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DALLAS WALBER FERRAZ SEGUNDO

APPLICATION OF COMPUTER SIMULATION FOR THE STUDY OF SUPPLY CHAIN MANAGERIAL ACTIONS OF MEDIUM-SIZED ENTERPRISES IN THE APPAREL CLUSTER OF PERNAMBUCO

Caruaru

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Dissertação apresentada ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal de Pernambuco, como requisito parcial para a obtenção do título de Mestre em Engenharia de Produção.

Área de concentração: Otimização e Gestão da Produção.

Orientadora: Prof.ª Dr.ª Maisa Mendonça Silva.

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Aprovada em: 13/03/2020.

BANCA EXAMINADORA

Prof.ª Dr.ª Maisa Mendonça Silva (Orientadora)
Universidade Federal de Pernambuco

Prof.ª Dr.ª Marcele Elisa Fontana (Examinadora Interna)
Universidade Federal de Pernambuco

Prof. Dr. Raphael Harry Frederico Ribeiro Kramer (Examinador Externo)
Universidade Federal de Pernambuco

To my family.

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“Truth serves only its slaves.” (SERTILLANGES, 1959, p. 4).

ABSTRACT

This work represents an effort to model the internal dynamics of a manufacturing cluster's supply chain strategy by computational means, through an agent-based modelling (ABM). As a case study, we have selected an apparel-manufacturing cluster in Pernambuco, Brazil. The cluster's supply chain strategy was first expressed by means of the Conceptual System Assessment and Reformulation (CSAR) theoretical framework, and then key elements of it were represented as agents, each one embodying a supply chain manager from one of the medium-sized enterprises (ME) in the cluster. Machine Learning (ML) was used to guide the development of these agents, informed and constrained by real data from the cluster. Therefore, the resulting system allows insights on how elements relate to each other, such as the difference between the conceptual and the implemented model, which variables affect the decision-making process of the agents, whether the perceived current market share position matters more or less in budget allocation, which actions would be performed under specific agent temperaments according to demand forecasting and so on. This approach is relevant by virtue of granting not only stress test and sensitivity analysis of impactful factors regarding supply chain management of the ME, but it also avows ad hoc confirmation of theoretical propositions, such as CSAR itself, onto simulated environments.

Keywords: Supply Chain Management. Computer Simulation. Artificial Intelligence. Medium-sized Enterprise. Agent-based Simulation. Apparel Cluster of Pernambuco.

RESUMO

Este trabalho representa um esforço para modelar a dinâmica interna da estratégia da cadeia de suprimentos de um arranjo produtivo de manufatura através de uma modelagem computacional baseada no agente. Como estudo de caso, foi selecionado o Arranjo Produtivo Local de Confecções do Agreste de Pernambuco, Brasil. A estratégia da cadeia de suprimentos das empresas do arranjo foi primeiro expressa em forma de sistema conceitual de avaliação e reformulação, do escopo teórico do Conceptual System Assessment and Reformulation (CSAR). Os elementos chave representados na simulação são os agentes, cada um deles figurando como um gerente de cadeia de suprimentos de uma empresa de médio porte do Arranjo Produtivo Local. A técnica de Aprendizado de Máquina foi utilizada para guiar o desenvolvimento destes agentes, limitando-se por dados reais colhidos sobre o arranjo produtivo. Portanto, o sistema resultante permite a observação do relacionamento dos componentes do arranjo, como a diferença entre a implementação do modelo e seu esquema conceitual, a forma como as variáveis afetam o processo de decisão dos agentes, o grau de relevância da percepção da fatia de mercado de uma empresa na alocação de recursos, quais ações devem ser executadas por diferentes perfis gerenciais, entre outros. Esta abordagem é relevante devido não apenas à possibilidade de fornecer uma análise de sensibilidade dos fatores impactantes em relação à gestão de cadeia de suprimentos para empresas de médio porte, mas, também, por permitir modificações e confirmações *ad hoc* de proposições teóricas, como o próprio modelo CSAR, em ambientes simulados

Palavras-Chave: Gestão da Cadeia de Suprimentos. Simulação Computacional. Inteligência Artificial. Empresas de Médio Porte. Simulação Baseada no Agente. Arranjo Produtivo Local de Pernambuco.

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LIST OF ACRONYMS

ABM	Agent-based Model
AI	Artificial Intelligence
ANN	Artificial Neural Network
CRM	Customer Relationship Management
CSAR	Conceptual System Assessment and Reformulation
DM	Demand change index for the computer model
EF	Efficiency index for the computer model
GDP	Gross domestic product
ME	Medium-sized enterprise
ML	Machine Learning
MS	Market share index for the computer model
RB	Rule-based algorithm
SC	Supply chain
SCM	Supply chain management
SCS	Supply chain strategy
TW	Total wealth index for the computer model

SUMMARY

1 INTRODUCTION

1.1 GENERAL DISPOSITIONS

Under regular conditions, every company is part of a network of other companies that either supply it with raw materials and other types of unfinished goods that will be processed and turned into other unfinished items to be supplied to other companies downstream in this network, or even finished goods for the final customer (LUOMARANTA; MARTINSUO, 2019). This type of relationship among companies can be described as a Supply Chain (SC), even though not always it is as direct as a chain and might more often than not behave like a network of participant companies (KAMALAHMADI; MELLAT-PARAST, 2016).

For this reason, most companies participate in a SC, and are in fact subject to restrictions and fluctuations that happen along the connections and interactions among them, from the very first supplier of raw materials to the final retailer (HECKMANN; COMES; NICKEL, 2015). Thus, understanding how and what kind of behavior a SC might present can help not only the companies label their connections as “Supply Chain” just as an end in itself, but also to encircle a scope of knowledge in order to better understand what happens with the entities and actions that compose this field of work (COOPER; LAMBERT; PAGH, 1997).

In this context, it is important to be able to recognize the main activities that in fact compose and either directly or indirectly contribute to modifying a company’s performance within the Supply Chain (BEAMON, 1998). In this context, the area responsible for studying and applying the conjunction of logistics, production, financial, marketing, customer relationship management and other fields of work for better performance of a company can be known as Supply Chain Management, or SCM (TAN, 2001).

However, since a company is not isolated and is part of a chain or a network of other companies, it is important that the SC managers of all enterprises in the chain have their interests and practices aligned for better conjunct performance (GANDHI; SACHDEVA; GUPTA, 2018).

According to current literature (KOT, 2018), several indicators exist for performance assessment of a the SC management of companies, such as quality control, low prices, and available goods for the final customer and so on. Hence, it is also necessary for the SCM to be guided by a theoretical framework and strategic planning (CHANDRA; KUMAR, 2000). Existing literature (FROHLICH; WESTBROOK, 2001) state that this field of knowledge that helps companies understand better their role in the SC and plan better practices for the SCM is known as Supply Chain Strategy, or SCS.

According to the literature (PEREZ-FRANCO; SINGH; SHEFFI, 2010), even with the SCS being a crucial part of a company's success over their competitors, not many companies have a grasp on their own strategies regarding the SCM and are increasingly looking for a better understanding of it. The resistance to adopt good practices not only in SCM but also in a wide range of fields is more common in smaller and medium-sized enterprises than in larger ones (OKREGLICKA; MYNARZOVA; KANA, 2015; VALDEZ-JUÁREZ; GALLARDO-VÁZQUEZ; RAMOS-ESCOBAR, 2018).

This situation represents a problem for these companies because knowing their own SCS and having a thoroughly planned SCM can help the company stand out from the competition for the customer and gain market share (KHERBACH; MOCAN, 2016). One clear example of this situation where the majority of the companies of a productive geo-economic area is composed mostly of individual, small and medium-sized companies with no investment in SCM is the Apparel Cluster of Pernambuco, in Brazil (SEBRAE, 2013).

This cluster of companies in the state of Pernambuco has a very particular distribution of companies of all sizes over more than 10 towns, three of them being the main ones (Santa Cruz do Capibaribe, Caruaru and Toritama), still according to official reports (SEBRAE, 2013). The amount of revenue these companies generate and the number of people employed both directly and indirectly in the apparel-manufacturing sector make this region of the country an important candidate for evaluation of SC conditions, due to the amount of revenue generated in the region (BRAGA; ABREU, 2017).

Still according to the aforementioned authors, the Apparel Cluster of Pernambuco is located in the Brazilian Northeastern region, one of the poorest and with less investment in technology, state-of-the-art solutions for industry and qualified personnel of the country (IBGE, 2015). Consequently, the solutions for SCM problems tend to be informal and to allocate logistics, production and marketing resources in a way it does not generate ideal indicators for the companies (IEMI, 2017). As expected, the solutions applied in entrepreneurship in the area are mostly rudimentary.

The lack of professional and academic investment in SCM innovative solutions is not only a problem for the overall performance of companies in the Apparel Cluster of Pernambuco but also for other companies in the world (WONG; NGAI, 2019). A closer look in the current literature shows that this problem originates partly due to literature itself, because is still being consolidated and has few grounding concepts and practices that are accepted by most specialists. This is to say that there is much conflict or lack of standardization among specialists in the area regarding best practices.

Therefore, suggesting methodologies and theoretical frameworks for analyzing interactions among components of a SC in order to improve SCM for the companies in the Apparel Cluster of Pernambuco is an effort that needs to overcome these difficulties: finding and working SCM tools and methodologies in the current literature and practical fields and combining them into a feasible tool or approach, and also suggesting this technique that is easily understandable by small and medium-sized companies' general managers or SC managers.

Since the scope of such an effort would become overwhelming for designers of this intended framework or technique, it is natural that simplifications and focusing on certain methodologies occur. This is especially true if the suggested solution is of quantitative nature, whether it is computational or algorithmic (LI; CHAN, 2013). Among the possible solutions, there is the computationally simulated environment with intelligent agents (LABARTHE et al., 2007).

Choosing a quantitative approach not only allows this work to provide a precise answer for specific questions in a complex environment dealing with an also complex area of expertise (a large number of companies and their respective SCM and SCS), but also creates the opportunity for the decision-makers to know how trustable the provided solutions are, by analyzing errors, efficiency and other measurements of the same sort (JAYANT; GUPTA; GARG, 2014).

As for the limiting trait of this quantitative approach, the very system being represented in the simulated environment must be simplified, with just one aspect of the entity being represented in the simulation (HAILEGIORGIS; CROOKS; CIOFFI-REVILLA, 2018). In the case of the Apparel Cluster of Pernambuco, the number of companies representing each size is large enough to allow and encourage a choice of a certain part of the market.

Since the current literature already provides many solutions for small companies and also for large companies in several aspects of development and theoretical fundaments, it is advantageous for the ME to be represented and analyzed for this work, for there is still a lack of dedicated material focusing solely on ME, whether it is financial relater, or technology related or engineering related (BATISTA et al., 2016; DE et al., 2018; KASHAV S., CERCHIONE R., CENTOBELLI P, 2017; MAKSIMOV; WANG; LUO, 2017; NDIAYE et al., 2018; TOURATIER-MULLER; MACHAT; JAUSSAUD, 2019).

1.2 JUSTIFICATION AND RELEVANCE

Medium-sized enterprises represent an intermediate status between small companies and large companies considering revenue, number of employees and hierarchy levels, amongst other characteristics. This is to say that whereas in larger companies it is easier and more visible to find clear boundaries between responsibilities, sectors and personnel, there is a tendency of accumulating higher degrees of responsibilities and information with few personnel in smaller companies (CHIRICO, 2008).

Still according to the aforementioned author, most of the time well-trained employees in small and medium companies accumulate functions and overlap activities and strategic planning within the same company due to the lack of clear division among task definitions, creating conflicts of authority and a blurred hierarchy. Another reason stated for this accumulation of information and responsibilities is the fact that there is a tendency for this kind of business present a familiar structure, with preference for more strategic attributions be placed within family members.

The organizational chart of most companies in the Apparel Cluster of Pernambuco is not an exception of this situation, according to specialized reports (IEMI, 2017). Even large companies of the area present an organogram and activities flowchart either wanting in clarity or confuse for the employees due to the high degree of informality and large revenue and demand for all companies involved. Most companies would benefit from applying literature recommendations on self-assessment of financial, production, quality management, organizational level of maturity and subsequent prognostics, especially for strategic guidance (CIORCIARI; BLATTNER, 2008; PORTER, 2008; R; D, 1992; SAUERWEIN et al., 1996).

Provided the fact that it is not granted that ME grow to be large companies just by existing in a non-proactive fashion when it comes to market share gain, it is important for a company this size to invest in knowledge and technology that makes it stand out from the competition (SANTI; SANTOLERI, 2016). Adopting state-of-the-art tools, methodologies and techniques for strategic planning is highly recommended in this case.

Strategic planning encapsulates several areas of theoretical formulation and also application of procedures. In this field, Supply Chain Strategy poses as one very important component for companies (DUBEY et al., 2017). Thus, for the ME in the Apparel Cluster of Pernambuco, it is only natural to invest in studies and researches involving SCS and SC management.

Nevertheless, according to official reports (SEBRAE, 2013), there is less than 1000 companies that can be classified as medium-sized in the Apparel Cluster of Pernambuco. This is akin to the amount of information available in literature regarding ME, which is an underrepresented theme in the specific literature, whether it concerns applied works or theoretical approaches. The literature regarding small-sized companies or large companies is plentiful, whereas literature focusing specifically on ME is lacking.

This claim is backed by a research in Elsevier's academic database Scopus, which contains more than 34,000 associated peer-reviewed journals. The terms "medium-sized" were searched, referring to either "companies" or "enterprises", and only 99 articles were published exclusively towards medium-sized companies, from 16,082 responses in the database, of publications ranging from the years of 2010 to 2019 and written in English. In comparison, around 98.77% of the results associated recommendations, theoretical frameworks, case studies and development of methodologies for both small and medium-sized companies as a whole.

Thus, it is important to enable this type of company understand its internal processes and components, in order to aid them to better allocate resources and plan for market growth and competitive advantage gain. For this reason, using tools and techniques such as intelligent algorithms embedded in agent-based simulation environments is fitting, because the very structure of the computational system is designed specifically for problems where the solution being sought out is not of forecast or optimization nature, but rather of understanding of visible interactions between the company and the market (WILENSKY; RAND, 2015).

It is also important to notice that the system composed of intelligent algorithms and simulation systems is only the technical part of the enterprise, the other crucial part being the choice of the appropriate methodological framework that will in turn capture and manipulate in an understandable fashion the SC management nuance of companies of all sizes. This step is also crucial, due to a lack of standardization in the current literature of a proper methodology for representing assessing SCM role and performance.

In this context, SCM is mainly responsible for metrics and is supported by SCS, whereas the SCS itself is composed primarily of competitive priorities, information technology and relationship with other companies. The debate on whether SCS is composed of preset models or if it is unique to each company is still happening in the current specialized literature. Regardless of the outcome of the debate, SCS is considered crucial for the success rate of the SCM.

Hence, there is a high potential of lucrative and vital scenario for ME from the Apparel Cluster of Pernambuco, provided they invest in computational technologies in order to evaluate SC management and strategy performance. Naturally, Agent-based Modelling and Artificial Intelligent play an important role in this effort, given the possibilities of generating insights for the ME, common in simulation applications (CZUPRYNA et al., 2018; GORE et al., 2018; MOGLIA; PODKALICKA; MCGREGOR, 2018; TYKHONOV et al., 2008; WALBERT; CATON; NORGAARD, 2018).

1.3 OBJECTIVES

1.3.1 General objective

The main goal of this work is to create a system that allows decision-making personnel, such as governmental offices responsible for economic and market planning, have a panoramic view on the relationship conditions between components of a SC for Medium-sized companies.

1.3.2 Specific objectives

The general objective is achievable by following a series of necessary and previous steps, which will in turn facilitate the comprehension of the system. The aforementioned steps are as follows:

- Delimitating the simulation environment to a specific geo-economic location;
- Focusing on a specific type of entity to be represented in the system;
- Clarifying the differences between forecasting and simulation systems;
- Choosing an appropriate computational simulation technique;
- Choosing a set of appropriate Artificial Intelligence approaches for composing simulated agents;
- Implementing a verified and validated computational system representing the real situation;
- Enabling easy modifications to the system to provide fine-tuning of parameters and sensitivity analysis.

1.4 STRUCTURE OF THE WORK

The present work is composed of several Sections, and each Section is responsible for a part of the making of the system. As seen in the first Section, it was presented the importance of Supply Chain Management and Supply Chain Strategy for the Supply Chain as a whole and for the focal company, as well as a brief history of the Apparel Cluster of Pernambuco, Brazil. The justification for more investment in studying new techniques to approach the problems of ME of the companies' cluster was also presented, and then which computational and mathematical techniques were going to be used for this research effort in order to help decision-makers better understand their context.

Section 2 is structured not only to present a literature review and show fundamental concepts the way they are described by experts in the field, but also formulates a synthetized definition of the very concept specifically for this work and show literature gaps. The concepts related to SC, ME, Agent-Based Simulation and Artificial Intelligence were defined as used in the entirety of this work.

The adopted methodology of the work is presented in Section 3. It brings information regarding how the whole work was structured, from the initial effort of capturing the problem until the very results obtained with the implemented system. This Section also brings information on how the simulation environment represents the CSAR model computationally, both by describing the components used in the algorithms and their counterparts in the literature and in the reality of the Apparel Cluster, and also by describing how the source code of the simulated environment was designed and implemented.

After the presentation of the methodology, Section 4 subsequently displays the results of the simulation. It does so by showing what was obtained and how many iterations and entities were used for the execution of the system. This Section also brings information about sensitivity analysis and intermediate steps whilst constructing and validating the system. All the information is presented in graphic and statistic form for better visualization and comprehension.

Thusly, Section 5 is responsible for bringing the insights resulting from the fourth Section. This is to say that fifth Section enables decision-makers to draw conclusions regarding the relationship and synergy between components of the simulated system representing the Apparel Cluster of Pernambuco. Finally, Section 6 concludes the work by commenting on limitations of the system and also by suggesting further modifications and new applications for the simulated intelligent system.

1.5 ORIGINAL CONTRIBUTION

The findings of this work include not only a review of the state of the art of the Supply Chain management, Computer Simulation and Artificial Intelligence fields of knowledge, but it also complements and unifies the utilization of some of their concepts and methodologies in one unified system.

Regardless of the fact that it is common in current literature to utilize intelligent agents in computer simulations, especially when the simulated environments act out social interactions, the present work innovates in this field by utilizing *in silico* data generated with Monte Carlo simulation as source of training inputs for the Artificial Neural Network that embodies the intelligent aspect of the simulated agent.

Furthermore, the simulated environment encompasses the behavior of Medium-sized Enterprise entities, which are lacking in current literature. By the way the Agent-based Modeling simulation works, it is possible to understand that the insights taken from the results are suitable only to this size of company.

This is true because both small-sized and large companies have characteristics so different from medium-sized ones that the whole system should have to be reformulated in order to be adapted to other sizes of companies.

For instance, the theoretical framework used for constructing the Supply Chain Strategy of the manager encompasses types and numbers of actions typically associated with Medium-sized companies, as well as the way the market works regarding its size, demand, competition and type of goods being sold. Hence the characteristic of being suitable precisely for Medium-sized companies.

2 LITERATURE REVIEW AND BACKGROUND

In this Section, fundamental concepts for the research and application of methodologies are presented. The current formal and specialized literature for each of the fields mentioned is broad and may present conflicting viewpoints when it comes to formalizing even simple concepts. For this reason, a few definitions for each concept are presented from specialists in the field and then synthetized for simplicity and clarity in this work.

This Section is also responsible for identifying the gaps in the current literature and the state of the art for most areas, methodologies and concepts being developed and applied that are somehow connected with the present work. The database research has been also conducted in Elsevier’s academic database Scopus from a period spanning from the year 2010 until the year 2019 for all the concepts mentioned.

The literature review was conducted by researching key words of the focal area, namely “supply chain”, “supply chain management”, “supply chain strategy”, “logistics”, “medium-sized enterprises”, “computer simulation”, “agent-based simulation”, “artificial intelligence”, “SCS Pillars”, “backpropagation function”, “neural network”, “cost function”, “Apparel Cluster of Pernambuco” and other terms that could bring up recent and useful results to the formulation of concepts. This search was conducted in Elsevier’s academic database Scopus.

The presentation and the subsequent summarized explanation of each concept also represents in this Section the choice for each area of focus, tool, technique and methodology adopted, provided the justification and all objectives presented in the previous Section are taken into consideration. Hence, the ideas presented in this Section are found in other academic works, such as the aforementioned terms.

Therefore, any other concept, sentence, term or idea appearing in subsequent Sections of this work are created exclusively by this work and for this work, explained and deployed accordingly. This includes terms such as “temperament”, “margin revenue”, “margin cost”, “constraints table” and “environment table”, which will have their meanings and utilizations clarified whenever they appear.

For the term “Supply Chain” alone, the research in the aforementioned database under the aforementioned conditions returned 26,918 document results, with the most cited by other authors having 966 citations and focusing on food waste within supply chains (PARFITT; BARTHEL; MACNAUGHTON, 2010), against 676 of the second most cited work, which describes the role of Internet of Things in supply chains (WEBER, 2010). Only 209 works have more than 100 citations, the majority of them studying practical applications and deployments within supply chains.

When including the term “management” in the previous database research, 54,636 results appear, with the most cited by other authors being a 1,220 citations paper regarding supply chain integration (FLYNN; HUO; ZHAO, 2010). Followed closely by the second most cited work that studies criteria for supplier selection with 1,156 citations (HO; XU; DEY, 2010), only 712 works have more than 100 citations.

Now including the term “strategy” and excluding “management”, the database returned only 239 results for “Supply chain strategy”. None of the results were cited more than 100 times, the most cited one being a work that assesses the impact of both competitive and supply chain strategy on business performance, with 96 citations (QI; ZHAO; SHEU, 2011). The second most cited one, with 88 citations, implements a responsive supply chain strategy in global complexity (ROH; HONG; MIN, 2014).

Whereas no results were found for the term “Pillars” associated with “Supply chain” in the research, nor for “Apparel Cluster of Pernambuco”, and the results for “Medium-sized enterprises” have been presented in the previous Section as justification for the present work, the term “Logistics” returned a massive number of 324,805 works ranging from theoretical foundation to application of techniques, with works being cited more than 7,000 times.

Similar great numbers were presented for terms as broad as “computer simulation”, with 345,213 results ranging from theoretical foundations, literature reviews and application of techniques, with the most cited work being cited more than 31,000 times, followed by the second most cited work with more than 7,600 citations.

Narrower than the results for “computer simulation”, both “agent-based model” and “agent-based simulation” resulted combined a result of 16,227 published works. The most cited of them is a chapter of a book explaining fuzzy logic within engineering, mentioned 2,210 times in the literature (ROSS, 2010). With 1,203 citations, the second most cited work reviews the standardization of agent-based models’ description (GRIMM et al., 2010). In summary, most works in this field apply the concepts of simulation based on the agent instead of only developing theoretical concepts.

The broad theme of “Artificial Intelligence” has also shown a massive number of works, with 207,132 research results, spanning from theoretical studies to application of methodologies and techniques. The two most cited papers were cited over 15,000 times and almost 6,000 times, in order. One clear trend is that most papers are related to the areas of Deep Learning and Machine Learning, very important and growing topics within the scope of Artificial Intelligence, including the 1,620 most cited works, with more than 100 citations each.

On the topic of Machine Learning alone, specifically with terms related to “Artificial Neural Network” such as “backpropagation function” and “cost function”, the dataset research returned 10,788 for the first and only 447 results for the latter. Even with result numbers so different, the research of both terms are similar in the fact that the most cited work in each field is cited more times than the other works combined, and they are more practical than theoretical, in the sense of studying the impact of parameter change within the equations.

From these researches, it is possible to summarize and narrow down the concepts used in the present work. It is also possible to recognize the limitations and literature gaps concerning each concept and propose not only new questions regarding the fields, but also a methodology in order to expand and unify the knowledge stemming from the aforementioned fields.

2.1 SUPPLY CHAIN

According to the consolidated literature (HUSSAIN; JUSOH; GILLANI, 2020), Supply Chain, or SC can be described as a set of actions and activities regarding logistics, stock control and service level. It can also be implied as a replication of logistic activities of several companies linked towards a certain final good for the customer.

For simplicity and clarity, a vision akin to the previous two presented is adopted, therefore the concept of Supply Chain in use for this work is then a collective effort comprising of entities and events, such as production companies, suppliers, transport companies, integration actions and consumer-oriented planning, aiming to lower prices, satisfy quality standards and make final goods available for the end consumer using information for improving resource allocation.

With this definition in hand, it is necessary to expand the concepts of how such an effort may be feasible taking into consideration boundaries and limitations of budget, final goods nature, market share and stakeholders' interests and the relationship with suppliers and customers' managers (MENTZER et al., 2001).

It is also necessary to conceptualize Supply Chain Management and Supply Chain Strategy, because it explains in a concise manner what kind of long-term planning and guidelines guide the personnel responsible for designing resources allocation on the SC that are crucial for the company maintaining good scores in their own metrics of success and other relevant managerial indicators (GUNASEKARAN; PATEL; MCGAUGHEY, 2004).

2.1.1 Supply Chain Management

Specialists in the field (XU et al., 2020) state that Supply Chain Management goes from the first step of a SC in a company, which is outlining the scope of activities, how to keep it working when it is implemented and the details of each operation, even if it means allocating resources on goods that does not necessarily represent a strong asset for the company, as long as it represents customer's satisfaction.

There is also the understanding in the current literature of SCM as being a series of practices in all levels over the SC in order to influence it to output the expected results, when it comes to activities that comprehend logistics but also encompasses other areas and departments of a company, such as marketing, product development, and finance and customer services (CHIAPETTA JABBOUR et al., 2019).

From the previous definitions, a synthetized explanation for SC Management can be outlined as a series of managerial actions within the scope of visible entities of a company, such as agents, departments and companies, that present an effort to follow a thoroughly planned outline regarding all aspects of a SC, aiming thus to achieve sustainable and competitive advantage gain for the company via customer’s satisfaction.

Hence, any activity or company area that has the potential of increasing serviceability, perceived quality by the customer, affordable vending prices and help establish market share growth for the company may be placed under the scope of the Supply Chain Manager (MIN; ZACHARIA; SMITH, 2019). This way of organizing a company conflicts with more traditional organograms, where the activities and limitations of each department were clear and solidified, with little interference or interaction among managers of different fields (TERSINE, 1976). Thus, there must exist a corpus of knowledge and planning to support this line of management, and it is provided by the Supply Chain Strategy.

2.1.2 Supply Chain Strategy

According to current literature (PONKRATOV et al., 2019), the Supply Chain Strategy can be narrowed down to a way of improving competitive strategy, which is not a decrease in the spectrum of components of the type of strategy. It can be clearly seen due to the fact that the aforementioned author considers it as a key way of maintaining superiority over competitors through correct actions when managing logistics and the SC management.

This is different from the definition of Supply Chain Strategy, although they complement each other rather than contradict themselves, because the authors define it as a general tendency for weighing the trade-off between market responsiveness and physical efficiency of a company when dealing with the management of actions and entities related to the SC (JAJJA et al., 2016).

A different view of Supply Chain Strategy sees the field as a set of practices and ideas to guide plans and actions in order to enable SC Management efforts to succeed by organizing such plans in a hierarchical order, from long-term strategies concerning the key elements for the customer to operational daily actions that help these plans be achieved (PEREZ-FRANCO; SINGH; SHEFFI, 2010).

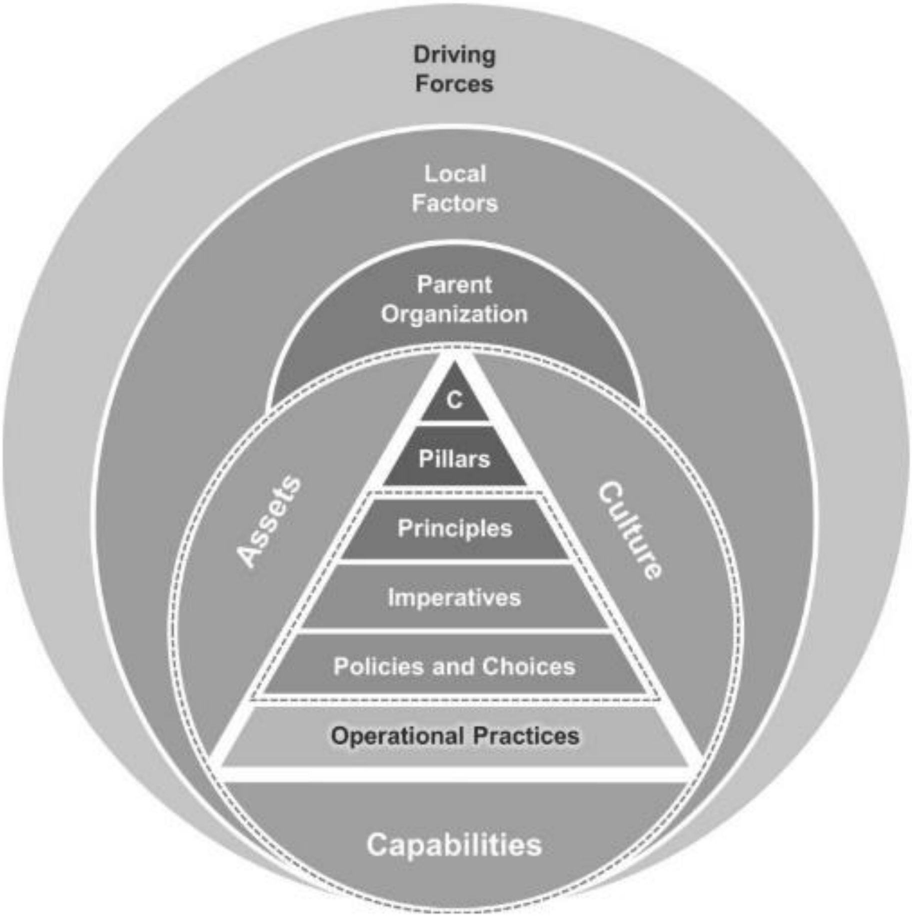
In this context, Supply Chain Strategy is treated in this work as a group of plans and actions structured in a hierarchical fashion, from long-term term guidelines to routinely events, that aim to facilitate a SC Manager help achieve the company’s success over competitors by intelligently allocating resources on key areas of the company, such as Logistics, Production, Finances and any other areas of interest that directly interfere in the customer’s serviceability, quality or price of the final good.

Since most companies tend to face competition and have to satisfy customer’s needs, most companies have a Supply Chain Strategy, even though it might be of tacit nature. Naturally, the literature presents a wide variety of options for Supply Chain Strategy measurement of alignment with the real goals of the company, suggestions of indicators and modifications to improve performance (WANKHADE; KUNDU, 2018). It is necessary to present a thorough and suitable one for the present work, the Conceptual System Assessment and Reformulation model.

This model proposed as a type of Supply Chain Strategy assessment in the literature covers the challenges of capturing and judging the adequacy of a company’s SCS with their general strategy and daily actions, anticipating future SC needs of the company and elaborating a better version of a SCS for the company (PEREZ-FRANCO, 2016). The methodology does so by making the key areas of the company visible and then ranking their importance towards achieving acceptable values of SCM indicators chosen by the company.

The way CSAR model characterizes the importance and placement of the SCS within the scope of general strategy and daily actions of a company can be seen in Figure 1.

Figure 1 - Visual presentation and location of a SCS in the company



Source: Adapted from Perez-Franco (PEREZ-FRANCO, 2016)

From Figure 1 we notice that the inner section of the triangle in the image is separated from the remaining upper and lower part of the triangle by a dotted line. It represents the SCS itself, whereas the top part is composed of the general strategy of the company and the basis comprises the daily actions of the company. The surrounding elements of the triangle represent constraints and external influences.

