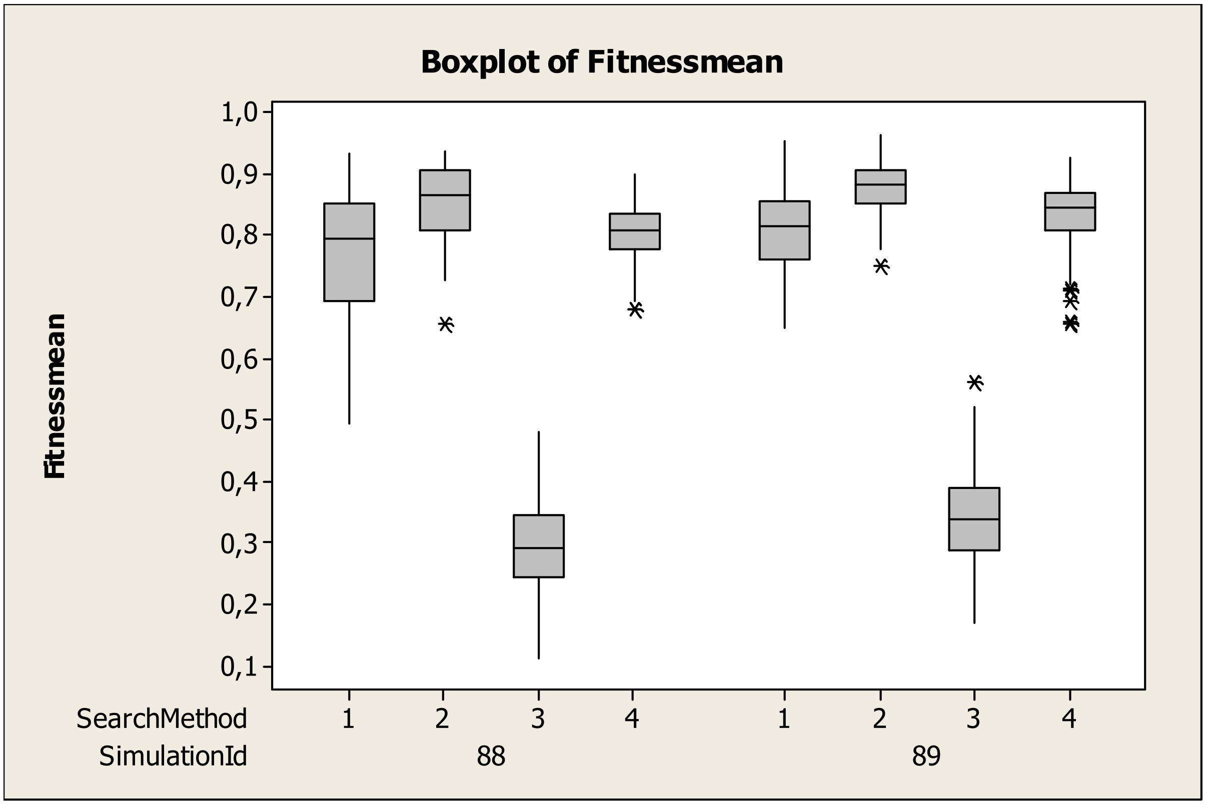
The first comparison considers our baseline scenario, simulation 63, and a variation in which endogenous change doesn´t occur – simulation 90. The most significant impact is that firms don´t face the reduction in the fitness contribution for matching characteristics that almost all other firms matched as well. In this situation, imitators benefit because the process of massive copying doesn´t lead to decreasing returns of what is copied. All firms in fact benefit from the situation:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 65 Boxplot of fitness mean by search method. Simulations 63 and 90

The comparison of simulations 88 and 89 provides the same verification, the difference of these scenarios being the higher Vision and higher AdjustCap parameters[11]:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 66 Boxplot of fitness mean by search method. Simulations 88 and 89

There is no validation to be performed with the NK model this time, as our model doesn´t provide comparable outcomes in this regard.

[11] As we already explored in a previous subsection, these parameter values make the firms with the minority mimetism search strategy outperform those with the market reading search method, while the firms with the majority mimetism search method get close but remain less efficient.

5.3. About the persistence of above and below average performances

Now we turn our analysis to investigate the persistence of above average and below average performance, that is, the specific conditions that explain why some firms consistently outperform or underperform others.

Our investigation considers two different sets of simulations:

- The first set, already presented in the previous subsection, where we look for above average and below average performers in scenarios where the firms have one of the four designed search methods, the same values for their Vision and AdjustCap attributes, and only differ in their initial endowment and relational positioning (ProximityDensity matrix);
- The second set, comprised of simulation settings where we vary Vision and AdjustCap, the two other possible parameters that might help explain competitive advantage under the designed boundaries of our model.

We make use of two arbitrarily defined parameter values to identify above average and below average performance:

- 1 (one) standard deviation above or below average - which represents a proportion of the population that is close to the percentage of firms with competitive advantage and competitive disadvantage according to Vasconcelos and Brito in their study (2004);
- 1.96 standard deviations above or below average, which accounts for roughly 5% of the firms in each simulation run.

We also created in our model another measure to help identify high performers; following Powell (2003b), at each round we identify the firm (or firms) with the highest fitness score, and count it as one “win”. We sum up the number of wins each firm has in a simulation run. Some firms win many times more than the others, and this outliers are identified as the above average performers.

The following frame summarizes our investigative efforts and outcomes, further detailed along this subsection:

PERSISTENCE OF ABOVE AND BELOW AVERAGE PERFORMANCES

Subsection	Changes in simulation parameters	Impact detected?	Description	References (simulations)	Key considerations
5.3.1	Combinations of ProximityDensity / Vision parameter (equally defined for the whole population)	Yes	Impacts the distribution of wins among the competing firms; Identification of outliers as simple heuristics.	57 to 62	Convergence towards fit. Informational traps explain some below averagers. For mimetism methods, a successful strategy depends on the success of others.
5.3.2	Capacity to adjust at the population level	Yes	Reduces below averagers associated with mimetism methods	61-88	Mimetism methods improve as capacity to adjust gets higher (given other favorable conditions). Firms with mimetism strategies less prone to get into path dependent, low performance levels.
5.3.3 5.3.4	Variations in individual firm attributes for the same population (Vision and AdjustCap parameters)	Yes, but only for capacity to adjust	Vision is not a predictor for above or below average performance AdjustCap is correlated A regression model with them has little explanatory power	76 77; 84	Efficiency of mimetism methods depend on the quality of information obtained. A successful strategy depends on luck and/or the unfolding interactions with others.
5.35	Search method population distribution	Yes	Changes in the proportion of above and below averagers utilizing each search method	64-66	Increase of path dependence effects. Even the search method that doesn´t rely on the practices of others depend on the strategy of others – since competitive advantage is a relative matter
5.3.6	Landscape number and interdependency of characteristics	Yes	Changes in the proportion of above and below averagers utilizing each search method	63-74; 65-75; 78	Complexity influences search method efficiencies to some extent.

Frame 3 Persistence of above and below average performances: issues and impacts identified

5.3.1. The effects of ProximityDensity and Vision at the population level

As demonstrated earlier in this work, the increases in the ProximityDensity and Vision parameters contribute to a convergence towards high fitness levels in stable environments (those with low frequency of landscape changes).

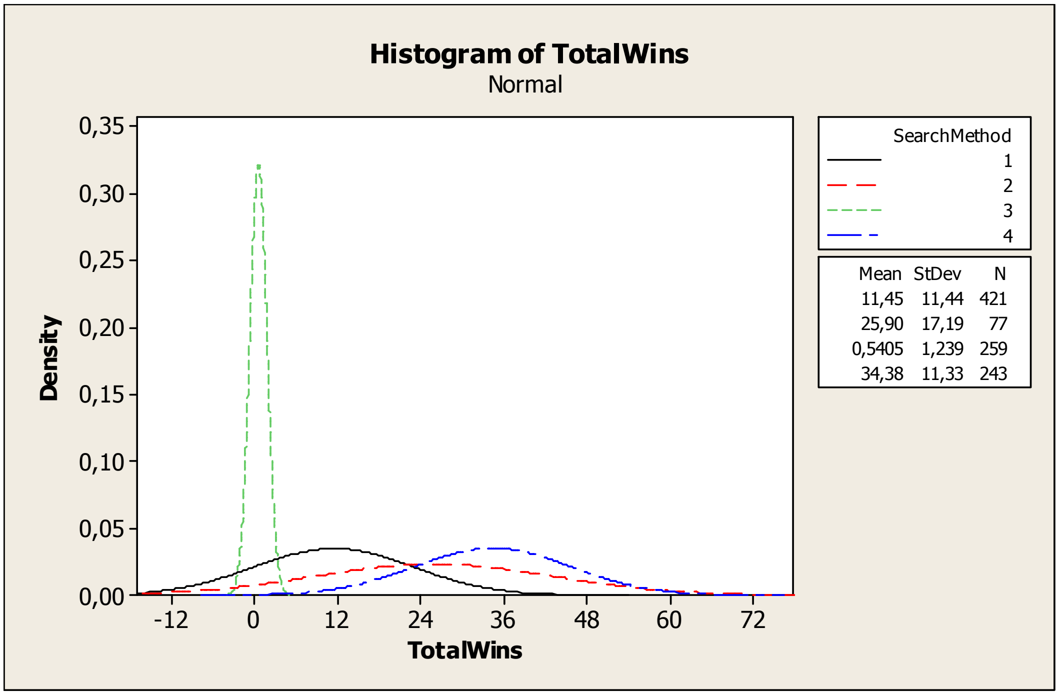
At the population level, we noted that:

- By design, random search underperforms;
- Market reading and minority mimetism search methods compete. The relative performance of each search method is impacted in a variety of ways, as explored in the previous section;
- Majority mimetism can be a competitive search method under some settings, but is frequently subject to informational traps (path dependence, bandwagon effects, and limited information to improve performance).

Nevertheless, there is significant variance in fitness performance for the firms that employ each of those search methods. It is important to notice that simple heuristics can justify above and below average performance in settings where all firms have the same attributes, randomly defined initial states and randomly assigned relationships to others.

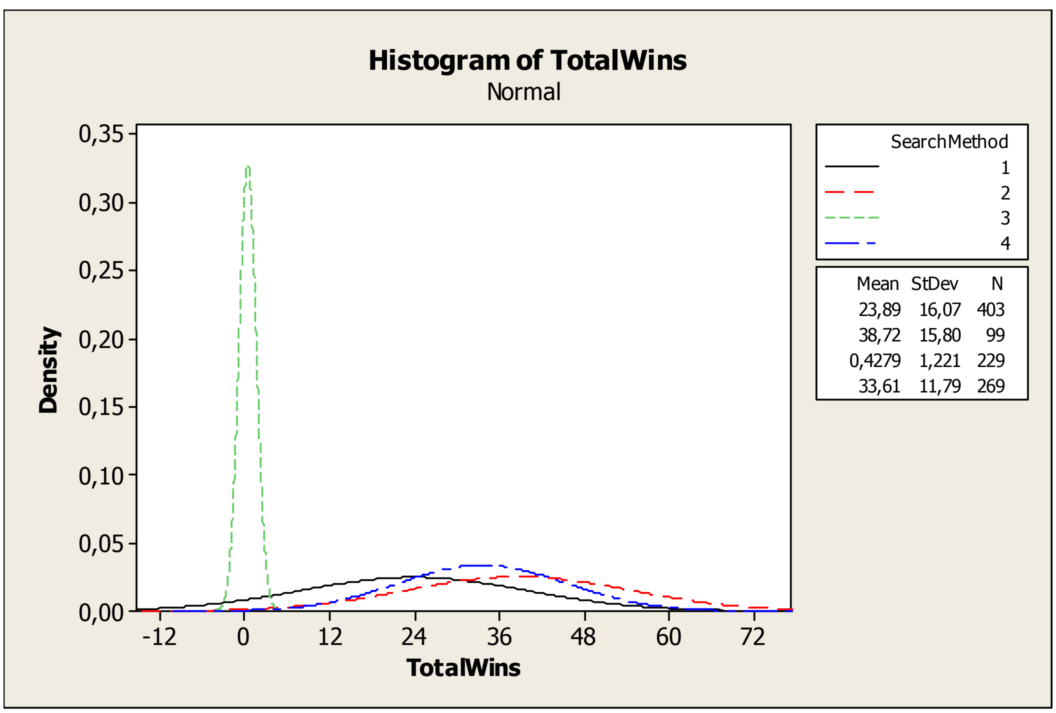
We first present a sequence of charts that make use of the discrete variable number of wins to analyze relative performance[12]:

[12] We will later turn back to the use of the conventional measure of competitive advantage through a continuous variable, in our case, the fitness value.



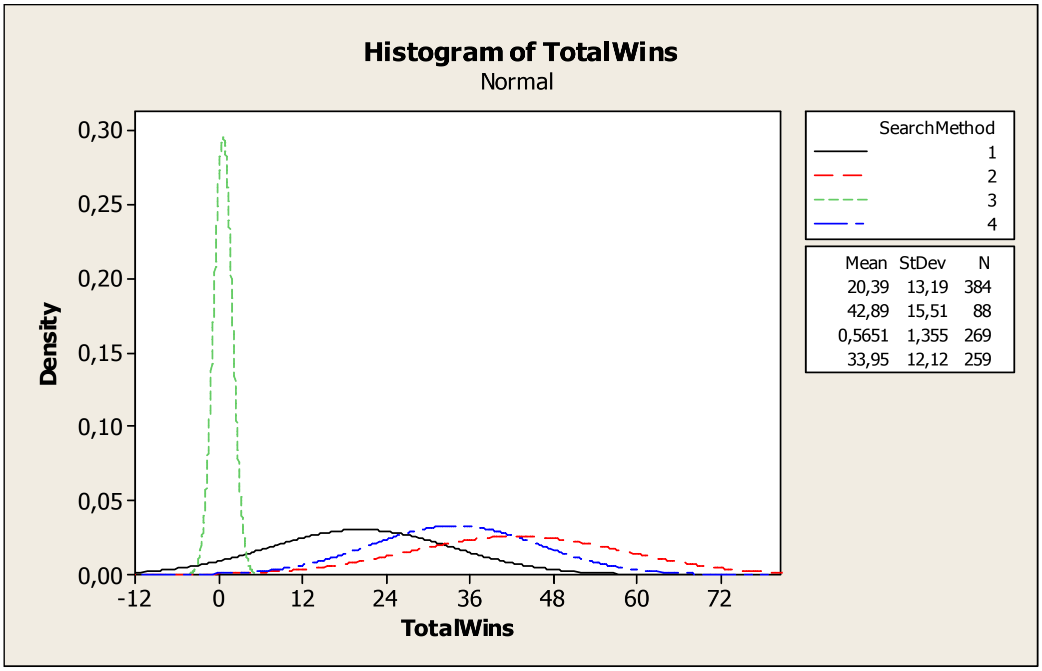
Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 67 Histogram of firm´s wins by search method. Simulation 57, all runs



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

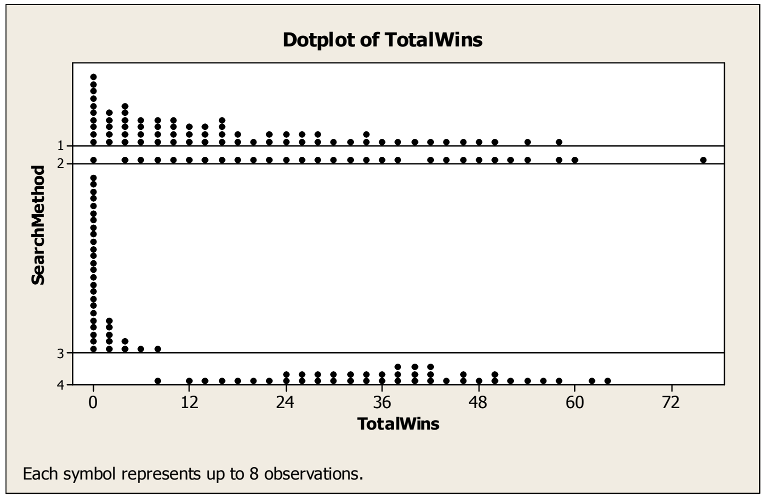
Chart 68 Histogram of firm´s wins by search method. Simulation 60, all runs



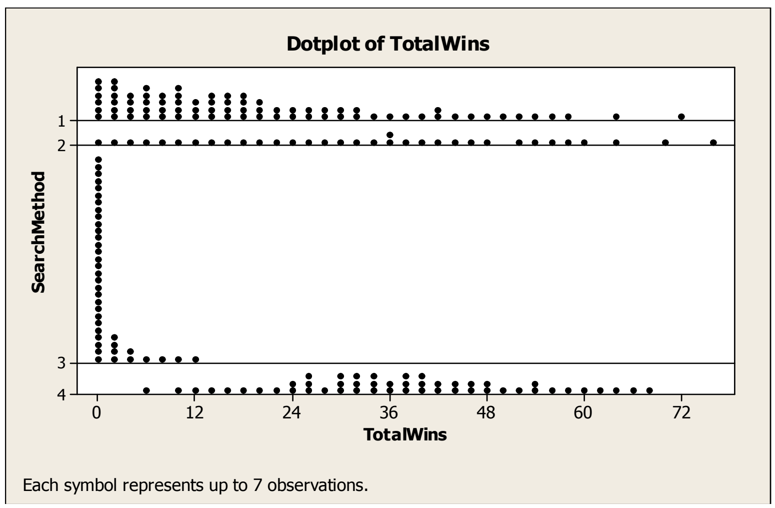
Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 69 Histogram of firm´s wins by search method. Simulation 62, all runs

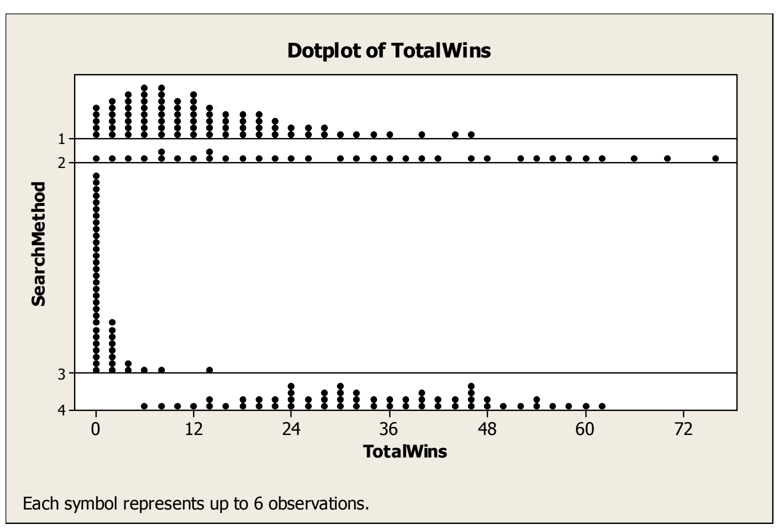
A better visualization of outliers and the improvements of mimetism methods performances are provided in the following sequence:



Simulation 57, all runs

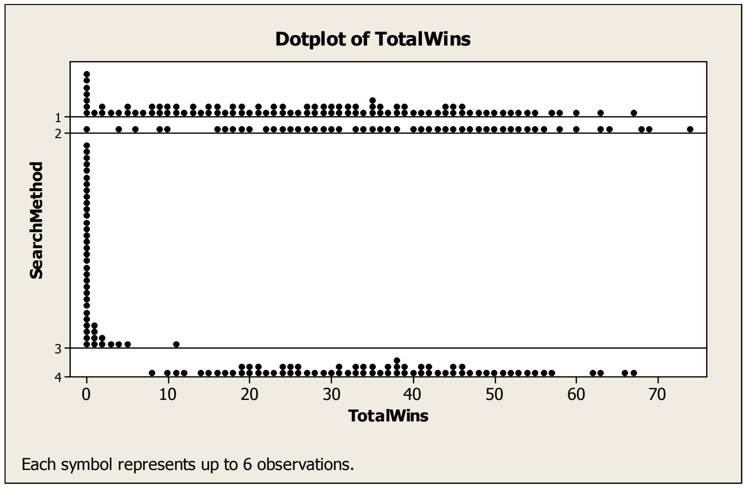


Simulation 58, all runs

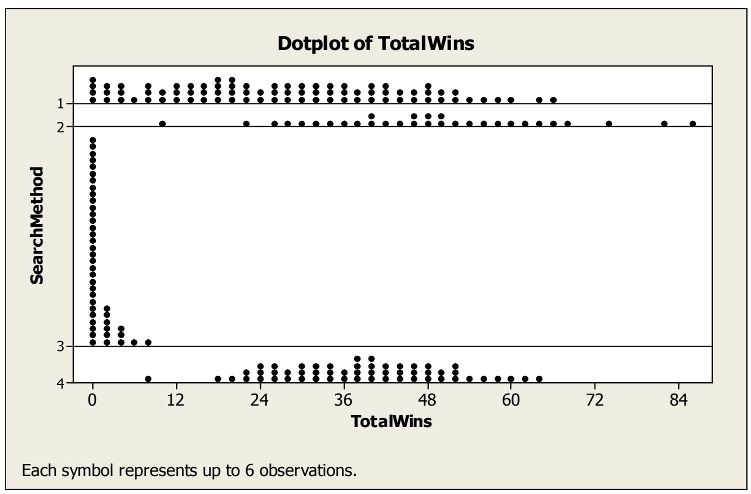


Simulation 59, all runs

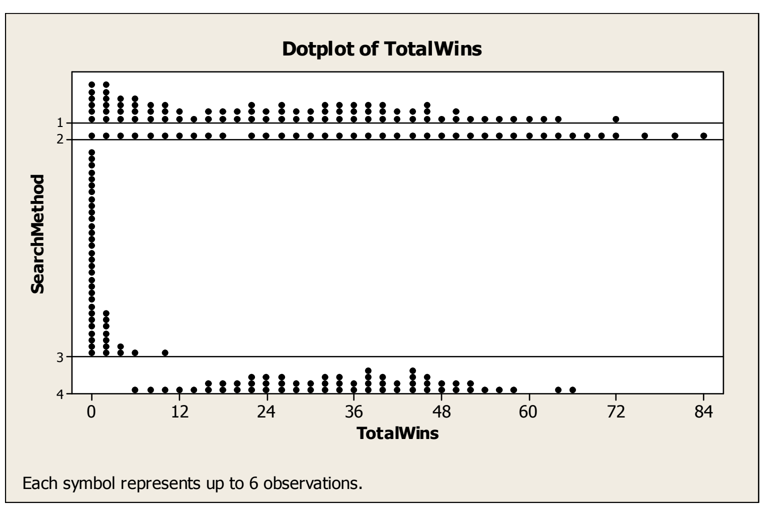
Chart 70 Dotplot of firm´s wins by search method. Simulations 57, 58 and 59



Simulation 60, all runs



Simulation 61, all runs



Simulation 62, all runs

Chart 71 Dotplot of firm´s wins by search method. Simulations 60, 61 and 62

A quick look at the statistics for these simulations shows the occurrence of below average performance by search method. Random searches dominate, but we also find trapped firms that were performing majority mimetism search:

Table 8 Classification of firms according to fitness performance , by search method[13]

Tabulated statistics: SimulationId; Indicator _above&belowaverage; SearchMethod

Rows: SimulationId / Indicator _above&belowaverage   Columns: SearchMethod

		1	2	3	4	All
57						
	A	7	19	0	143	169
	B	24	0	166	0	190
	M	390	58	93	100	641
58						
	A	8	21	0	107	136
	B	12	0	174	0	186
	M	402	73	65	138	678
59						
	A	4	25	0	125	154
	B	8	0	178	0	186
	M	404	66	67	123	660
60						
	A	9	23	0	66	98
	B	5	0	186	0	191
	M	389	76	43	203	711
61						
	A	3	29	0	61	93
	B	11	0	204	0	215
	M	386	77	37	192	692
62						
	A	13	28	0	93	134
	B	2	0	208	0	210
	M	369	60	61	166	656

Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average
Note: Above / below average indicator considered for firms with average fitness 1 (one) standard deviation from the population fitness mean.

The simulation results seem to support the argument stressed by Powell regarding the definition of competitive advantage (2001) - such competitive advantage may be much more in the eye of the observer than in the firm itself. The outliers identified in these simulations had

[13] Output analysis from Minitab 16, utilizing the simulation data

luck, as all firms operating with the same search method had the same attribute values (Vision, AdjustCap).

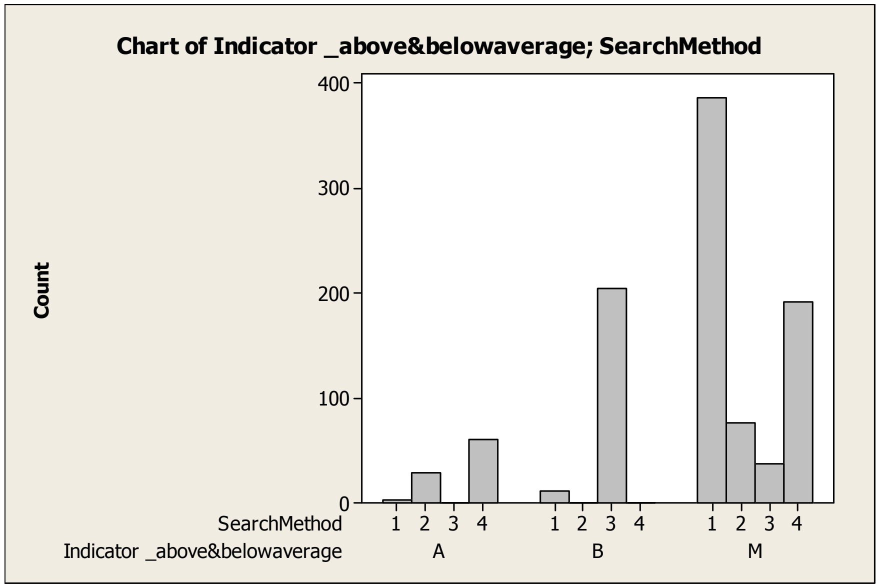
We may agree to some extent with Powell´s claim. Nevertheless, “luck” can be further explored and understood. While the outliers operating with the market reading search method can only count on luck to outperform others, the firms adopting mimetism strategies had to count on the luck of obtaining quality information during their searches. The quality of information depends on the specific relationships the firm has. If the firm has access to other firms that evolve efficiently during the simulation, then the firm will perform well. A successful strategy, in this case, depends on the successful strategy of others. We will get back to this discussion in the final section of the present study.

5.3.2. The effect of changes to AdjustCap at the population level

The AdjustCap parameter, as demonstrated before in this work, significantly affects the ability of firms utilizing the mimetism search methods to move towards higher levels of fitness[14]. Firms utilizing the majority mimetism search method no longer get stuck because of lack of information (relationship to other firms and vision), because firms move faster towards proper configurations.

We bring additional information on the simulations 61 and 88 (already discussed in previous topics) to illustrate the impact:

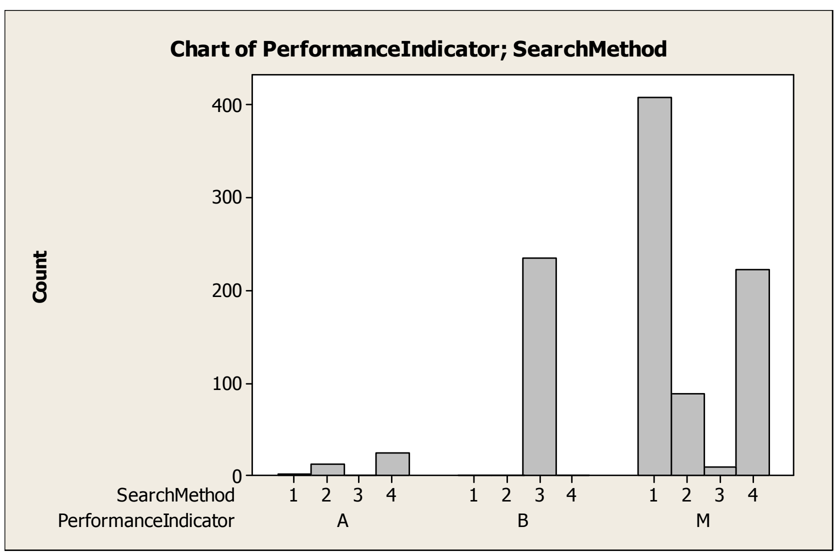
[14] The efficiency of mimetism methods depends on other simulation settings. Firms utilizing the market reading search strategy benefit from the increase in AdjustCap as well (however, only to some extent).



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average

Note: Above / below average indicator for firms with average fitness 1 (one) standard deviation from the population fitness mean.

Chart 72 Classification of firms according to fitness performance, by search method. Simulation 61, all runs

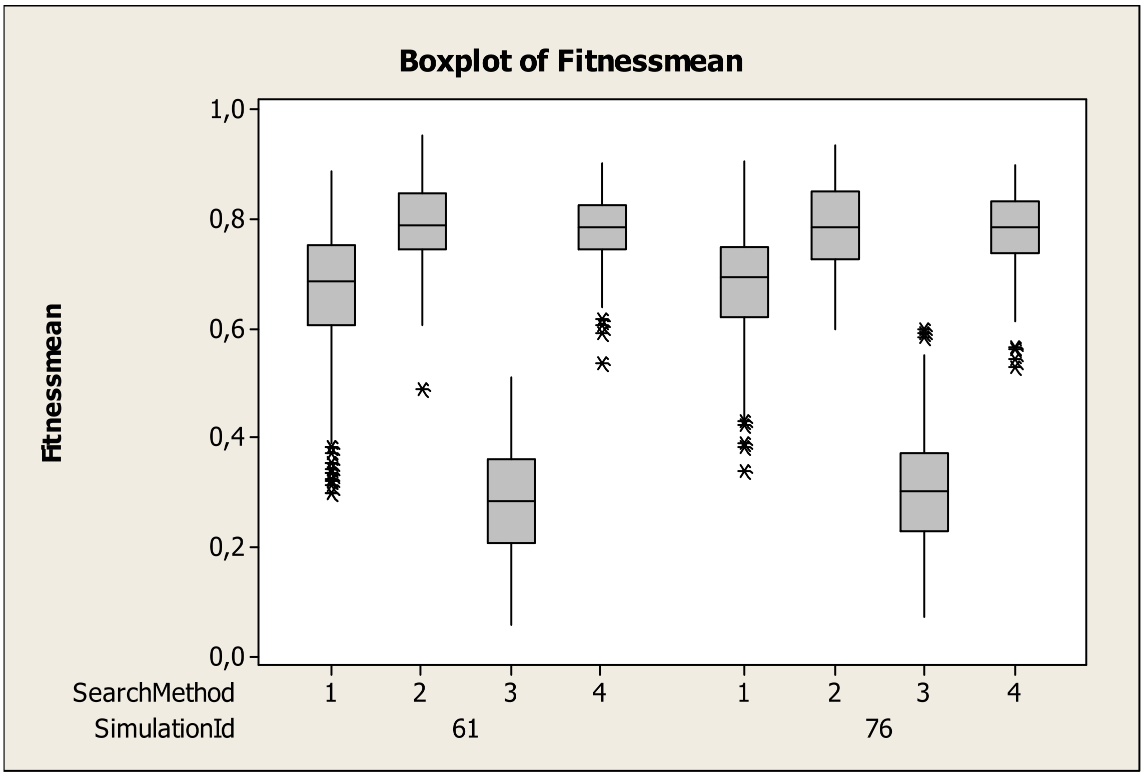


Note: same legend and note as the previous chart in this same page

Chart 73 Classification of firms according to fitness performance, by search method. Simulation 88, all runs

5.3.3. The effect of distinct values for the Vision attribute

As expected, the use of a different input distribution curve for the values of the Vision attribute didn´t change the relative efficiency of the search methods at the population level:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading

Chart 74 Boxplot of fitness mean by search method. Simulations 61 and 76

Our interest in this case, though, is the identification of above and below averagers, to evaluate the extent that the competitive advantage is explained by firm specific attributes (Vision, in this case).

We concentrate the analysis in simulation 76, in which we look for the above and below averagers. The distribution curve of fitness performance shows most of the firms successfully converged towards high levels of fitness, in spite of a large variation in the Vision parameter[15]:

[15] It is worth remembering that the parameter is utilized only by search methods that look for other firms´ information, that is, the mimetism methods.

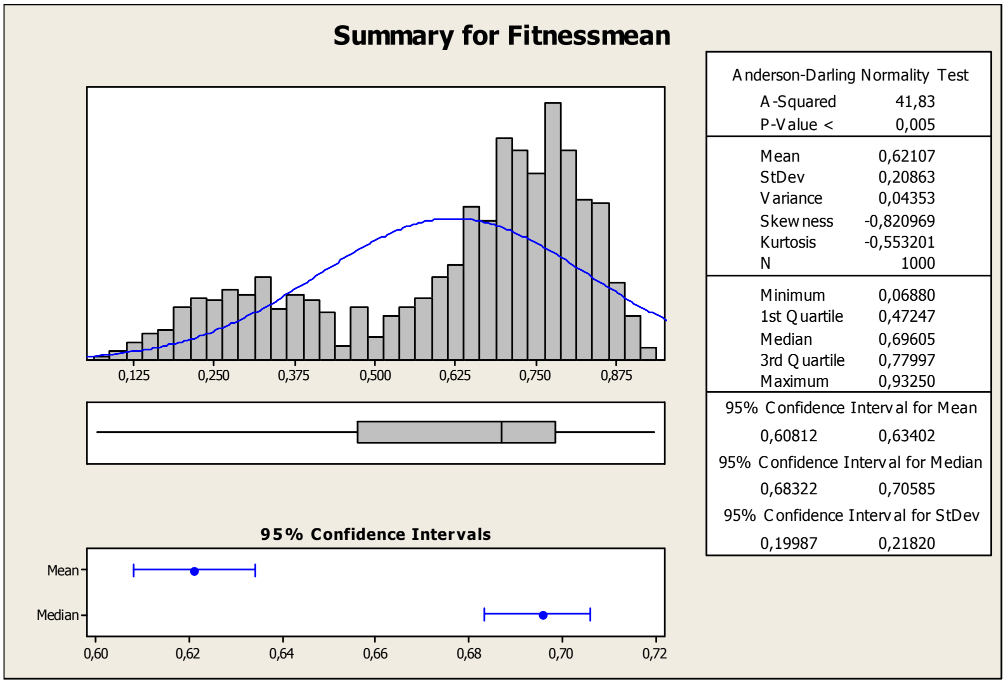


Chart 75 Graphical summary of statistics: fitness mean. Simulation 76, all runs

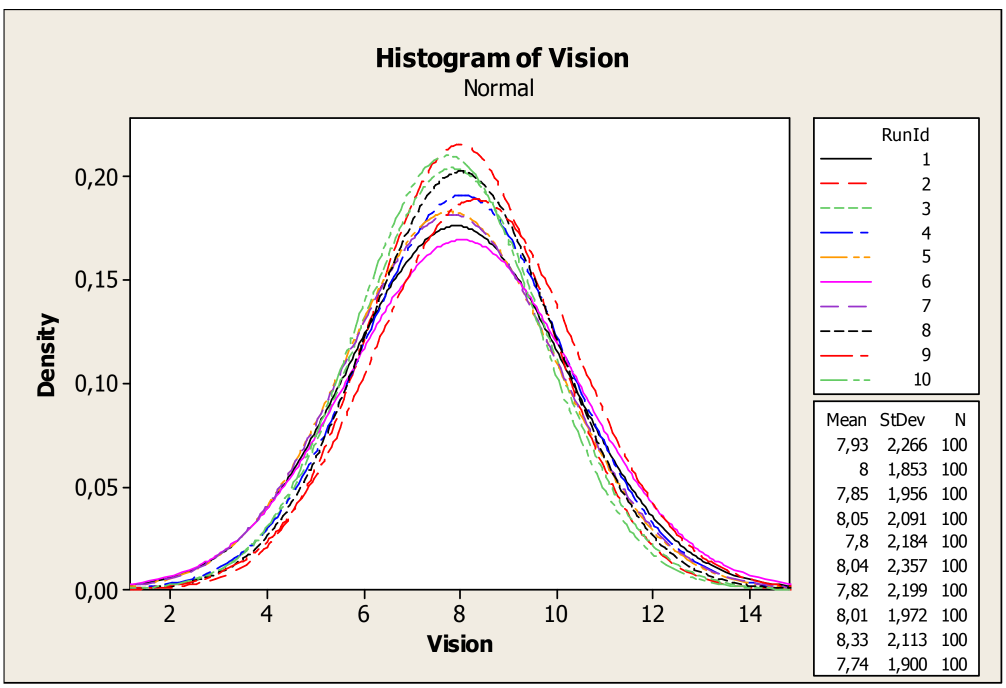
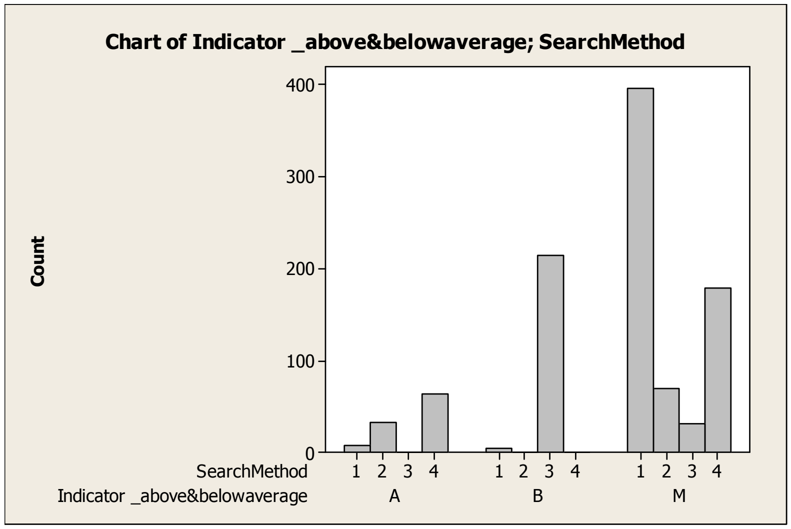


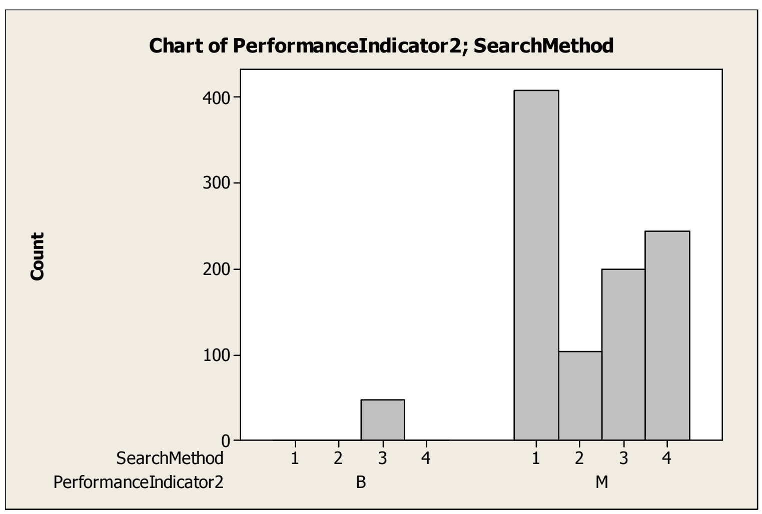
Chart 76 Histogram of Vision, by run. Simulation 76

We initially identified above and below average performers, both utilizing 1 and 1.96 standard deviations from the mean ("1 STD DEV" or "1.96 STD DEV"):



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M – Parity B – below average

Chart 77 Classification of firms according to fitness performance, by search method. Simulation 76, all runs, 1 STD DEV

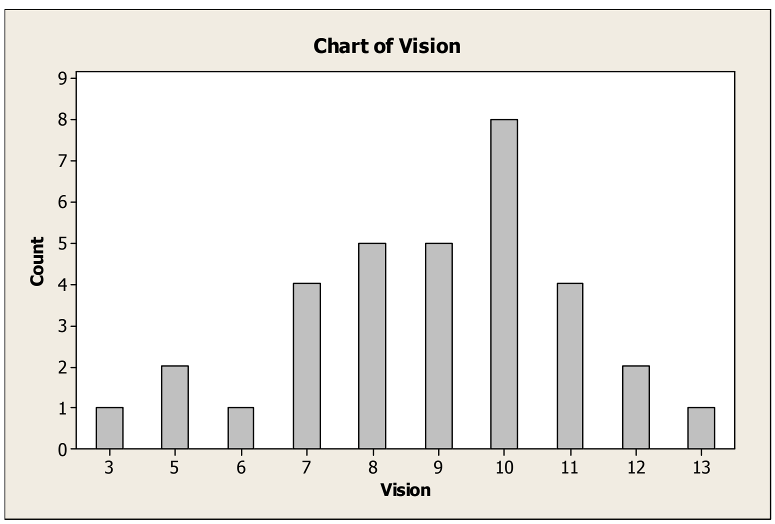


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average

Chart 78 Classification of firms according to fitness performance, by search method. Simulation 76, all runs, 1.96 STD DEV

It is worth noting that, due to the high convergence towards fit, no firm could reach competitive advantage as measured by 1.96 standard deviations above the mean. And all firms that underperformed were operating under the random search method. The mimetism method may become quite efficient, but, if others are successful as well, there is only competitive parity. The same way efficient imitators erode competitive advantages from innovators, no firm operating under the market reading search method could sustain it as measured by such a rigorous metric.

Back to the analysis considering the above average performers identified as those with fitness one standard deviation above the population mean, it can be noticed that firms with relatively low levels of vision were able to sustain above average performance during our simulation runs:



Notes:
1 – Only firms operating with the minority mimetism search method (market reading doesn´t utilize the Vision attribute)
2- Firms identified as above average performers when fitness mean was at least 1 STD DEV above the population mean.

Chart 79 Histogram of above average firms by Vision attribute value. Simulation 76, all runs

In fact, a simple observation of the population of firms utilizing both types of mimetism strategies reveals that this attribute is not strongly correlated with individual firm average fitness:

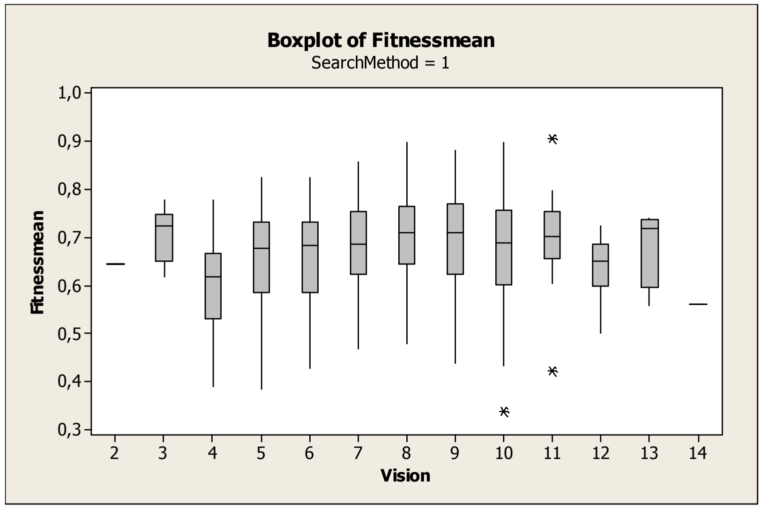


Chart 80 Boxplot of fitness mean by Vision attribute value. Simulation 76, all runs – Majority mimetism

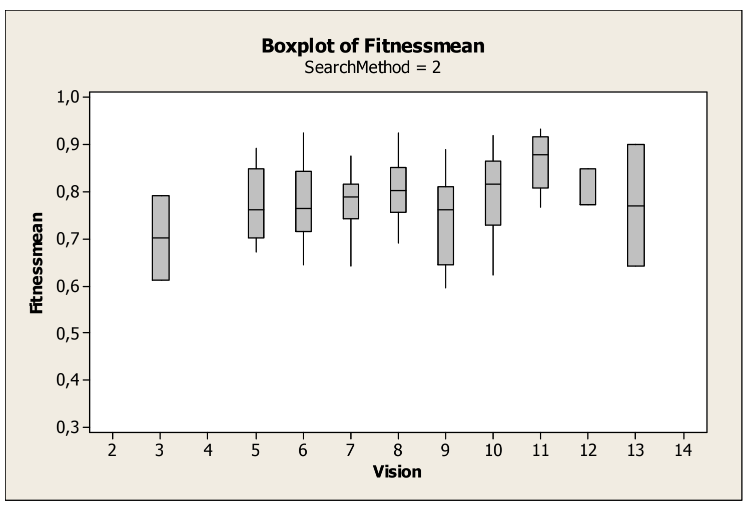


Chart 81 Boxplot of fitness mean by Vision attribute value. Simulation 76, all runs – Minority mimetism

We performed a formal regression test with Vision, which formalizes the little explanatory power this variable provide in this specific simulation setting[16]:

[16] Output analysis from Minitab 16, utilizing the simulation data.

```
Regression Analysis: Fitnessmean versus Vision

The regression equation is
Fitnessmean = 0,658 + 0,00530 Vision


Predictor       Coef   SE Coef      T      P
Constant     0,65775   0,01855  35,45  0,000
Vision      0,005297  0,002274   2,33  0,020


S = 0,105438   R-Sq = 1,1%   R-Sq(adj) = 0,9%

Note: the test was applied in the subset of firms that comprises
those utilizing the two mimetism search methods. Although the
variable is significant (at 5%), the parameter value is very low
as compared to fitness mean and fitness standard deviation.
```

In the next subsection we will further analyze the effects of variation in the Vision attribute within a population, but, this turn, combined with variation in the AdjustCap parameter at the same time.

5.3.4. The effect of distinct values for the Vision and AdjustCap attributes

We report some of the results obtained in simulations where firms differ in both their AdjustCap and their Vision attributes.

The following graphics provide information about the distribution curves for each attribute value as randomized in the population of firms in one of those simulations:

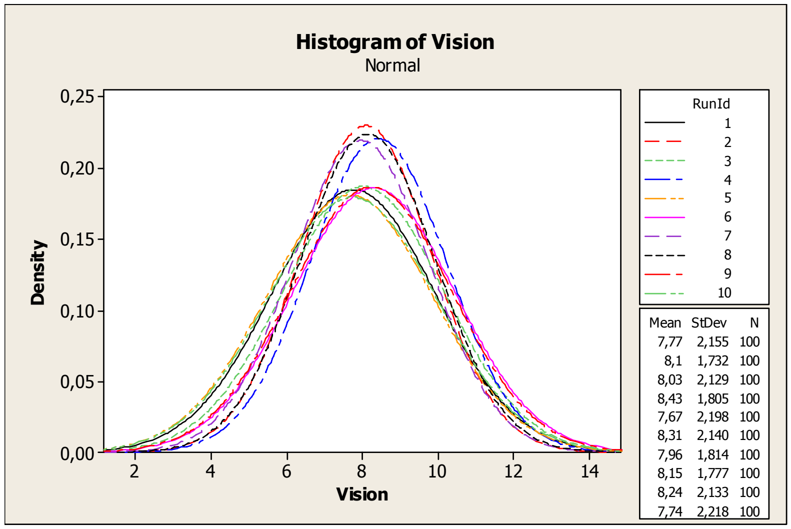


Chart 82 Histogram of Vision, by run. Simulation 77

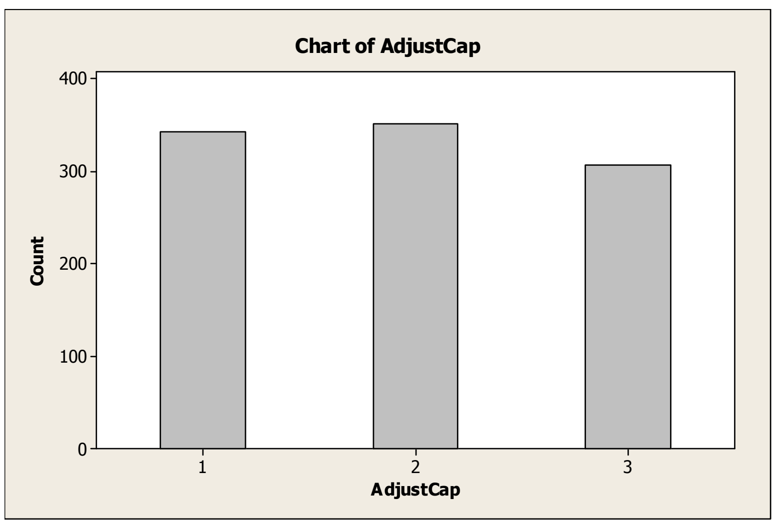


Chart 83 Histogram of AdjustCap. Simulation 77, all runs consolidated

The simulation results confirm previous discussions on these attributes. Vision is not quite correlated with fitness, differently from the AdjustCap parameter, which is correlated in the case of all search methods that utilize it:

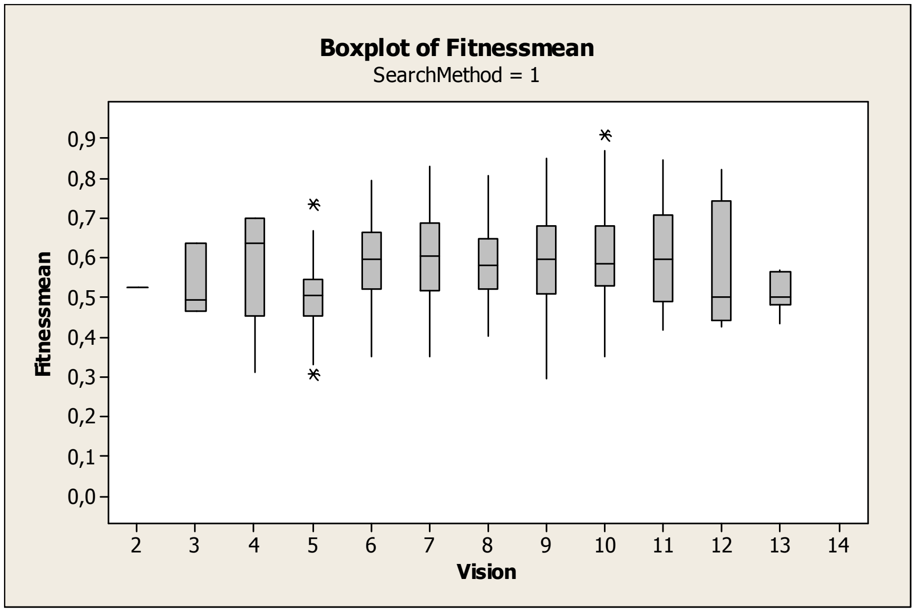


Chart 84 Boxplot of fitness mean by Vision value. Simulation 77, all runs – Majority mimetism

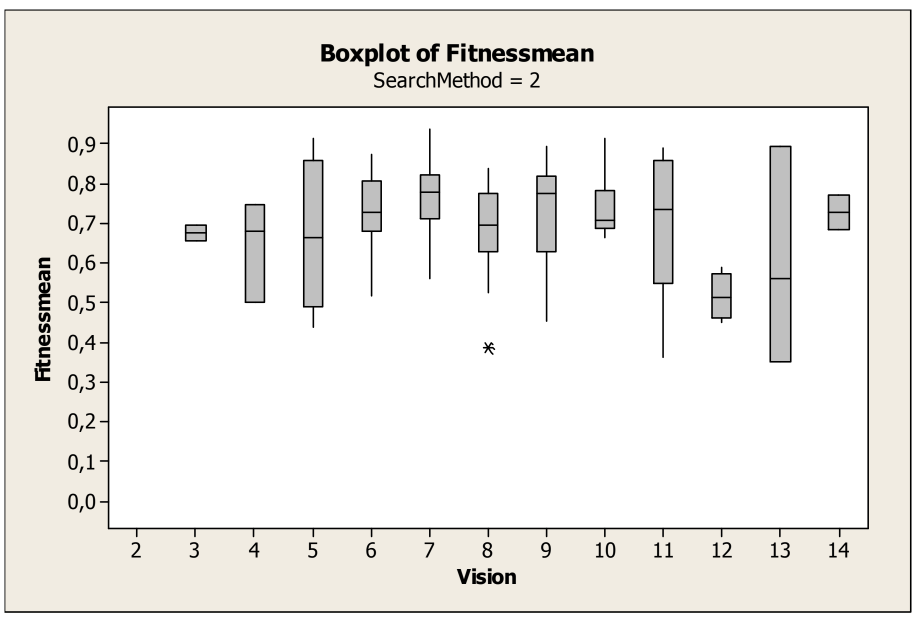


Chart 85 Boxplot of fitness mean by Vision value. Simulation 77, all runs – Minority mimetism

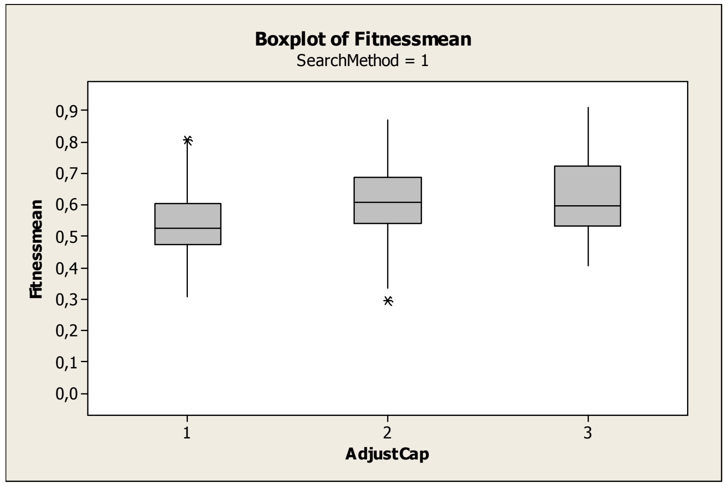


Chart 86 Boxplot of fitness mean by AdjustCap value. Simulation 77, all runs – Majority mimetism

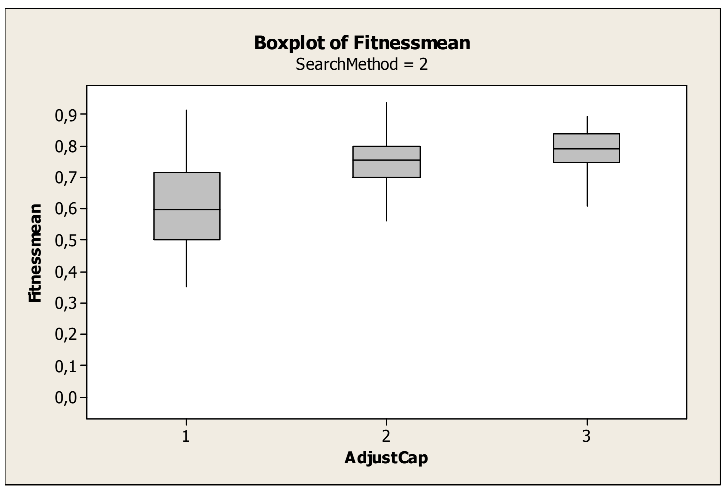


Chart 87 Boxplot of fitness mean by AdjustCap value. Simulation 77, all runs – Minority mimetism

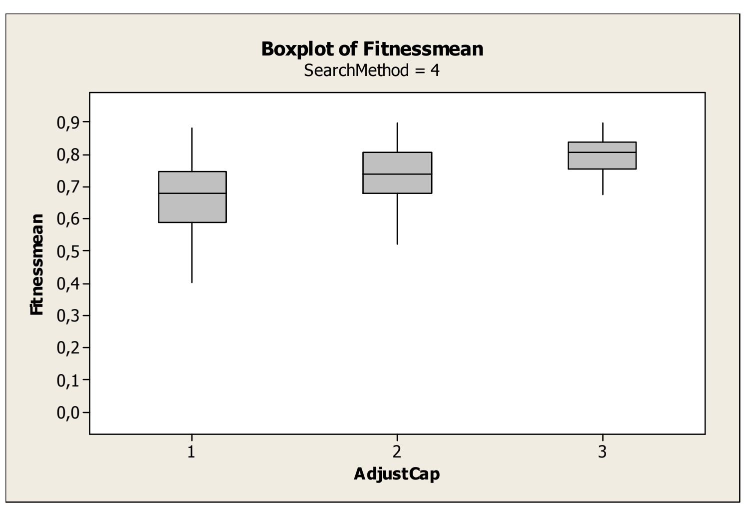
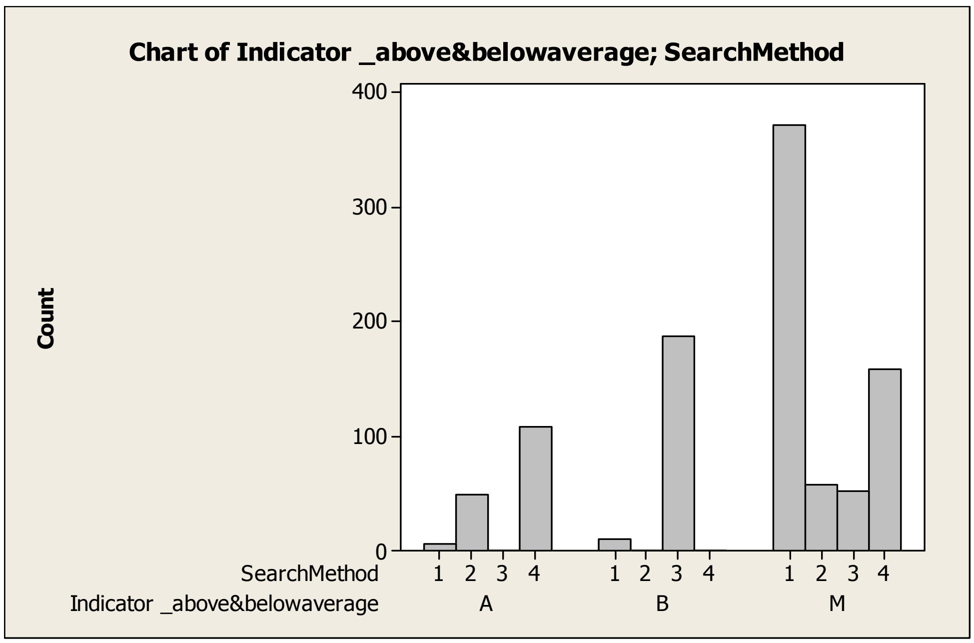


Chart 88 Boxplot of fitness mean by AdjustCap value. Simulation 77, all runs – Market reading

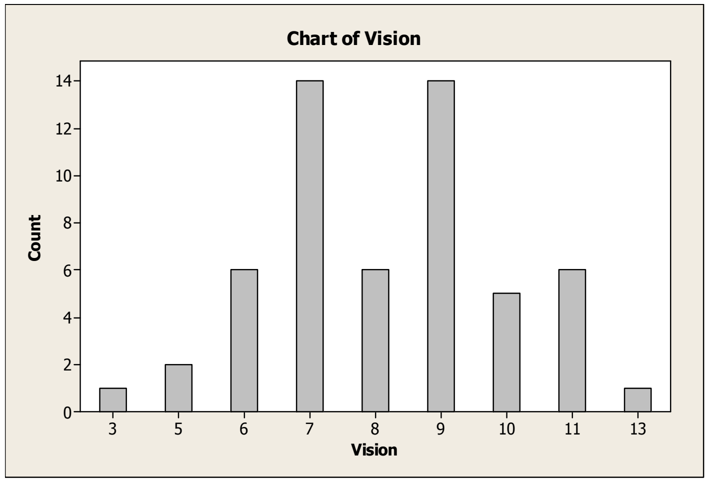
Looking at the efficiency of the search methods, it is possible to identify both above average and below average performers utilizing majority mimetism; the minority mimetism search strategy accounts for a significant proportion of above averagers, given the proportion of firms within the population that was assigned with this method:



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average
Note: Above / below average indicator for firms with average fitness 1 (one) standard deviation from the population fitness mean

Chart 89 Classification of firms according to fitness performance, by search method. Simulation 77, all runs

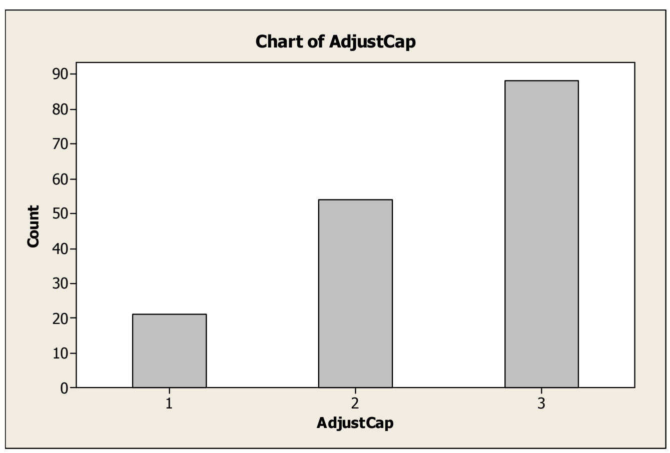
The Vision attribute, as shown before, doesn´t justify why some firms outperformed the others.



Note: Only above averagers utilizing mimetism search methods were considered (firms with fitness 1 STD DEV above the population fitness mean)

Chart 90 Histogram of above average firms by Vision attribute value. Simulation 77, all runs

We then look at the AdjustCap parameter for the above / below averagers[17]:



Note: Above averagers with 1 STD DEV. Firms employing mimetism methods or market reading search method.

Chart 91 Histogram of above average firms by AdjustCap attribute value. Simulation 77, all runs

[17] In this case in a different subset of firms in this same simulation, as the firms operating with the market reading search method also benefits from higher values in this attribute.

A formal regression test combining Vision and AdjustCap, however, still provides little explanatory power for the average fitness of firms, confirming only the AdjustCap parameter[18]:

```
Regression Analysis: Fitnessmean versus Vision; AdjustCap

The regression equation is
Fitnessmean = 0,544 - 0,00084 Vision + 0,0607 AdjustCap


Predictor        Coef   SE Coef      T      P
Constant      0,54433   0,02086  26,10  0,000
Vision      -0,000843  0,002179  -0,39  0,699
AdjustCap    0,060652  0,005528  10,97  0,000


S = 0,121423   R-Sq = 13,7%   R-Sq(adj) = 13,5%
```

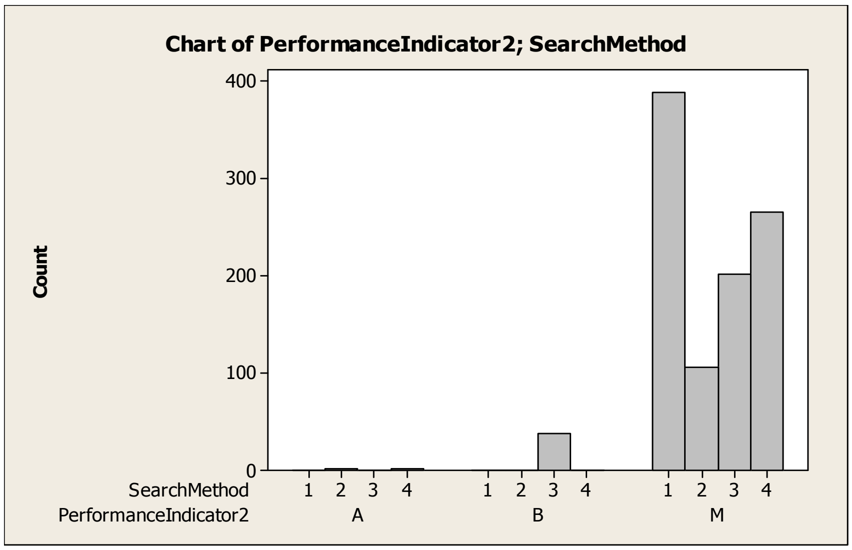
We also conducted the multivariate statistical method of discriminant analysis utilizing the SearchMethod attribute together with Vision and AdjustCap. It doesn´t increase the predictive power, as seen below[19]:

```
Linear Method for Response: Indicator _above&belowaverage

Predictors: SearchMethod; Vision; AdjustCap

Group          A         B         M
Count        163        10       588


Summary of classification

                     True Group
Put into Group      A      B      M
A                 134      0    160
B                   6      8    155
M                  23      2    273
Total N           163     10    588
N correct         134      8    273
Proportion      0,822  0,800  0,464

N = 761           N Correct = 415           Proportion Correct = 0,545

Note: Population of firms except those with the random search method.
```

If we narrow down our analysis to 1.96 standard deviations from the population mean as

[18] Output analysis from Minitab 16, utilizing the simulation data
[19] Same as above.

the boundary to define above and below performance, we get almost the same profile as simulation 76 previously presented:

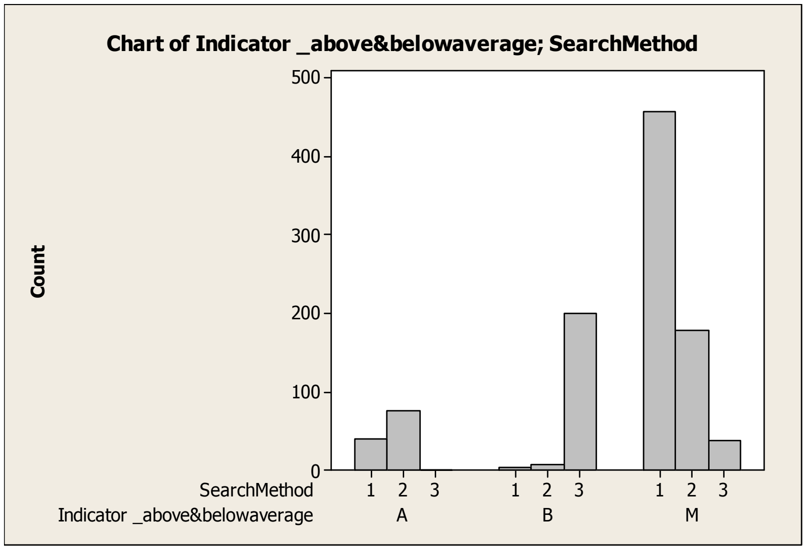


Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average
Note: Above / below average indicator for firms with average fitness 1.96 standard deviations from the population fitness mean

Chart 92 Classification of firms according to fitness performance, by search method. Simulation 77, all runs

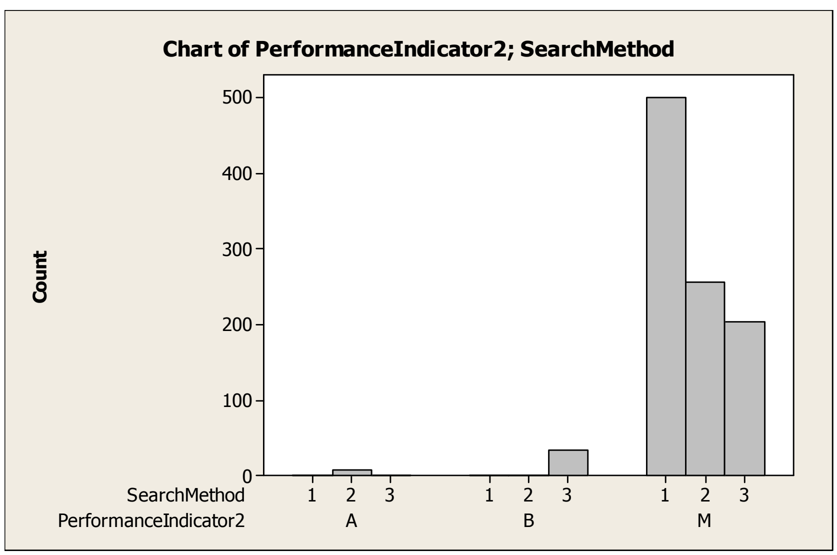
We also run simulations utilizing the NK model under similar conditions; as expected[20], we find similar results:

[20] As mentioned before in this document, that is the objective of having implemented the NK model: to provide additional support for our verification and validation processes.



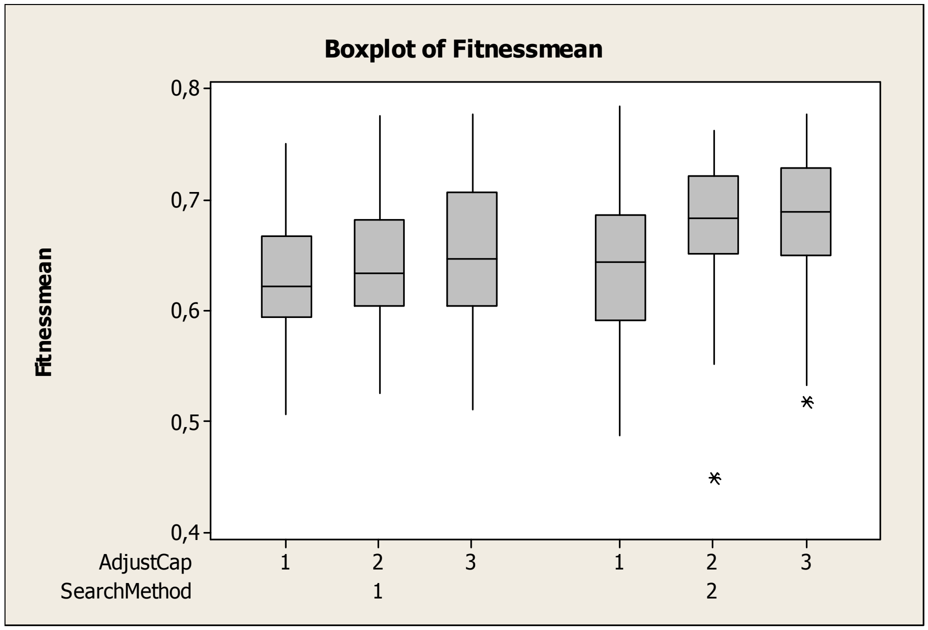
Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search
A- Above average M- Parity B- Below average
Note: Above / below average indicator for firms with average fitness 1 (one) standard deviation from the population fitness mean

Chart 93 Classification of firms according to fitness performance, by search method Simulation 84, all runs, 1 STD DEV



Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search
A- Above average M- Parity B- Below average
Above and below average with 1.96 standard deviations from the mean

Chart 94 Classification of firms according to fitness performance, by search method. Simulation 84, all runs, 1.96 STD DEV



Legend: 1-Majority mimetism   2- Minority mimetism

Chart 95 Boxplot of fitness mean by AdjustCap value. Simulation 84, all runs

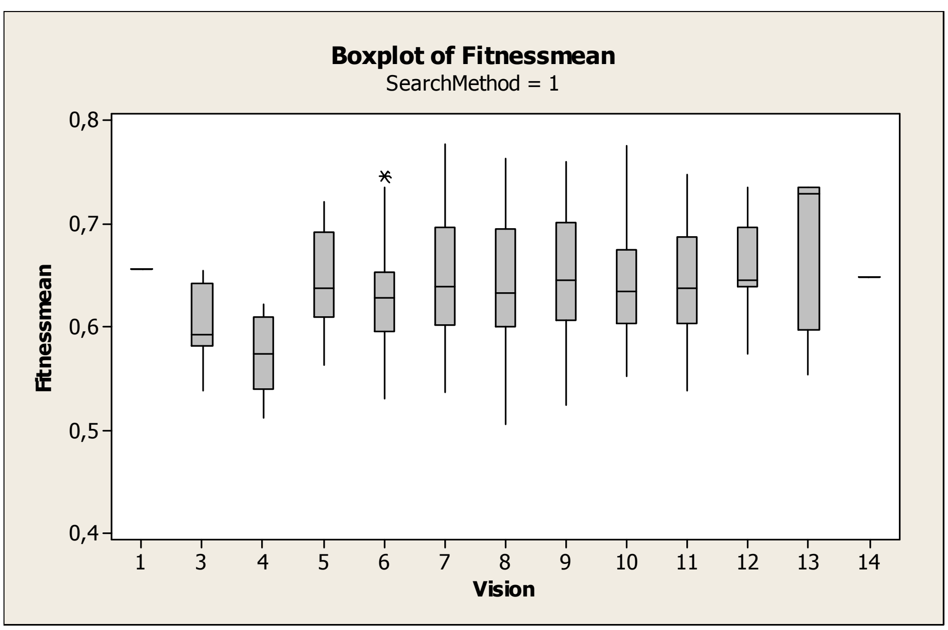


Chart 96 Boxplot of fitness mean by Vision value. Simulation 84, all runs – Majority mimetism

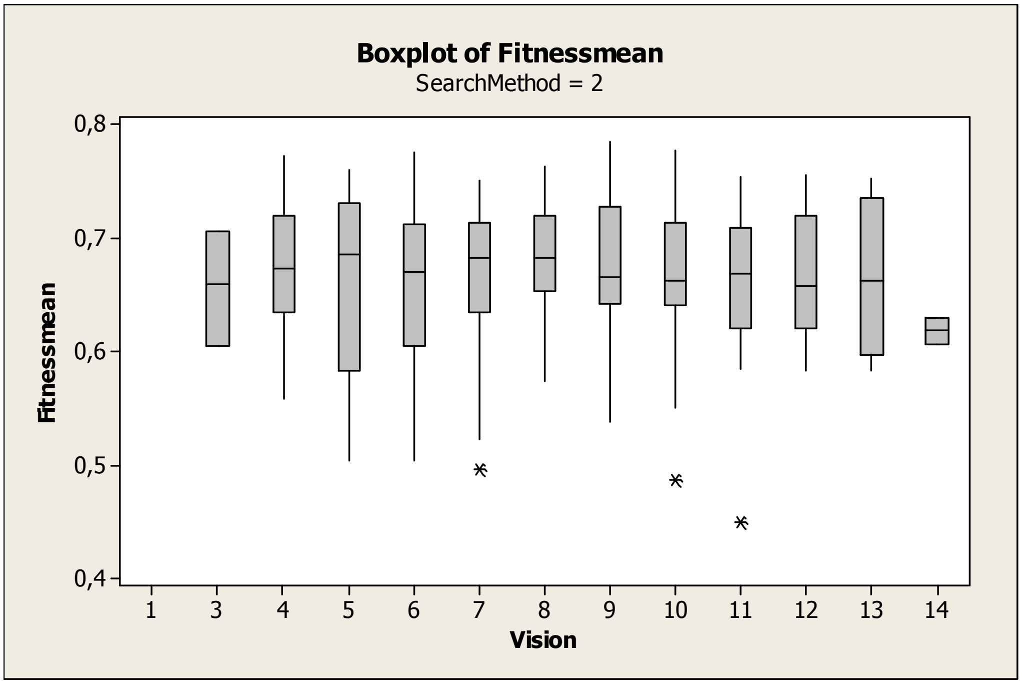


Chart 97 Boxplot of fitness mean by Vision value. Simulation 84, all runs – Minority mimetism

We formalized a regression analysis of fitness mean for this simulation setting, having AdjustCap and Vision parameters as predictors. It shows that only AdjustCap can be considered a predictor (P-value less than 0,05). The explanatory power of this model is quite low (R-sq adjusted of 5,1%). Results confirmed what we previously found with the custom landscape model[21].

```
The regression equation is
Fitnessmean = 0,602 + 0,0167 AdjustCap + 0,00199 Vision

Predictor       Coef   SE Coef      T      P
Constant     0,60169   0,01008  59,71  0,000
AdjustCap   0,016694  0,002660   6,28  0,000
Vision      0,001989  0,001037   1,92  0,055

S = 0,0588804   R-Sq = 5,4%   R-Sq(adj) = 5,1%


Analysis of Variance

Source           DF        SS        MS      F      P
Regression        2  0,149784  0,074892  21,60  0,000
Residual Error  760  2,634848  0,003467
Total           762  2,784632

Note: Considered only the firms with the mimetism methods.
```

[21] Output analysis from Minitab 16, utilizing the simulation data.

These findings are at first somehow intriguing, as the mimetism methods supposedly improve with the amount of information the firms can handle at each round. As we discussed in the prior section, however, the relationships with other firms plays a key role, and the unfolding of specific interactions among the firms is also a crucial factor for firm performance. When a firm happens to observe other inefficient firms, it gets "trapped", even if it happens to have a high Vision attribute value.

.

5.3.5. The effect of search method population distribution

As we have seen in subsection 5.2.3, mimetism methods may lose efficiency when too many firms are looking at each other to decide on what practices to adopt. The relative performances of the other search strategies, of course, depend on these two. The following table, with the comparison of settings 64 and 66 helps to confirm it:

Table 9 Classification of firms according to fitness performance , by search method[22]

```
Tabulated statistics: SimulationId; Indicator _above&belowaverage; SearchMethod
Rows: SimulationId / Indicator _above&belowaverage   Columns: SearchMethod

                  1    2    3    4   All
64
        A         2   36    0   62   100
        B         3    4  203    0   210
        M       258  213   52  167   690
66
        A        11   51    1   83   146
        B        40    0  125    0   165
        M       535   36   95   23   689
All
        All     849  340  476  335  2000
```

Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average
Note: Above / below average indicator considered for firms with average fitness 1 (one) standard deviation from the population fitness mean.

[22] Output analysis from Minitab 16, utilizing the simulation data

The comparison of these two simulations provides interesting outcomes for discussion:

- A large number of firms with the majority mimetism method underperforms in simulation 66, but there is also an unexpected increase in the number (and proportion) of above average performers;
- Few firms searching with the minority mimetism method underperform in simulation 64 (4 out of 253), and none in the other setting. Minority mimetism is less prone to bandwagon effects or informational traps – although it does depend on the strategy of others to improve, it is selective when considering new practices to be adopted;
- Random search performs better in simulation 66, with one firm being classified as above average! That is simple heuristics as competitive advantage.
- The firms with the market reading search method are able to improve substantially their relative performance. Even search methods that don´t rely on the practices of others depend on the strategy of others – since competitive advantage is a relative matter.

.

5.3.6. Landscape complexity and its impact on individual fitness performance

The impact of landscape complexity at the population level was addressed in subsection 5.2.5 of our study. We complement the discussion of this aspect by looking at the persistence of above and below average performance, the second area of interest in this study.

The following table helps to verify that the different settings have little influence in the proportion of above and below average performers by search method:

Table 10 Classification of firms according to fitness performance , by search method[23]

```
Tabulated statistics: SimulationId; Indicator _above&belowaverage; SearchMethod
Rows: SimulationId / Indicator _above&belowaverage   Columns: SearchMethod
```

SimulationId	Indicator	1	2	3	4	All
63						
	A	7	22	0	90	119
	B	14	0	181	0	195
	M	375	75	57	179	686
74						
	A	17	17	0	122	156
	B	10	0	190	0	200
	M	380	89	64	111	644
65						
	A	9	51	0	84	144
	B	44	0	75	0	119
	M	549	102	19	67	737
75						
	A	18	34	0	109	161
	B	57	0	83	0	140
	M	525	103	22	49	699
78						
	A	24	46	0	93	163
	B	66	3	75	1	145
	M	522	97	20	53	692

Legend: 1-Majority mimetism 2- Minority mimetism 3- Random search 4- Market reading
A- Above average M- Parity B- Below average
Note: Above / below average indicator considered for firms with average fitness 1 (one) standard deviation from the population fitness mean.

Simulations 63-74 and 65-75 are pairs of comparable scenarios, with the same settings, except for the proxy we utilized in our study to represent complexity, the number of structural and flexible characteristics[24]. Simulation 78 varies the Vision and AdjustCap parameters within the population of firms, keeping the other settings already defined for simulation 75.

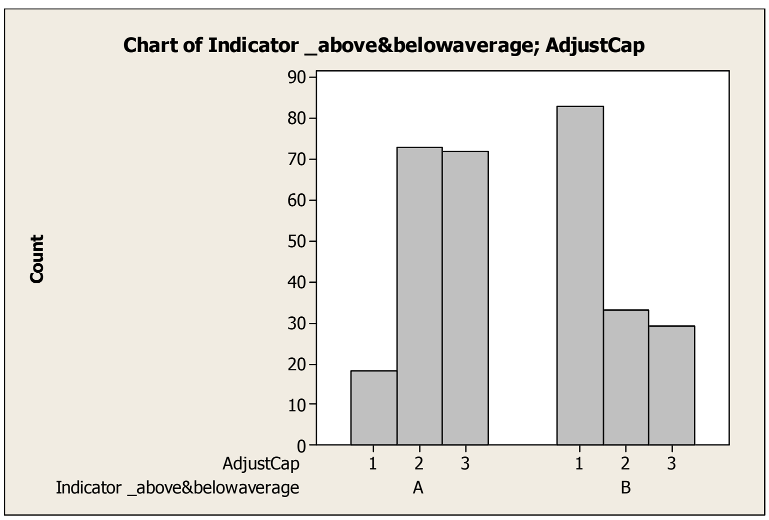
Although the simulation results show similar occurrences for each method in each category of performance, some small variations deserve comments. More firms with the majority mimetism method classify as above average in scenarios of high complexity (although still a small number). Scenarios 65-75, as expected, have more traps for firms searching with majority

[23] Directly copied from the output analysis performed in the software Minitab 16, utilizing the simulation data
[24] The interdependency was always set at the baseline, 20% of all possible combinations of pairs of characteristics; as the number of characteristics increase so does the number of interdependencies.

mimetism and thus causing below average performance[25]. The market reading search method is associated with a larger number of above average performers as complexity increases. Simulation results of scenario 78 are similar, as expected, the salient difference being a small number of firms with the minority mimetism or random search strategies classified as below average.

Then our analysis turn to the specific firm attributes and their potential influence over fitness performance in scenarios of higher complexity. In so doing, we complement some of our previous discussions[26].

We provide a quick look of the attributes for below and above average performers in this simulation setting:



Legend: A- Above average B- Below average (1 STD DEV)

Chart 98 Capacity to adjust of above and below averagers. Simulation 78, all runs, 1 STD DEV

The chart illustrates that AdjustCap is associated to some extent with fitness performance, as previously discussed.

