

# Supply Chain Efficiency and Effectiveness Management Using Decision Support Systems

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## ABSTRACT

In supply chain management, decision support systems and time series forecasting play an essential role. The accuracy of time-series predictions is critical for the performance optimization of every supply chain. This article suggests a method based on state-space modelling (SSM) for structured time series forecasting. Technology and advance implementations of decision support systems (DSS) have improved considerably. DSS has been used as a more restricted functionality of the database, modelling, and user interface, although technical advances made DSS even more effective. Web development has facilitated inter-organizational decision-making support systems and has resulted in many innovative implementations of current technology and many new decision-making technologies. The study of multiple configurations shows that the SSM and DSS are ideal for solving the problem being studied; in particular, the DSS guarantees appropriate prediction errors and a correct computational effort to provide adequate customer order plans.

## KEYWORDS

Decision Support Systems, Efficiency, Effectiveness, Management, Supply Chain

## 1. INTRODUCTION

The latest advancements in information technology have created a decision support system with the supply chain. The implementation of the decision support system has helped in decreasing the complexity of decision making. Various decisions and forecasting related to the market trends can be easily made using the decision support system. This scheme helps the decision making authority to make correct decisions (W. A. Teniwut and C. L. Hasyim, 2020). All companies and individual contributors to a product range from raw materials to finished products comprise a supply chain. Examples of supply chain activities include agriculture, refining, design, manufacturing, packaging, and transport. Various supply chain partners work together to ensure the sustainability of the supply chain. This collaboration is designed such that there are minimal risks involved. During the collaboration, the first step is data collection. Supply Chain management refers to managing

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transactions engaged in raw material procurement, processing, and distribution to end-users. Their transformation into finished goods, moral management of the supply chain ensures a balance between demand and supply. The second step is data analysis, and the third step is data visualization. The final step is the result interpretation (M. V. C. Fagundes, et al. 2020). To reach the desired supply chain management system that enables competitive administrations, inter-organizational systems allow the data flux between organizations to be automated. This supports customer requirements and product and service delivery.

Big data analytics is another important component of the supply chain system. It is used to analyse the data generated using the internet of things (IoT) devices. These devices collect data in real-time from numerous sensors, and the collected data is stored in the cloud. The collected data can be processed using big data analytics systems to design supply chains (A. K. Jha, et al. 2020). With the development of a more digital environment in which the value chains are linked, and distribution systems are increasingly intelligent autonomy, and automation the future of supply chains is being transformed globally. Various decision support models are designed for the improvement of support chain systems. These models are used for the standardization of the overall framework. Thus they are implemented to improve the finance and the manufacturing process. The digitization phase enables gathering numerous real-time data to infer useful information (K. Yildiz and M. T. Ahi, 2020).

The development of support tools is a recently trending area that can be used for automating decisions (V. Vedanarayanan, et al. 2020). Algorithms based on machine learning, deep learning, artificial intelligence, big data analysis, etc., can be used to integrate software tools into the support chain environment. These techniques are used for the optimization of the decision-making models (N. Akbarian-Saravi, et al. 2020). Decision support in the support chain is done based on the optimization criterion. The optimization is done using genetic algorithms. These algorithms perform the optimization of the available resources using bio-inspired models (M. E. Bounif and M. Bourahla, et al. 2013). The efficiency of the supply chain is thus the way to get the right product to the correct position at the lowest cost at the right time. While processors want to measure the efficiency of their supply chain, customers often judge them.

Health care supply chains deploy a decision support system based on the knowledge of medical experts. These experts are used to making decisions for multiple situations. These decisions are converted to software (D. Joshua Jeyasekar, et al. 2019). The converted software is then used for automation. The automation is based on the real-time decisions that are taken by the physicians (K. Govindan, et al. 2020). A DSS (Decision support system) is a computerized program used to support organizational or business determinations, judgments, and action paths. A DSS scans and analyses huge amounts of data and compiles comprehensive information to resolve problems and make decisions. Increasing the capacity of the supply chain is a crucial task. The planning systems for capacity allocation must ensure the availability of resources. Based on the available resources and the corresponding demand, resource allocation is done. Furthermore, the market is tracked online based on IoT devices (R. Oger, et al. 2020). The lifeline of the medical industry is a reliable and robust supply chain. It ensures that the health of this essential sector is as fit, as it provides the retailers and patients are reached easily by medical devices, medical supplies, and medications.

Supply chain management for biomass is done to ensure resources' availability in the future (V. Vedanarayanan, 2020). Usage of renewable resources helps to increase the sustainability of the supply chain. The biomass supply chain must be designed such that the endurance is assured (L. J. R. Nunes, et al. 2019). To improve the performance of the supply chain, various models have been proposed in the literature. These models include logistic models, blockchain models, inverse constraint models, information technology model, machine learning model, manufacturing model, flexible constraint model etc. Using these models, the supply chain is integrated to improve its endurance and reliability (S. K. Mangla, et al. 2019).

Based on the supply chains' introduction, supply chain management has been designed using the decision support system.

The contributions of this paper are as follows

- A novel scheme of supply chain management based on a decision support system is presented.
- A new model for supply chain modelling using machine learning and time series forecasting is proposed.
- A new architecture called state-space modelling-based decision support systems (SSM-DSS) architecture is designed.
- The proposed scheme is validated using simulation analysis.

The study's remainder is structured as follows: section 1 and section 2 discussed the introduction and existing food chain supply system. In section 3, state-space modelling-based decision support systems (SSM-DSS) have been suggested. In section 4, the numerical results have been performed. Finally, section 5 concludes the research article.