These external elements can be comprehensively described as influencing a company's SCM and SCS via parent organization (in case of companies that are branches of corporations), social components, economic limitations of the area where the company is based on, political interference, market trends, demographics, culture, weather conditions and so on. Clearly, those elements are present and taken into consideration when planning for a SCS or during SC management, but are not part of what is handled and controlled by the SCM of a single company.

Regarding the SCM and SCS itself, the structure shows that there is a hierarchy among the inner elements of the CSAR model, and it is called *Conceptual Elements* in the literature (PEREZ-

FRANCO, 2016). From the uppermost of the elements, "C" represents precisely the core values of the company and this is the reason it is not under the scope of the SCS, because the company's strategy transcends it. Below the core components, the Pillars represent general areas of interest for the SCM in order to directly address the SCS and is usually not composed of more than 5 elements or strategic assertions with directly linked to the core values and goals.

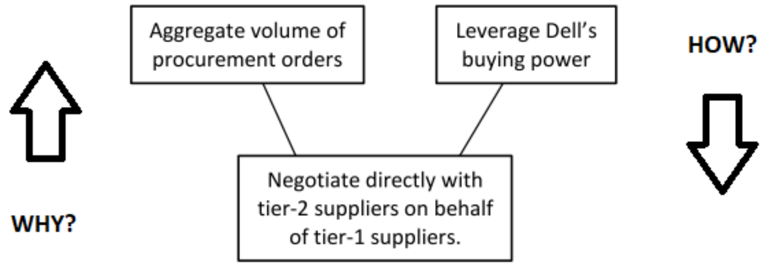
The levels composing the SCS itself start at the Principles, right below the Pillars. Principles can be understood as a direct continuation of the previous upper level. Each Pillar is based upon, and supported by usually 3 to five Principles, which correspond to tactic planning directly under the responsibilities of the SC managers. Below the Principles, the level of Imperatives works the same way and each 3 to 5 components support a Principle, and are more related to operational guidelines than to tactics.

The last and lower level of the SCS is a composed Element that can either address Policies of the SCS or Choices. Since they have an operational nuance than strategic or tactical, the Policies/Choices refer to short-term decisions on actions that support the Principles they are directly under. Under this level, the SCM has jurisdiction, even though Operational Practices cannot be properly described as part of SCS, because they are practical actions themselves instead of planning. Nevertheless, they work in the same way the upper layers, by supporting the Policies or the Choices above them.

With this structure, it is easy to notice that CSAR has a dependence factor throughout the levels, which means that each superior level is dependent on their lower level. It is also noticeable that the lower levels have more components than the upper levels, and that the time horizon and strategy-driven nature of each level decreases and become more short-term and action-driven the lower the level. In this way, the Conceptual Elements of the CSAR model are firmly linked and can be clearly understood when presented in a strategic map, prescribed as a good visualization tool (PEREZ-FRANCO, 2016).

Another feature of this dependent and pyramid-shaped structure of the Conceptual Elements is the fact that, since each element is strongly advised to be expressed ad simple and assertive sentences, even untrained personnel can understand the link from the Operational Practices up until the Core just by answering "*why?*" each step upwards. The same is also possible downstream, where each Core can answer a "*how?*" until it reaches the very last Operational Practice. An example can be seen in Figure 2.

Figure 2 – Relationship between layers of the SCS



Source: Adapted from Perez-Franco (PEREZ-FRANCO, 2016)

Provided there is not any conflicts and contradictions among elements that compose the levels of the CSAR by following the recommendations (PEREZ-FRANCO, 2016), the captured model represents the current state of SCS of the company. The time horizon of validity of this SCS is dependent on the nature of the company, the size, market conditions, and so on. Consequently, it is necessary to redo new installments of this capturing stage each time the company notices there is a misalignment between the practices, the SCS represented in the map and the goals of the company.

Although the CSAR methodology is wide in scope, the part of interest for the present problem is the very description of how to represent the SCS and the existence of the three phases of capturing, evaluating and modifying a SCS, which is valid for both large companies and small to medium ones, with just few adaptations. The logical construction of the model and broad coverage of themes are the primary reasons for the choice of CSAR model as the used theoretical methodology for this work.

2.2 THE APPAREL CLUSTER OF PERNAMBUCO

According to official reports (SEBRAE, 2013) and entrepreneurship reports (IEMI, 2017), the Apparel Cluster of the state of Pernambuco, Brazil is composed of more than 20,000 companies of all sizes spread over 15 towns, amongst which three encompass more than half of the work force and the generated revenue: Santa Cruz do Capibaribe, Caruaru and Toritama. Located entirely in the countryside of the state, 150 to 200 km distant from Recife, the capital city of the state, the Apparel Cluster has been an important source of gross domestic product index (GDP) for the state for more than six decades.

The main products manufactured by the companies in the Cluster are clothes ready to use, such as pants, underwear, dresses, and clothes for children and an assortment of garments, not tailored clothes nor shoes nor addons, such as wallets, hats and purses. These items are not part of the regular production of the Apparel Cluster, according to the reports (IEMI, 2017), which focus mainly on clothes that are associated with large-scale production and low prices for the customers. It is also important to state that most of the production is sold for stores of all sizes, not directly to the customer.

Still according to the aforementioned reports, the annual GDP generated by the Apparel Cluster is of roughly R$ 2 billion, around US$ 500 million, with a little less than 100,000 jobs generated both directly and indirectly. These are significantly relevant numbers, provided the state of Pernambuco is composed of 185 municipalities and almost 9.5 million inhabitants, of which 3.5 million are participant in the workforce.

They also show that the GDP of the state is of around R$ 165 billion dollars a year, equivalent to $ 40 billion US dollars, with the technological and industrial sector representing US$ 9 billion dollars of the total. This means that the Apparel Cluster represents roughly 6% of the industrial sector of the state, that also counts with several other types of components in the industrial sector, such as food growth and exportation, naval activities, a gypsum cluster and so on (PERNAMBUCO STATE GOVERNMENT, 2016).

As the reports also show, most companies in the Apparel Cluster of Pernambuco are of small size or even micro-enterprises. They estimate that almost 75% of the companies are in this category, the remaining 25% being composed of medium-sized and large companies. Even within the 25% remaining companies of the Apparel Cluster, the ME companies are the minority, representing roughly 1,000 of the companies spread throughout a dozen towns in the Cluster.

In this context, the Apparel Cluster of Pernambuco represents not only an important geo-political asset for the governmental administrative offices of the state and the country, but especially for the population of the region. The low rates of education in the Northeast region in Brazil is still considered high by developed countries and Gini index standards (GINI, 1921; TODOS PELA EDUCAÇÃO, 2018). Consequently, the majority of the workforce in the region is composed of personnel not fully trained or formally instructed.

Considering all this information, it is important to remember that few materials are available to guide ME navigate in highly competitive scenarios. This makes it difficult for these companies to succeed in any competitive market, especially in a market as competitive and surrounded with difficulties, such as the Apparel Cluster of Pernambuco. This could help explain the small number of companies of this size in the region.

2.3 AGENT-BASED SIMULATION

The literature (PIDD, 2004) explains that computational simulation is any process that takes place in a virtual environment and that follows not only mathematical procedures but also pre-programmed boundaries of the system it is reproducing. In other words, the behavior of a given system can be analyzed in a computational environment via a mathematical model that represents a conceptualized frame of reference.(HEERMANN, 1990).

In this context, specialists in the field present several different manners for classifying a simulation, regarding the elements that compose it (ABDALLAH; TATSIS; CHATZI, 2020; LAW, 2014; LEE et al., 2002; LEMAIRE; THIEULLEN; THOMAS, 2018; PERKINS et al., 2019). From this, the dimensions mentioned for classification of simulation can be expressed as:

- Type of event: continuous or discrete;
- Nature of the simulation: stochastic or deterministic;
- Processing environment: local or distributed.

However, this type of classification focuses on the system as the object of the simulation. Whether a simulated system is of continuous events, stochastic nature and processed locally, or of discrete events with deterministic nature and processed locally, or even with continuous events, deterministic in nature and processed in a distributed environment, it focuses on the system rather than in the individual pieces of the system (WILENSKY; RAND, 2015).

Although the utility of simulated systems which models sets of entities or entire frameworks instead of individual pieces is largely known in different fields such as engineering, biology and social sciences (KHEIR, 1995), this is insufficient for modeling and extracting insights about individual components of the simulation (MACAL, 2016). For this reason, there is the need for Agent-Based Simulation, or Agent-Based Modeling, also known as ABM.

As suggested by previous works (HOCAOĞLU, 2018), ABM is responsible for closing the gap of traditional simulation due to the fact that it allows for the designer of the simulation and the decision maker to have a better grasp on the components of the system. Furthermore, by controlling the individual agents that compose the whole system instead of designing the entire environment in a top-down manner demand a better knowledge of the system, which will in turn enable more insights when the system is running.

First developed in a proper, recognizable, and intentional manner (SCHELLING, 1971), ABM began precisely as an approach of simulated systems that intended to allow for designing and implementing environments where the whole system has to be constructed in a bottom-up manner. It was initially developed to represent entities in form of agents, and it draws most of the theory behind not only traditional simulation, but also Game Theory and self-replicating theoretical entities (NASH, 1950; VON NEUMANN; BURKS, 1967).

It is important to notice that, as in traditional simulation, ABM is not suited for forecasting of the system that is being represented in the simulated environment. Rather, simulations are mostly constructed for better understanding the synergy and the relationship between the components of the system, or even the relationship of the system with the entities interacting with it, and how the system would react with modifications, as highlighted by literature's recent and common use of the approach (BULLINARIA, 2018; SERRANO-HERNANDEZ et al., 2018).

Another interesting feature of ABM is the fact that it is suited for problems where the number of agents, or types of agents, is not as small as to be easily replaced by an equation-based solution, nor is it too populated with similar entities that it can be easily replaced by a statistical approach (WILENSKY; RAND, 2015). Hence, ABM overlaps in the fringe cases with those two other types of solutions methods.

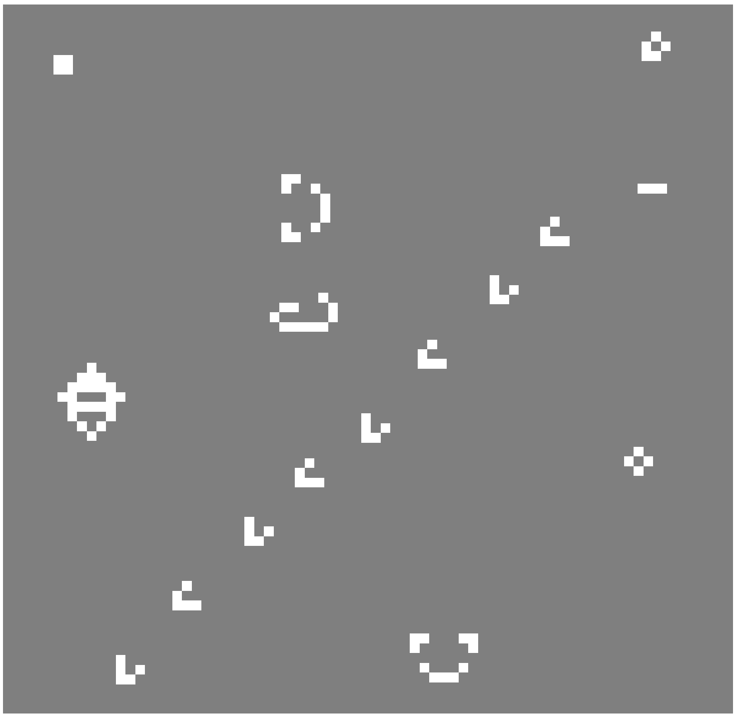
Whilst equations can model and give the decision-maker a good understanding of a specific entity being represented with all its important particularities, it can show its limitations when the number of agents increases to the point the number of equations for specific agents extrapolates the utility of the system due to slow computational time or lack of clarity and excess of details, as stated by the aforementioned authors. Computationally, ABM can then be used for modeling specific features of these agents without much penalties for variations in the characteristics or difference between agent types.

On the other end of the spectrum, it is possible to demonstrate throughout their work that statistic approach for large populations or broad samples is in general a good option, because statistics have been developed with distinct rigorous mathematical tests involving prediction, adhesion, correlation and other types of relationships between sets of data.

However, the statistical approach depends on a certain degree of uniformity of the components of such a set of data, rendering it not so trustworthy with data sets smaller than 30 entities or with components so different, they cannot be generalized as being the same type. This is a type of environment where ABM can be applied with no penalty as well.

Despite being so useful in different fields and with possibilities of being applied to situations where both number of agents and types of agents can vary drastically, the quantity of rules programmed for the ABM can be small, e.g. in the *Game of Life* model (CONWAY, 1970), represented in Figure 3. In this simulated environment, the visual grid may have its cells colored with one of two colors according to a set of 4 simple rules involving similarities with neighboring cells.

Figure 3 – Frame of Conway's Game of Life



Source: Adapted from Conway (CONWAY, 1970)

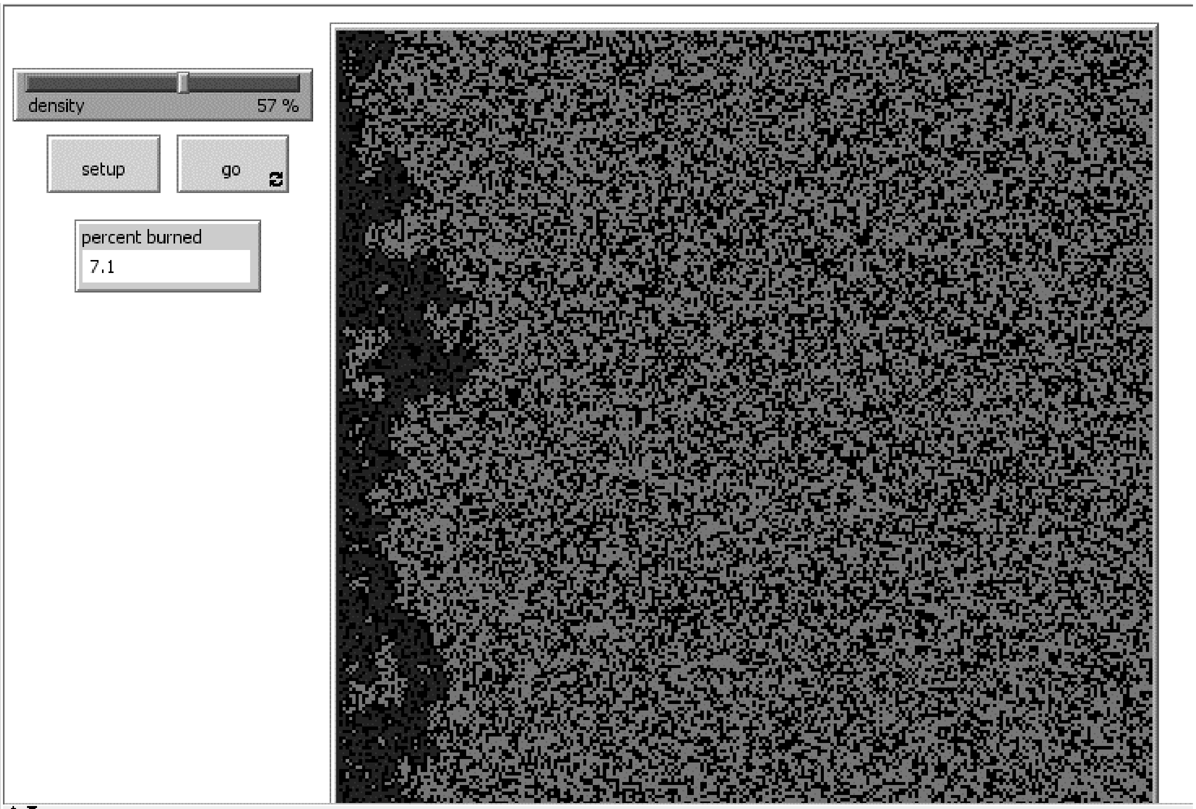
The initial state of the simulation in the Game of Life is generated at random, and after that, no further stimuli are necessary. Regardless of the initial configuration and the overall dimensions of the grid – which could extend from a small 10 x 10 cell grid up until no limitation for both dimensions, for instance – the simulation tends to stabilize with a known number of patterns divided in groups, known as "still blocks", "oscillators" and "spaceships". A still frame of the Game of Life stabilized state can be seen in Figure 3.

It is observable that there is no mathematical way of predicting in advance at what point or whether the simulation of Game of Life will stabilize, or what the shapes in this state would be (GERSHENSON, 2013). The lack of predictability in simulations that are focused in agents rather than in top-down structures is a well-documented issue. This is due to a property shown by ABM simulations in general labelled as *emergency* or *emergent behavior* (KOLEN et al., 2018).

This property grants ABM systems the capacity of displaying features while running that are not present in by individual agents. This is an important feature of ABM systems, provided they are aimed to generate insights on complex systems and can only display the characteristics of such system after the agents are programmed and interacting to each other (WILENSKY; RAND, 2015). In this way, ABM cannot only offer the opportunity to analyze new features of the system, such as the agents, but also systems that are usually analyzed through traditional simulation (RAND; RUST, 2011).

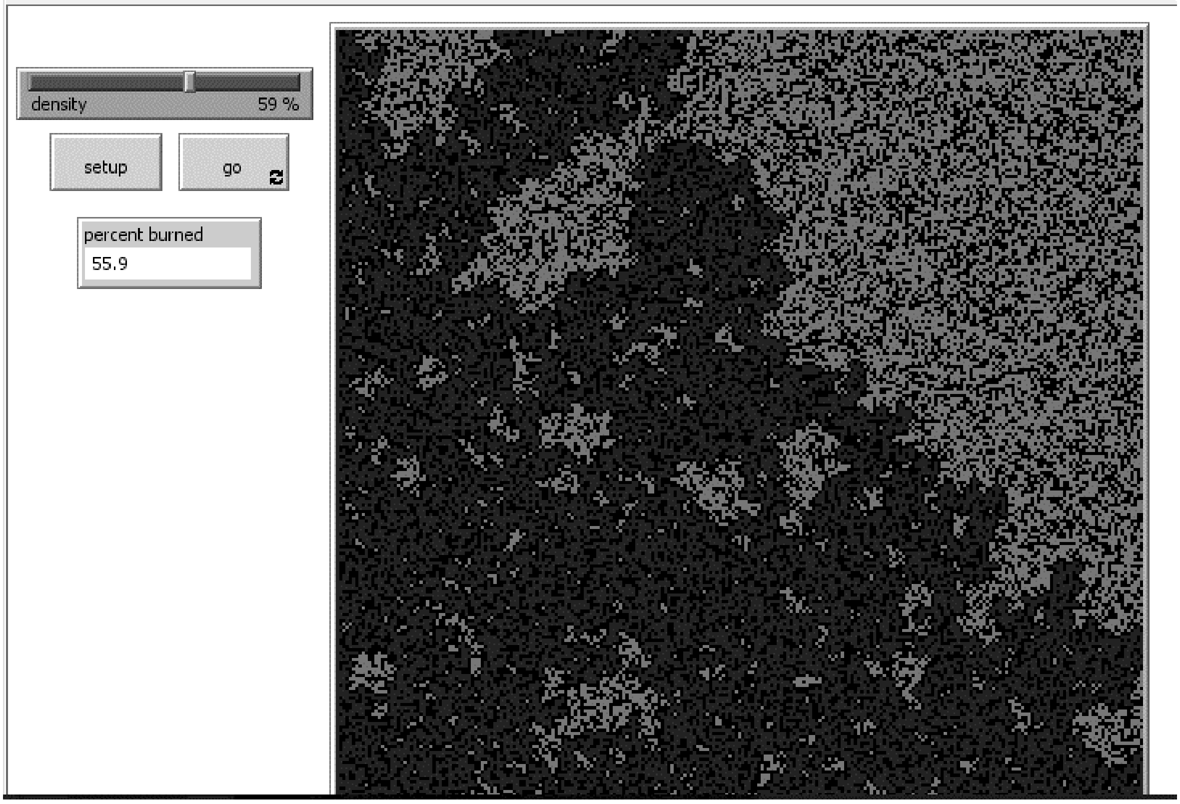
For the emergency to take place in an ABM system, it is necessary that the running simulation achieve a certain threshold. This means that the interaction among entities, whether those entities are agents only or agents and limiting scenario components, must surpass a certain value, e.g. *NetLogo Model Fire* model (WILENSKY, 1997). In this ABM forest simulated environment, a few rules of how a fire spreads among trees is sufficient for the model to work.

Picture 1 – Controlled flames with parameters below the threshold in the fire model



Source: Wilensky's NetLogo Model Fire model (WILENSKY, 1997)

Picture 2 – Flames spread across the forest with parameters above the threshold in the fire model



Source: Wilensky's NetLogo Model Fire model (WILENSKY, 1997)

As seen in Picture 1 and Picture 2, the lighter gray area represents trees, the black background color indicates clearance among trees, and the dark gray represents burnt trees. The sliding bar allows the decision-maker to choose the density of trees in the grid. The emergency property of generalized fire appears regardless of the fact that the agent programmed for this specific simulation is the single burning tree, not the whole forest.

Furthermore, it is noticeable that, whereas in Picture 1 there is 57% of terrain occupied by trees with less than 10% of forest burned in the end, Picture 2 has 59% of its terrain covered by the trees and more than half of them were burned in the end of the simulation. This shows how a threshold was achieved around the value of 58% of trees in the simulation, and it happens regardless of where the trees are placed in the beginning of the simulation – an event of random nature by design. According to the literature (WILENSKY; RAND, 2015), this is not only true for this ABM system, but for most agent-based simulated environments.

Another similarity that most ABM systems share among themselves is the process of layer building (BULLINARIA, 2018). This literature recommendation involves the notion of implementing the final desired system after a series of steps. This means that the simulation has to grow in complexity each step on the way to completion. By acting accordingly, many programming errors can be prevented by the system designer, which allows for a better overall understanding of the system, instead of programming all the particularities at once.

However, before the step of implementation, it is necessary for the system to be verified and validated (GRÄBNER, 2018). As the author points out, both processes aim at assessing the quality of the ABM system and are more akin to a spectrum of practices rather than a dichotomist test. While verification comprehends actions for comparing the link between the conceptual systems to the programmed simulation, validation assesses the representation of the real problem by the programmed simulation.

In this context, ABM systems differ from traditional simulated systems on how they treat behavior variation during the validation process. Whereas traditional simulation benefits from robust models which vary slightly even with significant changes in the input variables, this situation is not beneficiary for the validation process in ABM (WILENSKY; RAND, 2015). The opposite is also true: a sensitive system that varies significantly with slight changes in input is ideal for ABM but not useful for most traditional simulations.

This is true because ABM is based on bottom-up design, which means that the agent is the focal construction component of the simulation. In turn, it creates a situation where the agent has to be programmed appropriately, not the whole system. Hence, whenever the agent is programmed in a non-realistic manner or disconnected from the conceptual system, the final ABM simulation will present emergent properties that do not correspond to the real system, as stated by the aforementioned authors.

Thus, according to the aforementioned authors, an ABM system with high sensitivity towards parameters and input variables is more desirable than a system that displays high resistance to change in the output, even with abrupt modifications in the input, because these types of systems do not allow for a refined validation of the agent.

From this, it can be concluded that the more detailed and complex the agent is, the easier the task for ABM validation. Even though simple agents can be programmed with few commands, there are also ABM systems where the agent is more sophisticated, constructed by embedding some sort of Artificial Intelligence (ARTHUR, 1994).

2.4 ARTIFICIAL INTELLIGENCE

According to consolidated literature, Artificial Intelligence is defined in the lines of an attempt to simulate human level rationale of problem-solving skills, by using computational and mathematical techniques (RUSSELL; NORVIG, 2009). Naturally, any agent capable of showing intelligent behavior is then known as an intelligent agent. This effort is represented by a convergent area of study and practice of the same name, and includes several different kinds of areas of knowledge, such as psychology, mathematics, engineering and computer science.

Still according to the aforementioned authors, the capability shown by an intelligent agent can vary in range and depth, when taking into consideration the types of problematics being treated. Intelligent agents can work on solving language-related problems, allocation of resources, image recognition, anticipation of expectations and much more. Whilst humans and other animals present some breadth of skills within these problematics acquired due to their very nature, artificially created intelligent agents must be programmed in order to show these capabilities (LEVIN, 2019).

However, demonstration of intelligence ought not to be conflated with the existence of consciousness behind an agent (SEARLE, 1982). In fact, this aspect of an intelligent agent is not yet clearly defined by epistemologists, computer scientists and programmers, but it does not limit the progress (MUELLER; BOSTROM, 2016; YAMADA; MORI, 2019). As implied in consolidated works (TURING, 1950), the behavior of intelligence presented by an agent is enough for most tasks that will be faced by it, even though they may fail to present traces of consciousness.

In this context, Artificial General Intelligence differs from applied Artificial Intelligence (RAMAMOORTHY; YAMPOLSKIY, 2018). Whereas the former is a conceptual situation in which an artificial intelligent agent is expected to develop some sort of self-consciousness, the latter is in line with the idea of intelligent behavior being sufficient for an agent be classified as intelligent. Hence, the present work will focus solely on applied Artificial Intelligence, or simply AI.

Provided there are several different manners to construct an agent to perform human-like intelligent decision-making choices (RUSSELL; NORVIG, 2009), state-of-the-art and best practices will favor and develop further the approaches that better suit current problematics and present promising development possibilities. Among the approaches, the literature lists Genetic Algorithms (KADRI; BOCTOR, 2018), Robotics (WANG et al., 2018) and Machine Learning, or ML (JACKSON et al., 2019) as prominent examples of AI applications and studies.

The present work focus in ML applications due to the nature of the problem being treated, since it is necessary for the intelligent agents to be able to learn with real data from a previously treated data set and then act out according to what was learned in an environment that still sends stimuli for the intelligent agents akin to those which were used to feed the learning process. This approach is required and part of the ML algorithms formulation process (ALPAYDIN, 2014).

2.4.1 Machine Learning

Intelligent constructed agents, as stated previously, might present an intelligent behavior due to the fact that they were programmed before execution to act thusly. However, this approach is costly because the designer of the artificial intelligent agent has to consider in advance a wide range of possible instances or approaches that might appear for the agent and this can take much time and processing power, defeating the purpose of the implementation of the agent (YAMPOLSKIY, 2015).

Hence, another way to approach the designing of an AI is through Machine Learning. Generally, ML constructed intelligent agents present the capacity to learn with previous data sets and align the utility of its performance by correcting the output of the task performed during the training phase (ĐOZIC; URO, 2019).

Furthermore, ML agents can be programmed to be either supervised or unsupervised; the former being responsible for solving problems that the real answer for the task is known in advance, the latter is implemented mostly in an exploratory fashion for finding tendencies within a data set (BENVENUTO et al., 2017).

Regarding the types of tasks an ML agent can perform both supervised and unsupervised agents are fit for the effort of classifying entities in groups, ordering lists, choosing from a set of items, predicting values and creating clusters. Thus, ML agents are relevant pieces for solving a wide assortment of problems not only in academia but also in managerial environments (ALPAYDIN, 2014).

Among the supervised approaches, Artificial Neural Networks (ANN) are used for classification. It is also suggested by current literature (LANTZ, 2013) that ANN can be applied not only on a wide range of areas for classification, but also as regression. For this reason, ANN fits in this work appropriately.

2.4.1.1 Artificial Neural Network

Feeding data to an Artificial Neural Network is an essential part of the system, composed by artificial brain cells (ĐOZIC; URO, 2019). First proposed by as a conceptual system

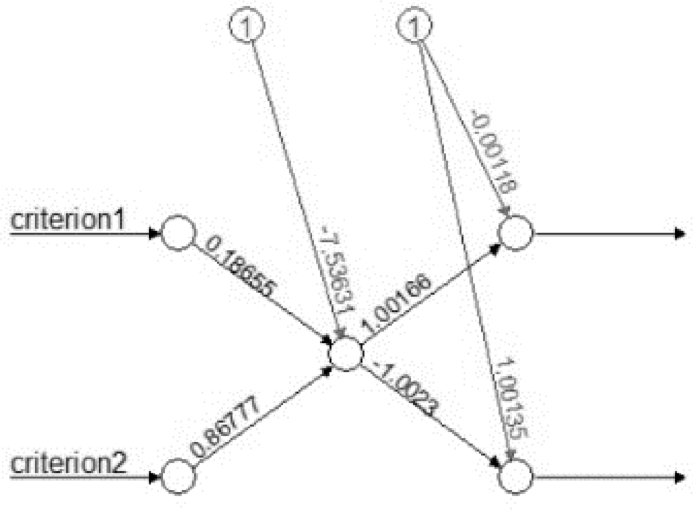
(ROSENBLATT, 1958), the network was composed by just one brain cell and was called Perceptron.

The way it works is by receiving both a bias value and normalized data in the input side of the Perceptron cell and outputting a value after multiplying the input by a vector of weights, which are initially generated at random. After a series of computational and mathematical procedures, weights are tuned to output a correct classification for the input data.

The correct classification rate of the ANN being trained is measured against the real classification of the entity being inputted in the system. Still according to the aforementioned author, the input data is composed of relevant characteristics of the entities in the original training data, which are in turn converted numerically to normalized data for the ANN. The output is the classification to which the entity supplying the input data belongs.

In a simplified example, the criteria are inputted to the ANN cells, each being responsible for a characteristic of the entity. The connecting lines among cells are the final weights of the network, along with the bias. Finally, output represent the dichotomist classification: there is a [0,1] interval related to a probability distribution, which will output values within this interval according to the probability of the entity represented by the given criteria belong to a determined class. Figure 4 shows the general representation.

Figure 4 – Representation of a single layer Perceptron

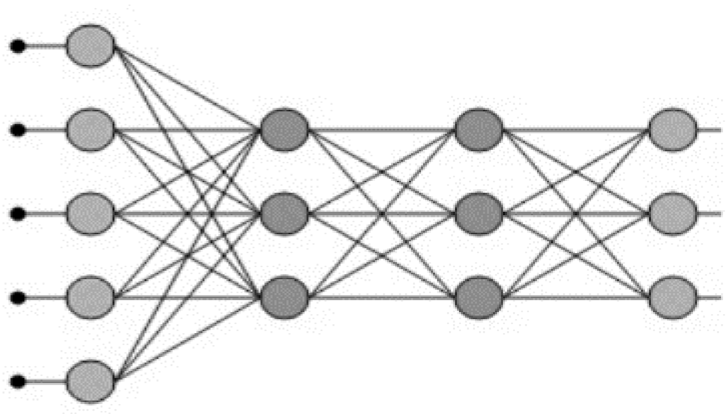


Source: The author (2020)

Modified versions of the Perceptron for classification followed, in which the modification consists in adding more layers to the network, granting it in turn to solve more complex and non-linear models. This practice brings not only performance enhancement in exchange of computational power, which creates a trade-off situation for the designer of the network (HINTON; SALAKHUTDINOV, 2006).

Regardless of how many intermediate layers a Perceptron has, these layers are known to the literature as hidden layers, and the network itself receives the title of multilayer Perceptron (JACKSON et al., 2019). Figure 5 shows an example of such a network.

Figure 5 – Representation of a Perceptron with hidden layers



Source: The author (2020)

It is visible in Figure 5 that the hidden layers are represented in the center, whilst the input layer is the outermost to the left and the output layer is the outermost to the right. However, complexity is greatly expanded in this type of network, in comparison with a single layer Perceptron. The reassignment of randomly generated initial weights with less components is a faster task and converges more rapidly in general (PANCHAL et al., 2011).

This problem is handled by varying the function used for treating the input values being inputted to the cell, the threshold it activates and what kind of value it outputs to the system, as well as with an auxiliary function that measures the distance between the outputted value and the value it should have outputted. The first function is known as activation function, whereas the second one is called backpropagation function (ALPAYDIN, 2014).

