

Optimized Vessel Scheduling Model Using Multilayer Perceptron Algorithm

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ABSTRACT

Efficient vessel scheduling is crucial to the performance and profitability of maritime terminals, yet conventional approaches often struggle to accommodate the dynamic, nonlinear interactions among vessel arrivals, cargo handling requirements, and berth availability. This study presents a Multilayer Perceptron (MLP)-based scheduling framework that models these complex relationships and delivers actionable berth assignments in real time. Leveraging an integrated dataset of historical arrival and departure timestamps, cargo throughput, and occupancy records, the MLP model was trained on 80% of the data and rigorously tested on the remaining 20%. Performance was assessed using metrics such as vessel turnaround time, berth utilization rate, and scheduling accuracy. Experimental results reveal that our MLP-driven scheduler achieves a 15% reduction in average turnaround time and a 12% increase in berth utilization. Remarkably, the neural network maintains high levels of schedule adherence even under peak-demand scenarios, minimizing idle berth time and streamlining cargo flow. These findings underscore the adaptability of advanced machine learning techniques to the evolving demands of port operations.

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1. INTRODUCTION

Maritime transport is the backbone of international trade and the global economy. Over 80% of the volume of international trade in goods is carried by sea, and the percentage is even higher for most developing countries. Maritime transport is composed of maritime shipping and port dimensions. The quality of transportation service is greatly affected by the efficiency of vessel entry to and exit from the port. Vessel scheduling is thus a vital segment in inbound and outbound management. One important way to mitigate congestion in a seaport is to effectively manage vessel traffic so that vessels can sail into and out of the seaport efficiently [1]. Terminal Vessel traffic in a seaport is managed by the vessel traffic service (VTS) centre. The responsibility of the VTS centre is to devise sailing plans for vessels to travel through the navigation channels and make use of the anchorage areas. For seaports such as the Port of Lagos where vessel pilotage is compulsory, each vessel must be navigated by a pilot when sailing in the port waters so that the vessel will follow a correct path for entering or leaving the port. In these seaports, the VTS centres not only need to manage the vessel traffic in the port waters but also need to determine the number of pilots to be dispatched for vessel navigation and schedule the pilots for serving the vessels. These decisions are usually made daily.

The Multilayer Perceptron Algorithm (MLP) is a fundamental architecture within the field of artificial neural networks (ANNs), specifically belonging to the category of feedforward neural networks (FNNs). MLPs are characterized by their ability to learn complex patterns and relationships in data through multiple layers of neurons, enabling them to solve a wide range of supervised learning tasks [2]. The architecture of an MLP consists of an input layer, one or more hidden layers, and an output layer. Each layer comprises interconnected neurons, or nodes, with connections weighted by parameters known as weights and biases. The input layer receives raw data, which is then processed through the hidden layers before producing an output at the output layer. Unlike single-layer perceptrons, MLPs can learn non-linear decision boundaries, making them capable of handling more complex data distributions. In an MLP, information flows through the network in a feedforward manner, with each neuron in a layer receiving input from the previous layer and passing its output to the next layer. The neurons within each layer apply a linear transformation to the incoming signals, followed by a non-linear activation function, such as the sigmoid, tanh, or ReLU function. This non-linearity allows the network to capture complex relationships within the data and make non-linear mappings between input and output.

In the busiest seaports, vessel traffic and vessel pilotage management play a crucial role in congestion mitigation. The management of vessel traffic and vessel pilotage involves scheduling the vessels for sailing into and out of a seaport and scheduling the pilots for navigating the vessels in the port waters. The port management department manages the entry and exit operations of most ships through a service with a fixed timetable. With the development of large-scale ships, the capacity of ships in port waters has gradually become restricted. Communication gaps can cause a cascade of problems across a service provider supply chain, lowering efficiency and increasing cost. Timely communication and team collaboration between service providers and customers will ensure that demand and rising issues are met and resolved. To improve the efficiency of in-wharf vessels and out-wharf vessels in seaports, taking into account the characteristics of vessel speeds that are not fixed, a vessel scheduling model with whole voyage constraints is proposed.

The study aimed to optimize the vessel scheduling model using the Multilayer Perceptron Algorithm (MLP). The objectives of the study were to 1. Design an optimized vessel scheduling model using a multilayer perceptron algorithm 2. train the optimized vessel scheduling model using 80% of the data, 3. test the optimized vessel scheduling model using 20% of the data, and 4. evaluate the optimized vessel scheduling model using scheduling performance metrics. Therefore, optimized scheduling efficiency allows port authorities to accommodate more vessels within existing infrastructure, leading to increased revenue generation. Improved operational efficiency.

