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Calculating the Access Probability of Network Arcs to Determine the Maximum Flow in Path

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Abstract

Today, many companies are trying to reduce operating costs and improve performance to cope with severe demand fluctuations. For this purpose, optimizing the supply chain process is important and necessary to improve performance in some parameters, including financial components. Therefore, today, companies have realized that optimizing operations within the company's four walls is not enough to achieve business excellence, but to improve performance, they need the participation of suppliers in improving quality on the one hand and meeting customer demands on the other. This partnership and alliance often takes the form of a supply chain, which shows the importance of the supply chain. Considering the sanctions and their consequences on the country's economy, which make it difficult to import raw materials, an increase in exchange rates, an increase in prices, inflation, economic recession, and an increase in production costs, it is necessary to identify effective factors in optimizing the financial supply chain. This article aims to improve the financial efficiency of the supply chain and, in fact, reduce the volume of working capital of buyers and suppliers in the home appliance industry. For this purpose, the factors were identified using a descriptive method and by studying books and articles in the field of supply chain. Then, using the opinions of experts, the main and effective factors were selected using the Delphi Method. The results of this study showed that the factors effective in optimizing the financial performance of the financial supply chain include: operational risk, the threat of price fluctuations, exchange rate risk, futures contract risk, planning risk, the need to increase working capital, severe environmental changes, uncertainty about the future, exchange rate fluctuations, increased production costs, stagflation, reduction in bank facilities, interest rate risk, cost transfer to other members of the chain, risk of losing customers, cost inflation, risk of non-continuity of the firm's activity, and risk of losing suppliers.

Keywords: Transportation network, Perishable product supply chain, Probability, Accessibility, Multi-criteria decision-making.

1 | Introduction

To sustain life, humans consume various goods on a daily basis. These goods are often delivered to final customers through different supply chains after passing through one or more stages [1]. Therefore, supply chains play a very important role in everyday human life. A large portion of these sensitive and essential goods

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consists of food and pharmaceutical products, which are classified as perishable goods. Perishable goods are defined as a group of products that lose quality and deteriorate over time or when exposed to certain conditions [2]. It is evident that, due to time constraints and the risk of deterioration, such goods require more effective management and planning. In many cases, products may face stoppages and waiting times at different levels of the supply chain. These stoppages may be part of various processes such as production, packaging, and so forth. Long waiting times are undesirable, and efforts are generally made to minimize those [3]. Considering such delays, it is preferable to prevent the occurrence of additional time delays.

A significant portion of the time spent throughout supply chains is devoted to the transportation of goods between different levels. Shipping raw materials to factories, handling in warehouses, transportation to other levels, delivery to final customers, and similar activities are all part of the transportation cycle of goods in product supply chains [4]. For this reason, transportation is of great importance in supply chains and has received considerable attention. Transportation planning in perishable product supply chains should be considered from the very initial stages where raw materials are located until the moment the final product is delivered to consumers [5]. Under such conditions, the time required for transporting goods can be measured and evaluated in order to support transportation planning. Improving the transportation process throughout the supply chain can lead to cost reductions and increased revenues [6].

In addition to economic aspects, the transportation of goods is also important from other perspectives. Demand responsiveness (on-time delivery of goods) and environmental impacts are among the most significant of these aspects. Customers at every level prefer to receive the required goods within a specified time frame and in perfect condition. Any event in the transportation process that leads to delays, quality degradation, or loss of goods can severely affect customers' perceptions [7]. On the other hand, the loss of any type of product and its release into the environment can cause serious damage. Some products introduce chemical pollution into nature, while others, such as agricultural products, result in the waste of resources that were consumed during their production when they are lost [8].

Considering the issues discussed regarding perishable product supply chains, the importance of the goods involved, and the role of transportation in improving this type of supply chain, the need to enhance transportation processes is strongly felt. Numerous studies have been conducted in this field, which can be divided into two groups. In the first group, researchers have mainly focused on transportation planning from a time-value perspective. In fact, these studies attempt to reduce goods transfer time by improving transportation networks. Manouchehri et al. [3] designed transportation models to manage the transfer time of poultry to demand points. Since poultry is a highly sensitive product, they sought to reduce waiting times and consequently prevent product deterioration by proposing a scheduling model. However, their model did not consider the possibility of the inaccessibility of some routes.