There are different types of activation functions used in literature, such as sigmoid function and linear function (JACKSON et al., 2019), both working with many similarities, such as being capable of handling continuous input and outputting results within the [0,1] interval by sum and multiplication operations of the input values and their correspondent weights, and measuring it against a threshold value for final classification.

The relevant difference between the functions is the fact that the linear outputs values linearly, whereas the sigmoid outputs it in a smooth curve. The Equation 2.1 and Graph 1 for this type of linear activation function with threshold expresses it clearly.

$$\begin{cases} L(x) = \sum_{i=1}^{c} (\alpha \times x) \\ A(x) = 1, when\ L(x) > T \\ A(x) = 0, when\ L(x) \leq T \end{cases} \quad (2.1)$$

L(x) – linear activation function

α – vector of weights

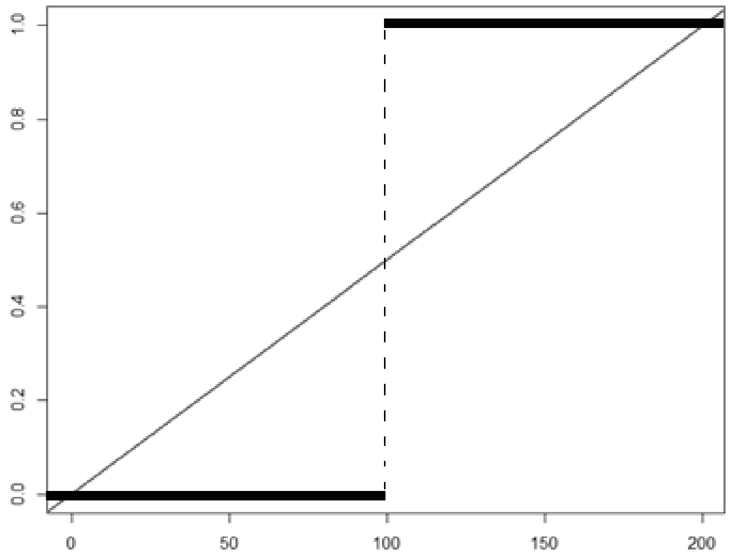
X – vector of normalized data

A(x) – step function

T – threshold value for the step function

c – number of input cells for the current layer

Graph 1 – Graph representation of an activation function



Source: The author (2020)

In Graph 1, it is visible that the activation function outputs any value from zero to one according to the input, which is in turn representing an associated probability of that classification. The step function acts on the value outputted via the activation function. It is important to notice that this operation happens for each cell, with their respective weights.

It is also important to notice that the Equation 2.1 presents the reasoning for a single layer Perceptron. This can be easily noticed due to the fact that the only weight vector in the equation is α, whereas a multilayer Perceptron would need other vectors, each one for a layer, independent from the precedent and the successor layers of cells (ALPAYDIN, 2014). For a generalized version of the L(x) component of the ANN, Equation 2.2 presents a formalized expression in this regard.

$$L(x) = \prod_{j=1}^{l}(w) \times \sum_{i=1}^{c}(\alpha \times x) \tag{2.2}$$

w – vector of weights of other layers of cells

l – number of layers

Regardless of the situation, the rationale for both single layer and multiple layers regarding the propagation of information is the same: as long as the propagation of data in the system has not reached the last cell with the final classification, the output of intermediate cells must be passed onto the next layer of cells.

This data will now be treated as input for the subsequent layer. Equation 2.2 also explains how the data coming from a previous layer is inputted in the next layer, because the output of the previous step will be the input of the current step. The variation that may happen is the dimension of the vector, because it will have the length of the output vector of the last iteration.

This kind of forward propagation is necessary for the training of the vector of weights (ALPAYDIN, 2014). The backpropagation function, however, is necessary for performance assessment of the current system state. According to the original designed functionalities (ROSENBLATT, 1958), the training of an ANN requires multiple instances of inputting data and evaluating the output, each time with a different entry. This evaluation step is performed by the backpropagation function.

In turn, a backpropagation function is any type of function that minimizes the number of misclassifications of the ANN by adjusting the vector of weights according to each data inputted (LIU; ZHU; CAO, 2017). This process may happen via different kinds of actions, even though all of them take some form of using the difference between the real classification and the result from a current entry to the system, and so it propagates this information back to the beginning of the network for adjustment. Hence, the title of backpropagation function.

There is, according to current literature (JAMES; STEIN, 1992), a suitable option to estimate error for a backpropagation functions is the computation of the loss function, which can be expressed by the Equation 2.3 whenever the output is dichotomist and Equation 2.4 when the output is of probabilistic type and accepts results within the [0,1] interval.

$$L = {}^{1}/_{2} \times \sum (y - A(x))^2 \tag{2.3}$$

$$L = {}^{1}/_{2} \times \sum (y - L(x))^2 \tag{2.4}$$

L – cost for the current entry

y – real classification

If the nature of the ANN is not dichotomist and the real output value is desired, A(x) must be replaced by L(x). Taking advantage of the quadratic nature of the loss function, the loss function not only can compute both positive and negative distances from the desired value, but it presents a differentiable aspect to it. This enables a mathematical advantage during the training part of the ANN compared to non-differentiable functions.

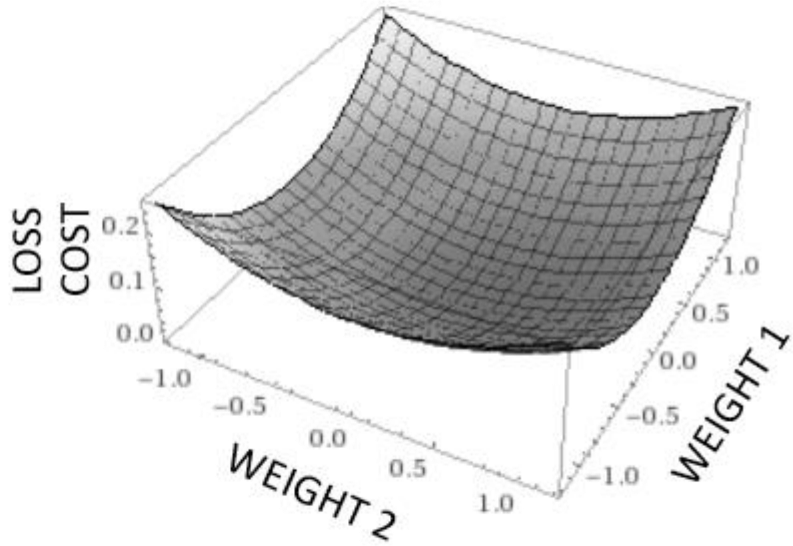
The role of the backpropagation function in an ANN is to minimize the mathematical error, for it means in turn that the network is able to predict the correct classification for the training data (JACKSON et al., 2019). Provided that changing weight values in the weights vector manually or even randomly would mean a brute force approach for minimizing the error, this choice could bring few advantages compared to the many problems for the ANN training of such approach, such as the dimensionality complexity problem (HINTON; SALAKHUTDINOV, 2006). This means that the more the number of weights, the longer the ANN takes to fine tune the correct values.

For this reason, the gradient descent approach takes advantage of the quadratic nature of the loss function presented in Equation 2.5 to shorten the computational time needed for the adjustment of the weights (AMARI, 1993). This process is then called as training the ANN with a backpropagation function. It presents the gradient descent for the loss function, which is in turn dependent on the linear activation function for multiple layers, whilst Graph 2 demonstrates graphically the meaning of the gradient descent for the loss function considering the weights.

$$\frac{\partial \mathrm{L}}{\partial \alpha} = {}^{1}/_{2} \times \sum [y - L(x)]^{2} \tag{2.5}$$

$\frac{\partial \mathrm{L}}{\partial \alpha}$ – gradient descent of loss function

Graph 2 – Example of paraboloid for loss function and its cost relation to gradient descent of two weights



Source: The author (2020)

Amari (1993) denotes that the way to minimize the value of the loss function is to follow iteratively the negative slope of the gradient descent by adjusting the weights accordingly. By doing so, a good adjustment of the weights for the ANN can be achieved in a convenient computational time. Finally, after the final adjustments of the network for the training data, it is necessary to test how appropriately it can perform when confronted with data that was not used for training.

2.4.1.2 Efficiency measurement

ML algorithms are useful for decision-makers in the task they were designed for, provided they may have their performance assessed (ALPAYDIN, 2014). One of the simplest and most intuitive way to understand the performance of a system is by measuring the proportion of errors committed by it. In classification algorithms, such as ANN, the misclassification rate can be expressed as shown in Equation 2.6.

$$Pe = \frac{E}{T} \tag{2.6}$$

Pe – proportion of classification error

E – total misclassifications

T – total amount of data

This is a rather simplistic approach and does not cover all the aspects of an ANN in regards to its efficiency (LANTZ, 2013). However, the proportion of errors can easily convey another performance evaluation, which is the proportion of correct classifications, show in Equation 2.7.

$$Pc = 1 - Pe \tag{2.7}$$

Pc – proportion of correct classification

Another used manner for measuring the proportion of errors during classification found in the works of Alpaydin (2014) is the confusion matrix. This method of error measuring allows the decision-maker to visualize not only the proportion of errors and correct classifications, but also which classes present the larger number of each type of proportion. This can be useful for insights during the interpretation part of the simulated system, after the ML algorithm has finished classifying entities. An example of confusion matrix can be found in Table 1.

Table 1 – Example of a confusion matrix

	safe	**critical**	**deadly**
safe	37	1	7
critical	2	48	7
deadly	9	5	22

Source: The author (2020)

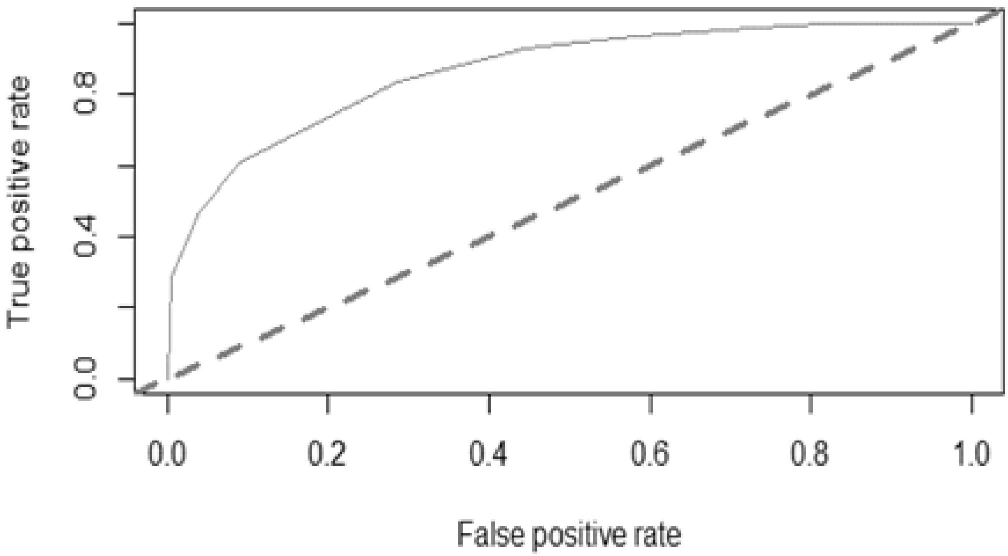
The confusion matrix exemplified in Table 1 informs the decision-maker that there are three classes (safe, critical and deadly). The columns represent the actual classes, whereas the lines represent the classification of the ANN. For instance, 37 of safe cases were correctly classified as safe, while 8 remaining entries were misclassified, 1 being classified as critical and 7 as deadly. Another advantage of this form of efficiency measurement is that it is easily understandable for the decision-maker even with a large number of classes.

As inferred from Alpaydin (2014), the confusion matrix is not only easily understandable but can facilitate the extraction of other types of efficiency measurement, such as the sensitivity of the system and the specificity, both related to the true classification rate, and also the precision

– which is the capacity for correct predictions – and accuracy of the system, among other derivations of the matrix.

Besides the confusion matrix, the author also brings another way of measuring the efficiency of a ML algorithm, known as receiver operating characteristic curve, or ROC curve. The ROC curve presents graphically a comparison between the ML algorithm in question and a dummy classifier as efficient as random chance at classifying entities. It does so by measuring the true positive rate in the Y axis and the false positive rate in the X axis, as shown in Graph 3.

Graph 3 – Example of ROC curve



Source: The author (2020)

As can be seen in Graph 3, the dashed line represents the ROC curve for the dummy random classifier. The better a classifier is the further up in the graph the ROC curve of this given classifier has to be plotted. In the example shown, the upper curve of the ML algorithm is better suited for the classification out of the two options due to the fact that it is plotted higher in the graph. This means that the true positive rate increases faster than the false positive rate.

However, confusion matrixes, ROC curves and efficiency indicators are not the only measurement techniques used to assess the utility of a ML system. There is also a need for the decision-maker and the designer of the system to be aware that some external may play a role in the overall performance of the system (e.g. for classification, ordering).

The testing phase of any learning tool or technique is plenty of insightful states the system may present (POWELL; BAKER, 2010). Included in those states is the overfitting, which is be summarized as an extremely specialized and well-adapted system that predicts with enormous precision all the data in the training set. This may present a problem related to the real data that will supply the system after the testing phase.

The problem that may appear in a system in the state of overfitting is, according to the authors, that the classification is not easily applicable nor adaptable to different problems that share similarities in the structure to the problem being solved at the moment, rendering the system limited and prone to obsolescence even in the very problem, provided the data set with new entries vary over time.

It is also claimed in current literature that overfitting appears either because the conceptual modeling of the system was judged in a way that the mathematical component of the classification system takes into consideration variables that are not relevant in reality to the problem, or because noise, or bias, is interfering with the real data information supplied to the system during the training phase (LANTZ, 2013). The author then implies that the latter case generates a bias that will, in the case of ANN, train weight vectors to predict data along with noise, not only the data, as desired.

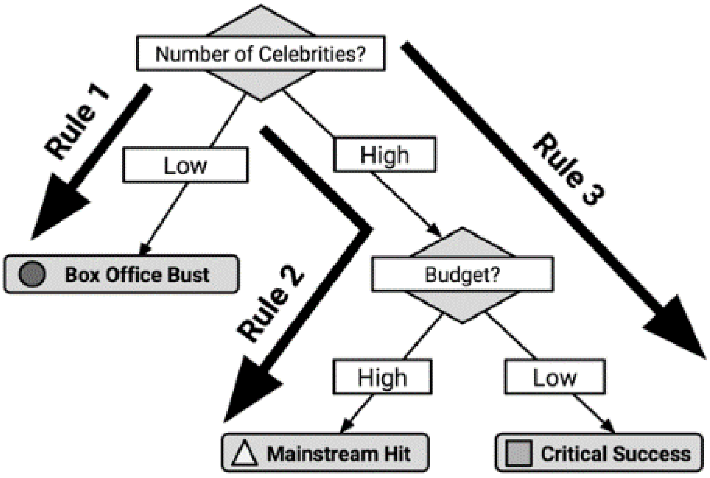
Lantz (2013) also says that a good indication of an overfitting situation of the system, especially in applied classification methods, such as ANN, is the large discrepancy between the efficiency of classification from the training data and the testing data. Whenever the ANN is classifying correctly more in the training set than in the testing set of data, that there might be an overfitting situation.

This may cause problems not only to the efficiency of the system but also on the results interpretation, when the system starts being fed with real data, due to the fact that the real data does not possess a previous classification that can help detect when the data was misclassified (ALPAYDIN, 2014). Hence, it is important for the ANN to minimize any overfitting situation by training it with a large and as clean as possible data set, along with a well-formulated input-output system.

2.4.2 Rule-Based Algorithm

According to specialized literature (LANTZ, 2013), classification algorithms based on rule learning are akin to decision trees, which are also ML algorithms. The resulting system of a rule-based ML algorithm is a set of rules which can be fed a data set and then classify each individual instance as belonging to a particular class previously trained within the system itself. Flowchart 1 shows an example of a rule-based ML algorithm that can classify with only three rules whether a certain movie is a box office bust, a mainstream hit or a critical success.

Flowchart 1 – Rule-based algorithm example



Source: Adapted from Lantz (2013)

Similar to the ANN, rule-based ML algorithms can learn how to classify and be assessed through its performance via a set of techniques prescribed in the literature, and also depend on the training and testing datasets. Each ML approach has different benefits and limitations, depending on the nature of the problem being solved.

The rule-based system resulting from the training set and assessed by the testing set works in an intuitive form: the new data is fed in the initial block and it passes through a flowchart where each characteristic being scrutinized in the current step is then answered by the algorithm. Depending on the answer, the next step scrutinizes another characteristic picked by the training phase of the algorithm for answering. The steps continue with the same structure until classification is reached for the entity fed to the system.

However, in the simulated system proposed by this work, the only part of the rule-based ML algorithm that will be used is the rule-based algorithm itself. The assumption of previous training and testing of efficiency is not going to be part of the complete scheme, because there is no new instances to be classified, only previously situations that will be explained in their proper Sections. Suffices to know that the rule-based classification nuance of the algorithm is backed and tested by the current literature (LANTZ, 2013).

2.5 LITERATURE REVIEW FINDINGS

It is possible to notice from both the literature review and the theoretical foundation conducted in this Section that most concepts and ideas have been not only developed but are presented as a consolidated and applied technique in their area of specialization. For other concepts, there is gaps in the literature that are fulfilled by the present work or at least brought to light to be examined and further developed in future works.

What is visible from the literature review is that, despite the distribution of work publication numbers being fairly distributed with a positive slope year after year, most relevant and most cited works have been published earlier rather than later in time. This is to say that works produced from 2010 to 2012 have been cited more times than works produced after this period, until 2019.

The only exceptions are the works about Supply Chain Strategy, with a relevant number of citations of works from 2014, and the works that involve Artificial Neural Networks and their cost and backpropagation functions, with the most cited and relevant works being published 2014, 2015 and 2017.

It is possible to see that there is a literature gap in the literature concerning the combined utilization of Agent-based Modeling and Artificial Neural Networks, because the dataset research of the terms combined returned only 710 results, with the most cited work in the area having almost 400 citations, with less than 20 of the works being cited more than 100 times. This happens despite the fact that both major areas have a massive number of publications each.

It is also visible that there is a gap in the current literature regarding the unified use of Agent-based simulation in the context of Supply Chain, because only 538 results stemmed from the combined research of these two terms. The same applies to the combined use of Artificial Neural Networks and Supply Chain, with a little over 1,000 results stemming from the research of the two areas.

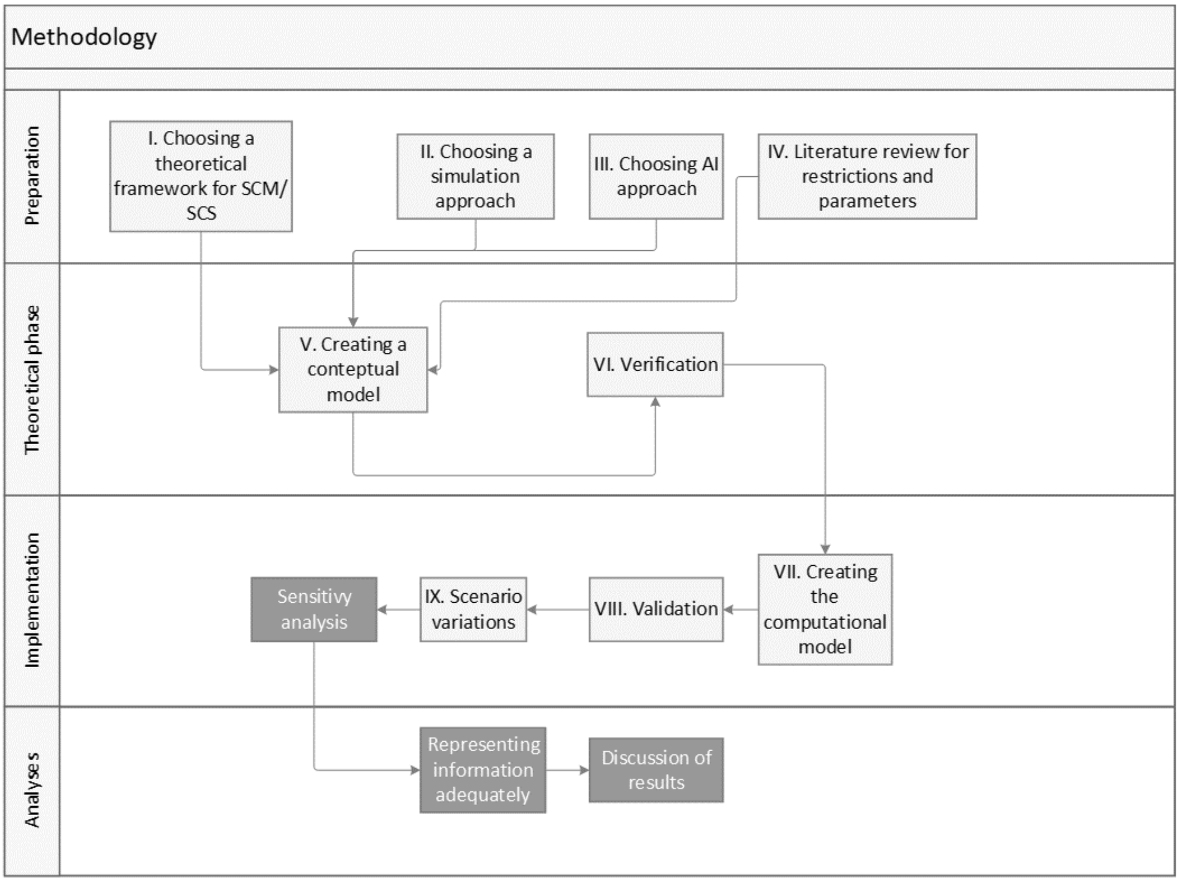
3 METHODOLOGY

After going through the objectives of the work and the precise definition of each concept used in the body of this work, the current Section aims to explain the structure of the research for developing a computer simulation suited to the problem at hand. This present Section also deploys the technical details of the proposed model, after the completion of the steps for creating the computer model. Finally, this Section explains the meaning of each technical step, computer element and other components of the model, such as the initial dataset and the necessity of performance indicators.

3.1 STRUCTURE OF THE RESEARCH

The complete course of action concerning this work can be seen in details in Flowchart 2 as a flowchart containing an overall description of the main steps of the system construction process. The filled and not numbered blocks are whole activities with no subdivisions, contrary to the blank numbered blocks.

Flowchart 2 – Flowchart of computer model creation



Source: The author (2020)

As can be seen in Flowchart 2, the methodology flowchart comprises of four major phases, the first one being Preparation phase. Block I is composed of a series of activities that obey a specific order, where the first step is a thorough and systematic literature review on the topic, followed by a trade-off of each methodology on SCM and SCS found, and then choosing a particular proposition of SCM/SCS methodology.

Block II also encapsulates two activities necessary for its completion, the first one being a clear explanation of the differences between traditional simulation techniques and agent-based simulation. The second activity of this block consists of choosing the appropriate approach for the current problem. Block III in turn is composed of four internal and subsequent steps, beginning with a general explanation of Artificial Intelligence, then delving into Machine Learning, for only then explaining and choosing ANN for the current problem. Lastly, in this block, an explanation on rule-based algorithm is expected.

Closing the Preparation Phase, block IV also presents within itself three numbered actions, composed of a complete presentation of the Apparel Manufacturing Cluster of Pernambuco, Brazil. The second activity within block IV is a literature review on small to medium enterprises, culminating in the last action, which is collecting and utilizing official reports on the aforementioned Apparel Cluster of Pernambuco for model construction.

The Theoretical Phase starts with block V, which takes into consideration the constraints and features of the previous four blocks, to then enable the step of suggesting a simple theoretical model of variables, parameters, constraints, cycles, goals and reward and punishments. After this step, the current literature for layer-building simulation is implemented. It is interesting to notice that what the current literature recommends is gradually increasing the number of actions and components of the simulation in order to make it work as similar as possible to the desired model. In this case, the CSAR theoretical framework.

As for the variables considered for input for this step, it may include demand, market share, budget and so on. Revenue, total assets and strategy adopted may serve as output variables. Errors, demand distribution, data visibility, forecast power and production capacity are useful candidates for parameters, whereas cycles may vary from days to years, or even months, four-month periods, trimesters etc. The goals of the system may also vary and be just one event or even a combination of events, such as going bankrupt, a certain threshold of market share or profit to be achieved. Finally, rewards and punishments may be based on financial aspects or combinations of indicators. After deciding about these traits, block V is then completed.

Block VI also recommends following the current literature for agent-based simulation for the verification process of models. It is a separate and distinct process of validation, because verification consists of a continuum of measurements and judgements on robustness and representation of the Apparel Cluster when transferred to the ABM and ANN rule-based system, whereas validation consists of assessing how appropriately the implemented computational version of the Apparel Cluster provides understanding and insights for studying the real situation of the geo-political and managerial situation for the apparel ME in Pernambuco, Brazil. Block VI is composed of a series of observations between the chosen SCS model and the proposed simulation model.

Block VII is the first of the Implementation phase and it starts by creating a *in silico* data base containing information akin to the real data that will be used to train the ANN, since the real data is scarce and insufficient for the given purposes (IEMI, 2017; SEBRAE, 2013). After training the ANN with the *in silico* data, the algorithm for rule-based decision-making is created and will serve as part of the decision-making process of the agent for deciding how much each company in the simulation will invest in each strategy and action. This step is constrained by the kind of items, costs, vending price, demand visibility, temperament of the agent, which actions are available and a combination of other possible limitations.

It is important to notice that the concept of temperament in the precise manner it is being used for this system was coined specifically for this work and is not present in other works regarding the utilization of ABM nor AI. In this work, the temperament means the managerial style. Thus, any further mentions to temperaments in this work is restricted to this system and may not correspond directly to the meaning of this term in other works regarding intelligent agents.

Similar to the verification step, the literature on agent-based modelling for validation is clear to state that the activity of block VIII comprises of stress tests on the parameters, exhausting execution to assess any random behavior that may emerge during simulation and searching for needed adjustments, such as varying the number and types of agents. Only then, the system is ready for scenario variations, present in block IX.

This step of varying the scenarios depends initially of adjusting the parameters, generating initial conditions for the simulation and then starting the loop. In turn, the tick is completed and can be repeated once the investment for each Pillar and its actions is made and the demand for the period is split proportionally for each agent that has not been bankrupt and having them calculate and decide how much of the goods will be produced for the tick. After that, rewards and punishments are added to the assets of the agent, which will adjust their measures or go bankrupt before the following tick.

As the last phase, when the simulation comes to a halt, it is possible to vary the initial values to check the presuppositions of the model and test how the whole system behaves whenever a parameter is altered during the setup stage, before the loop unwinds. With all this information in hand, it is possible to proceed to the data analysis step, comprising of both graph analysis and statistical analysis of hypotheses and aggregates.

3.2 PROPOSED MODEL

Current ABM literature recommends building the final model in layers of complexity. Specialists in the field (BULLINARIA, 2018) constructs his model by adding parameters and different kinds of agents every step taken. The system runs and if it does not break with algorithmic or out of boundaries values, another layer of complexity is added, until the final desired system is achieved. The same rationale is used for the system proposed for this work.

The proposed system can be described as a rule-based and artificial neural network model (RB/ANN) embedded in an ABM environment that simulates the behavior of a ME SC manager facing different easing and strengthening difficulty factors in their routine. It is the result of the layer-building simulation implementation recommended by literature.

It is based on the SCS methodology for capture, reformulation and evaluation of the SCS efficacy, CSAR (PEREZ-FRANCO, 2016). The simulation approaches this theoretical framework by creating a simplified computational model of each component of the CSAR theory, as well as each rule of precedence, hierarchy, ranking and inner checks, so the final SCS flowchart is not only comprehensible by the public but also feasible computationally.

From the outermost to the innermost level of abstraction, the whole ABM works by simulating periods of time, also known as “ticks” (in this simulated environment, four-month periods of years), where each individual agent acts according to their inner behavior calculations, plus some stochastic error and external reports (market and governmental updates).

It is important to notice that at the end of each tick, the self-evaluation process takes place and agents redefine their strategy for the next four-month period. It does so by measuring how they were rewarded or punished according to a score table based on recommendations of literature (IEMI, 2017), composed of:

- *Efficiency (EF);*

- *Demand (DM);*
- *Market Share (MS);*
- *Total wealth (TW)*

While EF measures a relation between the current tick's usage of material (production cost per unit) in comparison to last tick's situation, DM is calculated via a sum of how much of the assigned demand was supplied, plus the amount of lost exceeding items. MS indicates how much market share growth the company has undergone from the last tick and total wealth, TW, a normalized measure of how much is funding the company holds in liquid assets compared to the previous tick.

All indicators are normalized indexes of rations between different parameters. EF is the normalized ratio output of unit production cost of past and present simulated period, whereas DM informs in the same way the difference between real and observed demand for the company, MS does the same for market share percent and TW for financial resources gains or losses between current and the last period for the company.

Since simulations differ from games, there is no concept of winning involved (WILENSKY; RAND, 2015). When the simulation comes to a halt, every agent assesses their own performance by examining their assets (if the agent reaches a lower threshold of initial budget, the company goes bankrupt). Another way for an agent to leave the simulation is if it gets low in any of the indicators: if it reaches a certain percentage of the initial value, they go bankrupt.

Systematically, the current tick presents a total demand, which will be divided according to each market share for each company. The company then calculates what they observe as forecasted demand via a probabilistic approach and then assesses how much it can and should produce of the product. For simplicity, all the companies produce the same product, there is only one product to be sold and there is no way a company can interfere with the other companies share, even if one company does not supply their customers and the other company has a surplus production.

After the previous step, the aforementioned calculations are made and the rewards or punishments for excess of inventory or for not supplying their customers are provided and then applied to the company next tick’s assets. This then trickles down into signaling whether the investment strategy adopted was fit for the period or if it should be changed. Each temperament responds differently to the signal, whether it is positive or negative. The temperament and the assessment of the last period influence which investment strategy is chosen.

The maximum production capacity, the forecasting precision and the variations on vending price for each agent are given according to each action chosen in the previous tick (e.g. "hiring a consultant", "bargaining discounts with the supplier"). The probabilistic coefficients are generated beforehand and stored in the *environment constraints table*, along with the real margin costs, and they vary each tick under a probabilistic distribution. For simplicity, all probabilistic distributions used in the system are Gaussian. It is important to notice that the cost of not supplying a customer and excess inventory are also known beforehand are also displayed in this table.

The second level of abstraction is responsible for designing the action of the agent at each tick. The individual agent takes into consideration the environment noise and the external reports as inputs to their RB/ANN system. According to the type of temperament assigned to the agent in the beginning of the simulation, it updates actions and resource allocation priorities for the next tick. The temperaments are based on the literature concerning degrees of conservativeness towards strategical actions of the managers (FLYNN; GOLDSMITH, 1993). They are presented as follows:

A. **Proactive:** it sets trends of resource allocation for the whole market;
B. **Reactive:** it keeps investing in the most conservative resource allocation strategy;
C. **Stubborn:** it tends to allocate resources the same way every tick.

Whenever a temperament is assigned to an agent, they cannot change it and have to be as they were constructed until the end of the simulation. This is not to say that there is no innovation or variation in the actions of the agents. Reactive agents change towards best practices every tick, Proactive agents always seek to find ways to earn more money and increase market share for the next tick and Stubborn agents do not perform variations in their strategies, so they can try to earn more money within the same guidelines.

