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Predictive Machine Learning Modeling for ERP Global Order in Supply Chains Based on Hybrid Attention SNN Approach

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Abstract:

Management of supply chains is of the utmost significance to today's successful businesses operating in the global market. Innovation in supply chain solutions, including methods to make them quicker, better, and cheaper, is a constant focus for companies as they strive to maintain a competitive edge. Improving consumer happiness is essential, and one way to do this is by reliably delivering on promises. The ability of a corporation to fulfill its promises in this particular scenario is contingent upon its ability to plan and execute effectively. The three main components are feature selection, model training, and preprocessing. The process of preprocessing involves transforming the format of unstructured data in order to make it more understandable. Data mining also relies on this step, since raw data is useless without it. Among the two methods used in feature selection PCA and DPCA—DPCA produces superior results. We used the Attention-SNN framework to train the model for greater precision. With an accuracy of approximately 96.48%, the suggested method surpasses rival approaches, such as SNN and Attention mechanism.

Keywords: Principal Component Analysis (PCA), Spiking Neural Networks (SNN), Global Order Promising Supply Chain.

Introduction

Coordinating the flow of items and data between suppliers, factories, and warehouses is an essential part of supply chain management (SCM). An essential component of any supply chain is the coordination of logistics, distribution, production planning, and management. Among the many facets of production planning and control are the design and administration of manufacturing processes, which encompass material handling, scheduling, inventory control, and more. How products flow from the factory or warehouse to the end user is determined by the logistics and distribution process. When all of these processes are well-managed, manufacturing businesses gain a substantial edge in time-based competitiveness. Modern companies can differentiate themselves from the competition by delivering products quickly and on schedule. This can be taken care of with better production planning, scheduling, and due-date setting. Since due dates are intrinsically related to production planning and scheduling, these activities are essential for effective due date management. Lot sizes, inventory, and other production planning and scheduling issues have traditionally been addressed by large-scale enterprises by utilizing Enterprise Resource Planning (ERP) modules. An issue that has received a lot of attention in the field of supply chain management is the importance of network integration and cooperation for achieving cost savings. The phrase "supply chain" describes a series of interrelated steps that start with the procurement of raw materials and conclude with the shipment of finished goods to customers. The literature identifies three levels of planning that comprise supply chain management: strategic, tactical, and operational. Long-term strategic planning is when data is consolidated. In contrast, operational planning happens in a flash and takes accurate data into consideration. The article's subject falls under tactical planning, a subset of strategic and operational planning that takes into account the quantity and duration of aggregated data. An "enterprise resource planning" (ERP) system is a database-driven software platform that integrates all of an organization's processes and data. Of paramount importance is the order promising module of the ERP system. Order promise refers to the process of accurately estimating when a product will be sent to a client in reaction to their purchase. Enterprise Resource Planning (ERP) systems rely heavily on order planning and management features. This function includes the Available-To-Promise (ATP) and Capability-To-Promise (CTP) functions. Whenever a client sends an RFQ to ATP, the system checks the firm's current channels to see if the product they want is in stock. When feasible, we base our quotations on the stock levels of neighboring warehouses and delivery centers. Despite the failure of an ATP check, the corporation is still able to make commitments based on its production and delivery capabilities. Our CTP check is right here. While the ATP and CTP tests do a good job at estimating due dates, they aren't perfect. The term advanced Available-To-Promise (AATP) to refer to ATP and CTP testing, as well as various methods and technologies that facilitate the function. Numerous books and articles discuss various promising order strategies, including AATP with substitute products, multi-location AATP, and AATP with partial delivery. One of the most challenging difficulties in the airline industry is preventing the circumstance when a reasonably priced economy class customer books the last available seat minutes before a hastily booked, high-margin business class customer cannot get a seat. To combat these challenges, revenue management has proposed using booking classes to segment customers and limit the number of times each class can be booked. In contrast, make-to-stock (MTS) supply chains in the consumer goods industry rely on predictions to stockpile finished goods, which are subsequently used to fulfil client orders. Having said that, not dissimilar. In this region, you can find both major and minor customers, each with their own profit margin. There is no better way to convey "not as desired" than to leave customers seriously short on supply. Customer frustration and potential churn are the long-term effects of delivery delays.

