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ASRS, AMR INTEGRATION WITH WMS - CHALLENGES AND SOLUTIONS

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ABSTRACT

Purpose- The study investigates the integration of Automated Storage and Retrieval Systems (ASRS) and Autonomous Mobile Robots (AMRs) with Warehouse Management Systems (WMS), aiming to enhance operational efficiency through machine learning. Key challenges addressed include data compatibility, real-time decision-making, and effective resource allocation.
Methodology- Machine learning models were applied to optimise system performance: Bayesian Neural Networks (BNNs) for demand forecasting, Random Forests for resource allocation, K-means clustering for task prioritisation, and Support Vector Regressor (SVR) for performance evaluation using Mean Squared Error (MSE).
Findings- BNNs improved demand prediction, enabling adaptive adjustments of ASRS and AMRs. Random Forests efficiently optimised resource distribution, while K-means clustering successfully prioritised high-demand tasks to support lean operations. The SVR achieved an MSE of 2.47, confirming low prediction error and model effectiveness.
Conclusion- Integrating machine learning into ASRS-AMR-WMS systems provides a scalable framework for modern warehouses, fostering real-time adaptability, improved resource utilisation, and enhanced productivity.

Keywords: ASRS, AMR, WMS integration, machine learning, Bayesian Neural Networks, Random Forest, K-means clustering, demand forecasting, resource optimisation, warehousing efficiency
JEL Codes: M11, C53, O33, L91

1. INTRODUCTION

Technology has taken over warehousing functions by increasing the speed of operations, cutting employment expenses, and increasing the precision of orders. ASRS and AMRs are critical enablers for this change, such as storage, picking, and moving objects and people in warehouses (Basaldúa & Cruz Di Palma, 2023). AASRs enhance performance density and update rates, which are adequate for handling large amounts of stock and controlling existing space (Jie et al., 2024). At the same time, AMRs perform navigation in the warehouse independently, explaining the delivery of goods from storage to picking and packing zones (Torchio, 2023). Combined, ASRS and AMR technologies enhance the warehouse inventory's accuracy and the speed at which orders can be fulfilled, a requirement in current fast-paced and complex warehouses.

Implementing ASRS and AMRs with WMS is a subject of controversy. One of the potential concerns is the compatibility of the data produced by ASRS and AMR systems with WMS data storing and processing architecture (Broughton, 2024). The first one is technology heterogeneity, which refers to the ability of disparate protocols and actual procedural processing scenarios to disrupt the efficient interaction of automatic and WMS technologies. Also, real-time decision-making requires almost accurate time data processing and acting, and many of the existing WMS need to be equipped for or would need significant tweaking or replacement to handle the flow of information efficiently. This study will tackle these challenges by presenting the main difficulties in ASRS-AMR-WMS integration and providing solutions through machine learning models, clustering, and predictive analysis. These approaches can enhance the demand prediction, resources, and real-time goals of ASRS and AMR systems.

However, it is essential to note some research limitations concerning real-time data processing and forecasting about ASRS and AMR-WMS integration. To the best of the author's knowledge, little research focuses on how machine learning could extend functionality and resource share in integrated systems. This study addresses these gaps by applying a state-of-the-art machine learning and clustering approach to create solutions to enhance ASRS and AMR integration for orchestrating automatic and adaptive warehouse operations.

2. LITERATURE REVIEW

2.1. ASRS and AMR Technologies in Warehousing

Automated Storage and Retrieval Systems and Autonomous Mobile Robots of present-day warehousing involve complex technology employing storage, retrieval and mobility of goods (Dhaliwal, 2020). ASRS, widely used for main-stream automatic storage and collection of products, reduces the use of space and human intervention as the movement of stocks is managed vertically and horizontally. These systems are most useful in high cube warehousing where conventional methods cannot deliver the required throughput. Due to the importance of these sectors, ASRS technologies ensure precise stock storage and location, fast stock access and efficient use of space (Jie et al., 2024).

On the other hand, AMRs offer dynamic movement and autonomy, moving throughout a warehouse to pick up and transport products from storage to build and pack zones (Merkert et al., 2023). While relying on tracks like conventional conveyors, AMRs utilise navigation sensors and optimisation algorithms to perform in compliance with the warehouse configuration and navigate around the obstacles encountered (Harb, 2023). The integration process of ASRS and AMRs with WMS enhances the efficiency of stock positioning and picking processes and reduces the manual efforts needed (Jie et al., 2024). Integrating ASRS and AMRs also helps WMS get in touch with the latest real-time information for inventory storage and order management (Dinh, 2020).

