Predictive Modeling for Demand-Driven Distribution Planning Based on Hybrid LSTM-DANN Approach

Narendra Sharad Fadnavis

Principal Engineer
Cisco Systems Inc.
nfadnavi@cisco.com

Abstract

Recent developments in business and technology have prompted distribution channels in a number of industries to adjust to new performance criteria. Increased service level expectations from retail consumers and the trend of suppliers and manufacturers outsourcing distribution have introduced new difficulties into the field of supply chain management. As a result, most companies will face the challenging challenge of restructuring their distribution networks. The other side is that not many companies look at the customer journey as a complete.Training the model, selecting features, and preprocessing are the main components. As part of the data pre-processing phase, data cleansing is carried out, which involves identifying and fixing dataset anomalies, quantization normalization, and smoothing. Attribute or feature selection refers to the process of choosing a subset of pertinent features to simplify the challenge. In order to accomplish this, we trained our models using the LSTM-DANN framework. To the contrary, it makes LSTM and DANN ineffective. The numbers point to a success percentage of 97.48%.

Keywords: Demand Driven Distribution, Long Short Term Memory (LSTM), Domain Adversarial Neural Network (DANN)

I. INTRODUCTION

Numerous researches have focused on finding the most efficient way to transport items through a distribution network. The relevance of this inquiry is warranted by the market forces and inventory expenses. The most common method for managing the flow of products over a distribution network is DRP, or Distribution Resource Planning. The literature on the topic varies in its efforts to integrate the Just-In-Time concept into the DRP approach and its focus on inventory management as a tool for optimizing flows. Due to the increasing complexity, decreased customer tolerance time, and confined product life cycles of the modern supply chain, old methodologies like DRP urgently need to be improved. So, this study takes a Demand Driven approach to supply chain distribution. "Demand Driven Material Requirement Planning" (DDMRP) method, a multi-stage strategy for demand and supply planning and implementation. With this new method, "Demand Driven Distribution Resource Planning" (DDDRP), the aim is to manage lead times, on-time deliveries, and reduced cost of goods sold while controlling several kinds of "demand, operational, supply, and management" variability. Demand fluctuations, lengthy lead times, erroneous predictions, vast product variety, and intricate networks are all examples of stochastic systems that impact production planning and inventory control in today's complicated networked environment. But MRP works better with systems that are already known to be deterministic. In light of this, MRP has various shortcomings that make it unsuitable for use in today's business world. In order to achieve good service level goals in the face of unpredictable demand and lead time, few research have proposed modified MRP for stochastic settings. With the DDMRP method, even situations with long lead times, environmental uncertainty, and fluctuating demand and supply may be managed. However, there is a lack of research that specifically addresses the benefits of DDMRP. The possibility of comparing MRP with DDMRP appears to exist. To fill that information gap, this study compares DDMRP and MRP for purchased components in conditions of long lead times and uncertain demand, as indicated by average industrial inventory levels. Time horizons and the collection of end-item information often separate three stages of production systems governed by pushed, pulled, or hybrid flow management tactics. These three stages are commonly referred to as the operational, tactical, and strategic levels. Some approaches to material management adhere rigidly to this three-tiered structure, while others provide their own unique definition of it. More contemporary frameworks, such as the Demand Driven Adaptive Enterprise (DDAE), also follow this division of tasks. In following its initial presentation, one may find a detailed description of the DDAE. Regarding the actual execution operations, all three methods show the operational level as the most up-to-date. Quick decisions are required at the lowest level of the bill of materials, down to the smallest item, and the time horizon is usually quite short, like a day or a week. Detailed instructions for carrying out processes at the operational level are provided by the majority of material management techniques, such as MRP, CONWIP, Kanban, and DDMRP. Supply chain management and operational efficiency must be top priorities for management in businesses and markets with intense competition. These days, a plethora of planning, management, and supply chain control systems are in operation. However, optimizing such systems isn't always easy, especially under circumstances marked by "Volatility, Uncertainty, Complexity, and Ambiguity". This article provides a preliminary assessment of Demand Driven MRP and the more traditional methods of MRP (Material Requirement Planning), within this context. This study's findings could encourage creative manufacturing methods among Moroccan enterprises and enhance the quality of future research in the field. This study was initiated because researchers failed to properly utilize the opportunities that the DDMRP approach offered. There has been an explosion in the number of research published on DDMRP over the past decade, which is why this work primarily contributes by surveying that literature.

