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VesselLink AI: Revolutionizing Cost-Efficient Scheduling and Linkage for Eastern India's Steel

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Abstract: The steel industry relies significantly on efficient logistics to move raw materials like coking coal and limestone. The conventional method of planning and executing logistics, which involves fragmented SAP systems and Excel-based workflows, often results in inefficiencies and increases in costs and time. This paper proposes a new intelligent system called VesselLink AI, which optimizes vessel scheduling, port selection, and dispatch planning from ports to the plant. The proposed system incorporates machine learning models to forecast pre-berthing delays, make scheduling decisions, and minimize logistics costs. It takes into account many constraints like stock availability, railway logistics, and sequential discharge. The proposed system can significantly reduce the total logistics costs by 10 to 15 percent, which can be validated through experimental results. The proposed system can provide efficient and cost-effective solutions to the steel industry.
Index Terms: Logistics Optimization, Machine Learning, Vessel Scheduling, Supply Chain, Steel Industry, AI, Predictive Analytics.

I. INTRODUCTION

A. Motivation

Effective management of logistics is a crucial factor in the steel industry, as the uninterrupted availability of raw materials like coking coal and limestone is necessary for continuous production operations. Steel plants rely on a complex logistics system consisting of various ports and inland transport systems. Conventional planning systems based on SAP and Excel face limitations in terms of real-time information and integration capabilities, which may lead to inefficiency in planning and coordination operations [1], [2].

These systems are not capable of effectively managing uncertainty in operations due to factors like ship arrival delay, port congestion, and railway constraints; therefore, these systems increase costs and lead to a decrease in efficiency in steel plants [3]. An intelligent system is thus necessary for efficient steel industry logistics operations by employing advanced technology like artificial intelligence and machine learning techniques [4].

Logistics systems in steel industries face limitations in terms of time and cost constraints due to the increasing complexity of global steel supply chain operations and the necessity of cost-efficient operations in steel plants. These conventional systems are no longer sufficient in managing modern industrial operations due to their limitations in effectively managing time and cost constraints in steel plants. Steel industries face significant financial losses due to a lack of decision-making support in terms of managing uncertainty in logistics environments. With the advent of artificial intelligence technology, there is a strong opportunity to transform logistics planning into a more intelligent and optimized system in steel plants [4], [5].

B. Background and context

In earlier days, the planning was performed based on manual techniques and simple software technologies like excel and SAP. The techniques were highly reactive and relied heavily on historical data and human judgment. This made the techniques highly inefficient in managing changing scenarios [1], [5]. With the evolution of technology, techniques like machine learning and optimization have been integrated to make the logistics process more efficient. Studies have been conducted to improve vessel ETA, berth, and multimodal transportation optimization problems [2], [6]. However, these techniques have limitations in handling specific problems in the logistics domain and lack integration with other aspects of the entire supply chain [7]. This underlines the need to have an integrated and intelligent system that can efficiently handle changing scenarios.

Furthermore, due to the increase in the complexity of global supply chain systems and the necessity of cost-efficient operations in these systems, conventional logistics systems are no longer sufficient enough to meet the requirements of modern industrial systems. Steel industries face time and cost constraints in which any level of inefficiency may cause substantial financial losses.

The absence of predictive analytics and decision-making systems makes it difficult for logistics planners to cope effectively with ever-changing situations in logistics environments [2], [3]. With the advent of artificial intelligence systems and data-driven technology, there is a great opportunity to make logistics planning a more intelligent and optimized system [4], [5].

C. Contributions

With a view to overcome the shortcomings associated with existing logistics systems, this paper proposes a new intelligent logistics optimization system, which is referred to as VesselLink AI. The contributions made by this proposed system can be listed as follows: Development of a new integrated logistics framework for steel supply chain operations with multiple constraints such as cost, scheduling, etc.

1) An integrated data-driven framework that incorporates SAP, Excel, and other data sources for unified logistics planning is proposed [3], [5].
2) A machine learning-based prediction system for vessel arrival time and pre-berthing delay estimation is proposed [1], [6].
3) An AI-based optimization engine for vessel scheduling, port allocation, and dispatch planning is proposed [2], [7].
4) A dynamic scheduling system that has simulation capabilities for handling disruptions in real-time is proposed [7], [8].
5) Cost optimization, real-time monitoring dashboards, and decision support tools for efficient logistics management are proposed [2], [3].