2.2. Challenges in ASRS and AMR-WMS Integration

Despite their potential, ASRS and AMRs have integration issues with WMSs. In this case, data synchronisation is one significant concern mainly due to the compatibility and data standard because the real-time data transfer from ASRS, AMRs and WMS is affected (Halawa et al., 2020). These two systems produce massive amounts of data, and WMS should process and react to it swiftly. However, many WMS solutions are ancient systems that cannot process frequent data or make real-time decisions (Khan et al., 2022). The issue of operational compatibility is also present because ASRS and AMRs work by protocols and specific operating workflows that may need to be more harmoniously related to WMS functions. It is also often that solutions require tailoring of ASRS or AMRs to WMS demands or redesigning of WMS to fit ASRS or AMR affordances (Khan et al., 2022); it is also a time-consuming and often manually intensive process of prototyping and testing as well as continuous maintenance.

Another significant issue is the flexibility of image WMS systems again: The real problem is that the older WMS platforms need to be more flexible and can support real-time autonomous approaches that are more effective than a much more straightforward and more scalable process (Liu et al., 2023). Introducing autonomous technologies into such systems may require system enhancement, middleware or API upgrades, which may bring extra costs and challenges. All these challenges call for superior data management solutions and predictive analytics for integrated real-time implementation and operational peculiarities of automated warehouses.

2.3. Machine Learning in Warehousing Systems

Analysing WMS and utilising machine learning systems, including Bayesian Neural Networks (BNNs) and Random Forests, shows more effective ASRS and AMR integration solutions. The advantage of BNNs is seen in demand forecasting since they also provide methods for uncertainty estimation, such that systems can anticipate demand variability and adapt if necessary (Mahajan et al., 2024). Demand planning allows the scheduling of storage and picking tasks in ASRS and AMR, avoiding time-wasting moves and matching inventories to expected demand.

Resource allocation or use and prediction of maintenance needs in the context of warehousing systems have been implemented with excellent results through Random Forest models that are characterised as robust and easily explainable (Ribeiro et al., 2022). These models utilise historical data to forecast inventory stocking levels, provide the correct stock deployment advice, and estimate future maintenance requirements for the ASRS/AMR facilities. Random forest models also learnt about high data, probably from area irregularity (Talukdar et al., 2021), making them apt for implementation in environments that tend to be highly variable, such as the integrated warehouse system.

In addition to demand forecasting and resource optimisation, machine learning helps maintain ASRS and AMR systems' optimal conditions. Using performance data, these models can predict future failures, plan maintenance activities, and minimise system downtime (Moore & Starr, 2006). This capability is critical, especially in fully automated warehouses where system interruption may mean disrupting a complete chain of processes. Lean warehousing is enhanced by predictive maintenance due to reduced repair costs and increased product life cycles of ASRS and AMR (Broughton, 2024).

2.4. Research Gaps

Despite the emergence of machine learning models in warehousing, research voids are still present in real-time data handling and system scheduling in ASRS and AMR-WMS interfaces. Prior work mainly deals with isolated ASRS or AMR efficacy, and few studies examine the coordination of developing WMS with other systems such as ASRS or AMR, especially when facing real-time operating conditions (Broughton, 2024). It has also been revealed that there needs to be more literature on integrating ASRS and AMR-WMS using machine learning techniques to address the problem of data compatibility for efficient integration.

Furthermore, there needs to be more literature on how clustering and prioritisation models can extend the functionalities of ASRS and AMR in a WMS environment. Current research needs to focus on how the prioritisation of tasks for such comprehensive product ranges can be accomplished dynamically in response to demand or how real-time predictive analysis might be used to refine allocation. Therefore, this paper proposes to address these gaps by developing a dynamic integration model based on the Machine learning and clustering model of ASRS, AMR and WMS to enhance the efficiency of the operations and resource utilisation.

3. METHODOLOGY

This study employs data analysis, predictive modelling, and clustering methods to overcome ASRS and AMR integration limitations with WMS. These particular data fields were analysed with the help of machine learning models and clustering algorithms to enhance the processes of demand forecasting, resources and task management.

