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Competitive Market Simulation

Alife-base System to Simulate Competition Between Companies in a Competitive Market

Pedro Costa Sequeira

Dissertation

presented as partial requirement for obtaining the Master Degree Program in Data Science and Advanced Analytics

NOVA Information Management School

Instituto Superior de Estatística e Gestão de Informação

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COMPETITIVE MARKET SIMULATION

by

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Dissertation presented as partial requirement for obtaining the Master's degree in Advanced Analytics, with a specialization in Data Science

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

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ABSTRACT

Artificial Life is a study field that examines the imitation and the amalgamation of life-like behaviors and systems via computational, machinelike and biochemical means. The scientists can scrutinize the subtleties of the life progressions, genetic evolution, and environmental interactions in a controlled, simulated setting by applying the computational models. A chiefly exciting application of these Alife systems is in the imitation of competitive surroundings, such as those that are found in the business markets. Consequently, this thesis examines the use of artificial life systems to imitate the rivalry between firms in a competitive market. The thesis probes into the notion of the Alife, the competitive surroundings, the enterprise triumph, and the simulation modelling in order to comprehend how these systems can be anticipated to advance the achievement of enterprises in dynamic markets. This thesis verified how artificial life systems can be employed in the imitation and the analysis of the rivalry between firms in a competitive market while probing the existing research and theories. Still, the verdicts exemplified that Alife has been pragmatic in numerous fields, from understanding the evolutionary methods to the development of progressive artificial intelligence systems, improving synthetic biology methods, and making realistic environmental imitations. Also, the verdicts recommended that artificial life-based systems can irradiate the adaptive and evolutionary methods that depict competitive markets. Thus, the incorporation of innovative technologies and improved model realism can supplement the capabilities and applications of these imitations, offering new avenues for strategic decision-making and innovation in business.

KEYWORDS

Artificial Life; Corporate DNA; Competitive Strategy; Enterprise Architecture; Enterprise DNA; Evolutionary Algorithms; Genetic Algorithms

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1. INTRODUCTION

1.1 CONTEXT AND PROBLEM IDENTIFICATION

The likelihood of imitating a competitive atmosphere to envisage the survival or even the triumph of the firms is acquiring some traction with the evolution and maturing of mockup models (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019; Vassolo, 2024). The notion of Artificial Life has appeared as a prevailing tool for simulating intricate systems and phenomena in the realm of current business, providing intuitions into the subtleties of biological, social and economic methods (Alam et al., 2020; Trotsyuk, 2019). Numerous factors influence the triumph of enterprises in severely contested markets (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019; Vassolo, 2024). Though, the imitation of competitive surroundings to examine and understand these factors that impact the triumph of firms in competitive markets is a gripping application within the field of Alife (Luan, 2024; Trotsyuk, 2019; Vassolo, 2024).

However, there have been numerous research exertions converging on the viability of this imitation, but a practical application has yet to be brought forward in the academic discourse (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019; Vassolo, 2024). The paper stresses on generating an Alife-based system that can competently emulate the contention between businesses in competitive surroundings. The study purposes to develop a lively, evolving surrounding where businesses can compete, adjust and perhaps thrive based on their approaches and competences by using the ideologies of the Alife. Also, the paper trails to address the intrinsic complexity and spontaneity of competitive markets. The initiatives must pilot a scenery rampant with real-world trade conditions with difficulties such as shifting consumer penchants, technological instabilities, regulatory adjustments and the maneuvers for rival firms (Alam et al., 2020; Trotsyuk, 2019). Therefore, understanding how these multifaceted issues correlate and impact the triumph or fiasco of enterprises is remarkable for corporate leaders, legislators, and experts (Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019; Vassolo, 2024). Consequently, by emerging an erudite Artificial Life-based simulation system personalized to match the competitive subtleties of real-world markets, this research aims to highlight the distinctions of the competition and triumph in controlled, experimental settings (Kartina et al., 2020; Lehman et al., 2020; Trotsyuk, 2019; Vassolo, 2024).

1.2 OBJECTIVES

The key aim of this thesis is to build a system to simulate rivalry between firms in a competitive market in order to assess the main features allied to their triumph.

In order to reach the desirable goal, the following intermediate objectives were defined:

- Make a comprehensive study on market and enterprise simulations
- Build a system to simulate competition between companies in a competitive market
    - Define a company DNA modeling system that allows better simulations through the Alife principles
    - Derive an approximate fitness function and simulating parameters,

- Evaluate the model
    - Analyze the simulation outcomes and compare them to theoretical propositions and, using historical data, gauge the closeness of the simulation outcomes to reality.

1.3 Study Importance and Relevance

Given the lack of simulation outcomes, it could be very beneficial to develop a minimum viable model that is accurate enough to give general predictions of macro-level movements within the competitive environment for a reasonable timeframe. The intuitions acquired from the Alife imitations can apprise strategic decision-making, menace management, and innovation exertions for the corporations (Alam et al., 2020; Trotsyuk, 2019). For example, corporate leaders can enhance their approaches, forestall the market drifts, and recognize the potential drawbacks before they occur by observing the behaviors and outcomes of the virtual firms in competitive markets (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). Also, this paper subsidizes to the growing body of knowledge neighboring the applications of Alife in corporate and economics. This study augments to the interdisciplinary discourse between artificial intelligence, finances, and evolutionary ecology by signifying the efficacy of Alife imitations for studying intricate adaptive schemes like competitive markets. Additionally, understanding how the firms interrelate and contest in simulated surroundings can help the legislators craft more effective regulations, improve competition, and support monetary growth and innovation (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019).

2. LITERATURE REVIEW

2.1. INTRODUCTION TO ARTIFICIAL LIFE

Artificial Life is a study field that examines the imitation and the amalgamation of life-like behaviors and systems via computational, machinelike and biochemical means (Baltieri et al., 2023; Blackiston et al., 2023). The computational modeling, artificial ecology and robotics are the various approaches covered by this field (Baltieri et al., 2023; Blackiston et al., 2023). However, the computational modeling such as the genetic algorithms and the agent-based models involves the development of software programs that simulate the life process. The artificial ecology covers the forming of innovative hereditary parts, devices, and schemes that are absent in the real world. On the contrary, robotics covers the making of physical schemes with realistic recitals, such as independent robots that are proficient in correlating with their surroundings in complex ways (Baltieri et al., 2023; Blackiston et al., 2023).

Many researchers have dissected the use of Alife in emulating viable environs to comprehend the delicacies of the market struggle and its consequence on the achievement of the enterprises (Alam et al., 2020; Baltieri et al., 2023; Blackiston et al., 2023). The model of competitive environs using artificial life schemes is a propitious technique that has the latent to convert the research and the modelling of complex schemes. For instance, one can attain insights into the approaches and behaviors that can result to victory in a competitive market by creating virtual environs where the organizations challenge each other (Baltieri et al., 2023; Blackiston et al., 2023). Still, the use of the Alife has many advantages in the imitation of competitive surroundings.

The aptitude to experiment with varied situations and variables that would be dreadful or even impractical to scrutinize in the real biosphere is one of the noteworthy aids of using the Alife in the imitation of competitive surroundings (Alam et al., 2020; Baltieri et al., 2023; Blackiston et al., 2023). Hence, altering constraints such as market demand, pricing approaches and contestant behavior can enable one to perceive how miscellaneous factors interrelate and influence the outcomes of a competition (Alam et al., 2020; Trotsyuk, 2019). Still, Alife imitations can offer a platform for the testing and refining of the fiscal philosophies related to the competitive markets. For example, emerging genuine models of market subtleties can enable a person to authenticate the existing philosophies or even develop new ones that better define the intricacies of real-world competition (Alam et al., 2020; Baltieri et al., 2023; Blackiston et al., 2023). Besides, Alife imitations can also have practical applications for industries and legislators. Consequently, using simulated surroundings to test numerous strategies and policies can enable a corporation to make more knowledgeable choices about pricing, marketing, and the progression of the products (Alam et al., 2020; Baltieri et al., 2023; Blackiston et al., 2023). Therefore, artificial Life can be used in the modelling of the competitive surroundings in order to simulate the market subtleties, competitive approaches, and the evolution of the organizations within the market.

2.2. APPLICATION OF ARTIFICIAL LIFE IN MODELLING COMPETITIVE ENVIRONMENTS

The Alife has been used in several sections such as comprehending the evolutionary approaches, creating progressive AI systems, developing artificial ecosystem methods and realistic ecological simulations (Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). A vivacious use of the Alife is in the analysis of the monetary and business environments, where Alife ideas are used to emulate the complex relations between firms in viable markets. However, the competitive surroundings are categorized by the existence of numerous firms that vie for inadequate resources such as market share and customer base (Alam et al., 2020; Lehman et al., 2020; Trotsyuk, 2019). Also, these surroundings are dynamic, with persistent discrepancy in the strategies, technologies, consumer predilections and regulations.

For example, miscellaneous factors such as supply and demand, price instabilities and fiscal cycles influence the market dynamics (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). The approaches adopted by the contestants in the corporate competition, including pricing, marketing and innovation, also influence the competitive landscape. However, the legal and regulatory frameworks set the boundaries for competition. In addition, innovation and technological developments can disrupt the markets and redefine the competitive advantage (Alam et al., 2020; Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). Therefore, these factors can greatly impact the success of the firms existing in the competitive markets.

2.3. Enterprise Success in Competitive Markets

Deriving an approximate fitness function and simulating parameters involves the determination of how the success or performance of the company is evaluated within the simulation (Alam et al., 2020; Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020). Success in a competitive market is usually measured in terms of profitability, market share, revenue growth and sustainability. However, various factors affect the success of the companies in these competitive environments, such as strategic planning, resource allocation innovation and research and development (Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020). For instance, effective planning and the execution of business strategies can contribute greatly to the success of a firm in competitive markets, as illustrated by the enterprise architecture indicated in the following figure (Alam et al., 2020; Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020; Trotsyuk, 2019).

Figure 1 – Enterprise Architecture as a Management Tool (Trotsyuk, 2019)

The Enterprise Architecture (EA) outlines the structure and operation of an organization, as illustrated in Figure 1. The EA bridges business strategy and IT infrastructure, ensuring alignment between an enterprise's goals and the technology that supports them (Trotsyuk, 2019). However, the EA assists in designing robust, scalable and adaptable virtual environments where diverse organizational models can be tested when applied to an Alife-based simulation. Consequently, the amalgamation of the Enterprise DNA and EA in an Alife imitation can bid a prevailing tool for understanding the competitive subtleties of the business (Alam et al., 2020; Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020; Trotsyuk, 2019). The Enterprise DNA covers the vital abilities and behaviors programmed within the virtual units that signify the organizations. These traits might involve preemptive choice-making measures, resource dispersal, competitive and modernization methods (Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020; Trotsyuk, 2019).

Subsequently, the ideal use of monetary, human and technological capitals can also enhance the victory of the corporation in competitive settings (Alam et al., 2020; Lehman et al., 2020; Trotsyuk, 2019). Incessant reserves in research and progression to advance novelty can also increase the success of the corporations in competitive markets. Additionally, customer relationships and working aptitude can impact the achievement of a firm in competitive sceneries. For example, constructing and upholding robust consumer relations can promote the achievement of the company in competitive markets (Alam et al., 2020; Lehman et al., 2020; Marakova et al., 2021; Singh et al., 2020; Trotsyuk, 2019). Also, validation of the process for the purpose of lessening outlays and inflate output can result in the victory of the firm in competitive markets (Alam et al., 2020; Lehman et al., 2020; Marakova et al., 2021; Trotsyuk, 2019). Therefore, the capacity of the firm to adapt, revolutionize and use the ersatz modelling is considerable for long-term achievement, primarily in competitive markets.