Literature Survey

One well-known strategy for long-term company performance is order promise, which is a part of order management. Quick and dependable order fulfilment is a key factor in a company's capacity to keep consumers and grow its market share. Giving clients accurate delivery dates is becoming more challenging, which is another obstacle[1]. Because of the growth of order channels and the complexity of global supply chains, businesses are confronting more and more problems with demand and supply volatility. [2]Half of all manufacturing and tech companies struggle to meet customer expectations when it comes to providing customers with accurate and guaranteed delivery dates, according to research. An important component of demand fulfilment expenses, according to[3], is inaccurate order promising. This is because there is more effort needed to achieve delivery schedules, such as bringing in expensive outside production capabilities soon, initiating emergency logistical operations, or interacting more directly with customers and suppliers. [4]Not only do sales drop because orders are promised too late, past the earliest probable delivery date, but the order promising method can't predict when production plans can alter in response to an order. When consumers cancel or do not place orders because of the late promise, potential earnings are sometimes not realized. [5]Two forms of uncertainty in the demand data utilized for production planning have made it necessary to make adjustments to the plan. Predicting future demand is already notoriously tough when it comes to volume.The literature on OPP models is extensive. To hone down on relevant sources, a thorough explanation of the research topic and a literature review came next. [6] Client order proposals might be difficult for LHP manufacturing MTS&MTO product companies to respond to in terms of acceptance or rejection because of shared resources. Nonhomogeneous product units, further differentiated into subtypes according to customer-relevant criteria, are a distinctive feature of LHP enterprises. [7] Due to the requirement to fill customer orders with identical units of the same product (the same subtype), companies must make decisions regarding: 1) the allocation of existing uncommitted homogeneous quantities (ATP-LHP) for orders containing MTS products; 2) the scheduling of new production lots in the master plan for orders requesting MTO products or MTS products for which there is insufficient [8] ATP-LHP but uncommitted capacity when considering the homogeneity of customer requirements (CTP-LHP). If consumers do not mention the subtype when placing their orders, it is enough to describe the ATP-LHP in terms of subsets of [9] homogeneous quantities (e.g., if they desire ceramic tiles of the same tone and gauge regardless of specific tone and gauge). Regardless, it is important to calculate the quantities of ATP-LHP and to estimate the specific subtype. It is not feasible to meet the same order in either case by combining discrete non-homogeneous quantities of different subtypes of ATP-LHP. [10] It is vital to establish standards for the allocation of ATP-LHP to customer orders because booking from a given homogeneous subset of a FG can effect later promises. Keep in mind that not all resources will produce the same amount of work when it comes to CTP.[11]The OPP is heavily influenced by the production plan and the type of supply chain, among other factors. Actually, the fruit supply chain's (FSC) distinct features add complexity to the OPP. Among these characteristics is the fact that the end result is impacted by elements beyond human control, such as climate, topography, water scarcity, [12]natural catastrophes, etc., and that these elements cause variation amongst the units of a single, consumable product. Because the products must be uniform throughout all units, managers encounter a hurdle when making orders in these supply chains. [13]For example, oranges must adhere to certain standards for size, variety, origin, quality, and maturity level in every package. The policy on pricing may also be influenced by the product's shelf life (SL) and how fresh it is when delivered. When a product's supposed initial implicit features are no longer present, it has reached SL [14]. A large portion of the first ATP literature centered around the features and needs of the systems. The three "add-on" characteristics discussed partial delivery, multi-location, and substitute items—expand upon the overall ATP system. Based on APS, the "Allotted ATP" idea proposed by [15] presents a search technique along three dimensions: time, customer, and product. According to [16], it is vital to use ATP systems to support order fulfilment and promising judgments. There is a lack of consensus on how to improve resource visibility, competitive advantage, and profitability; some studies have offered quantifiable solutions to real-world ATP problems, while others have offered more general explanations. [17]Developed a stochastic model to illustrate the impact of better demand knowledge on the cost-effectiveness of inventory systems. It uses a batching interval to divide up the available resources among customer requests that arrive within that time. In order to support the daily order promise, [18]utilized the MIP model in conjunction with a make-to-stock production approach. The available-to-sell (ATS) model, which improves operational efficiency in the supply chain by combining demand shaping with profitable demand response.[19] Academics and businesses alike have recently placed a premium on Supply Chain (SC) concepts like cooperation, coordination, and collaboration. Various frameworks employ terms like "cooperative," "collaborative," "co-optative," "coordinated," and "communicative SC" to describe different ways of managing SC. But these ideas have been defined in a number of research. [20] The majority of them believe that a fair system of dividing up profits and losses is essential to the efficient functioning of corporate networks. The success of such a cooperation depends on the members seeing tangible and financially beneficial results. Despite the fact that working together does more work than doing things alone at the corporate level, the advantages seem to be worth it[21]. The planning style is described as "an interactive process in which both customers and suppliers of a value chain collaborate continuously sharing information about demand for conjointly planning their activities". In order to improve the quality of planning and decision-making processes, that more information beyond what is gathered at the organizational level should be considered. A number of planning domains must be involved for planning to be a collaborative effort. The core idea is to broaden the scope of planning beyond its traditional local context to incorporate many planning domains.

