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Streamlining Business Operations Through ERP Implementation

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Abstract
This research paper presents the design and implementation of an Enterprise Resource Planning (ERP) system, named Optiware, for Divine Enterprises. Divine Enterprises specializes in manufacturing metal springs, lock covers for IC boards, and cap locks, catering to clients like Tata and Tech Mahindra. The primary objective of this project is to streamline Divine Enterprises' business operations, automate various tasks, and eliminate the conventional paper-based record-keeping system. The proposed system majorly focuses on managing the business activities like accounting, inventory, human resources, supply chain by providing a full fledged ERP system. It also incorporates an automated inventory management module to enhance efficiency and comprehensive sales forecasting section employing various advanced algorithms, facilitating better decision-making, resource allocation, and overall business optimization.

Keywords: Customised Enterprise Resource Planning System, Supply Chain Management, Inventory Automation Practices, Data Analytics

1. Introduction

In today's digital world, the existing manual record-keeping practices within Enterprise Resource Planning (ERP) are error-prone and lack comprehensive data for meaningful analysis. This leads to issues of inconsistent and duplicated data, particularly in inefficient and slow systems, ultimately causing delays in product development, undermining the core purpose of ERP. Moreover, the absence of predictive and analytic features hinders proactive decision-making. These challenges result in elevated IT and maintenance costs due to the lack of system optimization, further compounded by difficulties in seamlessly integrating various ERP systems and technologies. Divine Enterprises, an established manufacturer of metal components for electronic and industrial applications, is in need of an Customized ERP system to optimize their operations. The Optiware project represents a pivotal initiative undertaken for Divine Enterprises, a company specializing in the production of metal springs, lock covers for IC boards, and cap locks. With esteemed clients such as Tata and Tech Mahindra, Divine Enterprises is poised for growth, and the Optiware project is aimed at catalyzing this evolution. This innovative system will not only automate numerous tasks but also usher in a new era by eliminating their paper-based record-keeping system. The ERP solution will encompass critical functions, including order management, inventory tracking, and salary management, all with the goal of enhancing efficiency, reducing manual labor, and fostering streamlined operations. In this introduction, we present a glimpse of the transformative potential of the Optiware project in propelling Divine Enterprises toward greater productivity and success. The envisioned ERP solution is comprehensive, encompassing critical functions such as order management, inventory tracking, and salary management. By embracing advanced ERP capabilities, the Optiware project promises to deliver tangible benefits, including improved data accuracy, streamlined processes, and enhanced decision support mechanisms.

2. Literature Review

Samithamby Senthilnathan (2019) emphasizes EOQ's role in minimizing total handling and ordering costs. They discuss trial and error versus mathematical EOQ determination methods, favoring the mathematical model for better inventory management. Insights include EOQ's impact on Total Incremental Cost, relationships with Economic Number of Orders (ENO), inventory cycle length, and reorder point. Further analysis areas suggested include varying Total Ordering Costs and Holding Costs, cost dependencies, discounts' impact, and sensitivity analysis [1].

R. Chopra, et al. (2022) delves into the adoption and benefits of Enterprise Resource Planning (ERP) systems in manufacturing industries, focusing on process integration, data management, and operational efficiency. It discusses how ERP systems streamline operations, leading to strategic and operational advantages such as enhanced data transmission, process automation, improved customer satisfaction, cost savings, better decision-making, and increased productivity. However, challenges like initial investment costs, integration complexities, and ongoing maintenance are acknowledged, emphasizing the importance of effective post-implementation activities for sustained success [2].

R.R. Panigrahi, et al. (2022) utilizes structural equation modeling to analyze data from key officials in steel manufacturing firms in Odisha, India, focusing on inventory automation practices' (IAP) impact on firm productivity (FP), mediated by knowledge of IAPs. Results show a significant positive relationship between IAP and FP, with knowledge of IAPs mediating this effect. The study highlights the importance of automation in enhancing productivity dimensions like sales revenue and capital utilization. Limitations include non-standardized measurement criteria in the questionnaire, suggesting future research directions in exploring operational performance and studying inventory management across different industry contexts [3].