## 2. RELATED WORK

D. G. Mogale et al. 2020, have proposed a scheme for a food chain supply system using a new approach based on bi-objective function. The first objective was cost minimization. Since food is an essential commodity, the reduction of cost is a vital task. The second task considered was the reduction in the amount of carbon-di-oxide being emitted. The second objective was designed to increase the sustainability of the environment. G. Baryannis et al. 2019, implemented artificial intelligence systems for the risk management of the supply chain. The artificial intelligence module was used for making intelligent decisions to reduce the risk and increase the reliability of supply chain systems. Risk management was performed using assessment and mitigation steps.

H. Allaoui et al. 2019, presented a scheme for decision support in the supply chain based on a collaboration planning system. Information and communication technology platform was utilized for the implementation of decision support. This system was designed to ensure the sustainability and endurance of the supply chain. C. Bai et al. 2019, proposed a decision support approach based on the supplier evaluation. Thus the assessment was performed using the social sustainability dimension. The decision framework was evaluated using a grey-based criterion. This criterion was designed for the applicability of the decision framework.

M. Zarte et al. 2019, designed decision support systems to ensure the sustainability of the manufacturing unit. The production systems were analysed to produce suitable sustainability-based indicators. These indicators were incorporated into the decision modules to enable support systems with greater reliability. N. K. Dev et al. 2019, presented a scheme for supply chain modelling using multi-criteria evaluation. The real-time dynamic performance was evaluated using unstructured key indicators. The fuzzy analytic system was used in the decision making in these systems. S. Singh et al. 2020, proposed a scheme for increasing the resilience of the supply chain. An ontology-based method was used for decision making. Ontology was used for the generation of a knowledge base using which the entire supply chain was constructed.

G. Dellino et al. 2018, presented a scheme for ensuring the fresh food supply chain's reliability. Highly perishable products were the main focus of the supply chain. Forecasting was done using machine learning based on unique tools. Ş. Y. Balaman et al. 2016, designed a scheme to optimise the supply chain using an integrated optimization technique. A fuzzy constraint method was used for the decision support system. This scheme was dedicated to the bio-based production system. P. Centobelli et al. 2018, used a three-dimensional fuzzy system for the knowledge management systems. Small and medium enterprises were used as the main focus in supply chain management. The misalignment in the supply chain was reduced.

Based on the above research, supply chain modelling has developed as a framework for using state-space modelling-based decision support systems.

### 3. PROPOSED METHODOLOGY

#### 3.1. Supply Chain Management Framework

The supply chain management framework comprises multiple levels between the raw material production unit and the customer unit. The two main sectors include the production sector and the distribution sector.

Figure 1 illustrates the supply chain management framework. In the framework, the first component is the raw material unit. This unit is dedicated to the preparation of raw material necessary for product production. The second component of the supply chain management framework is the manufacturing unit. Using the generated raw materials, the products are manufactured using the manufacturing unit. The next component is the assembling and storage unit. The individual components being manufactured are assembled to form the complete product in this unit.

Further, the assembled product is stored in this unit. The components assembled are then shipped to various locations using the distribution unit. The final unit comprises the customers. The first three units, namely, the raw material unit, manufacturing unit and assembling the unit, constitutes the production sector. The last three units, namely, the storage unit, distribution unit and the customer unit, involve the distribution sector. In control engineering, a representation of the state is a mathematical model of a physical system, as a set of variables related to initial differential equations or differential equations, input, output, or state. The “Status Space” is the Euclidean space where the axis variables are the status variables.

#### 3.2. The Decision Support System in Supply Chain Management

The main backbone of supply chain management is the decision support system (DSS). DSS is used to make essential time series forecasting and other vital decisions in improving the customers’ satisfaction rate. Find the target users of the proposed system software for decision support. Identify possibilities and menaces for a DSS proposed. Determine whether the proposed DSS with desired functionality falls within the organization’s budget. Identify the techniques to develop a DSS that can be used.

Figure 2 shows the implementation of a decision support system in the supply chain management system. In this system, the manufacturers provide the products to the customers. The customers generate feedback based on the products’ quality and are given the decision support system module. The software in this module makes suitable decisions and gives the findings as input to the manufacturing unit. The manufacturer unit makes suitable changes based on these decisions. In this way, the decision support system connects the customers to the manufacturers based on a feedback loop. The extent to which

Figure 1. Supply chain management framework

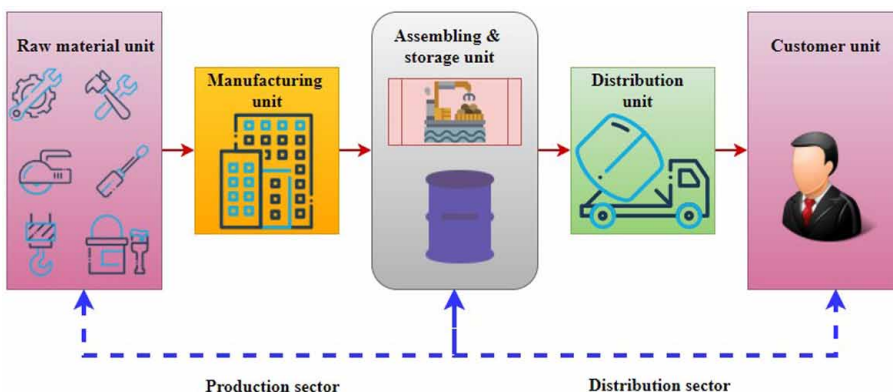
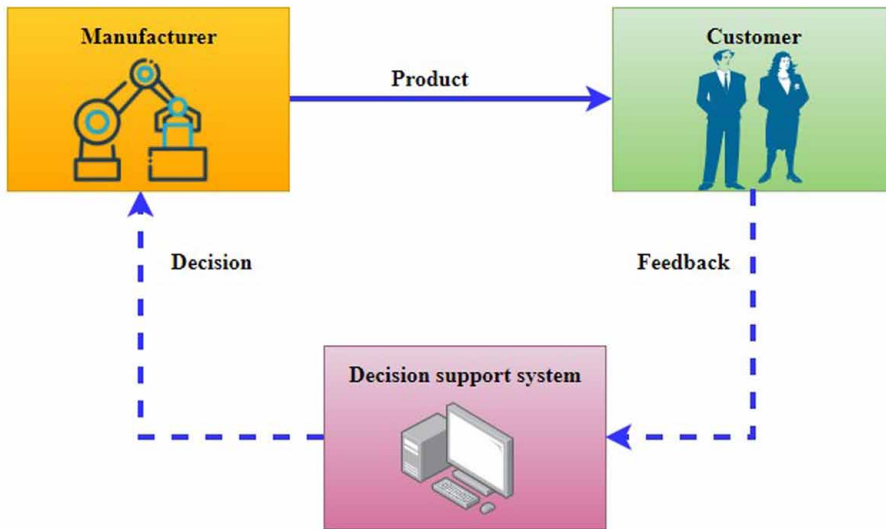


