



Multi-objective supplier selection process: a simulation–optimization framework integrated with MCDM

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Abstract

As a multi-criteria decision-making (MCDM) problem, supplier selection plays a key role in achieving the objectives of a supply chain system. Multiple strategic, operational, quantitative, and qualitative criteria influence the supplier selection process. A wide spectrum of criteria have been introduced, classified, and used by researchers and practitioners to evaluate the suppliers' performance; however, measuring and employing all of these criteria is impractical in real-world scenarios due to the budget, time, and information limitations. In this study, a decision support system (DSS) is developed, which helps managers to select a set of most effective criteria for the supplier selection process. This DSS is a threefold integration of MCDM and simulation and optimization. In this framework, the MCDM module incorporates a combination of criteria to select the suppliers. Then, a simulation model is used to evaluate the performance of the supply chain system considering the selected suppliers. Based on the simulation results, a multi-objective metaheuristic algorithm is utilized to find the ideal combinations of the criteria to maximize the supply chain system performance.

Keywords Supplier selection · Simheuristics · Simio-MATLAB integration · TOPSIS · NSGA-II

1 Introduction

To improve performance and focus on core business, numerous firms have been downsizing and outsourcing extensively (Karpak et al., 2011). In manufacturing industries, a large portion of sales revenue is spent on materials, parts, and equipment. For most U.S. firms the raw material purchased from outside vendors constitutes 40–60% of the unit cost of a product (Sucky, 2007). Manufacturers can reap large profits from a small percentage reduction in the cost of materials, which makes supply chain management a key competitive weapon (Krajewski et al., 1999). A rigorous supplier selection process could considerably improve organization performance and final product quality (Bozorgmehr & Tavakoli, 2015) and substantially

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create more cost savings for the supply chain (Mohammaditabar et al., 2016). Companies hope to establish a long-term relationship with suppliers to achieve cost competitiveness and excellence in services (Khan, 2011), which makes the importance of the supplier selection procedure even more pronounced.

Essentially, supplier selection is a complex multi-criteria decision-making (MCDM) process aiming to reduce the initial set of potential suppliers to well-rounded choices (Junior et al., 2014). This complexity stems from a number of quantitative and qualitative factors influencing supplier choices as well as the intrinsic difficulty of making numerous trade-offs among these factors (Min, 1994). Therefore, this process requires combining multiple rules to outline the problem and the tuning of many membership functions for inference (Dogan & Aydin, 2011). This paper considers three important aspects of this problem to introduce a new solution approach. These aspects are discussed as follows.

1.1 Criteria selection

There are some studies that have extensively explored numerous suppliers' selection problems and tried to list the widely used evaluating criteria. However, the criteria selection is the crucial part of the evaluation, which reflects the qualification aspects of supplier alternatives (Soner Kara, 2011). Determining appropriate and adequate criteria is a primary challenge in supplier selection and could fundamentally affect the overall outcome. Defining the most effective criteria is not trivial and requires careful analysis, which is key to getting the most qualified supplier(s). It is obvious that the more criteria involved, the more likely it is that a decision is accurate. Although it is desirable to include all possible criteria into the analysis, the supplier selection process needs to be carried out with limited data and changes in criteria prioritization (Sandeep et al., 2011). Measuring all criteria for all suppliers is cumbersome and requires a significant amount of data collection effort. This issue becomes more critical for firms that periodically need to evaluate and re-select their supplier(s). In these cases, the criteria selection and measurement could induce additional costs on firms due to the efforts required for obtaining suppliers' information. Therefore, a practical supplier selection process has to be aligned with real-world scenarios due to the budget, time, and information constraints.

In addition, as a result of the associated complexities and uncertainties in supply chain systems, including all possible criteria to analysis may not necessarily lead to the best supplier selection. Each firm has a different strategy in the supply chain in terms of the characteristics of the product, and does not necessarily need to include all the criteria into final decision-making (Rouyendegh & Saputro, 2014). As suggested by Holm and Vo (Holm & Vo, 2015), there might be a mismatch between supplier selection practices and supplier evaluation criteria. Therefore, a practical supplier selection DSS has to consider important real-life criteria and provide guidance to decision-makers. Buying companies need to establish criteria that pertain to their own organizations (Holm & Vo, 2015), which could reflect the real drivers of profit for the firm (Mont, 2002). As a result, instead of considering all criteria, it is more desirable to quantify major criteria that cumulatively fulfill the supply chain requirements with the most significant impact. Limiting the number of criteria to the most effective ones permits decision-makers to easily investigate suppliers' performance in a reproducible and timely manner with minimal effort.

1.2 Criteria weighting

Another leading obstacle in MCDM studies is the determination of criteria weights (Liu, 2007a), which is a very sensitive and complicated process (Savić et al., 2012). A variety of approaches including direct assignment, Delphi survey, pairwise comparison, eigenvector method, weighted-least-square technique, entropy model, and linear programming have been developed by researchers to obtain criteria weights (Liu, 2007b), but still, there is a need for a more efficient method with the rigorous application.

Literature review reveals the fact that several efforts have been devoted to devise individual or integrated methodologies to continuously evaluate suppliers (Ghorbani et al., 2013). Extensive decision-making techniques have been attempted for supplier selection using either individual or hybrid approaches (Ho et al., 2010). Proper weighting is a crucial step in the supplier selection process and in most cases could significantly affect the final results. Therefore, an efficient model not only needs to use a set of appropriate criteria but also has to offer a robust method to determine criteria weights.

1.3 Uncertainty

Uncertainty is an integral and unavoidable part of supply chain management. Factors such as customer demand, lead times, processing times, etc., are stochastic parameters that account for variability in the supply chain system. Considering these factors into the analysis is essential to minimize the risk and maintain the supply chain sustainability.

Simulation modeling is one of the best tools for analyzing supply chains due to its capability for handling variability (Schunk & Plott, 2000). Simulation is a technique that can indeed predict and support the design of supply chains in practice (Kleijnen & Smits, 2003). Modeling with operational details, including stochastic factors, and capturing the non-linear relationship between operations, are some of the great features of simulation which makes it a suitable means to support supplier decision-making procedure. One can use simulation modeling to design the supply chain system accurately and configure the input parameters to obtain the desired performance of the system.