U. Khan, et al. (2022) evaluates ERP systems' impact on supply chain management (SCM) for distribution firms using surveys and data analysis. Results show significant improvements in SCM operations, including automation reducing errors and improving decision-making, enhanced record keeping aiding in forecasting, and time management efficiencies leading to cost reductions. Despite benefits, challenges such as initial costs, staff training, and potential disruptions during integration need consideration, highlighting the importance of system customization, scalability, and ongoing maintenance for ERP effectiveness in SCM [4].

Nazar Koval, et al. (2022) applies SARIMA models to forecast milk procurement volumes in rural areas using the Mito platform for data preparation and model selection. Parameters were optimized based on autocorrelation and partial autocorrelation functions, resulting in a SARIMA model (4, 3, 0, 1) with low Akaike information criterion values and accurate forecasts. While effective for seasonal volume forecasting, future research could explore SARIMA performance in dynamic environments and consider hybrid models to enhance adaptability, especially when facing significant seasonal pattern variations [5].

Anshul Agarwal and Arvind Jayant (2019) evaluate SVM models for demand forecasting in the piston manufacturing industry's supply chain. They compare SVM models using radial basis and sigmoid kernel functions with traditional methods like exponential smoothing and moving average. Results favor SVM models, especially with sigmoid kernels, showing superior forecasting accuracy over traditional methods. Moving average is identified as the best traditional method. Future research could explore additional ML algorithms, boosting techniques, and extend the study to forecast demand for various automotive parts for broader insights. This would enhance understanding beyond pistons, providing valuable insights for optimizing demand forecasting across different product categories [6].

Murat Akkaya (2021) presents the Vector Autoregressive model as a solution for complex economic systems, highlighting its dynamic relationship handling without constraints, ideal for time series analysis. VAR models simplify endogenous variable management, enhance prediction accuracy, and often outperform more intricate models, revealing variable interconnections. They face challenges like limited prior knowledge (atheism) and lag length selection, especially in smaller datasets [7].

Zuokun Ouyang, et al. (2021) compares forecasting strategies using the STL decomposition method, evaluating statistical methods (ARIMA, ETS) and machine learning methods (KNN, SVR) on industrial data across forecast horizons. STL improves statistical methods' accuracy, notably with the STL-Theta method performing well, while machine learning methods experience reduced accuracy with STL preprocessing, indicating challenges in integrating STL into such models. The drawback highlighted is STL's negative impact on machine learning methods, suggesting the need for further research on optimal preprocessing approaches for machine learning-based time series forecasting [8].

Nurhayati Buslim (2023) proposes using Ensemble Learning, a Voting-based approach combining SVM and KNN algorithms, to predict scholarship recipients in educational institutions. Data collection involved an online survey with 106 respondents, gathering variables like personal data. Ensemble Learning achieved 100% accuracy in prediction, demonstrating its effectiveness in outperforming individual models. Potential drawbacks include the need for extensive training data, complexity in integrating multiple algorithms, and deployment challenges for real-time predictions and scalability [9].

3. Proposed Solution

The Optiware ERP system will be designed to provide a comprehensive and integrated solution for Divine Enterprises, focusing on enhancing operational efficiency, automating various tasks, and eliminating the conventional paper-based record-keeping system. Key components of Optiware ERP system includes a User-Friendly Interface for clean and intuitive user interface that enhances the user experience, Inventory Automation using technologies, software to streamline, manage, and optimize the process of monitoring, tracking, and replenishing inventory to reduce manual effort and errors in inventory management, Demand Forecasting providing advanced analytics and predictive algorithms, the platform aids in accurately forecasting demand patterns and Data Analytics to analyzes key performance metrics to inform continuous improvement and strategic decision-making This would assist businesses in planning their resource allocation and scheduling to match fluctuating demands.

