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Applying the Learning WASPAS Technique to Determine the Optimal Green Route in the Distribution of Dairy Products (Case Study: Kaleh Company)

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ABSTRACT

In today's world, choosing the optimal route for distributing dairy products is recognized as a major challenge in the supply chain. The present study aims to systematically review the weighted sum product evaluation method as well as the step-by-step weighted evaluation tool to present an improved learning model. This paper seeks to determine a green route for dairy products to reduce both cost and time of sending goods, while also minimizing the environmental impacts associated with dairy product transportation in Kaleh Company's distribution system in Amol City. To achieve this goal, the WASPAS multi-criteria decision-making method, with a very high accuracy, has been used to select the optimal route. For this purpose, by proposing the VASPAS learning method, this study seeks to correct the weaknesses in the computational methods. The presented model is able to identify and evaluate the optimal routes using machine learning algorithms and multi-criteria analyses. The results of implementing the proposed method for distributing dairy products in the cities of Mazandaran province indicate a significant increase in accuracy in identifying the optimal route and, consequently, a reduction in cost, time, and environmental impacts. According to the results obtained by implementing and comparing the proposed learning algorithm in two modes within the WASPAS method, the two routes Amol to Babol and Amol to Chamestan are identified as the optimal routes, with weights of 0.2712 and 0.2307, respectively. The weighted importance of the entire selected route has also been calculated as 0.50193 based on the proposed method. The findings of this study can help in decision-making in the field of information management, particularly in contexts involving interconnected or contradictory criteria and uncertain environments.

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1) Introduction

In operations research, mathematical modeling and complex statistical analysis have been used to solve a number of business and organizational problems and improve decision-making processes. Given the increasing complexity of the business environment, companies rely on analysis that was previously based on managers' intuition (Merad et al., 2013). Research on operations provides the tools required by governmental organizations and large corporations to make better decisions to reduce risks and improve their performance quality (Psarommatis & Kiritsis, 2022; Weistroffer & Li, 2016). Challenges related to technological development and the global economy have further complicated the business environment. Operations research, based on advanced software tools and complex mathematical models, can help evaluate all available options for a company based on potential project outcomes and perform risk analysis associated with specific decisions. The results obtained from these analyses provide comprehensive information based on which managers, decision-makers, and policymakers can make the necessary decisions and develop appropriate policies. As an effective approach, multi-criteria decision-making has been widely used to evaluate a limited number of decision-making options with multiple criteria (Felsberger et al., 2016; Gandhi et al., 2018). This method has been used in various scientific fields, including business and management (Santoyo-Castelazo & Azapagic, 2014; Mardani et al., 2015; Wimmler et al., 2015), risk management (Diaz-Balteiro et al., 2017; Ibáñez-Forés, 2014), computer science (Kumar et al., 2017; Vandebroek et al., 2016; Wimmler et al., 2015), health and medicine (Al-Alawi & Coker, 2018; Grevenitis et al., 2019; White & Lee, 2009), and engineering (Cinelli et al., 20114; Moghaddam et al., 2011; Rajeev et al., 2017). In many real-world problems, accurate ranking of performance and the calculation of the weight of criteria for decision-makers is difficult (Dahiya et al., 2022). Therefore, multi-criteria decision-making methods can be effectively used to determine the value and desired degree of various regions and create a priority order for their implementation (Hemmati et al., 2024). Using these methods, a discrete set of options can be examined based on a set of decision-making criteria (Abolghasemian et al., 2024). Different criteria represent different dimensions of the options. As a result, they may be in conflict with one another. For example, in construction processes, complex decisions, involving several conflicting and interactive criteria, are analyzed. Consequently, multi-criteria decision theory, with elements of mathematical statistics and the consideration of statistical relationships between criteria, can be highly useful. In this regard, some researchers have attempted to develop and expand new multi-criteria decision-making methods and techniques in recent years (Hascalik et al., 2007; Sazegari et al., 2024).

Various approaches have been proposed in relation to multi-criteria decision-making methods. In this regard, two new approaches, VSpace and Soara, were introduced in 2010 and 2012, respectively (Jagtap & Karande, 2023). In the VSpace method, there is a fundamental weakness that the current research seeks to rectify. This weakness lies in the algebraic sum of the results obtained from both the weighted summation model and the weighted multiplication model. In the VSpace method, the results of the weight factors are summed algebraically with equal shares. Subsequently, this share was changed, and a coefficient was considered for it. In this research, the methods of calculating this weight coefficient and their weaknesses are examined, and finally, a new model of VSpace is presented. Considering what mentioned above, addressing the topic of multi-criteria decision-making, using the proposed learning VSpace method, is of particular importance in selecting the optimal path. This is because selecting the optimal path in a city can include multiple factors, such as time, cost, safety, and road quality. The learning VSpace method helps analyze and manage these complexities and enables the simultaneous evaluation of multiple criteria. Using this method, decision-makers can obtain more accurate results. This assist them in comparing different options based on multiple criteria and choose the best route. In route selection, there may be different priorities. The VSpace method makes it easy to determine priorities and examine their impact on the final route selection. Employing this method can enhance transparency in the decision-making process. This leads to public trust and the acceptance of decisions made by city officials. Consequently, addressing the topic of multi-criteria decision-making, using the learning VSpace method in optimal route selection, not only helps improve the efficiency of the transportation system but also leads to sustainable development and citizen satisfaction. Therefore, what distinguishes the current research from others is the improvement and upgrade of the VSpace method. In other words, a new model of the VSpace method is presented in this article. Additionally, concepts and formulas from the VSpace method are used to upgrade the conventional VSpace method, thereby increasing its accuracy without a significant rise in the volume and time for calculations. In this article, the proposed method is used for selecting the optimal route to reduce both cost and time of goods delivery in the transportation system of Amol city. Amol city has four main entrances, which are: Haraz Road, Amol-Babol Road, Noor-Chamestan Road, and Mahmoudabad Road. This article aims to examine these routes using green supply chain criteria and, ultimately, to identify the route with the lowest transportation cost and time, as well as the lowest amount of greenhouse gas emissions. The method used to select the optimal route is the VSpace method, and efforts have been made to increase both the computational volume and decision-making accuracy by making some modifications to it, as well as proposing and introducing the learning VSpace method.

