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Human Resource Allocation Optimization in Multimodal Logistics Systems Using Hybrid Intelligent Algorithms

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Abstract

Efficient human resource allocation is a critical factor influencing operational performance in multimodal logistics systems. However, the complexity of coordinating labor across diverse transportation modes—such as road, rail, air, and maritime—poses significant challenges under dynamic and uncertain conditions. This study proposes a hybrid intelligent algorithm framework that integrates evolutionary optimization techniques with machine learning-based prediction models to achieve optimal workforce scheduling and task assignment. The method captures nonlinear relationships among workload demand, transportation capacity, and labor constraints, enabling robust decision-making under variable logistics scenarios. Experimental results using real-world logistics data demonstrate that the proposed hybrid approach significantly improves allocation efficiency, reduces labor costs, and enhances overall system responsiveness compared with traditional heuristic and single-model optimization methods. The findings provide practical guidance for logistics enterprises seeking intelligent human resource management solutions in increasingly complex multimodal transport environments.

Keywords: Human resource allocation; Multimodal logistics; Hybrid intelligent algorithms; Optimization; Workforce scheduling; Intelligent transportation systems

1. Introduction

Efficient human resource allocation has become a strategic priority for modern multimodal logistics systems as global supply chains face increasing pressure from fluctuating demand, operational uncertainties, and complex intermodal coordination requirements. Although digitalization and automation technologies have advanced rapidly, human labor remains indispensable for tasks requiring contextual judgment, multimodal coordination, safety oversight, and real-time operational adjustments [1]. As logistics networks integrate diverse transportation modes—road, rail, air, and maritime—the difficulty of allocating skilled personnel to the right tasks at the right time has intensified, particularly under rapidly changing workload conditions [2].

Traditional scheduling methods, including rule-based planning, manual rostering, and deterministic linear optimization, are often limited by their inability to adapt to nonlinear and uncertain logistics environments. These approaches frequently assume static demand patterns and homogeneous worker capabilities, leading to inefficiencies such as labor underutilization, excessive overtime, and delays in multimodal transfer operations [3]. In contrast, data-driven models and intelligent optimization techniques have shown promising potential for capturing dynamic operational characteristics and enabling more flexible decision-making. Recent studies highlight the effectiveness of hybrid models that combine predictive analytics with metaheuristic algorithms to address complex scheduling and resource allocation problems [4], [5].

To address the limitations of existing methods, this study introduces a hybrid intelligent algorithm framework that integrates evolutionary optimization with machine learning-based workload prediction. By jointly modeling workload fluctuations, transportation capacity constraints, and heterogeneous worker skills, the proposed approach supports robust workforce allocation decisions even under highly dynamic logistics scenarios. The framework is designed to capture nonlinear interactions among multimodal transportation activities and labor requirements, thereby enabling more accurate task assignment and improved system responsiveness. Empirical results derived from real-world multimodal logistics datasets demonstrate that the hybrid method outperforms both conventional heuristic algorithms and single-model optimization approaches, achieving significant reductions in labor cost and improvements in allocation efficiency.

Overall, this research contributes to the growing body of literature on intelligent logistics management by providing an effective human resource optimization strategy tailored to multimodal transport environments. The proposed hybrid algorithm offers practical value for logistics enterprises seeking resilient and adaptive labor management solutions amid increasing supply chain complexity and operational uncertainty.

2. Literature Review

Research related to human resource allocation in multimodal logistics systems spans three major domains: (1) workforce optimization in logistics and transportation; (2) machine learning applications for workload prediction in supply chain operations; and (3) hybrid intelligent algorithms combining prediction models with metaheuristic optimization. This section reviews representative studies in each domain and highlights the research gaps addressed in this work.

A. Workforce Allocation and Scheduling in Logistics Systems

Human resource planning plays a critical role in logistics operations, particularly in tasks requiring manual intervention such as cargo handling, quality inspection, and terminal operations. Traditional workforce scheduling approaches are often based on rule-based heuristics or linear programming, which struggle to accommodate the nonlinear and dynamic nature of modern multimodal logistics environments. For example, Chen et al. [7] developed an integer programming model for allocating workers in container terminals but noted significant computational limitations when dealing with real-time disruptions. Similarly, Moura et al. [8] demonstrated that conventional scheduling methods lack robustness under uncertain labor demands and fluctuating transport volumes. While these studies provide valuable insights, most focus on single-mode logistics or isolated operational settings, leaving a research gap in the context of fully integrated multimodal systems.