Figure 2. The decision support system in supply chain management



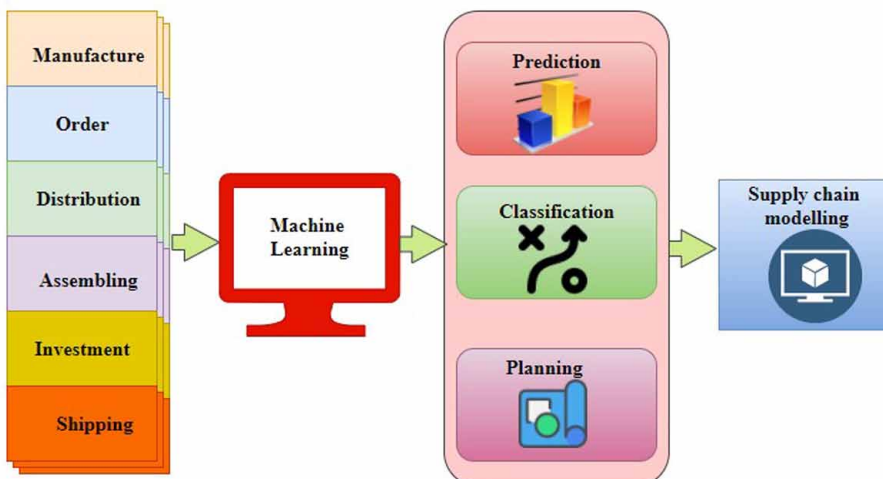
a process makes the most resources to ensure the fast and smooth operation of systems is all about efficiency. However, effectiveness is the level to which a particular process gives the desired results.

### 3.3. Supply Chain Modelling Using Machine Learning and Time Series Forecasting

The supply chain modelling is done using suitable machine learning engines to provide suitable time series forecasting. It is done to enhance the quality and sustainability of the supply chain model.

The architecture of supply chain modelling using machine learning is shown in Figure 3. The supply chain components like the manufacturing unit, order system, distribution sector, assembling unit, investment sector and the shipping unit are given input to the machine learning engine. This engine is used for making suitable time series forecasting, prediction, classification and planning.

Figure 3. Supply chain modelling using machine learning



The forecasting is done using the past and the present supply chain data. Based on the forecasted information, supply chain modelling is done. Decision Support Systems (DSS) are an information system class supporting decision-making activity. DSS are computer-based, interactive systems and subsystems designed to help policymakers utilize communication technologies, data, documents, knowledge, and models in completing decision-making processes.

### 3.4. Proposed State-space Modelling-based Decision Support Systems (SSM-DSS) Architecture

The state-space modelling is done to model the supply chain using the decision support system module. The state-space modelling is designed based on a feedback loop in which suitable metric computation is done to ensure the supply chain's optimisation.

Figure 4 shows the model of the state-space modelling-based decision support system (SSM-DSS). In this model, the supply chain components are subject to optimization. The output of the optimization module is given as an input to the decision support system module. Using the decisions taken, a suitable metric evaluation is done. The computed metric is used for providing feedback to the optimization module. Thus the optimization is modified until stability is ensured. This loop is continued until the variance between two continuous loops is low. Finally, the supply chain is finalized. Knowledge acquisition was the first stage in developing the system for decision support. Knowledge can be considered the “brain” in the decision support system for processing the data and information provided by the system.

Figure 5 shows the SSM-DSS system's proposed architecture; the four main inputs include the customer requirement, raw resources, profitability, and objectives. These inputs are used for the computation of the metric. The computed metric is given as input to the optimization module. This module optimizes the data and provides the optimized data to the decision support system module. The decision taken by this module can be of two types, namely yes or no. If the decision is yes, the supply chain model is finalized. If the decision is no, the decision is given as input to the optimization module for further optimization. The optimization is continued until the supply chain model is finalized.

The objective function for the SSM-DSS module is based on the following steps. Initially set of inputs are considered. These include a set of tasks  $T = \{t_1, t_2, \dots, t_m\}$ , a set of resources  $R = \{r_1, r_2, \dots, r_m\}$ , a set of objectives  $O = \{o_1, o_2, \dots, o_m\}$ , a set of schedules  $S = \{s_1, s_2, \dots, s_m\}$ , a set of constraints  $C = \{c_1, c_2, \dots, c_m\}$ , set of looping  $L = \{l_1, l_2, \dots, l_m\}$  and a set of directions  $D = \{d_1, d_2, \dots, d_m\}$ .