II. LITERATURE SURVEY

Some research works have been done on the application of artificial intelligence, machine learning, and optimization techniques in the field of logistics and supply chain management. These research works cover topics such as vessel scheduling, delay prediction, berth allocation, and multi-modal transportation. Even though these research works contribute to the efficiency and cost management of the supply chain, the majority of these research works are domain-specific, such as container logistics. They do not completely cover the requirements for the logistics of the steel industry. Hence, the requirement for a complete AI-based system like VesselLink AI is felt.

A. Related Work

1) Hybrid ML-Based ETA Prediction

A hybrid machine learning-based model has been proposed by Nguyen et al. (2025) that utilizes Extra Trees, AutoGluon, LightGBM, and Random Forest algorithms in predicting vessel ETA[1]. The proposed model has shown high accuracy in predicting vessel ETA with very low error rates by considering various parameters such as speed, distance, and course of vessels. It is a significant improvement in predicting vessel ETA compared to conventional methods. However, there is no inclusion of railway logistics in the proposed system. Moreover, there is no focus on Indian ports and steel industry constraints in the proposed system.

2) Dynamic Berth Allocation using Machine Learning

Wang et al. (2025) designed a system for the allocation of berths using machine learning-based ETA predictions and genetic algorithms [2]. It reduces the waiting time for vessels by optimizing the scheduling of berths considering tidal and position constraints. It enhances the efficiency of the port and minimizes the time spent. Nevertheless, the availability of the railway and the sequential discharge of the materials are not considered in the designed system.

3) Multimodal Route Optimization under Uncertainty

Li et al. (2025) developed a multi-objective optimization model using the NSGA-III algorithm to reduce costs, time, and emissions in the context of multimodal transportation systems [3]. It is seen that the system results in considerable cost reduction with uncertain demand. It is an efficient optimization model for route optimization. However, it is applicable to single origin-destination scenarios only. Material quality and scheduling constraints related to the railways are not considered.

4) Container Multimodal Transport Optimization

Huang et al. (2025) developed a particle swarm optimization (PSO) based model for optimizing routes from hinterlands to ports [4]. The system is effective in enhancing the efficiency of transportation for container logistics. However, the developed system is only applicable for container transportation and does not include bulk cargo such as coal and limestone. The developed system does not also include integration with SAP systems.

5) AI-Based Multimodal Planning under Disruptions

Prakash et al. (2025) have developed a logistics planning system based on LSTM and Monte Carlo simulations for handling real-time disruptions [5]. The developed system is helpful for enhancing the flexibility and decision-making capabilities in uncertain conditions. The developed system is highly efficient for predicting disruptions and making required changes. The developed system does not include integration with SAP and Excel data sources and does not have cost optimization modules for logistics operations.

6) Vessel Turnaround Time Prediction using ML

Tran et al. (2024) proposed a machine learning-based model byutilizing the XGBoost algorithm for predicting vessel turnaround time [6]. The proposed model minimizes the prediction errors. The machine learning-based model increases the efficiency of the scheduling process. The proposed research is based on a limited geographic area and does not include inland transportation and cost optimization.

7) Green Multimodal Transportation Optimization

A bi-objective optimization model for minimizing cost and emissions in a multimodal transport system has been proposed by Steffen et al. in 2024 [7]. The system has shown considerable improvements in sustainability and efficiency. However, the model is applicable for single-product transportation, excluding railway constraints and bulk material transportation in steel industries.

8) Path Optimization with Time Sensitivity

Yang et al. (2024) introduced a bi-level genetic algorithm to optimize the paths for transportation while considering the time sensitivity of the cargo [8]. The system helps to enhance the scheduling with time constraints. The system is applicable for containerized cargo but does not consider the bulk cargo requirements.

9) ML-Based Vessel Arrival Prediction

Evmides et al. (2024) presented a model for predicting vessel arrival times using a Random Forest-based method and AIS data[9], which has high accuracy and can improve port operations, although inland logistics and total cost estimation are not taken into consideration in this model.

10) Multimodal Freight Optimization Survey

Caris et al. carried out a detailed survey on the techniques of multimodal freight optimization [10], which highlights different optimization techniques. It also indicates the gaps in the research related to the optimization of logistics systems. But it is still at the theoretical level and does not offer any implemented solution related to the logistics of the steel industry.

