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Decision support system for adaptive sourcing and inventory management in small- and medium-sized enterprises

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ABSTRACT

Elevated business uncertainties and competition over recent years have caused changes to the data-driven supply chain management of sourcing and inventories across industries. However, only large-sized enterprises have the resources to harness data for aiding their decision-making and planning. By contrast, small- and medium-sized enterprises (SMEs) commonly have limited resources and knowledge, which affects their ability to collect and utilize data. Thus, it is a challenge for them to implement advanced decision support tools to mitigate the effects of market uncertainties. This paper proposes a decision support system (DSS) for sourcing and inventory management, with the aims of helping SMEs compile and exploit data, and supporting their decisions under business ambiguities. The DSS was developed using a simulation-optimization approach by incorporating an artificial neural network and a genetic algorithm for problem representation and optimizing decision support solutions. The exploitation of observational and empirical data reduces the burden of data compilation obtained from unorganized data sources across SME operations. Further, uncertainty factors such as raw material demand, price, and supply lead time were considered. When implemented in a medium-sized food industry company, the DSS can provide decision support solutions that integrate the selection of recommended suppliers and optimal order quantities. It can also help decision-makers to shape their inventory management policies under uncertain raw material demands, while also considering service levels, sales promotions, lead times, and material availability from multiple suppliers. Consequently, implementation of the DSS helped to reduce the total purchased raw material costs by an average of 51.62% and reduced the order interval and on-hand inventory costs by an average of 54.24%.

1. Introduction

As the rate of globalization has increased in recent years, modern businesses have been exposed to higher levels of disruptions and uncertainties. These disruptions (such as fabricated and natural disasters) can induce negative impacts and reduce supply chain performance [1, 2]. However, nothing can compare to the unprecedented crisis of COVID-19, which the World Health Organization declared as a pandemic on March 11, 2020 [3]. Unlike other disruptions, this pandemic has highlighted the lack of supply chain resilience on a global scale [4] and has created unprecedented supply chain disruptions, with severe and long-lasting effects [3]. Moreover, the unparalleled magnitude, scope, and speed of this disease has forced almost every nation to shut down their economy, resulting in drastic demand-supply shocks and interrupted flows of commodities and consumer products [5, 6]. For example, demand spikes for essential products (such as medical supplies and food) have caused supply shortages and distribution bottlenecks [5]. Fear of infection has also resulted in unexpected market trends, such as price spikes and hoarding of essential supplies [4]. Hence, recent studies have indicated that the pandemic has affected supply chains in multiple areas, including demand management, supply management, production management, and logistics [7].

Since the pandemic, research trends in supply chain management have focused on supply chain resilience [4], disruption mitigation [8], and deglobalization [9]. Among these trends, deglobalization is a radical move as companies seek to reduce levels of global interdependence [10]. Further, as global sourcing has been questioned in terms of supply chain risks, several research articles on post-pandemic supply chains have revealed a shift from globalization to localization [9, 11]. While the competitive and disruptive environment of recent years has had a significant effect on all firms, it has also increased the incidences of

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List of Abbreviations

AHP	Analytic hierarchy process
AI	Artificial intelligence
ANN	Artificial neural network
API	Application programming interface
BI	Business intelligence
BP	Backpropagation
CSV	Comma separated value
DEAP	Distributed Evolutionary Algorithm in Python
DSS	Decision support system
EOQ	Economic order quantity
ERP	Enterprise resource planning
FIS	Fuzzy inference system
FOI	Fixed order quantity
GA	Genetic algorithm
IT	Information technology
LEs	Large-sized enterprise
MAE	Mean absolute error
MCDM	Multi-criteria decision making
MLP	Multilayer perceptron
MSE	Mean squared error
MTO	Made-to-order
MTS	Made-to-stock
PCA	Principal component analysis
QFD	Quality function deployment
SMEs	Small and medium-sized enterprises
VMI	Vendor managed inventory

operational supply risk [12]. This risk is associated with the expression of variations in expected performance of the upstream supply chain, meaning variations in terms of time, quality, and quantity [13]. Recent studies have confirmed that companies can suffer greatly from the adverse effects of these risks, with the results being more severe for small- and medium-sized enterprises (SMEs) [12, 14, 15]. For example, SMEs in the food industry have suffered from the effects of COVID-19 more than large companies (in terms of survivability and sustainability) due to limited resources [16, 17].

The vulnerability of SMEs is not only caused by internal limitations in terms of resources, knowledge, and skills. From the supply chain perspective, SMEs also lack negotiating power, mitigation strategies, resilience, and supportive partners [12, 18]. These issues can result in operational supply risks for SMEs, which are exacerbated in times of crisis with the ensuing demand spikes and supply shortages. Without appropriate strategies and decision guidance, SMEs can suffer significantly from the adverse effects of supply risks and uncertainties [14]. Further, even though SMEs are the major contributors to countries' economies around the world [19], they are more vulnerable to operational supply risk compared to large enterprises [12]. Moreover, as stated by numerous researchers, existing research in this area has mainly focused on large companies, leaving a research gap with respect to SMEs [20].

Accordingly, the question of how SMEs can leverage existing knowledge and resources to benefit their decision capabilities in sourcing and inventory management is examined in this study [12, 21]. Moreover, the focus is on sourcing and inventory management due to their substantial effects on purchasing decisions and the financial performance of companies [22]. For instance, manufacturing companies have strived to achieve zero inventory manufacturing over the past decades. A tendency of industry 4.0 has also driven a massive investment in advanced warehouse automation and smart manufacturing platform to enhance their inventory management efficiency [23]. Unfortunately, since SMEs are known to lack appropriate knowledge and resources, the support tools used by large companies are usually unsuitable for them, as they are either too complex or too expensive [20]. Therefore, the aim of this paper is to propose a decision support system (DSS) for adaptive sourcing and inventory management for SMEs to support their decisions in sourcing and inventory management. The proposed DSS utilizes an artificial neural network (ANN) and a genetic algorithm (GA) for determining decision-support solutions to problems. Because an ANN treats complex systems as a black box, it is used to represent functions of the sourcing and inventory management operations. Moreover, the DSS is adaptable according to various parameters and can accommodate any nonlinearities and uncertainties of the model. The GA is exploited for determining the optimal parameter values of sourcing and inventory management problems based on the predicted output of the ANN. This hybrid GA–ANN system combines the good predictive performance of the ANN with the effective and robust optimization of the GA [24-26]. The contributions of this work are summarized as follows:

(1) This paper focuses on the development of a DSS for sourcing and inventory management in SMEs that have limited resources and knowledge in utilizing data to support their decision-making. This is achieved using a hybrid GA–ANN approach.
(2) There is an attempt to exploit both unorganized 'observational data' and 'empirical data' in SMEs' operational processes, based on the experience and knowledge of managers for synthesizing decision support solutions.
(3) Because the proposed DSS utilizes an ANN for pattern recognition and prediction, comparisons with other machine learning (ML) techniques were conducted to validate the performance of the system.
(4) Through testing the DSS with generated instances and a real-world case, this research demonstrates the performance and practicability of the proposed approach in providing decision-support solutions for SMEs under uncertainties.

The article is organized as follows: Section 2 presents a literature review on sourcing and inventory management problems in SMEs and DSS applications in sourcing and inventory management. The materials and methods used for the DSS development are described in Section 3, followed by the results and discussion in Section 4. Section 5 presents the managerial implications and a discussion of the results based on the findings of this research. Finally, the conclusions and future work are discussed in Section 6.

2. Literature review

This section presents the literature review and relates to two main issues: sourcing and inventory management problems in SMEs and applications of DSSs in sourcing and inventory management. The goals are to explore the problems and characteristics of SMEs and assess the validity of using the DSS to support sourcing and inventory replenishment in SMEs.

2.1. Sourcing and inventory management problems in SMEs

Supply chains rely on their supply base (or groups of suppliers), from which they purchase goods and services [27]. Accordingly, effective management of sourcing and inventory management processes is essential for successful operations [28]. Sourcing problems are mainly related to supplier selection, in which potentially reliable suppliers should be selected [29]. However, business enterprises also have to address inventory management interrelated problems, which involve replenishing, stocking, tracking, and prioritizing inventories [28]. Since they are both critical issues in business and supply chain operations, improving sourcing and inventory management decisions could help to increase the performance of enterprises' operations [27]. These integrated problems regarding improvements to the supplier selection process and inventory management strategies have attracted increasing attention by numerous researchers [30]. Moreover, coordination between these two problems can provide advantages in supply chain management [31]. For example, effective coordination between supply and inventory management can improve supply chain resilience [7]. With resilience strategies such as supply base diversification [32], near-shoring and local sourcing [33], emergency sourcing [3], and supply chain collaboration [34], the effects of supply risks (i.e., supply failure) can be mitigated [3]. Companies generally use multiple sources [35]; hence, the ultimate goal is to determine the correct replenishment policy (i.e., time and quantity to order) that satisfies specific criteria (basically related to costs or service level) [36].

Several studies have confirmed the complexity and ambiguity of sourcing and inventory management. However, most of the cases studied were supply chain scaled or large-sized enterprises (LEs). Large amounts of business operational data (i.e., sourcing and inventory activities) are generally available in LEs, and data analysis is regularly conducted to improve decision-making effectiveness [37]. By comparison, SMEs have a common problem of data unavailability due to the absence of data analytics [38] and limited resources [12]. Accordingly, SMEs cannot effectively exploit advanced support tools such as DSSs or enterprise resource planning (ERP) [39, 40]. Therefore, most SME decision-making competencies have relied on intuition combined with entrepreneurial experience and knowledge [41]. In some cases, SMEs may concentrate on their core competencies and outsource some non-core expertise or operations. However, these outsourcing activities can increase the complexity of their operations and will only be useful under the right decision regarding what and where to outsource [42]. Moreover, while LEs can afford large ERP systems (i.e., SAP and ORACLE) that are devoted to supporting inventory management activities, SMEs have relied on less systematic approaches that do not provide many advantages in a competitive environment [43]. Therefore, SMEs are more vulnerable to operational supply risk effects [44]. For example, studies have indicated that the COVID-19 pandemic has posed significant threats to the sustainability and survivability of some businesses Ivanov and Dolgui [45], Ali, Suleiman [16]. In situations such as this, the effects are more severe for SMEs due to their limited resources.

2.2. Applications of DSS in sourcing and inventory management

In supply chain management, the main purpose of a DSS is to support decision-makers by navigating them toward the best possible solution, enhancing the performance of supply chain activities [46]. Within this area, sourcing and inventory management are the focus of this study. Supply chains have encountered fierce competition, disruptions, and uncertainties more frequently in recent years [12]. Therefore, practitioners and researchers have attempted to develop and provide tools such as DSSs to support decision-makers (e.g., supply chain managers) [47].

Sourcing and inventory management are associated with the upstream operations of supply chains, including supplier selections, supply allocations, and fulfillment [48]. Moreover, researchers have recently focused on these issues because they have been the cause of major supply chain disruptions since the COVID-19 pandemic [7]. The application of DSSs in the areas of sourcing and inventory management has been reported in several studies. Moreover, the effects of supply chain disruptions, risks, and uncertainties have been considered an integral part of DSS development by numerous researchers [47]. Sourcing activities begin with the supplier selection process, and numerous studies have focused on this topic. However, these studies usually focused on manufacturing industries and most used multiple-criteria decision-making (MCDM) and numerical simulation approaches [46]. The process of supplier evaluation and selection is known to require a huge amount of supplier data. For example, Scott, Ho [49] proposed a DSS for supplier selection and order allocation considering stochastic environments and stakeholder requirements. They used a hybrid of analytic hierarchy process and quality function deployment (AHP–QFD) combined with chance-constrained optimization, which could be applied to other industries such as food, agriculture, and fuel blending. However, given the need for sophisticated data management for the implementation of QFD, supplier performance data and stakeholder requirements may become an obstacle for an evaluation of material quality where data is not available (such as in SMEs). Eydi and Fazli [50] developed a DSS for supplier selection under uncertain environments using a hybrid data envelopment analysis (DEA) approach. However, the study did not implement the approach on a real-world case due to the unavailability of data. Moreover, considering the uncertainties of the business environment, multiple sourcing should have been considered to increase the resilience of the supply base.

Some researchers have attempted to use expert opinions instead of collecting large amounts of data for supplier selection. For example, Kumar, Garg [51] developed a DSS for e-supplier selection using the modified distance-based approach (MDBA) and ranking. More than 52 sub-criteria and eight major groups of ranking criteria were utilized for selecting the most suitable supplier, which covered both financial and non-financial dimensions. However, this number of criteria can cause difficulties in data collection. Although the data relied on expert opinions, there was no consensus on the number of experts required. This can result in the validity of expert opinions being questioned in addition to raising concerns over whether all aspects of the selection criteria were covered.

Numerous researchers have also published literature on DSSs for integrated supplier selection and inventory optimization. This combination of two problems requires more data and a more advanced approach. For instance, Mohammed, Harris [52] proposed a sustainable supplier selection and order allocation model under uncertainties using a hybrid MCDM and multi-objective optimization. This research contributed effective managerial and practical implications on sustainable supplier selection using fuzzy AHP and TOPSIS. The multi-objective optimization also contributed to the optimal order allocation problem. However, a gap remains for further study on changes in the number of suppliers and the MCDM method. A hybrid meta-heuristic and AI approach were also used in a large-sized problem by Nezamoddini, Aqlan [25]. They proposed a risk-based optimization framework for strategic supplier selection, capacity allocation, and assembly line placement. They utilized a hybrid GA-ANN to address the multiple effects of uncertainty factors, such as supplier disruption, order changes, and delays. Nonetheless, only one configuration for GA and ANN was presented. This issue can be studied further to investigate the robustness of the approach. Recent trends in green and sustainable supply chains have also been considered through sourcing activity by many studies [22, 25, 52, 53].