Meidute-Kavaliauskiene et al. [9] designed an appropriate network to reduce transportation time. They argued that reducing transportation time through proper routing can decrease product deterioration due to spoilage, reduce environmental damage, and increase customer satisfaction and profit. They developed a mixed-integer nonlinear multi-objective model for a four-level supply chain consisting of suppliers, manufacturers, distributors, and retailers. The model pursued four objectives: minimizing costs, minimizing environmental costs, reducing delivery time, and increasing customer satisfaction. The results showed that these objectives could be conflicting; in some cases, despite reduced operational costs, environmental costs increased significantly. Overall, the proposed model was flexible and capable of addressing complex issues. Wu et al. [10] examined this issue in a specific case study, focusing on reducing food delivery time to passenger trains, since prepared food spoils rapidly within a few hours. They redesigned the supply chain network and reduced delivery times to minimize deterioration. They developed a nonlinear model that maximized final profit by reducing waste and transportation costs. Their results indicated that the model was highly sensitive to delivery deadlines and that increasing delivery time windows significantly improved supply chain profitability. Agrawal et al. [2] designed a supply chain aimed at reducing transportation time through appropriate route selection. They emphasized that vehicle capacities are not uniform, which complicates supply chain design, allocation, and routing. Nevertheless, routing remains an effective solution for reducing delivery times in supply chains.

As the review of the first group of studies shows, most research in this area pays little attention to the probability of disruptions occurring along routes. In a limited number of studies, this issue has been considered; however, solving the models is often difficult due to their reliance on precise data. Clavijo-Buritica et al. [11] investigated route disruptions by designing a supply chain in which alternative short routes were preselected in the event of accidents or disruptions. This approach reduces the risk of spoilage and deterioration caused by disruptions and increased delivery times. However, their model depends on various data sources, including meteorological data, making it relatively difficult to solve.

Another group of studies has focused on transportation planning and management during natural disasters such as floods and earthquakes. Based on historical records, the probability of some routes becoming inaccessible can be estimated and incorporated into decision-making. In such cases, routes with minimal accessibility are removed from transportation planning. This increases the reliability of goods transfer under emergency conditions. However, since this type of planning is probability-based, alternative routes may also be damaged during actual events. Therefore, removing certain routes can reduce the robustness and accuracy of the model [12]. Many studies in this area focus on identifying critical routes and locations. Bono and Gutiérrez [13] evaluated network damage and post-earthquake accessibility using geographical data. analyzed networks based on reliability by examining travel time reliability, capacity reliability, and network connectivity reliability, and proposed a method for identifying critical links and their impact on network disruptions. Jiang Dong et al. [14] developed a bi-level optimization model to determine the minimum and maximum vulnerability of a transportation network using various evaluation criteria, showing that such models can be used to identify critical routes and strengthen transportation networks. Gu et al. [15] examined the performance of transportation networks and concluded that a network's ability to transfer goods and maintain capacity is a key criterion for evaluating network reliability. A network must be able to satisfy demand through arc capacities under various conditions. They evaluated network flows and reliability by considering incidents such as traffic and treated capacity as a variable, which in turn affected travel times and goods handling. Through this evaluation approach, Gu et al. [15] took a step toward ensuring demand satisfaction under crisis conditions.

Although all the methods reviewed in the aforementioned studies appear scientific and effective, most of them focus on finding the shortest paths for time management or identifying alternative routes in emergencies. In contrast, estimating the amount of goods that can be transported through different routes over different time periods, while considering the probability of other routes becoming inaccessible, can greatly assist in more effective planning and management of transportation networks under varying conditions.

2 | Problem Statement

Based on the reviewed studies and an examination of the existing literature in this field, determining the maximum flow in a network as a function of the probability of accessibility of links and routes has rarely been addressed. In particular, in the design of supply chains for perishable products, greater emphasis has been placed on time-related criteria. However, due to demand-related challenges, ensuring the availability of sufficient quantities of products at any given time is of critical importance, an issue that has been more thoroughly considered in the second group of studies. Accordingly, the main objective of this research is to propose an approach for estimating the probability of route accessibility and calculating the maximum flow that can pass through a route. Typically, calculating such probabilities requires an analysis of data related to the occurrence of incidents affecting routes and links, which leads to increased complexity in conventional models. In this study, however, a hybrid multi-criteria decision-making model is proposed to measure accessibility probabilities, thereby simplifying the probability estimation process. Three hypothetical routes are considered, and their accessibility is calculated and evaluated based on criteria identified by experts. By incorporating these probabilities, it becomes possible to estimate an overall average of the amount of goods that can be transported through a specific route over a given time period.

