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Analysis of the Impact of Big Data and Artificial Intelligence Technology on Supply Chain Management

Xiao Zeng [1,2,*] and Jing Yi [3]

[1] Kmitl Business School, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand
[2] Guiyang Institute of Humanities and Technology, Guiyang 550001, China
[3] School of Economics and Management, Guizhou Normal University, Guiyang 550001, China; yijing@gznu.edu.cn
* Correspondence: zengx202304@163.com

Abstract: Differentiated production and supply chain management (SCM) areas benefit from the IoT, Big Data, and the data-management capabilities of the AI paradigm. Many businesses have wondered how the arrival of AI will affect planning, organization, optimization, and logistics in the context of SCM. Information symmetry is very important here, as maintaining consistency between output and the supply chain is aided by processing and drawing insights from big data. We consider continuous (production) and discontinuous (supply chain) data to satisfy delivery needs to solve the shortage problem. Despite a surplus of output, this article addresses the voluptuous deficiency problem in supply chain administration. This research serves as an overview of AI for SCM practitioners. The report then moves into an in-depth analysis of the most recent studies on and applications of AI in the supply chain industry. This work introduces a novel approach, Incessant Data Processing (IDP), for handling harmonized data on both ends, which should reduce the risk of incorrect results. This processing technique detects shifts in the data stream and uses them to predict future suppressions of demand. Federated learning gathers and analyzes information at several points in the supply chain and is used to spot the shifts. The learning model is educated to forecast further supply chain actions in response to spikes and dips in demand. The entire procedure is simulated using IoT calculations and collected data. An improved prediction accuracy of 9.93%, a reduced analysis time of 9.19%, a reduced data error of 9.77%, and increased alterations of 10.62% are the results of the suggested method.

Keywords: big data analysis; federated learning; supply chain; sustainable production

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1. Introduction

SCM is a process that helps determine the flow of goods and services among locations and businesses. SCM also manages the storage space and the sizes of the services available in an application [1]. SCM mainly handles the entire service or production flow of goods and services provided to users. The Internet of Things (IoT) is an emerging techniques that is widely used in real-time applications to improve the overall communication and service process for users without any failure rate [2].

As the IoT and Artificial Intelligence advance rapidly, new retail has emerged as a viable alternative to the conventional shopping experience. Powered by Artificial Intelligence, big data, and other technologies, businesses can use Artificial Intelligence to learn about their customers' interests and hobbies and then apply that information to supply-chain demand forecasting, ad targeting, and product recommendations. However, data security and user privacy protection are incompatible with any organization's simple data integration. The practice of keeping private information safe often goes head-to-head with running an effective advertising campaign.

IoT-based SCM services are primarily used nowadays to provide uninterrupted services and features to users. IoT-based technologies are used in SCM to process various processes and services for users [3]. Radio Frequency Identification (RFID) is one of the

IoT technologies used in SCM to improve the efficiency and reliability of applications by providing a better service flow for users. RFID is used in SCM to obtain accurate information and details about the flow of goods and services based on specific features. RFID senses goods and services via fixed sensors on the products, helping to provide a better communication process for both the organization and consumers [4,5].

SCM plays a vital role in every company, application, and industry in obtaining accurate information about goods and services, which helps to provide better services and communication processes for users [6]. SCM manages a more significant amount of data, which helps to prevent unwanted problems and failures while providing services to users. Big data analytics is an essential technique for managing big data in various fields [7]. Big data analytics is mainly used to collect, maintain, and analyze a large amount of data, which helps to enhance the efficiency and effectiveness of the data management process. The extensive process of data analytics maintains vast data in a real-time application, helping to ensure the size and availability of storage space for further operations [8]. Big data analytics provides an exceptional, disciplined approach to managing data that helps to reduce problems and errors. Technologies for big data analytics are used in SCM to provide better accuracy rates in the service flow detection process [9]. Both methodology and strategies are improved in SCM with the help of the big data analytics process, which provides an accurate data set for the management process. The big data technique enhances the storage space, availability, processing, and management process of SCM, which helps improve the efficiency level of an application and organization [10].

Machine learning (ML) techniques are widely used in various applications and systems, helping to improve an application's overall performance and efficiency. ML techniques provide better services and experiences to users in various fields [11]. ML techniques are also used in the supply chain management (SCM) process, which is used here to avoid unwanted problems and failures while providing goods for users. Reinforcement learning algorithms are mostly used in SCM and help to improve the reliability and performance of the SCM process [12,13]. Reinforcement learning algorithms are based on specific patterns, parameters, and values, helping to reduce the failure rate in the detection process. Reinforcement learning algorithms in particular are used for SCM, which helps to improve the accuracy rate in detecting the rate of flow of goods in an application [14]. The clustering method is also used in SCM to group a particular data set for the analysis process and to produce a proper set of data for the SCM process. The clustering process uses the segmentation method, which helps classify data based on specific patterns and features. ML also provides a proper decision-making process for SCM which helps to reduce cost and time while the analysis process is performed [11,15].

With respect to Big Data, Artificial Intelligence plays a significant role in processing intelligent data that are classified based on specific features. Improving the rate of accuracy in detecting the rate of flow of goods is less of a focus. IDP is implemented to handle the harmonized data on both ends to reduce conclusive inaccuracies. The main contributions of IDP are listed below.

- The IDP processing approach recognizes changes in the data stream to produce an accurate forecast for demand suppression.
- The learning model is educated to foretell further supply chain activities based on peaks and valleys in demand. Internet of Things calculations and collected data simulate the whole procedure.
- The IDP evaluation is based on prediction accuracy, analysis time, data error, and alterations.

The rest of the paper is described as follows: in Section 2, a brief study regarding the related works is outlined, Section 3 describes the complete process of the proposed method, Section 4 provides a discussion of the evaluated parameters, and Section 5 presents the conclusion.

2. Related Works

Yang et al. [16] introduced a significant data-driven edge–cloud collaboration architecture for cloud manufacturing systems. Both edge and cloud computing systems are used in the proposed method to provide a better data management process for the analysis process. The proposed method increases the optimization and accuracy rate in the analysis process. Experimental results show that the proposed method increases the efficiency and effectiveness of the system by providing better services to the users.

Jiang et al. [17] proposed a smart-contract-based data transaction method for the Industrial Internet of Things (IIoT). The proposed method is used for data packet transactions, and the data analytics service is a transaction process in IIoT. The smart-contract-based data transaction method improves the efficiency and security of the system. Compared with other methods, the proposed method increases the overall performance and feasibility of the system by providing an accurate analysis process.

Kazancoglu et al. [18] proposed a fuzzy-based hybrid decision framework for dairy supply chains using big data solutions. The proposed method determines the classification among the data based on certain ranking and matching features. The fuzzy technique is used here to improve the accuracy rate in the classification process. The supply chain management system plays a vital role in the proposed method in obtaining appropriate information about every service. Experimental results show that the proposed method increases the overall performance and efficiency of the system.

Wang et al. [19] introduced a hybrid big data analytical approach using an integrated supply chain for the customer pattern analysis process. The k-means clustering approach is used here to fetch and divide data based on certain features and patterns. The proposed method provides better strategies for users to obtain appropriate services from the organization. Experimental results show that the proposed method increases the efficiency and reliability of the system by providing better services to its users.

Zhan et al. [20] proposed an analytic infrastructure for supply chain management (SCM) systems using big data. The big data analytics process is used here to obtain related data, which helps enhance SCM's performance. Supply chain strategies are used in the proposed method to obtain roadmaps and firms' information for the analysis process. The big data analysis process provides various ideas and approaches for the system, which helps to improve the system's overall performance rate and effectiveness.

