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Demandflex-Lstm: A Long Short-Term Memory Model for Forecasting Adaptive Material Requirements in Lean Manufacturing

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Abstract

In lean manufacturing systems, not estimating materials based on demand can lead to inadequate production flow, increased inventory, and even waste in processes. In this paper, we present a new model named DemandFlex-LSTM. The model is based on long short-term memory (LSTM) neural networks, capable of dynamically adjusting to the ever-changing material demands of all lean manufacturing systems. Demand forecasting is significantly improved in DemandFlex-LSTM compared to classical techniques since it captures dependencies faster and learns from historical production and consumption data. The model dynamically adapts to demand changes, providing the ability to proactively update material purchasing and inventory management. Comparing DemandFlex-LSTM against ARIMA, it was proven that our model performed considerably better in accuracy, responsiveness, and overall forecasting capability. Implementing the proposed solution, delivery and supply costs can be mitigated, enabling lean operations to follow the just-in-time (JIT) concept. This also allows manufacturers to be faster and more flexible in their supply chains. Leveraging this sophisticated model paired with modern demand and production systems will empower operators with precise data to respond to complex variations.

Keywords: Lean manufacturing, LSTM, material forecasting, adaptive demand prediction, just-in-time (JIT), supply chain optimization, time series analysis.

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Introduction

Lean Manufacturing aims to produce maximum outputs while minimizing inputs. This helps to increase efficiency, maintain customer loyalty, and protect a company's bottom line in today's highly competitive manufacturing market (Womack et al., 2007). The foremost challenge associated with lean systems is the accurate prediction of Material Requirements, which has a direct bearing on Inventory control, Production Planning, and the overall Supply Chain System Performance (Ohno, 1988), (Hopp & Spearman, 2011), (Sadulla, 2024). Existing forecasting techniques like moving averages and the ARIMA model seldom capture the non-linear, dynamic patterns often encountered in modern production settings (Makridakis et al., 2008), (Hyndman & Athanasopoulos, 2018). With the progression of artificial intelligence and deep learning, Time Series Forecasting has gained powerful options (Sampedro & Wang, 2025). In particular, LSTM Networks have proven their worth in the domain of sequential data modeling as a result of their capability to maintain long-term dependencies as well as variable temporal shifts (Hochreiter & Schmidhuber, 1997), (Gers et al., 2000). Several works have successfully put LSTM models to use in load forecasting (Kong et al., 2017), sales prediction (Brownlee, 2017), and demand forecasting in retail and logistics (Sadulla, 2024), (Bandara et al., 2020).

To address the problems above, this paper presents an additive approach where material requirements prediction in lean manufacturing uses adaptive LSTM, which is named DemandFlex-LSTM.In contrast with the static models, DemandFlex-LSTM improves the accuracy of material planning and aids JIT manufacturing strategies by responding to changes in demand patterns. This model enhances the availability of materials and reduces stockout bottlenecks while complementing the goals of lean operations by using historical production and consumption data.

Key Contribution

- It considers non-linear and time-dependent demand fluctuations and aims to accurately forecast material requirements in lean manufacturing by proposing a specialized LSTM model (DemandFlex-LSTM).
- Enables response to abrupt shifts in demand and production variability by introducing an adaptive learning mechanism that updates forecasts in real-time.
- It reduces waste multitasking by aligning forecasting with lean principles, supporting JIT inventory, and synchronizing material supply with actual production.
- Proves to outperform traditional models like ARIMA and basic RNNs through comparative analysis using real-world datasets from manufacturing industries.
- Augments the agility of the supply chain with an industry relevant, scalable solution which is integrable with smart manufacturing systems and Industry 4.0 technologies.