II. Literature Survey

The DRP approach streamlines system deployment by including planning and management from networked resources; it's a way to replenish inventory at distribution centers. The literature indicates that many businesses have reaped benefits from DRP deployment since its start[1]. The physical distribution business in the US investigated several innovative management strategies, such as DRP, JIT, and Material Requirement Planning (MRP)[2]. The DRP has an advantage over the order-point replenishment approach since it considers the distribution network as a whole, rather than just one node at a time. According to a simulation research conducted, DRP outperforms the order-point replenishment approach when the periods of both demand and replenishment are unpredictable. Many in the supply network are worried about the DRP because it is based on dependent demand logic[3]. Therefore, little changes made farther down the line can have a significant effect further upstream, as sales estimates are what power DRP. The bullwhip effect—small changes in demand at lower levels will have a much larger influence as we go higher—becomes increasingly apparent, the network takes too long to respond to actual need, and distorted signals emerge as a result of interdependence[4].The inherent unpredictability of the environment rendered conventional approaches to production planning and management ineffective. Developing demand-driven techniques has been the primary emphasis of operations management research over the past two decades. Research by[5], for example, looked at how Materials Requirements Planning (MRP) depends on demand forecasts and how PIC theory relates to it. However, this is not always implied by PIC theory. Though did examine PPC, their focus was on MTO production rather than PPC in general. According to research by[6], manufacturers are being encouraged to switch from Make-To-Stock (MTS) to MTO or an intermediate system because of the advantages in diversity and shorter production cycle times. An additional domain that delved into was Master Production Schedule (MPS) planning in the face of stochastic demand. Assuming knowledge of the lower-level schedule modification cost, their preplanning actions aimed to ascertain their value. In addition, [7] developed a new co-innovation toolset to educate both suppliers and consumers on the importance of demand-supply chain synchronization. Integrative synchronization, supply visibility point—demand visibility point, and supply penetration point are all part of the tool set. [8]proposed a new method they called Demand Driven Material Requirements Planning (DDMRP) to accomplish a comparable aim. The DDMRP technique incorporates novel aspects into its material flow management while incorporating traits from prior systems. [9] The goal of this strategy is to manage uncertainty, adjust inventory levels, and maintain or enhance customer service. This improves information visibility and flow, which in turn makes material requirements planning easier[10]. The DDMRP was created in reaction to problems with previous methods. People are worried about this circumstance because everything is dependent on MRP. The end-to-end transfer of information, resources, and money is what makes up manufacturing organizations' supply chains. [11] The management and construction of supply chains determine a manufacturing organization's competitive capacity. Their capacity for customization, delivery dates, product costs, and working capital are all profoundly affected by this[12]. To stay ahead of the competition, it's said that supply chain design must be in sync with product and demand features. That is precisely what seminal work on the topic of "supply chain fit" argues for[13]. Since then, supply chain fit has been the subject of numerous studies that have stressed its importance, all agree that product kinds, market demands, and information and material flow should all be considered when managing manufacturing organizations' supply chains. Complicating things further, a good supply chain architecture will change over time to accommodate new circumstances and customer needs[14]. In order to stay ahead of the competition, these companies are focusing their business strategies on meeting the demands of their customers. Some demand-driven manufacturing organizations, for instance, are event customer order driven, meaning they produce goods in response to actual customer orders and can modify their products to suit the unique requirements of each customer.[15] Public healthcare SCNs in poor countries have not been systematically investigated using DDSCM, despite its widespread use in other industries to manage supply chain complexity, demand volatility, and unpredictability. This is so even though it's used in many different businesses, including those dealing with computers, flowers, telecommunications, transportation, meat, and fashion [16]. A more integrated "demand pull" strategy would help healthcare supply chains better track product usage, which would benefit pharmaceutical corporations. Hence, the main focus should be on ensuring that the PHS's supply chains are built to fulfil demand requirement[17]. To create a plan that works for both the supplier and the end user, it is necessary to learn the customer's needs and constraints inside and out. Although DDSCM was first implemented as a pull production system by manufacturing companies, it has shown to be as valuable for supply chains. [18] The two-card 'kanban' technique is widely regarded as the pioneering pull system, and it was first presented. Workers at one station are not supposed to start making anything according to the kanban system unless the components are "pulled" by another unit or the client. [19] Pull and push production systems are the two main categories in manufacturing. The difference between pull and push systems is that pull systems explicitly restrict the quantity of labor in process. In a strategic pull system, customers define the rate of production; in a tactical pull system, demand specifically regulates the quantity of work in progress [20]. The make-to-stock and make-to-order philosophies are like pull and push systems, respectively. Therefore, the goal of demand-driven manufacturing is to satisfy customers by coordinating the logistics of the supply chain and production processes to ensure they comply with laws [21]. A pull-based strategy has the ability to provide information in a timely and relevant manner. This leads to a more streamlined supply chain. Always remember that the backbone of demand chain management (DCM) is the continuous dissemination of information about customer demand to every link in the supply chain.

