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Performance Evaluation of Omni-Channel Distribution Network Configurations considering Green and Transparent Criteria under Uncertainty

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Abstract: Satisfying customer demand is one of the growing concerns of supply chain managers. On the other hand, the development of internet communications has increased online demand. In addition, the COVID-19 pandemic has increased the demand for online shopping. One of the useful concepts that help to address this concern is the omni-channel strategy, which integrates online and traditional channels with the aim of improving customer service level. For this purpose, this paper proposes an algorithm for evaluating Omni-channel Distribution Network Configurations (OCDNCs). The algorithm applies an extended Data Envelopment Analysis (DEA) model to evaluate OCDNCs based on cost, service, transparency, and environmental criteria; and then, forms a consensus on the evaluation results generated according to different criteria by utilizing an uncertain optimization model. To the best of our knowledge, this is the first attempt in which such an algorithm has been employed to take into account the mentioned criteria in a model to evaluate OCDNCs. The application of the proposed models was investigated in a case study in relation to the Indian retail industry. The results show that the configuration with the most connections among its members was the most stable, robust, and efficient.

Keywords: omni-channel; performance evaluation; transparency; environmental criteria; uncertainty

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1. Introduction

With the growth of the world's population, the levels of consumption and demand have increased. Statistics show that 131 billion business-to-business and business-to-consumer parcels were shipped among businesses and consumers in 2021. It is predicted that in the next six years, by 2026, this figure will increase to 266 billion parcels [1]. Significant revenues are generated by transportation and logistics firms that deliver parcels, although the market for such firms is highly competitive. Deutsche Post DHL, one of the largest transport and logistics firms, delivered 5.9 million parcels daily in 2020 in Germany, generating a revenue of approximately USD 19.8 billion [2]. Similarly, Amazon Logistics delivered 4.2 billion parcels in the United States alone. Amazon's logistics revenue as an e-commerce company was USD 80 billion in 2020 [3]. Especially during the COVID-19 pandemic, the amount of online demand through e-commerce has increased, showing that in addition to the traditional channel, the online channel is important in delivering customer service [4]. In this line, a global survey found that over 50% of e-commerce companies have adopted the omni-channel strategy, thereby integrating online and traditional channels to meet growing demand [5]. It is worth noting that by 2030, the transport fleet of e-commerce firms will produce 25 million tons of CO_2 emissions [6]. Statistics demonstrate the importance of the omni-channel strategy not only in terms of demand and revenue, but also in terms of the environment and the tracking of goods in e-commerce [7].

The omni-channel concept integrates online and offline service channels to meet customer demands. Thus, customers can place their orders through various channels such

as physical stores, call centers, mail/mobile applications, and so on [8]. This leads to more convenience on the part of customers, because they face fewer limitations in terms of time, location and required devices when ordering. Increasing ordering options is essential for the customers, especially in the context of the COVID-19 pandemic, which has disrupted supply chain labor [9,10].

Distribution networks that use this concept efficiently have a positive impact not only on costs related to the supply chain but also on customer experience. Therefore, in order to select an efficient distribution network, supply chain managers need to evaluate the performance of network-related configurations in terms of common criteria such as costs and services [11,12]. Although there are different methods for performance evaluation, DEA is one of the most widely used methods for evaluation in supply chain management [13,14]. DEA is a non-parametric technique that measures the performance of peer Decision-Making Units (DMUs) and produces the maximum ratio of the weighted sum of the outputs to the weighted sum of the inputs [15]. Inputs and outputs are both evaluation criteria in DEA, where the consumption of inputs leads to the production of outputs. To measure efficiency, the number of times traditional DEA models have to be solved is equal to the number of DMUs. This is why Klimberg & Ratick (2008) proposed a model to measure the efficiency of all DMUs simultaneously.

In general, three research categories can be introduced for supply chain evaluation by DEA. In the first category, some components of the supply chain such as candidate locations, warehouses, and vehicles are evaluated by the DEA, and the results of this evaluation are used in optimization models that design or manage the supply chain with the aim of improving efficiency [16–18]. In the second category, the solutions derived from the optimization models that design and manage the supply chain are evaluated by DEA, and the most efficient of them is reported as the optimal solution [19–21]. In the last category, which is of great interest to researchers, the performance of peer supply chains or their components compared to each other, is evaluated by DEA [22–25].

Although the research literature demonstrates the need to investigate the performance of omni-channel distribution networks (OCDNs), only Prabhuram et al. [8] addressed this issue in depth. There are still many gaps in this field of research, which are described as follows:

- Although DEA is a very widely used and powerful tool for evaluating supply chains, it has not yet been used to evaluate the performance of OCDNs.
- To date, no method has been proposed to form a consensus on the rankings of OCDNs resulting from different decision-making methods.
- The ranking of OCDNs is done under assumed deterministic conditions, whereas such assumptions do not apply in reality.
- In addition to the common criteria, i.e., costs and services, there are very important criteria, such as transparency and environment that have not been considered simultaneously by researchers to evaluate OCDNs.

This research seeks to develop the study of Babaei et al. [26]. Proposing a new DEA model, forming a consensus under uncertainty based on a robust model, considering environmental criteria alongside cost, service and transparency criteria, and delivering comprehensive analysis for supply chain managers based on the criteria categories, are among the contributions added to Babaei et al. [26]. This is the first attempt to address such issues in the context of OCDNCs.

Our paper fills all the four research gaps which are outlined above. For this purpose, Section 2 presents an extended DEA model that measures the performance of OCDNCs with respect to costs, services, transparency, and the environment. In addition, a consensus on the results of the evaluations of OCDNCs is formed using an uncertain mathematical optimization model. Section 3 shows the application of the proposed models through a case study in the Indian retail industry. In this section, the weights and the level of uncertainty in the rankings are analyzed. In Section 4, supply chain applications and managerial implications are discussed. The study ends with a conclusion in Section 5.