Production throughput is computed as

Figure 4. Model of SSM-DSS

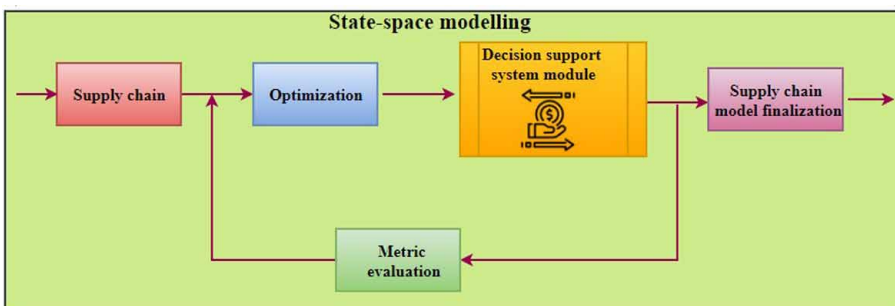
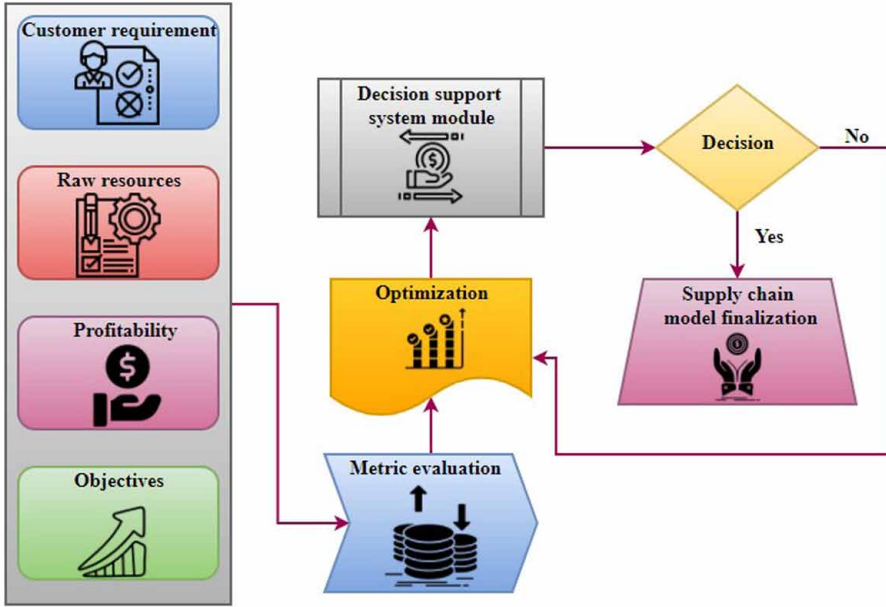


Figure 5. The proposed architecture of SSM-DSS



$$P(t) = \arg \min_i r_i * \sum_{i=1}^m [t_i * (\exp(o_i))] \quad (1)$$

As shown in equation (1)  $P(t)$  refers to the production throughput,  $t_i$  is the task function,  $o_i$  is the objective function,  $\exp(o_i)$  is the exponential objective function,  $\sum_{i=1}^m [t_i * (\exp(o_i))]$  gives the total product of the task with the objective function. The term  $\arg \min_i r_i$  gives the argument that provides minimum resources and  $m$  refers to the total number of instants.

Supply behaviour is calculated as

$$SB(t) = P(t) * \prod_{i=1}^m l_i * \left[ \|p(t) - s_i\|_2^2 + \|p(t) - d_i\|_2^2 \right] \quad (2)$$

As described in equation (2),  $SB(t)$  is the supply behaviour,  $P(t)$  is the production throughput,  $l_i$  is the looping function,  $s_i$  is the schedule function,  $d_i$  is the directional function,  $\|p(t) - s_i\|_2^2$  gives the 1-2 norm of the difference between the production throughput. And the schedule function and the term  $\|p(t) - d_i\|_2^2$  provides the 1-2 norm of the difference between the production throughput and the directions.

Simulation constraint is given by

$$SC(t) = \min_{i \geq 0} \|SB(t) - d_i\| - \frac{\max\{r_i, 0\}}{\|d_i\|_2^2} \quad (3)$$

Where  $SC(t)$  is the simulation constraint,  $SB(t)$  is the supply behaviour,  $d_i$  is the directional function,  $r_i$  is the resource function and  $\max\{r_i, 0\}$  refers to the maximum among 0 and the resource function, and the term  $\|d_i\|_2^2$  refers to the sum of the squares of the directional function.

Analytical distribution is computed as

$$A(t) = \sqrt{\frac{1}{m-1} \sum_{i=1}^m (SC(t) - SB(t)) * \exp(d_i - l_i)} \quad (4)$$

As inferred in equation (4),  $A(t)$  is the analytical distribution,  $\frac{1}{m-1}$  is the weighting factor,  $SC(t)$  is the simulation constraint,  $SB(t)$  is the supply behaviour,  $d_i$  is the directional behaviour,  $l_i$  is the looping behaviour,  $d_i - l_i$  is the difference between directions and looping function, and  $\exp(d_i - l_i)$  refers to the exponential difference between directions and looping function.

The dynamic business constraint is given by

$$DB(t) = \sum_{i=1}^m \frac{c_i * \exp(l_i)}{c_i * \exp(r_i)} * \sum_{i=1}^m \frac{o_i * \exp(s_i)}{o_i * \exp(l_i)} \quad (5)$$

As explored in equation (5),  $DB(t)$  is the dynamic business constraint,  $c_i$  is the constraint function,  $l_i$  is the looping function,  $\exp(l_i)$  is the exponential looping function,  $r_i$  is the resource function,  $\exp(r_i)$  is the exponential resource function,  $s_i$  is the scheduling constraint,  $\exp(s_i)$  is the exponential scheduling constraint,  $l_i$  is the looping function.