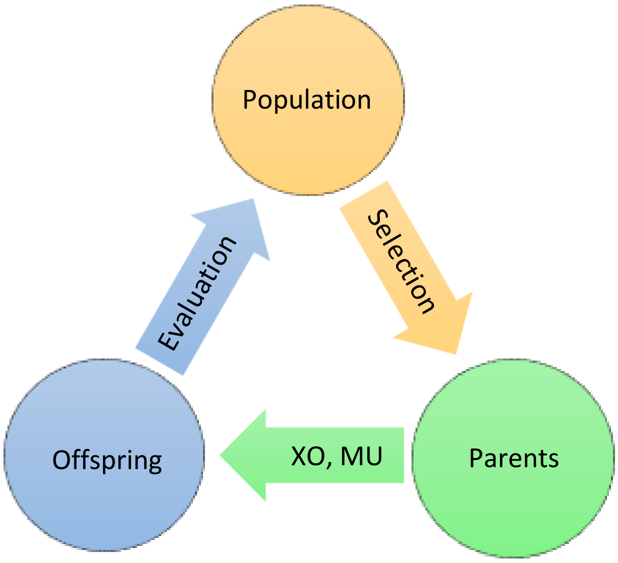
2.4. Simulation Modeling in Competitive Environments

Imitation modeling bids a device for the understanding and conjecture of elaborate systems by emulating their behaviors in a virtual setting (Alam et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). This modeling permits the experts and the firms to assess the theories, dissect the conditions and make conversant choices without the menaces and outlays related to the trials of the real world (Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). The several kinds of ersatz models include the agent-based models (ABM), the discrete event imitation and the scheme dynamic models (Katina et al., 2020; Luan, 2024). The ABM imitates the relations between the discrete agents, such as the organizations and the customers and can seizure the emergent behaviors within the markets. The system dynamics models emphasis on the feedback loops and the time delays that influence the behavior of the whole system (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). Still, the discrete event simulation mockups the explicit events that happen at certain points in time and are valuable for logistics and method optimization.

2.5. Artificial Life-Based Systems for Simulating Market Competition

The various artificial life-based systems that are applied in the simulation of the market competition include the evolutionary game theory, the complex adaptive systems (CAS) and the genetic algorithms (GA) (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). The evolutionary algorithm applies the principles of game theory and evolution to model the strategic interactions between the competing firms. On the other hand, complex adaptive systems view markets as adaptive systems where the firms constantly learn and adapt their strategies based on environmental variations (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024). The genetic algorithms use principles of natural selection and genetics to evolve optimal business strategies over time, as shown in the following figure (Alam et al., 2020; Trotsyuk, 2019).

Figure 2 – The Classical Generic Genetic Algorithm Workflow (Trotsyuk, 2019)



The genetic algorithm involves various steps such as the initialization, selection, execution of the genetic operators and evaluation, as illustrated by Figure 2. The initialization step involves the setup of the population with the individual, filling their chromosome with explicit values, achieved randomly via a particular algorithm (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). On the other hand, the selection stage involves selecting the individuals for the application of the genetic operators. The next step is the execution of the genetic operators, such as the crossover (XO) and mutation (MU) and the implementation of these genetic operators is explicit for the task (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). However, the evaluation step involves the application of the fitness function for each person in the population to decide which among them are better fit for the environment regarding the task. As a result, the more fitted individuals create a new population, and the cycle begins again, as illustrated in Figure 2.

However, the DNA of the individual must be represented digitally and conveniently for the implementation of the genetic algorithm for the purpose of making the solution possible (Aron & Abraham, 2022; Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). In order to define a corporate DNA modeling system for better simulations through the Artificial Life principles, one would need to establish the key genetic components or traits that define a company's strategy, structure, resources and capabilities (Kartina et al., 2020; Lehman et al., 2020; Luan, 2024; Trotsyuk, 2019). Therefore, this modeling system should allow for the representation of these components in a way that impacts the company's behavior and performance in the simulated competitive environment.

2.6. Consumer Behavior as a Performance Indicator

Given the simulation difficulties due to unquantifiability of business success factors, which is somewhat necessary for a predictive environment, a suitable analogous must be chosen. Consumer choice patterns are a viable alternative to extrapolate business performance (Gordon et al., 2021)(Kanten & Darma, 2017). These patterns can inform marketing strategies, enhance customer satisfaction, and ultimately influence business outcomes. However, the relationship between consumer choice patterns and business performance is complex and influenced by various factors.

Consumer behavior analysis integrates operant behavioral economics and marketing to evaluate firm performance. It considers how consumer buying patterns, influenced by factors like brand reinforcement and shopping environment, can be linked to firm behavior and profitability (Gordon et al., 2021).

Consumer behavior significantly impacts marketing strategy and customer satisfaction, which in turn affects business performance. However, consumer behavior alone may not directly translate to improved business performance without the integration of effective marketing strategies and customer satisfaction efforts (Kanten & Darma, 2017).

2.7. Business Inherent Factors's impact in Consumer choice

Location, product or service offerings, and reputation significantly influence consumer choice (Kolomytseva & Vasilchenko, 2022). While these factors are crucial, it is also important to consider the role of competition and consumer behavior in shaping market dynamics. Businesses must continuously adapt their strategies to remain competitive, leveraging their location, offerings, and reputation to meet evolving consumer expectations and preferences (Duralia, 2022) (Peter & Olson, 1990).

The location of a business can affect consumer choice due to convenience and accessibility. A favorable location can lead to increased traffic and visibility, which are crucial for attracting potential customers (Bar-Hillel, 2011).

The breadth and quality of a product range are critical in forming consumer value. Consumers are drawn to businesses that offer a diverse selection of high-quality products that meet their needs and preferences.Personalized and innovative product offerings can enhance consumer engagement and satisfaction, leading to increased loyalty and repeat purchases(Kolomytseva & Vasilchenko, 2022).

Trust and reputation are pivotal in influencing consumer confidence and choice. A strong reputation can serve as a competitive advantage, fostering consumer trust and encouraging positive word-of-mouth (Chang et al., 2006).

3. METHODOLOGIES

This research was composed by 4 phases, at it shown in Figure 3. In this section, each phase and how they contribute to the goal of creating a minimum viable simulation of a competitive business market using Alife algorithms will be explored in further detail.

Exploration Phase

- **Research Gap:** Inexintance of simulation results of competitive business markets
- **Objective:** Develop a minimum viable simluation environment to aproximate optimal features of businesses given specific market condition
- **Literature Review:** Study of theroetichal hipothesis that sugest the usage of genetic algorithms to simulate competitive markets

Conceptual Phase

- **Research Framework:** Exploratory (systematic litearature review)
- **Simulation Strategy Definition:** Decide on what featuses to represent in simulation and what kind of Alife algorithm to use (genetic algorithm)
- **Simulation Element Definition**: Define all the elements that will be represented in the simulation environment
- **Fitness Funtion**: Choose relevant features of elements to score
- **Genetic Operators**: Define how to represent the evolution(change over time) of the simulated market

Development Phase

- **Building the Simulator:** Programming the software
- **Functional tests:** Programming the software

Experimental Phase

- **Simulation:** Parameterize the simulation to cover a suitable range of both market conditions and fitness weights
- **Result Gathering and Analysis:** Produce and analyse simulation outputs and postulate trends and insights

Conclusive Phase

- **Conclusions:** Sumarize findings and implications.
- **Define Limitations and Sudgest Future improvements:** Frame the results in it's academic context, point out limitations and sudgest further improvements

Figure 3 – Phases of the Methodology

3.1. Exploration Phase

This phase consisted of identifying the gap in the research of simulations on competitive market characteristics and their effect on the best features of a business that competes in it and understanding why it exists and what are the obstacles in bridging it.

By reviewing academic papers on competitive market behaviors, the suggestion of using Genetic Algorithms to simulate them is found recurrently as are the challenges in its executions.

Providing an initial viable solution to those challenges was then defined as the scope of this research.

3.2. Conceptual Phase

Conceptualization of the simulation consists researching what similar works have been developed, and use those past experiences to choose appropriate simulation strategies, elements, fitness function and genetic operators.

3.3. Development Phase

During this development phase, simulation elements were encoded, genetic operators such as selection, reproduction and mutation were implemented and functions to assist the determination of fitness were developed.

To build the simulative environment, Phython was the chosen language using Jupyter Notebook as the IDE. The Pandas and NumPy libraries were the choice to handle data structures and aid calculations. These tools fit the simulation task and were chosen due to familiarity.

3.4. Experimental Phase

During the experimental phase, weights for the fitness function, parameters and configurations for the simulations were carefully selected.

3.5. Conclusive Phase

The Conclusive Phase consists of gathering and analyzing results, validating findings, developing recommendations, and drawing conclusions.

To take conclusions a comparison of simulation outputs and known market trends is made in order to point out convergences and divergences and access if the research question was answered and the goals were achieved.

4. SYSTEM DESIGN & DEVELOPMENT

4.1. SYSTEM DESIGN

4.1.1. Overview

To simulate a market, its composition must be decided. Taking into account the existing research and the transferability to a computational simulation environment, it was determined that a Market shall be composed by the products available, the businesses that make up said market and the consumers of those products, whose behavior will be used to calculate a fitness ranking for a market.

4.1.2. Simulation Elements

Products and/or services

To represent the Products and/or services universe, a NumPy array of float values is randomly generated with the parameters of the lowest and highest prices and a size for the array.

Business

Each business is represented by Location, Catalog of products or services, and Reputation and Age in generations. These elements are stored in a DataFrame that varies with the generations. Location is randomly generated divided into it's X and Y components and each is stored as an array of floats where the indexes are matched for a coordinate pair. A Business can have one or more locations. Catalog is stored as an array of unique indexes of the Product array sampled randomly and has random length that varies between 1 and a parameterized percentage of the length of Product. Reputation is a float that varies between 0.0 and 5.0. Age is an int and is incremented every time a business "survives" a generation.

Consumer

Each Consumer is represented by Location and a Shopping List. These elements are stored in a DataFrame that is randomized every generation of the market. Location is encoded similarly to Business Location but is only a float, as a consumer can't have more than one location. Shopping List is encoded and generated the same way as the Catalog of a business but with no length restrictions.

4.2. DEVELOPMENT

4.2.1. General description

DNA Sequencing

As previously mentioned, success factors in competitive markets are nuanced, market specific and most of the time unquantifiable. Therefore, to simulate a competitive market, we will be looking at it in a more focused manner: main factors that influence a consumer to choose a business in a market to acquire a product or service they already want.

As such, Location, Products and or Services offered by a business and Reputation were chosen as the genome for this simulation, given that these are strong influencers of consumer behavior and represent a robust analog for business performance in a given market (Gordon et al., 2021)(Kanten & Darma, 2017)(Kolomytseva & Vasilchenko, 2022).

4.2.2. Fitness

A score for each of business's genome components is determined for each consumer every generation. Each of the components is then computed in a weighted sum, where the weights for location scores, catalog scores and reputation scores are passed as a parameter of the market.

The Location component's fitness is calculated by the sum of the Euclidean distance between a business's closest location to each consumer in the market.

The Catalog component's fitness is determined by the sum of the value each consumer would have spent there, had that business been the choice. This is calculated by summing the value of the matching indexes in the business Catalog for each Consumer's Shopping list. To introduce variance and more closely resemble real market conditions and product pricing fluctuations, the value of each product that is summed varies between 80 and 120% of the original value in the Products array. Each match is also has a parameterizable change of being multiplied by 0 to simulate it being "out of stock".

The Reputation score is plugged directly into the weighted sum.

4.2.3. Reproduction

Reproduction is handled in a way analogous to corporate acquisition: the acquiring business absorbs the catalog and location(s) of the acquired business. The businesses are ranked by fitness and are randomly selected from the top third of the rankings to be acquiring businesses and the middle third to be acquired businesses. From the bottom of the rankings the failing businesses are selected in ascending order of ranking. The count of businesses that are reproduced and that fail are passed as a parameter.

4.2.4. Mutation

Location - In terms of location, a business can change by adding new physical locations, moving locations or closing a location. The percentage of businesses that undergo "mutations" in location, and the probabilities for each of the three options above are passed as parameters. This is achieved by generating two random floats and appending them to the Location_X and Location_Y arrays, randomly selecting a possible index of Location_X and Y and setting the values with a new randomly generated pair of floats or dropping a randomly selected index of Location_X and Y respectively.

As described previously, the location pairs have match indexes, meaning that the index that is selected is the same for the Location_X array and the Location_Y array, mutating that specific location.

Catalog - In terms of Catalog, a business can change by adding new offers and/or dropping offers. The probability of change of each product and/or service in the businesses Catalog is passed as a parameter. This is achieved by summing a mask to the array of products with random choice between the values -1, 0 and 1, where 0 represents a non mutation and -1 and 1 a mutation. The probability of mutation is split equally for both cases.

Reputation - In terms of Reputation, a business can fluctuate quite significantly depending on conditions both in and outside its market. As such, a random amount is added every generation to every business determined by a normal distribution centered on 0 and with standard deviation passed as a parameter.

New Generation

For each generation, the Age of each surviving business is incremented, a new set of consumers is generated and new businesses are generated to “replace” failed and acquired businesses.