2. Problem Statement

The omni-channel strategy integrates online and physical channels in distribution networks [27]. In this regard, the customer can order from any device and at any time. For this reason, planning, forecasting and servicing of distribution networks are strengthened. In addition, traffic congestion and unnecessary transportation are avoided and consumption of limited resources of supply chains is saved. In this way, the efficiency of supply chains is improved by designing an effective distribution network considering omni-channel strategy [8]. The aim of this paper is to evaluate the performance of OCDNCs. For this purpose, first, it is necessary to identify the candidate configurations according to the various types of relationships that exist between traditional and online channels. Then, a DEA model is developed that evaluates candidates. It is worth noting that different criteria lead to different evaluation results. Hence, a consensus must be formed on the different results of the evaluations in order to prioritize the candidates. A graphical representation of the proposed algorithm is shown in Figure 1 as the general framework.

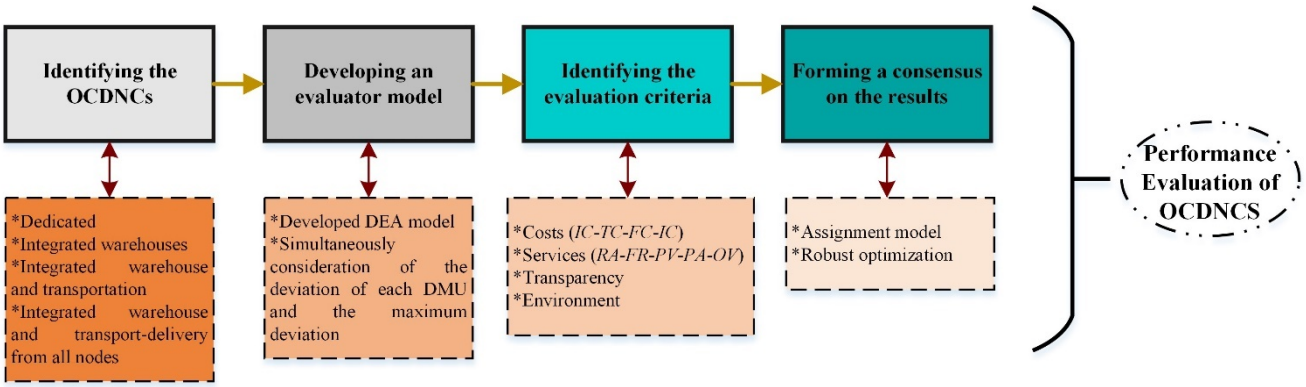


Figure 1. General framework of the proposed algorithm (Source: Author).

2.1. Identifying the OCDNCs

OCDNs generally consist of suppliers, distribution centers (DC), stores, and customers [8]. Since such networks have both traditional and online channels, customers can place their orders through the Internet Protocol (IPC). The four possible OCDNCs are shown in Figure 2 and described below:

i. Configuration 1: This is a dedicated network in which traditional and online channels are not integrated.

ii. Configuration 2: This is an integrated network of warehouses in which all demands, both online and traditional, are met by a distribution center.

iii. Configuration 3: This is an integrated network of warehouses and transportation activities in which logistics and warehousing activities are integrated so that traditional and online stores are merged.

iv. Configuration 4: This is an integrated network of warehouses and transport-delivery from all nodes in which customer demands, in addition to the common online and traditional channels, can be satisfied directly through the distribution center. In this configuration, third-party logistics are assumed to be responsible for the direct flow.