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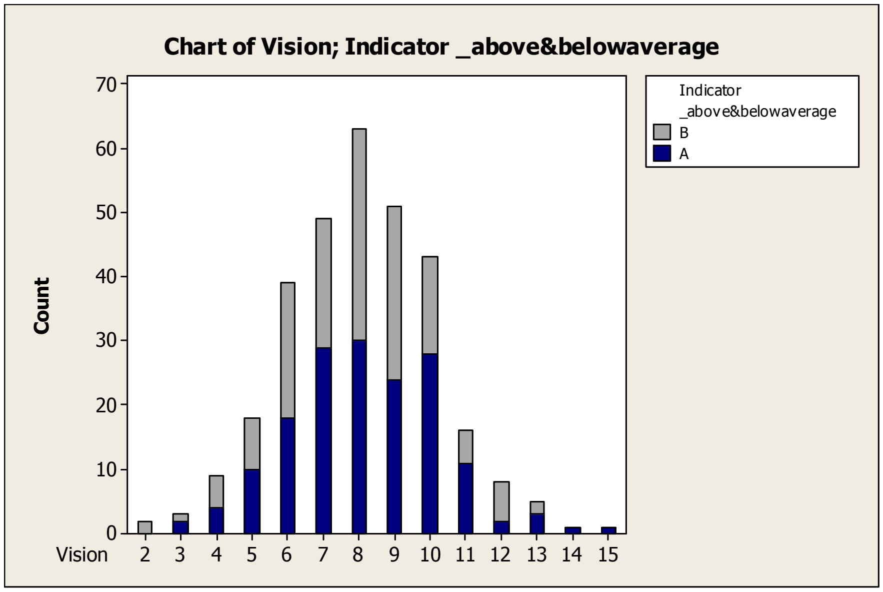
[25] The reason is that there is a larger proportion of these firms within the population. This effect was explained earlier in this document.

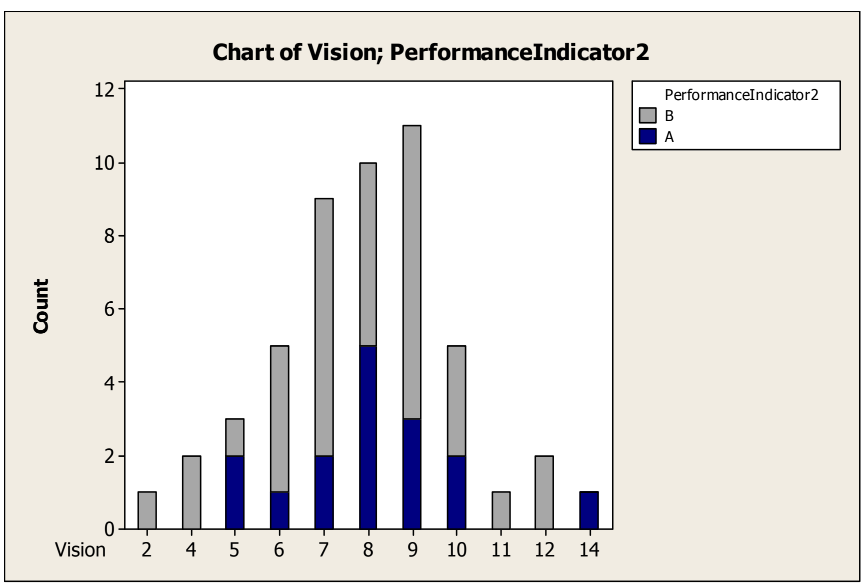
[26] We already analyzed the influence of distinct Value and AdjustCap parameters in previous subsections utilizing our baseline settings.



Legend: A- Above average B- Below average

Chart 99 Vision of above and below average performers. Simulation 78, all runs, 1 STD DEV

The chart illustrates that Vision is not a good predictor of fitness performance, as already discussed previously in this study. That can be verified even if we select only the outliers for our analysis, defined as those firms with fitness performances 1.96 or more standard deviations away the population mean:



Legend: A- Above average B- Below average

Chart 100 Vision of above and below average performers. Simulation 78, all runs, 1,96 STD DEV

We developed a formal regression analysis with the data of simulation 78, excluding the random search method, to verify the explanatory power of both AdjustCap and Vision illustrated in previous charts. We got results very close to those previously presented in other statistical tests in this study:

```
The regression equation is
Fitnessmean = 0,441 + 0,0524 AdjustCap + 0,00228 Vision

Predictor       Coef   SE Coef      T      P
Constant     0,44132   0,02151  20,52  0,000
AdjustCap   0,052449  0,005580   9,40  0,000
Vision      0,002279  0,002235   1,02  0,308

S = 0,135996   R-Sq = 9,0%   R-Sq(adj) = 8,8%


Analysis of Variance

Source           DF        SS       MS      F      P
Regression        2   1,65492  0,82746  44,74  0,000
Residual Error  902  16,68244  0,01849
Total           904  18,33736
```

A discriminant analysis to identify above and below averagers based on the SearchMethod, Vision and AdjustCap variables as predictors[27] would not achieve great precision. Although such model would be slightly better than if performed solely on the basis of the SearchMethod variable:

```
Discriminant Analysis: Indicator _above&belowaverage versus
SearchMethod; Vision;AdjustCap

Linear Method for Response: Indicator _above&belowaverage

Predictors: SearchMethod; Vision; AdjustCap

Group         A         B         M
Count       163       145       692

Summary of classification
                     True Group
Put into Group      A      B      M
A                 118     51     84
B                  19     28     86
M                  26     66    522
Total N           163    145    692
N correct         118     28    522
Proportion      0,724  0,193  0,754

N = 1000          N Correct = 668          Proportion Correct = 0,668
```

27 Output of Minitab 16 software with simulation data.

```
Discriminant Analysis: Indicator _above&belowaverage versus
SearchMethod

Linear Method for Response: Indicator _above&belowaverage

Predictors: SearchMethod

Group         A         B         M
Count       163       145       692

Summary of classification
                     True Group
Put into Group      A      B      M
A                  93     76     73
B                  46      3     97
M                  24     66    522
Total N           163    145    692
N correct          93      3    522
Proportion      0,571  0,021  0,754

N = 1000           N Correct = 618           Proportion Correct = 0,618
```

We performed the same analysis for above and below averagers identified with fitness at least 1.96 standard deviations from the population fitness mean. The model improved to some extent its predictive power:

```
Discriminant Analysis: PerformanceIndicator2 versus SearchMethod; Vision;
AdjustCap

Linear Method for Response: PerformanceIndicator2

Predictors: SearchMethod; Vision; AdjustCap

Group         A         B         M
Count        16        34       950

Summary of classification
                     True Group
Put into Group      A      B      M
A                  14      7    108
B                   0     24    118
M                   2      3    724
Total N            16     34    950
N correct          14     24    724
Proportion      0,875  0,706  0,762

N = 1000           N Correct = 762           Proportion Correct = 0,762
```

These results have coherence with previously descriptive data analyzed in this study. The large variance identified in the fitness variable in all search methods and the overlap of their fitness mean confidence intervals were early indications that competitive advantage can´t be explained by the firms´ internal attributes as designed in our model.

6. CONCLUSION AND FUTURE DIRECTIONS

This study, by its very nature, produced outcomes that foster a research agenda rather than a verification of formal hypotheses. It is about generating insights rather than performing confirmatory analysis.

In this manner, the last section briefly reviews the main findings and indicates the insights or relevant aspects in the dynamics of business competition that we might have helped to enlighten or address with our work.

6.1. Closing our initial research agenda: the *ex-ante* hypotheses

As stated at the beginning of this study, we identified that simulation methods would be an appropriate research strategy to investigate business competition dynamics. It is largely supported by behavioral theories of the firm and evolutionary economics. Indeed, the seminal works of Cyert and March (Cyert & March, 1992) and of Nelson and Winter (Nelson & Winter, 1982) both utilize simulations. The conjunction of these two streams of work is currently pointed as a promising research field (Dosi & Marengo, 2007). The evolutionary perspectives in strategy have a distinctive role in addressing the longitudinal problem that characterizes sustainable competitive advantage (Gavetti & Levinthal, 2004; Porter, 1991).

As we started this research endeavor four years ago, we set a preliminary agenda that directed most of the efforts to design and execute our computer model. The following *ex-ante* research questions were defined, and addressed through the simulations presented in the previous section:

I. About the search methods employed by the firms as modeled in the application:

   a. Is there a search method that explains why some firms outperform the others?

   b. What is the impact of high-changing market conditions on the relative efficiency of the search methods (observed in a.)?

II. About the persistence of above and below average performers, and the existence of outliers:

   a. What causes some firms to be above and below average performers?

   b. Can simple heuristics account for sustained competitive advantage?

Each of the research questions were addressed in many ways, by changing the simulation parameters and analyzing the outcomes of our simulation model. That is how we organized the previous section. Most of the times, we made use of graphical displays of descriptive statistics to provide a glance of the simulation results, but we also provided some formal hypothesis testing of the influence of the independent variables on fitness performance.

In our first question, we answered the first item (I. a.) under a variety of conditions, one of them being the issue initially formulated in the second item (I. b.). This first area of interest made us look at the population level; we draw some conclusions about the relative performances of the search methods. Our findings can foster the theoretical discussions of mimetism strategies and their potential impact on the performance of the firms, a subject frequently addressed by institutional theory and strategy (Abrahamson, 1996; Abrahamson & Fairchild, 1999; DiMaggio & Powell, 1983; Oliver, 1991; Scott, 2001; Strang & Macy, 2001).

The second question turned our attention to the individual performance of the firms. This level of perspective furnished distinct insights. While, on average, firm attributes are correlated to performance, at the individual level some of the same attributes are not. The strategies of others count. Idiosyncratic, path dependent situations place an important role to achieve sustainable competitive advantage. Many firms outperform others due to luck or to the lucky unfolding of interactions with other firms, by which they get access to better information of practices that improve performance. These findings are in line with what Alchian said long ago *"...the greater the uncertainties of the world, the greater the possibility that profits would go to* *venturesome and lucky rather than to logical, careful, fact-gathering individuals."* (1950, p. 213).

As we noted before, there is relevant criticism on the construct of competitive advantage, with many discussions of what one can deduct from the empirical observation of superior performance or its persistent character (Arend, 2003; Jacobsen, 1988; Powell, 2001, 2003b; Vasconcelos & Brito, 2004; Wiggins & Ruefli, 2002). The business competition dynamics modeled in this study provided room for the emergence of above and below averagers as simple heuristics. At the same time, theorized firm attributes could help explain superior performance to some extent. We simulated scenarios where landscape changed frequently, and some firms were able to achieve and sustain competitive advantage in such scenarios[28].

Although our computer model has important design limitations, as we mentioned in section 3.3, we believe it provided simulation outcomes that shed light on relevant considerations regarding the existing theory in the field of business strategy.

6.2. Competitive advantage and idiosyncrasy of unfolding interactions

Competitive advantage is said to be either resulting from strategic positioning within the industry structure or from specific firm resources (and/or capabilities). However, recognized representatives of the different schools of thought take care not to dichotomize the debate:

- Porter asserts an emphasis on "the external side" while recognizing the need of an internal activity system that provides continuous, differentiated fit (1996);
- Barney provides a framework that looks at the internal resources but questions whether they are valuable in the context of the external environment (Barney & Hesterly, 2006);
- Other researchers working with Dynamic Capabilities, by definition, focus on the continued match of organizational resources and environmental demands to

[28] Alchian, cited previously, states that chance doesn´t imply nondirected, random allocation of resources.

account for competitive advantage.

The evolutionary perspectives in strategy place much more emphasis in the so-called longitudinal problem of competitive advantage (Schendel, 1996), with the recognition of the role of idiosyncrasy in the acquisition of sources of competitive advantage (Ahuja & Katila, 2004).

While neither the notion of asset accumulation is new (Dierickx & Cool, 1989a), nor the role of idiosyncrasy (Barney, 1986), there is a clear contribution of evolutionary perspectives in the study of the competitive dynamics to understand how sources of competitive advantage are acquired and maintained over time.

In our study, our simulation outcomes suggest that a firm may have competitive advantage not because it accumulated specific resources or capabilities, but because of the specific interactions it had with other firms, which helped the firm to continuously modify its resource configuration in ways that better addressed the environmental demands.

Such account would call attention to a locus of competitive advantage that is not within the firm (its resources base), nor outside (the market structure). As network theorists already pointed, the source may be of a “relational” nature. But different to what they usually emphasize, the economic rents don´t come from arbitrage or bargaining because of the network positioning (Burt, 1992; Padgett & Ansell, 1993; Podolny, et al., 1996) . Rather, idiosyncrasy plays a fundamental role. Firms that happen to be connected to others with successful strategies will perform better.

The managerial implication is not a nihilistic theory that firms are unable to build such source of competitive advantage. While we cannot give advice to innovators that face the problem of uncertainty based on our study, we may well suggest imitators to be aware of the potential informational traps they might get caught.

Mimetism strategies may work quite well under stability, but firms are expected to suffer with misleading information as the environment turns more turbulent. This is likely to happen both in the case of those looking at best positioned companies (minority mimetism) and in the case of those going with the flow, applying commonly recommended practices (majority mimetism). In order to avoid such traps, firms should constantly try to renew informational connections that allow them to know what other firms are doing.

6.3. Turning a simple model into good theory

Under the scope of this work we built a computer model that may help investigate theoretical worlds in longitudinal perspective. It is centered on the dynamics of search for higher fitness levels, with competing firms sharing to some extent their information and organizational choices. They employ organizational routines that do not improve over time.

Our agent-based modeling application ended up being a simple model, as recommended by more experienced researches. Parsimony was observed, but there are many enhancements to consider in relation to its current version, for sure.

As next steps, we believe that the outcomes observed in this study require additional theoretical development, and then empirical investigations. There are many simulation studies that address how firms perform their search processes, but, to the extent of our knowledge, there is still little effort in providing the empirical evidences of their relative performances within the same competitive context.

Additional knowledge on search processes and their potential impact of firm performance would be of great value for management practice as well as for the advancement of the research field. But it is a challenging task, as these organizational routines usually are not formalized within the organizations, and they are somewhat ambiguous or even inconsistent within the same organization. The causal link to performance is also a controversial one, as exemplified by the struggle of competing theories of competitive advantage.

We end the present study at this point, cognizant that the picture we have provided is just a shot of a movie that is going on. We quote here Nelson and Winter´s words said long ago:

"*One hopes that others will come to appreciate the view*" (Nelson & Winter, 1982, p. 414)

Indeed.

APPENDIX

I) DOCUMENTATION OF THE AGENT-BASED MODELING SYSTEM

This documentation package contains pertinent information from the project detailed specifications for those seeking to understand in more depth the design of the agent-based modeling system as it is in the latest version, v. 2.1.0.6, updated in september, 2010.

CONTENT

Overall application flow

Model specification

In the following pages the Dynamics of Business Competition application is represented as originally modeled; there are minor differences in the way the specifications got programmed into the language in the end, in special due to the available resources of the object-oriented platform .NET, under which the system was built.

Nevertheless, the diagram provides a good overview of the application purpose, scope, general functions and sequence of processing. It helps one understands the overall architecture and thus considers its potential structural limitations, as well as future enhancements to address relevant theoretical issues.

INITIAL MODEL SPECIFICATION

GENERAL FLOW OF APPLICATION AND RELATED FUNCTIONS TO BE PERFORMED

(Please refer to the programming code for more details and fully updated information)

Set/2010

Initialization / control for multiple executions (runs)

Load Simulation Panel with simulation parameters of last simulation run;
Get simulation parameters from screen;
Create new SimulationID and set RunID to 1 if simulation parameters differ or increase RunID by one if simulation parameters remain the same.
IF several runs asked, control for multiple executions of this program routine under the same simultation settings.

Fitness Landscape Creation

Get parameters that define the number of structural and flexible characteristics that may affect the performance of firms (NumOfStructs; NumOfFlexs);
Create new landscape databases for the simulation run with the proper number of characteristics:
IF landscape model=custom model:
- Assign randomly generated values 0 or 1 to the characteristics;
- Assign randomly generated fitness values between 0 and the maximum value of fitness for a structural or flexible characteristic (MaxIndStructFitness; MaxIndFlexFitness);
- Choose by chance pairs of characteristics that will have combined impact (number of combinations depend on NumOfStructs, NumOfFlexs &CombFitnessImpactFrequency);
- Define combined impact for each pair by randomly assigning Upside or Downside effect, and the value of such impact (from an uniform distribution of numbers in the range of 0 and MaxCombFitnessImpact).

ELSE (landscape model= NK):
- Generate NK landscape (according to the reported method in other papers), that is:
  - Set an order of characteristics based on their type and sequencial number;
  - For each characteristic: generate all possible combinations of values with the other subsequent K characteristics, assigning a fitness value to each of them.

Agent and agent relationships Creation

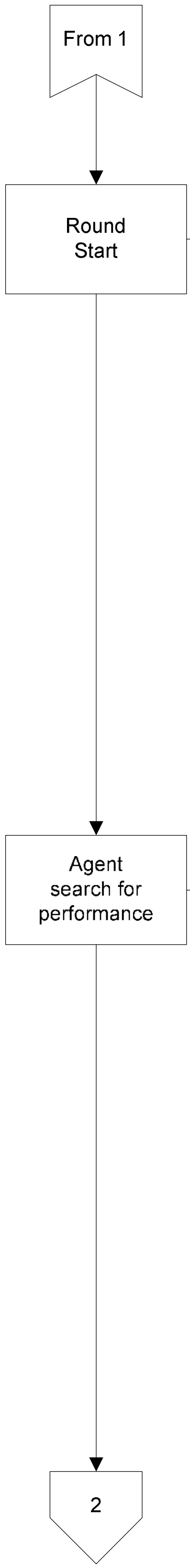
Create Agent databases for the simulation run – consider the number of agents (NumOfAgents), each with the number of structural and flexible characteristics defined (NumOfStructs; NumOfFlexs).
For each agent:
- Assign a randomly generated vision breadth value between 0 and MaxVision parameter with uniform distribution or a value from a normal distribution with VisionMean and VisionSTD as parameters;
- Assign a randomly generated adjustment capacity value between 0 and MaxAdjustCap parameter with uniform distribution or a value from a normal distribution with AdjustCapMean and AdjustCapSTD as parameters;
- Assign a randomly generated search method, from a stratified pool according to the search method percentages defined by the simulation settings;
- Assign randomly generated values 0 or 1 to the structural and flexible characteristics.

Create the AgentProximityMatrix by randomly choosing pairs of agents that will be subject to mutual observation (according to their respective search methods) - based on the ProximityDensity parameter and the NumOfAgents.

Simulation Run Start

Get NumofRounds from Current Settings and set round=1
Initialize databases for tracking landscape changes, agent states and fitness values (for agents and for the population of agents summarized by search method)

1



Create temporary tables to update configuration and fitness of all agents (information from AgentStruct, AgentFlex and AgentFitnessTrack databases will remain frozen for the processing of the round, that is, all agents are considered to move simultaneously – thus, utilizing the information available at the beginning of the round).

For each agent:

Get agent SearchMethod, Vision and AdjustCap parameters;

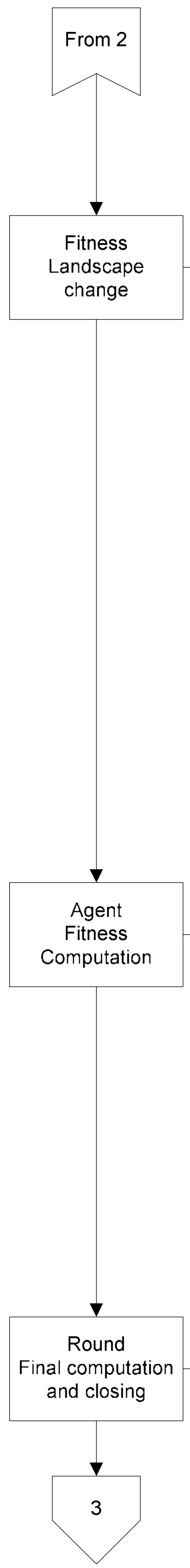
IF search method = Majority mimetism:
- Choose by lot the agents to be observe, considering the agent Vision and the AgentProximityMatrix (agents from whom to gather information about potential configurations to adopt);
- Choose by lot the characteristics to be observed and potentially changed (number defined by the agent AdjustCap parameter);
- Perform search in the databases containing the configurations of struct and flex characteristic values for the selected agents. Find out the value adopted by the majority of agents for the characteristic.
- IF the value is the same, keep the current value as it is. If the value is different:
  - In the case of a structural characteristic, update AgentStruct with one observation for that specific characteristic and value. IF three consecutive observations are done with the same value, and the value is different from the current characteristic value, then update the characteristic value.
  - In the case of a flexible characteristic, adopt its value if different from the current one.

IF SearchMethod=Minority mimetism:
- Choose by lot the agents to be observe, considering the agent Vision and the AgentProximityMatrix (agents from whom to gather information about potential configurations to adopt);
- Find out the agent with highest fitness among these selected agents in the current round
- Choose by lot the characteristics to be observed and potentially changed (number defined by the agent AdjustCap parameter);
- Find out the value adopted by the leader for the observed characteristic. In performing such task, consider an error rate of reading according to the MinorityError parameter.
- IF the value is the same, keep the current value as it is. If the value is different, perform the same logic as the majority mimetism search method.

IF SearchMethod=Random searching:
- Choose by lot the characteristics to be potentially changed (number defined by the agent AdjustCap parameter);
- Change the characteristics randomly (structural characteristics with less probability than flexible charateristics).

IF SearchMethod=Market reading (method avaialable only in the custom landscape model):
- With the error rate defined by the MarketReadingError parameter, find out what is the landscape value for the characteristic and adopt it according to the same rules that apply to the mimetism methods.

Create records in the AgentStructTrack (if any characteristic gets updated or observed for potential future change) or in the AgentFlexTrack (if any characteristic gets updated).



Fitness Landscape change

Exogenous cause of change

- Get LandscapeChangeSpeed parameter (probability) from simulation settings;
- Select by chance landscape change, and if true, choose by lot one characteristic (struct or flex, from a stratified pool);
- IF characteristic is flex, change its current value, ELSE (characteristic is struct), change its value with p=0.25.
- IF characteristic value changes:
  - Get randomly a new fitness impact value for that characteristic between 0 and the maximum value according to the simulation settings (MaxIndStructFitness or MaxIndFlexFitness parameters);
  - Search for all pairs of characteristics in the CombinedFitnessImpact table that includes the changed characteristic and replace its impact value by a new impact value (drawn randomly from an uniform distribution between 0 and MaxCombFitnessImpact).

Endogenous cause of change

- Get information of the new configuration of all agents after their search processes in this round (AgentStruct and AgentFlex characteristic values);
- Compute percentage of matches for all characteristics (agents *versus* landscape);
- Reduce or increase the individual fitness impact of each characteristic by the MatchesforEndogeneousChangeImpact parameter defined in the simulation settings if that percentage of matches is over or under the respective simulation setting parameters (final fitness value must be between zero and the upper limits defined in the simulation settings.

In case of any changes due to exogenous or endogenous causes, create track records in the LandscapeStructTrack, LandscapeFlexTrack and CombinedFitnessImpactTrack tables.

Agent Fitness Computation

IF landscape model = custom:

- Get landscape characteristics and individual fitness values (LandscapeStruct and LandscapeFlex tables);
- Get combinations of characteristics that impact fitness and their respective values (CombinedFitnessImpact table);
- For each agent:
  - Compare the value of each agent´s structural and flexible characteristic against the correspondent landscape characteristic value;
  - First compute fitness as the sum of individual fitness impact for the matched characteristics; then verify whether the combinations of characteristics that impact fitness apply for the agent configuration (interdependency):
    - IF first characteristic matches (SortedCharacteristic1):
      - IF UpsideEffect and second characteristic (SortedCharacteristic2) matches compute the positive impact (bonus)
      - ELSE IF DownsideEffect and second characteristic doesn´t match compute negative impact (penalty).
  - Create AgentFitnessTrack record for the round, with the fitness value scored.

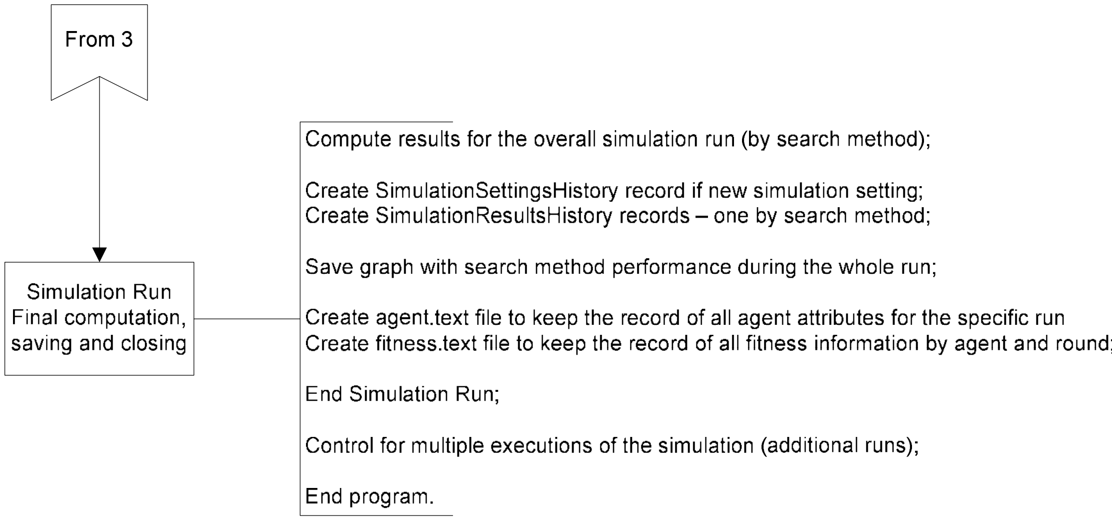
IF landscape model = NK

- Get NKLandscape information on fitness contribution by characteristic
- For each agent:
  - Identify the NK characteristic fitness contribution value to each combination hold by the agent (characteristic + K related characteristics);
  - Compute fitness of the agent;
  - Create AgentFitnessTrack record for the round, with the fitness value scored.

After all agents are computed, define highest fitness value and set all agents with this value as winners (in the AgentFitnessTrack table).

Round Final computation and closing

Compute results for the round, by search method;
Create ComputedResultTrack record;
Exhibit graphical results for the round, by search method;
Delete temporary table with agent characteristics and fitness information;
Go to next round.


From 3
Simulation Run
Final computation,
saving and closing
Compute results for the overall simulation run (by search method);
Create SimulationSettingsHistory record if new simulation setting;
Create SimulationResultsHistory records – one by search method;
Save graph with search method performance during the whole run;
Create agent.text file to keep the record of all agent attributes for the specific run
Create fitness.text file to keep the record of all fitness information by agent and round;
End Simulation Run;
Control for multiple executions of the simulation (additional runs);
End program.

Overview of Tables and their relationships

The agents (or firms)

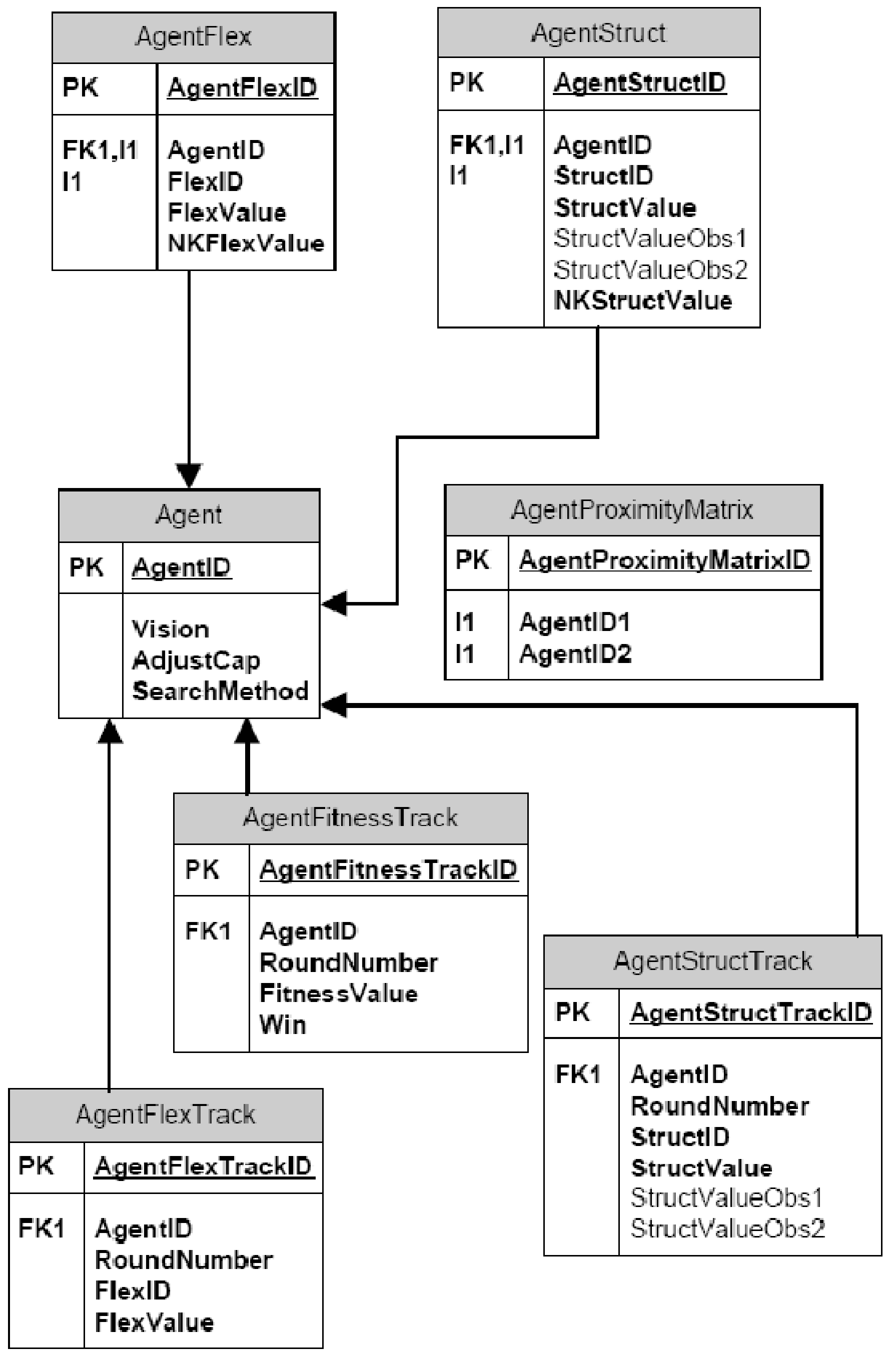
Agents (or firms) have attributes assigned for the duration of a whole simulation run. These attributes are in the Agent table. Each agent has a configuration of resources and capabilities whose representation is a set of structural and flexible characteristics. The current configuration of an agent is in the AgentFlex and AgentStruct tables. The AgentProximityMatrix represents all the connections among the firms, that is, it defines all the firms that each firm might be able to observe during the simulation.

During a simulation run, all firms search for fitness making use of their assigned search methods, regulated by the other specific attributes and limited to the observation of firms with whom they are connected, according to the AgentProximityMatrix. They may change their characteristic values many times throughout the simulation run, whenever perceiving such a need.

At each round, the system calculates the fitness performance for each firm, based on the current configuration (at the end of the round) and the landscape. The AgentFitnessTrack table contains these computations for all rounds of a simulation run.

We track all changes in the configuration of the agents throughout the simulation run and record them for verification purposes in the AgentFlexTrack and AgentStructTrack tables.

The following diagram depicts the tables and relationships; detailed descriptions of each table are available in the next section of this document.


AgentFlex
PK
AgentFlexID
FK1,I1
I1
AgentID
FlexID
FlexValue
NKFlexValue
AgentStruct
PK
AgentStructID
FK1,I1
I1
AgentID
StructID
StructValue
StructValueObs1
StructValueObs2
NKStructValue
Agent
PK
AgentID
Vision
AdjustCap
SearchMethod
AgentProximityMatrix
PK
AgentProximityMatrixID
I1
I1
AgentID1
AgentID2
AgentFitnessTrack
PK
AgentFitnessTrackID
FK1
AgentID
RoundNumber
FitnessValue
Win
AgentStructTrack
PK
AgentStructTrackID
FK1
AgentID
RoundNumber
StructID
StructValue
StructValueObs1
StructValueObs2
AgentFlexTrack
PK
AgentFlexTrackID
FK1
AgentID
RoundNumber
FlexID
FlexValue

Search Methods

There is a list of all search methods configured in the system. Each agent will have one of these SearchMethods assigned randomly as an attribute at the beginning of each simulation run, according to the simulation settings. The table only contains the description of each search method; their logic are coded into the program.

SearchMethod
SearchMethodID1 **SearchMethodDescription**

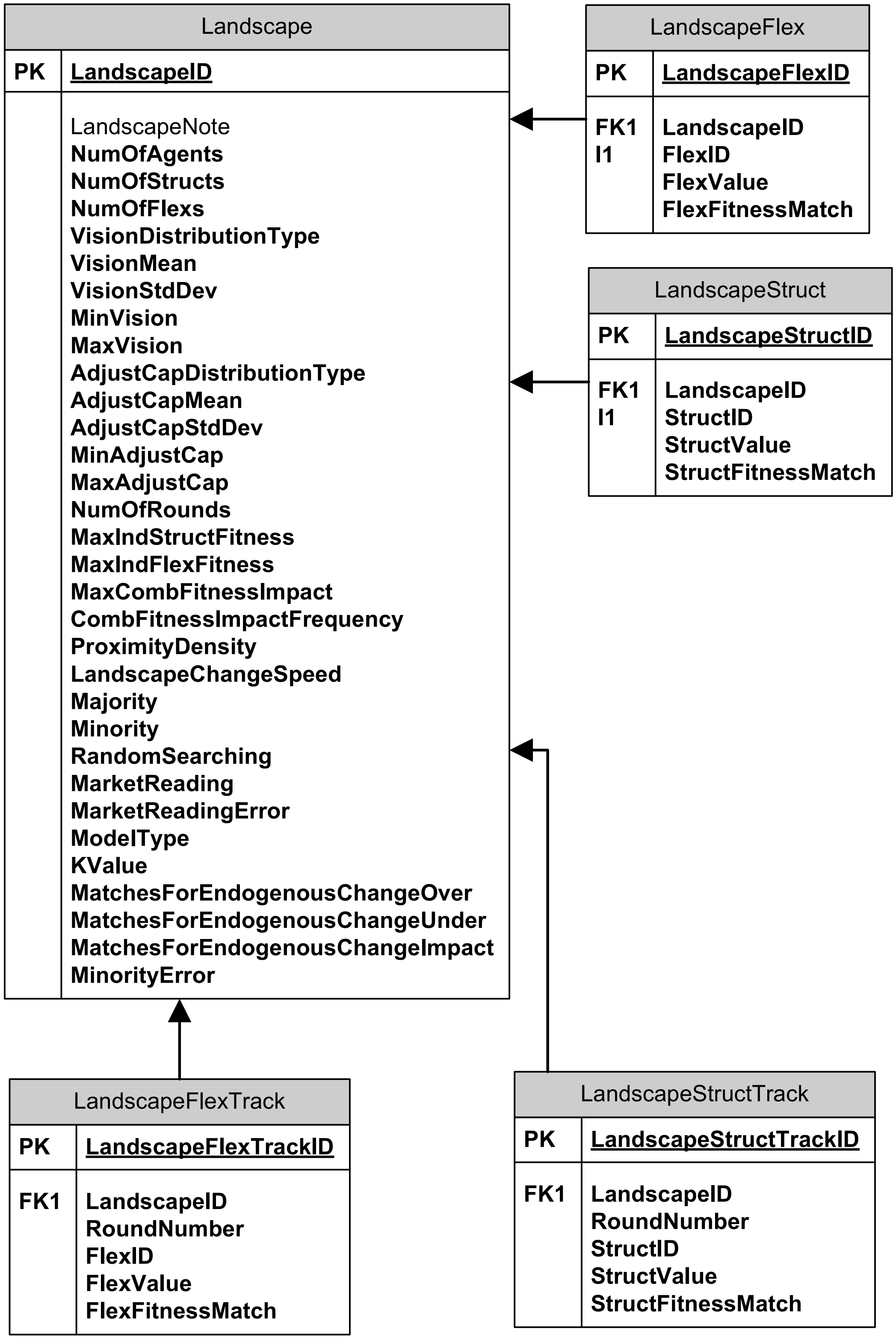
The landscape and parameters for the simulation

The Landscape table contains the parameters required to set up and run a simulation. It defines the landscape model, and for each case (custom or NK), defines its parameters. These include not only characteristics of the landscape itself, but also the characteristics of the population of agents.

If the custom landscape model is chosen for a simulation, then the system will generate LandscapeFlex and LandscapeStruct tables. These tables will define the values for each characteristic (flexible or structural) that constitutes the configuration of a firm operating in the market (landscape) – always zero or one values. It also defines the respective fitness contribution value in the case a firm characteristic value matches the characteristic value defined in the landscape. The interdependency among the various characteristics is defined in the CombinedFitnessImpact table, which contains pairs of characteristics and related impact for the match or mismatch that a firm presents in its configuration when compared to the landscape respective configuration. As the landscape may change due to exogenous and/or endogenous causes (both parameterized for each simulation), the system tracks all changes during the course of a simulation run and records them in the LandscapeFlexTrack, LandscapeStructTrack and CombinedFitnessImpactTrack tables.

If the NK landscape model is chosen, the representation of the landscape is done through the NKLandscape table, and the system doesn't make use of LandscapeFlex, LandscapeStruct, CombinedFitnessImpact tables (and their related "track" tables).

The following diagram depicts the tables and relationships; detailed descriptions of each table are available in the next section of this document.


Landscape
PK LandscapeID
LandscapeNote
NumOfAgents
NumOfStructs
NumOfFlexs
VisionDistributionType
VisionMean
VisionStdDev
MinVision
MaxVision
AdjustCapDistributionType
AdjustCapMean
AdjustCapStdDev
MinAdjustCap
MaxAdjustCap
NumOfRounds
MaxIndStructFitness
MaxIndFlexFitness
MaxCombFitnessImpact
CombFitnessImpactFrequency
ProximityDensity
LandscapeChangeSpeed
Majority
Minority
RandomSearching
MarketReading
MarketReadingError
ModelType
KValue
MatchesForEndogenousChangeOver
MatchesForEndogenousChangeUnder
MatchesForEndogenousChangeImpact
MinorityError
LandscapeFlex
PK LandscapeFlexID
FK1 LandscapeID
I1 FlexID
FlexValue
FlexFitnessMatch
LandscapeStruct
PK LandscapeStructID
FK1 LandscapeID
I1 StructID
StructValue
StructFitnessMatch
LandscapeFlexTrack
PK LandscapeFlexTrackID
FK1 LandscapeID
RoundNumber
FlexID
FlexValue
FlexFitnessMatch
LandscapeStructTrack
PK LandscapeStructTrackID
FK1 LandscapeID
RoundNumber
StructID
StructValue
StructFitnessMatch

CombinedFitnessImpact	
PK	<u>CombinedImpactID</u>
FK1	LandscapeID
I1	CharType1
I1	SortedCharacteristic1
I1	CharType2
I1	SortedCharacteristic2
	Effect
	Impact

CombinedFitnessImpactTrack	
PK	<u>CombinedImpactTrackID</u>
	CombinedImpactID
FK1	LandscapeID
	RoundNumber
	CharType1
	SortedCharacteristic1
	Effect
	CharType2
	SortedCharacteristic2
	Impact

NKLandscape	
PK	<u>CharType</u>
PK	<u>CharId</u>
PK	<u>NKCharValue</u>
	CharFitnessValue

Results and settings of recorded simulation executions

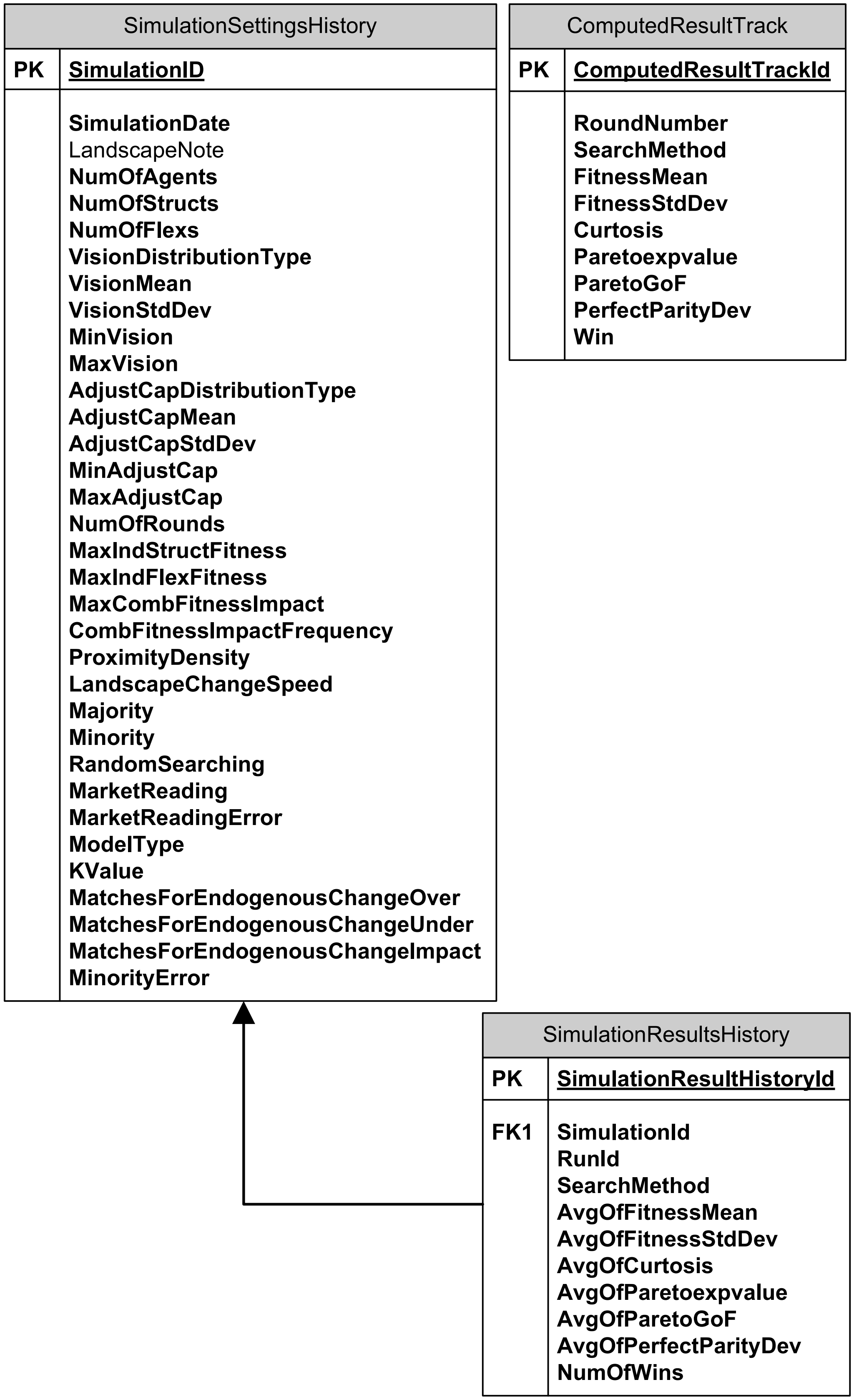
During a simulation run, at each round, the system computes the results obtained by all firms utilizing each search method. While individual firm results are stored in the AgentFitnessTrack table (already mentioned in 1.1), the computations by search method are stored in the ComputedResultTrack table.

Whenever a simulation run starts, the system initializes all tables. The graphical image of the agents searching for performance is exhibited during the simulation, by search method. It ca be saved at the end of the simulation run, upon request.

The system allows for the recording of both the consolidated results of the simulation run (by search method) and the detailed agent information from the tables Agent and AgentFitnessTrack.

The SimulationSettingsHistory is the table that records all the settings utilized for the executed simulations while the SimulationResultsHistory table contains the consolidated results by search method.

The following diagram depicts the tables and relationships; detailed descriptions of each table are available in the next section of this document.


SimulationSettingsHistory
PK
SimulationID
SimulationDate
LandscapeNote
NumOfAgents
NumOfStructs
NumOfFlexs
VisionDistributionType
VisionMean
VisionStdDev
MinVision
MaxVision
AdjustCapDistributionType
AdjustCapMean
AdjustCapStdDev
MinAdjustCap
MaxAdjustCap
NumOfRounds
MaxIndStructFitness
MaxIndFlexFitness
MaxCombFitnessImpact
CombFitnessImpactFrequency
ProximityDensity
LandscapeChangeSpeed
Majority
Minority
RandomSearching
MarketReading
MarketReadingError
ModelType
KValue
MatchesForEndogenousChangeOver
MatchesForEndogenousChangeUnder
MatchesForEndogenousChangeImpact
MinorityError
ComputedResultTrack
PK
ComputedResultTrackId
RoundNumber
SearchMethod
FitnessMean
FitnessStdDev
Curtosis
Paretoexpvalue
ParetoGoF
PerfectParityDev
Win
SimulationResultsHistory
PK
SimulationResultHistoryId
FK1
SimulationId
RunId
SearchMethod
AvgOfFitnessMean
AvgOfFitnessStdDev
AvgOfCurtosis
AvgOfParetoexpvalue
AvgOfParetoGoF
AvgOfPerfectParityDev
NumOfWins

Detailed definitions of the Tables

In this section we present the detailed documentation regarding all tables and respective fields. We included some notes at the table notes level to facilitate understanding the system design.

Agent

Notes:	Table of Agent Firms are created and have attributes assigned at the beginning of a simulation run according to the simulation parameters. These attributes remain the same for the whole simulation run.

Foreign keys	Child	Parent
Agent_AgentFitnessTrack_FK1	AgentFitnessTrack.AgentID	AgentID
Agent_AgentFlex_FK1	AgentFlex.AgentID	AgentID
Agent_AgentFlexTrack_FK1	AgentFlexTrack.AgentID	AgentID
Agent_AgentStruct_FK1	AgentStruct.AgentID	AgentID
Agent_AgentStructTrack_FK1	AgentStructTrack.AgentID	AgentID

Column details

1. AgentID

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification for a specific firm

2. Vision

Conceptual name:	Vision
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Number of firms that a specific firm can observe each round

3. AdjustCap

Conceptual name:	AdjustCap
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Number of characteristics that a firm is able to consider for changing at each round

4. SearchMethod

Conceptual name:	SEARCHMETHOD3
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Search strategy employed by the firm during the simulation

AgentFitnessTrack

Notes: Table of AgentFitnessTrack

Records the performance of each firm in each round of a simulation run. This table and all other tables labeled with the word "track" allow for complete understanding of what happened to each firm and the landscape in every round of a simulation run.

Under request, the system consolidates the results for the whole run (alll rounds) by search method, and records them in the SimulationResultsHistory table.

Whenever a simulation run starts this table is reset (as well as all others "track" tables).

Foreign keys	Child	Parent
Agent_AgentFitnessTrack_FK1	AgentID	Agent .AgentID

Column details

1. AgentFitnessTrackID

Conceptual name:	AgentFitnessTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. AgentID (FK)

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the firm

3. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the round

4. FitnessValue

Conceptual name:	FitnessValue
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Performance (or fitness) achieved by the firm in the round

5. Win

Conceptual name:	Win
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Indicator whether the firm achieved the highest fitness value in the round

AgentFlex

Notes:	Table of AgentFlex Each firm has a set of flexible characteristics (or configuration of resources) that is assigned randomly in the beginning of a simulation and is subject to change every round in its individual search process. The flexible characteristic is changed whenever the firm perceives that adopting a different value might yield better performance.

Foreign keys	Child	Parent
Agent_AgentFlex_FK1	AgentID	Agent .AgentID

Column details

1. AgentFlexID

Conceptual name:	AgentFlexID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of a specific flexible characteristic that composes the configuration of a firm

2. AgentID (FK,I1)

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the firm

3. FlexID (I1)

Conceptual name:	FlexID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific flexible characteristic (from 1 to N, according to the num_of_flexs parameter)

4. FlexValue

Conceptual name:	FlexValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Assumes value zero or one - initializes with a given value and potentially modifies during the simulation according to the decision of the firm, based in its context, information and search method

5. NKFlexValue

Conceptual name:	NKFlexValue
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Utilized only in the NK landscape model. Calculated as the corresponding value (from 0 to 255) for the combination of values of this characteristic and the next K characteristics of this firm (where K is the parameter of interdependency defined for the simulation)

AgentFlexTrack

Notes: Table of AgentFlexTrack

Tracks all changes to the values of the flexible characteristics in all firms during a simulation run.

Foreign keys	Child	Parent
Agent_AgentFlexTrack_FK1	AgentID	Agent .AgentID

Column details

1. AgentFlexTrackID

Conceptual name:	AgentFlexTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. AgentID (FK)

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the firm

3. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the round

4. FlexID

Conceptual name:	FlexID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific flexible characteristic (from 1 to N, according to the num_of_flexs parameter)

5. FlexValue

Conceptual name:	FlexValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Value of the characteristic in the round, prior to the change that occurred (the current value is always in the AgentFlex table).

AgentProximityMatrix

Notes: Table of AgentProximityMatrix:

It is utilized only by the custom landscape model.

This table represents all the relationships that each firm has with the others. It is utilized for the majority mimetism and minority mimetism search methods (in which firms search for performance looking at what others are doing).

The relationships don´t change during the course of a simulation run, but it is important to notice that a firm doesn´t necessarily look for all related firms in a round. It depends on the vision attribute of the firm (number of firms to be observed each round). Every round the firms to be observed by one firm are selected randomly from the pool of related firms.

Column details

1. AgentProximityMatrixID

Conceptual name:	AgentProximityMatrixID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the relationship between two firms

2. AgentID1 (I1)

Conceptual name:	AgentID1
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of firm

3. AgentID2 (I1)

Conceptual name:	AgentID2
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of another firm

AgentStruct

Notes: Table of AgentStruct:

The model proposes that a firm only obtain the committment and/or succeeds to change a structural characteristic after three consecutive observations of a different value for that characteristic. That is the difference between the structural and the flexible types of characteristic.

Additional note: Structural characteristics were designed in this model to represent the strategic choices that require greater committment, demand more investments and/or represent resource rigidity from the part of a firm in order to change it.

Foreign keys	Child	Parent
Agent_AgentStruct_FK1	AgentID	Agent .AgentID

Column details

1. AgentStructID

Conceptual name:	AgentStructID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. AgentID (FK,I1)

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the firm

3. StructID (I1)

Conceptual name:	StructID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific structural characteristic (from 1 to N, according to the num_of_structs parameter)

4. StructValue

Conceptual name:	StructValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Assumes value zero or one - initializes with a given value and potentially modifies during the simulation according to the decision of the firm, based in its context, information and search method

5. StructValueObs1

Conceptual name:	StructValueObs1
Physical data type:	CHAR(1)
Allow NULLs:	Allowed
Notes:	Last observed value for this structural characteristic when the firm performed its search method

6. StructValueObs2

Conceptual name:	StructValueObs2
Physical data type:	CHAR(1)
Allow NULLs:	Allowed
Notes:	Second last observed value for this structural characteristic when the firm performed its search method

7. NKStructValue

Conceptual name:	NKStructValue
Physical data type:	TINYINT

Allow NULLs:	Not allowed
Notes:	Utilized only in the NK landscape model. Calculated as the corresponding value (from 0 to 255) for the combination of values of this characteristic and the next K characteristics of this firm (where K is the parameter of interdependency defined for the simulation)

AgentStructTrack

Notes: Table of AgentStructTrack

Tracks all changes and/or observations to the values of the structural characteristics in all firms during a simulation run.

Foreign keys	Child	Parent
Agent_AgentStructTrack_FK1	AgentID	Agent .AgentID

Column details

1. AgentStructTrackID

Conceptual name:	AgentStructTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. AgentID (FK)

Conceptual name:	AgentID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the firm

3. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the round

4. StructID

Conceptual name:	StructID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific structural characteristic (from 1 to N, according to the num_of_structs parameter)

5. StructValue

Conceptual name:	StructValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Value of the characteristic in the round, prior to the change or observation that occurred (the current value is always in the AgentStruct table).

6. StructValueObs1

Conceptual name:	StructValueObs1
Physical data type:	CHAR(1)
Allow NULLs:	Allowed
Notes:	Prior value observed

7. StructValueObs2

Conceptual name:	StructValueObs2
Physical data type:	CHAR(1)
Allow NULLs:	Allowed
Notes:	Second prior value observed

CombinedFitnessImpact

Notes: Table of CombinedFitnessImpact

Utilized only in the custom landscape model.

Represents the interdependency of characteristics in a firm configuration. The value of one characteristic may interfere in the performance (fitness) atributed because of the value of other characteristics.

Contains combinations (pairs) of characteristics randomly drawn from all possible combinations of two firms that add or reduce fitness of the firm, according to the rule:
1) Efect= Upside: the match of both characteristic values gives an additional fitness value -positive impact
2) Effect= Downside: the match of the first characteristic value but with the mismatch of the second characteristic value gives a penalty in the fitness value - negative impact.

Foreign keys	Child	Parent
Landscape_CombinedFitnessImpact_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. CombinedImpactID
Conceptual name: CombinedImpactID
Physical data type: INTEGER
Allow NULLs: Not allowed
Notes: Identification of the record in the database

2. LandscapeID (FK)
Conceptual name: LandscapeID
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Identification of the landscape under simulation

3. CharType1 (I1)
Conceptual name: CharType1
Physical data type: CHAR(1)
Allow NULLs: Not allowed
Notes: Type of characteristic chosen at random in the beginning of the simulation run - flex or struct

4. SortedCharacteristic1 (I1)
Conceptual name: SortedCharacteristic1
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: FlexID or StructID chosen at random in the beginning of the simulation run (numbered from 1 to N, according to numofflexs or numofstructs parameters)

5. CharType2 (I1)
Conceptual name: CharType2
Physical data type: CHAR(1)
Allow NULLs: Not allowed
Notes: Type of characteristic chosen at random in the beginning of the simulation run - flex or struct

6. SortedCharacteristic2 (I1)
Conceptual name: SortedCharacteristic2
Physical data type: TINYINT

Allow NULLs:	Not allowed
Notes:	FlexID or StructID chosen at random in the beginning of the simulation run (numbered from 1 to N, according to numofflexs or numofstructs parameters)

7. Effect

Conceptual name:	Effect
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Positive (Upside) or Negative (Downside) impact to be considered

8. Impact

Conceptual name:	Impact
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Fitness impact for the match (Upside) or mismatch (Downside) of the pair of characteristics

CombinedFitnessImpactTrack

Notes: Table of CombinedFitnessImpactTrack

Utilized only in the custom landscape model.

Tracks all the changes in the effects and impacts caused by the interdependencies (randomly defined) among pairs of characteristics for the simulation run. These changes happen when one of the characteristics changes its value in a specific round - all effects related to that characteristic are udated (with random mechanisms under the parameter settings).

This table records the values that were replaced in a given round; current values are always in the CombinedFitnessImpact table.

Foreign keys	Child	Parent
Landscape_CombinedFitnessImpactTrack_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. CombinedImpactTrackID

Conceptual name:	CombinedImpactTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. CombinedImpactID

Conceptual name:	CombinedImpactID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of a specific pair of characteristics

3. LandscapeID (FK)

Conceptual name:	LandscapeID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the landscape under simulation

4. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Round in which a change occurred

5. CharType1

Conceptual name:	CharType1
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Type of characteristic chosen at random in the beginning of the simulation - flex or struct

6. SortedCharacteristic1

Conceptual name:	SortedCharacteristic1
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	FlexID or StructID chosen at random in the beginning of the simulation

7. Effect

Conceptual name:	Effect
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Efect replaced in the round. Positive (Upside) or Negative (Downside)

8. CharType2

Conceptual name:	CharType2
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Type of characteristic chosen at random in the beginning of the simulation- flex or struct

9. SortedCharacteristic2

Conceptual name:	SortedCharacteristic2
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	FlexID or StructID chosen at random in the beginning of the simulation

10. Impact

Conceptual name:	Impact
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Fitness impact for the match (Upside) or mismatch (Downside) that was replaced in the round

ComputedResultTrack

Notes:	Table of ComputedResultTrack Have the results yielded by each search method (strategy) in each round of the simulation run. It records only the results of the last simulation run. Consolidated results are saved in the SimulationResultsHistory table if requested (under sequential simulation and run numbers, tied to the simulation settings recorded in the SimulationSettingsHistory table.

Column details

1. ComputedResultTrackId

Conceptual name:	ComputedResultTrackId
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification field created by the system for internal use only

2. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Number of the round in the simulation run

3. SearchMethod

Conceptual name:	SEARCHMETHOD2
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Identification of the search method (1=Majority Mimetism; 2=Minority Mimetism; 3=random searching; 4=market reading)

4. FitnessMean

Conceptual name:	FitnessMean
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Average of fitness of all firms searching with the specific search method in the round

5. FitnessStdDev

Conceptual name:	FitnessStdDev
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Standard deviation of the fitness for the group of firms searching with the specific search method in the round

6. Curtosis

Conceptual name:	Curtosis
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Statistical measure of the curtosis for the distribution curve of performance composed of the fitness values for the firms searching with the specific searching method in the round

7. Paretoexpvalue

Conceptual name:	Paretoexpvalue
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Not implemented yet

8. ParetoGoF

Conceptual name: ParetoGoF
Physical data type: DECIMAL(8;4)
Allow NULLs: Not allowed
Notes: Not implemented yet

9. PerfectParityDev
Conceptual name: PerfectParityDev
Physical data type: DECIMAL(8;4)
Allow NULLs: Not allowed
Notes: Not implemented yet

10. Win
Conceptual name: Win
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Indicator that the firm with highest fitness value in the round utilized this search method

Landscape

Notes: Table of Landscape

The landscape table contains only one record, with all the definitions required to set a simulation: parameters to create the landscape, the population of firms, their relationships and search methods to be applied.

After a simulation the parameters utilized can be recorded in a different table - SimulationSettingsHistory, as well as its results (in the SimulationResultsHistory table). In this process, a SimulationID is defined for that specific setting of parameters.

This process can be done several times for the same setting of parameters. Each execution of a simulation under a setting of parameters is called a simulation run. Each simulation run will have the same SimulationID and is sequencialy numbered for appropriate recording, having its own RunID.

The last simulation settings utilized remain in the landscape table record, as to facilitate the operation of the model (such as running additional times or slightly changing the previous parameters). However, once new parameters are defined, a new LandscapeID is set (for internal use of the system) and it is not possible to return for the same setting of parameters and run additional times. In this case, additional runs will be sequentially created under a new SimulationID.

Foreign keys	Child	Parent
Landscape_CombinedFitnessImpact_FK1	CombinedFitnessImpact.LandscapeID	LandscapeID
Landscape_CombinedFitnessImpactTrack_FK1	CombinedFitnessImpactTrack.LandscapeID	LandscapeID
Landscape_LandscapeFlex_FK1	LandscapeFlex.LandscapeID	LandscapeID
Landscape_LandscapeFlexTrack_FK1	LandscapeFlexTrack.LandscapeID	LandscapeID
Landscape_LandscapeStruct_FK1	LandscapeStruct.LandscapeID	LandscapeID
Landscape_LandscapeStructTrack_FK1	LandscapeStructTrack.LandscapeID	LandscapeID

Column details

1. LandscapeID

Conceptual name: LandscapeID
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Identification of the record in the database

2. LandscapeNote

Conceptual name: LandscapeNote
Physical data type: LONGVARBINARY
Allow NULLs: Allowed
Notes: Description of the setting being simulated - free use for researcher's notes

3. NumOfAgents

Conceptual name: NumOfAgents
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: number of agents (firms)

4. NumOfStructs

Conceptual name: NumOfStructs
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: number of structural characteristics that each agent(firm) will have

5. NumOfFlexs

Conceptual name: NumOfFlexs
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: number of flexible characteristics that each agent(firm) will have

6. VisionDistributionType
Conceptual name: VisionDistributionType
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Type of distribution curve from which values of vision will be randomly drawn (normal or uniform)

7. VisionMean
Conceptual name: VisionMean
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Mean of vision parameter for the population of firms in the case the normal distribution type of curve is choosen

8. VisionStdDev
Conceptual name: VisionStdDev
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Standard deviation of vision parameter in the case the normal distribution type of curve is choosen

9. MinVision
Conceptual name: MinVision
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Minimum value of vision parameter for the population of firms in the case the uniform distribution type of curve is choosen

10. MaxVision
Conceptual name: MaxVision
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Maximum value of vision parameter for the pópulation of firms in the case the uniform distribution type of curve is choosen

11. AdjustCapDistributionType
Conceptual name: AdjustCapDistributionType
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Type of distribution curve from which values of adjust cap will be randomly drawn

12. AdjustCapMean
Conceptual name: AdjustCapMean
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Mean of adjustcap parameter for the population of firms in the case the normal distribution type of curve is choosen

13. AdjustCapStdDev
Conceptual name: AdjustCapStdDev
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Standard deviation of adjustcap parameter for the population of firms in the case the normal distribution type of curve is choosen

14. MinAdjustCap
Conceptual name: MinAdjustCap

Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Minimum value of the adjustcap parameter for the population of firms in the case the uniform distribution type of curve is choosen

15. MaxAdjustCap
Conceptual name: MaxAdjustCap
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Maximum value of the adjustcap parameter for the population of firms in the case the uniform distribution type of curve is choosen

16. NumOfRounds
Conceptual name: NumOfRounds
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Number of rounds that a simulation run will execute

17. MaxIndStructFitness
Conceptual name: MaxIndStructFitness
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only. Maximum value for an individual structural characteristic match (fitness). Values will be randomly drawn from uniform distribution between zero and this parameter.

18. MaxIndFlexFitness
Conceptual name: MaxIndFlexFitness
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only. Maximum value for an individual flexible characteristic match (fitness). Values will be randomly drawn from uniform distribution between zero and this parameter.

19. MaxCombFitnessImpact
Conceptual name: MaxCombFitnessImpact
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only. Maximum fitness contribution impact for a match (positive) or mismatch (negative) of a combination of two different characteristics. Values will be randomly drawn from uniform distribution between zero and this parameter.

20. CombFitnessImpactFrequency
Conceptual name: CombFitnessImpactFrequency
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only.Percentage of all possible combinations of two characteristics to be randomly drawn for the attribution of combined impacts on fitness value (based on match or mismatch when comparing the configurations of firm and the landscape)

21. ProximityDensity
Conceptual name: ProximityDensity
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only. Percentage of all possible combinations of pairs of firms that will be randomly drawn to determine connections among the firms.

22. LandscapeChangeSpeed
Conceptual name: LandscapeChangeSpeed
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed

Notes:	Custom model only. Probability of exogenous change in the configuration of the landscape at each round of a simulation run

23. Majority

Conceptual name:	Majority
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Percentage of firms with the majority mimetism search method

24. Minority

Conceptual name:	Minority
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Percentage of firms with the minority mimetism search method

25. RandomSearching

Conceptual name:	RandomSearching
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Percentage of firms with the random searching method

26. MarketReading

Conceptual name:	MarketReading
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Percentage of firms with the market reading search method (access to information regarding the landscape configuration). This method doesn't apply to the NK model

27. MarketReadingError

Conceptual name:	MarketReadingError
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Expected percentage of error of the market reading search method. Utilized in the custom model only.

28. ModelType

Conceptual name:	ModelType
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Landscape model utilized in the simulation (custom or NK)

29. KValue

Conceptual name:	KValue
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	K value when utilizing the NK model. Represents the number of characteristics upon which every specific characteristic depends upon in order to define its individual fitness contribution.

30. MatchesForEndogenousChangeOver

Conceptual name:	MatchesForEndogenousChangeOver
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Determines an endogenous change of the landscape; if the % of firms in the population that matched the right landscape configuration for a characteristic is greater than this parameter value, the respective characteristic turns to be less valuable – a reduction will be applied to its individual fitness value.

.

31. MatchesForEndogenousChangeUnder

Conceptual name:	MatchesForEndogenousChangeUnder
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Determines an endogenous change of the landscape; if the % of firms in the

population that matched the right landscape configuration for a characteristic is less than this parameter value, the respective characteristic turns to be more valuable – an increase will be applied to its individual fitness value.

.

32. MatchesForEndogenousChangeImpact

Conceptual name:	MatchesForEndogenousChangeImpact
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Defines the impact for an endogenous change (reduction or increase of an individual characteristic fitness value)

33. MinorityError

Conceptual name:	MinorityError
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Expected percentage of error of the minority mimetism search method.

LandscapeFlex

Notes:	Table of LandscapeFlex Utilized in the custom model only. Contains the values for the flexible characteristics that fit the market requirements (zero or one) and the fitness contribution value to be yielded in the case the firm matches this value in its configuration, that is, when a firm has the same value in the respective characteristic, the fitness value of this characteristic is summed up in the calculation of the firm´s fitness in a given round.

Foreign keys	Child	Parent
Landscape_LandscapeFlex_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. LandscapeFlexID

Conceptual name:	LandscapeFlexID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. LandscapeID (FK)

Conceptual name:	LandscapeID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the landscape under simulation

3. FlexID (I1)

Conceptual name:	FlexID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific flexible characteristic (from 1 to N, according to the num_of_flexs parameter)

4. FlexValue

Conceptual name:	FlexValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Value of the flexible caracteristic

5. FlexFitnessMatch

Conceptual name:	FlexFitnessMatch
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Fitness value in case of match (firm flexvalue = landscape flexvalue)

LandscapeFlexTrack

Notes:	Table of LandscapeFlexTrack Utilized in the custom model only. Tracks changes in the landscape flexible characteristic values and fitness values. Whenever a characteristic value is changed (due to exogenous change) the fitness contribution value is changed as well (randomly assigned value according to the parameter settings). When endogenous changes occur (according to the specific parameter settings) the fitness value change is also tracked.

Foreign keys	Child	Parent
Landscape_LandscapeFlexTrack_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. LandscapeFlexTrackID

Conceptual name:	LandscapeFlexTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the databse

2. LandscapeID (FK)

Conceptual name:	LandscapeID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the landscape under simulation

3. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Round in which a change occurred in the flexible characteristic value and/or fitness match value

4. FlexID

Conceptual name:	FlexID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific flexible characteristic (from 1 to N, according to the num_of_flexs parameter)

5. FlexValue

Conceptual name:	FlexValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Flex value (zero or one) replaced in the round (current value is stored in the landscapeflex table)

6. FlexFitnessMatch

Conceptual name:	FlexFitnessMatch
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Flex fitness contribution value replaced in the round

LandscapeStruct

Notes: Table of LandscapeStruct

Utilized in the custom model only.

Contains the values for the structural characteristics that fit the market requirements (zero or one) and the fitness contribution value to be yielded in the case the firm matches this value in its configuration, that is, when a firm has the same value in the respective characteristic, the fitness value of this characteristic is summed up in the calculation of the firm´s fitness in a given round.

Foreign keys	Child	Parent
Landscape_LandscapeStruct_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. LandscapeStructID

Conceptual name:	LandscapeStructID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the database

2. LandscapeID (FK)

Conceptual name:	LandscapeID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the landscape under simulation

3. StructID (I1)

Conceptual name:	StructID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific structural characteristic (from 1 to N, according to the num_of_structs parameter)

4. StructValue

Conceptual name:	StructValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Value of the structural caracteristic

5. StructFitnessMatch

Conceptual name:	StructFitnessMatch
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Utilized only in the custom model. Fitness value in case of match (firm structvalue = landscape structvalue)

LandscapeStructTrack

Notes: Table of LandscapeStructTrack

Utilized in the custom model only.

Tracks changes in the landscape structural characteristic values and fitness values.

Whenever a characteristic value is changed (due to exogenous change) the fitness contribution value is changed as well (randomly assigned value according to the parameter settings).

When endogenous changes occur (according to the specific parameter settings) the fitness value change is also tracked.

Foreign keys	Child	Parent
Landscape_LandscapeStructTrack_FK1	LandscapeID	Landscape.LandscapeID

Column details

1. LandscapeStructTrackID

Conceptual name:	LandscapeStructTrackID
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification of the record in the databse

2. LandscapeID (FK)

Conceptual name:	LandscapeID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the landscape under simulation

3. RoundNumber

Conceptual name:	RoundNumber
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Round in which a change occurred in the structural characteristic value and/or fitness match value

4. StructID

Conceptual name:	StructID
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Identification of the specific structural characteristic (from 1 to N, according to the num_of_structs parameter)

5. StructValue

Conceptual name:	StructValue
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Struct value (zero or one) replaced in the round (current value is stored in the landscapestruct table)

6. StructFitnessMatch

Conceptual name:	StructFitnessMatch
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Struct fitness contribution value replaced in the round

NKLandscape

Notes:

Table of NKLandscape

Utilized only when running the NK model.

For each characteristic, flex or stuct, contains all combinations of values for K+1 characteristics, and an associated fitness value (for each possible combination).

Example:
2 flex, 1 struct,K=2, values 0 or 1: 2^k+1=8 possible combinations for each characteristic

The table would contain 8 entries for every characteristic; To simplify internal operations, NKcharvalue is expressed as a value between 0 and 255 - imposing a system limit to K at the maximum value of 7(*):

chartype	charID	All possible combinations	NKcharvalue	charfitnessvalue
F	1	001	4	....
F	1	011	6	....
F	1	000	0	....
F	1	010	2	....
F	1	101	5	....
F	1	111	7	....
F	1	100	1	....
F	1	110	3	....

(*) We consider that this simplification doesn´t compromise the scope of our simulations since literature in business strategy considers values higher than 3 as very high complexity in Kauffmann´s representations.

Column details

1. CharType

Conceptual name: CharType
Physical data type: CHAR(1)
Allow NULLs: Not allowed
Notes: Type (flex or struct)

2. CharId

Conceptual name: CharId
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: FlexID or StructID

3. NKCharValue

Conceptual name: NKCharValue
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Value between 0 and 255 that represents the combination of K+1 characteristic values (of zeros and ones)

4. CharFitnessValue

Conceptual name: CharFitnessValue
Physical data type: DECIMAL(4;4)
Allow NULLs: Not allowed
Notes: Fitness contribution for each specific combination for the characteristic with the K other characteristics

SearchMethod

Notes: Table of SearchMethod

Lists all search methods available in the apllication. Currently there are four methods.

Column details

<u>1. SearchMethod</u>

Conceptual name:	SearchMethodID1
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed

<u>2. SearchMethodDescription</u>

Conceptual name:	SearchMethodDescription
Physical data type:	LONGVARBINARY
Allow NULLs:	Not allowed

SimulationResultsHistory

Notes: Table of SimulationResultsHistory

It records the results by search method for each simulation run - on average or in total depending on the type of information. The results are saved under sequential numbering of simulation and run, tied to the simulation settings recorded in the SimulationSettingsHistory table.

Foreign keys	Child	Parent
FK_SimulationResultsHistory_SimulationSettingsHistory	SimulationId	SimulationSettingsHistory.SimulationID

Column details

1. SimulationResultHistoryId

Conceptual name:	SimulationResultHistoryId
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification field created by the system for internal use only

2. SimulationId (FK)

Conceptual name:	SimulationId
Physical data type:	INTEGER
Allow NULLs:	Not allowed
Notes:	Identification field that ties the results history to the simulation settings history

3. RunId

Conceptual name:	RunId
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Sequential number generated by the system to identifies a new simulation run being saved under the same setting of parameters.

4. SearchMethod

Conceptual name:	SEARCHMETHOD1
Physical data type:	CHAR(1)
Allow NULLs:	Not allowed
Notes:	Identification of the search method (1=Majority Mimetism; 2=Minority Mimetism; 3=random searching; 4=market reading)

5. AvgOfFitnessMean

Conceptual name:	AvgOfFitnessMean
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Average of the fitness mean of all firms searching with the specific search method at all rounds of the simulation run

6. AvgOfFitnessStdDev

Conceptual name:	AvgOfFitnessStdDev
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Average of all standard deviations calculated at each run for all firms searching with the search method

7. AvgOfCurtosis

Conceptual name:	AvgOfCurtosis
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Average of the curtosis computed in all rounds of the simulation run for the search method

8. AvgOfParetoexpvalue

Conceptual name:	AvgOfParetoexpvalue
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Not implemented yet

9. AvgOfParetoGoF

Conceptual name:	AvgOfParetoGoF
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Not implemented yet

10. AvgOfPerfectParityDev

Conceptual name:	AvgOfPerfectParityDev
Physical data type:	DECIMAL(8;4)
Allow NULLs:	Not allowed
Notes:	Not implemented yet

11. NumOfWins

Conceptual name:	NumOfWins
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Sum of the wins observed in all rounds of the simulation run for the search method (number of rounds in which the firm with highest fitness was making use of the search method)

SimulationSettingsHistory

Notes: Table of SimulationSettingsHistory

Keeps one record for every setting of parameters utilized for a simulation run that was asked to be saved. Each setting receives an identification, the SimulationID. Many runs can be sequentialy executed under the same set of parameters. In this case, they will share the SimulationID and will be sequentialy numbered (RunID).If any parameter is changed and a simulation run is executed, a new SimulationID is assigned and the numbering restarts at 1 (RunID). However, if an old set of parameters is utilized again, the system doesn´t recognize it as an additional run for an old SimulationID.

Foreign keys	Child	Parent
FK_SimulationResultsHistory_SimulationSettingsHistory	SimulationResultsHistory.SimulationId	SimulationID

Column details

1. SimulationID

Conceptual name: SimulationID
Physical data type: INTEGER
Allow NULLs: Not allowed
Notes: Number generated by the system for internal control purpose

2. SimulationDate

Conceptual name: SimulationDate
Physical data type: DATETIME
Allow NULLs: Not allowed
Notes: Date of the simulation run

3. LandscapeNote

Conceptual name: LandscapeNote
Physical data type: LONGVARBINARY
Allow NULLs: Allowed
Notes: Frre space for comments or description of the simulation run

4. NumOfAgents

Conceptual name: NumOfAgents
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Number of firms to be created and utilized in the simulation

5. NumOfStructs

Conceptual name: NumOfStructs
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Number of structural characteristics each firm will have in its configuration

6. NumOfFlexs

Conceptual name: NumOfFlexs
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Number of flexible characteristics each firm will have in its configuration

7. VisionDistributionType

Conceptual name: VisionDistributionType
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Type of input distribution curve to be utilized for the generation of randomly

assigned vision attributes for the firms. Can be normal or uniform

8. VisionMean
Conceptual name: VisionMean
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Average of the value for the vision attribute for the normal distribution curve (if chosen)

9. VisionStdDev
Conceptual name: VisionStdDev
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Standard deviation of the vision attribute normal distribution curve (if chosen)

10. MinVision
Conceptual name: MinVision
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Minimum value for the vision attribute if uniform input distribution curve is chosen

11. MaxVision
Conceptual name: MaxVision
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Maximum value for the vision attribute if uniform input distribution curve is chosen

12. AdjustCapDistributionType
Conceptual name: AdjustCapDistributionType
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Type of input distribution curve to be utilized for the generation of randomly assigned capacity to adjust attributes for the firms. Can be normal or uniform

13. AdjustCapMean
Conceptual name: AdjustCapMean
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Average of the value for the capacity to adjust attribute for the normal distribution curve (if chosen)

14. AdjustCapStdDev
Conceptual name: AdjustCapStdDev
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Standard deviation of the capacity to adjust attribute normal distribution curve (if chosen)

15. MinAdjustCap
Conceptual name: MinAdjustCap
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Minimum value for the capacity to adjust attribute if uniform input distribution curve is chosen

16. MaxAdjustCap
Conceptual name: MaxAdjustCap
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Maximum value for the capacity to adjust attribute if uniform input distribution curve is chosen

17. NumOfRounds

Conceptual name:	NumOfRounds
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Number of rounds in the simulation run

18. MaxIndStructFitness

Conceptual name:	MaxIndStructFitness
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Maximum value for the fitness contribution of a structural characteristic (input distribution curve is uniform between zero and this parameter)

19. MaxIndFlexFitness

Conceptual name:	MaxIndFlexFitness
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Maximum value for the fitness contribution of a flexible characteristic (input distribution curve is uniform between zero and this parameter)

20. MaxCombFitnessImpact

Conceptual name:	MaxCombFitnessImpact
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Maximum value for the combined fitness impact (of a pair of characteristics). The input distribution curve is uniform between zero and this parameter

21. CombFitnessImpactFrequency

Conceptual name:	CombFitnessImpactFrequency
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Percentage of possible combinations of pairs of characteristics that will have interdependence (positive or negative impact). Pairs of firms will be pulled out so that some characteristics may relate to many others while some may remain independent (random process)

22. ProximityDensity

Conceptual name:	ProximityDensity
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Percentage of all possible connections between two firms. Pairs of firms are pulled out - some may be connected to many while others may have few or none connections depending on the parameter and the randomization process.

23. LandscapeChangeSpeed

Conceptual name:	LandscapeChangeSpeed
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Custom model only. Expected frequency of landscape change due to exogenous causes. If a change occurs, one characteristic will be chosen at random and change its value, fitness impact and associated combined fitness impacts.

24. Majority

Conceptual name:	Majority
Physical data type:	TINYINT
Allow NULLs:	Not allowed
Notes:	Percentage of firms that will search utilizing the majority mimetism method

25. Minority

Conceptual name:	Minority
Physical data type:	TINYINT

Allow NULLs: Not allowed
Notes: Percentage of firms that will search utilizing the minority mimetism method

26. RandomSearching
Conceptual name: RandomSearching
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Percentage of firms that will search utilizing the random searching method

27. MarketReading
Conceptual name: MarketReading
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Custom model only. Percentage of firms that will search utilizing the market reading method

28. MarketReadingError
Conceptual name: MarketReadingError
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Custom model only. Average expected error for the assessment conducted by firms utilizing the market reading method

29. ModelType
Conceptual name: ModelType
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Type of landscape model in use - can be the custom model or the NK model

30. KValue
Conceptual name: KValue
Physical data type: TINYINT
Allow NULLs: Not allowed
Notes: Use only in the NK model - number of characteristics each characteristic will depend upon to define its fitness contribution. All possible combinations will have a fitness contribution between zero and one.

31. MatchesForEndogenousChangeOver
Conceptual name: MatchesForEndogenousChangeOver
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Determines an endogenous change of the landscape; if the % of firms in the population that matched the right landscape configuration for a characteristic is greater than this parameter value, the respective characteristic turns to be less valuable – a reduction will be applied to its individual fitness value.

.

32. MatchesForEndogenousChangeUnder
Conceptual name: MatchesForEndogenousChangeUnder
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Determines an endogenous change of the landscape; if the % of firms in the population that matched the right landscape configuration for a characteristic is less than this parameter value, the respective characteristic turns to be more valuable – an increase will be applied to its individual fitness value.

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33. MatchesForEndogenousChangeImpact
Conceptual name: MatchesForEndogenousChangeImpact
Physical data type: DECIMAL(3;2)
Allow NULLs: Not allowed
Notes: Defines the impact for an endogenous change (reduction or increase of an individual characteristic fitness value)

34. MinorityError

Conceptual name:	MinorityError
Physical data type:	DECIMAL(3;2)
Allow NULLs:	Not allowed
Notes:	Expected percentage of error of the minority mimetism search method.

II) SIMULATION RESULTS

In the following pages we present the sequence of simulation results for the settings performed according to the final test plan, mentioned in section 5 of this study.

Evolution of fitness (by search method), all simulation executions

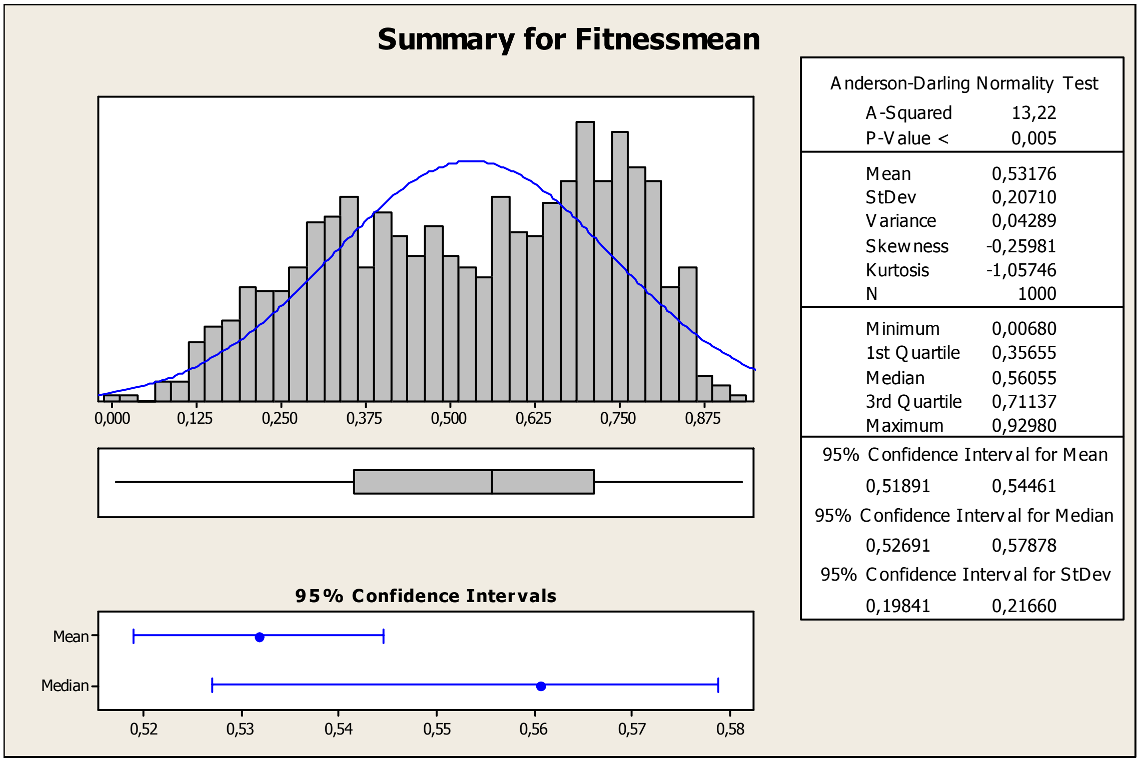
Every execution (run) of a simulation that is recorded generates a chart that shows the evolution of fitness by search method. In this subsection we make all these charts available for the reader[29].

