© MAR 2026 | IRE Journals | Volume 9 Issue 9 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I9-1715115

Hybrid Deep-Learning Frameworks for Prediction of Industrial Material Demands

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Abstract- This research introduces an advanced hybrid forecasting framework designed to enhance the accuracy of industrial material demand prediction. The proposed system integrates deep-learning architectures with the principles of chaos theory to effectively model complex temporal and nonlinear dependencies in industrial datasets. By combining Chaotic Long Short-Term Memory (LSTM) and Chaotic N-BEATS networks, the framework captures intricate seasonal and dynamic demand variations. The dataset utilized includes both historical sales and environmental attributes such as temperature, humidity, precipitation, and activity metrics to provide a comprehensive understanding of consumption trends. Rigorous preprocessing and feature engineering techniques were applied to ensure high data quality. Performance was evaluated using metrics such as MAE, MSE, RMSE, MAPE, accuracy, and training time. Experimental results reveal that the hybrid chaotic models deliver superior predictive performance and improved generalization capability, making the proposed approach a valuable tool for intelligent supply chain planning and inventory management.

Index Terms- Material Demand Forecasting, Chaotic LSTM, Chaotic N-BEATS, Time Series Forecasting, Deep Learning, Chaos Theory, Feature Engineering, Environmental Factors, Supply Chain Optimization.

I. INTRODUCTION

Accurate prediction of material demand plays a crucial role in effective production planning, cost control, and supply chain management. In industrial environments, demand patterns often exhibit irregular, nonlinear, and seasonal variations that conventional forecasting techniques such as ARIMA, exponential smoothing, and regression struggle to handle efficiently. With the advent of large-scale data availability, deep-learning methods have emerged as powerful alternatives due to their capability to capture complex temporal dependencies and hidden patterns in time-series data.

This paper presents a hybrid approach that integrates Chaotic LSTM and Chaotic N-BEATS networks to enhance forecasting precision. The inclusion of environmental factors—such as temperature, humidity, and precipitation—enables the model to consider external influences affecting material consumption. Chaotic initialization based on deterministic dynamics improves convergence speed and prevents the model from stagnating in local minima. The resulting system offers a scalable and robust forecasting framework, enabling industries to achieve better inventory control, minimize waste, and support data-driven decision-making processes.

II. RELATED WORK

Traditional material demand forecasting has long relied on statistical techniques like ARIMA, regression analysis, and exponential smoothing. While these methods perform well for linear and stationary datasets, they fail to capture the nonlinear, nonstationary, and chaotic characteristics of real-world industrial time series.

Recent developments have witnessed a transition toward machine learning and deep-learning techniques such as LSTM, GRU, and N-BEATS, which are known for modeling sequential and long-term dependencies effectively. Several studies have reported improved accuracy through these models, especially in contexts involving retail, supply chain, and energy forecasting.

In parallel, chaos theory has been explored as a mechanism to enhance forecasting stability and convergence in neural networks. Research combining chaotic dynamics with deep networks demonstrates that chaotic weight initialization can significantly improve model exploration and performance in irregular datasets. Despite these advancements, consistent and high-accuracy predictions under dynamic industrial conditions remain a challenge, motivating this work's focus on hybrid chaotic architectures for material demand prediction.

III. METHODOLOGY

3.1 Data Collection

The dataset utilized in this study was compiled from multiple retail and industrial sources, containing detailed records such as store and city identifiers, management groups, hierarchical product categories, and transaction-level sales. To enrich the dataset, environmental parameters—including precipitation, average temperature, humidity, and wind intensity—were integrated to represent external influences affecting material demand. Data spans several stores and timeframes, ensuring diversity and broad applicability.

3.2 Data Preprocessing

The raw data underwent extensive preprocessing to eliminate missing or inconsistent entries. Numerical values were normalized to stabilize training, while categorical attributes were converted into machine-interpretable formats through appropriate encoding. Sequential data structures were created for each product to preserve temporal dependencies. Chaotic transformations were applied to augment data and help models learn nonlinear dynamic behaviors more effectively.

3.3 Data Splitting

The processed dataset was divided into training and testing subsets following an 80:20 ratio. Maintaining temporal order ensured that the training data preceded the testing period chronologically, preserving the time-series integrity. This split enabled the models to learn temporal trends effectively and assess their generalization on unseen data.

