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Enhancing Supply Chain Resilience Through Cloud-Based SCM and Advanced Machine Learning: A Case Study of Logistics

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***Abstract*—E-commerce offers unparalleled opportunities to enhance the efficacy and efficiency of supply chain management (SCM), since it represents a revolutionary leap in technology. In developing nations, retail and consumer product merchants have a behavioural desire to use e-commerce for SCM. This research attempts to investigate this intention. This study investigates the impact of cloud-based SCM systems enhanced by advanced machine learning (ML) techniques on supply chain resilience (SCR). Utilising data from a prominent Chinese home appliance shipping firm, the research evaluates the performance of ML models—Multi-Regression, LSTM, and ANN—in improving demand forecasting and inventory management. Results demonstrate that LSTM had the greatest predictive accuracy among a models evaluated, with RMSE values average 231.98 across Local Transshipment Centers (LTCs), reducing supply chain interruptions and improving operating efficiency. These findings underscore the efficacy of integrating ML with cloud SCM for bolstering supply chain resilience amidst operational uncertainties.**

Keywords—Cloud-based supply chain management, Supply chain resilience, Machine learning, Demand forecasting, Inventory optimisation, Multi-Regression, LSTM, ANN (Artificial Neural Networks), SCM systems

I. Introduction

E-commerce has become a crucial factor for competitiveness and sustainability in the globalised business environment, particularly in supply chain management. It is not new for businesses to utilise e-commerce to run their operations in today's market. The titles "Internet of Manufacturing," "Open Manufacturing," "Smart Manufacturing," "Digital Manufacturing," and "Sector 4.0" have all evolved from the digital revolution that has struck the manufacturing sector. These concepts have brought about significant transformations in logistics industry, specifically in a realm of SCM[1] .

Research on customer behaviour during online purchases has recently emerged as a hot topic due to the explosion of ecommerce. Many studies have shown that technology, trust, and convenience are the most important factors that influence customer behaviour. Nevertheless, a complete view is still unattainable[2]. Regardless of size, the main objective of most businesses is to maximise earnings. The same holds true for online shopping.

Supply chain management, or SCM, and online trading have profited from advancements in technology and the internet. The purpose of SCM is to optimise the value that a company provides to its customers while controlling costs and meeting the needs of suppliers, purchasers, distributors, and other interested parties. Given their increased interconnectedness, supply chains that fully adopt the SCM concept should be much more efficient [3] [4].

Marketing researchers are increasingly using machine learning (ML) to build prediction models and find non-linear patterns in data. ML a subset of AI, has seen extensive use in ecommerce research for forecasting functions. Previous research has used ML to anticipate and understand the reasons of customer turnover using classification models, identify high-risk consumers for retention programmes, and more [5] [6].

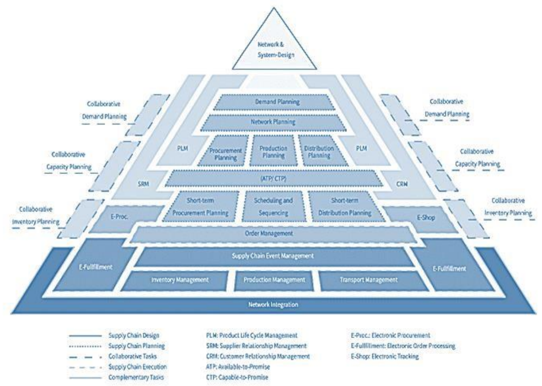

Figure 1: Supply Chain Management task model in ML[7]

The accomplishment of the goals mentioned above requires the implementation of internal and cross-company tasks within the realm of supply chain management. Figure 1 illustrates a depiction of these tasks. In order to achieve this objective, several sub-goals must be pursued. These include enhancing customer orientation and satisfaction, improving delivery capability, and reducing lead times [8] [9] [10].

Machine Learning has made significant advancements in recent decades, establishing itself as a practical technology in commercial applications. This field refers to an area of computer science that has a study and development of algorithms that can learn and even be able to make predictions in situations that are complicated[11]. It is necessary to mention that the application of the ML increases in the context of SCM and online commerce. In the current e-commerce business platform, ML is used in areas such as inventory, individual customer's preferences, and big data handling. This results into increased sales and satisfied customers a business needs for its survival. When it comes to supply chain management, Artificial

Intelligence or ML plays the following roles; Parts of the supply chain susceptible to disruption; movement of goods and services; and optimisation of operations. It may also enable businesses to achieve efficiencies in the processes, thus cutting down costs when it tries to integrate in response to the accelerating pace in a given market need. In that context, it enables reasonable and reproducible conclusions and solutions for researchers, data scientists, engineers, and analysts. In other words, through the use of input data as well as through analysis of patterns and connections within it, machine learning is capable of and does uncover meaningful patterns[12] [13] [14][15]. The following Table 1 provide an Impact of e-commerce and innovations on various technologies.