The choices of the temperaments for the SC managers, the agents, are represented in this system by allocating different shares of the budget in sectors of the company, also known as Pillars. The 3 Pillars were chosen to represent departments of the company and coincide with the areas in which agents can choose which strategy they will select for the period based on previous performance:

I. Logistics/Production;
II. Customers Relationship Management (CRM);
III. Finance/Procurement.

In Table 2, the *temperament table*, the resource allocation plans and the share each Pillar gets by each temperament in each situation can be seen as:

Table 2 - Example of temperament table

Temperament	**Last tick = 0**	**Last tick = 1**
A	• I: 20% • II: 35% • III: 45%	• I: 35% • II: 40% • III: 25%
B	• I: 50% • II: 35% • III: 15%	• I: 65% • II: 25% • III: 10%
C	• I: 50% • II: 30% • III: 20%	---

Source: The author (2020)

As can be seen in Table 2, whenever Proactive managers classify past period as 0, or bad, they will try to innovate by investing more in Finances/Purchase and Customers Relationship Management instead of going for the conservative strategy of investing in Logistics/Production. If they classify the past period as 1, or good, the investment rate tends to be less innovative, by having a strong investment in Logistics/Production and Customers Relationship Management.

Contrary to that, Reactive managers, when classifying the past period as bad, prefer to invest more in more conservative actions, such as Logistics/Production, reserving a share of the budget for Customers Relationship Management and neglecting the Finances/Purchase sectors. If the past period is classified as being good, the investment in Logistics/Production take more than half of the budget, the investment in Finances/Purchase falls even more and Customers Relationship Management investments also drop.

Lastly, the actions for the Stubborn manager do not vary and this is visible in Table 2, where there is no plan of investment when they judge the past period as being good. This reflects the tendency of managers that see the market of the Apparel Cluster of Pernambuco as being always plenty with obstacles and investing more in Logistics/Production rather than in Finances/Purchase or Customers Relationship Managers as the only correct strategy.

Based on the current literature (IEMI, 2017; PIRES, 2004), the order of relevance for each pillar to a SC manager is Logistics/Production, followed by Customers Relationship Management, followed then by Finances/Purchase. This is not to say that they are more crucial on the company as a whole, only for the SC manager. This also explains why there is this distribution of percent investment by the SC manager.

The punishment and rewards depend on how positively or negatively each company performed in each tick, according to EF, DM, MS and TW indicators. Another important feature of the indicators is that they represent combinations of the different choices of actions. For instance, a certain performance for an indicator can be increased by an agent allocating resources in some actions, but the performance according to other indicator might be decreased with the same combination.

It is also important to notice that both the second and third column of the temperament table show the values 0 and 1, respectively, for the last tick. This means that when the agent judges that the previous period of four months was not favorable, the simulation system is designed to make the agent interpret the previous tick as 0. On the other hand, if the agent classifies the last tick as favorable, the simulation system will read it as 1.

The third level of abstraction inscribes how the resources can be allocated. According to the CSAR model, the SCS can be described as a link in a section of a triangle shape, divided into levels, where the lower is represented by Policies/Choices, the middle is made of Imperatives and the upper part is composed of Principles. They go from top to bottom as strategic oriented (Pillars) to more action oriented (Imperatives).

The peak of the triangle, as well as the base, are outside of the reach of the SCS scope, but they are directly linked to it: while the "Core + Pillars" on the top represents long-term values, mission and vision of the company, the base is composed of operational actions. Thus, the RB/ANN takes place precisely in the third level of abstraction, in order to emulate the CSAR model.

The choice of having Pillars follows the current literature (PIRES, 2004). In the CSAR methodology, Pillars are based upon Principles, which are then based upon Policies and Choices, in turn based upon Operational Actions. This continuum goes from the more strategic to the more hands-on nuances of the system.

In total for the simulation, there will be a simplification with the possibility of expanding the layers and the breadth of each CSAR layer, but initially it will be set as three Pillars, comprising straight to Operational Actions, with five options each. This will leave every agent with 15 possibilities for budget allocation. The actions for this simulation are as listed:

1. *Warehouse reformulation/housekeeping;*
2. *Preventive maintenance on equipment;*
3. *Finding bottlenecks and balancing production;*
4. *Hiring a logistics consultant for the period;*
5. *Hiring a production consultant for the period;*
6. *Subscribing to a demand forecast software application for the period;*
7. *Taking into consideration customers' complaint in production;*
8. *Providing batch discount for certain customers;*
9. *Renewing loyalty program rewards for the period;*
10. *Advertising the brand more aggressively;*
11. *Reformulating cost rating system in the production site;*
12. *Bargaining discounts with the suppliers for A and B raw materials;*
13. *Increasing the budget for the SC manager for the period;*
14. *Hiring a finances consultant for the period;*
15. *Bargaining debts with suppliers.*

The actions listed were inferred and synthesized from the current literature (PIRES, 2004; ULTSCH, 2002). They do not represent the most important nor the only existing actions a SC manager can take in order to improve the performance of a company. Rather, they were chosen for simplicity, provided they are comprehensible for non-specialists of the field and present no further difficulties for computational implementation. The number of actions was also chosen due to simplicity, since each Pillar comprises of five actions under it, giving enough freedom of choice for the agents without being too broad and computationally expensive.

In addition, for simplicity, the steps between each layer that composes the SC triangle in the CSAR methodology were reduced to a simpler hierarchy, and the whole of the triangle was collapsed to a more compacted construction, composed only of Pillars and Actions. This does not represent a conflict with the CSAR literature because it implies that subdivisions of layers may be added or taken from the system, depending on several factors (e.g. CRM Pillar may have a 6^{th} action added).

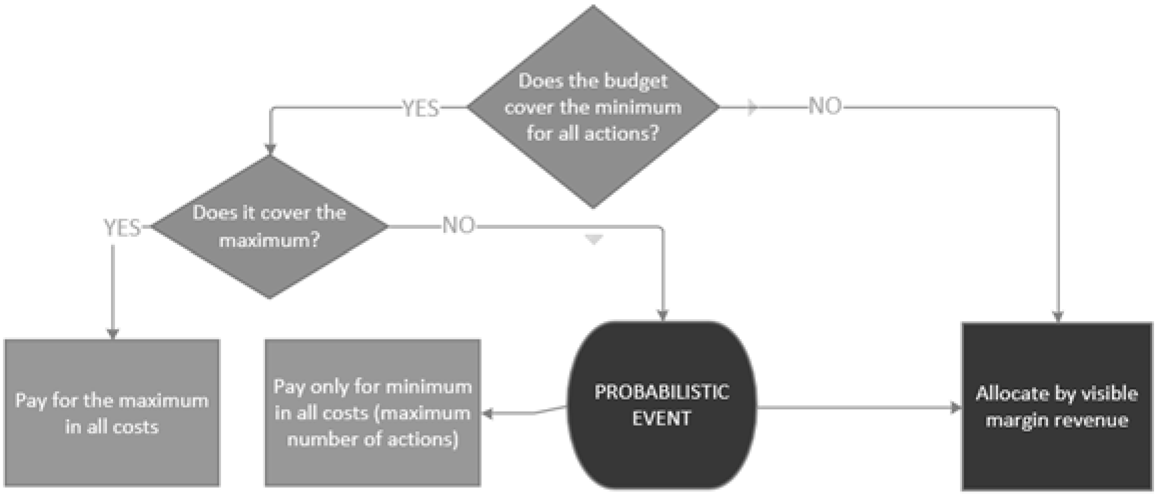
What makes each action computationally different of each other is the *allocation table*. It contains information about the minimum and maximum investment values, marginal costs and revenue for each action, and punishments and rewards for investing less than minimum, the minimum, the maximum or an intermediate value for each given action.

Except for the punishment and rewards, all these values change every tick according to a distribution probability present in the environment constraints table, and the visibility of the agent to the content of each marginal value is masked by a stochastic error coefficient, calculated upon the environment constraints table. This grants that no strategy will function as a "loaded dice" and the companies have to change their actions every tick, just like a real situation where it is difficult for SC managers to know what is the right course of action.

The fourth level of abstraction deploys how CSAR model will be represented computationally: via an RB/ANN model. This is to say that each Pillar of the SC triangle section is going to be represented by a rule-based algorithm, and the decision made of how much is going to be allocated in each action is represented by the very algorithm.

Only the first step is composed of an already-trained ANN, according to Equations 2.1 to 2.7. It will then ultimately decide where the resources for that current tick will be applied and how much (as seen in the temperament table and its dichotomic output: either the agent judges the previous tick as favorable or unfavorable). The steps for this rule-based algorithm can be seen in Flowchart 3.

Flowchart 3 – Rule-based decision scheme for budget allocation



Source: The author (2020)

The real difference between each action is explained by virtue of the *allocation table*, on the column “feature”, and it is adjusted according to a mathematical representation of CSAR’s Imperative, Principle or Policy/Choice (which were collapsed into the Actions for the simulation). Otherwise, there would not be any real difference between the actions other than their label titles. This would cause the analysis to be totally flawed and semantic based.

For instance, one could call the Pillars "alpha", "omega" and "gamma" and when the whole simulation halts, one can come to conclusions during the final analysis that "gamma is a better Pillar for Reactive temperament than for temperament Stubborn". Therefore, the column “feature” has to be constructed perfectly for each action and make the actions stand out from each other.

Another important column of the allocation table is the “marginal revenue”, which is only used when the algorithm cannot afford the maximum budget for all actions on the Pillar, or when it cannot afford the minimum budget as well. This means that the system that can pay for just a certain amount of actions will either (1) pay the minimum on the largest amount of actions or (2) use the “marginal revenue” column as guide, which shows a visible return to each action. This column only serves this purpose.

It is important to notice that there are several steps before and afterwards that need to be taken, even with the system working with no major computational difficulties. Firstly, it is necessary to calibrate all coefficients, thresholds and parameters in all tables. It can be made manually for some of the components, but some of them have to be computationally generated, such as the behavior of the ANN. It is trained via a dataset.

In the case of the simulation proposed in this work, it was trained with data generated *in silico*, based on a real aggregated dataset (IEMI, 2017; SEBRAE, 2013). Afterwards, each agent of each temperament in the system generates plenty of raw data for analysis, when the simulation terminates. These data can be analyzed on their own to be displayed in graph and dashboards in analytic environment applications.

Finally, it is also important to notice the temperament concepts used in this work for the design and conception of the simulated system are based on the works of Salleh et al. (2011) regarding risk-taking propensity of decision makers. The proper adaptation was necessary due to the fact that the Apparel Cluster of Pernambuco had its particularities, so the risk-taking agents could better fit the simulated system (SALLEH; BERKUNCI; CHEPA, 2011).

3.3 DESCRIPTION OF THE FINAL MODEL

After validation phase, the whole system is a combination of techniques and tools, such as Machine Learning classification algorithms, Monte Carlo generated data (ZHU et al., 2019), rule-based algorithms and the agent-based simulation itself.

The way it is all put together for the task of simulating and generating data for better understanding the behavior of SC managers in ME utilizes a broad spectrum of computational paradigms. They go from imperative bits of code to functional programming and specialized packages for data manipulation and Artificial Intelligence implementation.

Firstly, the implemented model has to be coherent and represent the conceptual model as designed in advance. Only after this step, the computational tools and techniques can be used to generate the proposed model. Thus, both the conceptual model and the implemented model follow the same guidelines and are aligned when it comes to functionality (GRÄBNER, 2018).

In the beginning, all the parameters that can be modified by the user in order to facilitate sensitivity analysis have to be listed and form a compound of entities easy to be spotted on the code, so modifications can be made quickly and easily. These parameters include the number of agents, the number of ticks, the size of the time series in use for demand generation, initial budget allocation for SC managers in each company, rewards and punishments for each wrong or right decision, initial assets, number of agents of a determined temperament, stochastic probabilities for random events and so on.

After that, a dataset containing the *in silico* data generated by Monte Carlo is used for training the ANN entities. It is important to notice that, even though the generated data generated has to fit loosely the real behavior of the companies of the Apparel Cluster of Pernambuco. This can be granted in turn by comparing the features and the entries of the generated data set with aggregated real data from official reports about the Apparel Cluster. If the generated data conveys aggregated data similar to the real one, this *in silico* data set is useful for ANN training.

Only after the generation of the *in silico* dataset can the ANN be trained. It is a given of the model that there are three different types of temperaments, which represent general behaviors found in the specific literature. However, one of the temperaments in question is unresponsive to changes in the environment, when it comes to strategy change. Thus, the generated data set is divided in two and each portion of the *in silico* data is then used to train a different temperament ANN classification system.

This is to say that the aforementioned generated dataset has to contain specific types of information for each ANN being trained. Since the simulation model is predicated on four indicators (EF, DM, MS and TW) and outputs a dichotomist response (whether the previous tick was considered favorable or not favorable for the company), each part of the dataset must contain instances of surveying of hypothetical artificial companies precisely on those indicators.

As an example, if it is expected of a Proactive company to classify a previous tick as “favorable” whenever EF, DM and MS indicator be above a certain threshold of value X and have TW at any value, then it is more present in the training *in silico* dataset for the Proactive ANN to find instances reporting the same behavior than in the Reactive *in silico* training dataset. This also explains the reason there is no need for a Stubborn *in silico* generated dataset, since there is no change in behavior and no need for classification.

After training a multilayer Perceptron neural network, the system now possesses two entities responsible for classifying how favorable the previous tick was based on the indicators, as seen in the Appendix A. The efficiency of classification and error rate of both ANN can be easily assessed by ML efficiency assessment standards known to current literature, as well as advantages and obstacles that appear depending on the number of layers and cells in each layer. For the current system, a 4 layers ANN was used, with five cells per layer.

All the steps of the programming of the system were performed in the R platform and language, with the addition of open source packages and libraries (FRITSCH; GUENTHER; WRIGHT, 2019; HADLEY WICKHAM, 2016; R, 2019; WICKHAM, 2017). Both the preparation of the neural networks and the subsequent simulation phases ran on the same machine, a computer with a 3.5 gigahertz microprocessor, 6 megabytes of cache and 16 gigabytes of RAM. The aforementioned ANN setup took an average of 0.2 seconds to process.

The choice of this number of layers and cells in each layer tends to be viewed as a trade-off between efficiency of the classification of the system and computational cost. Despite not representing an overload for the current computer before exceeding 50 layers with 50 cells in each layer, 4 layers with 5 cells per layer was seen as the minimum to have an efficient classification system without losing classification performance.

Once the ANN are trained and ready to be used, it is necessary to generate the tables used as environment constraints and characteristics for the simulation, as can be seen as an example in the Appendix B. The time series table containing the number of four-month periods is generated by normalizing and integrating real history data for the demand according to the number of agents; in parallel, the temperament table, the environment constraints table and the allocation table are generated along with the engine for slightly modifying some of the columns of these tables.

The temperament table includes information about how much of financial assets, in percentage, goes to each Pillar after each temperament classifies the previous tick as favorable or unfavorable. The environment constraints table contains information about the base cost of production of the good, the cost of not servicing the demand, the cost of maintaining excess stock of materials, the vending price of the final good and the visibility disturbance for demand forecasting for each tick. Intermediate investment is rewarded proportionally, taking a linear relation between minimum and maximum investment into consideration.

Only subsequently is the data set containing the agents created. It contains basic information of each of the agents, namely the SC managers for each of the companies. It must hold not only information for the current tick but also information of the immediate previous tick; otherwise, it would make indicator composing and judgment on classification more difficult.

Variables such as temperament, classification of the tick, unit fabrication cost, assets, real demand for the agent, observed demand by the agent, market share, values for the four indicators, budget for the SC manager, production capacity and real production for the tick are present in this table and were chosen for the system based on the specific literature (PIRES, 2004).

Along with the main tables containing information of the environment and the agents, it is also necessary for the system to be able to count on temporary tables, which ease the process of comparing, calculating and transferring values from one tick to another. It is the case for auxiliary tables for both environment constraints and allocation values for each agent to each action. Without those auxiliary tables, even the record keeping task for later analyses would be made more difficult.

Succeeding the phase of creating tables containing all the information and the generating data set of each table, the agent-based simulation system needs to operate via procedures and functions. The functions allow the code to repeat a certain chunk of code as many times as needed without overloading the computer with repetitive code. Since many commands and events will happen every turn, even though with different outcomes, it is the best choice for command code writing.

The aforementioned functions serve several different tasks and are activated within closed loops according to a certain order and utility, such as a function for market share distribution, a bankruptcy screening, real demand calculation, observed demand calculation, indicators calculation, four-month period classification, budget assignment, item production, actions rewarding and punishing, environment constraints modifying, total revenue calculating and asset balancing. After defining those functions, a main function, which calls each of them in the correct order within a loop, is also created.

Finally, the system is able to run and the results show up in output tables, containing not only intermediate values of each agent at each tick, but also final and aggregated values. This allows decision-makers analyze both graphically and statistically the results obtained via simulation, when the system terminates with the results.

It is also interesting to note that this feature provides a way of measuring goodness of fit with real environment and scenarios by the simulated environment, because variables and parameters can be modified for better adjustment whenever it is necessary. More details can be found in the pseudocode in Appendix C.

4 RESULTS AND DISCUSSION

4.1 LAYER-BUILDING PROCESS

The initial aspect before addressing the parameters of the simulation, such as time series, characteristics of the item being produced and the construction of necessary details in the agents is to determine the width of training and testing set from the *in silico* data. As stated in previous Sections, the data given to the ANNs are based on real data but generated computationally.

For these simulation runs, EF, DM, MS and TW will range from, respectively, 0.9533 to 3.0817, 0.0271 to 83.3333, 0.0000 to 1.0000 and 0.2966 to 52.1427 in functioning scenarios. The ranges were defined taking into consideration and then normalizing the values considered realistic for MEs in the Apparel Cluster of Pernambuco, according to field and official reports (IEMI, 2017; PERNAMBUCO STATE GOVERNMENT, 2016; SEBRAE, 2013).

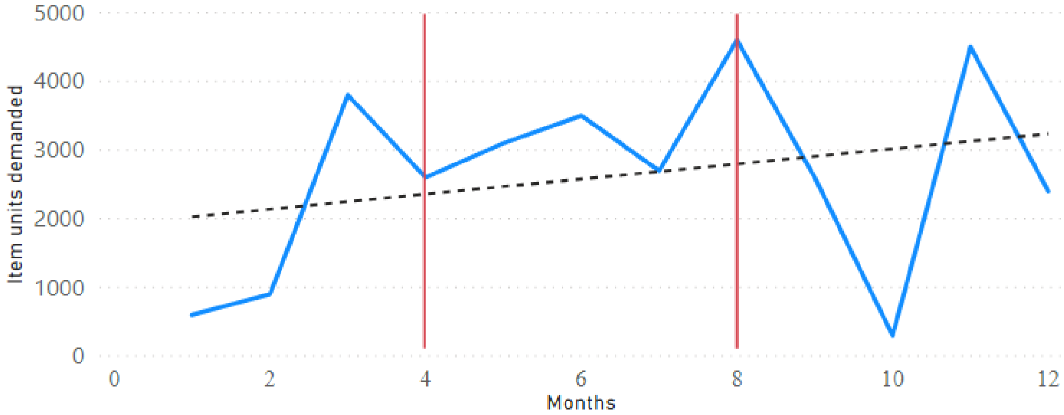
For the Reactive and Proactive temperaments, it will have two hidden layers with 5 and 4 neurons respectively, and the error for more than 200 steps of training is in the order of less than 0.01%. Just after this previous step is the system ready for layer building. Stubborn temperament is not trained because it is a simple rule: it always assesses the previous period as not being good.

For all the steps of the integrated elements in the layer-building process phase, no execution exceeded 10 minutes, for the aforementioned computer configuration. Runtimes that exceeded 10 minutes occurred only when a parameter was altered on purpose to overload the computational process and check the sensitivity of that particular parameter.

Firstly, it is necessary for the system to operate that a demand exists over time. Since only one type of product is being produced and sold in the simulation, a market demand for all companies will be split proportionally among them according to their respective market share.

It is only natural that the general demand follows a realistic pattern. In this case, works that have recorded the behavior of the demand in the Apparel Cluster of Pernambuco offer an option for generating a time series curve that resembles the real demand situation for the companies of the region (IEMI, 2017; SEBRAE, 2013), and behave as seen in Graph 4.

Graph 4 – Yearly demand of a particular item in the Apparel Cluster of Pernambuco



Source: The author (2020)

As Graph 4 shows, the choice of periods being four months long fits the seasonality of the yearly demand because there are three distinct demand patterns throughout the 12 months of the year. Choosing more commonly used time measurements, such as quarters, semesters or years for iterations in the simulation would render the system either unrealistic or too computationally demanding, if the periods in the simulation were days or hours, for instance.

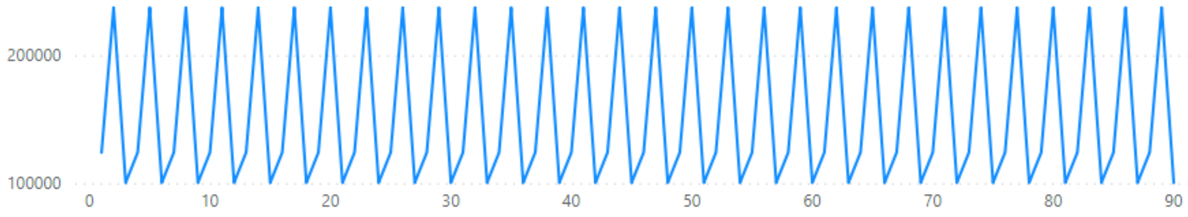
This happens because quarters do not match the seasonality of the demand and would take 120 iterations instead of 90, whereas semesters would only run for 60 iterations and years, 30 iterations. The last two options are too short for any conclusions, and the first one would create difficulties for realistic demand simulation.

It is important to notice that the extrapolation for all the companies from this single example represents no problem for the whole model, because there is the possibility of changing the characteristics of the time series in the simulation code. Hence, whenever a different type of demand curve is needed, it is possible to easily apply this modification onto the system. The same disclaimer is valid for most components and parameters of the present system.

As can be noticed in Graph 4, the time series can be represented in the simulation as a recurrence of three distinct general demand behaviors with some degree of realism, roughly starting in January and increasing in a fast fashion up until March or April, stabilizing and going in a slow and steady upwards slope until August, for then to go in a slow descent slope until the end of the year, with some mild high peaks within this time period.

In this case, the simulation utilizes four-month periods as ticks of iterations, and the whole system runs up until 90 cycles, which translates to 30 years of simulation, a realistic scenario for the Apparel Cluster of Pernambuco. Graph 5 shows the total demand for the given good used in the simulation over 30 years.

Graph 5 – *In silico*-generated time series of units demanded by the market per four-month period based in real data from the Apparel Cluster of Pernambuco



Source: The author (2020)

In Graph 5, it is noticeable that the demand ranges from 20,000 items to a few items over 50,000 clothing units in the entire Apparel Cluster. This situation is true for certain types of goods, not for the whole goods that are sold yearly.

Since this simulation focuses solely on medium-sized companies manufacturing interchangeable goods that present no difference for customers whether they were manufactured by one company or another, this particular item can be understood as something specific such as a lingerie kit (brassiere and panties), which is not manufactured in a large scale by all companies – small and large ones – only specific of the medium-sized niche companies.

This can be justified by the fact that most items, such as individual dresses, pants, t-shirts or shorts can be easily manufactured by companies of all sizes and represent no real niche of companies. This is to say that there is no correspondence between the kind of item being manufactured and the size of the company that manufactured it.

On the other end of the spectrum, if the item being manufactured has a high unit value, such as a tailored clothing or a suit, for instance, this can mean that the item manufactured might have been produced by either a tailor or a large company.

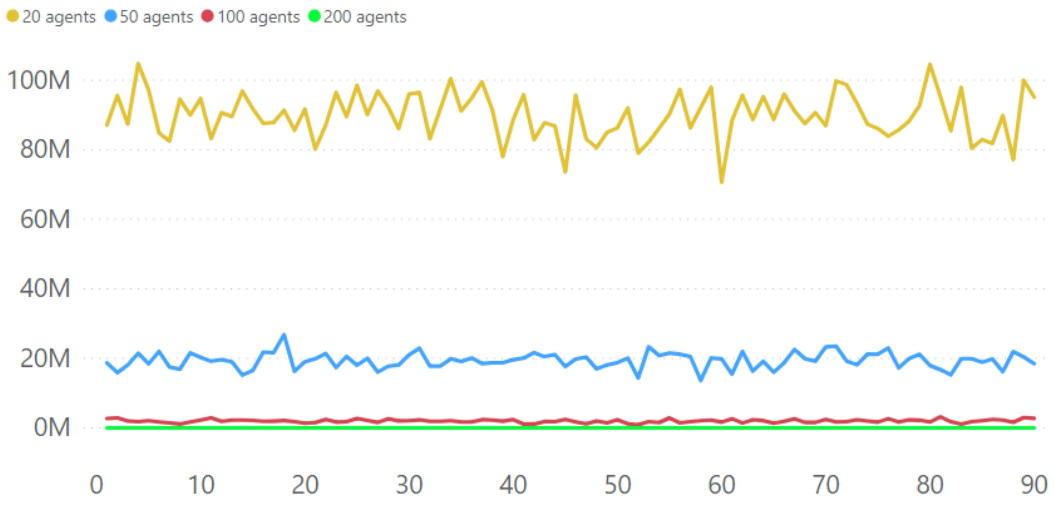
Hence, the safest way to represent medium-sized companies in a simulation is to choose a type of item that is representative of the size of the company, which is to say that the item of the simulation has to present a characteristic that dissociates it from small-sized companies and large-sized companies. The approach for guaranteeing this trait of the production is to set the parameters of total demand and vending price of the item to behave like real items in this category.

In the context of this simulation, this can be achieved by defining a demand not as exclusive and sparse as a high value item, nor so demanded by the market. Another way of defining it is to make it not so expensive that only exclusive customers can afford to buy it, but also not as low-priced as the simplest item in the Apparel Cluster of Pernambuco. For this reason, for a 100 agents' simulation, the demand in Graph 5 corresponds to a medium-sized demand production. In regards to the vending price, it fluctuates around R$ 50, roughly $13.

It is also important to notice that the number of agents in the simulation is kept in 100 for two main reasons, the first one being the computational time of each run, which increases exponentially the more agents there are in the simulation. While the runtime for 100 agents fluctuates around 7 minutes, an execution with both 200 and 500 agents surpasses 10 minutes of runtime, with the aforementioned computer configuration.

Hence, no more than 100 agents are needed for this reason, and fewer agents would not facilitate the emergency of certain properties and behaviors in the system. Graph 6, for instance, shows how yearly average assets differ for 20, 50, 100 and 200 agents, ceteris paribus. The second reason for utilizing 100 agents is that it represents roughly 10% of the real number of agents of this size in the Cluster Apparel of Pernambuco, and this is a number of entities good enough for generating valid insights.

Graph 6 – Average assets value in R$ throughout the four-month periods



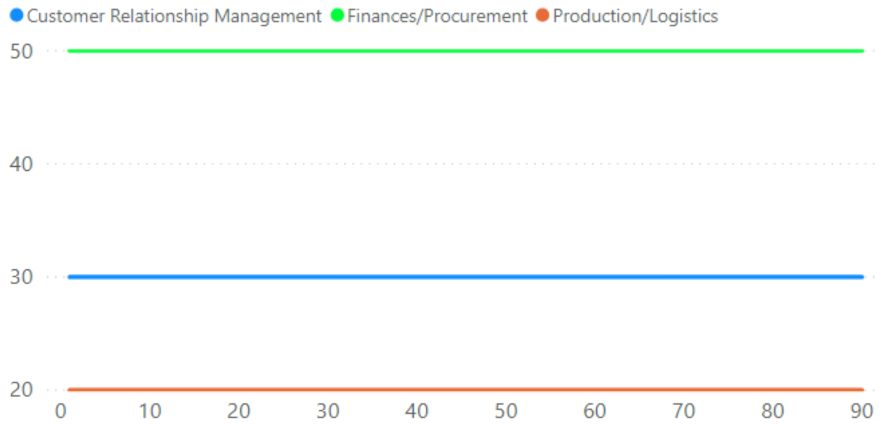
Source: The author (2020)

It is easy to understand the layer-building process works as a sensitivity analysis, and all parameters will undergo scrutiny. The second step is to determine initial values of parameters for a simplified baseline simulation run, so it can be used as a foundation for a more sophisticated implementation of the system.

It might present uncommon results that hold no real value for decision-makers nor relationship to the real Apparel Cluster of Pernambuco. Far from representing a problem, this is a key characteristic of the layer-building methodology adopted in this work, because it helps the verification and validation processes.

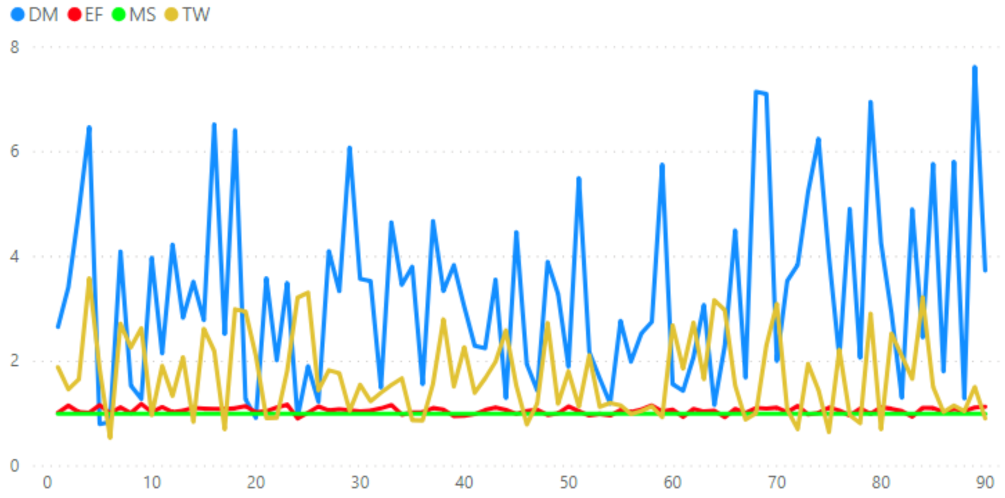
First, the simulation runs containing no ML element. This is to say that the agents do not learn along the way, and each time the previous four-month period sends a message it is ignored and not taken into consideration for the next four-month period. In this context, every one of the agents behave as if they presented the Stubborn temperament. Graph 7 shows general budget allocation in each Pillar during the entire simulation run, while Graph 8 shows the evolution of this same ME, regarding its indicator's performances.

Graph 7 – Investment in each Pillar in percentage for an average stubborn ME



Source: The author (2020)

Graph 8 – Performance indicators for an average ME with 100% Stubborn agents

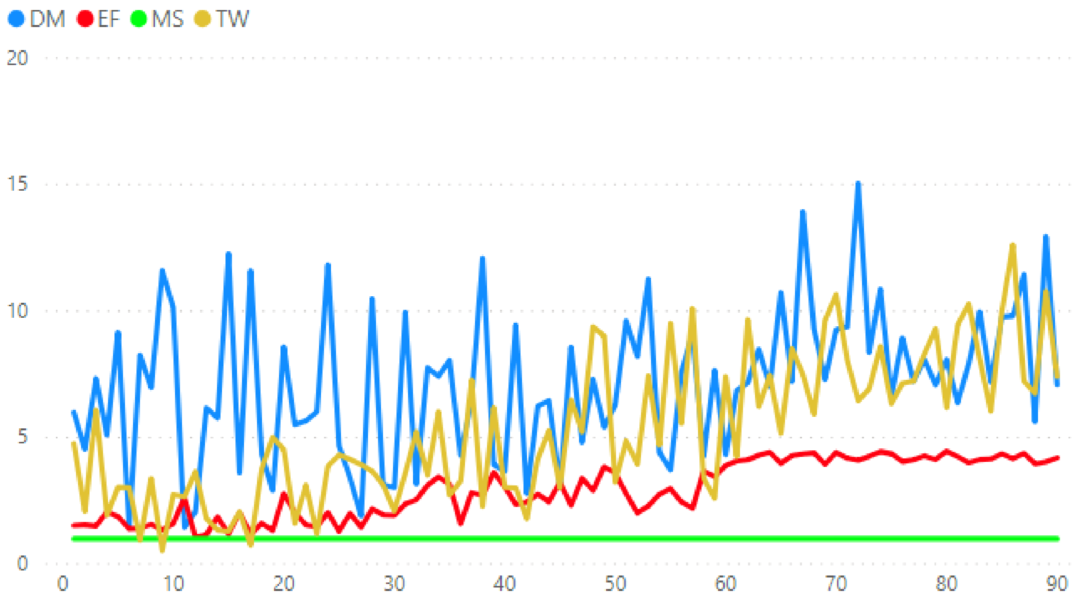


Source: The author (2020)

This clearly shows an anomalous behavior compared to real companies in the Apparel Cluster of Pernambuco, because the general trend is of growth for most companies, whereas the companies' statistics displayed in Graphs 7 and 8 show a clear tendency for cyclical market fluctuation due to the incapacity of adaptation and learning from previous mistakes.