3.1. Dataset Overview

The dataset used for this analysis involves the following significant variables: Variables needed to manage and understand operations related to the ASRS and AMR integration. The primary data fields include:

Order Volume- This field refers to the total number of items that have been ordered in a particular period and is helpful for the analysis of demand components and the identification of the distribution of workload in the warehouse.

Picking Time- Picking time transcends the time used to identify and select the product and the time required to transport the product to an appropriate area. This metric is handy on the operational level, revealing areas of constraints and measuring the working and performance of both people and robots.

Travel Time- This is the time taken by AMRs to move articles between store, pick and pack zones. Extended travel time can reveal inefficient layout or routing, influencing AMR resource use.

Stock Levels- This field reveals the quantity of each item in the warehouse as it is continually updated. Reducing inventory status monitoring helps forecast the stockout situation, synchronises ASRS with demand, and negates out-of-stock situations.

3.2. Models and Approaches

Several machine learning and clustering techniques were used to analyse and model the data, including Exploratory Data Analysis (EDA), Bayesian Neural Networks (BNNs), Random Forest and Clustering for task prioritisation.

3.2.1. Exploratory Data Analysis (EDA)

Exploratory data analysis was conducted to examine data distribution, association, and interaction between variables in the data preparation process for developing models (Behrens, 1997). Critical steps in EDA included descriptive statistics, which indices of central tendency, such as mean and median, and variability indices, such as variance, were computed for each variable. For instance, averages such as Order Volume and Picking Time were functional in identifying demand profiles besides indicating operating rhythms. Distribution plots such as histograms and density plots helped to describe data spread and define possible demand/sales/appeal fluctuations and times with lower operations intensity. In the same way, various patterns facilitate the depiction of operational needs and regulate the distribution of ASRS-AMR tasks. Furthermore, a correlation matrix was used to check the interrelationships between the variables, for example, between Order Volume and Picking Time. It is essential to know these dependencies to determine potential features to include in the forecast models and integration bottlenecks.

3.2.2. Bayesian Neural Network (BNN) for Demand Forecasting

The demand variation was identified, and the measures to use BNN in determining the distribution of ASRS and AMR tasks in the WMS framework were implemented. The primary purpose of the BNN model was to forecast the demand and order patterns to enable the WMS to reallocate the ASRS and AMR about demand automatically. This predictive capability is critical because lean warehousing requires direct correspondence between stock and usage of resources.

The BNN was designed to model demand fluctuations with uncertainty quantification to be flexible to the warehouse requirements. The neutered architecture was dense, with multiple concealed layers to capture complex dependencies. The model was trained over 10 epochs, ensuring good accuracy and avoiding high computational costs and long response times for the model.

Model performance was evaluated using Mean Squared Error (MSE) and R-squared. MSE translates into the goodness of demand forecast, while R-squared shows the proportion of demand variability that the modelling has explained. To this end, the following metrics validate the model and guarantee the responsiveness of the ASRS and AMR task schedule.

3.2.3. Random Forest for Resource Allocation

Regarding ASRS and AMR, resource utilisation was improved using Random Forest, as resources are assigned according to the forecasted utilisation and task priority. For specific order urgency, stock on hand, and forecasts, the Random Forest model was created to predict the ASRS and AMR allocations. As the model is derived from historical data, it can capture the daily distribution patterns regarding allocating resources most closely related to demand spikes to distribute warehouse resources more effectively.

Model validation was performed using MSE and R-squared because these metrics allow for understanding how accurately a model can predict the necessary resource allocation. A low MSE strengthens the hypothesis that the model accurately deploys resources based on the identified demand; high R-squared values confirm that it effectively adjusts resource distribution to WMS needs.