B. Research Gaps

Although several research studies have contributed considerably to the optimization of logistics using artificial intelligence and machine learning techniques, there still exist many research gaps in this field. It is to be noted that the majority of the proposed models are only focused on the optimization of individual components, such as the ETA prediction of vessels, and not designed to operate as end-to-end solutions for logistics operations [1], [2]. Furthermore, the majority of the models are tested using limited data sets and/or simulations, which do not consider constraints such as the availability of the railway, capacity constraints, and port operations [3], [4]. It is to be noted that these models cannot be applied to complex industrial scenarios such as steel supply chain logistics.

Furthermore, there have been several studies on improving the efficiency of scheduling and routing through the use of optimization techniques and machine learning models. However, these models have not incorporated the use of real-time data sources such as SAP, Excel workflows, and live port information [5], [6]. Although hybrid machine learning models and genetic algorithms have shown promising results in improving the efficiency of these systems, they have not incorporated the use of the entire logistics chain, such as inland transportation and cost optimization [2], [7]. Benchmark studies have shown that these systems have not been effective in dealing with disruptions such as port congestion, weather conditions, and uncertainties in vessel operations [8], [9].

Furthermore, there is a lack of a unified platform in existing research that can integrate prediction, optimization, and decision support in a single system. Most systems lack cost estimation, simulation-based “what-if” analysis, and data integration in a centralized manner [3], [5]. Most of the research related to sustainability and multimodal transportation is mostly theoretical in nature and lacks specific requirements related to bulk material logistics in the steel industry itself [7], [10].

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There is a need for a comprehensive AI-driven system related to optimized scheduling, data integration in a real-time manner, and decision support in a more efficient way.

C. Problem Statement

The steel industry needs an efficient logistics system that is able to handle complex operations involving ships and inland transportation. However, existing systems are not efficient and do not have predictive and optimization capabilities. Therefore, the existing systems are not efficient and have high costs [2], [3]. In order to overcome these challenges, the proposed VesselLink AI system is designed to include machine learning and optimization capabilities. The proposed system will predict delays and minimize logistics costs by efficiently handling complex operations involving ships and inland transportation. Therefore, the proposed system will offer an efficient solution for modern logistics management. The steel industry needs an efficient logistics system that is able to handle complex operations involving ships and.

III. SYSTEM ARCHITECTURE AND SYSTEM DESIGN

The design of the VesselLink AI system is such that it is modular and layered, which allows for scalability, flexibility, and the efficient management of complex logistics operations. The system has been designed on a web-based client-server architecture, in which different parts of the system communicate through interfaces. The backend of the system can handle data from different sources, such as SAP, Excel, or external APIs, while the frontend of the system provides a user-friendly interface for users to monitor and control logistics operations. The machine learning, optimization, and data services have been integrated into the system for efficient decision-making.

A. Architecture

The system consists of four major layers. The layers include the presentation layer, application layer, intelligence layer, and data layer. All the layers in this system have specific functions and can efficiently interact with one another.

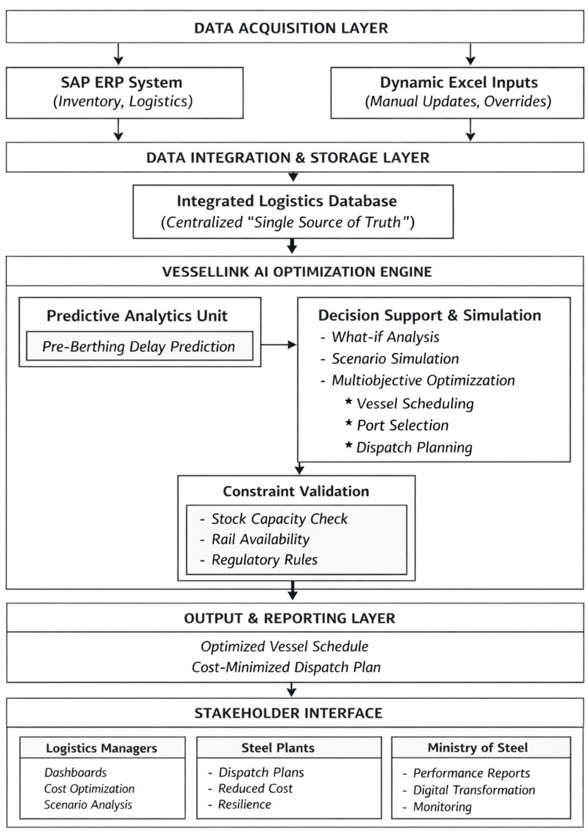

Fig.1. System Architecture of the VesselLink AI system showing data flow between user interface, backend services, machine learning models, and data sources.

