The Scientific Journal of Business and Finance

https://caf.journals.ekb.eg

A Framework for Inventory Optimization Based on Machine Learning and Gamification in SMEs Manufacturing Sector

Marwa AbdElwahab [a], Sara Hassan Al-Gazzar[b] , Khaled Mohamed Mohammed Mahar [c] and Hatem Mohamed Said Ahmad Abdul Qader [d]

[a] Teaching Assistant Lecturer, Department of International Trade.

College of International Transport and Logistics, Arab Academy for Science and Technology and Maritime Transport, Alexandria. Egypt.

[b] Professor of Supply Chain Management Faculty of International Transport and Logistics of the Arab Academy of Science, Technology and Maritime transport.

[c] Professor of Computer Science Faculty of Computing and Information Technology - Arab Academy of Science, Technology and Maritime Transport.

[d] Professor of Information SystemsFaculty of Computing and Information University of Menoufia

Published online: **March 2024.**

To cite this article: AbdElwahab, Marwa & Al-Gazzar, Sara Hassan& Mahar, Khaled Mohamed Mohammed and Abdul Qader, Hatem Mohamed Said Ahmad. A Framework for Inventory Optimization Based on Machine Learning and Gamification in SMEs Manufacturing Sector , The Scientific Journal of Business and Finance, 44 (1), 117-135.

DOI: https://doi.org/10.21608/caf.2024.351752

---

*Corresponding author: Marwa.AbdElwahab@aast.edu

A Framework for Inventory Optimization Based on Machine Learning and Gamification in SMEs Manufacturing Sector

Marwa AbdElwahab [a]

[a] Teaching Assistant Lecturer, Department of International Trade.

College of International Transport and Logistics, Arab Academy for Science and Technology and Maritime Transport, Alexandria. Egypt.

Sara Hassan Al-Gazzar [b]

[b] Professor of Supply Chain Management Faculty of International Transport and Logistics of the Arab Academy of Science, Technology and Maritime transport

Khaled Mohamed Mohammed Mahar [c]

[c] Professor of Computer Science Faculty of Computing and Information Technology - Arab Academy of Science, Technology and Maritime Transport

Hatem Mohamed Said Ahmad Abdul Qader [d]

[d] Professor of Information SystemsFaculty of Computing and Information University of Menoufia

Article History
Received 24 January2024, Accepted 15 February 2024, Available online March 2024

Abstract
As supply chains strive for continuous improvements to maintain their strength and their ability to compete in the market. Optimization of different operational concepts and practices has become strategically vital. This importance increases dramatically in small to medium industries (SMEs) sector, which severely struggles to compete in the market due to managerial challenges. Accordingly, this research aims at developing a framework for inventory optimization in the SMEs manufacturing sector based on game theory, gamification, and multi-agent reinforcement learning simulation models. The game theory will be used to set strategies among different stakeholders within the supply chain; gamification is used to increase user motivation by applying game elements to a digital data collection system, while reinforcement learning techniques will be employed to set policies for inventory estimation in terms of reorder point, inventory ordering cost, and inventory level, upon which inventory optimization can be achieved. This paper conducts a systematic review of inventory optimization, highlights some limitations of current approaches and then concludes with the proposed framework to overcome these limitations. The systematic review revealed that there is no comprehensive framework for inventory optimization in the SMEs manufacturing sector, using “Reinforcement Learning and Game theory techniques”. Practitioners can benefit from this model to optimize their inventory and make corrective actions considering inventory management system, particularly in SMEs.

Keywords: Reinforcement Learning, Inventory Management, Game Theory.

1. Introduction

Inventory management is one of the most important elements in the Manufacturing SMEs industries' supply chain; thus, the optimization is necessary. There is a huge waste in the supply chain, and one of the most sectors affected with this waste is the small to medium enterprises because they do not have the awareness or the tools as the big business.

Therefore, they need a technique to solve the inventory problems in a more efficient, effective way that helps them to take appropriate decisions at the right time in order not to fall into the problem of excessive inventory or lack of goods needed to fulfill the customer's request in stock.

Having the right stock at the right time is one of the biggest challenges facing the Manufacturing SMEs. Also, the inability to meet customer requests is another problem, and this may happen due to either a lack or an increase in inventory, which costs the company a lot.

Inventory management problems arise due to many reasons, including the lack of warehouse space, the wrong inventory, and insufficient profit, and finally, the goals may conflict between the different business functions of the company. No inventory optimization model solves all problems in inventory, especially in Manufacturing SMEs. For this reason, this research will be conducted in this field using different techniques. The proposed modeling technique is based on game theory, gamification, and multi-agent reinforcement learning simulation models.

Supply chain management (SCM) has become more critical as well as more challenging for any manufacturing company having a global supply chain in the current increasingly competitive and dynamic global economy. Besides the complex multitier supply chain structure, other factors have further complicated supply chain optimization in practice, such as the highly uncertain and rapidly changing market demand, the lead time between tiers, the tremendous variety of product types, and much-shortened product lifecycles (Kiuchi, et al.,2020).

Inventory is held throughout the supply chain in the form of raw materials, work in process, and finished goods. The mismatch between supply and demand results in inventory in the supply chain. This mismatch is intentional at a manufacturer, where it is economical to manufacture in large lots that are then stored for future sales. The mismatch is also intentional at a retail store where inventory is held in anticipation of future demand. Inventory is a major source of cost in a supply chain and has a huge impact on responsiveness. The important role that inventories play in the supply chain is (1) to increase the amount of demand that can be satisfied by having the product ready and available when the customer wants it. (2) to reduce cost by exploiting economics of scale that may exist during production and distribution. (3) to support a firm's competitive strategy. If a firm's competitive strategy requires a very high level of responsiveness, a company can achieve it by locating large amounts of inventory close to a customer. Conversely, a company can also use inventory to become more efficient by reducing inventory through centralized stocking (Yadav, et al., 2018).

