Supply Chain Efficiency and Effectiveness Management:

Decision Support Systems

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ABSTRACT

The optimal productivity model plays a significant role in various supply chain management (SCM) decision support systems. Therefore, the precision of the optimal productivity model is necessary to improve SCM's effectiveness. A factor often ignored is that transactions of certain goods are assembled within an enterprise as dynamic structures of various distribution ratios. Regardless of such structure, optimal model productivity is often produced; however, the productivity model's optimal precision can be enhanced by taking it into account. This focusses on strategic thinking and planning, where various process improvement mechanisms are developed. Therefore, in this study, data envelopment analysis (DEA) has been utilized to enhance supply chain efficiency and effectiveness management. This paper explores an optimal productivity model that evaluates the supply chain efficiency and effectiveness management. This paper discusses the policy preparation demands of the decision support systems and develops a framework that organisations can use to control the implementation process.

KEYWORDS

Data Envelopment Analysis, Effectiveness Management, Optimal Productivity Model, Supply Chain Efficiency, Supply Chain Management

1. INTRODUCTION TO DECISION SUPPORT SYSTEMS IN SCM

Nowadays, the dynamic and interrelated manufacturing environment's influence makes the SCM an essential element for many researchers. A significant portion of this SCM centered on supply chain elements such as assessing vendors, sales, and production with DEA involvement (Fallahpour et al., 2017 ; Vu DL et al., 2019 ; Govindan et al., 2020). DEA has measured the effect of corporate capital planning programs on supply chain management (Nguyen et al., 2021). However, DEA models may be efficient for Supply chain and effectiveness management (Chen et al., 2021), while modules may not be effective (Gao et al., 2020). Although attempts have been made to combine these modules into a common situation, little progress has been made because most compromises and the relationships

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between various supply chain modules are unknown (Song et al., 2019 ; Chaudhry et al., 2020). It is impossible that a single metric of performance will be appropriate for performance assessment, and DEA is a valuable measure for assessing the performance of the supply chains (Farivar et al., 201). Therefore, numerous DEA standards were proposed to encompass the analytic framework and case-based logic frameworks to determine supplier sourcing for the supply chain assessment (Tayal et al., 2020).

One frequently ignored factor is that sales of certain goods within a corporation are clustered into organizational systems within spatial or conceptual dimensions (Bai et al., 2019 ; Centobelli et al., 2018). The data are then predicted at various aggregate levels that are stated to help reliability and accuracy. However, the optimal productivity model from all integration stages has the undesired feature that they are hierarchically contradictory (Lindblom et al., 2017 ; Piri et al., 2017). Therefore, a strategy to reconcile predictions across aggregation levels is needed to improve accuracy (Bumblauskas et al., 2017).

SCM's successful approach includes compromises between principles, including maximization of value and convergence of systems (Abdel-Basset et al., 2020), enhancement of reliability (Priyan et al., 2019), and reduced processing time (Hu et al., 2020). Successful SCM calls for extensive coordination and participation to organize and improve competitivity within supply chains for production, distribution, and materials management activities (VE et al., 2020). When all individual participants (territorial organizations) integrate and operate as a single cohesive group in the supply chain environment, efficiency increases in the SCM (Nie et al., 2020 ; Manogaran et al., 2020 ; Orjuela et al., 2021).

Several conceptional mechanisms for assessing the performance of the supply chain were suggested in the literatures. Supply chain efficiency and effectiveness management measurements vary from conventional performance measurements, for example, supplier assessments, in different ways (Khalaf et al., 2019). Initially, supply chain efficiency occurs in two stages. The first phase is the accomplishment of the actual participants of the supply chain (Mishra et al., 2020). The second is the efficiency of an entire supply chain structure determined and characterized by the supply chain members (Shankar et al., 2018).

As a consequence of changes in the supply chain structure, output at both levels can improve. Structured performance and sub-structured performance during the measurement period should be taken into consideration (Allimuthu et al., 2017). Instead of merely evaluating the operational elements, the management process at the highest level should be underlined (Ahmed et al., 2017). Finally, it is really important to connect the numerous supply chains (Srivastava et al., 2019 ; Lima-Junior et al., 2017). A collection of related processes linking decentralized functions to centralized processes are known as the supply chain. DEA is an important method for assessing the analytical productivity frontiers and calculating supply chains' relative efficiency and effectiveness management using decision support systems (Park YB et al., 2018).

The rest of this research is structured as follows. Previous literatures are reviewed in Section II. Section III details the proposed DEA-based optimal productivity model and the individual sub-structure optimal efðciency model, and the supply chain optimal efðciency model. Section IV reveals the strategies and framework of the supply chain structure. Section V details the results and discussion obtained from the proposed supply chain model. Section VI lists the observed conclusions.

