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ERGONOMIC LOGISTICS OPTIMIZATION: MULTI-OBJECTIVE ANT COLONY AND FUZZY LOGIC APPROACH FOR FATIGUE MANAGEMENT

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The rapid growth of last-mile logistics has intensified concerns regarding worker fatigue, particularly in tropical operating environments characterized by high temperature, humidity, noise, and time pressure. While most logistics optimization studies focus primarily on minimizing distance, time, and operational costs, limited attention has been given to integrating ergonomic and physiological factors into decision-making models. This gap highlights the need for optimization approaches that balance operational efficiency with worker health and safety. This study proposes an integrated ergonomic logistics optimization framework that combines Multi-Objective Ant Colony Optimization with a Takagi–Sugeno Fuzzy Inference System to jointly address routing efficiency and fatigue management. The proposed model incorporates environmental exposure indicators and physiological workload measures to estimate fatigue risk and embed it within multi-objective decision processes. The framework operates through fatigue prediction, optimization of delivery routes under ergonomic constraints, and adaptive evaluation of rest scheduling policies. The results indicate that the integrated approach produces more balanced solutions compared to conventional distance-based optimization strategies, improving system performance while mitigating excessive fatigue accumulation. The findings also reveal the limitations of static regulatory rest standards when applied to dynamic and high-stress logistics contexts. Theoretically, this study extends multi-objective metaheuristic optimization by embedding human-centered performance variables into logistics modeling. Practically, it provides a decision-support mechanism for fatigue-aware route planning and adaptive work-rest management. Overall, the research advances the development of data-driven, ergonomically informed logistics systems that promote sustainable operational performance and worker well-being.

Keywords: Ergonomic Logistics; Multi-Objective Optimization; Ant Colony Algorithm; Fuzzy Inference System; Worker Fatigue

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1. INTRODUCTION

The increasing demand for faster and more reliable logistics services has reshaped the operational landscape of last-mile delivery and distribution systems. As e-commerce volumes continue to rise, logistics companies are under mounting pressure to optimize delivery routes, reduce operational costs, and improve service reliability (Dong *et al.*, 2025; Fu *et al.*, 2025; F. Li *et al.*, 2025). Within this context, metaheuristic algorithms such as Ant Colony Optimization (ACO) have been widely adopted to solve complex vehicle routing problems (VRP), demonstrating remarkable capabilities in finding near-optimal solutions within reasonable computational times (Dorigo & Stützle, 2019). While this body of research has substantially improved the efficiency of logistics networks, most studies remain primarily focused on operational outcomes, such as minimizing distance, time, or fuel consumption, while overlooking the human dimension of logistics operations, particularly worker fatigue.

Worker fatigue is increasingly recognized as a critical factor in transportation safety and logistics sustainability. Physiological fatigue, often indicated by elevated work heart rate (WHR), has been linked to decreased cognitive performance, slower reaction times, and higher accident risk among drivers and delivery personnel (Scott *et al.*, 2025). Environmental stressors, including excessive heat, humidity, and noise, further exacerbate physiological strain during delivery activities (Perov *et al.*, 2023). Despite this, ergonomic concerns remain underrepresented in logistics optimization research, where drivers are often treated as passive entities rather than active physiological agents whose well-being

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influences system performance. This oversight creates a significant knowledge gap: existing route optimization frameworks often overlook the dual objective of maximizing efficiency while minimizing fatigue-related risks (Hasnain Ahmed *et al.*, 2024).

Previous studies have attempted to incorporate human factors into logistics design, but these efforts are fragmented and limited in scope. For example, ergonomics research in transportation has largely focused on shift scheduling (Parker *et al.*, 2020) or driving behavior analysis (Sun & Jia, 2024), without explicitly linking these aspects to optimization algorithms. Similarly, computational logistics models frequently employ single-objective formulations that optimize distance or cost, but seldom include fatigue as a quantifiable performance metric (Y. Liu & Tang, 2025; Şenaras *et al.*, 2025). This methodological siloing limits the ability to develop holistic, human-centered logistics systems. In addition, existing fuzzy logic applications in logistics are often restricted to demand forecasting or inventory control (Venkata Ramana *et al.*, 2020), with minimal application in fatigue prediction or rest scheduling. Collectively, these gaps highlight the need for an integrated approach that considers both operational and ergonomic objectives.