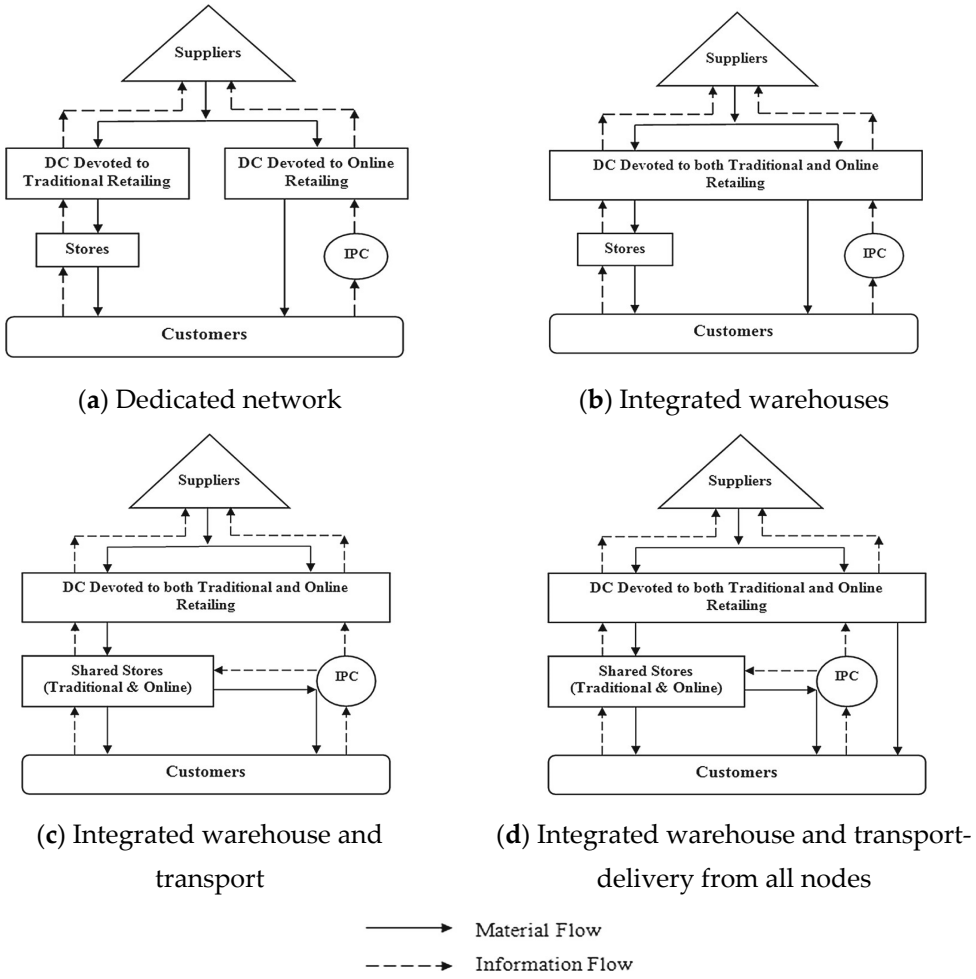


Figure 2. Four possible OCDNCs (Reproduced with permission from Prabhuram et al. [8], [Annals of Operations Research]; published by (Springer 2020)).

2.2. Developing an Evaluator Model

Since DEA is a powerful tool for the evaluation of supply chain management, a mathematical optimization model based on DEA is developed in this subsection to evaluate OCDNCs. In traditional DEA models, the efficiency of each DMU is measured compared to other peer DMUs using a mathematical optimization model. There are two points to consider for such models, which are related to the number of iterations of the solution and the power of discrimination. Each traditional DEA model needs to be solved for the number of DMUs to measure the efficiency of all DMUs. By defining the deviation variables for DMUs, Klimberg & Ratick [28] proposed a simultaneous DEA model that measures the efficiency of all DMUs by solving it once. To enhance the power of discrimination, Ghasemi et al. [29] considered the maximum inefficiency of all DMUs in addition to the deviation variables for each DMU in the mathematical optimization model. Due to these two points, the mathematical optimization model given in Equations (1)–(8), is proposed in our paper, and the notations are described in Table 1. It is worth mentioning that Prabhuram et al. [8] employed Multi-Criteria Decision-Making (MCDM) methods such as Technique of Order Preference Similarity to the Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP) and Fuzzy AHP (FAHP) to evaluate distribution networks, while the DEA technique is utilized in this work. From two points of view, our method has advantages over other methods. First, the DEA method obtains evaluation results by optimization and linear programming [30]. Therefore, compared to other methods, it provides more accurate and exact results for supply chain managers. Second, in this method, distribution networks are compared with each other in a relative manner. Unlike other methods that have been

used before, the score distance between distribution networks is meaningful in the DEA technique, and by reducing inputs or increasing outputs, distribution networks with the worse performances can improve their performance.

Table 1. Indices, Parameters, and Variables (Source: Author).

Indices	**Descriptions**
k	Index of failures ($k \in K = \{1, 2, \ldots, K'\}$),
r	Index of DMUs ($r \in R = \{1, 2, \ldots, R'\}$),
i	Index of inputs ($i \in I = \{1, 2, \ldots, I'\}$),
j	Index of outputs ($j \in J = \{1, 2, \ldots, J'\}$),
c	Index of ranks ($c \in C = \{1, 2, \ldots, C'\}$).
Parameters	**Descriptions**
I_{ir}	Amount of i-th input for r-th DMU,
O_{jr}	Amount of j-th output for r-th DMU,
ε	Infinitesimal value determined by decision makers' preferences,
$(\alpha^L,\ \alpha^M)$	Upper and lower bounds associated with the inefficiency of each DMU,
$(\beta^L,\ \beta^M)$	Upper and lower bounds associated with the inefficiency of all DMUs
p_H	Probability value that an honest node will find the next block,
p_a	Probability value that the attacker will find the next block,
I_{rc}^w	Importance value of each alternative (configuration) r in rank c,
Γ_0	A parameter that adjusts the robustness,
d_{rc}^R	Deviation from nominal values (deterministic importance).
Variables	**Descriptions**
d_r	Inefficiency level of DMU r,
ω_r^e	Efficiency level of DMU r,
M	Maximum inefficiency of all DMUs,
u_{rj}	Weight assigned to the j-th output for DMU r,
v_{ri}	Weight assigned to the i-th input for DMU r,
f^{Ie}	Inefficiency-related objective function,
θ	Relaxed inefficiency-related objective function,
p_f	Probability value that the attacker will fail,
F_p	Measure of progress made by the attacker in terms of its failure,
h_{rc}	If DMU (configuration) r is assigned to rank c, this variable is equals to 1; otherwise 0,
y_{rc}^R, z_0, p_{rc}^R	Variables related to the robust formulation.

Now, the proposed model is given as follows:

$$\text{minimize} \quad f^{Ie} = \sum_{r \in R} M\ d_r \tag{1}$$

$$\text{subject to} \quad \sum_{i \in I} v_{ri} I_{ir} = 1 \qquad \forall r \in R, \tag{2}$$

$$\sum_{i \in I} u_{rj} O_{jr} + d_r = 1 \qquad \forall r \in R, \tag{3}$$

$$\sum_{j \in J} u_{rj} O_{jk'} - \sum_{i \in I} v_{ri} I_{ik'} \leq 0 \qquad \forall k \in K, r \in R; k' \neq r, \tag{4}$$

$$\omega_r^e = 1 - d_r \qquad \forall r \in R, \tag{5}$$

$$M \geq d_r \qquad \forall r \in R, \tag{6}$$

$$u_{rj}, v_{ri} \geq \varepsilon \qquad \forall r \in R, i \in I, j \in J, \tag{7}$$