3 | Proposed Approach and Mathematical Model

Nowadays, many models developed by researchers rely heavily on related historical and recorded data. Although such models are usually more accurate, their strong dependence on diverse data sources leads to increased computational and analytical complexity. Therefore, in some cases, it is preferable to use models that have less dependence on such data. Decision-making methods, due to their greater reliance on expert judgments, generally involve lower solution complexity. The selection of an appropriate decision-making method largely depends on the nature of the problem.

In this study, a hybrid decision-making approach with probabilistic outputs is employed. A combination of Grey Analytic Hierarchy Process (Grey-AHP) and Grey TOPSIS is used to estimate the accessibility of transportation routes. This decision-making approach has an inherently probabilistic nature; therefore, its outputs can be interpreted as the probability of route accessibility. By calculating this probability, it becomes possible to estimate the amount of goods that can be transported through each route. The symbols and parameters used in this method are presented in *Table 1*.

Table 1. Parameters and explanation of symbols in the integrated grey TOPSIS and grey AHP method.

The element in the i-th row and j-th column of the pairwise comparison matrix	a_{ij}	Number of criteria or number of experts	n
The normalized pairwise comparison matrix	r_{ij}	Number of comparable alternatives	m
Weight of the option (or criterion)	W_i	Consistency ratio	CI
Positive ideal value	V_i^+	Random index	RI
Negative ideal value	V_i^-	Consistency index	CR
Average distance of each option from the positive ideal options	d_i^+	Maximum consistency value of the pairwise comparison matrix	λ
Average distance of each option from the negative ideal options	d_i^-	Numerical value of the expert's judgment in comparing i with j	$q_{t_{ij}}$
Similarity index	CC_i	Geometric mean value of the t-th expert's judgment	$Q_{t_{ij}}$
Gray probability level		$P(A_i \leq A^{max})$	

The AHP method is fundamentally based on the opinions of experts and specialists and assigns weights to evaluation criteria and alternatives through pairwise comparisons among decision elements. Since this method relies on expert judgments, experts may not always be able to express their opinions precisely. Grey-AHP is a method similar to AHP in which, to account for the uncertainty inherent in qualitative parameters, the scores of decision elements are expressed as intervals using grey numbers [16], [17]. In this study, there are three alternatives, namely three hypothetical routes with different capacities. Expert opinions are collected using qualitative scales and are converted according to *Table 2*.

Table 2. Gray numbers corresponding to definite numbers.

Corresponding Gray Value	Definite Amount	The Corresponding Value of Each Description	Descriptive Value
[1-1.5]	1	1	Very low importance
[1.5-3.5]	2 and 3	3	Low importance
[3.5-5.5]	4 and 5	5	Moderate importance
[5.5-7.5]	6 and 7	7	High importance
[7.5-9]	8 and 9	9	Very high importance
2,4,6,8			An intermediate state between two descriptions

In order to ensure the validity of the experts' judgments, the consistency ratio is used to evaluate the collected opinions. *Eqs. (1)* and *(2)* are applied for this purpose [18].

$$CR = \frac{CI}{RI}. \tag{1}$$

$$CI = \frac{\lambda_{max} - n}{n-1}. \tag{2}$$

The RI value is obtained using the values presented in *Table 3*.

Table 3. numerical value of the random index RI according to the number of criteria.

10	9	8	7	6	5	4	3	2	1	n
1.49	1.45	1.41	1.32	1.24	1.12	0.9	0.58	0	0	RI

If the value of CR is less than 0.1, the expert's judgment in the pairwise comparison matrix is considered acceptable; otherwise, it is rejected and requires revision and correction. After the experts' opinions are expressed in the form of grey numbers, it is necessary to aggregate these opinions. This is because the judgments now involve uncertainty, while their consistency has already been evaluated and confirmed. One of the approaches for aggregating expert opinions is the geometric mean method. The advantage of this method over other approaches is that the geometric mean is sensitive to different numerical values; that is, values with low frequency but large deviations can have an effect comparable to that of values with high frequency. Using the geometric mean method, the experts' opinions are aggregated according to *Eq. (3)*.

$$Q_{T_{ij}} = \left(\prod_{t=1}^{n} q_{t_{ij}}\right)^{\frac{1}{n}}. \tag{3}$$

After replacing the crisp numbers with grey numbers, the weight of each criterion or alternative is calculated. Before computing the weights, it is necessary to convert the pairwise comparison matrices into dimensionless (normalized) form. For this purpose, *Eq. (4)* is used.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}. \tag{4}$$

Then, using *Eq. (5)*, the weight of each alternative and criterion is calculated.

$$W_i = \frac{\sum_{j=1}^{n} r_{ij}}{n}. \tag{5}$$

The TOPSIS method is a technique for evaluating an $m \times n$ matrix consisting of m alternatives and n criteria. To apply the TOPSIS method, qualitative indicators must first be converted into quantitative values, and these quantitative data must then be normalized to become dimensionless. After calculating the weights of the criteria and alternatives, these weights are multiplied to obtain the weighted decision matrix, which is subsequently analyzed and evaluated.