2. RELATED LITERATURES

Research on supply chain efficiency and effectiveness management using decision support systems has been discussed in management research for several years. For example, disaggregated demand statistics for any shop and delivery center are typically available in supply chain environments. The aggregation of data corresponding to the interest parameters may be created (Gunasekaran et al., 2017). When data is clustered based on relevant business requirements, logical hierarchies may be created. (Lundström et al., 2018) used network evaluation metrics to select food supply chain quality management techniques and proposed a probabilistic model for its inventory strategy. (Maestrini et al., 2017) utilized DEA to evaluate environmental resilience in intercontinental supply chains.

(Glock et al., 2017) utilized the DEA to analyze vendor performance against many parameters and use vendor negotiations to estimate the supply chain's efficiency. Charles Cooper-Rhodes (CCR) and Banker Charnes Cooper (BCC) models have been suggested by (Marques et al., 2017) as the path to successful supplier efficiency. (Li et al., 2017) suggested a Linear Programming Model (LPM) for the optimum throughput scheduling of serial processes. Several outputs of one process become inputs for the following procedure; therefore, it is not clear that the optimal output is compatible with maximum technical performance (Marchi et al., 2017). The robustness of an ideal serial device output was not defined, which defines the functional utility of this approach to diagnose the efficiency of the entire supply chain.

(Situmorang et al., 2019) established a network evaluation model in which intermediate products or outcomes can be both final products and inputs for later development stages at one level. (Hazen et al., 2018) introduced the DEA model has two interlinked issues, poor discriminatory power, and unrealistic weight distribution, allowing inexact diagnosis to be eventually achieved. The optimal utility ratio has been proposed by (Jasri et al., 2017) for DEA analysis and a subset of decision-makers. Classic DEA with weight-bound constraints showed difficulties in optimizing the measured decision-making units' relative efficiencies and suggested an optimal DEA model for overcoming these limitations.

Optimal DEA models were introduced for better estimation. For the location of semi-noxious facilities models, an optimal intervention bicriteria model was utilized. Bilevel technology (BT) was submitted to enable system performance assessment under autonomous decision-making conditions. Increased capacities for inequality in contrast with conventional DEA have been seen in optimal DEA.

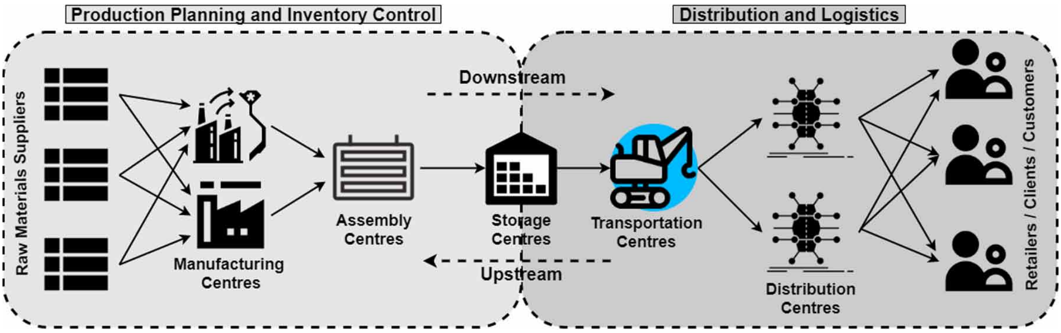
For analyzing the supply chain output, the proposal of a Multi-stage optimal productivity model is introduced. The suggested model can calculate supply chain efficiency and effectiveness management using decision support systems. Compared with conventional DEA models such as the CCR, BCC, LPM, and BT, the optimal productivity DEA's overall performance gives less sensitivity to input and output weights. Therefore, our model provides benefits in solving two interrelated problems in conventional DEA models: poor discrimination of force and unrealistic transfer of weight. This model specifically allows to achieve productivity measures at any level and achieve an average efficiency calculation taking specifically into the framework of the optimal supply chains. The research explores an optimal productivity model that evaluates supply chain efficiency and effectiveness management. The research discusses the policy preparation demands of the decision support systems and develops a framework that organizations can use to control the implementation process. The policy preparation demands the judgment system is for building chains to respond to the demand signals. Demand policy, in contrast to typical supply chains, employs a pull strategy. It allows the marketplace to exchange more data and collaborate with other supply chain partners.

3. PROPOSED DEA BASED OPTIMAL PRODUCTIVITY MODEL

Data envelopment analysis is the essential model to implement supply chain efficiency. It has a strong link to economic production, the benchmarking system for operating management with performance manufacturing operations. The supply chain is a series of networks (companies, employees, technologies, information, services, and distribution opportunities) executing the material sourcing functions, sorting such materials into intermediate and finished goods and their supply to the client. Both these installations are used to satisfy customer specifications. The supply chain's task is to deliver the best goods in the right location at the right time and a low cost in the appropriate proportions.

An example of a supply chain network is shown in Figure 1. Materials migrate downstream from raw materials suppliers to the processing stage that turns raw materials into intermediate goods. They

Figure 1. Supply chain network



are assembled to form goods at the next level. The goods will be delivered to clients and consumers at distribution centers.