The rest of the article is organized as follows: In the second section, a literature review is provided regarding domestic and foreign studies to identify the research gap. In the third section, the methodology of the proposed learning VSpace method is explained. In the fourth section, the results obtained from the application of the proposed model are presented. Finally, a general conclusion along with future suggestions is provided in the fifth section.

2) Literature Review

Sadeghi Moghadam et al. (2021) conducted a study to identify and prioritize reverse logistics implementation solutions in the large supply chain to improve the performance of supply chain. They also used an intuitive fuzzy WASPAS expert-based approach with range values. They employed range-based intuitive fuzzy sets for weighting and the range-based intuitive fuzzy WASPAS method for prioritizing solutions. Based on the results, the first solution (creating, developing, and investing in reverse logistics technology), the tenth solution (developing a closed-loop supply chain through integration with reverse logistics), and the ninth solution (building electronic collaboration for rapid and effective coordination among supply chain members) were introduced as the best solutions. Seifbarghy (2022) presented a hybrid model in three stages considering a closed-loop supply chain that includes production sites, separation, remanufacturing, and disposal sites. In the first stage, a hybrid "Swara-WASPAS" method in a hierarchical state was used to score suppliers. In the second stage, environmental-social scores of modernization sites were calculated considering the population of residential areas and the unemployment rate. In the third stage, a three-objective mixed integer linear programming model was proposed. In this model, in addition to maximizing supply from qualified suppliers, supply chain sustainability is addressed through economic and environmental-social objectives. Mortazavi and Seifbarghy (2024) aimed to develop a method for selecting the best locations for "Ofogh Koroush" retail stores through the strategic ranking of potential store locations, using criteria such as population, store location characteristics, economic considerations, and competition. A hybrid method of hierarchical analysis and AHP-TOPSIS based on range-based intuitive fuzzy sets were used to examine the criteria and rank the proposed options. The AHP, based on range-based intuitive fuzzy sets, was utilized to address the uncertainty of decision-makers and to calculate the weights of the criteria; furthermore, the prioritization of proposed new retail store locations was calculated using the TOPSIS method. Bagheri et al. (2025) proposed a model for a smart supply-distribution network, encompassing marketing, inventory control, and pricing decisions across the entire network. To this end, an intelligent algorithm is proposed to solve the mathematical model. It solves the model in real-time using data received from the decision support system and provides updated results. Among foreign studies, Aydiz and Taksin (2022) discussed the problem of location selection for an emergency supply warehouse to ensure the delivery of emergency relief materials to consumption points in the shortest possible time following a disaster. To this end, they proposed a two-stage integrated model for the discussed problem. In the first stage, the criteria engaged in determining the location of facilities were weighted using fuzzy distance AHP. In the second stage, the options were evaluated using neutrosophic WASPAS. The proposed model was applied to Istanbul province for the selection of an emergency warehouse location. Xiong et al. (2020) proposed a hybrid method based on BWM, WASPAS, and TOPSIS to solve critical issues. In the first stage, BWM was used to weight the criteria. In the second stage, intuitive fuzzy numbers were introduced to the ranking stage. Then, WASPAS and TOPSIS were integrated for ranking the options for selecting an optimal green resilient supplier. Yalcin Kavus et al. (2023) presented the selection of a suitable shelf location for product transportation and distribution in the Beylikdüzü district of Istanbul, Turkey. This problem was solved using multi-criteria decision-making (MCDM) due to the availability of multiple aspects that need to be addressed when selecting an optimal location. In addition, fuzzy logic was used to convert expert opinions into mathematical expressions and combine them in decision-making processes. For the selection of the ideal location, a new model was presented by integrating the best worst Bayesian (B-BWM) method and the Pythagorean fuzzy approach (PF-WASPAS) for the first time in the research literature. Darko et al. (2023) used WASPAS to prioritize areas at risk for patient care in the healthcare system of Ghana. Singh & Modgil (2020) employed WASPAS to propose an integrated weighting approach for fundamental factors affecting the selection of influential areas for the use of cosmetics to enhance customer satisfaction. de Assis et al. (2023) applied their proposed approach in a complex decision problem for the selection of state military police in Rio de Janeiro, considering optimal access to a helicopter. This study highlights various limitations involved, such as cost, operational adaptability, and safety criteria, and demonstrates the precise application of the proposed method, serving as a valuable resource for validating developed systems.

Given the above research studies, despite significant advances in supply chain optimization and route selection for product distribution, there remains significant gaps in the area of selecting an optimal green route for dairy products, especially using novel methods such as learning WASPAS. Most previous research has been limited to examining traditional methods and optimization algorithms, while less attention has been paid to environmental impacts and sustainability in the distribution process. In addition, in existing studies, data is typically used historically and statically, which may not have the necessary efficiency in changing market conditions and customer needs. Furthermore, the lack of attention to multi-criteria and specific complexities of the dairy industry leads to inaccuracies in the selection of optimized routes. This research aims to fill these gaps by examining and analyzing the use of learning WASPAS in selecting an optimal green route for dairy products and seeks to provide a comprehensive and dynamic model that can help improve efficiency and reduce negative environmental impacts in the distribution process. This study can serve as a starting point for future research in this field, leading to the development of more sustainable solutions in the dairy industry.