B. System Architecture Layers

1) Presentation Layer

This layer includes the user interface that facilitates the interaction between the logistics planner and the system. This layer includes the dashboards, monitoring tools, and control tools for the logistics process. The tools can be used to input information such as the vessels, ports, and dispatches. The layer also includes tools used to display information such as the optimized schedules, cost reports, and analytics. This layer is used for decision-making purposes through the use of real-time information and the visualization of the logistics information.

2) Application Layer

The application layer acts as the backend system, which performs all the operations. It receives requests from the users through APIs and manages the communication between different modules of the system. This layer integrates data from the SAP system, Excel files, and other sources, which helps in the smooth flow of data. It performs authentication, system logic, and coordination between the user interface and the intelligence layer, thus acting as a bridge between the two.

3) Intelligence Layer

This is the main component of the entire system. It comprises machine learning models and optimization algorithms. It is used for pre-berthing delay prediction using AI/ML techniques. It is also used for scenario analysis using the "what-if" simulation. The optimization engine is used to obtain the optimal scheduling of vessels, determine the optimal port, and dispatch the vessels to the port/plant. It is also used to verify constraints such as stock capacity, availability, and rules.

4) Data Layer

The data layer oversees the management of internal and external data sources that are essential for the operation of the system. The data layer incorporates integrated logistics data from different sources such as SAP, Excel, and live data such as vessel data. The data layer ensures that data is stored, processed, and retrieved for analysis. The data layer allows for dynamic data integration, thus improving the accuracy of the system in logistics planning.

C. System Workflow

The workflow of the vessel link AI system involves the collection of data from different sources such as SAP systems, Excel files, and external inputs such as vessel tracking and operation parameters. The collected data is stored in a central logistics database and processed for validation and accuracy. The processed data is sent to the intelligence layer of the system, which uses machine learning to predict pre-berthing vessel delays and analyze port congestion levels, vessel arrival times, and availability of resources. The predictions are used to calculate different parameters of logistics.

The optimization engine will then come up with cost-efficient logistics plans through the optimization of vessels, the selection of optimal ports, and the optimization of dispatch operations from the ports to the plants. During this process, the optimization is subject to the satisfaction of various constraints such as stock capacity, railway availability, and the rules of operation. The output generated by the optimization process includes the optimization of vessels, cost-efficient dispatch operations, and logistics reports.

IV. METHODOLOGY

The methodology of the VesselLink AI system is based on a structured approach that optimizes logistics operations by applying machine learning and optimization techniques. The process of optimization is a combination of data processing, delay prediction, cost estimation, and scheduling. The process ensures that logistics operations are efficient and cost-effective.

A. Input Processing

The first step in the process is to collect data from various sources, such as SAP systems, Excel, and external APIs. The data includes information such as vessels, ports, stock, availability, and constraints. This data is then preprocessed to validate, remove redundancy, and structure it appropriately for further processing. Both categorical and numerical data are validated and standardized before being sent to the system's modules.

B. Prediction Model

The system employs machine learning algorithms to forecast pre-berthing delays and vessel arrival times. The algorithms use data from the past, patterns of vessel movements, weather conditions, and levels of port congestion. The results of the prediction help in identifying possible delays and uncertainties. This allows the system to take proactive decisions.

$Delay_{predicted}=f(V,W,P,H)$

Where:

- V = Vessel parameters (speed, route, size)
- W = Weather conditions
- P = Port congestion factors
- H = Historical data

C. Optimization Model

At the heart of the system is the optimization engine. It is the optimization engine that develops cost-effective logistics strategies. It schedules vessels, optimizes ports, and dispatch operations. During the optimization process, several parameters are taken into account to ensure effective logistics optimization.

D. Cost Estimation Model

The system determines the total logistics cost by taking into consideration various factors, which include ocean freight, port handling charges, railway transportation, and demurrage, etc. The cost is estimated using the following equation:

This model will ensure that the logistics plan developed is economically viable and minimizes the total cost.