3.1 Optimal Productivity Model for Supply Chain Sub-structure

Figure 2 illustrates that interconnected supply chain with a Q-stage sequential structure composed of Q progressions. From Figure 2, U^Q denotes the direct data input for sub-progression (Q) and V^Q denotes output for sub-progression (Q) and data input for sub-progression (Q+1). The number of finished goods delivered from the manufacturer to the supplier and the supply chain's delivery times are intermediate inputs/output connected with two supply chain members. Optimized productivity model DEA efficiency for sub-progression (Q-stage) of the i th supply chain expressed in Equation (1).

$$F_i^Q = \frac{X^{QT} V_i^Q}{Y^{QT} U_i^Q + \vartheta X^{Q-1T} V_i^{Q-1}} \tag{1}$$

From Equation (1), i th supply chain consists of n number of inputs u_{ji}^Q and m number of outputs v_{ki}^Q at the Q th sub-progression. The measured input and output variables can be denoted as $U_i^Q = \left(u_{1i}^Q, u_{2i}^Q, \ldots, u_{ni}^Q\right)^T > 0$ and $V_i^Q = \left(v_{1i}^Q, v_{2i}^Q, \ldots, v_{mi}^Q\right)^T > 0$, respectively. Where, ϑ denoted as a non-negativity factor, $X^{QT} = \left(x_1^Q, x_2^Q, \ldots, x_n^Q\right)^T$ and $Y^{QT} = \left(y_1^Q, y_2^Q, \ldots, y_m^Q\right)^T$ denoted as weight factor for series of inputs and outputs interconnected with sub-progression (Q-stage) respectively.

The optimal criterion has been added in the sub-progression (Q-stage) to obtain an optimal efficiency model. Suppose the supply chain requires perfect knowledge of the complete set of statements (input, output values), and it is not feasible to identify each condition's probability. Then, as seen in Statistics, an entirely ignorant decision problem can conveniently be illustrated in a data

Figure 2. Supply chain with Q-stage sequential structure

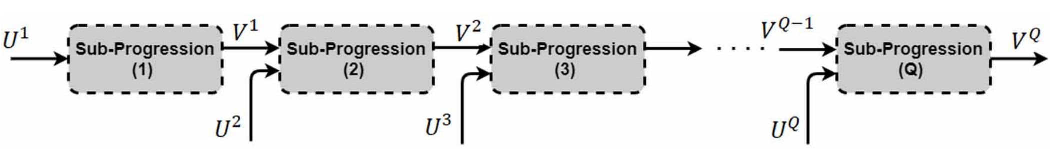
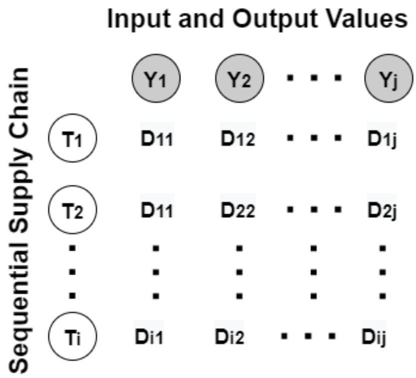


Figure 3. Sequential supply chain data structure



structure, as shown in Figure 3. D_{ij} is the payoff connected with i th supply chain and variable j expressed in Equation (2).

$$D_{ij} = \left[u_{ni}^{Q}, v_{mi}^{Q}\right] \tag{2}$$

Decision support system measure the minimum payoff for the optimal productivity DEA model expressed in Equation (3)

$$T_{i} = min_{j\in\left(1,j\right)}\left\{D_{ij}\right\} \tag{3}$$

Where, T_{i} denoted as a security indicator of the decision support system and measure the maximum payoff for the optimal productivity DEA model expressed in Equation (4)

$$T_{i}^{Q} = max_{\left(X^{Q},Y^{Q}\right)\in\mathbb{P}^{m}\times\mathbb{P}^{n}}\left\{min_{j\in\left[1,j\right]}\left\{D_{ij}\right\}\right\} \tag{4}$$

Minimum performance level by picking an optimum weight strategy from a series of weight restrictions, which is added to the protection level of all the units and provides an optimized factor γ^{Q} expressed in Equation (5)

$$\gamma^{Q} = min_{j\in\left(1,j\right)}\left\{D_{ij}\right\} = min_{j\in\left(1,j\right)}\left\{\frac{X^{QT}V_{i}^{Q}}{Y^{QT}\,U_{i}^{Q} + \vartheta X^{Q-1T}V_{i}^{Q-1}}\right\} \tag{5}$$

The optimized programming model for the given set of resources expressed in Equation (6)

$$max_{\left(X^{Q},Y^{Q}\right)\in\mathbb{P}^{m}\times\mathbb{P}^{n}}\ \gamma^{Q}$$

$$s.t.\ \frac{X^{QT}V_i^Q}{Y^{QT}\,U_i^Q + \vartheta X^{Q-1T}V_i^{Q-1}} \geq \gamma^Q \tag{6}$$

$$\frac{X^{QT}V_i^Q}{Y^{QT}\,U_i^Q + \vartheta X^{Q-1T}V_i^{Q-1}} \leq 1$$

Integrating the optimized model transformation in DEA efficiency ($\max \gamma^Q$) and expressed in Equation (7)

$$\mu^{1QT}U_i^Q + \vartheta\mu^{2QT}V_i^{Q-1} - \beta^{QT}V_i^Q \geq 0 \tag{7}$$