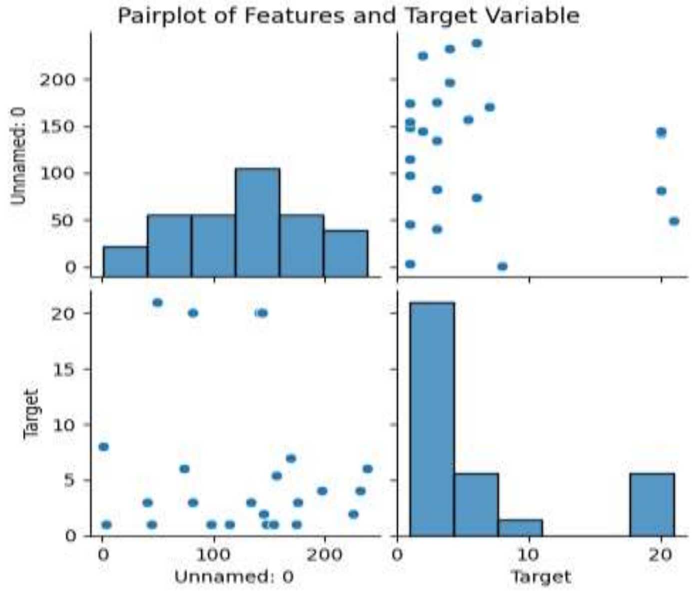
4. EMPIRICAL RESULTS

This section details the results of Exploratory Data Analysis (EDA), Bayesian Neural Network for demand prediction, Random Forest for resource distribution, and clustering for system categorisation. These analyses and models provide solutions to the competitive issue of managing ASRS and AMR interactions with WMS regarding demand forecasting, resource management, and scheduling.

4.1. Exploratory Data Analysis (EDA)

The first EDA involved descriptive statistics on Order Volume, picking time, and Stock Levels as critical variables to give an insight into the companies' operational and demand conditions. Order volume statistics produced demand patterns differentiating between high and low warehouse traffic. We found Picking time to fluctuate significantly, suggesting disparities in item availability and the ASRS and the AMR performance. At the same time, inventory dynamics were synchronised in stock-level summary statistics, and it was possible to predict when stockouts might occur, thus helping to make scheduling decisions for ASRS and AMRs. **Figure 1** depict the pair plots for the target and features variables.

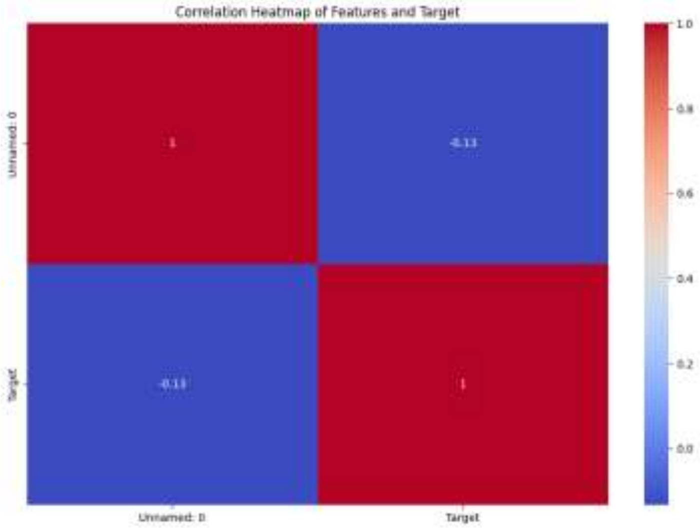
Figure 1: Pairplots of Features and Target Variables



4.2. Distribution and Correlation Analysis

Distribution plots of critical variables such as order volume, picking time, and stock levels identified shapes in data distribution and indicated general mid-range values where constrained operations or heightened usage could exist. For example, the Order Volume and Picking Time distributions highlighted seasonal variation or high traffic density, which is crucial in managing ASRS-AMR task distribution. The correlation matrix (in Figure 2) showed positive and statistically significant results, whereby Order Volume and Picking Time were moderately positive; thus, higher order volumes have more essential or increased picking time, which may affect the AMR utilisation and scheduling of tasks. This correlation insight aids in determining what features to include in the predictive models regarding the allocation of ASRS & AMR resources.