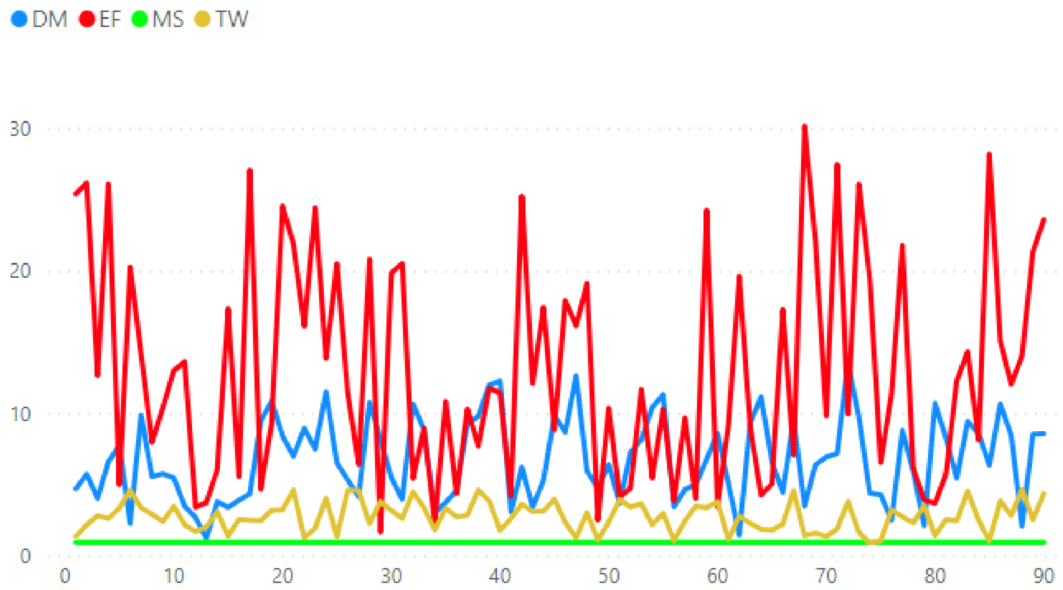
Provided that only a smaller number of companies display this neutral behavior towards performance indicators, it is necessary to add a layer that corresponds to behavior, namely the two other types of behavior pre-determined during the conception of the system. Graphs 9, 10 and 11 display the same data from previous Graph 8 for different proportions of stubborn, proactive and reactive companies in the simulation.

Graph 9 – Performance indicators for the average of MEs in an environment with 65% reactive, 25% proactive, 10% stubborn companies



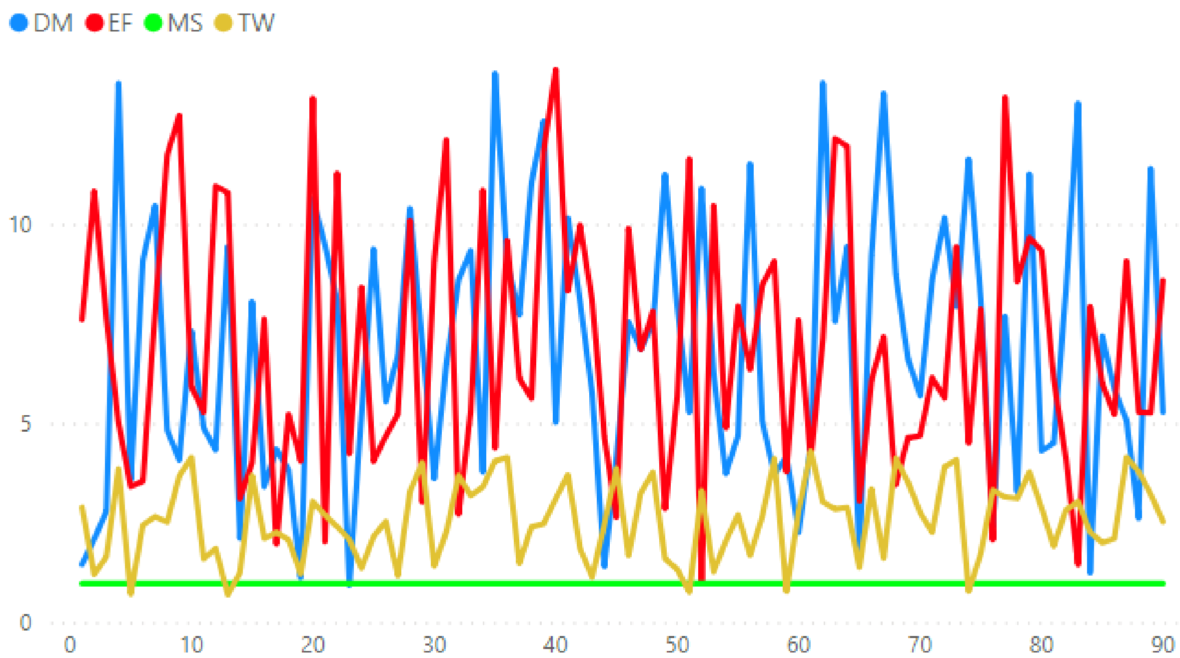
Source: The author (2020)

Graph 10 – Performance indicators for the average of MEs in an environment with 50% reactive, 40% proactive, 10% stubborn companies



Source: The author (2020)

Graph 11 – Performance indicators for the average of MEs in an environment with 60% reactive, 20% proactive, 20% stubborn companies

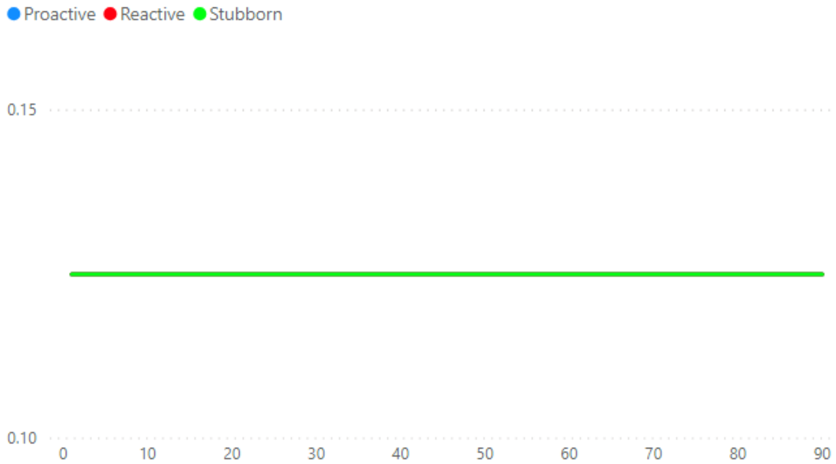


Source: The author (2020)

The addition of other temperaments is therefore justified due to a better fit to real data, because there is an increase of high peaks near the end of the simulation. Graph 9 shows the best proportion of temperaments, being 10% composed of risk neutral companies, namely stubborn, whereas 65% represent companies averse to risk, the reactive agents. Finally, 25% of the agents are proactive, which means that they are risk takers and are willing to change the allocation rate of budget in the Pillars available for better performance.

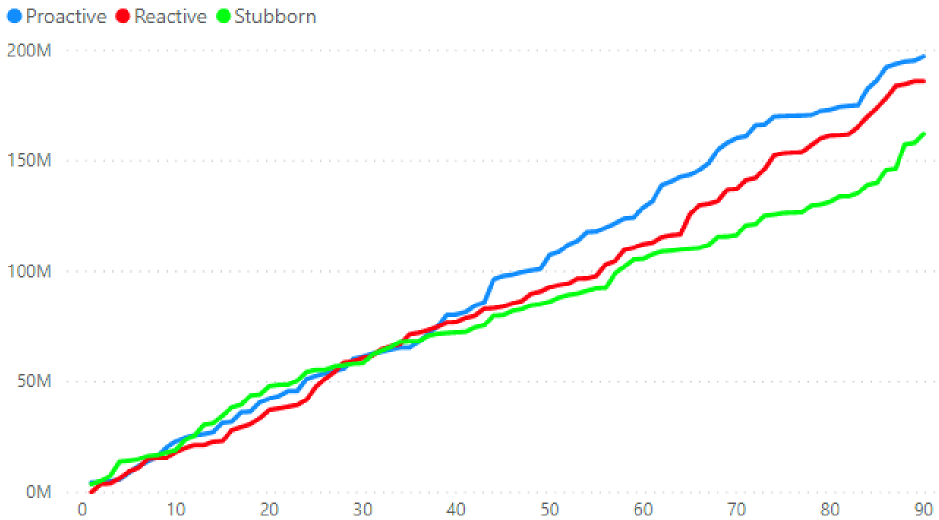
Another feature that can be built in layers is the initial asset value of each company, namely, how much of financial resources the company starts the simulation with, exclusively for SCM purposes. Ceteris paribus, all companies start with the same financial value for budget allocation, and all the money available goes directly for allocation in the Pillars, as shown in Graphs 12, 13 and 14, for different quantities.

Graph 12 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting with R$ 5,000.00



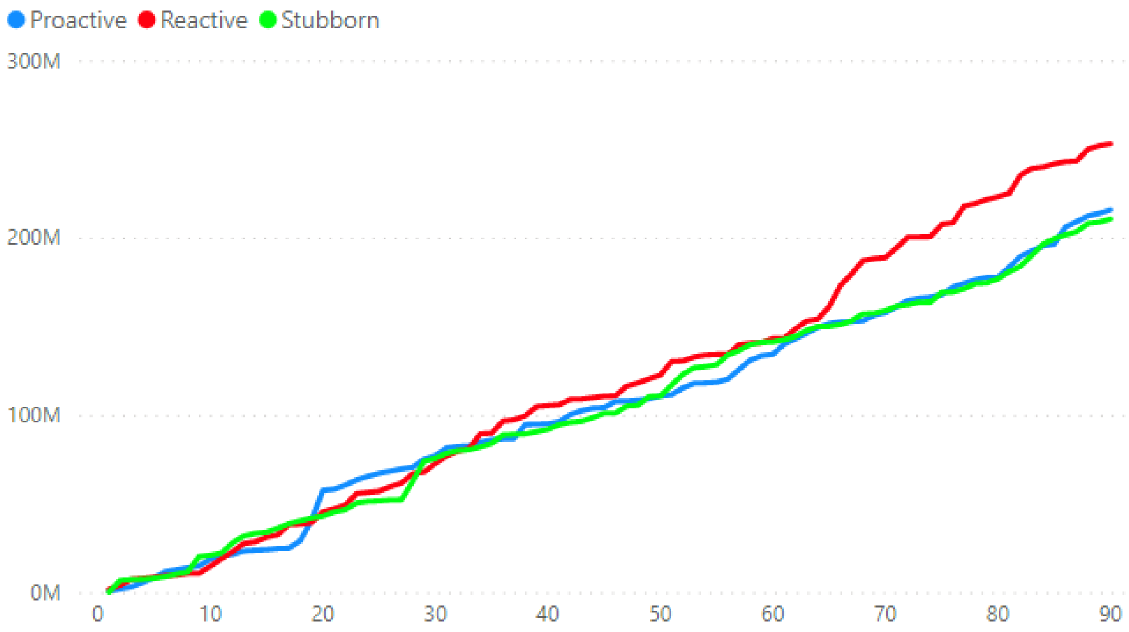
Source: The author (2020)

Graph 13 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting with R$ 50,000.00



Source: The author (2020)

Graph 14 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting with R$ 100,000.00

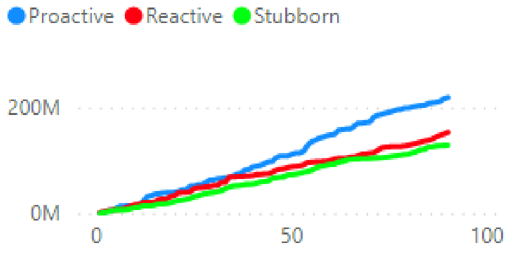


Source: The author (2020)

This shows an unusual behavior, because not all companies start with the same amount of assets available for production, nor invest all of it in SC management, nor go bankrupt in the first year. It is necessary then to add another layer responsible for different starting values of assets for each company, ceteris paribus.

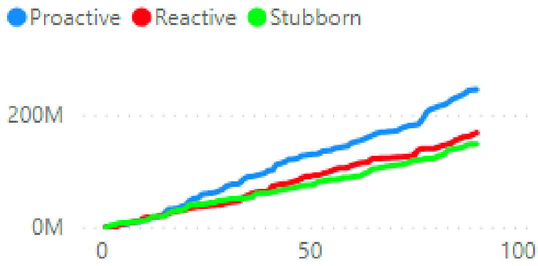
It is important to notice, however, the value invested in SC management is still kept the same, which means all the assets available in Graphs 15, 16, 17 and 18 are 100% utilized in the three Pillars. However, it is important to notice that the range of variation of initial assets chosen is closer to Graph 13, because it presented the intermediate condition between unstoppable and unrealistic growth and generalized bankruptcy.

Graph 15 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting within the range of R$ 25,000.00 to R$ 100,000.00



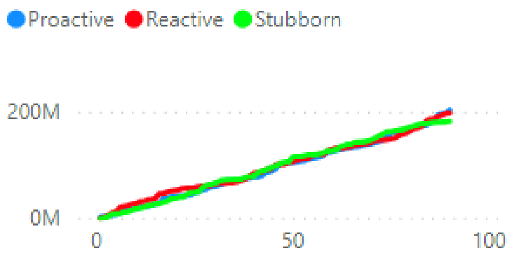
Source: The author (2020)

Graph 16 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting within the range of R$ 35,000.00 to R$ 90,000.00



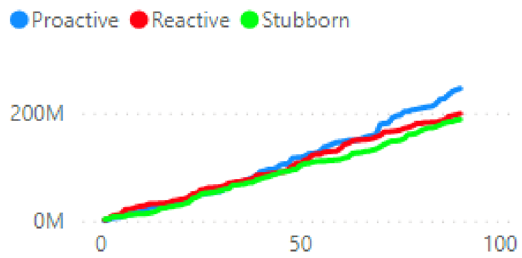
Source: The author (2020)

Graph 17 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting within the range of R$ 40,000.00 to R$ 70,000.00



Source: The author (2020)

Graph 18 – Assets available for investment in SCM in R$ for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00

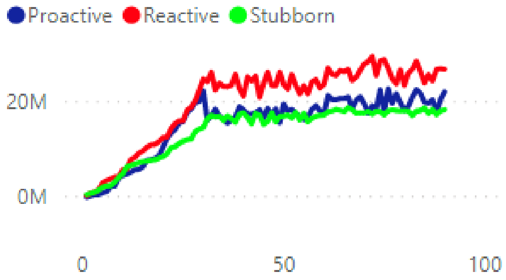


Source: The author (2020)

Even though the situation is more realistic in the Graphs 15, 16, 17 and 18 for each of the companies in the current run, Graphs 17 and 18 present a more realistic approach due to the fact that the final range between the wealthiest and the least wealthy ME is less wide than in Graphs 15 and 16. Hence, having companies start with different asset values for investment, ranging roughly R$ 15,000.00 between the initially wealthiest and the least wealthy of them, is a necessary feature for the simulation.

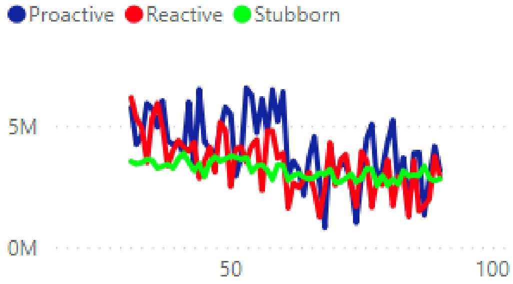
However, not all the assets are allocated SC management. Taxation, investment in other areas of the company, employee’s payment, fines, debts and other types of obstacles for investing all the assets directly in the three Pillars exist in reality. For this reason, Graphs 19, 20, 21 and 22 display different percentages of budget allocation in SCM, ceteris paribus.

Graph 19 – Assets available for investment in SCM in R$ after a 10% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



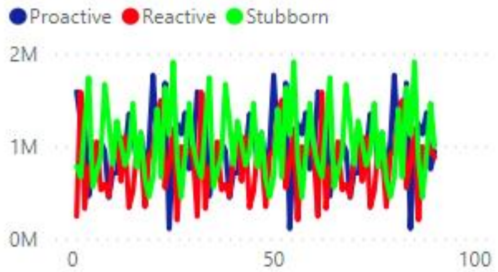
Source: The author (2020)

Graph 20 – Assets available for investment in SCM in R$ after a 50% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



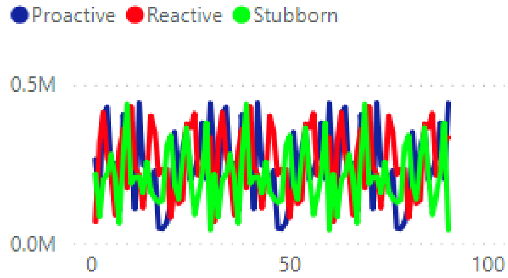
Source: The author (2020)

Graph 21 – Assets available for investment in SCM in R$ after a 70% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



Source: The author (2020)

Graph 22 – Assets available for investment in SCM in R$ after a 95% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



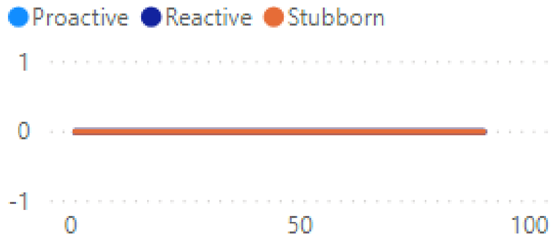
Source: The author (2020)

It is visible that having some control of percentage in how much financial assets are invested in SCM is a more realistic approach than the simplistic take that all the money available in the company goes directly to SC management. Therefore, this is another feature added for the final simulation.

The same is also valid for how much the profits in fact is available for re-investment, programmed initially in a simplified manner to be half of the available assets for the four-month period. Graphs 23, 24, 25 and 26 show different percentage values, ceteris paribus.

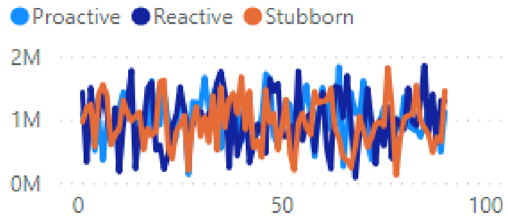
Despite clear visibility being hindered in Graphs 21 and 22 comparatively to Graphs 19 and 20, the discount rate of 70% is more realistic when it comes to the real value available for re-investment in SCM after taking financial planning and taxation into consideration. Furthermore, the range of R$ 4 million between the smallest budget available and the largest is also realistic considering the profile of the MEs in the Apparel Cluster of Pernambuco. Hence, this is the parameter used for Graphs 23, 24, 25 and 26.

Graph 23 – Low SCM rate of the available assets for investment in R$ after a 95% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



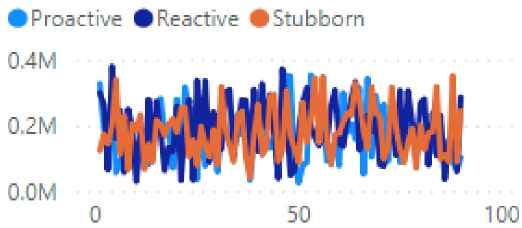
Source: The author (2020)

Graph 24 – Low to medium SCM rate of the available assets for investment in R$ after a 95% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



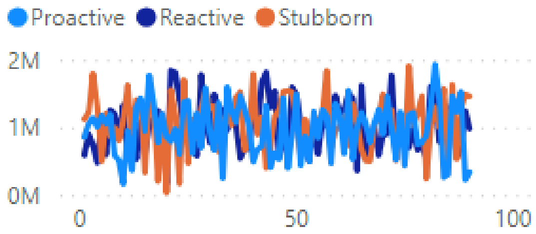
Source: The author (2020)

Graph 25 – Original SCM rate of half of the available assets for investment in R$ after a 95% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



Source: The author (2020)

Graph 26 – High SCM rate of the available assets for investment in R$ after a 95% value discount for randomly chosen MEs of all temperaments and starting within the range of R$ 45,000.00 to R$ 60,000.00



Source: The author (2020)

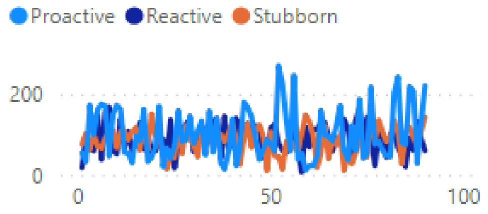
Once moreGraphs 23, 24, 25 and 26 provide evidence enough that having a percentage of the resources turned into re-investment assets instead of all the profit is a more realistic approach because assets do vary accordingly. In a scenario where there is no re-investment, companies all go bankrupt at the same time.

Therefore, the previous features are added to the final simulation: different proportions of different temperaments, different initial asset values within a given range, percentage of assets available for SCM and percentage of profit turned into re-investment resources. For this last feature in the case of this simulation, low rates represent early bankruptcy of all companies or limited range of assets variation. High rates also present a limitation. Hence, a low to medium rate is adopted for the system.

The last of the features that need to be examined whether they are necessary for a better fit of the simulation to the reality of the companies is in regards to real demand visibility by the companies. Therefore, it is important to take into consideration a type of forecasting fog for the manager, a computational structure that might either disturb his capacity to foresee the demand as it really is or present some kind of noise that will make company forecasting err.

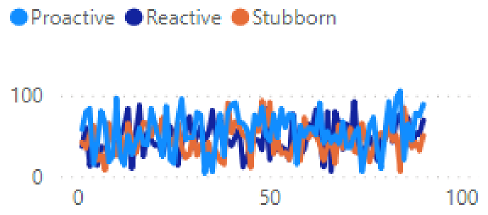
This is to say that either the company knows exactly how much to produce or they are clueless and might leave part of the demand unattended or produce unnecessary amounts of items. Both situations are possible and have different consequences, as shown in Graphs 27, 28, 29 and 30 for the companies in each simulation.

Graph 27 – Difference between real demand and forecasted demand in item units with high visibility fog for randomly chosen MEs of all temperaments



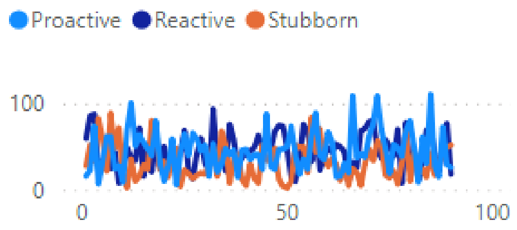
Source: The author (2020)

Graph 28 – Difference between real demand and forecasted demand in item units with medium visibility fog for randomly chosen MEs of all temperaments



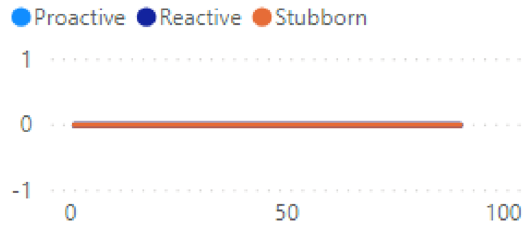
Source: The author (2020)

Graph 29 – Difference between real demand and forecasted demand in item units with minimum visibility fog for randomly chosen MEs of all temperaments



Source: The author (2020)

Graph 30 – Difference between real demand and forecasted demand in item units with no visibility fog for randomly chosen MEs of all temperaments



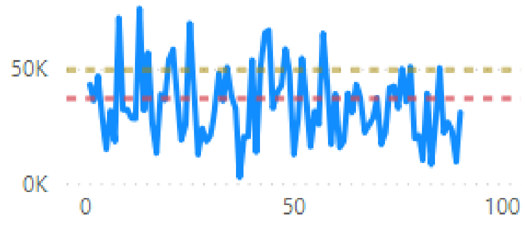
Source: The author (2020)

What Graphs 27, 28, 29 and 30 help understand is that it is necessary for the simulation to have a layer of complexity responsible for presenting an inherent difficulty for the companies to know the exact demand for the four-month period, otherwise they will never produce extra items and will only produce less than what is demanded in the situation where the production capacity is not enough. Since this is not a realistic situation, the demand visibility fog feature is also added to the final simulation, with low to medium intensity.

Regarding the micro-features, which are responsible for the characteristics of the production of each agent, there are also some layers of complexity that can be added to the simulation if needed. The first introduced is responsible for introducing the concept of marginal cost of each action under the Pillars.

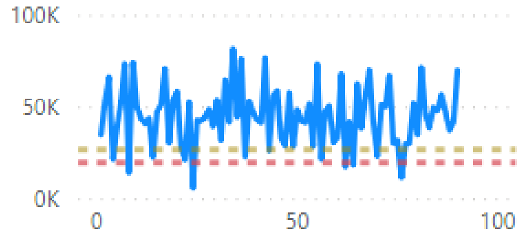
In a situation where all costs are too high for the budget available, the company will always be penalized or invest only the minimum value. On the other side of the spectrum, if costs are all affordable every time, companies will show no difference throughout the simulation, defeating the very perspective of the system, as seen in Graphs 31, 32, 33 and 34 for a representative ME in each run.

Graph 31 – SCM budget in R$ between high expensive investment costs for a randomly chosen ME



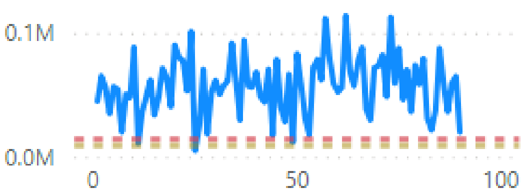
Source: The author (2020)

Graph 32 –SCM budget in R$ between medium to high expensive investment costs for a randomly chosen ME



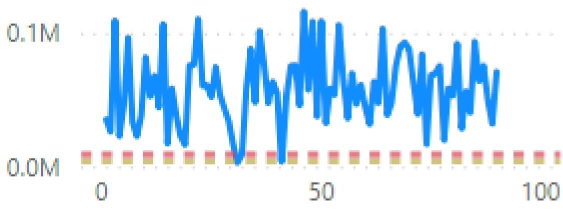
Source: The author (2020)

Graph 33 – SCM budget in R$ between medium investment costs for a randomly chosen ME



Source: The author (2020)

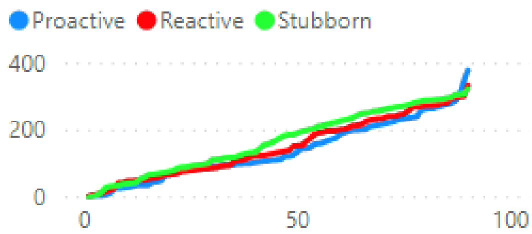
Graph 34 – SCM budget in R$ low investment costs for a randomly chosen ME



Source: The author (2020)

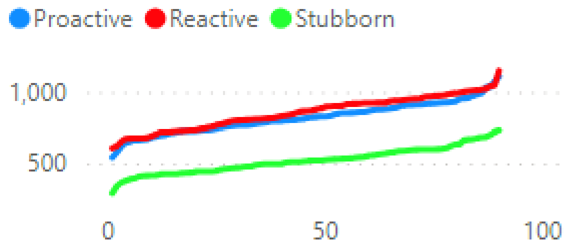
Another feature that can be assessed for a more realistic simulation is responsible for the range of the initial production capacity and the baseline production cost of the items. As shown in Graphs 35, 36, 37 and 38 for the production capacity and Graphs 39, 40, 41 and 42 for the initial cost of the items, each displaying a randomly chosen ME at a time, it is visible that the feature of modifying the initial value – whether it is too high or too low compared to the real demand and the vending price, respectively – is more important for the production capacity than it is for production base cost, which varies too little.

Graph 35 – Extremely limited initial production capacity and its consequent impact in posterior capacity in units for randomly chosen MEs of all temperaments



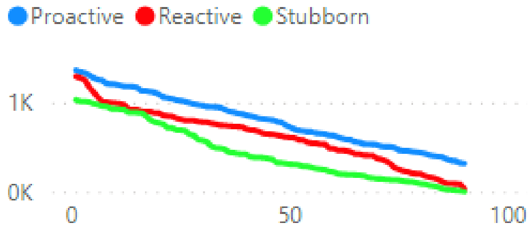
Source: The author (2020)

Graph 36 – Small to medium initial production capacity and its consequent impact in posterior capacity in units for randomly chosen MEs of all temperaments



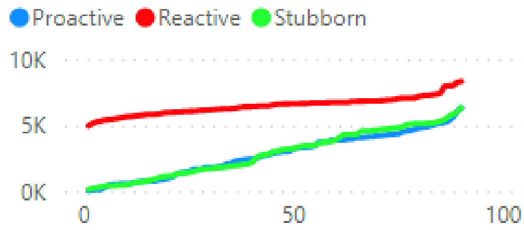
Source: The author (2020)

Graph 37 – Original and demand-compatible initial production capacity and its consequent impact in posterior capacity in units for randomly chosen MEs of all temperaments



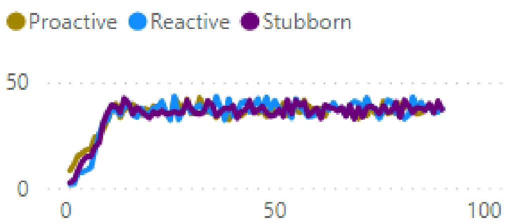
Source: The author (2020)

Graph 38 – Nearly unlimited initial production capacity compared to the demand and its consequent impact in posterior capacity in units for randomly chosen MEs of all temperaments



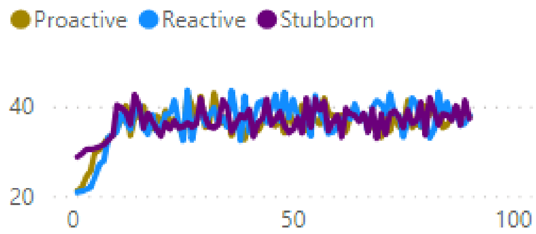
Source: The author (2020)

Graph 39 – Extremely low production base cost in R$ for randomly chosen MEs of all temperaments



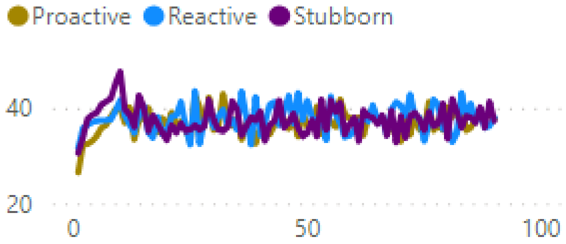
Source: The author (2020)

Graph 40 – Low production base cost in R$ for randomly chosen MEs of all temperaments



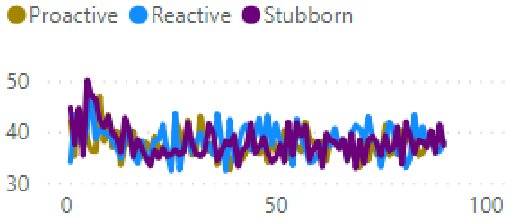
Source: The author (2020)

Graph 41 – Medium production base cost in R$ for randomly chosen MEs of all temperaments



Source: The author (2020)

Graph 42 – High production base cost in R$ for randomly chosen MEs of all temperaments



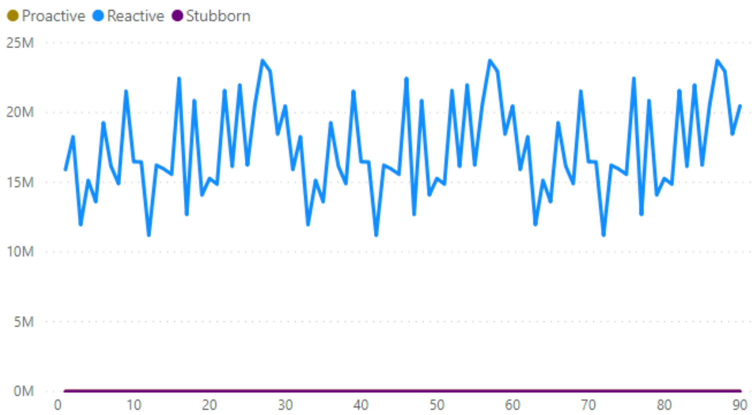
Source: The author (2020)

In this case, the micro-features of initializing each company with a different value for production capacity and a different value for baseline production cost is optional, with the possibility of starting all companies with equal values. However, it is necessary for the simulation that these values, whether equal or randomly generated, are within a range of values smaller than the vending price for the baseline cost and somewhat close to the real demand for the initial production capacity.