From Equation (7), μ^{1Q}, and μ^{2Q} can be defined as input weight factors and β^Q can be defined as the output weight factor. The decision support systems equilibrium constraints are expressed in Equation (8)

$$\boldsymbol{\mathit{3}}_{\boldsymbol{i}}^{\boldsymbol{Q}}\left(\mu^{1QT}U_i^Q + \vartheta\mu^{2QT}V_i^{Q-1}\right) - \beta^{QT}V_i^Q = 0 \tag{18}$$

Efficiency balancing is thus reached based on equilibrium constraints. This combination is accomplished for each supply chain and not for the entire supply chain system. Correlation between adjacent processes is not taken into consideration, as calling this kind of balance efficiency independent balance efficiency (E_O^{*Q}) is expressed in Equation (9)

$$E_O^{*Q} = \left[\mu_O^{*1QT}, \mu_O^{*2QT}, \beta_O^{*QT}\right] \tag{9}$$

$$OPM_i^Q\left(E_O^{*Q}\right) = \frac{\beta_O^{*QT}V_i^Q}{\mu_O^{*1QT}\,U_i^Q + \vartheta\mu_O^{*2QT}V_i^{Q-1}} \tag{10}$$

From Equation (10), $OPM_i^Q\left(E_O^{*Q}\right)$ denotes the optimized productivity model DEA-performance for sub-progression (Q-stage).

3.2 Optimal Productivity Model for Supply Chain Structure

This research's efficient supply chain and effective management are detailed as the individual sub-progression's weighted-sum effectiveness. Generally, the efficient supply chain and effective management is expressed in Equation (11)

$$SCE_i = \sum_{Q=1}^{Q}\delta_Q F_i^Q \sum_{Q=1}^{Q}\delta_Q \frac{X^{QT}V_i^Q}{Y^{QT}\left\langle U_i^Q, \vartheta V_i^{Q-1}\right\rangle} \tag{11}$$

Where user represented weight factor for Q th, sub-progression can be denoted as δ_Q and performance of supply chain members can be denoted as F_i^Q. The objective function attempts to optimize the weighted average amount of optimal productivity for each process, i.e., to maximize the weighted average sum of minimum and maximum efficiencies for each process expressed in Equations (12) and (13).

$$\zeta^1 = \underset{1 \le i \le m}{Min} \left(\frac{X^{1T} V_i^1}{Y^{1T} U_i^1} \right), \ \zeta^Q = \underset{1 \le i \le m}{Min} \left(\frac{X^{QT} V_i^Q}{Y^{QT} U_i^Q + X^{(Q-1)T} V_i^{Q-1}} \right) \tag{12}$$

$$Max \frac{1}{\sum_{j=1}^{Q} \delta_j} \left(\delta_1 \zeta^1 + \sum_{Q=2}^{Q} \delta_Q \zeta^Q \right) \tag{13}$$

The maximum supply chain efficiency and effective management of DEA performance using decision support systems can be easily obtained by solving Equation (14).

$$\underset{\mu^{1T}, \mu^{QT}, \beta^Q, kQ^{\leftrightarrow(Q-1)T}}{Max} \ \underset{1 \le i \le m}{Min} \frac{1}{\sum_{j=1}^{Q} \delta_j} \left(\delta_1 \zeta^1 + \sum_{Q=2}^{Q} \delta_Q \zeta^Q \right) \tag{14}$$

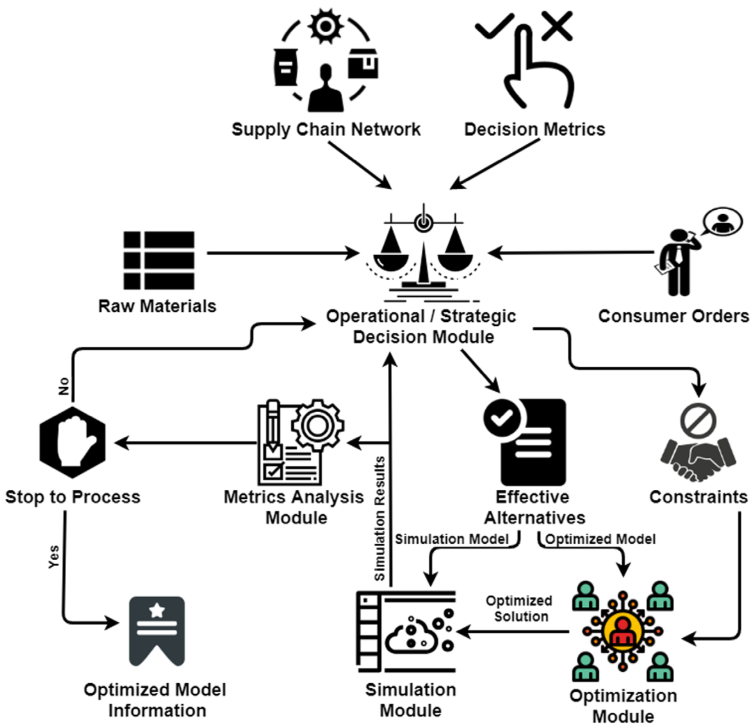
Equation (14) demonstrates the potential for efficiency enhancement by coordination between the background supply chain members. Equation (14) implies the organized productivity of supply chains with optimum DEA performance equilibrium.