Inventory management is a challenging problem area in supply chain management. Companies need to have inventories in warehouses to fulfill customer demand, meanwhile, these inventories have holding costs, which is a frozen fund that can be

lost; the companies must work to improve the inventory, or else many problems, such as excess inventory or shortage of stock will appear, and therefore this will lead to a decrease in the company's profits and may lead to bankruptcy (Çimen, et al. 2021).
Supply chain inventory optimization is an essential component of the supply chain to ensure supply chain efficiency and to increase customer satisfaction. The goal of inventory optimization is to determine a replenishment policy (i.e., when and how much to order) that optimizes certain criteria, such as inventory costs or service levels. Many academic research and excellent textbooks have dealt with inventory management. In the classical inventory management theory, facilitating analytical tractability and simplifying assumptions, such as pre-defined analytically solvable demand distribution, lead time distribution, stationary demand pattern over time, and fixed supply chain structure, are usually necessary to derive managerial insights. However, these assumptions are easily violated in practice (Kiuchi, et al.,2020).
According to what is mentioned before, supply chain performance can be enhanced through inventory management, which requires optimization of the inventory system, which in turn can be achieved through collaborative forecasting using different tools, such as game theory and multi-agent reinforcement learning simulation techniques. Therefore, it is important to make inventory optimization and collaborative forecasting to improve the efficiency of the supply chain and reduce its risk, which can be executed through forecasting and optimization techniques (Oroojlooyjadid, 2017).
However, the concluded SLR determined that a gap in the literature focusing on inventory optimization from the SMEs food sector exists. As the previous literature mainly adopted genetic Algorithms"; however, no papers were found merging the concepts of reinforcement learning and game theory.
In addition, findings from the literature reviews concluded that the majority of papers confirmed that there is a relationship between lead time and order quantity (Saripalli, 2011), lead time and stock level, (Izaguirre-Malasquez et al. 2022) lead time and inventory cost (Radhakrishnan, 2014); Accordingly, this research contributes to the current body of literature by proposing a model that merges the research constructs, lead time, demand, stock level, and order quantity.
Therefore, the research adopts a deductive research approach, using a descriptive method as this research aims at reviewing state-of-the-art literature on inventory optimization, considering the pros and cons of each technique adopted in this research area. In order to identify the research gap, up on which a framework for inventory optimization in the SMEs manufacturing sector using reinforcement learning and game theory methods.
The remainder of this paper is organized as follows: section two presents the background and literature review related to this research. section three illustrates the research methodology. The research findings and discussion are presented in section 4. Section five provides the proposed framework that will be developed by the end of the paper. Finally, the conclusion and direction for future work are presented in section six.

2. Literature Review

2.1 inventory management

Finding the quantity of inventories that will fulfill the demand and avoid overstock is the primary task of inventory management. Inventory also has a significant impact on the material flow time in a supply chain. Material flow time is the time that elapses between the point at which material enters the supply chain to the point at which it exits (Çimen, et al. 2021). Managers should use actions that lower the amount of inventory needed without increasing cost or reducing responsiveness to take the merit of reducing flow time in a supply chain. The goal of good supply chain design is to find the right form, location, and quantity of inventory that provides the right level of responsiveness at the lowest possible cost.
The fundamental trade-off that managers face when making inventory decisions is between responsiveness and efficiency. (Chopra & Meindl, 2013).
Business failures can happen due to inventory problems of too great or too small quantities on hand. If an organization experiences a stock-out of a critical inventory item, production halts could result. Inventory management indicates the broad framework of managing inventory.–The inventory management technique is more useful in determining the optimum level of inventory and finding answers to problems of safety stock and lead time. Inventory management has become highly developed to meet the rising challenges in most corporate entities, and this is in response to the fact that inventory is an asset of distinct features. Inventory costs have a lot of impact on the profitability of the firm and its success. Inventory management and its optimized decisions depend on the identification of key success factors, such as “lead time, financial factors, suppliers” and the right decisions at the right moment (Sohail& Sheikh, 2018).
In a dynamic market environment, decision-making and what affects it are the main concerns to optimize the results of inventory function. These lead decision makers to apply an optimization policy, where the Inventory optimization policy yields significantly higher profits than cost-based inventory policies (Sohail& Sheikh, 2018).
Several optimization ways have been introduced to solve problems in the supply chain, ranging from solving the optimal production plan to solving the optimal supply chain network. Deterministic analytical optimization, a classical and ideal method of optimization is used which can achieve a globally optimal. However, its inability to incorporate uncertainties makes it difficult to represent real-life scenarios under various uncertainties (Ji & Chiadamrong, 2019).
To reach the optimization, there will be a need to use modeling systems, and there are many applications made in this field, such as reinforcement learning, deep reinforcement learning, game theory, gamification, etc. Therefore, if this approach were applied in inventory management, optimization could be achieved, in the supply chain sector which has a lot of problems, such as" lack of traceability, inability to maintain the safety and quality of your products, inadequate communication between parties, rising supply chain costs, failure to track and control inventory in warehouses and stores", especially on SMEs that has a lot of problems, such as " quality and

safety standard is an essential factor, changing consumer demand and SC risks". Also, barriers consist of coordination difficulties due to the number of connecting entities, incomplete information sharing, malfunctions originating from diverse strategic planning practices, lack of trust among stakeholders, different entrepreneurial mentalities, and failure to understand opportunities in the SME and lead time.
Thus, to easily reach the optimum inventory management level, the Reinforcement Learning technique needs to be applied to the inventory management system.