In summary, the papers discuss various approaches to optimizing supply chains and selecting locations, often using fuzzy logic and WASPAS. The overarching theme is to improve efficiency and address environmental factors.

3) Methodology

The current research is an applied study, as a specific practical application of its implementation is envisioned in the real world. This study examines the route selection for transporting dairy products of Kaleh Company from Amol to Tehran, Babol, Mahmoudabad, and Chalus by light trucks. For this purpose, a learning algorithm based on the WASPAS method was proposed. Ultimately, the route selection results were presented using both the conventional WASPAS method and the proposed learning algorithm. The presented model was formulated in MATLAB software, utilizing the recorded data available in the archive documents of Kaleh Company. To conduct this research, the following steps were followed.

Problem definition and research objective:

First, the challenges and needs related to selecting the optimal green route for the distribution of dairy products in Amol city are identified. Then, a computational approach is presented to generalize distribution routes according to environmental and economic criteria. For this purpose, a review of previous studies on optimal route selection and green assessment methods is conducted through a library-based study of existing theoretical research to identify effective criteria for green route selection.

Identification of criteria and sub-criteria:

Using the Delphi technique, expert opinions on route selection criteria are gathered. The scoring of the criteria and the elimination of unnecessary items are conducted.

Determination of criteria weights:

The SWARA method is used to calculate the weight or relative importance coefficient of the sub-criteria. Experts' evaluations regarding the importance of the options are conducted.

Modeling and data analysis:

Using the relevant software, modeling of the learning WASPAS method for selecting distribution routes is performed. Additionally, data analysis is calculated according to the identified criteria and the assigned weights.

3-1- WASPAS Method

The field of multi-criteria decision making is rapidly expanding, and various methods and implementations are being developed. This area highlights the importance of research in operations decision-making, which has become more complex due to technological advancements and increased uncertainty. Baryannis et al. (2019) highlighted that to make decisions, organizations use methods that consider multiple criteria and data sources to identify and manage operational risks. This study proposes a solution to the challenges arising from multi-criteria decision-making problems by utilizing a wide range of optimization techniques, such as AHP, ANP, PROMETHEE, THOR, SAPEVO, TOPSIS, and WASPAS. The practical effectiveness of these methods has generally been demonstrated by Chakraborty and Zawadski (2014) through their application as an effective multi-criteria decision-making tool for addressing eight decision-making problems in industrial manufacturing processes. Furthermore, Chakraborty et al. (2015) confirm the applicability of WASPAS by optimizing the solutions for five common real-time manufacturing problems. The application of this method can be extended to all multi-criteria decision-making processes.

The WASPAS method, introduced by Zavadskas et al. (2012), is a high-precision multi-criteria decision-making method that combines both weighted sum and weighted product models. This method combines two models to improve decision-making accuracy and is not limited to quantitative data. The main steps of WASPAS include constructing a decision matrix and normalizing the values in this matrix. The decision matrix includes options and criteria, and normalization is performed to overcome differences between criteria. Finally, the performance values of each option are normalized according to different criteria to enhance decision-making accuracy.

In the WASPAS method, if $Q_i^{(1)}$ and $Q_i^{(2)}$ represent the total relative importance of the i-th option in both the weighted sum and weighted product models, respectively, they are determined through the following relationships (Zavadskas et al., 2021):

$$\boldsymbol{Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij} w_j} \tag{1}$$

$$\boldsymbol{Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}} \tag{2}$$

where $\boldsymbol{w_j}$ is the coefficient or the relative importance weight of the j-th criterion, also referred to as the weight (coefficient) of criterion j. In general, we have:

$$\boldsymbol{\sum_{j=1}^{n} w_j = 1} \tag{3}$$

On the other hand, $\boldsymbol{\bar{x}_{ij}}$ represents the normalized efficiency coefficient and indicates the efficiency and impact of option i on criterion j. Finally, the optimal option is selected based on the total importance equation:

$$\boldsymbol{Q_i = \lambda Q_i^{(1)} + (1-\lambda) Q_i^{(2)}; 0 \leq \lambda \leq 1} \tag{4}$$

In the method proposed by Zavadskas et al. (2012), $\boldsymbol{\lambda = 0.5}$. In other words, in the initial version of the WASPAS method, the impact of both models is considered equal. In the WASPAS method, criteria are initially scored using the Delphi technique. A group of experts fills out a questionnaire and assigns a score to each indicator from 1 to 5. The average scores are then calculated, and indicators with a score below 4 are removed (Dalkey & Helmer, 1963). This process can be repeated in several iterations until a final consensus is reached. After the final indicators are determined, it is time to calculate the weight or importance coefficient of the sub-criteria, at which point the SWARA method is highly useful for evaluating expert opinions on the importance of the options (Thakkar & Thakkar, 2021).