5. SIMULATION

5.1. ASSUMPTIONS

To allow for feasibility of the simulation, unquantifiable business characteristics and unpredictable market conditions (such as covid) were discarded. It was assumed that the business fundamentals are taken care of and that no businesses in the simulation are inherently unprofitable and thus fail regardless of consumer behavior.

It was also assumed that market conditions remain the same for all businesses in a given generation.

5.2. SIMULATION SETUP

Choosing the appropriate parameter set to maximize the significance of the insights of the simulated markets outputs, analyzing them and extrapolating possible trends they reveal. For this, configurations for 3 different market sizes, each with four different configurations.

After consideration, the configurations used were:

Table 1 – Simulation Parameter Configuration

small_size_low_variance_market	Market(grid_size = 100, product_universe_size = 25, product_lowest_price = 1.0, product_highest_price = 10.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=15, business_to_consumer_ratio=2.5)
small_size_high_variance_market	Market(grid_size = 100, product_universe_size = 25, lowest_price = 100.0, product_highest_price = 1000.0, p_out_of_stock=0.2, max_coverage=0.5, market_size=15, business_to_consumer_ratio=25)
small_size_low_variance_large_product_market	Market(grid_size = 100, product_universe_size = 100, product_lowest_price = 1.0, product_highest_price = 10.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=15, business_to_consumer_ratio=10)
small_size_high_variance_large_product_market	Market(grid_size = 100, product_universe_size = 100, product_lowest_price = 100.0, product_highest_price = 1000.0,

	p_out_of_stock=0.2, max_coverage=0.5, market_size=15, business_to_consumer_ratio=25)
medium_size_low_variance_market	Market(grid_size = 100, product_universe_size = 100, product_lowest_price = 1.0, product_highest_price = 100.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=30, business_to_consumer_ratio=2.5)
medium_size_high_variance_market	Market(grid_size = 100, product_universe_size = 100, product_lowest_price = 100.0, product_highest_price = 1000.0, p_out_of_stock=0.2, max_coverage=0.5, market_size=30, business_to_consumer_ratio=10)
medium_size_low_variance_large_product_market	Market(grid_size = 100, product_universe_size = 1000, product_lowest_price = 1.0, product_highest_price = 100.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=30, business_to_consumer_ratio=2.5)
medium_size_high_variance_large_product_market	Market(grid_size = 100, product_universe_size = 1000, product_lowest_price = 100.0, product_highest_price = 1000.0, p_out_of_stock=0.2, max_coverage=0.5, market_size=30, business_to_consumer_ratio=10)
large_size_low_variance_market	Market(grid_size = 1000, product_universe_size = 100, product_lowest_price = 1.0, product_highest_price = 100.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=50, business_to_consumer_ratio=10)
large_size_high_variance_market	Market(grid_size = 1000, product_universe_size = 100, product_lowest_price = 1.0,

	product_highest_price = 100.0, p_out_of_stock=0.2, max_coverage=0.3, market_size=50, business_to_consumer_ratio=25)
large_size_low_variance_large_product_market	Market(grid_size = 1000, product_universe_size = 1000, product_lowest_price = 1.0, product_highest_price = 100.0, p_out_of_stock=0.05, max_coverage=0.3, market_size=50, business_to_consumer_ratio=10)
large_size_high_variance_large_product_market	Market(grid_size = 1000, product_universe_size = 1000, product_lowest_price = 1.0, product_highest_price = 100.0, p_out_of_stock=0.2, max_coverage=0.3, market_size=50, business_to_consumer_ratio=25)

5.3. SIMULATION

Each of the configurations previously defined will then be simulated using a grid search approach.

Running simulation with the following parameter sets, analyzing outputs and gather significant metrics with the purpose of drawing general trends given the market typology.

The parameter sets bellow were chosen to represent a multitude of market characteristics and environments.

Table 5 – Simulation Parameter Sets

Parameter set	*Key*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*1*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*2*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*3*

{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*4*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*5*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*6*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*7*
{'location_weight': -0.2, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*8*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*9*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*10*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*11*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*12*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*13*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*14*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*15*
{'location_weight': -0.2, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*16*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*17*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*18*

{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*19*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*20*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*21*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*22*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*23*
{'location_weight': -0.3, 'catalog_weight': 0.6, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*24*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*25*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*26*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*27*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.2, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*28*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*29*
1{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.1, 'reproduction_rate': 0.3, 'mutation1_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 1'avg_change_in_score': 0.5}	*30*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 10.2, 'reproduction_rate': 0.2, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*31*
{'location_weight': -0.3, 'catalog_weight': 0.4, 'reputation_weight': 0.3, 'failed_rate': 0.2, 'reproduction_rate': 0.3, 'mutation_rate_location': 0.05, 'p_of_new_location': 0.2, 'p_of_close_down_location': 0.05, 'p_of_product_change': 0.05, 'avg_change_in_score': 0.5}	*32*

Each Market configuration will be simulated for 25 generations, assuming each generation is one year.

'location_weight': [-0.2, -0.3],

'catalog_weight': [0.6, 0.4],

'reputation_weight': [0.2, 0.3],

'failed_rate': [0.1, 0.2],

'reproduction_rate': [0.2, 0.3],

'mutation_rate_location': [0.05],

'p_of_new_location': [0.2],

'p_of_close_down_location': [0.05],

'p_of_product_change': [0.05],

'avg_change_in_score': [0.5].

5.4. Results and Discussion

5.4.1.1. small_size_low_variance_market

Table 3 – small_size_low_variance_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	8.34	25	6 0.20 2 0.24 9 0.24 10 0.24 14 0.20	6 1 2 1 9 1 10 1 14 1
2	8.934	25	12 0.20 0 0.72 7 0.40 2 0.44 4 0.64	12 1 0 15 7 2 2 3 4 5
3	6.467	25	0 0.68 4 0.68 2 0.52 3 0.48 5 0.24	0 10 4 9 2 6 3 3 5 1
4	6.33	25	7 0.24 4 0.20 2 0.48 5 0.20 3 0.36	7 1 4 1 2 5 5 1 3 2

5	6.866	23	7 0.20 3 0.20 6 0.84 12 0.20 8 0.24	7 2 3 2 6 20 12 1 8 1
6	10.34	25	4 0.76 1 0.56 3 0.48 6 0.20 0 0.56	4 6 1 12 3 2 6 1 0 4
7	4.2	16	4 0.68 3 0.68 0 0.36 1 0.16 2 0.20	4 4 3 19 0 3 1 1 2 1
8	5.667	20	1 0.76 5 0.40 4 0.40 3 0.48 8 0.24	1 15 5 2 4 3 3 3 8 1
9	7.467	24	4 0.36 6 0.52 0 0.80 8 0.56 10 0.16	4 2 6 4 0 22 8 5 10 1
10	6.934	18	0 0.80 8 0.20 3 0.16 5 0.20 1 0.24	0 12 8 1 3 1 5 1 1 3
11	5.134	25	1 0.56 0 0.92 2 0.60 6 0.24 8 0.20	1 5 0 19 2 6 6 1 8 1
12	6.73	23	6 0.52 0 0.68 1 0.64 2 0.40 9 0.20	6 7 0 8 1 16 2 2 9 1
13	8.34	25	0 0.80 6 0.20 2 0.72 1 0.68 8 0.24	0 14 6 1 2 6 1 6 8 1

14	8.934	25	3 0.80 2 0.64 4 0.36 13 0.24 10 0.20	3 16 2 7 4 4 13 1 10 1
15	8.53	25	0 0.80 2 0.60 7 0.20 1 0.52 4 0.24	0 14 2 10 7 1 1 7 4 1
16	6.2	25	0 0.72 4 0.36 1 0.64 3 0.36 7 0.24	0 23 4 2 1 5 3 2 7 1
17	6.6	21	4 0.20 6 0.28 2 0.20 7 0.24 0 0.76	4 1 6 2 2 1 7 1 0 13
18	5.4	18	5 0.24 6 0.24 0 0.76 1 0.64 3 0.24	5 1 6 1 0 14 1 7 3 2
19	6.0	24	1 0.56 10 0.20 13 0.20 2 0.40 0 0.80	1 7 10 1 13 1 2 3 0 13
20	8.2	25	4 0.52 3 0.72 2 0.64 1 0.40 12 0.24	4 7 3 7 2 6 1 6 12 1
21	7.667	20	2 0.68 13 0.20 5 0.36 1 0.52 0 0.76	2 8 13 1 5 2 1 5 0 16
22	8.73	25	0 0.64 7 0.60 1 0.56 4 0.48 8 0.20	0 13 7 6 1 7 4 4 8 1
23	7.53	25	1 0.60 0 0.56 2 0.60	1 9 0 5 2 17

			3 0.20 12 0.24	3 1 12 1
24	4.934	25	0 0.80 3 0.24 4 0.24 2 0.52 11 0.20	0 18 3 1 4 1 2 3 11 1
25	10.666	25	9 0.40 1 0.48 2 0.40 6 0.56 0 0.12	9 3 1 16 2 6 6 5 0 2
26	10.34	25	0 0.68 3 0.52 2 0.68 1 0.56 12 0.24	0 7 3 7 2 12 1 5 12 1
27	6.467	19	1 0.64 3 0.52 4 0.36 2 0.76 13 0.24	1 11 3 4 4 3 2 16 13 1
28	6.934	25	4 0.56 1 0.84 2 0.64 3 0.28 0 0.48	4 5 1 14 2 8 3 2 0 3
29	7.6	25	6 0.64 2 0.72 10 0.24 3 0.68 11 0.20	6 7 2 7 10 1 3 7 11 1
30	6.6	17	0 0.68 9 0.24 7 0.76 2 0.76 10 0.20	0 12 9 1 7 8 2 8 10 1
31	6.4	25	7 0.20 4 0.20 0 0.64 12 0.20 2 0.24	7 1 4 1 0 5 12 1 2 1
32	6.134	22	6 0.20 0 0.52 8 0.20 4 0.20 9 0.24	6 1 0 10 8 1 4 1 9 1

Looking at the average age of each population we have a mean for all sets of 7.23, with a low standard deviation of 1.57, only sets 1 and 5 have a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is quite high, with a minimum of 4.037 also for set 5. These sets are both in the lower values of reproduction and failure which might indicate that for small markets that present lower competition and less emphasis on location, age might not be as good of a predictor of success.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with the 75th percentile being approximately 1.36. A notable deviation of the mean is found in set 14, with a deviation value of 2.29.

In terms of product coverage for the most fit businesses, the mean for this Market configuration is 0.43. Looking at specific sets, Sets 1, 3, 4, 22, 25 and 26 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 25 and 26 being the exception.

In terms of the number of locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 5.225. Looking at specific sets, set 1 stands out by having all the fittest elements with only 1 location. All other sets have at least one element with more than one location and that element deviates on average 5.25 from the Set’s most fit mean business locations.