Nawaz et al. [21] introduced a predictive complex event processing (CEP) and reasoning method for Internet of Things (IoT)-based supply chain management (SCM). The proposed method uses the CEP approach to provide an accurate data set for a different management system, which helps to increase the system's efficiency. Probabilistic and logical reasoning methods are implemented in the proposed approach to obtain feasible solutions. Experimental results show that the proposed method improves the overall performance and reliability of SCM.

Sathyan et al. [22] proposed an analysis method combining fuzzy and big data analytics approaches for the automotive supply chain. A fuzzy decision-making trial and evaluation laboratory (DEMATEL) approach is used in the proposed method to obtain reliable information for the analysis process. The proposed method increases the accuracy rate in the detection process, which helps improve users' safety. Compared with other methods, the proposed analysis process enhances the efficiency and effectiveness of the supply chain system by providing accurate services to the users.

Wang et al. [23] introduced a new Internet of Things (IoT)-based supply-chain financial-risk-management model for supply chain management (SCM). The proposed method is mainly used for financial risk management processes which help to enhance the security and privacy of users from attackers. The proposed is also used to reduce data loss and storage space, helping to enhance the system's overall efficiency. Experimental results show that the proposed method increases the system's overall performance by providing a better analysis process.

Tamym et al. [24] proposed a big-data-based architecture method for supply chain networks. The big data analysis process increases the accuracy rate in the detection and analysis process, which provides uninterrupted services to its users. The proposed method provides better supply chain networks for the organization and application. Experimental results show that the proposed method increases the system's security, feasibility, and efficiency, which helps enhance the network's overall performance.

Kousiouris et al. [25] introduced a microservice-based framework for Internet of Things (IoT)-based supply chain management (SCM). The proposed method is primarily used in online and real-time applications that provide users with better services and communication processes. The proposed framework increases the system's overall performance and efficiency compared with other methods.

Bag et al. [26] proposed a new big data analytics (BDA) process for supply chain management (SCM). The proposed BDA method improves the overall management process of the system by providing more efficient and effective services to the users. The proposed method offers sustainable outcomes for the supply chain management process, which helps to enhance the capabilities of SCM. Experimental results show that the proposed method increases the overall performance and reliability of SCM by reducing the computation cost and energy consumption rate.

Choi et al. [27] introduced a circular supply chain management (CSCM) method for supply chain management (SCM). The proposed CSCM uses a macro–micro model in SCM to provide better communication and data management processes based on an extensive data analysis. The proposed method uses a large-scale group decision-making process to obtain appropriate services for users. The proposed method increases the overall performance and feasibility of SCM compared with other methods.

Munuzuri et al. [28] introduced a new Internet of Things (IoT) approach for port-based intermodal supply chain systems. The proposed method is used to manage a large amount of data with the help of an extensive data analysis process which helps to enhance the efficiency of the supply chain management system. The proposed method also tracks and detects information about the flow of goods and services provided to users.

Zhang et al. [29] have proposed a new data analytics process to enhance forest and biomass in biomass SCM. The enhancement of a forest is analyzed based on specific frameworks and tools, helping to provide a proper data set for the analysis process. Experimental results show that the proposed method increases the overall performance and efficiency of the system compared to other traditional methods.

M.M. Mansour et al. [30] introduced two-parameter Burr XII allocation. The new density distribution might be symmetric, right-skewed, left-skewed, or unimodal. The new failure rate has three possible trends: declining, uniform, and rising. We derive the properties of the revised model.

Narjes Mohammadi et al. [31] employed a range directional model (RDM) for optimal computation while dealing with negative data and a special instance of the directional distance function. A Malmquist-type index is derived using RDM efficiency measurements that can capture productivity shifts.

Alessia Munnia et al. [32] demonstrated how deploying blockchain technology improves trust and stability among logistic and supply chain operators and enterprises through creating and distributing shared value.

Smail Benzidia et al. [33] showed that environmental efficiency improved when businesses worked together on green supply chains and integrated ecological processes. A significant finding that has not been addressed in existing research is that sustainable digital learning moderates the connections between Big Data, Artificial Intelligence, and green supply chain interactions.

Efpraxia D. Zamani et al. [34] performed a comprehensive literature evaluation, examining Big Data Analytics–Artificial Intelligence research studies on supply chain robustness that were published in Chartered Association of Business Schools (CABS)-listed journals over 2011 and 2021; we aggregated and synthesized this scattered information. Thanks to the search method, 522 studies were found; however, only 23 were considered primary publications for this study.

Veronica Scuotto et al. [35,36] offered suggestions for improving chief information officers (CIOs), focusing on the impact of the micro-level in preventing disruptive technologies and maximizing expenditures in technological development and research at small- and medium-sized enterprises (SMEs).

Fetching data employing K-means clustering provides fewer services to the efficiently engaging users. The major drawback in the architecture of Big Data is its overall security, feasibility, and efficiency for detecting and analyzing big data from supply chain networks to enhance the services provided to users. The efficiency of maintaining the management process needs to be more effective to provide services to users. The overall problems need to be managed well via the implementation of IDP.

3. The Proposed Incessant Data Processing Method

SCM is all about expanding, designing, implementing, and keeping track of supply chain activities with the help of information and technology. If SCM is to succeed, it is necessary to ensure that information is symmetrical at every stage of the supply chain, from the procurement of raw materials to the transportation of finished products. Machine learning (ML) systems and neural networks can also significantly benefit supply chain management. The bullwhip effect can be anticipated with the help of methods like linear regression. Lead scoring using decision trees or a random forest can help supply chain managers prioritize their efforts. SCM uses Big Data and AI for lead-time planning and analyses of audio and video conversations between buyers and sellers. Machine learning and SCM go hand in hand in optimizing the distribution of goods and services. Time and materials can be spared if these techniques are used effectively. In particular, the scheduling process can profit from the widespread usage and extension of established statistical approaches via ML. AI has a significant benefit over conventional methods, especially for nonlinear issues. Despite the apparent advantages, according to a recent survey, only 15% of businesses used ML for at least one supply chain activity. This could be due to a lack of information or general unfamiliarity with the topic. These advancements in technology have an impact on human deployment, as well as the management of supplies and purchases [37].

The proposed IDP method is designed to improve the production, supply chain management, and the accuracy of predicting the production of surplus for any smart product factory. In the smart industry, the data processing model provides control by assimilating hardware and software and then provides computational abilities based on the circulation of products and the demand for any product and its operations. The proposed method of IDP, which is based on an IoT platform, intelligent data management processing, is designed to regulate the functions of the production management system employed in the smart industry. The proposed IDP method is illustrated in Figure 1.

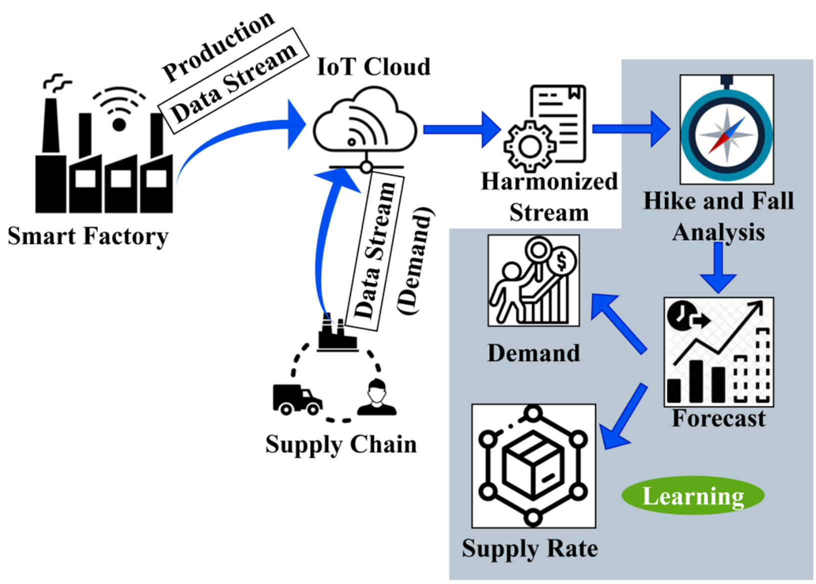

Figure 1. IDP method in a smart factory and SCM.