2.2 Reinforcement Learning

Reinforcement learning (RL) (Sutton & Barto, 2018) is an area of machine learning that has been successfully applied to solve complex decision problems.
Since the supply chain environment in nature is distributed, autonomous, and heterogeneous, agent-based approaches that are characterized by decentralization of computation and information processing are particularly attractive for supply chain modeling and problem-solving (Lin et. al., 2008).
Since learning and adaptation are crucial for some agents, this paper is going to combine the multi-agent optimization simulation with Reinforcement Learning, which is achieved by proposing a novel cooperative multi-agent reinforcement learning framework. With the dedicated design of the agent set, joint action space, state set, reward functions, transition probability functions, and discount factor, respectively, the proposed multi-agent reinforcement learning framework provides an end-to-end and high-capability solution, which can not only compensate for the imperfect forecasting results to avoid further error propagation but also enable to optimize the obtained action plans towards complicated constraints based on real business rules (Lin et. al., 2008).
Agents in logistics are used as an alternative computational paradigm for resource allocation problems. In the field of simulation, the multi-agent concept outperforms classical simulation technology by its support of migration to real-life control and decision-making tasks, provided that these tasks are performed in a decentralized fashion (Marik &McFarlane,2005).
To tackle this challenge, the researchers further introduce three levels of cooperative Metrics and, accordingly, improve the state and reward design to better promote cooperation in the complex logistics networks.
To demonstrate the superiority of the MARL framework, they implemented their approach under an empty container repositioning (ECR) task in a complex ocean transportation network (Li, Zhang, et.al., 2019).
To represent an actual supply chain, the agents should be able to mimic the decision-making rules adopted either by the personnel or local decision support systems in the physical world. This is accomplished by defining a set of properties for each agent, including decision logic, working priority, working cycle, etc. The ability to model individual styles and attributes gives us the flexibility to replicate any complex dynamics in the real supply chain (Kiuchi, et al., 2020). Therefore, in order to set various scenarios for players in the supply chain management, particularly the win-win situation, in order to enhance cooperation among those players.

2.3 Gamification

Gamification, which involves incorporating game aspects into a digital data collection system, is frequently used to boost user motivation. Gamification can boost user engagement and have an impact on the type and amount of data collected. According to (Supriyanto &Fahana, 2020), the use of gamification alone is insufficient to boost user engagement in the system since using game features requires the correct approach. To determine the best user interaction, game theory is a possible option, which might be applied to digital data collecting to identify the best gamification paradigm. In the gamification system, user engagement models are discovered using game theory. Implementing gamification is contrasted with doing it without using Game Theory. The results show that using game theory to implement gamification has significantly increased user engagement.

2.4 Game Theory

Game Theory is an effective formal tool for strategic behavior analysis as it describes agents that are self-interested and interacting through a shared environment. The goal of using game theory is to reach a Nash Equilibrium state (NE). NE is defined as a state where no agent would like to deviate from without losing utility to other agents (Khoury& Nassar, 2020).

The kinetic model was applied to represent quality loss of raw material through a supply chain which recently derived an integrated single-vendor multi-buyer production–inventory policy for food products incorporating quality degradation. The customer’s willingness to pay for a product starts decreasing once it is far getting closer to its expiration date. Freshness is one of the most decisive criteria affecting customers’ purchasing decisions. The effect of product freshness on consumer demand into consideration was investigated, and then the inventory strategies for perishable products were made when the demand is negatively impacted by the age of the on-hand stocks (S. Priyan &P. Mala, 2020).

In order to reach the best results, a merge between the Reinforcement Learning and Game Theory is needed; therefore, Multi-Agent Reinforcement Learning is implemented.

2.5 Multi-Agent Reinforcement Learning and Game Theory

Multi-Agent Reinforcement Learning (MARL) is considered as a framework for training computational agents in learning policies that solve serial decision problems through frequent interaction with an environment in which multiple agents interact. Learning in MARL is achieved through systematic trial and error in a shared and dynamic environment. The agents learn to choose actions that tend to increase their overall expected reward. A policy is a function that maps a state to an action. Optimal policies can be learned using a wide variety of algorithms, including deep reinforcement learning. The goal of MARL is to derive optimal policies. MARL assumes that the game converges to a Nash Equilibrium after the learning phase (Khoury & Nassar, 2020).

It has been obvious from the previous studies that there is a need for a comprehensive

model for inventory optimization using a hybrid approach based on game theory and Multiagent reinforcement learning, which will be used as main techniques in this research to achieve the inventory optimization; accordingly, the following research questions will be answered using the research methodology which will be presented in next section.
This review, therefore, aims to address the following research questions:
RQ1. What are the main variables should be managed to achieve inventory optimization?
RQ2. How these variables can be interrelated in a one comprehensive model to achieve inventory optimization based on game theory and reinforcement learning?
The methodology employed to conduct the literature review will be presented in the following section.
Based on the above discussion, the systematic review revealed that there is no comprehensive framework for inventory optimization in the manufacturing sector capturing the modeling techniques of game theory, multiagent reinforcement learning simulation model. In addition, the review declared that the inventory optimization requires estimation of order quantity, reorder point, in order to achieve the lowest possible cost whether to the holding inventory cost or inventory level. While managing several constraints such as Safety Stock, Cycle Stock Inventory, Inventory Holding Sum, Reorder Quantity, Total Value of Inventory, Demand During Lead Time, and Lead Time, based on which the research framework will be formulated. Therefore, based on the review of previous studies, this study fills the gap as those studies used many techniques, but researchers have not merged these techniques to reach the best level of inventory management.