$$d_r, \omega_r^e \geq 0 \qquad \forall r \in R. \tag{8}$$

Objective Function (1) minimizes the product of the inefficiency of each DMU and the inefficiency of all DMUs, i.e., both inefficiencies are minimized at the same time. In Constraint (2), the weighted sum of inputs is arbitrarily set equal to 1. The inefficiency of each DMU is measured by Constraint (3) with respect to the weighted sum of outputs. The upper bound of the efficiency of each DMU is set to one by Constraint (4). The levels of efficiency and maximum inefficiency are measured by Constraints (5) and (6), respectively. The positive and the non-negative decision variables are expressed by Constraints (7) and (8), respectively. As shown in Equation (1), the two continuous decision variables are multiplied by each other; therefore, the proposed model is nonlinear. McCormick [31] linearized such a non-linear term by piecewise McCormick envelopes when the decision variables have upper and lower bounds. Accordingly, Equation (1) is reformulated by Equations (9)–(13). It should be mentioned that in order to obtain the upper and lower bounds, it is necessary to solve the model proposed in Equations (1)–(8) based on each of M and $\sum_{r \in R} d_r$, independently.

$$\text{minimize} \quad f^{Ie} = \theta \tag{9}$$

$$\text{subject to} \quad \theta \geq \alpha^L M + \beta^L (\textstyle\sum_r d_r) - \alpha^L \beta^L, \tag{10}$$

$$\theta \geq \alpha^M M + \beta^M (\textstyle\sum_r d_r) - \alpha^M \beta^M, \tag{11}$$

$$\theta \leq \alpha^L M + \beta^M (\textstyle\sum_r d_r) - \alpha^L \beta^M, \tag{12}$$

$$\theta \leq \alpha^M M + \beta^L (\textstyle\sum_r d_r) - \alpha^M \beta^L. \tag{13}$$

2.3. Identifying the Evaluation Criteria

Two common criteria for evaluating OCDNCs are costs and services. Each of these consists of a number of sub-criteria. As mentioned in Prabhuram et al. [8], the costs of sub-criteria consist of the Inventory Cost (IC), Transportation Cost (TC), Facilities Cost (FC), and Information Cost (IFC). Similarly, the services sub-criteria entail Product Availability (PA), Returnability (RA), Fast Response (FR), Order Visibility (OV), and Product Variety (PV). However, important criteria such as distribution network transparency and environmental considerations have not been investigated by researchers to evaluate OCDNCs. The supply chain can be made transparent through blockchain technology to solve different problems such as product recalls, consumer dissatisfaction, and contamination securities. Moreover, supply chain sustainability is promoted through the transparency created by blockchain [32–34]. Since each block has its own hash value and the hash value of the previous block, the slightest manipulation of blockchain data is very difficult [35]. In other words, such manipulation requires a change in the hash value of the attacked block and a change in the hash values of all the blocks succeeding it. The attacker's progress in terms of failure is a criterion that can indicate transparency in the OCDNCs. As noted by Maity et al. [35], to measure this criterion, it is assumed that the probability of viewing k failures before the first successful attempt of the attacker is obtained by multiplying the negative binomial distribution by the probability of the attacker's failure, which is represented by Equation (14).

The attacker's progress in terms of failure is given in Equation (15) based on the expected value of Equation (14). In these equations, it is assumed that p_H is greater than p_a, and the number of failures is less than or equal to the number of blocks. The number of blocks is determined by the members of the supply chain. Members of the supply chain can create a digital flow, which is the counterpart of the supply chain layer, through digital technologies such as Quick Response (QR) codes, Radio Frequency Identification (RFID), and Near-Field Communication (NFC). Accordingly, any action performed by the supply chain member in the physical flow is recorded as a block in the blockchain [36,37].

As the number of blocks increases, the value of F_p increases. To illustrate the behavior of Equation (15), a small-scale numerical example has been used in Figure 3 to indicate F_p, where $p_H = 0.6$ and $p_a = 0.4$, and one to four blocks exist in the chain.

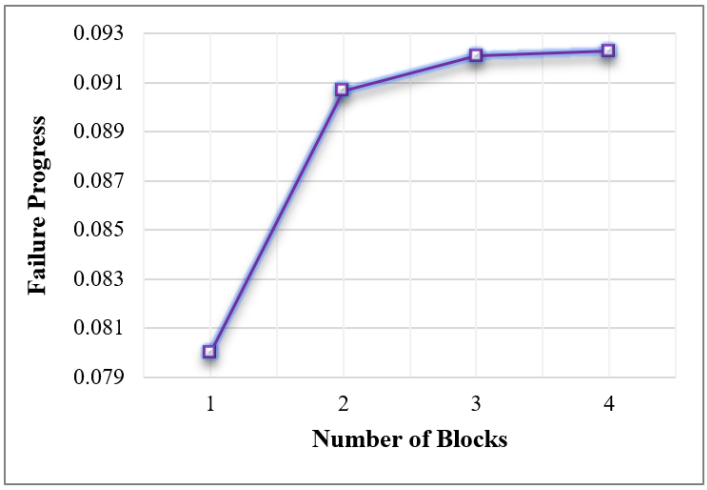


Figure 3. Failure progress vs. Block size (Source: Author).

$$p_f = \binom{k}{k} p_H (p_a)^k \left(1 - \frac{p_a}{p_H}\right)^k \forall k \in K, \tag{14}$$

$$F_p = \sum_{k \in K} p_f. \tag{15}$$

In addition to costs, services, and transparency, attention to the environmental impacts of online and traditional order fulfilment processes is essential because addressing such impacts is a key issue for logistics managers [38–40]. Environmental impacts are related to either the amount of emissions from transportation or the energy consumed by activities. Emissions are caused by transport activities that occur between the two nodes in OCDNs, such as suppliers to distributors, distributors to stores, and stores to customers. Energy consumption can be related to activities such as warehousing and handling, and thus create environmental impacts. Therefore, in this work, the number of activities of each OCDN that leads to environmental impacts is considered as an evaluation criterion along with other criteria. The criteria that are considered as inputs and outputs of the model developed in the previous subsection are displayed in Figure 4.