Volatile demand is given by

$$V(t) = \{DB(t-1) + A(t-1)\} \cup \{P(t-1) + SB(t-1)\} \quad (6)$$

As defined in equation (6),  $V(t)$  is the volatile demand,  $DB(t-1)$  is the dynamic business constraint of previous instant,  $A(t-1)$  is the analytical distribution of previous instant,  $P(t-1)$  is the production throughput of previous instant and  $SB(t-1)$  is the supply behaviour of previous instant.

Chain management is computed as

$$CM(t) = \sum_{i=1}^m \frac{[V(t) * \text{mod}(DB(t))]}{l_i} * \frac{[A(t) * \text{mod}(SC(t))]}{r_i} \quad (7)$$

As each state observation in equation (7)  $CM(t)$  is the chain management,  $V(t)$  is the volatile demand,  $DB(t)$  is the dynamic business constraint,  $\text{mod}(DB(t))$  is the modular dynamic business



constraint,  $l_i$  is the looping function,  $A(t)$  is the analytical distribution,  $SC(t)$  is the simulation constraint,  $\text{mod}(SC(t))$  is the modular simulation constraint and  $r_i$  is the resource function.

The economic decision is calculated as

$$E(t) = \{V(t-1) - A(t-1)\} \cap \{CM(t-1) - SB(t-1)\} \quad (8)$$

As denoted in equation (8),  $E(t)$  is the economic decision,  $V(t-1)$  is the volatile demand of previous instant,  $A(t-1)$  is the analytical distribution of previous instant,  $CM(t-1)$  is the chain management of previous instant and  $SB(t-1)$  refers to the supply behaviour of previous instant.

Planning demand is given by

$$PD(t) = \arg \max_i \frac{E(t) - \exp(DB(t) - CM(t))}{d_i} \quad (9)$$

As shown in equation (8),  $PD(t)$  is the planning demand,  $E(t)$  is the economic decision,  $DB(t)$  is the dynamic business constraint,  $CM(t)$  is the chain management,  $d_i$  is the directional function,  $(DB(t) - CM(t))$  is the difference between the dynamic business constraint and chain management.

The objective function for SSM-DSS is given by

$$SSM - DSS \triangleq \arg \min_i \left\| (PD(t) + E(t) + V(t)) - (CM(t) + DB(t) + A(t)) \right\|_2^2 \quad \text{subject to } t \geq 0 \quad (10)$$

As formulated in equation (9),  $SSM - DSS$  is the state-space modelling-based decision support system metric,  $PD(t)$  is the planning demand,  $E(t)$  is the economic decision,  $V(t)$  is the volatile demand,  $CM(t)$  is the chain management,  $DB(t)$  is the dynamic business constraint and  $A(t)$  is the analytical distribution.

The path diagram for the proposed state-space modelling-based decision support system metric derivation is shown in Figure 6.

Figure 6 shows the path diagram of the proposed  $SSM - DSS$  computation. In this figure,  $PD(t)$  is the planning demand,  $E(t)$  is the economic decision,  $V(t)$  is the volatile demand,  $CM(t)$  is the chain management,  $DB(t)$  is the dynamic business constraint and  $A(t)$  is the analytical distribution.

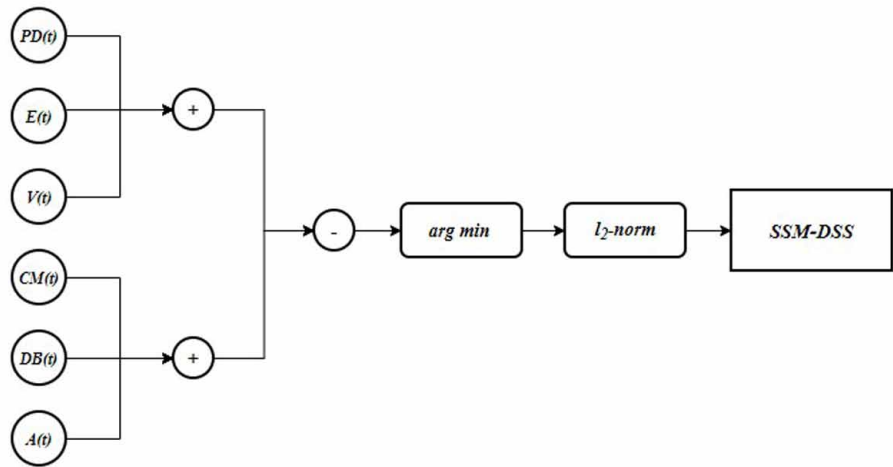
### 3.5. Advantages of the Proposed scheme

The main advantage of the proposed scheme is the optimization through state-space modelling. That is, the optimization is provided using a feedback module. It ensures that the supply chain model is finalized only when customer satisfaction is maximized. Thus, the stability of the supply chain is ensured.

## 4. RESULTS AND DISCUSSION

The proposed SSM-DSS model's numerical results have been executed based on the metrics optimization average strategic outreach, control modelling efficiency, overall profitability and highest satisfaction index.

Figure 6. Path diagram of the proposed SSM-DSS computation



#### 4.1. Performance Analysis

Metrics like strategic outreach, control modelling efficiency, overall profitability, customer satisfaction index, scheduling index, market index, delay, and optimization index have been employed for quantitative evaluation.