III. Proposed System

Complexity in supply chain networks is expected to increase due to Industry 4.0. More and more, customers will want individualized attention and a reaction time proportional to the length of time they are prepared to wait for the product. New methods of supply chain management are required because of these reasons.

A. *Data Preprocessing:*

The data pre-processing step includes tasks such as data normalization, smoothing, and data cleansing, which entails identifying and repairing dataset irregularities. This is an important part of the method that must be followed to ensure that the overall results are not unexpectedly high or low.

1) *OutlierDetection:*

Typically, anomalies or outliers will mislead the user. Expert outlier detection algorithms look for unusual circumstances by comparing them to typical instances and then explaining why they differ. To ensure that data is not biased during analysis, these techniques are used to eliminate anomalies. In addition, outliers vary depending on the case and industry. A number of factors, including the arrival of a new generation, seasonal sales, the impact of the financial crisis on shopping habits and returns, etc., led us to find some inconsistencies in our data[22]. The anomalies, which often included valid business reasons and could not be removed, are fixed by applying a smoothing approach to the data. Outliers are extracted from the dataset's features independently using Equation (1).

$$Outlier_Y = \left\langle \begin{matrix} Mean\ (F_Y) - 3 \times IP(F_Y) \leq (F_Y)Y_s|_{s=1}^{c} \\ Mean\ (F_Y) + 3 \times IP(F_Y) > (F_Y)Y_s|_{s=1}^{c} \end{matrix} \right\rangle \ (1)$$

2) *Normalization:*

It is usual to observe total amounts that are three to four times higher than the previous generation while examining the returns life-cycle. It seems that the average of generation C is three to four times greater than that of generation. That generation really had a standard deviation that was two to three times smaller than $C-1$. Since the standard deviation was low and the mean was higher, it was difficult to provide a suitable extrapolation to generation C. In order to solve this, we scale the overall quantity of historical data with the predicted generation and decrease the discrepancy. As a result, we know our model can generate reliable statistics once it's up and running. In order to normalize the features of generation $C-1$ with regard to generation C, Equation (2) is used.

$$Normalization_Y = \frac{\sum Generation\ C_Y}{\sum Generation\ C - 1_Y} \times F\ Y_s|_{s=1}^{c} (2)$$

3) *Smoothing:*

When applied to an entire dataset, the moving average smoothing approach helps to mitigate the effect of outliers, or numbers that are very low or high. To get an average, it uses the most recent 3, 6 etc. data points. Using this method, not only are spikes reduced, but the dataset attributes are also made statistically useful for predictive modeling. Each dataset characteristic is smoothed by applying a three-month moving average, as demonstrated in Equation (3).