Proposed System

To succeed in today's global market, supply chain management is an absolute must for all brands. In order to stay ahead of the competition, firms are always looking for innovative ways to develop their supply chain solutions. Investigating ways to make these solutions faster, better, and cheaper is part of this. Honesty and regular delivery of promised services is a key component of client happiness. It all comes down to how well a company plans and executes in this specific scenario and whether or not it can accomplish its promises.

Preprocessing:
In order to get better results from machine learning models, data must first be pre-processed. It was noted that data biases could occur, particularly when certain manufacturers or spare parts were overrepresented. Consequently, it took great care to inspect the data for bias. The answer involved analyzing the data distribution using visualization tools such as histograms and density plots. It looked for patterns and frequency of data values in each variable and characteristic of the dataset. In addition, we looked for statistics that revealed certain groups or variables were either over-or under-represented.

More data preprocessing approaches were employed to get the data ready for machine learning models after any biases were identified and important characteristics were selected [22]. All of these methods comprised: Data encoding is the process of transforming category data into numeric values that can be utilized by machine learning algorithms. As part of this procedure, methods like binary encoding, label encoding, or one-hot encoding can be used to transform text input into numerical data. The end result will be integer variables with either 32 or 64 bits. Reducing data to a standard size by normalization. One way to normalize data is by applying Min-Max normalization, which is sometimes called feature scaling. This technique converts the data into a range of one to one. For each observation, we do this by taking the least value of the data and dividing it by the difference between the maximum and minimum values of the data. Please find below the formula for Min-Max normalization:

$$h_{min} = \frac{h - h_{min}}{h_{max} - h_{min}} \tag{1}$$

The goal of data sampling is to create a training set and a testing set from the entire dataset. The data is used to create two samples: one for training and one for testing. The training sample is used to train machine learning models, and the test sample is used to test how well they performed.

Data Cleaning:
Thorough data cleaning and quality control procedures were applied to our dataset, which had 52,093 samples and sixteen characteristics. Using exploratory data analysis discovered and corrected any inconsistencies or deficiencies in data. Data formatting and coding checks, data consistency and accuracy checks, fixing missing or incomplete data, and checking for duplicate data were all components of this process. To illustrate the point, in the initial dataset, any negative values introduced by an internal procedure were substituted with zeros.