To address the above-mentioned aspects, this paper introduces a threefold integrated framework consisting of optimization, MCDM, and simulation scheme. This hybrid model determines the most appropriate and practical criteria for the supplier selection process and provides their corresponding weights. In an interactive manner within a simulated environment, the performance of different combinations of suppliers is evaluated until an optimal solution is found. Therefore, throughout this paper, the following contributions are presented:

- Define, design, and develop a practical decision support system for supplier selection
- Offer a method to distinguish relevant from irrelevant selection criteria
- Calculate the weight of important criteria for decision-making
- Evaluate the performance of the supplier selection model in accordance with a real-world system by using simulation

The rest of this paper is organized as follows. A structured literature review is discussed in Sect. 2 to provide insights about related works and show the position of the current study compared to others. Section 3 includes a descriptive discussion about the proposed framework structure and its elements. In Sect. 4, an effort is made to show the applicability of the proposed model in a supply chain case study. This work is concluded in Sect. 5, by providing brief remarks and future perspectives.

2 Literature review

The supply chain is a complex system in which a number of independent companies work together to accomplish the strategic goal of the supply chain. The main objective of supply chain management is to maintain a smooth flow of goods, financial resources, and information from raw material suppliers to the end customer. In order to have a flawless stream of goods along the supply chain, companies should select the most suitable supplier(s). However, the supplier selection problem is a complicated decision-making task and has been covered in many studies since the 1960s. Researchers who want to broaden their knowledge about the classic supplier selection problem can examine the systematic literature review studies conducted by Ho et al. (2010) and Chai et al. (2013) and Chai and Ngai (2020). A brief summary of these studies and their methods is provided in Table 8 (Appendix 1).

One of the well-known approaches to solve supplier selection and inventory management problems is using a simulation model. Simulation modeling provides an illustrative insight into critical decision-making to deal with uncertain models. It enables decision-makers to define what-if analysis scenarios and evaluate different model settings to obtain the best system configuration. However, in large solution spaces, simulation models are not capable of finding the optimum solution in terms of predefined objective function(s) (Göçken et al., 2017). In order to handle this limitation, integration of simulation and optimization is desired. Simulation optimization (SO) is one of the most powerful and flexible methods for solving complex and stochastic decision-making problems (Dehghanimohammadabadi & Kabadayi, 2020; Dehghanimohammadabadi et al., 2017). Decision-makers do not have to use restrictive assumptions in this method (Jalali & Nieuwenhuyse, 2015), which made SO to be widely applied in a variety of supply chain problems such as inventory management (Jalali & Nieuwenhuyse, 2015), transportation (Layeb et al., 2018), production planning (Manda & Uzsoy, 2018), supplier selection (Göçken et al., 2017), etc.

Sarhangian et al. used SO to optimize inspection strategies for multi-stage manufacturing processes (Sarhangian et al., 2008). Dang and Phan applied SO to design an assembly line for a manufacturing company (Dang & Pham, 2016). Keskin et al. developed a scatter search-based SO approach to solve an integrated vendor selection and inventory replenishment problem (Keskin et al., 2010). In their model, they aimed to select the best vendor which has the highest performance in terms of quality, delivery and, robustness while determining the optimum inventory levels at the plants. Tsai and Zeng presented a SO model for solving the two-echelon constrained inventory problem (Tsai & Zheng, 2013). The main objective of the proposed model was to identify the optimal setting of stocking levels to minimize the total inventory costs while meeting the predetermined response time targets for each field depot. In the optimization part of the SO approach, the Sample Average Approximation technique was combined with a cutting plane method and Ranking and Selection (R&S) procedures. Göçken and his colleagues applied a SO model to determine optimal (R,s,S) inventory policy for distribution center(s) and suppliers and to select the suitable suppliers for DCs under stochastic environmental conditions and lost sales system (Göçken et al., 2015). They aimed to determine the most appropriate inventory control policy configurations and suppliers while minimizing the total supply chain cost which is composed of inventory and distribution cost. In this model, they used predetermined values to determine the review period and used GA to optimize the control rest of parameters of the (R,s,S) and the most suitable supplier for each DC. Göçken et al. proposed a SO model to answer three questions which inventory review model (periodic or continuous) for the (s,S) inventory policy should be selected; which objective function (minimization of total supply chain cost or minimization of the

differences between overordering cost and underordering cost) is the best for the supply chain; what is the best inventory control policy configurations (initial inventory level, reorder point and order-up-to level) for each distributing centers and each supplier in the supply chain (Göçken et al., 2017). In the proposed SO model, GA was used to find the optimal result and a simulation model was constructed to evaluate the performance of candidate solutions. Dosdogru et al. presented a SO model to analyze the supplier selection and inventory control problems simultaneously. In this paper, the (R,s,S) policy was considered as an inventory control policy in a two-echelon supply chain with backorder. Additionally, GA is used as an optimization tool in the SO model (Dosdoğru et al., 2020).

This paper is distinguished from all of the above-mentioned works since it aims to identify a list of refined criteria for decision making. The goal is to develop a framework that is simple enough to be implemented and accurate enough to capture the most important factors into the calculation. Therefore, the proposed model is a multi-objective model in which the best set of suppliers is identified throughout a straightforward selection process. This enables firms to not only identify the most influential decision-making criteria but also helps them by making the process reproducible when re-selecting suppliers are needed. More importantly, this framework takes advantage of the simulation modeling to accurately include operational details, and an optimization module to obtain the best supplier mix.

3 Integrated simulation–optimization and MCDM framework

To support the aforementioned goals for the supplier selection process, this decision support system is built upon three modules including, (i) optimization, (ii) MCDM, and (iii) simulation. This section presents a description of the proposed model and discusses its design and key components. A detailed structure of the proposed framework is illustrated in Fig. 1.

The *optimization* module is the initial step, in which a shortlisted set of criteria and their corresponding weights are selected. Essentially, in every iteration of the framework, the optimization algorithm generates a new solution, which is decomposed into two different responses. The first response determines (i) the list of selected criteria to be used by the MCDM module, and the second one defines (ii) the corresponding weight or importance of the selected criteria. Therefore, in every iteration of the model, the selected criteria and their corresponding weights are subject to change based on the generated solution given by the optimization algorithm.