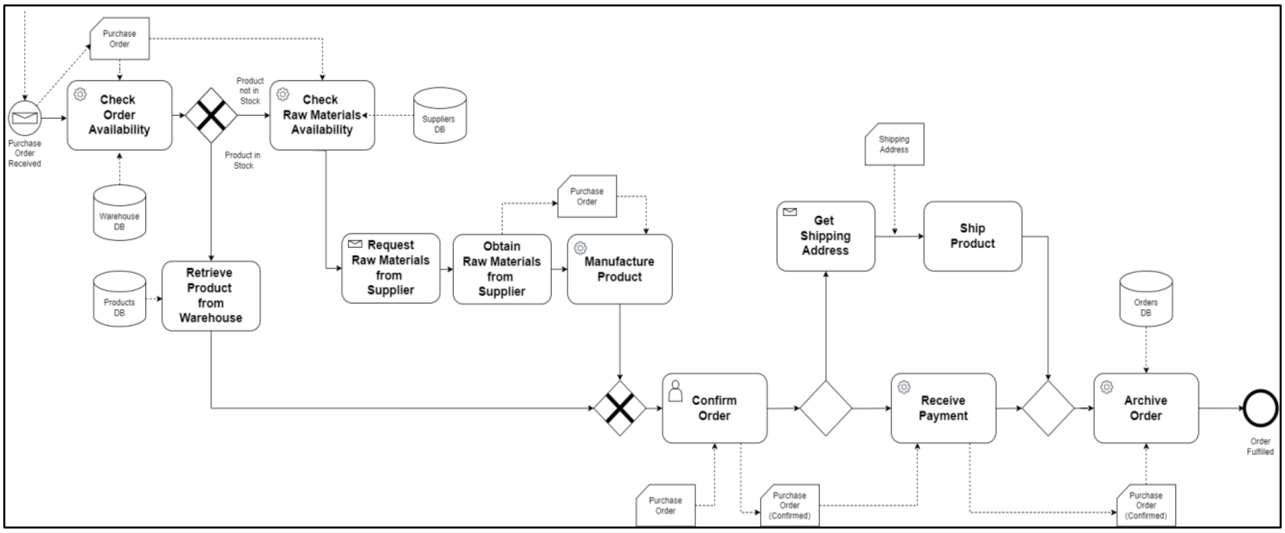


Fig. 1 Workflow of System

In our project Optiware, a robust ERP system tailored for divine enterprises, we're implementing a comprehensive sales forecasting section employing various advanced algorithms. These algorithms include SVM (Support Vector Machine), EOQ (Economic Order Quantity), ARIMA (AutoRegressive Integrated Moving Average), SARIMA (Seasonal ARIMA), VAR (Vector Autoregression), STL (Seasonal and Trend decomposition using Loess), and Ensemble methods.

These algorithms help predict sales by analyzing past data, considering trends, seasons, and relationships between different factors. By employing these algorithms within Optiware, divine enterprises can benefit from improved accuracy and efficiency in sales forecasting, facilitating better decision-making, resource allocation, and overall business optimization

Support Vector Machine (SVM): Support Vector Machine is a type of supervised machine learning. Its main goal is to find the best line to separate different groups of data or predict outcomes. It helps understand challenges like demand differences and market unpredictability. SVM models provide real-time analysis, aiding on-time delivery, reducing inefficiencies, and minimizing revenue loss, boosting customer satisfaction.

Implementation:

1. Define features and responsible variables and initialize SVM Hyperparemater.
2. Divide data into train and test set, preferably 70% and 30% respectively.
3. Use SVM model of train set and save the final model.
4. Make predictions using test set, find MAPE and validate the model.

In our project, we're using Support Vector Machine (SVM) for predicting future sales trends. First, we work on feature engineering to make sense of the data, focusing on things like monthly sales and sales changes over time. Then, we train the SVM model by adjusting its settings to better understand the patterns in the data. Finally, we evaluate the model's performance using metrics like Mean Absolute Percentage Error (MAPE) to see how well it predicts actual sales numbers.

Economic Order Quantity (EOQ): The ideal amount that a company should create or purchase in order to balance holding and ordering costs and lower total inventory expenditures is determined by the equity ordering quantity (EOQ) formula. The EOQ model considers variables like as demand rates, order charges, and holding costs to estimate the exact quantity that minimises the combined costs of keeping too much inventory and purchasing often.