Feature Selection:

PCA:

Principal component analysis (PCA) is a method for extracting uncorrelated components from correlated data. The data acquired at time c is represented by a G-dimensional vector h_c, and $H = [h_1, h_2, \ldots, h_W]^T$is the set of all vectors [23]. The first contains W samples, while the second contains data acquired across W time periods, denoted as T. It is feasible to construct the following associations by using principal component analysis to H after scaling it to have a zero-mean and a unit-variance.

$$R = HB \qquad (2)$$

$$H = RB^T + Q = \sum_{s=1}^{S} r_s b_s^T + Q \qquad (3)$$

Among its contents are: a principal component (PC) sample data set $r_s = Hb_s$, where a = 1,..., A; the scoring matrix $B = [b_1, b_2, \ldots, b_S]$; the loading matrix $R = [r_1, r_2, \ldots, r_S]$;; and the residual Q. Then maximize the score variance to find the loadings. In most cases, $S < G$ is necessary to achieve dimensionality reduction.

Both X and the sample covariance matrix $A = \frac{1}{W-1} H^T H$ can be subjected to eigen-decomposition or singular value decomposition (SVD) in order to conduct a principal component analysis (PCA). In addition to the Power method, another quick option to extract the PCs is the nonlinear iterative partial least squares (NIPALS) approach.

DPCA:

Warehouses or distribution facilities are the last links in the supply chain that often include producers, wholesalers, retailers, and consumers. It is possible to apply a wide range of inventory management policies to each agent. There are various types of flows in a supply chain. Things like goods, materials, and services move upstream, while information and money move downstream. Material and order information flows are considered in both the upstream and downstream directions in this proposal.

Supply chains, when viewed and represented as dynamic systems, exhibit behavior comparable to process plants in response to inputs and disturbances, enabling the application of control techniques such as model predictive control (MPC). According to this theory, the "process variables" (such as inventory levels and time-varying market needs) in a supply chain are correlated. Principal component analysis (PCA) has the potential to be helpful for dimensionality reduction and tracking future events if all levels and agents can be recorded. This is supported by the data correlation.

Training the Model:

SNN:

Spiking Neuron:

Spike neurons, the basic building blocks of SNN, communicate with one another using spikes encoded with binary activation. The global order promising in supply chain model is a common spiking neuron model because it strikes a balance between the complex dynamic features of actual neurons and the simplified mathematical form. For large-scale SNN simulations, it performs admirably, and it is described by a differential function.

$$\sigma \frac{dz(r)}{dr} = -z(r) + C(r) \qquad (4)$$

σ is a time constant, $z(r)$ is the membrane potential of the postsynaptic neuron, and $C(r)$ is the input that is received from the presynaptic neurons.

Conv-based SNN:

The solution to this differential equation controls an easily comprehensible iterative representation of the SNN layer for inference and training.

$$Z^{r,w} = X^{r-1,w} + H^{r,w} \qquad (5)$$

$$A^{r,w} = Hea(Z^{r,w} - z_{th}) \qquad (6)$$

$$X^{r,w} = Y_{reset}A^{r,w} + (\alpha Z^{r,w}) \odot (1 - A^{r,w}) \qquad (7)$$

in which the time step (r) and layer (w) are shown, The output spiking tensor $A^{r,w}$ should be given or kept as zero, and uth is the threshold that determines this. $Z^{r,w}$ is the membrane potential that is created by coupling the spatial feature $H^{r,w}$with the temporal input$X^{r-1,w}$. When h is greater than or equal to 0, the Heaviside step function $Hea(.)$ is defined as 1. Otherwise, $Hea(h)$ is defined as 0. The parameter $\alpha = e^{-\frac{dr}{\sigma}}$ is the decay factor, and stands for element-wise multiplication. Y_{reset} is the reset potential that is set after initiating the output spike.

The spatial feature $H^{r,w}$ in Eq. (5-6) can be obtained by doing a convolution operation using the initial input $A^{r-1,w}$.

$$H^{r,w} = Avgpool\left(PW\left(Conv(N^W, A)\right)\right) \qquad (8)$$

S t,n−1 (n 6= 1) is a spike tensor that only contains 0 and 1, and $H^{r,w} \in \mathbb{R}^{i_w \times x_w \times n_w}$, where $Avgpool()$,$PW\ (\cdot)$ and $Conv(.)$ imply the average pooling, batch normalization, and convolution operations, respectively. Aiming to streamline the notation, bias terms are eliminated. Since PW is the second default operation after $Conv$, it will furthermore be ignoring it for the duration of this article.