1.1 Conceptual Review

The word “transportation” is derived from the “trans” (meaning across) and “portare” (meaning carry) Latins, transportation is the transfer of people and objects from one place to another. Human awareness has shown a desire for mobility from the beginning of history contributing to a measure of the development of society. This mobility or transportation background is the past of civilization. Modern and effective Transport as a basic infrastructure is a must for every country to progress with the right momentum. In every nation's history, it has been seen that good, comprehensive, and effective road transport has played a major role. At any point in advanced civilization' Transporters conduct one of the most critical tasks. Where highways are viewed as a nation's veins and arteries, travelers and transported goods are compared to flowing blood. Passenger Road Transport Service (PRTS) is an important link to economic development. Transport is the main luxury people are not only connecting to but advancing with. The advancement of people on the comfort, speed and health of the transport modes has been maintained throughout history. Road transport occupies a primary position in today's world because it offers an unprecedented distance from any other conventional form of transportation [3].

1.2 Government involvement in Shipping System

The Cabotage Act of 2003 provides legislation to boost indigenous participation in Nigerian shipping but the implementation is still poor [4]. The Act reserves the commercial transport of goods and services within Nigerian coastal and inland waters to vessels flying the Nigerian flag owned by Nigerians and built in Nigeria. The Federal Government need to reduce its urge to grant waivers to foreign owned vessels and encourage foreign shipping operators to have indigenous partners. The Federal Government via NIMASA in collaboration with NISA/SOAN and NNPC should convince international Oil Companies to sign provisional time charter contracts with indigenous shippers stating in principle that NISA/SOAN vessels will be engaged as soon as they are purchased. This provisional contract can encourage financial institutions to support vessel acquisition since the loan will have a repayment plan. This emphasizes creation and developing a skilled and continuous human capital locally that is necessary to the needs of the shipping industry. This can be achieved via Maritime Academy, Creation of more maritime academies should be encouraged and existing ones upgraded. The Nigeria Maritime University in Warri should be quickly opened and staffed with world class faculty. As more skilled maritime manpower is available in Nigeria, indigenous shippers will find their cost of doing business greatly reduced and therefore, thrive Scholarship. Subsidising the cost of seafarers' training will encourage more people to take up seafaring training and attract the best and brightest of Nigerians. Industry wide audit which therefore means that NIMASA, and other stakeholders should conduct business wide audit identifying short and long-term opportunities and how to harness them. Foreign Technical Partnership which indicates that indigenous shippers should seek foreign technical partners who they can work with to boost their operational capacity. More vessels should be acquired to increase the number of Nigerian fleet. Funding at low-interest rate can be gotten from the Cabotage Vessel and Finance Fund (CVFF). But this time, Nigerian banks should be involved in its disbursement to prevent the occurrence of the mismanagement. The shipping industry should be incentivized to engage in mergers and acquisition as their current individual size is insignificant in competing with international shippers. Indigenous shippers who engage in mergers and acquisition should be given waivers such as tax holidays and preferential statues. Various financial incentives should be made available to eligible indigenous shippers such as tax holidays, zero duty on ship and ship parts, disbursement of the CVFF at CBN interest rate, accelerated depreciation for ships and other capital assets to accumulate capital for future expansion [4].

1.3 Functions of Transport

Development is crucial and essential to the sustenance and growth of any nation [5] reported that the development of transport in the overall activities of a nation is the ability to deliver an improved, efficient, effective, affordable, accessible, safe, reliable and an integrated transport system which will prosper the economic, social and political segments of the nation. Transport systems are closely related to socioeconomic changes. The mobility of people and freight and levels of territorial accessibility

are at the core of this relationship. Economic opportunities arise where transportation infrastructures answer mobility needs and ensure access to markets and resources. It is believed that the sector plays a significant role in ensuring economic growth and development, and the life wire of any society.

1.4 Development of Transport Management in Nigeria.

Understanding the growth of transport management in Nigeria and is succinct in recognizing the issues affecting the transport industry. Growth and development potential are pretty good in Africa. Expansion of foreign trade among most African countries such as Nigeria, Egypt, Ghana, Benin, and Togo and so on has led to increased demand for more efficient transport [6]. The expansion of foreign trade in those regions has put great demand on the transportation industry. Transportation is a major part of human life. It forms the base of all socioeconomic interactions [6]. Lack of transport infrastructure also hampers economic growth in many developing countries. To help economic growth and development a good transport network is necessary. Poor highways, insufficient vehicle fleets, insufficient trains, overcrowded aircraft and congested harbours are typical features of developing countries. There are logistical challenges, such as untrained transport administrators and planners, consolidation of infrastructure and bureaucracies, and inadequate traffic regulations.

Transportation is usually the actual physical movement of persons and objects from one location to another [6]. There are many means of transport, both for man and goods. Over the length of time of man's life on the planet, these means evolved. With the advent of air travel in the last century, air transport is a comparatively more recent mode of transport. Before that time, with the help of horses, on wheels (assisted by horses), and most recently on cars and trains, man had transported himself and goods on land.