Table 1 shows a comparison of strategic outreach. The optimization techniques like convex optimization (COO), unconstrained optimization (UCO) and stochastic optimization (STO) were used for comparison with the proposed state-space modelling-based decision support system (SSM-DSS) optimization. Table 1 finds that the average strategic outreach of convex optimization is around 52.57%. The unconstrained optimization attains average strategic outreach of about 58.06%, and the stochastic optimization attains average strategic outreach of 53.27%. The proposed SSM-DSS

Table 1. Comparison of strategic outreach (%)

Month	Strategic outreach (%)			
	COO	UCO	STO	SSM-DSS
1	52.95	62.14	60.00	89.82
2	40.46	48.07	45.34	81.56
3	69.53	52.68	43.84	88.56
4	45.01	56.44	69.98	86.45
5	43.18	68.29	45.13	83.76
6	51.17	52.53	40.97	81.91
7	45.94	69.50	56.84	84.28
8	54.69	49.04	66.46	84.82
9	50.18	61.03	60.08	81.20
10	68.55	59.99	45.71	85.90
11	67.61	56.17	51.07	82.26
12	41.58	60.95	53.82	83.85

optimization achieves the highest average strategic outreach of about 84.53%. It is because of the application of volatile demand and planning demand in the optimization function.

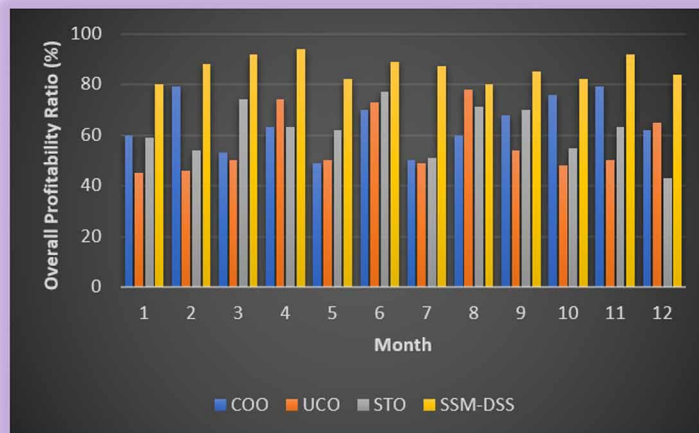
Table 2 shows the comparison of control modelling efficiency; the proposed SSM-DSS achieves the highest control modelling efficiency of 84.14%. The COO, UTO and STO achieve control modelling efficiency of around 56.21%, 51.92% and 55.14%. Thus, the proposed SSM-DSS has the highest control modelling efficiency due to the machine learning algorithm's effective implementation.

Figure 7 shows the variation of overall profitability. Figure 7 finds that the average overall profitability of convex optimization is around 64.08%. The unconstrained optimization attains average overall profitability of about 56.83%, and the stochastic optimization attains average overall

Table 2. Comparison of control modelling efficiency (%)

Month	Control modelling efficiency (%)			
	COO	UCO	STO	SSM-DSS
1	57.49	66.39	54.13	89.69
2	47.55	64.54	60.88	85.31
3	48.71	47.82	61.00	83.25
4	58.51	57.83	59.16	81.05
5	47.96	40.67	41.00	86.11
6	64.73	52.76	42.06	87.79
7	69.48	49.38	49.59	84.23
8	61.91	44.84	55.93	80.90
9	50.31	45.36	59.63	82.66
10	57.52	52.69	52.23	81.53
11	43.23	42.82	64.60	82.81
12	67.19	57.96	61.55	84.40

Figure 7. Variation of overall profitability



profitability of 61.83%. The proposed SSM-DSS optimization achieves the highest average overall profitability of about 86.25%. It is because of the usage of economic decision making in the decision support system.

Figure 8 shows the variation of the customer satisfaction index. For all 12 months, the highest satisfaction index is achieved by the proposed SSM-DSS scheme. The average value achieved is around 0.88. This value is closer to 1. It indicates that the customers achieve maximum satisfaction with the proposed system than other systems because of the simulation constraint mechanism.

Figure 9 shows the variation of the scheduling index. The scheduling index achieved for the proposed SSM-DSS scheme is 0.91. It is the only scheme that attains a scheduling mechanism greater than 0.9. All other schemes like COO, UCO and STO achieve the low average value of 0.62, 0.64 and

Figure 8. Variation of the customer satisfaction index

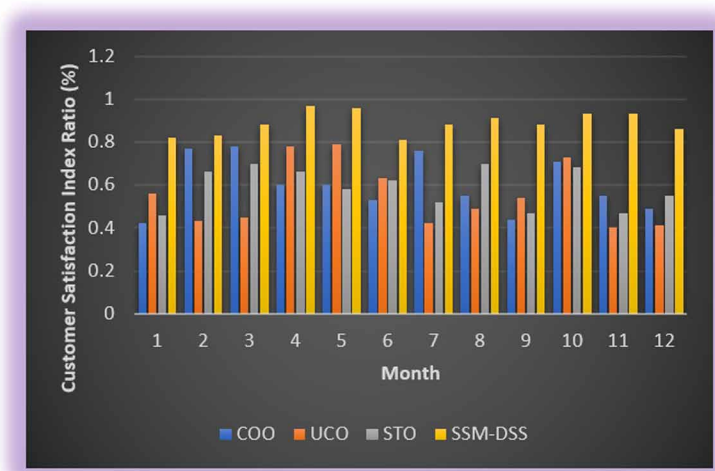
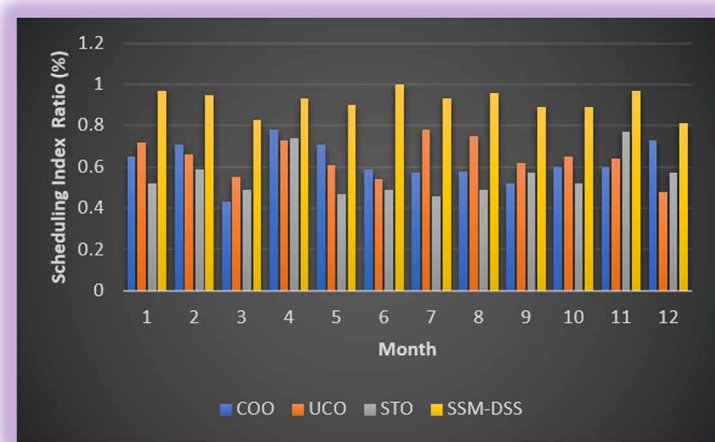


Figure 9. Variation of scheduling index



0.55, respectively. Thus, the proposed scheme is the best due to the effective scheduling mechanism used in the framework.