The proposed IDP method defines any product's production and supply chain to ensure better prediction accuracy in the smart industry. The influencing consecutive supply chain factors, such as increases and decreases in product demand falls, are supported by the product circulation process in a balanced manner. This ensures a harmonized stream of data and a solution for verifying the supply rate for IoT-based smart supply chain management. The demand and supply process differs from cumulative production and discrete supply-chain-based solutions. On an IoT platform, Big Data and smart industry data streams with respect to production and demand communicate through the IoT environment. Therefore, these data streams are responsible for balancing the production of and demand for products with the analysis of time and an errorless data process. This balance is modeled for the accumulated data prediction of the smart industry. The analysis of the increases and decreases in a product's demand and supply rate is reliable for other products within different supply chain intervals (Figure 1). Based on these alternations, in an intelligent industry environment, demand and production consist of D and P. Product circulations meet the delivery demands of suppliers (vendors) and customers through the production of surplus in the supply chain, with the aid of product demands. Let P_R represent the products consisting of N supply chains that are to be distributed for the available data streams D_{S1} performing computations. Initially, the supply chain S_P generates data streams as shown in Equation (1a–c).

$$\left.\begin{array}{c} D_{S1} = S_P[S_P(P_{R1} \oplus D_1)] \\ D_{S2} = S_P[S_P(P_{R2} \oplus D_2)] \end{array}\right\} \tag{1a}$$

For the consecutive supply chain,

$$D_{SN} = S_P[S_P(P_{RN} \oplus D_N)] \tag{1b}$$

Such that

$$\left.\begin{array}{c} I_\Delta = \sum_{i=1}^{SN} I_{D_i} - \left(1 - \frac{I_i}{I_P}\right) \\ \forall\ N = SN \ or\ N < SN \\ and\ N\ Data\ Stream\ \ of\ I_\Delta \end{array}\right\} \tag{1c}$$

In Equation (1a,b), $S_P[.]$ is the supply chain, P_p denotes the production of products, and D_d is the demand in the smart industry. D_{S1} and D_{S2} represent the data streams, S_P denotes the supply chain, P_{R1} and P_{R2} represent the number of products with the number N of supply chains, and D_1 and D_2 represent several demands in the smart industry. D_{SN} represents the number N of data streams. D_N represent the number of computations. Where the variable I_Δ is the supply chain interval for filling SN with D_S, I_D is the random number generating the data stream, and I_P is the total time interval for filling S_P. In Equation (1c) above, the constraint of $N \leq SN$ is to be achieved for all N that are analyzed in the time interval I_Δ, i.e., the analysis time provided time intervals $t_i > I_\Delta$. The smart factory vendor and customer use their production and demand data streams to meet the delivery demand [38]. These production circulations and demand are imposed to reduce the conclusive inaccuracies performed over the IoT during harmonized stream transmission. in the analysis, the increase and decrease in production and fall analysis are identified using federated learning prediction balances. The data streams are able to handle the harmonized data on both ends with the additional D_{SN}, depending on the alternations A_L in the data streams, which are denoted as

$$A_L(D_{SN}) = S_P[H_S \| D_{SN}]\ \forall\ H_S \in N \leq SN\ and\ D_{SN} \in I_\Delta < t_i \tag{2}$$

The production harmonized stream analysis (H_S) is prominent in handling the identification of spikes and decreases in production with the help of alternations in data streams. As per Equation (2), eligible data stream products are assigned for the harmonized streams to forecast alternating data streams. In this demand and supply rate-assigning process, if $N < SN$, then P_{RN}. Therefore, the remaining D_S is used for the successive harmonized streams requesting production and demand identification. The assignment of D_S follows an altered federated learning process. This process uses cumulative (production) and discrete (supply chain) data based on customer delivery demands. These processes meet the conditions $N > SN$ and $N \leq SN$. The case $N < SN$ is designed as a consecutive chained operation for predicting the harmonized stream D_{SN} based on t_i. The construction of IoT and data streams is altered for all the cases and follows cumulative productions and discrete supply-chain-assignment processes. The prediction process is the same for all the various streams' assignments of N and t_i. The prediction-balancing process is illustrated in Figure 2.

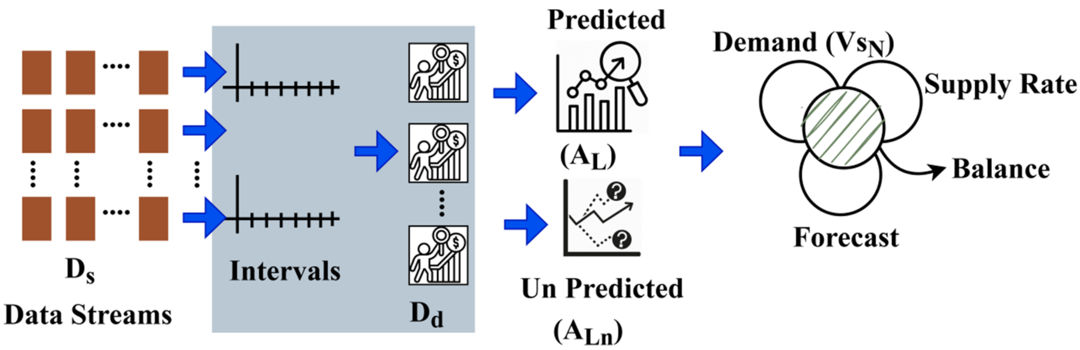

Figure 2. Prediction-balancing process.

The input D_s is classified based on different I_Δ values for D_d identifications from which the forecast is detected. In the forecast classification, A_L and A_{L_n} are identified $\forall$ P_R and S_P such that $1 \leq N < SN$ is satisfied. Therefore, the demand, supply, and forecast are balanced for two conditions:, i.e., $N < SN$ and $N > SN$. This is analyzed based on the D_d and I_Δ for retaining the balance $\forall$ D_S that generates D_d (Figure 2). The prediction-balancing process for the above cases is discussed in the following sessions.

Case 1: The count of H_S is less than the generated data streams, i.e., $N < SN$.

Solution 1: The roles of product production and vendor demand makes them reliable for reducing the chances of deficiency problems without increasing errors and alternations in the data. The streams stored in this process are reused for the supply chain interval assignment and the consecutive prediction of the harmonized stream data, where D_{SN}, the assignment, is identified in less analysis time. Let $N < SN$ such that $\frac{SN}{N}$ = even or odd, for which the data stream assignment is illustrated. Even odd cases are mentioned in this process, with the analysis of spikes and decreases during the demand for and production of products. The spike is denoted by an even number, and a decrease is denoted by an odd number. The demand and production ranges vary based on the harmonized data streams in the smart industry. Alternations in the data streams are identified using federated learning. The trained supply chain is processed sequentially with different time intervals from these spikes and decreases in demand.