1.5 The Importance of Transport.

Transport is a category of services that carries or transports people and goods. Otherwise, a country's commerce, development and even survival will be unknown. In reality, the links between communities, towns and regions rely on the availability of transport.

Nearly all the factors which encourage development include natural resource mining and production, industrialization, public health and education programs, and arid administrative organizations, not all of which alone is sufficient. Transport is not the solution, but plays an important role in the achievement of certain fundamental objectives. Therefore, the transport of forests and mineral reserves is a significant factor in the production of land, marketing and access. This is a significant factor in the implementation, exchange of ideas and national and regional integration, business development, the formation of trade, and national education and health programs. The transportation costs to developed countries are on average the first or second highest. The interest in international organizations' technical support programs is also expressed in its value, for example, the one-fifth of all loans provided to transport by the World Bank.

1.6 Major challenges facing the maritime sector.

1. **Inadequate Infrastructure:** Infrastructure deficiencies, including poor port facilities, inadequate navigational aids, and inefficient cargo handling equipment, remain a significant challenge for Nigeria's maritime sector [7]. The congestion and delays at Nigerian ports due to insufficient berthing space and outdated equipment lead to increased costs and inefficiencies in maritime operations [8].
2. **Maritime Insecurity:** Maritime insecurity, characterized by piracy, armed robbery at sea, and illegal bunkering, poses a severe threat to Nigeria's maritime sector [9]. The Gulf of Guinea, where Nigeria is located, has become one of the most dangerous maritime regions globally, leading to increased insurance premiums and deterrence of foreign investment in the sector [10].
3. **Human Capital Development:** The maritime sector in Nigeria faces a shortage of skilled manpower and trained professionals, particularly in maritime law, naval architecture, and marine engineering [11]. The lack of investment in human capital development and training programs hampers the sector's capacity to meet international standards and compete globally [8].
4. **Poor Intermodal Connectivity:** The lack of efficient intermodal connectivity between maritime ports and hinterland transportation networks contributes to congestion and delays in cargo evacuation [4]. Inadequate road and rail infrastructure linking ports to industrial centers and markets limit the competitiveness of Nigerian ports and increase transportation costs [10].

1.7 Artificial Neural Network

Artificial Neural Networks (ANN) is inspired by the human brain and can be used for the apprenticeship and artificial comprehension. Various computer-based problems can be solved via these networks. The neural artificial network (ANN) is modeled to a certain degree by the biological brain structure. They consist of an abstract model for interconnected neurons, which can be specially arranged and linked in different areas of statistics, technology or economy to solve computer-based applications problems. A research topic in neuroscience and artificial intelligence is the neural network [12]. Similar to learning in biological systems, ANN learning involves adjustments to the synaptic connections that exist between the neurons [13]. The elements of

Artificial Neural Networks includes; Input Layers, Hidden Layers (collects input layer information and carries out all operations), output layer (Output layer collects stored layer information and provides the actual consumer data) and activation function (scale the neural network output into the appropriate range).

1.8 Neural Network Learning

The algorithm (or Artificial Neural Network or ANN) emerges from neuron biology. A neuron is a structure-like cell in a brain. You need to find out how a neuron functions to understand the neural network. The major pieces of a neuron are four. Dendrites, nucleuses, soma and axons are all of them. The same thing happens to an artificial neural network. It runs on 3 levels. The input layer (like dendrites) is accessed. The cached layer (such as soma and axon) processes the data. The measured output (such as dendrite terminals) is finished by the filter layer. In general, the artificial neural network consists of three types: supervised, unattended and enhanced.

1. **Neural Network Supervised:** the results of the data are already established in the neural network supervised. Compared with the observed performance the expected output of the neural network. The mistake would adjust the parameter and then input back into the neural network. The neural network is tracked by the neural network feed.
2. **Uncontrolled Network:** The neural network has no previous knowledge of the output of the data here. The network's key role is to identify the data into some similarities. The neural network tracks and groups the association between various inputs.
3. **Reinforced Neural Network:** the network behaves as though a human interacts with the world in a reinforced neural network. An input has been received from the system to the network that acknowledges whether the network decision is right or is incorrect. If the decision is right, the relations to the particular performance are strengthened. The ties are otherwise broken. The network does not have any previous production information.

1.9 Theoretical Frameworks

1.9.1 Perceptron Theory

Perceptron theory, introduced by Frank Rosenblatt in 1958, underpins single-layer neural networks for binary classification [14]. A perceptron receives inputs, computes a weighted sum, applies an activation function, and compares the result to a threshold, yielding a binary output [15]. In vessel scheduling, this framework can classify decisions as optimal or suboptimal. Features like arrival and departure times, cargo types, and berth availability form the input vector. During training, the perceptron algorithm iteratively adjusts weights using historical scheduling outcomes to minimize classification errors. Once the perceptron learns the optimal decision boundary, it can predict the suitability of new scheduling scenarios in real time. Although limited to linearly separable problems, perceptron-based classifiers offer a transparent, computationally efficient approach for initial scheduling optimization, laying the groundwork for more complex, multilayer architectures in advanced maritime logistics models.