$$Moving\ Avg_Y = Avg \times (F_Y instance_s|_{s=r}^{r+2})|_{s=1}^{c} \qquad (3)$$

B. *Feature Selection:*

Feature selection, often called attribute selection, is a method for reducing complex problems to their essential components. Very versatile, it incorporates many search and evaluation methods in addition to a supervised attribute filter for selecting attributes. When choosing attributes, there are essentially two steps to take. First, you need to decide which characteristics to include in the subset. Then, you need to evaluate how good those subsets are. In order to determine which features were most important, this study used three feature selection methods: relief, FCBF, and supervised attribute filter. Relief ranks all of the dataset's attributes according to their significance as a feature selection method. It finds the average of both groups and then compares it to the most similar instance in the other group. The ranking of features has a direct correlation to their relevance.This algorithm is used to choose one, two, three, four, or five predictive characteristics[23]. Quick Correlation-Based Filter is the name of this algorithm. Finding the most important features requires a feature selection approach that searches for relationships between them. It works because we use the attribute-class label correlation with the maximum value. This approach chooses a set of prediction features from a scale of 1 to 12. Supervised Attribute Filter is a supervised learning-based feature selection method that can help you determine the most important attributes. The method relies on using the dataset to extract features that have a significant impact on the model's accuracy during training. Among the predictive features used are 12, 10, 11, 1, 2, 3, 4, 9, and 10. The feature selection strategy for the rest of the study was selected as the supervised attribute filter algorithm due to its remarkable performance.

1) *Resampling:*

It is the bootstrap method of resampling that has been selected. A bootstrap test is a lifesaver when it comes to analyzing the variability of a statistic or deriving conclusions from statistical analyses. Even though it's most often used to calculate the safe distance, it has other applications like altering hypothesis testing or determining an estimator's difference and deviation. This method utilizes random sampling techniques to approximate the sampling distribution of almost the entire statistic. It uses replacement or non-replacement sampling methods to randomly produce a subset of a dataset. One of bootstrap's strongest points is how simple it is to use. Using the percentile points, one can easily derive standard error estimates and assurance intervals for distance estimators of the distribution, like correlation coefficients, ratios, and probability ratios. Bootstrapping may appear to be a simple method, but it could actually be useful for complex sampling systems. Bootstrapping is a viable alternative to rerunning the experiment if you require data from more sample sets.

C. *Model Training:*

1) *LSTM-DANN:*

A hybrid LSTM-DANN architecture consists mainly of a feature extractor, a regression predictor, and a domain classifier. With the fully connected layers making up the regression predictor and domain classifier, the LSTM layer acts as the feature extractor.

a) *Feature Extractor:*

The input time series data is processed using the LSTM based feature extractor V_u to extract the temporal characteristics.

b) *Regression Predictor:*

In order to determine how the retrieved temporal aspects relate to demand-driven distribution planning, the regression predictor V_a uses data from both the source and destination domains.

c) *Domain Classifier:*

The goal of the domain classifier V_p is to separate the source domain from the target domain by extracting characteristics from each.The training optimization loss of the LSTM-DANN model consists of regression and domain classification losses. The regression loss for the energy prediction can be determined by calculating the mean square error:

$$\delta_a^s(\vartheta_u, \vartheta_a) = \frac{1}{c}\sum_{s=1}^{c}(a_s - \hat{a}_s)^2 \qquad (4)$$

where c represents the training data batch size. Here, a_s is the actual building energy value and $\hat{a}_s$ is the predicted value.By definition, binary cross entropy describes the domain label classification loss.

$$\delta_a^s(\vartheta_u, \vartheta_a) = \frac{1}{c}\sum_{s=1}^{c}\left(p_s\, log\frac{1}{\hat{p}_s} + (1-p_s)log\frac{1}{1-\hat{p}_s}\right) \quad (5)$$