Inventory management is also an important issue in supply chain management due to its influence on a firm's performance [22]. This area focuses on inventory replenishment, inventory optimization, and inventory control [36]. Currently, supply chains are facing more frequent disruptions, meaning uncertainties are a fundamental factor to be considered by researchers. Nakandala, Lau [54] proposed an optimization model for inventories with multiple suppliers using an integer programming optimization model, which was designed to be easily adoptable by SMEs. However, the requirement of reliable supplier data can also become an obstacle to the adoption of the proposed method, since such data may not be available or may have never been recorded by SMEs. In modern businesses, an automated DSS for inventory control is also emerging. For example, Deb, Kaur [55] proposed an adaptive inventory control system capable of dealing with uncertainties and imprecision of the inventory system. This DSS adopts the artificial intelligence (AI) and fuzzy inference system (FIS) instead of traditional inventory models. The combination of a traditional economic order quantity (EOQ) model and an AI approach for developing a DSS for modern inventory management systems was proposed by Sremac, Zavadskas [56]. The system provides more precise results when determining the amount of EOQ compared to classical mathematical models. Moreover, the use of neuro-fuzzy systems has advantages over conventional models due to their flexibility and adaptability. The adoption of AI-based simulations was also applied by Dosdoğru, Boru İpek [57] to inventory control and routing decisions. This provides the advantages of a realistic perspective and a flexible approach to handling problem variations and uncertainties. Moreover, the approach can easily adapt to similar problems and other real-world cases under uncertain environments.

Based on several studies, the development of decision support tools within the area of supplier selection and lot-sizing problems has exploited four categories of approaches: 1) MCDM approaches [49, 52]; 2) multi-objective optimization approaches using heuristics and metaheuristics [25, 58]; 3) ML/AI approaches [56]; and 4) other hybrid approaches [50]. Table 1 summarizes the research on DSS applications in sourcing and inventory management problems. The contributions of this study with respect to these dimensions are also listed.

2.3. Research gap

It has been noted that SMEs encounter both internal and external drawbacks in sourcing and inventory management, which have hindered any improvements to sourcing and inventory management performance among SMEs. Since external obstacles are difficult to control, performance improvements should initially emanate from SMEs' internal processes. A possible solution to this problem is to improve decision-making by providing a decision support tool. However, few studies have attempted to develop an integrated sourcing and inventory management DSS. Moreover, two main issues have been highlighted. The first is that SMEs lack a data-driven approach in their management and decision-making, rendering them more vulnerable than LEs in terms of competitive advantages. This will be especially true with the arrival of the fourth industrial revolution (Industry 4.0). The second issue regards opportunities for initializing the digital transformation of SMEs. Data and information are known to be the essence of decision-making. Moreover, the employment of IT tools (i.e., DSSs) would benefit SMEs through better business decisions and improved overall business performance. In summation, this study aims to propose a DSS that can address the research gaps mentioned previously.

3. The DSS for sourcing and inventory management

This section presents the development methodology of the proposed DSS, including the conceptual design, architecture, and details of the DSS development process.

3.1. Conceptual design of the DSS

In this research, the objective of the DSS is to support internal decision-making processes concerning sourcing and inventory management activities. Moreover, the aim of the proposed DSS is to minimize the total purchased cost of raw materials based on the company's behavioral preferences in supply and inventory management. Therefore, the proposed DSS utilizes a simulation-optimization approach using a combination of AI and metaheuristic techniques. An ANN was chosen due to its adaptability and learning capabilities with unusual patterns (such as poorly understood problems), enabling the forecasting, clustering, and classifying of input data [60]. For the metaheuristic, the GA was chosen because it can explore many parameters in each iteration and provide multiple local optima. These can then be combined to determine an individual set of optimal solutions based on generations of offspring [61].

It has been demonstrated that SMEs with reduced capability (compared to LEs) in continuously monitoring their inventory level should simplify their management policy. According to Stevenson [28], there are numerous cases where the fixed order interval (FOI) strategy has been embraced by suppliers' policies, which can facilitate the consolidation of orders from the same supplier to reduce shipping costs. Accordingly, the proposed DSS is designed based on two separate strategic issues: selecting suppliers and determining the reorder point and safety stock level for the FOI strategy. The conceptual design of the DSS is presented in Figure 1.

3.2. Problem scope and characteristics

In this section, the scope and characteristics of sourcing and inventory management operations for raw material in manufacturing SMEs are explained, which influenced the DSS design. Generally, manufacturing SMEs have multiple suppliers with redundant materials available across all sources. Accordingly, each supplier offers different sales promotions and discount percentages for each raw material. Since cost factors are a priority for SMEs to consider when purchasing raw materials (due to limited budgets), they should consider numerous factors before deciding to purchase. As a result, the selection of suppliers is based on four factors: cost of raw materials, availability of raw materials, discount percentages offered, and minimum order quantities.

Table 1
Review summary of DSS applications in sourcing and inventory management.

Authors	Approach	Demand				Problem conditions				Uncertainty	
		ST	DT	SP	MP	MS	SS	SA	CP	LT	CU
Scott, Ho [49]	The hybrid AHP-QFD and chance-constrained optimization.	●	-	●	-	●	-	●	●	-	-
Nakandala, Lau [54]	Customized integer programming optimization model	●	-	-	●	●	-	●	-	●	●
Eydi and Fazli [50]	DEA with the pair-wise comparisons-improved principal components analysis (DEAPC-IPCA) and the DEA-discriminant analysis (DEA-DA).	-	-	●	-	-	●	-	●	-	-
Mohammed, Harris [52]	The hybrid MCDM and multi-objective optimization.	●	-	-	●	●	-	●	●	-	●
Nezamoddini, Aqlan [25]	Hybrid GA-ANN	-	●	●	-	●	-	-	●	-	●
Sremac, Zavadskas [56]	Adaptive neuro-fuzzy inference systems (ANFIS)	-	●	-	●	●	-	-	-	-	●
Wang, Wu [53]	Mathematical formulation, in-depth policy study, and analysis, numerical study.	●	-	●	-	●	●	●	-	-	●
Firoozi, Babai [59]	a scenario-based modeling approach using a Sample Average Approximation (SAA) technique	●	-	-	●	●	-	●	●	-	●
This paper	Hybrid GA-ANN	✓	-	-	✓	✓	-	✓	✓	✓	✓

ST = Stochastic Demand, DT = Deterministic Demand, SP = Single-period, MP = Multi-period, MS = Multiple Suppliers, SS = Single Supplier, SA = Supply/Order Allocation, CA = Supply Capacity, LT = Lead time uncertainty, CU = Cost uncertainty of supply.

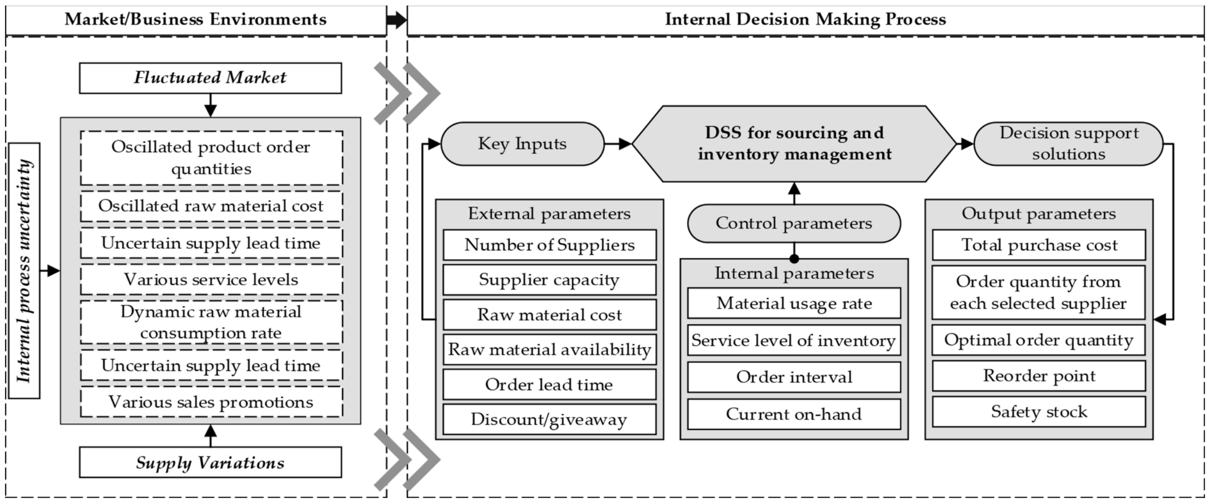


Fig. 1. Conceptual design of the DSS.

The following internal factors should be considered by manufacturing companies before purchasing raw materials under the FOI strategy: the consumption rate of the materials, safety stock levels, current on-hand levels, order intervals, and lead times. Therefore, the problem's scope can be classified as an inventory management model with variable demands, lead times, and quantity discounts [62]. Moreover, since flexibility is one of the critical advantages of SMEs in manufacturing, companies should adopt both made-to-stock (MTS) and made-to-order (MTO), depending on customer orders and seasonal factors. The production strategy can reflect fluctuations in product demand and can affect the quantities of raw materials used to manufacture the product.

3.3. DSS architecture

The architecture of the proposed DSS is presented in Fig. 2. The DSS utilizes raw data from internal operations and the external business environment. Generally, the raw data of business operations and the market are associated with variations and uncertainties, which should be incorporated into the model. Thus, the input variables derived from the raw data were divided into two categories (as shown in Fig. 2): 1) input data based on actual process characteristics and 2) the calculated theoretical parameter values.

The input is based on actual process characteristics and contains both empirical and observational data, which were collected from the operation's transactions and personal knowledge. For some parameters, a descriptive statistical analysis was also conducted to summarize features from collected data and simplify the inputs. The theoretical parameter values could also be calculated using input data from the first category. Two categories of input were utilized as input data for training the ANN. After training and optimization, the DSS returned decision support solutions that consisted of a set of objective values and another four key parameter values through the processes depicted on the right side of Fig. 2.

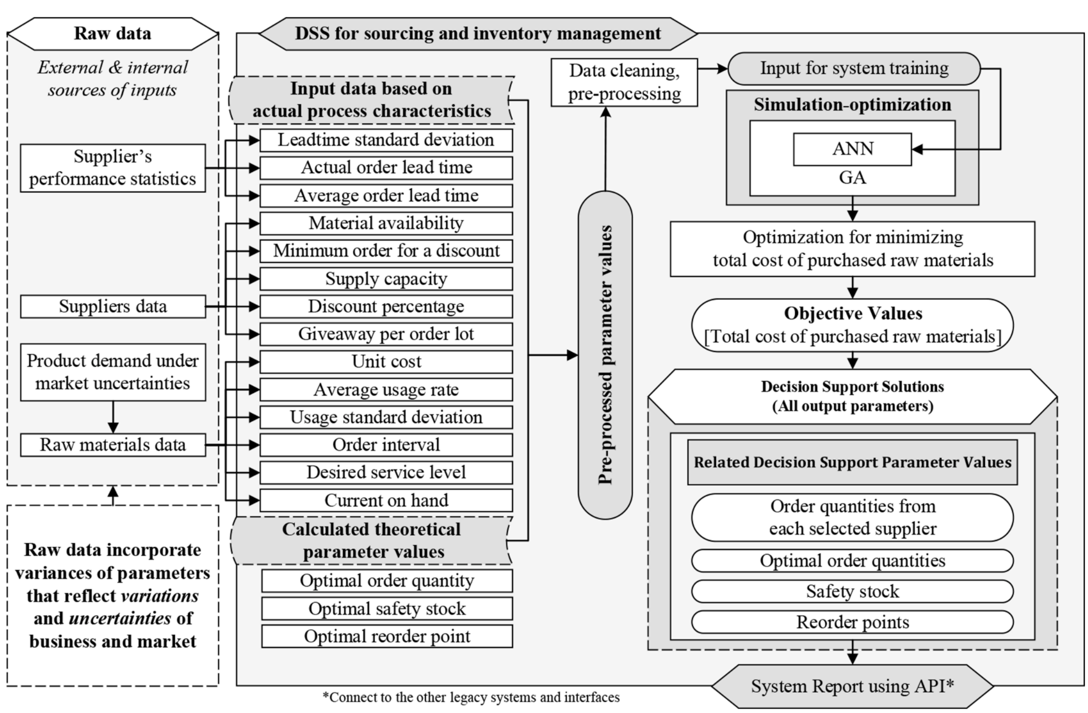


Fig. 2. Architecture of the proposed DSS.

3.3.1. Problem representation

The following section presents the formulation of the mathematical model of sourcing and inventory management and is based on the architecture of the system, as shown in Fig. 2.