5.4.1.2. small_size_low_variance_large_product_market

Table 4 – small_size_low_variance_large_product_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	10.2	25	4 0.36 2 0.52 3 0.68 11 0.20 5 0.33	4 3 2 9 3 10 11 1 5 2
2	11.0	25	2 0.36 0 0.51 5 0.60 1 0.57 11 0.08	2 6 0 6 5 14 1 9 11 1
3	7.6	25	2 0.71 0 0.63 5 0.31 8 0.24 3 0.47	2 10 0 10 5 2 8 1 3 5
4	4.933333333333334	25	4 0.23 0 0.64	4 1 0 12

			3 0.14 5 0.25 6 0.22	3 2 5 1 6 1
5	8.933333333333334	25	4 0.36 11 0.28 6 0.27 13 0.28 8 0.21	4 2 11 1 6 1 13 1 8 1
6	5.4	15	8 0.06 2 0.07 12 0.28 3 0.18 7 0.26	8 1 2 1 12 1 3 1 7 1
7	6.933333333333334	24	2 0.41 3 0.69 7 0.18 1 0.52 0 0.29	2 4 3 12 7 1 1 6 0 3
8	5.733333333333333	18	1 0.16 4 0.10 7 0.15 13 0.28 6 0.21	1 1 4 1 7 1 13 1 6 1
9	7.066666666666666	24	2 0.15 5 0.15 12 0.05 7 0.21 10 0.07	2 1 5 1 12 1 7 1 10 1
10	6.066666666666666	20	0 0.52 10 0.06 6 0.47 7 0.15 2 0.05	0 6 10 1 6 3 7 1 2 1
11	6.266666666666667	25	0 0.70 1 0.55 2 0.50 8 0.14 5 0.24	0 15 1 6 2 8 8 1 5 1
12	4.933333333333334	19	0 0.48 7 0.14 8 0.26 1 0.61 3 0.10	0 7 7 2 8 1 1 9 3 1
13	6.4	23	3 0.08 1 0.34 9 0.05 2 0.51 0 0.25	3 1 1 3 9 1 2 9 0 2

14	9.466666666666667	24	0 0.27 1 0.83 4 0.13 8 0.13 10 0.18	0 3 1 22 4 2 8 1 10 1
15	7.866666666666666	24	1 0.68 4 0.33 2 0.46 3 0.19 0 0.65	1 8 4 3 2 8 3 1 0 10
16	6.8	25	5 0.19 3 0.85 4 0.26 0 0.46 1 0.12	5 1 3 17 4 2 0 5 1 1
17	8.066666666666666	25	9 0.14 1 0.58 11 0.13 4 0.45 8 0.53	9 1 1 6 11 1 4 7 8 5
18	9.066666666666666	25	2 0.55 1 0.56 4 0.56 10 0.06 0 0.54	2 8 1 8 4 4 10 1 0 11
19	8.8	25	3 0.55 4 0.29 2 0.67 0 0.40 5 0.11	3 9 4 4 2 10 0 3 5 1
20	7.133333333333334	20	4 0.61 8 0.15 1 0.44 2 0.64 5 0.21	4 10 8 1 1 4 2 11 5 2
21	9.066666666666666	25	6 0.83 0 0.54 3 0.29 11 0.27 1 0.18	6 21 0 8 3 3 11 1 1 1
22	7.866666666666666	25	1 0.64 7 0.32 2 0.76 13 0.26 10 0.10	1 10 7 5 2 11 13 1 10 1
23	4.333333333333333	15	1 0.76 5 0.21 8 0.24	1 18 5 1 8 1

			2 0.18 4 0.14	2 1 4 1
24	4.8	21	0 0.73 8 0.22 3 0.52 7 0.34 11 0.28	0 19 8 1 3 3 7 1 11 1
25	10.333333333333334	25	4 0.55 0 0.64 3 0.52 2 0.64 7 0.26	4 8 0 10 3 7 2 11 7 1
26	6.533333333333333	25	7 0.15 5 0.13 0 0.45 3 0.15 8 0.13	7 1 5 1 0 9 3 1 8 2
27	7.466666666666667	24	1 0.44 2 0.71 0 0.56 4 0.48 9 0.06	1 5 2 12 0 8 4 4 9 1
28	7.066666666666666	25	1 0.69 4 0.35 2 0.37 5 0.18 3 0.08	1 16 4 2 2 4 5 1 3 1
29	8.0	25	5 0.20 0 0.73 1 0.31 8 0.26 4 0.51	5 1 0 15 1 3 8 1 4 5
30	8.533333333333333	25	0 0.50 6 0.53 4 0.21 1 0.38 10 0.22	0 6 6 4 4 3 1 2 10 1
31	4.466666666666667	12	4 0.51 2 0.82 14 0.20 1 0.26 0 0.07	4 6 2 24 14 1 1 1 0 2
32	5.666666666666667	25	7 0.54 2 0.23 1 0.71 5 0.49 4 0.12	7 6 2 2 1 14 5 3 4 1

Looking at the average Age of each population we have a mean for all sets of 7.23, with a low standard deviation of 1.78, only sets 5 and 9 have a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. These sets are both in the lower values of reproduction and failure which might indicate that for small markets that present lower competition and less emphasis on location, age might not be as good of a predictor of success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.5265, and a minimum of 3.36154 for set 15.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.8516666533111219, and the 75th percentile being approximately 1.09. A notable deviation of the mean is found in set 18, with a deviation value of 1.87.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.36. Looking at specific sets, Sets 1, 5, 8, 9, 25, 26 and 30 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 9, 25, 26 and 30 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 4.61. Looking at specific sets, sets 6 and 8 stand out by having all the fittest elements with only 1 location and set 5 only has one element with 2 locations and the rest all have only one. All other sets have at least one element with more than two locations and that element deviates on average 4.45 from the Set's mean number of business locations.

5.4.1.3. small_size_high_variance_market

Table 5 – small_size_high_variance_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	9.0	25	2 0.72 1 0.72 10 0.88 4 0.20 6 0.24	2 16 1 11 10 7 4 1 6 1
2	7.866666666666666	25	3 0.60 2 0.84 0 0.52 7 0.20 1 0.52	3 7 2 9 0 7 7 1 1 7
3	6.333333333333333	25	4 0.40 0 0.88 2 0.64 5 0.64 8 0.28	4 1 0 8 2 5 5 3 8 1

4	4.333333333333333	24	0 0.64 1 0.76 4 0.44 7 0.32 5 0.40	0 13 1 10 4 1 7 1 5 1
5	7.533333333333333	22	0 0.72 2 0.76 7 0.32 9 0.44 5 0.32	0 11 2 9 7 1 9 1 5 1
6	9.0	25	1 0.80 3 0.60 10 0.20 7 0.60 13 0.28	1 14 3 7 10 1 7 4 13 1
7	6.6	23	9 0.24 11 0.32 5 0.40 3 0.36 6 0.40	9 1 11 1 5 1 3 2 6 1
8	5.133333333333334	24	7 0.24 3 0.80 0 0.80 2 0.28 4 0.24	7 1 3 5 0 24 2 1 4 1
9	8.2	25	4 0.80 0 0.60 8 0.32 5 0.32 1 0.24	4 7 0 7 8 1 5 1 1 2
10	8.4	25	2 0.76 4 0.80 1 0.68 12 0.40 7 0.52	2 5 4 14 1 11 12 1 7 3
11	5.533333333333333	25	1 0.76 14 0.24 0 0.80 4 0.24 8 0.44	1 5 14 1 0 7 4 1 8 1
12	8.0	25	2 0.64 7 0.24 0 0.68 4 0.60 8 0.40	2 5 7 1 0 11 4 6 8 1
13	7.933333333333334	25	4 0.60 0 0.80 9 0.20	4 4 0 16 9 1

			6 0.44 12 0.40	6 2 12 1
14	9.4	25	8 0.68 0 0.48 7 0.72 1 0.52 2 0.44	8 7 0 9 7 6 1 6 2 3
15	6.266666666666667	25	3 0.72 0 0.76 6 0.68 2 0.68 13 0.28	3 11 0 12 6 4 2 3 13 1
16	5.0	23	4 0.24 2 0.48 13 0.36 1 0.68 7 0.32	4 1 2 3 13 1 1 5 7 1
17	8.8	25	0 0.76 2 0.80 1 0.72 3 0.20 10 0.36	0 9 2 12 1 8 3 1 10 1
18	8.333333333333334	25	4 0.40 1 0.40 5 0.20 0 0.84 12 0.32	4 2 1 3 5 1 0 18 12 1
19	7.2	25	3 0.24 5 0.44 6 0.24 4 0.80 1 0.40	3 1 5 2 6 1 4 6 1 4
20	7.133333333333334	25	1 0.64 2 0.72 0 0.64 11 0.24 14 0.44	1 12 2 9 0 9 11 1 14 1
21	7.066666666666666	23	0 0.64 2 0.52 3 0.76 8 0.28 14 0.32	0 8 2 8 3 10 8 1 14 1
22	6.466666666666667	17	6 0.56 8 0.68 5 0.84 10 0.36 0 0.52	6 4 8 11 5 11 10 1 0 2
23	6.4	25	9 0.44 1 0.48	9 1 1 7

			5 0.20 6 0.28 4 0.76	5 1 6 1 4 13
24	7.666666666666667	24	7 0.36 2 0.72 4 0.36 10 0.44 5 0.20	7 1 2 9 4 3 10 1 5 1
25	8.4	25	2 0.76 0 0.52 3 0.64 1 0.60 6 0.24	2 9 0 7 3 5 1 6 6 1
26	9.666666666666666	25	4 0.68 2 0.84 0 0.52 1 0.56 14 0.24	4 10 2 12 0 5 1 4 14 1
27	6.6	25	4 0.68 2 0.60 8 0.20 0 0.64 1 0.72	4 7 2 3 8 1 0 4 1 9
28	7.133333333333334	23	0 0.88 8 0.20 3 0.72 4 0.44 5 0.24	0 9 8 1 3 5 4 3 5 1
29	9.066666666666666	25	8 0.64 11 0.32 12 0.36 5 0.24 10 0.28	8 3 11 1 12 1 5 1 10 1
30	7.133333333333334	25	6 0.40 8 0.28 0 0.68 13 0.28 5 0.80	6 1 8 1 0 7 13 1 5 10
31	5.533333333333333	24	0 0.88 4 0.28 6 0.20 2 0.48 11 0.20	0 19 4 1 6 1 2 2 11 1
32	7.066666666666666	22	1 0.40 7 0.72 5 0.68 3 0.68 10 0.28	1 5 7 13 5 3 3 4 10 1

Looking at the average Age of each population we have a mean for all sets of 7.31, with a low standard deviation of 1.35, only set 29 has a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 8.64, and a minimum of 4.32 for set 29.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 1.0050, and the 75th percentile being approximately 1.25. A notable deviation of the mean is found in set 15, with a deviation value of 2.02.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.50. Looking at specific sets, Sets 4, 7, 10, 12, 14, 16, 22 and 29 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 10, 12, 14 and 29 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 4.75. Looking at specific sets, sets 29 stands out by having all but one of the fittest elements with only 1 location. All other sets have at least one element with more than three locations. Each element deviates on average 4.35 from the Set’s mean number of most fit business locations.

5.4.1.4. small_size_high_variance_large_product_market

Table 6 – small_size_high_variance_large_product_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	11.466666666666667	25	0 0.56 2 0.49 5 0.55 1 0.68 11 0.11	0 6 2 4 5 7 1 12 11 1
2	8.133333333333333	25	1 0.75 0 0.55 2 0.47 3 0.57 12 0.15	1 20 0 6 2 5 3 3 12 1
3	5.0	25	2 0.86 0 0.61 7 0.11 3 0.23 4 0.15	2 18 0 13 7 1 3 1 4 1
4	7.133333333333334	25	5 0.46 1 0.78 6 0.36	5 2 1 10 6 4

			2 0.62 10 0.16	2 2 10 1
5	8.866666666666667	25	8 0.25 7 0.35 2 0.80 3 0.65 6 0.38	8 1 7 2 2 22 3 3 6 3
6	7.333333333333333	25	1 0.86 9 0.42 12 0.37 8 0.42 13 0.09	1 16 9 1 12 1 8 1 13 1
7	6.466666666666667	22	4 0.61 2 0.73 10 0.38 9 0.24 13 0.09	4 3 2 8 10 1 9 1 13 1
8	7.333333333333333	25	5 0.43 2 0.52 3 0.40 10 0.45 0 0.64	5 2 2 4 3 3 10 1 0 18
9	10.133333333333333	25	5 0.58 2 0.58 0 0.72 3 0.76 1 0.33	5 4 2 11 0 11 3 6 1 2
10	9.0	25	3 0.27 0 0.83 8 0.18 13 0.36 2 0.55	3 3 0 9 8 1 13 1 2 5
11	6.0	25	0 0.78 5 0.24 4 0.57 1 0.61 3 0.48	0 19 5 2 4 4 1 7 3 2
12	6.733333333333333	25	1 0.59 0 0.71 3 0.75 5 0.35 4 0.49	1 6 0 15 3 8 5 1 4 3
13	8.533333333333333	25	0 0.73 2 0.83 8 0.35 12 0.32 11 0.37	0 12 2 13 8 1 12 1 11 1
14	7.8	25	0 0.54 11 0.49	0 11 11 4