4. STRATEGIES AND FRAMEWORK OF THE SUPPLY CHAIN STRUCTURE

The ultimate goal is to ensure the outstanding architecture of the supply chain network. A network is a sequence of theories on its behavior. The conclusion part has the interaction conversation among rational or scientific facts, with the objective purpose of assessing the remarkable construction of the supply chain. Suppose the links that make up the model are simpler enough to correct problems of interest. In that case, it might be accessible to utilize math techniques (arithmetic, calculus, and statistics), which is considered an empirical approach. Using mathematics, logic, and analytics expressions of basic techniques in approach, the model connection makes it easier to spot the difficulties of relevance. Most of the real-time structures are challenging to analyze functional modules, and those modules need to be analyzed with simulation. A supply chain simulation depicts the behavior of a transportation network over time. The conceptual principles of a supply chain are represented in a numerical simulation and then performed over time, rendering the simulation interactive. For example, if orders deplete the stock below the threshold, manufacturing is initiated. Such standards can be integrated to investigate and test their connections versus unexpected events such as protests and natural catastrophes.

The unpredictable and complex market environment today gives rise to chance and risk. The optimization of the supply chain framework is useful when the manufacturer or commodity having a complicated supply system, a complicated production mechanism, a complicated delivery system, and unpredictable demand. In general, where supply chain activities or business demands are unknown, the organization should strengthen the supply chain. Business demand is unknown in features of

Figure 4. Proposed supply chain framework



goods and services manufacturing and strategic planning in developing sources. The statistics of business demand must be checked for every traversal of the supply chain on the acquisition of goods details for further knowing the facts. However, the real difficulty in the management of the supply chain comes from the inherent complexities of regular occurrences at any stage in the chain, such as (1) consumer demand forecasting is barely reliable and sometimes misleading, (2) production is vulnerable to technological difficulties and (3) transportation delays are likely. The production of supply chain management is vulnerable because the technical difficulties based on transportation make it late for traversing the products and goods. The development of supply chain models that take variability and volatility into account is important.

The solution proposed is based on the Figure 4 framework. The total framework requires a supply chain model to explain the network layout comprising the supply chain installations. It transforms this systemic knowledge into a module of strategic, tactical, and/or organizational decisions.

The former has supplementary details from external sources of raw materials as arrival times and overseas buyers as requirements and payable dates. This segment focused on the decisions of supply chain architecture. It would recommend unpredictable political, tactical, and organizational decisions involving its framework outlined in the SCM and its restructuring by reducing the quantity to which capitals are involved. The former supplementary facts have limitations of decreasing the capital quantity, slowness of reach, and less attention to technological status.

The strategic operation module of data envelopment analysis is developed for filtering ideas on behalf of knowledge to define the efficiency and solutions based on restricted implementations. The guidelines of constraints from material suppliers and customer requirements to productive or non-effective supply chain solutions as the module's outputs are efficient, operationally restricted solutions. Uncertain (generic) models define the appropriate alternatives (using uncertain parameters values). These unsure criteria have to do with strategy, organizational and operating decisions.

At the strategic stage, the location, development, inventories, and transport are unknown parameters. The un-security of the supply chain institutions' location, such as factories, inventories, and delivery centres, relates to scale, number, and geographical place. Uncertain manufacturing parameters should specify the number of goods to manufacture, the quantity of products to be manufactured, which plants to use, which delivery centers to sell uses, etc. The monitoring of inventories in the supply chain concerns uncertain inventory criteria. The transport modes to be used are subject to unknown conditions. Tactically, unpredictable criteria include monthly demand projections, delivery and shipping plans, development planning, and preparing content specifications. The operational information then plans information to determine the quantity of goods, usage of energy, etc. Specifically, the workspace configuration (flow shop or workshop), the amounts of jobs/material, and the time/resources constraints are these unknown criteria at the organizational stage.

The appropriate definition of alternatives is divided into two unknown versions, input data for two segments. The optimization module is the primary module. This module creates the best scheduling structure for organizational resolution with a variety of constraints. In contrast, the second module's inputs, the simulation module, will be the optimal programming solution for the simulation model. Because of the supply chain's dynamic compliance, the integration of simulation and optimization modules is responsible. A process of dividing the action of the SCM into two sub-structures is therefore required for the advantage of logical and simulation techniques.