- Indices

i	: Material index, $i = \{1, 2, ..., m\}$
j	: Supplier index, $j = \{1, 2, ..., n\}$

- Decision variables

x_{ij}	: Order quantity of raw material$i$ from the supplier$j$

- Parameters

q_i^{opt}	: Optimal order quantity of raw material i
q_i^{rop}	: Optimal reorder point of raw material i
q_i^{SS}	: Optimal safety stock of raw material i
c_{ij}	: Unit cost of raw material$i$from the supplier$j$
U_i^R	: Average usage rate per time unit of raw material$i$
σ_i^u	: Standard deviation of usage rate of raw material i
h_i	: Current on-hand of raw material i
T_i^{LT}	: Actual order lead time of raw material i
$\overline{T}_i^{LT}$	: Average order lead time of raw material i
σ_i^{LT}	: Standard deviation of order lead time of raw material i
T_i^B	: Order interval (time between order) of raw material i
C_{ij}^R	: Total cost of purchased raw material$i$from the supplier$j$
C^{Rtotal}	: Total cost of all purchased raw materials from all selected suppliers
θ_i	: Desired service level of raw material i
z_i	: Standard score of the desired service level of raw material i
$q_{ij}^{\min}$	: Minimum order for a discount of raw material$i$ from the supplier$j$
a_{ij}	: Availability of raw material i from the supplier$j$
κ_{ij}	: Supply capacity of raw material$i$ at the supplier$j$
δ_{ij}	: Discount percentage of raw material$i$ at the supplier$j$
f_{ij}	: Giveaway per lot (free item add up for each minimum order) of raw material$i$ from the supplier$j$
Q_{ij}^{tsv}	: Total supply volume of raw material$i$from the supplier$j$
$Q_i^{receive}$	: Total received quantity of raw material$i$from all suppliers

- Objective function

Total material purchase cost minimization

$$Minimize C^{Rtotal} \tag{1}$$

Subject to the following:

Total cost of all purchased raw materials from all selected suppliers.

$$C^{Rtotal} = \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij}^R \tag{2}$$

Total cost of purchased raw materials$i$from all selected supplier(s)j.

$$C_{ij}^R = \sum_{i=1}^{n} \sum_{j=1}^{k} x_{ij} a_{ij} c_{ij} (1 - \delta_{ij}), \forall a_{ij} > 0 \tag{3}$$

Discount percentages$\delta_{ij}$of raw material$i$ purchased from supplier$j$ are ranging from 0% to a maximum of 20%.

$$0 \le \delta_{ij} \le 0.20, \forall i \forall j \tag{4}$$

Supply constraint: the total supply volume made by all selected suppliers must not exceed the optimal order quantity.

$$\sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} Q_{ij}^{tsv} \ge q_i^{op}, \forall a_{ij} > 0 \tag{5}$$

Desired service levels: the service level of raw material i desired by the decision-maker (constant values are also allowed from 0.00 to 1.00)

$$\theta_i = \frac{Q_i^{receive}}{q_i^{opt}} \tag{6}$$

Safety stock of raw material$i$: the safety stock level is based on usage rate, the standard deviation of usage, the standard deviation of order lead time, and the desired service level of the raw material.

$$q_i^{SS} = z_i \sqrt{\left((\sigma_i^{LT})^2 \overline{T}_i^{LT} \right) + \left(U_i^R \right)^2 (\sigma_i^u)^2}, \forall i \tag{7}$$

Here z_i denote the z-score needed for the desired service level of raw material$i$.

Reorder point of raw material$i$: the order point is based on usage rate, average order lead time, and optimal safety stock.

$$q_i^{rop} = U_i^R \overline{T}_i^{LT} + q_i^{SS}, \forall i \tag{8}$$

Optimal order quantity of raw material$i$: the order quantity depends on the required quantity of the raw material during the order interval, service level, and the current amount of raw material on hand.

$$q_i^{opt} = U_i^R \left(T_i^B + T_i^{LT} \right) + z_i \sigma_i^u \sqrt{T_i^B + T_i^{LT}} - h_i \tag{9}$$

Total supply quantity: this parameter refers to the total amount of raw materials (in which the giveaway is included) delivered from all suppliers.

$$Q_{ij}^{tsv} = \left(x_{ij} + \left(f_{ij} \left(\frac{x_{ij}}{q_{ij}^{\min}} \right) \right) \right) a_{ij}, \forall i \forall j \tag{10}$$

Where:

- The number of giveaways per order lot$f_{ij}$of raw material$i$purchased from supplier$j$ ranges from 0 to 50 units

  $0 \le f_{ij} \le 50, \forall i \forall j$

- The minimum order for a discount of raw material$i$ from supplier$j$ ranges from a minimum of 100 units per order to a maximum of 1000 units per order

  $100 \le q_{ij}^{\min} \le 1000, \forall i \forall j$

Supplier's capacity: the capacity of the supplier refers to the available quantity of raw material that is ready to be ordered.

$$x_{ij} \le a_{ij} \kappa_{ij}, \forall a_{ij} > 0 \tag{11}$$

Availability of raw material i at the supplier$j$

$$x_{ij} = 0, \forall a_{ij} = 0 \tag{12}$$

Minimum order quantity: the lowest quantity to be ordered from each supplier to obtain a discount.

$$x_{ij} \ge q_{ij}^{\min}, \forall i \forall j \tag{13}$$

Total received quantity of raw material i delivered by all chosen suppliers.

$$Q_i^{receive} = \sum_{j=1}^{k} \sum_{k=i}^{i} Q_{jk}^{tsv}, \forall j \tag{14}$$

Non-negative parameter value: All dependent parameters regarding the quantity must be positive.

$$x_{ij}, Q_{ij}^{receive}, Q_{ij}^{tsv} \geq 0 \tag{15}$$

3.3.2. Model assumptions

Due to the complexity of sourcing and inventory management operations, there are some differences between reality and the mathematical model. The following assumptions are made for sourcing and inventory management using the FOI strategy for multi-materials:

- A large capacity of each supplier is assumed to prevent deficiencies of raw materials.
- The following parameters are fixed as constant values in each discrete event: unit cost of the raw material, supplier capacity, actual lead time, minimum order quantity of the raw material, current on-hand of the raw material, discount percentage, order interval, and giveaway per lot. These can be altered manually by a decision-maker.
- The maximum length of the order interval for raw material is set to a maximum of 10 days to prevent overstocking and to maintain high inventory performance [63].
- Inventory holding and spoilage costs are not considered in this model.

3.4. DSS development and implementation

This section outlines the DSS development and implementation procedures for sourcing and inventory management in the case study company. There are four steps for DSS setup and deployment: 1) synthesizing a training dataset, 2) ANN construction and training, 3) Process parameter optimization, and 4) solution implementation. A diagram of these procedures is depicted in Fig. 3, and each step is explained in the following section.

3.4.1. Data synthesizing and pre-processing

In this study, two types of data were the focus as they are the primary sources of inputs: observational data (daily routine data and daily records of transactions) and empirical data (data based on experience and the knowledge of skilled workers) [24, 64]. To synthesize large quantities of data, the configed mathematical model also contained variations of the parameters. Then, the brute-force algorithm was exploited to search all possible parameter values based on a given range. Since it is common to modify (or filter) data before being utilized in ML training, the pre-processing algorithms from Scikit-learn in Python were employed. A standard scaler was used to standardize the data and reduce data dimensions after data synthesis [59]. The processed parameter values obtained from this step represent possible configurations of sourcing and inventory management operations based on the given conditions. The stopping criteria of the brute-force search were set to 120,000 iterations. After synthesizing process configurations, the data were prepared for ANN training by eliminating infeasible configurations and by normalization.

3.4.2. Construction and training of the ANN

After the training dataset was prepared, the next step was to construct the ANN with various configurations for learning the complex relationships between inputs [65] (e.g., raw materials, suppliers, usage rate, and safety stock) and outputs (e.g., reorder point, choice of suppliers, and optimal order quantity) of the sourcing and inventory

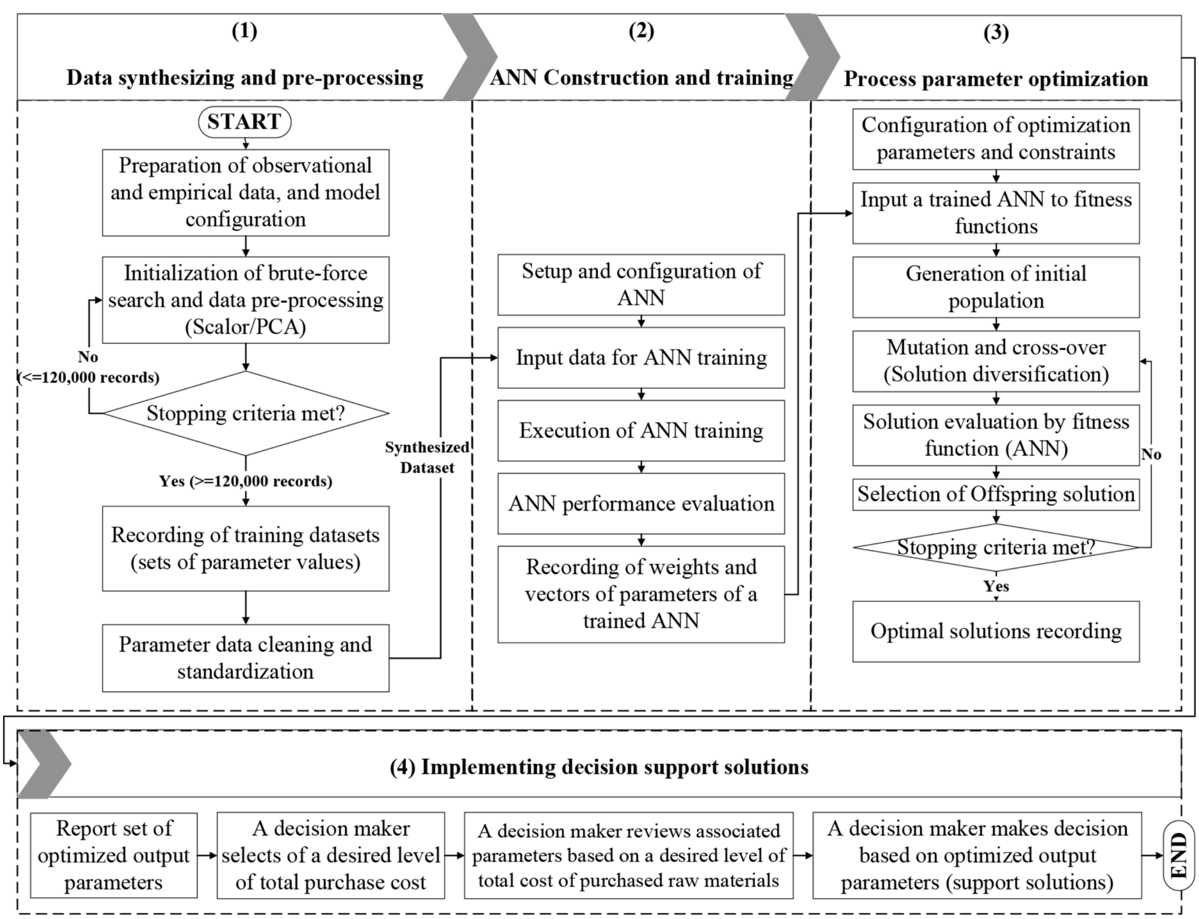


Fig. 3. DSS development and implementation.

management operations. This learning process is essential in intelligent approaches to adapting the sourcing and management processes based on various constraints and requirements of raw materials and suppliers. Therefore, the ANN represented the behaviors of the system realistically. In this paper, a multilayer perceptron ANN (MLP-ANN) with a back-propagation (BP) learning algorithm was employed. The configurations of the ANN are shown in Table 2 and the architecture of the implemented ANN is illustrated in Fig. 4.

There are various configurations for an ANN in terms of the number of hidden layer neurons and the vector of parameters (e.g., the weights and activation function parameters), which affect the learning and prediction performance of the ANN. Thus, this research used the 'grid search' algorithm in Python to determine the ANN's optimal configuration that was suitable for different training datasets [66, 67]. For the ANN training, a ready-to-use package from Scikit-learn (in Python) was used called MLPRgressor, which incorporated the grid search algorithm to determine the optimal configuration [68, 69]. The initial configurations for the ANN were as follows: model_mlp = MLPRegressor (activation = "tanh", "relu", hidden_layer_sizes = [50, 150, (100,100)], learning_rate = [adaptive, constant]", max_iter = 50, 100, 150, 200). Following the training, the performance of the ANN was evaluated using the following indicators: mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). The trained ANN with the best performance (relatively) was equipped with the known weights and vectors of the parameters, which were exploited as part of the GA's fitness function. This provided a solution space and computed the fitness function for the GA during optimization. The schematic of the ANN for the simulation of sourcing and inventory management operations is portrayed in Fig. 5.

3.4.3. Process parameter optimization

In this step, the aim of optimization is to adjust some parameters to obtain appropriate values of the output parameters using the GA. The trained ANN obtained from the previous step provided the GA goodness of fit of the solution. To accomplish this, all parameters were encoded into a binary number prior to the optimization process. Thus, the length of chromosomes could be varied depending on the target values. To exploit the GA, the distributed evolutionary algorithm in Python (DEAP) framework [70] was used. This is a programming language used for the rapid prototyping of custom evolutionary algorithms and for controlling the genetic optimization procedure [71]. The grid search algorithm is also deployed to determine the optimal configuration of GA [72, 73]. During optimization, the solutions were diversified via mutation and crossover. Then, the trained ANN evaluated the solution by measuring the fitness value. The interactions of the GA-ANN as the DSS are illustrated in Fig. 6.