			2 0.32 13 0.25 4 0.35	2 3 13 1 4 1
15	6.6	22	3 0.69 2 0.46 9 0.05 8 0.26 0 0.44	3 10 2 3 9 1 8 1 0 3
16	7.2	21	0 0.42 2 0.36 4 0.85 3 0.74 8 0.11	0 3 2 2 4 6 3 12 8 1
17	9.266666666666667	25	0 0.62 9 0.05 2 0.76 3 0.64 13 0.18	0 10 9 1 2 10 3 9 13 1
18	8.533333333333333	25	4 0.42 1 0.66 0 0.69 2 0.80 14 0.47	4 4 1 7 0 7 2 14 14 1
19	6.333333333333333	25	3 0.37 5 0.28 0 0.70 1 0.69 7 0.19	3 4 5 2 0 7 1 18 7 1
20	8.666666666666666	25	0 0.63 2 0.43 3 0.74 14 0.40 1 0.71	0 8 2 5 3 4 14 1 1 8
21	10.266666666666667	25	3 0.63 5 0.28 4 0.51 2 0.88 6 0.08	3 8 5 1 4 6 2 14 6 1
22	8.066666666666666	25	1 0.66 0 0.62 2 0.59 6 0.25 13 0.43	1 9 0 8 2 4 6 1 13 1
23	6.933333333333334	22	0 0.73 3 0.64 2 0.51 4 0.11 1 0.54	0 10 3 5 2 4 4 2 1 11

24	7.0	25	0 0.80 1 0.71 5 0.08 7 0.20 9 0.41	0 17 1 7 5 2 7 1 9 1
25	11.0	25	0 0.72 2 0.68 4 0.44 5 0.41 11 0.47	0 10 2 5 4 3 5 2 11 1
26	8.333333333333334	25	3 0.62 0 0.68 14 0.31 11 0.49 6 0.31	3 9 0 12 14 1 11 1 6 1
27	7.133333333333334	23	1 0.75 2 0.56 0 0.81 7 0.41 3 0.15	1 11 2 9 0 10 7 1 3 1
28	6.266666666666667	25	0 0.84 6 0.08 7 0.50 1 0.49 14 0.13	0 18 6 1 7 3 1 4 14 1
29	6.733333333333333	25	1 0.77 0 0.40 4 0.12 6 0.42 14 0.25	1 24 0 3 4 1 6 1 14 1
30	9.266666666666667	25	3 0.62 4 0.63 0 0.75 2 0.44 6 0.09	3 5 4 4 0 16 2 4 6 1
31	5.666666666666667	25	5 0.12 2 0.36 0 0.71 9 0.23 3 0.24	5 1 2 1 0 14 9 1 3 1
32	7.266666666666667	25	1 0.73 2 0.70 3 0.55 0 0.69 6 0.39	1 13 2 6 3 4 0 7 6 1

Looking at the average Age of each population we have a mean for all sets of 7.82, with a low standard deviation of 1.53, only sets 5 and 7 have a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. These sets are both in the lower values of reproduction and failure which might indicate that for small markets that present lower competition and less emphasis on location, age might not be as good of a predictor of success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 9.0570, and a minimum of 6.02 for set 9.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.85245, and the 75th percentile being approximately 1.08. A notable deviation of the mean is found in set 10, with a deviation value of 2.12.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.48. Looking at specific sets, Sets 8, 9, 12, 14, 18, 20, 25 and 32 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 9, 12, 14, 25 and 32 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 5.43. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 5.43 from the Set's mean number of business locations.

5.4.1.5. medium_size_low_variance_market

Table 7 – medium_size_low_variance_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	7.433333333333334	25	7 0.86 3 0.51 2 0.47 12 0.19 9 0.31	7 23 3 8 2 5 12 1 9 2
2	6.233333333333333	22	6 0.71 0 0.69 2 0.71 4 0.54 3 0.51	6 20 0 14 2 20 4 4 3 6
3	6.666666666666667	24	3 0.66 10 0.41 14 0.21 5 0.57 17 0.25	3 10 10 3 14 1 5 8 17 1
4	6.633333333333334	25	2 0.70 3 0.68 10 0.60	2 9 3 12 10 5

			4 0.54 9 0.51	4 3 9 3
5	8.133333333333333	25	9 0.18 2 0.65 0 0.46 3 0.62 5 0.23	9 1 2 8 0 7 3 11 5 2
6	6.233333333333333	25	3 0.66 6 0.77 1 0.75 0 0.64 5 0.60	3 10 6 20 1 18 0 11 5 11
7	5.666666666666667	25	1 0.41 6 0.62 3 0.26 4 0.82 0 0.57	1 7 6 10 3 2 4 18 0 10
8	5.733333333333333	25	7 0.69 3 0.49 11 0.28 8 0.40 5 0.76	7 11 3 5 11 2 8 3 5 11
9	7.566666666666666	25	1 0.31 3 0.49 7 0.69 8 0.10 11 0.28	1 5 3 8 7 11 8 1 11 2
10	7.166666666666667	25	4 0.67 2 0.61 0 0.60 14 0.18 6 0.68	4 18 2 13 0 9 14 1 6 9
11	6.3	25	4 0.79 2 0.73 1 0.62 11 0.48 16 0.07	4 20 2 9 1 10 11 5 16 1
12	5.533333333333333	24	0 0.75 3 0.07 6 0.20 9 0.32 1 0.46	0 17 3 1 6 2 9 5 1 5
13	8.033333333333333	25	4 0.68 3 0.19 1 0.48 8 0.29 0 0.63	4 14 3 4 1 7 8 2 0 7
14	6.2	25	0 0.78 10 0.14	0 15 10 1

			19 0.20 5 0.66 2 0.66	19 1 5 12 2 12
15	5.966666666666667	25	0 0.41 1 0.77 9 0.19 4 0.56 3 0.50	0 9 1 11 9 1 4 5 3 7
16	6.933333333333334	25	0 0.72 8 0.24 2 0.45 19 0.06 1 0.55	0 10 8 2 2 4 19 1 1 8
17	8.933333333333334	25	1 0.56 3 0.69 5 0.40 4 0.65 2 0.54	1 13 3 11 5 5 4 7 2 8
18	6.733333333333333	25	4 0.69 5 0.54 7 0.12 0 0.62 1 0.73	4 16 5 7 7 1 0 11 1 19
19	5.533333333333333	25	1 0.76 0 0.69 9 0.20 7 0.18 5 0.47	1 11 0 11 9 1 7 1 5 5
20	7.633333333333334	25	3 0.44 1 0.64 4 0.53 5 0.75 16 0.16	3 5 1 7 4 7 5 15 16 1
21	7.733333333333333	25	1 0.71 3 0.42 17 0.39 5 0.51 13 0.49	1 10 3 4 17 2 5 7 13 7
22	6.366666666666666	24	3 0.63 4 0.60 1 0.61 10 0.67 0 0.62	3 13 4 11 1 7 10 7 0 10
23	5.5	25	2 0.77 8 0.19 5 0.17 4 0.44 3 0.55	2 24 8 1 5 1 4 4 3 5

24	5.366666666666666	25	5 0.18 0 0.69 3 0.78 15 0.28 22 0.18	5 1 0 15 3 14 15 1 22 1
25	9.066666666666666	25	1 0.68 2 0.64 3 0.49 5 0.41 0 0.66	1 10 2 11 3 7 5 4 0 12
26	5.666666666666667	20	4 0.87 1 0.68 11 0.17 5 0.44 2 0.69	4 18 1 7 11 1 5 4 2 13
27	5.966666666666667	25	5 0.43 7 0.16 1 0.53 2 0.42 4 0.62	5 7 7 1 1 9 2 4 4 11
28	6.966666666666667	25	4 0.56 1 0.64 5 0.60 0 0.59 3 0.59	4 7 1 12 5 10 0 10 3 8
29	8.166666666666666	25	3 0.55 18 0.21 9 0.23 27 0.06 5 0.63	3 9 18 1 9 1 27 1 5 7
30	5.6	25	0 0.78 1 0.80 3 0.39 10 0.20 6 0.06	0 30 1 31 3 4 10 1 6 1
31	5.0	25	2 0.33 9 0.11 8 0.37 12 0.13 1 0.74	2 4 9 1 8 3 12 2 1 13
32	7.466666666666667	25	1 0.67 0 0.39 4 0.49 10 0.21 2 0.67	1 16 0 5 4 6 10 1 2 16

Looking at the average Age of each population we have a mean for all sets of 6.69, with a low standard deviation of 1.07, all sets have a higher average age for the 5 most fit businesses. This might point out that, for medium sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.13, and a minimum of 2.04 for set 17.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.675, and the 75th percentile being approximately 0.86. A notable deviation of the mean is found in set 30, with a deviation value of 1.6.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.49. Looking at specific sets, Sets 2, 4, 6, 17, 21, 22, 25 and 28 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 25 and 28 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 7.793. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 5.53 from the Set’s mean number of business locations.

5.4.1.6. medium_size_low_variance_large_product_market

Table 8 – medium_size_low_variance_large_product_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	7.066666666666666	25	8 0.437 1 0.270 17 0.281 11 0.220 3 0.702	8 6 1 3 17 1 11 1 3 9
2	7.066666666666666	25	2 0.742 0 0.691 3 0.719 4 0.503 10 0.153	2 24 0 12 3 17 4 12 10 1
3	5.8	25	1 0.704 2 0.732 17 0.263 3 0.580 0 0.486	1 10 2 19 17 1 3 10 0 8
4	6.533333333333333	25	13 0.018 8 0.151 4 0.021 2 0.530 0 0.545	13 1 8 1 4 2 2 7 0 7

5	7.5	22	4 0.547 1 0.296 3 0.531 11 0.674 10 0.474	4 11 1 4 3 7 11 16 10 4
6	5.6	25	4 0.774 3 0.619 29 0.200 7 0.168 11 0.051	4 18 3 11 29 1 7 1 11 1
7	7.033333333333333	25	2 0.547 3 0.631 0 0.280 1 0.625 7 0.224	2 8 3 10 0 6 1 11 7 3
8	6.333333333333333	25	0 0.817 3 0.454 9 0.088 21 0.121 12 0.148	0 12 3 4 9 1 21 1 12 1
9	8.6	25	2 0.583 11 0.241 13 0.182 0 0.478 1 0.501	2 6 11 2 13 2 0 6 1 9
10	6.166666666666667	25	3 0.720 7 0.470 2 0.626 5 0.232 10 0.421	3 19 7 5 2 15 5 1 10 6
11	6.266666666666667	25	2 0.717 7 0.512 1 0.695 3 0.546 5 0.410	2 22 7 8 1 8 3 4 5 4
12	6.8	25	4 0.463 6 0.519 3 0.496 19 0.015 8 0.028	4 3 6 5 3 8 19 1 8 1
13	7.333333333333333	25	12 0.128 10 0.501 5 0.079 4 0.120 0 0.456	12 1 10 5 5 1 4 2 0 4
14	7.0	25	0 0.807 1 0.672 7 0.648	0 27 1 15 7 12

			4 0.616 10 0.044	4 9 10 1
15	6.433333333333334	25	3 0.685 12 0.226 5 0.515 7 0.368 13 0.099	3 15 12 1 5 6 7 3 13 1
16	5.133333333333334	25	1 0.671 0 0.400 15 0.165 5 0.256 6 0.225	1 9 0 4 15 1 5 2 6 3
17	7.5	25	2 0.726 6 0.252 12 0.599 9 0.493 7 0.358	2 19 6 4 12 12 9 5 7 2
18	8.233333333333333	25	4 0.731 0 0.628 2 0.538 15 0.216 1 0.651	4 20 0 16 2 10 15 1 1 11
19	6.466666666666667	25	3 0.693 0 0.459 5 0.724 1 0.512 6 0.302	3 13 0 12 5 12 1 9 6 4
20	4.733333333333333	18	5 0.580 0 0.477 9 0.123 2 0.727 8 0.041	5 7 0 8 9 1 2 13 8 1
21	6.8	25	1 0.587 20 0.037 15 0.218 11 0.266 17 0.274	1 10 20 2 15 2 11 1 17 1
22	7.566666666666666	25	4 0.467 2 0.584 12 0.181 1 0.639 15 0.236	4 6 2 8 12 1 1 10 15 1
23	7.0	25	1 0.653 14 0.186 5 0.272 6 0.298 16 0.208	1 14 14 1 5 3 6 2 16 1
24	7.5	25	6 0.710 4 0.547	6 10 4 10

			5 0.298 2 0.483 13 0.135	5 4 2 6 13 1
25	7.766666666666667	25	0 0.535 7 0.655 1 0.452 2 0.613 5 0.402	0 12 7 7 1 6 2 11 5 4
26	7.7	25	0 0.715 4 0.699 9 0.195 8 0.650 1 0.689	0 14 4 12 9 1 8 17 1 11
27	5.766666666666667	25	4 0.442 0 0.786 12 0.077 3 0.656 6 0.124	4 5 0 15 12 1 3 13 6 1
28	6.833333333333333	24	0 0.588 1 0.569 3 0.688 11 0.509 4 0.331	0 11 1 10 3 11 11 4 4 4
29	7.8	25	6 0.493 4 0.716 1 0.533 3 0.517 23 0.054	6 7 4 11 1 10 3 13 23 1
30	8.466666666666667	25	3 0.674 4 0.652 5 0.699 12 0.320 11 0.009	3 12 4 8 5 20 12 3 11 1
31	5.2	24	3 0.764 4 0.025 8 0.193 1 0.538 9 0.093	3 13 4 1 8 2 1 9 9 1
32	6.066666666666666	25	9 0.254 12 0.422 6 0.396 0 0.496 7 0.250	9 1 12 2 6 2 0 4 7 1

Looking at the average Age of each population we have a mean for all sets of 6.81, with a low standard deviation of 0.95, all sets have a higher average age for the 5 most fit businesses. This might point out that, for medium sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.67, and a minimum of 4.97 for set 10.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.802, and the 75th percentile being approximately 1.11. A notable deviation of the mean is found in set 26, with a deviation value of 1.48.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.49. Looking at specific sets, Sets 5, 9, 11, 17, 19, 25, 28 and 32 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 9, 11, 25, 28 and 32 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 6.91. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 5.08 from the Set's mean number of business locations.