The primary values are gathered from the customer through the decision segment for unknown parameters at the beginning. The module will search these values for raw material suppliers' details and client orders according to decision rules and constraints. The optimization segment is then requested to achieve the optimum scheduling with its unknown system, time constraints, and resources. The simulation module would afterward use an optimum programming sequence to replicate the unknown simulation model. The simulation results will be used to determine the final success by calculating various suggested choice measurements. Suppose global output is below a threshold of fulfillment. In that case, the simulated outcomes will be moved to the strategic decision segment to advise decisions on similar values for unknown parameter estimates of the SCM. This method proceeds until equilibrium, or an optimal amount of iterations is obtained. A decision-finder should be pleased with the optimal solution discovered thus far, thereby halting the analysis process for developing similar solutions.

The goals of the proposed model are to deliver an efficient, high-performance SCM. The optimal model minimizes capital to achieve particular results while installing installations to offer goods or services that satisfy end-users is the successful approach. Effectiveness is identified by distribution time, cost of goods, number of requirements, and stock volumes. Simultaneously, efficient functional quality tests the principal company's service and the customer based on the focal company.

Modeling techniques are used to explore the linkages between decisions, limits, and goals. To produce the full effects of the supply chain, templates can catch the essence. This model can be both highly complex and detailed. Therefore, the model which is acceptable for the needs of the enterprise needs to be selected. For modeling purposes, a manufacturers' decision-maker in a supply chain can address questions such as the requirement of raw material is bought from a producer, order time, where and inventory quantity is delivered to a consumer or delivery centre. Decision restrictions include limits on the supply chain scheme, the willingness of a supplier to import raw products or parts, a manufacturing facility with productivity and a person working for excessive overtime, a consumer or delivery centre's storage and sorting of receipts.

The limits can be challenging or soft. The assigned working time in a shift or the full capability could be complicated and should be met. Instead, soft limits can be relieved or breached. Consumer due dates or space limits include soft restrictions. Penalties are enforced on a soft regulation that does not comply with the organization. The fines permit the weighting of restrictions. For starters, the absence of a customer's payment date is highly relevant than a storeroom hallway. The decision-goal makers may optimize revenues or boundaries, mitigate supply chain expenditures or functional times, maximize customer provision, reduce latency, maximize manufacturing performance, and meet customer demands.

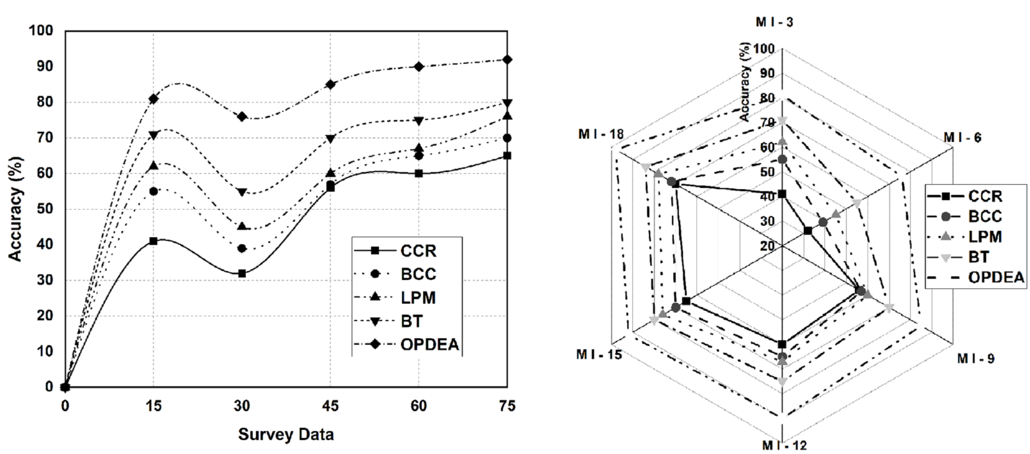
5. RESULTS AND DISCUSSIONS

This section details the importance of the proposed optimal productivity model-based DEA analysis to supply chain efficiency and effectiveness management using decision support systems. Inventory criteria in supply chain management related to uncertain service towards the growth of the industry by operational management, technological system, and managery control. In this research, 15 user reports are employed for collecting 75 survey data. As detailed in Figure 4, the developed model is when a combined server acts as a data synthesizer. This system is utilizing the existing reference for responding to 15 Monitoring Intervals (MI). The storage capacity of the integrated server is 2TB with a 2.4GHz processing speed. The performance is evaluated using significant metrics like accuracy, effectiveness, delay rate, and error rate. For confirming the developed framework's stability, a comparative analysis with conventional DEA models such as the CCR, BCC, LPM, and BT is performed.

5.1 Accuracy Analysis

Supply chain management (SCM) outcomes are evaluated with the above-mentioned parametric analysis for improving supply chain efficiency and effectiveness management using decision support systems for organizations with the proposed Optimal Productivity-based Data Envelopment Analysis (OPDEA). The research concluded that the strategy proposed is well-tailored to handling capital for successful strategic organizational planning and expressed as $\frac{\beta_O^{*QT} V_i^Q}{\mu_O^{*1QT} U_i^Q + \vartheta \mu_O^{*2QT} V_i^{Q-1}}$. The method's accuracy reaches the maximum for both survey data analysis and monitoring intervals, as illustrated in Figures 5(a) and 5(b) compared to conventional DEA models such as the CCR, BCC, LPM, and BT. OPDEA is refining and expanding the newly-developed computer approach of public and private investment management technologies.