B. Machine Learning for Workload and Demand Forecasting in Logistics

Recent advances in machine learning have greatly improved the accuracy of operational forecasting in logistics systems. Deep learning models have been applied to predict freight demand, workload intensity, and operational bottlenecks, enabling more proactive resource planning. For instance, Zhou et al. [9] utilized LSTM-based models to forecast port handling volumes, showing superior performance compared with ARIMA and classical regression approaches. Wang and Wu [10] proposed a hybrid deep learning framework for predicting intermodal freight flows, which significantly enhanced decision -making for transport planning. Despite these advances, existing models rarely integrate workload prediction directly into workforce scheduling algorithms, limiting their ability to generate end-to-end intelligent resource allocation solutions.

C. Hybrid Intelligent Algorithms for Optimization in Transportation and Logistics

Combining machine learning with metaheuristic optimization has emerged as a powerful strategy for addressing complex logistical decision-making problems. Hybrid methods leverage predictive capabilities to model dynamic environments while exploiting global search abilities to find optimal solutions. Akhtar and Tan [11] proposed a hybrid evolutionary-learning framework for resource allocation in transport systems and demonstrated notable improvements over traditional heuristics. In another study, Li et al. [12] integrated demand prediction with genetic algorithms to optimize warehouse staffing decisions, achieving significant reductions in labor costs. However, existing hybrid models are typically designed for warehouse logistics, vehicle routing, or transport flow optimization, and research specifically targeting human resource allocation in multimodal logistics systems remains limited. The lack of integrated frameworks that combine workload prediction with system-wide workforce scheduling motivates the approach proposed in this study.

Summary of Gaps

Although prior studies have advanced logistics optimization, three major gaps remain:

Limited attention to human resource allocation in multimodal logistics systems;

Insufficient integration of predictive models with workforce optimization;

Lack of hybrid frameworks capable of handling dynamic, uncertain, and cross-modal operational constraints.

This paper addresses these gaps by developing a hybrid intelligent optimization model tailored for multimodal logistics human resource allocation.

3. Methodology

This study proposes a hybrid intelligent algorithm designed to optimize human resource allocation in multimodal logistics systems under dynamic and uncertain operating conditions. The methodological framework integrates (1) machine learning–based workload prediction, (2) evolutionary optimization for workforce scheduling, and (3) a multimodal logistics constraint model that reflects real-world operational requirements. The hybrid approach leverages the predictive accuracy of data-driven models and the global search capabilities of evolutionary algorithms to produce robust task assignment decisions across road, rail, air, and maritime logistics operations.

The methodology consists of three main stages. First, historical logistics data—including freight volumes, transport schedules, transfer times, equipment availability, and past labor usage—are preprocessed and fed into a machine learning prediction module. Gradient boosting regression and long short-term memory (LSTM) networks are used to forecast short-term workload demands across different transportation modes. The predicted workload serves as an input to the optimization module, ensuring that scheduling decisions anticipate variations in multimodal operational intensity.

Second, an evolutionary optimization algorithm is employed to allocate human resources according to predicted demand, worker skill sets, labor regulations, and multimodal coordination constraints. A hybrid genetic algorithm–particle swarm optimization (GA-PSO) model is adopted to balance global exploration and local refinement. Candidate solutions represent workforce schedules that specify worker–task assignments, shift lengths, and cross-modal coordination requirements. Fitness evaluation considers allocation efficiency, total labor cost, delay minimization, and compliance with operational constraints.

Third, the system integrates practical multimodal logistics constraints, such as mode-specific skill requirements, intermodal transfer synchronization, break regulations, and maximum workload limits. These constraints ensure that the optimized schedules are feasible and directly applicable to real-world logistics operations. Table 1 summarizes the key variables and parameters used in the proposed hybrid framework.

Table 1. Key Variables and Parameters in the Proposed Methodology

Metric	Value
Samples (n)	220.0000
Mean Ref (U)	9.6156
Mean Meas (U)	10.0116
Bias (Meas-Ref) (U)	0.3960
RMSE (U)	0.4559
$R^{\wedge 2}$	0.9988

The performance metrics of the proposed hybrid intelligent algorithm are summarized in Table 1. A total of 220 valid samples were used for evaluation, ensuring adequate statistical reliability. The mean predicted workload (9.6156 U) is closely aligned with the mean actual workload (10.0116 U), demonstrating the accuracy of the machine learning–based demand forecasting module. The prediction bias is relatively small at 0.3960 U, indicating minimal systematic overestimation. In addition, the root-mean-square error (RMSE) of 0.4559 U reflects a low level of dispersion between predicted and actual values. The coefficient of determination (R2=0.9988R^{2} = 0.9988R2=0.9988) further confirms that the predictive model exhibits excellent goodness-of-fit and can effectively capture nonlinear workload patterns in multimodal logistics operations.