When the real domain label is represented by p_s and the predictive domain label is represented by$\hat{p}_s$.
When it comes to domain classification loss, the LSTM-based feature extractor and domain classifier have opposing effects because of their antagonistic roles in the hybrid LSTM-DANN architecture. In contrast to domain classifiers, feature extractors aim to maximize loss. The gradient update in a neural network's backpropagation process cannot be used to directly execute this min-max operation. To achieve this, a gradient reversal layer (GRL) can be inserted between the feature extractor and the domain classifier in a hybrid LSTM-DANN design. This idea is conceptually similar to generative adversarial networks (GANs), which align distributions in an aggressive way utilizing the domain classifier and feature extractor. Because the feature extractor and domain classifier are at odds with one another, the domain classifier can't tell which domain is the feature's source and which is its goal. The retrieved feature from LSTM is currently domain invariant. After been trained with data from both the source and target buildings, the LSTM-DANN model can be directly applied to assist with energy prediction for the target building. In backpropagation, the GRL changes the sign of the gradient from the previous level; in forward propagation, it switches identity. Eqs. (6) and (7) define the following "pseudo-function", which can be considered for both the forward and backward propagation processes:

$$J_\mu(m) = m \qquad (6)$$

$$\frac{dJ_\mu}{dm} = -\beta s \qquad (7)$$

$$\beta = \frac{2}{1 + exp(-\rho \times d)} - 1 \qquad (8)$$

$$d = \frac{r + t \times W}{x \times W}(1 \le r \le M/C\,, 0 \le t \le x)(9)$$

where the identity matrix is represented by $[s]$. The trade-off between domain classification loss and regression loss is executed by the positive hyper-parameter β, withρ set to 10. The variables r, t, and x stand for the current batch size, iteration count, and minimum total batch length of the source and target training data, respectively[24]. Then, the final objective "pseudo function" may be optimized using our technique and gradient descent. Optimization of loss function 4 is achieved by finding the minimize points ϑ_u, ϑ_a and ϑ_p in the following way:

$$(\hat{\vartheta}_u, \hat{\vartheta}_a) = argmin\delta(\vartheta_u, \vartheta_a, \hat{\vartheta}_p) \quad (10)$$
$$\hat{\vartheta}_d = argmin\delta(\hat{\vartheta}_u, \hat{\vartheta}_a,, \vartheta_p) \quad (11)$$

As an expression, gradient descent modifies the LSTM-DANN model's learning weights.

$$\vartheta_u \leftarrow \vartheta_u - \mu\left(\frac{\partial \rho_a^s}{\partial \vartheta_u} - \beta \frac{\partial \rho_p^s}{\partial \vartheta_u}\right) \quad (12)$$
$$\vartheta_a \leftarrow \vartheta_a - \mu \frac{\partial \rho_a^s}{\partial \vartheta_a} \quad (13)$$
$$\vartheta_p \leftarrow \vartheta_p - \mu \frac{\partial \rho_p^s}{\partial \vartheta_p} \quad (14)$$

when the letter μrepresents the learning rate. Through the application of the gradient descent approach, the optimization weight parameters can be determined by running Eqs. (12)–(14). At the end of the learning process, the regression predictor V_a can be used to forecast the labels of the target and source samples.

IV. Result and Discussion

Businesses face a challenging competitive landscape in this age of fast technological innovation, societal turmoil, and economic transformation. In order to stay in business, companies need to improve their supply chains and operations by being more nimble, collaborative, integrated, flexible, quick, transparent, and efficient. Academics and industry experts are coining the term "Demand-Driven" (DD) to characterize companies that are able to adjust to these evolving characteristics. Moreover, a crucial process that seeks to balance supply and demand is Sales and Operations Planning (S&OP).