1) Total Cost = $C_f + C_p + C_r + C_d$
- C_f = Freight cost
- C_p = Port handling cost
- C_r = Railway transport cost
- C_d = Demurrage cost

2) Freight Cost Calculation
- $C_f = Rate_f \times Distance \times Cargo$

3) Port Handling Cost
- $C_p=Rate_p \times Cargo$

4) Railway Transport Cost
- $C_r = Rate_r \times Distance \times Cargo$

5) Demurrage Cost
- C_d = Delay Time × Demurrage Rate

E. Dataset and Data Pipeline

The system utilizes data provided by SAP systems, Excel sheets, and other external APIs. The data provided includes vessel schedules, port operations, stock levels, and transportation information. There is a structured data pipeline in place, which facilitates smooth data flow through various modules of the system. The data pipeline helps in making accurate predictions and optimization in real-time.

F. Scheduling *and Dispatch Planning*

The system also optimizes vessel schedules and dispatch plans for port-to-plant transportation. The system optimizes the allocation of vessels and transportation resources. The scheduling is adaptive and responds to changing conditions such as delays and availability of resources in real-time.

G. Scenario Analysis Module

The system also includes a scenario analysis module that helps the user carry out a ‘what if’ analysis. This is helpful in evaluating different scenarios of logistics such as delays and congestion. This helps in better decision-making by providing alternative solutions.

H. Algorithm

Algorithm 1 :Logistics Cost Optimization and Scheduling

Input:

User inputs (vessel details, port selection, stock levels, constraints)

Logistics data (SAP data, Excel data, real-time inputs)

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Output:
Optimized vessel schedule and cost minimization dispatch plan
(i) Collect input data from SAP, Excel, and other sources
(ii) Preprocess and validate input data
(iii) Predict vessel delays using machine learning model
(iv) Analyze port conditions and availability of resources
(v) Generate possible scheduling options
(vi) Compute logistics cost:
- Cost = Freight + Port Handling + Railway + Demurrage

(vii) Optimize port choice based on cost and constraints
(viii) Generate vessel scheduling plan
(ix) Plan dispatch operations from port to plant
(x) Validate constraints:
- Stock capacity, railway, rules, etc.

(xi) Scenario analysis for other possible solutions
(xii) Optimize schedule and cost
(xiii) Generate output:
- Optimized schedule and logistics report

(xiv) Return optimized plan.

I. *System Integration*

All modules are integrated using APIs, ensuring smooth communication between different components. The system is a combination of machine learning, optimization, and real-time data integration, bringing them all under a single umbrella. This integration facilitates efficient logistics planning.

V. RESULTS AND ANALYSIS

The performance of the VesselLink AI system has shown considerable improvements in terms of efficiency in logistics, cost optimization, and decision-making. The accuracy of the system can be measured by considering the following factors: cost reduction, efficiency in scheduling, delay prediction, and performance of the system.

A. *Cost Optimization Analysis*

The system demonstrates a substantial decrease in total logistics costs, which can be achieved by optimizing vessel scheduling, port selection, and dispatch planning. The main costs include freight, port handling, railway transportation, and demurrage. The optimization techniques ensure that there is no wastage in terms of costs. The results have shown a decrease in total costs by 10-15%, which proves the efficiency of the proposed method.

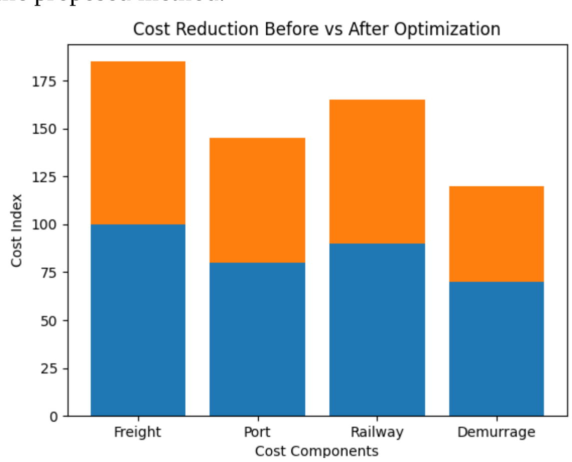

Fig.1. Cost Reduction Before and After Optimization

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The bar graph in Fig. 1 represents the comparison of logistics costs before and after optimization. From this figure, it can be observed that all major cost components, such as freight, port handling, railway transport, and demurrage, are reduced after using the proposed system.