3.4.4. Implementing decision support solutions

Fig. 7 portrays a process of implementing the decision-support solutions provided by the proposed DSS. After data processing, system training, and parameter optimization, the final step is having a decision-maker verify and validate the solutions. Practically, decision-makers can review the set of optimal solutions and use them to support their decision-making. The decision support solution generated by the system consists of five key results: objective values (total cost of purchased raw materials), optimal order quantity, order quantity from each supplier, safety stock, and reorder point, as portrayed in Fig. 2.

Table 2
ANN configuration.

Type of ANN	ANN Architecture	Training Algorithm	Data Partitioning	Performance Evaluations
Supervised learning ANN	MLP	BP	Varied (13%, 25%, 50%)	MAE, MSE, R^2

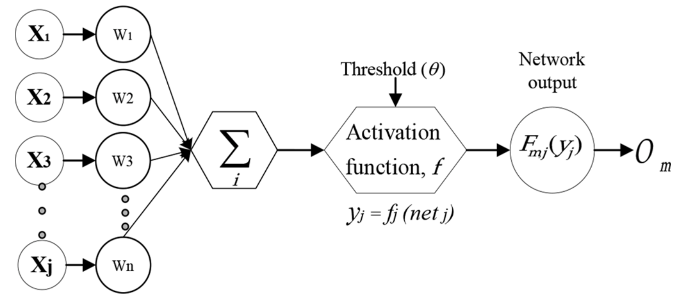


Fig. 4. The MLP-ANN.

Since SME decision-makers are not advanced users, DSS interactions and the resulting interpretations should be simple. Accordingly, decision-makers should only have to deal with data they are familiar with. Moreover, the implementation of support solutions can be iterative in terms of finding solutions. In some cases, the obtained solutions may not be feasible (or practical) to implement. The proposed method allows decision-makers to improve the solutions via interactions with the constraint parameters. Moreover, decision-makers can reconfig. some parameters into specific values as desired. For example, the manager may find that the discount rate of raw material is more than usual in a certain period; therefore, the manager would input the specific discount rate for the calculation during that period. Then, the genetic algorithm would treat such a discount parameter as a constant value (when a variation of the parameter value is not required) and then recalculate the result. Hence, managers can test their plan (or assumption) by adjusting the constraints with the iterative approach. Further, decision-makers can update input data using a spreadsheet, and the system can read all input data directly from the file. Decision-makers can also review the decision-support solutions from the spreadsheet generated by the system. ,

4. Development and implementation results

In this section, the DSS implementation results are discussed, including a description of the test case, observations, data collection results, data synthesizing, system training, process parameter optimization, and the solution report.

4.1. Process observation and data collection

The test case for the DSS took place in a pastry company in Thailand. The company is a medium-sized enterprise that produces MTS and MTO products with varying proportions. There are more than 400 products available for customers manufactured by eight sub-manufacturing divisions. As recommended by the plant manager, one product family named 'cake roll' was selected for this research. In general, the term product family refers to a group of associated products that share common features and functions derived from a common product platform [74]. In this case, the cake roll family consists of more than 26 products that share five vital common ingredients: cake flour, egg white, yolk, sugar, and vegetable oil. Their mixing formula distinguishes the differences in products. In other words, the differences in cake roll products are based on differences in the mixing proportions of ingredients and their flavors.

The daily consumption rate of each raw material varies due to the uncertainty of customer orders. However, each product has a minimum daily production quantity as a result of the MTS production strategy. Based on three-month historical records and information provided by the head of the manufacturing division, the minimum and maximum quantities to date of the five main ingredients of the cake roll family are presented in Table 3. Since the company's products are produced daily, the FOI rule is applied for purchasing most of the critical materials used

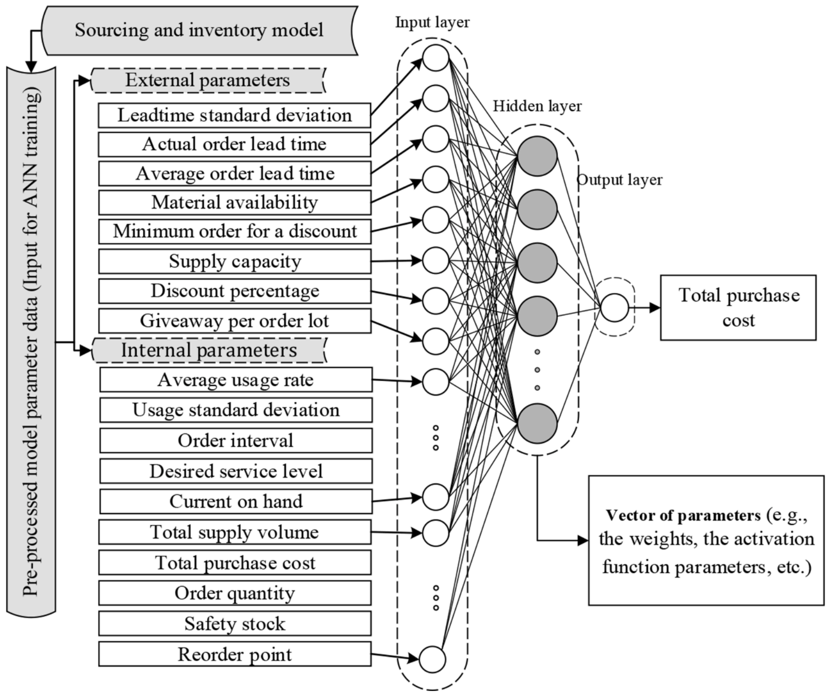


Fig. 5. The ANN architecture for sourcing and inventory management.

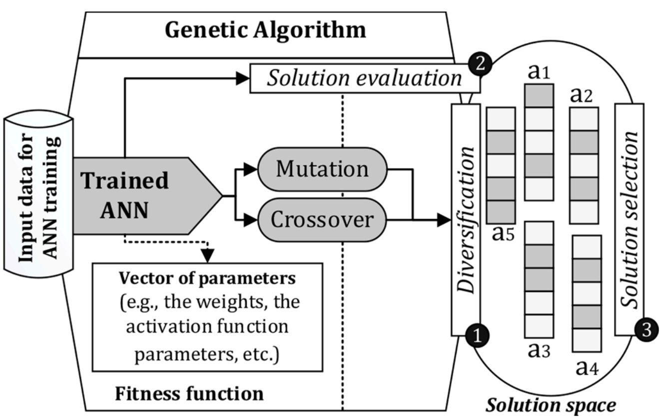


Fig. 6. Diagram of GA-ANN interactions.

in the company. The reason for this is to reduce the amount of work in inventory monitoring. The order interval of raw materials is continuously adjusted to prevent inventory overstock or stockout.

Table 4 presents the time factors that characterize the raw material management operation of the company. Three suppliers provide the presented raw materials. Although the FOI strategy is applied, the company still needs to manually decide which supplier to select and how much to order based on market demand and sale promotions offered by the suppliers. There are two types of sale promotions offered by suppliers: discounts and giveaways. When a quantity (or purchased value) meets the sale promotion's condition, the company receives a discount or giveaway (or both) from the supplier. The company frequently purchases more raw materials than its needs due to these sale promotions, causing overstocking and excess costs. Table 5 presents the descriptive statistics of purchased raw material costs for all five key materials and the total cost per order of three-month historical records. Based on the empirical and observational data, the mathematical model representing the actual system can be configed, and the training data can be synthesized. The next section will explain the processes of data synthesizing, data pre-processing, and ANN training.

4.2. Data synthesizing and training of ML algorithms

Since the data regarding sourcing and inventory replenishment processes collected by the company were quite limited and incoherent, both empirical and observational data were examined. With the two types of data in place, the data synthesis could proceed.

Table 6 presents a demonstration of an input dataset for training ML algorithms, which is based on the characteristics of the system. The data were synthesized via a brute-force search algorithm in Python. Under the context of the case study, there were five raw materials and three suppliers. An example of a training dataset was used for the ANN training to force the DSS to recognize the behavioral patterns of the process. The synthesized dataset was generated and exported into a comma-separated values (CSV) format, consisting of 170 columns representing all model parameters. A total of 17,572 instances were generated using the mathematical model from Section 3.3.1. The training procedure used the configurations of ANN presented in Section 3.4.2. Moreover, two further ML algorithms (linear regression and random forest) were deployed against the ANN. The configurations for the two algorithms were as follows:

- Linear regression = LinearRegressor ('normalize': [True, False])
- Random forest = RandomForest ('criterion': 'mse', 'max_depth': 3, 'n_estimators': [50, 100, 150, 200], 'random_state': [1, 2, 3, 4])

At each level of a training size, the data preprocessing algorithm (StandardScaler [75]) was deployed in all algorithms to compare with non-preprocessing. The aim of preprocessing data is to test whether it could enhance the ML's training performance via data transformation, which in this case was standardization via StandardScaler. During the training process, the grid-search algorithm determined the optimal configuration of the ANN. After training, the prediction performance of the ANN was measured by MAE, MSE, and R^2 at different proportions of the training data. In this case, the predicted total cost of raw materials purchased was measured against the synthesized values. The MSE and MAE of the ANN and the competitive algorithms at their optimum configuration in each level are shown in Table 7 and Table 8, respectively.

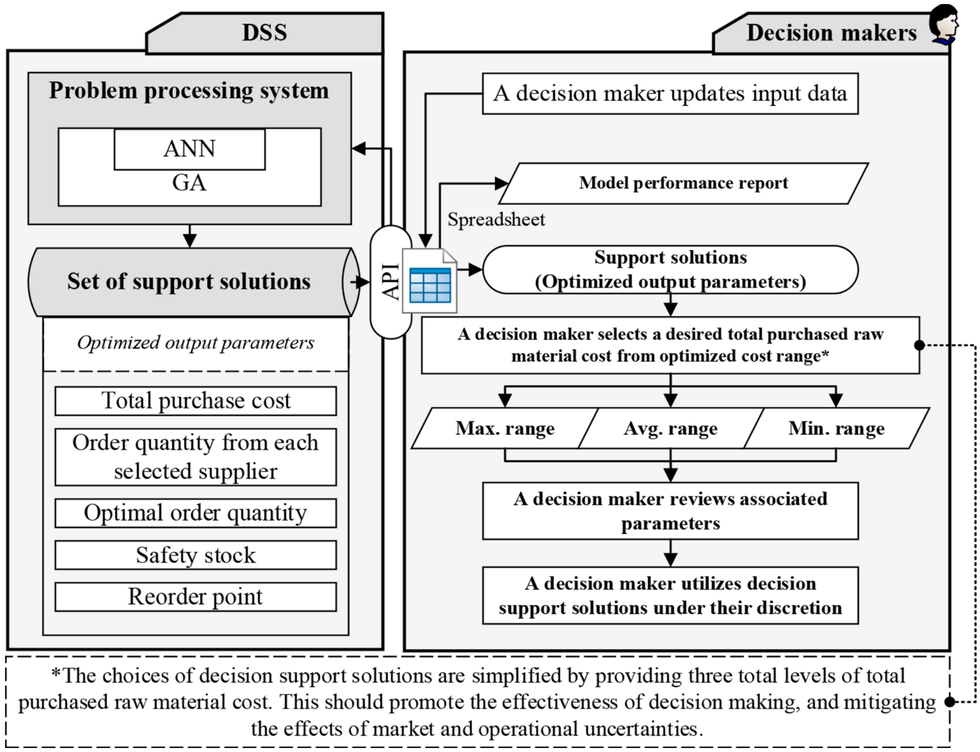


Fig. 7. Process of implementing the decision support solutions.

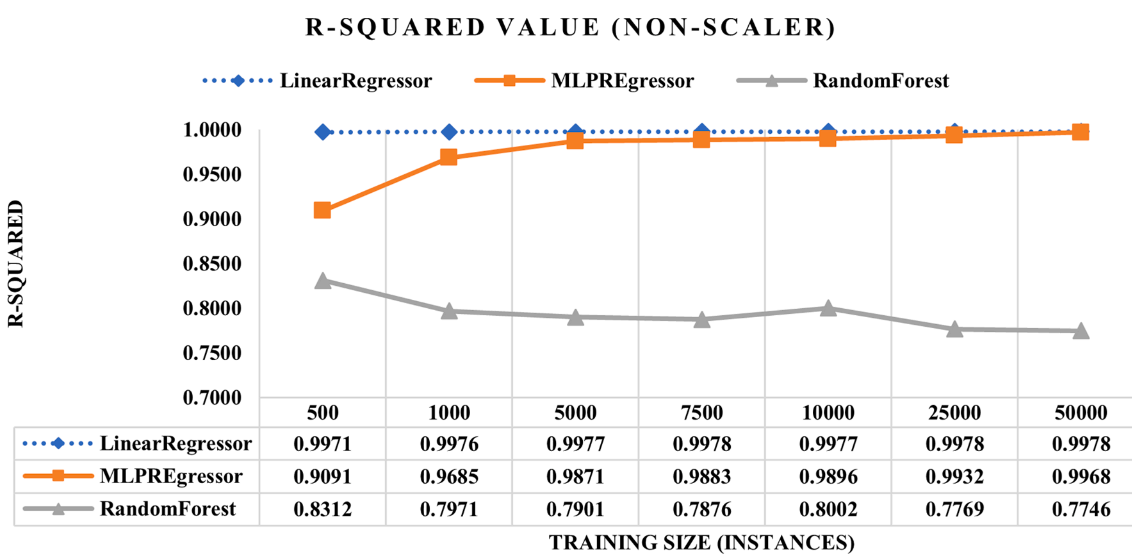


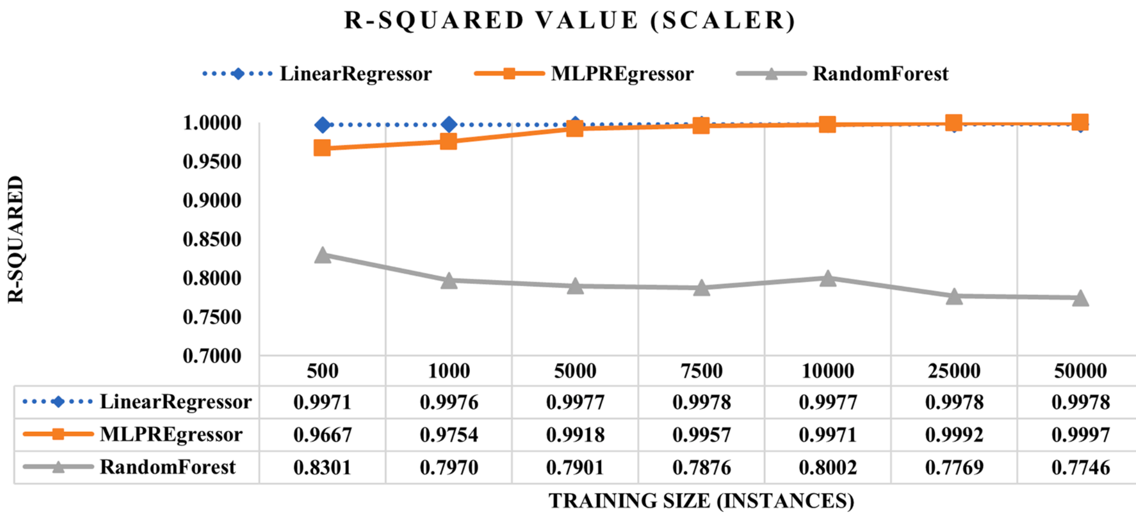
Fig. 8. R^2 values with non-scaler.