The following levels forecast sustainable production in the successive prediction process. In both cases of $\frac{SN}{N}$ = even or odd, the consequence of A_L depends on the forecasting (F_c) and the sequential supply chain of S_0. This consecutive process is estimated as $\left(\frac{F_c - A_L}{S_0} + 1\right)$, where S_o is the discrete supply chain value of the root data stream D_{SN}, i.e., the prediction identification. Now, when $\forall$ $1 \leq N < SN$, the demand D_d can be computed as follows:

$$[A_L(D_{SN}).S_0] \times \left[|D_{dSN}|\frac{1}{N - SN}\|V_{SN}\right] = [(|D_d| \times A_{LN-SN}) \oplus U_{SN}] \tag{3}$$

Here, the count of D_d is reduced to D_n, where $n = \left(\frac{(F_c - A_L)}{|S|+1}\right)$; hence,

$$[A_{LN-SN} \cdot S_0]\left[|D_{dN-SN}|\frac{1}{N - SN} + V_{N-SN_n}\right] = [|D_{dN-SN}| * A_{Ln} \oplus U_{N-SN_n}] \tag{4}$$

From the computation of the demand and supply rate prediction in Equation (4), U and V are are random integers, and S_0 represents the supply rate employed by the data streams that serve as the root of. The output of $D_S(.)$, D_{S1}, $D_{S2}, \ldots D_{SN}$, is assigned for the productions $P_c \in \{1, 2, \ldots SN \text{ or } N\}$. The alternations in $P_c = \{1 \text{ to } N - SN\}$ are transmitted. The above computation assists in predicting the sequence of data stream distributions without assigning all the generated SN values to the available N. Hence, an additional evaluation on $(SN - N)$ is not required, whereas the balanced sequence is to be required in the case of $\frac{SN}{N} = \text{odd}$. The resulting output of the prediction instance must be followed from $D_S(1,\ SN - N)$ such that there is no entry of the supply rate SR. On the other side, the prediction is different for the case in which $\frac{SN}{N} = \text{even}$. Therefore, $n - 2(SN - N)$ is considered for predictions of spikes and decreases in demand. This prediction sequence is provided in Equation (5).

$$\left.\begin{array}{c} [A_L(D_{SN}) \cdot S_0] \times \left[D_n \frac{1}{n} \| \oplus V_{SN}\right] = [|D_{SN}| A_{Ln} \oplus U_{SN} \oplus V_{SN}] \\ [A_{Ln} S_0] \times \left[D_n \frac{1}{n} \| \oplus V_{SN}\right] = [|D_n| A_{Ln} \oplus U_{SN} \oplus V_{SN}] \end{array}\right\} \quad (5)$$

Is the least possible estimation obtained for $(SN - N)$ data streams assigned in the above sequence? Therefore, the estimations do not need be complete for both $S = \{\ 0 \text{ to } A_L - N\}$ and $S = \{0 \text{ to } N\}$. The condition $N < SN$ is considered for increasing the forecasting rate with fewer data errors.

Case 2: The supply chain is insufficient for meeting the available customers' delivery demand, i.e., $N < SN$.

Solution 2: In this analysis process, the preference for the supply chain is initiated from $(SN - N)$ or from $S = \{0 \text{ to } N\}$. The condition of $S = \{0 \text{ to } N\}$ is the same as that of an idle case, whereas the initial data streams from $(SN - N)$ or from $S = \{0 \text{ to } N\}$ to the successive production of N data streams and the demand from the vendor. The representation of $N > SN$ obtains two types of forecasting. This consecutive process is obtained to proceed with the sequential prediction without needing more complex estimations. Hence, a complete set of data stream predictions is provided for the different vendors. Here, t_i and I_Δ are the metrics considered. If t_i is estimated in different supply chain intervals for the first instance of $(SN - N)$, then the interval I_Δ is aided to serve input as $S = \{0 \text{ to } N\}$ or $S = \{0 \text{ to } A_L - N\}$. The sequential prediction is initiated from the interval $(t_i - I_\Delta)$; therefore, the prediction is presented from $(t_i - I_\Delta)$, and t_i is given as

$$[D_S(SN - N) \times S_0 |D_{n-SN}|] \| [A_{LSN-N-1} * F_c * P_{N-SN-1} |D_{n-SN}], \ \forall\, t_i \geq I_\Delta \ and \ n - SN \neq 0 \quad (6)$$

Similarly,

$$\left.\begin{array}{c} [D_{S1} \times S_0 |D_{n-SN}|] \| [A_{Ln-SN} * F_c * P_{n-SN}] = [U_{SN} \oplus V_{SN}] \| A_{Ln-N}\ D_{n-N-1} \left| P_{p-n} \right| \\ \vdots \\ [D_{SN} \times S_0 |D_S|] \| [A_{Ln}\ F_c\ P_n] = [[U_{SN} \oplus V_{SN}] \| A_{Ln-N}\ D_{n-N-1} \left| P_{p-n} \right] \end{array}\right\} \quad (7)$$

In this consecutive manner of prediction in a supply chain interval, as differentiated by the above-mentioned instances of t_i and I_Δ, the alternations between the cases are maintained and controlled by assigning consecutive $A_L(D_{SN})$ values such that $A_{Ln-N} = A_{Ln-SN-1}\ \forall\, t_{i+1} = (t_i - I_\Delta + 1)$, reducing the additional computations in the process.

After the smart industry's hike and fall analysis of data streams, forecasting for inaccuracies is performed at the customer (receiver) end. The IoT cloud is a large data center that serves as a platform for various IoT services. Symmetry is very important. The servers and storage media that are essential for ongoing operations and real-time data processing fall under this category [39]. It ensures alternating streams and product supply between the vendor and customer without excess demand. The learning process for the joint solutions 1 and 2 is illustrated in Figure 3.

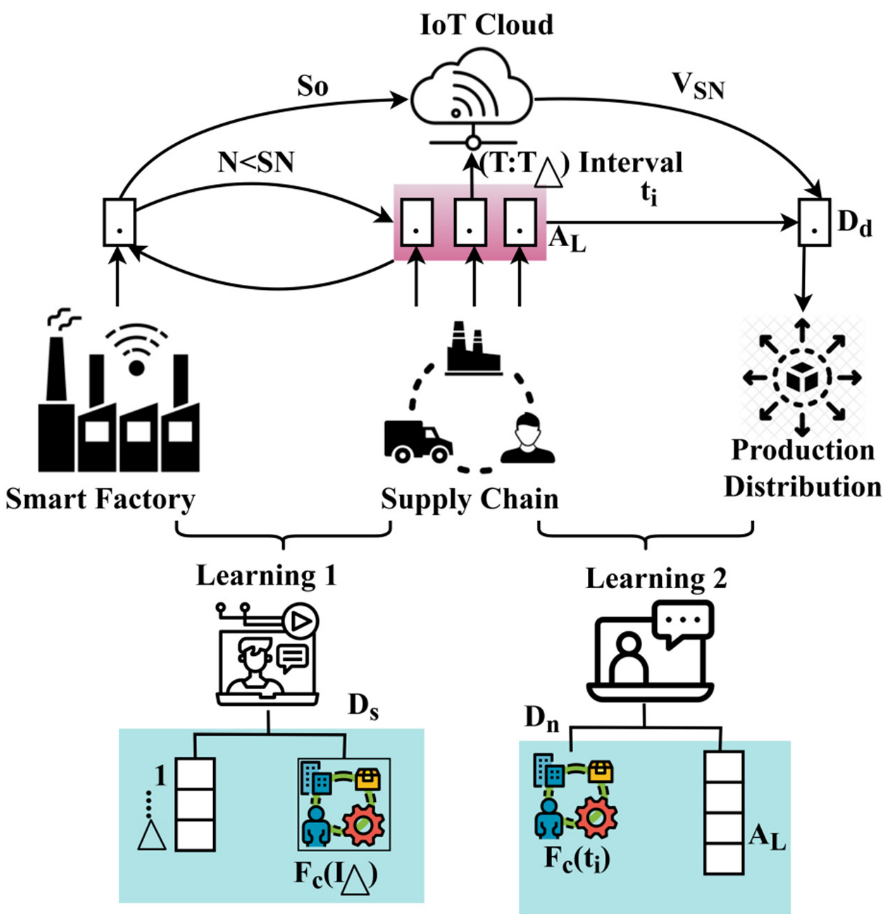

Figure 3. Learning process for Solutions 1 and 2.