Figure 5. Accuracy Analysis (a) Survey Data (b) Monitoring Intervals



(a) (b)

5.2 Effectiveness Aspects

Figures 6(a) and 6(b) illustrate the proposed Optimal Productivity-based Data Envelopment Analysis (OPDEA) effectiveness for the survey data and monitoring intervals. It reaches maximum effectiveness management and supply chain efficiency by effective utilizing of decision support systems and expressed as $\sum_{Q=1}^{Q}\delta_Q F_i^Q \sum_{Q=1}^{Q}\delta_Q \frac{X^{QT}V_i^Q}{Y^{QT}\left\langle U_i^Q, \vartheta V_i^{Q-1}\right\rangle}$. The model is evaluated to assess the better effect of resource sharing with varying sporadic quantities. This results well in contrast with the traditional mathematical approach expressed in Equation (9). Since an evolving development area is a good strategic business plan, a high yield ratio has been well developed.

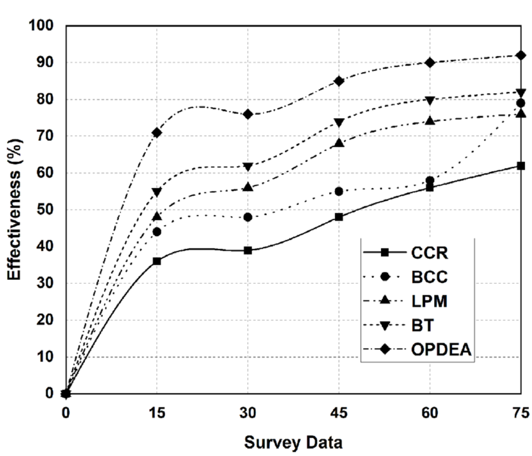
5.3 Delay Rate Analysis

Figures 7(a) and 7(b) detail the proposed Optimal Productivity-based Data Envelopment Analysis (OPDEA) for overall delay rate in optimizing supply chain efficiency and effectiveness management using decision support systems in effect deployment with security indicator of the decision support system for the survey data and monitoring intervals are expressed as $max_{\left(X^Q,Y^Q\right)\in\mathbb{P}^m\times\mathbb{P}^n}\left\{min_{j\in[1,j]}\left\{D_{ij}\right\}\right\}$. The delay rate is minimal than that of the other approaches. It is clear from the graph that the total delay rate for the OPDEA analysis technique is greatly minimized. The proposed OPDEA utilizes a decision support system in outcomes with an extensively low delay rate compared to the conventional DEA analysis.

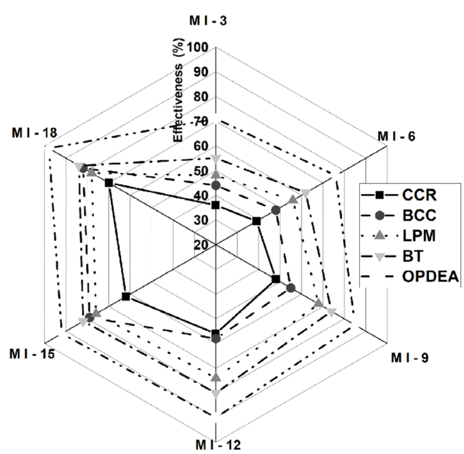
5.4 Error Rate Analysis

Figures 8(a) and 8(b) details the error rate of the proposed Optimal Productivity-based Data Envelopment Analysis (OPDEA) for the survey data and monitoring intervals. The developed model has a very low error rate, close to the delay rate. As the error rate decreases, with less time, the production is increased and expressed as $\zeta^Q = \underset{1\le i\le m}{Min}\left(\frac{X^{QT}V_i^Q}{Y^{QT}U_i^Q + X^{(Q-1)T}V_i^{Q-1}}\right)$. This makes the

Figure 6. Effectiveness (a) Survey Data (b) Monitoring Intervals



(a)



(b)