The EOQ formula is: $EOQ = \sqrt{(2DK/H)}$

In the formula:

1. D = The number of units purchased of product set-up for a periodic duration, it is usually yearly.
2. K = For each purchase the ordering cost
3. H = Storage and holding cost for the products

ARIMA (Autoregressive Integrated Moving Average): By examining previous sales data to identify patterns, seasonality, and erratic swings, it is used in sales forecasting. It has 3 components i.e. p,q and d. The "autoregressive" part (p) shows how past values relate to the current one. The "integrated" part (d) deals with making sure the data doesn't change too much over time. The "moving average" part (q) looks at how today's value connects with past errors or mistakes.

Implementation:

1. Create an instance of the ARIMA(p, d, q) model and fit it to the monthly sales training set.
2. Project future time steps using the fitted model.
3. Determine the MAPE, or mean absolute percentage error.
4. To see the difference between the projected and actual sales, make a line plot.
5. Show the plot to visually compare the actual and predicted sales.

SARIMA (Seasonal Autoregressive Integrated Moving Average): SARIMA is an extension of the ARIMA model that accounts for data seasonal fluctuations. Sales forecasting uses past sales data that exhibits recurring seasonal trends (weekly, monthly, quarterly, or yearly). It adds more flexibility to time series forecasting by introducing additional parameters: P, Q and D. ‘P’ and ‘Q’ denote the seasonal autoregressive and moving average orders, respectively, capturing the seasonal patterns in the data. ‘D’ represents the seasonal differencing order, indicating the number of times the seasonal component must be differenced to achieve stationarity.

Implementation:

1. Orders (p, d, q) (P, D, Q) may be used to create an instance of the SARIMA model and fit it to historical sales data.
2. Use the fitted SARIMA model to predict future time steps; if needed, convert the forecasts to integers.
3. To compare expected and actual sales, use a line plot.
4. Plot the sales to provide a visual comparison of the actual and anticipated numbers.

VAR (Vector Autoregression): The VAR model is a part of an economic model. It's like a group of autoregressive models. Each variable has its own equation that says how it's made, based on its past and the past of all the other variables. They all get treated the same way. The main job of the VAR model is to show the connections between variables over time. For this study, we used the VAR model with two variables, "Amount" and "Quantity," which are important sales measures. First, we prepared the data by picking only these two columns, making it monthly by adding up the numbers, and focusing on the next year. Then, we made a VAR model using this data. We figured out the best way to set it up and how the variables interact. After that, we predicted what the "Amount" and "Quantity" would be for each time period. We checked how well our predictions matched the real sales numbers using something called the Mean Absolute Percentage Error (MAPE)

STL (Seasonal and Trend Decomposition): It is a technique used to analyze time series data by breaking down a time series into its residual, trend, and seasonal components. By separating out these components, STL enables clearer insights into the underlying dynamics of the time series, facilitating more accurate predictions and informed decision-making. This technique is widely used across various fields, including economics, finance, and environmental science, to uncover hidden patterns and make more reliable forecasts.. Mathematical representation for decomposition: $Y_1 = f(St, T_1, E_1)$

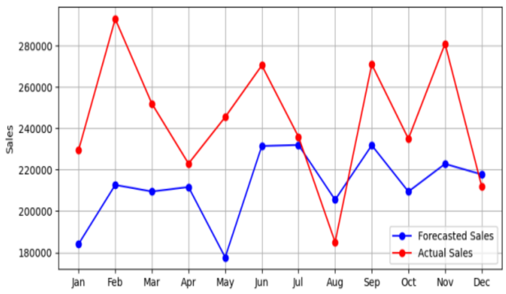
In the formula:

1. Yt: Actual data (time series value at period t),
2. S: Seasonal component at period t
3. T: Trend cycle component at period t,
4. E_1: Error or noise.