5.4.1.7. medium_size_high_variance_market

Table 9 – medium_size_high_variance_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	10.033333333333333	25	8 0.35 3 0.23 1 0.34 12 0.34 9 0.22	8 1 3 1 1 2 12 1 9 1
2	7.233333333333333	25	10 0.07 0 0.77 4 0.84 1 0.70 8 0.87	10 1 0 13 4 9 1 13 8 12
3	5.866666666666666	25	5 0.45 1 0.64 11 0.31 17 0.21 14 0.46	5 3 1 8 11 1 17 1 14 2
4	6.0	25	4 0.73 0 0.63 2 0.74 11 0.64 6 0.22	4 12 0 8 2 8 11 3 6 2
5	7.666666666666667	25	0 0.65 11 0.06	0 6 11 2

			22 0.24 7 0.35 9 0.45	22 1 7 2 9 2
6	5.966666666666667	25	1 0.75 2 0.70 0 0.79 5 0.35 9 0.22	1 12 2 11 0 30 5 2 9 1
7	5.633333333333334	25	8 0.50 21 0.38 17 0.45 16 0.05 5 0.28	8 2 21 1 17 1 16 1 5 1
8	7.533333333333333	25	3 0.61 4 0.67 0 0.52 10 0.37 7 0.27	3 10 4 5 0 4 10 2 7 2
9	7.9	25	0 0.66 16 0.22 1 0.65 3 0.64 29 0.12	0 14 16 1 1 10 3 9 29 1
10	7.233333333333333	25	8 0.87 9 0.81 0 0.70 1 0.62 3 0.73	8 21 9 12 0 11 1 8 3 10
11	6.166666666666667	25	6 0.22 13 0.42 5 0.74 10 0.37 7 0.54	6 2 13 1 5 15 10 1 7 2
12	6.266666666666667	25	0 0.82 4 0.25 10 0.19 18 0.06 3 0.64	0 11 4 1 10 2 18 1 3 7
13	7.8	25	0 0.55 19 0.41 18 0.32 13 0.21 7 0.41	0 5 19 1 18 1 13 1 7 1
14	7.3	25	13 0.13 0 0.80 1 0.67 8 0.76 19 0.24	13 1 0 7 1 15 8 7 19 1

15	4.7	22	5 0.45 21 0.21 8 0.09 13 0.38 12 0.25	5 2 21 1 8 1 13 1 12 1
16	5.866666666666666	25	8 0.55 13 0.14 3 0.72 4 0.67 0 0.61	8 3 13 1 3 12 4 6 0 7
17	8.933333333333334	25	1 0.68 0 0.59 7 0.68 5 0.65 10 0.65	1 7 0 6 7 9 5 16 10 5
18	7.9	25	9 0.12 6 0.54 1 0.62 5 0.65 4 0.72	9 1 6 8 1 9 5 7 4 6
19	5.2	21	1 0.76 5 0.56 20 0.29 6 0.56 2 0.52	1 11 5 4 20 1 6 3 2 5
20	8.0	25	2 0.84 7 0.56 5 0.62 1 0.80 6 0.44	2 12 7 4 5 11 1 10 6 5
21	7.033333333333333	25	0 0.71 10 0.22 3 0.23 7 0.29 12 0.38	0 11 10 1 3 1 7 2 12 1
22	6.8	25	5 0.71 0 0.85 3 0.64 2 0.64 10 0.33	5 5 0 17 3 5 2 10 10 1
23	7.833333333333333	25	3 0.82 5 0.67 9 0.14 11 0.17 0 0.71	3 13 5 8 9 1 11 1 0 10
24	6.066666666666666	25	2 0.54 9 0.31 1 0.62	2 6 9 1 1 6

			14 0.08 0 0.47	14 1 0 5
25	9.5	25	5 0.53 4 0.50 6 0.79 1 0.65 11 0.36	5 7 4 6 6 15 1 9 11 1
26	7.266666666666667	25	6 0.78 1 0.81 5 0.83 0 0.80 4 0.45	6 5 1 19 5 16 0 12 4 5
27	7.4	25	5 0.75 6 0.77 4 0.58 3 0.56 7 0.57	5 15 6 10 4 9 3 8 7 3
28	6.333333333333333	25	8 0.72 5 0.79 0 0.74 9 0.49 4 0.56	8 12 5 12 0 10 9 3 4 5
29	8.233333333333333	25	16 0.21 7 0.69 4 0.78 0 0.64 3 0.64	16 1 7 6 4 6 0 8 3 12
30	7.333333333333333	25	7 0.72 1 0.58 5 0.87 9 0.42 2 0.66	7 19 1 13 5 8 9 3 2 8
31	7.433333333333334	25	4 0.65 3 0.58 6 0.70 1 0.77 2 0.83	4 6 3 5 6 10 1 10 2 16
32	7.066666666666666	25	3 0.57 17 0.08 4 0.64 18 0.41 5 0.74	3 5 17 1 4 11 18 1 5 5

Looking at the average Age of each population we have a mean for all sets of 7.07, with a low standard deviation of 0.91, only sets 7 and 15 have a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. This might point out that, for medium sized markets with high variance, age is not as good of a predictor of high success compared to other medium configurations. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.22, and a minimum of 2.28 for set 15.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.694, and the 75th percentile being approximately 0.92. A the max deviation of the mean is found in set 24, with a deviation value of 1.54.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.52. Looking at specific sets, Sets 1, 10, 13, 15, 17, 27, 28 and 31 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 10, 13, 15, 27, 28 and 31 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 6.23. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 4.22 from the Set's mean number of business locations.

5.4.1.8. medium_size_high_variance_large_product_market

Table 10 – medium_size_high_variance_large_product_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	9.966666666666667	25	0 0.727 4 0.622 10 0.410 8 0.644 2 0.592	0 10 4 4 10 3 8 6 2 7
2	6.3	25	4 0.747 14 0.324 11 0.188 9 0.538 1 0.738	4 14 14 1 11 1 9 3 1 20
3	6.366666666666666	25	0 0.672 2 0.739 3 0.685 17 0.323 4 0.267	0 18 2 14 3 8 17 1 4 3
4	6.1	25	1 0.853 2 0.691 4 0.650 3 0.462 11 0.379	1 21 2 5 4 5 3 4 11 1

5	6.933333333333334	25	0 0.745 3 0.621 1 0.487 15 0.212 4 0.539	0 14 3 4 1 4 15 1 4 4
6	6.533333333333333	25	1 0.779 5 0.873 6 0.706 8 0.156 4 0.790	1 32 5 16 6 4 8 1 4 12
7	6.266666666666667	25	5 0.688 15 0.072 11 0.354 0 0.761 2 0.599	5 12 15 1 11 1 0 10 2 6
8	6.3	25	7 0.789 3 0.687 0 0.667 20 0.358 14 0.350	7 16 3 9 0 10 20 1 14 1
9	7.933333333333334	25	2 0.559 11 0.417 9 0.087 12 0.094 20 0.466	2 7 11 1 9 1 12 1 20 1
10	7.466666666666667	25	3 0.601 10 0.310 1 0.808 6 0.193 8 0.622	3 5 10 1 1 9 6 1 8 7
11	5.466666666666667	25	6 0.273 1 0.504 3 0.246 15 0.388 18 0.364	6 1 1 6 3 1 15 1 18 1
12	6.766666666666667	25	1 0.652 6 0.714 12 0.198 0 0.636 2 0.725	1 9 6 9 12 1 0 10 2 9
13	7.033333333333333	25	6 0.455 9 0.300 8 0.521 2 0.340 1 0.542	6 2 9 1 8 4 2 2 1 6
14	6.233333333333333	25	0 0.861 5 0.674 6 0.801	0 21 5 14 6 8

			4 0.708 10 0.413	4 8 10 1
15	7.166666666666667	25	2 0.786 7 0.124 15 0.419 0 0.700 5 0.214	2 13 7 1 15 1 0 10 5 1
16	6.5	25	1 0.622 0 0.555 6 0.310 10 0.130 12 0.258	1 11 0 9 6 2 10 1 12 1
17	9.133333333333333	25	1 0.710 0 0.343 12 0.730 10 0.514 2 0.417	1 9 0 4 12 9 10 5 2 3
18	7.933333333333334	25	2 0.720 0 0.701 3 0.763 9 0.423 1 0.713	2 13 0 11 3 12 9 4 1 17
19	8.266666666666667	25	1 0.704 0 0.563 4 0.694 19 0.276 5 0.683	1 10 0 4 4 7 19 1 5 11
20	7.433333333333334	25	1 0.714 4 0.631 2 0.513 3 0.671 7 0.677	1 8 4 10 2 7 3 7 7 5
21	8.033333333333333	25	4 0.295 5 0.712 1 0.087 6 0.398 11 0.124	4 1 5 12 1 1 6 4 11 1
22	6.966666666666667	25	9 0.007 7 0.417 1 0.610 4 0.713 0 0.654	9 1 7 4 1 7 4 11 0 12
23	7.533333333333333	25	3 0.822 6 0.519 0 0.601 7 0.290 1 0.745	3 21 6 4 0 9 7 1 1 12
24	6.566666666666666	25	2 0.765 1 0.541	2 14 1 7

			5 0.573 4 0.748 3 0.807	5 8 4 11 3 9
25	6.566666666666666	25	5 0.543 2 0.450 1 0.656 18 0.230 22 0.024	5 3 2 6 1 7 18 1 22 1
26	6.8	25	2 0.662 3 0.657 5 0.741 6 0.763 0 0.558	2 14 3 10 5 8 6 7 0 6
27	6.766666666666667	25	4 0.630 9 0.862 7 0.532 0 0.547 1 0.610	4 10 9 15 7 4 0 5 1 7
28	6.866666666666666	25	6 0.503 11 0.593 3 0.671 5 0.441 14 0.194	6 4 11 3 3 5 5 3 14 1
29	7.266666666666667	25	5 0.826 0 0.683 10 0.041 4 0.527 7 0.744	5 11 0 6 10 1 4 3 7 16
30	7.8	25	5 0.771 0 0.809 4 0.646 15 0.260 8 0.814	5 15 0 13 4 9 15 1 8 12
31	6.5	25	5 0.858 4 0.736 0 0.663 2 0.177 10 0.313	5 20 4 10 0 10 2 2 10 2
32	6.7	25	5 0.634 6 0.454 1 0.614 8 0.499 4 0.341	5 7 6 3 1 11 8 3 4 5

Looking at the average Age of each population we have a mean for all sets of 7.07, with a low standard deviation of 0.91, all sets have a higher average age for the 5 most fit businesses. This might point out that, for medium sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.64, and a minimum of 4.63 for set 26.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.76, and the 75th percentile being approximately 1.09. A the max deviation of the mean is found in set 15, with a deviation value of 1.899.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.54. Looking at specific sets, Sets 1, 11, 13, 20, 24, 26, 27 and 32 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 11, 13, 26, 27 and 32 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 6.84. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 4.85 from the Set's mean number of business locations.