Figure 7. Delay Rate (a) Survey Data (b) Monitoring Intervals

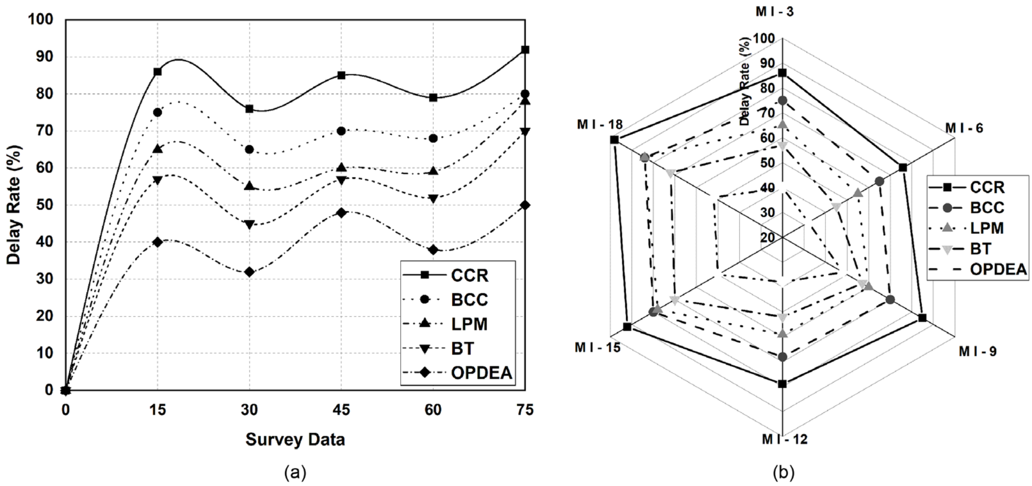
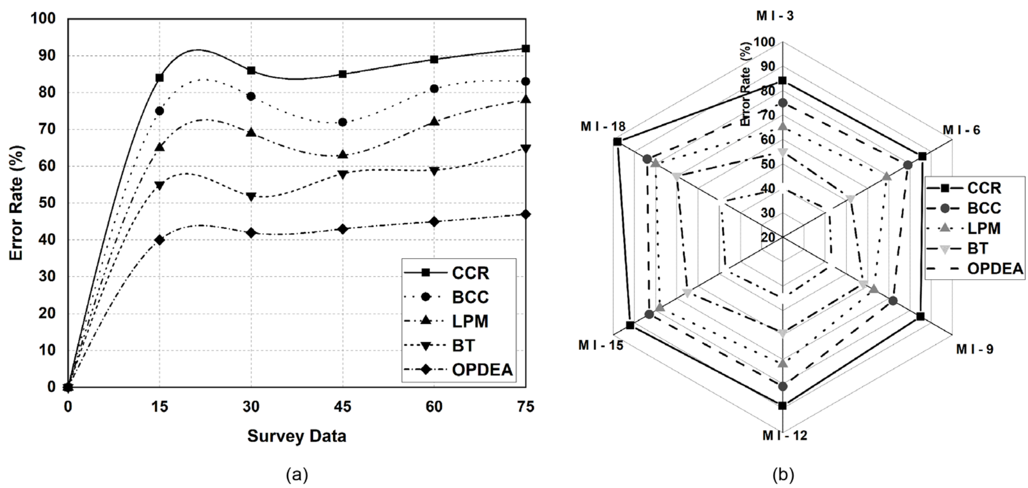


Figure 8. Error Rate (a) Survey Data (b) Monitoring Intervals



proposed model (OPDEA) outperformed better than the conventional DEA analysis such as the CCR, BCC, LPM, and BT. The comparison outcomes are listed in Tables 1 and 2.

Table (1) shows that the developed model (OPDEA) maximizes accuracy and effectiveness by 29.05% and 32.12%, respectively, and minimizes the delay rate and error rate by 46.77% and 47.95%.

Table (2) shows that the developed model (OPDEA) maximizes accuracy and effectiveness by 25.45% and 29.58%, respectively, and minimizes the delay rate and error rate by 43.56% and 46.65%, respectively.

Table 1. Comparison outcomes for Survey Data

Metrics	CCR	BCC	LPM	BT	OPDEA
Accuracy (%)	70.23	72.54	78.37	84.53	98.99
Effectiveness (%)	65.56	7052	73.45	81.56	96.58
Delay Rate (%)	98.58	84.56	82.52	72.58	52.47
Error Rate (%)	95.78	81.52	78.37	69.89	49.85

Table 2. Comparison outcomes for Monitoring Intervals

Metrics	CCR	BCC	LPM	BT	OPDEA
Accuracy (%)	69.12	71.43	77.26	83.42	97.88
Effectiveness (%)	64.45	7051	72.34	80.45	95.47
Delay Rate (%)	97.47	83.45	81.41	71.47	51.36
Error Rate (%)	94.67	80.41	77.26	68.78	48.74

6. CONCLUSION

The research shows how an optimum matching performance method can be extended to maximize a process sequence's effectiveness if output becomes the next entry in the sequence. It has been shown that optimum balance productivity is organized in the supply chain if all participants are optimally balanced and coordinated. Efficiency can be improved by coordination among adjacent supply chain members. A concrete implementation in the three processes' supply chain is illustrated to explain the optimum balance model supply chain (members). Numerical data are used to construct a standard scientific maximum output limit for the supply chain. The efficiency of supply chains is calculated based on a traditional boundary. The weight distribution significance is confirmed by correlation analysis.

There are several possible applications of our standardized model. One main factor is the use of productive supply chain representatives in the architecture of the supply chain. The surveillance of a particular value chain, including food movement, is another potential use. For instance, the model offers various optimal performance goals based on previous data on observable cycles. Based on the observed results and the optimal expectations of balance, these objectives are theoretically feasible. In this research, the optimum criterion represents pessimism and general rationality in decision-makers. Another factor is that the decision-maker should be optimist or opportunist using a minimum or optimum criterion.

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