According to the measurements of R^2 with both non-scaler and scaler, as shown in Fig. 8 and Fig. 9, the performance of Linear Regressor and MLPRegressor outperformed RandomForest. Although the performance of Linear Regressor and MLPRegressor were very similar, as the size of training data increased, the MLPRegressor with scaler eventually outperformed its competitors with a maximum R^2 value of 0.9997. The use of the ANN provided more advantages in dealing with non-linear relationship data sets or models in terms of both data fitting and prediction capabilities [76].

4.3. Process Parameter Optimization

The trained ML algorithms contained the vectors and relationships of parameters, enabling them to serve as a solution space to be utilized by the GA to determine the optimal solution. The configurations of the sourcing and inventory management parameters were encoded as binary numbers. Thus, the length of the chromosome depended on the configurations of the model parameters and the target. In this case, the target of configurations was set to determine the minimum total cost of purchased raw materials. Based on randomly generated instances, the test on optimization performance was conducted on the distributions of objective values. The descriptive statistics of the randomly generated objective values are presented in Table 9.

According to Table 9, it can be seen that the optimization performance was tested against three different levels of total purchased raw material cost: Q1 value ($C^{RTotal}_{Q_1} = 5{,}883$), median value($C^{RTotal}_{average} = 9{,}759$),



	500	1000	5000	7500	10000	25000	50000
LinearRegressor	0.9971	0.9976	0.9977	0.9978	0.9977	0.9978	0.9978
MLPREgressor	0.9667	0.9754	0.9918	0.9957	0.9971	0.9992	0.9997
RandomForest	0.8301	0.7970	0.7901	0.7876	0.8002	0.7769	0.7746

Fig. 9. R^2 values with scaler.

Table 3
Daily consumption rate of raw materials (Unit: kg. /day).

Raw material	Min. daily usage rate	Average daily usage rate	Max. daily usage rate	Usage standard deviation
Flour	100	253	458	132
Vegetable oil	95	185	324	124
Egg white	122	301	493	142
Yolk	112	212	464	136
Sugar	120	235	389	130

Table 4
Time factors of raw materials (Time unit: day).

Raw material	Order Interval	Min. order lead time	Avg. order lead time	Max. order lead time	Lead time standard deviation
Flour	7	2	3	5	2
Vegetable oil	4	3	5	7	2
Egg white	3	1	2	3	1
Yolk	3	1	3	4	1
Sugar	5	2	3	5	2

and maximum value($C^{RTotal}_{\max} = 21{,}760$). These numbers can then be used as a benchmark to simulate the different levels of the total purchased raw material cost per order. To obtain the optimized total purchased raw material cost and related parameters, the GA was implemented by the DEAP package to determine the chromosome that was most positively different from the current cost levels. This was achieved using the following objective function:

$$\underset{x_{ij},U_i^R,\ldots,\theta_i}{\operatorname{argmax}} = Y^{\text{target}} - Y^{\text{recall}}, Y^{\text{target}} > Y^{\text{recall}} \tag{16}$$

In Eq 16, the objective function for determining a feasible solution is presented. In this study, the objective function represents the difference between the current total cost(Y^{target}) and the optimized total cost. This value ranged from the minimum to maximum values of the cost, as shown in Table 9. Summary of. The term Y^{recall}represents the optimized total cost, which is the best-recalled value of the total cost. The recalled values were learned by the ANN and recalled by the GA during optimization. As part of the objective function, obtainingY^{recall}involves other related model parameters, as presented in Section 3.3.1. Thus, eachY^{recall}value will also provide decision support information on inventory management and a selection of suppliers. The objective values were considered feasible if $Y^{\text{target}} > Y^{\text{recall}}$. The negative objective value($Y^{\text{target}} < Y^{\text{recall}}$)was excluded.

Table 5
Cost of purchased raw materials and quantity statistics.

	Flour	Vegetable oil	Egg white	Yolk	Sugar
Average unit cost	$1.61-$1.85	$1.00-$1.23	$3.83-$3.95	$1.35-$1.45	$0.90-$1.02
Min. cost of purchased raw material /order	$2,297	$945	$5,526	$1,560	$2,066
Average cost of purchased raw material /order	$5,271	$2,620	$13,181	$3,024	$3,387
Max. cost of purchased raw material /order	$12,598	$6,063	$27,540	$6,785	$7,371
Ranges of discount (%)	2-10	2-5	3-18	3-10	5-10
Standard Deviation	$2,215	$946	$4,661	$1,307	$959
Minimum order quantity (kg.)/ order*	200-500	400-500	400-500	100-300	500-1000
	Total cost of Purchases			**Holding cost**	
Total minimum cost	$12,099			$4,096	
Total average cost	$21,676			$5,351	
Total maximum cost	$60,358			$7,254	
Total standard deviation	$10,107			$764	

The crossover and mutation rates varied between 10%, 30%, and 50% of the population. The crossover operation utilized a two-point crossover, and the mutation operation for a binary-encoded GA implemented a 'Bit Flip' mechanism. The bit flip selects one or more random bits of chromosomes and flips them to the opposite value. The maximum generation rounds have three levels: 10, 30, and 50 rounds, and the initial population was set to 10, 50, and 100. A summary of the GA configurations is presented in Table 10 . Summary of. As mentioned previously, 17,572 possible solutions were generated by three MLs. Accordingly, three new levels of purchased raw material costs were obtained. Further, the approach determined the best possible solutions for minimum, average, and maximum purchasing.

Table 6
Demonstration of an input dataset for ML.

objective	**order$_q$uanity00**	**order$_q$uanity10**	**order$_q$uanity20**	**order$_q$uanity30**	**order$_q$uanity40**	**order$_q$uanity01**	**order$_q$uanity21**	**order$_q$uanity31**	**order$_q$uanity41**	**order$_q$uanity02**	**order$_q$uanity12**	**order$_q$uanity22**	**order$_q$uanity32**	**order$_q$uanity42**
780482	784	500	1444	0	800	784	1444	1199	500	784	400	1444	1199	1000
651099	500	500	1157	0	814	500	1157	1229	814	400	400	1157	1229	1000
704379	851	978	1297	0	800	851	1297	314	500	851	978	1297	314	1000
660162	1647	644	500	0	1376	1647	500	1092	1376	1647	644	500	1092	1376
727575	607	590	1191	0	1361	607	1191	1167	1361	607	590	1191	1167	1361
440693	1038	573	500	0	800	1038	500	231	500	1038	573	500	231	1000

"i=0: flour, i=1: vegetable oil, i=2: egg white, i=3: yolk, i=4: sugar." The supplier indices are the following "j=0: supplier A, j=1: supplier B, j=2: supplier C.

Table 7
MSE values of all algorithms.

MSE Values Training Size	**LinearRegression** Non-Scaler	Scaler	**MLPRegressor** Non-Scaler	Scaler	**RandomForest** Non-Scaler	Scaler
500	8.96E+07	2.92E-03	2.77E+09	3.30E-02	5.14E+09	1.69E-01
1000	7.55E+07	2.53E-03	9.85E+08	2.57E-02	6.34E+09	2.13E-01
5000	7.19E+07	2.18E-03	4.00E+08	7.69E-03	6.51E+09	1.98E-01
7500	6.88E+07	2.22E-03	3.66E+08	4.39E-03	6.67E+09	2.15E-01
10000	7.12E+07	2.27E-03	3.23E+08	2.83E-03	6.19E+09	1.98E-01
25000	6.89E+07	2.19E-03	2.16E+08	7.70E-04	7.04E+09	2.24E-01
50000	6.99E+07	2.26E-03	1.03E+08	3.01E-04	7.20E+09	2.33E-01

Table 8
MAE values of all algorithms.

MAE Values Training Size	LinearRegression Non-Scaler	Scaler	MLPRegressor Non-Scaler	Scaler	RandomForest Non-Scaler	Scaler
500	7.31E+03	4.17E-02	3.67E+04	1.42E-01	5.74E+04	3.28E-01
1000	6.38E+03	3.69E-02	2.26E+04	1.24E-01	6.02E+04	3.49E-01
5000	6.24E+03	3.44E-02	1.55E+04	6.88E-02	6.19E+04	3.41E-01
7500	6.13E+03	3.48E-02	1.47E+04	5.08E-02	6.21E+04	3.53E-01
10000	6.21E+03	3.51E-02	1.38E+04	4.07E-02	6.13E+04	3.47E-01
25000	6.14E+03	3.47E-02	1.13E+04	2.05E-02	6.39E+04	3.61E-01
50000	6.17E+03	3.51E-02	7.70E+03	1.20E-02	6.43E+04	3.65E-01

4.4. Sensitivity analysis of approach parameters

In this approach, ML is the critical part for determining the optimal solution of the GA, because it is a part of the fitness function and provides a solution space for the GA. In the optimization process, associated parameter settings can have a significant influence on the performance of the approach. These settings include the sizes of the training data (size) and initial population (initial_pop), the maximum number of iterations (max_iter), the probability of crossover (p_crossover), and the probability of mutation (p_mutation). To examine the influence of the approach parameters, correlation and sensitivity analyses of the model parameters were conducted. The correlation analysis results on the influent factors are shown in Table 11, where it can be seen that the probability of crossover, the initial population, and the maximum number of iterations have the strongest positive correlation on the objective values.

The next step was sensitivity analysis of the parameters on the best recall values. Observations were made of the solution recalling performed by the GA and the three MLs. Each experiment exhibited the effect of model parameter configurations (i.e., the difference between recalled solutions and the target value). Fig. 10–Fig. 15 illustrate the performance of the MLs and their parameters (training size, initial population, probability of crossover, probability of mutation, and maximum numbers of iterations) with regard to solution recall performance.

According to the sensitivity analyses, the results confirmed the influence of parameter configurations on the solution recall performance.

Table 9
Descriptive statistics of objective values.

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Objective values	17572	0	9758.6	36.7	4867.8	149.4	5882.8	10273.1	13453.9	21759.6

Table 10
Summary of GA configurations.

Target objectives	$[Y_{\min}^{\text{target}} = C_{Q_1}^{RTotal} = 5,883]\left[Y_{avg}^{\text{target}} = C_{average}^{RTotal} = 9,759\right][Y_{\max}^{\text{target}} = C_{\max}^{RTotal} = 21,760]$
Crossover percentage	10%, 30%, 50%
Mutation percentage	10%, 30%, 50%
Max rounds of evolution	10, 30, 50
Initial population	10, 50, 100

First, Fig. 10 indicates that MLPRegressor outperformed the others in terms of recall performance, having the closest recalled values compared to the benchmark. Regardless of the model, the effects of the training size did not change as the training size of the data increased, as shown in Fig. 11. Moreover, Fig. 12 indicates that the initial population exhibited no significant impact on the solution recall performance as the initial population increased—the recalled solutions diverged from the benchmark. As shown in Fig. 13 and Fig. 14, the probabilities of crossover and mutation did not have significant effects on enhancing recall performance, which is quite different from the correlation test result. Finally, the effect of the maximum number of iterations was almost identical to the effect of the initial populations, exhibiting no significant impact on the recall performance (as shown in Fig. 15). Moreover, since the ANN is likely to provide the optimum recall result, the final test demonstrated solution recall performed by all MLs at different training sizes and probabilities of crossover. At each level, the optimum objective values from each algorithm were recorded. The results in Fig. 16 indicate that the ANN (MLPRegressor) provided objective values that were closest to the randomly selected target.