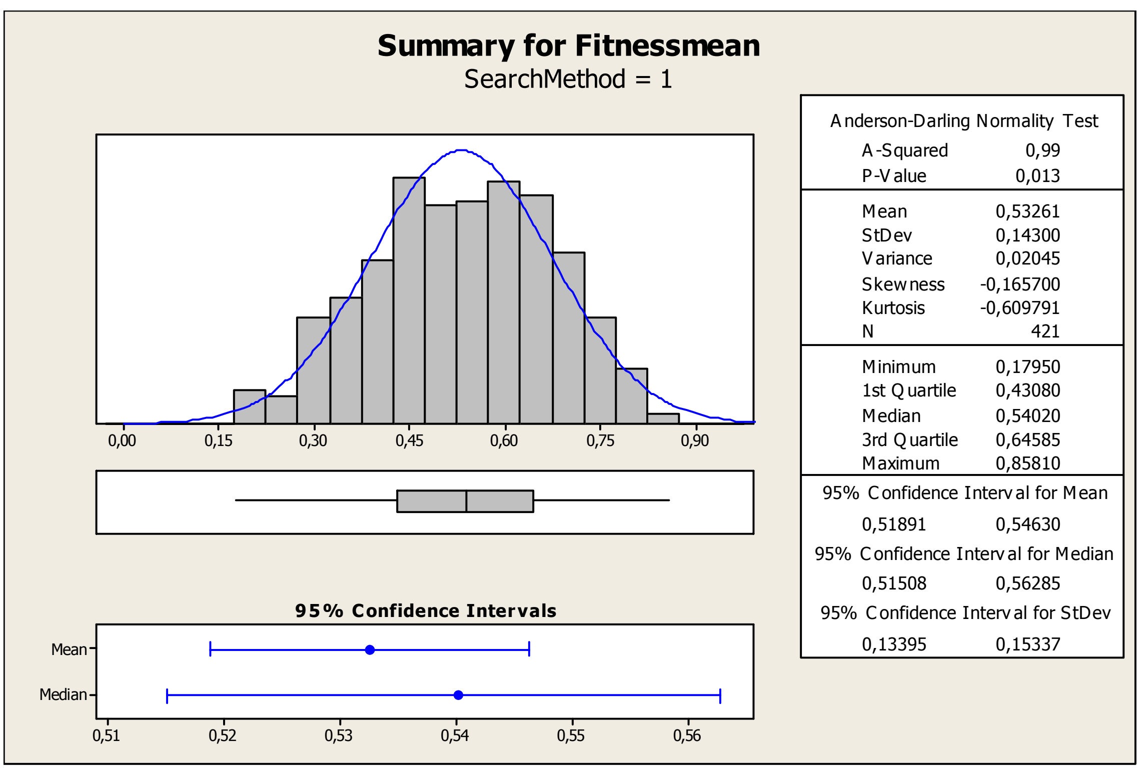
[29] We apologize for not being able to provide this section in the electronic version of this work, posted in PDF format. That is because our system outcomes are pre-configured, .htm page printouts. We commit ourselves to make all simulation results and the application itself available on-line in the near future.

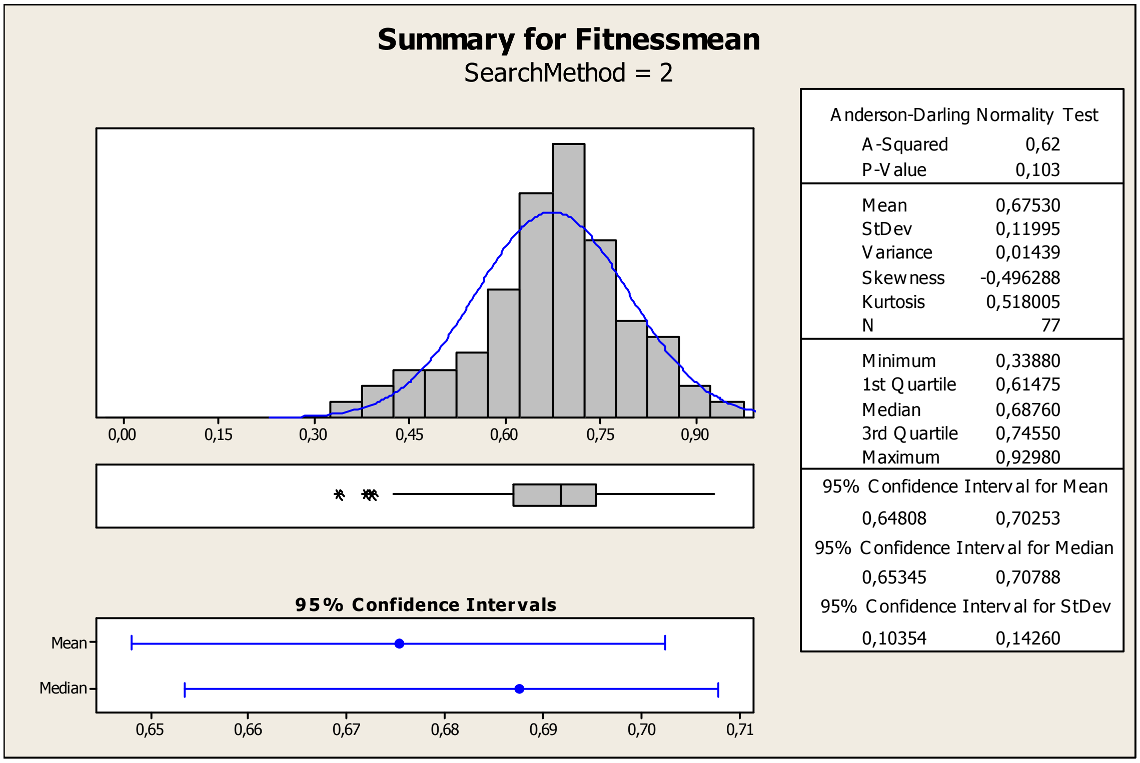
Descriptive statistics of all simulation executions

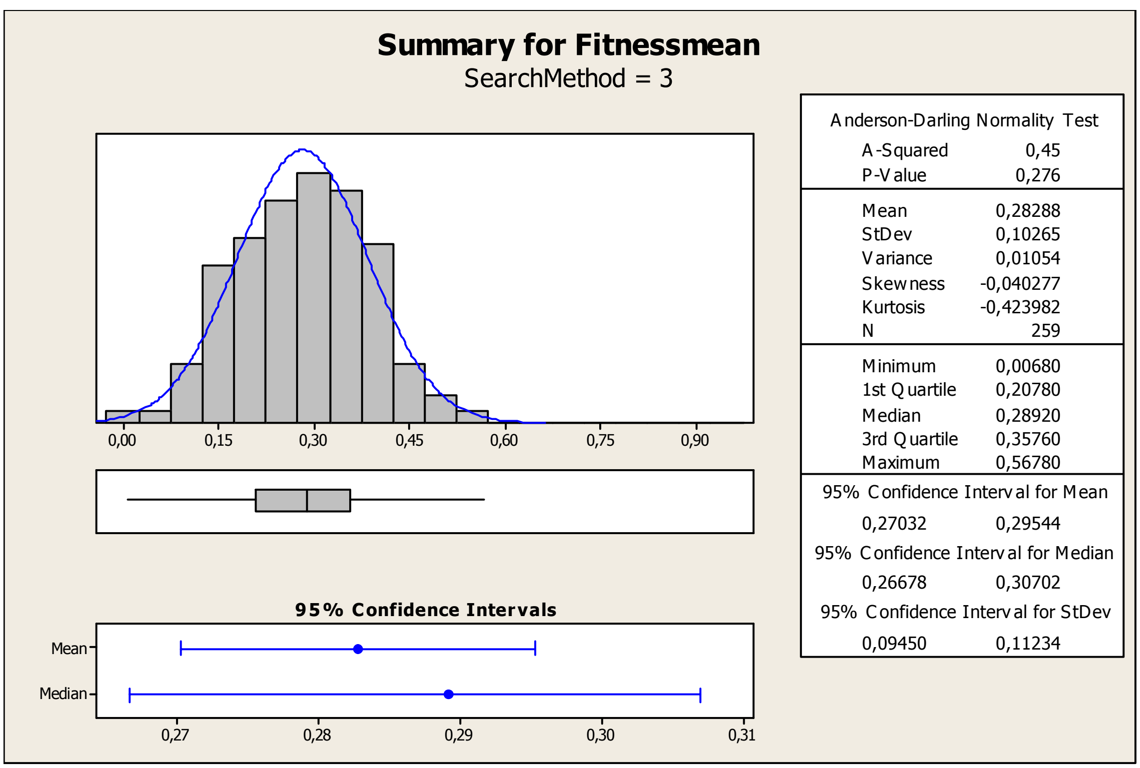
In this subsection we provide additional data and analysis of all simulation executions performed during the final test.

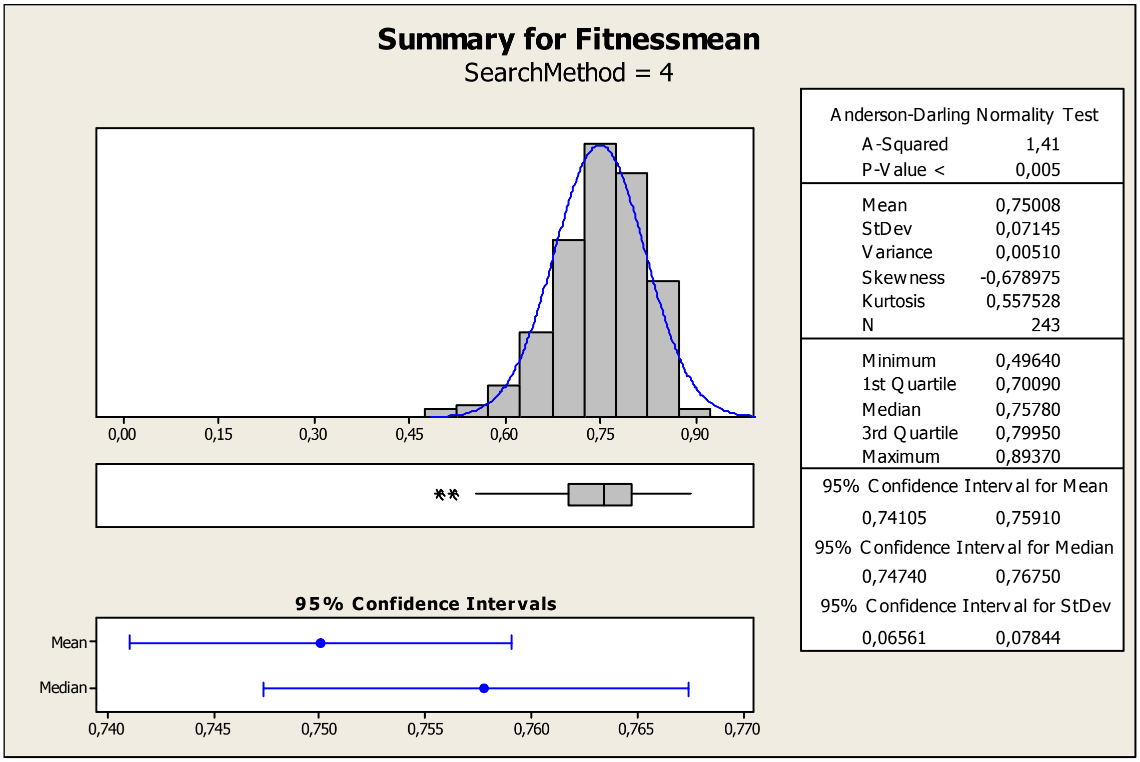
SIMULATION 57, ALL RUNS



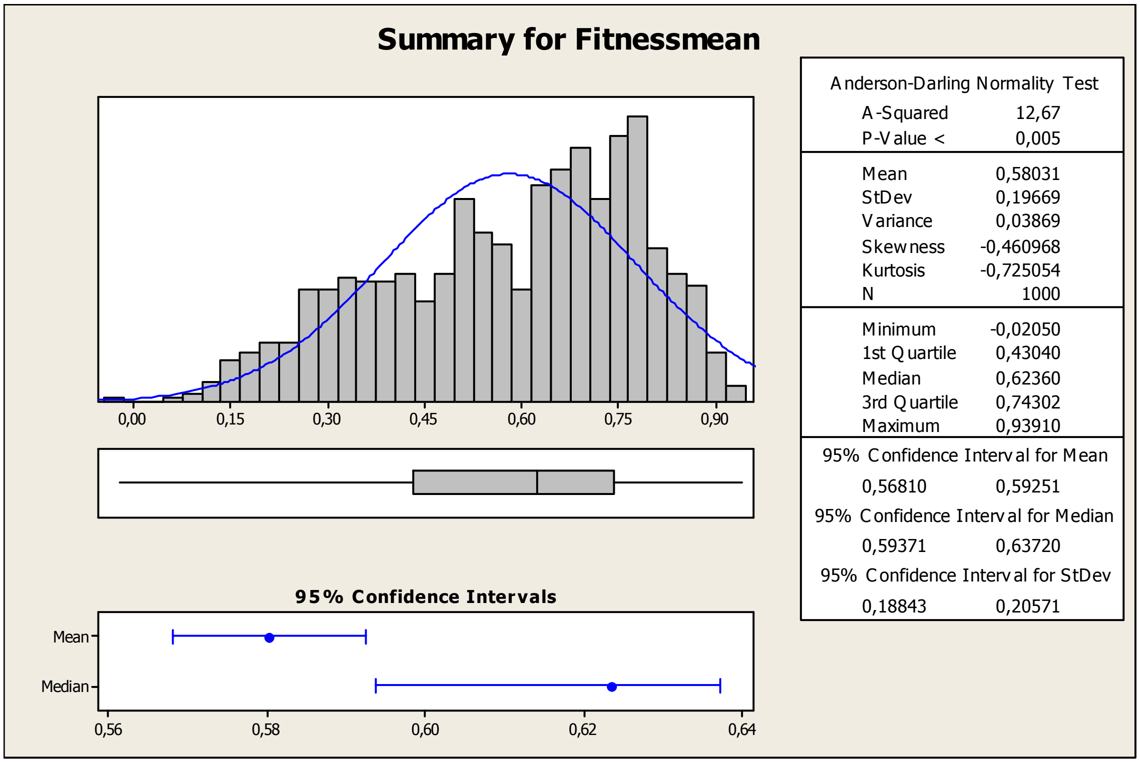


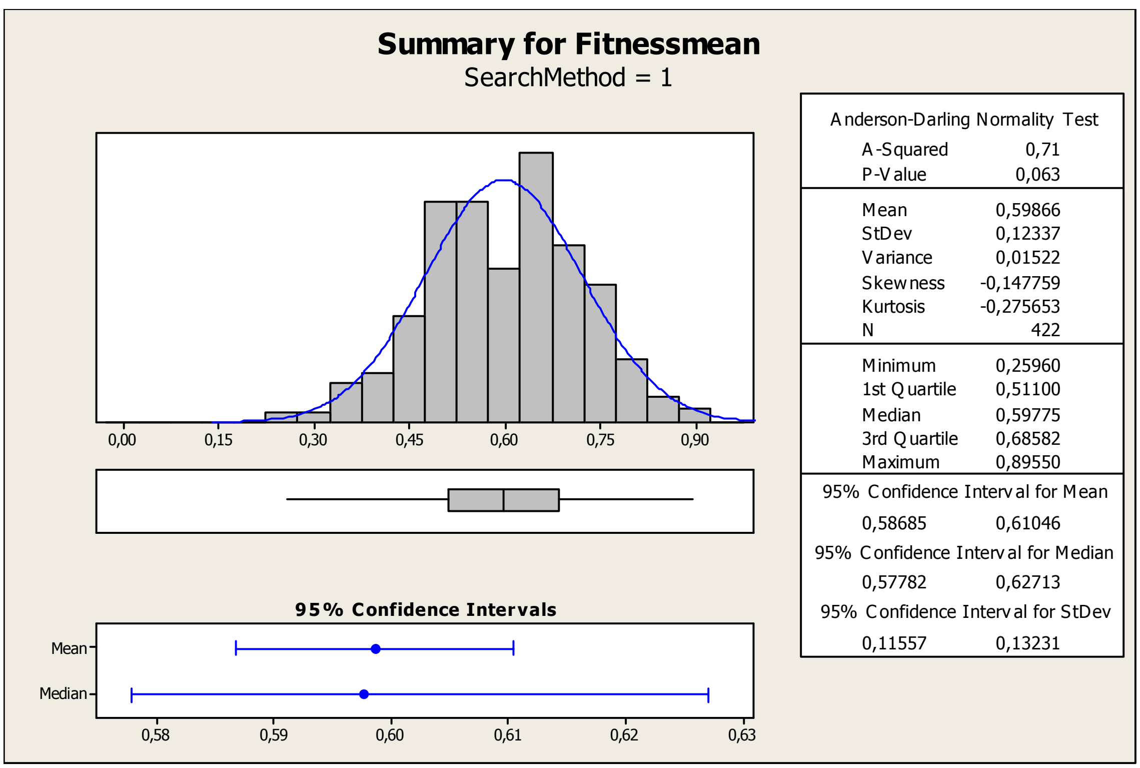

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,62
P-Value 0,103
Mean 0,67530
StDev 0,11995
Variance 0,01439
Skewness -0,496288
Kurtosis 0,518005
N 77
Minimum 0,33880
1st Quartile 0,61475
Median 0,68760
3rd Quartile 0,74550
Maximum 0,92980
95% Confidence Interval for Mean
0,64808 0,70253
95% Confidence Interval for Median
0,65345 0,70788
95% Confidence Interval for StDev
0,10354 0,14260
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,65 0,66 0,67 0,68 0,69 0,70 0,71

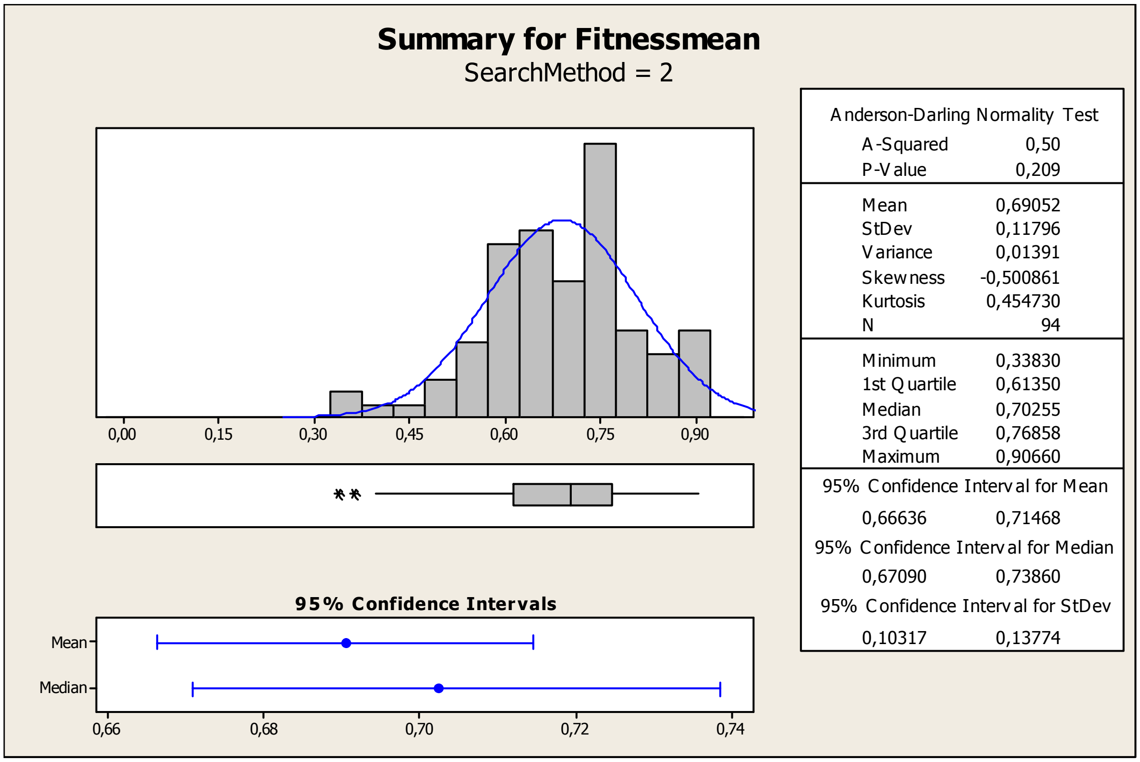

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,45
P-Value 0,276
Mean 0,28288
StDev 0,10265
Variance 0,01054
Skewness -0,040277
Kurtosis -0,423982
N 259
Minimum 0,00680
1st Quartile 0,20780
Median 0,28920
3rd Quartile 0,35760
Maximum 0,56780
95% Confidence Interval for Mean
0,27032 0,29544
95% Confidence Interval for Median
0,26678 0,30702
95% Confidence Interval for StDev
0,09450 0,11234
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,27 0,28 0,29 0,30 0,31

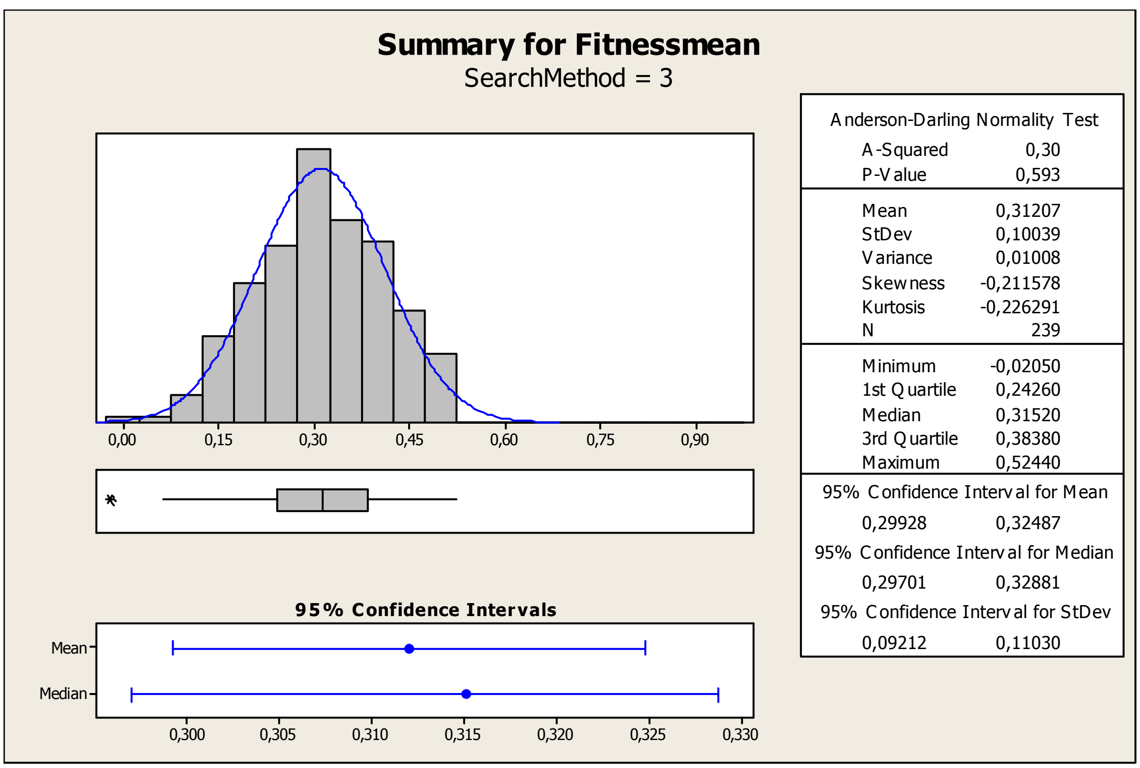

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,41
P-Value < 0,005
Mean 0,75008
StDev 0,07145
Variance 0,00510
Skewness -0,678975
Kurtosis 0,557528
N 243
Minimum 0,49640
1st Quartile 0,70090
Median 0,75780
3rd Quartile 0,79950
Maximum 0,89370
95% Confidence Interval for Mean
0,74105 0,75910
95% Confidence Interval for Median
0,74740 0,76750
95% Confidence Interval for StDev
0,06561 0,07844
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,740 0,745 0,750 0,755 0,760 0,765 0,770

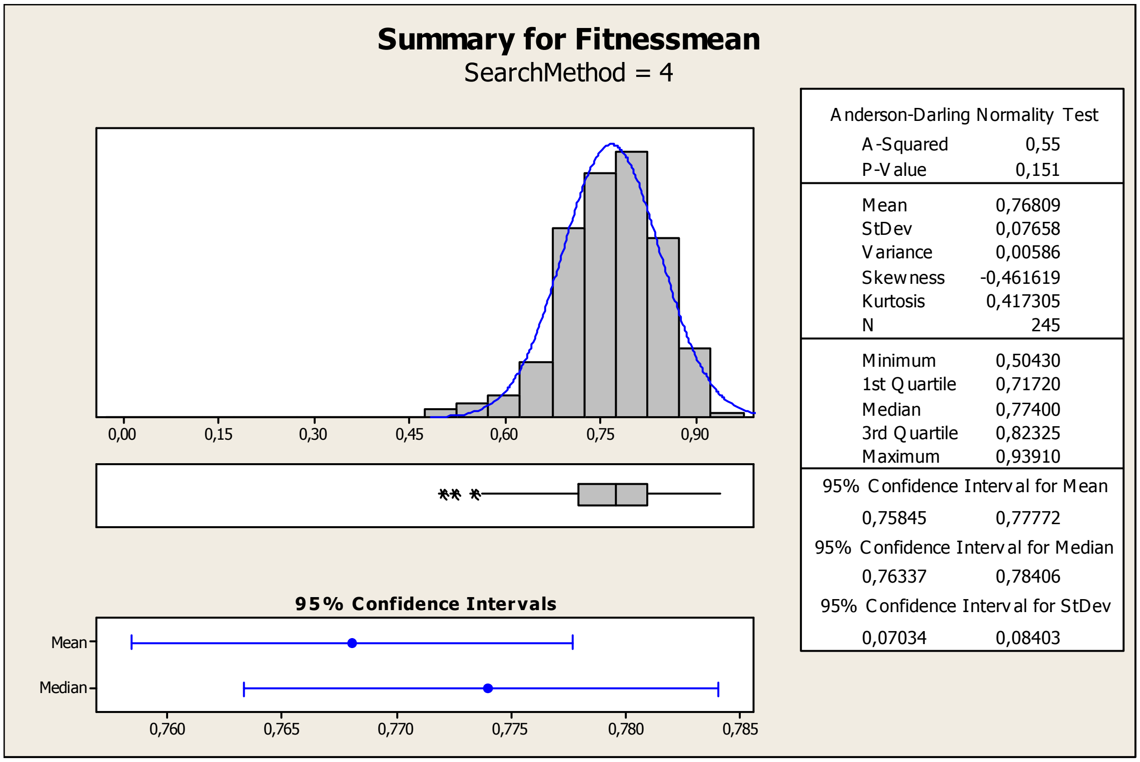
SIMULATION 58, ALL RUNS



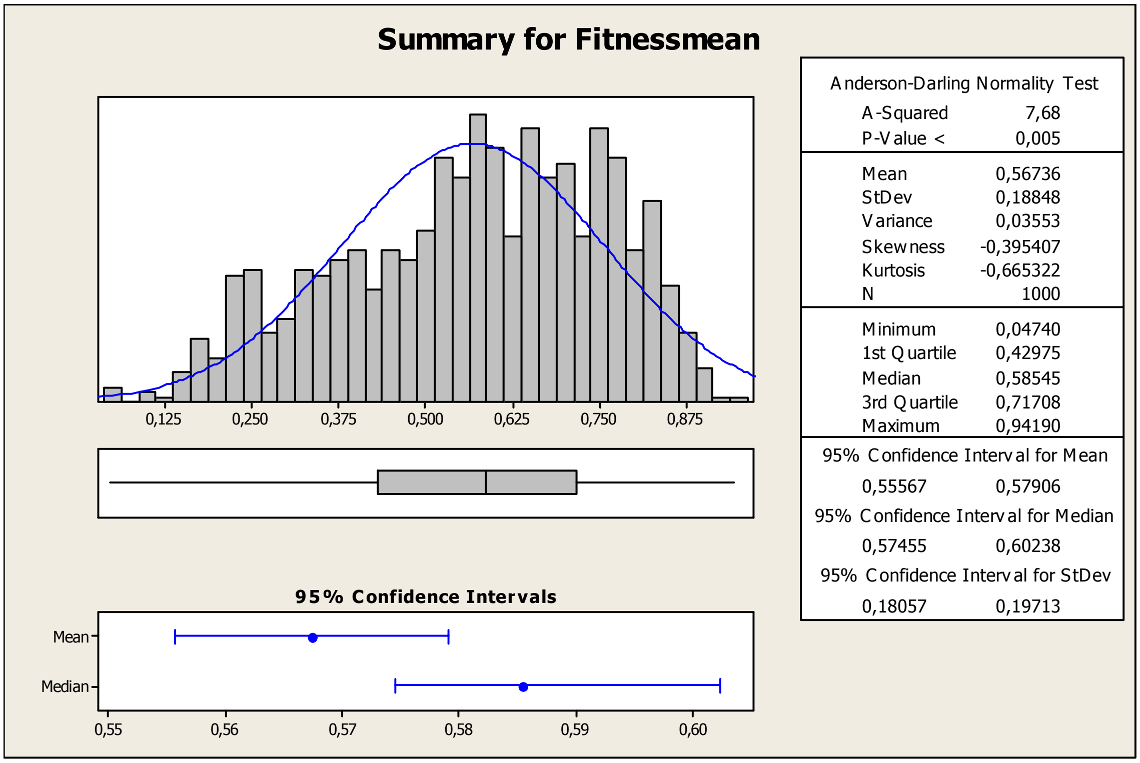


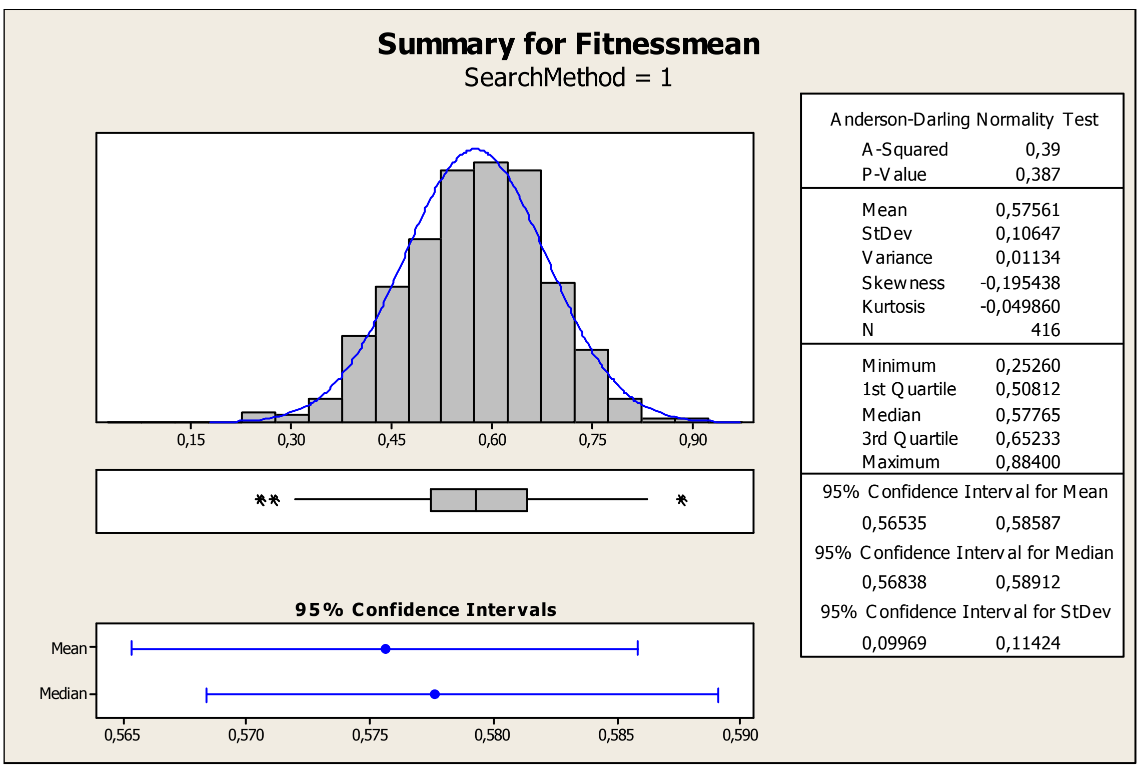

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,50
P-Value 0,209
Mean 0,69052
StDev 0,11796
Variance 0,01391
Skewness -0,500861
Kurtosis 0,454730
N 94
Minimum 0,33830
1st Quartile 0,61350
Median 0,70255
3rd Quartile 0,76858
Maximum 0,90660
95% Confidence Interval for Mean
0,66636 0,71468
95% Confidence Interval for Median
0,67090 0,73860
95% Confidence Interval for StDev
0,10317 0,13774
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,66 0,68 0,70 0,72 0,74

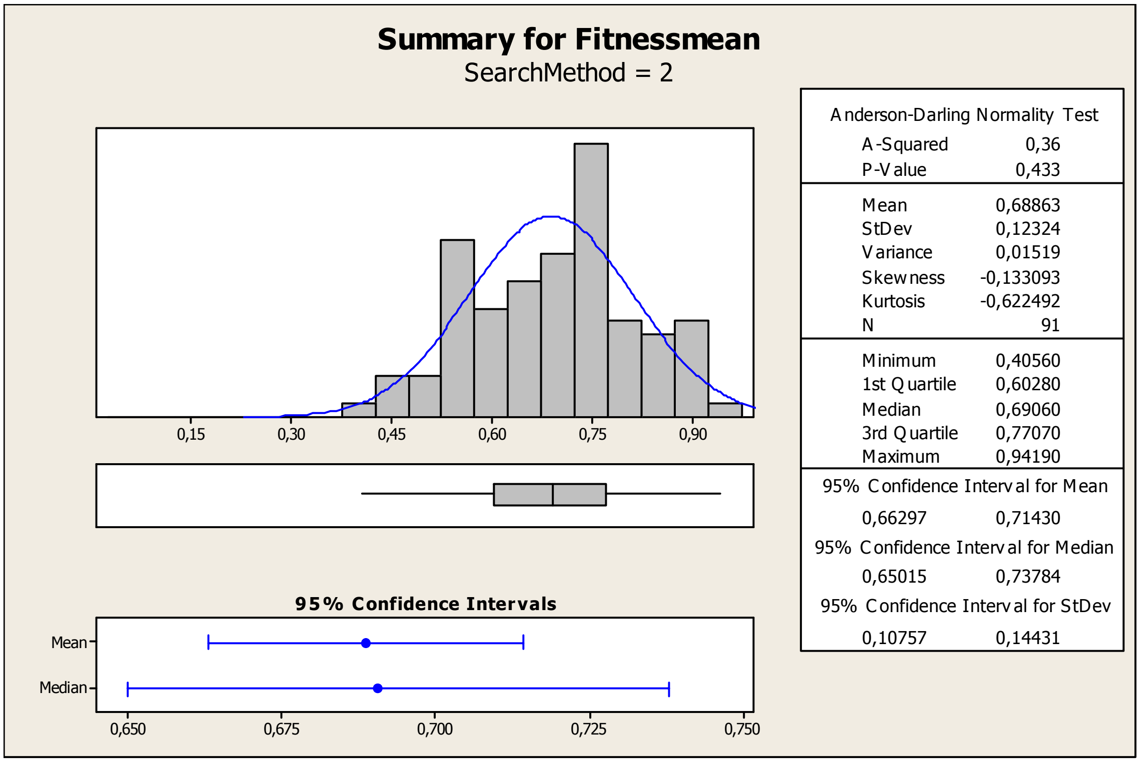

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,30
P-Value 0,593
Mean 0,31207
StDev 0,10039
Variance 0,01008
Skewness -0,211578
Kurtosis -0,226291
N 239
Minimum -0,02050
1st Quartile 0,24260
Median 0,31520
3rd Quartile 0,38380
Maximum 0,52440
95% Confidence Interval for Mean
0,29928 0,32487
95% Confidence Interval for Median
0,29701 0,32881
95% Confidence Interval for StDev
0,09212 0,11030
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,300 0,305 0,310 0,315 0,320 0,325 0,330

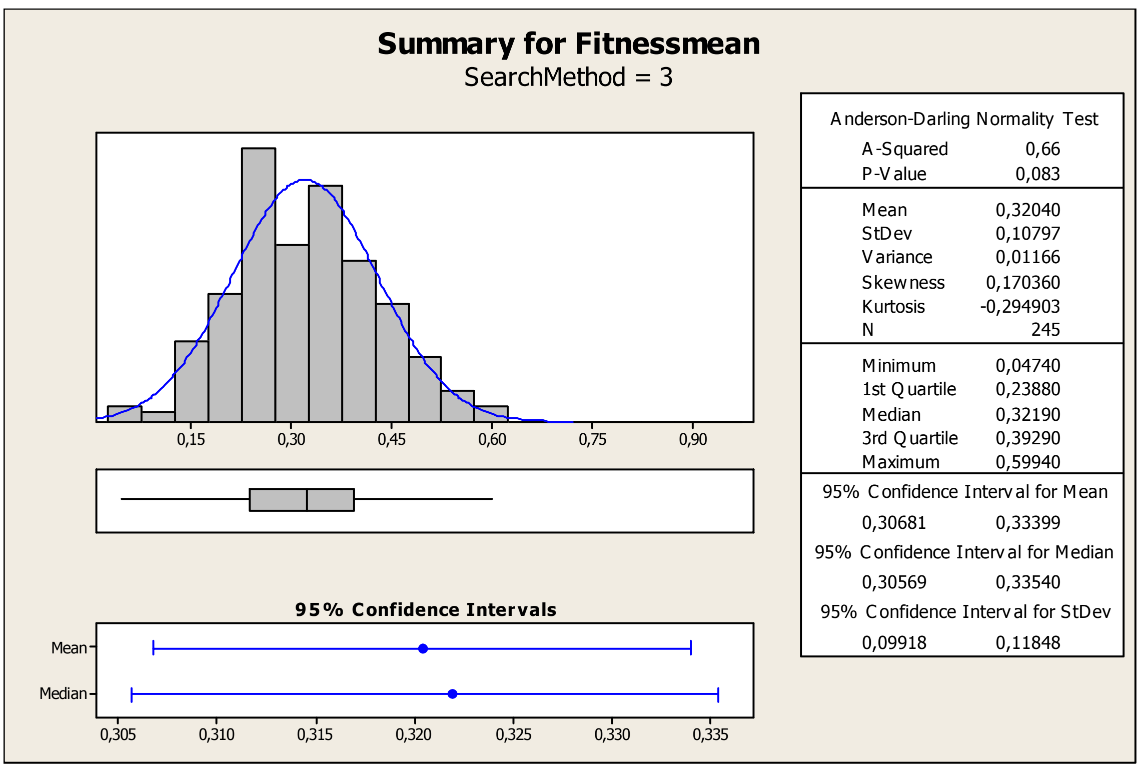

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,55
P-Value 0,151
Mean 0,76809
StDev 0,07658
Variance 0,00586
Skewness -0,461619
Kurtosis 0,417305
N 245
Minimum 0,50430
1st Quartile 0,71720
Median 0,77400
3rd Quartile 0,82325
Maximum 0,93910
95% Confidence Interval for Mean
0,75845 0,77772
95% Confidence Interval for Median
0,76337 0,78406
95% Confidence Interval for StDev
0,07034 0,08403
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,760 0,765 0,770 0,775 0,780 0,785

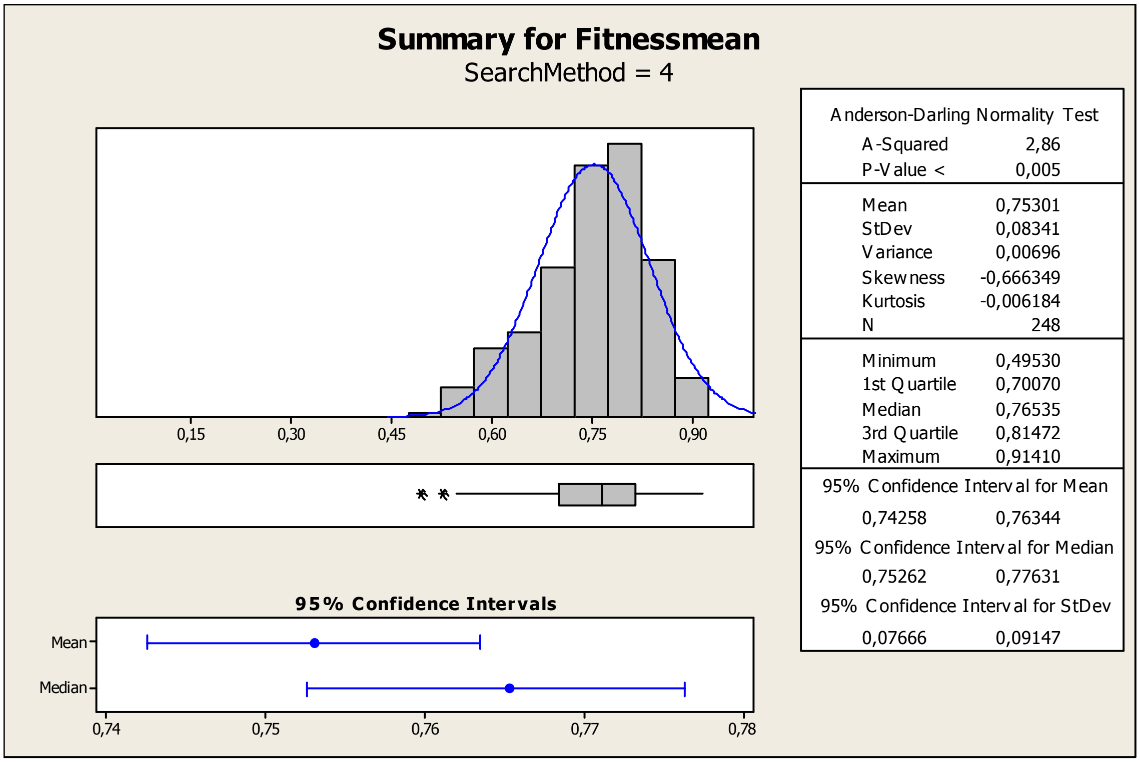
SIMULATION 59, ALL RUNS





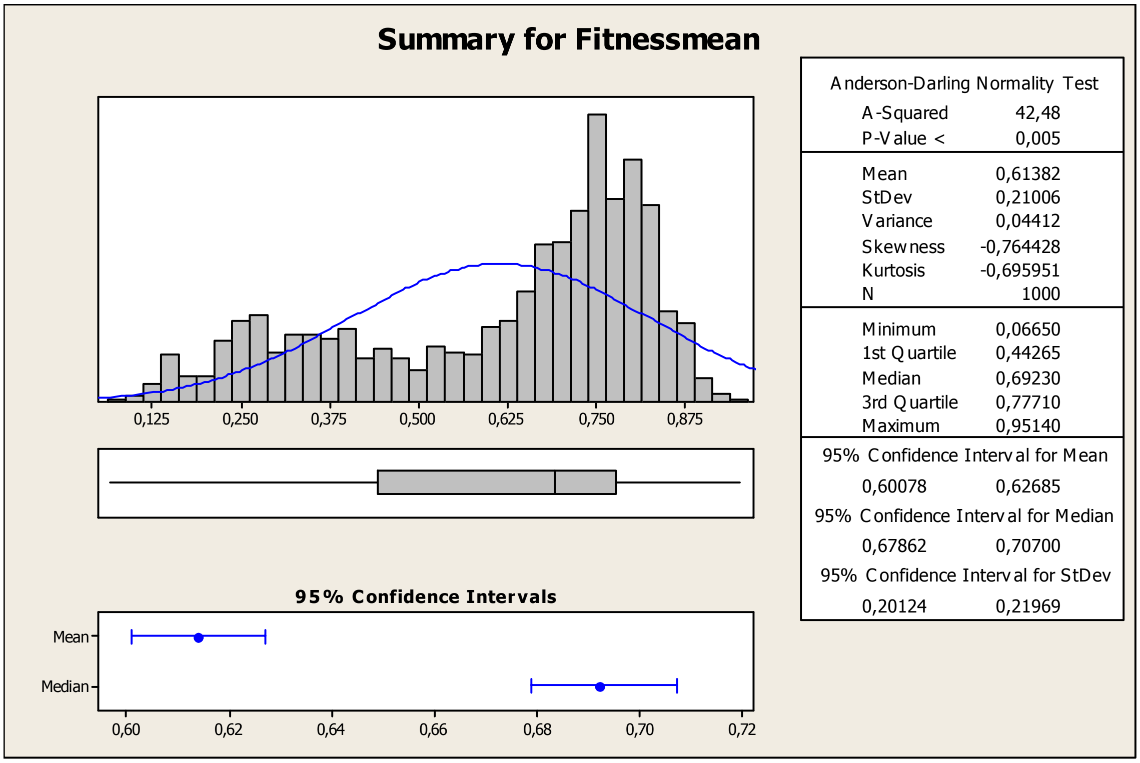

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,36
P-Value 0,433
Mean 0,68863
StDev 0,12324
Variance 0,01519
Skewness -0,133093
Kurtosis -0,622492
N 91
Minimum 0,40560
1st Quartile 0,60280
Median 0,69060
3rd Quartile 0,77070
Maximum 0,94190
95% Confidence Interval for Mean
0,66297 0,71430
95% Confidence Interval for Median
0,65015 0,73784
95% Confidence Interval for StDev
0,10757 0,14431
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,650 0,675 0,700 0,725 0,750

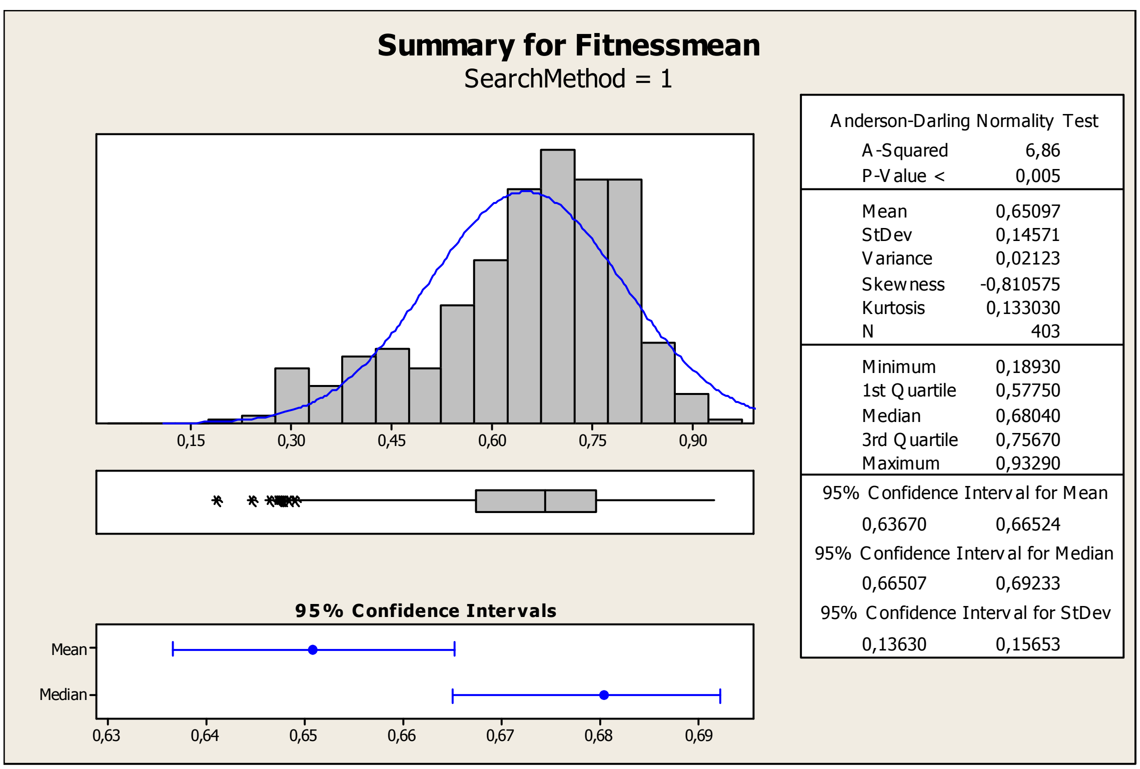

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,66
P-Value 0,083
Mean 0,32040
StDev 0,10797
Variance 0,01166
Skewness 0,170360
Kurtosis -0,294903
N 245
Minimum 0,04740
1st Quartile 0,23880
Median 0,32190
3rd Quartile 0,39290
Maximum 0,59940
95% Confidence Interval for Mean
0,30681 0,33399
95% Confidence Interval for Median
0,30569 0,33540
95% Confidence Interval for StDev
0,09918 0,11848
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,305 0,310 0,315 0,320 0,325 0,330 0,335

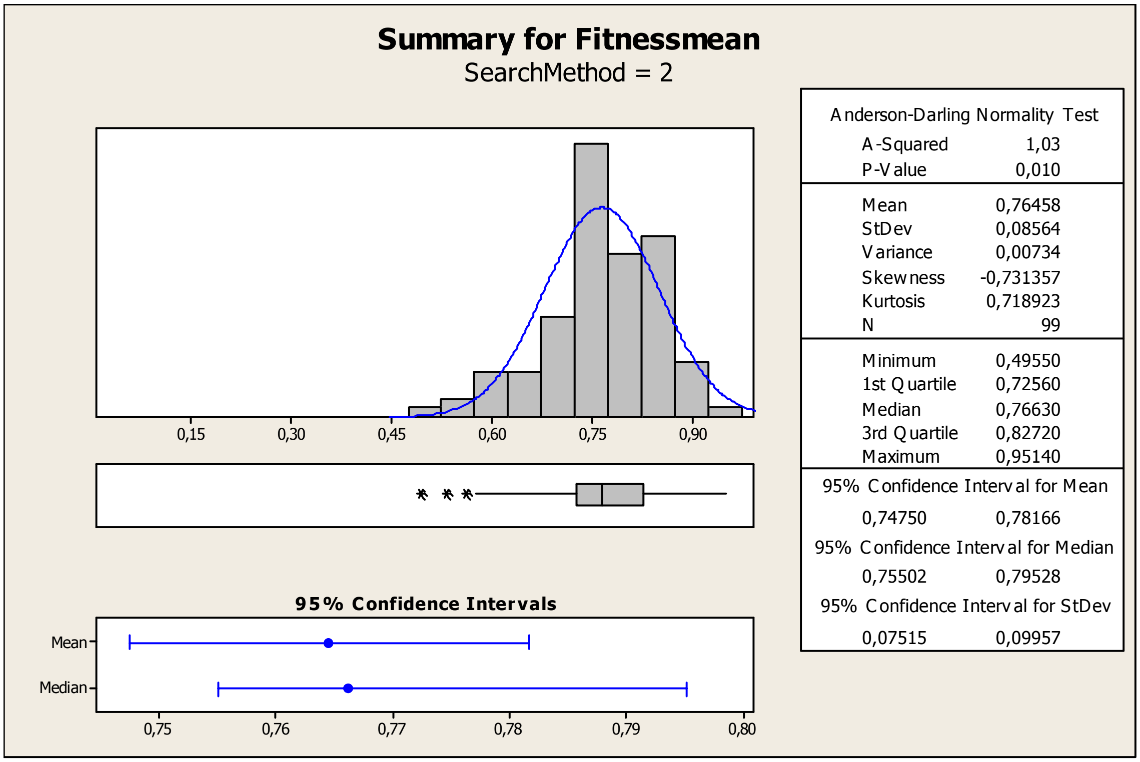


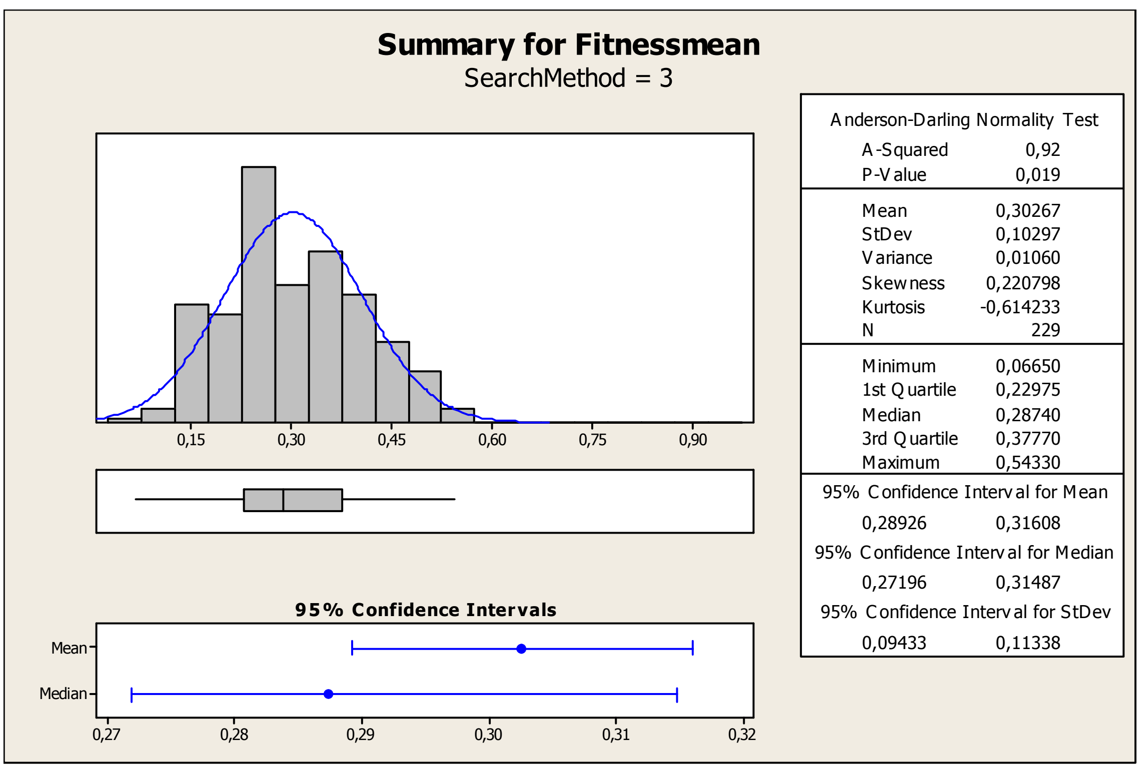
Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 2,86
P-Value < 0,005
Mean 0,75301
StDev 0,08341
Variance 0,00696
Skewness -0,666349
Kurtosis -0,006184
N 248
Minimum 0,49530
1st Quartile 0,70070
Median 0,76535
3rd Quartile 0,81472
Maximum 0,91410
95% Confidence Interval for Mean
0,74258 0,76344
95% Confidence Interval for Median
0,75262 0,77631
95% Confidence Interval for StDev
0,07666 0,09147
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,74 0,75 0,76 0,77 0,78

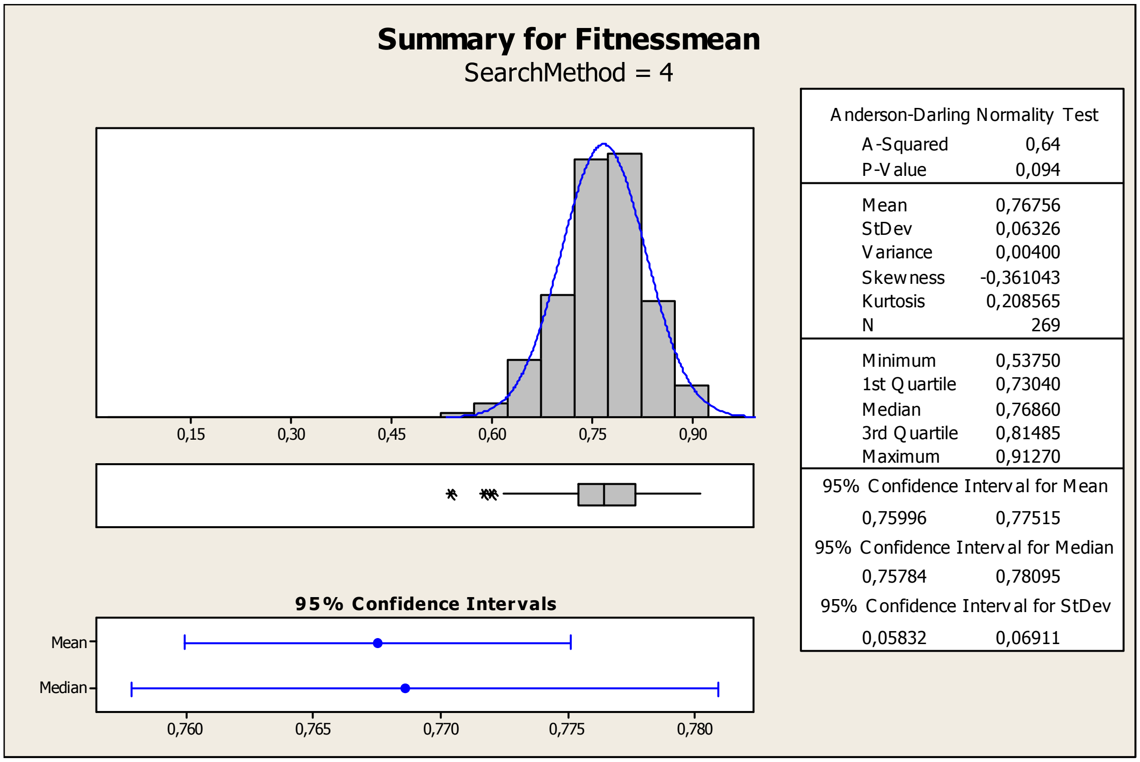
SIMULATION 60, ALL RUNS



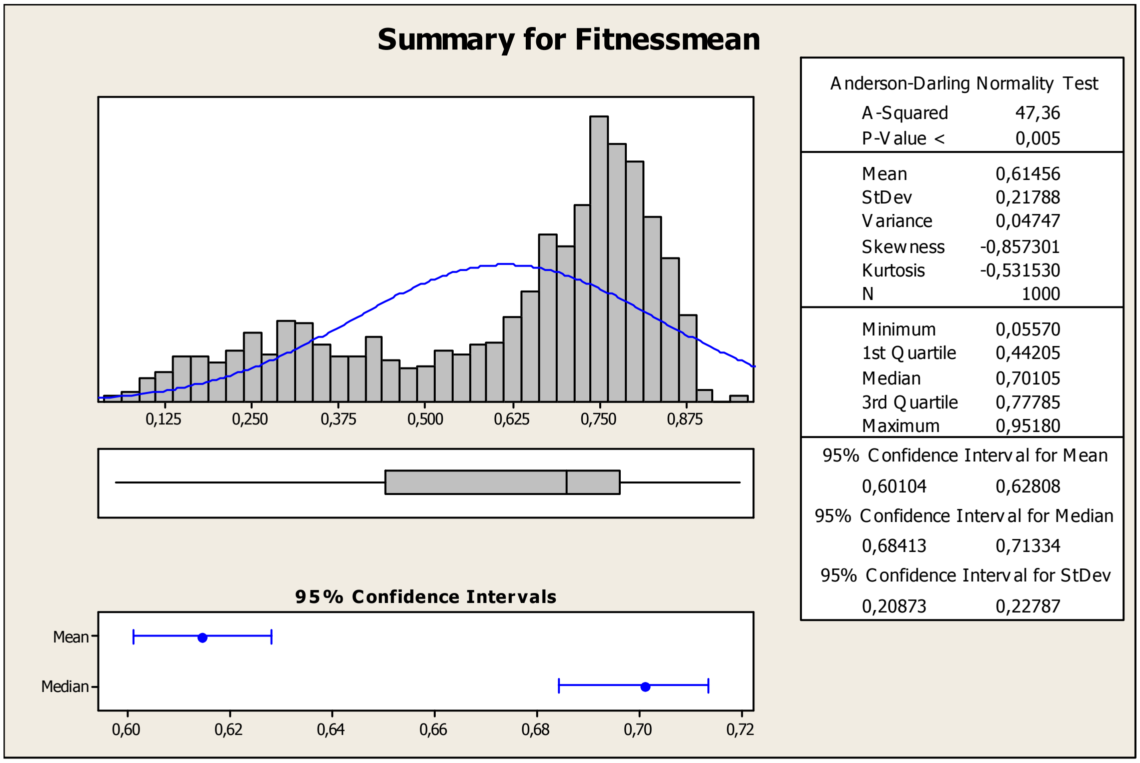


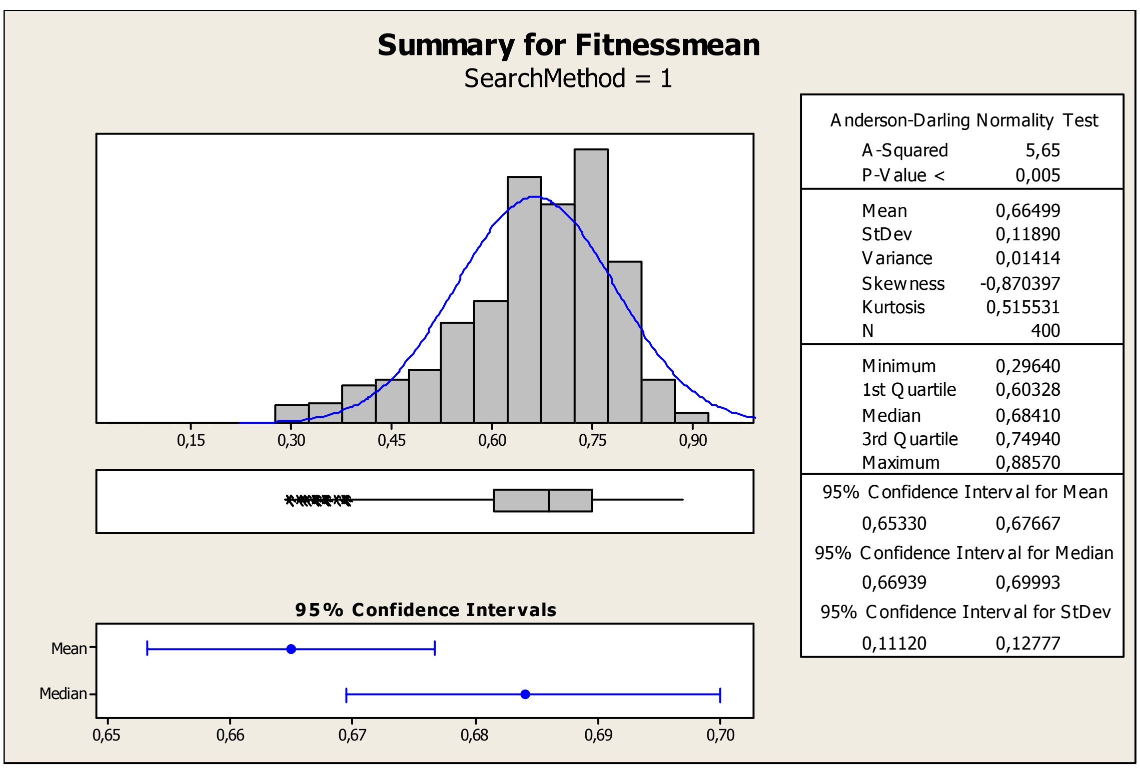

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,03
P-Value 0,010
Mean 0,76458
StDev 0,08564
Variance 0,00734
Skewness -0,731357
Kurtosis 0,718923
N 99
Minimum 0,49550
1st Quartile 0,72560
Median 0,76630
3rd Quartile 0,82720
Maximum 0,95140
95% Confidence Interval for Mean
0,74750 0,78166
95% Confidence Interval for Median
0,75502 0,79528
95% Confidence Interval for StDev
0,07515 0,09957
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,75 0,76 0,77 0,78 0,79 0,80

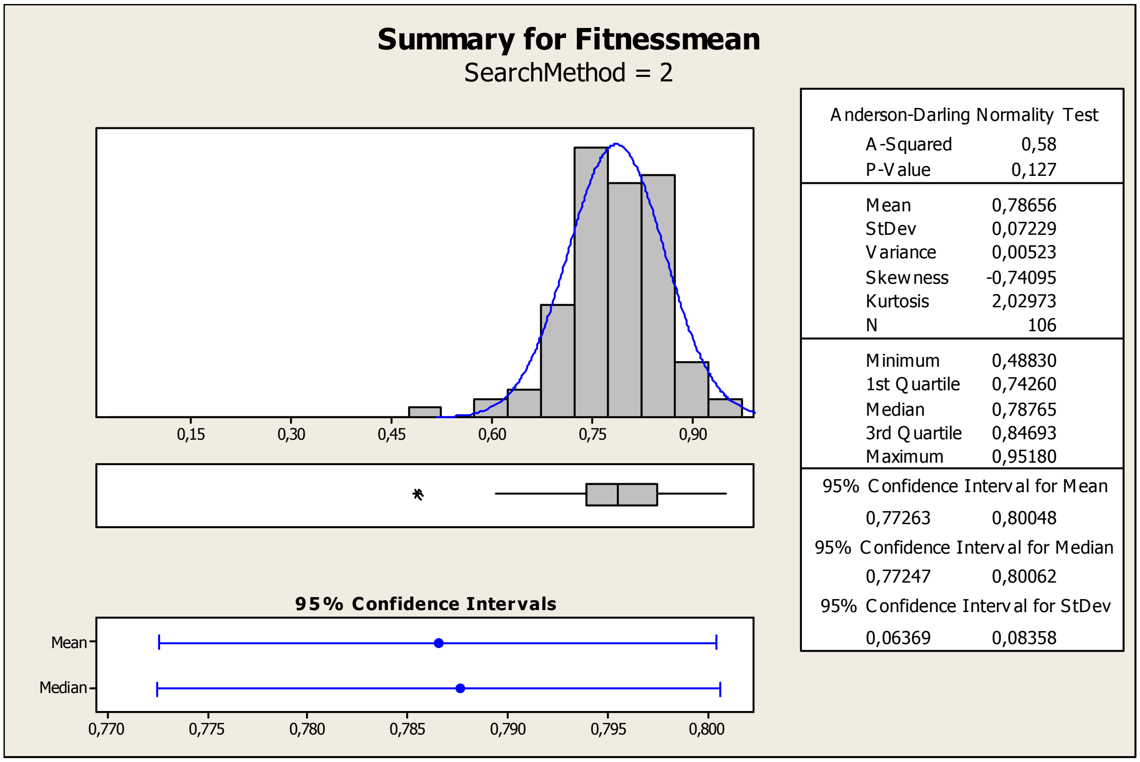

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,92
P-Value 0,019
Mean 0,30267
StDev 0,10297
Variance 0,01060
Skewness 0,220798
Kurtosis -0,614233
N 229
Minimum 0,06650
1st Quartile 0,22975
Median 0,28740
3rd Quartile 0,37770
Maximum 0,54330
95% Confidence Interval for Mean
0,28926 0,31608
95% Confidence Interval for Median
0,27196 0,31487
95% Confidence Interval for StDev
0,09433 0,11338
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,27 0,28 0,29 0,30 0,31 0,32

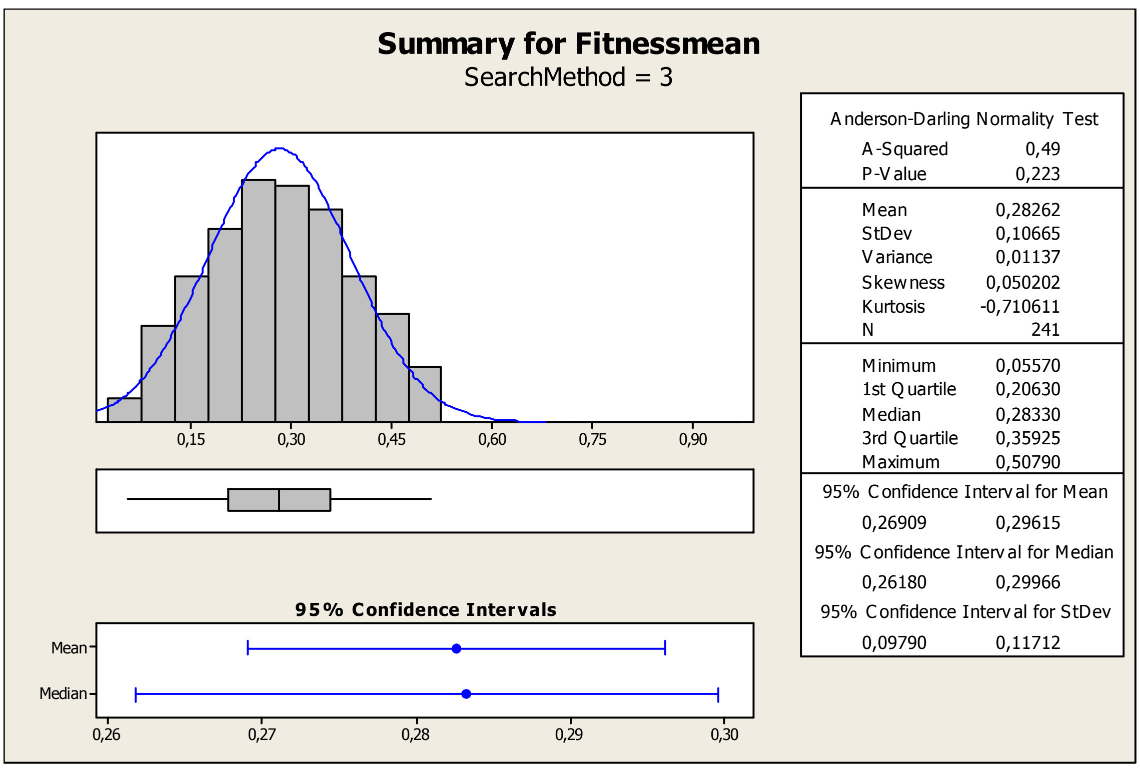

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,64
P-Value 0,094
Mean 0,76756
StDev 0,06326
Variance 0,00400
Skewness -0,361043
Kurtosis 0,208565
N 269
Minimum 0,53750
1st Quartile 0,73040
Median 0,76860
3rd Quartile 0,81485
Maximum 0,91270
95% Confidence Interval for Mean
0,75996 0,77515
95% Confidence Interval for Median
0,75784 0,78095
95% Confidence Interval for StDev
0,05832 0,06911
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,760
0,765
0,770
0,775
0,780

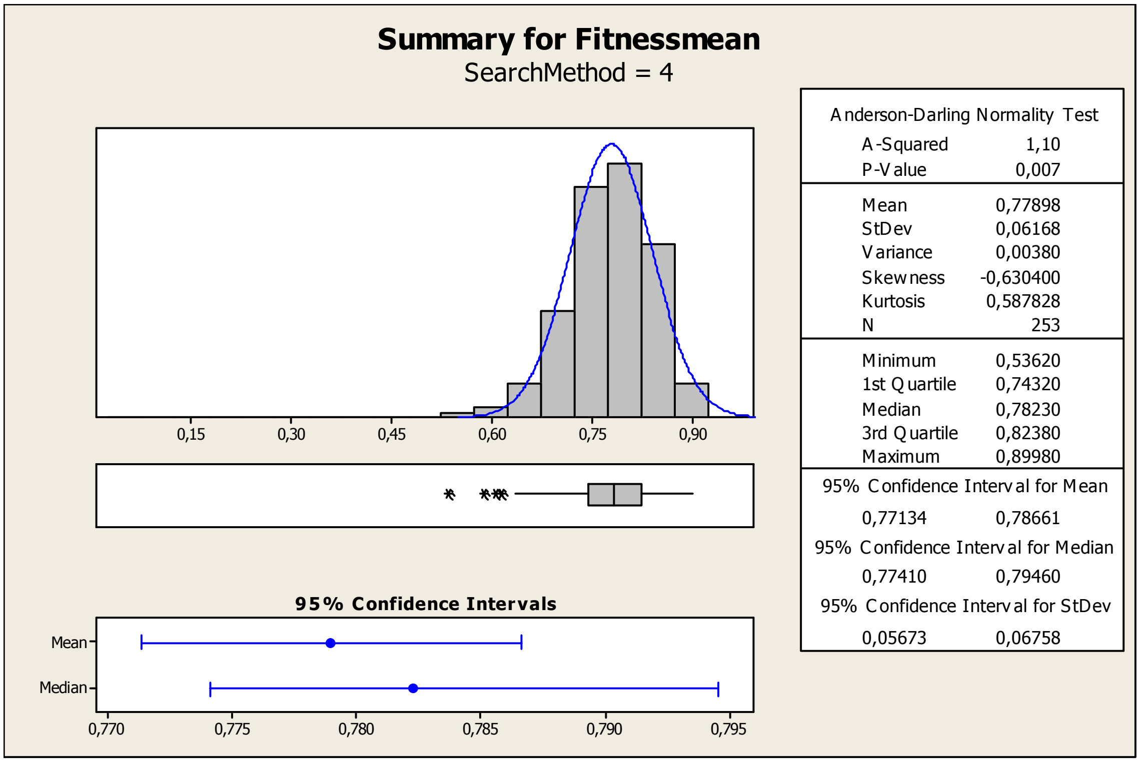
SIMULATION 61, ALL RUNS



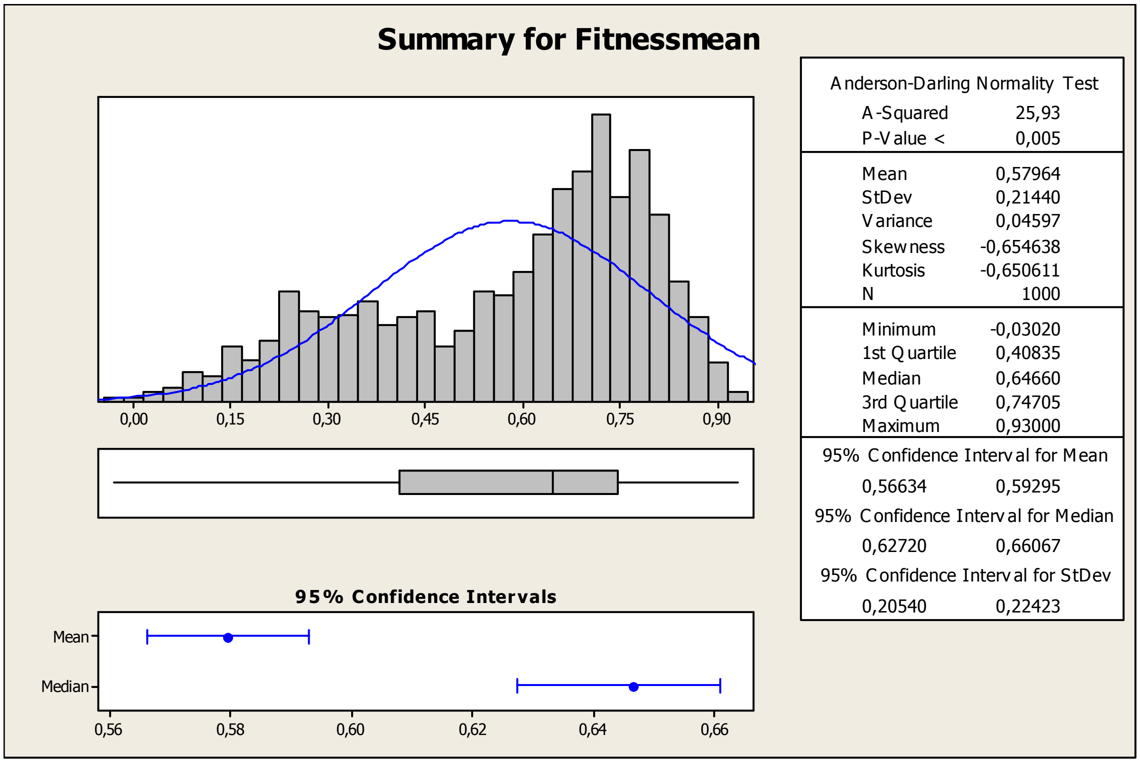


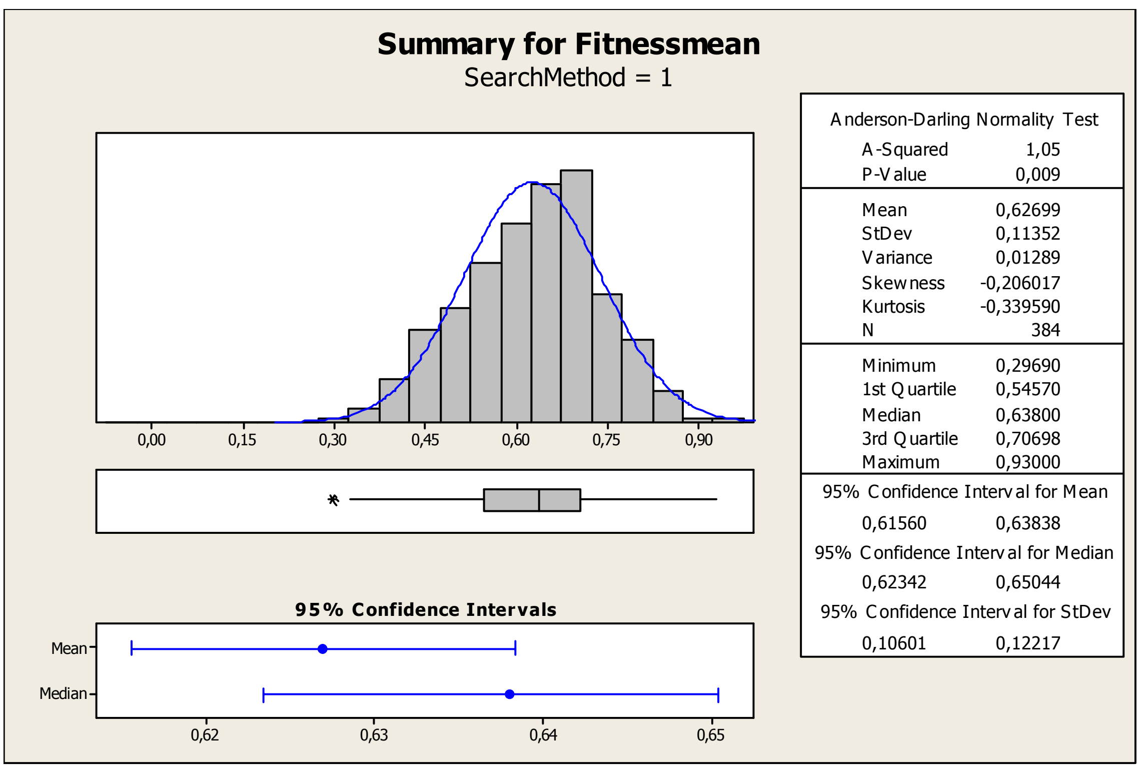

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,58
P-Value 0,127
Mean 0,78656
StDev 0,07229
Variance 0,00523
Skewness -0,74095
Kurtosis 2,02973
N 106
Minimum 0,48830
1st Quartile 0,74260
Median 0,78765
3rd Quartile 0,84693
Maximum 0,95180
95% Confidence Interval for Mean
0,77263 0,80048
95% Confidence Interval for Median
0,77247 0,80062
95% Confidence Interval for StDev
0,06369 0,08358
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,770 0,775 0,780 0,785 0,790 0,795 0,800

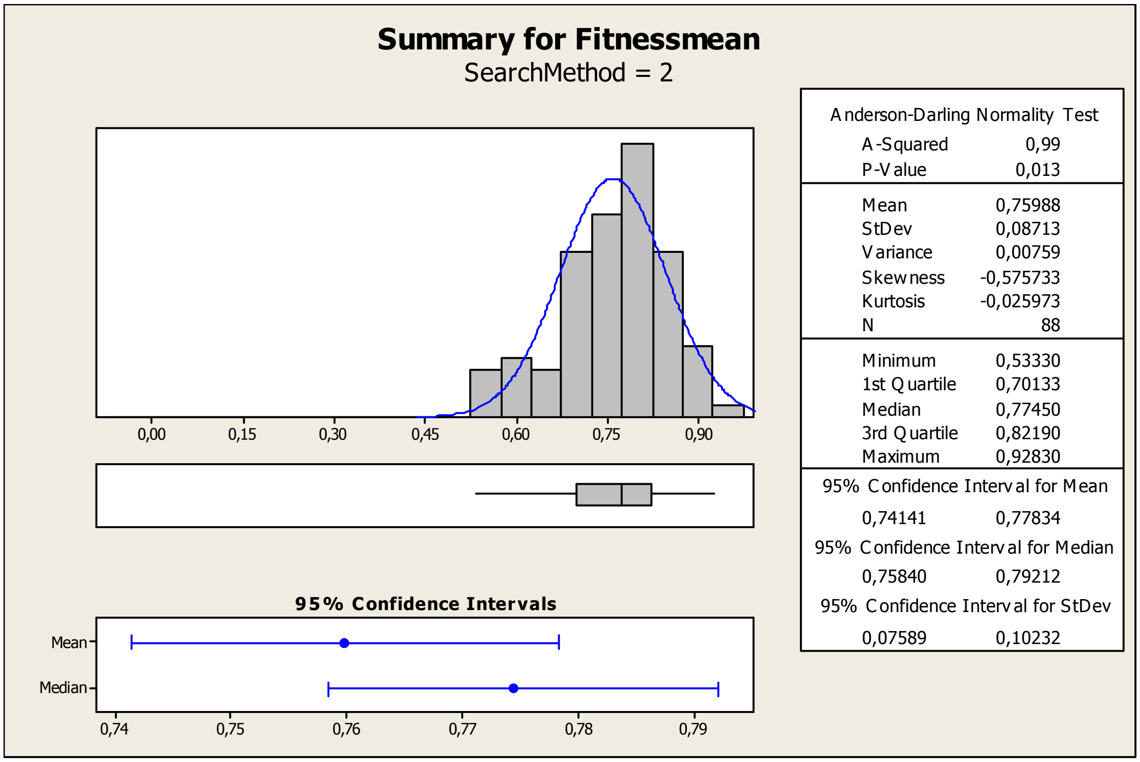

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,49
P-Value 0,223
Mean 0,28262
StDev 0,10665
Variance 0,01137
Skewness 0,050202
Kurtosis -0,710611
N 241
Minimum 0,05570
1st Quartile 0,20630
Median 0,28330
3rd Quartile 0,35925
Maximum 0,50790
95% Confidence Interval for Mean
0,26909 0,29615
95% Confidence Interval for Median
0,26180 0,29966
95% Confidence Interval for StDev
0,09790 0,11712
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,26 0,27 0,28 0,29 0,30


Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,10
P-Value 0,007
Mean 0,77898
StDev 0,06168
Variance 0,00380
Skewness -0,630400
Kurtosis 0,587828
N 253
Minimum 0,53620
1st Quartile 0,74320
Median 0,78230
3rd Quartile 0,82380
Maximum 0,89980
95% Confidence Interval for Mean
0,77134 0,78661
95% Confidence Interval for Median
0,77410 0,79460
95% Confidence Interval for StDev
0,05673 0,06758
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,770 0,775 0,780 0,785 0,790 0,795

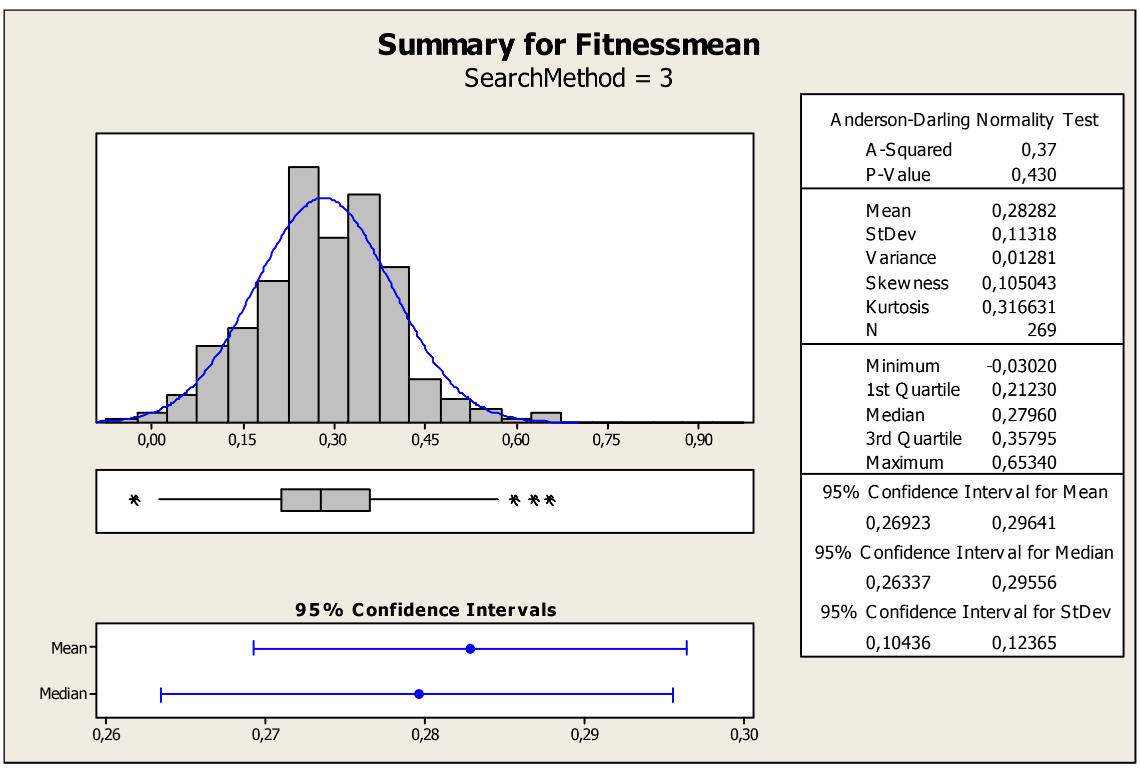
SIMULATION 62, ALL RUNS



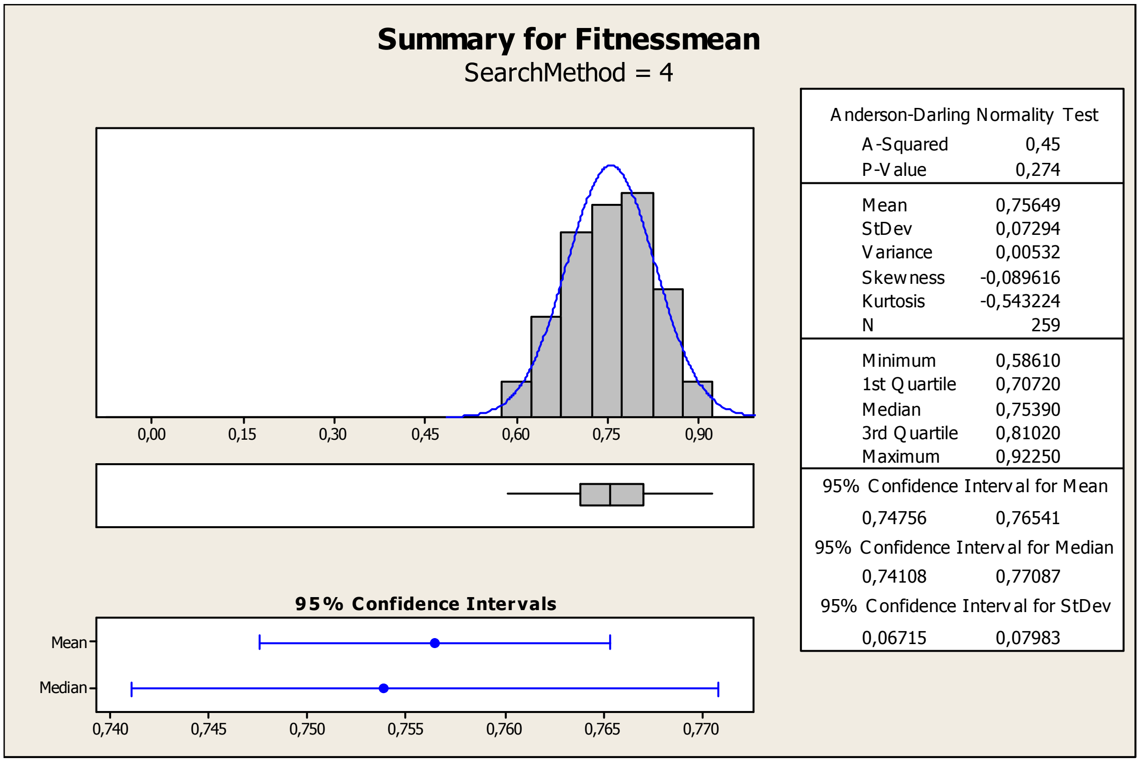




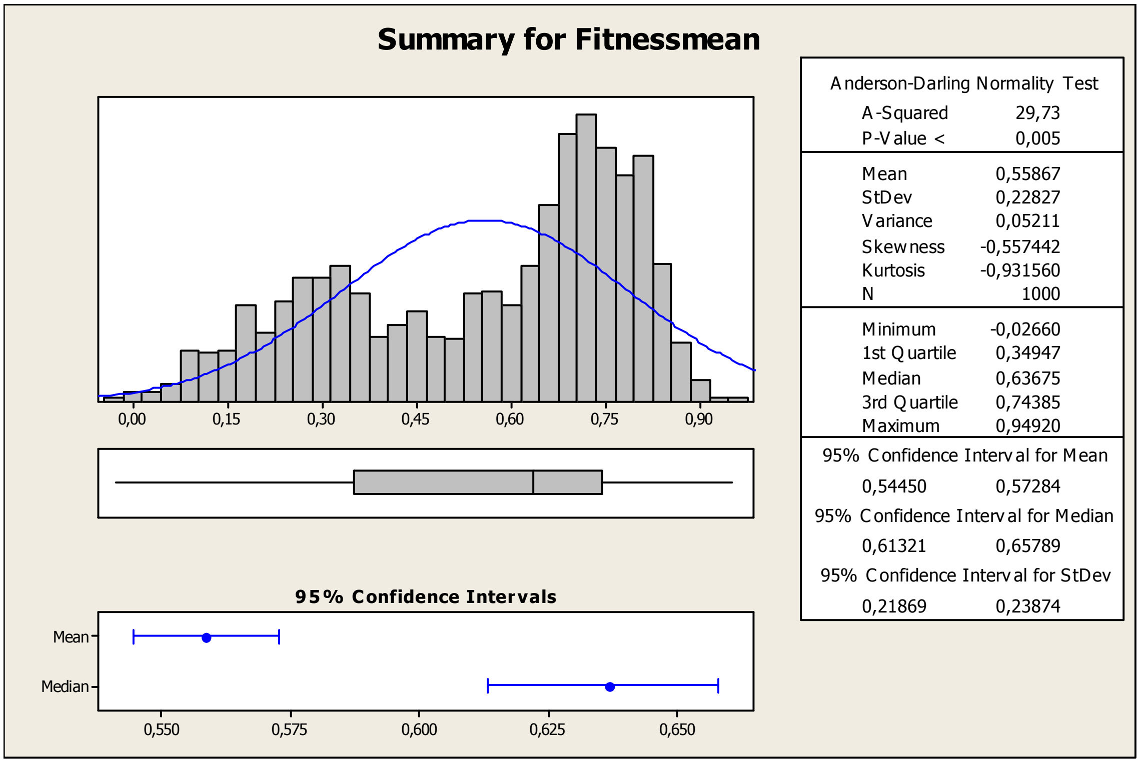
Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,99
P-Value 0,013
Mean 0,75988
StDev 0,08713
Variance 0,00759
Skewness -0,575733
Kurtosis -0,025973
N 88
Minimum 0,53330
1st Quartile 0,70133
Median 0,77450
3rd Quartile 0,82190
Maximum 0,92830
95% Confidence Interval for Mean
0,74141 0,77834
95% Confidence Interval for Median
0,75840 0,79212
95% Confidence Interval for StDev
0,07589 0,10232
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,74 0,75 0,76 0,77 0,78 0,79

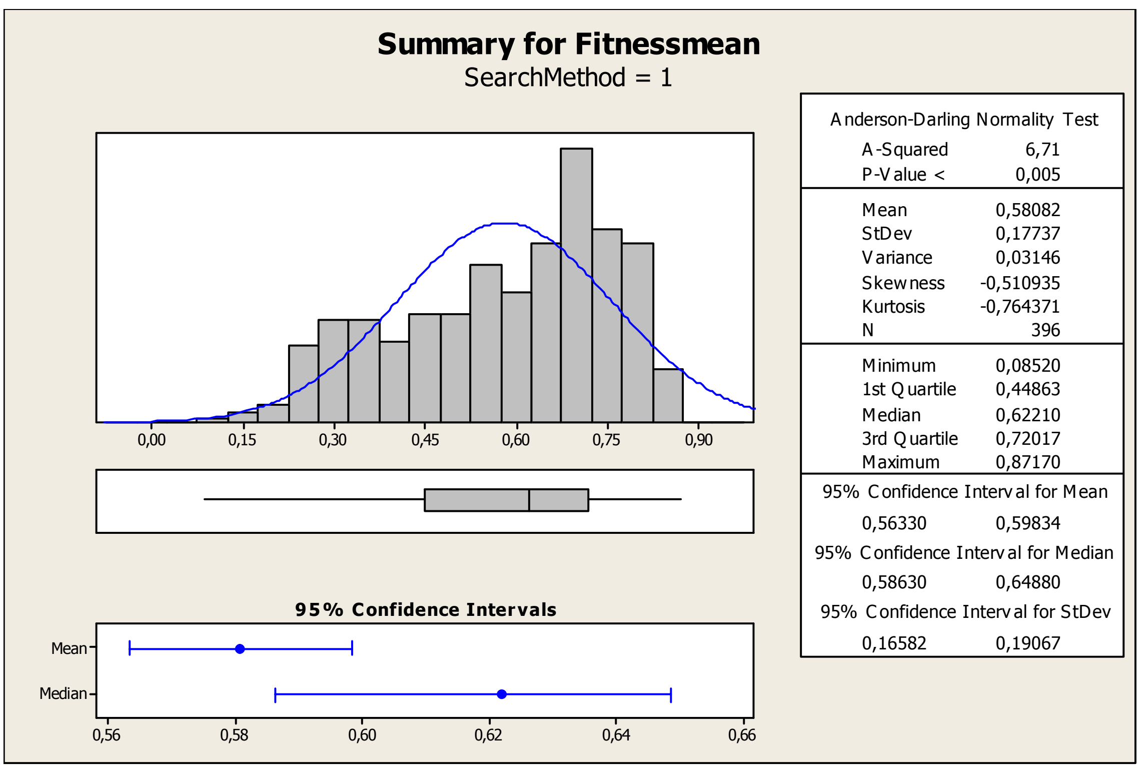


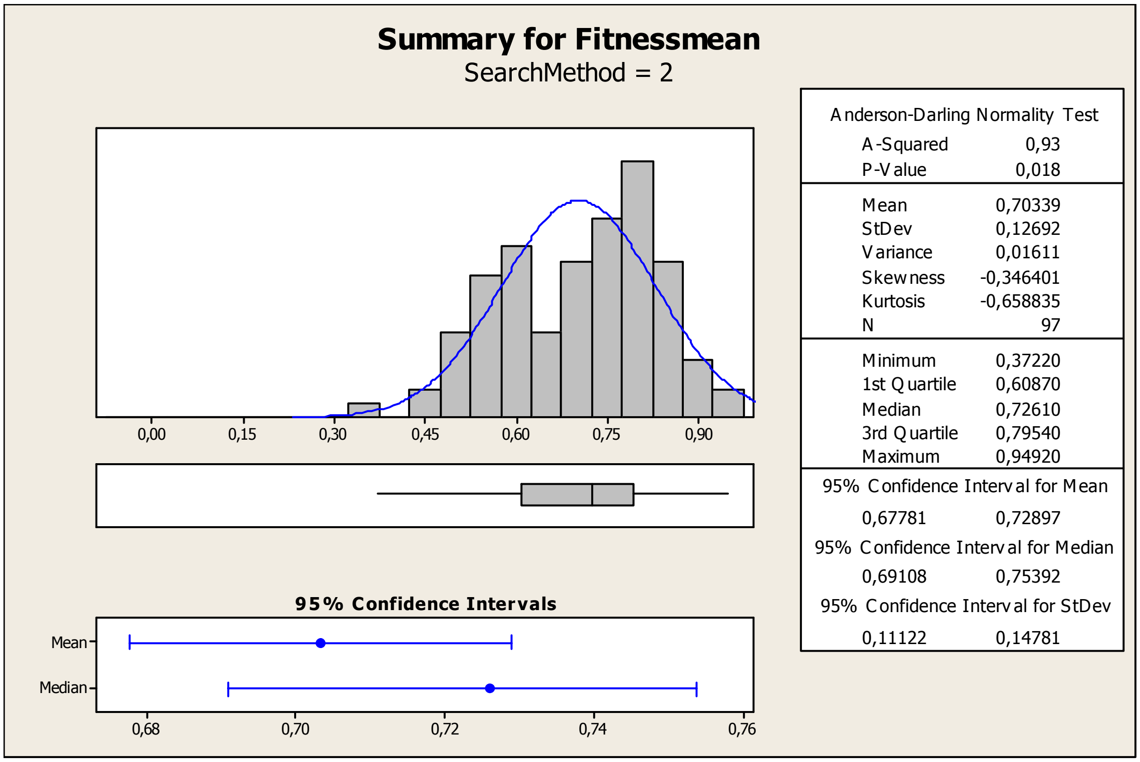
Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,37
P-Value 0,430
Mean 0,28282
StDev 0,11318
Variance 0,01281
Skewness 0,105043
Kurtosis 0,316631
N 269
Minimum -0,03020
1st Quartile 0,21230
Median 0,27960
3rd Quartile 0,35795
Maximum 0,65340
95% Confidence Interval for Mean
0,26923 0,29641
95% Confidence Interval for Median
0,26337 0,29556
95% Confidence Interval for StDev
0,10436 0,12365
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,26 0,27 0,28 0,29 0,30

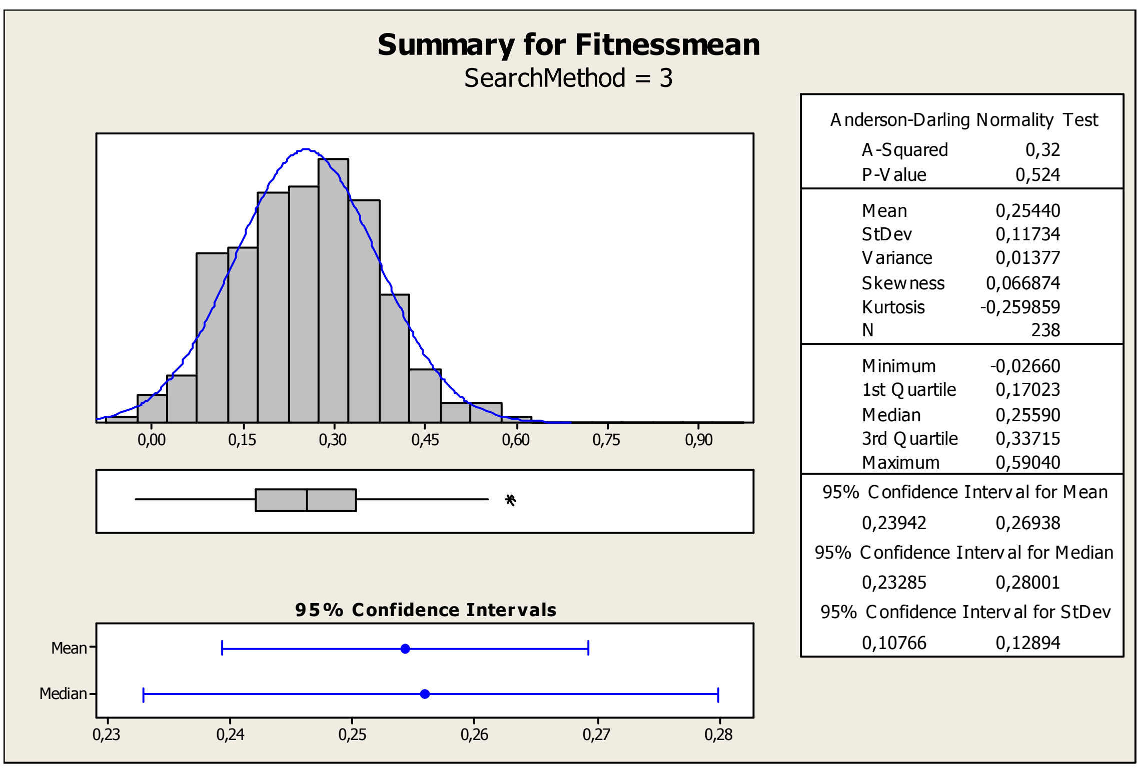

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,45
P-Value 0,274
Mean 0,75649
StDev 0,07294
Variance 0,00532
Skewness -0,089616
Kurtosis -0,543224
N 259
Minimum 0,58610
1st Quartile 0,70720
Median 0,75390
3rd Quartile 0,81020
Maximum 0,92250
95% Confidence Interval for Mean
0,74756 0,76541
95% Confidence Interval for Median
0,74108 0,77087
95% Confidence Interval for StDev
0,06715 0,07983
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,740 0,745 0,750 0,755 0,760 0,765 0,770

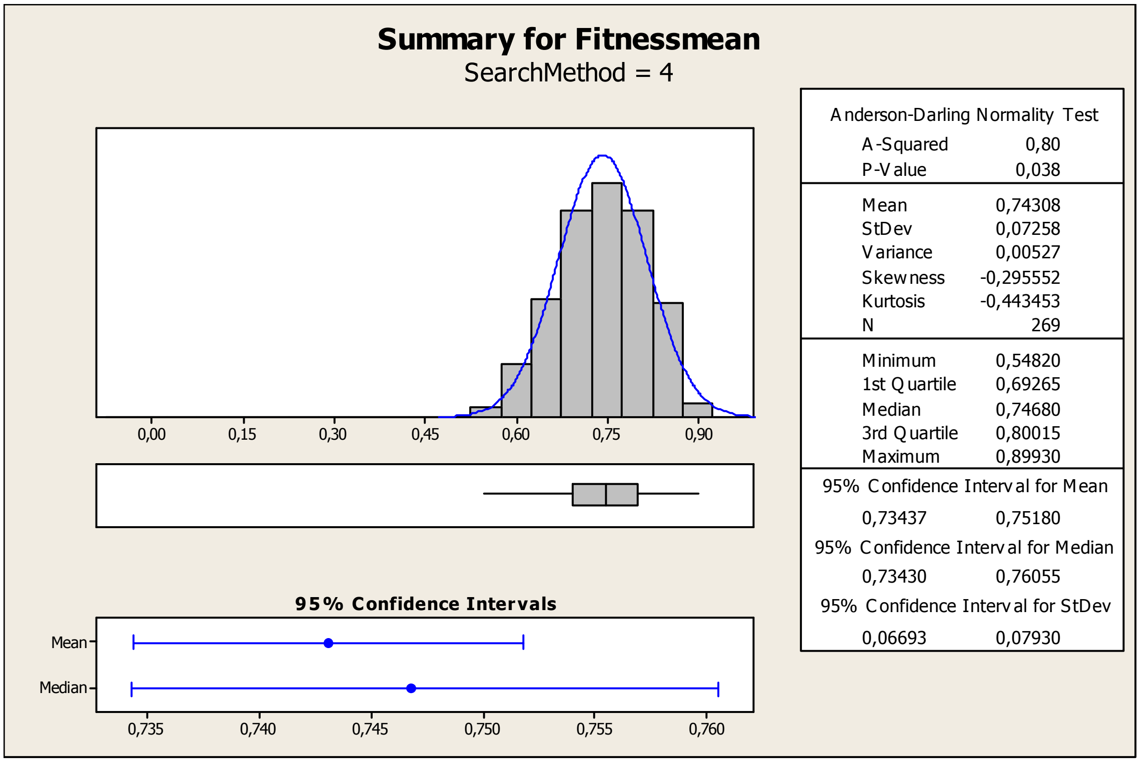
SIMULATION 63, ALL RUNS



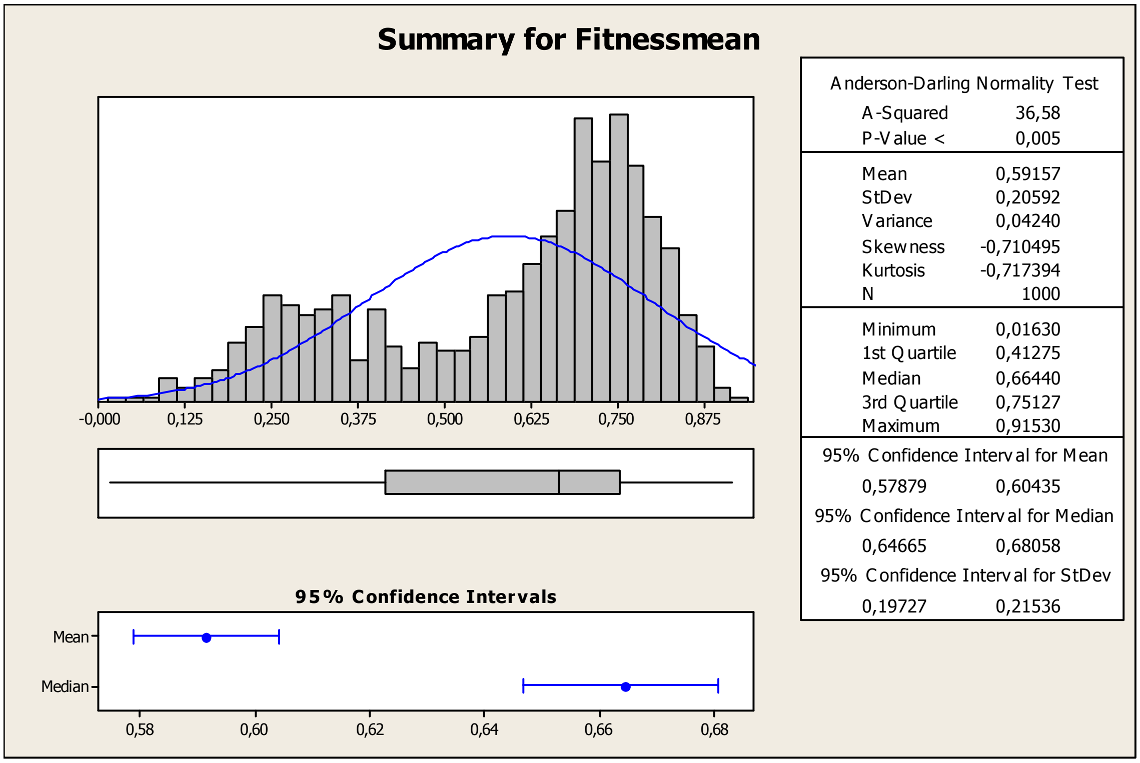


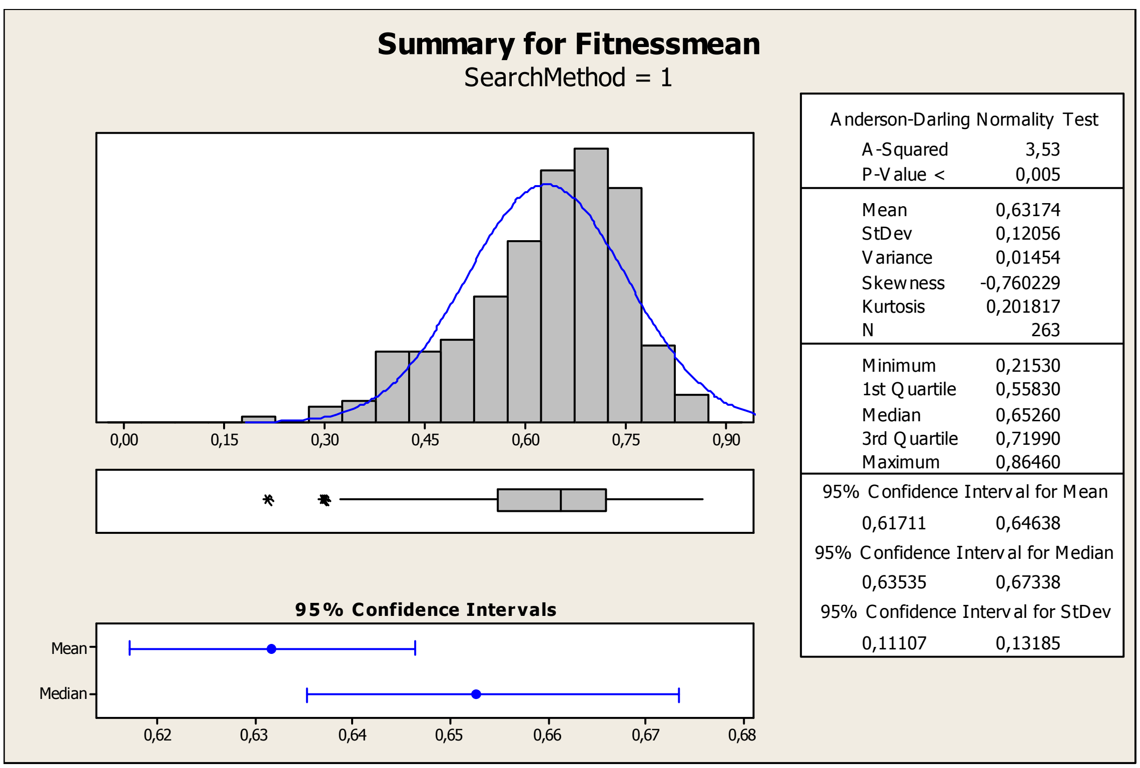

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,93
P-Value 0,018
Mean 0,70339
StDev 0,12692
Variance 0,01611
Skewness -0,346401
Kurtosis -0,658835
N 97
Minimum 0,37220
1st Quartile 0,60870
Median 0,72610
3rd Quartile 0,79540
Maximum 0,94920
95% Confidence Interval for Mean
0,67781 0,72897
95% Confidence Interval for Median
0,69108 0,75392
95% Confidence Interval for StDev
0,11122 0,14781
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,68
0,70
0,72
0,74
0,76

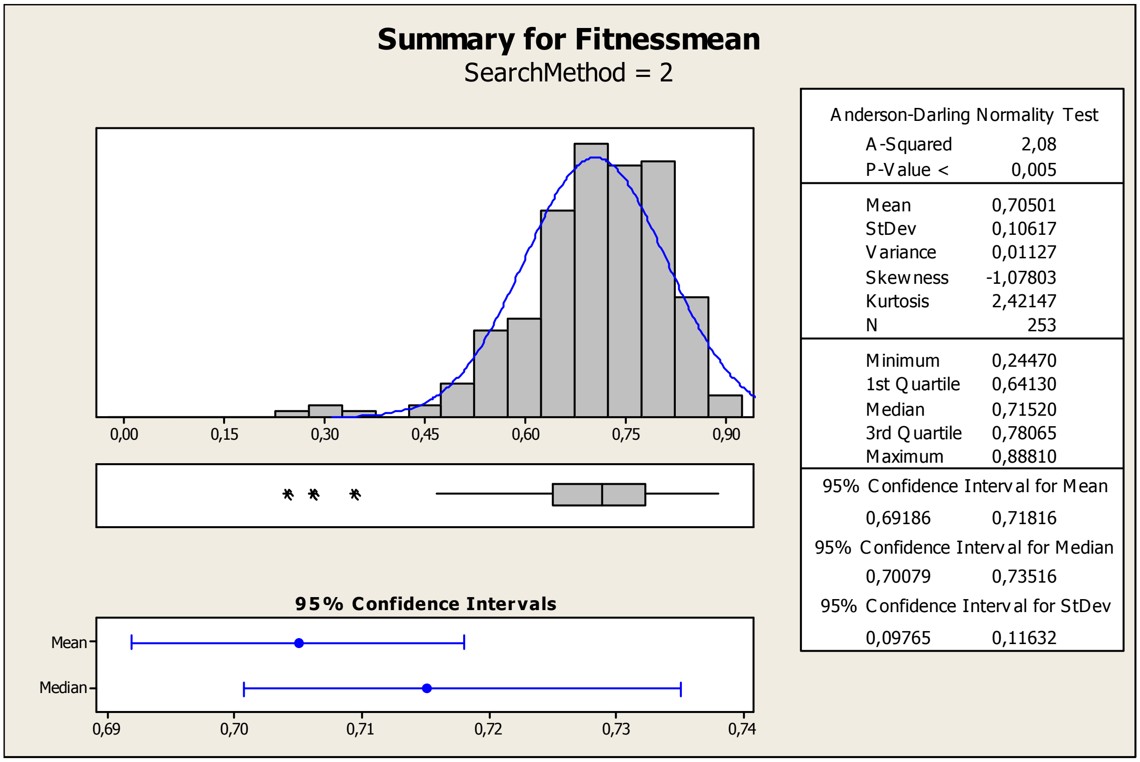

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,32
P-Value 0,524
Mean 0,25440
StDev 0,11734
Variance 0,01377
Skewness 0,066874
Kurtosis -0,259859
N 238
Minimum -0,02660
1st Quartile 0,17023
Median 0,25590
3rd Quartile 0,33715
Maximum 0,59040
95% Confidence Interval for Mean
0,23942 0,26938
95% Confidence Interval for Median
0,23285 0,28001
95% Confidence Interval for StDev
0,10766 0,12894
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,23
0,24
0,25
0,26
0,27
0,28

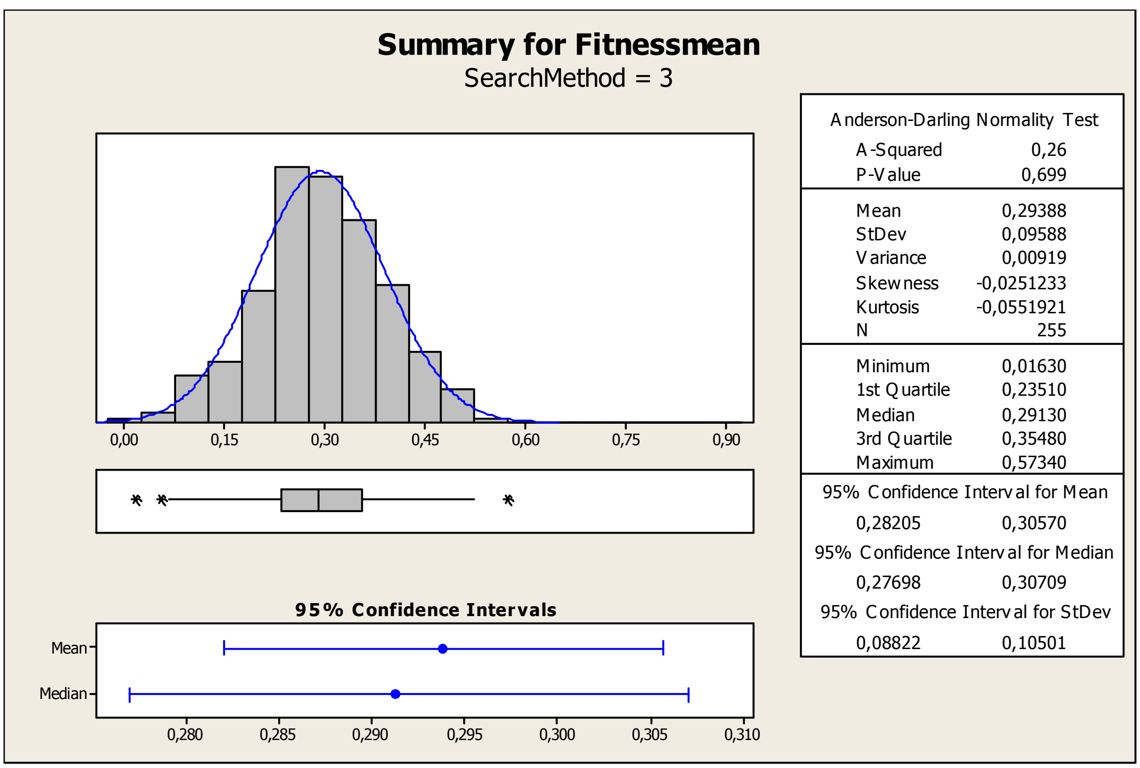

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,80
P-Value 0,038
Mean 0,74308
StDev 0,07258
Variance 0,00527
Skewness -0,295552
Kurtosis -0,443453
N 269
Minimum 0,54820
1st Quartile 0,69265
Median 0,74680
3rd Quartile 0,80015
Maximum 0,89930
95% Confidence Interval for Mean
0,73437 0,75180
95% Confidence Interval for Median
0,73430 0,76055
95% Confidence Interval for StDev
0,06693 0,07930
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,735 0,740 0,745 0,750 0,755 0,760

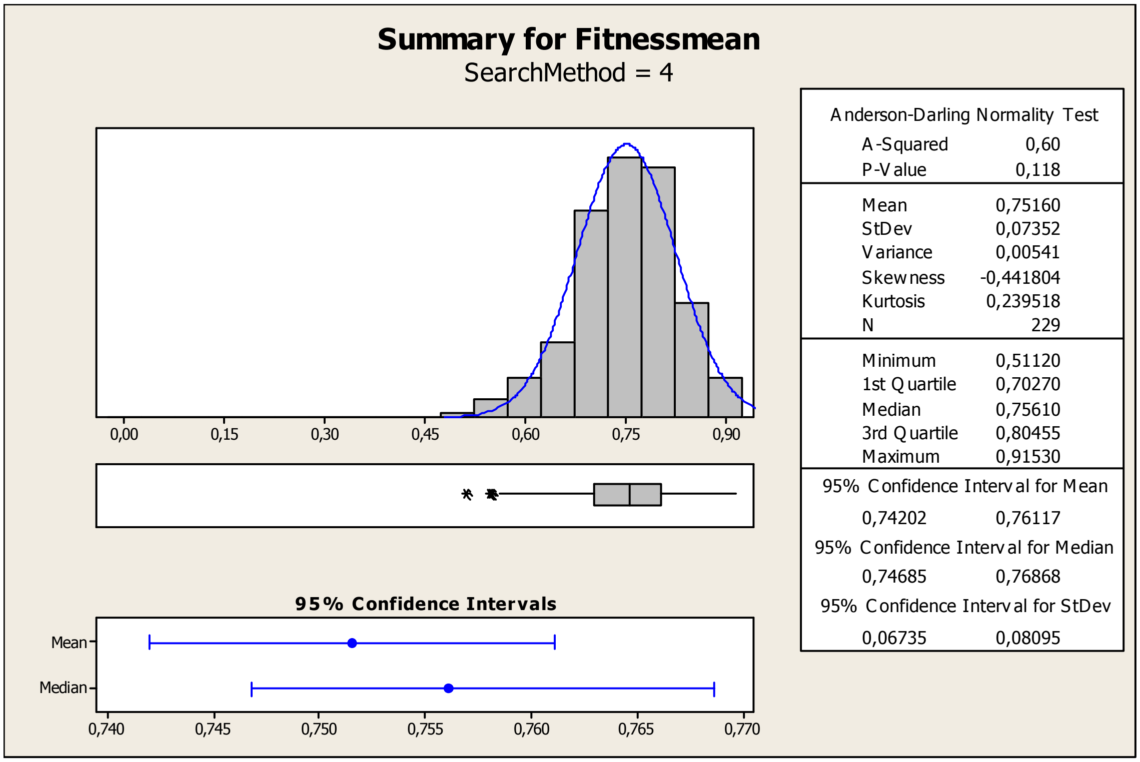
SIMULATION 64, ALL RUNS





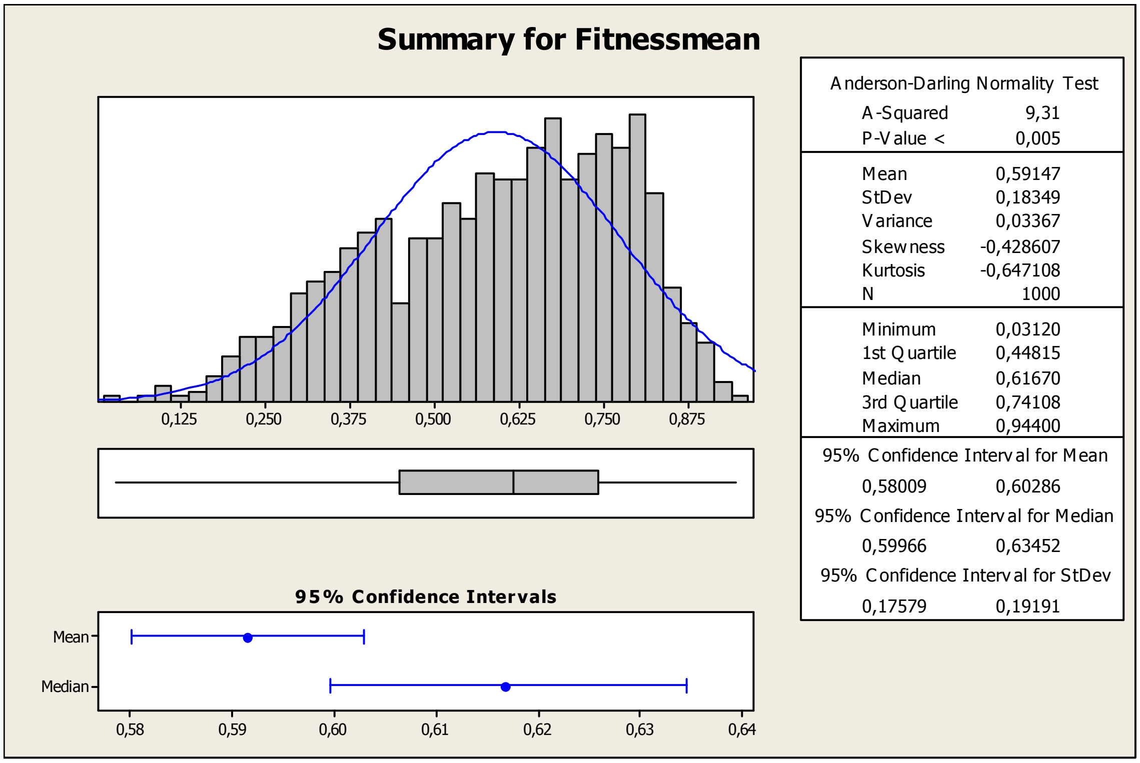

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 2,08
P-Value < 0,005
Mean 0,70501
StDev 0,10617
Variance 0,01127
Skewness -1,07803
Kurtosis 2,42147
N 253
Minimum 0,24470
1st Quartile 0,64130
Median 0,71520
3rd Quartile 0,78065
Maximum 0,88810
95% Confidence Interval for Mean
0,69186 0,71816
95% Confidence Interval for Median
0,70079 0,73516
95% Confidence Interval for StDev
0,09765 0,11632
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,69 0,70 0,71 0,72 0,73 0,74

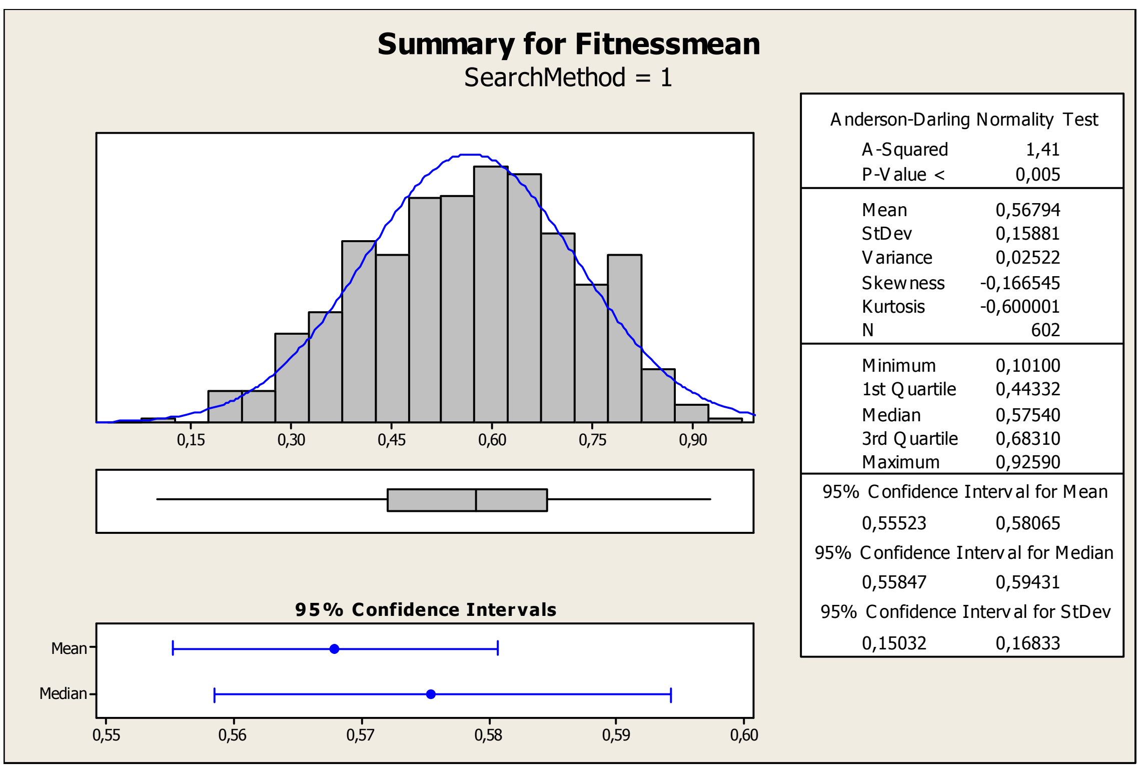

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,26
P-Value 0,699
Mean 0,29388
StDev 0,09588
Variance 0,00919
Skewness -0,0251233
Kurtosis -0,0551921
N 255
Minimum 0,01630
1st Quartile 0,23510
Median 0,29130
3rd Quartile 0,35480
Maximum 0,57340
95% Confidence Interval for Mean
0,28205 0,30570
95% Confidence Interval for Median
0,27698 0,30709
95% Confidence Interval for StDev
0,08822 0,10501
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,280 0,285 0,290 0,295 0,300 0,305 0,310

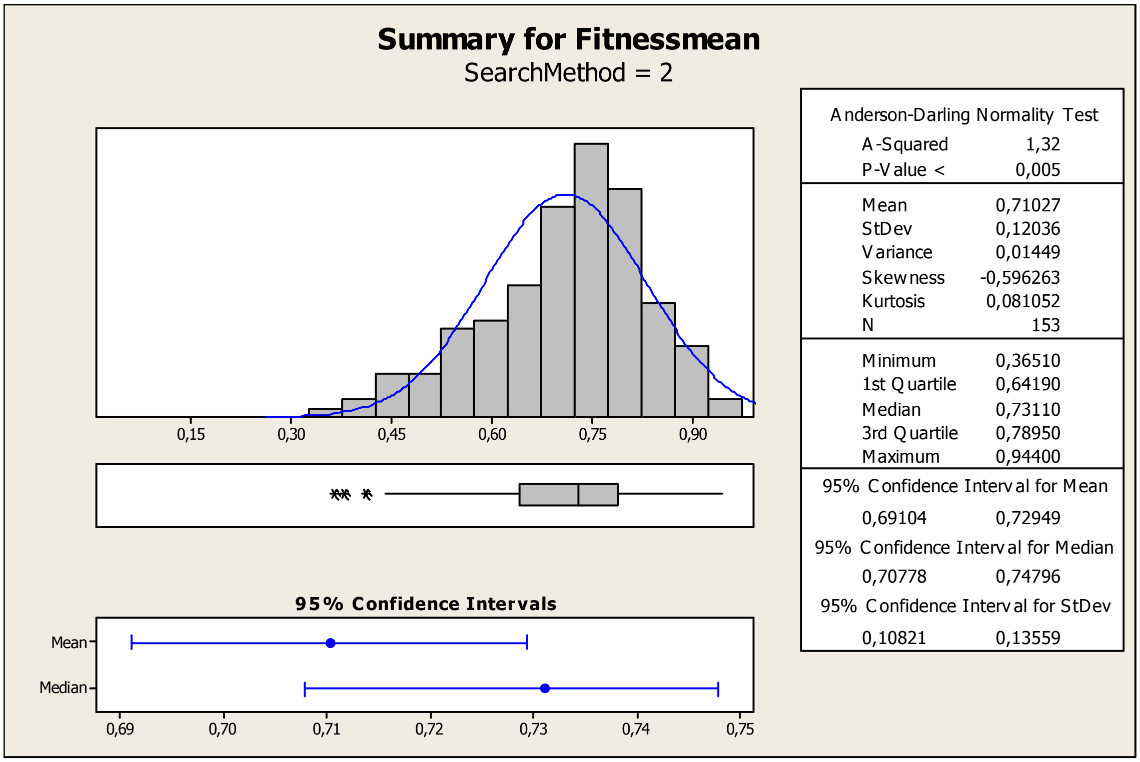


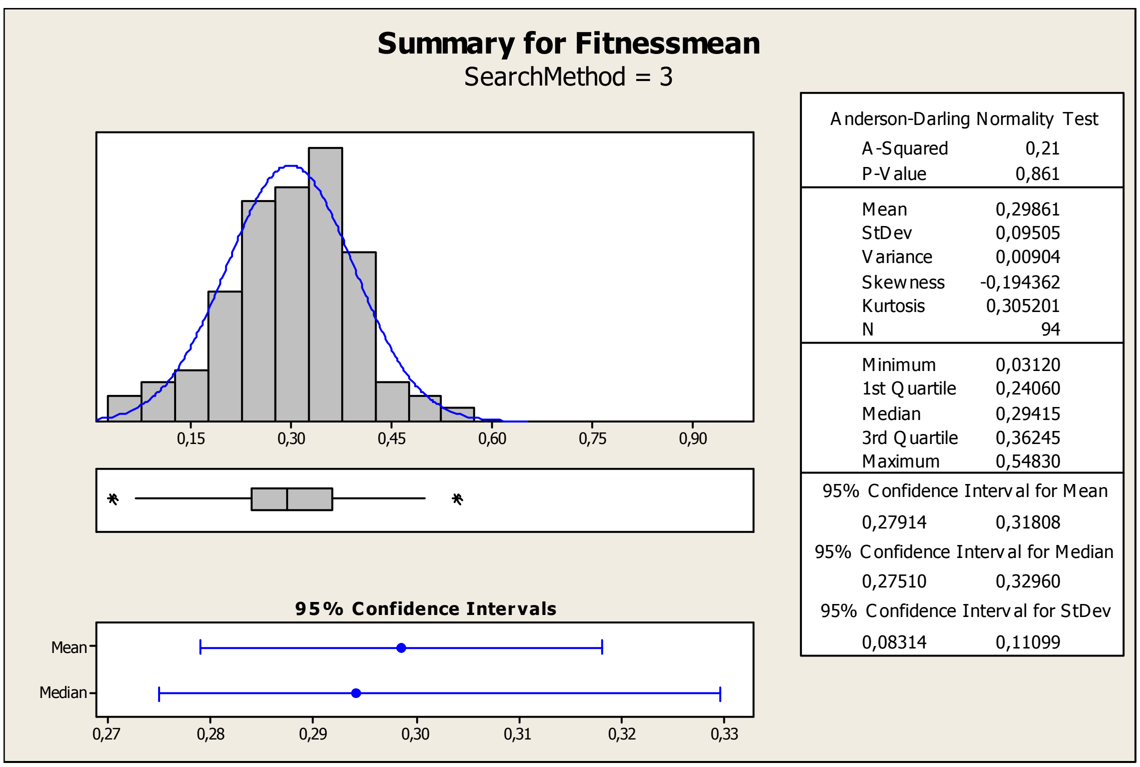
Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,60
P-Value 0,118
Mean 0,75160
StDev 0,07352
Variance 0,00541
Skewness -0,441804
Kurtosis 0,239518
N 229
Minimum 0,51120
1st Quartile 0,70270
Median 0,75610
3rd Quartile 0,80455
Maximum 0,91530
95% Confidence Interval for Mean
0,74202 0,76117
95% Confidence Interval for Median
0,74685 0,76868
95% Confidence Interval for StDev
0,06735 0,08095
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,740 0,745 0,750 0,755 0,760 0,765 0,770

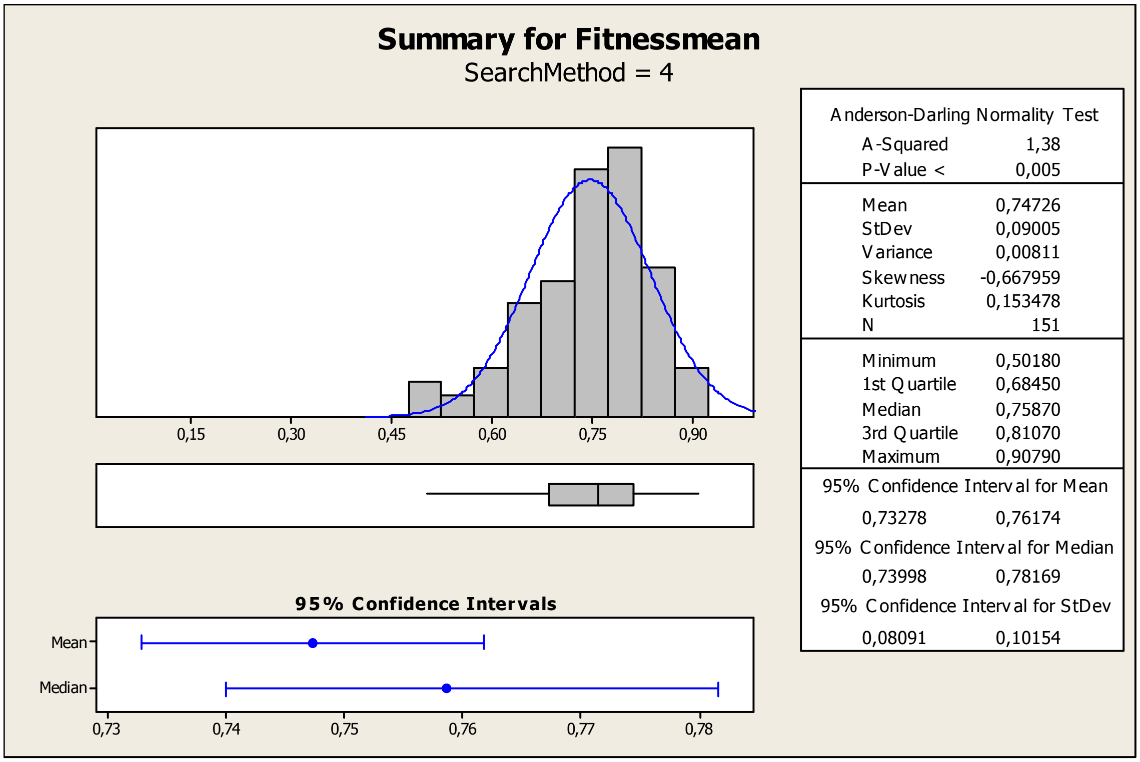
SIMULATION 65, ALL RUNS



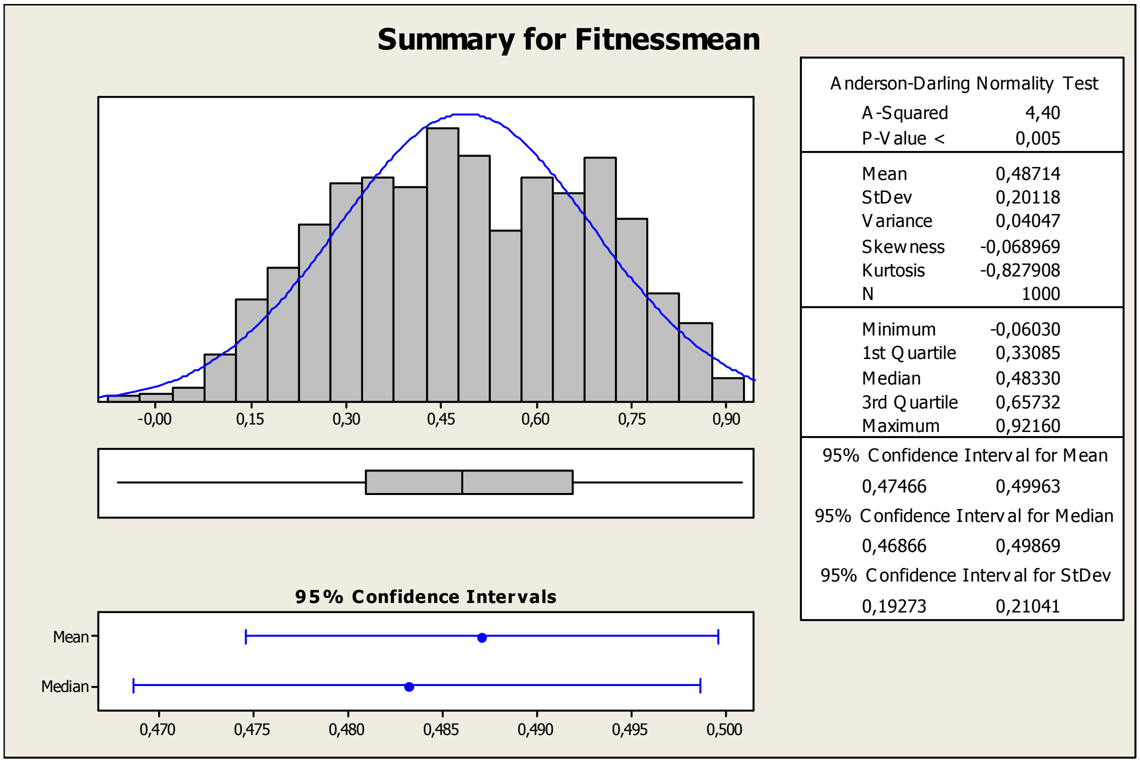


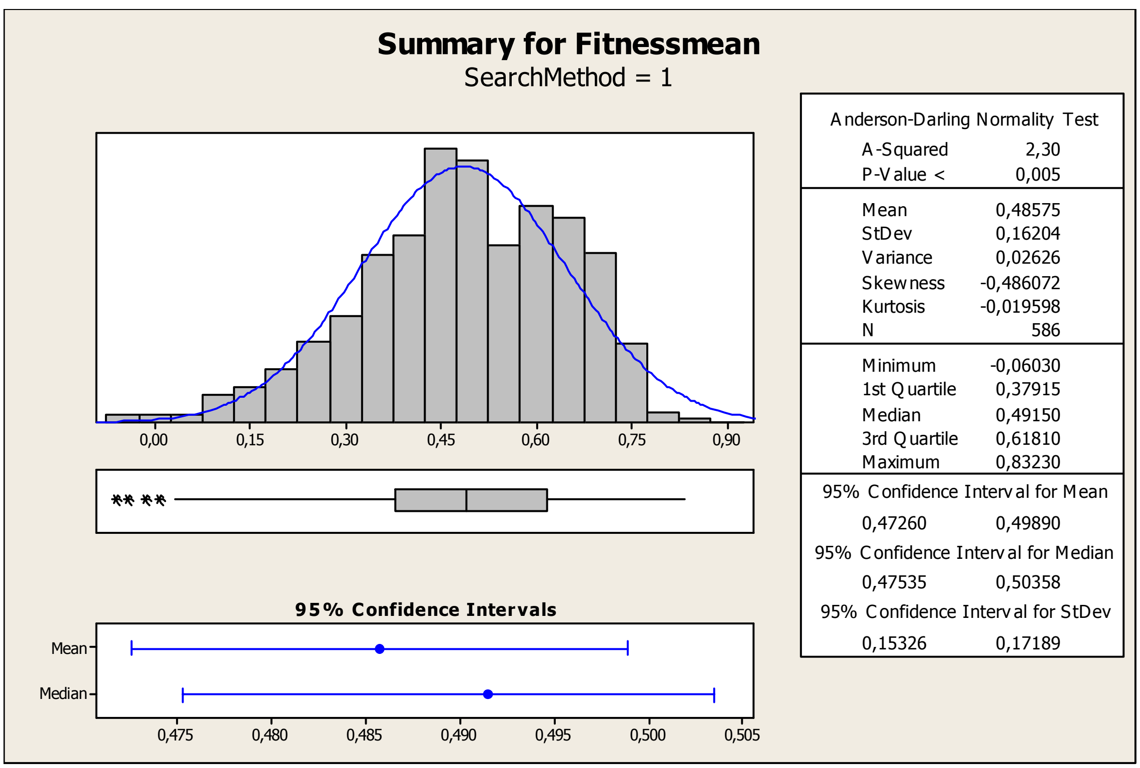

Summary for Fitnessmean
SearchMethod = 2
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,69 0,70 0,71 0,72 0,73 0,74 0,75
Anderson-Darling Normality Test
A-Squared 1,32
P-Value < 0,005
Mean 0,71027
StDev 0,12036
Variance 0,01449
Skewness -0,596263
Kurtosis 0,081052
N 153
Minimum 0,36510
1st Quartile 0,64190
Median 0,73110
3rd Quartile 0,78950
Maximum 0,94400
95% Confidence Interval for Mean
0,69104 0,72949
95% Confidence Interval for Median
0,70778 0,74796
95% Confidence Interval for StDev
0,10821 0,13559

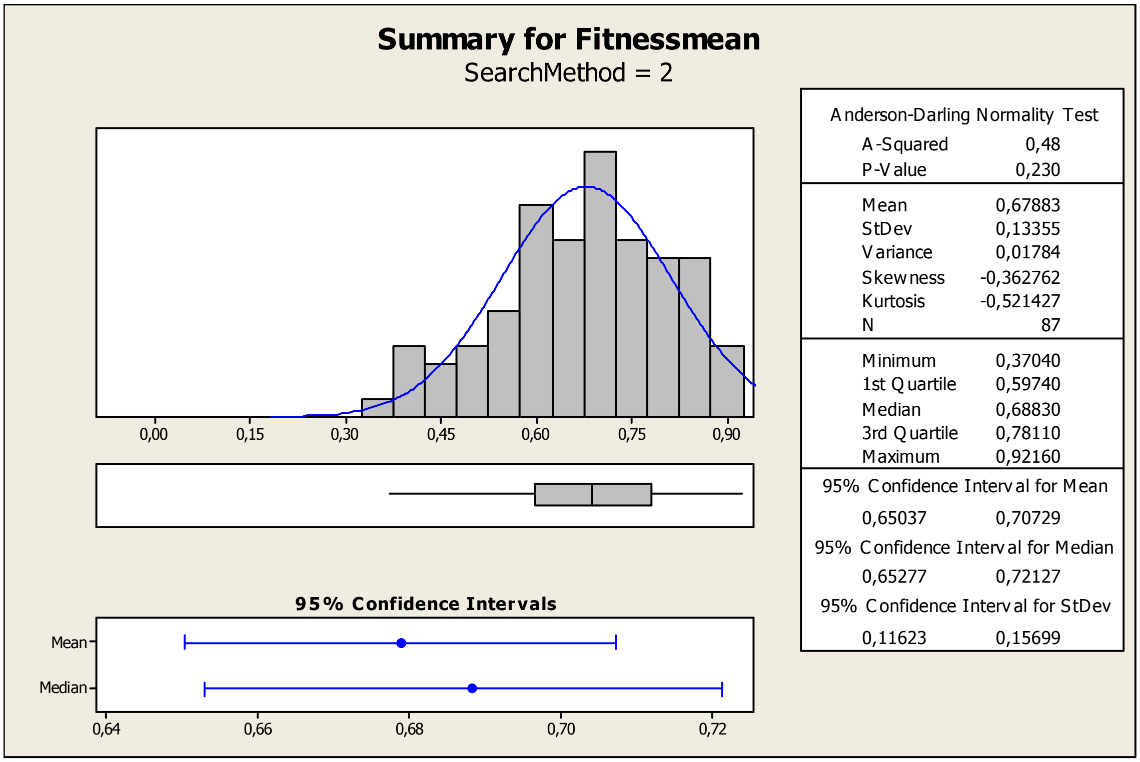

Summary for Fitnessmean
SearchMethod = 3
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,27 0,28 0,29 0,30 0,31 0,32 0,33
Anderson-Darling Normality Test
A-Squared 0,21
P-Value 0,861
Mean 0,29861
StDev 0,09505
Variance 0,00904
Skewness -0,194362
Kurtosis 0,305201
N 94
Minimum 0,03120
1st Quartile 0,24060
Median 0,29415
3rd Quartile 0,36245
Maximum 0,54830
95% Confidence Interval for Mean
0,27914 0,31808
95% Confidence Interval for Median
0,27510 0,32960
95% Confidence Interval for StDev
0,08314 0,11099

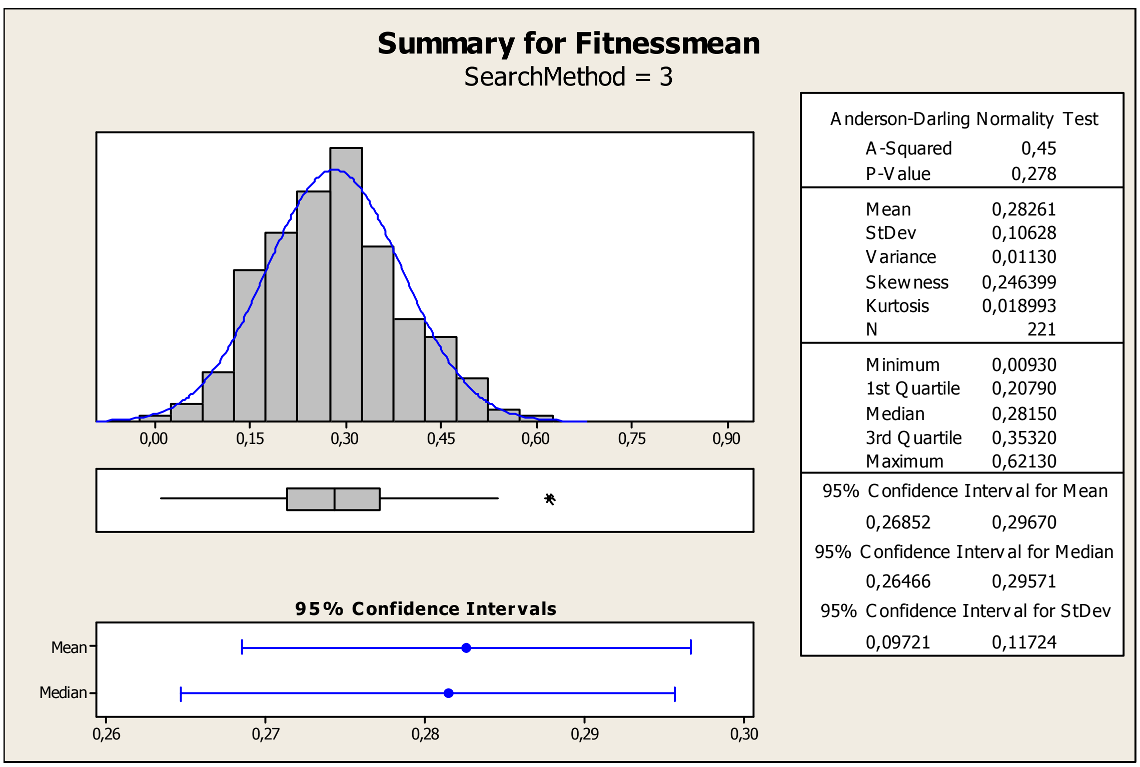

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,38
P-Value < 0,005
Mean 0,74726
StDev 0,09005
Variance 0,00811
Skewness -0,667959
Kurtosis 0,153478
N 151
Minimum 0,50180
1st Quartile 0,68450
Median 0,75870
3rd Quartile 0,81070
Maximum 0,90790
95% Confidence Interval for Mean
0,73278 0,76174
95% Confidence Interval for Median
0,73998 0,78169
95% Confidence Interval for StDev
0,08091 0,10154
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,73 0,74 0,75 0,76 0,77 0,78

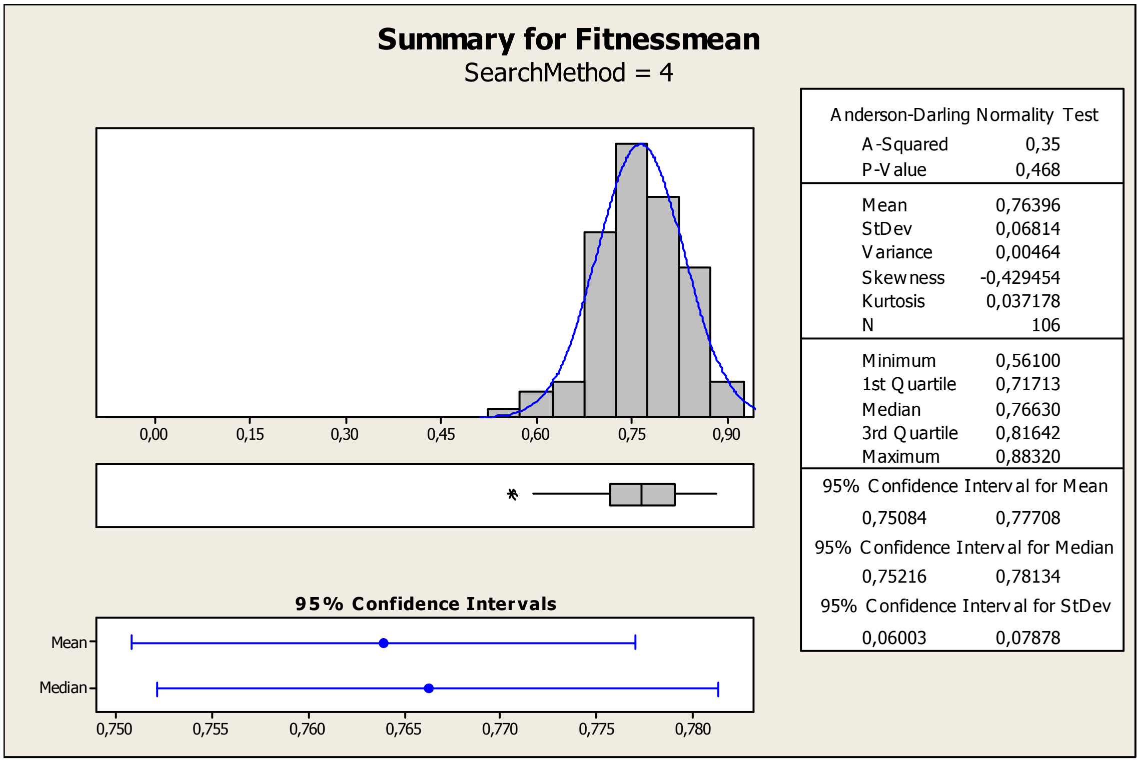
SIMULATION 66, ALL RUNS



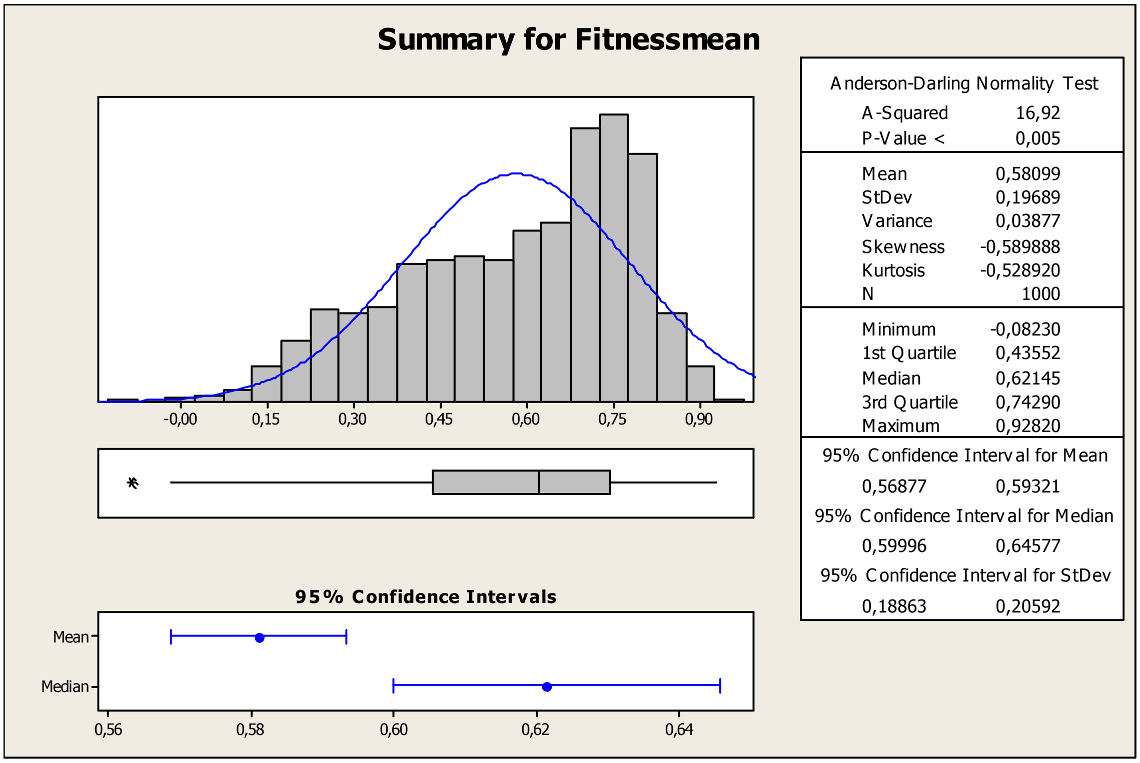


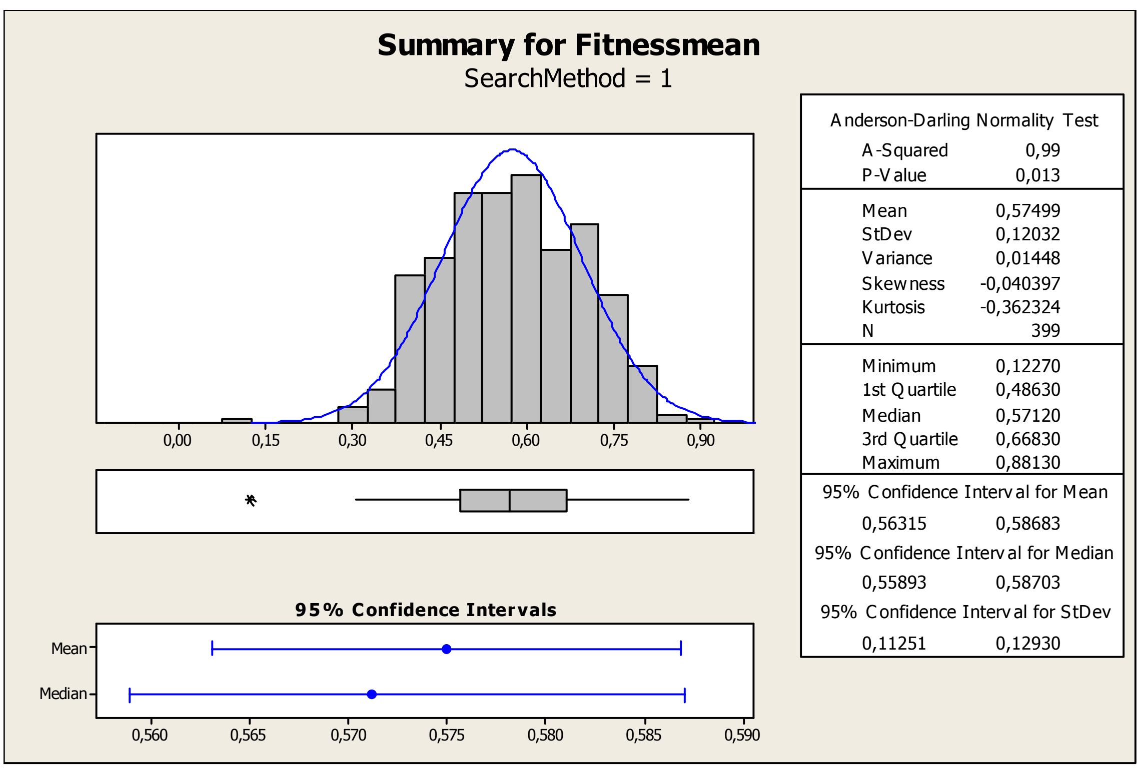

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,48
P-Value 0,230
Mean 0,67883
StDev 0,13355
Variance 0,01784
Skewness -0,362762
Kurtosis -0,521427
N 87
Minimum 0,37040
1st Quartile 0,59740
Median 0,68830
3rd Quartile 0,78110
Maximum 0,92160
95% Confidence Interval for Mean
0,65037 0,70729
95% Confidence Interval for Median
0,65277 0,72127
95% Confidence Interval for StDev
0,11623 0,15699
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,64 0,66 0,68 0,70 0,72

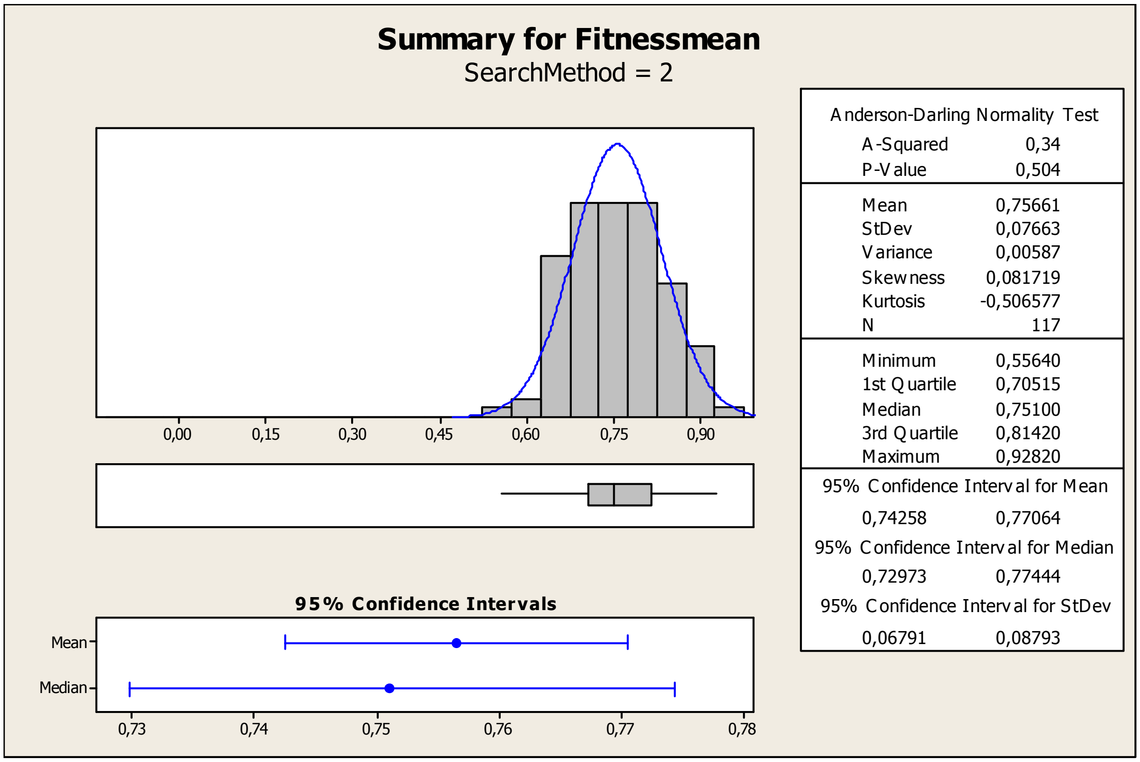

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,45
P-Value 0,278
Mean 0,28261
StDev 0,10628
Variance 0,01130
Skewness 0,246399
Kurtosis 0,018993
N 221
Minimum 0,00930
1st Quartile 0,20790
Median 0,28150
3rd Quartile 0,35320
Maximum 0,62130
95% Confidence Interval for Mean
0,26852 0,29670
95% Confidence Interval for Median
0,26466 0,29571
95% Confidence Interval for StDev
0,09721 0,11724
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,26 0,27 0,28 0,29 0,30

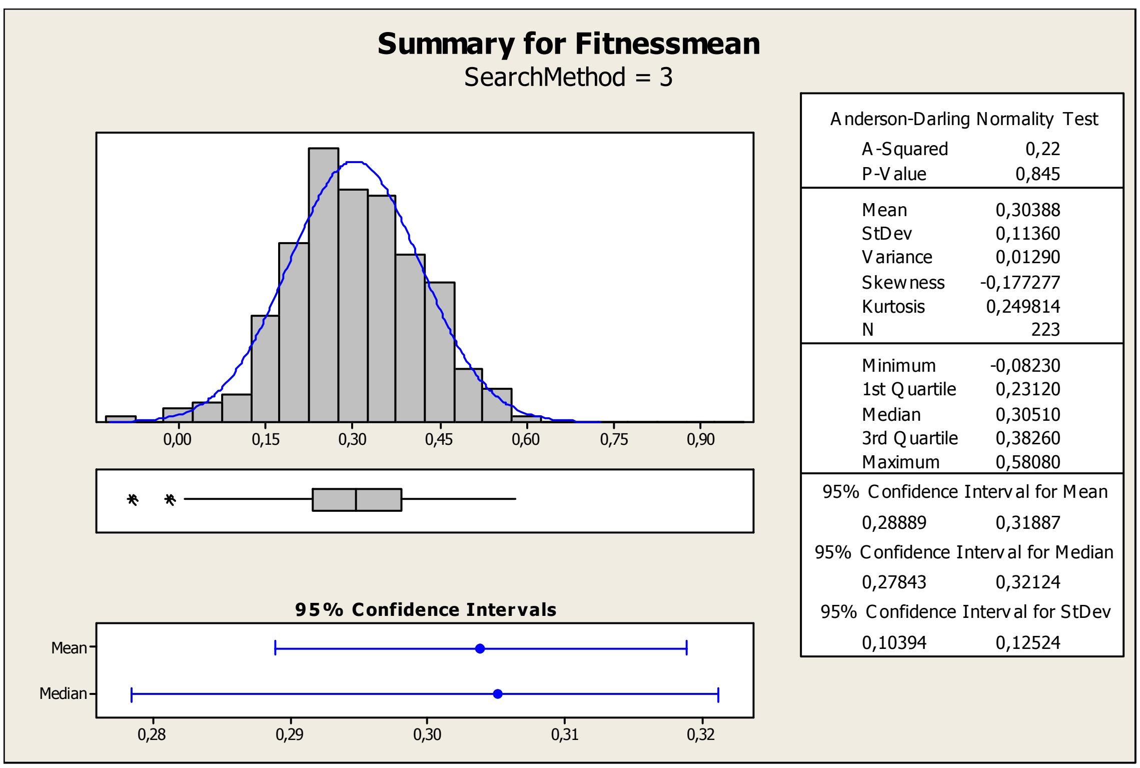

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,35
P-Value 0,468
Mean 0,76396
StDev 0,06814
Variance 0,00464
Skewness -0,429454
Kurtosis 0,037178
N 106
Minimum 0,56100
1st Quartile 0,71713
Median 0,76630
3rd Quartile 0,81642
Maximum 0,88320
95% Confidence Interval for Mean
0,75084 0,77708
95% Confidence Interval for Median
0,75216 0,78134
95% Confidence Interval for StDev
0,06003 0,07878
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,750 0,755 0,760 0,765 0,770 0,775 0,780