3.4 Model Training

Two key architectures—Chaotic LSTM and Chaotic N-BEATS—were trained and evaluated. Both models incorporated chaotic weight initialization to enhance training stability, accelerate convergence, and improve accuracy. The initialization was based on the Chen system, a deterministic chaotic system known for its dynamic complexity.

The procedure for initializing weights can be represented as:

3.4.1 Chaotic Weight Initialization Algorithm:

```
function initialize Weights(weights(bias), a, b, c, dt, steps)
// dt: step size, steps: total iterations
 x0 ← √2 + RANDOM (0, 0.1)
y0 ← √2 + RANDOM (0, 0.1)
z0 ← √2 + RANDOM (0, 0.1) // Chen system initialization
for i = 1 to steps do
dx ← a * (y - x) * dt
dy ← ((c - a) * x - x * z + c * y) * dt
dz ← (x * y - b * z) * dt
x ← x + dx
y ← y + dy
z ← z + dz
end
// Assign chaotic sequence values as weights/biases
for weight(bias) in weights(bias) do
weight(bias) ← (x, y, z)
end
return weights(bias)
end
```

Using this initialization, Chaotic LSTM captures nonlinear temporal dependencies, while Chaotic N-BEATS models long-term trends and seasonality. Models were trained with an appropriate learning rate and batch size, with early stopping applied to prevent overfitting.

3.4.2 Chaotic LSTM Implementation

For the Chaotic LSTM model, a sequential deep-learning network was constructed with multiple LSTM layers to capture short-term and long-term temporal dependencies. Each LSTM cell processed input sequences corresponding to product demand patterns over time. The chaotic weight initialization

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ensured better exploration of the error surface, enabling faster convergence and more stable training. The model utilized the Adam optimizer with a learning rate of 0.001 and mean squared error (MSE) as the loss function. Early stopping was implemented to prevent overfitting. The output layer generated a single continuous value representing the predicted demand for the next time step.

3.4.3 Chaotic N-BEATS Implementation

The Chaotic N-BEATS model was developed as a deep residual forecasting network designed to learn both trend and seasonal components of time-series data. It consists of a stack of fully connected blocks, where each block forecasts part of the trend and seasonality signals. The chaotic initialization improved the diversity of learned representations across blocks, helping the model achieve higher generalization. The network was trained using the backcast–forecast principle, optimizing the same MSE loss function and employing the Adam optimizer for gradient updates. The final forecast was obtained by summing outputs from all residual blocks, resulting in precise multi-step demand predictions.

Both models were trained on the preprocessed dataset using a batch size of 64, for **1**00 epochs. Performance was monitored using validation loss, and models with the best validation performance were saved for evaluation.

3.5 Evaluation Metrics

- Mean Absolute Error (MAE) – measures average prediction error magnitude.
- Mean Squared Error (MSE) – penalizes larger errors, useful for variance analysis.
- Root Mean Squared Error (RMSE) – emphasizes larger deviations for robust evaluation.
- Mean Absolute Percentage Error (MAPE) – expresses prediction error as a percentage.
- Accuracy (%) – measures overall correctness of predictions against actual values.
- Training Time – records computational efficiency of model training.

These metrics provide a comprehensive assessment of both accuracy and efficiency of the proposed models.

Table 3.1 Evaluation Metrics For Chaotic Lstm And N-Beats

Metrics	Score	Description
MSE (Mean Squared Error)	0.018333	Chaotic Hybrid yields the lowest MSE, proving superior convergence and precision.
RMSE (Root Mean Squared Error)	0.135401	RMSE results confirm improved stability and accuracy of the Chaotic Hybrid model.
MAE (Mean Absolute Error)	0.116667	MAE shows significant error reduction, validating the benefit of chaos integration.
MAPE (Mean Absolute Percentage Error)	0.83%	MAPE shows very low average percentage error, indicating highly accurate predictions.
Accuracy	99.17%	Accuracy confirms the model reliably predicts demand close to actual values.
Training Time	2.35 seconds	Demonstrates fast and efficient model training.