3. Methodology

A systematic review will be conducted to identify the main variables that will be considered in this research to present the research model that will be employed to start making the inventory optimization.
The term systematic review (SR) is used to refer to a specific methodology of research, developed in order to gather and evaluate the available evidence pertaining to a focus topic (Biolchini, et al. 2005).
Handing over a systematic review in which those keywords "inventory optimization, inventory opt*, optimize inventory, inventory management are chosen by assistance of those search engines "Scopus, Web of science" from year 2010 to year 2021, preferring the chosen papers to be journal or conference papers.
After that, taking all that into consideration and consequence to the selected papers. To be clarified on 79 papers and from the second search engine "Web of science" 306 papers then the total number was 511 papers; after that, filtering again by abstract to remove all duplications and all irrelevant papers, and then reaching the 50 useful and well-organized papers to be included on this research work, they are the ones the researchers worked on for the analysis purpose.
The search string for Web of Science was:
ALL FIELDS: ("logistics hub" OR "logistics energy hub") OR ALL FIELDS: ("energy hub" OR "energy corridor" OR "energy transit") AND ALL FIELDS: (oil) AND ALL FIELDS: (gas) AND LANGUAGE: (English) AND DOCUMENT

TYPES: (ARTICLE OR REVIEW). Timespan: All years, and the search string for Scopus was:
(TITLE-ABS-KEY ("inventory optimization" OR "inventory opt*") OR TITLE-ABS-KEY ("optimising inventory" OR "optimise inventory" OR "supply chain optimization") AND TITLE-ABS-KEY (inventory) AND TITLE-ABS-KEY (optimization)) AND DOCTYPE (ar OR re) AND (LIMIT-TO (LANGUAGE, "English")). Timespan: from year 2010 to 2021.
The initial results of the identification phase revealed a total of 511 records (306 records for WOS and 205 records for Scopus) including the article or review documents only and all subject areas of the database.
Once records were screened, papers were tested for eligibility by focusing on the largest and highest quality studies. Hence, exclusion criteria were developed to assess the eligibility of research papers (Rezaei, et al., 2018), (Attanayake& Kashef, 2014). The search focused on publications starting in 2010 to ensure that only recent work was considered, particularly as this is a topic with practical implications. In addition, to ensure the quality of the full text available for papers used in the review, the authors focused only on articles and reviews published in journals and conferences. Furthermore, studies not related to the objectives of this research were excluded to ensure that the papers reviewed fell within the scope of this research as papers in the healthcare and medical fields, inventory, storage, power and network security management. Table 1 below summarizes reasons for exclusion during the various stages of research, identification, and eligibility, as 28 papers from 49 papers met the criteria to be included in the review.

Table 1. Exclusion criteria.

Phase	Reason for Exclusion
Searching, identification, and screening	• Papers are not updated as before 2010 • Not an article or review in a journal • Full texts not available • Studies arenot relevant to the questions and objectives of this research.
Eligibility	• Low-quality studies • Papers related to health and medical sector • Studies that dealt with inventory management in pharmaceutical supply chain. • Papers that addressed warehousing, energy, and network security • Fully quantitative, meta-analysis, and programming studies.

To ensure completeness, additional studies were identified using other methods, e.g., searching online and reviewing bibliographies within the first round of articles and categorizing additional relevant literature, as well as identifying additional 41 studies. After implementing the same criteria of exclusion and filtration used above, only 50 papers remained as the other papers are off-point. Researchers worked on the same variables but in other different industries, and added to that, researchers analyze for dissimilar variables but seeking for the same indication as the next figure will show.

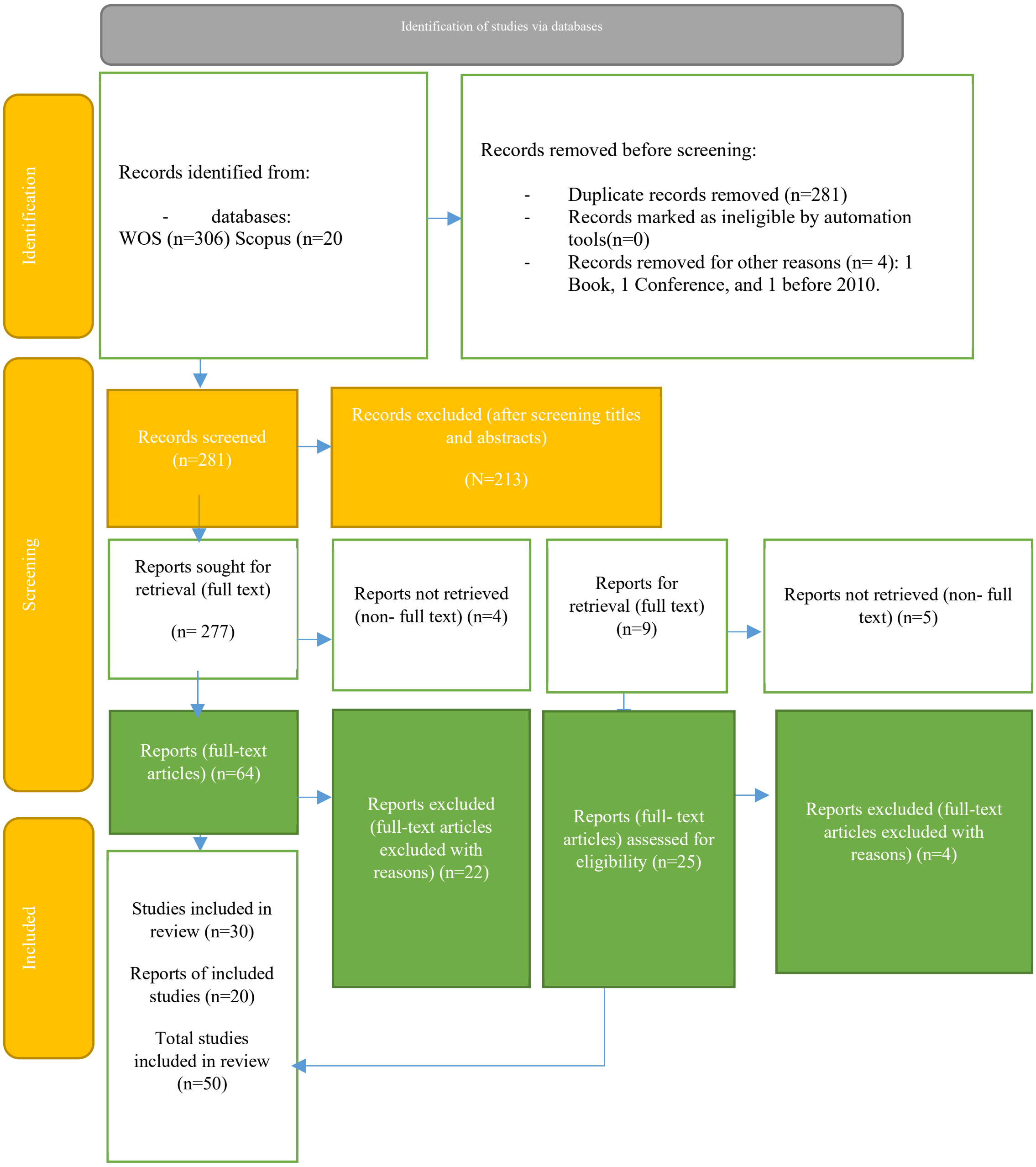

Figure 1. Flow of information through the different phases of the systematic review. Source: Adapted by the authors.