Multi-dimensional Attention for SNN:

Overview Attention:

Although both neuroscience and CNNs investigate attention, there are significant differences between the two. The potential energy savings brought about by attention are lost in continuous CNN activations since they obviously do not mimic the spiking activation properties of biological neurons. Similar to how attention influences neuronal spiking activity in the brain, we optimize the membrane potential of spiking neurons through attention in a data-dependent way, and as a result, the spiking response of SNN is regulated. In a nutshell, attention functions are:

$$h_{Att} = d(k(h), h) \qquad (9)$$

The process of paying attention to discriminative moments or areas is correlated with the output of an attention mechanism, h_{Att}, and the function that creates attention weights, $k(h)$. Input h is transformed into the attention weights $k(h)$ via the function $d(k(h), h)$. Make an attention module that can learn the three dimensions of what, when, and where on its own. Each dimension has its own set of attention modules that can be utilized independently or in conjunction with one another. Given that this is an MA thesis, it employs

$$h_{Att} = k(h).h \qquad (10)$$

The input h is usually an intermediate feature map.

Attention Residual Learning of SNN:

It has been shown that SNNs are theoretically computationally comparable to ANNs. Because of their tiny size, SNNs have limited representation capabilities, which makes them less applicable in practice and accentuates the performance gap between ANNs and SNNs [24]. Residual learning becomes a significant accomplishment in deep learning when an identity skip connection is implemented across the network, enabling the formation of "very deep" neural networks. Even while SNNs can be trained with a direct reproduction of the traditional residual structure, the degradation problem still exists because deeper SNNs have higher train loss than shallower ones. Among SNN residual structures, vanilla Res-SNN, SEW-Res-SNN, and MS-Res-SNN are the three most common. The main difference among Res-SNN works is that there isn't yet a defined way for building fundamental residual blocks within the SNN community.

Existing residual SNN topologies may easily incorporate MA, and attention is consistently used to enhance the membrane potential of spiking neurons. For residuals, this proposed employs the MS-Res-SNN building block.

The setup for Att-Res-SNN-1 is

$$Z_{I,S}^{r,w+1} = k_i\left(Z_{Ori}^{r,w+1}\right) \odot Z_{Ori}^{r,w+1} \tag{11}$$

$$Z_{CSA}^{r,w+1} = k_a\left(Z_{CA}^{r,w+1}\right) \odot Z_{CA}^{r,w+1} \tag{12}$$

$$Z^{r,w+1} = Z_{CSA}^{r,w+1} + Z^{r,w+1} \tag{13}$$

while Att-Res-SNN-2 is thought of as

$$Z_{I,S}^{r,w+1} = k_i\left(Z_{Ori}^{r,w+1} + Z^{r,w+1}\right) \odot \left(Z_{Ori}^{r,w+1} + Z^{r,w+1}\right) \tag{14}$$

$$Z_{CSA}^{r,w+1} = k_a\left(Z_{CA}^{r,w+1}\right) \odot Z_{CA}^{r,w+1} \tag{15}$$

$$Z^{r,w+1} = Z_{CSA}^{r,w+1} \tag{16}$$

The outputs of the Att-Res-SNN block, CA, and CSA modules are represented by $Z_{Ori}^{r,w+1}, Z_{CA}^{r,w+1}$ and $Z_{CSA}^{r,w+1}$, respectively. The fundamental Res-SNN block initially produced $Z^{r,w+1}$. To keep residual SNNs event-driven and prevent degrading problems in deep SNNs simultaneously, it is necessary to design attention sites in these networks. After reviewing the basic Res-SNN block selection and attention residual SNN ablation studies, it is suggested Att-Res-SNN-1 for attention residual learning.

Result and Discussion

In the context of an extended collaborative selling chain (ECOSELL), this article lays out a solution method that supplements the product-pack order promising (OP) procedure. Collaboratively commercializable goods with complementary functionalities are called a P-P. A P-P order request has four standard variables—the due date, quantity, delivery location, and price-plus one more variable the ability to define dependencies among the other variables. In addition, P-P products may be part of multiple supply chains, all of which need to work together to give customers dependable responses.