In the WASPAS method, the selection of the numerical value of the $\boldsymbol{\lambda}$ coefficient is of high importance. This is because its numerical value influences the extent to which each of the weighted sum and weighted product models plays a role in selecting the optimal option. If $\boldsymbol{\lambda = 0}$, then the WASPAS method will transform into the weighted product model, and if $\boldsymbol{\lambda = 1}$, then the WASPAS method is essentially the weighted sum model. In other words, smaller values of lambda cause the role of the weighted product model to increase compared to the weighted sum model, and the opposite occurs for larger values of $\boldsymbol{\lambda}$. In decision-making problems, the optimal value of $\boldsymbol{\lambda}$ can be calculated using the following equation (Hurley, 2020):

$$\boldsymbol{\lambda} = \frac{\boldsymbol{\sigma^2\left(Q_i^{(2)}\right)}}{\boldsymbol{\sigma^2\left(Q_i^{(1)}\right) + \sigma^2\left(Q_i^{(2)}\right)}} \tag{5}$$

where $\boldsymbol{\sigma^2}(.)$ represents the variance of the variables and is obtained according to the following equations:

$$\boldsymbol{\sigma^2\left(Q_i^{(1)}\right) = \sum_{j=1}^{n} w_j^2 \sigma^2(\bar{x}_{ij})} \tag{6}$$

$$\boldsymbol{\sigma^2\left(Q_i^{(2)}\right) = \sum_{j=1}^{n} \left\{\frac{\prod_{j=1}^{n}(\bar{x}_{ij})^{w_j} w_j}{(\bar{x}_{ij})^{w_j}(\bar{x}_{ij})^{(1-w_j)}}\right\}^2 \sigma^2(\bar{x}_{ij})} \tag{7}$$

where the estimated variance of the normalized initial criterion values is obtained as follows:

$$\boldsymbol{\sigma^2(\bar{x}_{ij}) = (0.05\bar{x}_{ij})^2} \tag{8}$$

The estimated variance of the options in the WASPAS method is dependent on the variances of both the weighted sum and weighted product methods and is therefore influential in the calculation of the $\boldsymbol{\lambda}$ value. By calculating an optimal value for $\boldsymbol{\lambda}$, the highest accuracy in selecting the optimal option is achieved. Accordingly, studying and examining methods for calculating the $\boldsymbol{\lambda}$ value is very important. This is because it significantly impacts the final ranking and prioritization of the options. Harley (2020) has proposed another method for calculating the optimal $\boldsymbol{\lambda}$ value, using the total relative importance instead of their variances:

$$\boldsymbol{\lambda = \frac{\sum_{i=1}^{m} Q_i^{(2)}}{\sum_{i=1}^{m} Q_i^{(1)} + \sum_{i=1}^{m} Q_i^{(2)}}} \tag{9}$$

In some sources, the $\boldsymbol{\lambda}$ coefficient is added to a fixed value:

$$\boldsymbol{\lambda = K + \frac{\sum_{i=1}^{m} Q_i^{(2)}}{\sum_{i=1}^{m} Q_i^{(1)} + \sum_{i=1}^{m} Q_i^{(2)}}} \tag{10}$$

If $\boldsymbol{K = 0.5}$, then the value of $\boldsymbol{\lambda}$ is shifted from the range $[\boldsymbol{0} \quad \boldsymbol{1}]$ to the range $[\boldsymbol{0.5} \quad \boldsymbol{1.5}]$. In other words, the WASPAS method will never tend toward the weighted sum model.

3-2) Weakness of the WASPAS Method

The role of the lambda coefficient is highly significant in determining the accuracy and efficiency of the WASPAS method. In other words, by selecting an optimal value, the method can be transformed into a highly effective approach; conversely, choosing an inappropriate value may lead to inaccurate and unreliable results. In Equation (5), consider the case where all $Q_i^{(1)}$values are equal to one another, denoted as $\sigma^2\left(Q_i^{(1)}\right)=0$. Consequently, we will have:

$$\boldsymbol{\lambda}=\frac{\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(2)}\right)}{\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(1)}\right)+\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(2)}\right)}=\mathbf{1}\Rightarrow\boldsymbol{Q}_i=\boldsymbol{Q}_i^{(1)} \tag{11}$$

Therefore, the WASPAS method transforms into a weighted sum method. Due to the equal values of $\boldsymbol{Q}_i^{(1)}$, it will not be possible to select a better option. In such a situation, decision-making will only be possible based on the values of $\boldsymbol{Q}_i^{(2)}$. Similarly, in the case where all values of $\boldsymbol{Q}_i^{(2)}$are equal to one another, because $\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(2)}\right)=\mathbf{0}$, we have:

$$\boldsymbol{\lambda}=\frac{\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(2)}\right)}{\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(1)}\right)+\boldsymbol{\sigma}^2\left(\boldsymbol{Q}_i^{(2)}\right)}=\mathbf{0}\Rightarrow\boldsymbol{Q}_i=\boldsymbol{Q}_i^{(2)} \tag{12}$$

On the other hand, in situations where $Q_i^{(1)}$values are much smaller than $Q_i^{(2)}$values ($Q_i^{(1)} \ll Q_i^{(2)}$) it is obvious that we should rely on the $Q_i^{(2)}$ values for decision-making. However, according to equations (9) and (10), the $Q_i^{(2)}$values will not play a role in the decision-making process:

$$\boldsymbol{\lambda}=\frac{\sum_{i=1}^{m}\boldsymbol{Q}_i^{(2)}}{\sum_{i=1}^{m}\boldsymbol{Q}_i^{(1)}+\sum_{i=1}^{m}\boldsymbol{Q}_i^{(2)}}\approx\mathbf{1}\Rightarrow\boldsymbol{Q}_i=\boldsymbol{Q}_i^{(1)} \tag{13}$$