4.Findings and discussion

This section will illustrate the most related researches in measuring inventory optimization using different techniques and models with different variables.

4.1 Systematic review Descriptive analysis

After that, the study came up with a systematic review analysis, which is divided into two parts: the first part is called fact sheet analysis, and the second part of the analysis is the one from which the data comes out.

Fact sheet analysis concluded that most papers from all journals and the application mainly exist on European countries, Mexico, and a European airline in these industries: industry shop floor environment, olive products in SMEs in the agro-industrial sector, SMEs in the sports retail sector, oil and gas plants, naval systems, military missions, space missions, spare parts of manufacturing equipment, industrial sector, business aircrafts industry and the agro-industrial company.

This analysis came out with a set of findings, explicitly:

1. Most of the papers confirmed that there is a relationship between Lead time, Order quantity, Demand, Demand forecast, Service level, and therefore confirming the research propositions.

2. Most of the findings emphasized that inventory optimization will improve corporate performance or when taking into account those variables "total inventory level, inventory cost, holding cost and reorder point", enhancing enterprise's performance, such as (Tsai, et al., 2017), (Dorado, et al., 2017), (Abdulghani, et al.,2019).

Findings from the literature reviews concluded that the majority of papers confirmed that there is a relationship between "lead time and order quantity", "lead time and stock level", "lead time, inventory cost" (Saripalli & Sheetal, 2011), (Radhakrishnan, 2014),

Furthermore, from the systematic review, it has been found that there are no previous studies that tackled that inventory optimization from SMEs. Moreover, the majority used "Genetic Algorithm"; however, no one in the methodology merged between reinforcement learning and game theory.

4.2 Systematic Review Findings

A detailed analysis of all studies conducted on inventory optimization and scanned on the systematic review will be shown in appendix 1. Papers have been analyzed based on objectives, methodology, variables, and findings/contributions (Saripalli, & Sheetal ,2011). The research presented a mathematical model that demonstrated the methodology for simplified system configurations using discrete time. The optimization method suggests a minimal cost replenishment strategy over a specified time horizon while considering uncertainty in demand, demand forecasts and lead time subject to a service level specification. The research is coupled with an extensive experimental performance evaluation to test the scope and validity of the model developed. The developed algorithm serves as a tool to aid in determining an optimal ordering policy with minimum cost and required customer service levels to all the purchasing managers and inventory stock keepers of companies with a fleet of printers (Çimen, et al., 2021).

The study analyzed 400 products, and best reorder points and amounts are selected with the help of heuristics. Heuristics' main structures and parameters are adjusted for the problem's need and improvement on quality of results. Parameters are determined according to trial and error with experts' guidance on heuristics. The best result suggests 8% improvement on cost and 37% improvement on inventory load, which could be achieved with the help of heuristics

(Tsai, et al., 2017). The paper developed algorithms that can exploit statistically valid R&S procedures and the desirable mechanics of conventional multi-objective optimization techniques. Also, the paper showed that the algorithms work better than using R&S or multi-objective solution approach alone (Kiuchi, et al., 2020).

The paper examined dynamic inventory system optimization for an assembly manufacturing enterprise. An optimization model for multi-period dynamic resolution is introduced, and the corresponding algorithm is presented for it. From the research carried out by the researchers, the following insights were noted. Supply chain cooperation is the effective way to improve supply chain operation efficiency and reduce cost. Inventory control and assembly manufacturing organization optimization is one of the key contents in supply chain management; its essence is that many suppliers are cooperating to improve inventory, and they need different purchasing strategies according to different components. It is better to adjust the control strategies according to the outcome of the process (Govindarajan, et al., 2020).

The paper provided a framework to analyze the distributional robust multilocation problem, where there are network flows after realization of uncertainty. It analyzed the two-location setting yields closed-form bounds, as well as a family of worst-case joint distributions with six support points. For the multilocation case, the paper provided a heuristic approximation and upper bound for the case, where the fulfillment costs exhibit a nested structure, where the cost function can be written as the sum of piecewise linear terms. The paper showed how any general fulfillment cost structure can be approximated by this nested fulfillment cost structure through simple agglomerative clustering algorithms and that the approximation of the expected total fulfillment cost is empirically tight for commonly seen distance-based shipping cost structures under various distributions. This yields the first computationally tractable heuristic for the distributional robust multilocation problem on general networks when only mean and covariance are known. The study introduced the multilevel inventory and supply chain ideology into inventory cost calculation (Sun & Kuang, 2014).

Most researchers used the deep learning method, the convex nonlinear programming (NLP) model, the mixed integer programming (MIP) model, the genetic algorithm (GA), the joint regeneration problem model (JRP), the EOQ inventory optimization model, the ABC-XYZ classification model, and the ABC-XYZ classification model, in addition to automatic adaptive production, Monte Carlo simulation, and news vendor model. However, no one has used or combined the reinforcement learning method with the game theory technique.

Therefore, there is a relationship between the reorder point, demand uncertainty, holding costs, ordering costs, preparation costs, transportation costs and the level of total inventory. However, no one has talked about Small and Medium Enterprises (SMEs), so the research gap will be determined based on that.