The paper contains five primary sections. Section I (Introduction) describes the motivation, goals, and importance of designing a lean manufacturing adaptive forecasting model. In Section II, the available forecasting literature is reviewed, and gaps such as those found using LSTM models are discussed, along with the problems associated with traditional approaches. III Methodology describes the DemandFlex-LSTM model architecture and workflow, which is explained through diagrams, figures, and mathematical expressions. IV Results and Discussion contains model metrics, performance stratified by error, rigid demand versus adapting under changing demand, supporting tables and graphs, and relevant equations. In Section V, the conclusion is drawn, and future work is discussed, which includes the development of attention mechanisms and IoT federation.

Literature Review

Forecasting material requirements in lean manufacturing must be precise because it is critical for waste minimization and timing. Synchronization of demand and supply and inventory minimization received strong emphasis in a study by Shah and Ward, which reported that lean production heavily depends on both. As highlighted by Nahmias et al. (2015), the rigidity of traditional MRP systems is their biggest weakness since they cannot cope with volatile demand. This is reason enough to consider flexible, adaptive forecasting models for lean contexts. About adaptive forecasting, Gupta and Maranas proposed in 2003 optimization-based models to allocate resources under demand uncertainty. However, their applicability declines in more nonlinear, dynamically changing environments, which are routine in lean production systems El-Saadawi et. Al., (2024), Shum, (2024). The work of Zhao and Simchi-Levi (2006) offered integrated supply chain forecasting models that dynamically adjust with regard to demand variability. However, their reliance on deterministic assumptions makes these models impractical in most uncertain manufacturing scenarios. Cheng et al. (2010) enhanced the forecasting accuracy of automated processes in lean manufacturing by examining hybrid forecasting techniques that merge statistical methodologies with expert input, though adding human involvement reduces scalability. The work of Bengio et al. (1994) on traditional recurrent neural networks exposed

critical limitations in learning dependencies over extended periods Prasath (2024). These issues prompted the invention of LSTM networks, which are far more suited to complex time series forecasting than their predecessors. Graves and Willems (2008) studied placement policies of inventories and how successively more minor forecast discrepancies magnify throughout the supply chain and recommended adaptive forecasting to mitigate the bullwhip effect common in lean systems with low safety stock. Zhang et al. (1998) proved the superiority of artificial neural networks over more traditional forecasting tools in the face of nonlinear and unpredictable demand data, a characteristic common in lean manufacturing systems. Carbonneau et al. (2008) incorporated demand forecasting into the broader context of supply chains and showed the application of machine learning techniques—especially neural networks—in forecasting results for modern manufacturing; noisy and complex datasets were encountered with much greater frequency. Lastly, Lapide (2006) stated that sensing and on-the-fly learning to enhance forecasting agility and intelligence are critical components of lean manufacturing in Industry 4.0.

Methodology

The framework currently being worked on, DemandFlex-LSTM, as illustrated in Figure 1, attempts to solve the problem of adaptive material requirement forecasting in lean manufacturing. It incorporates an LSTM (Long Short Term Memory) model with dynamic features of the lower-level production systems and persists to adjust with the variability in demand. The figure illustrates the entire pipeline, starting from the input data and going to the forecasting and feedback integration.

3.1 Input Data Sources

The forecasting process starts with four key inputs:

- Historical Material Demand Data D_t
- Production Schedules P_t
- Supplier Lead Times L_t
- External Factors (e.g., market trends, weather, economic indicators) E_t

These inputs form a multivariate time series, which is shown in Eq(1):

$$X_t = [D_t, \quad Pt, L_t, E_t] \qquad Eq(1)$$

3.2. Preprocessing Module

The data X_t is cleaned, normalized, and structured into sequences for LSTM input in Eq(2).