The opposite case also holds true; that is, when the $Q_i^{(2)}$ values are much smaller than the $Q_i^{(1)}$ values, and it is expected that the $Q_i^{(1)}$ values play a fundamental role in the decision-making process, in practice the $Q_i^{(1)}$values will have no role in decision-making, because:

$$\boldsymbol{\lambda}=\frac{\sum_{i=1}^{m}\boldsymbol{Q}_i^{(2)}}{\sum_{i=1}^{m}\boldsymbol{Q}_i^{(1)}+\sum_{i=1}^{m}\boldsymbol{Q}_i^{(2)}}\approx\mathbf{0}\Rightarrow\boldsymbol{Q}_i=\boldsymbol{Q}_i^{(2)} \tag{14}$$

As a result, the one-sided relationships (5), (9), and (10) do not possess the required efficiency for calculating $\boldsymbol{\lambda}$, because whenever either the weighted sum or the weighted product model becomes inefficient for reasons such as equal values or extremely small values, the WASPAS method, paradoxically, tends to gravitate toward that very model.

3-3) Proposed Learning WASPAS Method

The WASPAS method is a decision-making approach and, in terms of application, is similar to neural networks but with a major difference. In neural networks, one-sided and feedback-free formulations are avoided, and it is not necessary for the coefficients to be correct from the outset. Rather, what matters is the learning process and the continuous adjustment of coefficients during learning. Accordingly, this paper aims to propose a learning-capable formulation for calculating the optimal value of $\boldsymbol{\lambda}$.

By the learning WASPAS method, we mean a variant of the WASPAS model in which the value of $\boldsymbol{\lambda}$ is adjusted through a learning-based process. Learning in the proposed method implies that the results of previous decision-making processes are utilized in computing the new value of lambda, thus, feedback is obtained from prior outputs. In adjusting the lambda values, the concept of distance in the TOPSIS method, which to some extent evokes the Hebbian learning rule and the Delta rule in neural networks, is employed.

Unlike existing methods in which the value of $\boldsymbol{\lambda}$ is predetermined, the proposed approach calculates the value of $\boldsymbol{\lambda}$ during the learning process and, simultaneously, with solving the problem. Consequently, while selecting the optimal alternative, the optimal value of lambda is also obtained. The proposed method for calculating the $\boldsymbol{\lambda}$ coefficient is described as follows:

Definition 1) The coefficients n, m, and k denote, respectively, the optimal alternative selected by the WASPAS method, the optimal alternative selected by the weighted sum model, and the optimal alternative selected by the weighted product model.

1. Select the initial value of lambda equal to 0.5.
2. If k = m or k = n, lambda remains unchanged.
3. If k is different from m, then:

$$\boldsymbol{\lambda = 0.5 - \alpha \times \frac{Q_m^{(1)}}{\sum_{i=1}^{m} Q_i^{(1)}}} \tag{15}$$

If k is different from n, then:

$$\boldsymbol{\lambda = 0.5 + \alpha \times \frac{Q_n^{(2)}}{\sum_{i=1}^{m} Q_i^{(2)}}} \tag{16}$$

In the above relationships, it is suggested that $\alpha = 0.1$. The reason for this choice is to ensure that the magnitude of changes does not have an excessive impact on the process, thereby allowing the adjustment process to be carried out correctly and gradually.

3-4) Determination of Control Parameters for the Proposed Learning WASPAS Method

In the proposed learning WASPAS algorithm, control parameters play a crucial role in optimizing the algorithm's performance and accuracy. Two key parameters that need to be determined in this algorithm are:

1. **Learning Improvement Rate:**

The learning improvement rate determines how quickly the algorithm responds to changes and to new data. If this value is too high, the algorithm may easily follow fluctuations and fail to converge to a stable solution. Conversely, if it is too low, the algorithm may optimize slowly and require a significant amount of time to reach the desired result. Typically, values between 0.01 and 0.1 are suitable for the learning improvement rate. In this research, the learning improvement rate has been calibrated to 0.1.

2. **Number of Iterations:**

The number of iterations specifies how many times the algorithm should run on the data to reach an optimal result. This parameter should be set in such a way that it not only leads to optimization but also prevents problems such as overfitting. Typically, the number of iterations between 100 and 1000 is suitable; however, this value can vary depending on the complexity of the data and the model. Determining these parameters requires experimentation and evaluation to determine the best combination for achieving optimal results. According to the samples considered, a total of 250 iterations yields satisfactory results.

4) Findings and Discussion

In today's world, the optimization of distribution and transportation processes has become one of the main challenges faced by companies. Kaleh Company, as one of the largest dairy producers in Iran, requires an efficient system for transporting its products from the origin in Amol to various destinations, such as Tehran, Babol, Mahmoudabad, and Chamestan. This issue becomes even more critical under conditions where cost reduction and the minimization of environmental impacts are required.

Therefore, in this study, the selection of optimal routes for transporting dairy products from Amol to different destinations is carried out using two methods: (1) the WASPAS method, and (2) the proposed learning WASPAS algorithm. Initially, the criteria affecting route selection are identified. These criteria may include transportation cost, shipment transit time, greenhouse gas emissions, type of cargo, accessibility to the destination, and delivery conditions of the shipments. The Delphi technique is employed to collect expert opinions in this area and to score each criteria.

Based on field studies as well as the recommendations of experienced experts and practitioners, a set of initial criteria and sub-criteria is listed in this paper. Subsequently, the Delphi screening method is used to select the final criteria and sub-criteria. For this purpose, the initial criteria and sub-criteria are first presented to a panel of experts in the form of a questionnaire. Each expert assigns a score from 1 to 5 to each item based on its level of importance. After calculating the average score of each item (criterion and sub-criterion), those with an average score of less than 4 are removed from the questionnaire. The revised questionnaire is then redistributed to the panel of experts for re-evaluation and re-scoring. This process continues until no further items are eliminated.