The following table summarizes the reviewed literature papers classified by variables and methods.

4.2 The developed framework

In this section, a systematic review will be conducted on the previous studies concerning inventory optimization and inventory management in business sector upon which the research variables/ model will be formulated.

Most of the studies have examined Lead time, Order quantity, Demand, Demand Forecast, Service level variables, and others have studied the average value of the historical demands in a given period. The standard deviation of the past demands in a given period, cost, customer satisfaction, real-time location information, price, customer service level, historical customer data, and current inventory levels, lead time, minimum order quantity, and order bundles' variables, and after the researchers removed the duplication of the variables or the redundancy in them, the researchers distracted that those variables (system constraints represented as "Max. Reorder Period for Emergency Purchases, Order Lead Time, Avg. Usage/ consumption, Minimum stock level, Reorder Level, Safety Stock, Cycle Stock Inventory, Inventory Holding Sum, Reorder Quantity, Total Value of Inventory, Minimum Usage, Demand During Lead Time, Max Lead Time, Lead Time, Return Policy Lead time, Return Quantities "how much?" and when?") those are the variables that this research will be dealing with.

The following figure shows a forecast of how much and when to order and from which manufacturer it will be manufactured using reinforcement learning; optimum inventory will be determined using reinforcement learning also to improve inventory level, reduce inventory holding cost, increase profits and eliminate waste as much as possible; first, the data set is referenced using a prediction model based on game theory to retrieve data about the previous transactions of previous orders, whether it is the quantities of orders or a reorder point, or the manufacturer or customer data in the sector and then to reach the appropriate decision-making in the Manufacturing Small to medium enterprises. Second, this data is used to be able to predict the following: the quantities will be ordered, when these quantities will be ordered, the “orders” and prices at which they will be purchased, and from which manufacturer they will be dealt with, taking into consideration some of the constraints that will be placed in the system, which are the maximum stock level, the critical point of demand, the safety stock, the time when the order will be re-ordered, and finally the quantities that will be re-ordered and the time the return will be before the expiry date Validity “based on a prior agreement between the company and the manufacturer.

Third, this data will be used by “game theory” to do the estimation process to help the company achieve its most important goals, which is to reach the maximum inventory through the process of forecasting and the ability to make the right decisions at the right time. Fourth, after carrying out the estimation process, the program takes the appropriate decisions with the quantities, orders and appropriate dates for making these orders, and then sends them to the next stage to measure the stock level and see if it has reached the optimum level or not, and also measure the cost of holding inventory; accordingly, the order is rearranged and the process is repeated in case the goal that the company seeks to achieve is not reached; it will be done through the use of reinforcement learning technology. Fifth, there is a process called re-order again, and this process takes place either in the case of reaching the minimum stockpile or in the event of reaching the critical point to achieve it. This will also be done through the use of reinforcement learning technology, which has been pre-fed to the system in an effort to create inventory deficits or surpluses. Inventory will be measured through three stages, which are pre-fed to the system as constraints on the system: First, Maximum Stock; second, Safety Point “Backup Stock” at which reorder is prepared after a specified period. Third, Critical Point: the order is reordered as absolutely necessary to avoid any imbalance in the stock level, and it will always try to stay at the optimum level as possible, and it can reach the other goal which is to reduce the cost and increase the profits of the company. When-order is required, it is returned to the forecast stage; sixth, to avoid being caught in the event that the stock is approaching or if the products are approaching the expiration date, the goods are returned back to the manufacturer. This is an existing agreement between the companies and the manufacturer that was previously talked about. The final output of the forecasting process will be saved in the company's existing database and restored again at the time when an order needs to be re-ordered again. A simulation will be conducted before implementation begins on the ground to ensure the accuracy of the data and decisions taken before implementation to avoid any errors in the inventory level. This process takes place between three parties: “manufacturer, distributor, and retailer”, and the role of the “distributor” will be represented here, either at the upstream or downstream level to avoid the impact of out-of-stock by improper transmission of information that causes disasters and material losses at the inventory level in supply chain.

A hybrid approach based on game theory has been proposed as a tool for formalizing game interaction among the human "dealer" who decides strategies. For example, how to handle stock order situations with different stock levels. From a distributor's point of view, which order is the components of the order posted, how is the inventory configured? How is system patching managed, etc. From the point of view of the manufacturer, who accepts the technologies of upcoming orders, how the order is packaged, etc. This game has an extended form because the stock status may change from low estimate to higher status, and most orders are multi-stage. It is also a game with incomplete information, since most of the time, both the distributor and the manufacturer may not know the exact stock status at the moment.

Depending on the game design and strategies selected, MARL-powered machine learning agents may decide on the best actions (proactive or reactive) to reach the optimum level. The states in the RL model are different because they are runtime states and perfect information states. Based on knowledge of the inventory network and distributor system alerts, the distributor chooses actions and navigates its own status space. The manufacturer navigates the parallel state space based on the manufacturer tree. Therefore, MARL agents learn the best policy for automated response at runtime.

The best policies of both the manufacturer and the distributor express themselves as aids at the strategic game level. Therefore, the Nash Equilibrium (NE) can be calculated at the strategic level which represents the best possible strategy in the presence of the stock level. NE is the point from which neither party is willing to deviate without losing utility. Problem formulation: Initial assumptions that the model will be adopted according to which “the distributor will be able to get all of the retailer’s orders”.

Finally, the improvement will be measured by measuring one variable, “measurement of the level of total inventory”, and the minimum should be reached as far as possible to ensure that the orientation is done towards the optimum level “The main objective of this research”. At this level, the strategies are implemented by machine learning agents who elicit optimal policies for runtime decisions. The results of these policies appear as optimally beneficial in favor of the distributor and the manufacturer, respectively.