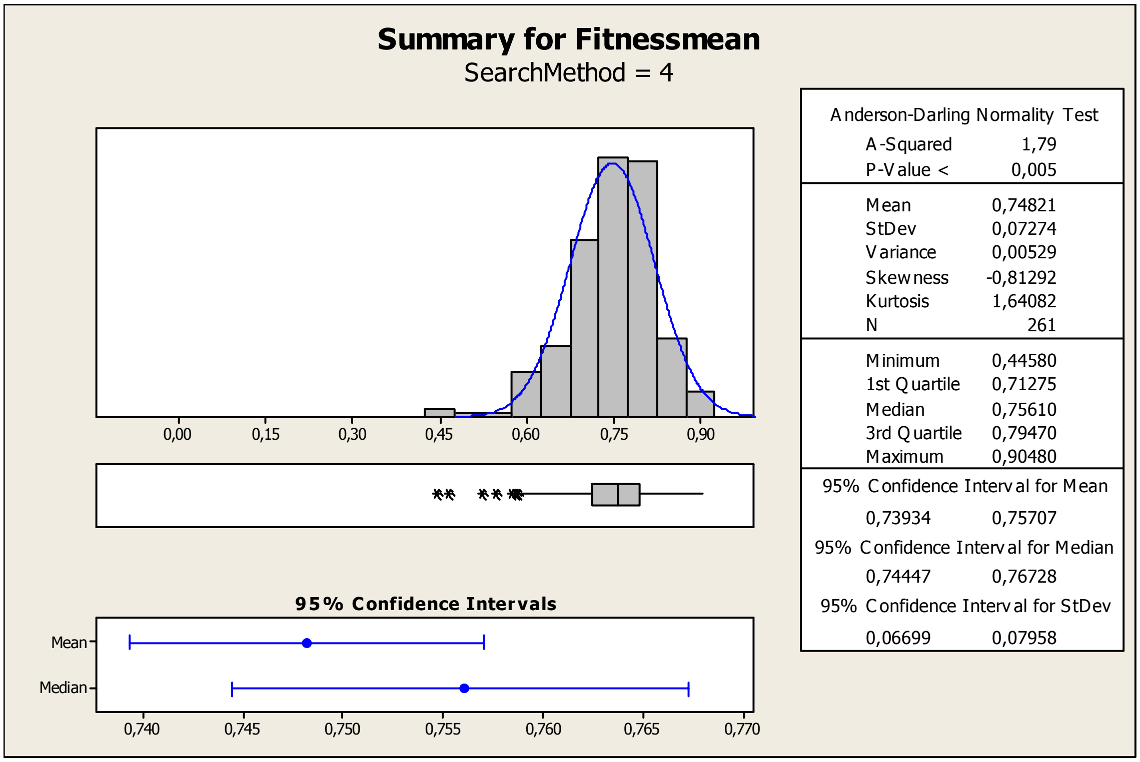
SIMULATION 67, ALL RUNS



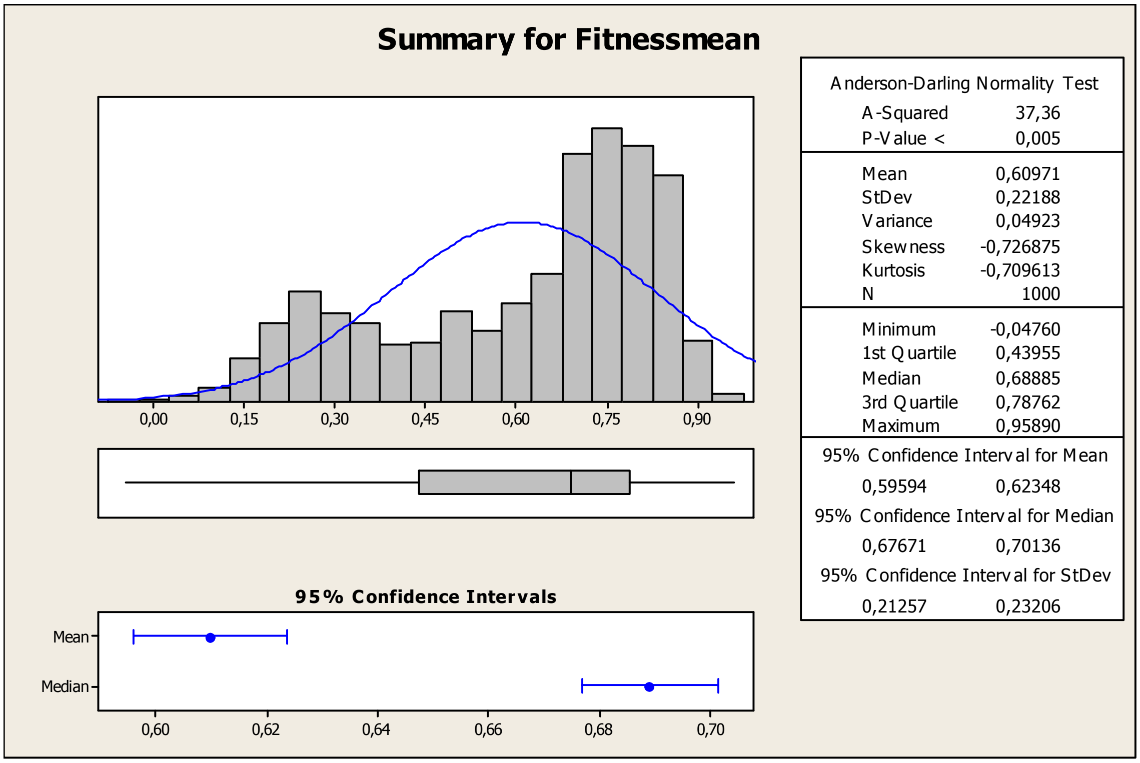


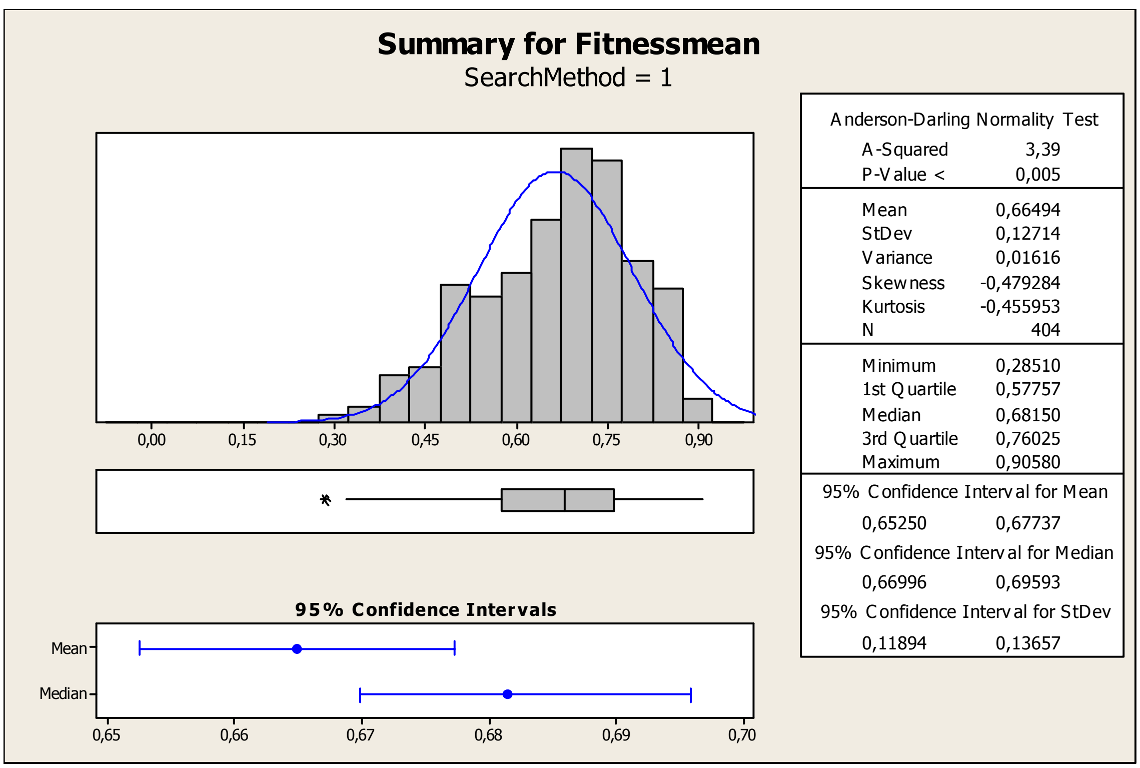

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,34
P-Value 0,504
Mean 0,75661
StDev 0,07663
Variance 0,00587
Skewness 0,081719
Kurtosis -0,506577
N 117
Minimum 0,55640
1st Quartile 0,70515
Median 0,75100
3rd Quartile 0,81420
Maximum 0,92820
95% Confidence Interval for Mean
0,74258 0,77064
95% Confidence Interval for Median
0,72973 0,77444
95% Confidence Interval for StDev
0,06791 0,08793
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,73 0,74 0,75 0,76 0,77 0,78

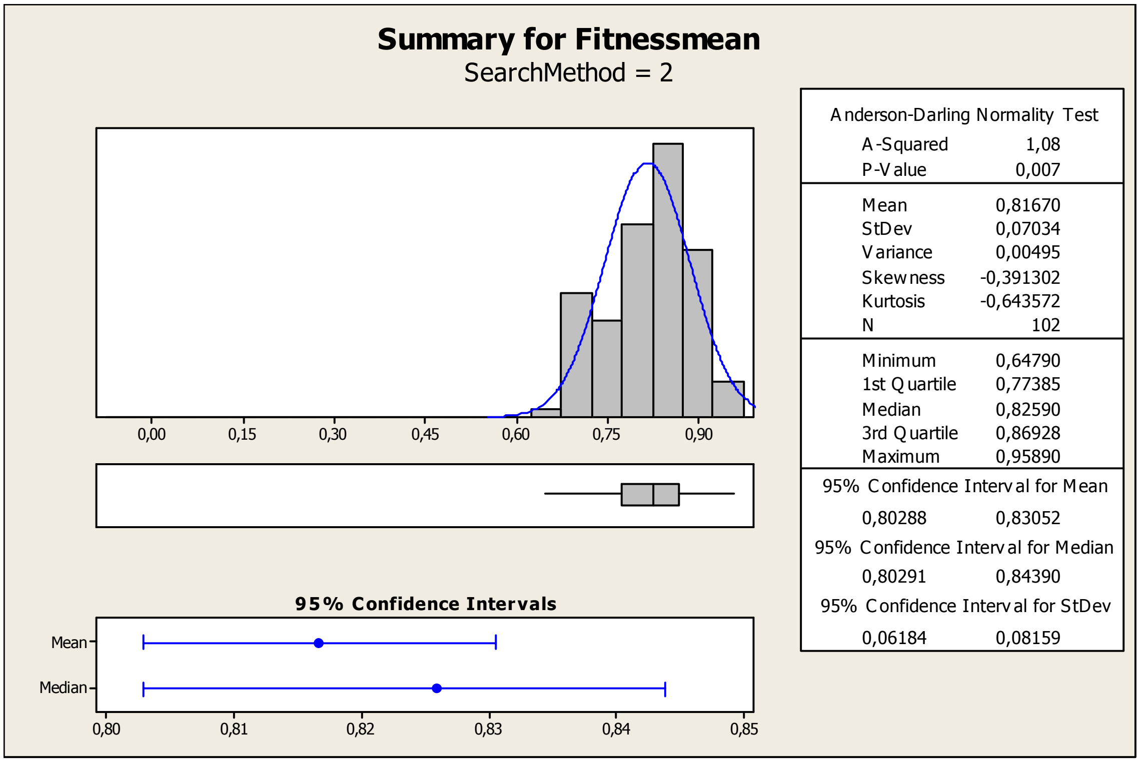

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,22
P-Value 0,845
Mean 0,30388
StDev 0,11360
Variance 0,01290
Skewness -0,177277
Kurtosis 0,249814
N 223
Minimum -0,08230
1st Quartile 0,23120
Median 0,30510
3rd Quartile 0,38260
Maximum 0,58080
95% Confidence Interval for Mean
0,28889 0,31887
95% Confidence Interval for Median
0,27843 0,32124
95% Confidence Interval for StDev
0,10394 0,12524
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,28 0,29 0,30 0,31 0,32

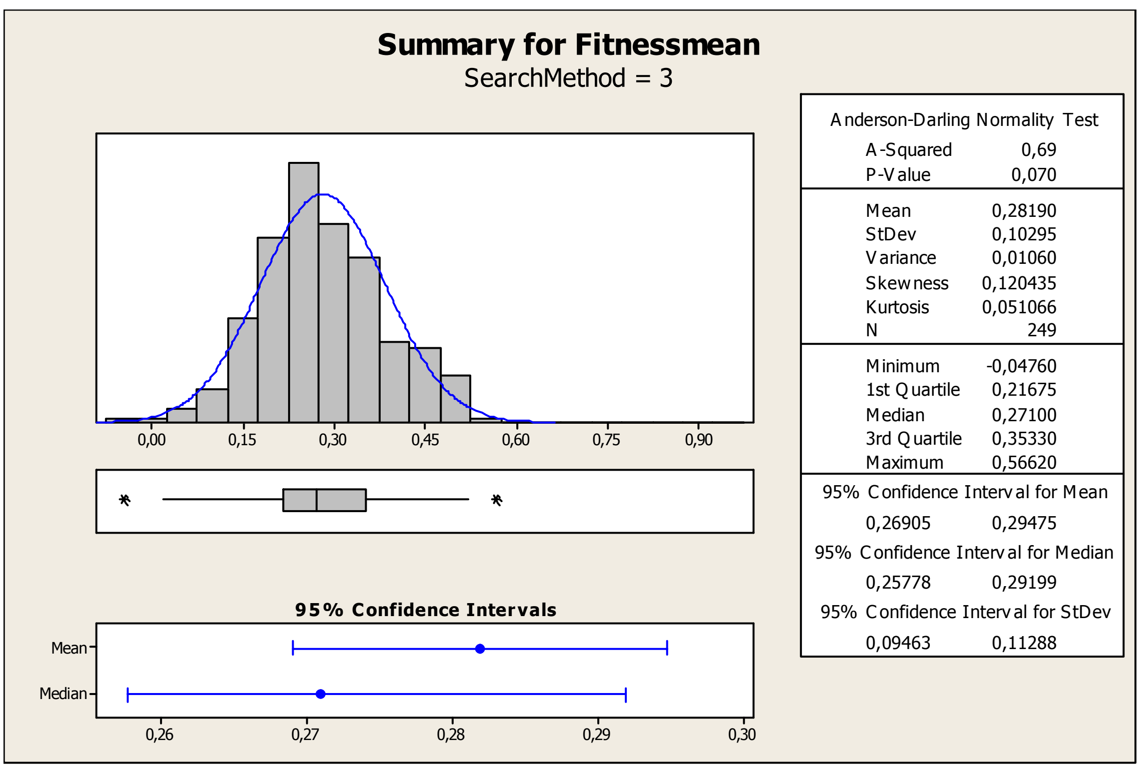

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,79
P-Value < 0,005
Mean 0,74821
StDev 0,07274
Variance 0,00529
Skewness -0,81292
Kurtosis 1,64082
N 261
Minimum 0,44580
1st Quartile 0,71275
Median 0,75610
3rd Quartile 0,79470
Maximum 0,90480
95% Confidence Interval for Mean
0,73934 0,75707
95% Confidence Interval for Median
0,74447 0,76728
95% Confidence Interval for StDev
0,06699 0,07958
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,740
0,745
0,750
0,755
0,760
0,765
0,770

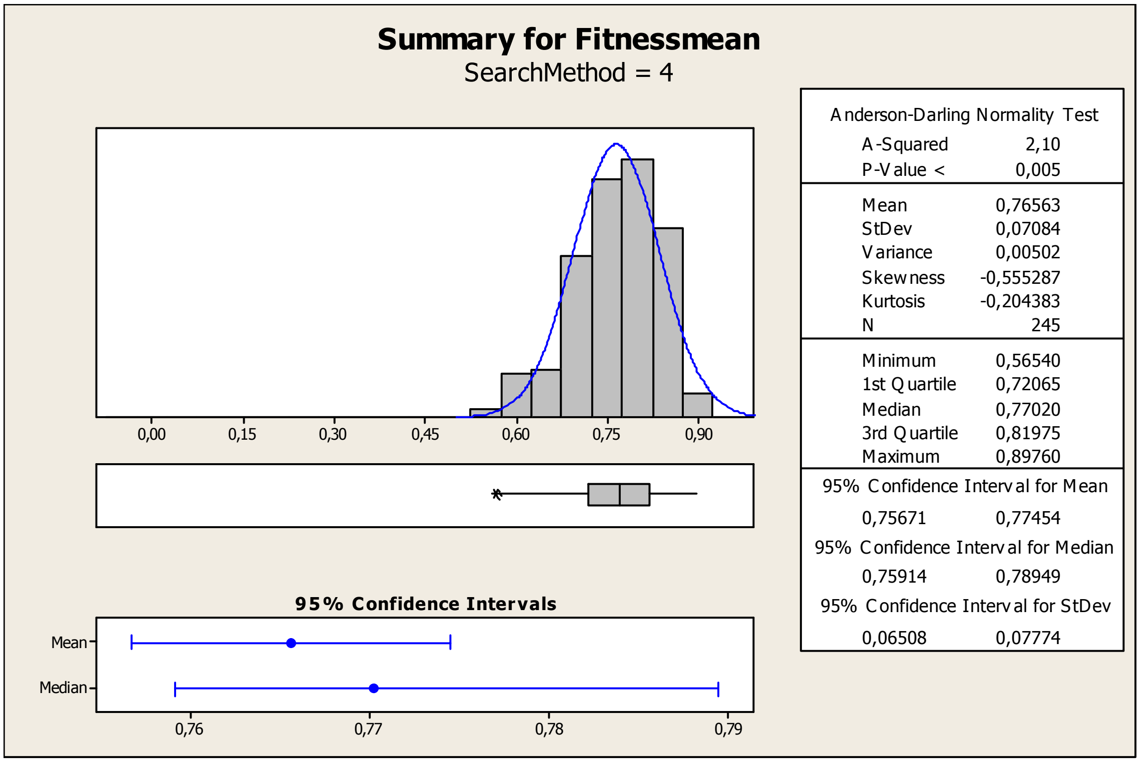
SIMULATION 68, ALL RUNS



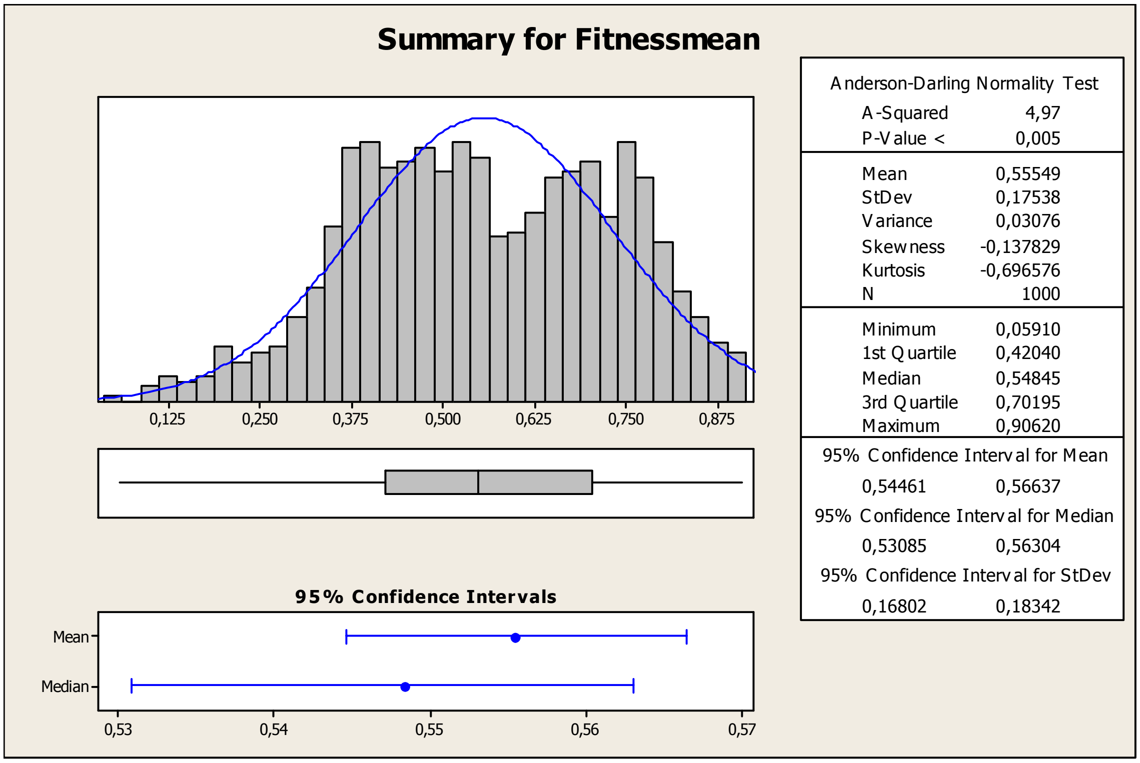


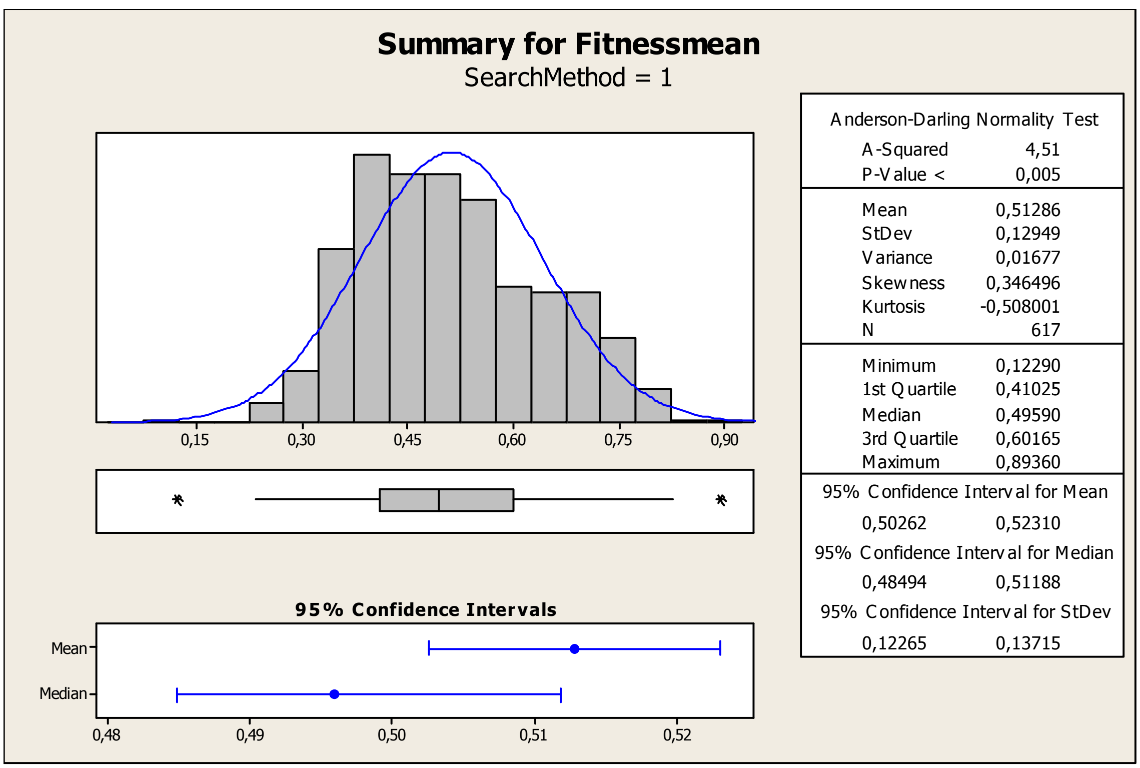

Summary for Fitnessmean
SearchMethod = 2
0,00 0,15 0,30 0,45 0,60 0,75 0,90
Anderson-Darling Normality Test
A-Squared 1,08
P-Value 0,007
Mean 0,81670
StDev 0,07034
Variance 0,00495
Skewness -0,391302
Kurtosis -0,643572
N 102
Minimum 0,64790
1st Quartile 0,77385
Median 0,82590
3rd Quartile 0,86928
Maximum 0,95890
95% Confidence Interval for Mean
0,80288 0,83052
95% Confidence Interval for Median
0,80291 0,84390
95% Confidence Interval for StDev
0,06184 0,08159
95% Confidence Intervals
Mean
Median
0,80 0,81 0,82 0,83 0,84 0,85

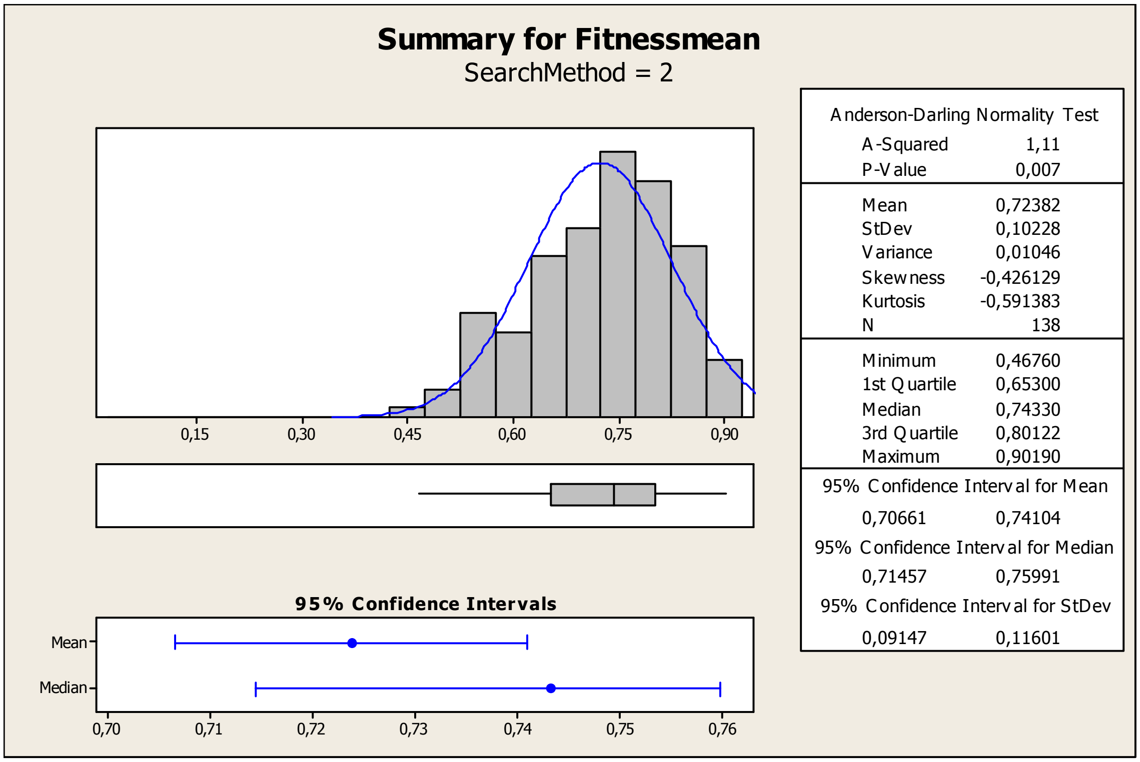

Summary for Fitnessmean
SearchMethod = 3
0,00 0,15 0,30 0,45 0,60 0,75 0,90
Anderson-Darling Normality Test
A-Squared 0,69
P-Value 0,070
Mean 0,28190
StDev 0,10295
Variance 0,01060
Skewness 0,120435
Kurtosis 0,051066
N 249
Minimum -0,04760
1st Quartile 0,21675
Median 0,27100
3rd Quartile 0,35330
Maximum 0,56620
95% Confidence Interval for Mean
0,26905 0,29475
95% Confidence Interval for Median
0,25778 0,29199
95% Confidence Interval for StDev
0,09463 0,11288
95% Confidence Intervals
Mean
Median
0,26 0,27 0,28 0,29 0,30

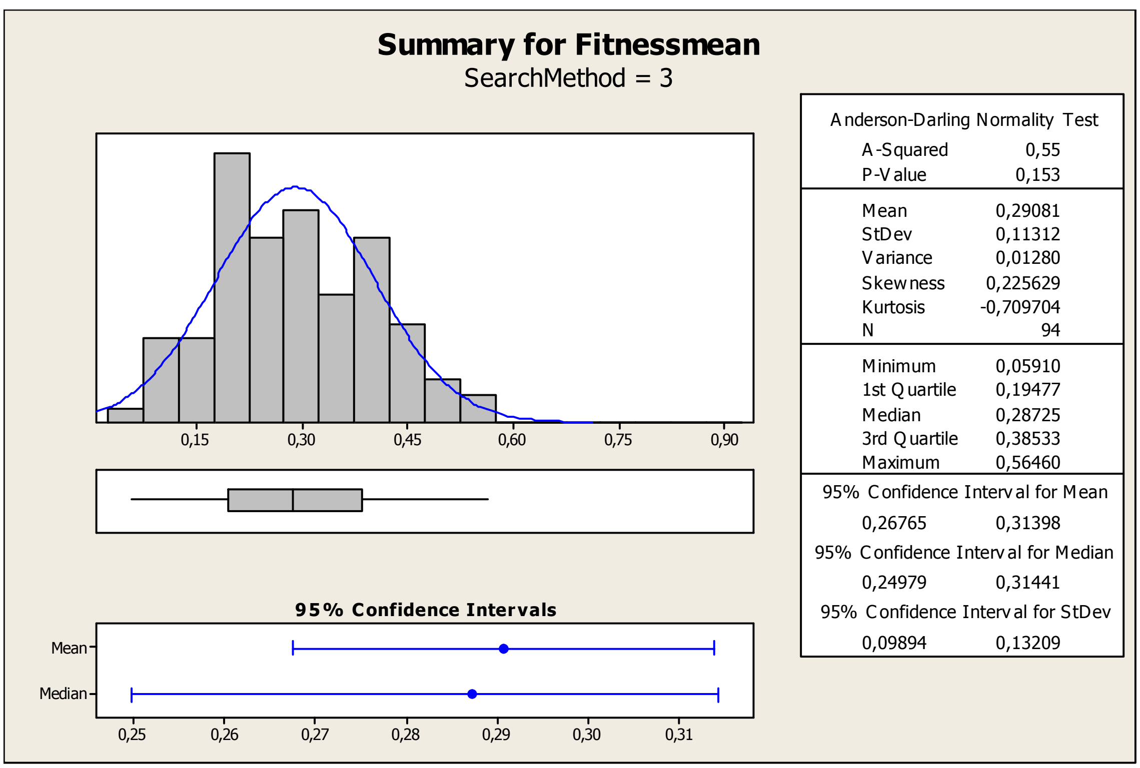

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 2,10
P-Value < 0,005
Mean 0,76563
StDev 0,07084
Variance 0,00502
Skewness -0,555287
Kurtosis -0,204383
N 245
Minimum 0,56540
1st Quartile 0,72065
Median 0,77020
3rd Quartile 0,81975
Maximum 0,89760
95% Confidence Interval for Mean
0,75671 0,77454
95% Confidence Interval for Median
0,75914 0,78949
95% Confidence Interval for StDev
0,06508 0,07774
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,76 0,77 0,78 0,79

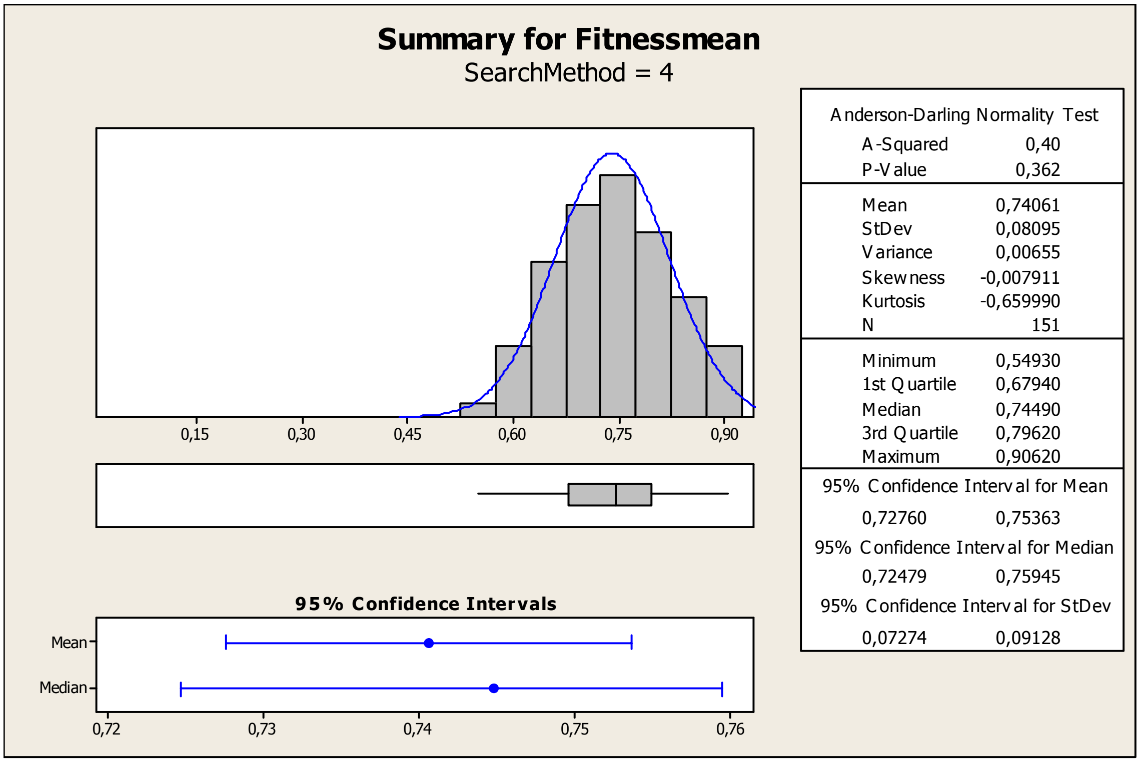
SIMULATION 69, ALL RUNS



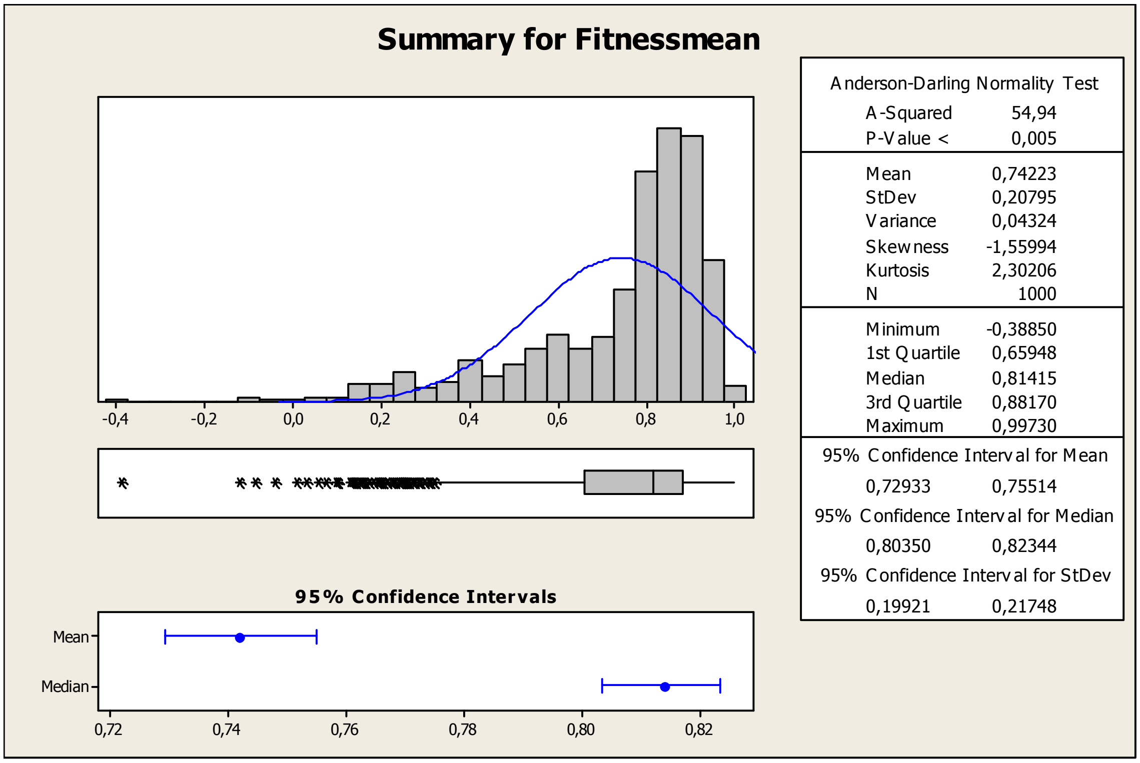


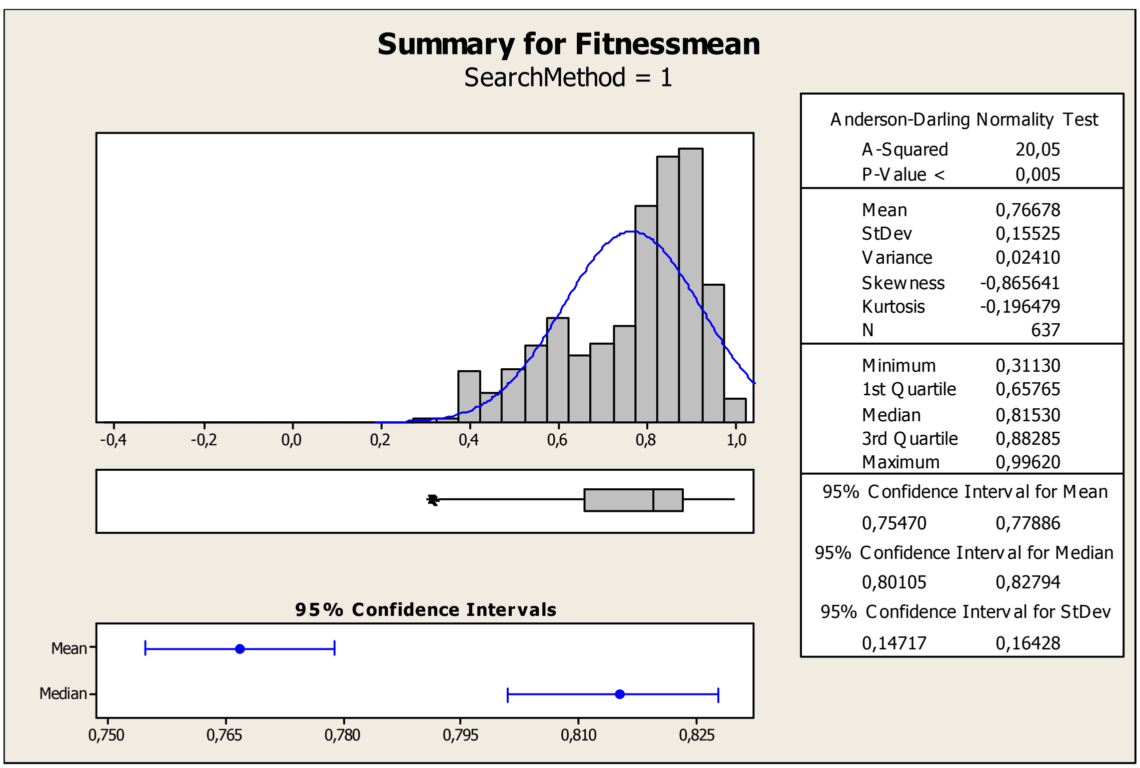

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,11
P-Value 0,007
Mean 0,72382
StDev 0,10228
Variance 0,01046
Skewness -0,426129
Kurtosis -0,591383
N 138
Minimum 0,46760
1st Quartile 0,65300
Median 0,74330
3rd Quartile 0,80122
Maximum 0,90190
95% Confidence Interval for Mean
0,70661 0,74104
95% Confidence Interval for Median
0,71457 0,75991
95% Confidence Interval for StDev
0,09147 0,11601
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,70 0,71 0,72 0,73 0,74 0,75 0,76

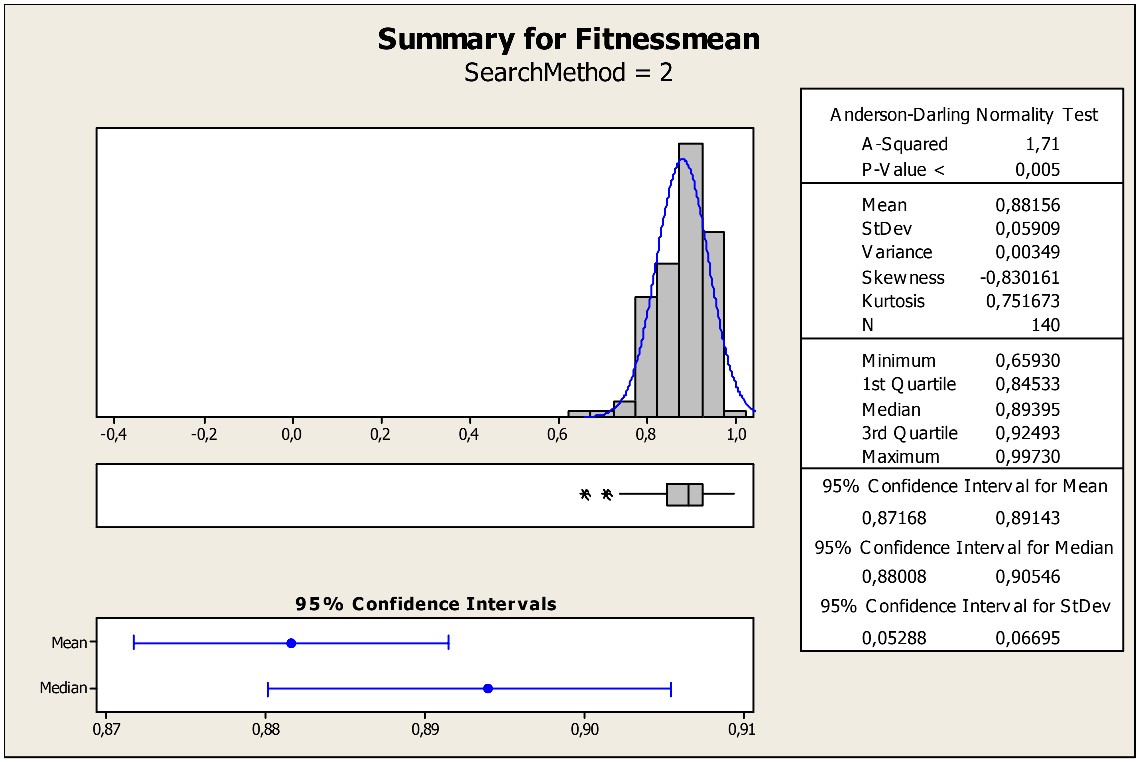

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,55
P-Value 0,153
Mean 0,29081
StDev 0,11312
Variance 0,01280
Skewness 0,225629
Kurtosis -0,709704
N 94
Minimum 0,05910
1st Quartile 0,19477
Median 0,28725
3rd Quartile 0,38533
Maximum 0,56460
95% Confidence Interval for Mean
0,26765 0,31398
95% Confidence Interval for Median
0,24979 0,31441
95% Confidence Interval for StDev
0,09894 0,13209
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,25 0,26 0,27 0,28 0,29 0,30 0,31


Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,40
P-Value 0,362
Mean 0,74061
StDev 0,08095
Variance 0,00655
Skewness -0,007911
Kurtosis -0,659990
N 151
Minimum 0,54930
1st Quartile 0,67940
Median 0,74490
3rd Quartile 0,79620
Maximum 0,90620
95% Confidence Interval for Mean
0,72760 0,75363
95% Confidence Interval for Median
0,72479 0,75945
95% Confidence Interval for StDev
0,07274 0,09128
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,72
0,73
0,74
0,75
0,76

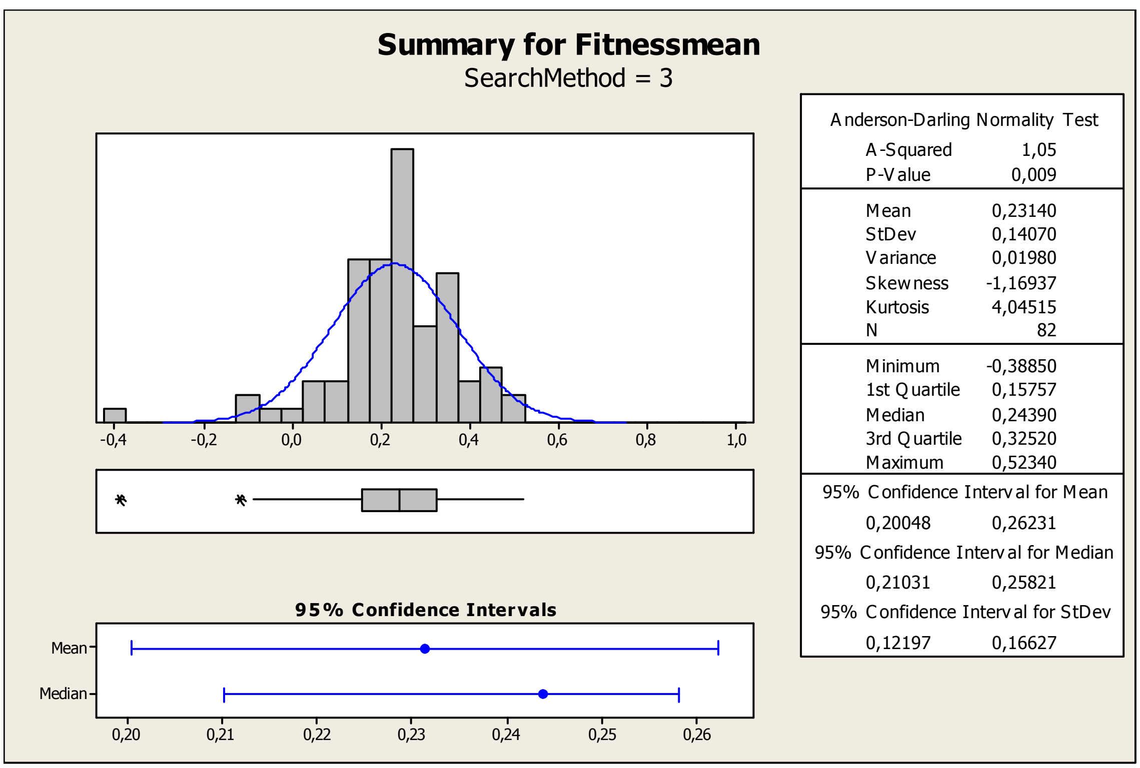
SIMULATION 70, ALL RUNS



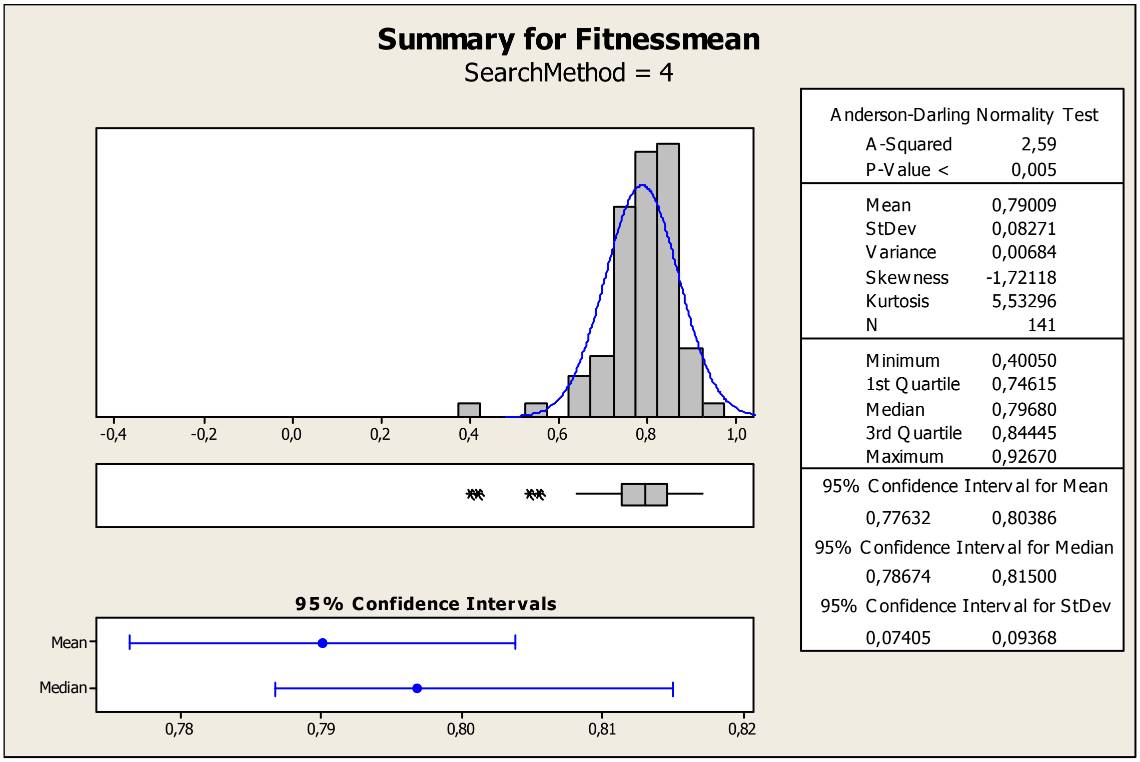




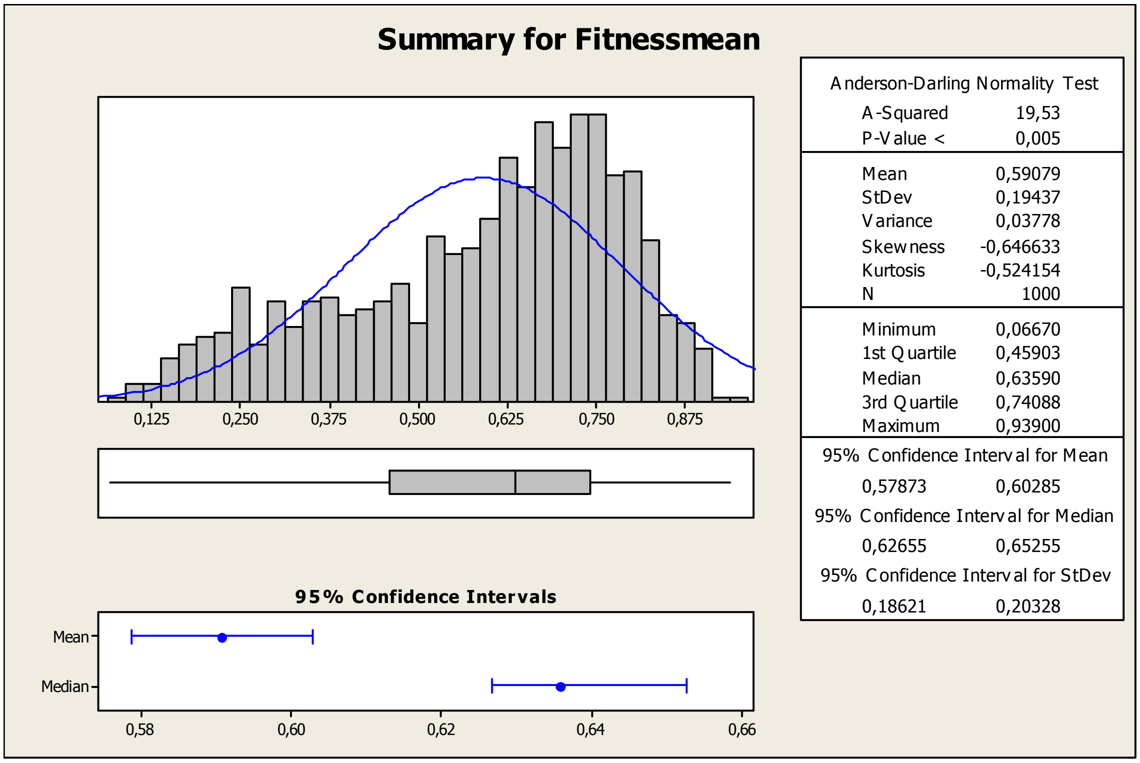
Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,71
P-Value < 0,005
Mean 0,88156
StDev 0,05909
Variance 0,00349
Skewness -0,830161
Kurtosis 0,751673
N 140
Minimum 0,65930
1st Quartile 0,84533
Median 0,89395
3rd Quartile 0,92493
Maximum 0,99730
95% Confidence Interval for Mean
0,87168 0,89143
95% Confidence Interval for Median
0,88008 0,90546
95% Confidence Interval for StDev
0,05288 0,06695
95% Confidence Intervals
Mean
Median

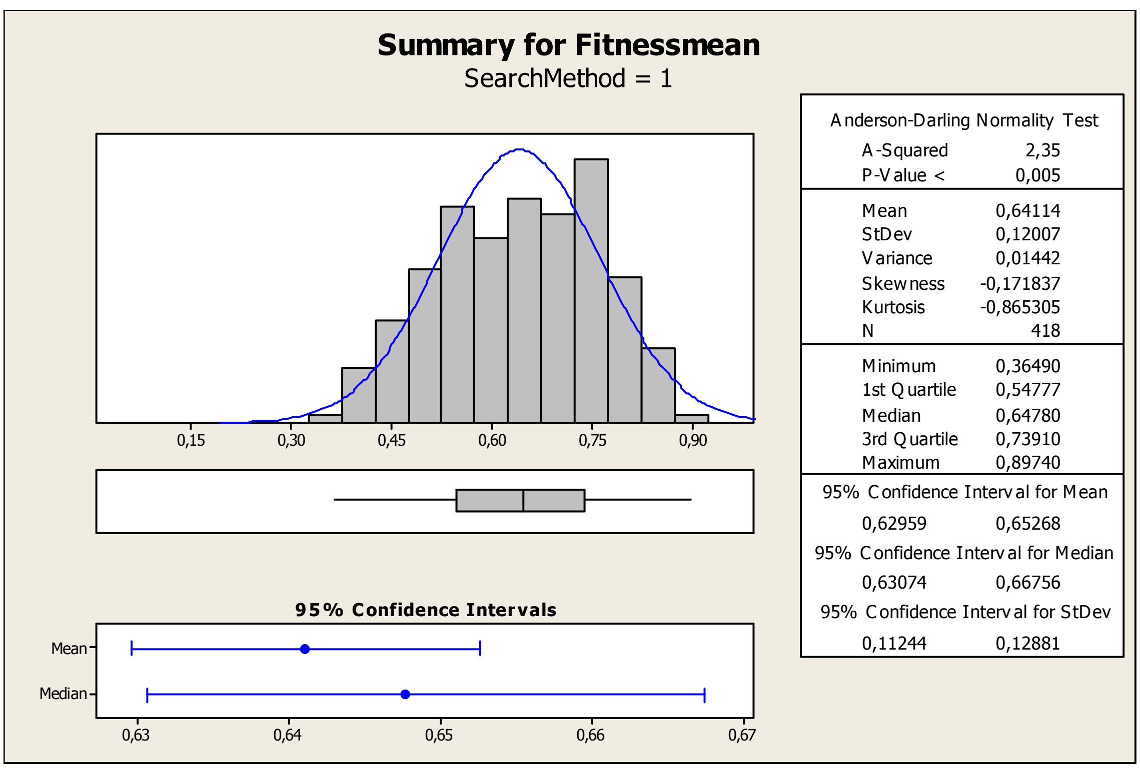


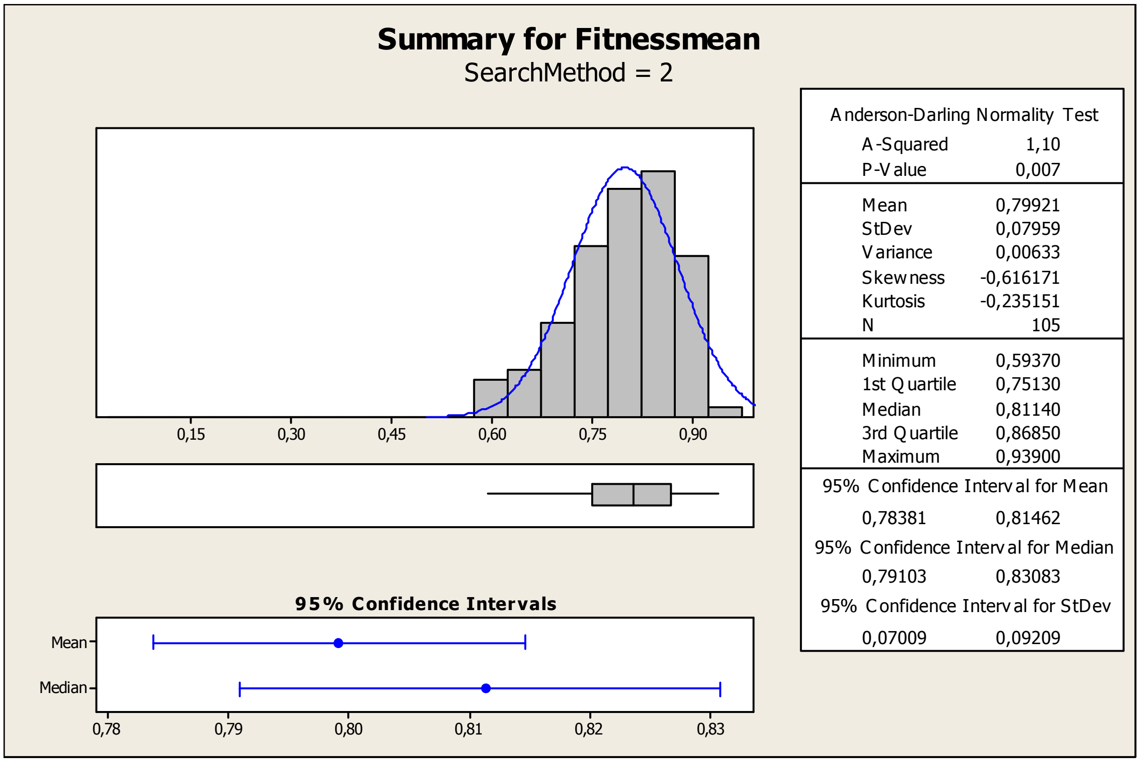
Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 1,05
P-Value 0,009
Mean 0,23140
StDev 0,14070
Variance 0,01980
Skewness -1,16937
Kurtosis 4,04515
N 82
Minimum -0,38850
1st Quartile 0,15757
Median 0,24390
3rd Quartile 0,32520
Maximum 0,52340
95% Confidence Interval for Mean
0,20048 0,26231
95% Confidence Interval for Median
0,21031 0,25821
95% Confidence Interval for StDev
0,12197 0,16627
95% Confidence Intervals
Mean
Median

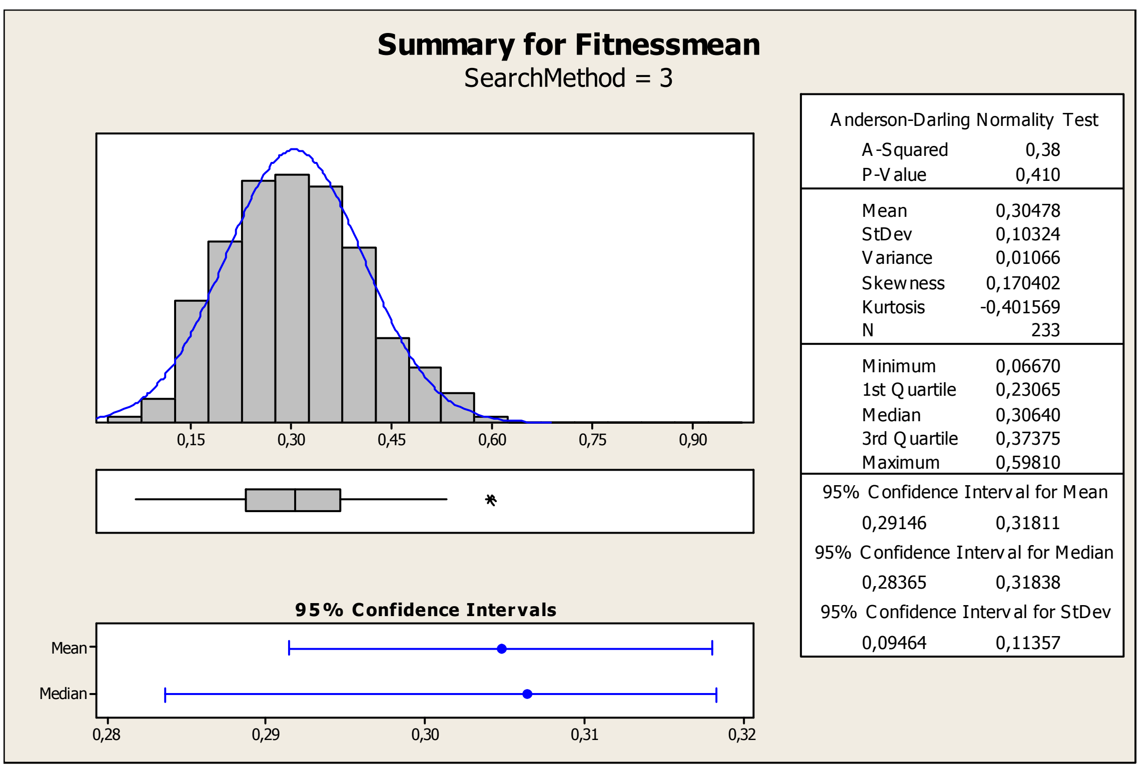

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 2,59
P-Value < 0,005
Mean 0,79009
StDev 0,08271
Variance 0,00684
Skewness -1,72118
Kurtosis 5,53296
N 141
Minimum 0,40050
1st Quartile 0,74615
Median 0,79680
3rd Quartile 0,84445
Maximum 0,92670
95% Confidence Interval for Mean
0,77632 0,80386
95% Confidence Interval for Median
0,78674 0,81500
95% Confidence Interval for StDev
0,07405 0,09368
-0,4 -0,2 0,0 0,2 0,4 0,6 0,8 1,0
95% Confidence Intervals
Mean
Median
0,78 0,79 0,80 0,81 0,82

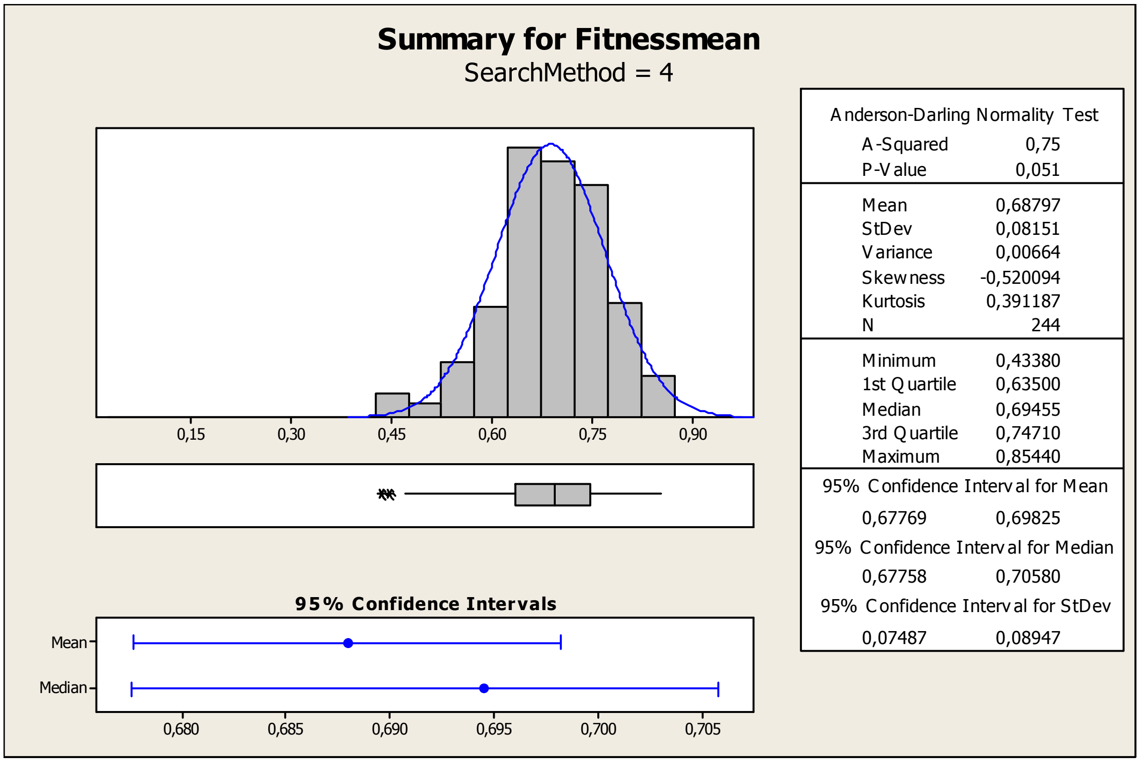
SIMULATION 71, ALL RUNS



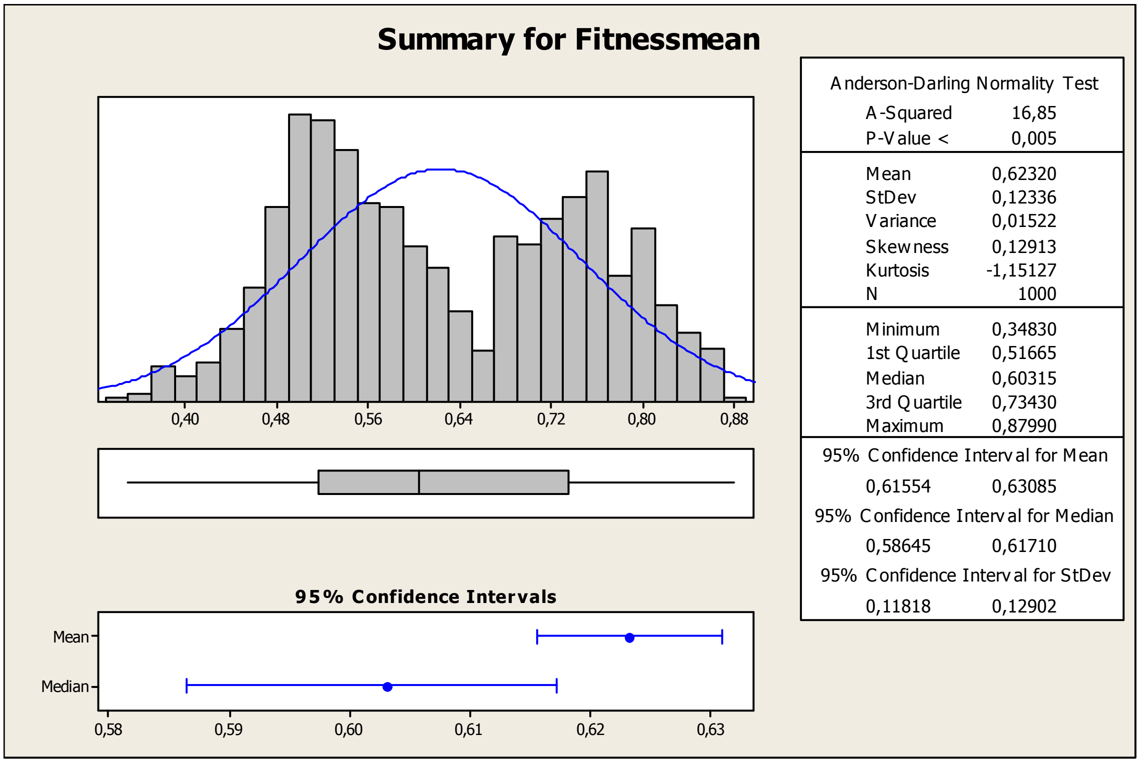


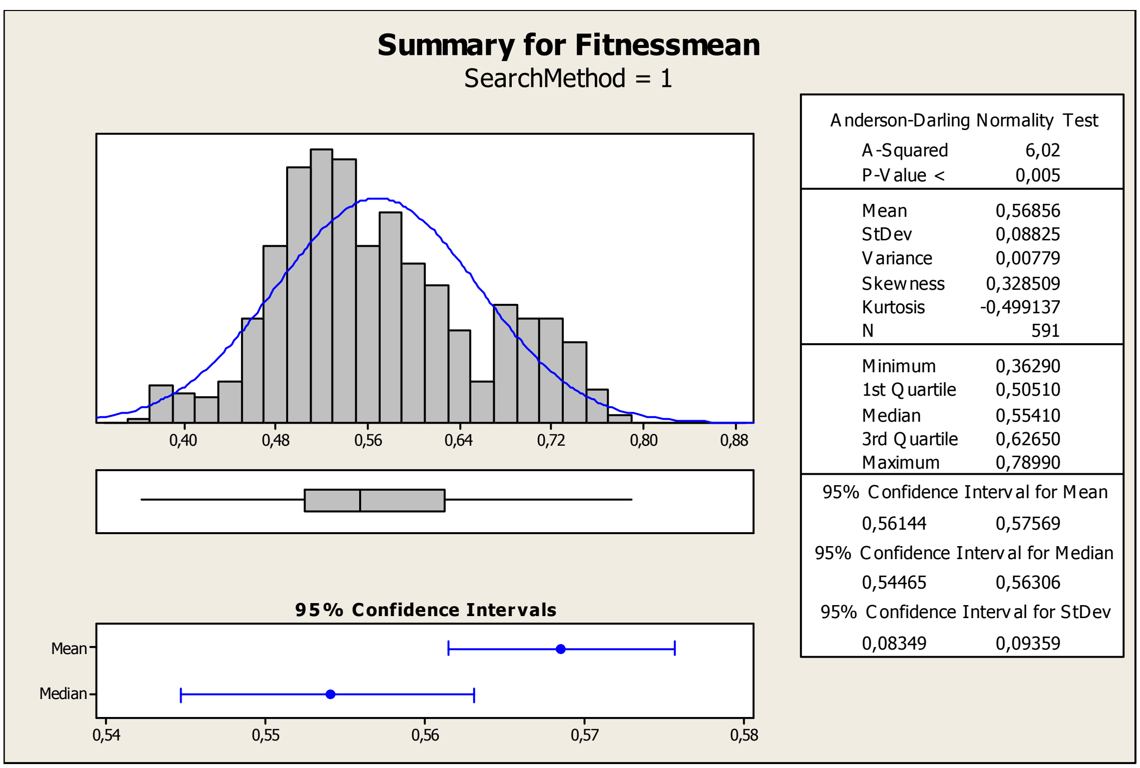

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,10
P-Value 0,007
Mean 0,79921
StDev 0,07959
Variance 0,00633
Skewness -0,616171
Kurtosis -0,235151
N 105
Minimum 0,59370
1st Quartile 0,75130
Median 0,81140
3rd Quartile 0,86850
Maximum 0,93900
95% Confidence Interval for Mean
0,78381 0,81462
95% Confidence Interval for Median
0,79103 0,83083
95% Confidence Interval for StDev
0,07009 0,09209
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,78 0,79 0,80 0,81 0,82 0,83

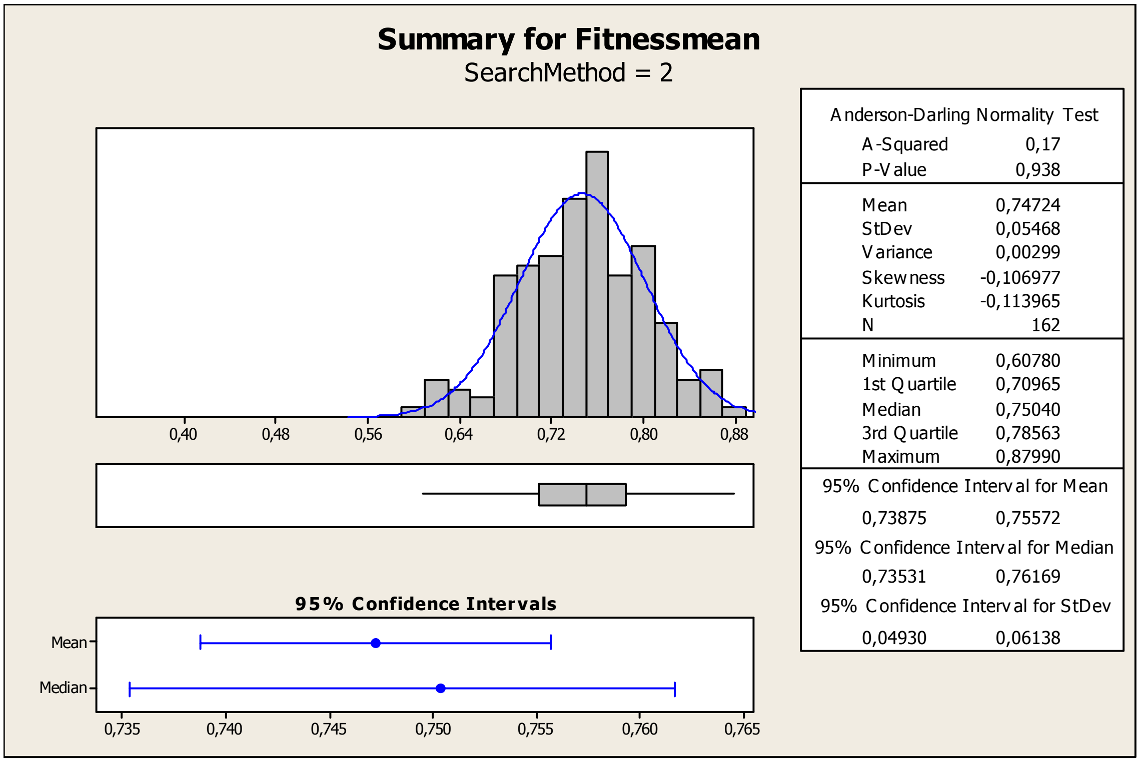

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,38
P-Value 0,410
Mean 0,30478
StDev 0,10324
Variance 0,01066
Skewness 0,170402
Kurtosis -0,401569
N 233
Minimum 0,06670
1st Quartile 0,23065
Median 0,30640
3rd Quartile 0,37375
Maximum 0,59810
95% Confidence Interval for Mean
0,29146 0,31811
95% Confidence Interval for Median
0,28365 0,31838
95% Confidence Interval for StDev
0,09464 0,11357
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,28 0,29 0,30 0,31 0,32

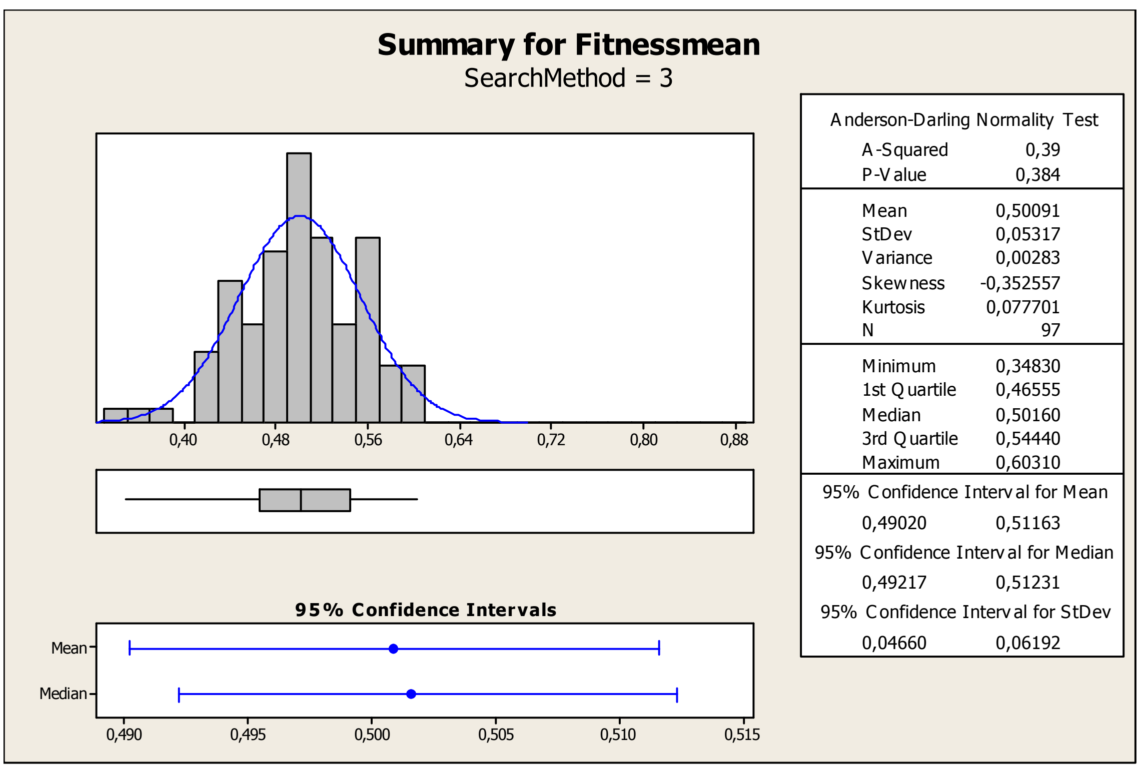

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,75
P-Value 0,051
Mean 0,68797
StDev 0,08151
Variance 0,00664
Skewness -0,520094
Kurtosis 0,391187
N 244
Minimum 0,43380
1st Quartile 0,63500
Median 0,69455
3rd Quartile 0,74710
Maximum 0,85440
95% Confidence Interval for Mean
0,67769 0,69825
95% Confidence Interval for Median
0,67758 0,70580
95% Confidence Interval for StDev
0,07487 0,08947
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,680 0,685 0,690 0,695 0,700 0,705