In this study, the SWARA method is used to calculate the weight of each criterion. This method is consistent with the Delphi technique employed for selecting criteria and sub-criteria and, directly, utilizes the scores assigned by experts in the Delphi process to compute the weights. Moreover, unlike some existing methods (such as the Analytic Hierarchy Process, Analytic Network Process, and the Best–Worst Method), SWARA does not require pairwise comparisons of criteria, thereby significantly reducing the computational burden.

Subsequently, using the conventional WASPAS method, each route is evaluated based on the obtained weights, and the best route is selected according to the calculated final scores. In addition, the design and implementation of the proposed learning algorithm, utilizing historical data and feedback, enable continuous improvement in route selection. Finally, a comparison is conducted between the results obtained from the conventional WASPAS method and those derived from the learning WASPAS algorithm.

Accordingly, this research can assist Kaleh Company in improving the optimization of its dairy product transportation processes by employing modern decision-making methods. By comparing conventional and learning-based approaches, a clearer understanding of the advantages and disadvantages of each method can be achieved, ultimately leading to the selection of the most optimal routes for dairy product transportation. This approach not only reduces both transportation costs and time but also contributes to more positive environmental impacts.

4-1) Selection of Criteria and Sub-Criteria and Their Weighting Coefficients

The number of expert panel members for applying the Delphi method in selecting the criteria and sub-criteria was set to 10. The Delphi technique was conducted in three rounds and was terminated in the third round upon reaching a final consensus. Based on this process, six main criteria and fifteen sub-criteria were identified.

Table 1) Main and Sub-Criteria of the Problem (Using the Delphi Technique)

Criteria	Sub-criteria	Average
Shipping Cost (C1)	Distance traveled (S11)	4.6
	Fuel consumption (S12)	4.8
	Vehicle depreciation level (S13)	4.3
Shipment Transit Time (C2)	Distance required to reach shipments (S21)	4.6
	Traffic level on the shipment delivery route (S22)	4.8
Greenhouse Gas Emission Level (C3)	Vehicle health (S31)	4.5
	Loading time (S32)	4.8
Shipment Type (C4)	Bulky shipments (S41)	4.7
	Heavy shipments (S42)	4.5
Destination Access Type (C5)	Destination on main street (S51)	4.6
	Destination on side street (S52)	4.8
	Destination in alleys and backstreets (S53)	4.5
Shipment Delivery Method (C6)	Number of shipment items (S61)	4.4
	Shipment weight (S62)	4.4
	Verification of shipment accuracy (S63)	4.6

Using the results presented in Table 1 and applying the SWARA method, the weight of each main criterion can be calculated. Finally, by multiplying this weight by the coefficient of each sub-criterion (branch weight), the final weight of each sub-criterion is obtained. Table 2 presents the weighting coefficients of the main criteria and the sub-criteria.

Table 2) Weights of the Problem's Main Criteria and Sub-Criteria (Using the SWARA Method)

Main Criteria		Sub-Criteria		
Signitaure	**Weight**	**Signitaure**	**Weight**	**Final Weight**
C1	0.340	S11	0.485	0.165
		S12	0.311	0.106
		S13	0.204	0.069
C2	0.244	S21	0.587	0.143
		S22	0.413	0.101
C3	0.162	S31	0.611	0.099
		S32	0.389	0.063
C4	0.116	S41	0.583	0.068
		S42	0.417	0.049
C5	0.081	S51	0.459	0.037
		S52	0.321	0.026
		S53	0.220	0.018
C6	0.056	S61	0.468	0.026
		S62	0.318	0.018
		S63	0.214	0.012

Figures 1 and 2 illustrate the weights of the main and sub-indices, respectively. Based on the plotted charts, the criteria with the highest and the lowest levels of importance are identified.

Figure 1) Weights of the Main Criteria Obtained Using the SWARA Methodfigure

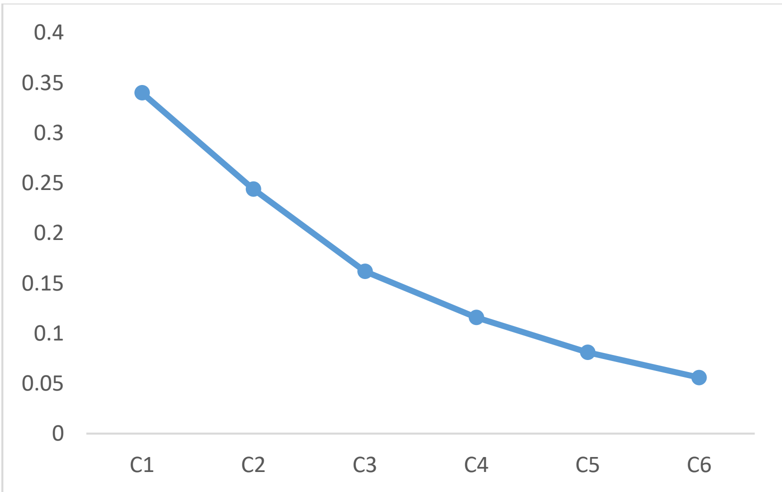


Figure 2) Weights of the Sub-Criteria Obtained Using the SWARA Method 2. 1. Weights of the main criteria obtained using the SWARA method