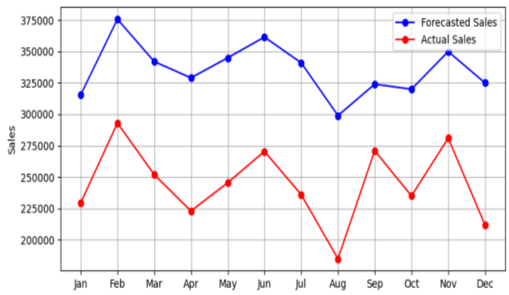
Ensemble Learning: Ensemble learning combines multiple forecasting models to make better predictions. By blending forecasts from different models, it often gives more accurate results than any single model alone. In this study, we used three different models: the STL (Seasonal-Trend Decomposition using Loess), VAR (Vector Autoregression), and ARIMA (Autoregressive Integrated Moving Average). Each model was chosen because it's good at capturing different aspects of sales data, like patterns over time and seasonal changes. After combining the forecasts from these models, we rounded the results to whole numbers, since sales figures usually don't have decimals. We checked how well our ensemble forecast matched the actual sales numbers using something called the Mean Absolute Percentage Error (MAPE). This helps us see how accurate our predictions are, on average, compared to the real sales data.

4. Results

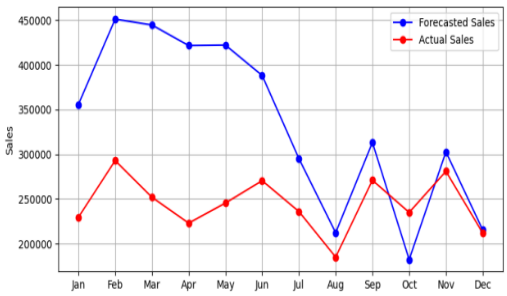
The results part shows how well our project's machine learning models are doing right now. First, we talk about how we predict sales. We use a mix of different methods like ARIMA, SARIMA, VAR, and STL to make sure our predictions are really accurate. Then, we look at demand forecasting. We use the SVM algorithm to figure out what demand might look like in the future. After that, we go into more detail about how each model is doing, and how accurate they are in their own areas. Additionally, the subsequent sections will provide more detailed information about the performance and accuracy of each model in their respective areas.