In the present model, since the weights are calculated using the Analytic Hierarchy Process (AHP), they are already dimensionless and therefore do not require further normalization. The positive ideal solution (V_i^+) and the negative ideal solution (V_i^-) for each beneficial criterion corresponds to the maximum and minimum scores of the evaluated alternatives under that criterion, respectively. After determining these values, the alternatives are ranked based on minimizing their distance from the positive ideal solution and maximizing their distance from the negative ideal solution. The mean distances of each alternative from the positive ideal solution (d_i^+) and the negative ideal solution (d_i^-) across different criteria are calculated using *Eqs. (6)* and *(7)* [19].

$$d_i^+ = \sqrt{\sum_{j=1}^{n}[(V_{ij} - V_j^+)^2]}. \tag{6}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}[(V_{ij} - V_j^-)^2]}. \tag{7}$$

Then, the parameters of the similarity index are determined and calculated for each criterion using *Eq. (8)*. The value of this index ranges between 0 and 1, and the closer it is to 1, the higher the desirability of the corresponding alternative. Accordingly, by calculating the similarity index for all available alternatives, they are prioritized in descending order from larger to smaller values [19].

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}. \tag{8}$$

The important point is that since grey numbers are used in this study, the rules of grey numbers must therefore be followed when calculating the weighted matrix, which is obtained by multiplying the criteria weights by the alternative weights. Accordingly, to multiply two grey numbers, the bound-to-bound formulation in *Eq. (9)* is used [20].

$$(\underline{V}_{ij}, \overline{V}_{ij}) = (\underline{a}_{ij} \times \underline{W}_j, \bar{a}_{ij} \times \overline{W}_j). \tag{9}$$

After constructing the weighted evaluation matrix in the Grey TOPSIS method, the grey reference ideal value is determined. Based on this value, the grey possibility degree of each alternative with respect to the reference ideal value for each criterion can be calculated using *Eq. (10)*.

$$P(V_{ij} \leq V_j^{max}) = \frac{\text{Max}\left(0, L^* - \text{Max}\left(0, \overline{V}_{ij} - \underline{V}_j^{max}\right)\right)}{L^*}, \tag{10}$$

where

$$L^* = L(V_{ij}) + L(V_j^{max}), \tag{11}$$

$$L(V_{ij}) = \overline{V}_{ij} - \underline{V}_{ij}. \tag{12}$$

By calculating the average grey possibility degree of each alternative across different criteria, the probability of that alternative being inferior to the other superior alternatives is obtained. An alternative with a lower probability of being smaller than the others has a shorter distance from the ideal alternative and therefore attains a higher rank. The numerical value of the average possibility degree is calculated using *Eq. (13)* [21].

$$P(A_i \leq A^{max}) = \frac{1}{n}\sum_{j=1}^{n} P(V_{ij} \leq V_j^{max}). \tag{13}$$

However, in this study, the probability of being smaller is of greater importance. The higher the probability of being smaller, the greater the vulnerability of the route (link). Consequently, such a route has a lower chance of being selected. Nevertheless, it is necessary to consider whether the selected route is capable of supporting the required demand over a specified time period. In order to calculate the average capacity of a route over a given time horizon, *Eq. (14)* is used.

$$(F_{max})_i = (1 - P)(A_i \leq A^{max}) \times f_i. \tag{14}$$

where $(F_{max})_i$denotes the maximum flow that can pass through route i, considering the probability of disruptions (incidents), and f_i represents the maximum flow of route i under disruption-free conditions. Obviously, the route that is capable of satisfying a higher level of demand over the specified time period is selected.

4 | Results

To perform the calculations and evaluate the decision-making model in this study, a hypothetical network, as shown in *Fig. 1*, was used.