Another feature that proves necessary subsequent integration in the model is the range of initial assets for the company. The simulation does not work properly when the values are equally low, as seen in Graph 43. This happens because companies with small budget go bankrupt early in the game due to poor demand forecast.

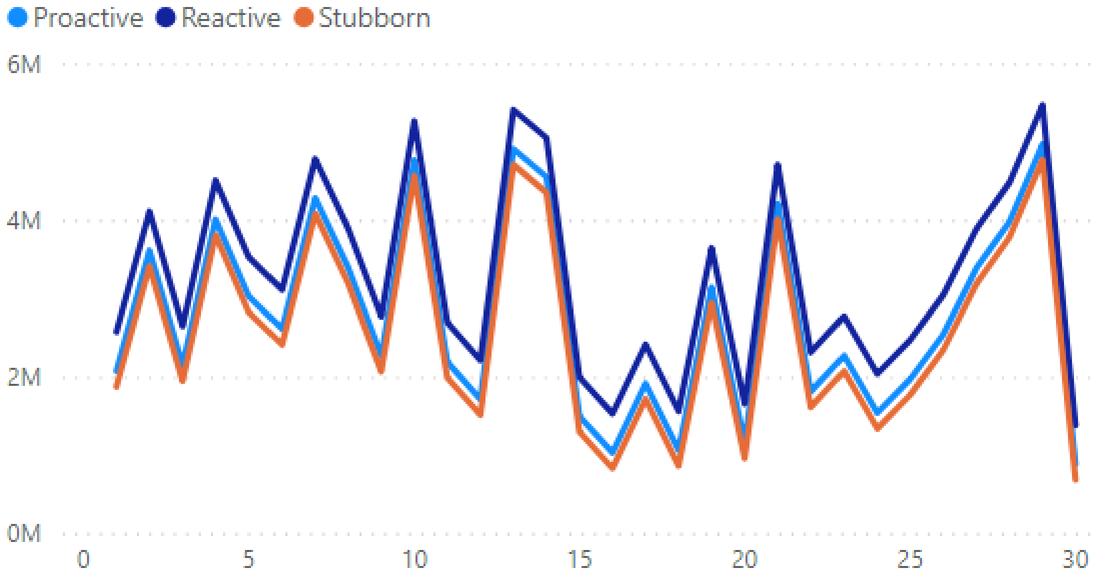
However, when initial assets values are equally high in the beginning of the simulation, as seen in Graph 44, it works the same way as if there was a range of values instead of equal values, as displayed by Graph 45.

Graph 43 – Assets available according to initial smaller budget in R$ of randomly chosen MEs of all temperaments throughout the years



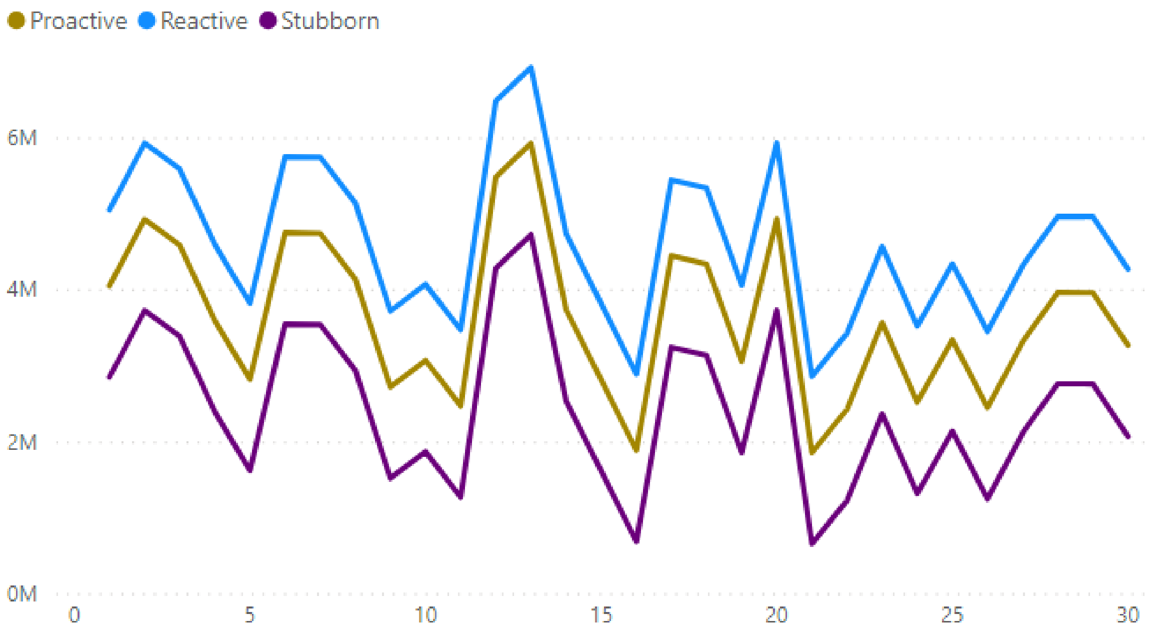
Source: The author (2020)

Graph 44 – Assets available according to initial higher budget in R$ of randomly chosen MEs of all temperaments throughout the years



Source: The author (2020)

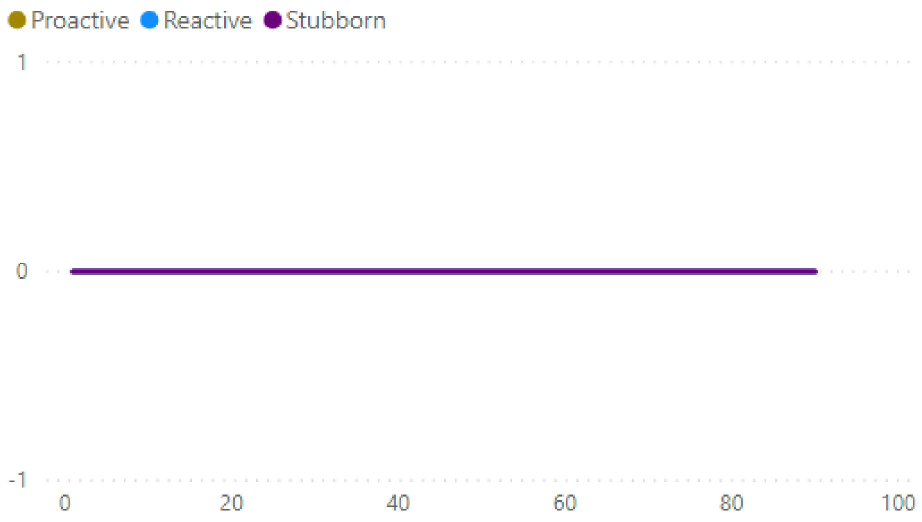
Graph 45 – Assets available according to different initial budget values in R$ of randomly chosen MEs of all temperaments throughout the years



Source: The author (2020)

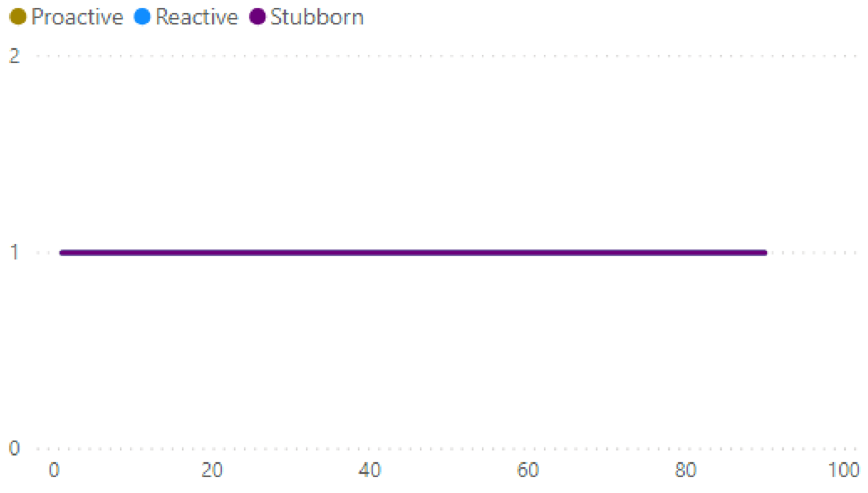
The same information is also seen in Graphs 46, 47 and 48 for the previous situations, but for market share. This can be interpreted as all companies losing their market share when initial assets are too low, as in Graph 46, or companies remaining stable throughout the whole simulation, as in Graph 46 and Graph 47. Hence, the variation among agents is not relevant for the simulation, whereas the absolute asset value is.

Graph 46 – Market share in percent according to initial assets starting from a low budget on financial assets of randomly chosen MEs of all temperaments



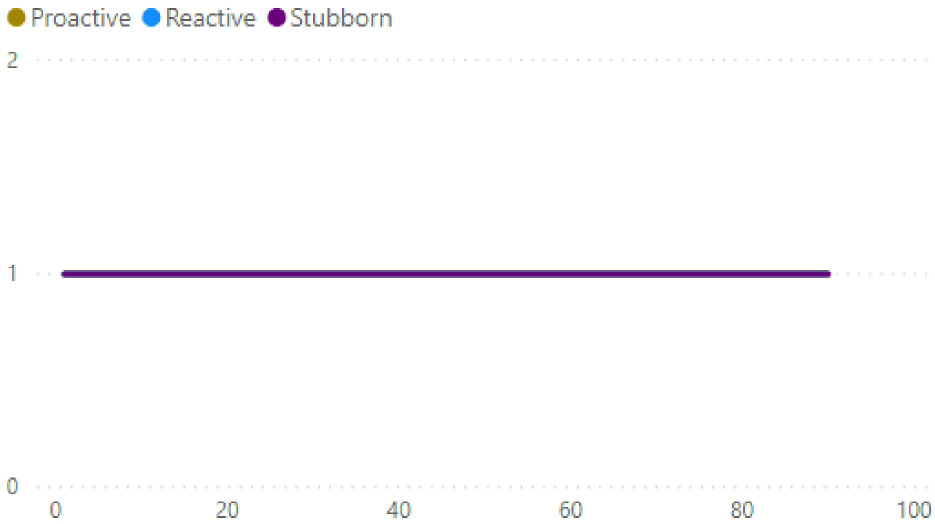
Source: The author (2020)

Graph 47 – Market share in percent according to initial assets starting from a high budget on financial assets of randomly chosen MEs of all temperaments



Source: The author (2020)

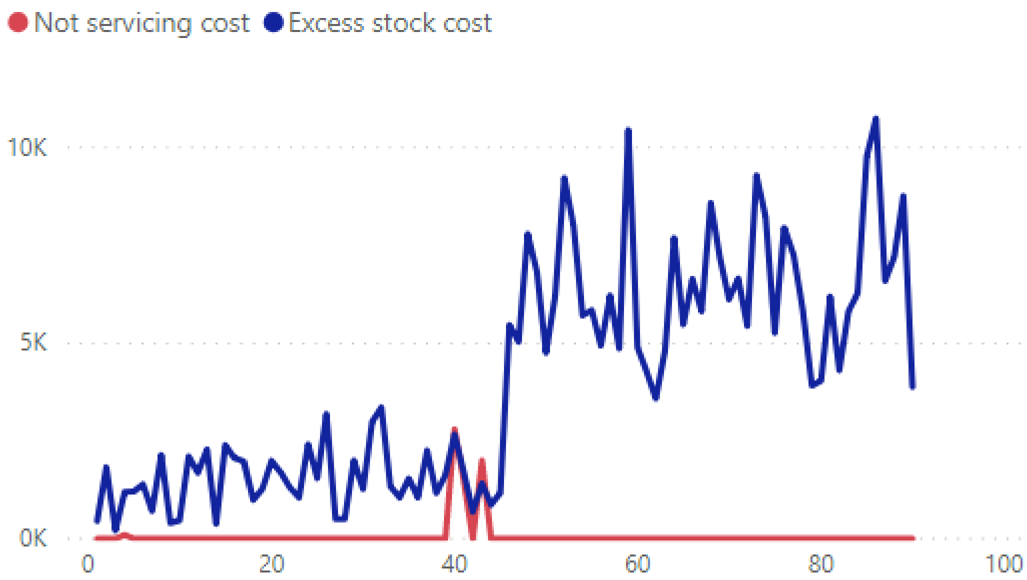
Graph 48 – Market share in percent according to initial assets starting from a bounded financial range of assets of randomly chosen MEs of all temperaments



Source: The author (2020)

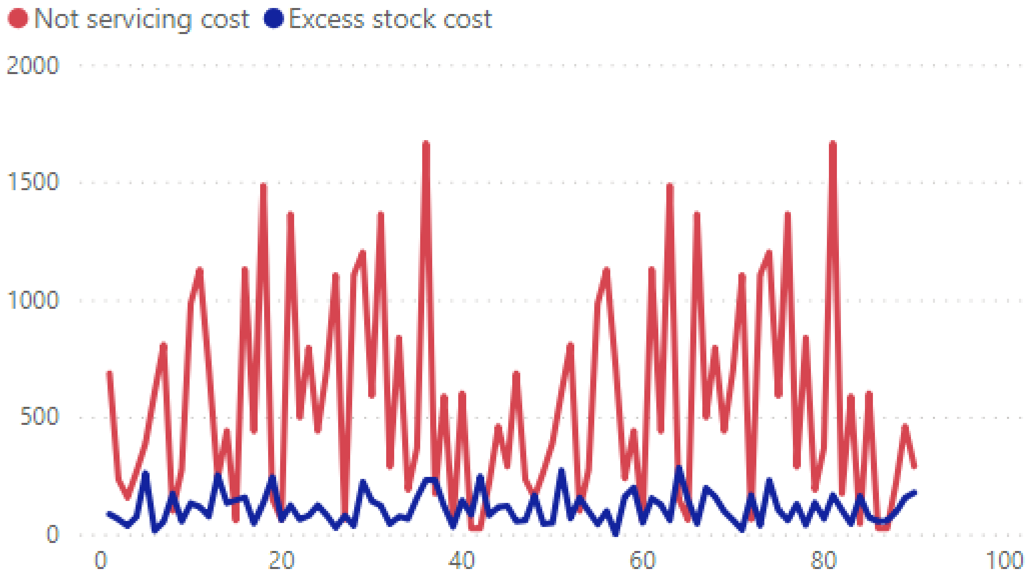
Other two features that also have to vary within a limited low range are the excess stock cost and the not servicing cost. As Graph 49 shows for the first one and Graph 50 shows for the second one, whenever any of those costs make final cost exceed vending price, companies go bankrupt before the end of the 30 years simulation span. Both Graphs show ceteris paribus situations taking into consideration all previous elements added in different abstraction layers.

Graph 49 – Extra costs in R$ from a wide range of values of a randomly chosen ME throughout the four-month periods



Source: The author (2020)

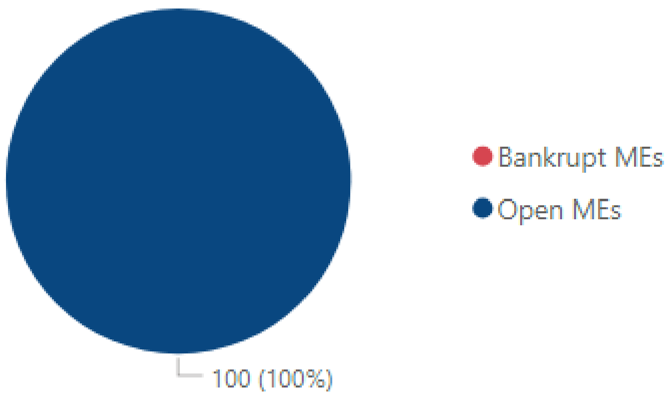
Graph 50 – Extra costs in R$ from a limited range of values of a randomly chosen ME throughout the four-month periods



Source: The author (2020)

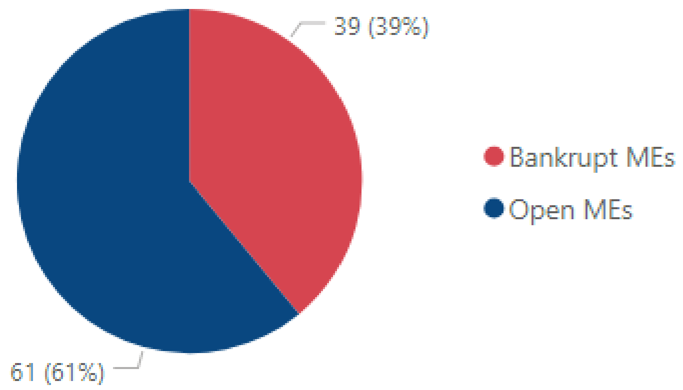
If loans are not taken into consideration in this simulation, the last resource being assessed, ceteris paribus, in the layer building of the simulated system is a threshold of bankruptcy that companies self-evaluate over. This is to say that if the total assets reach a certain low value, companies declare themselves bankrupt and leave simulation before the final 90th four-month period. Graphs 51, 52 and 53 show how companies behave when varying this threshold, defined by official reports (IEMI, 2017; SEBRAE, 2013).

Graph 51 – Percentage of bankrupt and open MEs with a low threshold in R$ for bankruptcy in the entire simulation



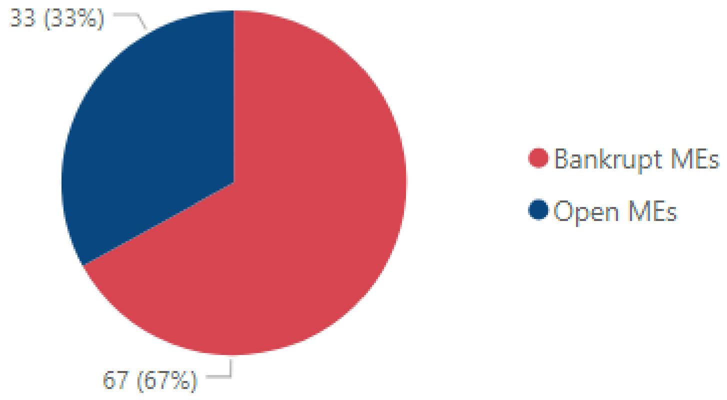
Source: The author (2020)

Graph 52 – Percentage of bankrupt and open MEs with an intermediate threshold in R$ for bankruptcy in the entire simulation



Source: The author (2020)

Graph 53 – Percentage of bankrupt and open MEs with a high threshold in R$ for bankruptcy in the entire simulation



Source: The author (2020)

This indicates that it is important for the simulation to take into consideration a certain assets value for the agents before they notice the company has not a chance to compete against other companies and they cannot invest any longer in any capacity for improving their production. This is also a realistic stance and has a place in the simulated system.

For this reason, the simulated system adopts this practice as well. After defining which elements will be part of the simulation by adding layer of complexities, the simulating system is ready to generate valid output data.

Despite the fact that the resulting source code is considerably long, the ABM system developed and used in this work is yet simpler than the full potential displayed throughout the execution of the algorithms. Hence, it is visible the emergent properties are present in this simulation and display certain characteristics that can be easily spotted when analyzing the parameters.

4.2 IMPLEMENTATION

Since the constructing elements of the simulated system are already decided and in accord with the conceptual model, the implementation phase containing all the aforementioned components is the following step for insights generation. Not only limited to, but mainly the aspects to be analyzed consist of the output generated by the system and the evolution of the input parameters, along with aggregated data.

This means that mainly the implementation phase is responsible for analyzing the resulting values of several runs of the system and the average behavior of the components and outputs. Typical examples of analyzed factors include, for instance, the performance indicators for each company according to the temperament assigned, how many companies went bankrupt during the run, total production cost in each four-month period, yearly assets, differences between vending prices and how it affects the SC manager budget for the period and so on.

Another important feature to be elucidated is that, unless stated the contrary, the results shown from this point forward are the outcome of either the mode or the mean of 7 different and independent simulation runs, all instances being composed of 100 companies, being roughly 10% of them managed by an agent of stubborn temperament, whilst 30% are managed by agents which the temperament was previously determined as proactive.

Naturally, the 60% left of the 100 MEs are managed by agents with reactive temperament. No ME went bankrupt during the simulation runs, which took an average of 7 minutes with the aforementioned computer configuration. It is important to note that the values presented for the simulation runs are all based on official reports of the Apparel Cluster of Pernambuco (IEMI, 2017; SEBRAE, 2013).

Whenever the graph shows the mean value of the population, this approach was chosen because the focus is not on the individual behavior, rather it is constructed this way in order to facilitate the understanding of a general trend. Whenever the agent is chosen randomly to be plotted in the graphs, this happens because the behavior stays the same regardless of their temperament. The same applies to the mean value for each temperament, because no significant change was visible within groups among agents.

For the other parameters, the range of initial assets goes from R$ 45,000.00 to R$ 60,000.00, the investment range in SC actions goes from R$ 290.00 to R$ 1,800.00, the budget that goes to the SC manager comprises of 50% of the four-month period available financial assets, which is in turn 30% of the final profit from the previous four-month period, and the demand fog has a mean that varies from 5 to 23 and standard deviation of 3 units, applied onto a time series composed of three seasons, the first one ranging from a total of 90,000 to 210,000 demanded units, the second season going from 200,000 to 300,000 units and the last season stretching from 85,000 to 140,000 units.

Regarding to unit values, all monetary Illustrations are expressed in BRL or R$ (Real). In the context of the simulation runs, the base cost ranges from R$ 18.00 to R$ 21.00, whilst the not servicing cost ranges from R$ 1.00 to R$ 1.50, the excess stock cost ranges from R$ 5.50 to R$ 7.50 and the vending price ranges from R$ 48.00 to R$ 53.00. The same disclaimer regarding the currency of the money is also valid both for action investment costs, margin cost of the actions and margin revenue of the actions. Penalties, both minimum and maximum features, as well as the minimum investment cost and maximum investment cost for each action can be found in Table 3.

Table 3 - Value constraints and features for one typical simulation run

Action	**Min investment (R$)**	**Max investment (R$)**	**Margin cost (R$)**	**Margin revenue (R$)**	**Penalty (feature for simulation purposes)**	**Minimum (feature for simulation purposes)**	**Maximum (feature for simulation purposes)**
1	358	1223	1.00	3.00	2.00	-1.00	-2.00
2	304	289	1.35	3.70	-4.00	5.00	9.00
3	337	457	1.09	3.17	-5.00	4.00	7.00
4	458	1664	1.42	3.84	0.00	-2.00	-3.00
5	367	1330	1.46	3.92	0.00	-1.00	-2.00
6	345	1747	0.83	2.66	0.95	1.00	1.05
7	382	1798	1.17	3.34	--	--	--
8	373	747	1.42	3.85	1.00	0.80	0.50

9	477	1010	1.19	3.37	1.00	-3.00	-5.00
10	488	1435	1.12	3.24	0.00	3.00	4.00
11	376	1755	1.47	3.94	3.00	-1.00	-3.00
12	323	1455	1.12	3.23	1.50	-1.00	-1.50
13	352	527	1.27	3.55	0.90	1.10	1.20
14	309	1372	1.20	3.40	1.00	1.05	1.15
15	374	802	0.87	2.74	0.90	1.00	1.10

Source: The author (2020)

It is also important to notice the fact that companies start the simulation with different amount of financial assets due to a random generation code for the first four-month period. This is necessary for creating a more realistic scenario, provided no company start out equal to other companies, although the range is not wide enough so to create disparities that damage the analysis.

From the information available of the simulation runs, it is possible to extract insights regarding the relationship of the parameters and their outcome. This is to say that the type of information available by assessing the graphs and results of the system relate to synergy and interaction between parameters, system components and their possible relationship outcomes, excluding any reference to forecast or any sort of prediction.

The constraints to these insights are mostly present due to the type of perspective of the system, which is a macro perspective and not micro perspective. This is to say that managerial outcomes focus on how the pieces of the system relate to each other – how major behavior trends appear, the role of certain factors and so on – but not on the specifics of each piece, such as the number of months a company may wait until changing strategy, for instance.

Taking into consideration the synergy aspect rather than the forecasting aspect of simulation, the elements scrutinized in this system are related to the initial assets of the MEs, temperaments, reinvestment rate in SCM, demand forecast capacity, production capacity, not servicing cost, excess stock cost, marginal cost of each action, production cost and market share. They represent the general themes of factors that were either impactful in the simulation or of no impact at all.

For the simulation elements that have proven either not affected or irrelevant for the model are the marginal cost of each action, base production cost and market share percent. This might happen because all three factors affect all companies the same way, so it does not present an element of chaos in the system.

Another reason for these elements demonstrates null impact on the system may be related to the fact that the range of each variable be insufficient for them to play a relevant role in the model. Therefore, these features only continued being part of the system because they do not pose any disturbance to results and can have values modified in future works.

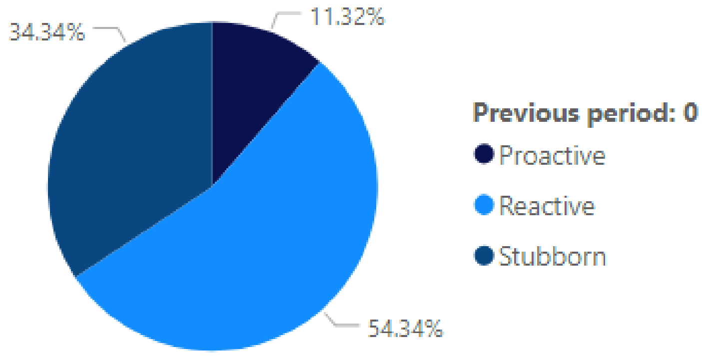
It is important to notice that the temperaments are not responsible for costs nor profits as well. Consequently, the investment strategies in each Pillars are not responsible for neither of the values. Thus, the profit in the long run for the MEs is determined by surrounding macro factors, such as the number of competitors, real demand. This is corroborated by the real reports regarding the Apparel Cluster of Pernambuco (IEMI, 2017; SEBRAE, 2013).

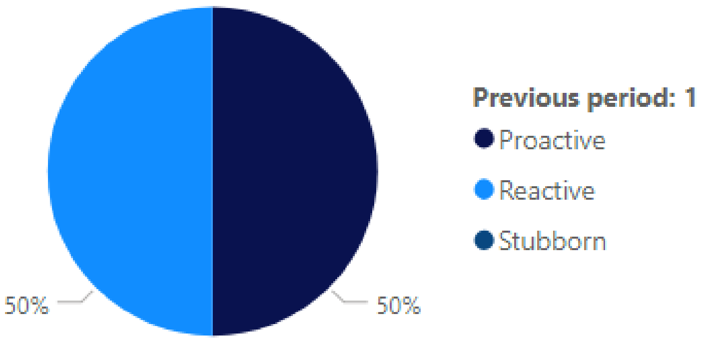
The results that the CSAR model is a good fit for representing the ABM model of the Apparel Cluster of Pernambuco, because the representation of the external factors are taken into consideration in the SCS scheme of the company, although it is outside of the reach of the SC manager and only affects the company either indirectly or as direct boundaries. Some of these real factors are not represented in the current model, such as brand image, customer perception of the reputation, but are represented by some other macro factors, such as number of competitors and tax rates.

4.2.1 Initial assets

Beginning by the most visible aspect of the simulation, Graph 54 displays how distributed the four-month period classification for each temperament was during the entire simulation. It is important to reinforce the idea that the classification is binary, and 0 indicates that the previous four-month period was understood as not satisfactory by the AI of the company, provided the four indicators are taken into consideration for this assessment, whereas 1 indicates that the previous period was deemed satisfactory by the ME.

Graph 54 – Pie charts displaying the percentage of classification as 0 or 1 by all temperaments throughout the entire simulation run

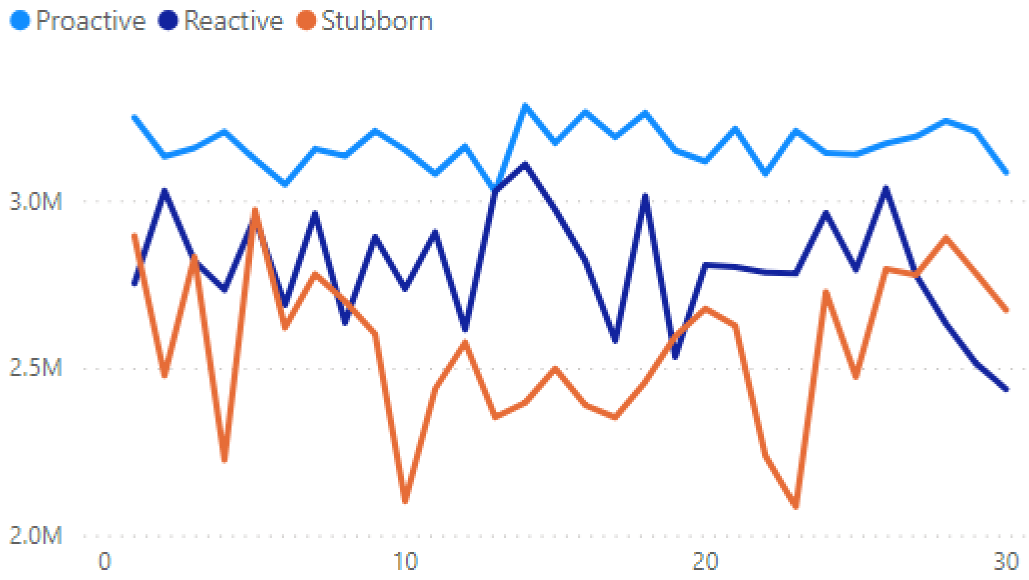




Source: The author (2020)

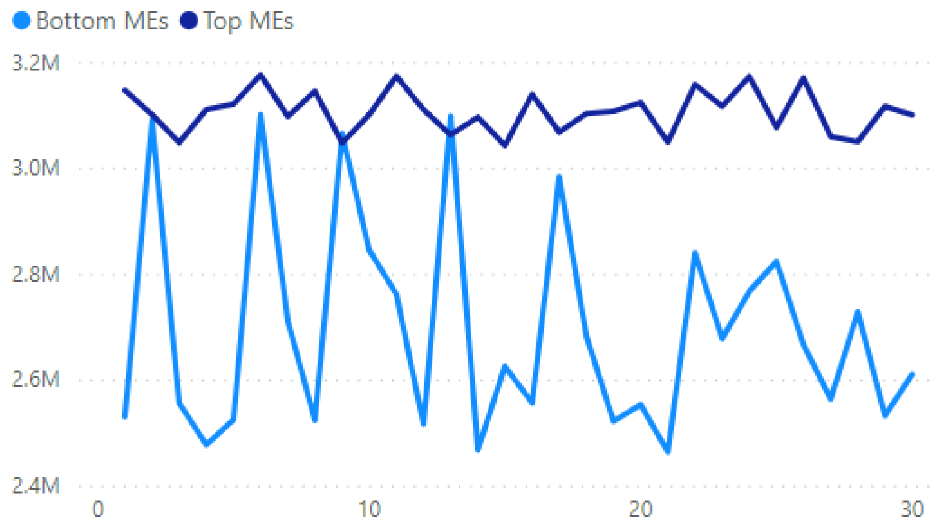
Another feature that can be observed in evolution during the simulated 30 years period is the financial assets of the company throughout the simulation, as shown in Graph 55 and Graph 56. For this component, Graph 55 shows the mean values for each temperament, whereas Graph 56 shows the mean values for the 20% wealthiest companies, the 20% least wealthy companies.