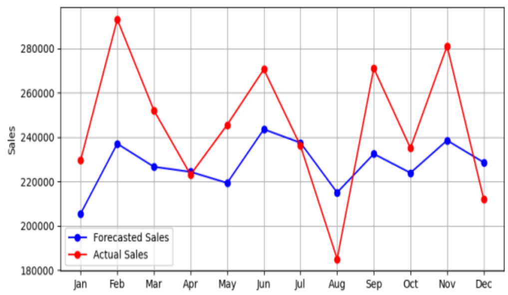
(a) Arima



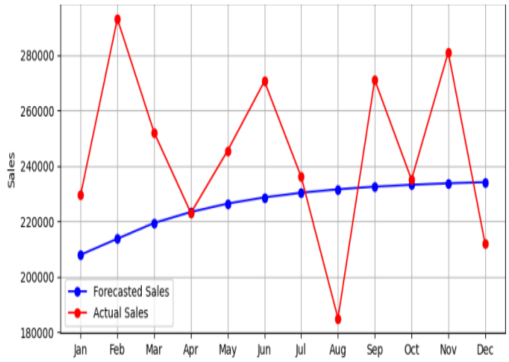
(d) STL



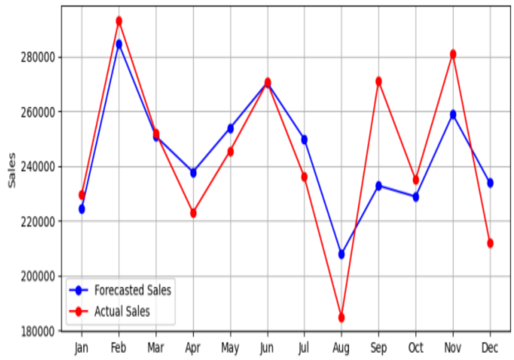
(b) SARIMA



(e) Ensemble - Arima, VAR, STL



(c) Vector Autoregression

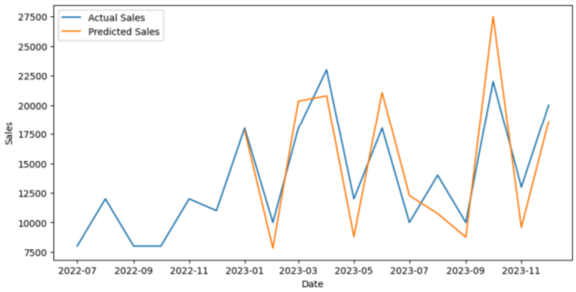


(f) STL - Offset Adjustment

Fig. 2 Performance of Sales Forecasting Algorithms

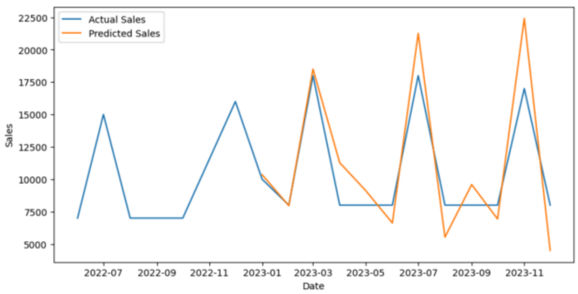
Forecasting Model	MAPE(%)
ARIMA	14.39
SARIMA	39.79
VAR	11.89
STL	38.55
STL - Offset Adjustment	5.73
Ensemble	10.31

Table 1 Comparison of MAPE of Sales Forecasting Algorithms

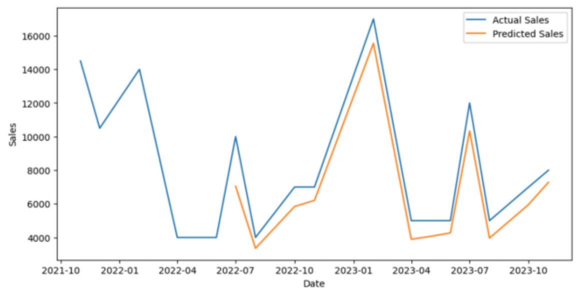


(a) Debring

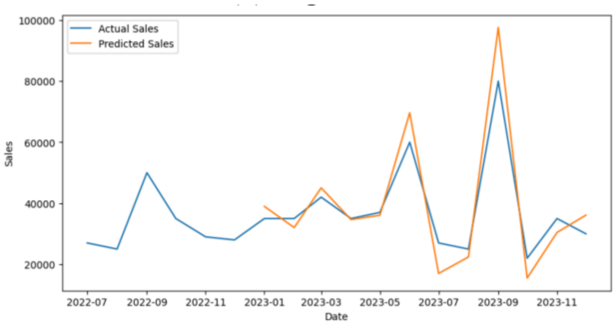
(d) Compression Spring



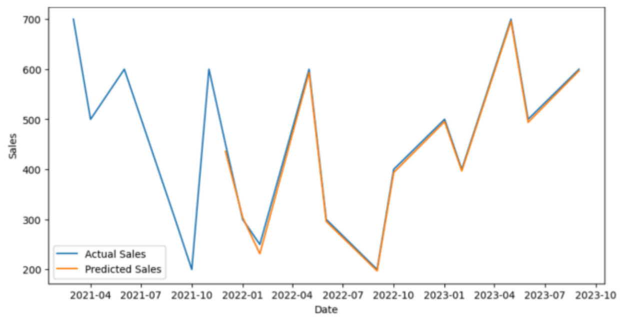
(b) Caplock



(e) Security Metre Wire



(c) Torsion Spring



(f) IC Lock Cover

Fig. 3 Performance of SVM in Demand Forecasting for Different Products

Products	MAPE(%)
Debring	13.69
Caplock	19.72
Torsion Spring	14.90
Compression Spring	9.83
Security Metre Wire	15.32
IC Lock Cover	0.92

Table 2 Comparison of MAPE for Different Products Using SVM

5. Conclusion

This paper emphasizes the significance of ERP systems in the manufacturing industry and the potential benefits for Divine Enterprises. The development of a customized ERP system for Divine Enterprises offers a game-changing solution to their supply chain challenges. By enabling predictive analytics, seamless integration, real-time visibility, and efficient data management, this ERP system empowers proactive decision-making, streamlines operations, and drives strategic success.

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