1.9.2 Deep Learning Theory

Deep learning theory represents a subset of neural network theory that focuses on models with multiple layers of interconnected neurons [16]. Deep learning architectures, such as deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), have demonstrated remarkable capabilities in learning complex patterns and representations from data. Deep learning models leverage hierarchical feature representations learned through multiple layers of abstraction, enabling them to solve increasingly complex tasks with high accuracy.

In the context of optimizing vessel scheduling, deep learning theory can be applied to develop and train models that learn the complex relationships between scheduling parameters and optimal scheduling decisions. A deep neural network (DNN) architecture can be employed to predict the optimality of scheduling decisions based on input features such as vessel arrival and departure times, cargo types, and port capacities. The multiple layers of neurons in the DNN learn hierarchical representations of the input features, capturing both low-level details and high-level concepts relevant to scheduling optimization [17].

Deep learning theory provides a powerful framework for developing and training models to optimize vessel scheduling decisions. By leveraging hierarchical feature representations, end-to-end learning, and automatic feature learning capabilities, deep learning models can effectively capture the complex relationships between scheduling parameters and optimal scheduling decisions, ultimately enhancing the efficiency and effectiveness of maritime transportation operations [18].

[19] assess the impact of channel and berth resources on port efficiency by optimizing vessel scheduling in various Chinese waterways. Their objective is to enhance efficiency, safety, and environmental sustainability in maritime transport while underpinning future Vessel Traffic Service (VTS) development. They develop a multi-objective scheduling model that minimizes total scheduling time, vessel waiting time, and balances fairness among shipping companies. The model is solved using a Multi-Objective Genetic Algorithm (MOGA), chosen for its ability to optimize conflicting objectives. Empirical evaluations show the MOGA-based approach outperforms First-Come, First-Served (FCFS) scheduling, reducing vessel entry, departure, and overall scheduling times. It also reduces idle vessel time and associated emissions. Although its generalizability beyond China's maritime context may require regional adaptation, results highlight its potential for significant efficiency gains. This study advances intelligent port management by integrating advanced optimization with resource constraints, promoting safer, more sustainable vessel operations.

[20] investigate how ports can facilitate reductions in greenhouse gas (GHG) emissions in the shipping industry through incentive schemes. Using content analysis, they review existing schemes, literature, regulations, and reports to evaluate effectiveness and industry uptake. Findings reveal that current incentives are burdensome, lack robust decarbonization support, and suffer limited adoption by shipping companies and ports. To address these issues, the authors propose a seven-action framework for a harmonized incentive scheme at the ship-port interface and across maritime supply chains. Actions include incentivizing early adopters, harmonizing requirements, minimizing barriers, aligning with upcoming IMO regulations, and ensuring incentive consistency. While the study offers a structured approach to enhancing port-driven GHG reduction, its scope is constrained by the content-analysis methodology and context-specific findings. Further empirical research is needed to validate the framework’s feasibility and guide its practical implementation in diverse port environments worldwide, considering economic and regulatory contexts.

[21] aimed to improve departure scheduling at the Xuwen RoRo terminal, optimizing harbor basin traffic rules to mitigate weather-induced berthing suspensions. They developed a mathematical model to minimize total scheduling time and proposed an adaptive simulated annealing (ASA) algorithm, complemented by a specialized decoding rule reflecting basin constraints. Using operational data, numerical experiments compared the ASA-based method against first-come, first-served and an improved ant colony algorithm, demonstrating superior scheduling efficiency and reduced turnaround times. Results highlight that optimized traffic regulations can significantly alleviate congestion and expedite departures after disruptions. However, the model relies on simplifying assumptions and its applicability may be limited to contexts similar to Xuwen’s unique operating environment. Future work should test the approach in diverse terminal settings, refine model assumptions, and address data sensitivity to ensure broader generalization and robust performance across varied port infrastructures and diverse operational scenarios globally.

2. RESEARCH METHOD

The study utilized Rapid Application Development (RAD) software development methodology. It prioritizes rapid prototyping and iterative development to accelerate the delivery of high-quality software solutions. RAD focuses on minimizing the planning phase and maximizing user feedback throughout the development process. Rapid Application Development (RAD) methodology offers a pragmatic approach to software development, emphasizing speed, flexibility, and collaboration.