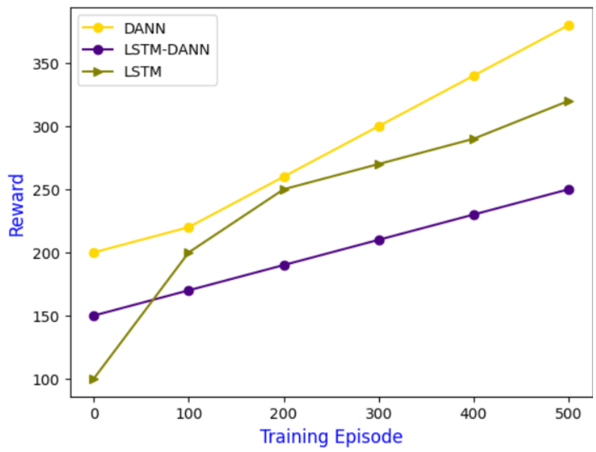

Fig. 1. Learning Curve for Different Methods

As shown in Figure.1, centralized LSTM converges after 320 episodes; however DANN needs less than 380 episodes to reach convergence. The LSTM-DANN method reaches convergence in approximately 250 episodes; however, due to the separate learning mechanism, the learning process is not stable. The outcomes prove that our distributed reinforcement learning method has a much faster convergence time.

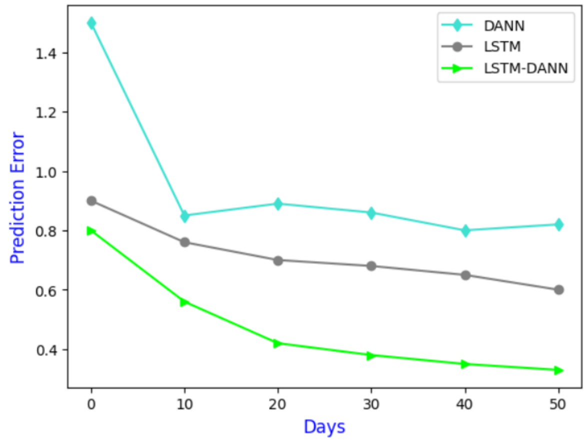

Fig. 2. Root Mean Square Error for the Different Methods

The averaged RMSE for cluster demand predictions across all forecasting models is displayed in Figure 2. Given the complex interrelationships and ever-shifting trends in demand forecasting data, it is unreasonable to assume that any prediction will converge to a stable error level. Nevertheless, the contrast does bring attention to the forecasters' pure performance.

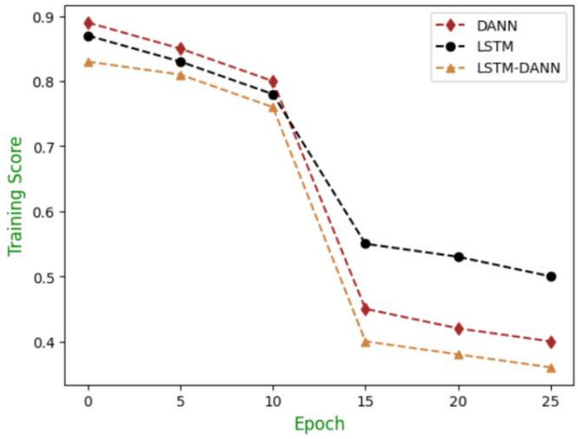

Fig. 3. Training Score Along the Epochs

Figure 3 show that our suggested strategy outperforms baseline models in terms of convergence speed while achieving a somewhat reduced training loss.

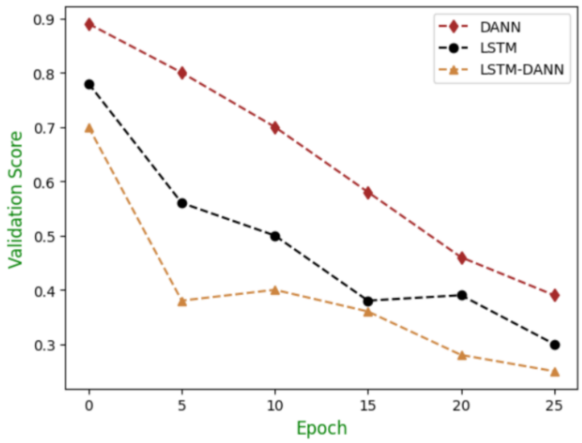

Fig. 4. Validation Score Along the Epochs

Figure 4 shows a comparison of the validation scores of our method and two baseline approaches, LSTM and DANN. Figure 4's validation score curves prove that our method gets the highest possible score.