The provided responses from the optimization module are transferred to the second stage to deploy a supplier selection process. At this point, the *MCDM* module judges supplier alternatives using the suggested criteria and weights from the optimization module. Using a structured and numerical approach, MCDM module tries to find a set of top suppliers from

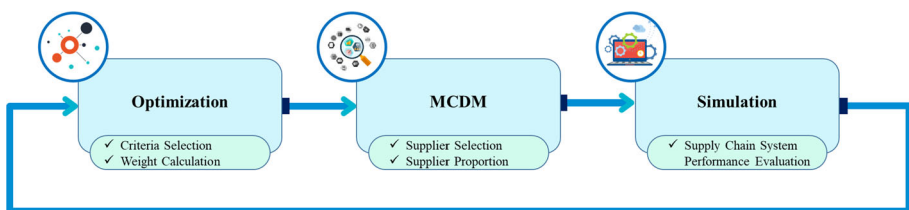


Fig. 1 Design of the proposed simulation–optimization framework integrated with MCDM

the decision matrix. The obtained solution at this stage consists of a list of top suppliers and their proportions. The supplier proportion indicates what percentage of the total demand is supplied by each supplier, and all add up to 100%.

The third component of this framework is the *simulation* module which incorporates a detailed representation of the real-world supply chain system with all of its dynamic processes and stochastic events. Simulation offers a testbed to evaluate the goodness of the selected supplier(s) from the decision-making module. In each iteration, the simulation model considers the characteristics of the newly selected suppliers while running the model. Therefore, simulation results effectively reflect the efficiency of the selected suppliers for the actual supply chain system. Once the simulation run is completed, the system performance measures are sent to the optimization module to initiate a new iteration and generate the next solution. This cycle continues until the stopping criteria are met.

Therefore, due to its novel design and structure, the proposed model provides the following advantages:

- **Generic structure:** This model offers a generic structure by including any type of optimization and MCDM approach. Depending on the modeling needs, this framework allows applying a variety of optimization methods (single or multi-objective, exact, heuristic or metaheuristic algorithms, etc.) integrated with the desired MCDM technique (AHP, ANP, TOPSIS, etc.). This capability makes the proposed framework a useful tool to support supplier selection decision-making.
- **Refined criteria selection:** Depending on the supply chain system structure and business needs, any number of criteria or supplier alternatives could be included in this framework. A decision-maker could easily consider a list of potential factors which intuitively might be crucial for the supplier selection process, and ultimately narrow it down to a limited set of the most important ones. Moreover, this approach removes the need for criteria weight configuration. The criteria weights are automatically calculated, and another layer of complexity is removed from the problem. Therefore, this framework identifies a shortened list of important criteria with their weights. This could benefit the decision-makers by reducing the time and effort required to perform the decision-making analysis in the future. Whenever the need of selecting a new supplier arises, the decision-making team could just focus on the shortened list of the most preferred factors rather than all criteria. This mechanism could significantly simplify the future supplier selection processes without compromising the analytical quality.
- **Supplier selection flexibility:** This framework could be applied either for a single-source or multiple-source strategy supply chain system. If a single source strategy is desired, the model tries to find the most efficient supplier for the system; however, if the multiple-source strategy is attempted, the model provides a pool of suppliers with a supply proportion for each.
- **Handling uncertainty and complexity:** Supply chain is a complex system with a wide variety of engaged members with multiple functions and mechanisms. Using a simulation model ensures that the selected supplier(s) perform(s) well for the real-world system.

A detailed description of this framework components along with the implementation steps are provided in the following section.

4 Implementation

Three software packages are combined to implement this framework. As depicted in Fig. 2, MATLAB, Simio, and MS Excel are integrated to construct the software architecture of the framework. The optimization and decision-making processes are deployed in MATLAB, while Simio is utilized to build the simulation model. The data transfer between MATLAB and Simio is facilitated via MS Excel.

Essentially, the developed framework is a simheuristic model, in which a metaheuristic algorithm is incorporated with a simulation model. As shown in Fig. 3, the framework starts with the *Initial Decision Matrix* which includes all of the predefined criteria. The objective of the optimization module is to find the most relevant, practical, and useful criteria for the supply chain system. To do this, a multi-objective version of the Genetic Algorithm (GA) is used as the optimizer of the model. Each chromosome (solution) derived from GA is translated into responses in order to obtain a *pair of selected criteria* and their corresponding *weights*. Then, the initial Decision Matrix is updated, and un-selected criteria are removed. The updated.

Decision Matrix is a cross table of supplier alternatives and the selected criteria. At this point, the decision-making algorithm which is TOPSIS is triggered to find the set of preferred suppliers and their proportion. In order to incorporate the supplier’s characteristics into the simulation model, an input data-table is created in Excel, which provides suppliers’ info for the Simio model. Whenever the combination of the suppliers’ changes, the input table gets updated. Therefore, after each TOPSIS run, the simulation input data is adjusted according to the newly selected suppliers. At this point, the simulation model is ready to run. To trigger Simio from MATLAB, the developed module by Dehghanimohammadabadi (2016) is used, which particularly calls Simio and runs experiments to provide the simulation results. The obtained results from Simio are used as a *Cost Function* for GA to determine the quality of the suggested solution (selected criteria and weights). At each iteration of GA, the best solutions are retained, and the process repeats until the algorithm reaches its stopping criteria. In the following subsection, a brief overview of the applied optimization and MCDM approach are discussed.

4.1 Optimization module: NSGA-II

Multi-objective evolutionary algorithms (MOEAs) evaluate multiple solutions simultaneously during the solution process to provide a set of trade-off solutions for decision-makers. There are five common phases in a typical evolutionary process; population initialization,