5.4.1.9. large_size_low_variance_market

Table 11 – large_size_low_variance_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	8.9	25	1 0.49	1 5
			0 0.53	0 8
			6 0.37	6 6
			8 0.69	8 12
			24 0.25	24 1
2	6.82	25	3 0.58	3 14
			2 0.52	2 8
			13 0.22	13 1
			10 0.27	10 2
			12 0.71	12 11
3	6.9	25	15 0.77	15 22
			3 0.57	3 7
			26 0.05	26 1
			1 0.39	1 6
			5 0.42	5 6
4	5.12	25	2 0.57	2 12
			4 0.83	4 16
			0 0.68	0 10
			9 0.54	9 5
			19 0.78	19 22
5	8.68	25	2 0.66	2 15
			29 0.25	29 1

			10 0.51 9 0.24 1 0.33	10 6 9 3 1 3
6	7.3	25	6 0.54 1 0.42 12 0.68 15 0.15 22 0.11	6 6 1 4 12 11 15 2 22 1
7	6.64	25	21 0.06 15 0.28 5 0.61 14 0.24 16 0.26	21 1 15 3 5 16 14 2 16 1
8	5.96	25	4 0.79 1 0.51 6 0.83 15 0.17 12 0.42	4 31 1 4 6 23 15 2 12 4
9	7.18	25	3 0.80 2 0.51 31 0.21 18 0.15 16 0.38	3 19 2 5 31 1 18 1 16 3
10	6.94	25	10 0.14 9 0.67 2 0.61 16 0.15 4 0.22	10 1 9 15 2 17 16 1 4 2
11	6.4	25	4 0.65 19 0.37 20 0.20 2 0.31 0 0.81	4 14 19 6 20 1 2 2 0 14
12	5.66	25	1 0.75 3 0.61 7 0.48 6 0.59 13 0.10	1 18 3 8 7 5 6 6 13 1
13	7.56	25	17 0.19 16 0.70 23 0.06 13 0.14 5 0.48	17 1 16 12 23 2 13 1 5 4
14	7.72	25	4 0.67 1 0.80 3 0.44 13 0.47 14 0.15	4 22 1 20 3 7 13 4 14 1

15	6.7	25	1 0.68 2 0.52 8 0.69 4 0.64 13 0.41	1 15 2 10 8 6 4 5 13 4
16	4.82	25	12 0.79 4 0.61 3 0.70 5 0.51 1 0.67	12 20 4 7 3 23 5 7 1 14
17	8.68	25	5 0.47 2 0.66 14 0.19 33 0.09 21 0.16	5 9 2 10 14 1 33 1 21 1
18	8.24	25	5 0.55 0 0.81 2 0.47 35 0.17 8 0.21	5 9 0 16 2 7 35 1 8 1
19	7.84	25	5 0.68 2 0.57 15 0.60 16 0.30 14 0.44	5 13 2 12 15 5 16 2 14 3
20	6.28	25	5 0.71 1 0.64 0 0.54 4 0.64 7 0.43	5 22 1 15 0 14 4 9 7 5
21	7.64	25	25 0.51 24 0.08 4 0.41 13 0.19 14 0.35	25 4 24 1 4 5 13 2 14 4
22	8.68	25	7 0.29 5 0.64 2 0.61 4 0.86 11 0.08	7 5 5 13 2 12 4 22 11 1
23	6.48	25	10 0.48 4 0.54 3 0.64 5 0.65 7 0.16	10 9 4 10 3 7 5 7 7 1
24	5.62	25	6 0.55 9 0.25 5 0.71	6 7 9 1 5 7

			19 0.18 7 0.42	19 1 7 2
25	7.94	25	9 0.45 2 0.63 14 0.46 15 0.57 1 0.58	9 5 2 12 14 4 15 8 1 8
26	8.72	25	9 0.08 4 0.61 5 0.64 6 0.72 13 0.22	9 1 4 17 5 7 6 16 13 1
27	7.12	25	10 0.64 18 0.26 12 0.42 14 0.09 3 0.52	10 13 18 1 12 3 14 1 3 7
28	5.68	25	7 0.48 20 0.13 8 0.23 4 0.40 3 0.80	7 5 20 1 8 1 4 3 3 30
29	8.58	25	8 0.28 21 0.34 12 0.30 13 0.36 3 0.76	8 2 21 2 12 3 13 3 3 18
30	8.18	25	6 0.74 2 0.58 5 0.64 0 0.60 11 0.14	6 13 2 12 5 9 0 10 11 1
31	6.62	25	1 0.56 3 0.54 15 0.11 4 0.70 5 0.72	1 8 3 7 15 1 4 11 5 12
32	6.04	25	3 0.66 5 0.80 0 0.55 7 0.60 15 0.23	3 9 5 19 0 6 7 8 15 1

Looking at the average Age of each population we have a mean for all sets of 7.13, with a low standard deviation of 1.14, all sets have a higher average age for the 5 most fit businesses. This might point out that, for large sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.08, and a minimum of 3.57 for set 20.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.69, and the 75th percentile being approximately 0.94. A the max deviation of the mean is found in set 6, with a deviation value of 1.54.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.46. Looking at specific sets, Sets 1, 4, 15, 16, 19, 20, 21 and 25 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 15, 16 and 25 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 7.59. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 6.17 from the Set's mean number of business locations.

5.4.1.10. large_size_low_variance_large_product_market

Table 12 – large_size_low_variance_large_product_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	8.26	25	2 0.478	2 7
			4 0.536	4 5
			1 0.779	1 17
			3 0.599	3 11
			10 0.299	10 6
2	8.5	25	4 0.688	4 12
			13 0.549	13 7
			1 0.585	1 12
			11 0.322	11 3
			6 0.595	6 10
3	6.74	25	6 0.027	6 1
			8 0.372	8 3
			3 0.659	3 9
			9 0.483	9 3
			13 0.078	13 1
4	6.22	25	4 0.681	4 19
			1 0.634	1 11
			12 0.178	12 1
			3 0.513	3 9
			10 0.315	10 4
5	8.62	25	5 0.539	5 10
			20 0.461	20 4
			3 0.448	3 5
			14 0.529	14 6
			13 0.442	13 6

6	7.34	25	3 0.733 2 0.513 21 0.206 4 0.790 20 0.383	3 22 2 6 21 1 4 17 20 2
7	6.68	25	10 0.533 0 0.575 14 0.452 12 0.437 5 0.726	10 12 0 11 14 5 12 5 5 19
8	4.72	25	4 0.756 0 0.737 10 0.453 1 0.459 11 0.109	4 12 0 16 10 5 1 5 11 1
9	8.8	25	14 0.527 6 0.412 35 0.261 17 0.222 12 0.148	14 10 6 8 35 1 17 1 12 1
10	7.74	25	7 0.454 0 0.477 9 0.620 10 0.560 11 0.545	7 5 0 6 9 9 10 5 11 8
11	6.8	25	0 0.637 3 0.547 15 0.223 6 0.140 12 0.126	0 14 3 12 15 1 6 4 12 4
12	6.68	25	1 0.602 12 0.078 0 0.685 5 0.586 25 0.011	1 9 12 1 0 8 5 10 25 1
13	7.98	25	8 0.623 31 0.288 7 0.339 21 0.068 35 0.066	8 9 31 3 7 6 21 1 35 1
14	6.98	25	3 0.546 10 0.210 27 0.097 0 0.672 2 0.582	3 9 10 1 27 1 0 11 2 9
15	5.2	23	21 0.113 5 0.251 13 0.253	21 2 5 2 13 1

			11 0.383 14 0.168	11 4 14 1
16	6.24	25	17 0.216 1 0.664 4 0.495 11 0.098 8 0.585	17 1 1 11 4 9 11 1 8 7
17	7.72	25	1 0.309 14 0.087 4 0.279 8 0.380 21 0.118	1 5 14 1 4 2 8 3 21 1
18	8.6	25	2 0.677 7 0.486 5 0.297 9 0.671 12 0.142	2 15 7 8 5 6 9 11 12 3
19	7.56	25	3 0.587 9 0.572 4 0.579 0 0.547 25 0.040	3 9 9 11 4 6 0 8 25 1
20	6.02	25	8 0.679 1 0.535 5 0.775 9 0.426 4 0.573	8 15 1 9 5 16 9 3 4 9
21	7.56	25	17 0.094 10 0.514 18 0.076 6 0.201 35 0.155	17 2 10 13 18 1 6 3 35 1
22	8.16	25	2 0.600 8 0.417 31 0.057 0 0.818 7 0.724	2 9 8 7 31 1 0 13 7 23
23	7.12	25	14 0.666 17 0.249 5 0.603 7 0.795 15 0.113	14 11 17 3 5 7 7 21 15 3
24	4.5	25	32 0.252 1 0.649 11 0.396 7 0.747 5 0.397	32 1 1 15 11 3 7 24 5 6
25	9.3	25	4 0.597 19 0.307	4 11 19 2

			9 0.467 12 0.315 1 0.330	9 8 12 6 1 3
26	8.58	25	4 0.730 7 0.741 3 0.575 17 0.135 0 0.451	4 14 7 21 3 8 17 1 0 10
27	6.58	25	7 0.653 19 0.303 4 0.577 0 0.581 3 0.223	7 12 19 3 4 9 0 14 3 2
28	6.06	25	0 0.691 2 0.636 18 0.667 8 0.795 4 0.524	0 15 2 14 18 16 8 21 4 5
29	7.74	25	1 0.465 18 0.169 15 0.092 0 0.418 6 0.576	1 7 18 1 15 1 0 5 6 9
30	8.2	25	13 0.331 14 0.154 17 0.288 9 0.555 2 0.513	13 3 14 1 17 3 9 6 2 9
31	6.88	25	1 0.626 6 0.801 4 0.508 11 0.331 3 0.379	1 12 6 17 4 9 11 3 3 6
32	5.12	25	6 0.702 1 0.296 3 0.584 0 0.538 17 0.091	6 13 1 6 3 8 0 11 17 1

Looking at the average Age of each population we have a mean for all sets of 7.16, with a low standard deviation of 1.23, all sets have a higher average age for the 5 most fit businesses. This might point out that, for large sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.21, and a minimum of 3.27 for set 15.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.655, and the 75th percentile being approximately 0.83. A the max deviation of the mean is found in set 6, with a deviation value of 1.25.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.43. Looking at specific sets, Sets 5, 7, 10, 15, 17, 20, 25 and 28 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 10, 15, 25 and 28 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 7.27. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 4.92 from the Set's mean number of business locations.

5.4.1.11. large_size_high_variance_market

Table 13 – large_size_high_variance_market

Parameter Set Key	Average Age	Max Age	Product Coverage Most Fit	Number of Business Locations Most Fit
1	8.12	25	9 0.70 4 0.49 1 0.60 17 0.51 5 0.20	9 13 4 7 1 11 17 3 5 1
2	7.26	25	11 0.57 2 0.67 6 0.57 34 0.09 24 0.08	11 8 2 11 6 8 34 1 24 1
3	6.74	25	12 0.62 0 0.57 20 0.25 5 0.62 23 0.21	12 7 0 7 20 2 5 11 23 1
4	5.46	25	25 0.28 10 0.05 17 0.10 13 0.06 0 0.58	25 1 10 1 17 2 13 1 0 9
5	7.46	25	20 0.14 0 0.76 4 0.55 2 0.56 21 0.11	20 1 0 22 4 10 2 7 21 1
6	6.46	25	4 0.39 9 0.50	4 7 9 5

			1 0.49 10 0.60 25 0.13	1 10 10 9 25 1
7	6.24	24	5 0.64 4 0.64 8 0.73 11 0.79 1 0.63	5 13 4 11 8 10 11 19 1 9
8	5.68	25	0 0.77 1 0.61 22 0.55 18 0.50 2 0.54	0 27 1 13 22 4 18 3 2 6
9	8.62	25	1 0.60 17 0.22 9 0.68 10 0.27 7 0.30	1 11 17 2 9 7 10 2 7 2
10	7.42	25	1 0.64 15 0.22 11 0.38 12 0.34 7 0.71	1 11 15 1 11 4 12 2 7 17
11	6.34	25	0 0.72 5 0.67 9 0.27 2 0.77 1 0.59	0 12 5 9 9 2 2 16 1 8
12	5.14	25	0 0.85 2 0.68 6 0.64 3 0.61 11 0.25	0 34 2 13 6 8 3 7 11 1
13	7.7	25	21 0.43 1 0.48 28 0.24 33 0.24 0 0.29	21 2 1 5 28 1 33 1 0 2
14	7.32	25	0 0.80 1 0.62 3 0.71 4 0.35 22 0.14	0 17 1 14 3 15 4 4 22 1
15	7.06	25	8 0.65 9 0.53 3 0.48 6 0.55 2 0.50	8 13 9 5 3 7 6 6 2 7