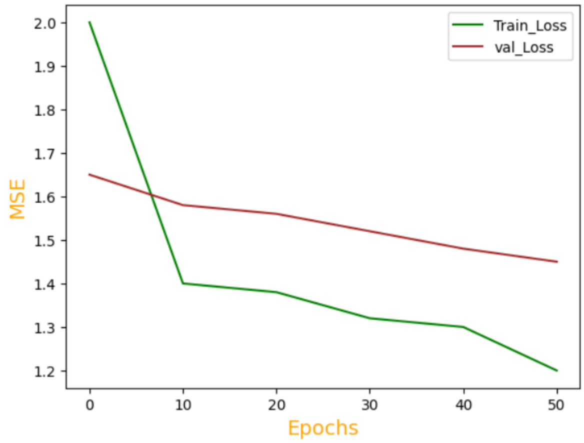

Fig. 5. Training and Validation Loss

As seen in Figure 5, the LSTM-DANN models fail miserably when it comes to generalizing models that match the validation data.

V. CONCLUSION

Companies need to optimize their supply networks, especially their production processes, if they wish to remain competitive. The related literature that has addressed distribution network techniques in the supply chain is of particular interest to this study. Current approaches and processes, such as Distribution Resource Planning (DRP), strive to optimize inventory levels and total holding costs in the supply network.Data cleansing, this includes locating and repairing dataset outliers, quantization normalization, and smoothing, is performed during the data pre-processing step. Choosing a subset of relevant features to simplify the issue is called attribute or feature selection. The model is trained using a technique called LSTM-DANN. On a consistent basis, the proposed method outperforms the LSTM and DANN models in terms of accuracy (97.48 percent).

REFERENCES

[1] A. Adarsh, "Demand Driven Material Requirements Planning," *Master Thesis*, vol. 14, no. 3, p. 48, 2020.

[2] V. G. N. zandieh M. nassibeh janatyan R. Sanskar Varshney, "Demand Driven DRP: Assessment of a New Approach to Distribution," *Int. J. Supply Oper. Manag.*, vol. 7, no. 3, pp. 295–298, 2019.

[3] H. Hou, S. Chaudhry, Y. Chen, and M. Hu, "Physical distribution, logistics, supply chain management, and the material flow theory: a historical perspective," *Inf. Technol. Manag.*, vol. 18, no. 2, pp. 107–117, 2017, doi: 10.1007/s10799-015-0229-1.

[4] I. Rizkya, K. Syahputri, R. M. Sari, I. Siregar, M. M. Tambunan, and Anizar, "DRP: Joint Requirement Planning in Distribution Centre and Manufacturing," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 434, no. 1, 2018, doi: 10.1088/1757-899X/434/1/012243.

[5] M. Ihme and R. Stratton, "Evaluating Demand Driven MRP: a case based simulated study," *Int. Conf. Eur. Oper. Manag. Assoc.*, pp. 1–10, 2015, [Online]. Available: http://irep.ntu.ac.uk/id/eprint/26668/

[6] M. Pekarcíková, P. Trebuna, M. Kliment, and J. Trojan, "Demand driven material requirements planning. some methodical and practical comments," *Manag. Prod. Eng. Rev.*, vol. 10, no. 2, pp. 50–59, 2019, doi: 10.24425/mper.2019.129568.

[7] A. Kortabarria, U. Apaolaza, A. Lizarralde, and I. Amorrortu, "Material Management without

Forecasting: From MRP to Demand Driven MRP," *J. Ind. Eng. Manag.*, vol. 11, no. 4, pp. 632–650, 2018, [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/34103776/

[8] G. Martin, M. Lauras, P. Baptiste, J. Lamothe, A. Fouqu, and R. Miclo, "Process control and decision-making for Demand Driven Sales and Operations Planning," *Proc. 2019 Int. Conf. Ind. Eng. Syst. Manag. IESM 2019*, pp. 1–6, 2019, doi: 10.1109/IESM45758.2019.8948077.