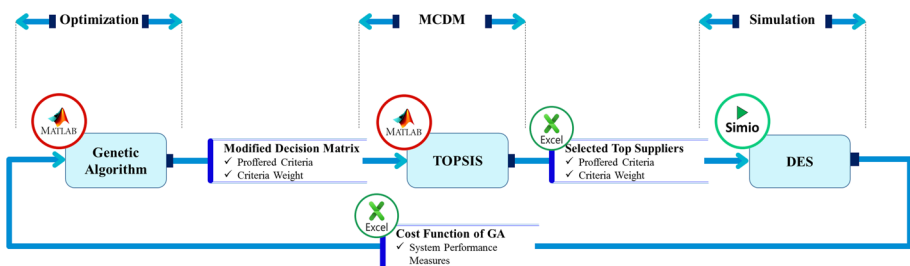
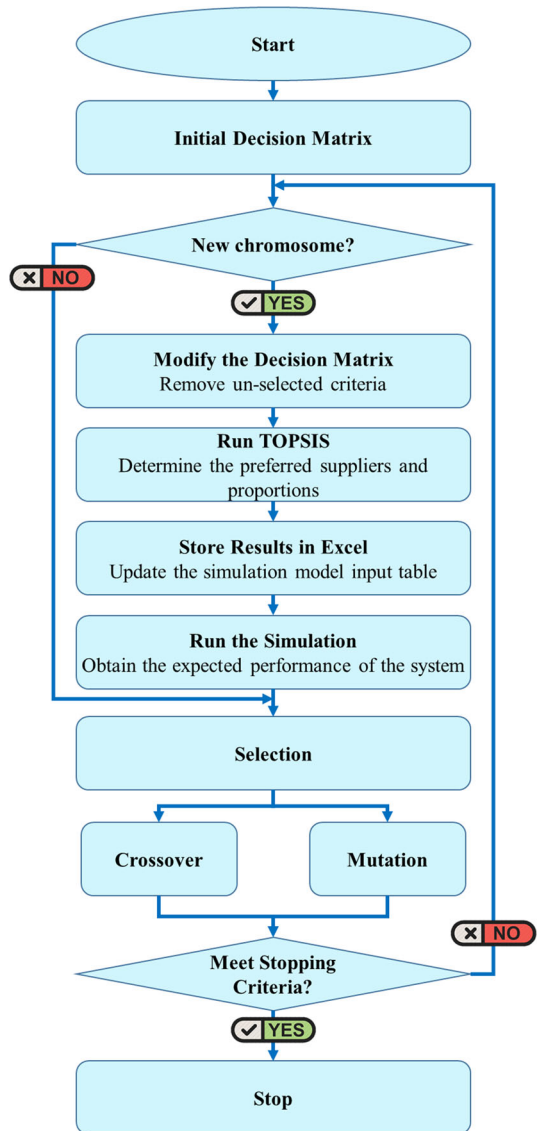


Fig. 2 Software architecture of the proposed framework

Fig. 3 The algorithm of the Simheuristic model combined with MCDM



fitness evaluation, crossover, mutation, and selection. The selection phase is a critical phase in which the individual solutions are ranked, non-dominated solutions are determined, and a diversity preservation mechanism is applied to protect a well-spread of solutions (Kadziński et al., 2017).

Non-dominated Sorting Genetic Algorithm (NSGA-II) is one of the MOEAs which uses a crowding distance approach to evaluate individuals in the search space based on a non-dominated sorting method (Türk et al., 2017). NSGA-II is a multi-objective version of genetic algorithm, which mimics biological evolution (Dehghanimohammadabadi & Keyser, 2017). It was developed by Deb et al. (Deb et al., 2002) to improve the first version of NSGA. NSGA-II is an efficient constraint-handling method that has fewer parameters, less complexity, and

an elitist strategy as compared to the NSGA. For this reason, it has been preferred by many researchers to solve various engineering problems. NSGA-II searches non-dominated Pareto-optimal solutions through evolutionary processes. The NSGA-II parameters of this study are listed in Table 9 (Appendix 2).

4.2 TOPSIS

TOPSIS or Technique for Order Preference by Similarity to Ideal Solution is one of the well-known MCDM approaches which is based on easy and simple logic (Ziaei et al., 2016). It is one of the MCDM techniques which was first introduced by Hwang and Yoon in 1981. The main idea of this method is based on choosing the best alternative having the shortest distance to the positive-ideal solution and the farthest distance from the negative-ideal solution. The positive ideal solution maximizes the benefit criteria and minimizes the total cost when the negative ideal solution minimizes the benefit criteria and maximizes the total cost (Azadeh et al., 2011).

In this method, it is possible to consider an unlimited number of alternatives and performance attributes without causing any mathematical cumbersome. Additionally, linking this method with computer databases is practical. For this reason, TOPSIS method is an easy and appropriate method for solving decision-making problems (Azadeh et al., 2011).

In the literature, TOPSIS has been applied to solve a wide range of real-life problems in many different fields. Supply chain management and logistics is the most popular topic in TOPSIS applications whereas healthcare management is one of the recent topics that utilize the TOPSIS method (Behzadian et al., 2012). Solution steps of the TOPSIS method is given below:

Step 1: Construction of Decision Matrix.

Decision matrix = $(x_{ij})_{n \times m}$, is the initial matrix in which decision-makers evaluate each alternative i according to each criteria j .

$$D = \begin{bmatrix} \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1j} \\ x_{21} & x_{22} & \cdots & x_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} \end{pmatrix} \end{bmatrix} \quad (1)$$

Step 2: Normalization of the decision matrix.

The normalization of the decision matrix D is done using Eq. (2) as follows.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^n x_{ij}^2}}, i = 1, 2, \dots, n \quad (2)$$

Step 3: Construction of the weighted normalized decision matrix.

The columns of the normalized decision matrix are multiplied by the associated weights to calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is computed using Eq. (3)

$$v_{ij} = w_i x_{ij}, j = 1, 2, \dots, J; i = 1, 2, \dots, n \quad (3)$$

where w_i is the weight of the i th attribute or criterion, and $\sum_{i=1}^n w_i = 1$.

Step 4: Determination of the positive ideal and negative ideal solution.

In this step, a positive ideal solution S^+ and negative ideal solution S^- are determined respectively as below;

$$S^+ = \{x_1^+, \dots, x_m^+\} = \{(maks_i x_{ij} | j \in I), (min_i x_{ij} | j \in J)\} \quad (4)$$

$$S^- = \{x_1^-, \dots, x_m^-\} = \{(min_i x_{ij} | j \in I), (maks_i x_{ij} | j \in J)\} \quad (5)$$

where I is associated with the benefit criteria and J is associated with the cost criteria.

Step 5: Determination of the separation measures from the positive and negative ideal solutions.

The separation measures are respectively calculated for each alternative using Euclidean distance.