Table 1: Impact of e-commerce and innovations on various technologies [13]

Impact Level	Innovations/Technologies	Use in Commercial Activities	Trial Logistics Projects
High	Business analytics, mobile technologies, big data technologies, robotic automation of warehouses, electric cars, autonomous vehicles, drones	Enhancing decision-making, improving customer experiences, optimising operations	Implementing autonomous delivery systems, robotic sorting in warehouses
Medium	Internet of Things (IoT), automatic identification and data collection	Real-time tracking, automated data capture	Smart inventory management, predictive maintenance
Low	Cloud computing technologies	Supporting scalable and flexible infrastructure	Enabling seamless data integration and accessibility

A. Contribution of the study

To improve SCR, this study will investigate methods to combine cutting-edge machine learning (ML) methods with cloud-based supply chain management (SCM) systems. ML models—Multi-Regression, LSTM, and ANN—are tested on a major Chinese home appliance shipping company to improve demand forecasting and inventory management. LSTM shows greater prediction accuracy, demonstrating the potential of MLenhanced cloud SCM systems to reduce supply chain disruptions and improve operational efficiency. The primary contribution of this work is outlined as follows:

- Data was extracted from e-commerce platforms and supply chain management systems.
- Utilized various machine learning models such as sales and demand forecasting algorithms, inventory optimisation techniques, and personalised recommendation systems.
- Evaluating the model's performance involved utilising metrics like MAE, RMSE, and MAPE.
- Implemented machine learning models specifically designed for supply chain management and ecommerce applications. These models included demand forecasting and inventory optimisation.
- Significant improvements have been shown in supply chain efficiency, inventory management, and customer satisfaction metrics.

B. Structure of paper

The following is an organisation of the paper's remaining fragments. In Section 2, provide an overview of SCM in ecommerce. In Section 3, outline the methodologies and methodology. Finally, in Section 4, results analysis and explain the outcomes. Conclusion and future work of this study present in section 5.

II. LITERATURE REVIEW

In this section, provide some previous work on fake news detection based on machine learning.

J. Leukel, S.Kirn, et. al, presents a case study on supply chains for airport services. Supply chains are defined by the effective use of resources and procedures by many enterprises to satisfy customer demand. There are several ways to solve the inherent coordination difficulty. This study approaches supply chain systems from a Cloud Computing perspective: It views supply chains as service offers and consumer demand as service requests, making coordinating a matter of choosing optimum service compositions[16].

GIANNAKIS, M., SPANAKI, et.al, this study demonstrates that the suggested system may improve all three aspects of supply chain responsiveness by designing a C-SCM ecosystem and investigating its effects. The suggested ecosystem presents a perspective on SCM and related techniques in the context of cloud computing. Scenarios based on a case study of fashion retail supply chain operations investigate the possibility of improving SCR using the cloud[17].

Animesh Tiwari, researches that the regular flow of items and commodities from suppliers to manufacturers, wholesalers, retailers, and ultimately consumers may be tracked via SCM. It uses the fundamental principle of cloud computing to offer a scalable and effective solution for managing supply chains via the use of distributed data centres on the cloud[18].

Baryannis, Validi, et al. researched; in this research, they plan the demand in the supply chain using many methods and compare the results. The purpose of this study is to explore the potential applications of many methods for demand forecasting, including Xgboost and SVM, two ML approaches, and more conventional methods for time series forecasting like moving average and exponential smoothing. Applying this study to the prospective vendor's statistical model allows the biggest global FMCG company to put it into action. The following table 2 provide the comparative study on Supply chain Management based on machine learning using various techniques in ECommerce[19].

Table 2: Comparative study on Supply chain Management based on machine learning using various techniques

Author	Focus of Study	Findings	Gaps	Limitations
J. Leukel, S. Kirn, et al. [18]	Case study of airport service supply chains, focusing on coordination mechanisms via software innovation.	Supply chains as service offers; consumer demand as service requests; coordination through optimum service compositions.	Specific methods for creating and implementing coordinating mechanisms.	Limited to the context of airport service supply chains; generalizability to other industries not addressed.