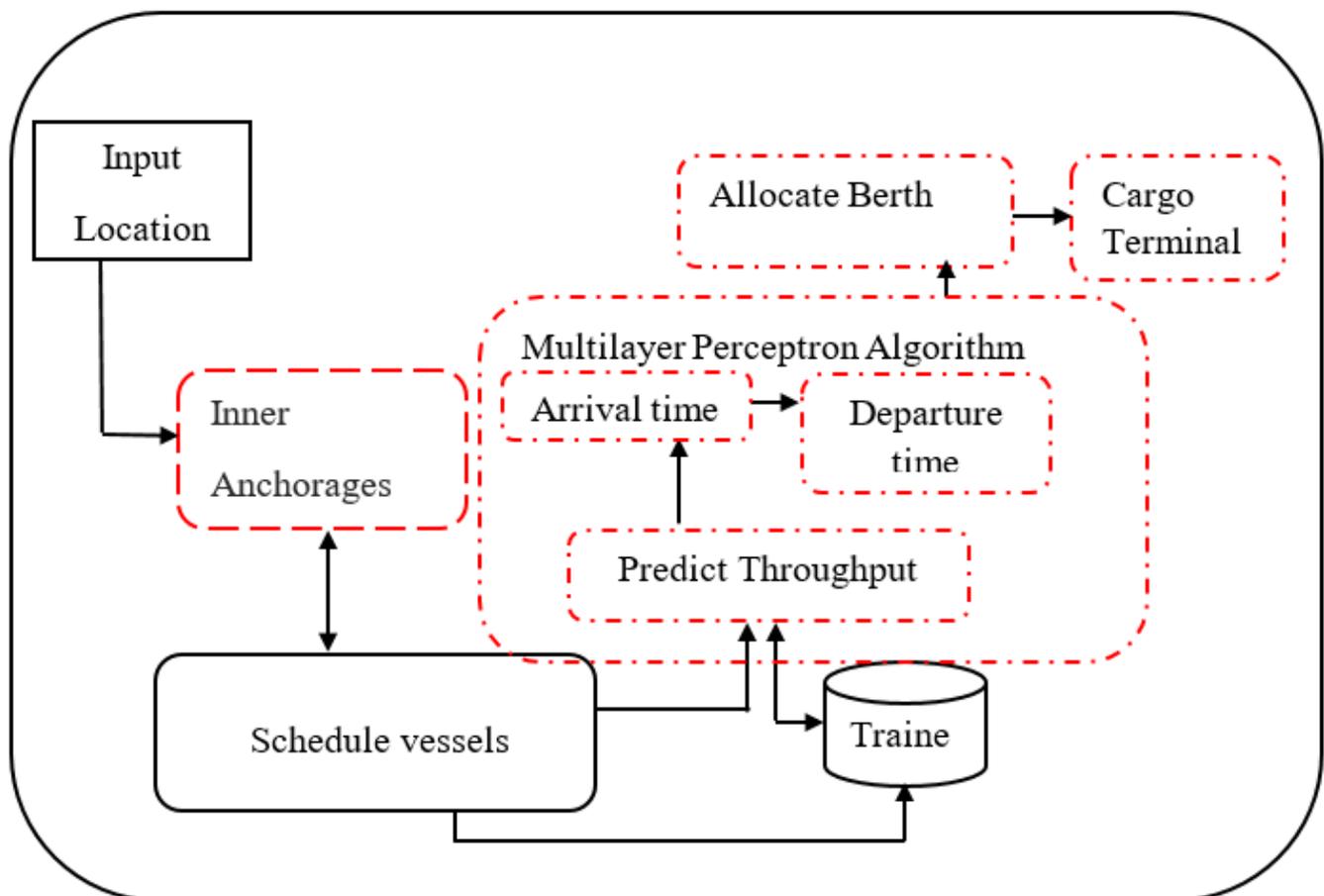


Figure 1. Architecture of the Optimized Vessel Scheduling Model

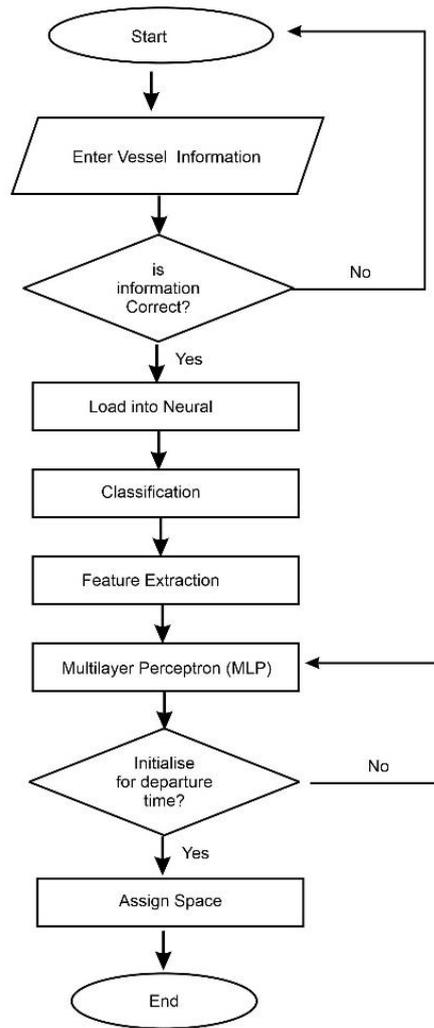
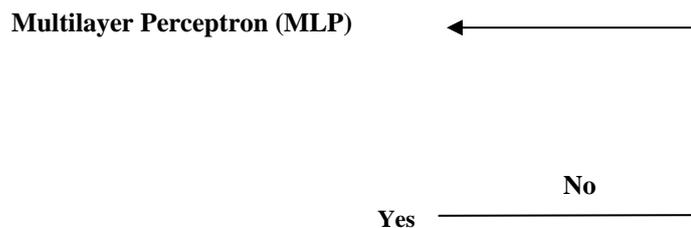