μ_i^+ of each alternative from the positive ideal solution is calculated as follows;

$$\mu_i^+ = \sqrt{\sum_{j=1}^m (x_{ij} - x_j^+)^2}, \quad i = 1, 2, \dots, n. \quad (6)$$

μ_i^- of each alternative from the negative ideal solution is computed as below;

$$\mu_i^- = \sqrt{\sum_{j=1}^m (x_{ij} - x_j^-)^2}, \quad i = 1, 2, \dots, n. \quad (7)$$

Step 6: Determination of the closeness coefficient T

The relative closeness to an ideal solution is calculated with Eq. (8) and the ranking order of all alternatives is obtained.

$$T_i = \frac{\mu_i^-}{\mu_i^+ + \mu_i^-} \quad (8)$$

where $T_i = [0, 1]$ and the larger the index value, the better the performance of the alternatives.

5 Case study: supplier selection

The proposed model in this paper is applied in a supply chain case study to show its applicability. This case study is a modified version of Simio example in Joines and Roberts (2015). The model has three tiers consisting of Supplier(s), Manufacturer Distributing Center (DC), and Store. As depicted in Fig. 4, the initial demand is generated by customers in the store, where gets its supply from the DC. Both customers' demand and the replenishment time for the store are stochastic.

The main production operations take place in the DC where it receives raw materials from a set of suppliers to manufacture products. This center uses a make-to-stock policy to keep up with store demands. Therefore, it utilizes a (s,S) periodic review inventory model in which the inventory level is monitored periodically to re-stuck raw materials from suppliers. In this model, a re-order will take place if the inventory level drops below a pre-determined *re-ordering point* (s). The order amount is calculated by subtracting the *order-up-to amount*, S , and the recorded inventory level. A graphical representation of this model is shown in Fig. 5. It needs to be noted that, this study has nothing to do with the supply chain settings

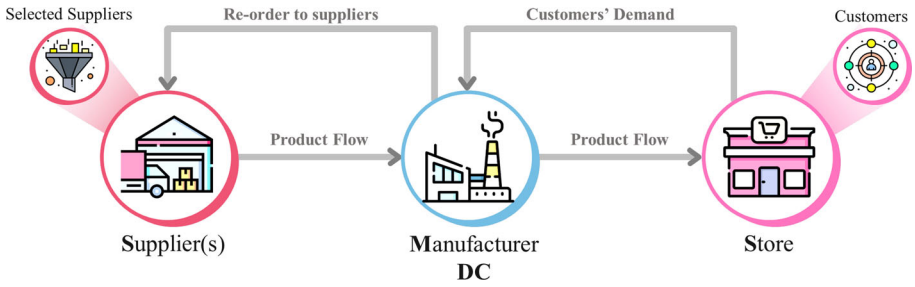


Fig. 4 The three tier supply chain model

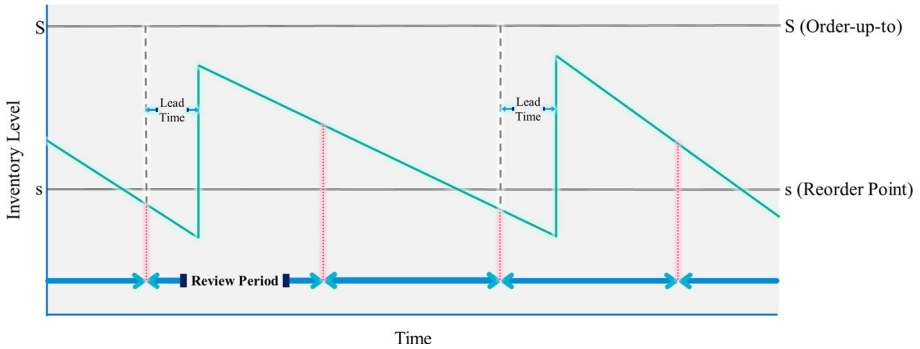


Fig. 5 Graphical representation of the (s,S) periodic review inventory model

such as s , S , and review period configurations and it is assumed these parameters are properly defined by the manufacturer. The focus of this work is to determine an ideal supplier selection procedure.

Depending on the supply chain structure, DC can receive its raw materials from single or multiple suppliers. The base scenario in the case study includes a set of three suppliers who supply the raw materials for DC proportionally. In other words, once a re-order is triggered, one of the suppliers is selected according to the suppliers’ distribution. This supply chain model is simulated in Simio (Fig. 6) and the periodic review inventory model parameters are tabulated in Table 1. To keep the focus of this research on the supplier selection model, these parameters are selected arbitrarily. However, future works can consider optimizing (i) the

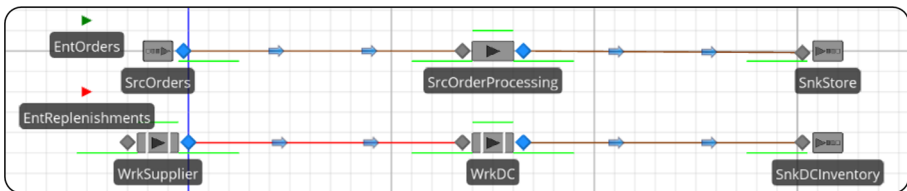


Fig. 6 Snapshot of the created simulation model in Simio

Table 1 Periodic review inventory model parameters

Parameter	Value
Reorder Point (s)	500
Order-up-to (S)	700
Initial Inventory	700
Shipping time	8

periodic review inventory model parameters and (ii) the supplier selection simultaneously. This requires a slight change in the optimizer and modification of the simulation model.

In this problem, the order is initiated based on the selected supplier characteristics (criteria) which are listed below:

- Criteria 1: Order processing time per unit (t): the amount of time (min) takes for the supplier to process the order internally and ship it to the DC,
- Criteria 2: Lead time (l): reflects the shipping time (days) between supplier and DC,
- Criteria 3 Fixed ordering cost (c_o): the fixed amount of cost (\$) for placing an order,
- Criteria 4 Variable ordering cost/unit (u_o): the variables cost of order depending on the order quantity
- Criteria 5 Fixed transportation cost (c_t): includes fixed elements of the transportation cost such as truck rental, etc.,
- Criteria 6: Unit transportation cost (u_t): indicated variable components of the transportation cost,
- Criteria 7: Quality (q): represents the acceptance rate of the provided raw materials by the supplier. This rate can be achieved by checking the historical data and supplier records. The 100% quality indicates that the supply is received in full order amount, whereas a lower quality rate is an indicator of some rejections for the received supply.