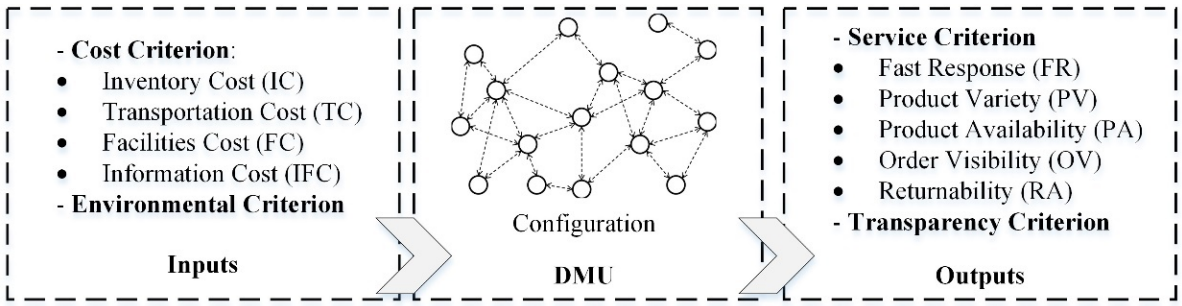


Figure 4. Inputs and outputs for evaluating OCDNCs (Source: Author).

2.4. Forming a Consensus on the Results

Different criteria were introduced in the previous subsection to evaluate OCDNCs. Not all of these criteria may be considered by all supply chain managers at the same time. However, different evaluations by managers should ultimately provide a single ranking. Since transparency and environmental criteria are innovative in nature, some supply chain managers may not agree about the simultaneous impact of both criteria on the evaluation of OCDNCs. To consider the opinions of managers and decision-makers, OCDNCs are

evaluated in this paper based on three categories of criteria, which are the common criteria along with the transparency and environmental criteria (C&TE), the common criteria and the transparency criterion (C&T), and the common criteria and the environmental criterion (C&E). Then, a consensus on the results of these categories is formed by adopting the approach offered by Bernardo [41] to obtain a single ranking for OCDNCs. In this approach, the importance of each alternative in each rank is first obtained. The number of times each alternative is placed in each rank based on different evaluation results is defined as its importance [41]. Then, using a mathematical model, each alternative is assigned to each rank according to its importance. Considering importance as a deterministic value for this approach is challenging because the results of evaluations may be affected by uncertainty, especially where the importance is a bounded random variable. In this light, Bertsimas and Sim [42] proposed a robust formulation that controls the level of conservatism of solutions where there are uncertain parameters. Therefore, we improved Bernardo's approach by incorporating the robust formulation of Bertsimas and Sim [42] to take into account the uncertain importance of forming a consensus on the results of the evaluations of OCDNCs. The improved model is shown in Equations (16)–(22). The objective function (16) maximizes the importance of alternatives in their rankings. Constraints (17) and (18) assign a configuration to each rank and a rank to each configuration. Constraints (19) and (20) relate to the robust formulation. Constraints (21) and (22) indicate binary and continuous decision variables, respectively. It is worth noting that other categories of criteria can exist; however, since we proposed the model in general, it can be also utilized in other categories.

$$\text{maximize} \quad \sum_{r\in R}\sum_{c\in C} I_{rc}^{w}\, h_{rc} - z_0\Gamma_0 - \sum_{r\in R}\sum_{c\in C} p_{rc}^{R} \tag{16}$$

$$\text{subject to} \quad \sum_{r\in R} h_{rc} = 1 \qquad \forall c \in C, \tag{17}$$

$$\sum_{m} h_{rc} = 1 \qquad \forall r \in R, \tag{18}$$

$$z_0 + p_{rc}^{R} \geq d_{rc}^{R}\, y_{rc}^{R} \qquad \forall r \in R, c \in C, \tag{19}$$

$$-y_{rc}^{R} \leq h_{rc} \leq y_{rc}^{R} \qquad \forall r \in R, c \in C, \tag{20}$$

$$h_{rc} \in \{0,1\} \qquad \forall r \in R, c \in C, \tag{21}$$

$$y_{rc}^{R}, z_0, p_{rc}^{R} \geq 0 \qquad \forall r \in R, c \in C. \tag{22}$$

Finally, based on Sections 2.1–2.4, the flowchart of the developed algorithm is illustrated in Figure 5 in more detail. According to Section 2.1, the configurations and the way of connection between the members of each configuration are identified and the data related to that configuration are collected. Then, based on Section 2.3, the criteria required for evaluation are determined by the decision maker, and the data related to those criteria are extracted. The configurations are evaluated according to the extracted data and the optimization model presented in Section 2.2. According to the opinion of decision-makers and supply chain managers, the results of different criteria categories should be aggregated. The importance of each category of criteria is determined by the supply chain managers, and then a consensus on the different results is formed by the robust optimization model presented in Section 2.4.