Figure 2: Correlation Heatmap



4.3. Bayesian Neural Network (BNN) for Demand Forecasting

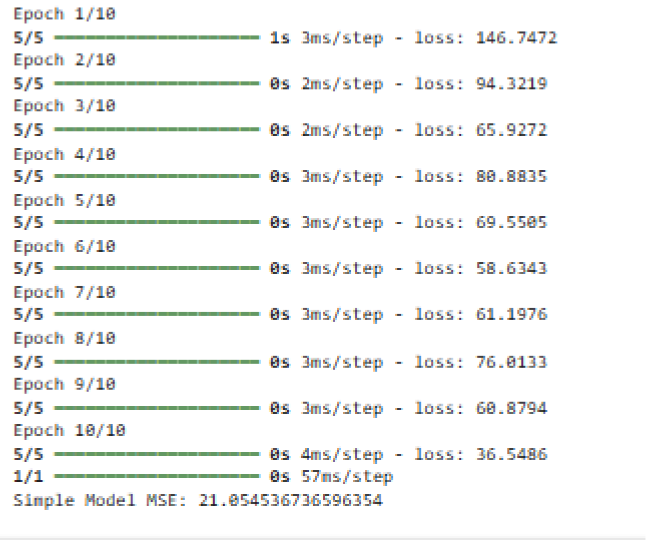
The development and use of the Bayesian Neural Network (BNN) model resulted in a lower Mean Squared Error of 40.08 in demand forecasting (shown in Table 1). This moderate error level points to the ability of the model to identify changes in demand and help WMS collocate ASRS and AMR operations with predicted demands. The additional estimation of uncertainty around demand predictions adds reliability to BNN's benefits for WMS in modifying the ASRS-AMR operations to meet fluctuating demand and increase system effectiveness.

Table 1: BNN Model

Model	MSE
BNN (Dense Layers)	40.089055

An analysis of the plot of the predicted demand against the actual demand showed that BNN fitted into the variable demand drums. As for the model, it reached actual demand with minor deviations made during fluctuations. This view underscored the demand forecasting capability of BNN, thus rendering schedules for ASRS and AMR before demand spikes in lean-based warehousing, where demand sensitivity is exceptionally high. BNN can make these predictions, which helps reduce unnecessary stock and improve workflow, as shown in Figure 3.

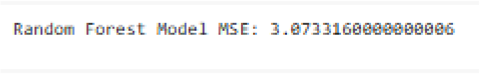
Figure 3: Model MSE



```
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 146.7472
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 94.3219
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 65.9272
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 80.8835
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 69.5505
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 58.6343
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 61.1976
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 76.0133
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 60.8794
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 36.5486
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 57ms/step
Simple Model MSE: 21.054536736596354
```

4.4. Random Forest

The Random Forest model had an MSE of 3.07, reflecting good model accuracy in predicting optimal resources to invest in ASRS and AMR systems. The above low error rate implies that the model will be competent in warranting proper resource provisions according to demand forecasts, adapting to variations in order frequency and other operational demands. Random forest determination of the likely distribution of workloads helps WMS ensure the utilisation of all ASRS and AMR resources. It ensures there is a healthy response to periods that experience high workloads.



```
Random Forest Model MSE: 3.0733160000000006
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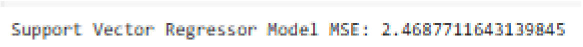
Given the results of RMSE and the accuracy of the Random Forest model, it is relatively efficient to be applied for resource allocation in complex changing warehousing conditions. The flexibility to respond to customer demand further enhances the model since it perfectly aligns with lean warehousing objectives. With the consideration of working with real-time adjustments, Random Forest helps avoid extra labour costs, optimise the existing ASRS-AMR functioning, and achieve better resource sharing, which is why it remains appropriate when integrated and automated.

```
Random Forest CV MSE: 55.01774959999999
Random Forest CV R-squared: -0.3937002430693771
```

The Random Forest model's cross-validation shows high MSE (55.02) and negative R-squared (-0.39), indicating poor predictive accuracy and model fit.

4.5. SVR

The Support Vector Regressor (SVR) model's Mean Squared Error (MSE) of 2.47 indicates a relatively low error rate, suggesting that it provides accurate predictions with minimal deviation from actual values. This low MSE makes SVR a reliable choice for precise forecasting in this dataset.



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Support Vector Regressor Model MSE: 2.4687711643139845
```

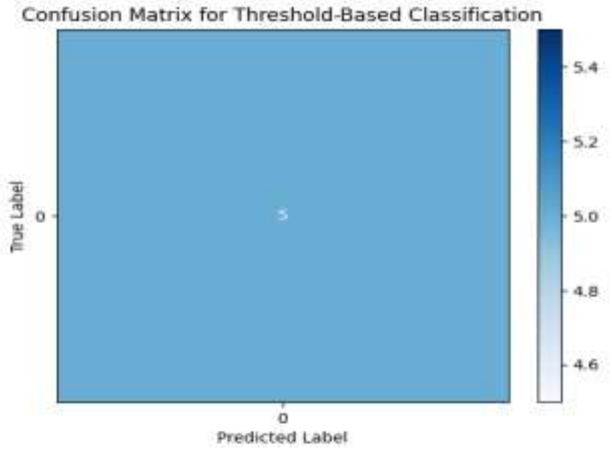
4.5.1. Clustering for System Prioritisation