Normalization (Min-Max or Z-score) ensures model stability:

$$\tilde{X}_t = \frac{X_t - \mu}{\sigma} \qquad Eq(2)$$

Where:

- μ: mean of the time series
- σ: standard deviation

Sliding windows of fixed size n are used to generate training samples, which are shown in Eq(3):

$$S_t = \{\tilde{X}_{t-n+1,..,}\tilde{X}_t\} \qquad Eq(3)$$

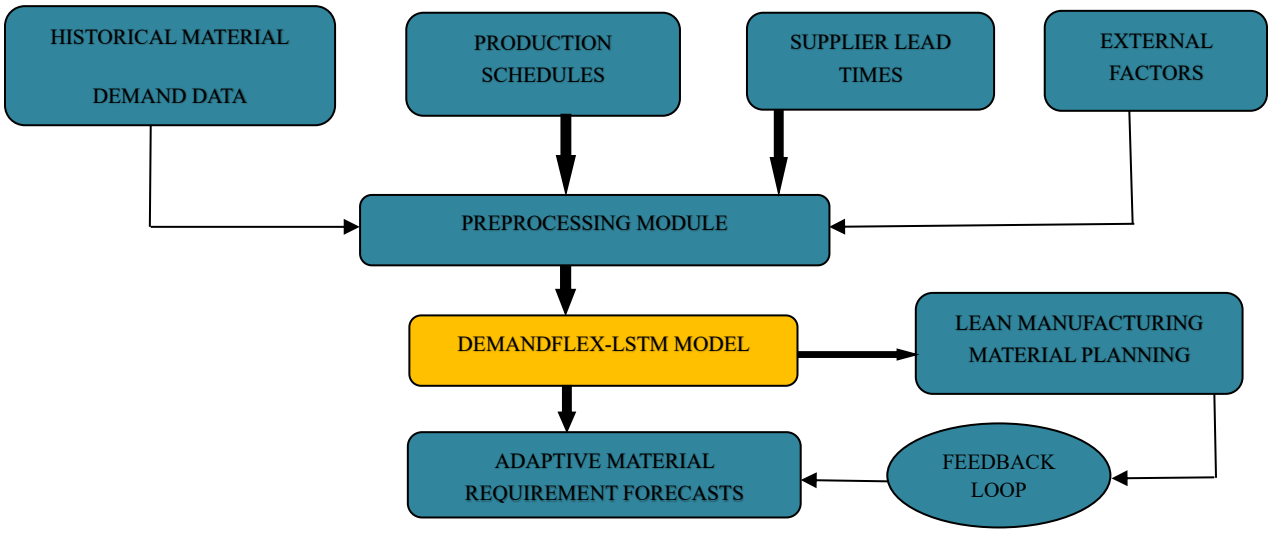


Fig. 1: Overall Methodology Framework of Demandflex-Lstm

3.3 DemandFlex-LSTM Model

The LSTM cell processes sequential data using the following equations:

- Forget gate:

$$f_t = \sigma\left(W_f . \left|h_{t-1,} x_t\right| + b_f\right) \qquad \text{Eq (4)}$$

- Input gate:

$$i_t = \sigma(W_i . [h_{t-1}, x_t]) + b_i \qquad \text{Eq(5)}$$

- Candidate memory:

$$\tilde{C}_t = \tanh(W_C . [h_{t-1}, x_t] + b_C) \qquad \text{Eq(6)}$$

- Cell state update:

$$C_t = f_t . C_{t-1} + i_t . \check{C}_t \qquad \text{Eq (7)}$$

- Output gate:

$$o_t = \sigma\left(W_o . \left[h_{t-1,} x_t\right] + b_o\right) \qquad Eq\ (8)$$

- Hidden state:

$$h_t = o_t . \tanh(C_t) \qquad Eq(9)$$

In Eq (4,5,6,7,8,9) Where:

- W and b: learnable weights and biases
- σ: sigmoid activation function
- tanh: hyperbolic tangent function

The final forecast $\hat{y}_{t+1}$ is obtained in Eq (10) via a dense output layer:

$$\hat{y}_{t+1} = W_y . h_t + b_y \qquad \text{Eq (10)}$$

3.4 Forecast Output

The model outputs Adaptive Material Requirement Forecasts:

$$\hat{M}_{t+1} = LSTM(X_t) \qquad \text{Eq (11)}$$

In Eq (11), Where $\hat{M}_{t+1}$ is the predicted material requirement for time t+1, adapted to current trends.