Figure 10 shows the variation of a market index. The market index shows the increase in market demand for a particular scheme. The proposed scheme achieves the highest market index of 0.88. This shows that the market demand is the maximum when the proposed system is implemented in real-time. Whereas other algorithms like COO,UCO and STO achieve the low average value of 0.58, 0.56 and 0.60, respectively.

Table 3 shows the comparison of tardiness. Table 3 finds that the average tardiness of convex optimization is around 58.72%. The unconstrained optimization attains average tardiness of about 54.42%, and the stochastic optimization attains an average delay of 52.76%. The proposed SSM-DSS

Figure 10. Variation of a market index

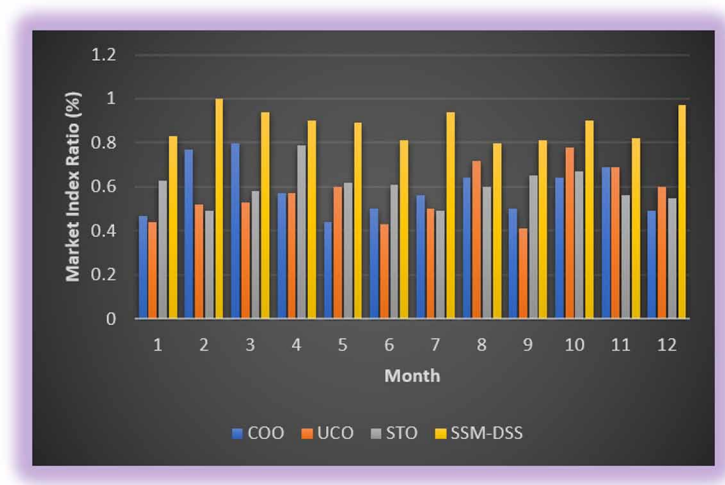


Table 3. Comparison of tardiness (%)

Month	Tardiness (%)			
	COO	UCO	STO	SSM-DSS
1	55.81	42.04	40.03	81.52
2	53.72	47.64	53.87	83.41
3	66.26	46.72	52.73	86.07
4	55.54	60.04	53.83	81.91
5	68.31	65.34	63.11	87.39
6	59.13	50.33	49.67	82.43
7	68.74	63.42	63.55	89.18
8	47.22	60.26	54.14	82.69
9	60.29	40.20	41.07	87.66
10	48.67	58.07	45.27	81.88
11	60.16	51.60	61.65	82.87
12	60.86	67.48	54.20	80.91

optimization achieves the highest average lateness of about 83.99%. The proposed SSM-DSS scheme achieves the highest tardiness as it encompasses production throughput and supply chain behaviour.

Table 4 shows a comparison of the optimization index. It gives the rate at which the DSS model is optimized. Its value ranges from 0 to 1. Our proposed system achieves the highest optimization index of 0.8808. The other models like convex optimization, unconstrained optimization and stochastic optimization achieve an optimization index of 0.632, 0.615 and 0.619. The maximum optimization is achieved due to the implementation of the feedback loop in the SSM-DSS model.

The maximum average strategic coverage has been 84.53%; control modelling efficiency seemed to be 84.14%, overall rentability is about 86.25% and the highest satisfaction index 0.88.

## 5. CONCLUSION AND FUTURE WORK

A new model for supply chain management using a decision support system was presented in this research. The decision support system was used for connecting the customers to the manufacturers based on a feedback loop to enhance the quality and sustainability of the supply chain model. The proposed model computed a novel metric called state-space modelling-based decision support system (SSM-DSS). The computed SSM-DSS metric was employed for providing suitable feedback to the optimization module. The proposed model was validated using suitable metrics like strategic outreach, control modelling efficiency, overall profitability, customer satisfaction index, scheduling index, market index, tardiness and optimization index. It was found that the proposed SSM-DSS optimization achieved the highest average strategic outreach of about 84.53%, control modelling efficiency of 84.14%, the overall profitability of about 86.25% and the highest satisfaction index of 0.88.

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Table 4. Comparison of optimization index (%)

Month	Optimization index			
	COO	UCO	STO	SSM-DSS
1	0.63	0.44	0.65	0.92
2	0.68	0.64	0.63	0.90
3	0.62	0.58	0.62	0.94
4	0.57	0.58	0.75	0.90
5	0.66	0.67	0.5	0.99
6	0.66	0.71	0.53	0.84
7	0.67	0.54	0.44	0.82
8	0.66	0.67	0.78	0.82
9	0.78	0.57	0.66	0.81
10	0.48	0.74	0.59	0.88
11	0.69	0.74	0.66	0.88
12	0.49	0.50	0.62	0.87