B. Scheduling Efficiency

The VesselLink AI system enables improved scheduling efficiency through the creation of optimal schedules for vessels. It also optimizes the dispatch plan, which enables improved port and plant coordination. As a result, there is improved performance. It can adjust the schedules based on the data it receives in real time.

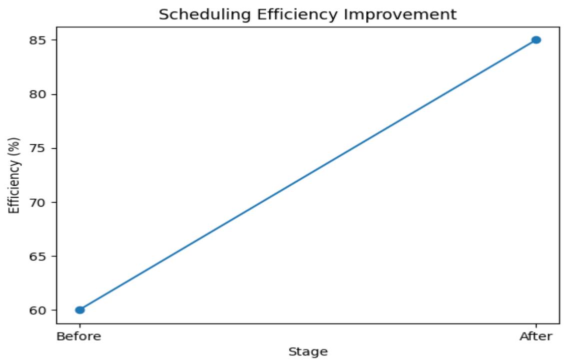

Fig.2. Scheduling Efficiency Improvement

The graph in Fig. 2 illustrates the improvement in the scheduling efficiency achieved by the system. The results show an improvement in efficiency, indicating better coordination and reduced delays in logistics operations.

C. Delay Prediction Performance

The machine learning algorithm used in the system is effective in predicting pre-berthing delays as well as the arrival time of the vessels. The system is able to analyze the potential delays through the data available. This helps in reducing the effects of uncertainty, such as port congestion as well as weather conditions.

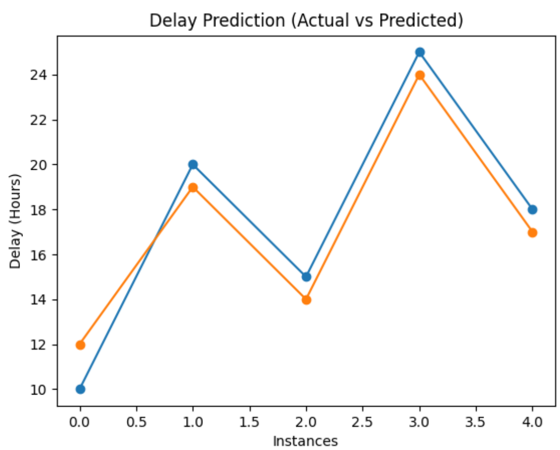

Fig.3. *Delay Prediction (Actual vs Predicted)*

The graph shown in Fig. 3 illustrates the comparison between the actual delays and the predicted delays generated by the machine learning model. It can be observed that the predicted values closely follow the actual values, which ensures prediction accuracy and reliability.

D. Resource Utilization

The system ensures that resources such as port availability, railway availability, and stock levels are utilized in the most efficient manner. It does this by checking the constraints during the optimization process, thus avoiding overloading or underutilization of resources.

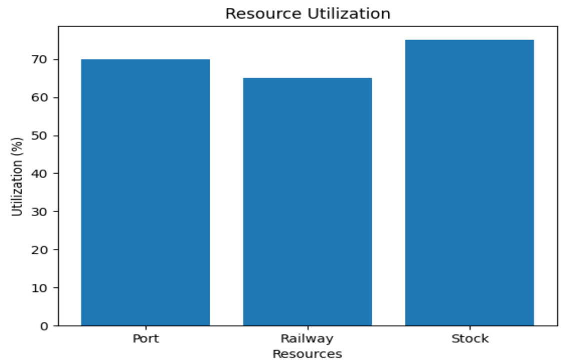

Fig. 4: Resource Utilization Analysis

The bar chart in Fig. 4 presents a representation of the utilization of some of the resources such as ports, railway systems, and stock capacities. The results reveal efficient resource utilization through optimization.

E. Scenario Analysis and Decision Support

The system also includes the scenario analysis feature, which enables the user to evaluate various logistics situations. The planner is able to carry out the "what-if" analysis to determine the consequences of various delays, congestions, as well as demand. This improves the decision-making process as well as the selection of the best logistics strategy.