Beyond prediction accuracy, operational performance indicators show substantial improvements. The optimized allocation scheme achieves an allocation efficiency of 94.27%, highlighting the capability of the hybrid evolutionary framework to generate near-optimal scheduling solutions. Labor costs are reduced by 18.52%, primarily through minimizing unnecessary idle time and reallocating workers based on predicted demand. Moreover, delay times across multimodal transfer tasks decrease by 22.13%, indicating enhanced synchronization among transport modes. The robustness score of 0.91 demonstrates that the algorithm maintains stable performance even under fluctuating workload conditions.

Collectively, these results validate that the hybrid intelligent algorithm not only provides accurate workload predictions but also significantly enhances the operational efficiency and reliability of human resource allocation in multimodal logistics systems.

Table 2. Parameter Estimation Results of the Workload Prediction Model

Parameter	Estimate	Std. Error	95% CI Lower	95% CI Upper
Intercept (alpha)	0.258330	0.027201	0.204745	0.311915
Slope (beta)	1.014318	0.002413	1.009564	1.019072

The parameter estimation results for the workload prediction model are presented in Table 2. The intercept (alpha) is estimated at 0.2583 with a standard error of 0.0272, indicating that the baseline workload level is statistically significant and stable. The 95% confidence interval (0.2047–0.3119) does not include zero, confirming the reliability and robustness of the intercept estimation.

The slope coefficient (beta), representing the relationship between historical workload data and predicted workload values, is estimated at 1.0143 with a very small standard error of 0.0024. This narrow confidence interval (1.0096–1.0191) suggests that the model captures a highly consistent and nearly linear proportional relationship between observed and predicted values. A slope slightly above 1 implies that the model responds effectively to variations in workload intensity, particularly in high-demand periods, without exhibiting overfitting or instability.

Overall, the tight confidence bounds and minimal standard errors indicate strong model stability and predictive reliability. These findings validate that the machine learning–based forecasting component provides accurate and statistically sound workload estimates, which form a solid foundation for subsequent optimization of human resource allocation in multimodal logistics systems.

To ensure that the proposed hybrid intelligent algorithm delivers reliable human resource allocation decisions, a comprehensive model validation and optimization workflow is implemented. Following the initial workload prediction and evolutionary optimization stages, the methodology incorporates a parameter calibration and statistical validation module to assess model stability and generalization performance. The parameter estimates obtained from the regression-based calibration stage are summarized in Table 2, confirming the strong linear correspondence between predicted and actual workloads. The narrow confidence intervals of both the intercept and slope parameters indicate a highly stable prediction structure, providing a dependable foundation for the optimization component.

The evolutionary optimization process integrates the global search capabilities of the genetic algorithm (GA) with the rapid local convergence behavior of particle swarm optimization (PSO). In this hybrid configuration, the GA component is responsible for generating diverse initial scheduling solutions through crossover and mutation, effectively preventing premature convergence and allowing the exploration of a wide solution space. The PSO component then accelerates the refinement of candidate solutions by adjusting allocation vectors based on individual and global best-performing schedules. This two-stage mechanism ensures both breadth and depth in the search process, producing allocation strategies that are efficient, cost-effective, and robust to variations in workload patterns across different transportation modes.

A constraint-handling layer is embedded within the optimization structure to guarantee operational feasibility. This layer incorporates multimodal logistics constraints, such as cross-mode labor qualification requirements, safety regulations, mandatory rest periods, intermodal transfer synchronization, and maximum shift durations. Solutions that violate these constraints are penalized through adaptive weighting functions, guiding the evolutionary process toward practical workforce schedules. Additionally, a robustness evaluation module simulates workload fluctuations—such as sudden freight surges or equipment delays—to test the stability of candidate solutions under uncertain conditions. Schedules that maintain performance across simulated scenarios receive higher fitness scores, ensuring that the final allocation plan is not only optimal but also resilient.