[9] R. Miclo *et al.*, "An empirical comparison of MIRPII and Demand-Driven MRP," 2018.

[10] R. Miclo, M. Lauras, F. Fontanili, J. Lamothe, and S. A. Melnyk, "Demand Driven MRP: assessment of a new approach to materials management," *Int. J. Prod. Res.*, vol. 57, no. 1, pp. 166–181, 2019, doi: 10.1080/00207543.2018.1464230.

[11] Y. Aviv and A. Federgruen, "Design for postponement: A comprehensive characterization of its benefits under unknown demand distributions," *Oper. Res.*, vol. 49, no. 4, pp. 578–598, 2001, doi: 10.1287/opre.49.4.578.11229.

[12] M. Mahdavi and T. L. Olsen, *Designing effective supply chains in strategic alignment with demand characteristics and market requirements*, vol. 10, no. 2. 2017. doi: 10.1561/0200000049.

[13] J. Småros, J. M. Lehtonen, P. Appelqvist, and J. Holmström, "The impact of increasing demand visibility on production and inventory control efficiency," *Int. J. Phys. Distrib. Logist. Manag.*, vol. 33, no. 4, pp. 336–354, 2003, doi: 10.1108/09600030310478801.

[14] C. Paper, C. Verdouw, A. J. M. Beulens, and J. Trienekens, "Modelling Demand-driven Chain Networks using Multiple CODPs," *Lean Bus. Syst. Beyond*, no. January, pp. 0–9, 2008, doi: 10.1007/978-0-387-77249-3.

[15] M. Bvuchete, S. S. Grobbelaar, and J. van Eeden, "Best practices for demand-driven supply chain management in public healthcare sector: A systematic literature review," *South African J. Ind. Eng.*, vol. 31, no. 2, pp. 11–27, 2020, doi: 10.7166/31-2-2006.

[16] M. Akbarpour, S. Ali Torabi, and A. Ghavamifar, "Designing an integrated pharmaceutical relief chain network under demand uncertainty," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 136, no. May 2019, p. 101867, 2020, doi: 10.1016/j.tre.2020.101867.

[17] M. Bvuchete, S. S. Grobbelaar, and J. van Eeden, "A network maturity mapping tool for demand-driven supply chain management: A case for the public healthcare sector," *Sustain.*, vol. 13, no. 21, pp. 1–29, 2021, doi: 10.3390/su132111988.

[18] A. P. Velasco Acosta, C. Mascle, and P. Baptiste, "Applicability of Demand-Driven MRP in a complex manufacturing environment," *Int. J. Prod. Res.*, vol. 58, no. 14, pp. 4233–4245, 2020, doi: 10.1080/00207543.2019.1650978.

[19] W. Selen and F. Soliman, "Operations in today's demand chain management framework," *J. Oper. Manag.*, vol. 20, no. 6, pp. 667–673, 2002, doi: 10.1016/S0272-6963(02)00032-3.

[20] J. B. Santos and S. D'Antone, "Reinventing the wheel? A critical view of demand-chain management," *Ind. Mark. Manag.*, vol. 43, no. 6, pp. 1012–1025, 2014, doi: 10.1016/j.indmarman.2014.05.014.

[21] R. Bjartnes, J. O. Strandhagen, H. Dreyer, and K. Solem, "Intelligent and demand driven manufacturing network control concepts," *Third World Conf. Prod. Oper. Manag.*, pp. 1–15, 2008.

[22] A. R. Ali, "Demand-Driven Asset Reutilization Analytics".

[23] M. Önder, M. U. Dogan, and K. Polat, "Classification of smart grid stability prediction using cascade machine learning methods and the internet of things in smart grid," *Neural Comput. Appl.*, vol. 35, no. 24, pp. 17851–17869, 2023, doi: 10.1007/s00521-023-08605-x.

[24] X. Fang, G. Gong, G. Li, L. Chun, W. Li, and P. Peng, "A hybrid deep transfer learning strategy for short term cross-building energy prediction," *Energy*, vol. 215, p. 119208, 2021, doi: 10.1016/j.energy.2020.119208.