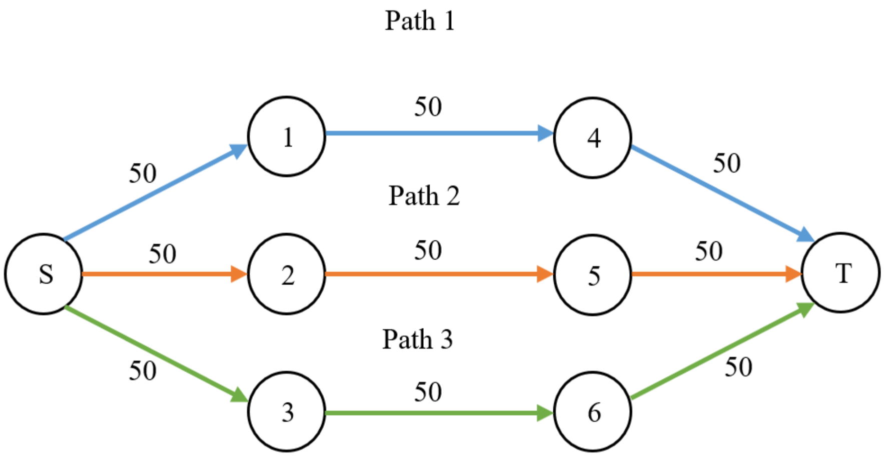

Fig. 1. Hypothetical problem network.

This network consists of three mutually independent routes that start from the source node S and end at the destination node T. All three routes can be selected based on their probability of accessibility, provided that they are able to satisfy the required demand of the destination node. For simplicity of calculations, the capacity of all links is assumed to be 50 units per day. Five experts with sufficient knowledge and experience in transportation systems, routing, and product demand were selected, and their opinions were collected. Four criteria were chosen to calculate the probability of route accessibility. These criteria were derived from expert judgments and the exchange of opinions during two sessions and include accident-proneness potential, road (link) quality, traffic load, and route length. The obtained results are presented below. The order of the criteria

The matrices are road quality, accident-proneness, traffic load, and route length.

$$\text{Criteria average matrix } = \begin{matrix} [1,1] & [4.19, 6.23] & [4.19, 6.23] & [5.85, 7.78] \\ [0.16, 0.24] & [1,1] & [2.49, 4.59] & [3.87, 6.05] \\ [0.16, 0.24] & [0.22, 0.40] & [1,1] & [1.38, 2.95] \\ [0.13, 0.17] & [0.17, 0.26] & [0.34, 0.72] & [1,1] \end{matrix},$$

$$\text{Criteria weight} = [\,[0.52, 0.67] \quad [0.19, 0.29] \quad [0.08, 0.13] \quad [0.05, 0.07]\,],$$

$$\text{Vulnerability of routes} = [\,0.894 \quad 0.60 \quad 0.713].$$

The results indicate that Route 2 is the most accessible route throughout the year, as it has the lowest probability of damage. Clearly, this route must be capable of meeting the demand of the destination node on a daily, weekly, monthly, or annual basis. Otherwise, other routes should be utilized to increase the volume of goods transported. It should also be noted that these values are probabilistic in nature and may fluctuate over the course of the year for various reasons.

5 | Conclusions

The present study was conducted with the aim of calculating the accessibility level of freight transportation routes in supply chains. Although the proposed model applies to various supply chains, due to the high importance of perishable products and the difficulty of managing them during the occurrence of different disruptions, this research focused on improving this type of supply chain. Perishable products may experience quality deterioration and spoilage under the influence of various factors, among which time is one of the most critical. Therefore, waiting and holding times for these products throughout the supply chain should be minimized. To reduce transportation times along the supply chain, identifying routes and being aware of the probability of their unavailability is of great importance.

In many previous studies, researchers have mainly focused on redesigning supply chains in order to reduce waiting times. In some cases, scheduling and routing systems have also been considered. However, the accessibility of transportation network routes is an issue that has rarely received sufficient attention. This important topic has been examined by various researchers, particularly in the context of natural disasters. Hence, simultaneously addressing these two issues is crucial for improving freight supply chains. Solving this problem requires sufficiently accurate models with limited dependence on diverse data sources. In this study, a hybrid decision-making approach was proposed as a solution for estimating route accessibility based on expert opinions. Using this approach, a hypothetical network with three routes was evaluated based on four criteria: road quality, accident proneness, traffic volume, and route length. The results showed that the second route, with approximately 60% vulnerability, was the best option for freight transportation during the considered time period.

As a suggestion for future research, it is recommended that the proposed model be applied to a real transportation network in order to evaluate its effectiveness. In addition, networks with links having different capacity levels can be considered, and the results of the model can be further analyzed and assessed. There are various criteria for evaluating routes, and the type of product can also play a role in determining these criteria. Therefore, it is recommended that the model be applied and evaluated for other types of goods by incorporating additional evaluation criteria.

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Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

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