Graph 55 – Mean assets value in R$ for each temperament throughout the years



Source: The author (2020)

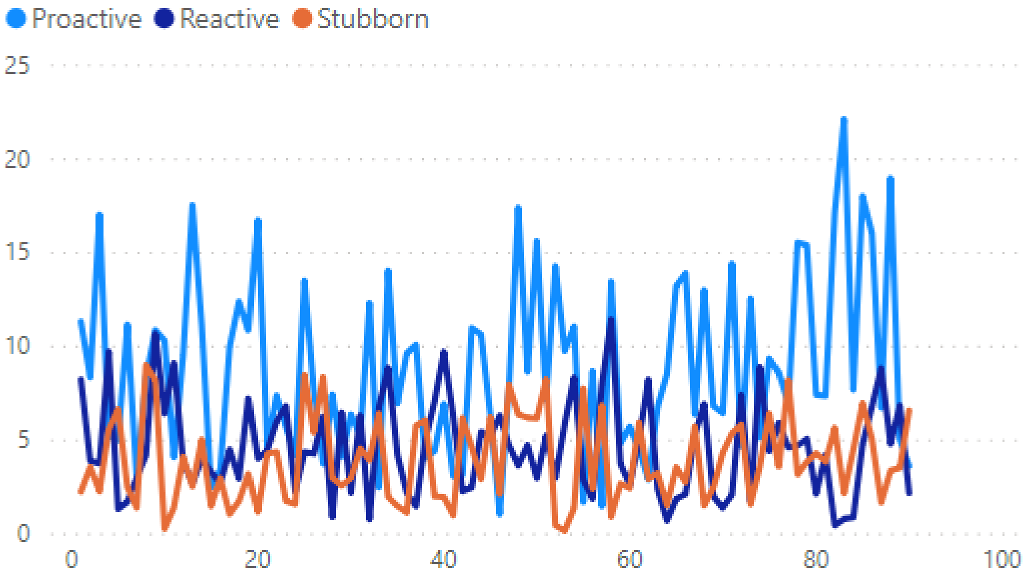
Graph 56 – Mean initial assets value for top 20% wealthiest and bottom 20% MEs aggregating all temperaments throughout the years



Source: The author (2020)

The simulation runs allows for the observation of the correlation between the company's assessment of the previous four-month period and how much it affects the financial aspect of the company. Thus, it is possible not only to understand whether there is a direct link between company's financial success and the evaluation of whether the last four-month period was considered successful or not by the SC manager, but it also allows for the measurement of whether the SC manager's assessment itself is accurate, provided it is worse for the company to lose money than to profit less than in the previous four-month period. Graph 57 shows one of the instances of the evolution of one SC manager of each temperament and their indicator TW for all four-month periods.

Graph 57 – Evolution of indicator TW for one company of each temperament chosen at random



Source: The author (2020)

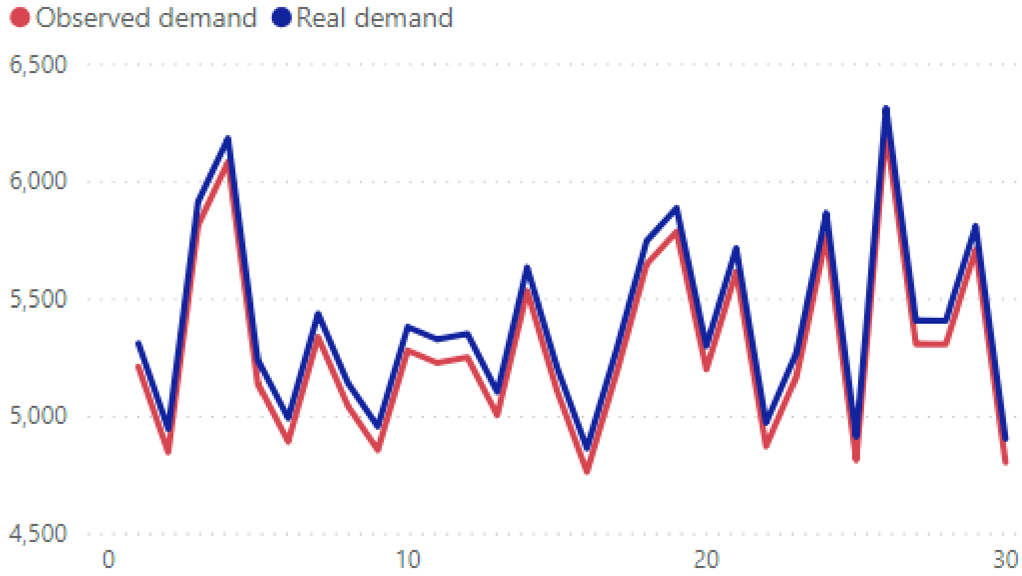
Graph 56 helps understanding that companies that start the simulation among the wealthiest tend to fluctuate less throughout the years and also tend to keep being part of the wealthiest companies up until the end. On the other hand, companies that start on the bottom in relation to the initial resources for investment might get close to the top initial wealthy companies, but they also fluctuate more and tend to lose more resources.

In regards to the role of the temperament in some features, it is possible to see that proactive managers tend to present positive variations more frequently than the other two types of temperaments for managers, as it is visible in Graph 57, when it comes to wealth gain throughout the years. This happens in spite of how careful and conservative the companies tend to be, as it is also visible in Graph 54, for proactive managers tend to classify last period as negative less frequently than stubborn or reactive managers do.

4.2.2 Demand forecast capacity

Indirectly, the total production cost is influenced by the demand forecast capacity, because the budget assigned for investment in forecasting improvement actions is determined by how much is financially available from the previous four-month period, which is in turn dependent on producing correct quantities of items. Graph 58 demonstrates the relationship between actual demand for one ME chosen at random and its forecast capacity.

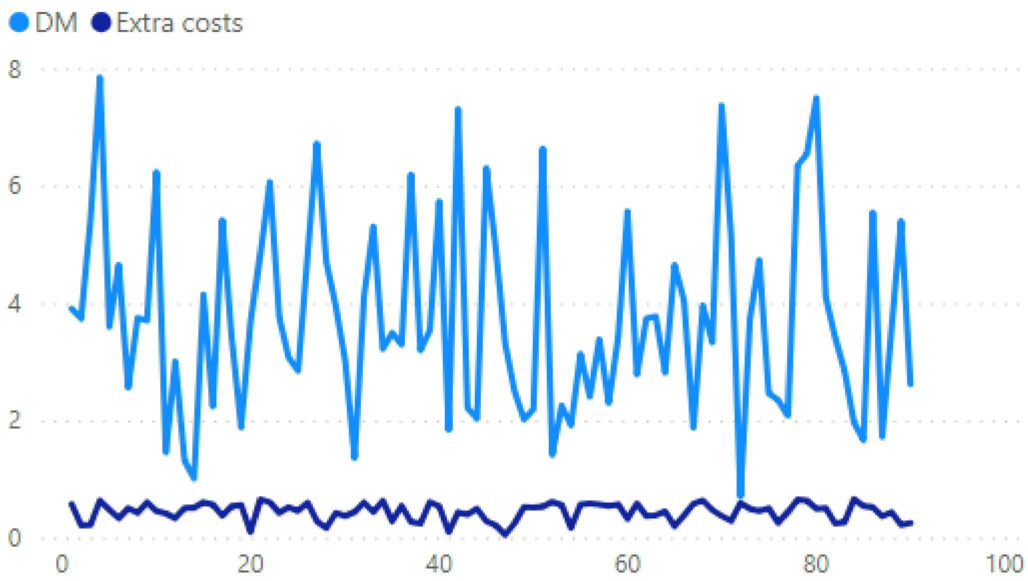
Graph 58 – Real demand and observed demand of item units for a randomly chosen of reactive temperament ME throughout the years



Source: The author (2020)

It is possible also to analyze the correlation between costs other than the production cost, namely not servicing and excess stock cost, and the increase or decrease of real demand for the company, regardless of how much of market share the ME possesses. Thus, Graph 59 shows the indicator DM compared with the mean sum of excess stock cost and not servicing cost for the mean of Stubborn ME agents, provided they have the highest mean sum of these types of costs of the three temperaments.

Graph 59 – Indicator DM being compared to the mean sum of excess stock cost and not servicing cost per unit in R$ for the average of all Stubborn ME agents



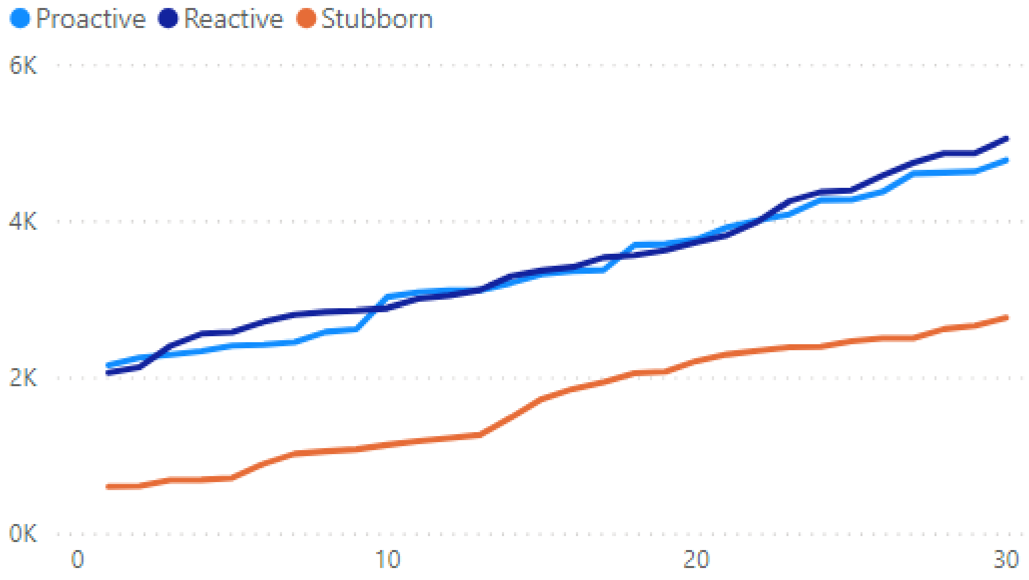
Source: The author (2020)

It is visible that the demand forecast capacity of the companies is really close to the real demand regardless of how much the SCM of the ME invested in actions that would decrease the demand visibility fog in Graph 58. It is also visible that there is a clear connection between indicator DM with high values and low extra costs in the past period, according to Graph 59. Therefore, it corroborates the official real reports regarding the Apparel Cluster of Pernambuco, provided MEs tend not to have any difficulties towards forecasting their demand.

4.2.3 Production capacity

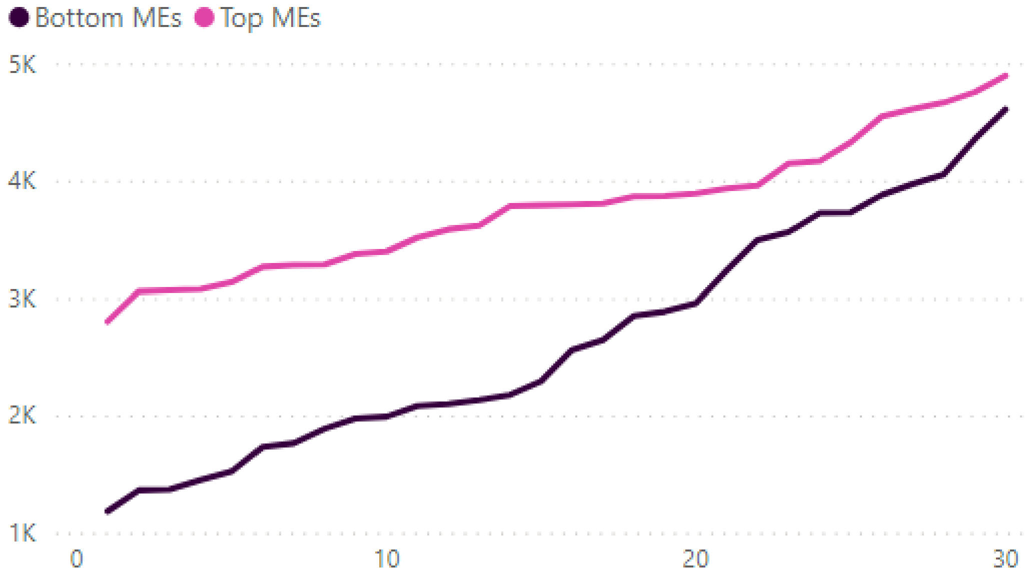
The production capacity of the ME is also a key point for determining whether the company is successful in servicing the current demand. Graph 60 shows the average yearly production capacity for one company of each temperament, whilst Graph 61 brings information of the average production capacity of the initial 20% wealthiest companies in comparison with the least wealthy 20% companies.

Graph 60 – Average production capacity in units for each temperament throughout the years



Source: The author (2020)

Graph 61 – Average production capacity in units for top 20% wealthier and bottom 20% MEs aggregating all temperaments throughout the years



Source: The author (2020)

Since production capacity and the not servicing cost due to poor demand forecast are responsible for letting part of the demand unattended, it is necessary to analyze their relationship and to assess the influence of these two aspects in the overall performance of the company, referring to serviceability and financial assets available for reinvestment in the SCM.

Proactive managers have shown to have a slightly greater capacity of growth than the other two types of temperaments, as displayed in Graph 60. This happens despite the fact that all temperaments show a positive slope in this feature, although stubborn behavior shown to be the temperament with the lesser growth capacity out of the three temperament.

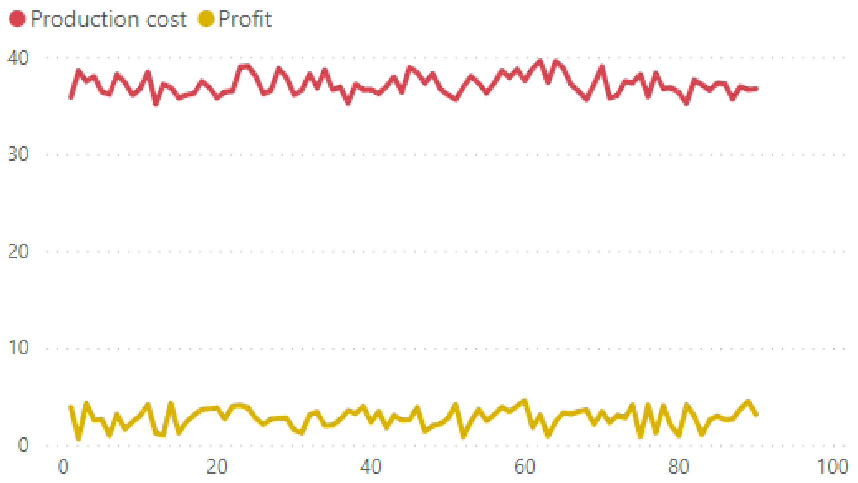
Reactive managers have shown to be the best performance in situations where less seasonal and random variations occur. This can be inferred from the fact that throughout the year – composed of three periods with different demand variations – reactive managers tend to be punished more in their production capacity than in the aggregated scenario shown in Graph 60, displayed annually instead of in smaller periods.

So, in the long run, reactive managers perform better than stubborn managers, but within each year, reactive managers are punished more than stubborn managers. There is compensation in more stable periods of the year for the reactive managers than there is for the stubborn managers, regarding production capacity and the punishment applied onto them via difference of real demand and forecasted demand.

4.2.4 Not servicing cost and excess stock cost

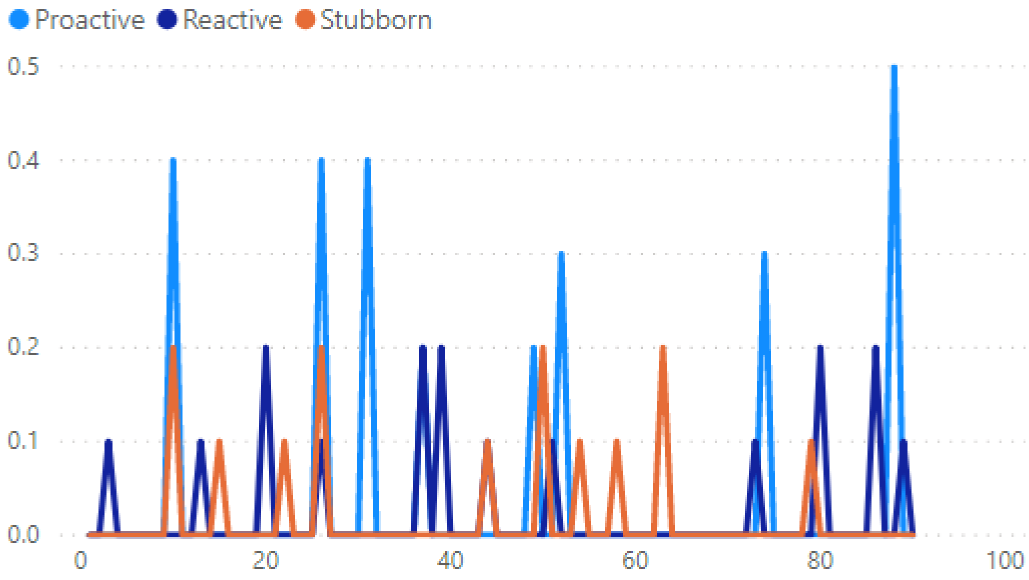
Other types of costs that can be scrutinized in comparison to other parameters are the excess stock cost and the not servicing cost. Graphs 62, 63 and 64 bring information about the excess stock cost and not servicing cost for the MEs. In Graph 62, the average profit and the production cost variation per produced unit of all MEs is shown, whilst in Graph 63 the excess stock cost is being exhibited. In Graph 64, it shows the not servicing cost.

Graph 62 – Average of profit per unit and production cost per unit in R$ for all MEs



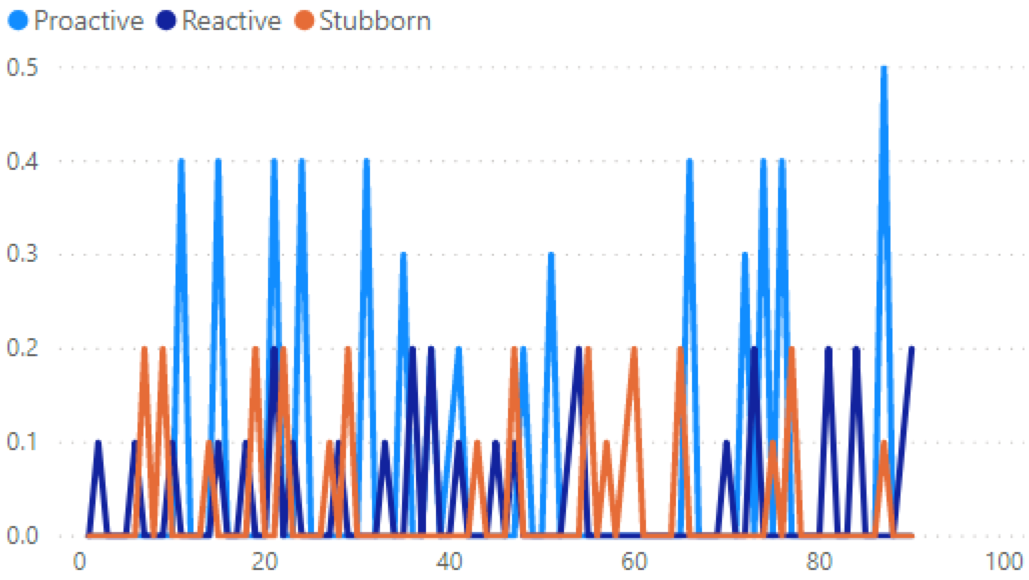
Source: The author (2020)

Graph 63 – Excess stock cost per unit in R$ of 3 randomly chosen MEs representing the different temperaments



Source: The author (2020)

Graph 64 – Not servicing cost per unit in R$ of 3 randomly chosen MEs representing the different temperaments



Source: The author (2020)

The way the system is designed puts emphasis on the capacity of the SC manager to forecast in a proper manner the demand assigned to the ME. Thus, both excess stock cost and not servicing cost are directly influenced by the quality of the judgement of the SC manager.

It is possible to see that proactive managers have a slightly lesser accurate capacity than the other two types of temperaments, as shown in Graphs 63 and 64. Stubborn managers usually are punished with both not servicing cost and excess stock cost at a rate closer to the proactive managers than to reactive managers. At the same time, reactive managers tend to be punished the most among the three types, when it comes to excess stock costs.

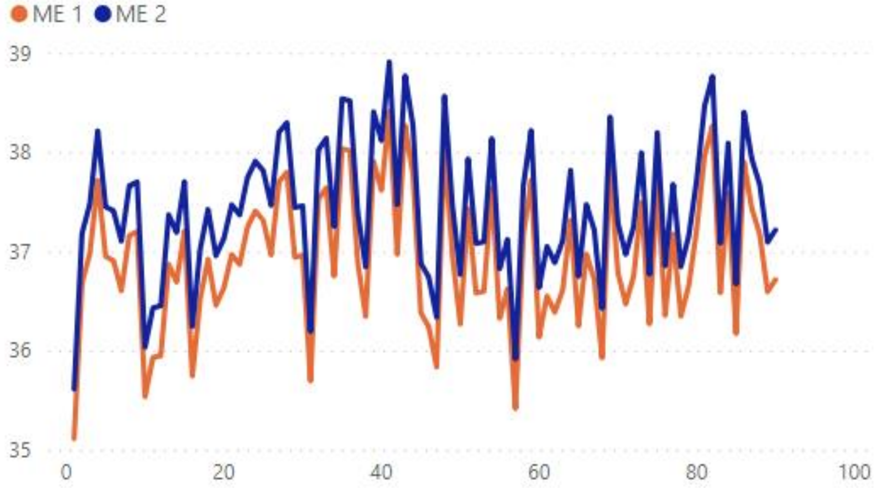
This might happen due to the fact that producing more than what is needed can only happen when the forecast demand is poorly executed and the information of the real demand differs too much from the real demand. On the other hand, not servicing cost punishment depends on two factors instead of just one: a company has to either forecast poorly and produce less than what the market demands, or the company might forecast properly but its production capacity is less than what it aims to produce.

The results in Graph 62 show the difference between the production cost and the profit after taxes are taken into consideration. It could have been expressed differently, as the difference between the revenue and the cost, and the profit would be the resulting difference between the two plotted lines throughout the periods. Nevertheless, this graph clearly shows that the costs are low enough to never compromise the income of the companies.

4.2.5 Production cost

The unit production cost can also be analyzed both taking into consideration the aggregated data of the companies and by comparing it to other parameters throughout the four-month periods. Provided the final vending cost of the item is composed of the base cost and the margin cost of the actions the ME's manager invested in that particular four-month period, there ought to be differences in these values from company to company, as shown in Graph 65, which displays any two companies of randomly chosen temperaments.

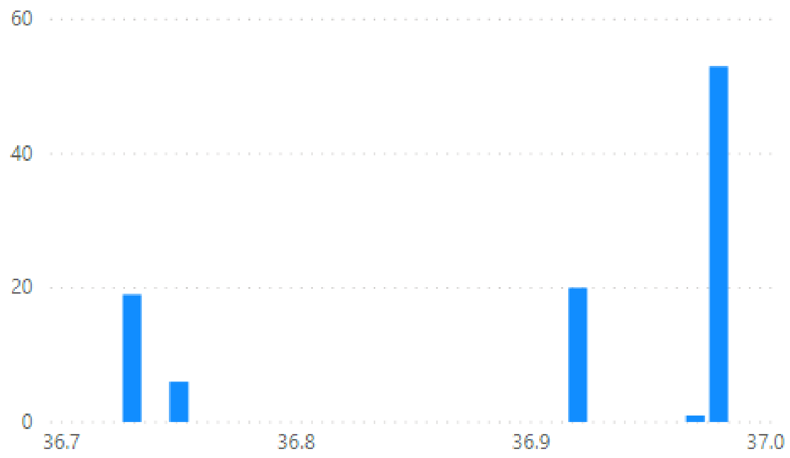
Graph 65 – Comparison of two randomly chosen MEs regarding their unit production cost in R$



Source: The author (2020)

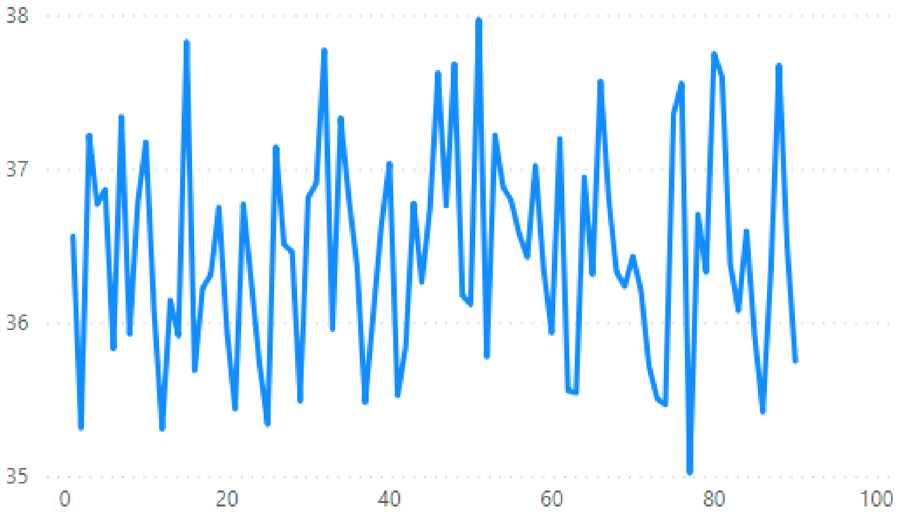
The change in these values over the years can be justified by the amount of money available for the SC manager, which is a direct consequence of the previous performance of the company. Graphs 66, 67, 68, 69 and 70 show comparisons for the production cost and other measurements, with Graph 66 displaying average production cost distribution, Graph 67 showing the production costs of a ME. Graph 68 bringing information on indicator EF, Graph 69 exhibiting a comparison between the mean unit production cost of the initial 20% most costly items MEs and 20% least costly ones, and Graph 70 providing information on the average of each temperament and their production cost unit.

Graph 66 – Distribution of MEs with average unit production cost in R$ for all four-month periods of each ME



Source: The author (2020)

Graph 67 – Unit production cost in R$ of a randomly chosen ME

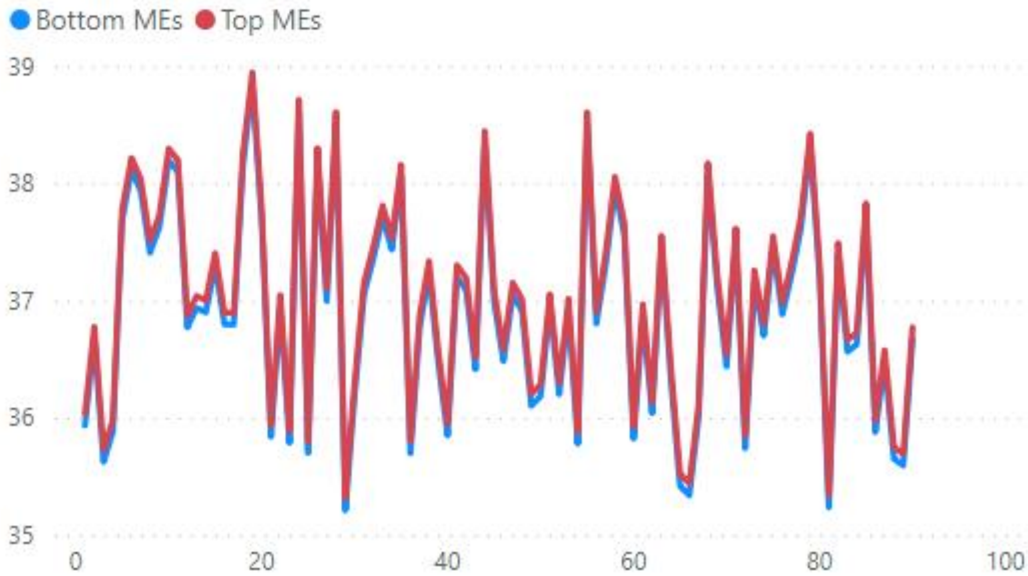


Source: The author (2020)

Graph 68 – Indicator EF of a randomly chosen ME throughout the four-month periods

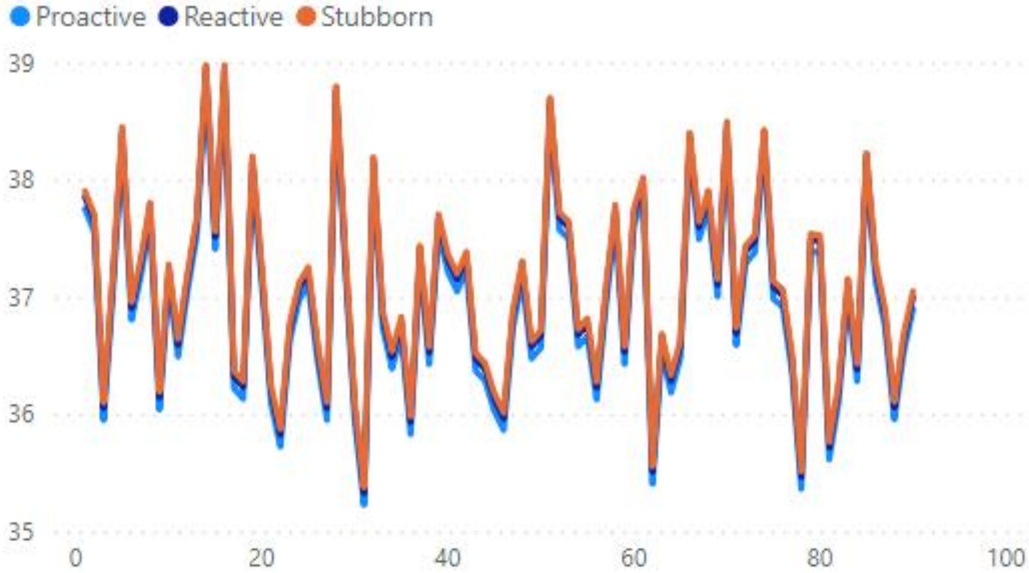
Source: The author (2020)

Graph 69 – Average of unit production cost in R$ for the 20% most costly items and 20% least costly items



Source: The author (2020)

Graph 70 – Average of unit production cost in R$ for each temperament



Source: The author (2020)

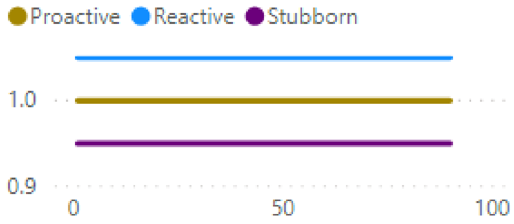
Another observation that can be inferred from the simulation is implied in Graph 65. It is visible that the unit cost of production is not meaningful to determine whether an ME goes bankrupt or not. There are possibly other factors that determine this situation. The difference in the prices exist, but they are proportional.

Graphs 67, 68, 69 and 70 corroborate the same type of information in different approaches when it comes to costs. It variates harmonically and are independent from any other factor, such as temperament, initial cost and so on. The magnitude of the different is at maximum R$ 3 in the interval.