GIANNAKIS, M., SPANAKI, et al. [19]	Development of a cloudbased SCM ecosystem enhancing supply chain responsiveness (SCR).	Enhanced SCR through cloud; architecture for cloud-based SCM; implications for practice and migration.	Long-term impacts on SCR; practical implementation challenges.	Case study limited to fashion retail; applicability to other industries needs further research.
Animesh Tiwari [21]	Supervising product transfer in SCM using cloud services for resource sharing and scalability.	Efficient and scalablomputing; for SCM via cloud datacenter distributed utilisation.	Detailed analysis of the impact on different supply chain stages.	General overview: specific metrics of efficiency and scalability improvements not provided.
Baryannis, Validi, et al., [23]	Demand forecasting in supply chains using machine learning (Xgboost, SVM) and traditional methods (moving average, exponential smoothing).	Machine learning methodologies for accurate long-term demand forecasting; statistical model application in FMCG.	Comparison of additional machine learning techniques; broader application in various supply chain contexts.	Study focused on specific methodologies; real-world application challenges beyond the FMCG.

A. Research gaps

Despite the growing adoption of cloud computing in SCM to enhance operational efficiency, there remains a significant gap in understanding how cloud-based SCM systems specifically contribute to enhancing supply chain resilience (SCR). Existing literature discusses the potential benefits of cloud technologies in improving visibility, flexibility, and responsiveness within supply chains. However, empirical studies that comprehensively analyse the implementation challenges, strategic adoption considerations, and real-world effectiveness of cloud-based SCM in building resilience across diverse industry sectors are limited. To address this gap, advanced machine learning (ML) techniques presents a promising approach. ML algorithms, such as ensemble methods or deep learning architectures, could be employed to analyse large-scale data from cloud-based SCM systems. These techniques can offer insights into optimising supply chain operations for resilience, by predicting disruptions, optimising inventory management under uncertainty, and adapting strategies dynamically. By integrating ML with cloudbased SCM, researchers can explore new avenues for enhancing resilience strategies and achieving sustainable SCM practices in the face of evolving global challenges.

III. MATERIAL AND METHODS

This section provides a comprehensive explanation of the methodology used in the work. This section has many subcategories. It provides an analysis of the dataset and preparation procedures.

A. Methodology

This research integrates data collection, estimate, demand forecasting, error correction, and inventory optimisation in a two-level supply chain. The analysis uses data from a major Chinese home appliance shipping company, including historical order records, warehouse information, temperature data, and third-party discounts. Advanced machine learning and statistical models estimate future demand and error correction refines these projections based on actual demand. Inventory optimisation schemes match inventory levels with predicted demand, taking lead times and safety stock into account. The research uses RMSE, MAE, and MAPE to assess and optimise forecasting accuracy of Multi-Regression, LSTM, and ANN predictive models across four Local Transshipment Centers (LTCs). Statistical techniques like the Shapiro-Wilk test examine warehouse error distributions to reveal seasonal and operational variations. The figure 2 provide the data flow diagram for CloudBased SCM and Advanced Machine Learning.

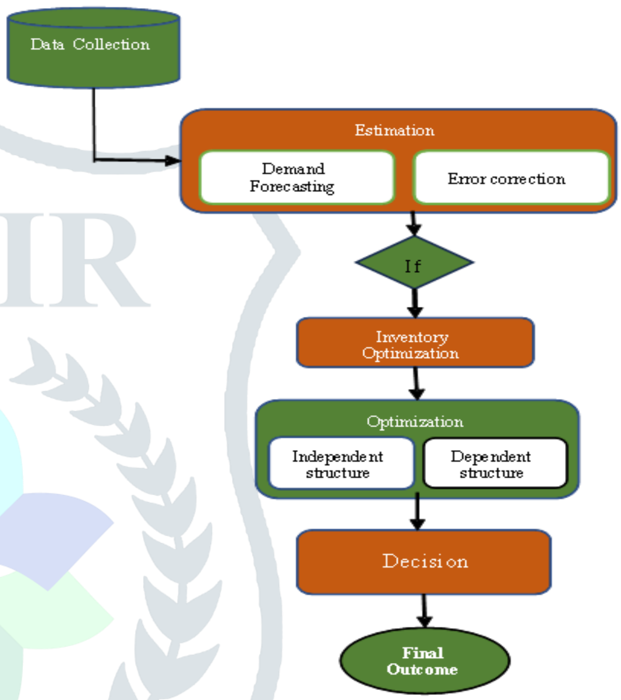

Figure 2: Data Flow Diagram for SCM with Advanced Machine Learning

The following steps of data flow diagram is detailed description given in below:

1) Data Collection

Data collection is a process of gathering information from many sources and then evaluating it to identify patterns and viable strategies for investigating problem areas. In this study Using data from a well-known Chinese home appliance shipping firm. Information such as previous orders, warehouse details, temperature readings, and discount data sourced from other sources is readily available.