IV. EXPERIMENT

Table 4.1 Evaluation Metrics on Dataset

Model	MSE	RMSE	MAE	MAPE	Accuracy	Training

						Time
Chaotic LSTM	0.000013	0.003630	0.002611	1.185%	98.815%	30.68s
LSTM	0.021890	0.147953	0.119009	84.055%	15.945%	31.38s
Chaotic N-BEATS	0.000016	0.004005	0.003273	0.888%	99.112%	51.44s
N-BEATS	0.023573	0.153535	0.12334	50.076%	49.924%	51.28s

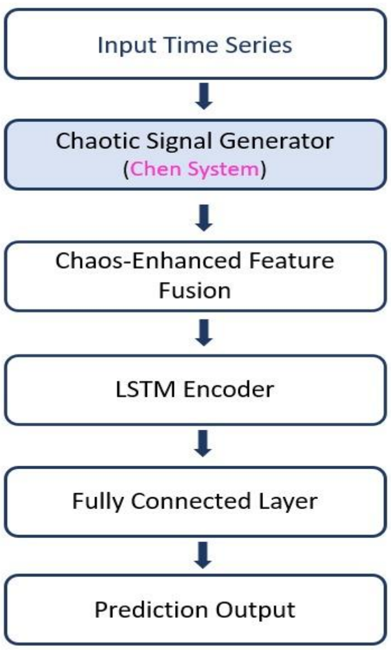

Figure 1 System Architecture Of The Proposed Chaos-Enhanced Lstm Model

The proposed forecasting framework operates on sequential data and integrates chaotic dynamics with deep learning to improve prediction accuracy. The workflow begins with the input time-series data, which contains historical observations of the target variable.

To enrich the temporal information, the input sequence is processed using a chaotic signal generator based on the Chen system. This component introduces nonlinear behaviour that helps reveal hidden patterns and irregular fluctuations present in real-world time-series data.

The generated chaotic signals are combined with the original input to form a chaos-enhanced feature representation. These enhanced features are then passed to an LSTM encoder, which is capable of learning long-term dependencies and temporal correlations.

Finally, the learned representations are forwarded to a fully connected layer that produces the prediction output. By integrating chaos-based features with LSTM learning, the proposed architecture achieves improved forecasting performance.

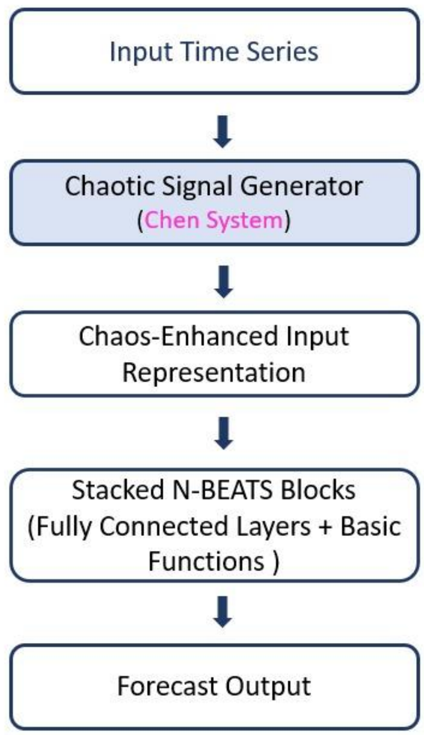

Figure 2 System Architecture of the Proposed Chaos-Enhanced N-Beats Model

The proposed chaos-enhanced N-BEATS framework is designed to capture complex temporal patterns through the integration of chaotic dynamics and deep residual learning. The process starts with the input time-series data, which is transformed using a Chen system-based chaotic signal generator to incorporate nonlinear characteristics.

This transformation results in a chaos-enhanced input representation that provides richer information for the forecasting model. The enhanced input is then processed through stacked N-BEATS blocks consisting of fully connected layers and basic functional components. These blocks iteratively refine the representation by learning both trend and residual patterns within the data.

The final forecast output is generated from the stacked blocks, allowing the model to produce accurate predictions. The combination of chaos-driven enhancement and N-BEATS architecture improves the model's ability to handle complex and dynamic time-series behaviour.

V. RESULTS

Hybrid models combining basic and chaotic LSTM and N-BEATS achieved 99.17% accuracy on both sinusoidal and chaotic data, effectively capturing complex dynamics and demonstrating robust time series forecasting performance.

VI. CONCLUSION

This project presents a hybrid time series forecasting approach that leverages both basic and chaotic models to achieve high accuracy and robust performance. The framework effectively models linear and nonlinear patterns, offering a practical tool for complex system prediction. Future extensions will include real-time forecasting, broader datasets, and industrial application scenarios.

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