Forecasting

As per the two cases discussed, the instances of forecasting are performed unanimously. In this analysis, the metrics $A_L(D_{SN})$ and S instances are predicted other than the product demand (V_{SN}) and supply rate (U_{SN}) on the customer side. Let $F_c(I_\Delta)$ and $F_c(t_i)$ be the two cumulative and distinct functions designed based on supply chain intervals that are computed as

$$\left.\begin{array}{c} F_c(I_\Delta) = \{0,1\}^n = \{0,1\}^{SN+\log|SN|-1}\ \forall\ n \leq SN \\ and \\ F_c(t_i) = \{0,1\}^{n-SN} \oplus \{0,1\}^n \end{array}\right\} \tag{8}$$

In Equation (8), the precise forecast for demand suppression based on the supply chain interval t_i, and the I_Δ value for the customer data stream instance is determined such that if x is the customer instance; thus, the forecasting is performed as follows:

$$\left.\begin{array}{c} \{D_{n1}, D_{n2}, \ldots D_{SN}\} = \{x_1, x_2, \ldots x_n\}\ \forall\ N \leq SN \\ else \\ \{D_{n1}, D_{n2}, \ldots D_{SN-n}\} \oplus \{D_{SN-n+1},\ D_{SN-n+2}, \ldots, D_{SN}\} = \{x_1, x_2, \ldots, x_{SN-n}\} \oplus \{x_1, x_2, \ldots, x_n\} \end{array}\right\} \tag{9}$$

The model for forecasting the demand and supply rate of products is designed as in Equation (10) for the above instance and is given as

$$\left.\begin{array}{c} D_n \leftarrow y \in F_c(I_\Delta) \\ and \\ [D_{SN} \times S_0|P_{SN}|]||[A_L(D_{SN})S_nF_c|P_{SN}|]||[A_L(D_{SN})A_{Ln}|P_{SN}|] = \left[D_{S1}(n,\ P_{SN}), \ldots, D_{S\log|n|}(n, P_{SN})\right] \end{array}\right\} \tag{10}$$

Such that

$$D_{SN}(n,\ P_{SN}) := \left(\sum_{i=1}^{n} A_{Li}|y_n|_i\right) \forall\, n \le i \log|P_{SN}| \tag{11}$$

The above forecasting is computed following the function of $F_c(I_\Delta)$ provided, which is the consequence of $x_n \le N$. If this forecasting exceeds the analysis time, then $F_c(t_i)$ is employed such that

$$\left.\begin{array}{l} [D_{SN}(SN-n) \times S_0|P_{SN}-N|]\|[A_{LSN-N-1}F_c|P_{n-SN}|] \oplus [D_{SN}S_0|P_{SN}|]\|[A_{Ln}\ F_c\ D_S] = \\ \left[D_{S1}(n,x),\ldots,\ D_{S\log|SN-n|}(SN-N,y)\right] \oplus \left[D_{S\log(SN-N+1)}(SN,y),\ldots,D_{S\log|n|}(n,x)\right] \end{array}\right\} \tag{12a}$$

From the above estimation, the forecasting process is illustrated in Figure 4.

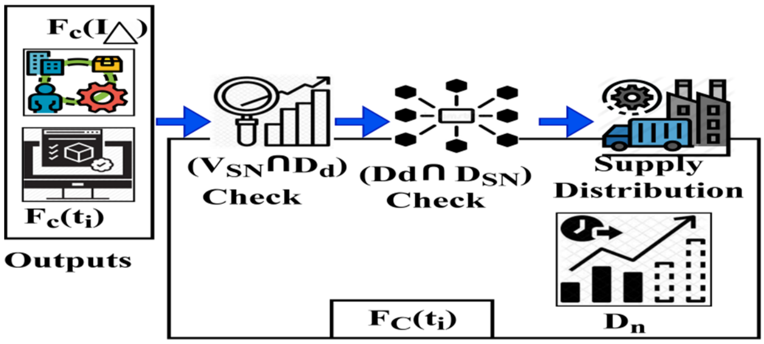

Figure 4. Forecasting process.

The classified $F_C(I_\Delta)$ and $F_C(t_i)$ are distinguished from the learning outputs. The process further includes $(V_{SN} \cap D_d)$ and $(D_d \cap D_{SN})$ estimations and verifications of the supply distribution and forecast. The forecast information is required for $F_c(t_i)$ to improve the production and supply chain requirements. From the precise forecasting of the case $n < SN$, the prediction is performed as follows:

$$[A_L(D_{SN})S_0]\left[\frac{|P_{N-x}|1}{SN} - n \,\|\oplus V_{SN}\right] = \left[D_{S1}(N,P_{SN}),\ldots,D_{S\log|SN-N|}(n,P_{SN})\right] \tag{13}$$

where the RHS of the above computations is predicted with either $F_c(t_i)$ value. Because this forecasting process serves as the midpoint of the consequence dividend, i.e., $x = \{1 \text{ to } N-SN\}$ and $x = \{N-SN \text{ to } n\}$, the $F_c(I_\Delta)$ demand is given as $x_{SN-N} \oplus F_c(t_i)D_{SN-N}(n-SN,\ P_n)]$ or $x_n \oplus F_c(t_i)D_{SN}(SN, D_{SN})]$, which is the predicting instance. The prediction is performed for a specific concern for any product receiving the data streams, obtaining no additional data errors and analysis time. This sequential smart supply chain management process increases prediction accuracy and demand suppression. In Figure 5, the D_d-indifferent I_Δ and D_s values are analyzed.

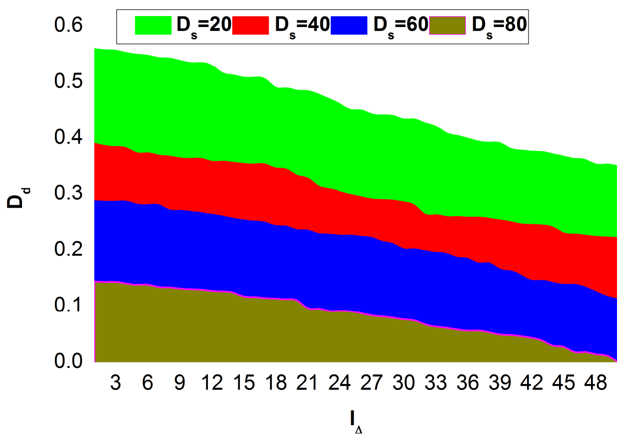

Figure 5. D_d for different I_Δ.