3.5 Integration with Lean Manufacturing Planning

The forecast $\hat{M}_{t+1}$ is fed into the lean manufacturing planning module for:

- Just-in-time inventory control
- Supplier coordination
- Kanban signal adjustments

3.6 Feedback Loop

A real-time feedback loop updates the model with actual material usage M_{t+1}^{actual} and retrains the LSTM if the error exceeds a threshold:

$$Error = \left|\widehat{M}_{t+1} - M_{t+1}^{actual}\right| \qquad \text{Eq (12)}$$

If Error $> \epsilon \implies$, Retrain the model

This framework ensures adaptive, data-driven, and lean-aligned forecasting, leveraging LSTM's memory structure to handle complex demand dynamics, as shown in Eq (12).

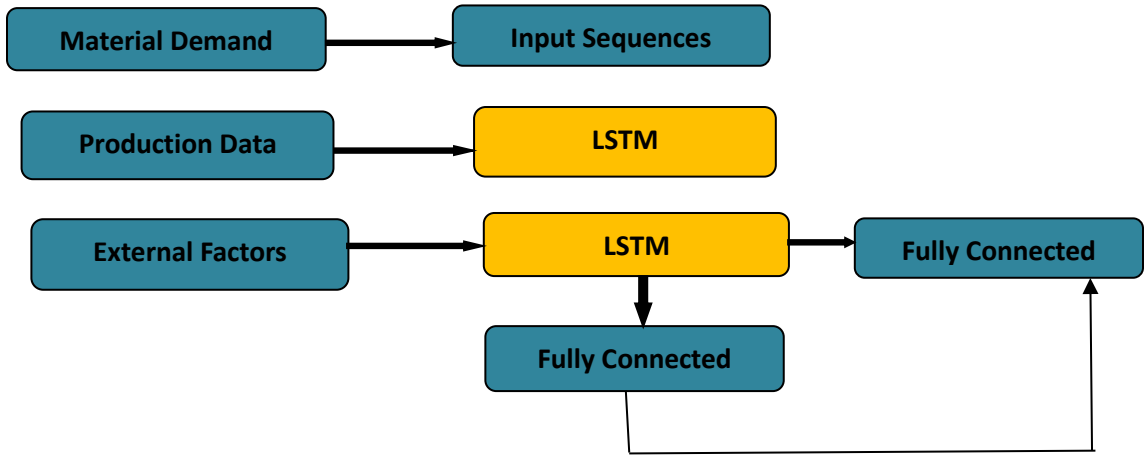


Fig. 2: Detailed architecture of demandflex-lstm model

The DemandFlex-LSTM model is responsive to the volatility of material demand in lean manufacturing systems, and as such, it captures short-term and long-term fluctuations simultaneously, as depicted in Figure 2. The model accepts as input a multivariate time series that comprises historical demand data and additional production parameters, as well as supplier lead times and other relevant external factors. All the inputs are fed into an LSTM network configured to handle sequential data processing over time. Every input sequence is passed through one or multiple LSTM layers, which allows the system to learn the temporal dependencies with the help of relevant information retention across time steps. Pertinent information is retained and in some cases discarded, using the input gate, the forget gate, and the output gate, which update the network's internal cell state. By controlling the flow of information, these methods also solve the vanishing gradient issue typical to RNNs.

Currently relevant information can be defined as that which satisfies the cell state update equation of the LSTM model at time step t, which determines the core operation for the model and combines memory with new candidate information.