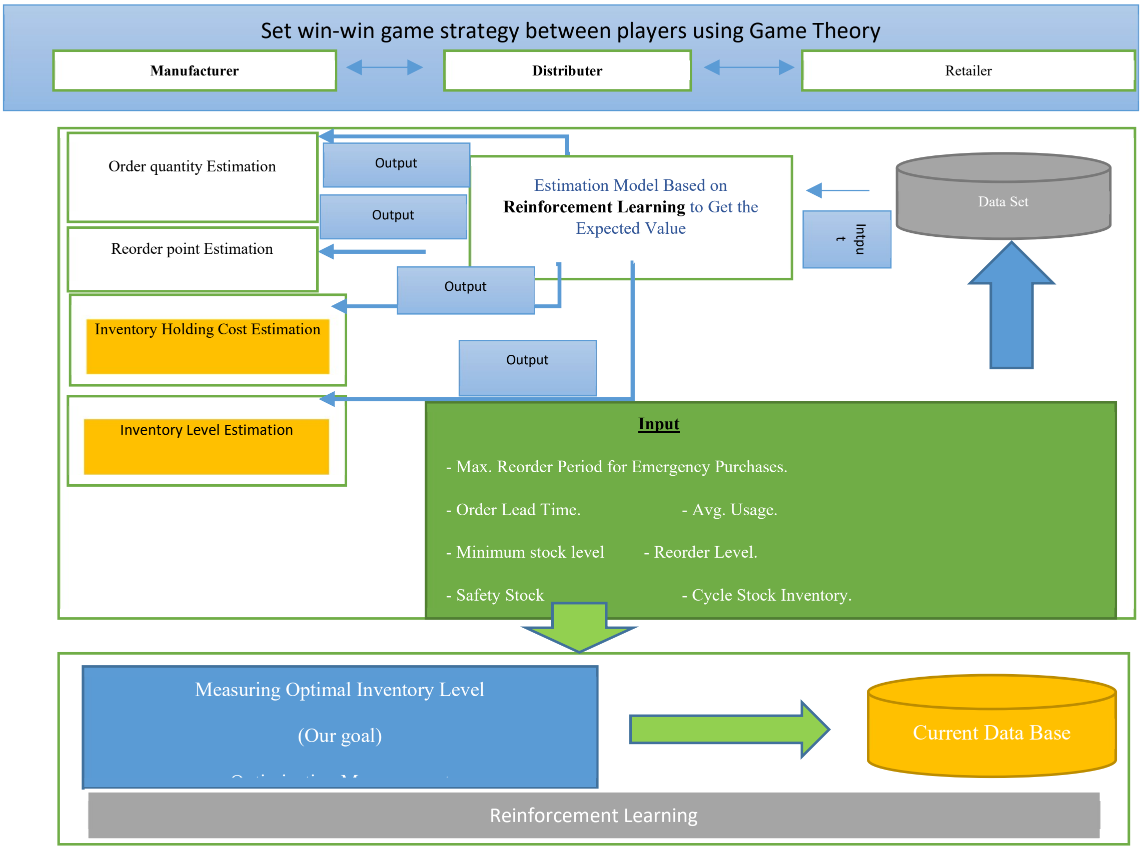

Figure 2. The proposed model using Game theory and Reinforcement Learning

The proposed framework provides a comprehensive view concerning inventory management in manufacturing companies since the model captured various and integrated variables to improve the level of forecast. In addition, the reinforcement learning technique has been used to estimate the reorder point, the inventory ordering cost, and the inventory level, upon which the optimum inventory level has been identified. Also, the game theory allowed to achievement a win-win situation between different stakeholders in the supply chain based on a non-zero-sum game to set strategies from manufacturer till distributer.

5 Conclusion/ further research

In this paper, the research illustrated the main concepts of the research model, including supply chain management, inventory management optimization, game theory, machine learning, and reinforcement learning, followed by an extensive systematic review to identify all previous studies on inventory optimization, based on which the research model and variables are identified.

The paper proposed this research model, which can be useful in improving the performance and competitiveness of manufacturing SMEs. The inventory management can improve the performance, increase customer satisfaction, improve information sharing between supplier and distributor, maintain enterprises cooperation, use information systems, improve decision making, decrease inventory cost, decrease holding cost, decrease total cost, and to reach the optimum inventory level.

In further research, this model can be validated by running it in companies in the manufacturing sector; these companies can also help with the correct use of this proposed model. For future studies, different manufacturing sectors can apply and manage this framework.

Reference:

Abdulghani, I., Bermamet, H., & Altarazi, S. (2019, April). Pharmaceutical Supply Chain Cost Optimization Model Considering Multiple Echelons and Multiple Drugs. In *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)* (pp. 709-713). IEEE.

Attanayake, N., Kashef, R. F., & Andrea, T. (2014, May). A simulation model for a continuous review inventory policy for healthcare systems. In *2014 IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-6). IEEE.

Avci, M. G., & Selim, H. (2017). A Multi-objective, simulation-based optimization framework for supply chains with premium freights. *Expert Systems with Applications, 67*, 95-106.

Biolchini, J., Mian, P. G., Natali, A. C. C., & Travassos, G. H. (2005). Systematic review in software engineering. *System engineering and computer science department COPPE/UFRJ, Technical Report ES, 679(05)*, 45.

Chopra, S., & Meindl, P. (2013). *Supply chain management*. Essex, England: Pearson Education.

Costantino, F., Di Gravio, G., Patriarca, R., & Petrella, L. (2018). Spare parts management for irregular demand items. *Omega, 81*, 57-66.

Çimen, E. B., Kurban, İ., Selmanoğlu, Ö., Şahin, M., & Kılınç, D. (2021, June). A Hybrid Stock Optimization Approach for Inventory Management. In *2021 3rd International Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA)* (pp. 1-4). IEEE.

Dorado, J. F., Perez-Gonzalez, P., & Framinan, J. M. (2017, December). Simulation results of optimal solution for a multiechelon inventory system. In *2017 Winter Simulation Conference (WSC)* (pp. 4548-4549). IEEE.