The initial decision matrix for this study includes information of 10 suppliers with the above-mentioned criteria (Table 2). Table 3 shows some of these criteria are applied in modeling parameters of the simulated supply chain system.

The effectiveness of the supply chain model is determined based on three objective functions, namely *Total Cost*, *Average Inventory Level*, and *Service Level*.

- Objective 1: Total Cost (TC): one of the major performance indicators in any supply chain is system expenditures. In this case, this measure captures all of the costly components of the system such as the ordering and transportation costs. As shown in Eq. 9, the quality factor (q) can also impact Total Cost and induce the DC to spend more for the suppliers with low qualities.

$$TC = \frac{Q * (u_t + u_o) + c_t + c_o}{1 - q} \quad (9)$$

where Q is the order quantity from the supplier.

- Objective 2: Service Level (SL): another goal of the model is to keep the Service Level (Fill Rate) high enough to ensure the Store demands are satisfied. As presented in Eq. 10, if the DC inventory is greater than the order amount received by the Store, then 100% of the demand appears to be met.

$$SL = \text{Min}(1, I/Q) \quad (10)$$

Table 2 Suppliers information and criteria

Suppliers	Fixed transportation cost(\$)	Unit transportation cost (\$)	Order Processing time/Unit (min)	Lead Time (days)	Fixed ordering cost (\$)	Variable ordering cost/unit (\$)	Quality
1	1378	0.051	25	2.090	241	20	78.81
2	1030	0.091	19	1.751	128	20	89.98
3	1096	0.135	20	2.676	232	23	99.19
4	1011	0.088	17	2.175	278	22	88.75
5	742	0.101	27	2.765	186	22	95.89
6	1270	0.082	24	1.441	160	24	93.98
7	1669	0.140	15	1.639	134	23	92.90
8	1522	0.073	16	1.425	245	21	88.74
9	1790	0.086	16	1.450	299	24	99.34
10	682	0.146	22	4.026	146	22	86.40

Table 3 Simulation model stochastic parameters

Operations	Distribution	Unit
Customer order arrival	Fixed:1	day
Customer order size	<i>Poisson</i> (40)	–
Customer order processing	<i>Uniform</i> (0.4, 0.5)	day
Supplier order processing	<i>Normal</i> (t , 2)	min
DC receiving	<i>Pert</i> (1, 2, 3)	min
Shipping time	<i>Exponential</i> (l)	day

where I is the recorded inventory level.

- **Objective 3: Average Inventory Level (IL):** to reduce the operational complexities and costs, it is crucial to maintain the average inventory level as minimum as possible. This is another objective function in this model where the system tries to find a balance between high service level and low excessive finished goods inventory. This measure is a time-persistent statistic that is provided by the simulation model.

An ideal supplier selection model needs to incorporate all of the above-mentioned factors into the calculation and determine the best set of suppliers that meet the supply chain requirements the best. This procedure needs to be simple enough that can be easily replicated and find the solution with a reasonable effort. To better analyze the model and its performance under different settings, the three scenarios are considered which are listed in Table 4. The first scenario is the base model which considers a maximum of three suppliers being selected by three criteria. The other two scenarios, scenarios 2 and 3, provide a sensitivity analysis for an extension of the model by changing number of selected suppliers and applied criteria. Details of these scenarios and the experimental results are provided as follows.

Table 4 Experiments settings

Scenarios	Number of suppliers	Number of criteria
1- Base model	3	3
2- Multi-suppliers	2, 3, 4	3
3- Selection criteria	3	2, 3, 4

5.1 Scenario 1: base model

In the first scenario, the default setting of the proposed model is set to three suppliers and three criteria. That indicates, in each iteration of the model, TOPSIS selects three suppliers based on three pre-determined criteria. Then, the selected suppliers and their proportions are applied in the simulation model to evaluate their efficiency in the supply chain settings. The applied optimization module, NSGA-II, uses an iterative and evolutionary approach to improve the selected suppliers' mix and finds a trade-off between the three objective functions. Figure 7 provides a 3D view of the final solution Pareto frontier of the case study. All of the provided points in this graph are the non-dominated solutions obtained by the NSGA-II. Each of these results uses different combinations of criteria and offers a different set of suppliers for the model.

A detailed list of the frontier solutions is provided in Table 5. These results suggest that the most appropriate criteria for the supplier selection are the most repeated combinations which consist of criteria 1 (order processing time per unit), 6 (unit transportation cost), and 7 (quality). These factors appeared more frequently than the other measures and had the most influence to find the desired suppliers. In addition, it can be observed that the most common mix of suppliers belongs to suppliers 2, 10, and 5.

The provided result by the model suggests almost an equal distribution between the suppliers, however, this can be changed if more real-life criteria are applied or the supply chain

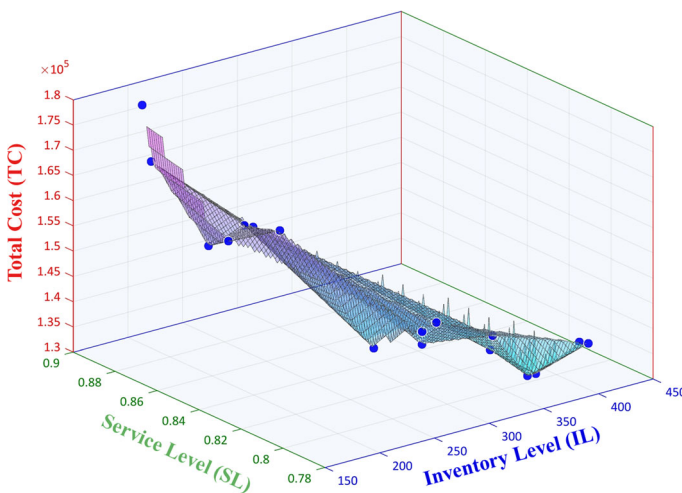


Fig. 7 The Pareto frontier of three objective functions: Total Cost (\$), Service Level (%), and Average Inventory Level