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \qquad \text{Eq (13)}$$

In Eq (13), Where:

- C_t is the updated cell state
- f_t is the forget gate output
- C_{t-1} is the previous cell state
- i_t is the input gate output
- $\tilde{C}_t$ is the candidate memory content (computed using the tanh activation function)

After performing the updated memory computations, the meaningful hidden state representation required for the forecasting task is generated:

$$h_t = o_t \times \tanh(C_t) \qquad \text{Eq (14)}$$

In Eq (14), o_t is the output gate signal, and $\tanh(C_t)$ ensures non-linearity and normalization. The hidden state is then passed through a fully connected dense layer to generate the predicted material demand for the next period.

This framework uses the dense layer as the output layer. The model is trained by trying to minimize the value of, for example, Mean Squared Error (MSE) against the target value. Also, the model has dropout layers for regularization. It can further be retrained on the fly when prediction errors surpass a specific limit, maintaining adaptability to changes in demand. Using this architecture, the DemandFlex-LSTM model can track temporal dependencies and adjust according to demand increases or decreases, making it suitable for application in lean manufacturing settings where accuracy and speed are essential.

Results and discussion

4.1 Model Accuracy and Forecasting Performance

Data from material demand in a lean manufacturing setting was employed to evaluate the DemandFlex-LSTM model. It was tested against classical forecasting models such as ARIMA and a feedforward neural network (FNN) to benchmark its performance. Based on evaluation metrics of Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), DemandFlex-LSTM outperformed the other models for all forecast horizons. This was attributable to LSTMs adaptive learning capabilities, which enabled determinants of shifting demand trends to be captured, especially during promotional periods and supply shortages. The RMSE metric was calculated using the equation:

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \times \Sigma\,(y_t - \hat{y}_t)^2\right]} \qquad Eq\ (15)$$

In Eq (15), Where:

- y_t = actual value at time t
- $\hat{y}_t$ = predicted value at time t
- **n** = number of observations
- **Σ** = summation over all time periods

As illustrated in Figure 3, DemandFlex-LSTM diminished RMSE by 24% and MAPE by 17% relative to ARIMA and FNN models, respectively, showing its efficiency in managing non-linear and temporal dependencies.