The Silhouette Coefficient of 0.935 was found for the clustering model implemented to prioritise ASRS and AMR tasks within WMS. This high ratio shows that clustering for the above tasks can be efficient, and it is also evident that the priorities for these tasks are distinct. The K-means clustering algorithm classified tasks depending on the Order Urgency, Travel Time, and Item Location to ensure that essential tasks, such as the frequently used items or urgent orders, utilise the ASRS AMR resources.

4.5.2. Confusion Matrix

Additional assessment of clustering could be done with a confusion matrix to refine the evaluation of the accuracy of classification and coherence of high and low-priority task allocation. Proper prioritisation benefits the lean warehousing process, enabling ASRS and AMR resources to handle critical tasks with minimal travel time and maximise robotic operations in the warehouse context, as shown in Figure 4.

Figure 4: Confusion Matrix



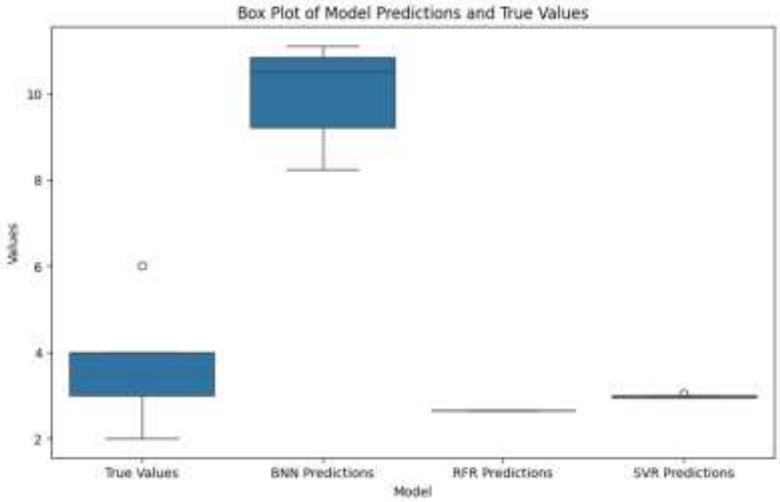
4.6. Comparison Table and Plots

A consolidated table presents the key performance metrics across all models. It provides a comparative view of their effectiveness in addressing ASRS and AMR integration challenges within WMS, as shown in Table 2.

Table 2: Comparison Table

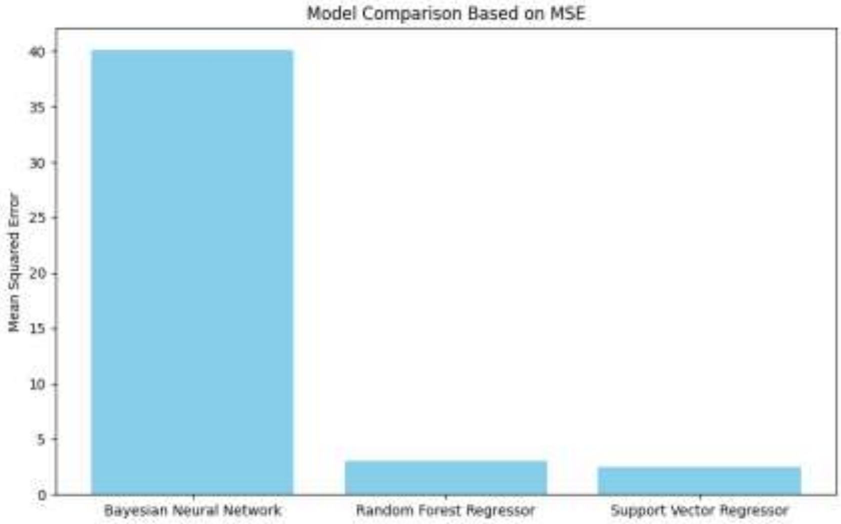
Model	MS	R-squared
Bayesian Neural Network	40.089055	-21.777872
Random Forest Regressor	3.073316	-0.746202
Support Vector Regressor	2.468771	-0.402711

Figure 5: Box Plot of the Model



The box plot shows (in Figure 5) notable differences between true values and model predictions. BNN predictions exhibit a wider range and higher median, diverging from true values, indicating over-prediction. Random Forest Regressor (RFR) and Support Vector Regressor (SVR) predictions are more closely aligned with true values, showing better accuracy.