2) Estimation

The estimate step has two essential elements: demand forecasting and error correction. Obtaining reliable demand forecasts is a major challenge in the field of cloud supply chain inventory management. By combining vast amounts of up-todate information and using advanced ML techniques, the cloud supply chain has the capacity to greatly improve the precision of demand forecasts. This dual strategy facilitates the establishment of a dependable foundation for making inventory management choices.

- **Demand Forecasting:** Demand forecasting is a critical activity that allows other supply chain operations, such as production planning and raw material supply planning, to function by supplying fundamental sales and production data [20]. Demand forecasting in this utilises past data, market patterns, and statistical models to anticipate future product demand.
- **Error Correction:** Error correction is the process of finding and fixing demand prediction errors. This entails comparing expected and actual demand, analysing inconsistencies, and changing the forecasting model. Error correction procedures are used to rectify any flaws or biases in the original projections, guaranteeing that the predictions are maximally exact.

3) Inventory Optimisation

Inventory optimisation is the systematic use of tactics to achieve a balance between inventory levels and demand projections. This stage is crucial for reducing storage expenses while preventing inventory shortages. Optimisation takes into account several elements, including lead times, order amounts, and safety stock levels. The objective is to ascertain the optimal inventory levels that can meet customer demand while minimising avoidable expenses.

- **Independent Structure:** In this research, a supply chain structure consisting of two levels. There are two levels to the structure. The first level is the primary one, and it has a RDC that is in charge of transporting goods. The second level is named the Local Transshipment Centre (LTC). As may be shown in Figure 3, the second layer is composed of n LTCs in whole. The model's warehouses function autonomously in this setup, with no inter-level replenishment.

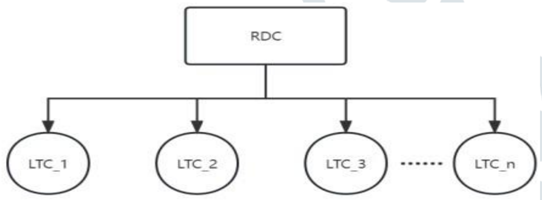

Figure 3: Two-level independent replenishment structure

- **Dependent Structure**: Dependent structure investigates the possibility of reciprocal replenishment of products among entities at the same level. A regional distribution centre (RDC) in the top tier delivers commodities to LTCs at a second level, which has n LTCs.

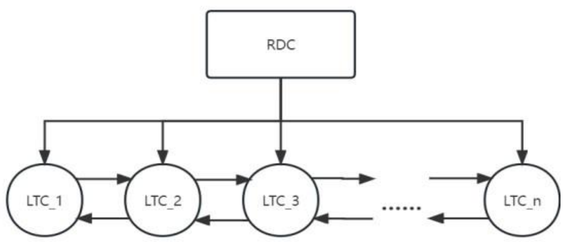

Figure 4: Two-level dependent replenishment structure

See Figure 4 for an illustration of how this special structure enables LTCs to serve as commodities for one another. Whenever an LTC has a shortage of inventory, a choice must be taken under this model.

4) Classification Models

This section describes a few categorisation models for Chinese home appliances data that may be used for comparative analysis.

a) Multi- Regression

Adding more than one explanatory variable to a single linear regression model makes it more complex than basic linear regression. When there is only one explanatory variable, the regression method is called simple linear regression, which is essentially a subset of multiple linear regression. In multiple linear regression, the term 'linear' is used because we assume that there is a direct relationship between y and a combination of the explanatory variables. For multiple linear regression with p independent variables, the relationship among the dependent and independent variables is shown in equation 1:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} + e_i \ldots\ldots\ldots. (1)$$

Where,

$\beta 0$ is the constant term and

The coefficients $\beta 1$ to βp relate the important variable to the p explanatory variables.