Conclusively, the tests of the proposed DSS with a hybrid GA-ANN approach suggest it would be able to provide a promising result in a real-world case. The tests were also simulated with several obstacles that could be found in real SME environments. For example, testing the approach against small sizes of training data simulated SME environments with limited data. The use of a mathematical model with unknown parameter relationships (to generate more training data based on

Table 11
Correlation analysis on factors affecting the best objective.

	size	initial_pop	p_crossover	p_mutation	max_iter	best_recall	best_objective
size	1.000						
initial_pop	0.000	1.000					
p_crossover	0.000	0.000	1.000				
p_mutation	0.000	0.000	0.000	1.000			
max_round	0.000	0.000	0.000	0.000	1.000		
best_recall	0.047	-0.316	-0.073	-0.180	-0.415	1.000	
best_objective	-0.032	**0.214**	**0.386**	0.122	**0.281**	-0.697	1.000

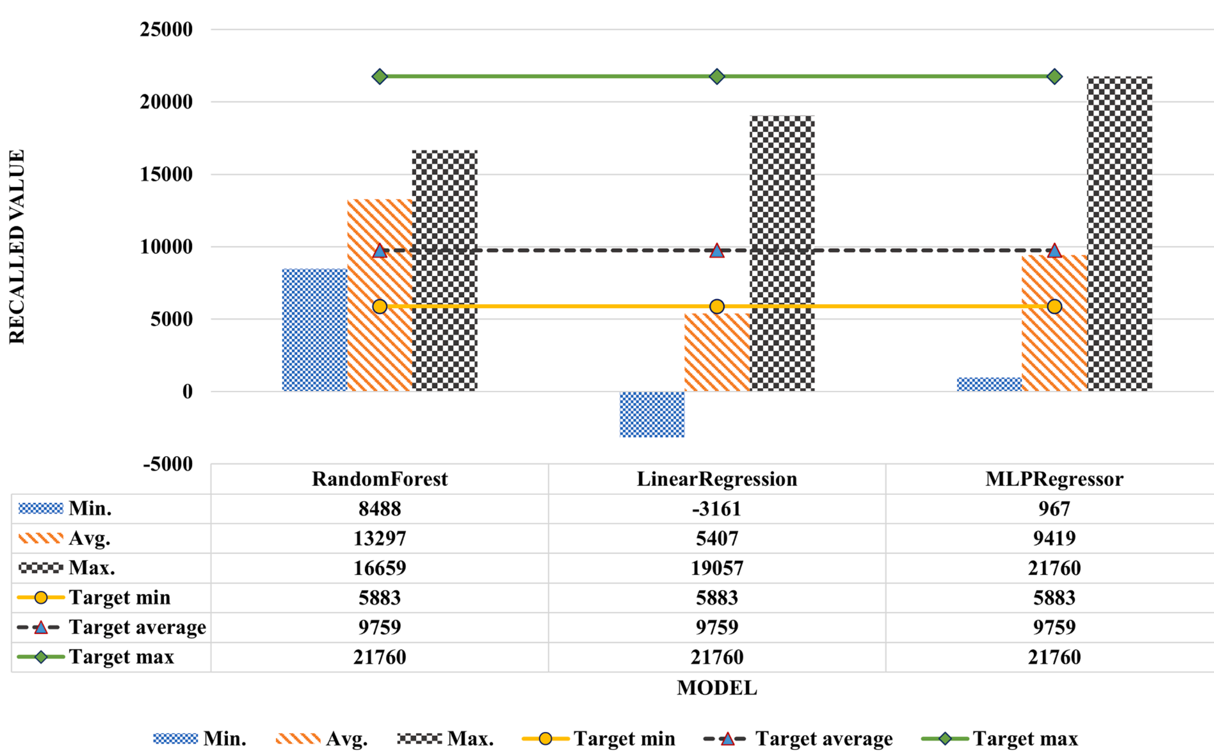
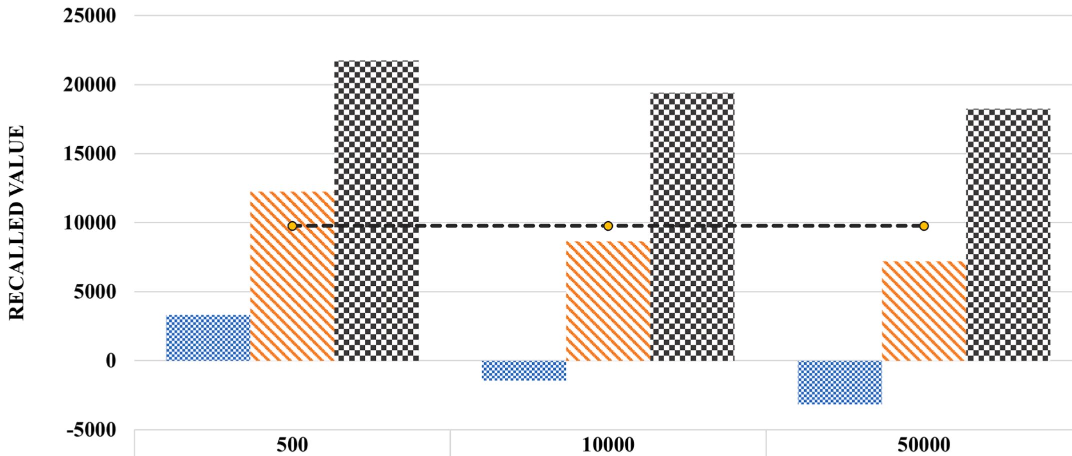


Fig. 10. Solution recall performance of each model.

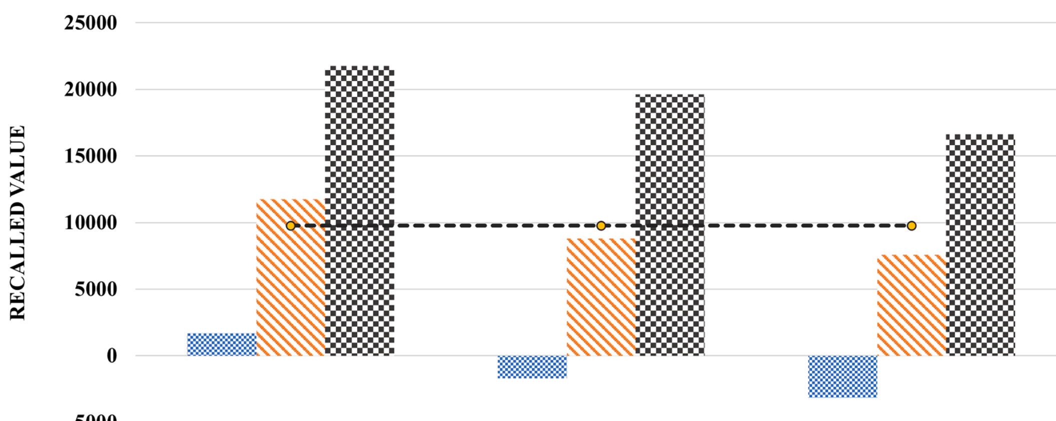


	500	10000	50000
Min.	3328	-1441	-3161
Avg.	12265	8641	7217
Max.	21760	19416	18256
Target	9759	9759	9759

TRAINING SIZE

Min. Avg. Max. Target

Fig. 11. Effects of training size on solution recall performance.



	10	50	100
Min.	1676	-1709	-3161
Avg.	11739	8798	7585
Max.	21760	19614	16636
Target	9759	9759	9759

INITIAL POPULATION

Min. Avg. Max. Target

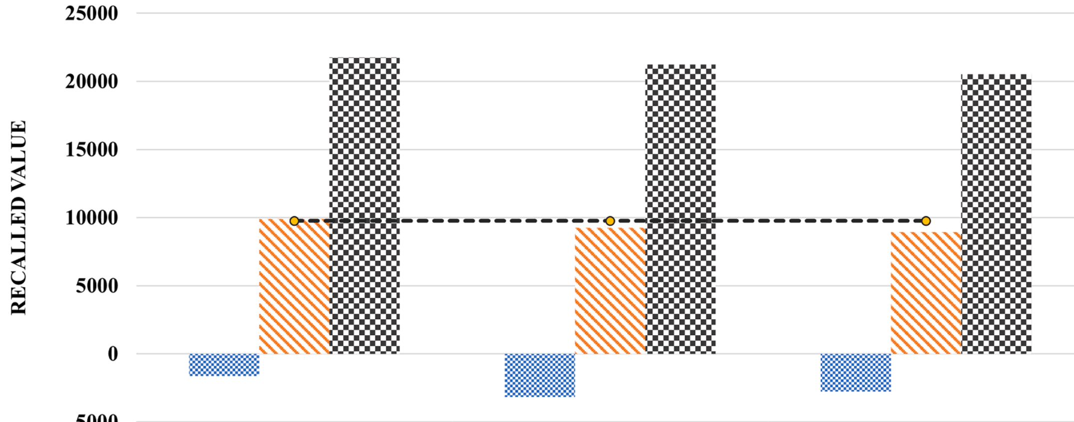
Fig. 12. Effects of initial population on solution recall performance.

the system characteristics) is also feasible. In addition, the proposed approach is comparable with other algorithms in terms of overall performance. Further, using the ANN to learn the relationships of process parameters before utilizing it as a solution space for GA could help SMEs save time and resources in data collection and avoid mathematical sophistication.

4.5. DSS implementing results

After experimental testing confirmed the reliability of the approach, the next step was to apply the DSS in a real-world case. Here, the statistical data of raw material movements and inventory levels based on three-month historical records are depicted in Table 5. Thus, the implementation considered three scenarios for different levels of total purchased raw material costs. Accordingly, the three targets considered in this case emanate from the total cost of purchases. After inputting new data for system training and optimization, the optimum recall target values of the minimum total cost of purchased raw materials were obtained, as presented in Table 12. A comparison of the total purchased raw material costs and on-hand inventory costs indicates a significant cost reduction. With these target values obtained, the decision-makers can obtain other corresponding parameter values that constitute each level of the total purchased raw material cost.

Based on the DSS recommended total cost values, decision-makers can start to choose the desired level of total purchased raw material cost based on their available budget. The selected target cost value will

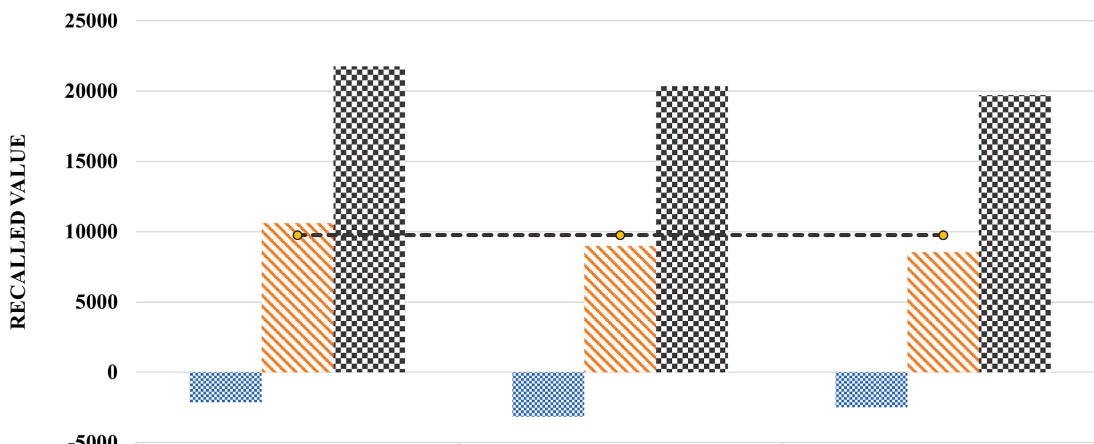


	0.1	0.3	0.5
Min.	-1631	-3161	-2756
Avg.	9922	9265	8935
Max.	21760	21231	20536
Target	9759	9759	9759

PROBABILITY OF CROSSOVER

Min. Avg. Max. Target

Fig. 13. Effects of probability of crossover on solution recall performance.



	0.1	0.3	0.5
Min.	-2123	-3161	-2498
Avg.	10610	8981	8532
Max.	21760	20362	19723
Target	9759	9759	9759

PROBABILITY OF MUTATION

Min. Avg. Max. Target

Fig. 14. Effect of probability of mutation on solution recall performance.

reveal associated, optimized output parameters, which will support sourcing and inventory management operations. Nevertheless, since the problem considered in this paper is NP-hard, the exact solution cannot be discovered in such a massive, complex problem [77, 78]. The recommended parameter values based on the input data provided by the decision-maker are presented in Table 13.

The example solution in Table 13 was recalled from the system. Practically, managers can adjust the numbers at their discretion. For example, the purchased quantity can be adjusted to match the supplier's conditions prior to purchasing. New input data should be updated daily to ensure the system can gradually learn from new input data. In addition, decision-makers can use the DSS to test the raw material purchasing plan. For example, the manager may have planned to adjust the order intervals of raw materials. In this case, the manager would need to input the new order intervals and then have the system recalculate the output solution.

The use of average parameter values is another option to utilize in the DSS. In some cases, the solution provided by the DSS may not fit reality (or the usual decision patterns of the managers). Here, the average parameter values from multi-levels of the total costs can help to reduce the difficulty in interpreting and selecting the correct parameter values. Accordingly, a demonstration of corresponding parameter values as per the DSS's suggestions is shown in Table 14.