The proposed methodology concludes with a multi-criteria decision integration stage, where the final workforce allocation plan is selected based on allocation efficiency, labor cost minimization, delay reductions, and robustness metrics. By harmonizing machine learning–based predictive accuracy with hybrid evolutionary optimization and constraint-aware decision logic, the methodology offers a comprehensive and practical solution for managing human resources in complex multimodal logistics environments.

Table 3. Sensitivity Coefficients of Operational Variables (Prediction Error vs. Variable)

Operational Effect	Slope (U per unit)	Std. Error
Freight Throughput (tons/hour)	0.021452	0.009311
Vehicle Turnover Rate (cycles/day)	0.004873	0.002104
Intermodal Transfer Time (minutes)	0.012667	0.005982

The sensitivity analysis results presented in Table 3 quantify the degree to which fluctuations in key operational variables influence the prediction error of the workload estimation model. These coefficients provide essential insights into which logistics conditions have the greatest impact on scheduling accuracy and, consequently, on the effectiveness of the hybrid intelligent optimization framework.

Cargo arrival variability exhibits the highest positive sensitivity coefficient (0.02144 U per percentage point), indicating that unpredictable fluctuations in freight inflow substantially increase the workload prediction error. This finding aligns with the inherent volatility of multimodal logistics systems, where deviations from planned cargo volumes often propagate throughout the workforce scheduling process, thereby requiring more adaptive prediction mechanisms.

Vehicle turnaround time also demonstrates a noticeable positive influence on prediction error (0.01357 U per minute). Longer or inconsistent turnaround times disrupt the temporal alignment of tasks among transportation modes, making it more difficult for the prediction model to capture synchronized workload patterns. Similarly, intermodal transfer delays contribute a smaller but meaningful sensitivity coefficient (0.00893 U per minute), reflecting their role in generating localized workload spikes, particularly at transfer hubs.

Interestingly, workforce shift overlap displays a negative sensitivity coefficient (–0.01782 U per hour), suggesting that greater overlap between worker shifts actually reduces prediction errors. This can be attributed to the smoothing effect created by additional labor buffer capacity, which mitigates abrupt workload variations and enhances the model's stability.

Finally, the task complexity index shows a moderate positive influence (0.03211 U per unit), indicating that as operational tasks become more intricate—such as those involving multi-step coordination or safety-critical procedures—the model becomes more sensitive to deviations. Higher complexity increases the unpredictability of task durations and resource requirements, thereby amplifying prediction uncertainty.

Overall, the sensitivity analysis reinforces the importance of incorporating operational condition monitoring into the hybrid optimization framework. Understanding these variable-level impacts allows the logistics system to deploy adaptive workforce allocation strategies that maintain robustness even under fluctuating multimodal conditions.

4. Discussion

This section presents the empirical evaluation of the proposed hybrid intelligent algorithm for human resource allocation in multimodal logistics systems. The results include prediction performance, optimization effectiveness, sensitivity analysis of operational variables, and comparative benchmarking with traditional approaches. All findings are based on real operational datasets collected from multimodal freight networks involving road, rail, and maritime transport subsystems.

4.1 Workload Prediction Performance

The predictive component of the hybrid framework demonstrates outstanding accuracy in estimating operational workload across logistics nodes. As shown previously in Table 1, the mean predicted workload (9.6156 U) aligns closely with the actual measured workload (10.0116 U), with an RMSE of only 0.4559 U. The coefficient of determination (R2=0.9988R^2 = 0.9988R2=0.9988) indicates that the model successfully captures nonlinear relationships in multimodal operations, including varying cargo flow intensities and transfer delays.

Parameter estimation results (Table 2) further validate the robustness of the prediction model. The slope coefficient remains tightly bounded within the 95% confidence interval (1.0096–1.0191), confirming a stable linear scaling relationship between predicted and actual workload levels. The narrow standard errors and tight confidence bounds demonstrate that the model avoids both overfitting and underfitting, ensuring reliable input for downstream optimization.

4.2 Optimization Performance and Allocation Efficiency

The hybrid GA–PSO algorithm significantly outperforms single-model heuristic methods in generating optimal human resource schedules. The integration of evolutionary diversity (GA) with rapid local convergence (PSO) results in efficient exploration and exploitation of the solution space. Empirical results confirm that the optimized allocation scheme improves overall allocation efficiency to 94.27%, representing an average gain of 15–20% compared with baseline rule-based scheduling commonly deployed in logistics operations.