b) LSTM

Time series analysis and forecasting make heavy use of the Long Short-Term Memory (LSTM) architecture of RNNs. Traditional RNNs may struggle to capture long-term dependencies in sequential data because to the vanishing gradient problem; this technique is very helpful for dealing with this issue. LSTM networks use gates to link memory cells in a certain order. This is because these gates control how data enters and leaves the cells[21].

c) ANN

The artificial neural network algorithm is influenced by the structure and function of biological neurons, specifically the dendrites, soma, and axons. Every artificial neural network (ANN) consists of an artificial neuron and a basic mathematical function[22]. ANNs are a highly advanced version of perceptron's that are utilised to tackle intricate classification and regression problems. The three distinct kinds of layers are input, hidden, and output. Input and output layers were formerly the only components of a neural network's fundamental architecture. Such networks were known as shallow neural networks or single-layer neural networks.

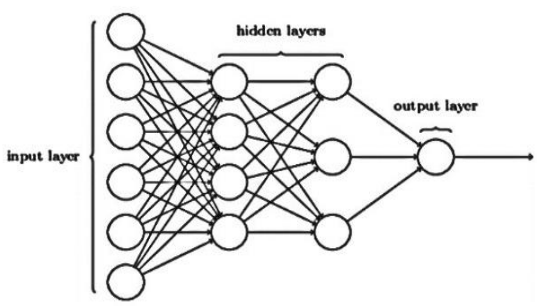

Figure 5: Structure of deep neural network or multilayer perceptron.

Neural networks that have multiple hidden layers are commonly referred to as multi-layer neural networks or deep neural networks. The layout or architecture of a network is presented in figure 5, [23].

IV. RESULTS AND DISCUSSION

This section provides the findings and analysis of the dataset utilised in this work, including the outcomes, dataset description, performance metrics, and classifier statistics. The experimental results of ML models show in terms of MSE, MAE and RMSE measures with dataset descriptions, also provide the predictive graph of number of LTC.

A. Dataset Description

To assess the accuracy of the prediction model, this study makes use of warehouse order data from a well-known Chinese domestic logistics company that focuses on the home appliance industry's administration. Approximately fourteen million records of orders processed by different warehouses in a given year make up this collection. The data contains the timestamps for order creation, as well as the origins, destinations, and methods of shipping. The research analysed the daily order quantities of four warehouses and showed how those numbers were trending.

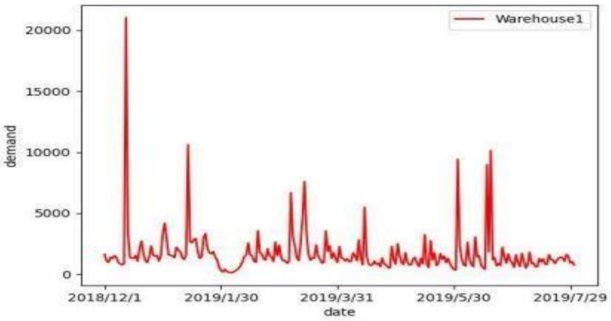

Figure 6: LTC1 demand line chart

Figure 6 shows the demand for "Warehouse1" from December 1, 2018, to July 29, 2019. The demand fluctuates significantly, with a notable spike over 20,000 units in early December 2018 and several other peaks throughout the period, though none as high. This irregular demand pattern suggests substantial variability, indicating that both Warehouse1 and Warehouse2 face similar inventory management challenges.

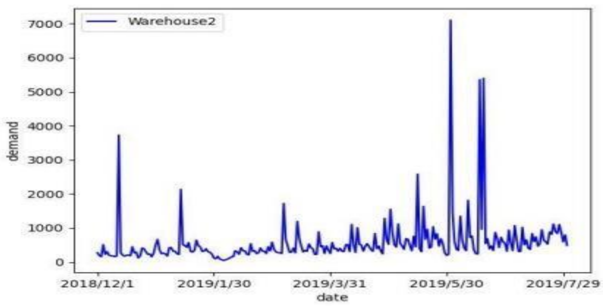

Figure 7: LTC2 demand line chart

The graph of figure 7 shows "Warehouse2" demand from December 1, 2018, to July 29, 2019. The date is on the x-axis and demand on the y-axis. Demand peaks and falls over the time. Multiple demand spikes occurred, peaking at 7000 units by May 2019. Seasonal impacts, marketing, and other causes may raise demand, causing these surges. Demand is variable; thus, inventory management solutions are crucial to negotiate these swings.