16	5.56	25	4 0.28 11 0.09 17 0.26 10 0.60 6 0.68	4 3 11 1 17 1 10 12 6 10
17	9.24	25	3 0.70 11 0.59 10 0.60 5 0.50 9 0.51	3 12 11 13 10 11 5 6 9 5
18	8.34	25	9 0.64 16 0.68 10 0.62 3 0.72 0 0.42	9 14 16 9 10 7 3 14 0 5
19	7.2	25	1 0.60 5 0.50 2 0.71 9 0.59 6 0.66	1 7 5 9 2 18 9 8 6 8
20	6.64	25	10 0.70 2 0.68 8 0.65 6 0.62 14 0.35	10 11 2 8 8 8 6 10 14 4
21	9.78	25	3 0.71 18 0.57 2 0.43 1 0.61 11 0.40	3 10 18 8 2 4 1 9 11 2
22	7.26	25	18 0.24 1 0.73 3 0.53 12 0.05 4 0.54	18 1 1 16 3 9 12 1 4 8
23	7.46	25	16 0.24 12 0.39 8 0.17 20 0.14 4 0.61	16 3 12 3 8 1 20 1 4 12
24	5.8	25	15 0.20 11 0.12 5 0.38 16 0.11 27 0.25	15 1 11 1 5 2 16 1 27 1
25	9.24	25	2 0.62 4 0.40 7 0.53	2 10 4 5 7 6

			1 0.66 18 0.24	1 8 18 1
26	7.6	25	0 0.59 3 0.77 2 0.69 13 0.18 10 0.52	0 9 3 18 2 11 13 2 10 10
27	6.18	25	3 0.43 1 0.65 17 0.36 8 0.59 11 0.46	3 5 1 14 17 3 8 9 11 4
28	5.24	25	8 0.13 26 0.14 1 0.45 4 0.80 0 0.79	8 1 26 1 1 10 4 23 0 17
29	9.54	25	10 0.57 6 0.65 17 0.22 11 0.74 0 0.33	10 9 6 11 17 1 11 13 0 5
30	7.74	25	0 0.54 12 0.70 5 0.59 3 0.69 2 0.52	0 9 12 9 5 10 3 11 2 6
31	7.08	25	4 0.52 1 0.45 0 0.86 3 0.68 18 0.26	4 10 1 6 0 27 3 12 18 1
32	6.08	25	3 0.61 0 0.51 6 0.62 21 0.11 2 0.78	3 9 0 8 6 7 21 1 2 12

Looking at the average Age of each population we have a mean for all sets of 7.15, with a low standard deviation of 1.25, all sets have a higher average age for the 5 most fit businesses. This might point out that, for large sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 7.29, and a minimum of 3.63 for set 17.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.57, and the 75th percentile being approximately 0.79. A the max deviation of the mean is found in set 13, with a deviation value of 1.24.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.48. Looking at specific sets, Sets 7, 8, 13, 15, 17, 19, 24 and 30 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 13, 15 and 30 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 7.59. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 5.09 from the Set's mean number of business locations.

5.4.1.12. large_size_high_variance_large_product_market

Table 14 – large_size_high_variance_large_product_market

Parameter Set Key	**Average Age**	**Max Age**	**Product Coverage Most Fit**	**Number of Business Locations Most Fit**
1	8.28	25	2 0.528 7 0.027 18 0.178 10 0.185 11 0.615	2 5 7 1 18 1 10 1 11 10
2	6.9	25	0 0.631 2 0.587 1 0.515 30 0.154 11 0.652	0 15 2 15 1 7 30 1 11 10
3	6.64	25	1 0.516 5 0.127 7 0.828 24 0.232 8 0.271	1 13 5 1 7 23 24 1 8 2
4	5.46	25	0 0.790 3 0.675 6 0.539 13 0.287 7 0.207	0 29 3 16 6 8 13 5 7 3
5	7.48	25	0 0.688 15 0.522 4 0.309 10 0.445 13 0.424	0 19 15 8 4 3 10 4 13 5
6	6.64	25	10 0.364 4 0.595 15 0.748 11 0.098 2 0.275	10 4 4 6 15 19 11 1 2 4

7	5.88	25	5 0.528 26 0.243 13 0.076 1 0.534 9 0.521	5 12 26 1 13 1 1 8 9 6
8	5.8	25	3 0.500 6 0.349 2 0.715 4 0.577 13 0.755	3 5 6 3 2 17 4 13 13 25
9	9.34	25	6 0.506 3 0.629 4 0.696 11 0.420 30 0.152	6 7 3 9 4 15 11 3 30 1
10	9.1	25	13 0.600 19 0.059 6 0.426 11 0.493 7 0.613	13 9 19 1 6 9 11 8 7 10
11	5.92	25	4 0.141 6 0.122 3 0.827 1 0.418 2 0.592	4 2 6 1 3 25 1 5 2 10
12	6.26	25	10 0.741 1 0.674 0 0.586 8 0.553 4 0.556	10 18 1 18 0 13 8 7 4 5
13	8.64	25	23 0.025 13 0.128 16 0.046 5 0.446 8 0.429	23 1 13 1 16 1 5 4 8 7
14	7.76	25	3 0.744 26 0.032 14 0.306 10 0.371 2 0.466	3 16 26 1 14 3 10 3 2 8
15	6.8	25	0 0.760 4 0.521 17 0.235 8 0.350 19 0.222	0 16 4 12 17 1 8 7 19 1
16	6.58	25	7 0.844 4 0.550 5 0.457	7 16 4 6 5 3

			0 0.724 22 0.060	0 22 22 1
17	8.86	25	1 0.775 7 0.349 0 0.530 9 0.430 20 0.097	1 20 7 3 0 7 9 4 20 1
18	8.2	25	7 0.482 15 0.488 1 0.425 0 0.625 5 0.539	7 11 15 4 1 7 0 13 5 9
19	6.38	25	11 0.199 9 0.501 0 0.618 5 0.553 2 0.541	11 2 9 4 0 14 5 10 2 13
20	6.64	25	5 0.654 3 0.628 6 0.458 4 0.527 2 0.678	5 12 3 10 6 5 4 7 2 24
21	7.68	25	6 0.363 3 0.798 4 0.503 10 0.176 9 0.232	6 4 3 25 4 8 10 1 9 1
22	7.88	25	17 0.039 7 0.704 0 0.701 3 0.696 5 0.642	17 1 7 11 0 10 3 20 5 10
23	7.52	25	2 0.554 1 0.592 11 0.418 3 0.438 8 0.593	2 17 1 14 11 7 3 4 8 5
24	5.98	25	7 0.703 12 0.138 4 0.590 5 0.437 2 0.682	7 17 12 1 4 8 5 5 2 14
25	9.62	25	14 0.532 22 0.087 20 0.664 19 0.299 33 0.178	14 6 22 1 20 8 19 3 33 1
26	9.22	25	4 0.678 10 0.558	4 10 10 12

			2 0.742 22 0.246 8 0.626	2 18 22 1 8 12
27	6.58	25	1 0.611 5 0.495 7 0.373 22 0.159 8 0.616	1 7 5 7 7 3 22 1 8 9
28	6.86	25	2 0.718 0 0.599 3 0.695 1 0.579 7 0.657	2 14 0 12 3 13 1 11 7 11
29	7.94	25	2 0.701 6 0.303 10 0.371 15 0.727 16 0.180	2 11 6 3 10 6 15 17 16 1
30	8.18	25	17 0.231 3 0.778 6 0.633 2 0.668 25 0.242	17 1 3 16 6 8 2 17 25 1
31	6.26	25	4 0.468 13 0.429 5 0.591 0 0.760 10 0.317	4 6 13 3 5 8 0 14 10 3
32	5.52	25	9 0.080 0 0.745 21 0.131 23 0.152 11 0.297	9 1 0 21 21 1 23 1 11 3

Looking at the average Age of each population we have a mean for all sets of 7.27, with a low standard deviation of 1.20, only set 25 has a lower average age for the 5 most fit businesses, while the reverse is true for the rest of the final populations for each parameter set. This might point out that, for large sized markets, age is a good predictor of high success. Looking at the most fit businesses of each set individually, standard deviation of the Age metric is high, with average value 6.70, and a minimum of 2.88 for set 20.

In terms of Reputation score, as previously referred, it is very dependent on external factors, making it impossible to find change patterns, so looking at the averages for the population is not useful, but looking at its standard deviation for the most fit elements is. Most sets show a low standard deviation, with mean value 0.76, and the 75th percentile being approximately 1.05. A the max deviation of the mean is found in set 10, with a deviation value of 1.83.

In terms of Product Coverage for the most fit businesses, the mean for this Market configuration is 0.46. Looking at specific sets, Sets 5, 8, 12, 18, 19, 20, 23 and 28 show a particularly close grouping of coverages, in the 25th percentile of standard deviation for the Market setup. These Sets mostly have a higher weight parameter on the catalog score, with 12 and 28 being the exception.

In terms of the Number of Locations for the most fit businesses, we see a mean for this Market configuration's most fit elements of 8.14. Looking at specific sets, no sets stand out by having all the fittest elements with only 1 location. All sets have at least one element with more than two locations and that element deviates on average 6.29 from the Set's mean number of business locations.

5.5. General Analysis

Most of the sets present coverage values for the 5 most fit businesses quite close together, while some present two outliers who usually match with the outliers in number of locations. One might infer that, for this simulation, there is a high correlation between the number of locations and coverage of the market's product universe.

For this market configuration, high product coverage and a more locations seem to be a good predictor of fitness, although not consistently, which suggests that a good reputation might skew the choices of consumers.

High variance market configurations produce, as expected, more values outside the majority windows then the low variance configuration. This seems to have a higher impact on the smaller market sets, as values that deviate from the norm seem to decrease with market size and product universe size, when comparing configurations with similar variance levels.

When looking at market size, high product coverage and number of locations seem to be a better predictor of fitness the larger the market and the larger the product universe.

5.6. Validation

To determine if this method is a suitable option to simulate market behaviors, and given that the simulation outputs are consistent amongst themselves, we need to verify its consistency with real world observations. While no specific markets were simulated, thus excluding direct cross examination between real examples of successful business's characteristics and simulated ones, the average age of the market businesses, assuming that each generation is equivalent to one year, should be consistent with real world observations.

The life expectancy of a business in a competitive market is influenced by several factors, including industry competition, entrepreneurial human capital, and firm characteristics. In highly competitive industries, businesses face lower survival probabilities and slower growth rates, particularly when the average price-cost margin is small and when competing with imports (Mengistae, 2006).

For small firms the average annual death rate of 8.3% over the first five years, with half of these firms ceasing operations within six years(McKenzie & Paffhausen, 2017).

Research indicates that the typical lifespan of publicly traded companies is about a decade, with mortality rates being independent of a company's age(Daepp et al., 2015). This suggests that while some firms may survive longer, many face significant challenges that limit their longevity. The following sections explore key aspects that affect business life expectancy.

These findings are consistent with our average age values windows for small markets being slightly lower than medium and large sized markets which themselves have similar values.

6. CONCLUSIONS

Our findings indicate that ALife models can effectively model the adaptive, nonlinear nature of market behaviors, which are often difficult to model using traditional economic frameworks. Moreover, the results suggest that the presented simulation provide a reasonable means of testing hypotheses about market mechanisms, forecasting trends, and evaluating the impact of various policy interventions.

While there remain challenges related to model calibration, validation, and the integration of real-world data, the evidence presented in this thesis shows the potential of ALife algorithms as a valuable complement to existing economic modeling techniques.

In sum, this work contributes to the growing body of knowledge that recognizes the relevance of ALife in the study of complex systems, and offers a promising avenue for future inquiry into the dynamics of market systems and their behavior under different conditions.

6.1. LIMITATIONS

To contain scope, factors with less recognized weight in the success and complex influencing factors such as broad social and economic conditions were not modeled. Market size and product universe size are also kept the same in all generations.

6.2. RECOMMENDATIONS FOR FUTURE WORKS

The next steps are identifying possible divergences from real word observations and suggesting possible different approaches that could lead to better representation, summarizing findings and defining implications.

Future research should focus on refining these simulation, improving it's predictive capabilities, and exploring new applications in areas such as financial markets, resource allocation, and economic forecasting.

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