Figure 6: Model Comparison



The Figure 6 bar chart reveals that the Bayesian Neural Network (BNN) has a significantly higher Mean Squared Error (MSE) than the Random Forest Regressor and Support Vector Regressor, indicating that BNN is less accurate in predicting outcomes. The lower MSE values for the latter models suggest better predictive performance.

5. DISCUSSION

The findings illustrate the benefit of using BNNs, Random Forest models and clustering in integrating ASRS and AMR with WMS for flexibility in warehouse operations. The Bayesian Neural Network (BNN) made a relatively good forecast in the demand variation with an overall Mean Squared Error (MSE) of 40.08. The performance of the BNN indicates the BNN construction, as it can integrate the uncertainty estimation that allows for the calculation of demand variability and the provision of confidence intervals for the expectation. In a warehouse context, this flexibility is relevant since it will enable ASRS and AMR systems to adapt the task list according to the expected traffic level, thus avoiding overstock and stockout conditions. Consequently, BNN facilitates a reduced stock forecast, limiting wastage and absolute optimisation of resources within the WMS environment.

The Random Forest model's low MSE of 3.07 proves the tool to be accurate in optimising resource allocation for real-time application in complex warehouses. Due to the sophistication of this model in estimating the number of resources required, ASRS and AMR resources will be appropriately positioned to reflect the varying demand for the resources and functionality needed in the system. Random Forest helps to work ASRS and AMR systems with maximal efficiency without overloading and unnecessary idling by changing allocations according to real-time data. This aligns with lean warehousing objectives because the model reduces employee costs and sub-optimisations, enhancing the cycle of work and the time taken to complete those cycles.

The clustering model developed here with a Silhouette Score of 0.935 supports the utility of task prioritisation in integrating ASRS and AMR. This way of organising work allows for evaluating the essential characteristics of functions and identifying high-priority jobs so that they can be completed immediately. This approach also means that ASRS and AMR resources are working on the most critical processes, decreasing their movement time and increasing productivity. From the above realisations, it is evident that task prioritisation through clustering conforms with lean inventory management by limiting unnecessary movement of resources within the facility.

The advantages of these models are apparent but using them in practical warehouses is not a piece of cake, mainly due to data demands and facility support issues. The efficiency of accurate demand forecasting and an optimal distribution of resources requires a constant supply of clearly distinguishable data on the frequency of orders, inventory levels, and picking durations. There may be constraints within the warehouses if the information needs to be validated or is relatively old, which causes poor work from the model. However, as previewed by the setup of the BNNs coupled with the Random Forest models, the application of these solutions is computational. It entails some technical facilities in its initial stage. Another area for improvement is interfacing these models with the traditional and often non-real-time WMS systems. Despite these challenges, using BNNs, Random Forest and clustering models substantially improves ASRS and AMR interfaces with WMS. As such, these models promote the adoption of lean principles and the ability of the warehouses to adapt to meeting customers' needs faster.

6. CONCLUSION

This study illustrated how machine learning models can inform the maintenance and improvement of existing ASRS and AMR integration with WMS regarding demand prediction, resource optimisation, and task scheduling. Overall, the BNN provided a moderate level of accuracy with an MSE of 40.08, captured the demand variability and thereby supported the scheduling of ASRS and AMR tasks. The Random Forest model has a relatively low MSE (3.07), which indicates good applicability in dynamically adjusting resources and ASRS and AMR performance to the demands that occur in real-time. The clustering based on the work priority list where the Silhouette Score was obtained with a high value of 0.935 facilitated task sequencing so that the proper task could be accomplished at the right time based on lean warehousing concepts.

These models improve the effectiveness of ASRS and AMR; they provide a flexible and application-based means of responding to demand fluctuations and managing high-priority tasks. Possible future developments in a similar field include using the real-time adaptation of data in Bayesian models to enhance predictive performance and applying various clustering methods to facilitate more detailed approaches to resolving the problem of prioritising among tasks. This approach would only enhance optimised ASRS and AMR functional integration in WMS and introduce enhanced warehouse automation.

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