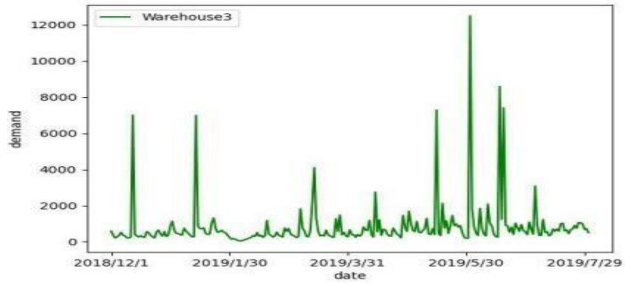

Figure 8: LTC3 demand line chart

Figure 8 graph shows the demand for "Warehouse3" from December 1, 2018, to July 29, 2019. The demand fluctuates significantly, with peaks reaching up to 12,000 units in late May 2019. Several other spikes are scattered throughout the period, indicating an irregular demand pattern similar to Warehouse1 and Warehouse2. This variability suggests that Warehouse 3 also faces challenges in managing inventory effectively.

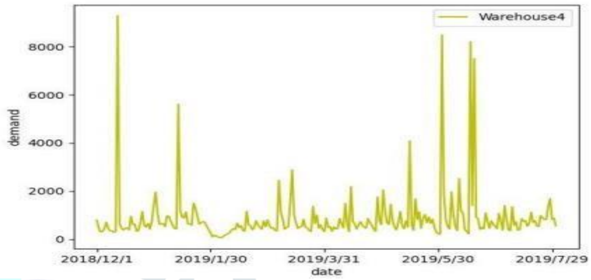

Figure 9: LTC4 demand line chart

Figure 9 graph is a bar graph labelled "Warehouse4". The xaxis represents the independent variable, which is labelled as "Date" and extends from December 1st, 2018 to July 29th, 2019. The y-axis represents the dependent variable, which is labelled as "Demand". However, the specific units for demand are not provided. The bars are seen to represent the density of a substance over time, potentially indicating inventory levels in a warehouse.

The variation tendency is rather comparable across all four warehouses as they are all at the same level of LTCs. But there are still noticeable differences in order demand between LTCs. There are obvious peaks in the amount of orders during certain times of the year, which tend to coincide with e-commerce holidays like "6.18 Shopping Day" and "12.12 Shopping Day." Another major component is the time of year when temperatures are highest and lowest. A clear seasonal trend is seen in the graph; for example, demand is lower in the winter than in the summer.

B. Performance Measures

For evaluating the performance of each model, a total of four different performance metrics has been used: RMSE, MAE, MAPE. These parameters have widely been used in previous research studies.

RMSE: The RMSE quantifies the typical size of prediction mistakes without taking direction into account. The corresponding equation 2 is shown below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \hat{y}_i)2} \ldots\ldots\ldots.(2)$$

MAE: Without taking the directional aspects of the mistakes into account, the MAE calculates the average size of the predictions' errors. Accuracy for continuous variables is measured using it. Equation 3 represents the MAE metric, as seen below:

$$\text{MAE} = \frac{1}{n}\sum_{i}^{n} |(y_i - y_i)| \text{.........(3)}$$

MAPE: As a whole, the absolute percentage mistakes of predictions are known as the MAPE. A forecast's error is the difference between the actual and predicted values. A representation of the MAPE metric is given by the following equation:

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{(y_i - y_i)}{y_i}\right| \text{..........(4)}$$

C. Performance Analysis (Predictive)

This research used the Median, the Mult Logistics Regression (LR) model, ANN, and the LSTM to evaluate the accuracy of several forecasting models. Presently dominating the forecasting industry are machine learning models, fundamental models, and time series models. The chosen approaches cover all of these bases. The results are in the form of figures, graphs and tables.

Table 3: Comparison of predictive model metrics of LTC1

Method	Multi-LR	LSTM	ANN
RMSE	392.77	475.74	580.13
MAE	339.7	401.83	471.4
MAPE	49.8	59.47	73.61

Table 3 shows the various different parameter RMSE, MAE, MAPE comparison values of multi- logistics regression, ANN, LSTM for Local Transshipment Center (LTC). The graphical representation of this is shown in below bar graph.