The demonstration of parameter values is provided by exhibiting the

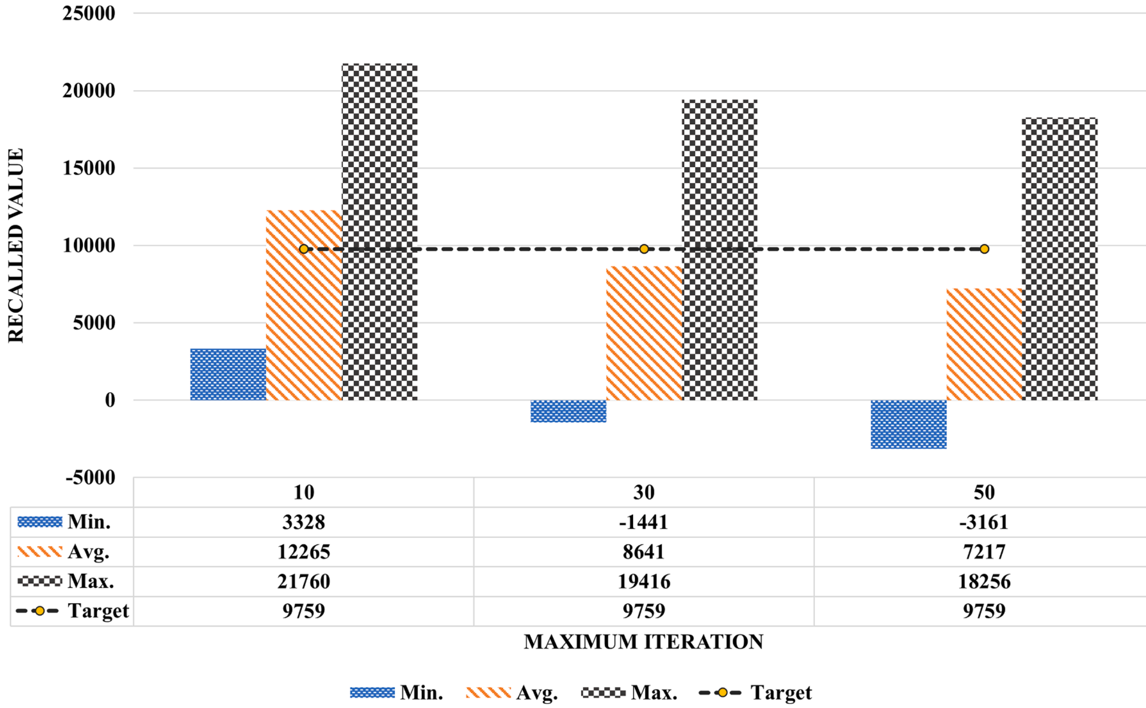


Fig. 15. Effects of maximum number of iterations on solution recall performance.

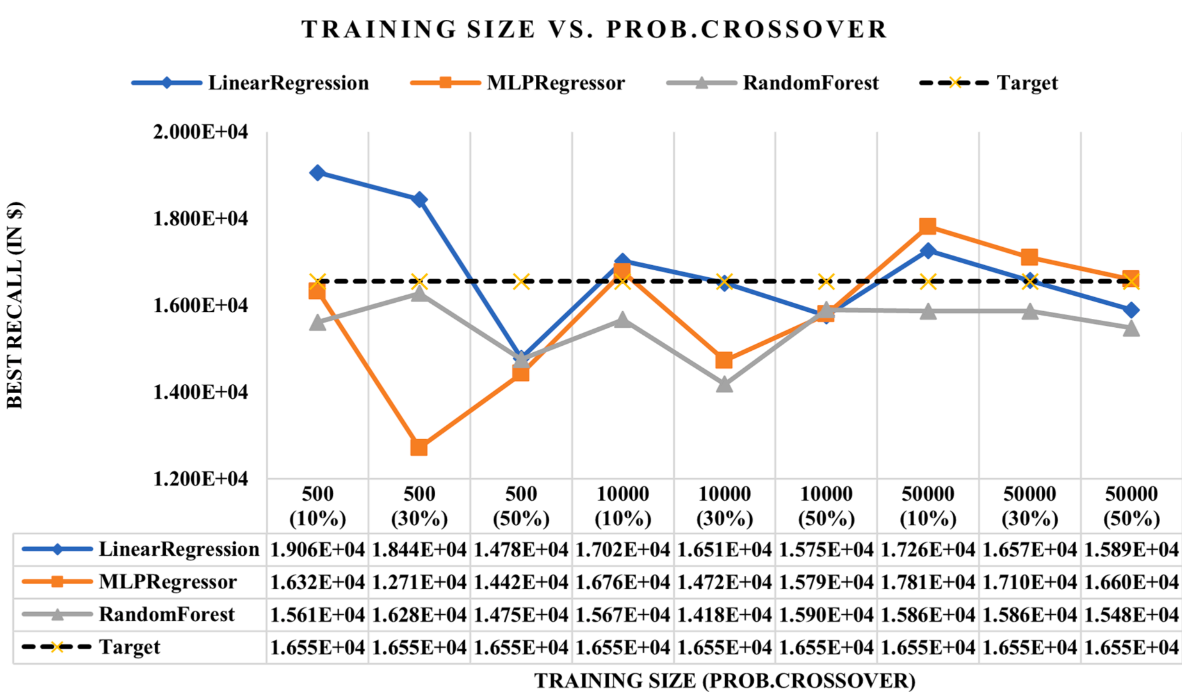


Fig. 16. Effects of training size and probability of crossover on solution recall.

Table 12
Comparison of total costs based on three targets.

	Total cost of purchased raw materials			On-hand inventory cost		
	Before	**After**	**%Changes**	**Before**	**After**	**%Changes**
Total minimum cost	$12,099	$6,887	-43.07%-	$4,096	$1,579	-61.45%
Total average cost	$21,676	$10,488	-51.61%	$5,351	$2,449	-54.23%
Total maximum cost	$60,358	$13,986	-76.83%	$7,254	$3,314	-54.31%
Total standard deviation	$10,107	$1,934	-80.86%	$764	$414	-45.81%

Table 13
Suggested parameter values.

Input data Target budget	**$10,000**	Material#1	Material#2	Material#3	Material#4	Material#5
Avg. daily usage	Unit(s)	162	128	167	130	180
Usage standard deviation	Unit(s)	50	35	50	25	20
Supply availability	Supplier 1	✓	✓	✓	N/A	✓
	Supplier 2	✓	N/A	✓	✓	✓
	Supplier 3	✓	✓	✓	✓	✓
Unit cost	Supplier 1	50	35	120	45	30
	Supplier 2	55	37	121	43	28
	Supplier 3	52	36	119	44	29
%Discount	Supplier 1	0.00	14.00	0.00	10.00	4.00
	Supplier 2	0.00	15.00	12.00	0.00	5.00
	Supplier 3	10.00	0.00	18.00	8.00	4.50
Minimum order to get discount	Supplier 1	500	500	500	100	800
	Supplier 2	500	700	500	100	500
	Supplier 3	400	400	500	100	1000
Avg. Lead time	Day(s)	2	3	3	2	2
Planned Order interval	Day(s)	6	3	4	3	2
Current On-hand	Unit(s)	36	234	98	87	154
Output - *Decision Support Solution*						
Recalled Optimized Cost	**$9943.62**	Material#1	Material#2	Material#3	Material#4	Material#5
Optimal order quantity		1755	2722	2092	1413	717
Order quantity	Supplier 1	712	1669	21	0	372
	Supplier 2	10	0	422	169	1210
	Supplier 3	118	357	995	401	1041
Safety stock	Unit(s)	715	1450	446	244	137
Reorder point	Unit(s)	1244	402	581	921	1737

Table 14
Demonstration of multi-level parameter values based on the total cost.

Levels of parameter values based on the total cost Ranges	$2,000	$4,000	$6,000	$8,000	$10,000	$12,000	$14,000	$16,000	Average
x_{10}	79	79	199	120	175	215	347	248	**189**
x_{20}	17	17	69	148	219	204	1168	628	**339**
x_{40}	22	22	248	436	245	616	611	1379	**594**
x_{01}	27	27	24	92	212	321	142	390	**144**
x_{31}	383	383	288	887	887	95	452	975	**494**
x_{41}	304	304	8	91	1355	191	679	667	**613**
x_{02}	84	84	15	141	222	464	287	261	**183**
x_{12}	157	157	124	460	419	1017	1145	232	**623**
x_{32}	227	227	419	125	134	263	227	1973	**618**
q_1^{opt}	40	40	2388	1725	1469	3758	2107	2074	**1809**
q_2^{opt}	169	169	3093	177	98	541	947	947	**1014**
q_3^{opt}	234	234	350	389	930	99	414	286	**372**
q_4^{opt}	79	79	645	1316	1320	923	1095	1223	**863**
q_1^{rop}	2859	2859	1950	293	1822	659	3933	3679	**2411**
q_2^{rop}	1556	1556	629	1760	2743	1990	2010	2011	**1807**
q_3^{rop}	2110	2110	1533	2557	1733	2084	73	512	**1492**
q_4^{rop}	1510	1510	1734	1453	351	1408	810	299	**1098**
q_1^{SS}	355	355	1913	1504	1430	1587	1960	1685	**1414**
q_2^{SS}	502	502	83	454	262	133	72	450	**310**
q_3^{SS}	1835	1855	815	341	351	58	1995	494	**914**

optimized parameters based on different levels of the total cost, ranging from minimum to maximum values. The provided levels of the total cost help to mitigate the influence and effects of oscillating raw material demands and their dynamic cost, which could induce ambivalence and bias in the decision-makers. The managers can simply review and utilize the average values to support their decisions.

After three months of implementation in the case company, the recommended solutions provided broad ranges of inventory management parameters that could satisfy the company's desired level of the total cost. The company's general manager reviewed the results provided by the proposed DSS and decided to reduce the level of total cost of purchased raw materials to $9,677–$12,903 per day to match the current levels of daily raw material consumption. Using the recommended solutions, a comparison of the system recommended costs and actual raw material purchased costs is shown in Fig. 17. Further, Fig. 18 presents a comparison of daily raw material consumption and actual raw material purchased costs that occurred during the three months of DSS implementation.

The DSS provided recommendations throughout the three-month horizon with daily updated consumption data and on-hand inventory requirements. During the implementation, the average on-hand inventory cost of raw materials reduced from $5,351 to $2,449 per day

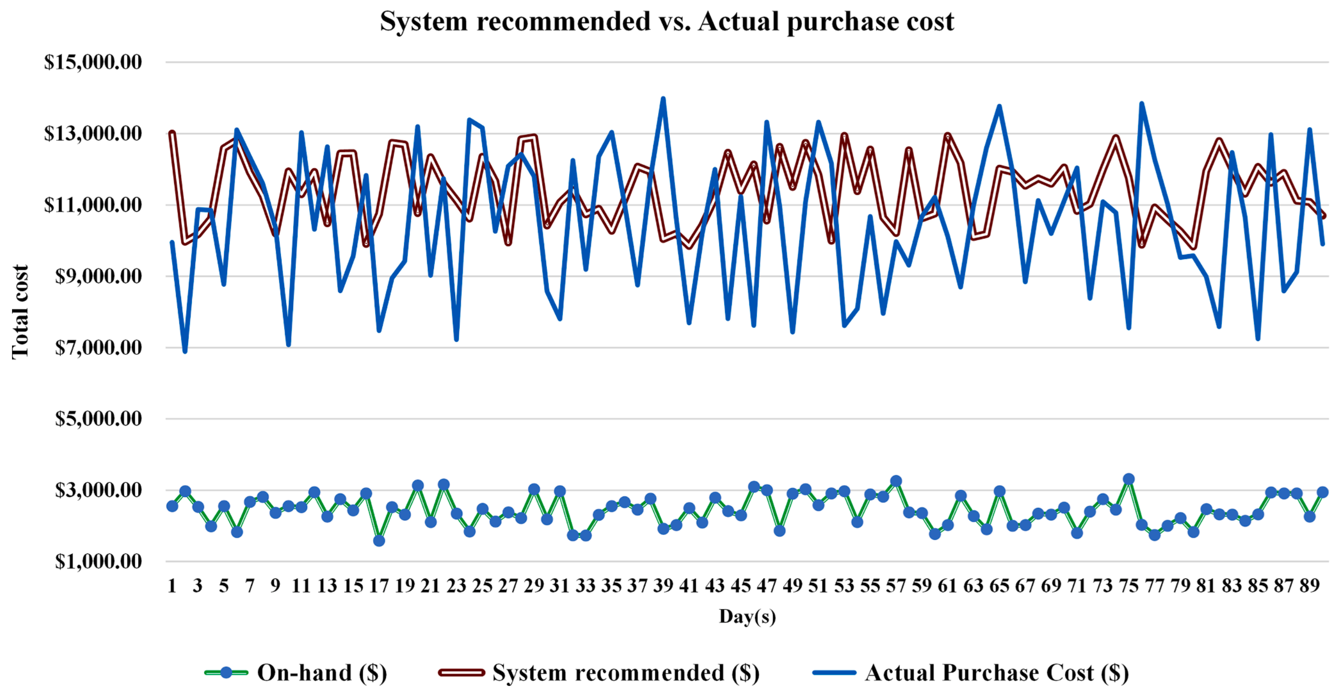


Fig. 17. Comparison of system recommended costs vs. actual purchase costs.