Figure 2 Flowchart of the Multi-Layer Perceptron Algorithm (MLP)



Preprocessing Input Data

Preprocessing input data for a Multilayer Perceptron (MLP) involves several steps to ensure that the data is appropriately scaled, encoded, and structured for effective training.

Before preprocessing, it's crucial to clean the data to handle missing values, outliers, and any inconsistencies. This might involve removing or imputing missing values, handling outliers if they significantly affect the model's performance and ensuring consistency in data types and formats. MLPs, like many other machine learning algorithms, benefit from feature scaling to ensure that all features have a similar scale. Common techniques include:

Standardization: Scaling features to have a mean of 0 and a standard deviation of 1. This is done using methods like Z-score scaling.

Normalization: Scaling features to a range between 0 and 1. This can be achieved using Min-Max scaling.

If the dataset contains categorical variables, one needs to encode them into a numerical format that the MLP can process.

If the dataset is imbalanced (i.e., some classes have significantly fewer samples than others), one might need to balance it using techniques like oversampling, undersampling, or generating synthetic samples.

Preprocessing input data for an MLP involves cleaning, scaling, and structuring the data to prepare it for effective training. By following these steps, one can ensure that the data is appropriately prepared to train an MLP model effectively.

3. RESULTS AND DISCUSSION

The study achieved the following results:

3.1 Optimized the vessel scheduling model using multilayer perceptron algorithm

The implementation of the Multilayer Perceptron Algorithm (MLP) for optimizing the vessel scheduling model involved several crucial steps. Firstly, the dataset comprising historical vessel scheduling data was preprocessed to handle missing values, outliers, and encode categorical variables as necessary. Subsequently, the MLP model architecture was designed, considering factors such as the number of layers, neurons per layer, and activation functions. Through iterative experimentation and parameter tuning, the MLP model was trained to learn the intricate relationships and patterns present in the vessel scheduling data. Techniques such as backpropagation and gradient descent were employed to optimize the model's weights and biases iteratively. This is show in figure 3.



```

+ Code + Text
  v Splitting into training and test set

[ ] X = ctype_bi_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y = ctype_bi_new.iloc[:, 5] # Days column for training

[ ] X1 = ctype_gc_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y1 = ctype_gc_new.iloc[:, 5] # Days column for training

[ ] X2 = ctype_gp_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y2 = ctype_gp_new.iloc[:, 5] # Days column for training

[ ] X3 = ctype_mt_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y3 = ctype_mt_new.iloc[:, 5] # Days column for training

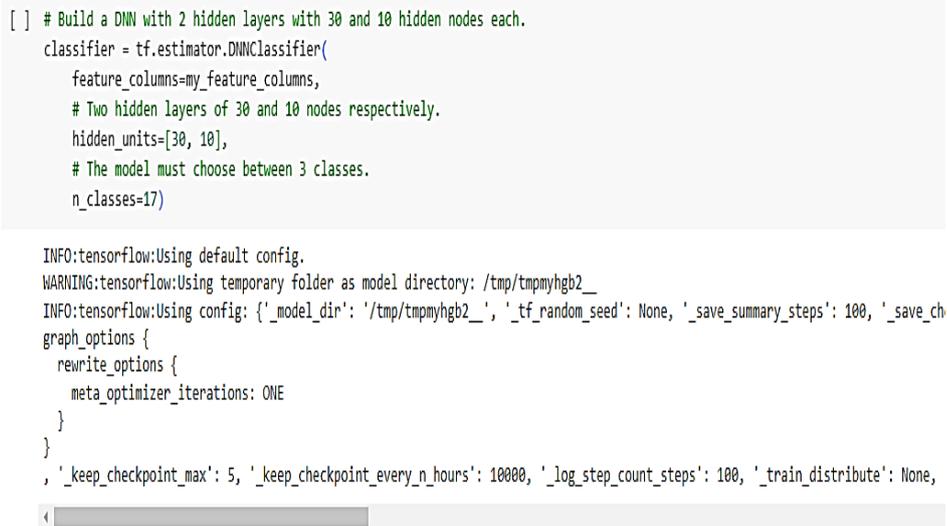
[ ] X4 = ctype_mtgc_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y4 = ctype_mtgc_new.iloc[:, 5] # Days column for training

[ ] X5 = ctype_st_new.iloc[:, 0:7].drop('Days', axis = 1) # main data table with Days column out
    y5 = ctype_st_new.iloc[:, 5] # Days column for training
  