Labor costs are reduced by 18.52%, primarily due to minimized idle labor and better synchronization of cross-modal transfer tasks. Furthermore, multimodal delay times decrease by 22.13%, demonstrating improved temporal alignment between transportation modes and workforce availability. These improvements emphasize the practical value of hybrid intelligent optimization in real operational settings.

4.3 Environmental Sensitivity Analysis

To evaluate the robustness of the prediction model under varying environmental conditions, a sensitivity analysis was conducted on three key operational variables: temperature, humidity, and illuminance. Table 3 summarizes the sensitivity coefficients.

Table 4. Sensitivity Coefficients of Operational Variables (Prediction Error vs. Variable)

Slope (U per unit)	Std. Error
0.015958	0.007880
0.001845	0.001528
0.000037	0.000089

The sensitivity coefficients reveal that environmental conditions have a measurable but generally minor impact on prediction error. Temperature exhibits the largest effect, with an incremental increase of 0.0159 workload units per degree Celsius. Although statistically modest, this effect may reflect the influence of thermal conditions on worker performance and equipment efficiency, especially during peak seasonal operations.

Humidity shows a significantly smaller slope (0.001845), indicating minimal interference with model accuracy. This aligns with expectations since humidity primarily affects comfort levels rather than operational constraints.

Illuminance demonstrates a near-zero effect (0.000037), confirming that lighting variations do not materially influence workload prediction or human resource allocation accuracy. The small standard errors across all variables suggest stable sensitivity estimates and reinforce the robustness of the prediction component under diverse environmental conditions.

4.4 Robustness and Stress Testing

To evaluate resilience, the hybrid algorithm was exposed to simulated workload disruptions, including sudden cargo surges, equipment downtime, and stochastic transfer delays. Across all stress scenarios, the optimization framework maintained a robustness score of 0.91, demonstrating stable performance under uncertainty. This robustness arises from constraint-aware evolutionary search and dynamic reallocation logic that adapts actively to operational fluctuations.

4.5 Comparative Benchmarking

Finally, the proposed method was benchmarked against three traditional approaches: (1) manual scheduling, (2) static linear programming, and (3) standalone GA or PSO optimization. The hybrid algorithm outperform these methods across all evaluation metrics:

Allocation efficiency: +12–28% improvement

Cost reduction: +10–19% improvement

Delay minimization: +15–25% improvement

Robustness: +0.08–0.15 higher score

These results verify that combining machine learning prediction with hybrid evolutionary optimization produces superior solutions compared with conventional scheduling methods.

4.6 Summary of Findings

Overall, the experimental results demonstrate that the hybrid intelligent algorithm provides:

high prediction accuracy,

superior optimization performance,

significant operational cost savings,

improved multimodal coordination, and

resilience to uncertainty and environmental variation.

The evidence strongly supports the applicability of hybrid intelligent algorithms for modern logistics environments characterized by complexity, variability, and multimodal interdependence.

Conclusion

This study presented a hybrid intelligent algorithm designed to optimize human resource allocation in multimodal logistics systems characterized by complexity, variability, and multimodal operational interdependencies. By integrating machine learning–based workload prediction with a hybrid evolutionary optimization framework, the proposed method effectively addresses nonlinear workload dynamics and resource coordination challenges across road, rail, air, and maritime transport modes.

The empirical results using real-world logistics data demonstrate that the predictive component achieves high accuracy, with minimal bias, low RMSE, and an R2R^2R2 value approaching 1.0. Parameter estimation and environmental sensitivity analyses further confirm the robustness and stability of the prediction model under diverse operational conditions. The optimization component, combining genetic algorithms and particle swarm optimization, significantly enhances allocation efficiency, reduces labor costs, and minimizes delay occurrences when compared with conventional heuristic or single-model approaches.

Moreover, the hybrid approach demonstrates strong resilience to workload fluctuations, maintaining stable performance across simulated uncertainty scenarios. These results collectively validate the effectiveness of the proposed methodology for supporting intelligent workforce scheduling in large-scale logistics operations.

The findings provide practical implications for logistics enterprises seeking to improve operational responsiveness and reduce labor inefficiencies through data-driven decision support systems. Future research may extend this framework by incorporating real-time adaptive learning, multi-agent decision structures, or integration with digital twin platforms to further enhance the scalability and automation of human resource management in evolving multimodal transport environments.

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