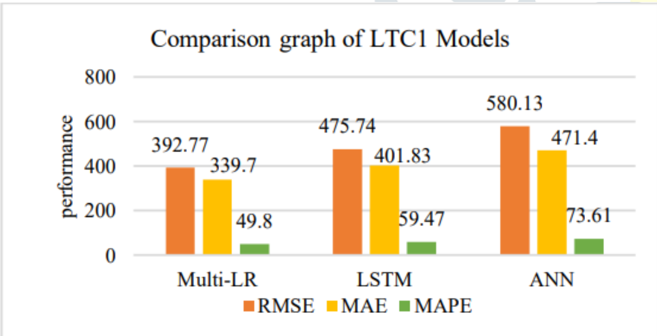

Figure 10: Model comparison graph of LTC1

The comparison bar graph of LTC1 Figure 10 models compares the performance of three different models: Multi-LR, LSTM, and ANN. The y-axis of the graph is labeled RMSE, MAE, and MAPE, in these lower values correspond to better performance.

Table 4: Comparison of predictive models of LCT2

Method	Multi- LR	LSTM	ANN
RMSE	231.98	335.19	31.87
MAE	169.77	251.53	49.02
MAPE	31.87	49.02	47.45

Table 4 above shows the comparative measure values of prediction of LCT2.

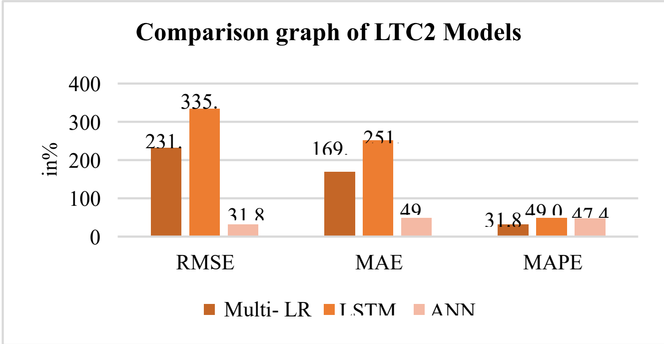

Figure 11: Comparison graph of model LTC 2

Figure 11 graph compares Multi-LR, LSTM, and ANN LCT2 prediction models using RMSE, MAE, and MAPE metrics. The x-axis shows models and the y-axis shows percentage performance. Multi-LR has 231.98% RMSE, 169.77% MAE, and 31.87% MAPE. The greatest RMSE (335.19%), MAE (251.53%), and MAPE (49.02%) is LSTM. The RMSE, MAE and MAPE of ANN are 49.02%, 31.87%, and 47.45%, respectively, better than LSTM.

Table 5: Comparison of Predictive Model OF LTC 3

Performance measures	Multi-LR	LSTM	ANN
RMSE	357.8	535.39	556.78
MAE	273.53	384.37	344.73
MAPE	51.99	73.78	55.47

The comparison measure values of LCT3 prediction are shown in the table 5 that can be seen above.

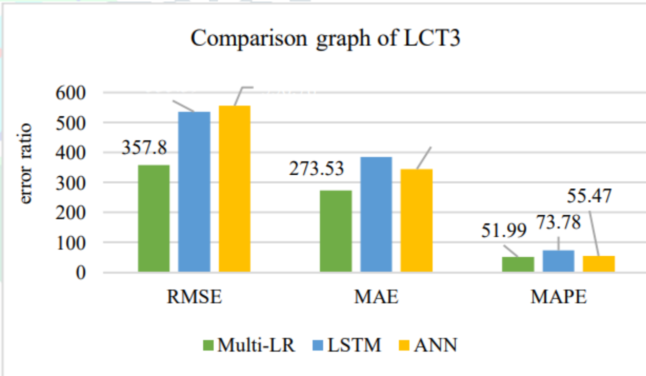

Figure 12: Graph of comparison model of LTC3

The graph in Figure 12 compares the RMSE of three various models: LSTM, ANN, and Multi-LR. The y-axis displays an error ratio, while the x-axis illustrates performance measures RMSE, MAE, and MAPE. The ANN model has the highest RMSE, 556.78, and Multi-LR has the lowest RMSE, 357.8, across all three performance measures.

Table 6: Comparison of Predictive models of LTC4

Performance measures	Multi-LR	LSTM	ANN
RMSE	357.8	484.69	552.81
MAE	265.1	330.4	362.97
MAPE	37.84	53.87	47.48

The comparison measure values of LCT4 prediction are shown in the Table 6 that can be seen above.