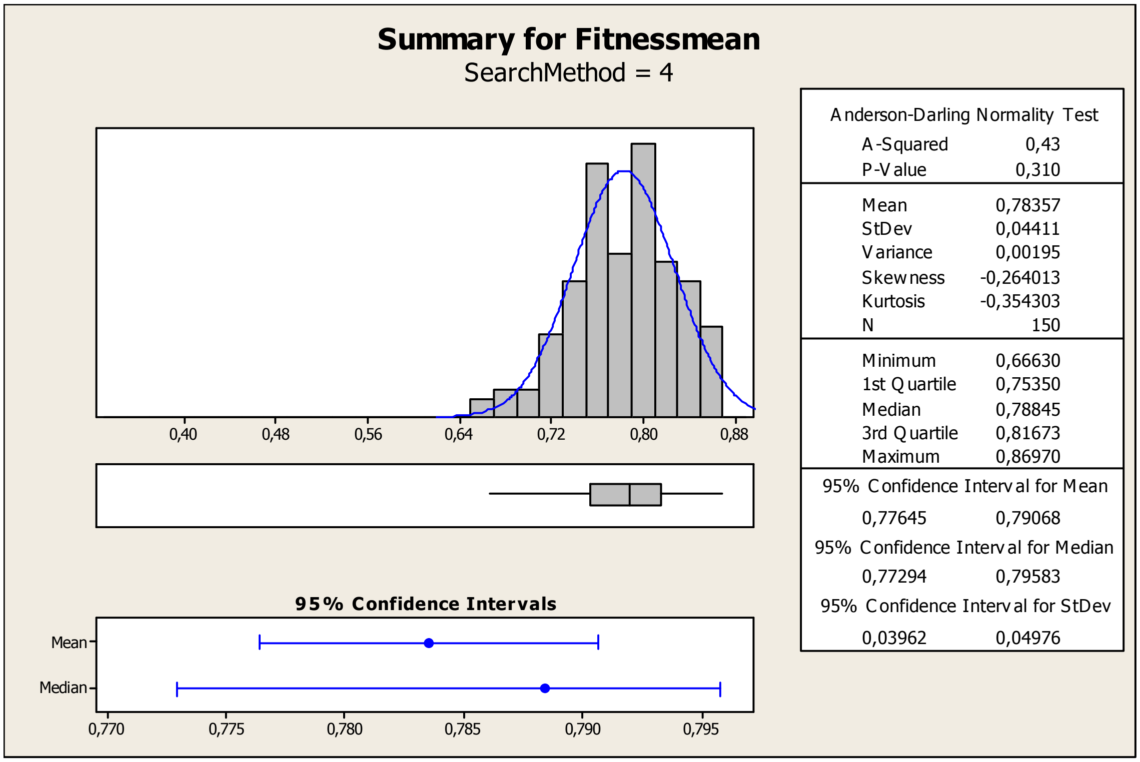
SIMULATION 72, ALL RUNS



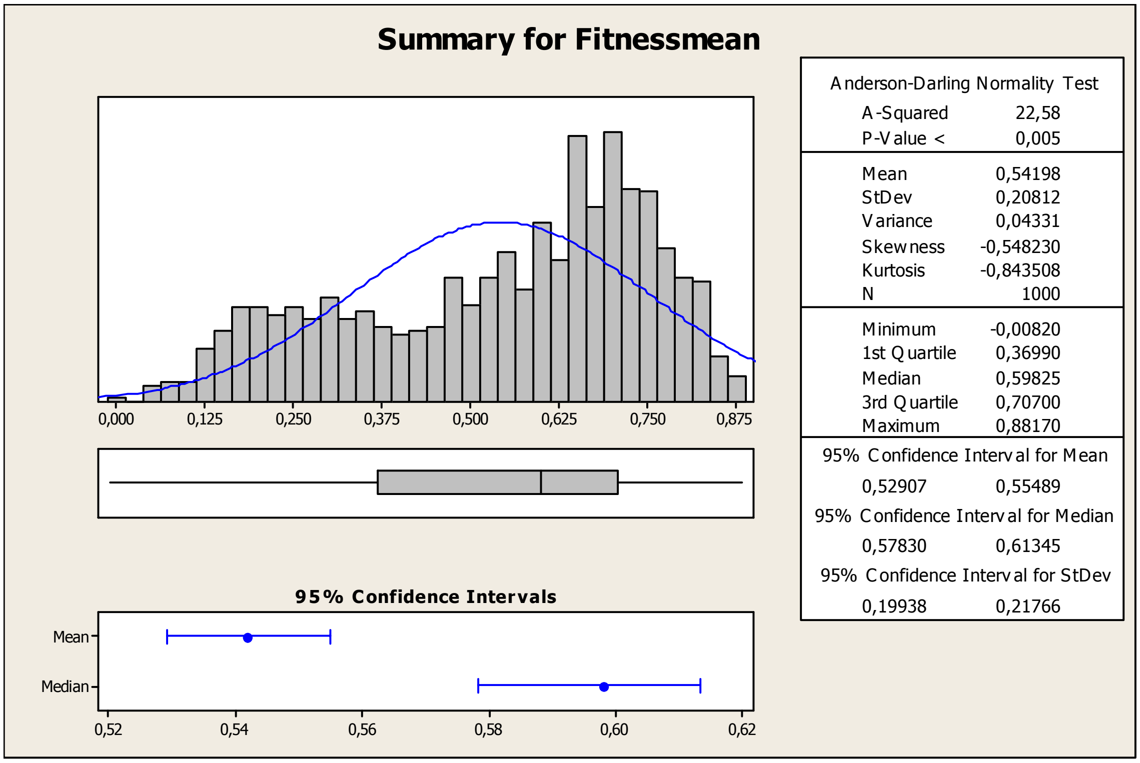


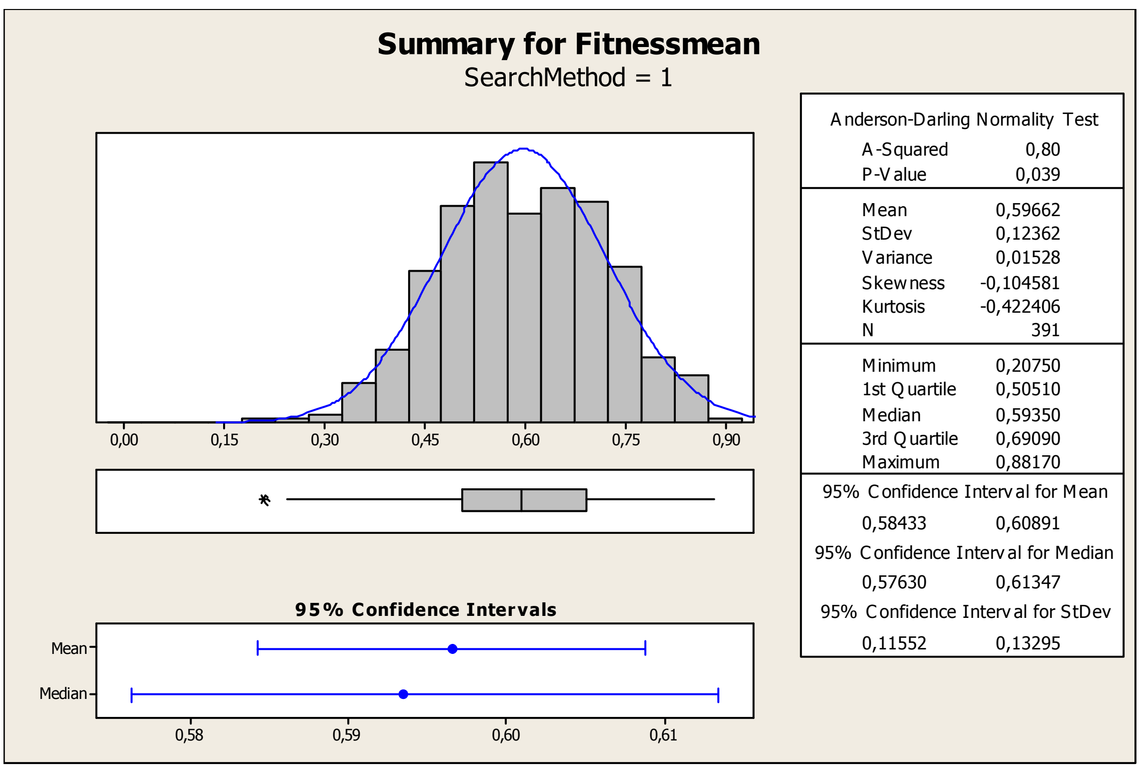

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,17
P-Value 0,938
Mean 0,74724
StDev 0,05468
Variance 0,00299
Skewness -0,106977
Kurtosis -0,113965
N 162
Minimum 0,60780
1st Quartile 0,70965
Median 0,75040
3rd Quartile 0,78563
Maximum 0,87990
95% Confidence Interval for Mean
0,73875 0,75572
95% Confidence Interval for Median
0,73531 0,76169
95% Confidence Interval for StDev
0,04930 0,06138
0,40 0,48 0,56 0,64 0,72 0,80 0,88
95% Confidence Intervals
Mean
Median
0,735 0,740 0,745 0,750 0,755 0,760 0,765

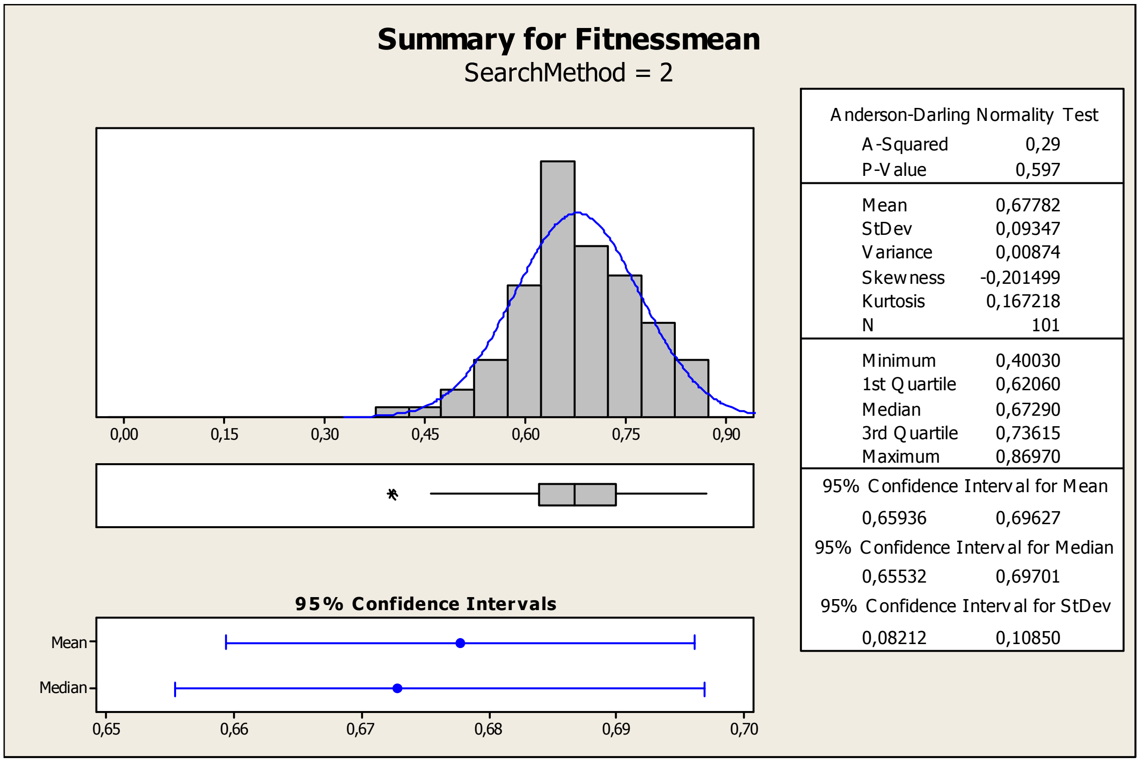

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,39
P-Value 0,384
Mean 0,50091
StDev 0,05317
Variance 0,00283
Skewness -0,352557
Kurtosis 0,077701
N 97
Minimum 0,34830
1st Quartile 0,46555
Median 0,50160
3rd Quartile 0,54440
Maximum 0,60310
95% Confidence Interval for Mean
0,49020 0,51163
95% Confidence Interval for Median
0,49217 0,51231
95% Confidence Interval for StDev
0,04660 0,06192
0,40 0,48 0,56 0,64 0,72 0,80 0,88
95% Confidence Intervals
Mean
Median
0,490 0,495 0,500 0,505 0,510 0,515

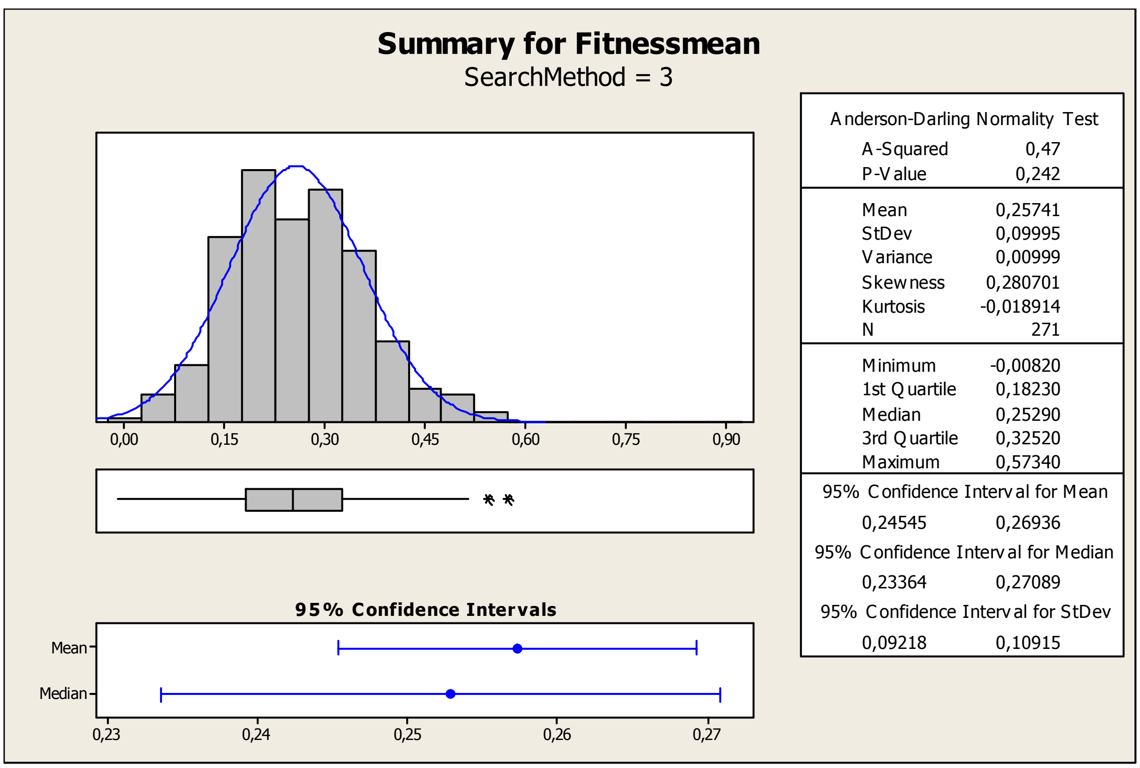

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,43
P-Value 0,310
Mean 0,78357
StDev 0,04411
Variance 0,00195
Skewness -0,264013
Kurtosis -0,354303
N 150
Minimum 0,66630
1st Quartile 0,75350
Median 0,78845
3rd Quartile 0,81673
Maximum 0,86970
95% Confidence Interval for Mean
0,77645 0,79068
95% Confidence Interval for Median
0,77294 0,79583
95% Confidence Interval for StDev
0,03962 0,04976
0,40 0,48 0,56 0,64 0,72 0,80 0,88
95% Confidence Intervals
Mean
Median
0,770 0,775 0,780 0,785 0,790 0,795

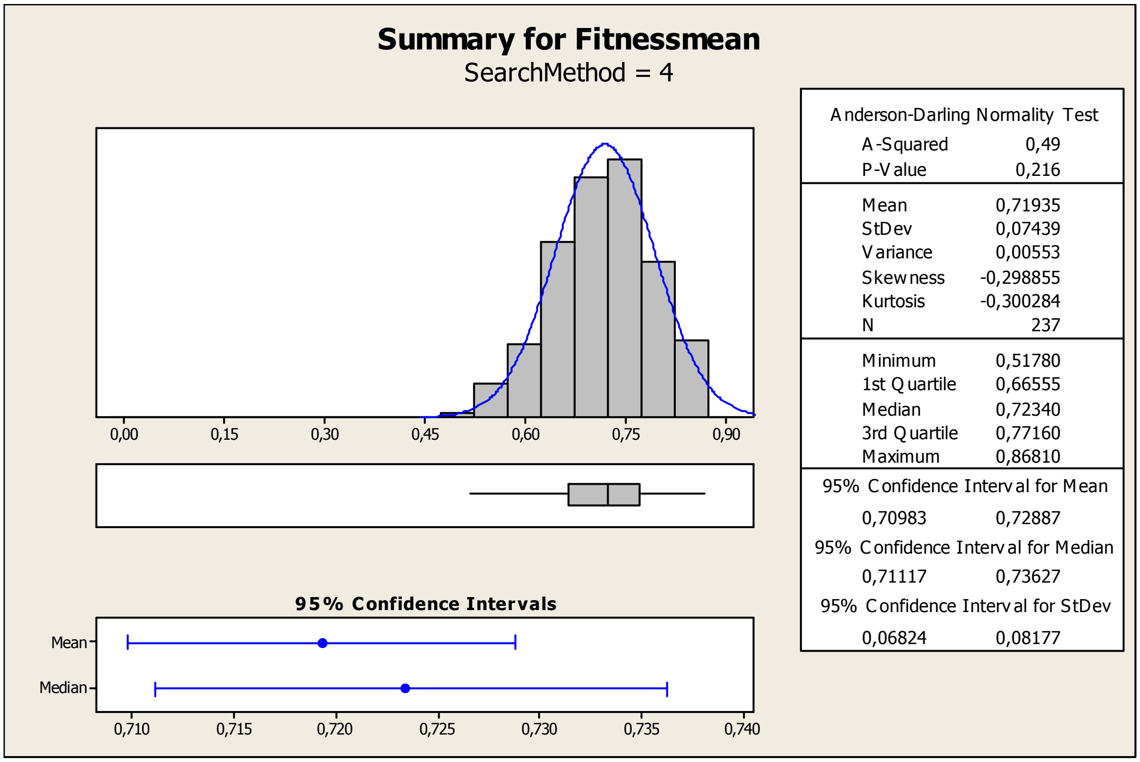
SIMULATION 73, ALL RUNS





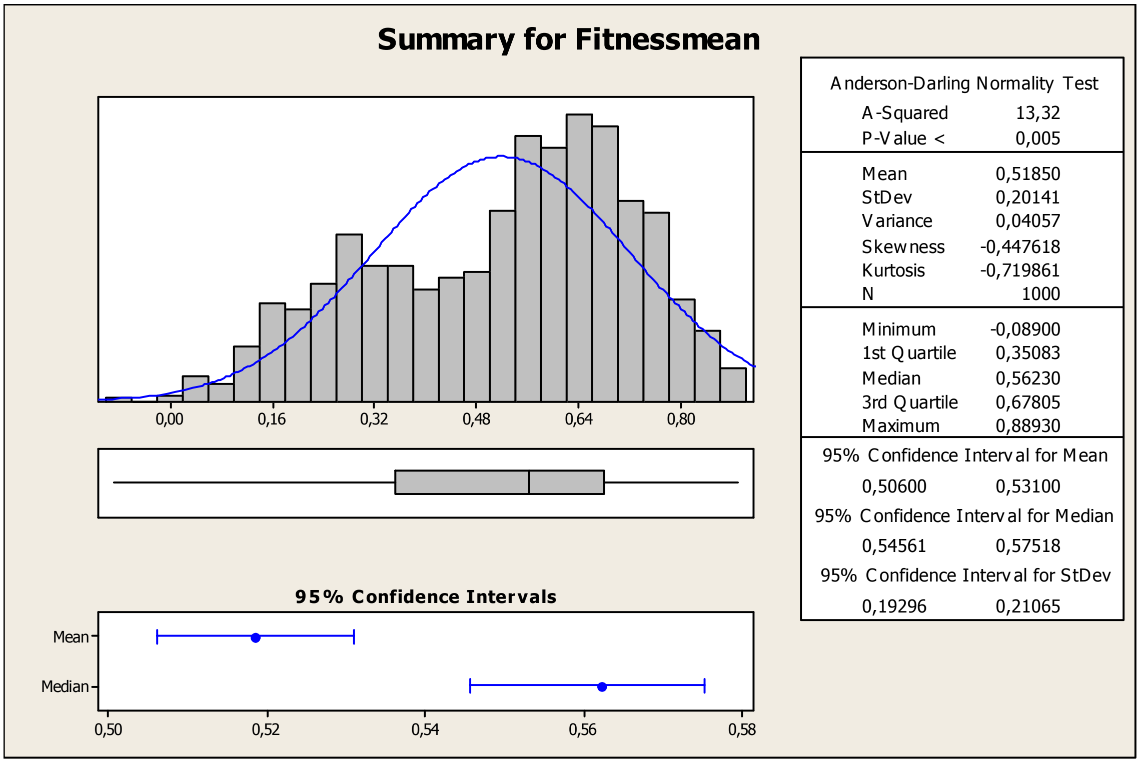

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,29
P-Value 0,597
Mean 0,67782
StDev 0,09347
Variance 0,00874
Skewness -0,201499
Kurtosis 0,167218
N 101
Minimum 0,40030
1st Quartile 0,62060
Median 0,67290
3rd Quartile 0,73615
Maximum 0,86970
95% Confidence Interval for Mean
0,65936 0,69627
95% Confidence Interval for Median
0,65532 0,69701
95% Confidence Interval for StDev
0,08212 0,10850
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,65 0,66 0,67 0,68 0,69 0,70

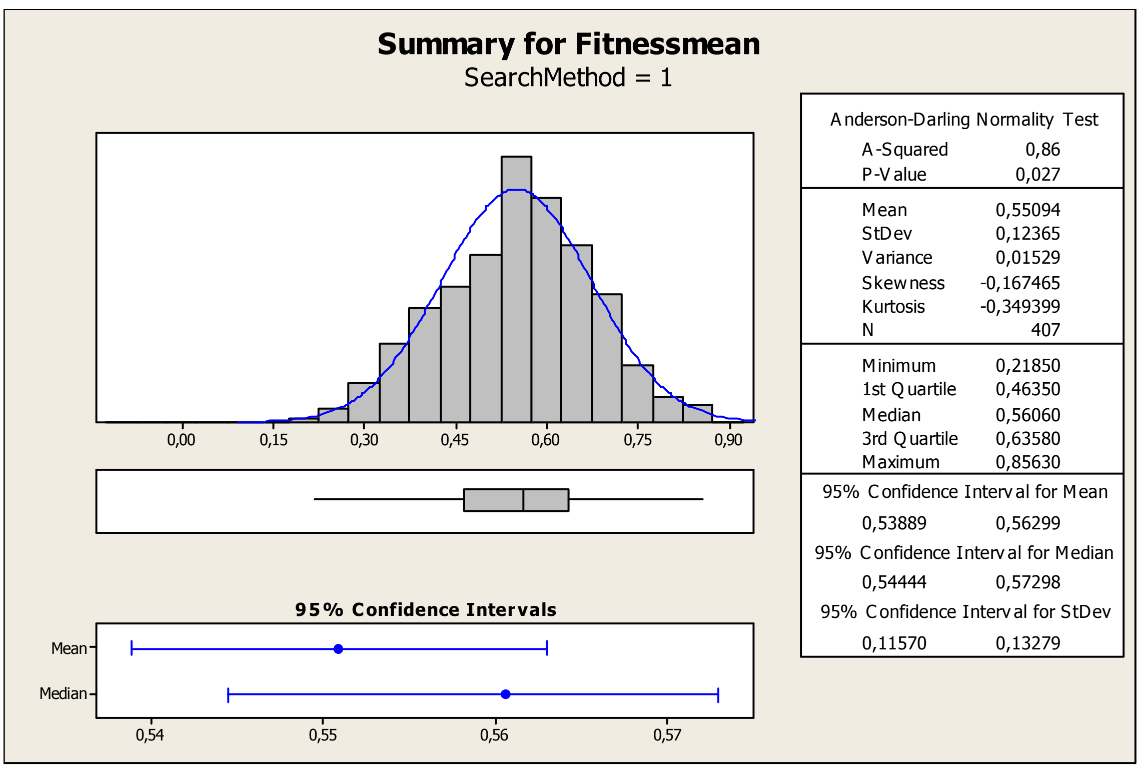

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,47
P-Value 0,242
Mean 0,25741
StDev 0,09995
Variance 0,00999
Skewness 0,280701
Kurtosis -0,018914
N 271
Minimum -0,00820
1st Quartile 0,18230
Median 0,25290
3rd Quartile 0,32520
Maximum 0,57340
95% Confidence Interval for Mean
0,24545 0,26936
95% Confidence Interval for Median
0,23364 0,27089
95% Confidence Interval for StDev
0,09218 0,10915
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,23 0,24 0,25 0,26 0,27

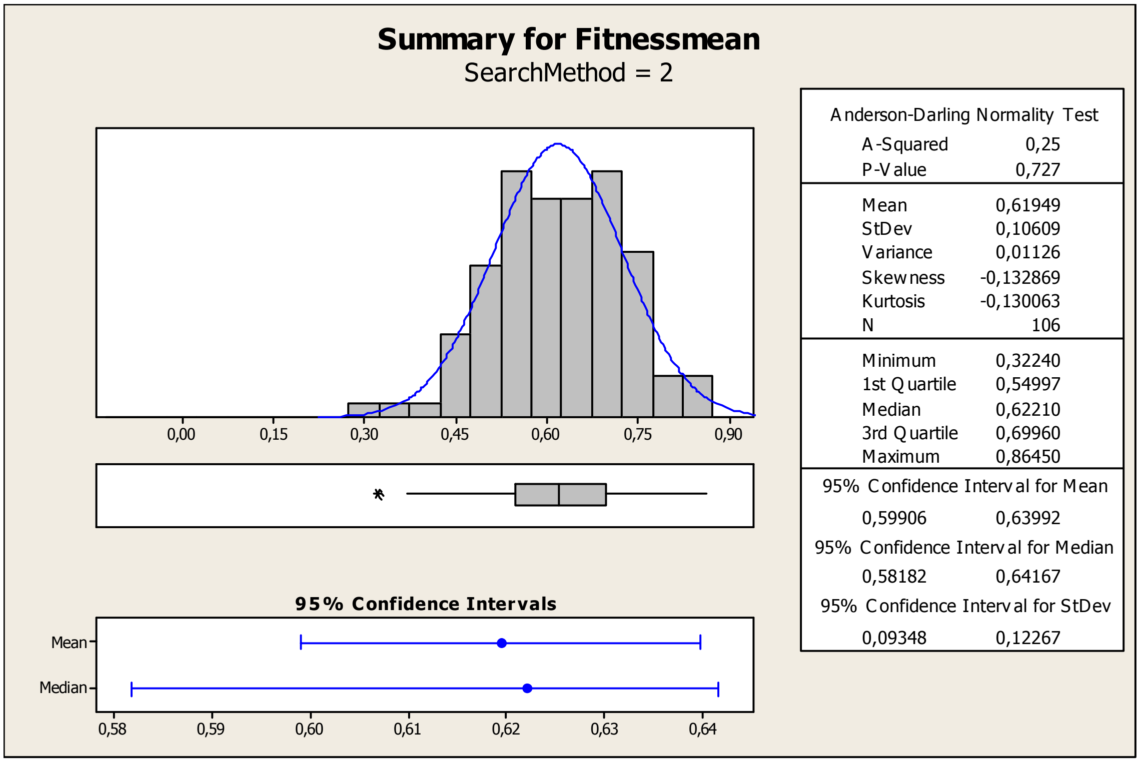


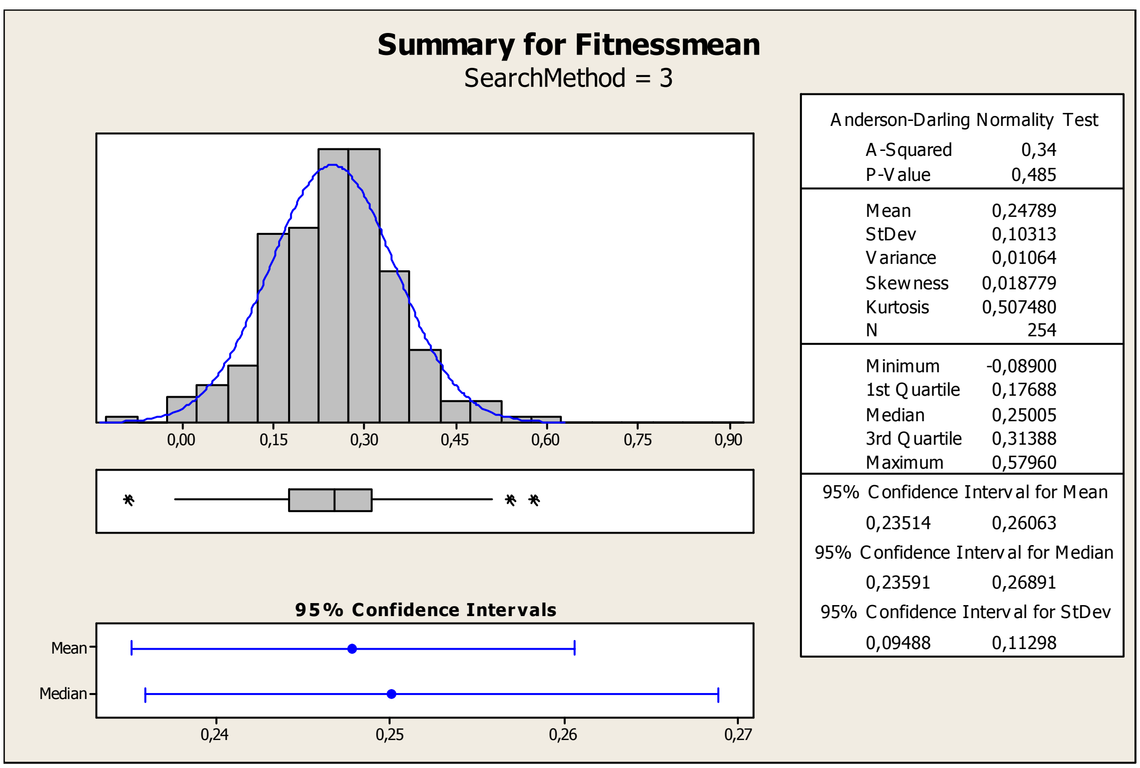
Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,49
P-Value 0,216
Mean 0,71935
StDev 0,07439
Variance 0,00553
Skewness -0,298855
Kurtosis -0,300284
N 237
Minimum 0,51780
1st Quartile 0,66555
Median 0,72340
3rd Quartile 0,77160
Maximum 0,86810
95% Confidence Interval for Mean
0,70983 0,72887
95% Confidence Interval for Median
0,71117 0,73627
95% Confidence Interval for StDev
0,06824 0,08177
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,710 0,715 0,720 0,725 0,730 0,735 0,740

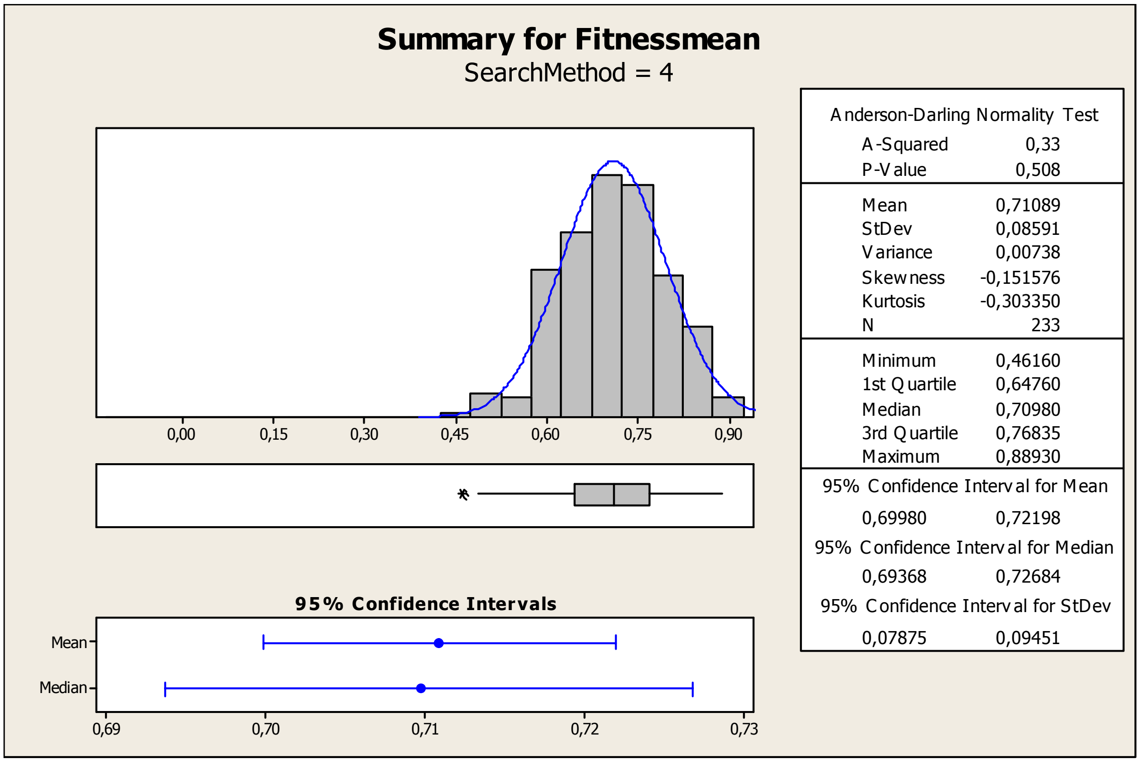
SIMULATION 74, ALL RUNS



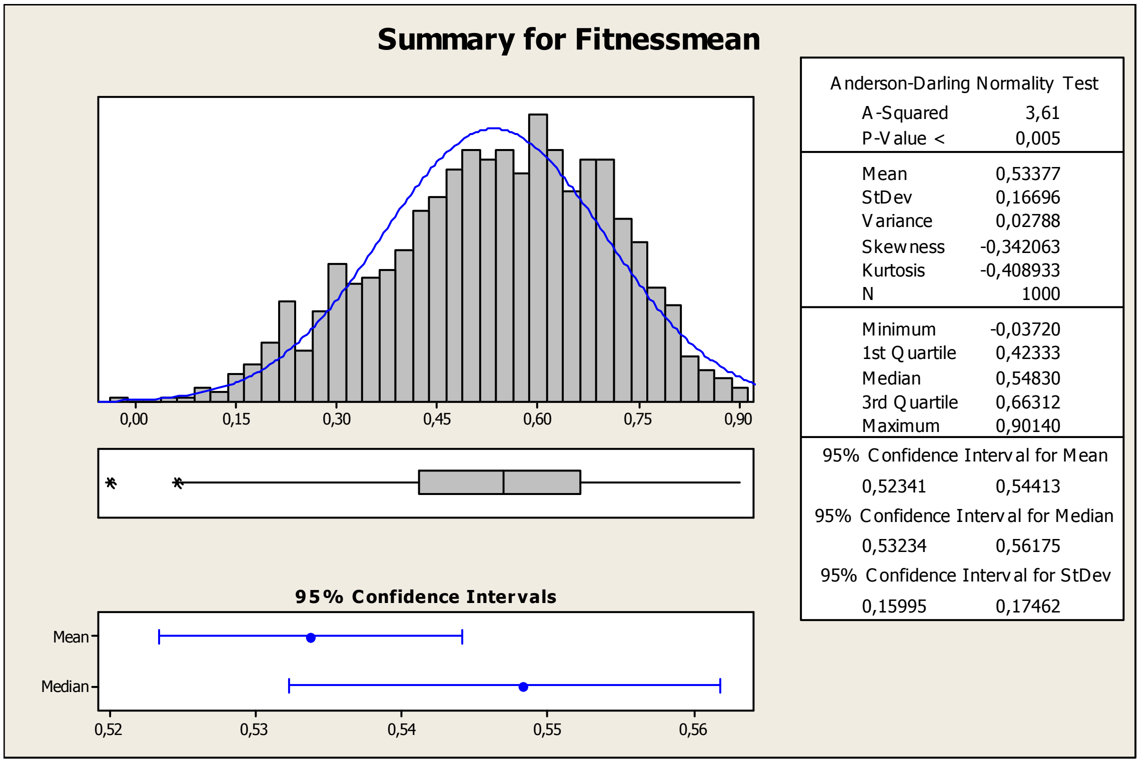


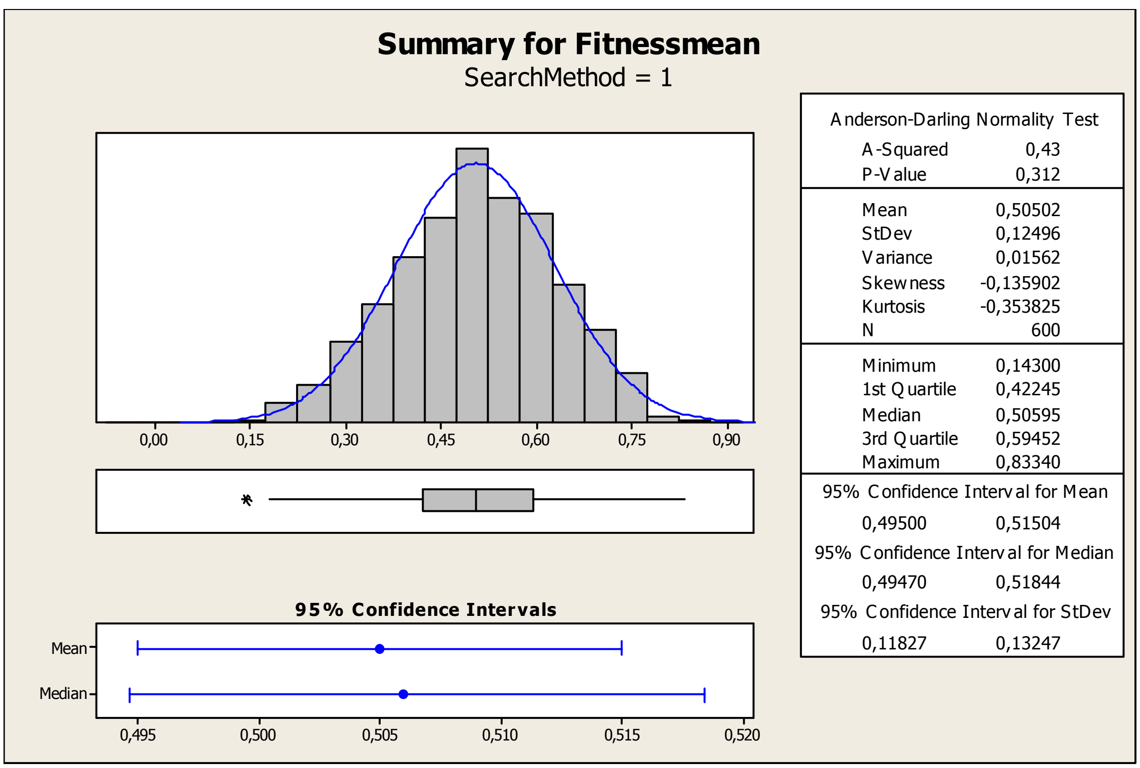

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,25
P-Value 0,727
Mean 0,61949
StDev 0,10609
Variance 0,01126
Skewness -0,132869
Kurtosis -0,130063
N 106
Minimum 0,32240
1st Quartile 0,54997
Median 0,62210
3rd Quartile 0,69960
Maximum 0,86450
95% Confidence Interval for Mean
0,59906 0,63992
95% Confidence Interval for Median
0,58182 0,64167
95% Confidence Interval for StDev
0,09348 0,12267
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,58 0,59 0,60 0,61 0,62 0,63 0,64

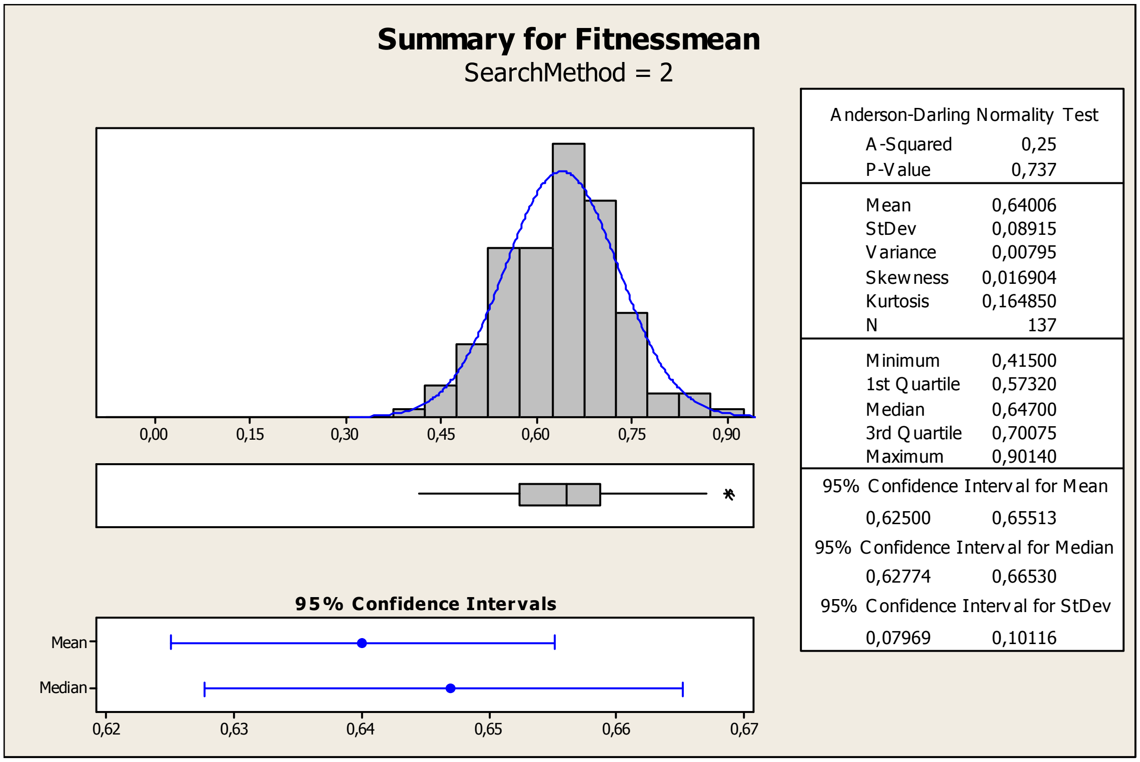

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,34
P-Value 0,485
Mean 0,24789
StDev 0,10313
Variance 0,01064
Skewness 0,018779
Kurtosis 0,507480
N 254
Minimum -0,08900
1st Quartile 0,17688
Median 0,25005
3rd Quartile 0,31388
Maximum 0,57960
95% Confidence Interval for Mean
0,23514 0,26063
95% Confidence Interval for Median
0,23591 0,26891
95% Confidence Interval for StDev
0,09488 0,11298
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,24 0,25 0,26 0,27

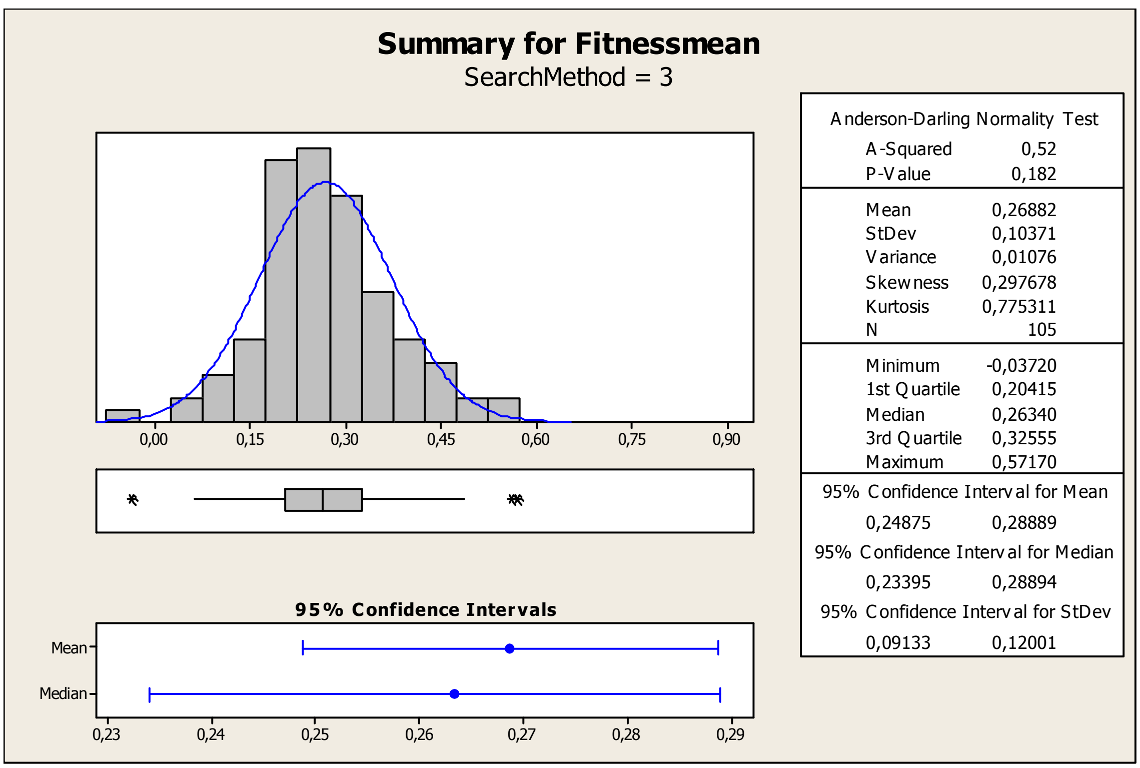

Summary for Fitnessmean
SearchMethod = 4
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,69
0,70
0,71
0,72
0,73
Anderson-Darling Normality Test
A-Squared 0,33
P-Value 0,508
Mean 0,71089
StDev 0,08591
Variance 0,00738
Skewness -0,151576
Kurtosis -0,303350
N 233
Minimum 0,46160
1st Quartile 0,64760
Median 0,70980
3rd Quartile 0,76835
Maximum 0,88930
95% Confidence Interval for Mean
0,69980 0,72198
95% Confidence Interval for Median
0,69368 0,72684
95% Confidence Interval for StDev
0,07875 0,09451

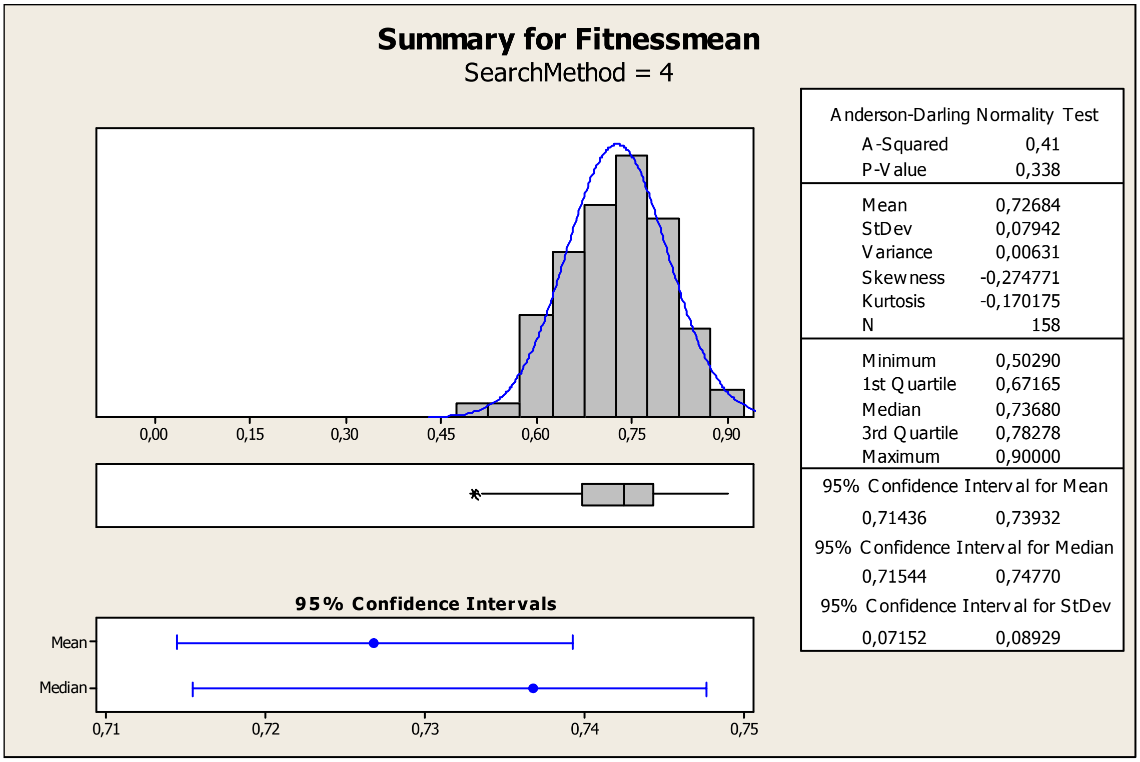
SIMULATION 75, ALL RUNS



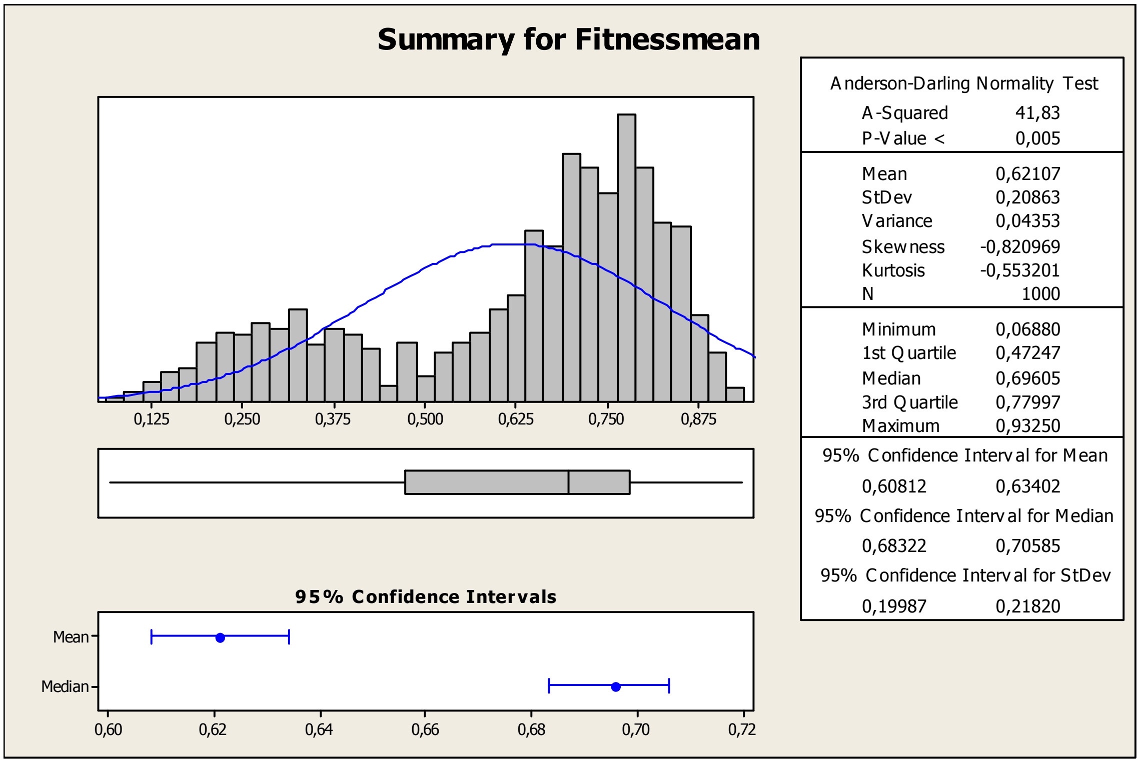


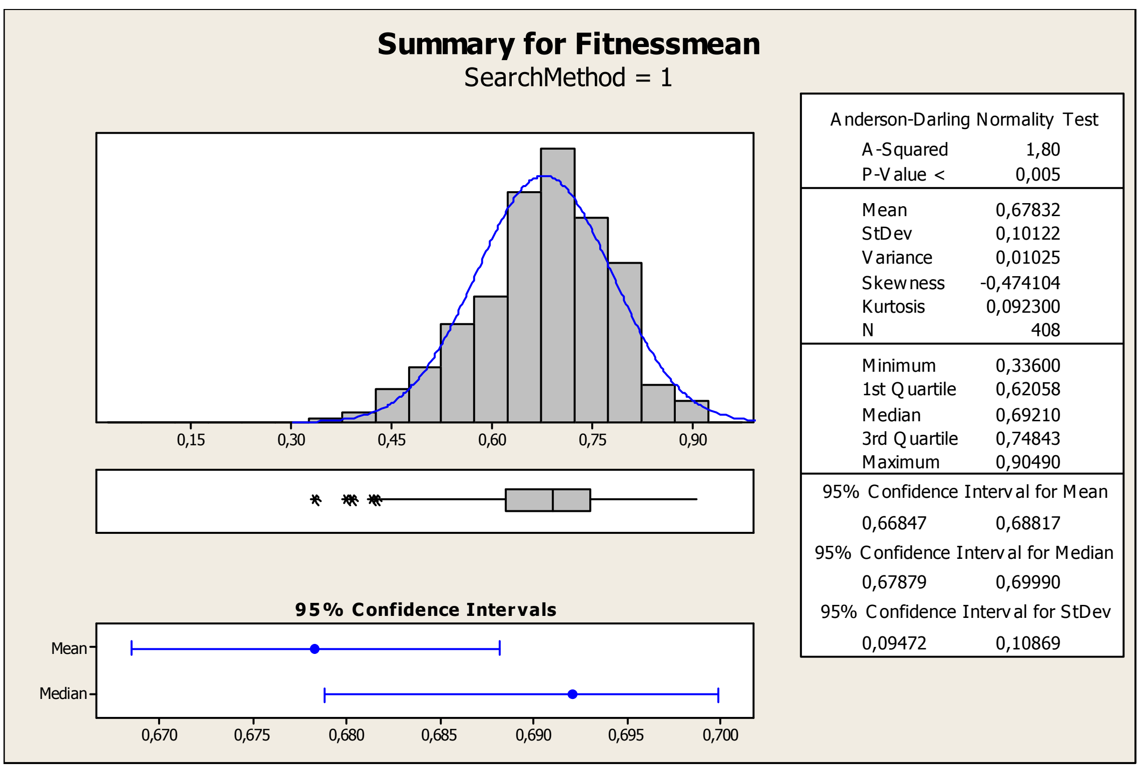

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,25
P-Value 0,737
Mean 0,64006
StDev 0,08915
Variance 0,00795
Skewness 0,016904
Kurtosis 0,164850
N 137
Minimum 0,41500
1st Quartile 0,57320
Median 0,64700
3rd Quartile 0,70075
Maximum 0,90140
95% Confidence Interval for Mean
0,62500 0,65513
95% Confidence Interval for Median
0,62774 0,66530
95% Confidence Interval for StDev
0,07969 0,10116
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,62 0,63 0,64 0,65 0,66 0,67

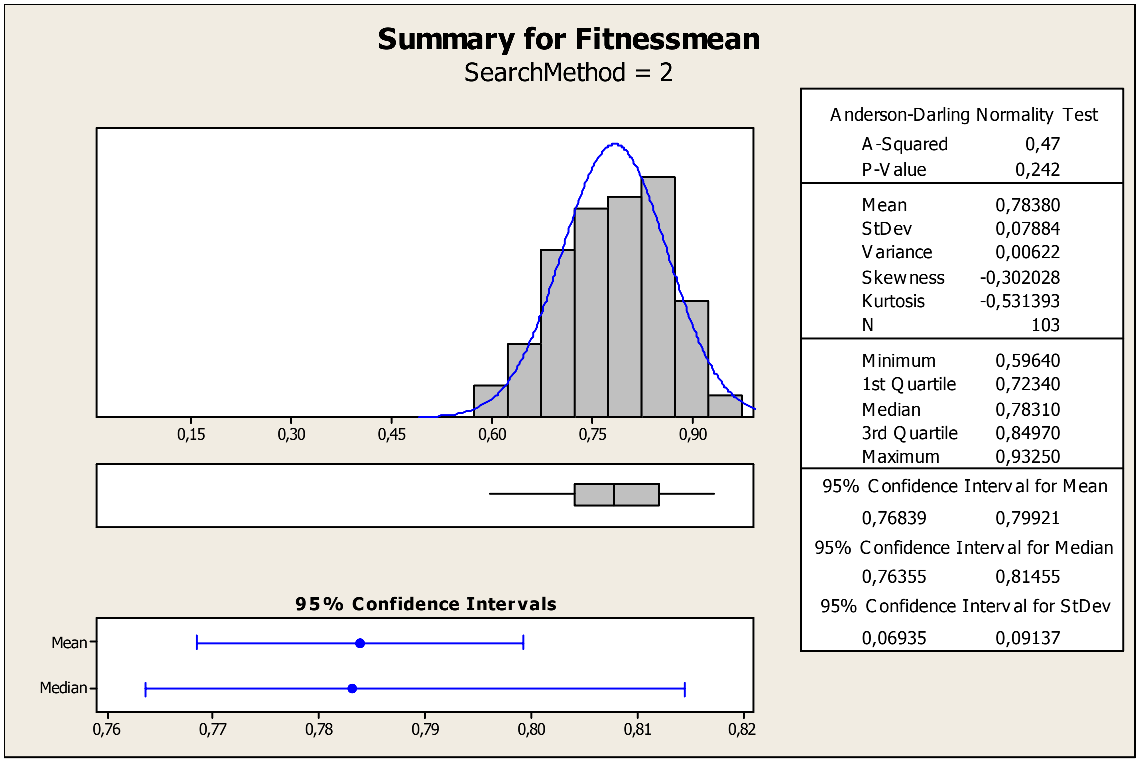

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,52
P-Value 0,182
Mean 0,26882
StDev 0,10371
Variance 0,01076
Skewness 0,297678
Kurtosis 0,775311
N 105
Minimum -0,03720
1st Quartile 0,20415
Median 0,26340
3rd Quartile 0,32555
Maximum 0,57170
95% Confidence Interval for Mean
0,24875 0,28889
95% Confidence Interval for Median
0,23395 0,28894
95% Confidence Interval for StDev
0,09133 0,12001
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,23 0,24 0,25 0,26 0,27 0,28 0,29

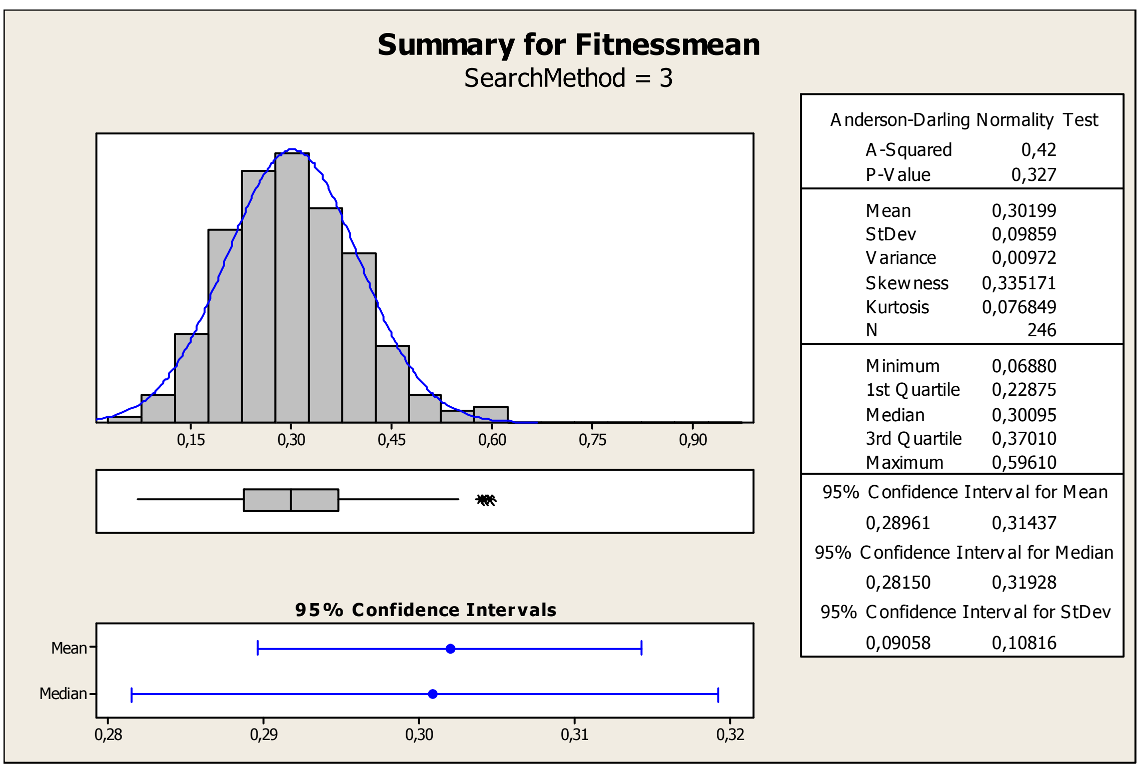

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,41
P-Value 0,338
Mean 0,72684
StDev 0,07942
Variance 0,00631
Skewness -0,274771
Kurtosis -0,170175
N 158
Minimum 0,50290
1st Quartile 0,67165
Median 0,73680
3rd Quartile 0,78278
Maximum 0,90000
95% Confidence Interval for Mean
0,71436 0,73932
95% Confidence Interval for Median
0,71544 0,74770
95% Confidence Interval for StDev
0,07152 0,08929
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,71 0,72 0,73 0,74 0,75

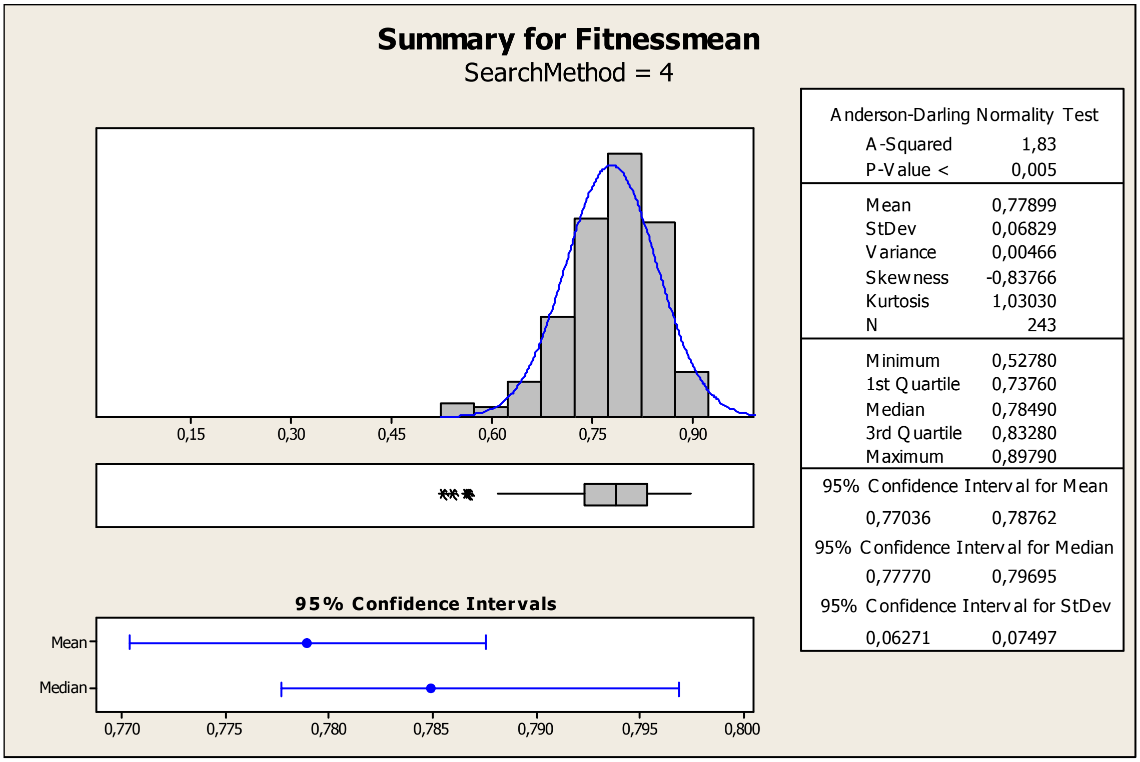
SIMULATION 76, ALL RUNS



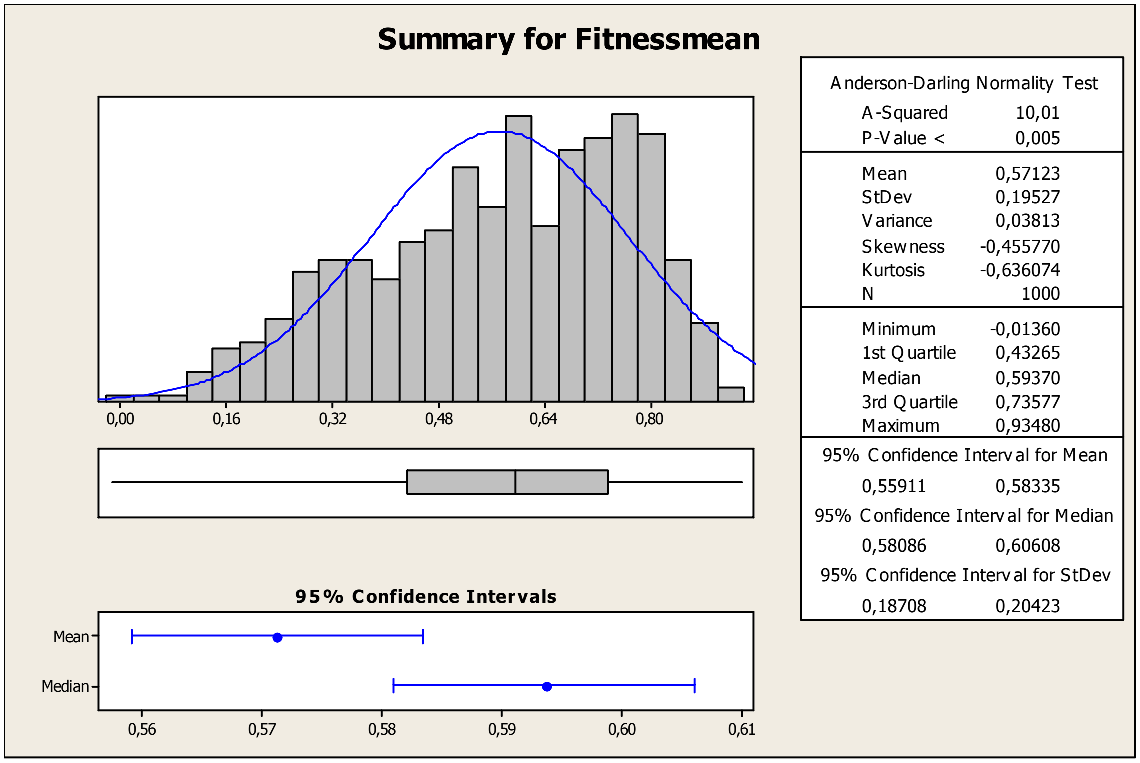


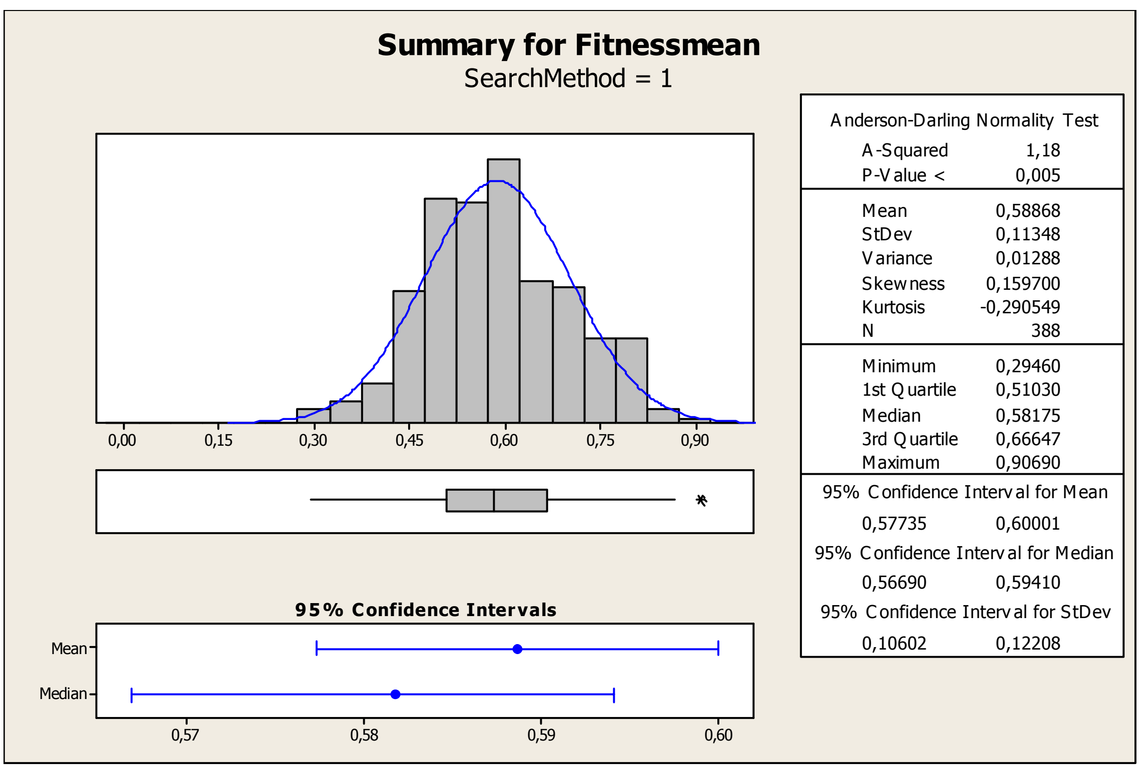

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,47
P-Value 0,242
Mean 0,78380
StDev 0,07884
Variance 0,00622
Skewness -0,302028
Kurtosis -0,531393
N 103
Minimum 0,59640
1st Quartile 0,72340
Median 0,78310
3rd Quartile 0,84970
Maximum 0,93250
95% Confidence Interval for Mean
0,76839 0,79921
95% Confidence Interval for Median
0,76355 0,81455
95% Confidence Interval for StDev
0,06935 0,09137
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,76 0,77 0,78 0,79 0,80 0,81 0,82

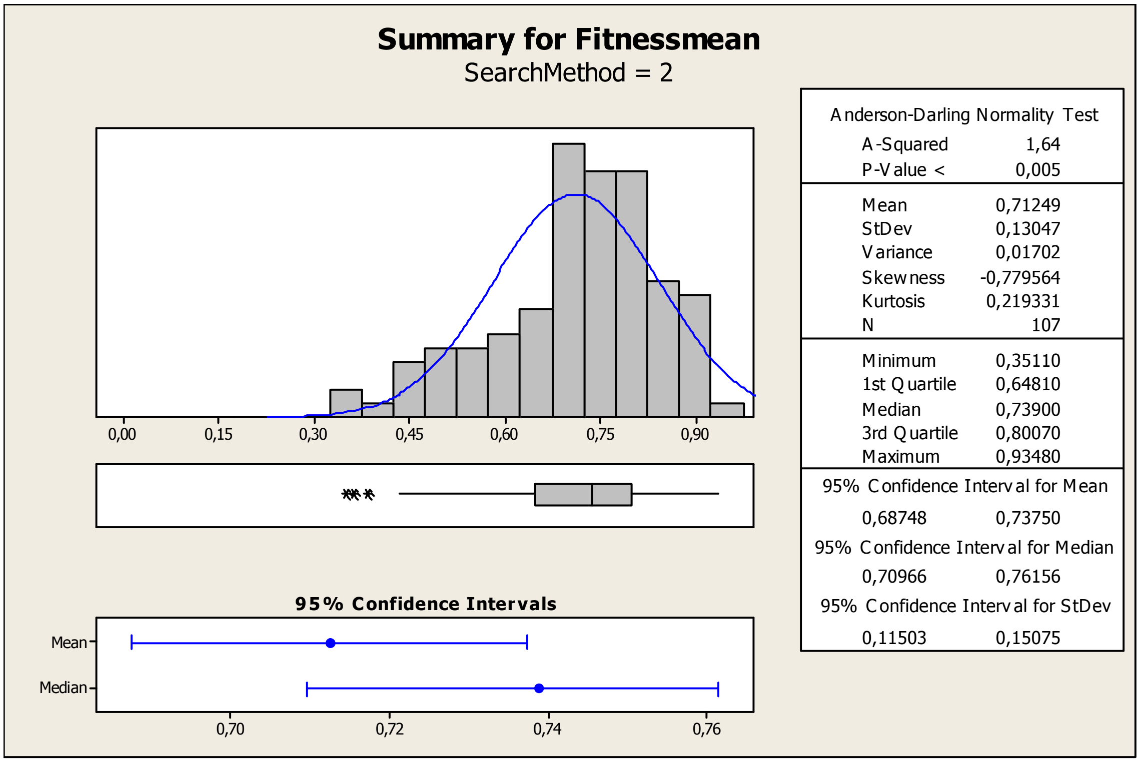

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,42
P-Value 0,327
Mean 0,30199
StDev 0,09859
Variance 0,00972
Skewness 0,335171
Kurtosis 0,076849
N 246
Minimum 0,06880
1st Quartile 0,22875
Median 0,30095
3rd Quartile 0,37010
Maximum 0,59610
95% Confidence Interval for Mean
0,28961 0,31437
95% Confidence Interval for Median
0,28150 0,31928
95% Confidence Interval for StDev
0,09058 0,10816
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,28 0,29 0,30 0,31 0,32

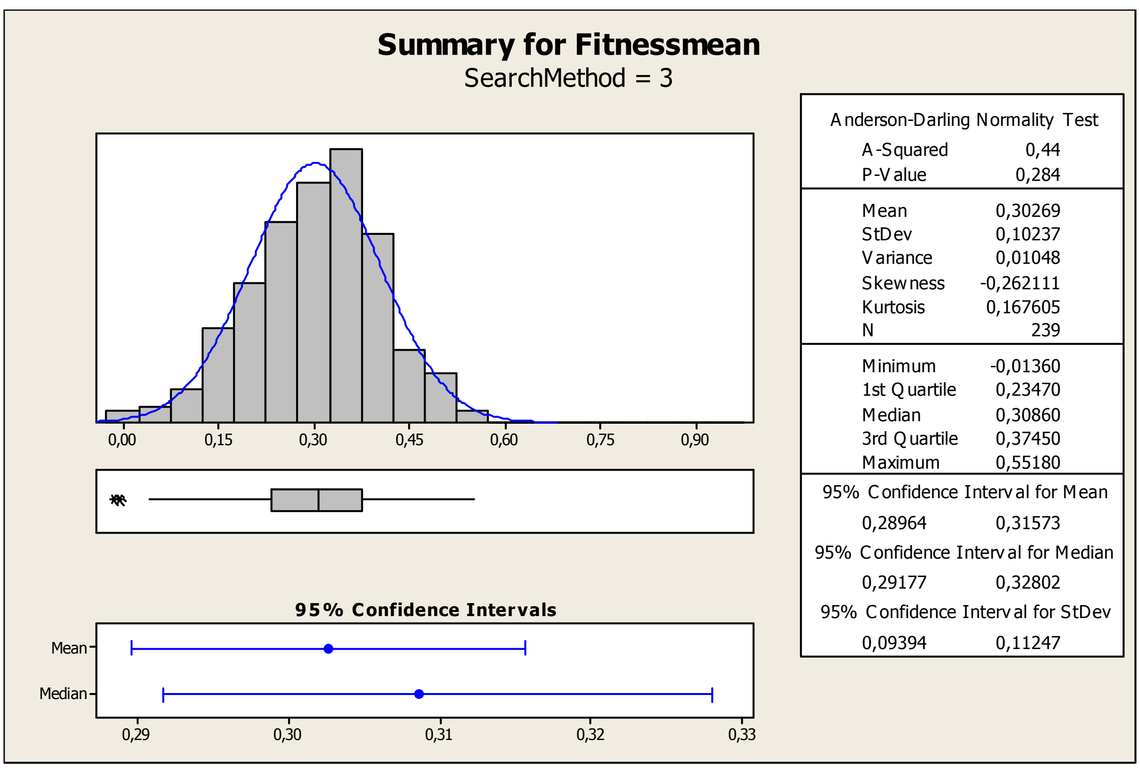

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,83
P-Value < 0,005
Mean 0,77899
StDev 0,06829
Variance 0,00466
Skewness -0,83766
Kurtosis 1,03030
N 243
Minimum 0,52780
1st Quartile 0,73760
Median 0,78490
3rd Quartile 0,83280
Maximum 0,89790
95% Confidence Interval for Mean
0,77036 0,78762
95% Confidence Interval for Median
0,77770 0,79695
95% Confidence Interval for StDev
0,06271 0,07497
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,770
0,775
0,780
0,785
0,790
0,795
0,800

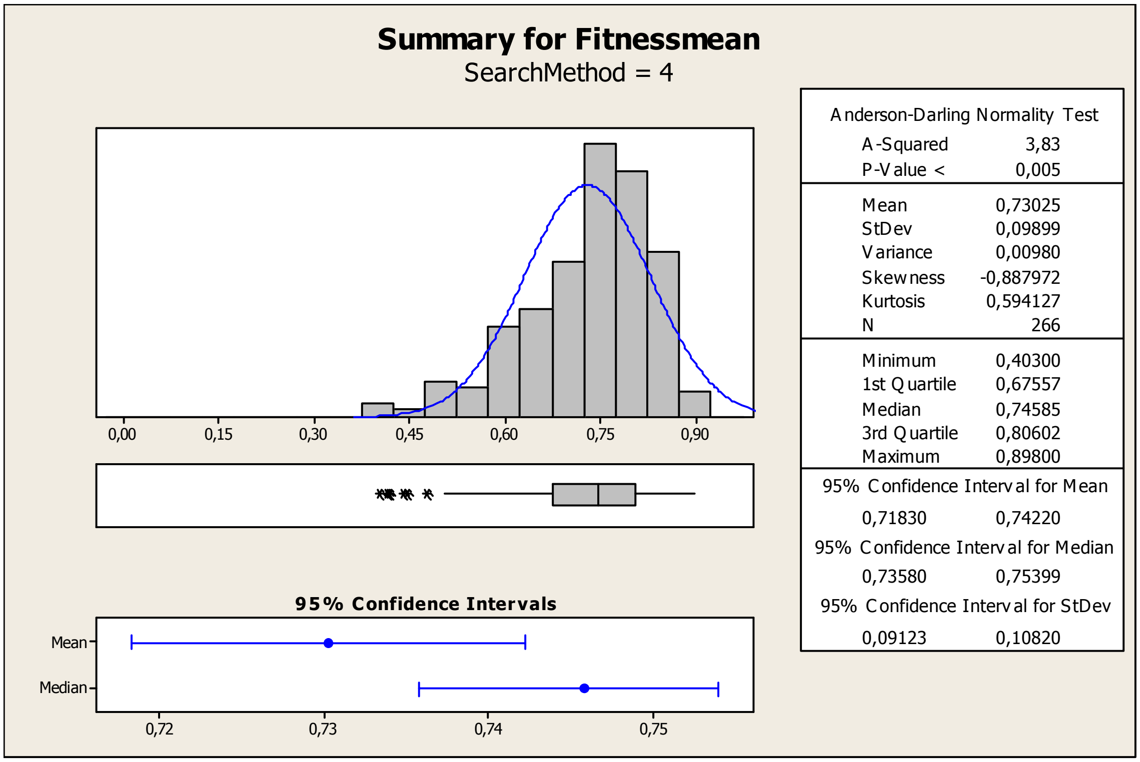
SIMULATION 77, ALL RUNS



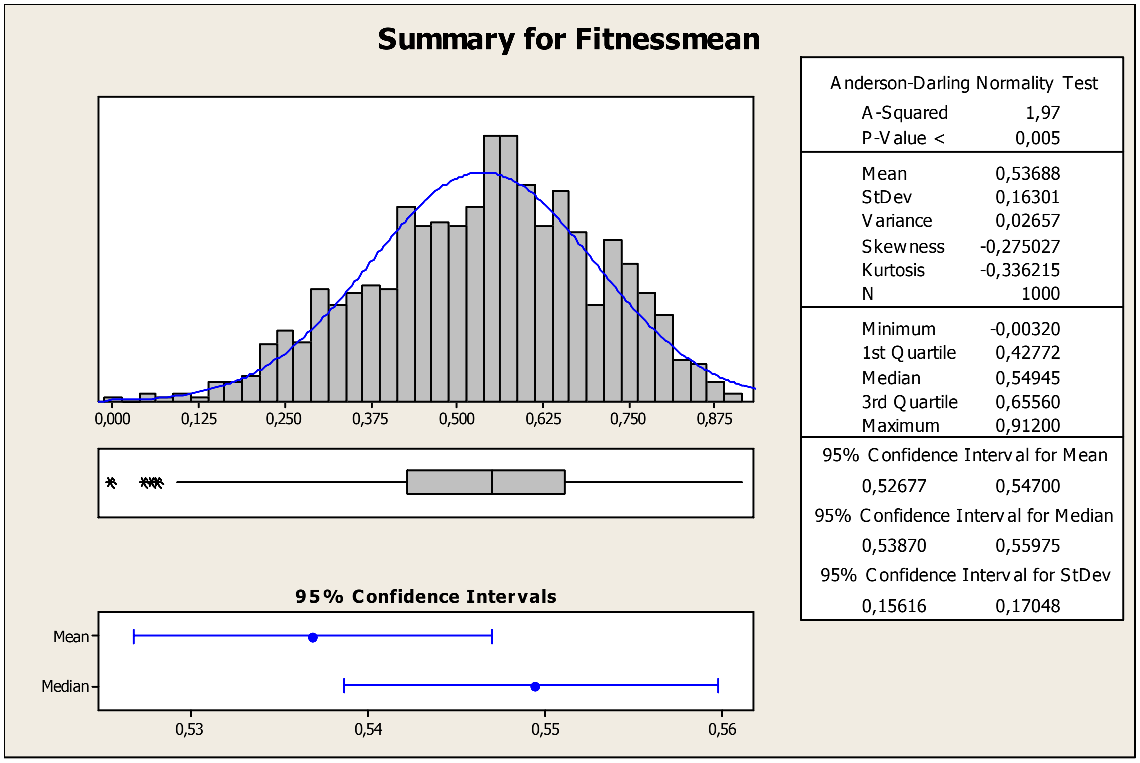


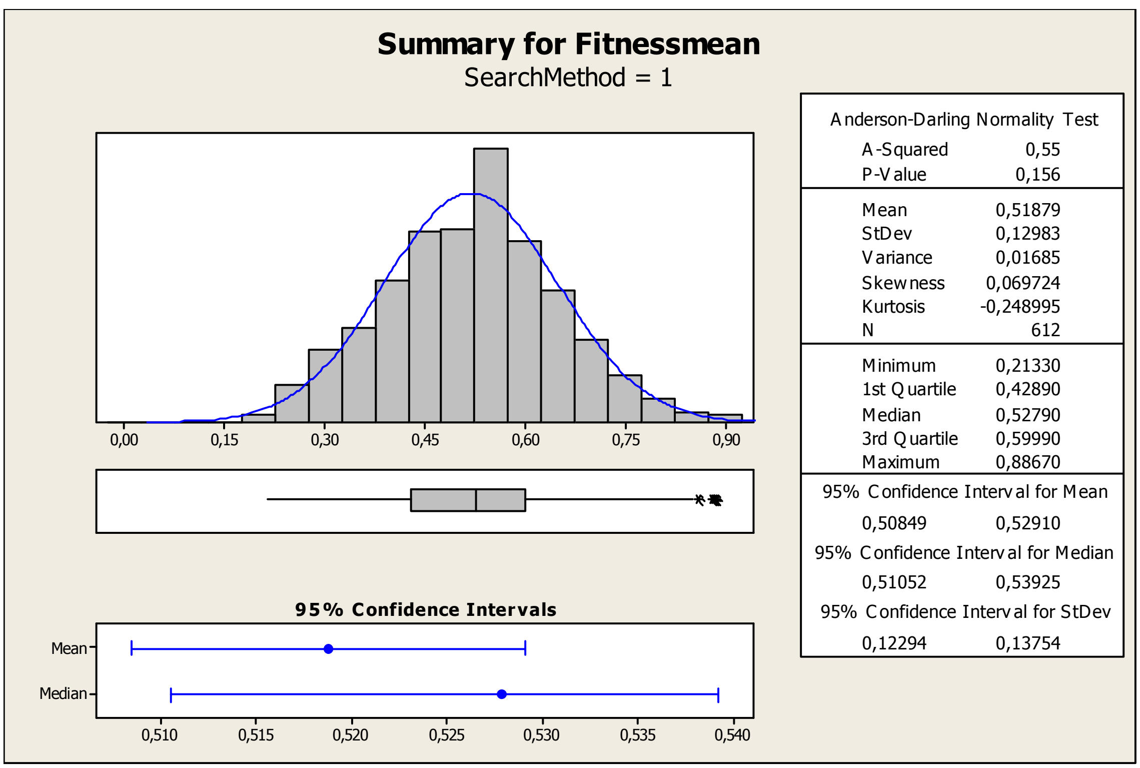

Summary for Fitnessmean
SearchMethod = 2
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,70
0,72
0,74
0,76
Anderson-Darling Normality Test
A-Squared 1,64
P-Value < 0,005
Mean 0,71249
StDev 0,13047
Variance 0,01702
Skewness -0,779564
Kurtosis 0,219331
N 107
Minimum 0,35110
1st Quartile 0,64810
Median 0,73900
3rd Quartile 0,80070
Maximum 0,93480
95% Confidence Interval for Mean
0,68748 0,73750
95% Confidence Interval for Median
0,70966 0,76156
95% Confidence Interval for StDev
0,11503 0,15075