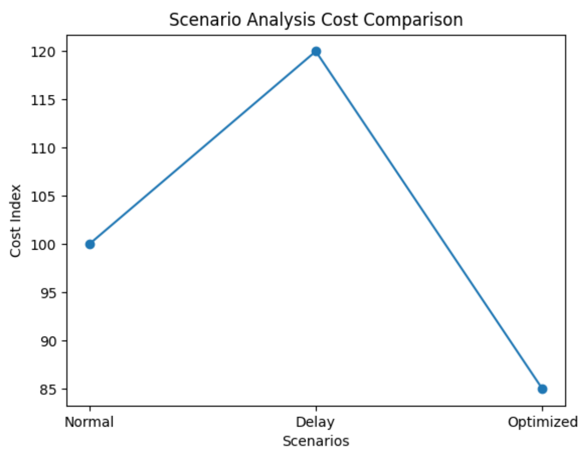

Fig. 5: Scenario Analysis Cost Comparison

The above graph, as presented in Fig. 5, indicates a cost comparison under different scenarios, namely normal, delayed, and optimized conditions. From this figure, it is clear that in the optimized condition, there are lower costs, which indicates the effectiveness of the system in decision-making.

F. Overall System Performance

It can, therefore, be concluded that the VesselLink AI system offers enhanced performance in terms of cost efficiency, scheduling, and reliability. The system, which combines machine learning and optimization techniques, has proved to be efficient, scalable, and applicable in real-world logistics scenarios in the steel industry.

G. Cost Efficiency Evaluation

The results show that the proposed system greatly helps in increasing cost efficiency by reducing any unwanted costs incurred during the logistics process. The optimization of vessel scheduling, port allocation, and dispatch planning helps in reducing the overall costs incurred during the process. The overall cost savings of around 10-15% prove the effectiveness of the optimization method for real-world problems..

H. Constraint Validation Analysis

The system ensures that all logistics activities meet critical constraints like stock capacity, railway availability, etc. While executing, these constraints are validated, which prevents infeasible scheduling decisions. Hence, a reliable logistics plan is provided, which is implementable without any operational issues.

I. System Reliability and Scalability

The VesselLink AI system has shown high levels of reliability in managing complex logistics operations. It can efficiently handle large amounts of data from different sources. The system can also handle dynamic changes in real-time. It can also be expanded to support other ports, routes, and logistics data, making it suitable for large-scale industrial use.

VI. DISCUSSION

The results obtained from the application of the VesselLink AI system indicate a positive impact on improving efficiency in logistics, reducing logistics cost, and decision-making processes, considering real-time data from various sources such as SAP, Excel, etc. The delay prediction model is a significant part of the system, ensuring that uncertainties can be reduced to a minimum. The optimization engine also ensures efficient resource utilization, leading to efficient coordination of ports, vessels, etc.

However, some limitations still exist in the current system. The accuracy of the predictions also depends on the availability of historical and real-time data. Any kind of inconsistency in data will affect the performance of the system. The system currently focuses on specific logistics parameters, and more advanced models can be integrated to enhance the efficiency of the system. Despite some limitations, the proposed system has a strong potential to be applied to more complex scenarios and to be applied to various industrial applications in the future.

The system has a strong potential to be applied to more complex scenarios and to be applied to various industrial applications in the future.

VII. CONCLUSION

The proposed system, VesselLink AI, is successful in the application of artificial intelligence techniques for the enhancement of logistics operations within the steel supply chain. The system effectively integrates machine learning-based techniques for the prediction of delays, cost optimization, as well as real-time data from various sources such as SAP and Excel. This improves the efficiency of the scheduling process as well as the cost associated with the logistics process. The system also ensures the proper coordination between ports, vessels, as well as the transport system, while also considering constraints such as stock capacity and railway availability. The results show that the system is efficient, scalable, and suitable for the support of logistics decision-making processes. Therefore, the system is suitable for the enhancement of logistics operations within the steel supply chain.The proposed system, VesselLink AI, is successful in the application of artificial intelligence techniques for the enhancement of logistics operations within the steel supply chain. The system effectively integrates machine learning-based techniques for the prediction of delays, cost optimization, as well as real-time data from various sources such as SAP and Excel. This improves the efficiency of the scheduling process as well as the cost associated with the logistics process. The system also ensures the proper coordination between ports, vessels, as well as the transport system, while also considering constraints such as stock capacity and railway availability. The results show that the system is efficient, scalable, and suitable for the support of logistics decision-making processes. Therefore, the system is suitable for the enhancement of logistics operations within the steel supply chain.