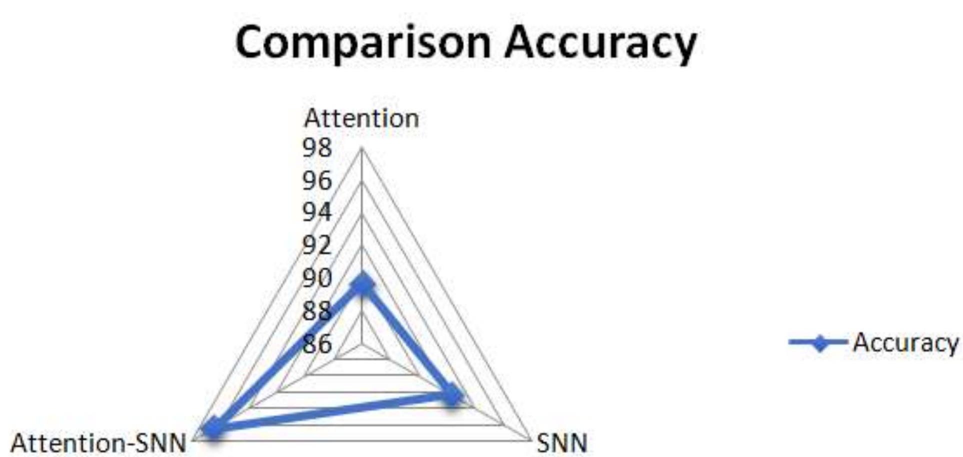

Fig. 1. Comparison of Recognition Accuracy

Figure 1 shows a visual comparison of the suggested method's recognition accuracy with other methods.

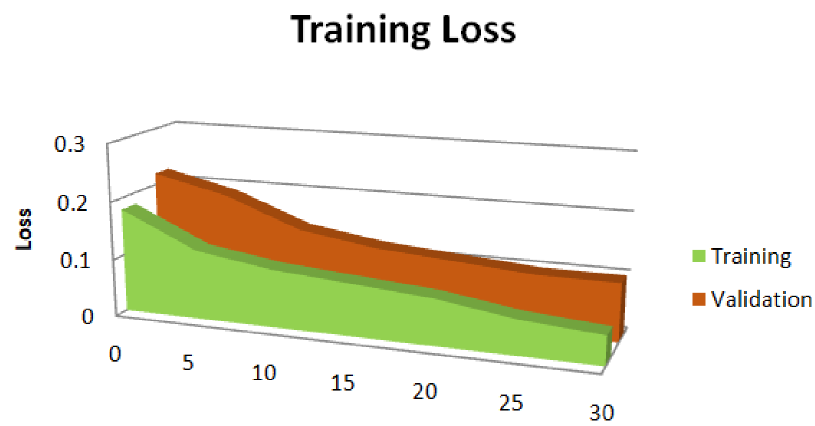

Fig. 2. Training and Validation Loss of Attention-SNN Model

Over the course of 30 iterations, Fig. 2 displays both the training and verification progress. Up to epoch 15, the line charts in Figure 2 demonstrate a steady decline in the loss values for both the training and validation operations, which is indicative of high learning performance.