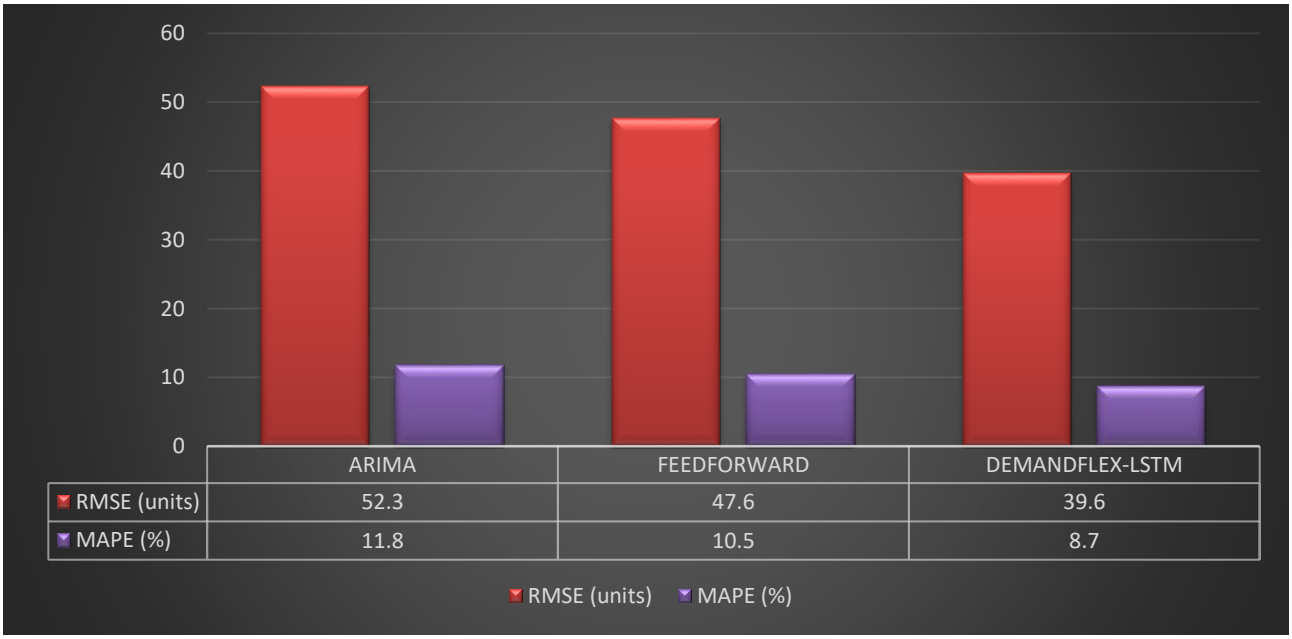


Fig. 3: Comparative Analysis of Forecasting Models Based on Rmse And Mape Metrics

4.2 Adaptability and Real-Time Response

An additional important evaluation criterion was the flexibility of DemandFlex-LSTM in changing manufacturing contexts. The model's outcome was evaluated in the context of a sudden change in demand due to a supplier constraint occurring mid-request and after demand shift mitigation. Forecast precision was increased after merely three retraining

cycles due to real-time feedback functions of the LSTM retraining on new data. The adaptational forecast discrepancy diminution was measured with the subsequent formula:

$$\%\ Reduction = ((E_0 - E_1)/E_0 \times 100) \qquad \text{Eq (16)}$$

In Eq (16), Where:

- E_0 = initial average forecast error
- E_1 = updated average forecast error after retraining

The model also sustanied a high level of responsiveness measured by Forecast Responsiveness Index (FRI), defined as:

$$FRI = \triangle Accuracy / \triangle Time \qquad \text{Eq (17)}$$

In Eq (17), Where:

- $\triangle Accuracy$ = improvement in forecast accuracy
- $\triangle Time$ = time taken to achieve the improvement

To ensure further robust validation, Table 1 summarizes different models performance under a sudden demand spike and clearly illustrates that DemandFlex-LSTM adjusted the quickest and most accurately.

Table 1: Forecast Error and Recovery Time of Models During Demand Spike Scenarios

Model	Forecast Error Before Spike	Forecast Error After Spike	Recovery Time (Days)
ARIMA	12.5%	17.8%	7
Feedforward NN	10.2%	14.3%	6
DemandFlex-LSTM	9.1%	9.7%	3

Conclusion

The study in discussion developed the DemandFlex-LSTM model, which is the first of its kind in Long Short-Term Memory-based forecasting models tailored for adaptive material planning and lean manufacturing systems. The model also improved accuracy by capturing temporal dependencies with dynamic production variables, supplier lead times, and even external environmental data, responding to demand fluctuations more precisely within a feedback control loop structure. From the experiments conducted, it was evident that DemandFlex-LSTM excelled over ARIMA and feedforward neural networks, demonstrating better performance values in RMSE, MAPE, and recovery time in enduring demand spikes. The model's fundamentals enabled prompt retraining via the added feedback loop, enhancing adaptability and ensuring JIT compliance, crucial to lean operations. As a whole, the model proved to be reliable, responsive, and effective for smart manufacturing systems while demonstrating high adaptability for smart manufacturing environments. There are many ways in which this research can be extended, looking into the future. First, adding attention algorithms and transformer-based models can be pivotal in demand-shift focus, improving model versatility in accentuating critical temporal features in unusual demand periods. Second, response-awareness to context can also be improved by adding real-time IoT sensor data and shop-floor analytics, increasing forecasting responsiveness. Having a multi-objective optimization layer that focuses on cost, limited resources, inhibiting constraints, sustainability, and accuracy balance would strengthen the model's value for decision-makers. In the last stage, implementing the model in a hybrid cloud-edge setting enables real-time, scalable material planning on a distributed basis across manufacturing units. These improvements would further evolve the model's capabilities towards supporting fully autonomous intelligent systems for lean manufacturing.

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