Figure 5 presents the D_d values observed for different D_S and I_Δ values. In the proposed method, D_d is reduced for increasing intervals through learning identifiers in $(t_i - I_\Delta)$ and $(A_{L_n}S_o)$. This is performed for different D_s for identifying A_L(if any) and reductions in D_n. Based on the prediction sequences of the $F_C(I_\Delta)$ and $F_C(t_i)$ functions, the demand requirements are satisfied. Here, the conditions are forecasted through $F_c(t_i)$, as in the $\forall\, n < SN$ condition for Equation (12a). This improves data utilization in S_p management with fewer alterations. Figure 6 presents the sequences observed under different I_Δ values and conditions.

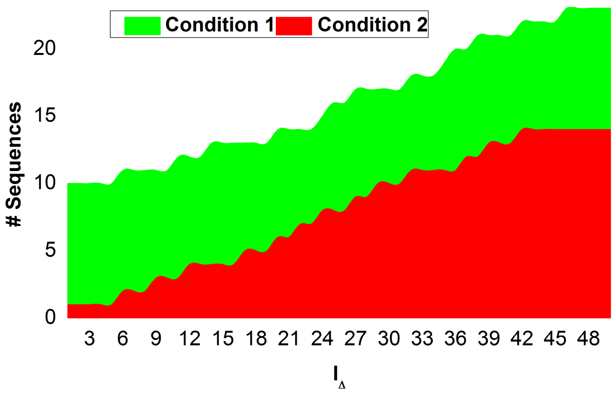

Figure 6. Sequences under different $I_\Delta$values.

An analysis of the different sequences under varying values of I_Δ and two different conditions are presented in Figure 6. In the above Figure, the conditions $N > SN$ and $N < SN$ are considered. Based on the assessment, the proposed method identifies the increases and decreases in V_{SN} such that $A_L(D_{SN})$ is required post $F_C(I_\Delta)$ and $F_c(t_i)$. Depending on the learning process, supply rate, and sequences, the second is due to D_n. The analyses for D_n and A_L for different predictions and factors are presented in Figure 7.

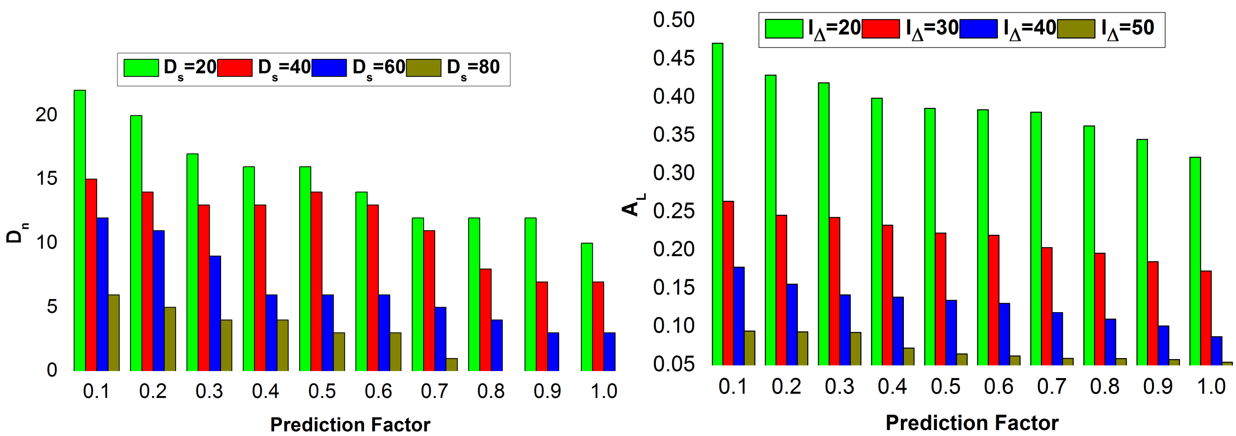

Figure 7. D_n and A_L for different prediction factors.

Figure 7 presents the analysis of the D_n and A_L required for varying prediction factors under D_S and I_Δ. This is performed if the values from D_d and D_{n1} to D_{SN} vary due to $\{A_L \Delta S_o\}$ and $\{A_{L_n}\ S_o\}$. In this process, instead of A_L, reductions from D_d to D_n are performed. This has been accomplished in past differentiations of $F_c(I_\Delta)$ and $F_c(t_i)$. Contrarily, A_L is required if $D_d \oplus D_{n1}$ to D_{SN} and V_{SN} is not satisfied from D_n. In this case, the consecutive alteration requires $\{A_L \Delta S_o\}\forall\, D_S$ and $\{A_{Ln} \Delta S_o\}\ \forall\, I_\Delta$. The processes are distinct for meeting the demands; hence, the S_p is retained with better accuracy. The errors observed for different D_s values due to A_L and V_{SN} are shown in Table 1.

Table 1. Errors observed in different D_s values.

D_s	V_{SN}	A_L	Prediction Factor	Error
10	0.12	0.064	0.16	−0.18
20	0.23	0.078	0.25	−0.16
30	0.45	0.102	0.41	−0.14
40	0.36	0.098	0.36	−0.157
50	0.58	0.21	0.54	0.16
60	0.64	0.341	0.69	0.32
70	0.68	0.428	0.72	0.25
80	0.71	0.48	0.89	0.3

For different $D_s$values, the prediction errors due to V_{SN} and A_L are presented in Table 1. The P_p, P_r, and D_d information is fetched from the data source for which the forecast of V_{SN} is estimated using IDP. Based on the analysis, using $F_c(I_\Delta)$ and $F_c(t_i)$, the predictions $\{A_L \Delta\ S_o\}$ and $\{A_{L_n}\ S_o\}\}\ \in (t_i - t_\Delta)$ are estimated. The prediction outputs are handled under D_{SN} $(n,\ P_{SN})$ such that $n < SN$ in $(N < SN)$ or $(N > SN\ )$ is detected. In this detection, $\forall\ D_d \in 1 \le N < SN$; the A_L is less, and hence the error is less (negative). Contrarily, if D_d is classified under $F_C(t_i)$, then the A_L requirements are high, and the error of D_n is therefore high. This is suppressed through consecutive sequence predictions such that D_s is completely utilized for further D_n.

4. Results and Discussion

The performance of the proposed method is analyzed using the Weka tool and the data source [40]. This data source contains 23 fields related to production, forecast, supply, and sales. The input is classified into a maximum of 80 streams and 16 sequences for analysis. The sales forecast is based on production, supply, and distribution field data using an eight-column training data source. Based on this setup, the accuracy of the metrics predictions, analysis time, data errors, alterations, and demand suppression are analyzed. In the comparative analysis, the existing methods, PERCEPTUS [21], PLS-SEM [26], and MSF [25], are considered.

4.1. Prediction Accuracy

In Figure 8, the data stream productions and the analysis of the increase and decrease in demand for cumulative and discrete data do not provide supply chain management between the vendors and customers in different intervals. The harmonized-stream demand and supply rate from the previous prediction and the delivery demands are not met due to data errors based on the analysis time and demand suppression computations for both case 1 and case 2 in different accumulated data sets from the smart industry. This deficiency problem is addressed by using a data stream production analysis based on $N > SN$ and $N \le SN$ which satisfies successive production to the supply chain, preventing $\frac{SN}{N}$ = even or odd; therefore, further supply chain management processes are not predicted, and reliable predictions are not provided. Both cases satisfy the need for high prediction accuracy that the smart industry demands, and a production analysis is forecasted based on the delivery demands. Therefore, a high level of success in IoT computations is observed with consecutive data streams, with comparatively fewer data errors and a shorter analysis time. Thus, the discrete supply chain is reduced, preventing high prediction accuracy due to increases and decreases in demand rates.