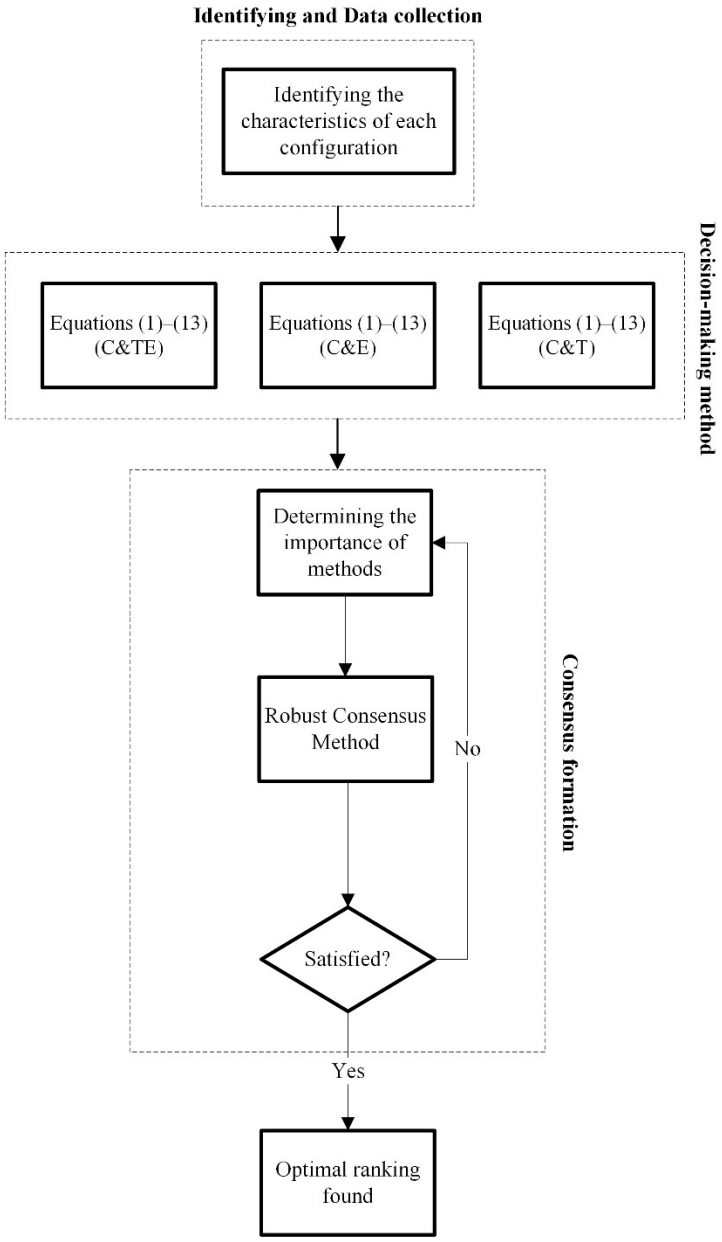


Figure 5. Flowchart of the proposed algorithm (Source: Author).

Optimal ranking is obtained if the formed consensus is approved and satisfied by the decision makers and managers. Otherwise, the importance of the criteria categories will change to ensure the satisfaction of managers. Using this proposed algorithm, supply chain managers can not only evaluate the configurations based on different categories of criteria such as cost, service, environment and transparency, but can also form a consensus on the evaluation results.

3. Results and Managerial Analysis

The application of the proposed models was demonstrated through a case study in the Indian retail industry where the industry intends to select a configuration for OCDN that is superior in terms of costs, services, the environment and transparency. This case study was adapted from Prabhuram et al. [8]. Candidate configurations are shown in Figure 2. Costs and services data related to four candidate configurations were extracted from Prabhuram et al. [8]. Based on the number of nodes that generate the physical flow in each configuration, the number of blocks in Configurations 1-4 is 5, 4, 5, and 6,

respectively. It is worth noting that it is common in the research literature to consider each node (a member of the supply chain and distribution network) as a block generator [43]. The number of transport activities among nodes in Configurations 1-4 is 5, 4, 4, and 5, respectively. The number of activities related to energy consumption by the distributor and the store in Configurations 1-4 is 3, 2, 2, and 2, respectively. The results obtained from the criteria categories are reported in Figure 6. As can be seen in this figure, Configuration 4 always ranks best in all categories. Configuration 1 is appropriate when the managers' strategy focuses on costs, services, and transparency. Configuration 2, on the other hand, is appropriate when the strategy focuses on all criteria. Lastly, Configuration 3 is appropriate for a strategy focused on costs, services and the environment. When managers focus on C&TE, both Configurations 2 and 4 rank first. Configuration 4 is much more cost-effective, more service-oriented, and more transparent than Configuration 2, but the latter is environmentally friendly. Due to the fact that the proposed models calculate the weight of the environmental criterion for Configuration 2 as greater than that of Configuration 4, Configuration 2 is finally reported as desirable as Configuration 4. Therefore, Configuration 2 is recommended when the strategy is highly focused on the environment.