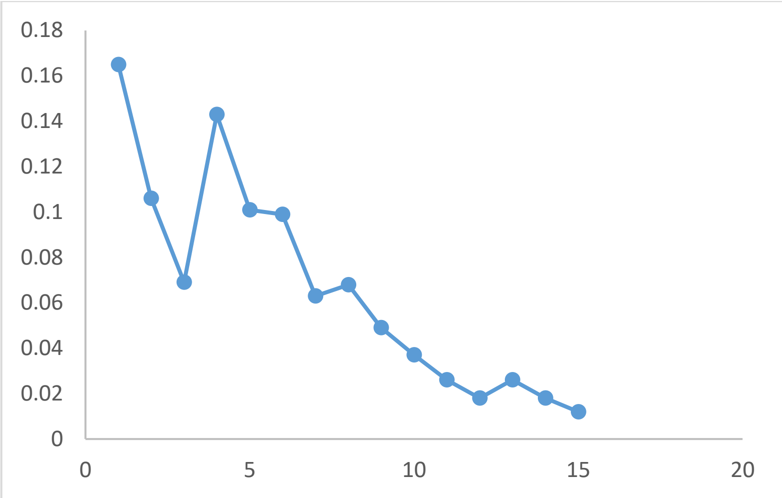


Figure Weights of the sub-criteria obtained using the SWARA method

4-2) Selection of the Optimal Route

The city of Amol has four entry routes, namely: the Haraz Road, the Amol–Babol Road, the Mahmoudabad Road, and the Noor–Chamestan Road. To select the optimal route in the green supply chain using the WASPAS method, the λ coefficient must first be calculated. By applying Equations (5) and (9) and performing the necessary calculations, we obtain:

$\boldsymbol{\lambda_1 = 0.5056}$ Using Eq. (5)

$\boldsymbol{\lambda_2 = 0.5022}$ Using Eq. (9)

In the proposed method, the value of k is first calculated by assuming an initial value of $\lambda = 0.5$, and consequently, $k = 4$ is obtained. By comparing the values of $Q_i^{(1)}$and $Q_i^{(2)}$, we have n = 4 and m = 3. Using the proposed algorithm, suppose that $k \neq m$; we have:

$$\boldsymbol{\lambda = 0.5 - \alpha \times \frac{Q_3^{(1)}}{\sum_{i=1}^{m} Q_i^{(1)}} = 0.5 - 0.1 \times \frac{0.888}{3.444} = 0.4742}$$

By employing the obtained coefficient value, the relative importance of each option can be determined. After calculating the relative importance using equations (1) and (2), the total importance of each route can be calculated by equation (4) and the $\boldsymbol{\lambda}$ coefficient. By dividing the total importance of each route by the sum of the total importance of all routes, the optimal importance weight of each route is obtained. Consequently, the optimal route is the one with the highest importance weight (or the highest total importance). Table 3 presents the importance weights of the routes for different lambda calculation methods. As shown in the data within the table, the Amol-Babol route is the optimal route for all values of the $\boldsymbol{\lambda}$ coefficient.

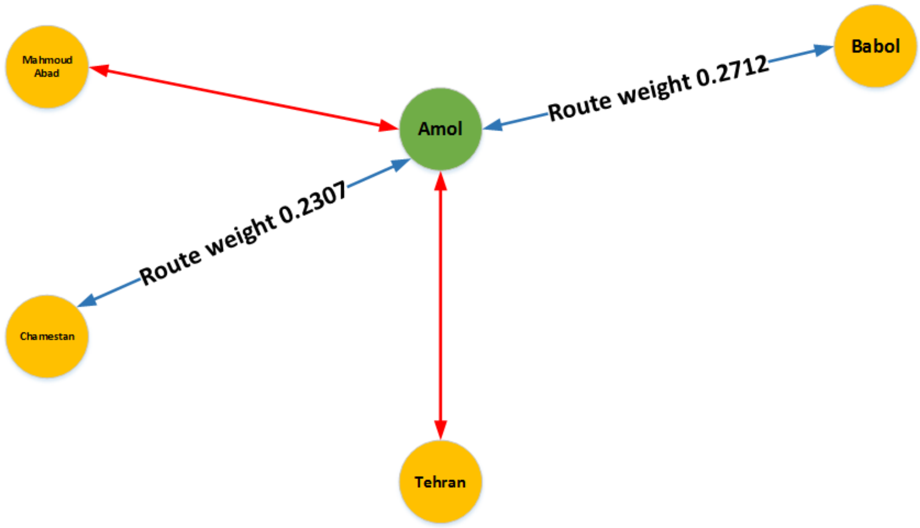
Table 3) Optimal Weights of the Routes Using the WASPAS Method (for Different Methods of λ Calculation)

Start-to-End	Based on λ_1	Based on λ_2	Proposed method
Amol to Babol	0.264	0.267	0.271
Amol to Tehran	0.261	0.261	0.254
Amol to Mahmoudabad	0.241	0.240	0.243
Amol to Chamestan	0.233	0.231	0.230