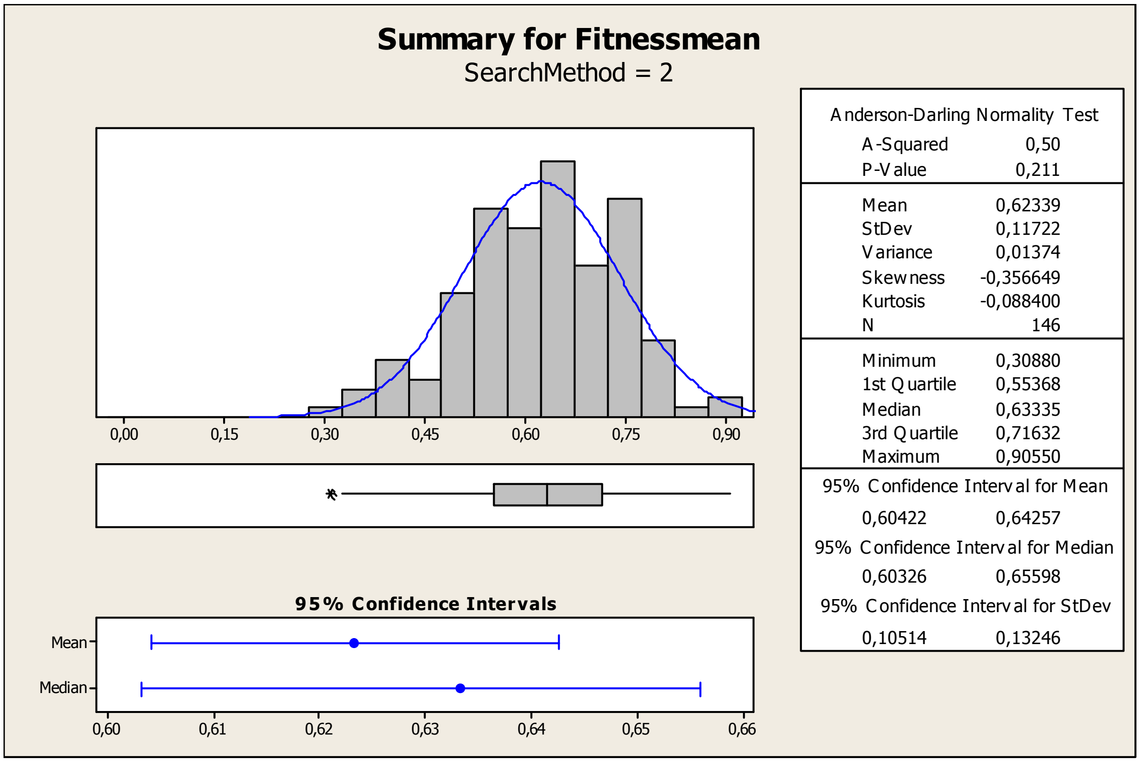

Summary for Fitnessmean
SearchMethod = 3
0,00
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,29
0,30
0,31
0,32
0,33
Anderson-Darling Normality Test
A-Squared 0,44
P-Value 0,284
Mean 0,30269
StDev 0,10237
Variance 0,01048
Skewness -0,262111
Kurtosis 0,167605
N 239
Minimum -0,01360
1st Quartile 0,23470
Median 0,30860
3rd Quartile 0,37450
Maximum 0,55180
95% Confidence Interval for Mean
0,28964 0,31573
95% Confidence Interval for Median
0,29177 0,32802
95% Confidence Interval for StDev
0,09394 0,11247

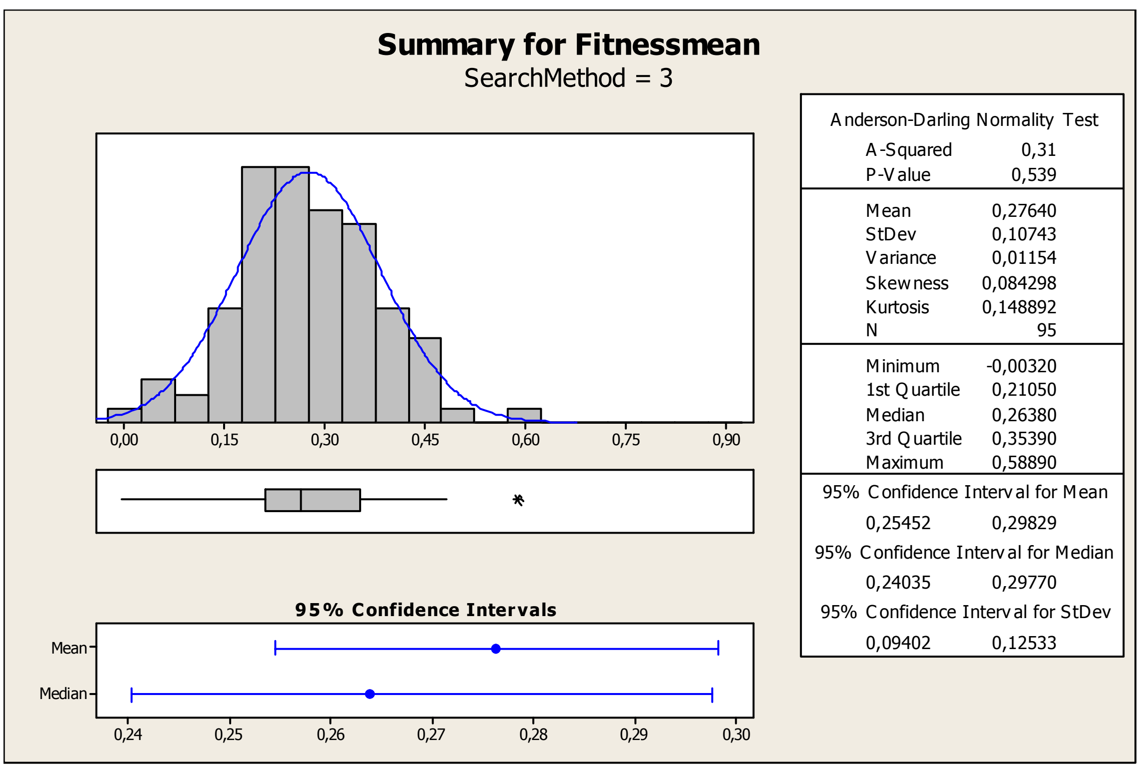

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 3,83
P-Value < 0,005
Mean 0,73025
StDev 0,09899
Variance 0,00980
Skewness -0,887972
Kurtosis 0,594127
N 266
Minimum 0,40300
1st Quartile 0,67557
Median 0,74585
3rd Quartile 0,80602
Maximum 0,89800
95% Confidence Interval for Mean
0,71830 0,74220
95% Confidence Interval for Median
0,73580 0,75399
95% Confidence Interval for StDev
0,09123 0,10820
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,72 0,73 0,74 0,75

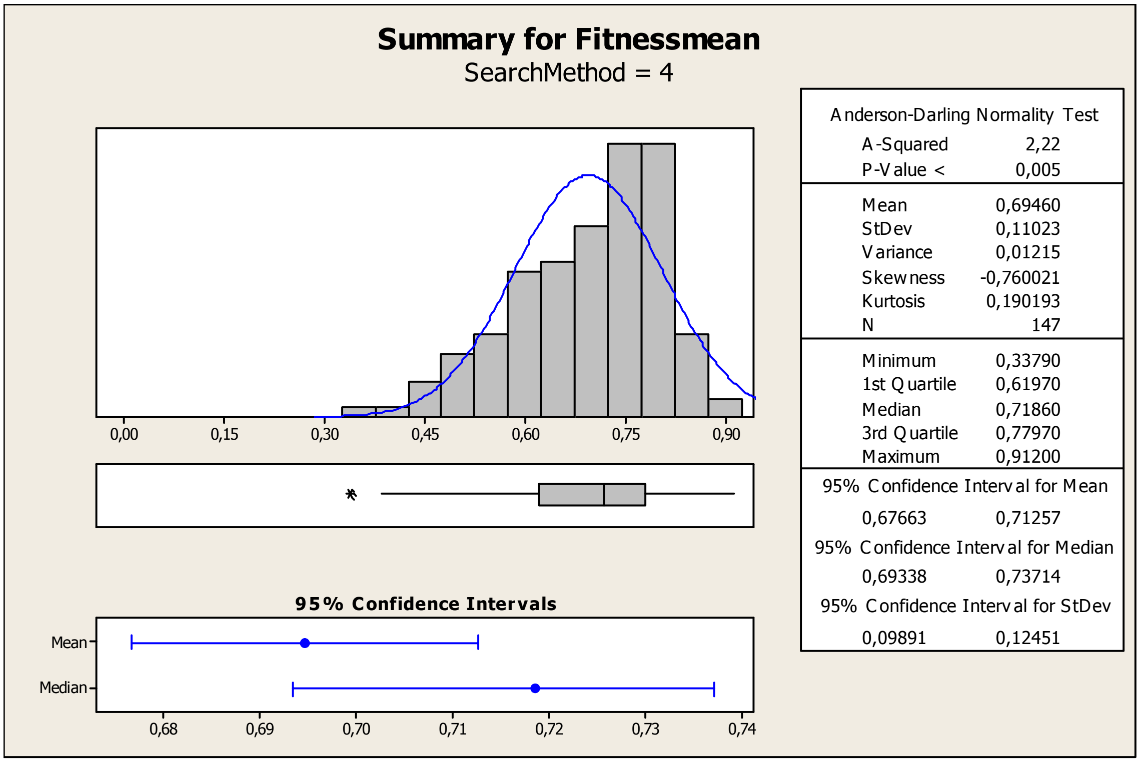
SIMULATION 78, ALL RUNS



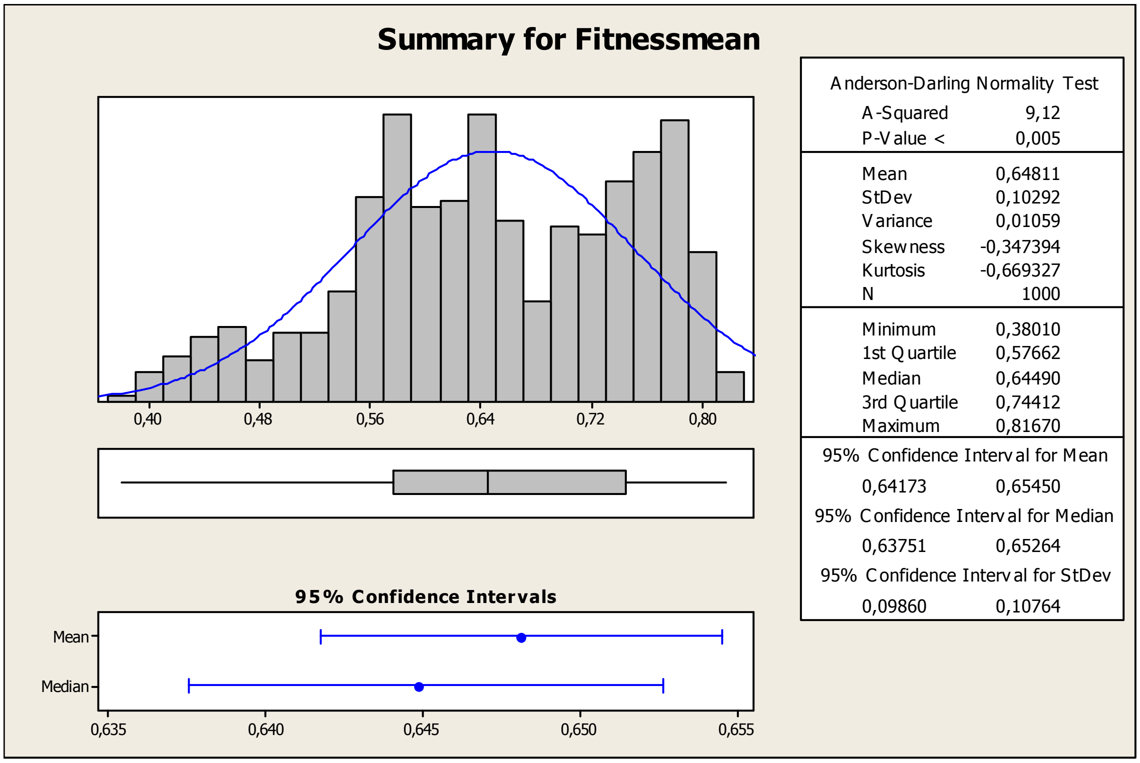


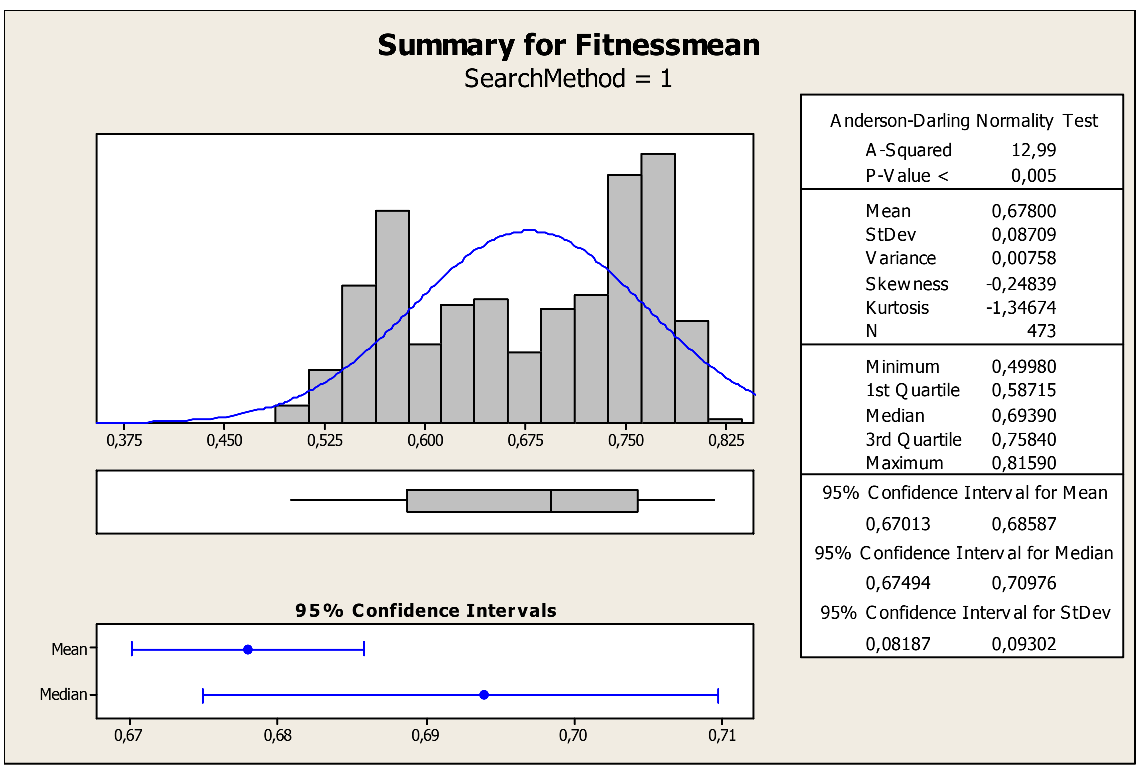

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,50
P-Value 0,211
Mean 0,62339
StDev 0,11722
Variance 0,01374
Skewness -0,356649
Kurtosis -0,088400
N 146
Minimum 0,30880
1st Quartile 0,55368
Median 0,63335
3rd Quartile 0,71632
Maximum 0,90550
95% Confidence Interval for Mean
0,60422 0,64257
95% Confidence Interval for Median
0,60326 0,65598
95% Confidence Interval for StDev
0,10514 0,13246
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,60 0,61 0,62 0,63 0,64 0,65 0,66

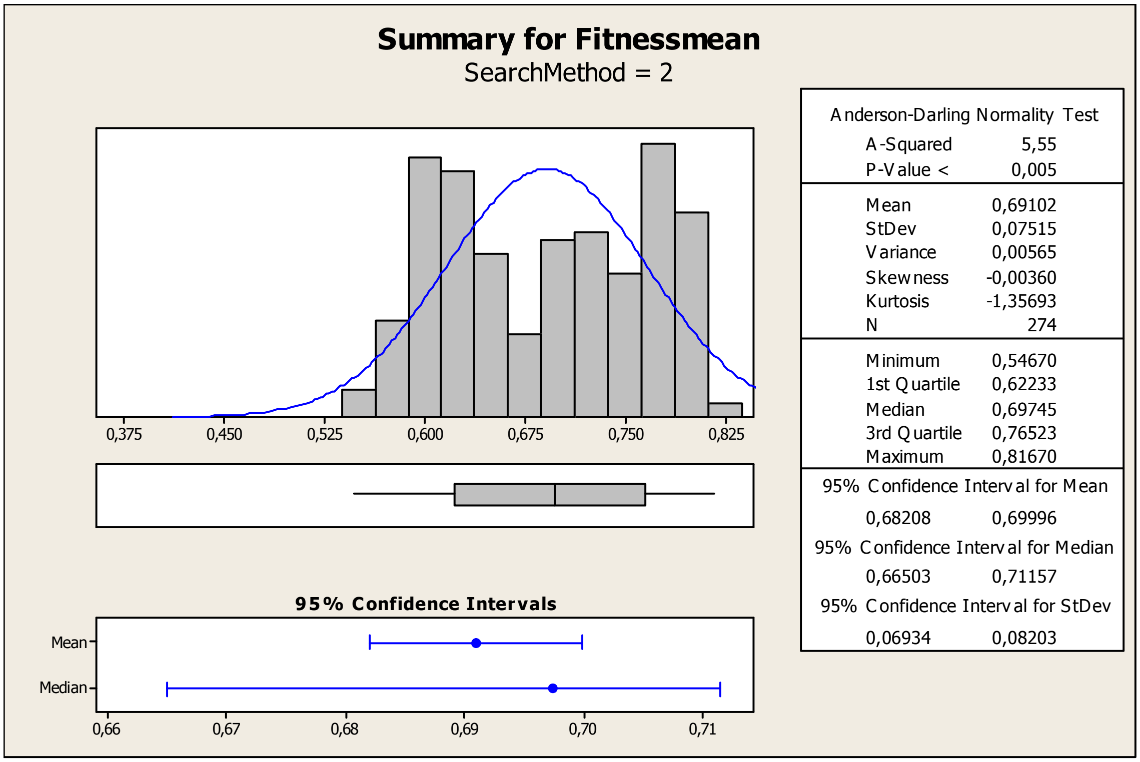

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,31
P-Value 0,539
Mean 0,27640
StDev 0,10743
Variance 0,01154
Skewness 0,084298
Kurtosis 0,148892
N 95
Minimum -0,00320
1st Quartile 0,21050
Median 0,26380
3rd Quartile 0,35390
Maximum 0,58890
95% Confidence Interval for Mean
0,25452 0,29829
95% Confidence Interval for Median
0,24035 0,29770
95% Confidence Interval for StDev
0,09402 0,12533
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,24 0,25 0,26 0,27 0,28 0,29 0,30

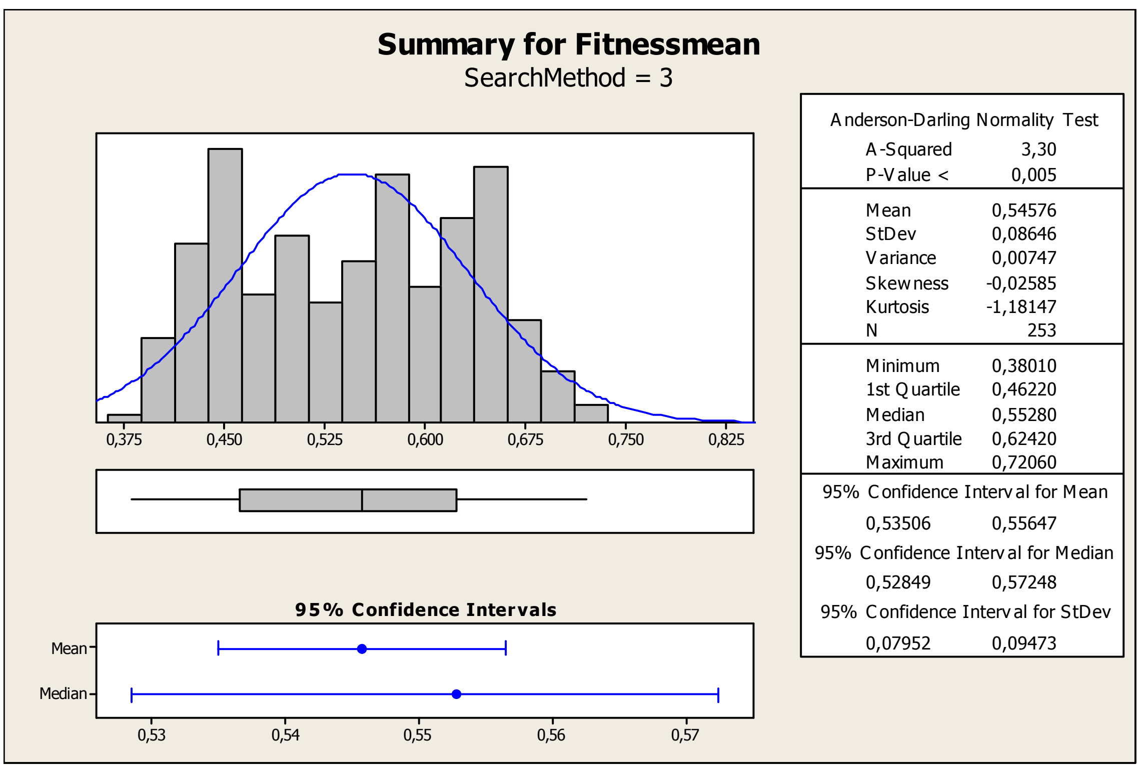

Summary for Fitnessmean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 2,22
P-Value < 0,005
Mean 0,69460
StDev 0,11023
Variance 0,01215
Skewness -0,760021
Kurtosis 0,190193
N 147
Minimum 0,33790
1st Quartile 0,61970
Median 0,71860
3rd Quartile 0,77970
Maximum 0,91200
95% Confidence Interval for Mean
0,67663 0,71257
95% Confidence Interval for Median
0,69338 0,73714
95% Confidence Interval for StDev
0,09891 0,12451
0,00 0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,68 0,69 0,70 0,71 0,72 0,73 0,74

SIMULATION 79, ALL RUNS

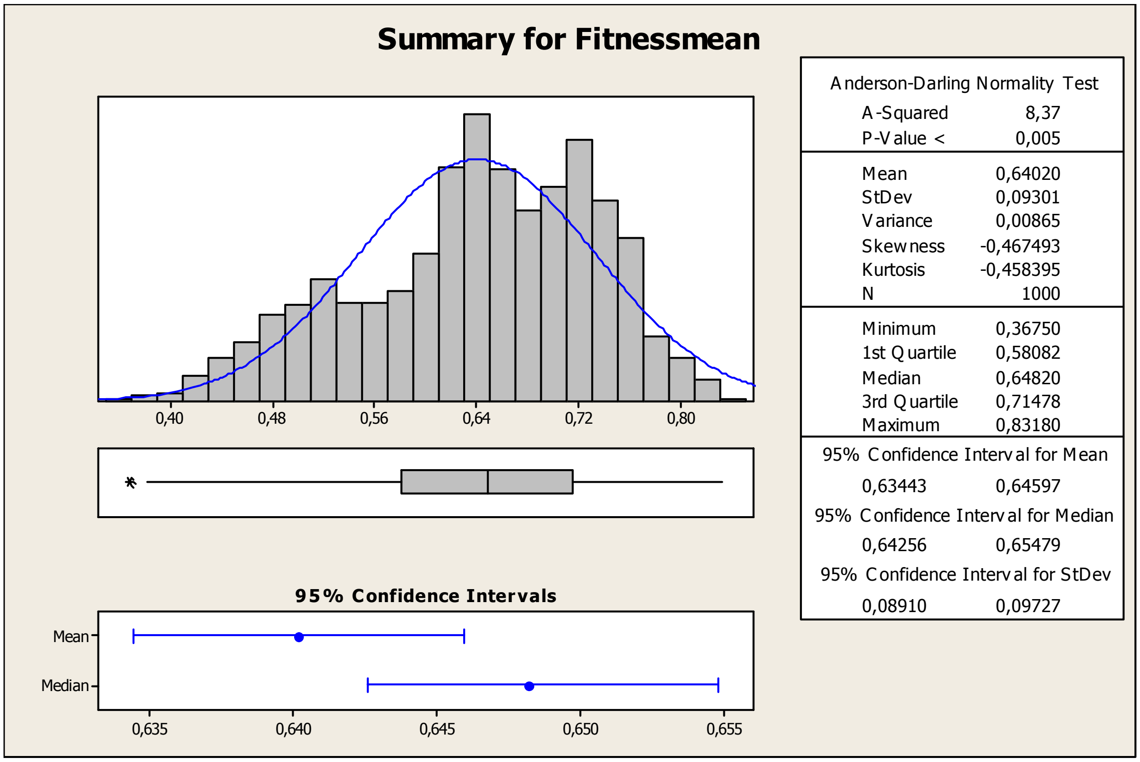


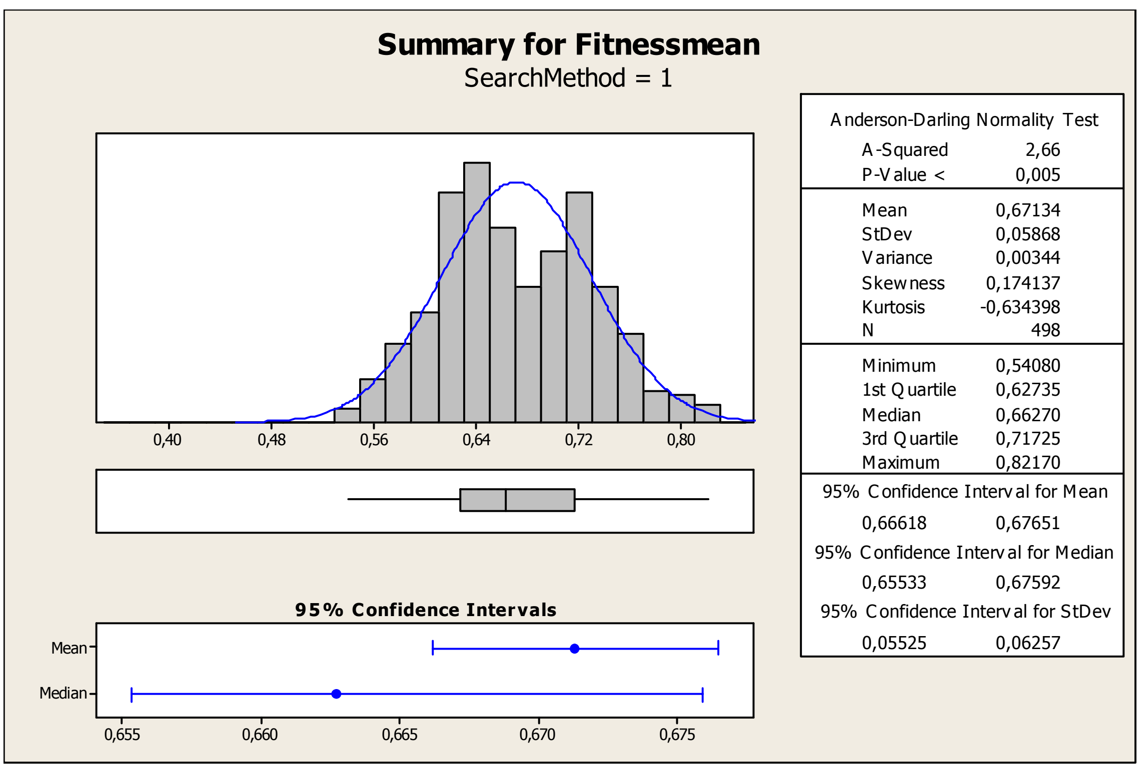


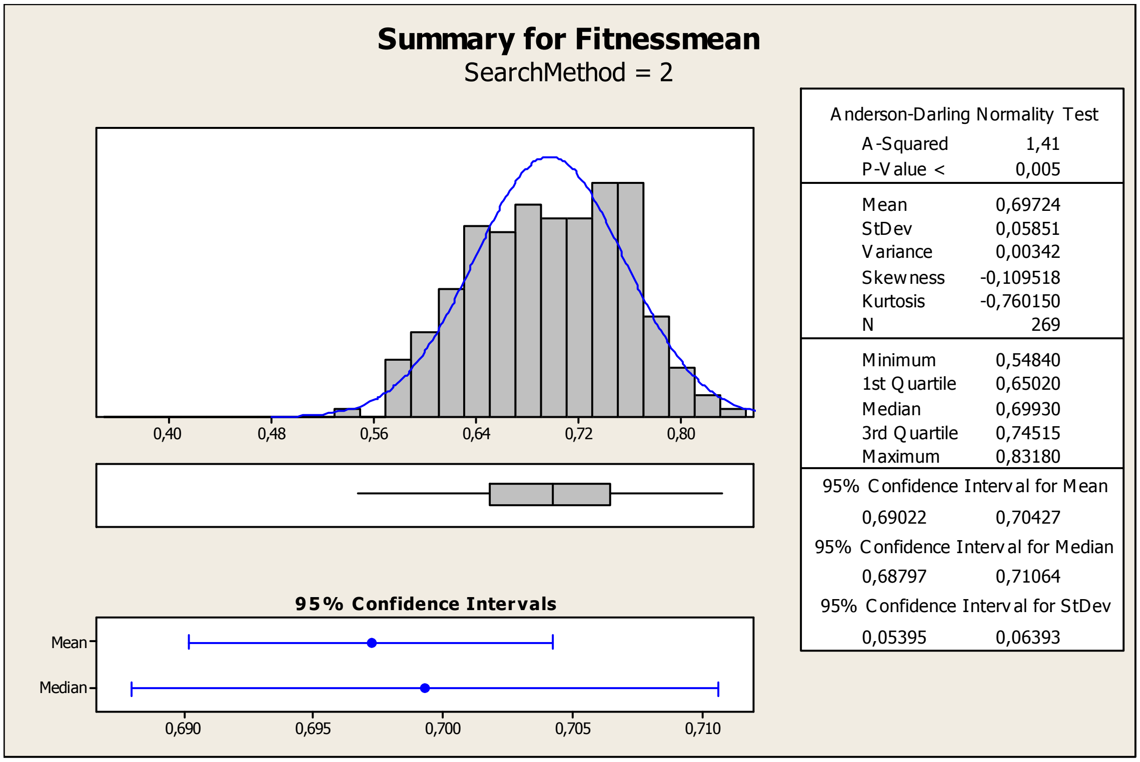

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 5,55
P-Value < 0,005
Mean 0,69102
StDev 0,07515
Variance 0,00565
Skewness -0,00360
Kurtosis -1,35693
N 274
Minimum 0,54670
1st Quartile 0,62233
Median 0,69745
3rd Quartile 0,76523
Maximum 0,81670
95% Confidence Interval for Mean
0,68208 0,69996
95% Confidence Interval for Median
0,66503 0,71157
95% Confidence Interval for StDev
0,06934 0,08203
0,375 0,450 0,525 0,600 0,675 0,750 0,825
95% Confidence Intervals
Mean
Median
0,66 0,67 0,68 0,69 0,70 0,71

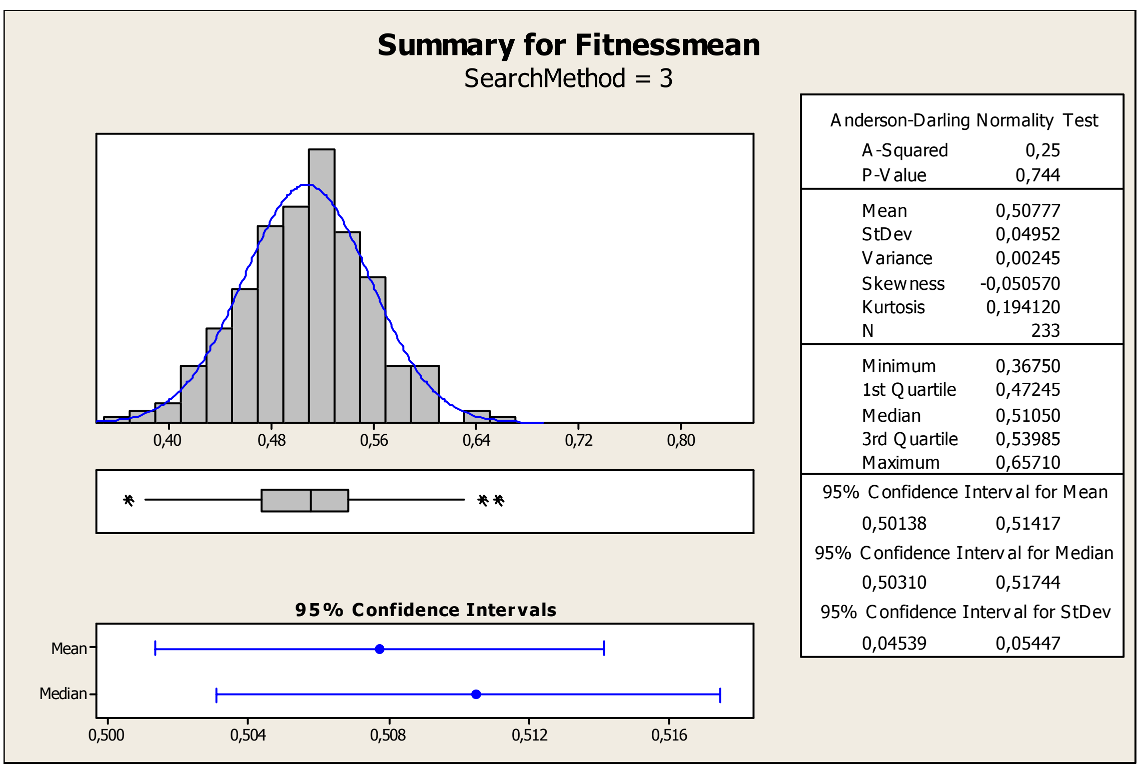

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 3,30
P-Value < 0,005
Mean 0,54576
StDev 0,08646
Variance 0,00747
Skewness -0,02585
Kurtosis -1,18147
N 253
Minimum 0,38010
1st Quartile 0,46220
Median 0,55280
3rd Quartile 0,62420
Maximum 0,72060
95% Confidence Interval for Mean
0,53506 0,55647
95% Confidence Interval for Median
0,52849 0,57248
95% Confidence Interval for StDev
0,07952 0,09473
0,375 0,450 0,525 0,600 0,675 0,750 0,825
95% Confidence Intervals
Mean
Median
0,53 0,54 0,55 0,56 0,57

SIMULATION 80, ALL RUNS

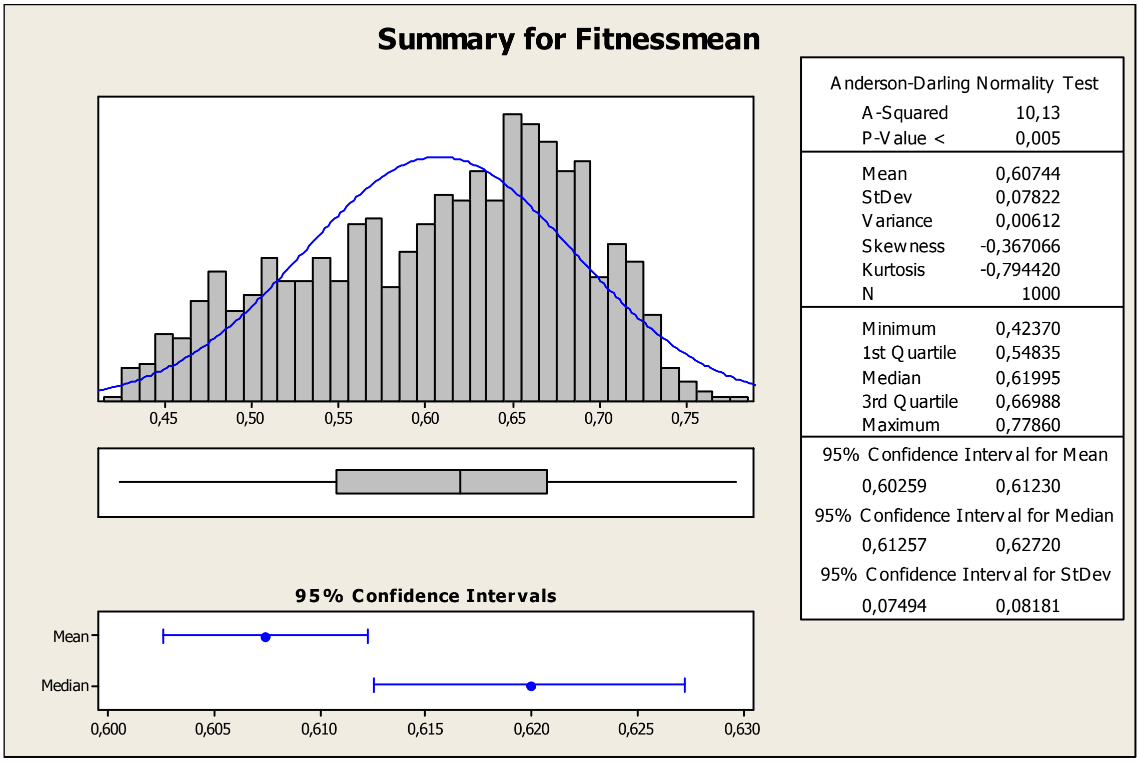


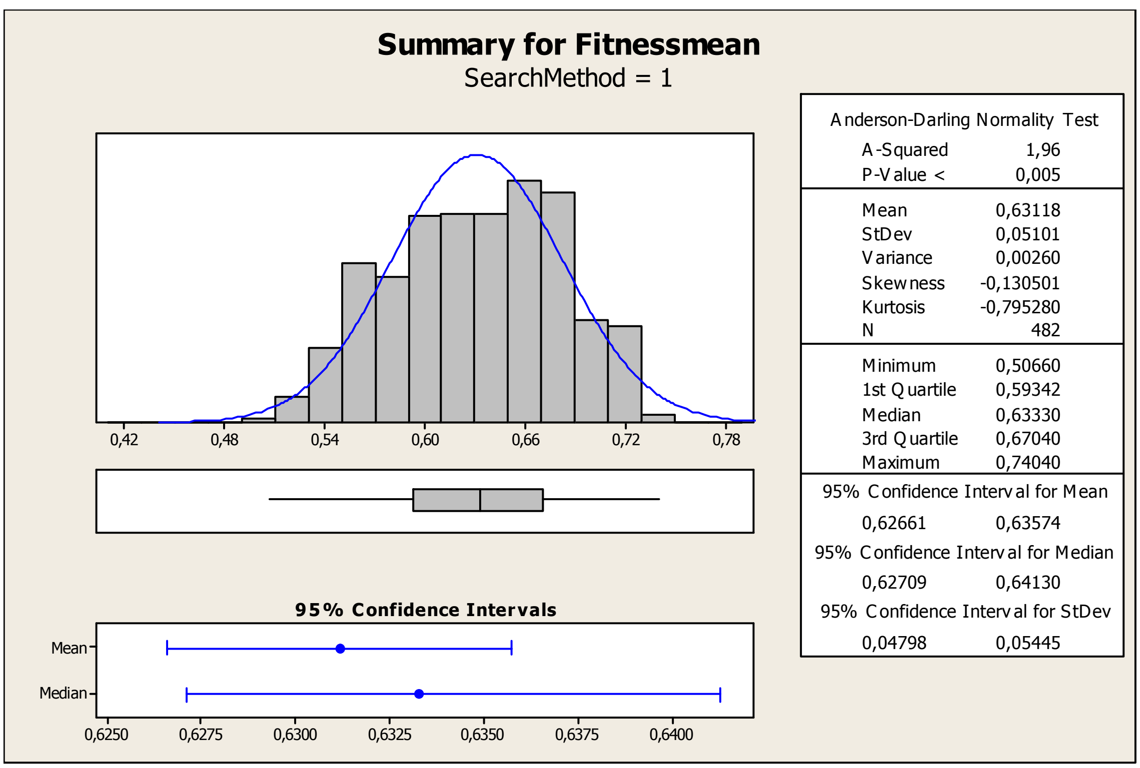


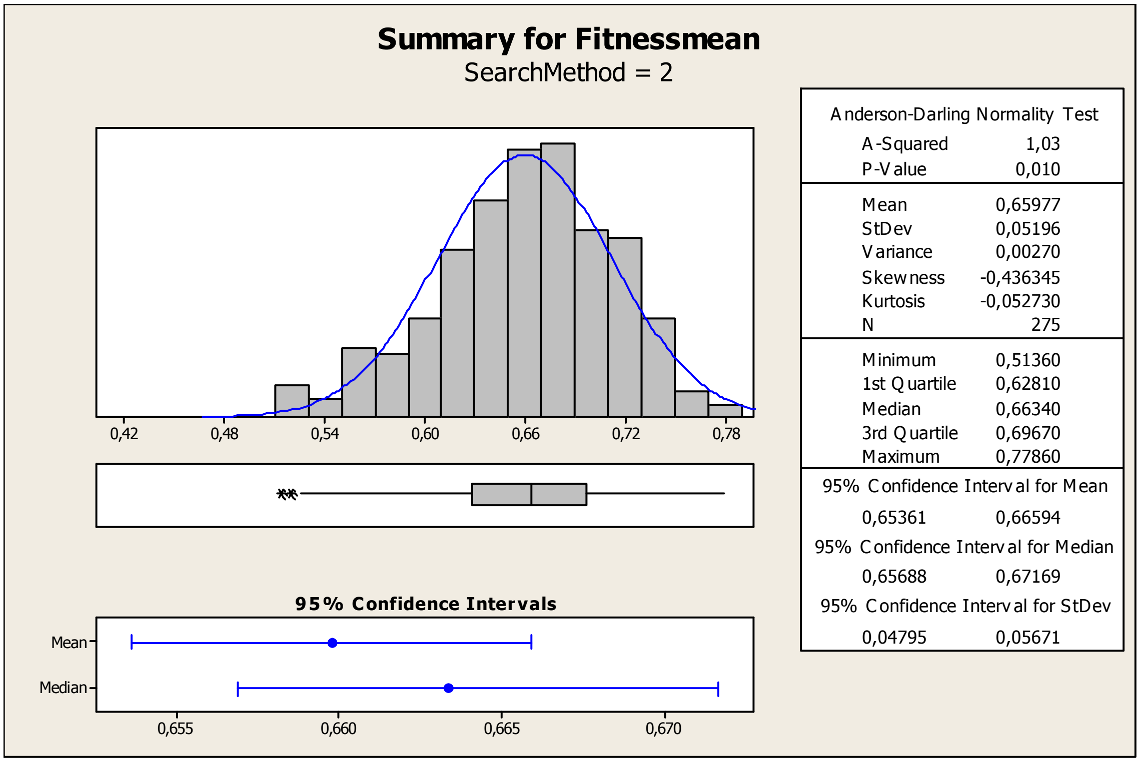

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,41
P-Value < 0,005
Mean 0,69724
StDev 0,05851
Variance 0,00342
Skewness -0,109518
Kurtosis -0,760150
N 269
Minimum 0,54840
1st Quartile 0,65020
Median 0,69930
3rd Quartile 0,74515
Maximum 0,83180
95% Confidence Interval for Mean
0,69022 0,70427
95% Confidence Interval for Median
0,68797 0,71064
95% Confidence Interval for StDev
0,05395 0,06393
0,40 0,48 0,56 0,64 0,72 0,80
95% Confidence Intervals
Mean
Median
0,690 0,695 0,700 0,705 0,710

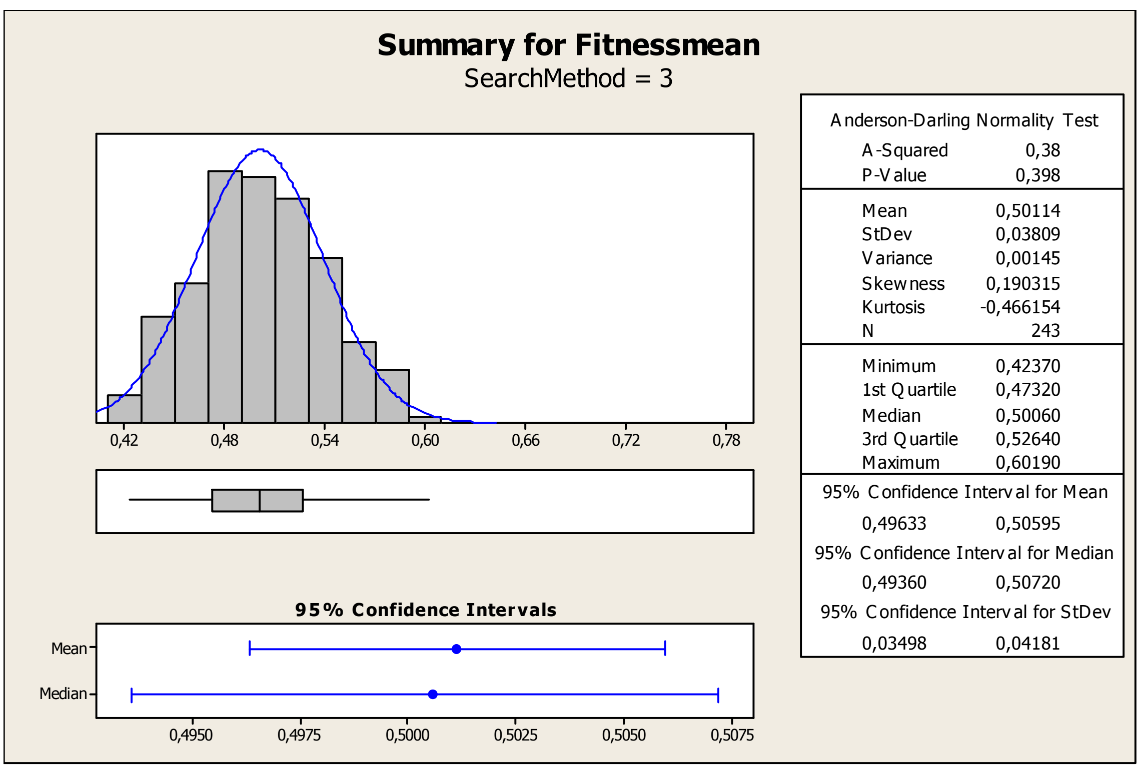

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,25
P-Value 0,744
Mean 0,50777
StDev 0,04952
Variance 0,00245
Skewness -0,050570
Kurtosis 0,194120
N 233
Minimum 0,36750
1st Quartile 0,47245
Median 0,51050
3rd Quartile 0,53985
Maximum 0,65710
95% Confidence Interval for Mean
0,50138 0,51417
95% Confidence Interval for Median
0,50310 0,51744
95% Confidence Interval for StDev
0,04539 0,05447
0,40 0,48 0,56 0,64 0,72 0,80
95% Confidence Intervals
Mean
Median
0,500 0,504 0,508 0,512 0,516

SIMULATION 81, ALL RUNS

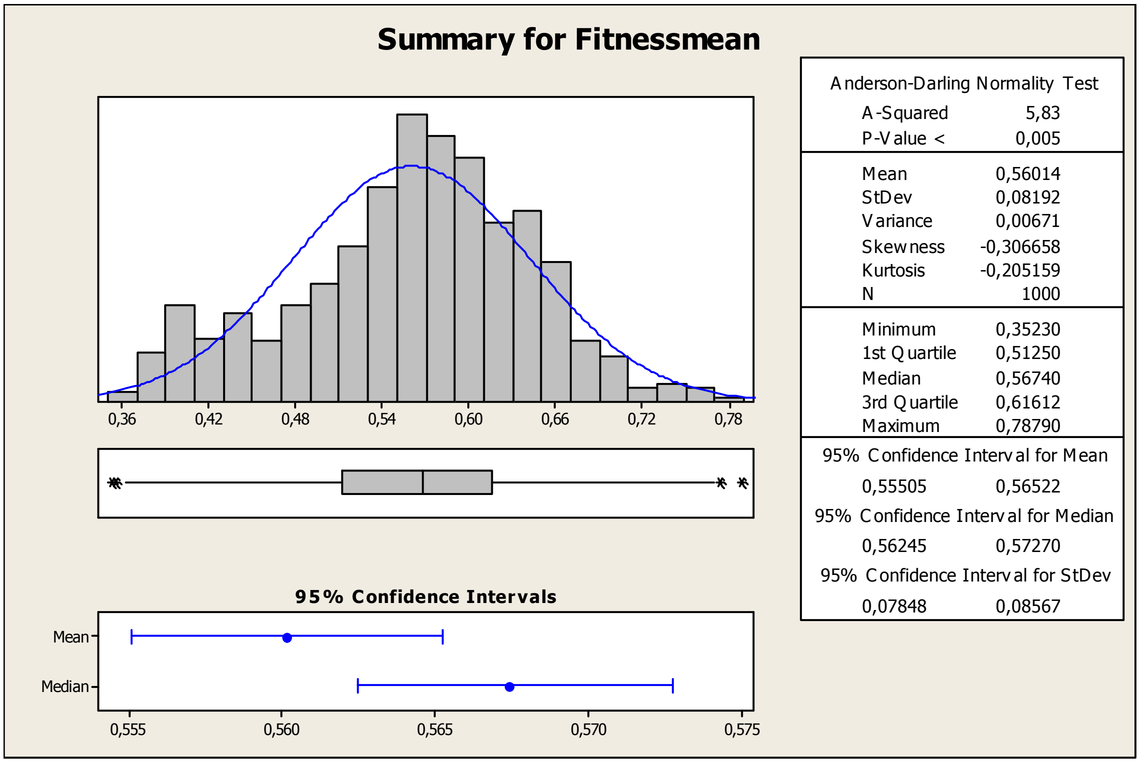


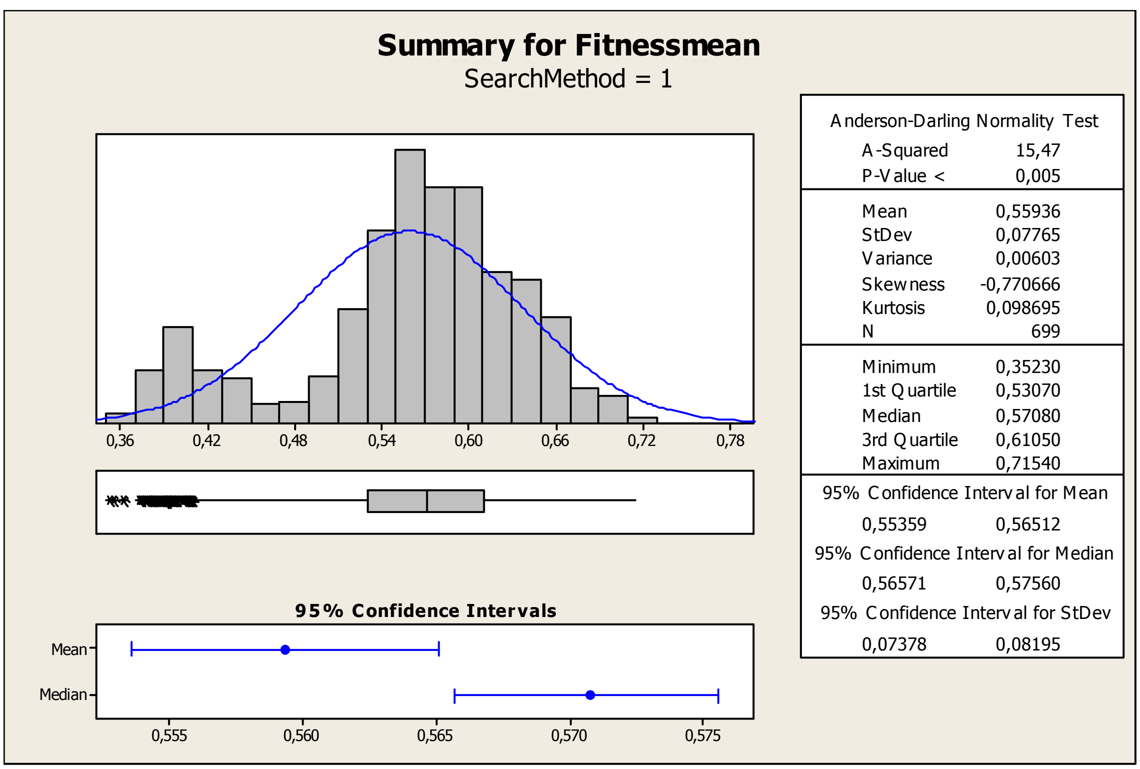


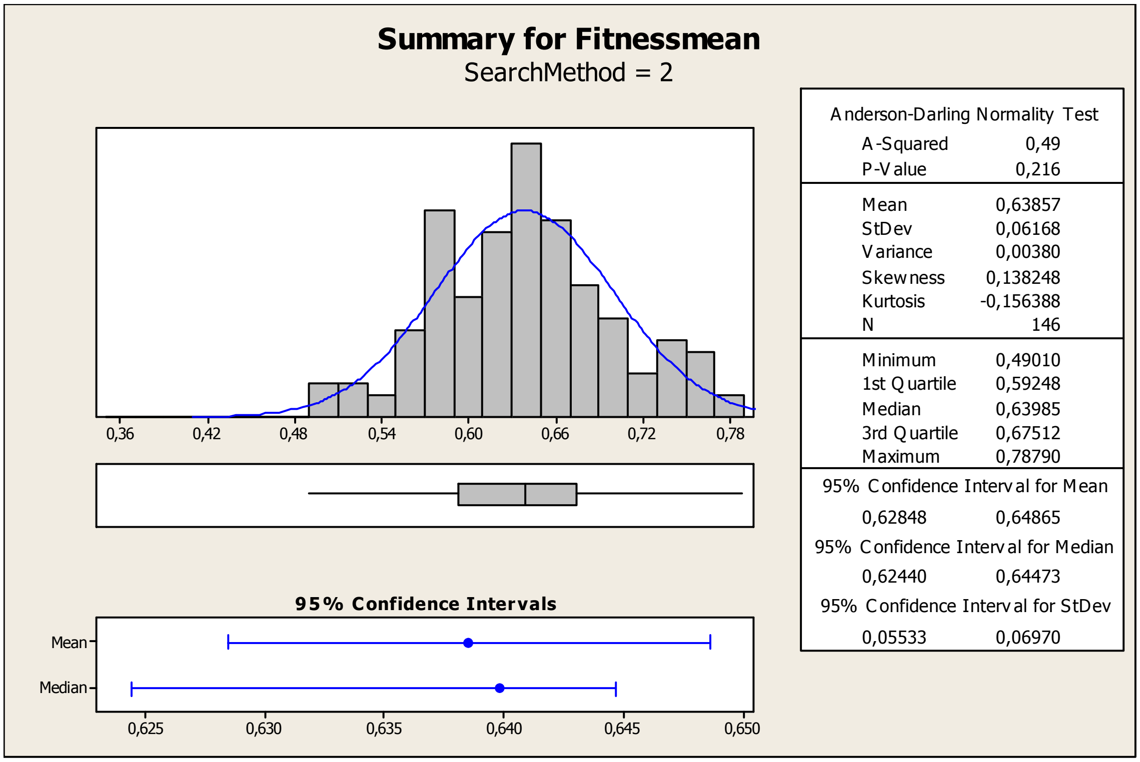

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,03
P-Value 0,010
Mean 0,65977
StDev 0,05196
Variance 0,00270
Skewness -0,436345
Kurtosis -0,052730
N 275
Minimum 0,51360
1st Quartile 0,62810
Median 0,66340
3rd Quartile 0,69670
Maximum 0,77860
95% Confidence Interval for Mean
0,65361 0,66594
95% Confidence Interval for Median
0,65688 0,67169
95% Confidence Interval for StDev
0,04795 0,05671
0,42 0,48 0,54 0,60 0,66 0,72 0,78
95% Confidence Intervals
Mean
Median
0,655 0,660 0,665 0,670

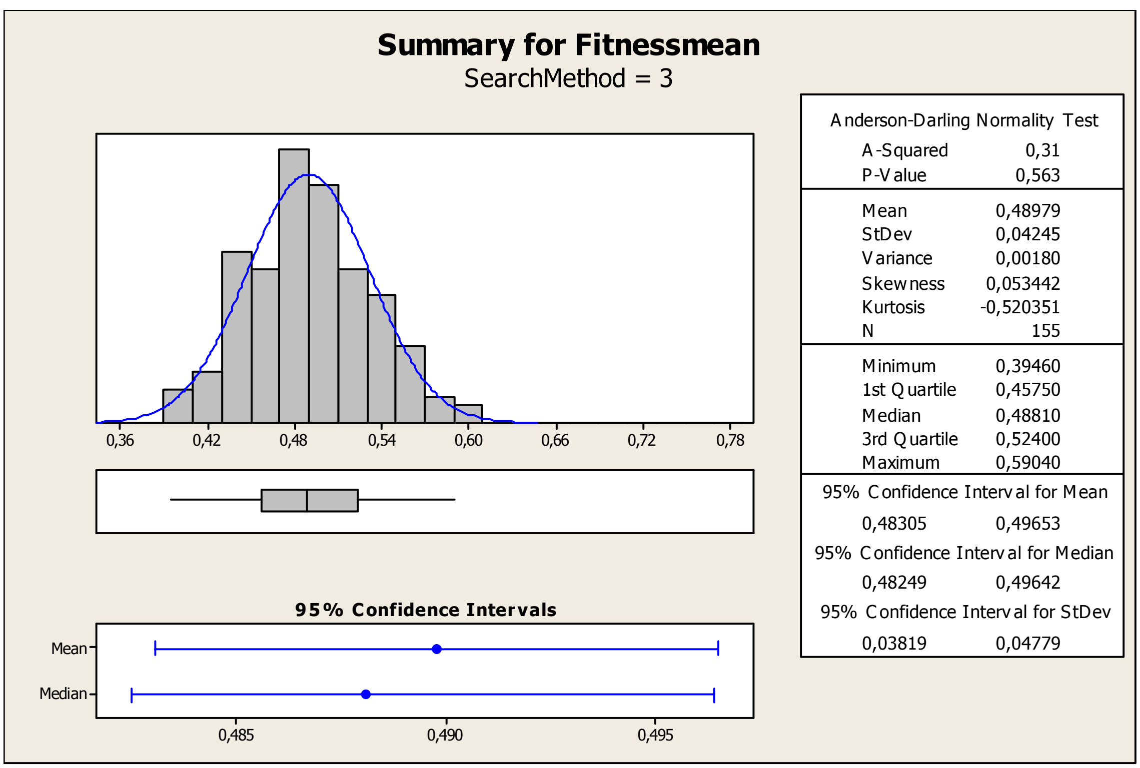

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,38
P-Value 0,398
Mean 0,50114
StDev 0,03809
Variance 0,00145
Skewness 0,190315
Kurtosis -0,466154
N 243
Minimum 0,42370
1st Quartile 0,47320
Median 0,50060
3rd Quartile 0,52640
Maximum 0,60190
95% Confidence Interval for Mean
0,49633 0,50595
95% Confidence Interval for Median
0,49360 0,50720
95% Confidence Interval for StDev
0,03498 0,04181
0,42 0,48 0,54 0,60 0,66 0,72 0,78
95% Confidence Intervals
Mean
Median
0,4950 0,4975 0,5000 0,5025 0,5050 0,5075

SIMULATION 82, ALL RUNS

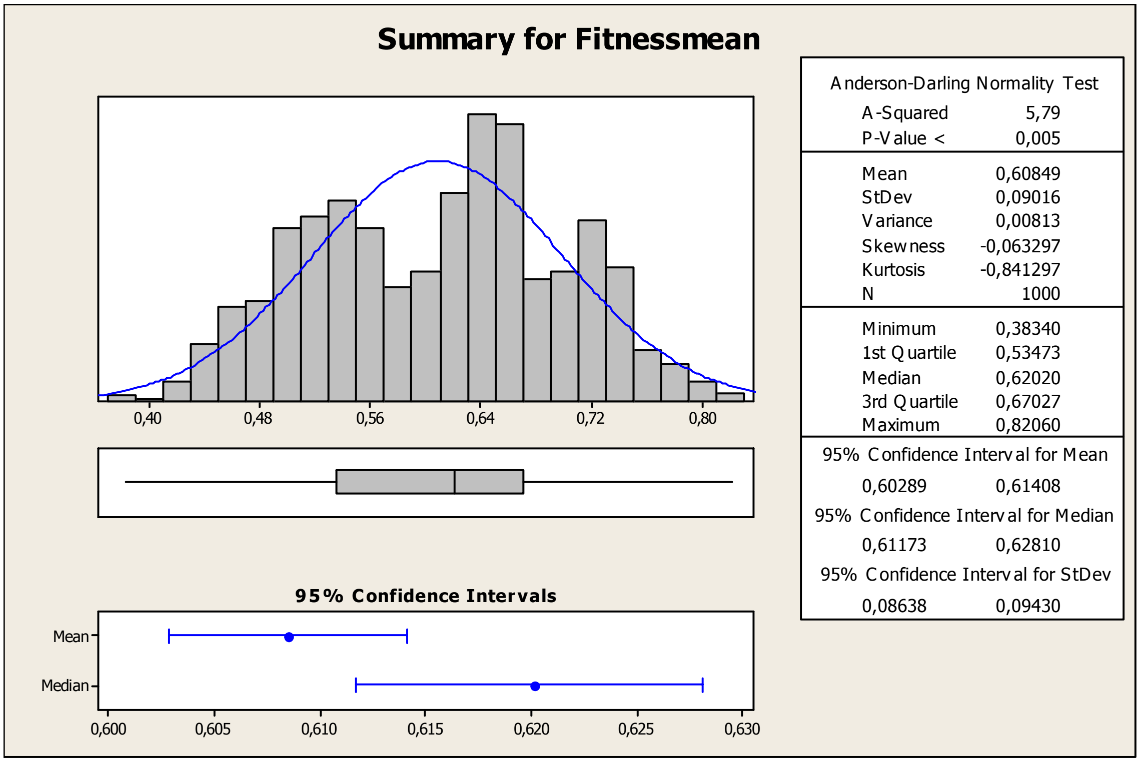


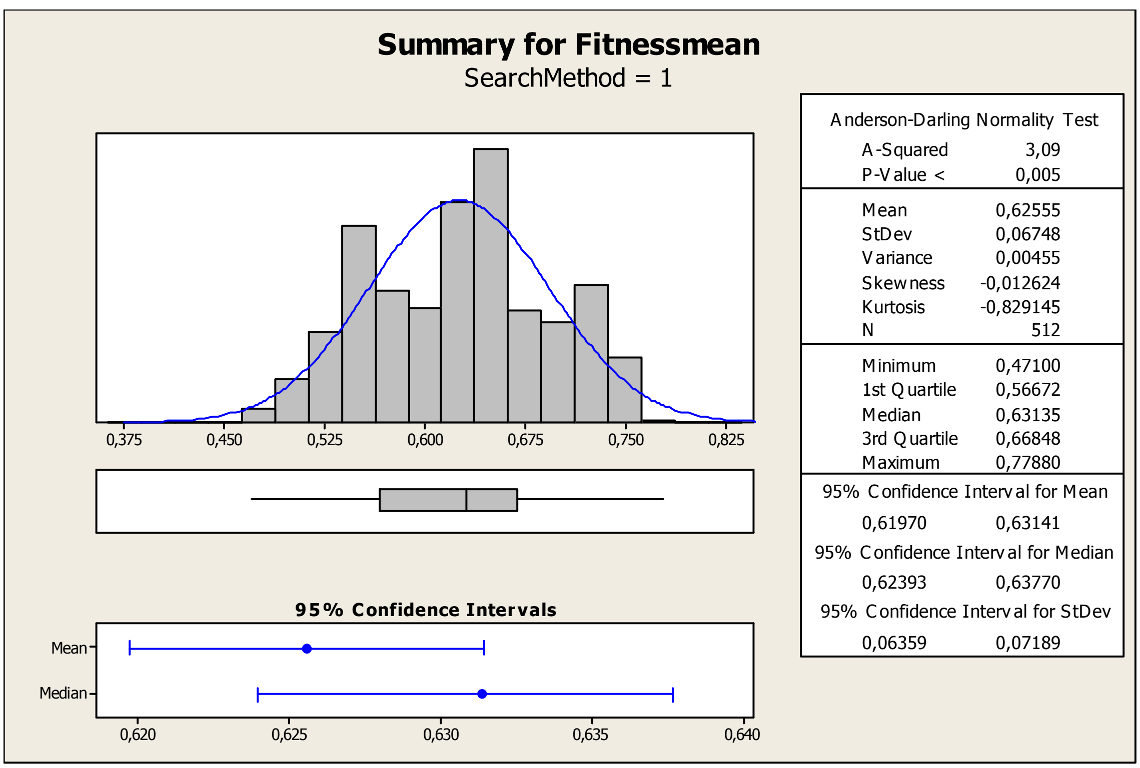


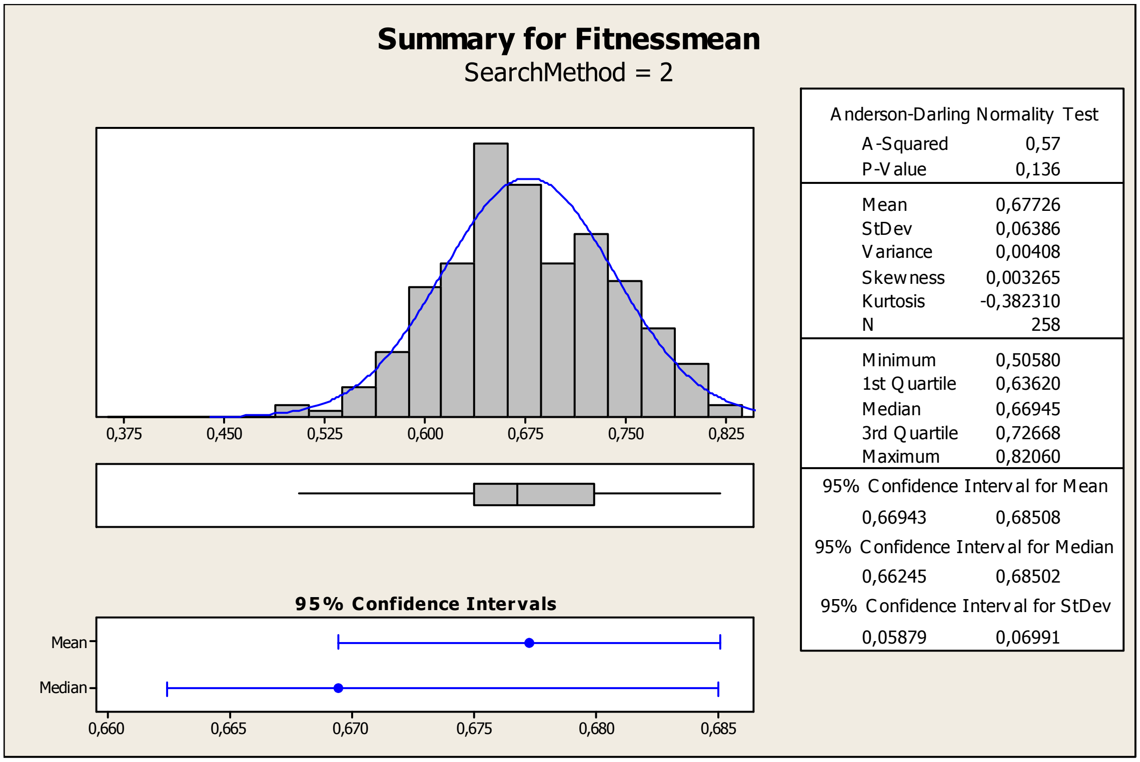

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,49
P-Value 0,216
Mean 0,63857
StDev 0,06168
Variance 0,00380
Skewness 0,138248
Kurtosis -0,156388
N 146
Minimum 0,49010
1st Quartile 0,59248
Median 0,63985
3rd Quartile 0,67512
Maximum 0,78790
95% Confidence Interval for Mean
0,62848 0,64865
95% Confidence Interval for Median
0,62440 0,64473
95% Confidence Interval for StDev
0,05533 0,06970
0,36 0,42 0,48 0,54 0,60 0,66 0,72 0,78
95% Confidence Intervals
Mean
Median
0,625 0,630 0,635 0,640 0,645 0,650

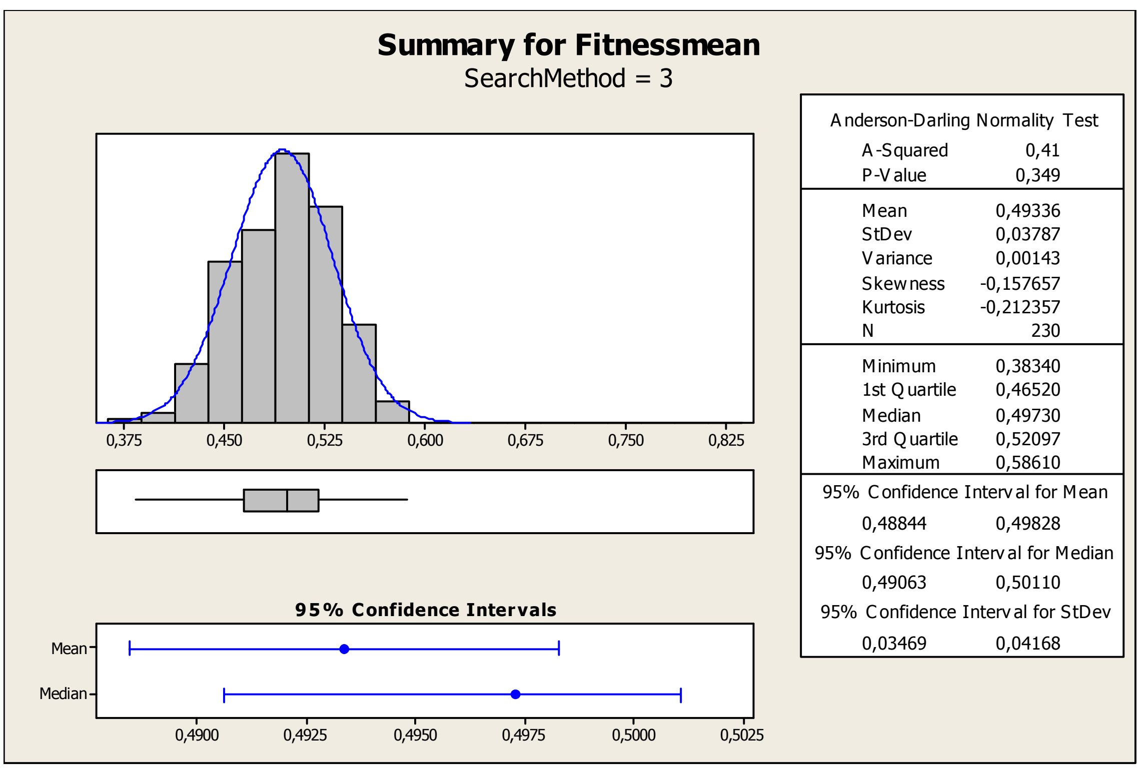

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,31
P-Value 0,563
Mean 0,48979
StDev 0,04245
Variance 0,00180
Skewness 0,053442
Kurtosis -0,520351
N 155
Minimum 0,39460
1st Quartile 0,45750
Median 0,48810
3rd Quartile 0,52400
Maximum 0,59040
95% Confidence Interval for Mean
0,48305 0,49653
95% Confidence Interval for Median
0,48249 0,49642
95% Confidence Interval for StDev
0,03819 0,04779
0,36 0,42 0,48 0,54 0,60 0,66 0,72 0,78
95% Confidence Intervals
Mean
Median
0,485 0,490 0,495

SIMULATION 83, ALL RUNS

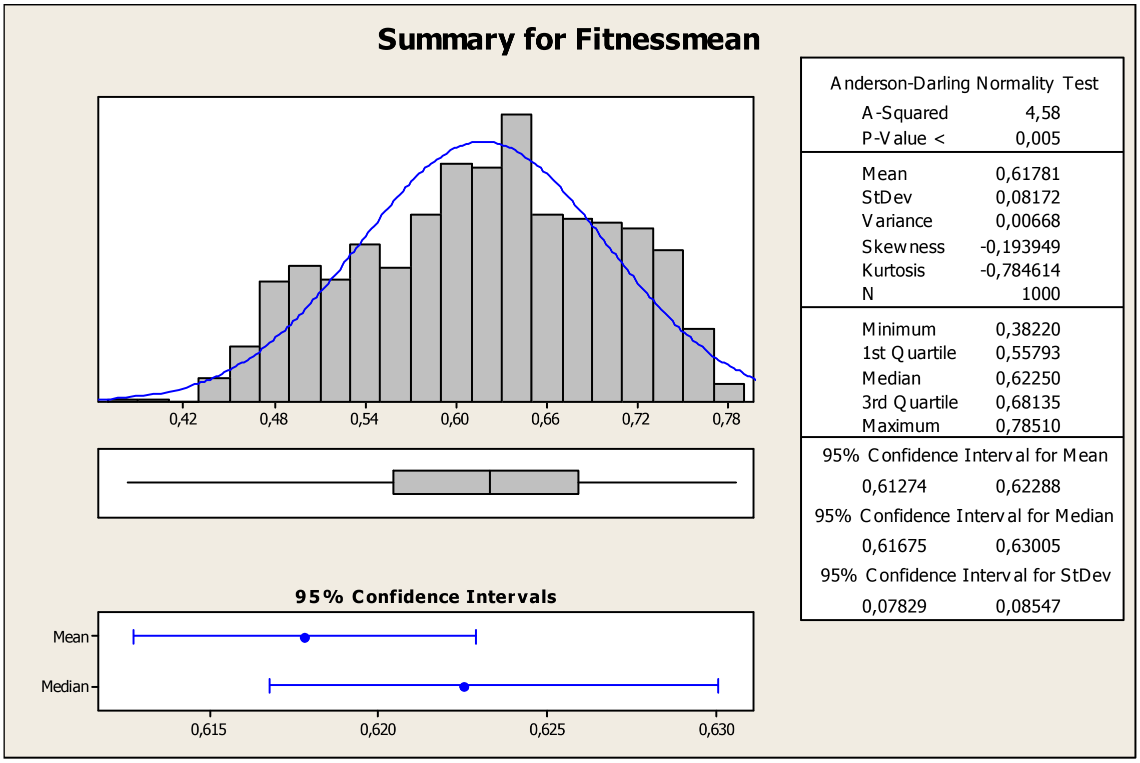


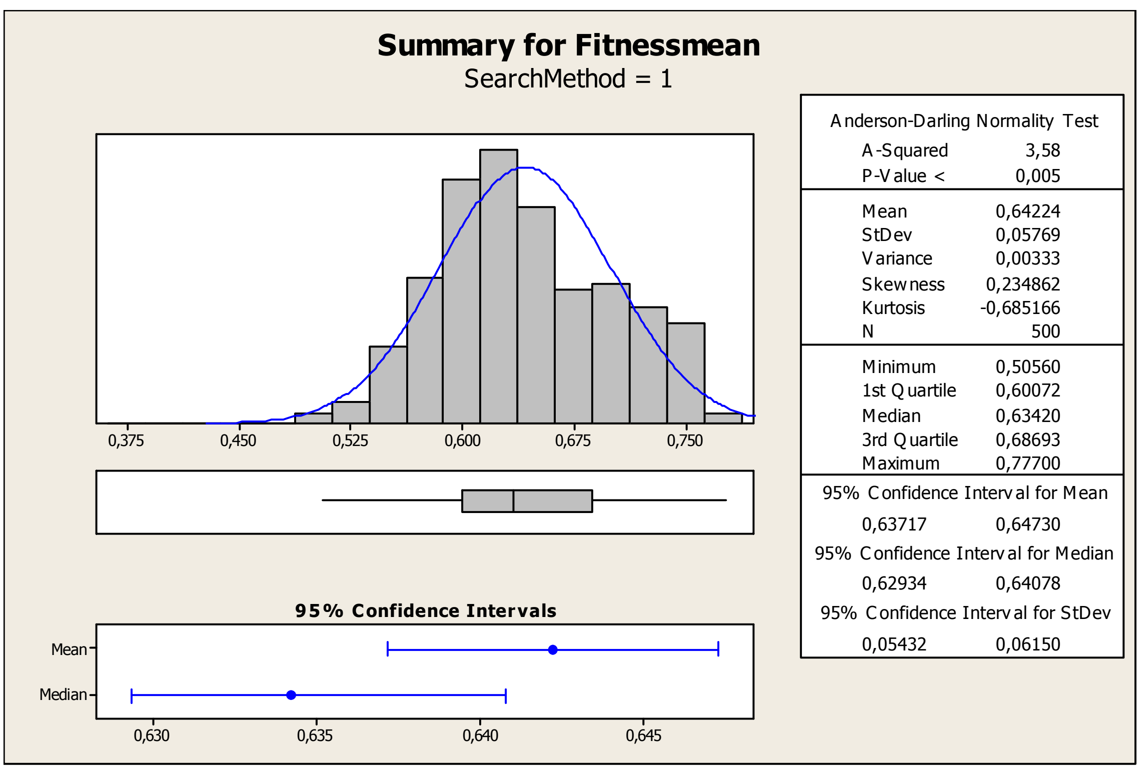


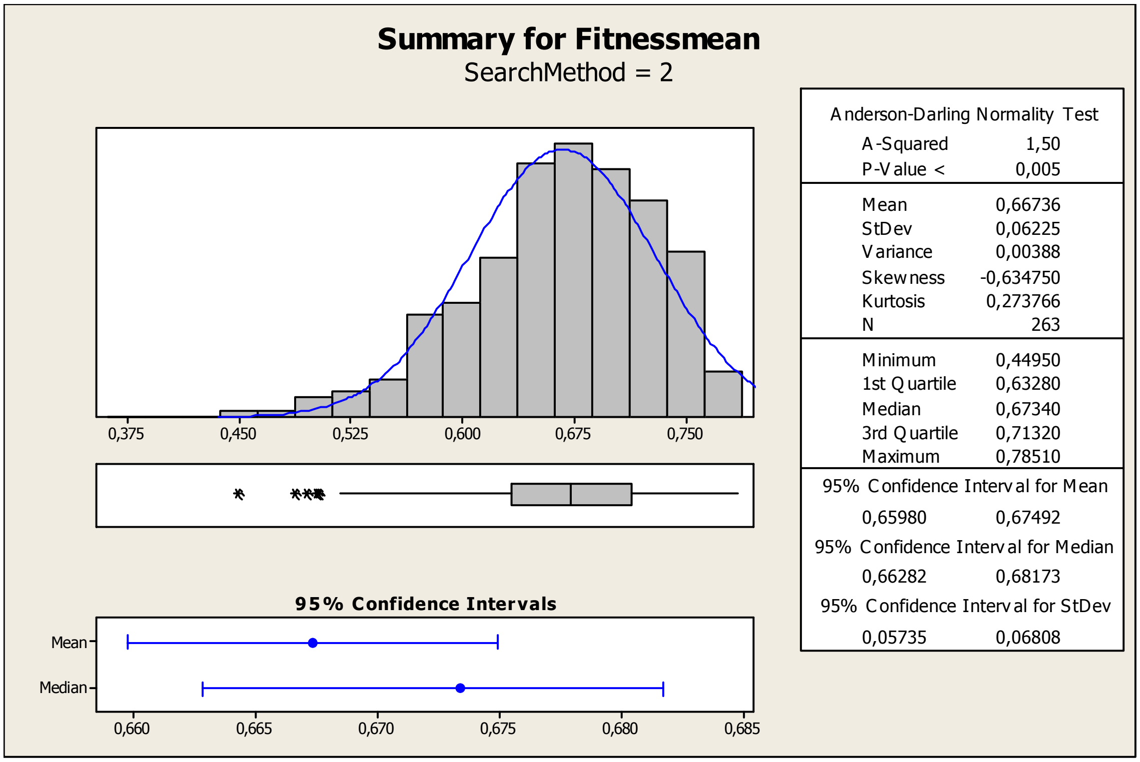

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,57
P-Value 0,136
Mean 0,67726
StDev 0,06386
Variance 0,00408
Skewness 0,003265
Kurtosis -0,382310
N 258
Minimum 0,50580
1st Quartile 0,63620
Median 0,66945
3rd Quartile 0,72668
Maximum 0,82060
95% Confidence Interval for Mean
0,66943 0,68508
95% Confidence Interval for Median
0,66245 0,68502
95% Confidence Interval for StDev
0,05879 0,06991
0,375 0,450 0,525 0,600 0,675 0,750 0,825
95% Confidence Intervals
Mean
Median
0,660 0,665 0,670 0,675 0,680 0,685