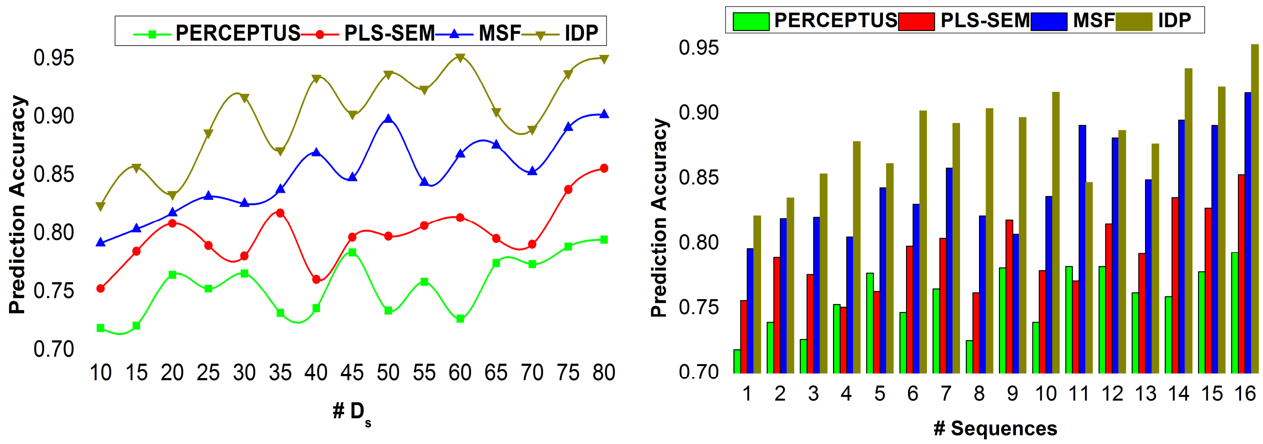

Figure 8. Prediction accuracy.

4.2. Analysis Time

For the proposed model, the analysis time and the data errors of the smart supply chain management prediction are fewer as the model does not provide data stream analyses or processing between smart industry and IoT platforms. The production- and demand-based data stream required from the previous production observation and the predictions of increases and decreases in the rate of demand based on product availability and analysis time estimations for both the cases $S = \{0 \text{ to } N\}$ and $S = \{0 \text{ to } A_L - N\}$ are obtained in a consecutive manner for different supply chain intervals. This data suppression is addressed by using a harmonized stream analysis based on $(t_i - I_\Delta)$ and t_i in previous predictions and forecasts, preventing data errors. The two cases are analyzed and processed based on the smart industry product demand and supply rate, which are based on the production of surplus, providing different intervals for cumulative production and a discrete supply chain of altered data streams in autonomous supply chain management. The discrete supply chain is computed for harmonized data on both ends and meets the delivery demands, preventing an increase in analysis time and computational complexities. The cumulative smart industry product production is processed for both cases for which the proposed model satisfies the need for a shorter analysis time, as presented in Figure 9.

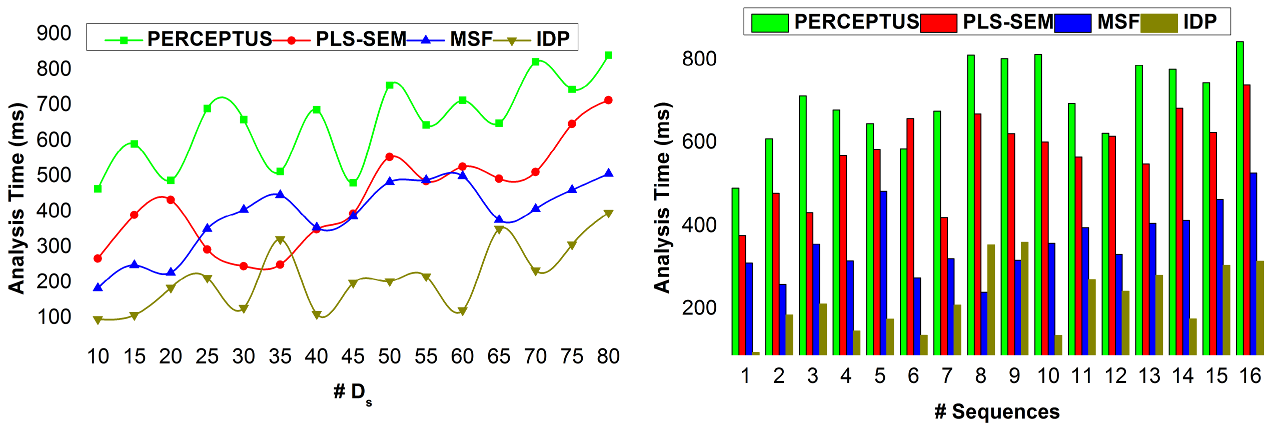

Figure 9. Analysis time.

4.3. Data Errors

The deficiency problem and the demand suppression identification process for data errors are presented in Figure 10. This proposed model satisfies the requirement for fewer data errors by estimating the surplus production. In this smart supply chain management, different intervals, $N > SN$ and $N \leq SN$, are analyzed based on any products in the smart industry. The harmonized streams for alleviating the supply chain depend upon the two cases, the group of productions and the production of a distinct supply chain, wherein the analysis of different increases and decreases is preceded using the estimations in Equations (5)–(7). In this proposed model, the two cases' product demand and supply rate prediction conditions are processed and computed to further decide on delivery demands. This sequential process prevents different demands and productions under distinct supply chain intervals (as in Equation (10)) and the alternations in data streams under cumulative data productions. Hence, there are far fewer errors in the data than other factors observed in the smart industry. The data errors are estimated for different vendors and customers based on consecutive supply chain proceedings.

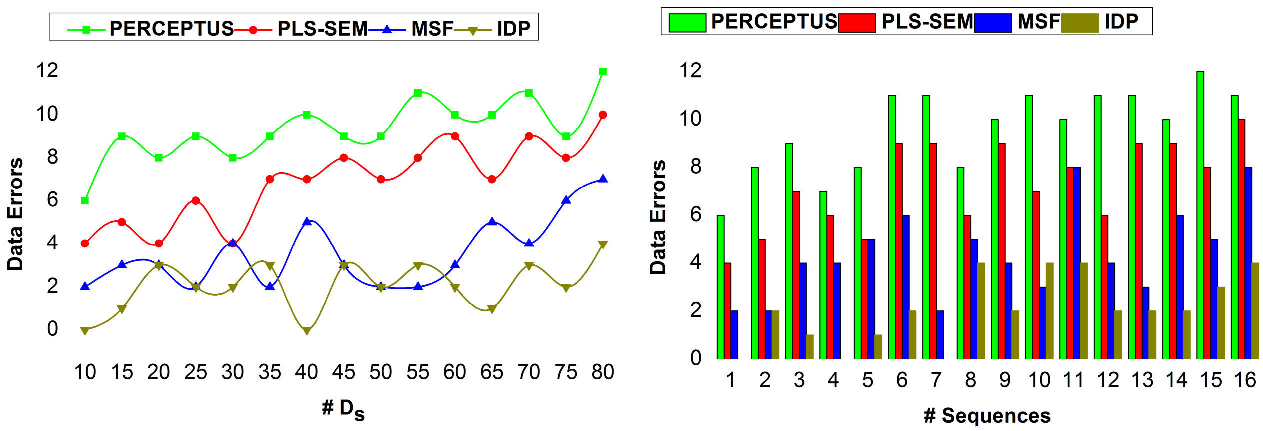

Figure 10. Data Errors.