Fu, M. C. (2002). Optimization for simulation: Theory vs. practice. *INFORMS Journal on Computing, 14*(3), 192-215.

Govindarajan, A., Sinha, A., & Uichanco, J. (2021). Distribution-free inventory risk pooling in a multilocation newsvendor. *Management Science, 67*(4), 2272-2291.

Govindarajan, A., Sinha, A., & Uichanco, J. (2021). Joint inventory and fulfillment decisions for omnichannel retail networks. *Naval Research Logistics (NRL), 68*(6), 779-794.

Izaguirre-Malasquez, R., Muñoz-Gonzales, L., Cabel-Pozo, J., & Raymundo, C. (2022). Inventory Optimization Model Applying the FIFO Method and the PHVA Methodology to Improve the Stock Levels of Olive Products in SMEs of the Agro-Industrial Sector in Peru. In *Human Interaction, Emerging Technologies and Future Systems V: Proceedings of the 5th International Virtual Conference on Human Interaction and Emerging*

Technologies, IHIET 2021, August 27-29, 2021 and the 6th IHIET: Future Systems (IHIET-FS 2021), October 28-30, 2021, France (pp. 736-742). Springer International Publishing.

Ji, J., & Chiadamrong, N. (2019, May). Hybrid optimization approach for supply chain planning. In *Proceedings of the 2019 International Conference on Management Science and Industrial Engineering* (pp. 76-83).

Khoury, J., & Nassar, M. (2020, April). A hybrid game theory and reinforcement learning approach for cyber-physical systems security. In *NOMS 2020-2020 IEEE/IFIP Network Operations and Management Symposium* (pp. 1-9). IEEE.

Kiuchi, A., Wang, H., Wang, Q., Ogura, T., Nomoto, T., Gupta, C., ... & Zhang, C. (2020, August). Bayesian optimization algorithm with agent-based supply chain simulator for multi-echelon inventory management. In *2020 IEEE 16th International Conference on Automation Science and Engineering (CASE)* (pp. 418-425). IEEE.

Lorentziadis, P. L. (2016). Optimal bidding in auctions from a game theory perspective. *European Journal of Operational Research, 248*(2), 347-371.

Liao, C. J., & Shyu, C. H. (1991). An analytical determination of lead time with normal demand. *International Journal of Operations & Production Management, 11*(9), 72-78.

Lin, F. R., Kuo, H. C., & Lin, S. M. (2008). The enhancement of solving the distributed constraint satisfaction problem for cooperative supply chains using multi-agent systems. *Decision Support Systems, 45*(4), 795-810.

Li, X., Zhang, J., Bian, J., Tong, Y., & Liu, T. Y. (2019). A cooperative multi-agent reinforcement learning framework for resource balancing in complex logistics network. *arXiv preprint arXiv:1903.00714*.

Marik, V., & McFarlane, D. (2005). Industrial adoption of agent-based technologies. *IEEE Intelligent Systems, 20*(1), 27-35.

Ni, Y., Cheng, Y., & Xiong, F. (2017). Integrated optimization of multiple warehouse replenishment for semiconductor manufacturing. *Journal of the Brazilian Society of Mechanical Sciences and Engineering, 39*, 4601-4612.

Oroojlooyjadid, A., Nazari, M., Snyder, L., & Takáč, M. (2017). A deep q-network for the beer game: A reinforcement learning algorithm to solve inventory optimization problems. *arXiv preprint arXiv:1708.05924, 5*, 10-11.

Priyan, S., & Mala, P. (2020). Optimal inventory system for pharmaceutical products incorporating quality degradation with expiration date: A game theory approach. *Operations Research for Health Care, 24*, 100245.

Pěchouček, M., & Mařík, V. (2008). Industrial deployment of multi-agent technologies: review and selected case studies. *Autonomous agents and multi-agent systems, 17*, 397-431.

Perrucci, D. V., & Baroud, H. (2021). Temporary housing operations: A simulation-based inventory management approach using the newsvendor model. *International Journal of Disaster Risk Reduction, 65*, 102512.

Radhakrishnan, P. (2014). Genetic Algorithm Model for Multi Product Flexible Supply Chain Inventory Optimization Involving Lead Time. *Organizational Flexibility and Competitiveness*, 325-334.

Rezaei, H., Baboli, A., Shahzad, M. K., & Tonadre, R. (2018). A new methodology to optimize target stock level for unpredictable demand of spare parts: A Case Study in Business Aircrafts' Industry. *IFAC-PapersOnLine, 51*(11), 538-543.

Saripalli, S. S. (2011). A Dynamic inventory optimization method applied to printer fleet management. *Rochester Institute of Technology*.

Stojanović, M., & Regodić, D. (2017). The significance of the integrated multicriteria ABC-XYZ method for the inventory management process. *Acta Polytechnica Hungarica, 14*(5), 29-48.

Sun, H., & Kuang, M. (2014). Supermarket Multi-Level Inventory and Distribution Optimization Research. In *ICLEM 2014: System Planning, Supply Chain Management, and Safety* (pp. 32-38).

Supriyanto, S., & Fahana, J. (2020). Gift-exchange Game Theory for Gamification on Digital Data Collection Systems. *Lontar Komputer: Jurnal Ilmiah Teknologi Informasi, 11*(1), 57.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT Press.

Tsai, S. C., & Chen, S. T. (2017). A simulation-based multi-objective optimization framework: A case study on inventory management. *Omega, 70*, 148-159.

Yadav, A. S., Maheshwari, P., Swami, A., & Pandey, G. (2018). A supply chain management of the chemical industry for deteriorating items with warehouse using genetic algorithm. *Selforganizology, 5*(1-2), 1-9.

Zapata-Cortes, J. A., Arango-Serna, M. D., & Serna-Urán, C. A. (2018). Application of the joint replenishment problem in a collaborative Inventory approach to define resupply plans in urban goods distribution contexts. *Dyna, 85*(207), 174-182.