## REFERENCES

- Akbadian-Saravi, N., Mobini, M., & Rabbani, M. (2020). Development of a comprehensive decision support tool for strategic and tactical planning of a sustainable bioethanol supply chain: Real case study, discussions and policy implications. *Journal of Cleaner Production*, 244, 118871. doi:10.1016/j.jclepro.2019.118871
- Allaoui, H., Guo, Y., & Sarkis, J. (2019). Decision support for collaboration planning in sustainable supply chains. *Journal of Cleaner Production*, 229, 761–774. doi:10.1016/j.jclepro.2019.04.367
- Bai, C., Kusi-Sarpong, S., Badri Ahmadi, H., & Sarkis, J. (2019). Social sustainable supplier evaluation and selection: A group decision-support approach. *International Journal of Production Research*, 57(22), 7046–7067. doi:10.1080/00207543.2019.1574042
- Balaman, Ş. Y., Matopoulos, A., Wright, D. G., & Scott, J. (2016). Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production: A decision support system based on fuzzy e-constraint method. *Journal of Cleaner Production*, 172, 2594–2617. doi:10.1016/j.jclepro.2017.11.150
- Baryannis, Dani, Validi, & Antoniou. (2019). *Decision Support Systems and Artificial Intelligence in Supply Chain Risk Management*. Springer International Publishing.
- Bounif, M. E., & Bourahla, M. (2013). Decision support technique for supply chain management. *J. Comput. Inf. Technol.*, 21(4), 255–268. doi:10.2498/cit.1002172
- Centobelli, P., Cerchione, R., & Esposito, E. (2018). Aligning enterprise knowledge and knowledge management systems to improve efficiency and effectiveness performance: A three-dimensional Fuzzy-based decision support system. *Expert Systems with Applications*, 91, 107–126. doi:10.1016/j.eswa.2017.08.032
- Dellino, G., Laudadio, T., Mari, R., Mastronardi, N., & Meloni, C. (2018). A reliable decision support system for fresh food supply chain management. *International Journal of Production Research*, 56(4), 1458–1485. doi:10.1080/00207543.2017.1367106
- Dev, N. K., Shankar, R., Gupta, R., & Dong, J. (2019). Multi-criteria evaluation of real-time key performance indicators of supply chain with consideration of big data architecture. *Computers & Industrial Engineering*, 128, 1076–1087. doi:10.1016/j.cie.2018.04.012
- Fagundes, M. V. C., Teles, E. O., Vieira de Melo, S. A. B., & Freires, F. G. M. (2020). Decision-making models and support systems for supply chain risk: Literature mapping and future research agenda. *European Research on Management and Business Economics*, 26(2), 63–70. doi:10.1016/j.jedeen.2020.02.001
- Govindan, K., Mina, H., & Alavi, B. (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation Research Part E, Logistics and Transportation Review*, 138(April), 101967. doi:10.1016/j.tre.2020.101967 PMID:32382249
- Jha, A. K., Agi, M. A. N., & Ngai, E. W. T. (2020). A note on big data analytics capability development in supply chain. *Decision Support Systems*, 138(August), 113382. doi:10.1016/j.dss.2020.113382
- Joshua Jeyasekar, Arulselvi, Vedanarayanan, & Poornima. (2019). Bone cancer identification and classification using hybrid fuzzy clustering with deep learning classification. *J. Adv. Res. Dyn. Control Syst.*, 11(10), 88–98. .10.5373/JARDCS/V11SP10/20192779
- Mangla, Guest, Kusi-sarpong, & Luthra. (2019). Operational excellence for improving Sustainable Supply Chain Performance. *Resour. Conserv. Recycl.*, 142, 277–278. .10.1016/j.resconrec.2018.11.014
- Mogale, D. G., Cheikhrouhou, N., & Tiwari, M. K. (2020). Modelling of sustainable food grain supply chain distribution system: A bi-objective approach. *International Journal of Production Research*, 58(18), 5521–5544. doi:10.1080/00207543.2019.1669840
- Nunes, Causer, & Ciolkosz. (2020). Biomass for energy: A review on supply chain management models. *Renew. Sustain. Energy Rev.*, 120. .10.1016/j.rser.2019.109658
- Oger, R., Lauras, M., Montreuil, B., & Benaben, F. (2020). A decision support system for strategic supply chain capacity planning under uncertainty: Conceptual framework and experiment. *Enterprise Information Systems*, 00(00), 1–45. doi:10.1080/17517575.2020.1793390

Singh, S., Ghosh, S., Jayaram, J., & Tiwari, M. K. (2019). Enhancing supply chain resilience using ontology-based decision support system. *International Journal of Computer Integrated Manufacturing*, 32(7), 642–657. doi:10.1080/0951192X.2019.1599443

Teniwut, W. A., & Hasyim, C. L. (2020). Decision support system in supply chain: A systematic literature review. *Uncertain Supply Chain Management*, 8(1), 131–148. doi:10.5267/j.uscm.2019.7.009

Vedanarayanan, Arulselvi, Poornima, & Joshua Jeyasekar. (2020). Autonomous integrated precise medical bed (PMB) using secured IOT. *J. Adv. Res. Dyn. Control Syst.*, 12(4), 1125–1136. .10.5373/JARDCS/V12SP4/20201586

Vedanarayanan, V. (2020). *Real Time Health Remote Monitoring of Out Patients and Data Transmission Using Gsm and Iot Interface*. Academic Press.

Yildiz, K., & Ahi, M. T. (2020). Innovative decision support model for construction supply chain performance management. *Production Planning and Control*, 0(0), 1–13. doi:10.1080/09537287.2020.1837936

Zarte, M., Pechmann, A., & Nunes, I. L. (2019). Decision support systems for sustainable manufacturing surrounding the product and production life cycle – A literature review. *Journal of Cleaner Production*, 219, 336–349. doi:10.1016/j.jclepro.2019.02.092