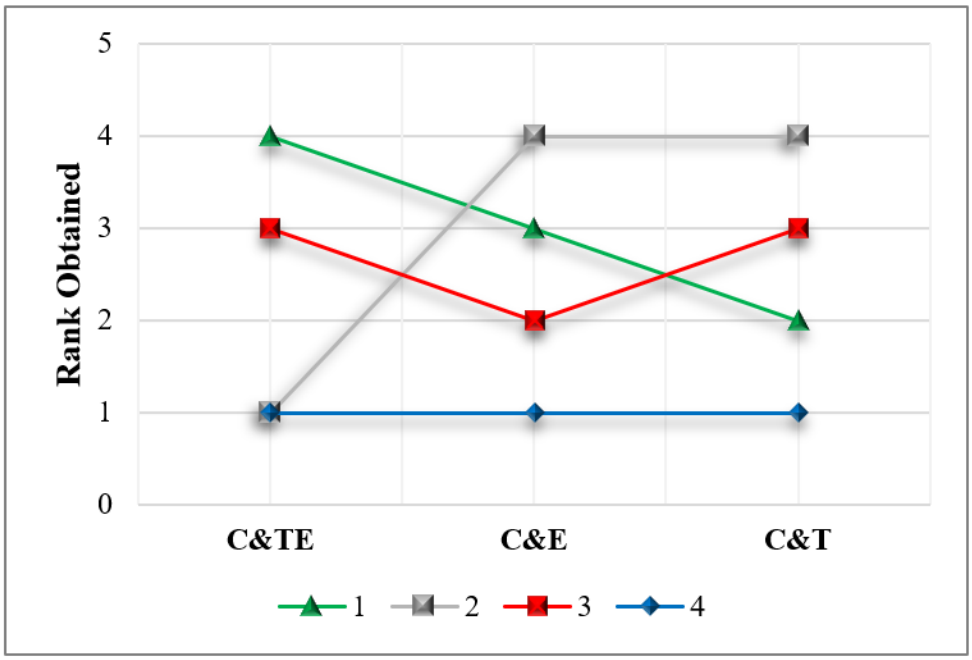


Figure 6. Priority of each configuration (Source: Author).

Figure 7 shows the score distance between the ranks and Figure 8 shows the ranking of the configurations based on the types of consensus after the efficiency of each of the configurations was measured by Equations (1)–(13) based on the data of Prabhuram et al. [8]. The gap between the efficiency scores of the two adjacent ranks indicates the certainty level of the rankings obtained for each category of criteria. The larger the gap, the more certain the ranking. As Figure 7 represents the level of certainty, for Ranks 1 and 2, C&E provides the most certain level. For Ranks 2 and 3, as well as Ranks 3 and 4, C&T provides the highest level of certainty. Therefore, when decision-makers and supply chain managers are conservative, they need to use C&E to select the best configuration.

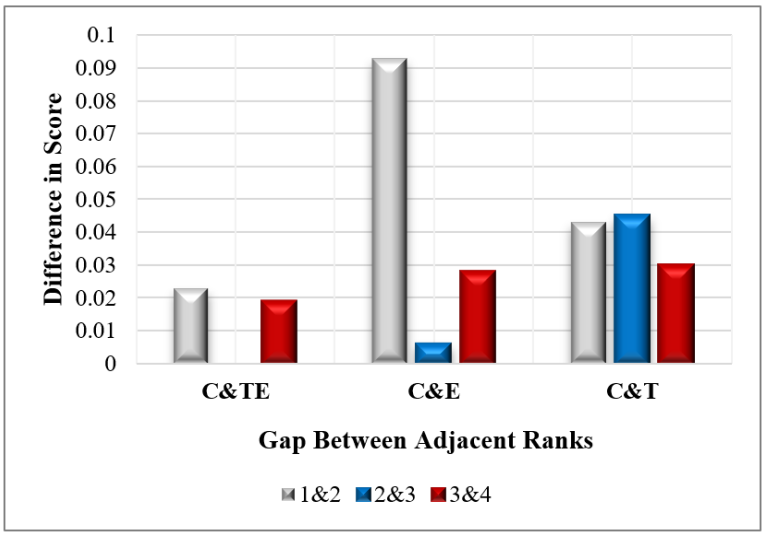


Figure 7. Gap analysis (Source: Author).

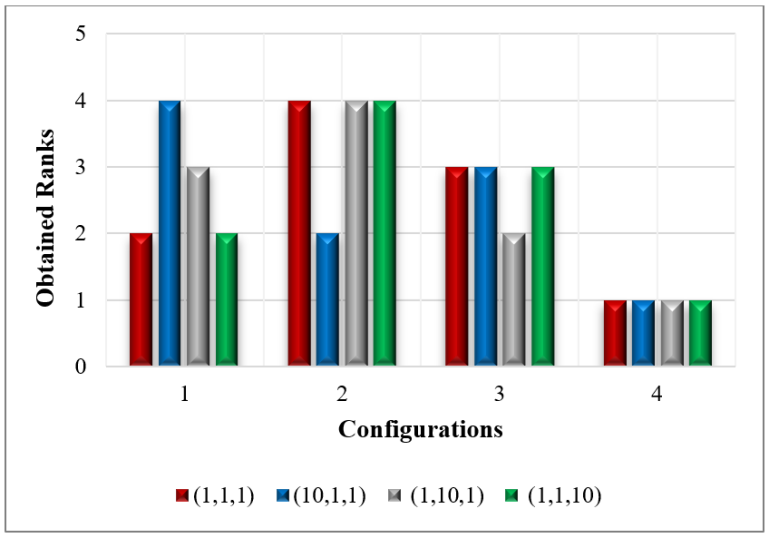


Figure 8. Sensitivity Analysis with respect to the weights of categories (Source: Author).

In this paper, in addition to assuming the attribute of indifference for the criteria categories, it is assumed that one of the criteria categories can weigh more and be more effective in calculating the importance of each alternative. In this way, the weight of the most important category is each time set equal to 10, then a consensus on the categories is formed and the value of the importance is calculated. The numbers in parentheses from left to right represent the weights of C&TE, C&E, and C&T. The results derived from Figure 8 show that an increase in weight leads to a change in the ranking on which consensus was formed. In other words, the ranking resulting from the formation of consensus inclines toward the ranking with a higher weight category. It should be noted that Configuration 4 is not affected by the weight of the categories, and therefore this configuration is stable. Hence, where the categories of criteria are not the same weight, managers and decision-makers can select Configuration 4 because, with this selection, all categories of criteria are satisfied. Thus, in Figure 8, with the aim of consensus between the results of criteria categories C&TE, C&E, and C&T, the ranks of the configurations are presented, where C&TE, C&E, and C&T are equally weighted or each of them has more weight against the others. To demonstrate the weight of each criteria category, the weight of that category is

assumed to be 10 times that of other categories. Hence, the consensus results are illustrated in this figure under all weight conditions.