4-3) Comparison of the Proposed Algorithm with the WASPAS Method

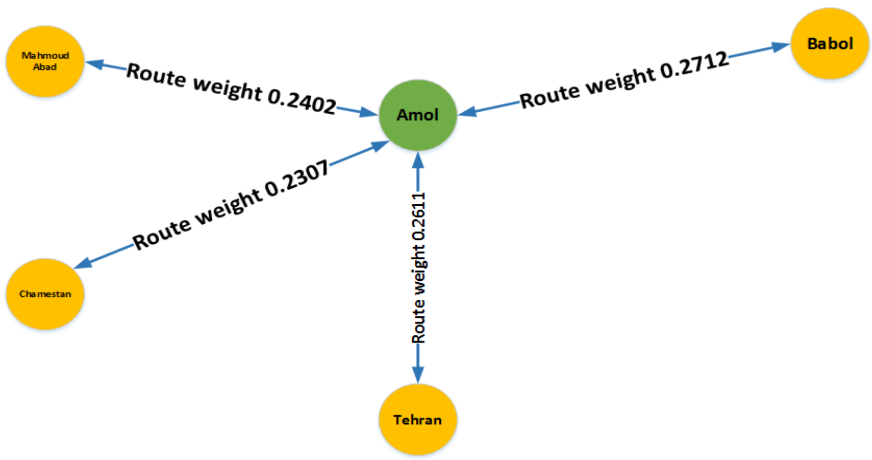
Based on the results obtained from implementing and comparing the proposed learning algorithm with the two cases in the WASPAS method for $\boldsymbol{\lambda_1 = 0.5056}$ and $\boldsymbol{\lambda_2 = 0.5022}$, the routes from Amol to Babol and Amol to Chamestan are identified as the optimal routes, with weights of 0.2712 and 0.2307, respectively. The total weighted importance of the selected routes, according to the proposed method, is 0.50193. Figure 3 illustrates the optimal routes selected using the proposed learning algorithm.

Figure 3) Optimal Routes Selected From the Amol Origin and the Weighted Importance Assigned to Each



According to the WASPAS method, the routes from Amol to Mahmoudabad and Amol to Tehran were added to the routes from Amol to Babol and Amol to Chamestan, and the optimal routes, with the respective weights of 0.2402, 0.2611, 0.2712, and 0.2307, were determined. The total weighted importance of the selected route, according to the WASPAS method, is 1.0032. Figure 4 shows the optimal routes selected using the WASPAS algorithm. Based on the calculated weights, it is evident that the weighted importance according to the learning algorithm is lower than that of the WASPAS method. This indicates that the learning algorithm, by discarding unfavorable routes, creates a more desirable objective function value.

Figure 4) Optimal Routes Selected From the Amol Origin and the Weighted Importance Assigned to Each Using the WASPAS Algorithm



5) Cunclusion

This study demonstrated that the use of the learning-based WASPAS method, as an effective multi-criteria decision-making tool, can contribute to improving the process of optimal route selection in the city of Amol. Given the diverse criteria that influence route selection, this method enables their simultaneous and accurate evaluation and helps decision-makers compare different alternatives based on predefined priorities. The results of this study indicate that, by using the learning-based WASPAS, it is possible to select a route that not only reduces travel time but also minimizes costs while enhancing safety and travel quality. Moreover, this method facilitates sensitivity analysis and the examination of the effects of changes in different criteria on the final route selection, allowing decision-makers to make better decisions under variable and complex conditions.

The lambda coefficient is the most important parameter in the WASPAS method, and its importance is significantly greater than that of WSM and WPM, since the selection of the optimal alternative is essentially determined by this coefficient. This coefficient can specify which optimality values play a more prominent role in determining the optimal option. The shortcomings of existing methods become apparent when the variance of the optimality values of the alternatives is low or when one optimality value is much smaller than another. The main objective of this paper is to select the optimal alternative (route) in transportation to minimize travel time, transportation costs, and greenhouse gas emissions in the green supply chain. Accordingly, the proposed learning-based WASPAS method is used for optimal route selection.

Table 3 presents the results obtained from existing methods and the proposed method for optimal route selection. In this table, the optimality weights of the routes obtained from different methods are compared. All methods are based on the WASPAS approach, and their differences lie in the way the lambda coefficient is calculated. The first point evident in Table 3 is that all methods yield identical results and that the priority ranking of routes is the same across all methods. Consequently, the proposed algorithm confirms the results of the existing methods, and likewise, the existing methods validate the correctness of the proposed algorithm. However, the main strength of the proposed algorithm can be found in the differences among the optimality weights of the routes. The efficiency of existing methods decreases sharply when the priorities are close to one another, and even a simple computational or measurement error may lead to a change in the priority order. In contrast, in the proposed method, the distance between the optimality weights of priorities is increased, allowing alternatives and routes to be ranked with greater confidence. In other words, for the lambda value calculated using the proposed algorithm, the discriminating power among priorities and the confidence level in computations and option selection are enhanced. Unlike existing methods, in which the lambda value is predefined and static, in the proposed algorithm this value is determined dynamically during the learning process and simultaneously with solving the selection problem; thus, it is optimized during the selection of the optimal alternative. In addition, the computational volume is reduced compared to existing methods, especially Equation (5), and the accuracy of calculating the coefficient is significantly increased due to the incorporation of feedback and the learning process. According to the results obtained from the learning-based method, it is recommended that routes from Amol to Tehran should not be selected for transportation using Nissan or light trucks; instead, the use of these vehicles should be limited to nearby cities, such as Babol, Mahmoudabad, and Chamestan. This is in contrast to the conventional WASPAS method, allowing the route from Amol to Tehran to be used $\lambda_1 = 0.5056$ times. Given Tehran's high potential and the difficulty of the route, this does not represent an optimal choice. Therefore, it can be concluded that the learning-based method is capable of considering various aspects in selecting the optimal route. For future studies, it is recommended that, by drawing on the learning-based WASPAS algorithm, this approach be extended to TOPSIS, VIKOR, and other decision-making methods. In addition, evaluating the random selection of an action from the set of available actions and applying it to the environment, using learning automata, can provide valuable assistance in selecting the optimal action for route determination.

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