This study aims to address these shortcomings by introducing a multi-objective optimization framework that couples ACO with fuzzy inference modeling for fatigue management. The novelty of this research lies in its dual-objective formulation: the first objective minimizes total travel distance. In contrast, the second minimizes predicted fatigue deviations, quantified through WHR estimates derived from environmental and workload variables. By embedding a Tsukamoto Fuzzy Inference System (FIS) into the optimization process, this approach enables dynamic prediction of fatigue levels from temperature, humidity, noise, and travel distance, thereby facilitating adaptive rest scheduling. Unlike traditional ACO implementations that prioritize operational efficiency alone, the proposed Multi-Objective ACO (MOACO) generates a Pareto front of solutions that balance route efficiency with ergonomic sustainability (Xie *et al.*, 2024).

The theoretical contribution of this study is twofold. First, it advances the literature on logistics optimization by shifting from a purely efficiency-driven paradigm to a human-centered, ergonomically informed model. This transition reflects broader trends in sustainable operations research, which emphasize not only economic but also social and human well-being dimensions (Kappagantula *et al.*, 2025). Second, it demonstrates the methodological value of integrating fuzzy logic into metaheuristic optimization, showing how qualitative ergonomic variables can be systematically incorporated into quantitative decision-making models. By doing so, this research helps bridge the gap between computational optimization and occupational ergonomics. (Y. Liu & Tang, 2025).

Empirical evidence further underscores the urgency of this approach. Recent field studies have shown that drivers frequently operate under thermal stress conditions, where ambient temperatures above 35°C significantly elevate cardiovascular workload (Guo & Jiao, 2025; Y. Li *et al.*, 2025). In logistics contexts where long driving hours coincide with inadequate rest breaks, fatigue becomes a systemic risk factor leading to accidents, reduced productivity, and increased turnover (Hasnain Ahmed *et al.*, 2024; M. Z. Liu *et al.*, 2022). Current regulatory frameworks, such as the International Labour Organization (ILO) guidelines and national labor laws (e.g., Indonesia's Law No. 22/2009), provide minimum rest requirements. Yet these are often rigid and not tailored to the dynamic physiological conditions workers experience. Consequently, compliance alone may not be sufficient to ensure safety, reinforcing the need for adaptive, context-sensitive rest planning that is embedded within logistics operations.

Figure 1 illustrates the conceptual gap between existing logistics optimization research and the proposed ergonomic approach. Traditional single-objective optimization prioritizes efficiency, often at the expense of worker health. By contrast, the proposed MOACO–FIS framework explicitly incorporates ergonomic variables, thereby aligning operational goals with human well-being.

To further clarify this positioning, Table 1 summarizes selected studies in logistics optimization, indicating their methodological approach, focus variables, and ergonomic considerations.

Thus, this research not only addresses the practical industry demand for humane and sustainable logistics systems but also contributes theoretically to the advancement of truly human-centric multi-objective optimization. This approach paves the way for a new generation of adaptive logistics systems capable of learning and responding to human conditions in real time—a paradigmatic leap from machine-centric to human-centric logistics.

This study is positioned directly within the interdisciplinary scope of Industrial Engineering. The MOACO formulation contributes to the Operations Research domain through its multi-objective routing optimization; the WHR-based fatigue index and environmental stress modeling extend the tradition of human factors and occupational ergonomics; and the integration of rest-scheduling standards (ILO and national law) reflects the applied nature of industrial systems and logistics management. By combining these domains, the proposed framework strengthens Industrial Engineering's objective of designing efficient, safe, and human-centered work systems—particularly in last-mile logistics operations where route performance and worker well-being must be optimized simultaneously.