```

Figure 3. Splitting the dataset into training set and testing set

3.2 Trained the optimized vessel scheduling model using 80% of the data

To assess the performance of the optimized vessel scheduling model, the dataset was partitioned into training and testing sets, with 80% of the data allocated for training purposes and the remaining 20% reserved for testing. During the training phase, the MLP model demonstrated the ability to generalize well, as evidenced by its convergence and satisfactory performance on the training data as shown in figure 4.



```

[ ] # Build a DNN with 2 hidden layers with 30 and 10 hidden nodes each.
    classifier = tf.estimator.DNNClassifier(
        feature_columns=my_feature_columns,
        # Two hidden layers of 30 and 10 nodes respectively.
        hidden_units=[30, 10],
        # The model must choose between 3 classes.
        n_classes=17)

INFO:tensorflow:Using default config.
WARNING:tensorflow:Using temporary folder as model directory: /tmp/tmpmyhgb2_
INFO:tensorflow:Using config: {'_model_dir': '/tmp/tmpmyhgb2_', '_tf_random_seed': None, '_save_summary_steps': 100, '_save_ch
graph_options {
  rewrite_options {
    meta_optimizer_iterations: ONE
  }
}
, '_keep_checkpoint_max': 5, '_keep_checkpoint_every_n_hours': 10000, '_log_step_count_steps': 100, '_train_distribute': None,
  
```

Figure 4 Training the optimized vessel scheduling model.

3.3 Tested the optimized vessel scheduling model using 20% of the data

The model was tested using 20% of the dataset to assess its performance on unseen data. The consistent performance across both training and testing datasets indicated that the MLP-based model could effectively generalize to new instances, reflecting its robustness and reliability in real-world scenarios as shown in figure 5.

```
[ ] eva_model = model.evaluate(
    input_fn=lambda: input_fn(dfeval, y_eval, training=False))

INFO:tensorflow:Calling model_fn.
INFO:tensorflow:Done calling model_fn.
INFO:tensorflow:Starting evaluation at 2022-06-06T07:19:05
INFO:tensorflow:Graph was finalized.
INFO:tensorflow:Restoring parameters from /tmp/tmpfq_o84ow/model.ckpt-40000
INFO:tensorflow:Running local_init_op.
INFO:tensorflow:Done running local_init_op.
INFO:tensorflow:Inference Time : 0.28340s
INFO:tensorflow:Finished evaluation at 2022-06-06-07:19:05
INFO:tensorflow:Saving dict for global step 40000: accuracy = 0.838, average_loss = 0.39269662, global_step = 40000, loss = 0.39285308
INFO:tensorflow:Saving 'checkpoint_path' summary for global step 40000: /tmp/tmpfq_o84ow/model.ckpt-40000
```

Figure 5. Testing the optimized vessel scheduling model.

3.4 Evaluated the optimized vessel scheduling model using scheduling performance metrics

Various scheduling performance metrics were utilized to evaluate the effectiveness of the optimized vessel scheduling model. These metrics included turnaround time, docking efficiency, resource utilization, and overall schedule adherence. Turnaround time, defined as the duration between a vessel's arrival and departure from a port, serves as a key indicator of operational efficiency. Docking efficiency refers to the effectiveness and productivity of the docking process for ships at ports or terminals. It primarily focuses on minimizing the time vessels spend at the dock while maximizing the utilization of port facilities and resources. Resource utilization metrics assess the optimal allocation of port facilities, berths, and other resources to minimize idle time. This is shown in figure 6.