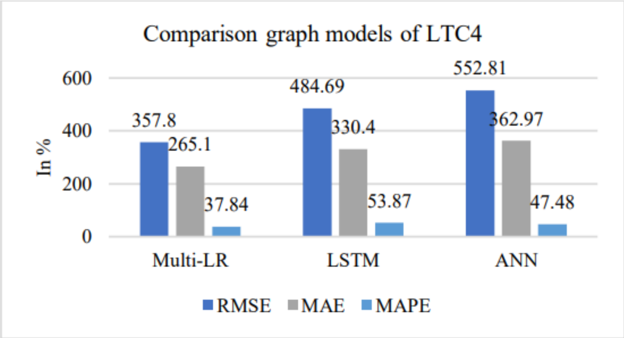

Figure 13: Comparison model of LTC4

Figure 13 The bar graph compares the performance of MultiLR, LSTM, and ANN models for predicting LTC4 using three error metrics: RMSE, MAE, and MAPE. The x-axis displays a different model, while the y-axis shows the error percentages. Multi-LR shows the lowest RMSE (357.8%) and MAE (265.1%) but a MAPE of 37.84%. LSTM has an RMSE of 484.69%, MAE of 330.4%, and the highest MAPE (53.87%). ANN has the highest RMSE (552.81%) and MAE (362.97%) but a lower MAPE (47.48%) compared to LSTM.

D. Comparative analysis and Discussion

In this work, we compared the real demand data with the demand projection data and matched the empirical error distribution with both sets of data.

Table 7: Predictive error analysis results of Shapiro-Wilk test.

Warehouse	p-value
LCT1	3.15x10^-1
LCT2	1.01x10^-1
LCT3	9.9x10^-3
LCT4	2.9x10^-2

Table 7 shows that all three of the p-values for LTC1, LTC2, and LTC3 are greater than 0.05, suggesting that these variables probably follow a normal distribution. Unfortunately, there is insufficient evidence to conclude that LTC4 follows a normal distribution, since its p-value is less than 0.05. What this means is that different warehouse distribution centres seem to have different error distributions when using the data-driven approach, which is likely due to a combination of criteria.

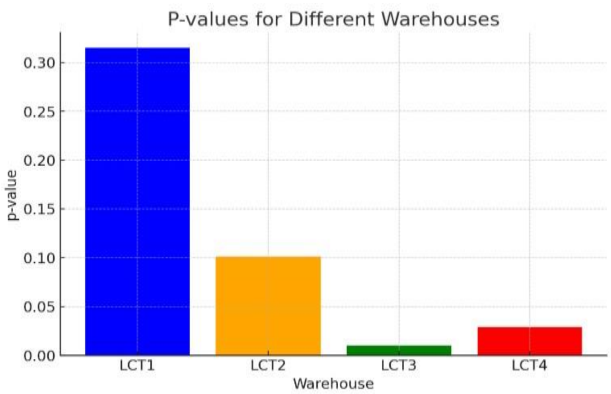

Figure 14: P-values for Different Warehouses

The p-values for LTC1, LTC2, and LTC3 are all larger than 0.05, suggesting that they follow a normal distribution, as shown in Figure 12. But because LTC4's p-value is less than 0.05, we may infer that it deviates from normality. That means there are certainly a lot of variables that contribute to the fact that error distribution differs between warehouses.

V. CONCLUSION AND FUTURE SCOPE

The overall examination of inventory management within cloud supply chains is provided by this research. A better understanding of the ever-changing relationship between cloud computing and stock management may be gleaned from research on cloud supply chain inventory management. Our study analyses data from different supply chain topologies to identify inventory allocation concerns and provide remedies. The study has produced distinct results, clarified some constraints, and established a foundation for future research paths.

Advanced machine learning (ML) and cloud-based supply chain management (SCM) were examined to improve supply chain resilience (SCR) at a major Chinese home appliance shipping firm. The results show that cloud technologies improve supply chain efficiency and responsiveness. This research showed that ML models like Multi-Regression, LSTM, and ANN improve demand forecasting and inventory management by analysing historical order records, warehouse details, temperature data, and third-party discounts.

Valuable insights show that machine learning and cloudbased supply chain management systems may spot problems early, enabling more flexible decision-making and strategy adaptation. RMSE, MAE, and MAPE performance indicators from predictive models across several Local Transshipment Centers (LTCs) highlight the complicated difficulties and possibilities in distinct supply chain topologies.

In summary, there is still much to learn about cloud supply chain inventory management even if our research has enhanced our knowledge of it. The continuous evolution of supply chain management techniques in the cloud computing era will be aided by filling up these research gaps and applying our results to other situations.

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