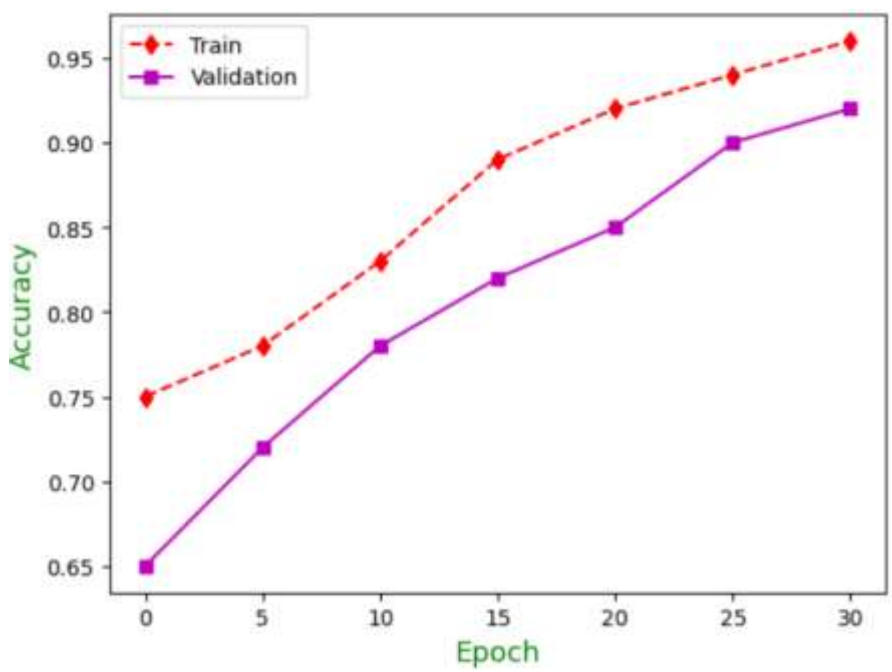

Fig. 3. Training and Validation Accuracy

The accuracy values show the trend; at that epoch, training achieved 96% accuracy and validation reached 92%. As a result of the training values being in a constant state of flux relative to the validation data, the model begins to overfit once this occurs.

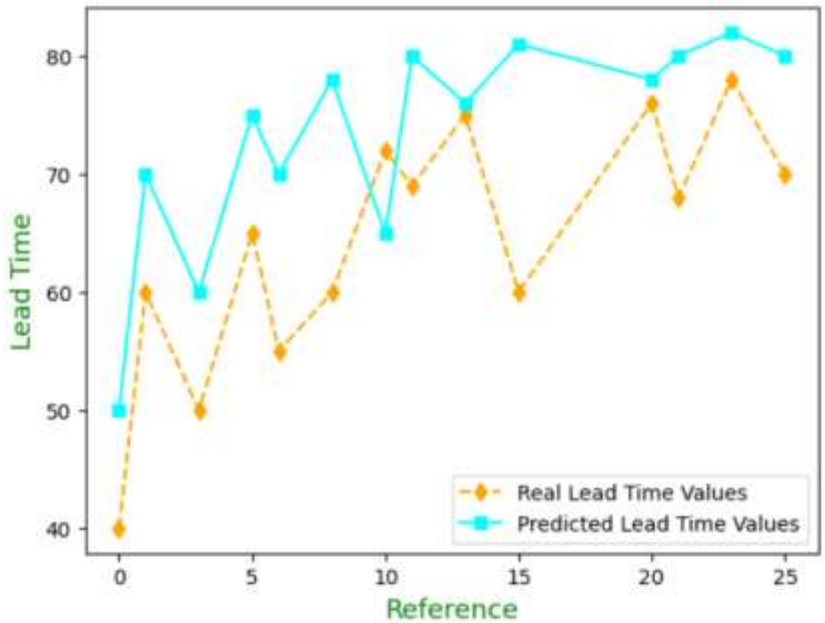

Fig. 4. Real vs Predicted Lead Time using Attention-SNN

Check out Figure 4 for a comparison of the predicted and actual real lead times values.

Conclusion

This research delves into the functions of a company's order promising and fulfillment, customer and channel coordination, and more. Improved definitions aside, we also locate and assess state-of-the-art approaches in these two domains that leading corporations across nine sectors aviation, computing, transportation, petroleum, consumer packaged goods, retail, pharmaceuticals, and telecommunications are utilizing. Preprocessing involves transforming the format of unstructured data in order to make it more understandable. Data mining also relies on this stage because raw data is useless without it. If you're looking for a feature selection method, DPCA is the way to go above PCA. In order to train the models, we employ the Attention-SNN technique. With a consistency rate of 96.48%, the proposed method outperforms the Attention mechanism and SVM models.

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