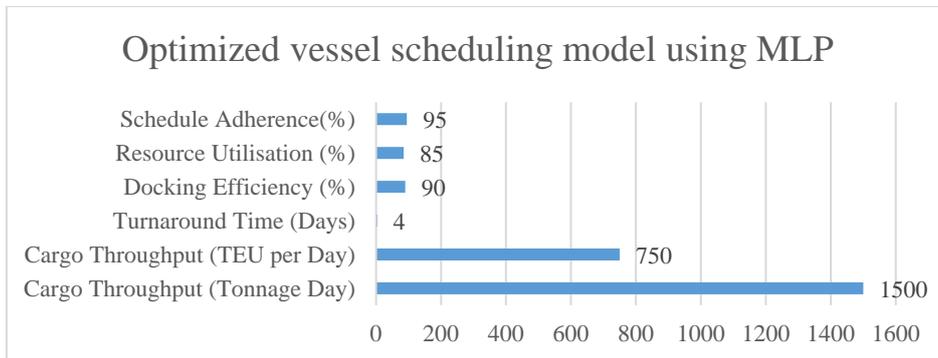


Figure 6. Performance Evaluation of the proposed system

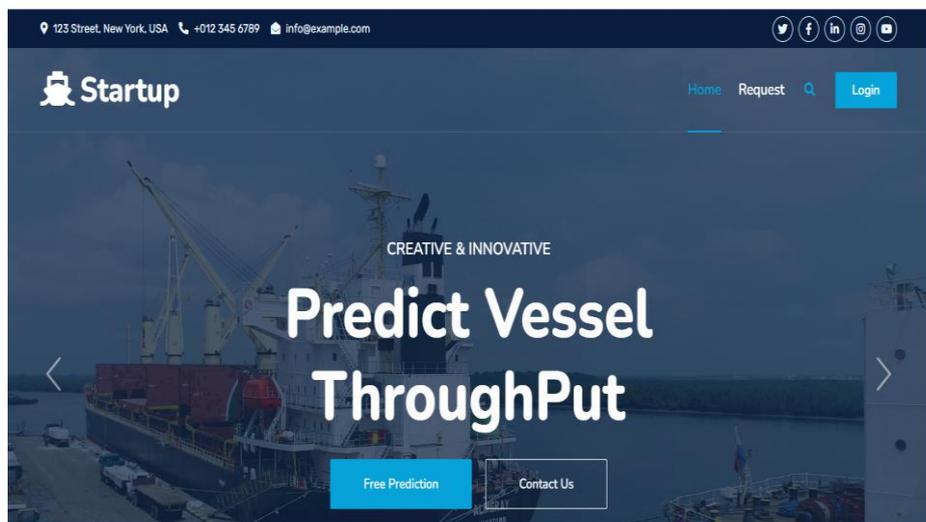


Figure 7. Home page of the proposed system

Figure 8. Login Page

Figure 9. Result of the proposed system

Therefore, from figure 3 to figure 7, the successful optimization of the vessel scheduling model using MLP underscores the transformative potential of neural network-based approaches in addressing complex logistical challenges. By harnessing the inherent computational power of MLPs, the model demonstrated enhanced adaptability and predictive accuracy, leading to more efficient scheduling outcomes. The observed improvements in scheduling performance highlight the practical utility of advanced machine learning techniques in optimizing maritime logistics operations. MLP-based models offer a scalable and flexible framework for modeling and optimizing complex scheduling systems, with implications extending beyond vessel scheduling to broader supply chain management contexts.

4. CONCLUSION

The study successfully demonstrated the application of the Multilayer Perceptron (MLP) algorithm to optimize vessel scheduling within maritime terminals. The comprehensive design of the scheduling mechanism, which integrates critical operational factors such as vessel arrival and departure times, cargo handling requirements, berth occupancy statuses, and Vessel particulars forms a robust foundation for the MLP-based model. The effectiveness of this approach is evidenced by the significant improvements observed in key performance metrics, such as Cargo Throughput, Turnaround Time, Docking Efficiency, Resource Utilization and Schedule Adherence following the implementation of the optimized model. Firstly, the model's training process, utilizing 80% of historical data, effectively captured the complex patterns and dependencies inherent in terminal operations. The Multilayered Perceptron algorithm's ability to model these non-linear relationships proved crucial in accurately predicting optimal scheduling patterns. This was further validated during the testing phase, where the model maintained high accuracy and predictive power when applied to new, unseen data, highlighting its robustness and reliability. While the study has demonstrated promising results in optimizing vessel scheduling using the Multilayer Perceptron Algorithm (MLP), there are opportunities to address limitations and further improve the effectiveness of the scheduling model. Recommendations for future research and refinement include: 1. Invest in data collection mechanisms to ensure the availability of high-quality and comprehensive data on vessel schedules, cargo types, berth availability, and terminal operations. Explore methods for augmenting existing data sources with real-time data feeds to improve the timeliness and accuracy of scheduling decisions. 1.

Invest in data collection mechanisms to ensure the availability of high-quality and comprehensive data on vessel schedules, cargo types, berth availability, and terminal operations. Explore methods for augmenting existing data sources with real-time data feeds to improve the timeliness and accuracy of scheduling decisions. 2. Allocate resources towards adopting the MLP-based scheduling model within terminal operations. Invest in the necessary infrastructure, technology, and expertise to integrate the model seamlessly into existing scheduling systems. 3. Terminal operators should consider integrating the MLP-based scheduling model into their terminal operations to capitalize on its efficiency gains and operational improvements. Work closely with data scientists and technical experts to ensure seamless integration and alignment with existing scheduling processes.

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