In the following, deterministic and uncertain conditions in the formation of consensus are examined. To consider uncertainty, Equations (16)–(22) are applied, where the importance of the criteria categories is assumed to be uncertain. It is assumed that the importance of the criteria categories is affected by uncertainty. For uncertainty conditions, it is assumed that Γ_0 and d_{rc}^R are both equal to 1. The results are given in Table 2. Ranking based on C&TE and C&E in uncertain conditions is similar to the ranking based on C&T. Thus, given the number of times this ranking is repeated, it seems that the decision-maker or supply chain manager can rely more on this ranking. Configuration 4, on the other hand, is not affected by uncertainty conditions, so the configuration is robust. According to the reported variance, Configuration 3, disregarding Configuration 4, is least affected by uncertainty.

Table 2. Ranking under deterministic and uncertain conditions (Source: Author).

Configuration	C&TE		C&E		C&T		
	Deterministic	Uncertain	Deterministic	Uncertain	Deterministic	Uncertain	Variance
1	4	2	3	2	2	2	0.583
2	1	4	4	4	4	4	1.250
3	3	3	2	3	3	3	0.139
4	1	1	1	1	1	1	0.000

4. Discussion

Distribution networks have a significant impact on supply chain efficiency because they can change the costs and customer experiences of supply chains. For this reason, it is necessary to evaluate the performance of such distribution networks. Common criteria related to money (such as cost) and service level have been considered for such evaluations in numerous studies [8,19,20,44]. Although other criteria have many applications in the supply chain field, few researchers have focused on them. For example, adopting blockchain to the supply chain can bring sustainability, transparency and traceability. In this regard, applied research on the Wal-Mart food supply chain and the IBM Food Trust has shown that blockchain can also strengthen the pillars of sustainability [45]. In the context of the food supply chain, it has been shown that the meat industry can be equipped with traceability and transparency by using blockchain technology [35]. Another criterion is related to the green management of the supply chain, which has not yet received enough attention, especially in small and medium-sized factories. From a practical point of view, by examining the management of the green supply chain in the Korean electronics industry, it was concluded that such management can lead to the improvement of operational efficiency [46]. In green supply chain management, energy consumption is an issue that can affect the operation of any node of the supply chain. From a practical point of view, such an issue in the energy supply chain has been investigated by Huang et al. [47]. As mentioned above, despite the importance of blockchain technology and green management in terms of application in supply chains, researchers have not focused enough on them in the context of omni-channel networks. Our article is the first attempt in this field that considers blockchain and green management criteria in the omni-channel distribution networks. Therefore, the proposed evaluation approach of this article is more up-to-date and practical than other articles in this field due to the simultaneous consideration of common, green, and blockchain criteria. In addition, considering uncertainty conditions in the ranking of distribution network configurations brings our evaluation approach closer to the real world. For this reason, the approach presented in this paper is recommended for supply chain managers who seek to integrate supply chains with cutting-edge technology and consider environmental requirements along with cost and service level. According to the findings of our research, the managerial implications of supply chain managers are summarized based on evaluation criteria and candidate configurations in Table 3.

Table 3. Managerial implications of the study (Source: Author).

Supported by the Results of	Goals	C&TE	C&E	C&T	Conf. (1)	Conf. (2)	Conf. (3)	Conf. (4)
Figure 6	Manager's appropriate strategy based on cost, service, and transparency			✓	✓			
Figure 6	Manager's appropriate strategy based on cost, service, environment, and transparency	✓				✓		
Figure 6	Manager's appropriate strategy based on cost, service, and environment		✓				✓	
Figure 6	Manager's best strategy based on any number of evaluation criteria	✓	✓	✓				✓
Figure 6	Manager's strategy based on cost, service, and environment (emphasis on the environment)		✓			✓		
Figure 7	Creating more differentiation of configurations (ranks one and two)		✓					
Figure 7	Creating more differentiation of configurations (ranks two and three or three and four)			✓				
Figure 8	Choosing the stable configuration							✓
Table 2	Choosing the robust configuration							✓

5. Conclusions and Outlook

With growing customer demand, advances in virtual communication technology, higher transaction security, lower environmental impact due to transportation and energy consumption, and improved supply chain efficiency, managers and decision-makers need to select distribution networks that are characterized by better economic and environmental performance, as well as transparency and efficiency in customer service. On the other hand, the omni-channel concept strengthens the efficiency of distribution networks by integrating traditional and online service channels. In this paper, a DEA model was developed to evaluate OCDNCs. In this regard, criteria such as transparency through blockchain technology and environmental were introduced in addition to the common costs and services criteria. The configurations were then evaluated based on the categories of the criteria and a consensus on their results was formed using an uncertain assignment model. To the best of the authors' knowledge, this is the first paper to evaluate OCDNCs based on the components of costs, services, transparency, and the environment by developing a DEA and uncertain consensus model. The results reveal that the configuration with the most connections among members of its distribution network, not only has the highest efficiency score, but is also stable and robust. Supply chain managers can take into account new criteria such as blockchain, big data and Internet of Things (IoT) [48,49] in evaluations through the method presented in our article. In addition, the owners of the investigated retail industry can adjust their decisions according to the findings of this research based on the importance of items such as the environment, transparency, stability, and robustness. In addition, through the method presented in this work, supply chain managers are able to build a consensus on evaluation results that take into account real-world conditions using uncertainty approaches; e.g., robust optimization [50].

In order to overcome the main limitations of the study, we recommend investigating the criterion of sustainability, developing other optimization models for evaluation, applying the criterion of transparency by adopting other technologies, and implementing the proposed models in other case studies for future research directions.

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