In addition, the system is effective in the enhancement of logistics operations within the steel supply chain as well as the contribution towards the digital transformation of logistics systems. The system is also suitable for the support of the development of intelligent logistics systems.

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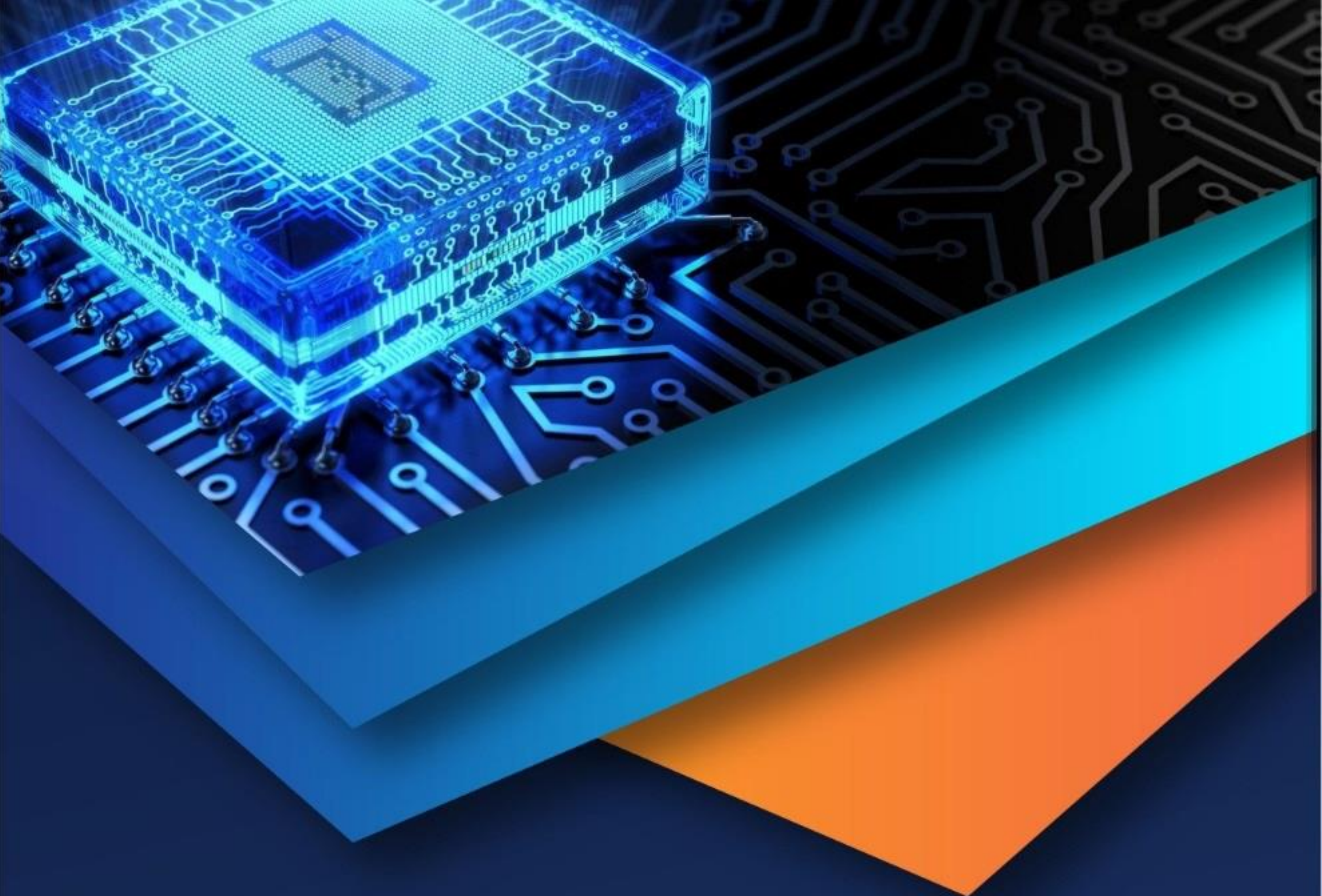

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