4.2.6 Market share

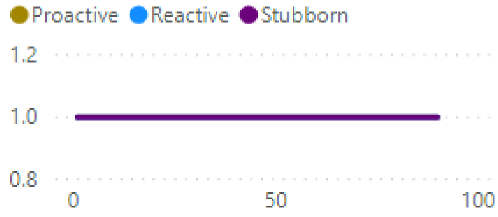
Since market share is directly linked to real demand, analyzing how the indicator MS behaves throughout the simulation for the companies is also an indirect form of analyzing the demand. Graph 71 shows the evolution of MEs chosen at random and their respective MS indicators. Graph 72 displays the same companies, but with the actual percentage of their market share, in a scenario where there were no bankrupt MEs.

Graph 71 – Market share distribution in percent for 3 randomly chosen MEs of each temperament



Source: The author (2020)

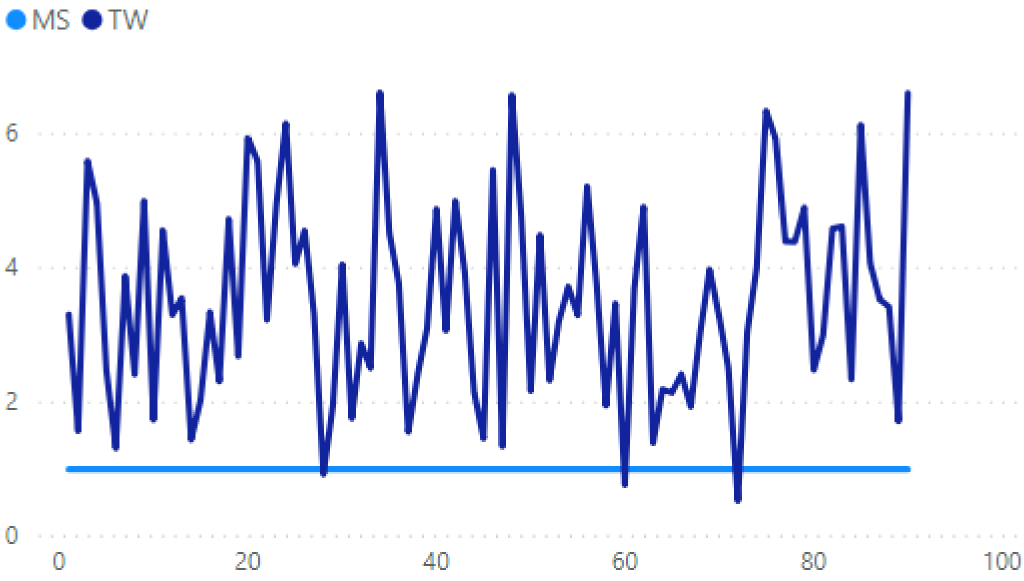
Graph 72 – Indicator MS for the same 3 randomly chosen MEs of each temperament



Source: The author (2020)

It is also interesting to analyze how is the relationship between the evolutions of the company's financial assets related to market share evolution. The justification for this analysis resides in the fact that a company may present any type of behavior for these two indicators regardless of its market size, provided their performance depend not only on their capacity for servicing their demand properly, but also how their competitors are performing during the same period, as shown in Graph 73, where indicators MS and TW are being compared for a randomly chosen ME.

Graph 73 – Indicators MS and TW being compared for a randomly chosen ME



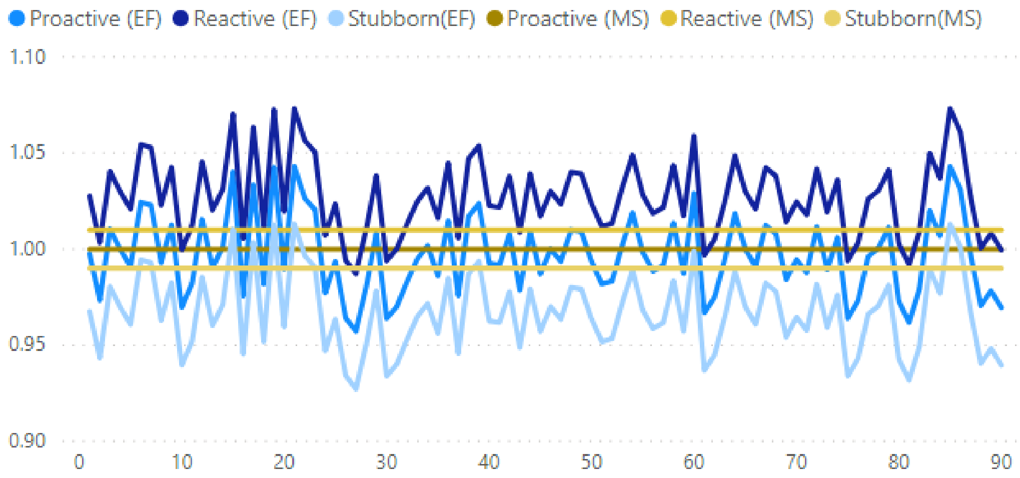
Source: The author (2020)

Of the four indicators used in the simulation, market share growth indicator has shown to be not significant, as can be seen in Graph 71, 72 and 73, where the indicator is compared to other parameters and variables and shows no sign of change in any of the situations. This also fits the description of the official reports about the Apparel Cluster of Pernambuco, because most MEs either loose competitive capacity and become small companies or grow to become large-sized companies after a long while, but barely go bankrupt or change size rapidly.

4.2.7 Temperaments

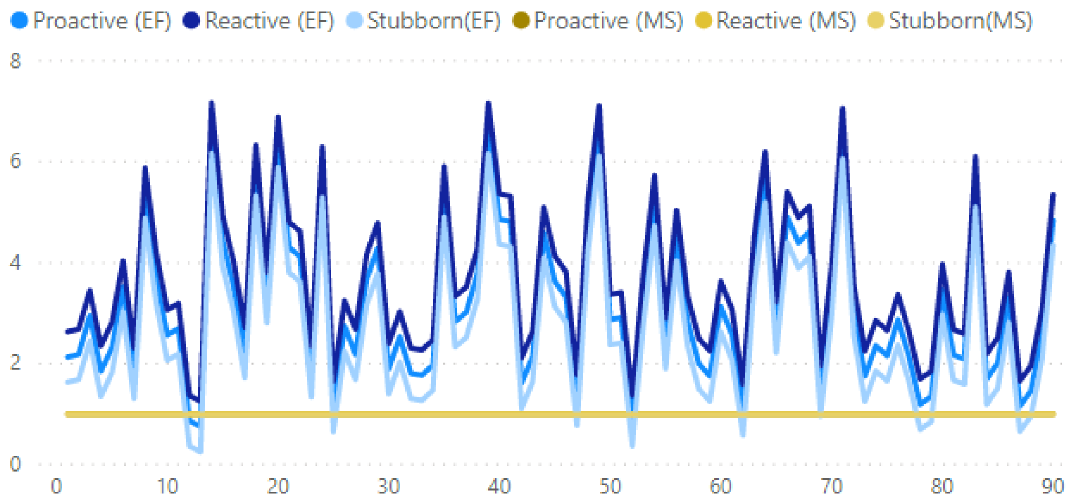
Comparing the three temperaments is also necessary in several different aspects. This type of analysis can be performed in the form of stratified random sample, so differences can be better scrutinized. Graph 74 shows randomly chosen MEs regarding their indicator EF and MS. Likewise, Graph 75 also brings the same information for the indicators DM and EF, whereas Graph 76 does the same for indicator TW in comparison with EF.

Graph 74 – Indicators MS and EF of one randomly chosen ME of each temperament



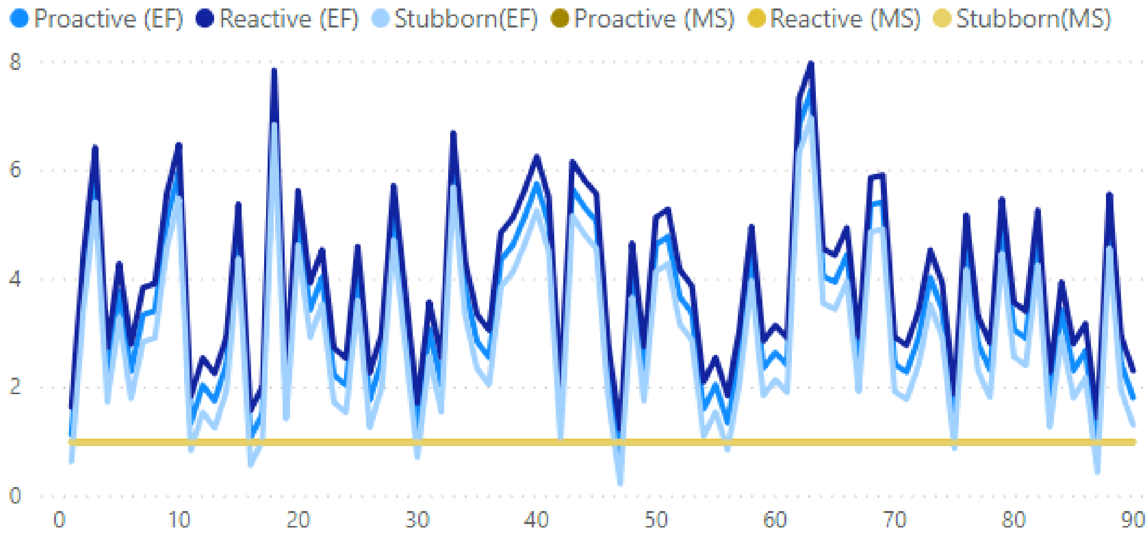
Source: The author (2020)

Graph 75 – Indicators DM and EF of one randomly chosen ME of each temperament



Source: The author (2020)

Graph 76 – Indicators TW and EF of one randomly chosen ME of each temperament



Source: The author (2020)

With all the results in Graphs 74, 75 and 76, it is possible for the decision-maker to see that there is in fact a considerable difference among temperaments. This, in turn, corroborates not only the validity of the *in silico* data used to train the ANN, but also the rules used in order to construct the whole simulated environment, when it comes to the temperaments.

5 CONCLUSION

This work helps clarify not only the decision-making process, choices and actions of a medium-sized enterprise manager from the supply chain department of the Apparel Cluster of Pernambuco, but it also facilitates the comprehension of how company personnel view obstacles and act upon them. And it does so by simulating the environment and the agents in a computational system that can be modified and adapted to suit any strata of decision-making power, industry sector and company size.

As for the limitations, simplicity can be cited regarding the Actions, that remained the same throughout the run for all the agents, the only difference being how much of the resources is going to be allocated in each of them. This is clearly different from reality, where ME supply chain managers could come up with different and newly ways of building up the SCS. However, this would challenge the *ceteris paribus* condition of the simulation and can be further experimented in another simulation environment as suggestion for future works.

It is also important to notice that, when implemented, the computational model was able to use CSAR methodology as basis for the structure of budget allocation and hierarchical order among actions and Pillars. However, the fact that the simulation only took into consideration two levels instead of Imperatives, Principles and Policies/Choices, that were collapsed all into Actions, was a simplification that may be addressed for improvement in future works. Each step from one level to another could be interpreted as a rule-based algorithmic decision and programmed as so.

Managerially, considering the CSAR as the only theoretical structure of this work can be viewed as a challenge, due to the fact that this methodology is from an academic background and has only been applied in large companies. The concepts and elements that compose CSAR are still not well known by most managers of small and medium-sized enterprises worldwide. This can either be solved by incorporating different and simpler theoretical elements into the simulation or raising awareness in the marketplace regarding the CSAR.

Future implementations regarding actions may also apply to some degree of memory of the agents. This is to say that, in the current state of the system, it is not possible for the agent to formulate a different strategy of what it was assigned in the setup phase of the simulation. A possible way for implementing this modification is to analyze which actions received more investment throughout the four-month periods and then act upon this new knowledge. Agents acting regardless of which actions are neglected the most is certainly a limitation that can be eliminated with further development of the source code.

As for further developments of this very system, it is possible for the simulated environment incorporate not only the element of memory of the intelligent agents, but also take into consideration the possibility of embedding small-sized enterprises or large companies as competitors, with more than one type of goods being sold in the marketplace.

Also, implementing different features other than revenue to classify a company regarding its size, such as the number of personnel employed by the company. This would widen both the comprehension of the Apparel Cluster of Pernambuco and also the possibilities for adaptation of this system to represent other real environments.

Another limitation of the model is the fact that programming new actions and new temperaments makes the computational cost grow exponentially. It is not a simple parameter such as vending price, number of agents or number of four-month periods in the simulation. This is true because both components of the computational model must be entered manually. It means that the actions have to be thought through considering its rewards, punishments and realm of activities, such as costs, budget allocation, demand visibility or a combination of other factors. Parallel to that, temperaments demand ANN training, which in turn demand normalized data derived from either real historical data or *in silico* generated data.

Regarding the indicators utilized throughout the simulation, MS has proven to be of no significant use, since it has not been modified throughout the four-month periods not even in the sensitivity analysis phase for any company selected. This is true even in the simulation runs where bankruptcies happened, because the MEs that undergone this process happened to do so in the initial phases of the simulation, not changing the market share of the remaining MEs during the rest of the four-month periods. Future improvements may also remove this indicator from the AI aspect of the ABM and either implement another indicator or yield the indicators to the remaining three.

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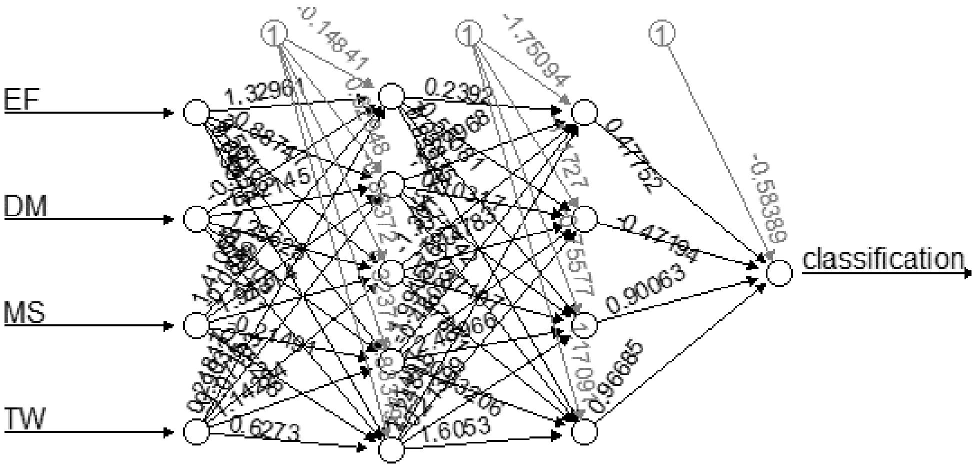
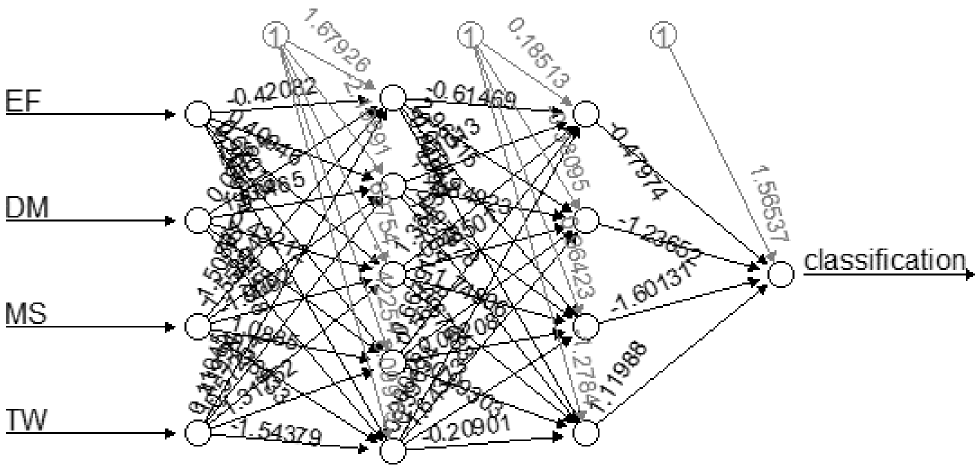
APPENDIX A – ANN of the model



Error: 0.008949 Steps: 157

PROACTIVE ARTIFICIAL NEURAL NETWORK MODEL

#---



Error: 0.01139 Steps: 898

REACTIVE ARTIFICIAL NEURAL NETWORK MODEL

APPENDIX B – ABM tables examples

Allocation table example in R

	min	max	margin.C	margin.R	feature.penalty	feature.min	feature.max
1	358	1223	1.00	3.00	2.00	-1.00	-2.00
2	304	289	1.35	3.70	-4.00	5.00	9.00
3	337	457	1.09	3.17	-5.00	4.00	7.00
4	458	1664	1.42	3.84	0.00	-2.00	-3.00
5	367	1330	1.46	3.92	0.00	-1.00	-2.00
6	345	1747	0.83	2.66	0.95	1.00	1.05
7	382	1798	1.17	3.34	NA	NA	NA
8	373	747	1.42	3.85	1.00	0.80	0.50
9	477	1010	1.19	3.37	1.00	-3.00	-5.00
10	488	1435	1.12	3.24	0.00	3.00	4.00
11	376	1755	1.47	3.94	3.00	-1.00	-3.00
12	323	1455	1.12	3.23	1.50	-1.00	-1.50
13	352	527	1.27	3.55	0.90	1.10	1.20
14	309	1372	1.20	3.40	1.00	1.05	1.15
15	374	802	0.87	2.74	0.95	1.00	1.05

Environment constraints table example in R

	base.cost	not.servicing.cost	excess.stock.cost	vending.price	demand.fog
1	20	1.3	6.1	48	12
2	19	1.2	6.9	48	13
3	21	1.3	6.0	49	17
4	21	1.2	6.7	52	9
5	18	1.1	6.5	52	15
6	20	1.4	6.0	53	14
7	21	1.0	6.6	50	15
8	20	1.2	7.3	48	20
9	19	1.3	7.3	51	13
10	21	1.3	6.0	52	21
11	19	1.2	6.1	49	17
12	20	1.2	7.5	50	17
13	20	1.5	6.7	49	19
14	18	1.2	7.4	48	13
15	21	1.4	6.4	50	13
16	19	1.5	6.3	48	13
17	18	1.3	6.8	49	17
18	19	1.2	5.8	48	13
19	21	1.1	6.6	51	11

Temperament table example in R

	temperament	bad.LP	bad.CRM	bad.FP	good.LP	good.CRM	good.FP
1	PROACTIVE	0.2	0.25	0.45	0.35	0.40	0.25
2	REACTIVE	0.5	0.35	0.15	0.65	0.25	0.10
3	STUBBORN	0.5	0.30	0.20	0.50	0.30	0.20

APPENDIX C – Pseudocode of the ABM in R

#libraries for execution

#declaring number of agents, quarters for simulation, epoch numbers,

#supply chain manager budget percent share and supporting vectors and data frames

#creating a normalisation function

norm <- function(x){

  return(value)

}

#artificial neural network---

#--

#--

#training the proactive temperament--

#generating efficiency data frame with 1000 values within a proper range

proEF0

proEF1

#generating demand data frame with 1000 values within a proper range

proDM0

proDM1

#generating market share data frame with 1000 values within a proper range

proMS0

proMS1

#generating total wealth data frame with 1000 values within a proper range

proTW0

proTW1

#binding and classifying results for each data set

proEF <- bind(proEF0,proEF1)

```
proDM <- bind(proDM0,proDM1)
proMS <- bind(proMS0,proMS1)
proTW <- bind(proTW0,proTW1)
#normalising data set values
proEF <- norm(proEF)
proDM <- norm(proDM)
proMS <- norm(proMS)
proTW <- norm(proTW)
#creating the ANN model for proactive temperament
model.temperament.proactive <- neuralnet(classification ~
                                 EF + DM + MS + TW, train.proactive,hidden=c(5,4))
#training the reactive temperament (same proccess as before with different value
range)-----



#agent-based model-----------------------------------------------------------
#---------------------------------------------------------------------------
#---------------------------------------------------------------------------
#finances table--------------------------------------------------------------
finances.table <- data.frame(agents,batch.size,total.revenue,total.cost,total.balance)
#scenario table--------------------------------------------------------------
#data frame containing how each temperament reacts according to each scenario
scenario <- data.frame(temperament,bad.LP,bad.CRM,bad.FP,good.LP,good.CRM,good.FP)
#time series function----------------------------------------
set.series <- function(series){
       series <- functions(seasons)
  return(series)
}
```

```
#environment constraints table function----------------------------------------------------
set.env.table <- function(env.table){
  #since it will have 90 ticks, it generates 89 due to the first one already existing
  env.table <-
functions(base.cost,not.servicing.cost,excess.stock.cost,vending.price,demand.fog)
  return(env.table)
}
#allocation table--------------------------------------------------------------
#every turn, new values are generated for this table (except for features)
alloc.table <-
data.frame(min,max,margin.C,margin.P,feature.penalty,feature.min,feature.max)
#PL
a1 <- vector(value1,value2,value3) #warehouse reformulation (housekeeping)
a2 <- vector(value1,value2,value3) #equipment preventive maintenance
a3 <- vector(value1,value2,value3) #finding bottlenecks and balancing production
a4 <- vector(value1,value2,value3) #logistics consultant for the period
a5 <- vector(value1,value2,value3) #production consultant for the period
#CRM
a6 <- vector(value1,value2,value3) #software for demand forecast (customer request)
a7 <- vector(value1,value2,value3) #customer complaint to production
a8 <- vector(value1,value2,value3) #batch discount for the customer
a9 <- vector(value1,value2,value3) #loyalty program season
a10 <- vector(value1,value2,value3) #local media ads
#FP
a11 <- vector(value1,value2,value3) #cost rating system reformulation
a12 <- vector(value1,value2,value3) #discount bargaining w/ suppliers
a13 <- vector(value1,value2,value3) #budget for the SC manager
a14 <- vector(value1,value2,value3) #finance consultant for the period
a15 <- vector(value1,value2,value3) #bargaining debts with suppliers
```

```
#action modification per round function
alloc.round <- function(feature.table){
  feature.table <- functions(values)
  a.table <- feature.table
  return(a.table)
}
#creating agents data set-------------------------------------------------------
agents <- data.frame(id,temperament,prevTick,prevUnitCost,prevAssets,prevRealDemand,
                     prevObsDemand,prevMarketShare,prevEF,prevDM,prevMS,prevTW,

          budgetSCM,prodCap,realDemand,obsDemand,pctLP,pctCRM,pctFP,realProd,
                     unitCost,assets,marketShare,EF,DM,MS,TW,classification)
#first tick function-----------------------------------------------------------------
firstTick <- function(){
  var1 <- function(value) # defining the temperament
  var3 <- function(value) #range of initial unit cost
  var4 <- function(value) #range of initial assets
  var5 <- function(value) #range of initial demand
  var6 <- function(value) #observed previous demand
  var7 <- function(value) #initial market share
  var8 <- function(value) #uniform dist for previous EF
  var9 <- function(value) #unif dist for previous DM
  var10 <- function(value) #uniform dist for previous MS
  var11 <- function(value) #uniform dist for previous TW
  var12 <- function(value) # budget for SCM manager (10%)
  var13 <- function(value) #range of initial prod capacity
  var15 <- function(value) #observed demand
  #has to be calculated properly for the next ticks
  var16 <- function(value) #$ invested in pillar 1
```

```
  var17 <- function(value) #$ invested in pillar 2
  var18 <- function(value) #$ invested in pillar 3
  var19 <- ifelse(function(value))
  #has to be calculated properly for the next ticks
  var20 <- function(value) #range of current unit cost
  var21 <- function(value) #range of current assets
  var22 <- function(value) #current market share (all the same)
  #previous tick according to temperament (stubborn always considers it bad)
  var2 <- function(value)
        df$temperament <- function(var2)
  #data frame containing all variables generated for the first tick
  df <- var1,var2,var3,...,var22
  return(df)
 }
 #forced generated values for first tick (could be PENALTY, MIN, INTERMEDIATE
or MAX in status)
 set.first.alloc.tick <- function(){
  at <- data.frame(agent,a1,a2,a3,...,a15,marketShare.status)
  return(at)
 }
 #how the environment limitations will change for each agent each tick----------
 set.first.environment.tick <- function(){
        #random function values
  et <-
data.frame(agent,base.cost,not.servicing.cost,excess.stock.cost,vending.price,demand.fog)
  return(et)
 }
 #allocation rule function (action 2)-------------------------------------------
 #takes into consideration: alloc.tick, alloc.table and agents
```

```
m.share <- function(){
  #distribution rule------
  #step 1: counting how much is going to be available (5% of sum of penalized)
  #step 2: counting how many agents are in this situation
  #step 3: decreasing all penalized market share by the same order
  #step 4: counting how many max investors there are
  #step 5: distributing the amount taken in step 3 for max investors
  #step 6: counting how many intermediate investors there are
  #step 7: distributing the amount remaining for intermediate investors
  #step 8: counting how many min investors there are
  #step 9: distributing the amount remaining for min investors
  #return the new market share column
  return()
}
#market share adjustment for bankrupt agents---------------------------------------
m.share.bankrupt <- function(){
  #checking if the whole used market is 100% or if someone went bankrupt
  #if yes: proceed to return
  #if no: redistribute equally the remaining market
  #return the new market share column
  return()
}
#adjusting the first ticks demand according to market share-------------------------
realDemand.firstTick <- function(){
  return()
}
#adjusting visibility (fog) for first tick---------------------------------------
obsDemand.firstTick <- function(){
```

```
  #demand fog, real demand
  #how much was invested in action 1 (interacts with fog value)
  #whether the investment was min, max, intermediate or penalty
  #min for this round on this action, max for this round on this action and features for this action
  for(i in 1:population){
    #values for selection
    #attributing the correct value for the demand fog according to investment
    #either turning it to negative or positive (randomly)
  }
  #finally generating the proper observed demand for each agent and filtering for negative values
  observed.demand <- ifelse(value,0)
  return(observed.demand)
 }
 #adjusting indicators -----------------------------------------------------------
 #EF indicator adjusting function
 EF.tick <- function(){
  var23 <- function(var3,var20) #current efficiency indicator
  return(var23)
 }
 #the same applies for the other indicators and classification and their respective vars
 #setup function--------------------------------------------------------------------
 #first tick
 setup <- function(){
  #executing all the previous functions in each of the components of a list which will contain all values
  return(abm)
 }
```

```
#all set for the first tick---------------------------------------------------------
#creating a list containing all elements
abm.list <- list()
abm.list <- setup(abm.list)
agents <- abm.list[[1]]
time.series <- abm.list[[2]]
environment.table <- abm.list[[3]]
alloc.table <- abm.list[[4]]
alloc.tick <- abm.list[[5]]
environment.tick <- abm.list[[8]]
#following ticks----------------------------------------------------------------------
#--------------------------------------------------------------------------------------
#--------------------------------------------------------------------------------------
#pillars distribution phase-----------------------------------------------------------
#assigning assets to percent for each pillar
pillars <- function(agents){
        #for loop depending on performance and temperament
  return(agents)
}
#investment assigning phase------------------------------------------------------------
#internal functions for calculating allocation----
#------------------------------------------------
#allocation by efficiency (three pillars):--------
#pillar efficiency
eff <- function(){
  if(pillar==1){
    revenue, price <- function(values)
  }else{
```

```
    if(pillar==2){
      revenue, price <- function(values)
    }else{
      revenue, price <- function(values)
    }
  }
  #allocating by margin revenue within budget (and allocating $1 otherwise)
  while(k<=5){
    budget <- budget - order.pack[k,3]
    ifelse(values)
    k <- k + 1
  }
  return()
}
#market share status internal function:-----------
m.share.status <- function(){
  #changing status (PENALTY, MIN, INTERMEDIATE, MAX) with if else statements
  return()
}
#THE REAL FUNCTION OF THE PHASE (WHICH USES THE PREVIOUS
FUNCTIONS)------
#after knowing percents for each pillar, budget is distributed to actions
budget <- function(){
  #rule-based algorithm----------------------------
  #----------------------------------------------
  #does the budget cover the minimum for all actions?
    #if yes: does it cover the maximum?
      #if yes: pay for maximum in all costs
```

```
      #if no: probabilistic event
        #80% chance allocate by visible efficiency (margin R)
        #20% chance pay only for minimum in all costs
  #if no: allocate by visible efficiency (margin R)
  return()
}
#production adjustment phase----------------------------------------------------
#all the next 14 functions bellow obey the same basic structure:
#if current allocated value for the tick is less than min coeff: penalty
#if current allocated value for the tick is equal to min coeff: min reward
#if current allocated value for the tick is between min and max coeff: calutlation
#if current allocated value for the tick is equal to max coeff: max reward
#---------------------------------------
#action 1 (excess stock cost)
adjustment.action1 <- function(){
  for(i in 1:population){
                    #if else statements and changing values
  }
  return()
}
#---------------------------------------
#action 2 (production capacity)
adjustment.action2 <- function(){
  for(i in 1:population){
                    #if else statements and changing values
  }
  return()
}
```

```
#...
#action 5 (base cost)
adjustment.action5 <- function(){
  for(i in 1:population){
            #if else statements and changing values
  }
  return()
}
#---------------------------------------
#real demand for the tick
real.demand <- function(){
  agents$realDemand <- function(value)
  return()
}
#---------------------------------------
#observed demand for the tick
obs.demand <- function(){
  #demand fog, real demand and how much was invested in action 1 (interacts with fog
value)
  #whether the investment was min, max, intermediate or penalty
  #min, max and penalties for this round on this action
  for(i in 1:population){
    #attributing the correct value for the demand fog according to investment
    ifelse(functions(values))
  }
  return(observed.demand)
}
#---------------------------------------
```

```
#action 6 (demand forecast visibility)
adjustment.action6 <- function(){
  for(i in 1:population){
                    #if else statements and changing values
  }
  return()
}
#---------------------------------------
#action 8 (excess stock cost)
adjustment.action8 <- function(){
  for(i in 1:population){
                    #if else statements and changing values
  }
  return()
}
#...
#---------------------------------------
#action 15 (total finances)
adjustment.action15 <- function(){
  for(i in 1:population){
                    #if else statements and changing values
  }
  return()
}
#production calculation phase---------------------------------------------------
#production unit cost update:
#if a agent invested more than $1 in an action this tick, it pays the margin.C fee
unit.cost.update <- function(){
```

```
  #returning the data frame (costs)
  return()
}
#each agent will know how much it produced and how much it costed them
production <- function(){
  #calculating values
  #updating finances.table (real production, revenue, cost and balance)
        #returning finance table
  return()
}
#rewards/punishments calculation phase upon assets-------------------------------
#calculating and modifying assets value
reward.punishment <- function(){
  #taking X% of the profit off
  return()
}
#bankruptcy check phase----------------------------------------------------------
bankrupt <- function(){
  #lower limit for bankruptcy
  asset.cut <- value
        #ifelse check in each agent
        return()
}
#final phase---------------------------------------------------------------------
#final step where values will be filled for the current tick in the agents df
play <- function(indicator){
  for(i in 1:tick){
    if(sum(agents$marketShare)==0){
```

```
    break()
   }
   agents <- pillars()
   alloc.tick <- budget()
   temp.cost <- unit.cost.update()
   agents<- temp.cost()
   environment.tick <- temp.cost()
   environment.tick <- adjustment.action1()
   agents <- adjustment.action2()
       #...
   agents <- adjustment.action14()
   agents <- adjustment.action15()
   finances.table <- production()
   agents <- reward.punishment()
   agents$EF <- EF.tick(agents)
   #...
   alloc.table <- alloc.round()
   agents <- bankrupt()
   alloc.tick <- bankrupt()
   environment.tick <- bankrupt()
   agents <- m.share.bankrupt()
  }
      return()
}
```