4.4. Alternations

The prediction of increases and decreases in a smart supply chain management analysis for alternations in data streams is presented in Figure 11. This proposed model satisfies fewer alternations by computing the products' demand and supply rate forecast. In these processing-based supply chain intervals, $A_{Ln-N} = A_{Ln-SN-1}\ \forall\ t_{i+1} = (t_i - I_\Delta + 1)$ is processed based on different product surplus productions. The big data processing and conclusions depend upon the deviations of case 1 and case 2, wherein additional prediction accuracy is achieved using Equations (7)–(9) and computation (11). The smart industry products are analyzed in this proposed model based on the trained sequences. Rate of increase and decrease in demand are estimated for alternating data streams and forecasted under different fields. This consecutive manner of computation prevents demand suppression and data errors during extensive data modeling. Therefore, the alternations of varying data streams are fewer than the other metrics observed in the smart industry. Based on this prediction, the alternation is evaluated for different demands and supply rates.

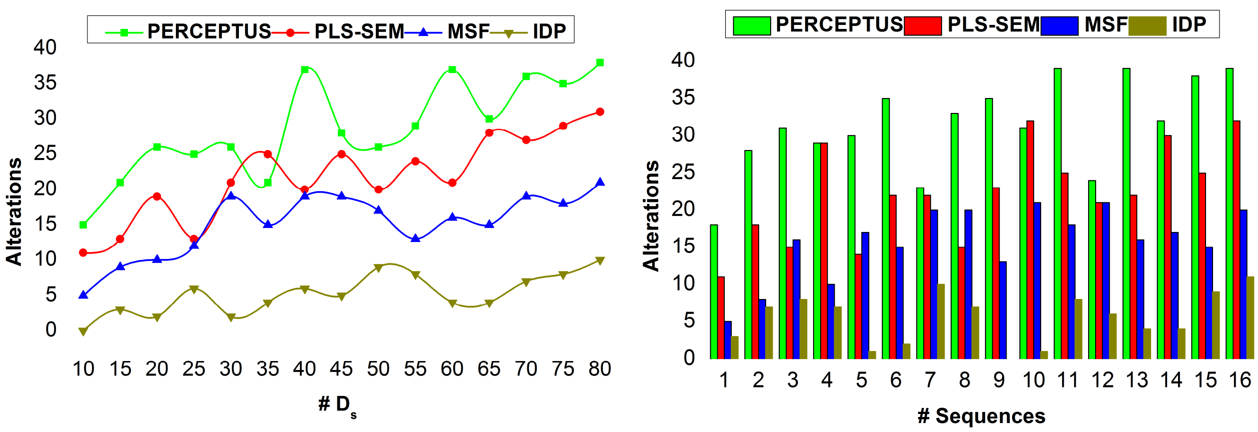

Figure 11. Alterations.

4.5. Demand Suppression

This model satisfies the need for high demand suppression in supply chain management and delivery demands in IoT-based smart industry data processing. The conclusions used to maintain continuity from production to the supply chain are promptly obtained for surplus production (Refer to Figure 12). The rates of supply and demand for smart industry products are mitigated based on data errors and conclusive inaccuracies for different cumulative outputs of data streams based on autonomous vendors. The analysis time depends upon distinct delivery demands and supply rates achieved via federated learning. The harmonized data at both ends and the processing of data streams between the smart industry and IDP helps to analyze the accuracy of predictions in the increases and decreases in demand and the errors in product circulation data retained with $D_{SN}(n, P_{SN}) := (\sum_{i=1}^{n} A_{Li}|y_n|_i)\ \forall\, n \leq i \log|P_{SN}|$ such that $x_n \leq N$, based on supply chain intervals. Therefore, the delivery demand is computed for maximizing the data error, verifying the harmonized stream and balancing. The surplus production for supply chain management and demand analyses in the smart industry highly suppresses demand. Tables 2 and 3 summarize a comparative analysis for varying D_s and sequences.

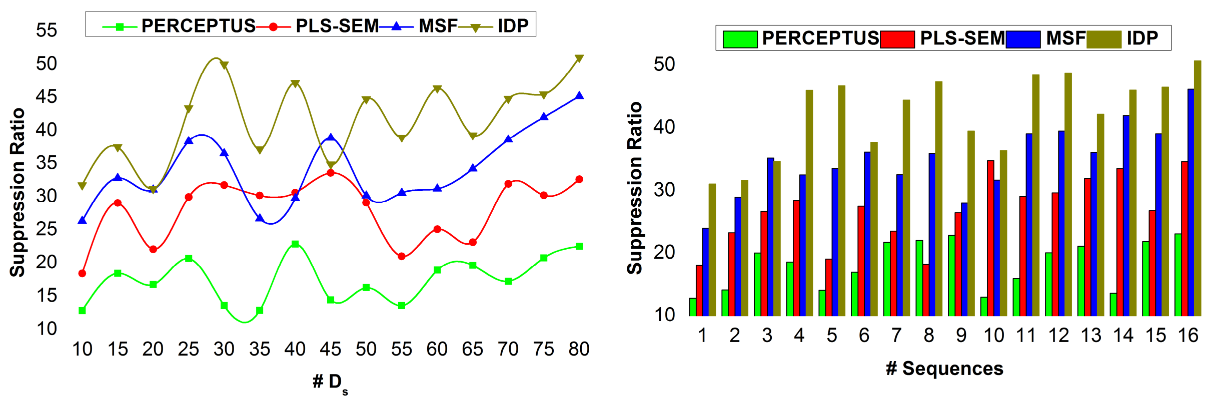

Figure 12. Demand suppression.

Table 2. Comparative analysis summary for # D_s.

Metrics	PERCEPTUS	PLS-SEM	MSF	IDP
Prediction Accuracy	0.795	0.856	0.902	0.9508
Analysis Time (ms)	841.54	713.78	507.3	397.984
Data Errors	12	10	7	4
Alterations	38	31	21	10
Suppression Ratio	22.53	32.65	45.19	51.075

Inference: The proposed IDP achieves a 9.98% higher accuracy, 7.02% less analysis time, 9.77% fewer data errors, 11.1% fewer alterations, and a 17.62% higher suppression ratio.

Table 3. Comparative analysis summary for # sequences.

Metrics	PERCEPTUS	PLS-SEM	MSF	IDP
Prediction Accuracy	0.793	0.853	0.916	0.9533
Analysis Time (ms)	844.22	740.04	528.32	315.53
Data Errors	11	10	8	4
Alterations	39	32	20	11
Suppression Ratio	23.09	34.63	46.14	50.711

Inference: The proposed method maximizes the prediction accuracy and suppression ratio by 9.93% and 16.09% for the different sequences, respectively. It reduces the analysis time, data errors, and alterations by 9.19%, 9.77%, and 10.62%.

5. Conclusions

This article introduced a continuous data processing method for significantly improving the efficiency of data analysis for IoT-based supply chain management. The proposed method handles cumulative and discrete data between the industry, supply chain, and distribution. Based on the identification, deficiency suppression is initiated through federated learning recommendations. The alterations required for data processing are extracted from different streams to identify increases and decreases in the learning process. This identification aids in the design of cumulative and independent data processing functions for forecasting distribution and supply demands. The information in distinct intervals is handled for reductions and alterations depending on the forecast in different sequences. Therefore, IoT-aided computations and data handling are jointly performed in precise intervals, maximizing the suppression ratio. The data processing and handling forecasted the different sequences in specific intervals. The proposed work can be extended in the future by concentrating on the cost analysis ratio and security aspects. The proposed method maximizes the prediction accuracy and suppression ratio for the different sequences by 9.93% and 16.09%, respectively. It reduces analysis time, data errors, and alterations by 9.19%, 9.77%, and 10.62%.

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