Table 5 Pareto frontier solution details

Populations	Criteria			Suppliers			Portion		
1	2	4	7	8	6	9	0.34	0.33	0.33
2	1	6	7	5	2	10	0.36	0.32	0.32
3	1	5	6	2	10	5	0.36	0.35	0.29
4	1	5	6	2	10	5	0.36	0.36	0.28
5	2	4	7	8	6	9	0.34	0.33	0.33
6	1	3	4	4	2	8	0.36	0.33	0.31
7	1	6	7	5	3	2	0.36	0.32	0.32
8	1	2	7	5	4	2	0.34	0.33	0.33
9	1	4	7	2	6	4	0.35	0.34	0.31
10	1	5	6	10	2	5	0.36	0.36	0.28
11	1	4	5	2	6	7	0.36	0.34	0.30
12	1	6	7	5	2	10	0.36	0.33	0.31
13	1	4	7	2	6	8	0.34	0.34	0.32
14	1	4	5	2	5	10	0.36	0.35	0.29
15	3	6	7	8	2	7	0.35	0.35	0.30
16	1	4	7	2	6	8	0.35	0.35	0.30
17	3	6	7	8	2	7	0.35	0.35	0.30
18	1	4	7	2	6	4	0.35	0.34	0.31
19	1	6	7	5	2	3	0.38	0.31	0.31
20	1	6	7	5	2	3	0.38	0.32	0.30

setting changes. It needs to be noted that, depending on the criteria, suppliers can have any proportion values between (0%-100%).”

The provided Sankey diagram in Fig. 8 is analogous to these results. This graph demonstrates a relational combination of criteria and supplier alternatives based on the 20 non-dominated solutions. It clearly shows which criteria (1, 6, and 7) were mainly involved in selecting the best suppliers (5, 2, 10). This implies the importance of unit cost criteria as well as the product quality in decision making.

5.1.1 Scenario 2: multi-suppliers sensitivity analysis

This experiment tests the capability of the model to include a different number of suppliers. The initial experiment was based on three suppliers, but in this scenario, the model was tested based on 2, 3, and 4 suppliers selection settings.

As shown in Fig. 9, a different number of suppliers, have a different impact on objective functions. The best total cost is obtained when the number of suppliers was 3, while the best service level is for the model with 2 suppliers. The results show that in the case of using 4 suppliers, the model is inferior to other options. This is mainly due to the fact that the supplier selection becomes more complex when a new supplier is added to the model. The decision-making, in this case, requires more analysis since the model not only needs to find the top 4 suppliers, but it also has to determine their proportion. In summary, it seems using 3 suppliers provides a good balance of objective functions. The detailed results of all different levels of

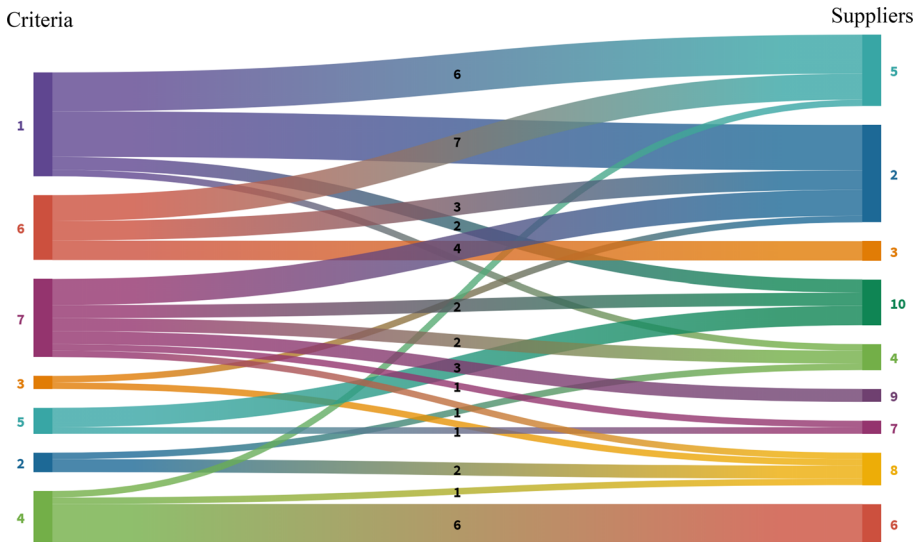


Fig. 8 Sankey diagram representation of criteria and selected suppliers

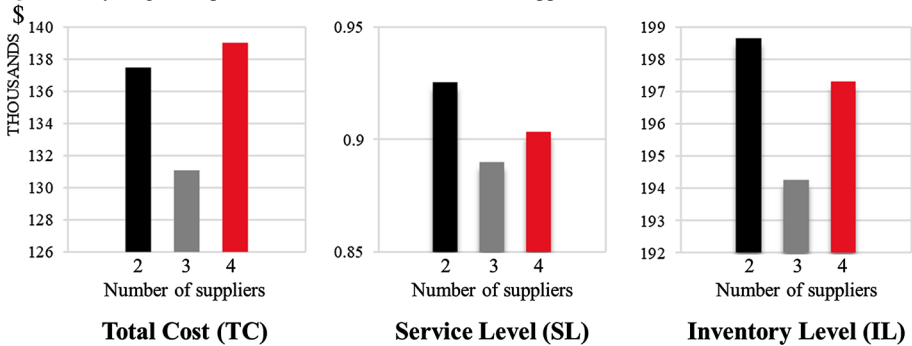


Fig. 9 Multi-suppliers sensitivity analysis results

the experiment are tabulated in Table 6. The only consistent supplier in these experiments is supplier 2, which was among the top selected choices almost in all settings.

5.1.2 Scenario 3: selection criteria sensitivity analysis

One of the main goals of this study was to develop a decision support system for the supplier selection with the minimal criteria. The rationale justified was to refine criteria selection and help the decision-makers identify the most influential suppliers in a rapid and efficient manner. Including additional criteria into the analysis adds a new layer of complexity, while it may not necessarily improve the end results. Therefore, this experimental scenario is designed to investigate the impact of the number of selected criteria in the supplier selection process. Originally, three criteria were used by the model, but in this scenario, the experiment is extended by choosing 2 and 4 criteria.