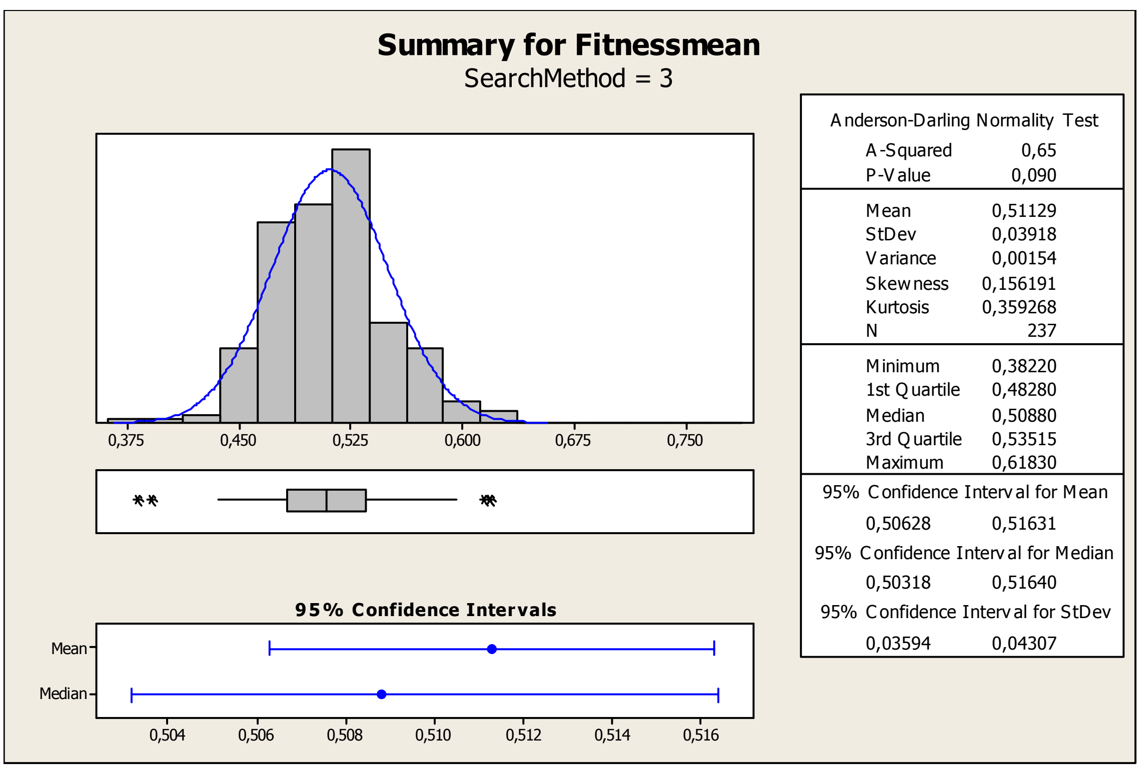

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,41
P-Value 0,349
Mean 0,49336
StDev 0,03787
Variance 0,00143
Skewness -0,157657
Kurtosis -0,212357
N 230
Minimum 0,38340
1st Quartile 0,46520
Median 0,49730
3rd Quartile 0,52097
Maximum 0,58610
95% Confidence Interval for Mean
0,48844 0,49828
95% Confidence Interval for Median
0,49063 0,50110
95% Confidence Interval for StDev
0,03469 0,04168
0,375 0,450 0,525 0,600 0,675 0,750 0,825
95% Confidence Intervals
Mean
Median
0,4900 0,4925 0,4950 0,4975 0,5000 0,5025

SIMULATION 84, ALL RUNS

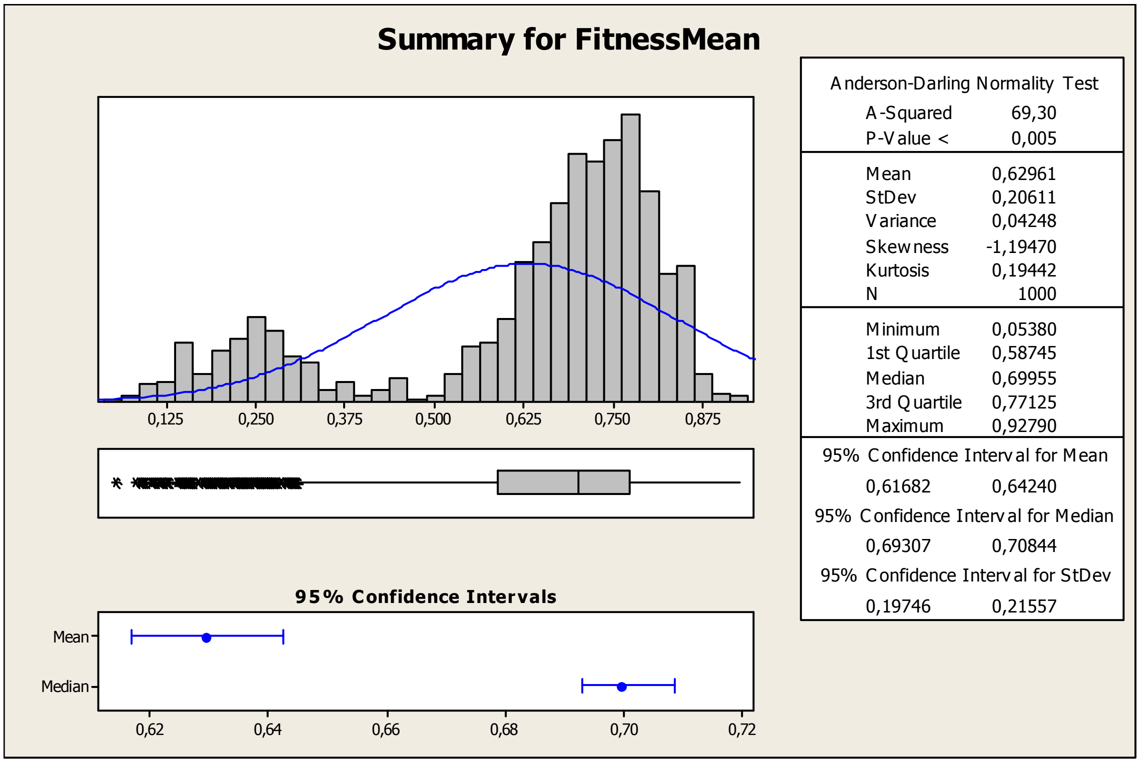


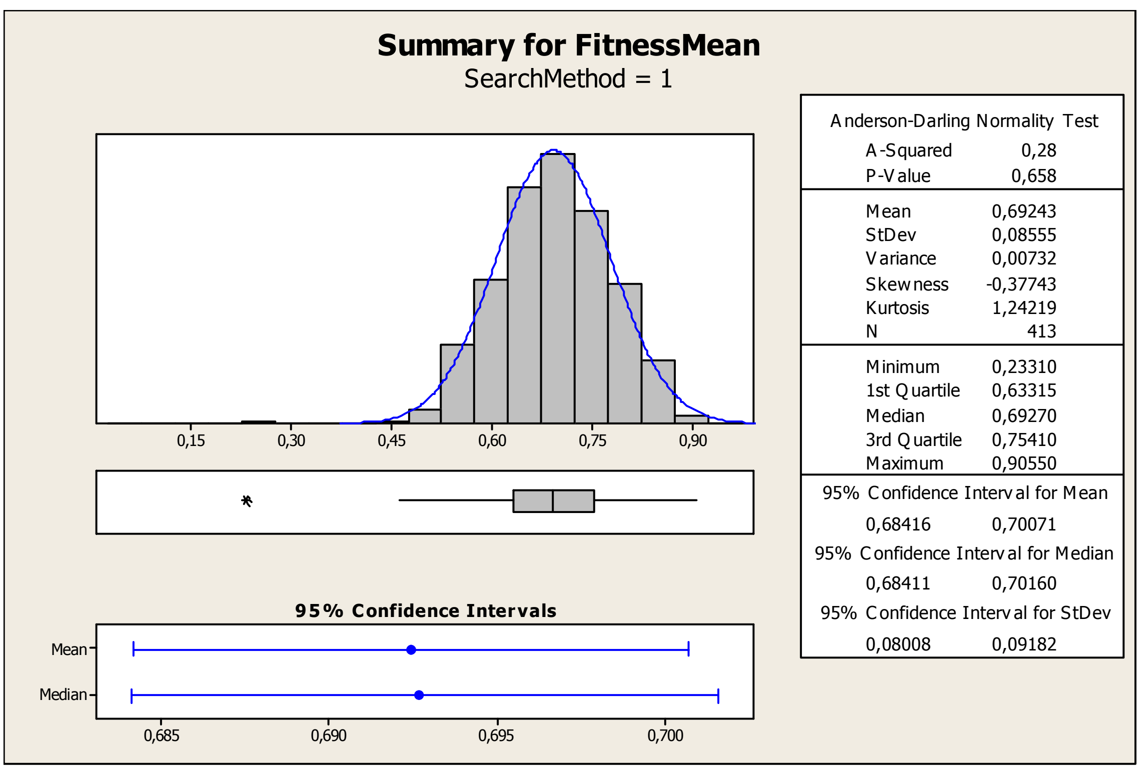


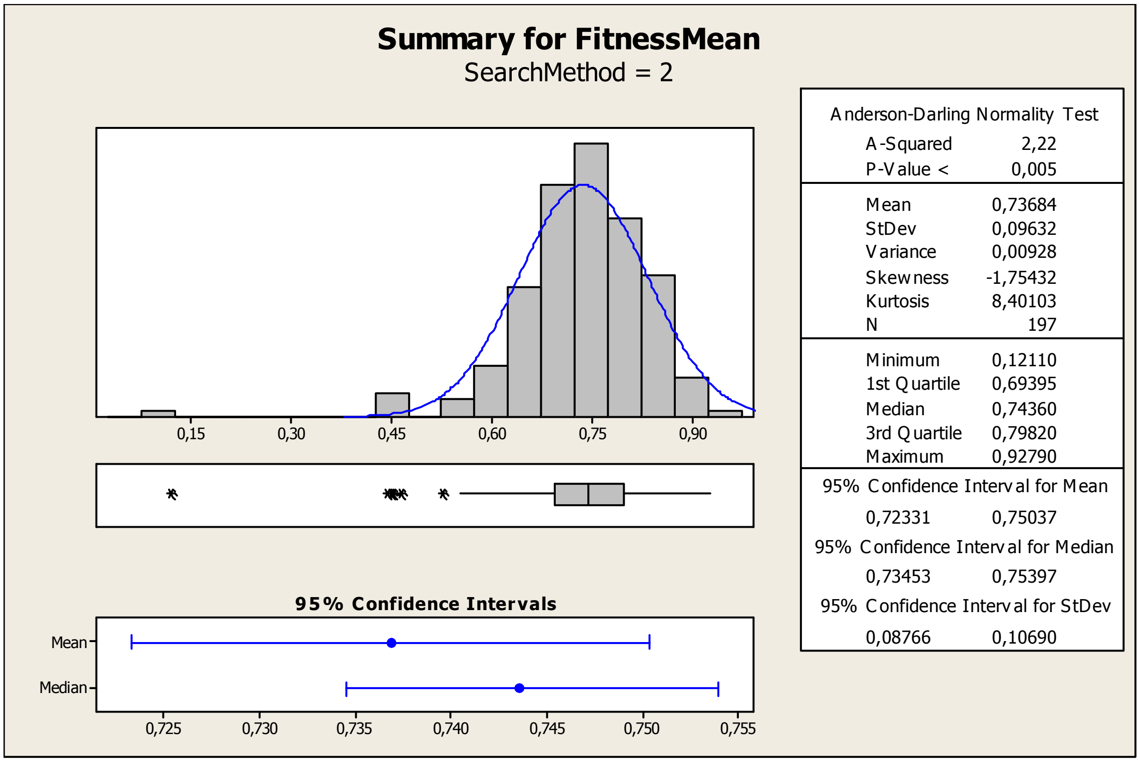

Summary for Fitnessmean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,50
P-Value < 0,005
Mean 0,66736
StDev 0,06225
Variance 0,00388
Skewness -0,634750
Kurtosis 0,273766
N 263
Minimum 0,44950
1st Quartile 0,63280
Median 0,67340
3rd Quartile 0,71320
Maximum 0,78510
95% Confidence Interval for Mean
0,65980 0,67492
95% Confidence Interval for Median
0,66282 0,68173
95% Confidence Interval for StDev
0,05735 0,06808
0,375 0,450 0,525 0,600 0,675 0,750
95% Confidence Intervals
Mean
Median
0,660 0,665 0,670 0,675 0,680 0,685

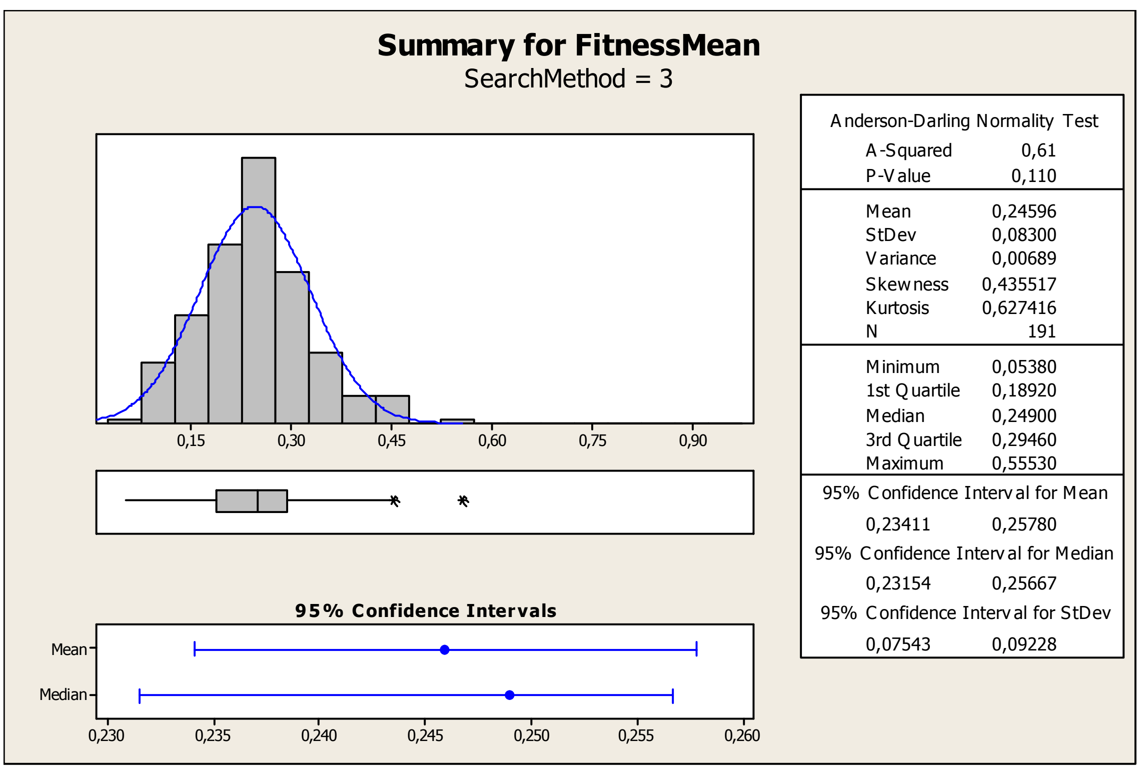

Summary for Fitnessmean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,65
P-Value 0,090
Mean 0,51129
StDev 0,03918
Variance 0,00154
Skewness 0,156191
Kurtosis 0,359268
N 237
Minimum 0,38220
1st Quartile 0,48280
Median 0,50880
3rd Quartile 0,53515
Maximum 0,61830
95% Confidence Interval for Mean
0,50628 0,51631
95% Confidence Interval for Median
0,50318 0,51640
95% Confidence Interval for StDev
0,03594 0,04307
0,375 0,450 0,525 0,600 0,675 0,750
95% Confidence Intervals
Mean
Median
0,504 0,506 0,508 0,510 0,512 0,514 0,516

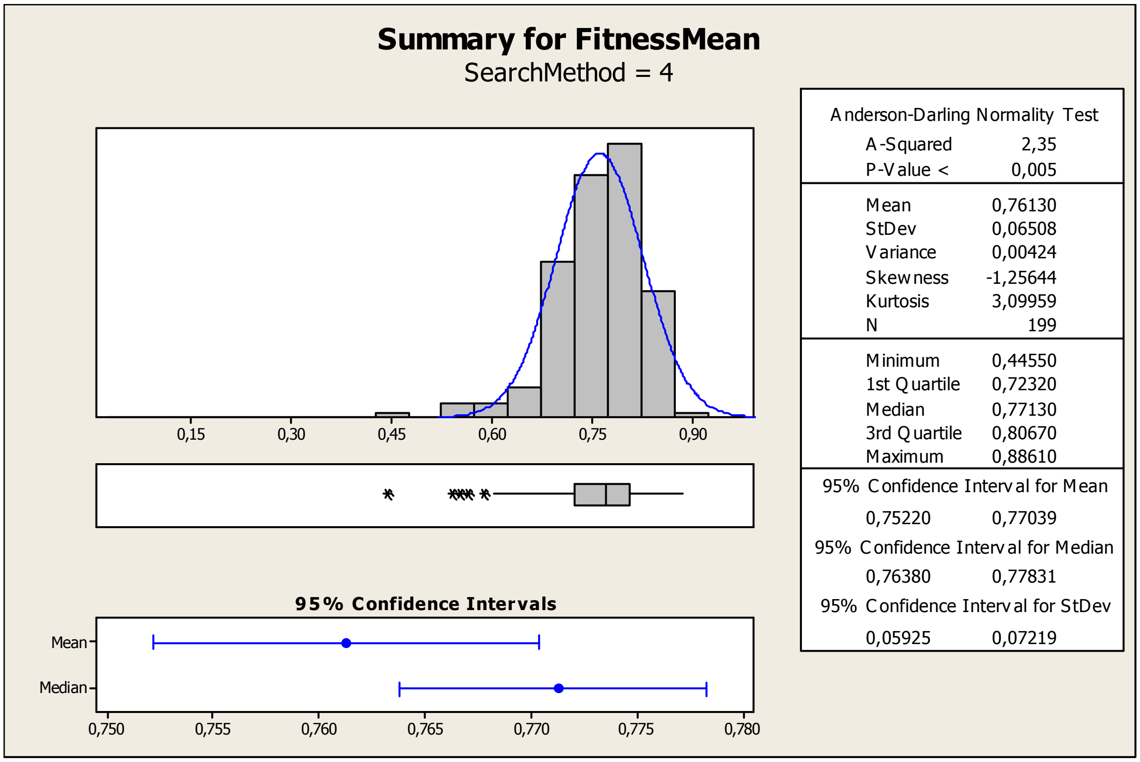
SIMULATION 85, ALL RUNS





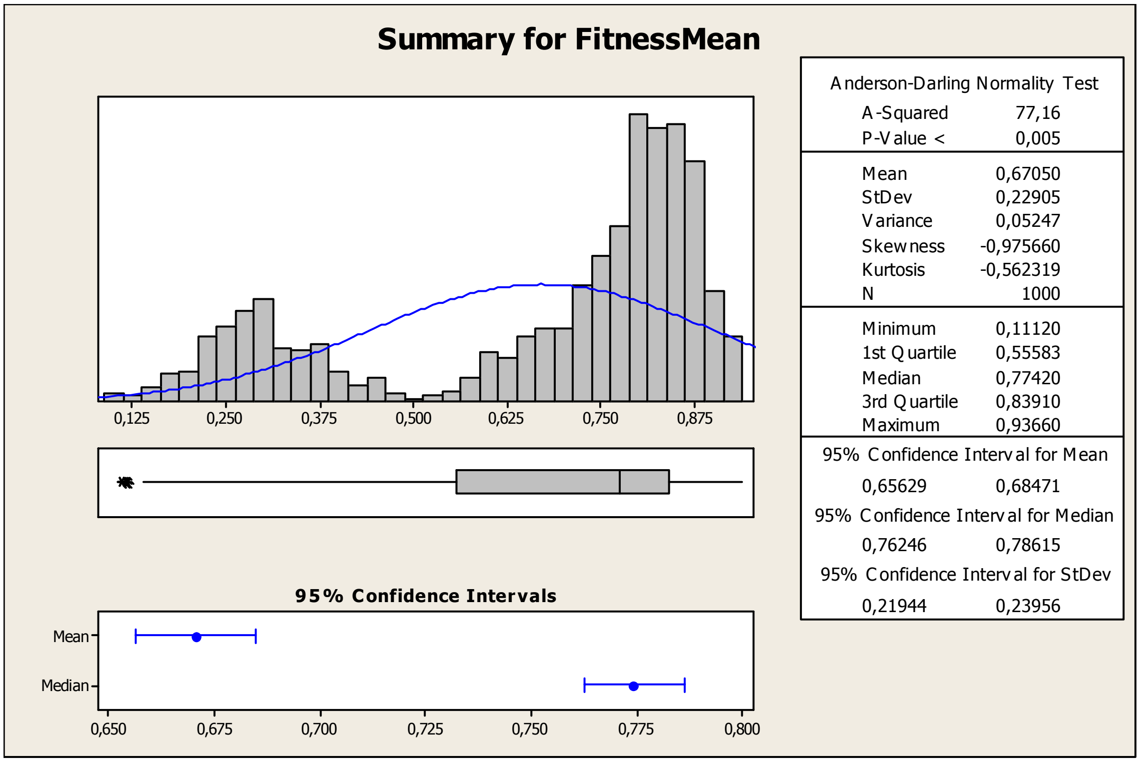

Summary for FitnessMean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 2,22
P-Value < 0,005
Mean 0,73684
StDev 0,09632
Variance 0,00928
Skewness -1,75432
Kurtosis 8,40103
N 197
Minimum 0,12110
1st Quartile 0,69395
Median 0,74360
3rd Quartile 0,79820
Maximum 0,92790
95% Confidence Interval for Mean
0,72331 0,75037
95% Confidence Interval for Median
0,73453 0,75397
95% Confidence Interval for StDev
0,08766 0,10690
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,725 0,730 0,735 0,740 0,745 0,750 0,755

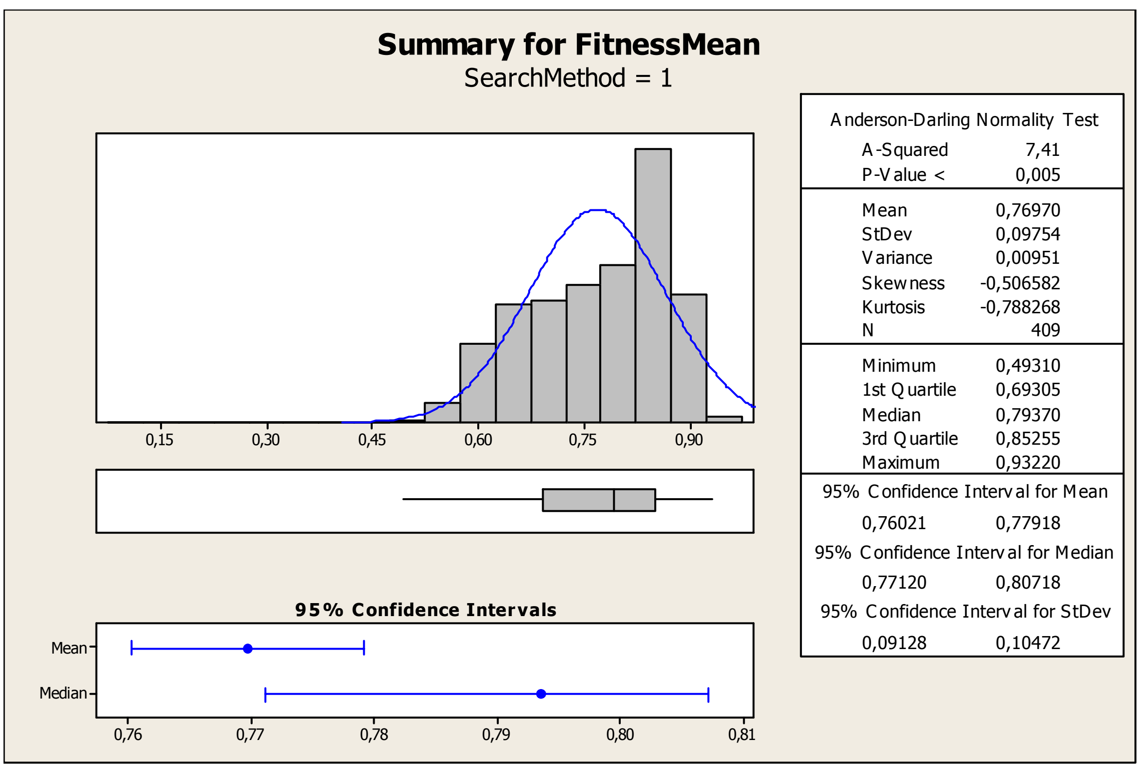

Summary for FitnessMean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,61
P-Value 0,110
Mean 0,24596
StDev 0,08300
Variance 0,00689
Skewness 0,435517
Kurtosis 0,627416
N 191
Minimum 0,05380
1st Quartile 0,18920
Median 0,24900
3rd Quartile 0,29460
Maximum 0,55530
95% Confidence Interval for Mean
0,23411 0,25780
95% Confidence Interval for Median
0,23154 0,25667
95% Confidence Interval for StDev
0,07543 0,09228
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,230 0,235 0,240 0,245 0,250 0,255 0,260

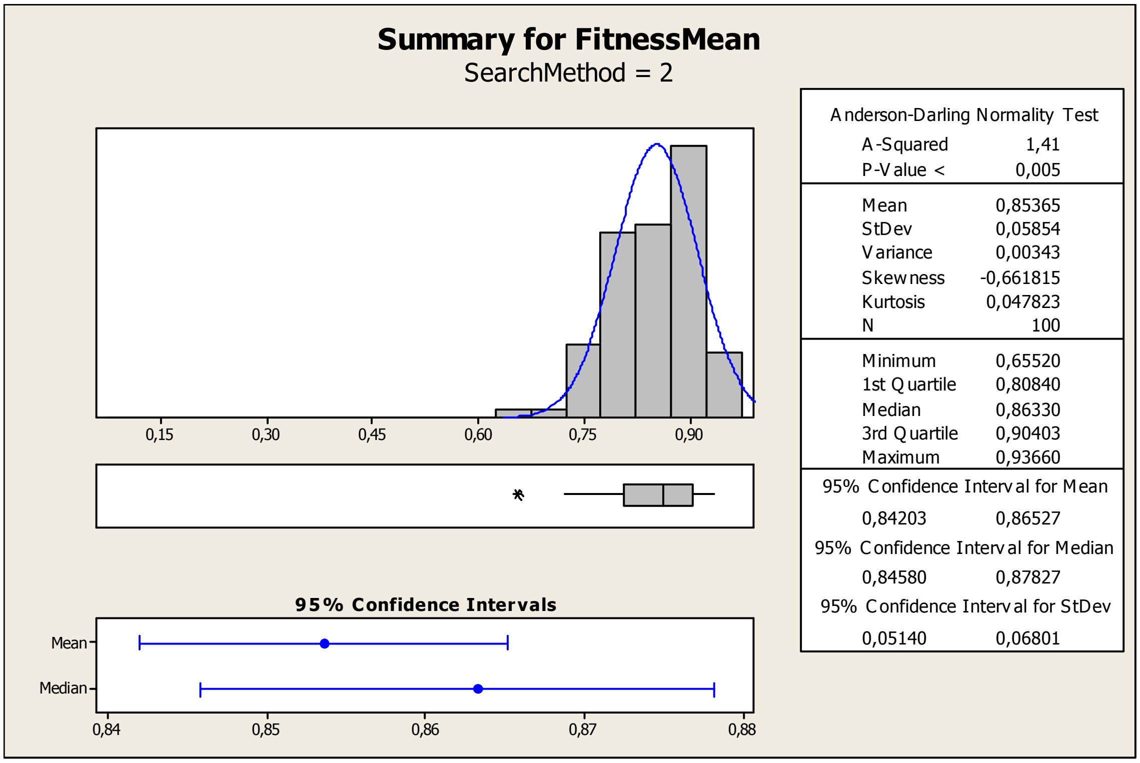


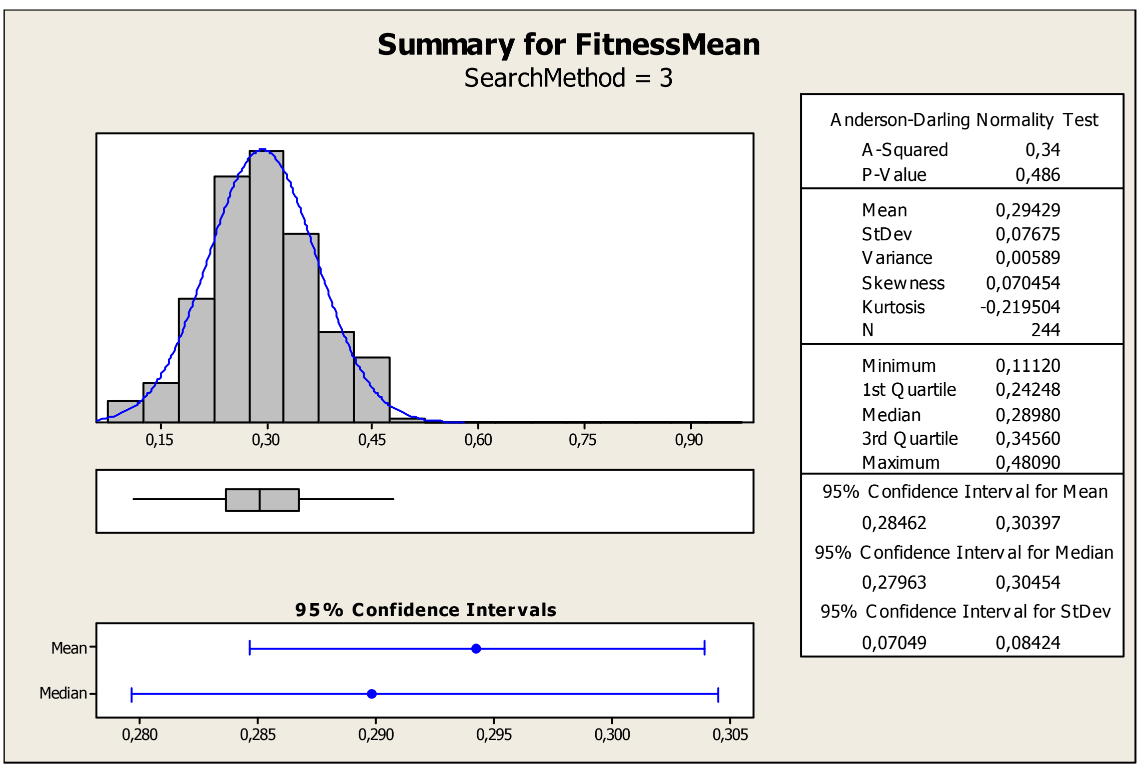
Summary for FitnessMean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 2,35
P-Value < 0,005
Mean 0,76130
StDev 0,06508
Variance 0,00424
Skewness -1,25644
Kurtosis 3,09959
N 199
Minimum 0,44550
1st Quartile 0,72320
Median 0,77130
3rd Quartile 0,80670
Maximum 0,88610
95% Confidence Interval for Mean
0,75220 0,77039
95% Confidence Interval for Median
0,76380 0,77831
95% Confidence Interval for StDev
0,05925 0,07219
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,750 0,755 0,760 0,765 0,770 0,775 0,780

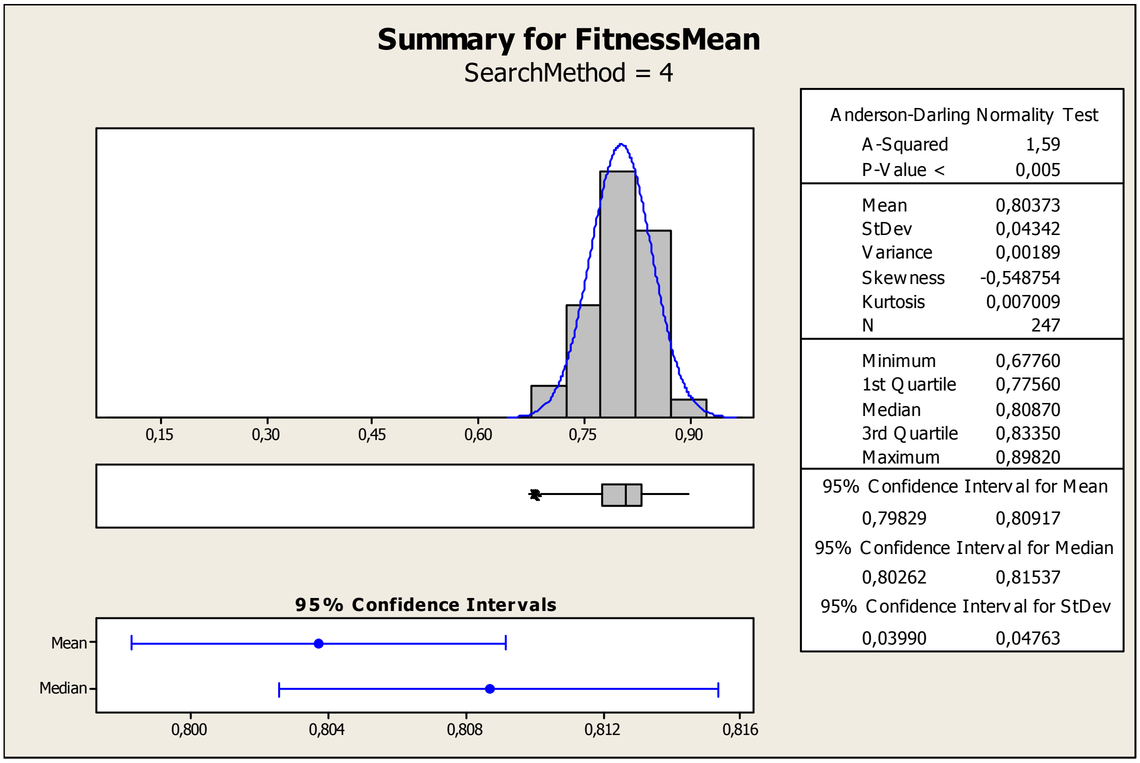
SIMULATION 88, ALL RUNS



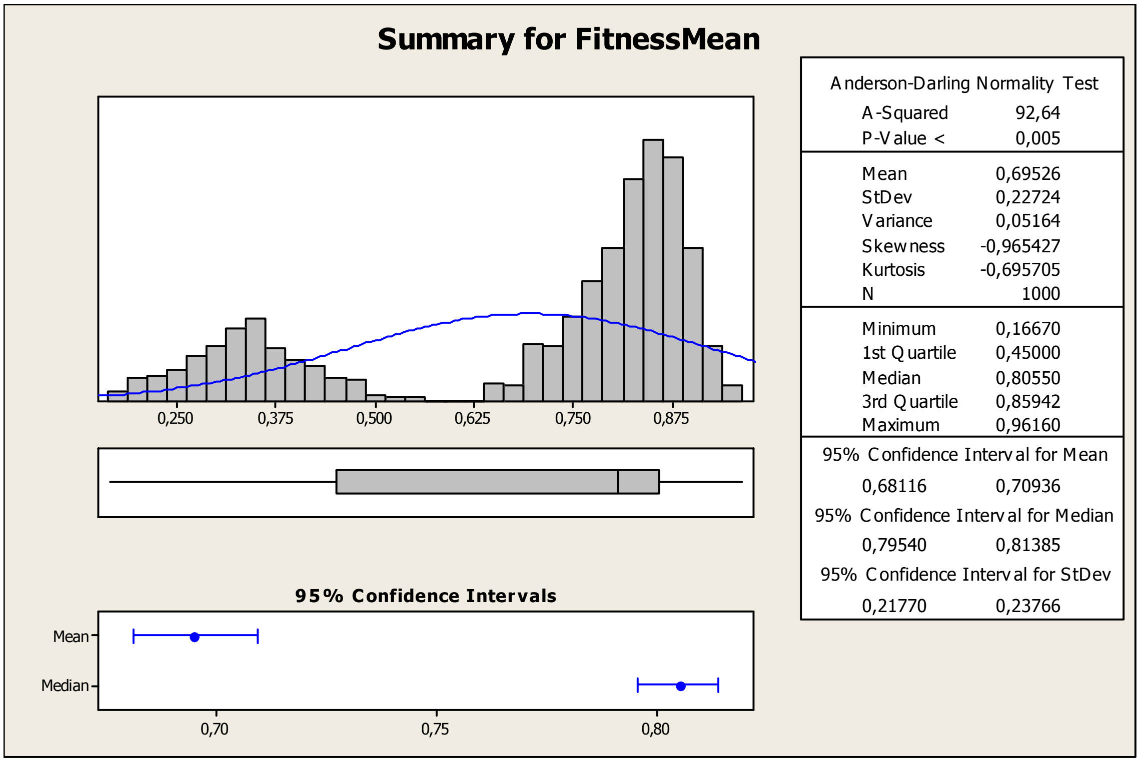


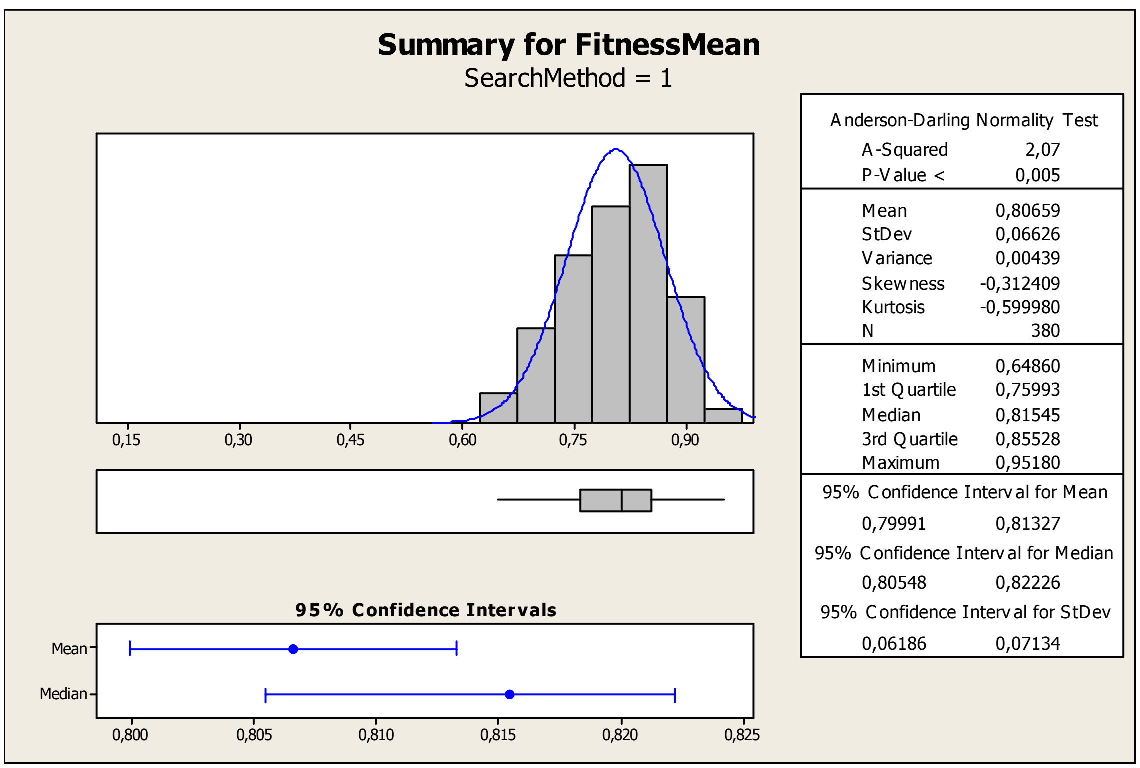

Summary for FitnessMean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 1,41
P-Value < 0,005
Mean 0,85365
StDev 0,05854
Variance 0,00343
Skewness -0,661815
Kurtosis 0,047823
N 100
Minimum 0,65520
1st Quartile 0,80840
Median 0,86330
3rd Quartile 0,90403
Maximum 0,93660
95% Confidence Interval for Mean
0,84203 0,86527
95% Confidence Interval for Median
0,84580 0,87827
95% Confidence Interval for StDev
0,05140 0,06801
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,84 0,85 0,86 0,87 0,88

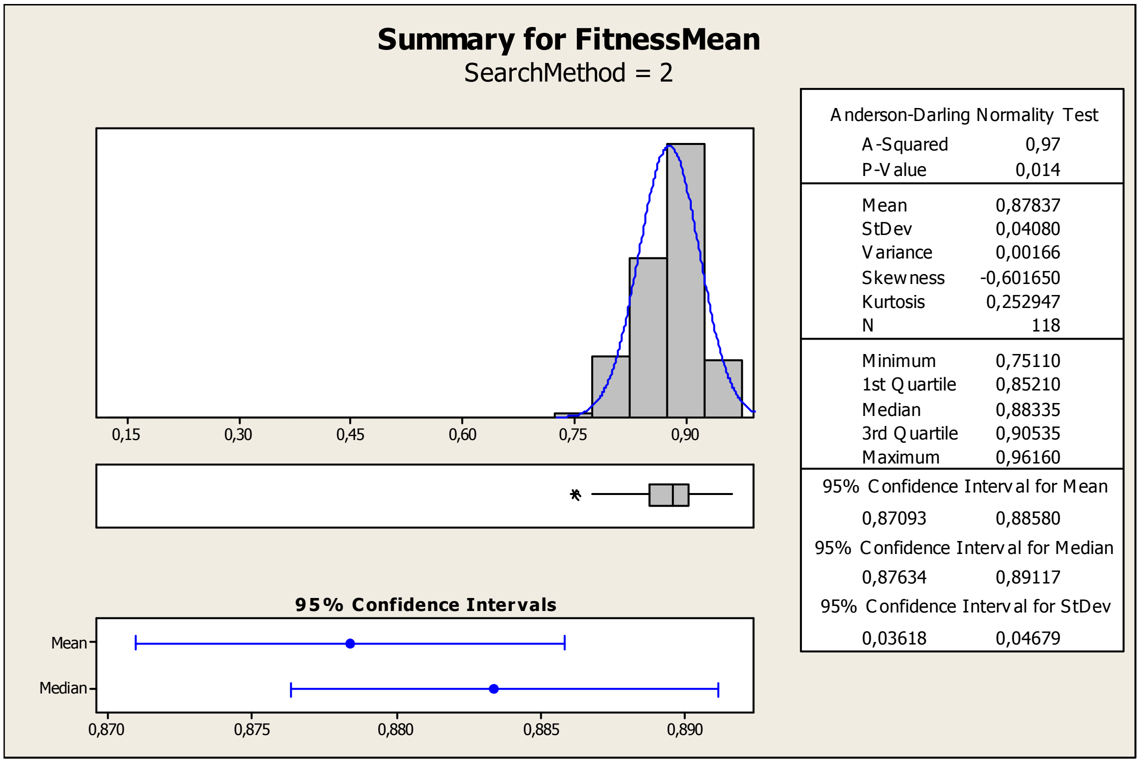

Summary for FitnessMean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,34
P-Value 0,486
Mean 0,29429
StDev 0,07675
Variance 0,00589
Skewness 0,070454
Kurtosis -0,219504
N 244
Minimum 0,11120
1st Quartile 0,24248
Median 0,28980
3rd Quartile 0,34560
Maximum 0,48090
95% Confidence Interval for Mean
0,28462 0,30397
95% Confidence Interval for Median
0,27963 0,30454
95% Confidence Interval for StDev
0,07049 0,08424
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,280 0,285 0,290 0,295 0,300 0,305

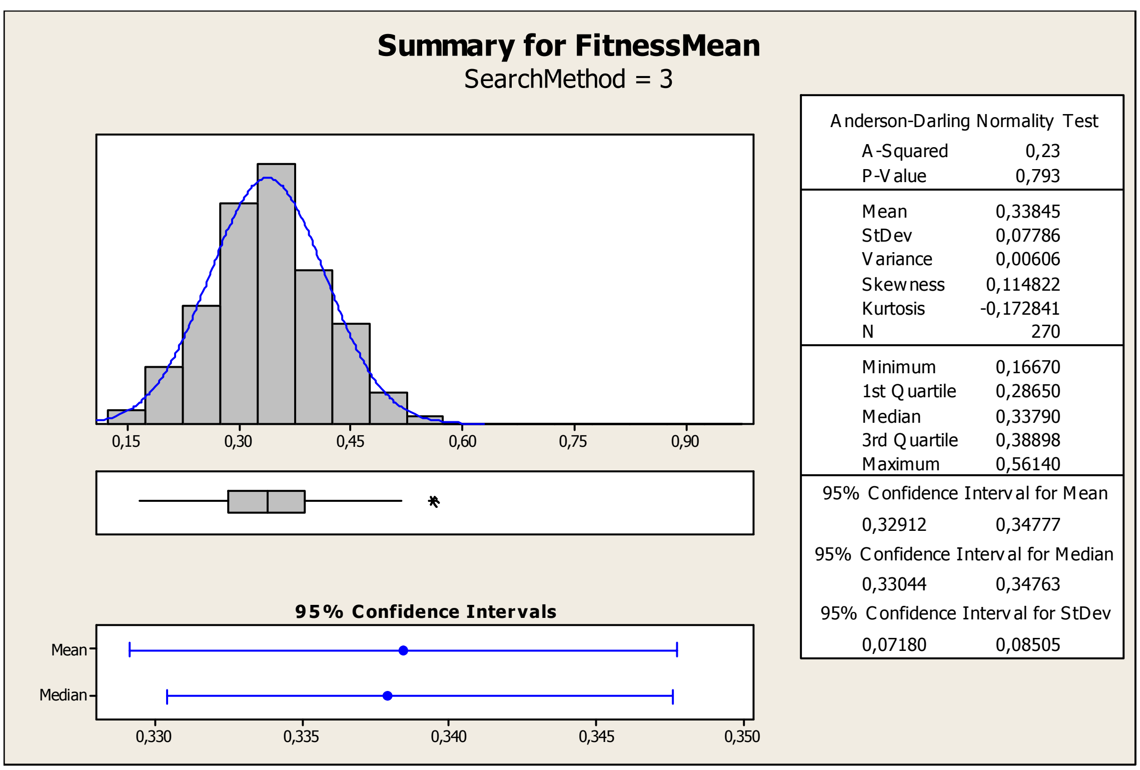

Summary for FitnessMean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,59
P-Value < 0,005
Mean 0,80373
StDev 0,04342
Variance 0,00189
Skewness -0,548754
Kurtosis 0,007009
N 247
Minimum 0,67760
1st Quartile 0,77560
Median 0,80870
3rd Quartile 0,83350
Maximum 0,89820
95% Confidence Interval for Mean
0,79829 0,80917
95% Confidence Interval for Median
0,80262 0,81537
95% Confidence Interval for StDev
0,03990 0,04763
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,800
0,804
0,808
0,812
0,816

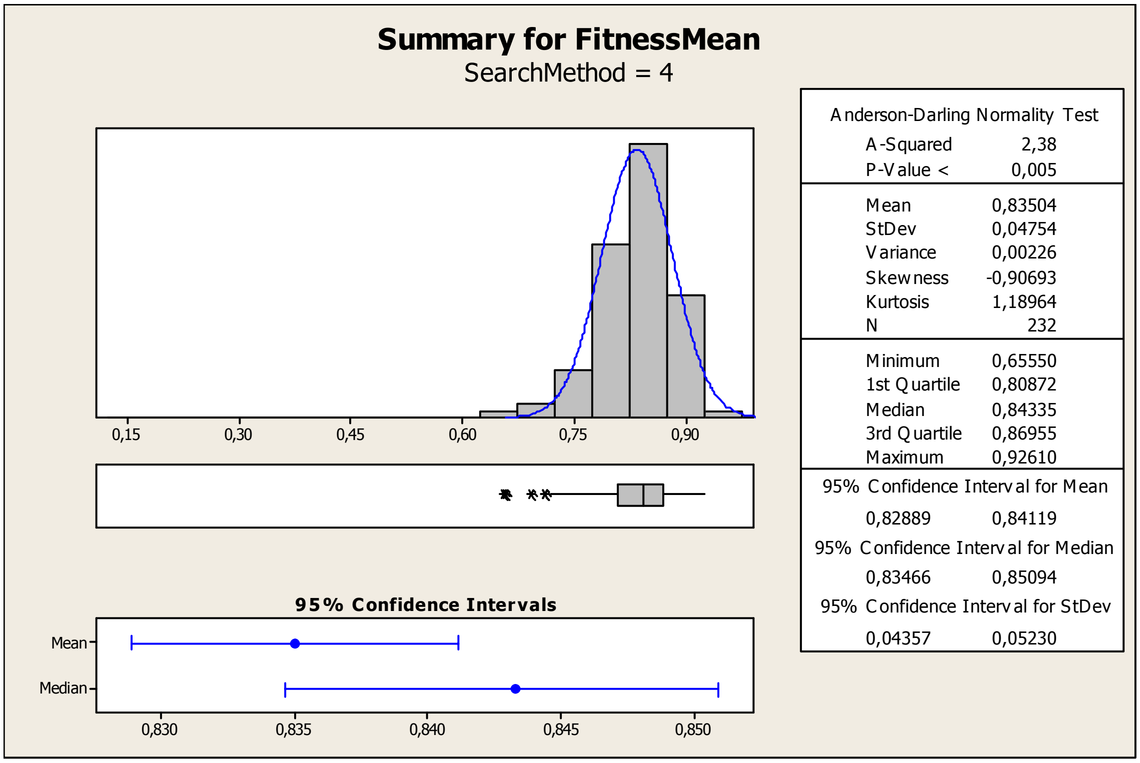
SIMULATION 89, ALL RUNS



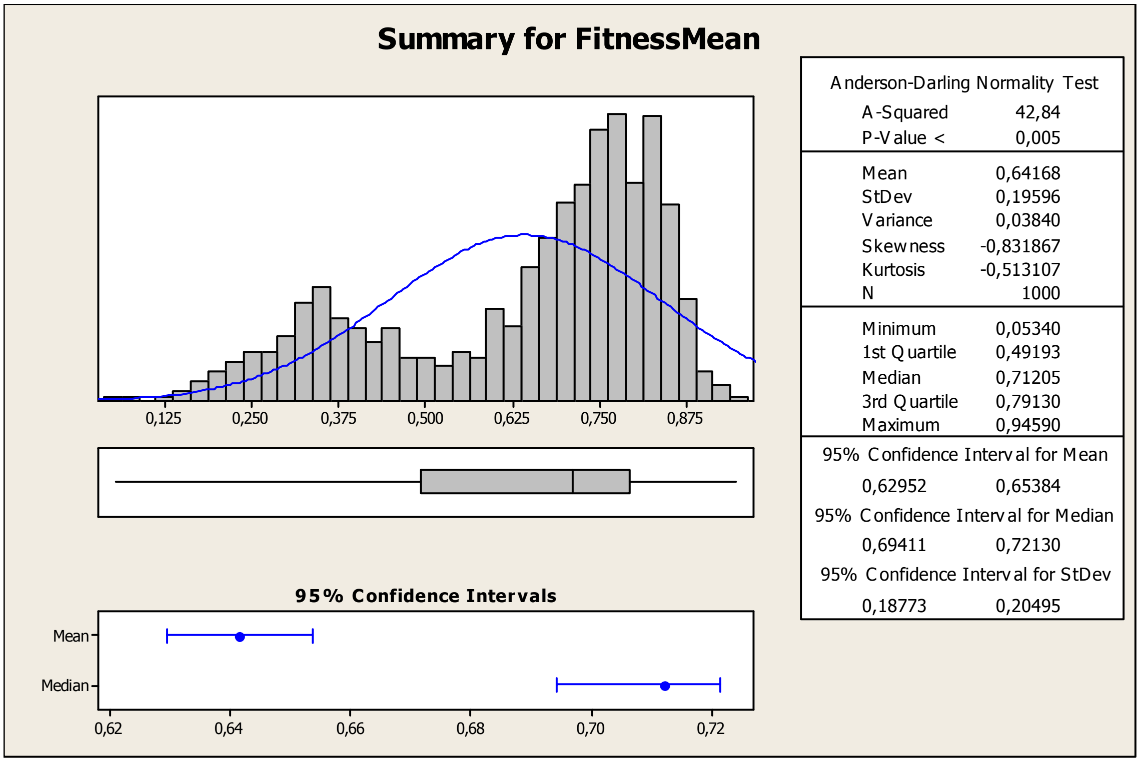


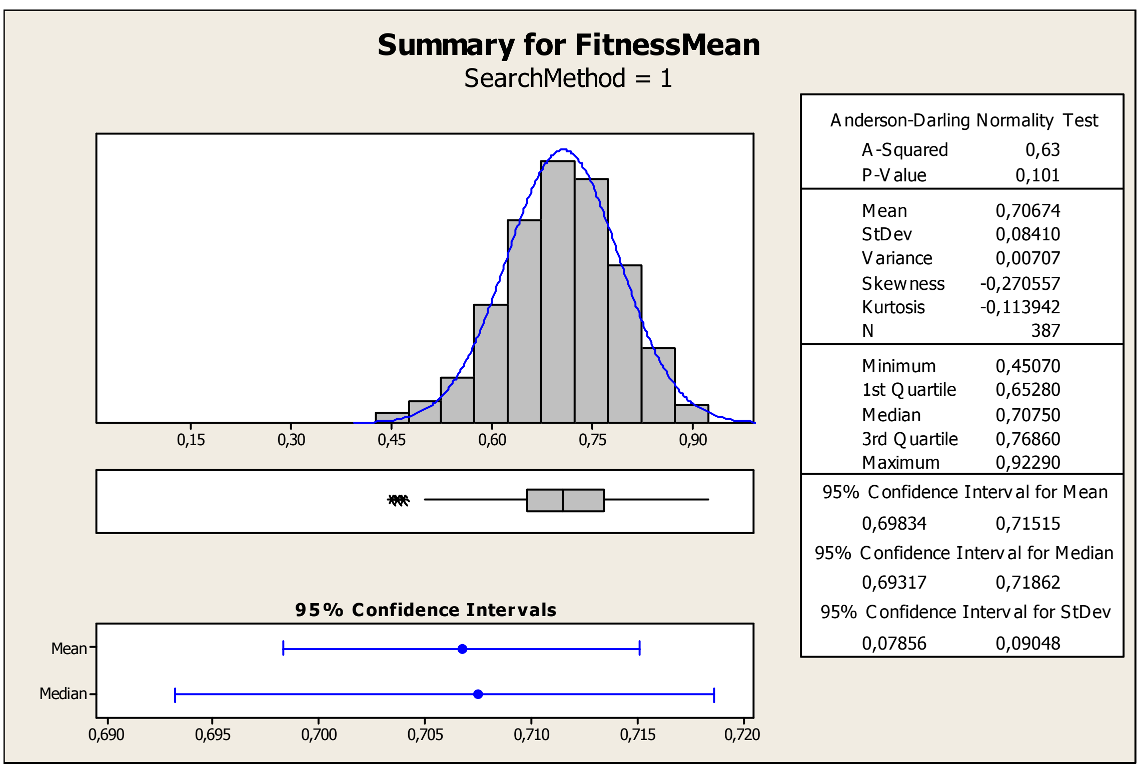

Summary for FitnessMean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,97
P-Value 0,014
Mean 0,87837
StDev 0,04080
Variance 0,00166
Skewness -0,601650
Kurtosis 0,252947
N 118
Minimum 0,75110
1st Quartile 0,85210
Median 0,88335
3rd Quartile 0,90535
Maximum 0,96160
95% Confidence Interval for Mean
0,87093 0,88580
95% Confidence Interval for Median
0,87634 0,89117
95% Confidence Interval for StDev
0,03618 0,04679
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,870 0,875 0,880 0,885 0,890

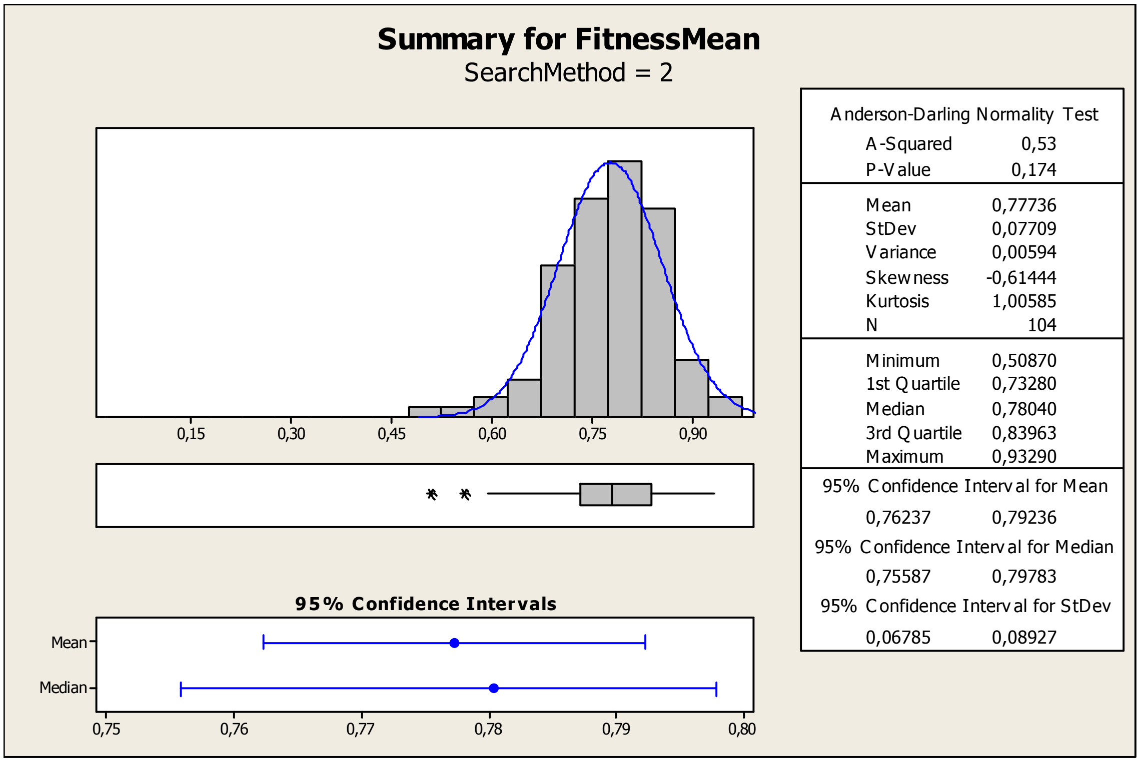

Summary for FitnessMean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,23
P-Value 0,793
Mean 0,33845
StDev 0,07786
Variance 0,00606
Skewness 0,114822
Kurtosis -0,172841
N 270
Minimum 0,16670
1st Quartile 0,28650
Median 0,33790
3rd Quartile 0,38898
Maximum 0,56140
95% Confidence Interval for Mean
0,32912 0,34777
95% Confidence Interval for Median
0,33044 0,34763
95% Confidence Interval for StDev
0,07180 0,08505
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,330 0,335 0,340 0,345 0,350

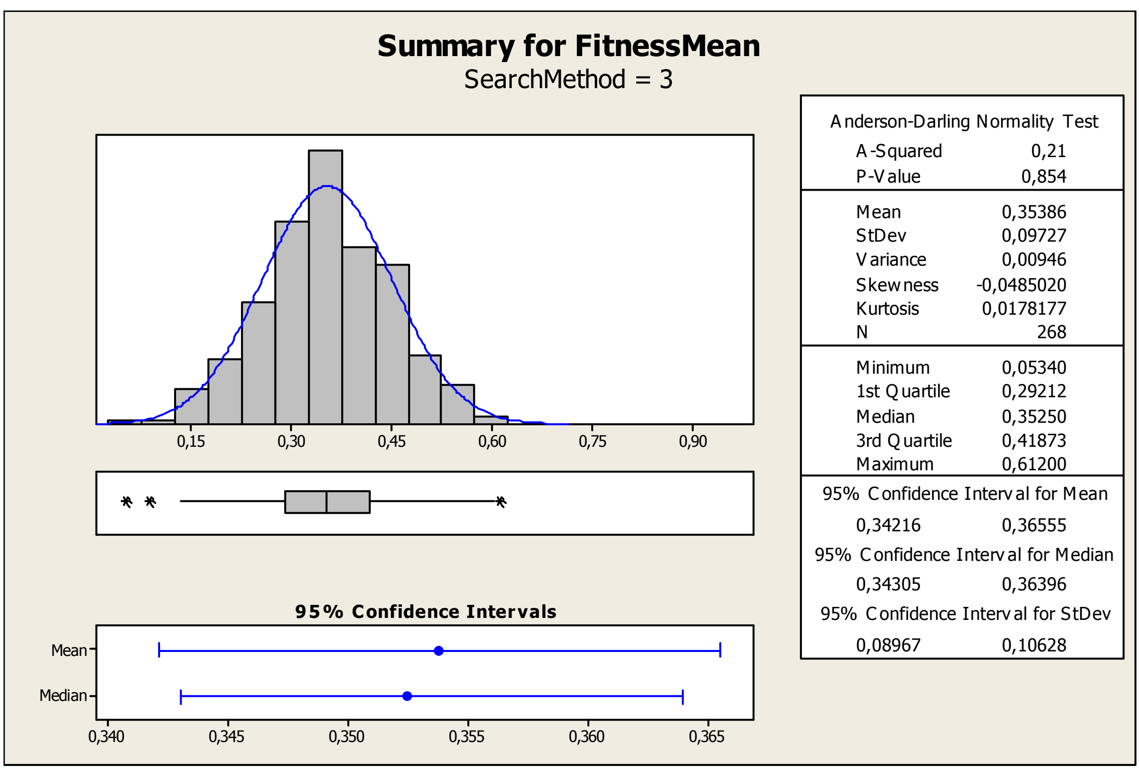

Summary for FitnessMean
SearchMethod = 4
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,830
0,835
0,840
0,845
0,850
Anderson-Darling Normality Test
A-Squared 2,38
P-Value < 0,005
Mean 0,83504
StDev 0,04754
Variance 0,00226
Skewness -0,90693
Kurtosis 1,18964
N 232
Minimum 0,65550
1st Quartile 0,80872
Median 0,84335
3rd Quartile 0,86955
Maximum 0,92610
95% Confidence Interval for Mean
0,82889 0,84119
95% Confidence Interval for Median
0,83466 0,85094
95% Confidence Interval for StDev
0,04357 0,05230

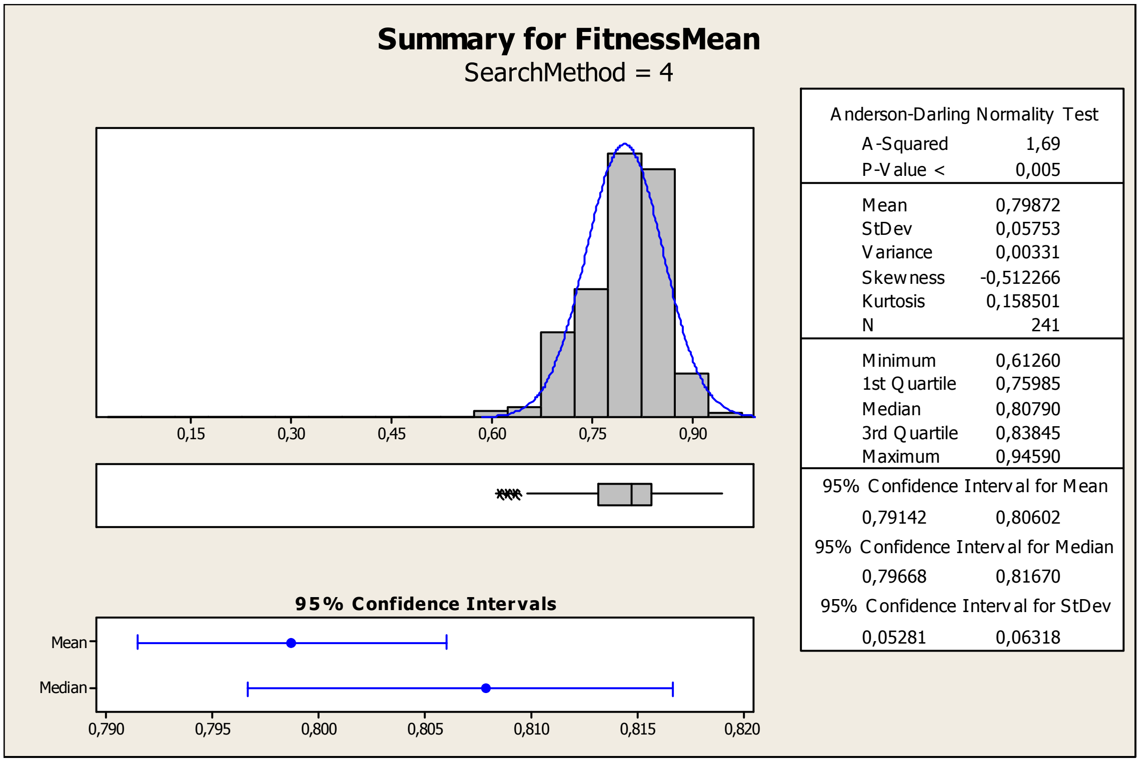
SIMULATION 90, ALL RUNS



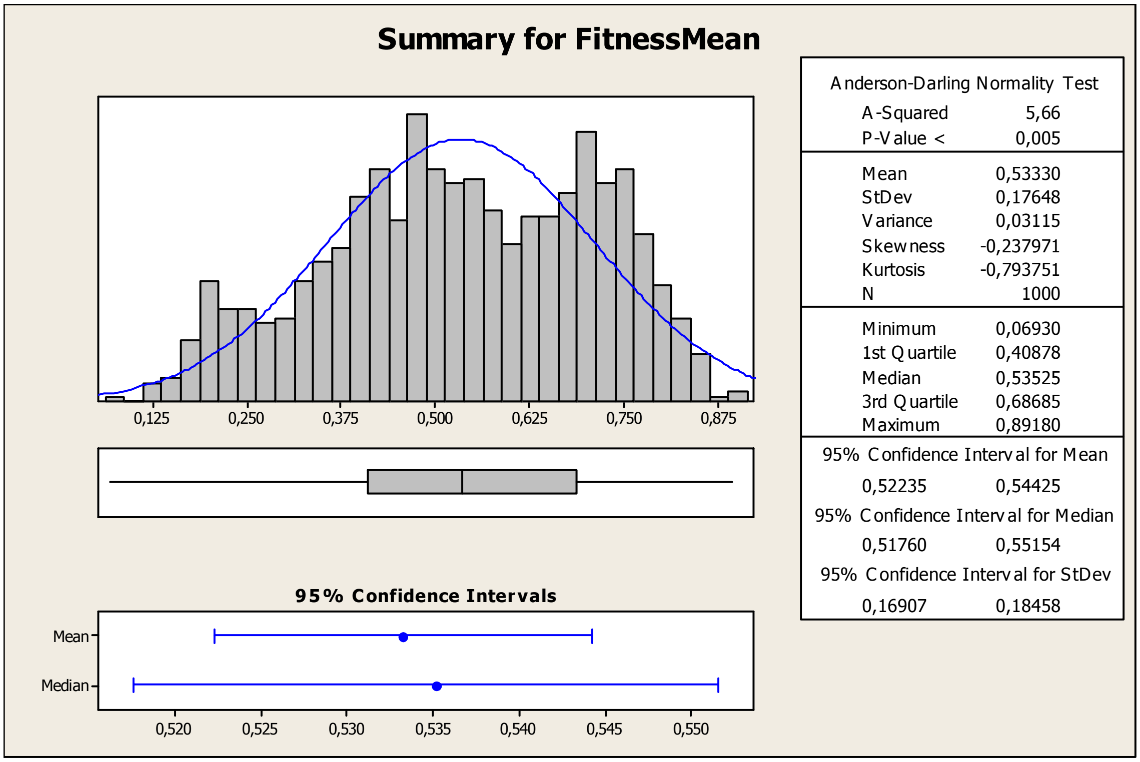


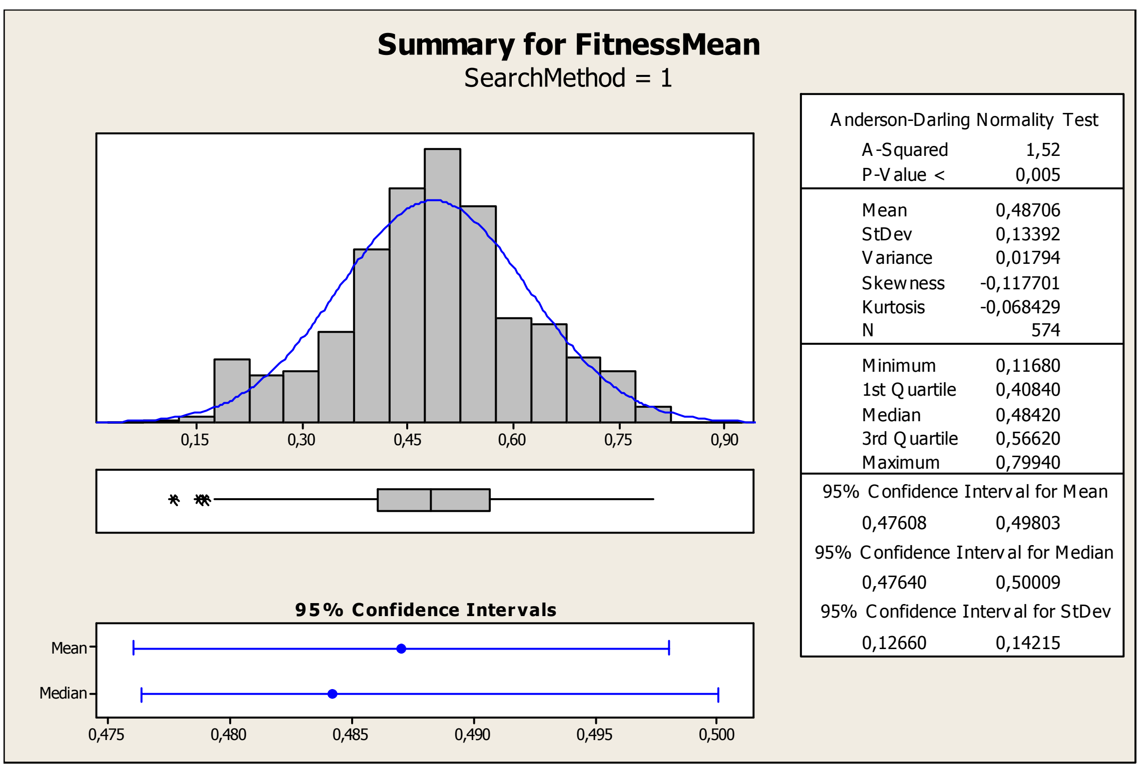

Summary for FitnessMean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,53
P-Value 0,174
Mean 0,77736
StDev 0,07709
Variance 0,00594
Skewness -0,61444
Kurtosis 1,00585
N 104
Minimum 0,50870
1st Quartile 0,73280
Median 0,78040
3rd Quartile 0,83963
Maximum 0,93290
95% Confidence Interval for Mean
0,76237 0,79236
95% Confidence Interval for Median
0,75587 0,79783
95% Confidence Interval for StDev
0,06785 0,08927
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,75 0,76 0,77 0,78 0,79 0,80

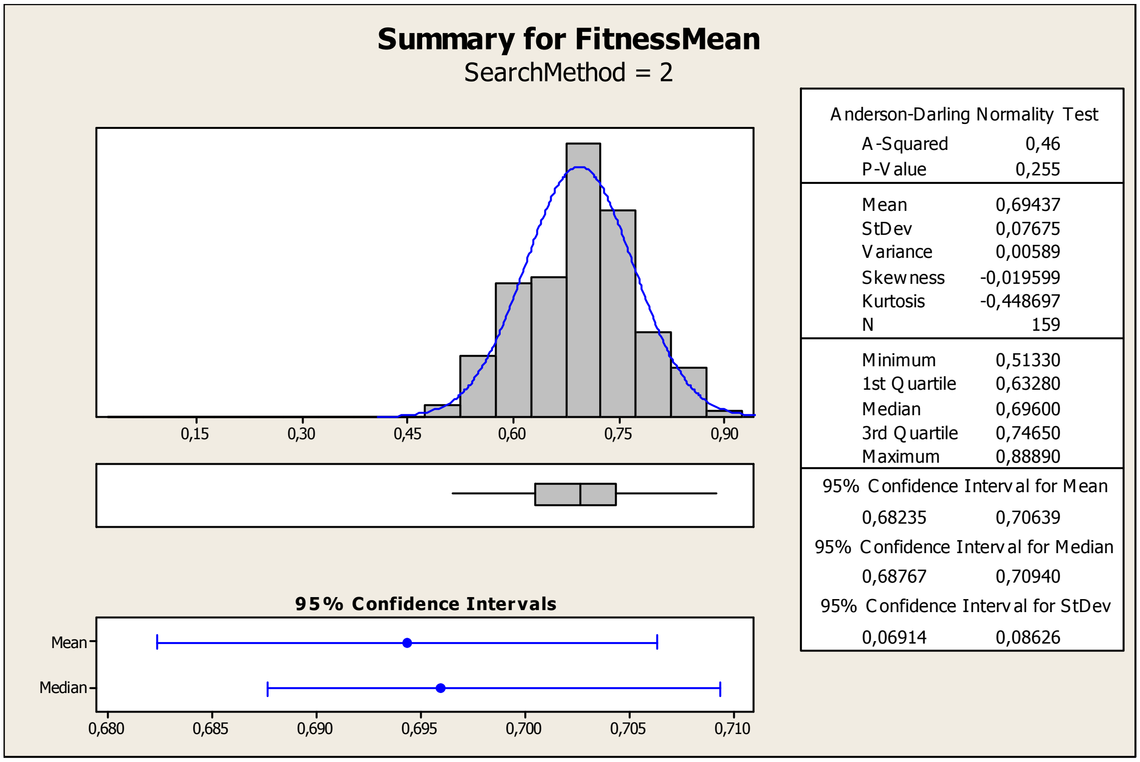

Summary for FitnessMean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,21
P-Value 0,854
Mean 0,35386
StDev 0,09727
Variance 0,00946
Skewness -0,0485020
Kurtosis 0,0178177
N 268
Minimum 0,05340
1st Quartile 0,29212
Median 0,35250
3rd Quartile 0,41873
Maximum 0,61200
95% Confidence Interval for Mean
0,34216 0,36555
95% Confidence Interval for Median
0,34305 0,36396
95% Confidence Interval for StDev
0,08967 0,10628
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,340 0,345 0,350 0,355 0,360 0,365

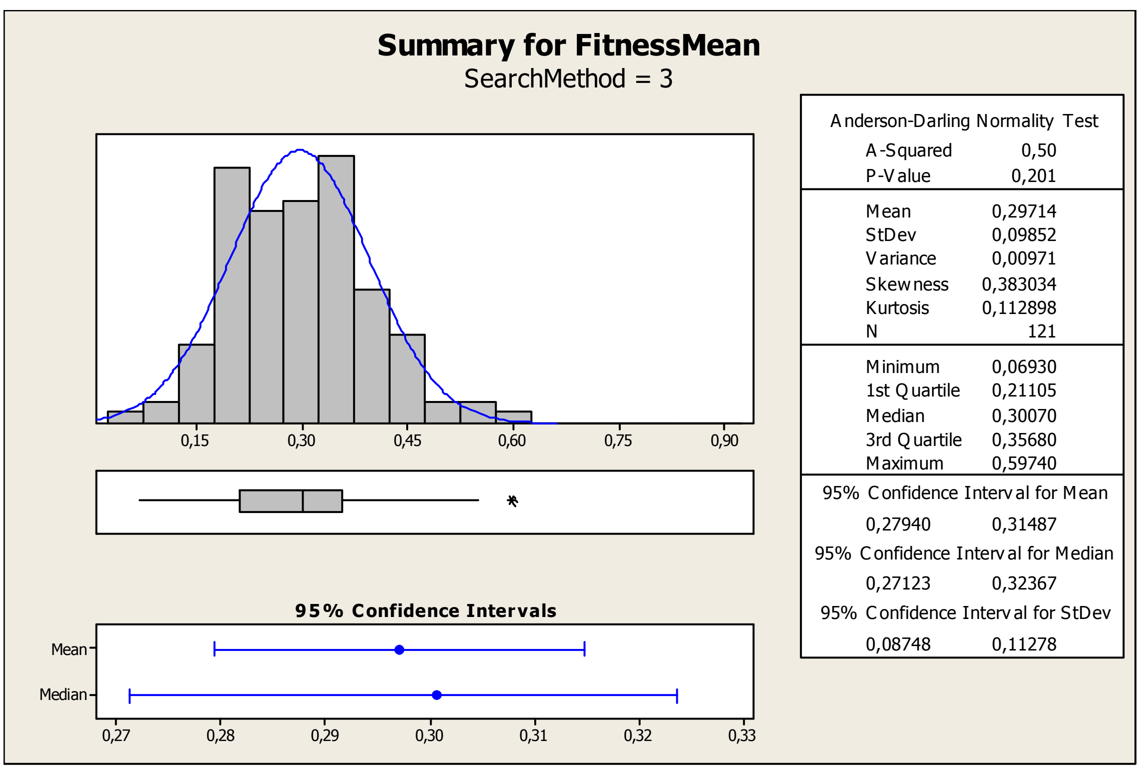

Summary for FitnessMean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 1,69
P-Value < 0,005
Mean 0,79872
StDev 0,05753
Variance 0,00331
Skewness -0,512266
Kurtosis 0,158501
N 241
Minimum 0,61260
1st Quartile 0,75985
Median 0,80790
3rd Quartile 0,83845
Maximum 0,94590
95% Confidence Interval for Mean
0,79142 0,80602
95% Confidence Interval for Median
0,79668 0,81670
95% Confidence Interval for StDev
0,05281 0,06318
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,790 0,795 0,800 0,805 0,810 0,815 0,820

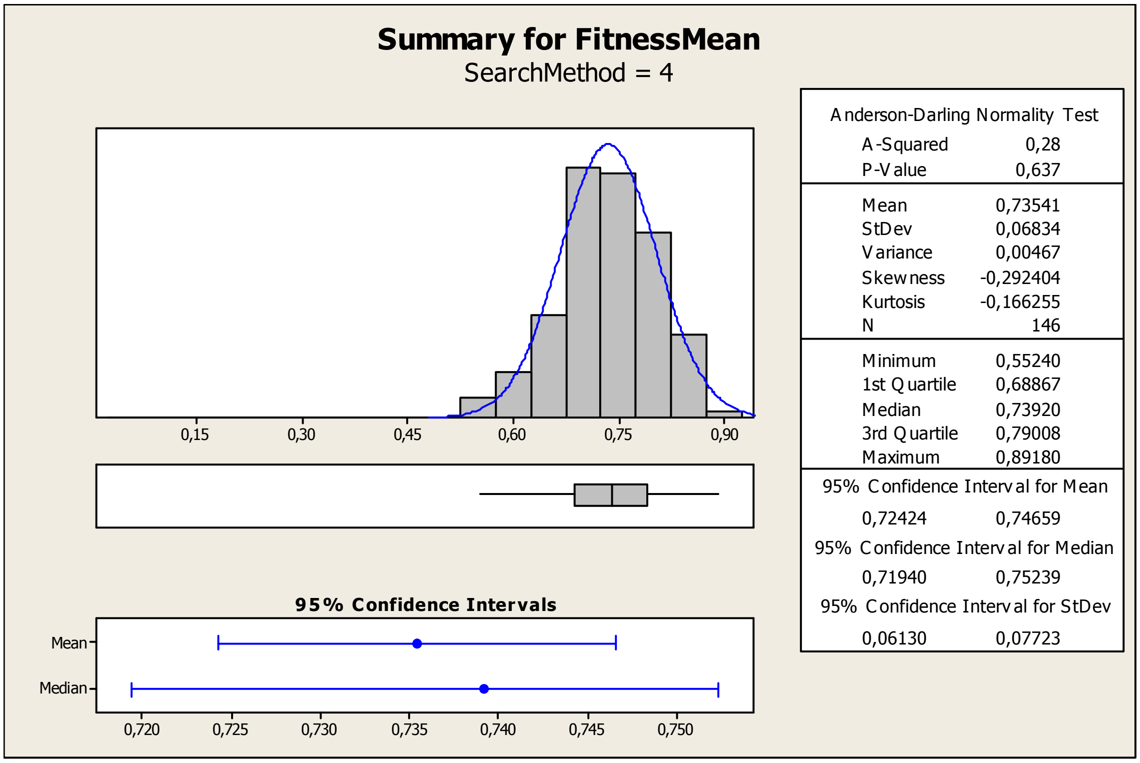
SIMULATION 91, ALL RUNS






Summary for FitnessMean
SearchMethod = 2
Anderson-Darling Normality Test
A-Squared 0,46
P-Value 0,255
Mean 0,69437
StDev 0,07675
Variance 0,00589
Skewness -0,019599
Kurtosis -0,448697
N 159
Minimum 0,51330
1st Quartile 0,63280
Median 0,69600
3rd Quartile 0,74650
Maximum 0,88890
95% Confidence Interval for Mean
0,68235 0,70639
95% Confidence Interval for Median
0,68767 0,70940
95% Confidence Interval for StDev
0,06914 0,08626
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,680 0,685 0,690 0,695 0,700 0,705 0,710


Summary for FitnessMean
SearchMethod = 3
Anderson-Darling Normality Test
A-Squared 0,50
P-Value 0,201
Mean 0,29714
StDev 0,09852
Variance 0,00971
Skewness 0,383034
Kurtosis 0,112898
N 121
Minimum 0,06930
1st Quartile 0,21105
Median 0,30070
3rd Quartile 0,35680
Maximum 0,59740
95% Confidence Interval for Mean
0,27940 0,31487
95% Confidence Interval for Median
0,27123 0,32367
95% Confidence Interval for StDev
0,08748 0,11278
0,15 0,30 0,45 0,60 0,75 0,90
95% Confidence Intervals
Mean
Median
0,27 0,28 0,29 0,30 0,31 0,32 0,33


Summary for FitnessMean
SearchMethod = 4
Anderson-Darling Normality Test
A-Squared 0,28
P-Value 0,637
Mean 0,73541
StDev 0,06834
Variance 0,00467
Skewness -0,292404
Kurtosis -0,166255
N 146
Minimum 0,55240
1st Quartile 0,68867
Median 0,73920
3rd Quartile 0,79008
Maximum 0,89180
95% Confidence Interval for Mean
0,72424 0,74659
95% Confidence Interval for Median
0,71940 0,75239
95% Confidence Interval for StDev
0,06130 0,07723
0,15
0,30
0,45
0,60
0,75
0,90
95% Confidence Intervals
Mean
Median
0,720
0,725
0,730
0,735
0,740
0,745
0,750

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