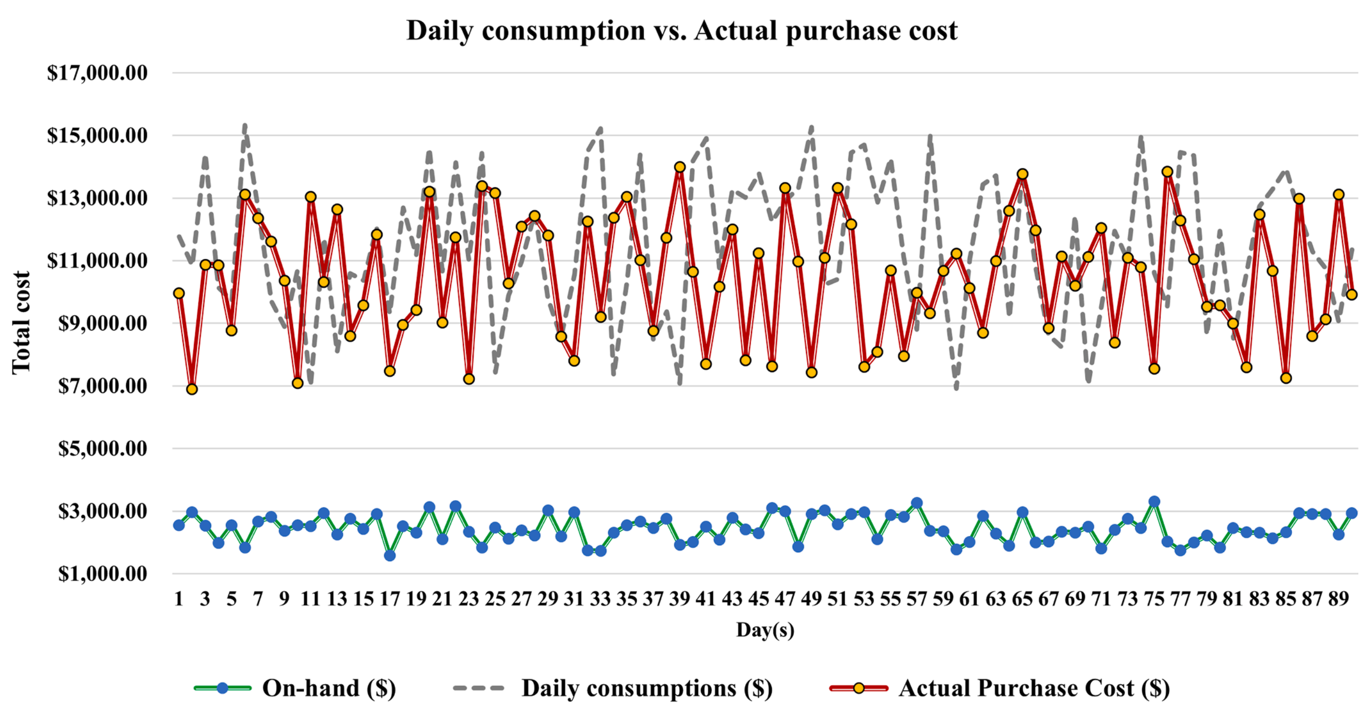


Fig. 18. Comparison of daily material consumption costs vs. actual purchase costs.

(54.24% on average), with an accumulated value of $220,367 in total. The actual raw material purchased cost over the time horizon was $943,928 in total, while the accumulated system-recommended cost was $1,026,813. The accumulated cost of raw material daily consumption was $1,030,647, which was close to the accumulated system-recommended cost. A summary of cost performance in all four categories is presented in Table 15.

The results indicate that the proposed DSS could provide reliable and accurate recommendations to purchase raw materials at a lower cost when compared to the accumulated raw material consumed cost. The accurate difference between actual purchased raw material and system recommended costs indicated that managers could rely on the solution provided by the DSS. This is because it could reduce decision bias due to the effects of fluctuating raw material demand and other business variances. However, manager discretion is still required when adopting the suggested solutions. Moreover, there was a preliminary improvement in the purchasing policy of the five key ingredients of the cake roll family, with both the budget and stock levels reducing. The average cost of purchased raw materials per day reduced from $21,676 to $10,488 (51.62%) during the three months. With the new policy in place, the

Table 15
Summary of cost performance.

	On-hand inventory cost	Raw material consumed cost	System-recommended cost	Actual material purchased cost
Min. cost / day	$1,579	$6,910	$9,833	$6,887
Average cost/ day	2,449	$11,452	$11,409	$10,488
Max. cost/day	$3,314	$15,320	$13,004	$13,986
Accumulated cost (3-month)	$220,366	$1,030,647	$1,026,831	$943,928

procurement division would also need to shorten the order interval of all five materials to compensate for the significantly reduced stocks. Although the order interval of each raw material was reduced to two days (maximum), there was no sign of inventory out-of-stock as the service level, reorder point, and safety stock were configed to guarantee inventory reliability.

4.6. Discussion

In this study, a DSS for sourcing and inventory management within SME contexts was developed. The aim was to provide the means of leveraging the decision capabilities of SMEs in sourcing and inventory management problems. The AI-based architecture offers flexibility to managers by allowing the utilization of existing observational and empirical data when performing robust decision-making on sourcing and inventory management for SMEs. This is under the uncertainties of material costs, supply lead times, and raw material demand. This study confirms the usability of empirical and observational data in accordance with the works of Sadati, Chinnam [64], and Teerasoponpong and Sopadang [24]. Two types of data were used in the model to represent the physical operations and to generate the training dataset for the ML. As a result, the proposed approach is flexible and can be implemented in other manufacturing industries that have the characteristics of uncertain raw material prices, consumption rates, and order lead times with an FOI strategy.

The experimental results indicated that the ANN outperformed the other MLs in terms of model fitting and prediction capability, as its capabilities in classification, prediction, and pattern recognition have been confirmed by several recent studies [24, 25, 56, 76]. The hybrid approaches of GA and MLs examined in this research have also exhibited promising results. The hybrid GA-ANN provided the optimum results compared to the other approaches in terms of solution-finding. Nonetheless, it was revealed that the performance of all approaches (and the quality of solutions) were affected by the following factors: the quality of training data, the number of initial populations for the GA, the probability of mutation and crossover, and the maximum number of iterations. For instance, increasing the initial population and the maximum number of iterations may have negative effects on the quality of solutions. Thus, improper configurations of these factors can illicit unintended effects on solution-finding. Accordingly, minimizing the risk of improper model configurations was accomplished in this study by using the DEAP framework and grid search to customize the GA and control the optimization process [70].

According to the case study, the AI-based approach was able to recognize the unique characteristics of the sourcing and inventory management decision patterns of the company. The observational and empirical data incorporating additional synthesized data proved their potential as critical components in generating decision-support solutions for sourcing and inventory management. There are two highlights of the proposed system. First, since the DSS aims to be exploited by SMEs that may not have in-depth technical knowledge, the system was designed to maximize the utilization of existing knowledge and data found in SMEs to support their managers. Second, all parameters shown in the mathematical model were based on a real-world system and did not require expert knowledge to interpret their meaning, as they are general terms. Thus, the proposed DSS should fill the existing gap in DSS applications in SMEs.

The effects of utilizing the proposed DSS may have triggered the company to improve its agreements with suppliers through new delivery planning and scheduling in the future. However, some drawbacks and concerns were also disclosed by related personnel, such as the head of the procurement division and the head of the manufacturing division. These concerns regarded the full implementation of the DSS, since its engine is based on AI and requires a large amount of data. Another drawback was the decision maker's misinterpretation of support information provided by the DSS. This interpretation may require people who have the technical knowledge and understanding of inventory management and procurement operations.

Although the case company lacked some vital data, the proposed DSS proved its capability in providing a reasonable means of supporting sourcing and inventory management decisions with an acceptable range of variance. According to Chalupnik, Wynn [79], setting more realistic targets to reduce the difficulty of process objectives is one of the uncertainty mitigation strategies. Therefore, the proposed DSS embraced this strategy and achieved its purpose. Further, the core engine of the DSS (the hybrid GA-ANN approach) offers adaptability and flexibility. It has proved its capability by dealing with variations found in the case study and can be utilized with other inventory management cases using a new training dataset. Moreover, since the proposed DSS (which utilizes an ANN) is capable of learning new input, adding new input factors is also allowed.

Despite the impressive performance of the DSS, significant effort is required to characterize and generate a certain amount of data for the ANN training. Even so, the use of such an approach pertains to the principle of 'garbage in, garbage out'. All inputs must be validated to prevent the generation of meaningless data and to ensure the validity of the process characteristics. Consequently, this DSS can be used as a decision support tool, not as a decision-making tool. The decision-makers must use the information provided by the system at their discretion. Nonetheless, some previously mentioned drawbacks may need to be addressed further. Moreover, additional factors may need to be considered in some other contexts, in which a leveling manufacturing strategy and a dynamic scheduling approach could be applied to address fluctuating product demands [80].

5. Managerial and practical implications

It is known that SMEs incur complex decision situations in sourcing and inventory management due to uncertainties and their limited resources, tools, and data. Thus, the development of comprehensive decision support tools can help managers make better decisions. Accordingly, the aim of this work was to develop a DSS for sourcing and inventory management under the uncertainties of demand, lead time, and supply costs. Further, the DSS was designed to support SMEs that rely on multi-sourcing and the FOI strategy.

The numerical experiment and the case study presented in this paper demonstrated that the analyzed conditions (demand uncertainty, material cost variability, multiple sourcing, and FOI strategy) could account for substantial inventory costs and overused capacity. This is especially true for SMEs where negotiating power and resources are limited. Moreover, SMEs need to purchase raw materials under the suppliers' conditions, which in the studied case was a sales promotion and discount. Given the circumstances, SME managers must take advantage of these conditions by purchasing the right quantity of raw materials from each supplier to obtain the best possible offer at the lowest cost. Accordingly, the proposed DSS considers these variables and incorporates them into the design of the system. As a result, managers can utilize the same knowledge and existing data to make better decisions in sourcing and inventory management. The proposed DSS can provide some insights and practical implications for managers by helping to answer the following questions:

1 Which suppliers to order from? – The guideline for selection of suppliers can be provided to managers based on the existing data (e.g., supply availability, supplier capacity, and sales promotions).
2 How much of each raw material should be purchased from the selected suppliers? – Based on raw material demand, supply lead time, and uncertainty, the DSS can calculate and optimize the purchase quantity of raw materials to be ordered from each supplier.
3 What is the total cost of purchased raw materials? – The managers can review the total cost per order before purchasing raw materials. Further, adjustments to budget or quantity of supply can be made.
4 What is the safety stock level and reorder point of raw material? – The DSS calculates the safety stock levels based on given conditions, such as raw material usage rate, order interval, supply lead time, and desired service level.

Besides this information and the calculations for sourcing and inventory management, utilizing the ML technique provides several advantages. The hybrid GA-ANN proved to be effective in dealing with large, complex problems of sourcing and inventory management, where it can be difficult to determine the variable relationships by the application of other methods. The approach can also be employed for solving other case studies without the need for complex mathematical formulations. To implement the DSS in other cases, the managers can practically utilize the approach through the following practical alternatives:

- The managers can use the proposed mathematical formulation in Section 3.3.1 as a guideline for collecting data from the real process and then use that data for ANN training. The DSS can adapt to a new training dataset (as it represents new characteristics of the process) and determine the solution based on new data.
- The proposed system can interact with business intelligence (BI) tools such as Microsoft Power BI, Tableau, and SAP Business Objects, which aim to visualize the data for the user. However, data generated from real-world settings can be fragmental. Consequently, the missing data affects the visualization. Since the proposed method learns from the data and synthesizes a mathematical model to represent the data, the missing value can be generated from the method. For example, only the data of supplier A is available from the order of size 10,000 units and 30,000 units. Since the proposed method can capture relationships between orders and products, it can make an educated guess of the order size of 20,000 units. By setting the target, the GA can identify the remaining parameters, after which the estimated value can complete the missing data and create a complete visualization.

6. Conclusion and future works

The main contribution of this article is the development of a decision support tool for SMEs for sourcing and inventory management operations using an intelligent approach. To the best of the authors' knowledge and according to the recent findings of Mittal, Khan [81], the adoption of ML and intelligent approaches in SMEs is not currently ubiquitous. Unlike LEs, numerous researchers have highlighted the problems faced by SMEs when adopting IT tools or smart concepts due to their limited resources and capabilities of collecting and analyzing the data [39, 81, 82]. Nonetheless, attempts have been made by this research to exploit advanced IT tools (i.e., DSS) and ML (i.e., ANN) in manufacturing SMEs. Further, it is found that the ML-based approach can extract the key characteristics of the sourcing and inventory management operations, either from synthesized data or real-world data. The pre-processed training data also helps enhance the performance of MLs in model fitting and prediction. Nonetheless, the proper model configuration is required. A manual configuration of the model is not recommended, especially for a large-scale complex problem.

To improve the performance of the DSS, a more powerful machine-learning technique (such as deep learning or the optimal brain damage technique) may be required. Moreover, finding an optimization approach with a shorter computation time is another critical issue. Further, since the proposed DSS embraces the simulation-optimization approach, a combination of techniques to improve the prediction performance and optimization time is crucial. The improvements of data and information visibility using BI tools are also recommended for enhancing the usability of the DSS. Finally, the DSS development approach used in this research can be extended to other fields of supply chain management operations in SMEs, such as transportation and manufacturing.

Importantly, while the terms Industry 4.0 and SMEs 4.0 are gaining momentum across modern industries, large-sized companies have already proceeded in adopting and exploiting modern concepts and data-driven technologies such as cyber-physical systems, cloud manufacturing, and smart manufacturing [83]. Although the adoption of such concepts and technologies is still in the early stages in SMEs, this process represents the future of modern SMEs.

CRediT authorship contribution statement

Siravat Teerasoponpong: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization. **Apichat Sopadang:** Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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