A graphical representation of the comparative results is provided in Fig. 10. These results are counterintuitive since the model with two (2) criteria yielded better results based on the

Table 6 Distribution of selected suppliers based on different number of suppliers

Number of suppliers					
2		3		4	
Supplier	%	Supplier	%	Supplier	%
8	23	2	30	2	23
2	20	5	17	4	16
5	18	6	12	8	13
10	18	8	12	5	10
4	8	10	10	10	10
9	8	4	7	6	9
7	5	3	5	7	8
1	3	7	5	9	6
3	0	9	3	3	4
6	0	1	0	1	3

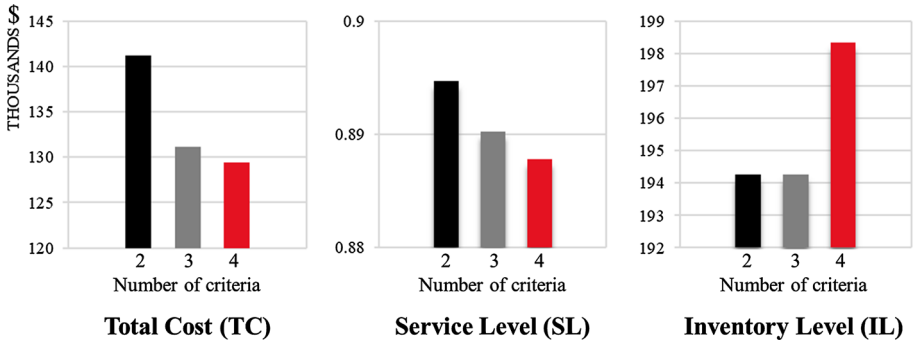


Fig. 10 Selection criteria sensitivity analysis results

service level and inventory level objectives, while its total cost is almost \$10 k (7%) greater than the other options. It needs to be noted that, these results are based on a 6-month horizon (simulated for 26 weeks), and therefore, a company may prefer a solution approach with a higher customer satisfaction rate by compensating a slight increase on its operational cost.

The distribution of selected suppliers based on NSGA-II non-dominated solutions in each setting is provided in Table 7. In all scenarios, the top selected supplier is always the same (supplier 2) in all settings. This implies that selecting a supplier to some extent depends on the number of criteria, but not necessarily improves by adding extra criteria.

6 Conclusion and future works

In today’s competitive environment, achieving success equally depends on the firm’s own performance and also the supply chain elements (Tosun & Akyüz, 2015). Suppliers are a critical element of this chain, and therefore appropriate candidates require a structured and practical approach. This paper introduces a new supplier selection framework by integrating a simulation–optimization approach with an MCDM model. This framework determines the Pareto optimal suppliers in a practical setting developed in a simulated environment. The key

Table 7 Distribution of selected suppliers based on different number of criteria

Number of criteria					
2		3		4	
Supplier	%	Supplier	%	Supplier	%
2	25	2	30	2	33
6	18	5	17	10	22
5	13	6	12	4	18
4	12	8	12	5	15
8	12	10	10	8	7
9	7	4	7	6	3
7	5	3	5	1	2
10	5	7	5	3	0
1	2	9	3	7	0
3	2	1	0	9	0

feature of this model is its design to identify the most appropriate criteria and their weight throughout the selection process. Instead of using a comprehensive list of criteria, this method aims to determine the most impactful criteria and their weights. This capability could benefit the decision-makers by reducing the time and effort required to perform the decision-making analysis in the future. Whenever the need for selecting a new supplier arises, the decision-making team could just focus on the shortened list of most preferred factors rather than all criteria.

The proposed model is developed by integrating MATLAB and Simio to deploy TOPSIS and the simulation model, correspondingly. The intermediate connection between these two software packages was handled by MS Excel. The applicability aspects of the proposed model are tested in a supply chain case study with three tiers. The experimental results indicate that increasing the number of criteria in the decision-making process may not necessarily improve the end results. This is aligned with one of this project's goals which is aiming to present a model working based on a shortlist of suppliers' criteria.

This work is one of the early frameworks that take advantage of MCDM and SO at the same time, and therefore can be extended in many different directions. The future models can apply different multi-objective metaheuristics in combination with some MCDM approaches to find the best combination approach. In terms of supply chain setting, the model can add some assumptions such as suppliers' capacity, and multi-product demands. Moreover, this work was just focused on the supplier selection process. However, one could present a model that optimizes the supplier selection as well as the supply chain setting such as re-order point (s), review period, and up-to-order amount (S) values. Another extension idea would be to include more realistic criteria for the analysis. The applied criteria in this study were more cost-related, and therefore, future research can consider a range of real-life measures such as reliability of the suppliers, timeliness, speed of delivery, reputation, geographical factors, and technology, among many.

Appendix 1: A brief summary of Supplier selection approaches

See Table 8.

Table 8 Supplier selection approaches

Approach	Category	Approach	Authors
Regular approaches	MCDM	AHP	Deng et al., (2014), Dweiri et al., (2016)
		ANP	Hashemi et al., (2015), Zhang et al., (2016)
Optimization		TOPSIS	Sahin and Yigider, (2014), Qiang and Zi-gang, (2008)
		Linear Optimization	Ghodsypour and O'Brien, (1998), Sanayei et al., (2008)
		Mixed Integer Programming	Kasilingam and Lee, (1996), Negahban and Dehghanimohammadabadi, (2018)
		Non-Linear Programming	Graves and Willems, (2005), Amini and Li, (2011)
		MODM	Liu et al., (2000), Narasimhan et al., (2001)
Intelligence Approaches		Genetic Algorithm	Sadeghieh et al., (2012), Rankovic et al., (2011)
		Neural Network	Wu et al., (2010)
		Simulation Optimization	Ding et al., (2005)
Hybrid approaches	Combined Methods	Fuzzy Sets and MCDM	Özder et al., (2015), Jafarnejad and Salimi, (2013), Kahraman et al., (2003)
		Fuzzy Sets and Optimization	Kumar et al., (2004), Weber and Ellram, (1993)
		MCDM and Optimization	Çebi and Bayraktar, (2003), Chamodrakas et al., (2010)
		Neural Network and Optimization	Xu and Xu, (2009), Wu, (2009)
		Simulation and MCDM	Azadeh et al., (2016)
		Simulation and Optimization	Göçken et al., (2015), Ding et al., (2008), Truong and Azadivar, (2003)

Acronyms: AHP: Analytic Hierarchy Process, ANP: The analytic network process, TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution, MODM: Multi-Objective Decision Making

Appendix 2: NSGA-II Parameters

See Table 9.

Table 9 NSGA-II Parameters

Parameters	Value/approach
Iterations	15
Population size	20
Crossover Percentage	0.7
Mutation Percentage	0.4
Selection method	Random

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