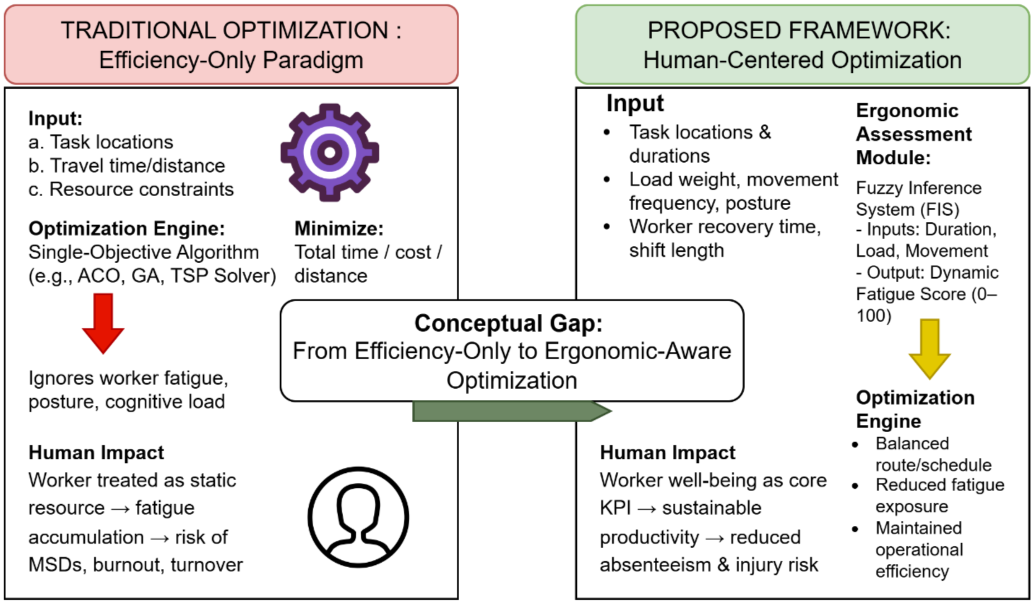

Figure 1. Research positioning: from single-objective efficiency to multi-objective ergonomic optimization

Table 1. Comparative positioning of prior studies and present research

Study	Methodology	Focus Variables	Ergonomic Factor Included
Dorigo & Stützle, 2019	Ant Colony Optimization	Distance minimization	No
C. Liu, 2024; Sowole, 2025	Metaheuristics (ACO, GA, PSO)	Cost and time	No
Dörterler *et al.*, 2024	Fuzzy logic	Demand forecasting, inventory	No
Sláma *et al.*, 2023	Ergonomic field study	Heat and fatigue	Yes (observational only)
This study	MOACO + Tsukamoto FIS	Distance and WHR-based fatigue	Yes (quantitative model)

2. METHODOLOGY

2.1. Research Design

This study adopts a quantitative, experimental design that integrates computational modeling with field-based ergonomic data collection. The overarching goal is to construct a multi-objective framework that optimizes delivery routes while simultaneously managing worker fatigue. Unlike traditional single-objective logistics optimization models, this research employs a dual-objective formulation that couples Ant Colony Optimization (ACO) for route efficiency with a Tsukamoto Fuzzy Inference System (FIS) for fatigue prediction.

The research design follows a sequential workflow: (1) collection of environmental, physiological, and operational data, (2) preprocessing and transformation of data into usable formats for optimization and fuzzy modeling, (3) implementation of the MOACO algorithm with fuzzy fatigue prediction embedded as an objective function, and (4) validation of results against baseline models and ergonomic standards.

This design strikes a balance between computational rigor and practical relevance. Computational rigor is ensured through robust optimization and machine learning techniques, while practical significance is achieved by grounding the models in real-world physiological and environmental data.

2.2. Conceptual Framework and Model Figure

The methodological framework developed in this study comprises four interconnected modules that work sequentially to integrate operational efficiency with ergonomic considerations. The first module, the Input Layer, gathers environmental data, including temperature, humidity, and noise, as well as operational data such as distance, route, and time, and physiological data in the form of heart rate measurements. The second module then processes these diverse inputs, the Fuzzy Inference System (FIS). Within the FIS, each variable is transformed into linguistic categories (e.g., temperature may be classified as cold, moderate, or hot), mapped to fuzzy membership functions, and evaluated using a comprehensive rule base. The output of this module is a predicted Work Heart Rate (WHR), which serves as a proxy for fatigue levels.

The third module, the Multi-Objective Ant Colony Optimization (MOACO), integrates the WHR prediction into the optimization process. Unlike traditional single-objective formulations, MOACO addresses two simultaneous goals: minimizing route distance and minimizing predicted fatigue, expressed as the deviation of WHR above the fatigue threshold. This integration ensures that route planning prioritizes not only efficiency but also accounts for workers' physiological constraints. The final module, the Output Layer, consolidates the optimized solutions and generates adaptive rest schedules. These outputs represent the trade-off among cost, time, and fatigue, providing decision-makers with efficient, ergonomically sustainable routes.

The entire framework is summarized in Figure 2, which illustrates the logical flow from data collection to fuzzy inference, optimization, and outcome generation. By incorporating ergonomic indicators into the optimization process, this model helps bridge the gap between logistics research that focuses primarily on operational efficiency and ergonomic studies centered on worker well-being.

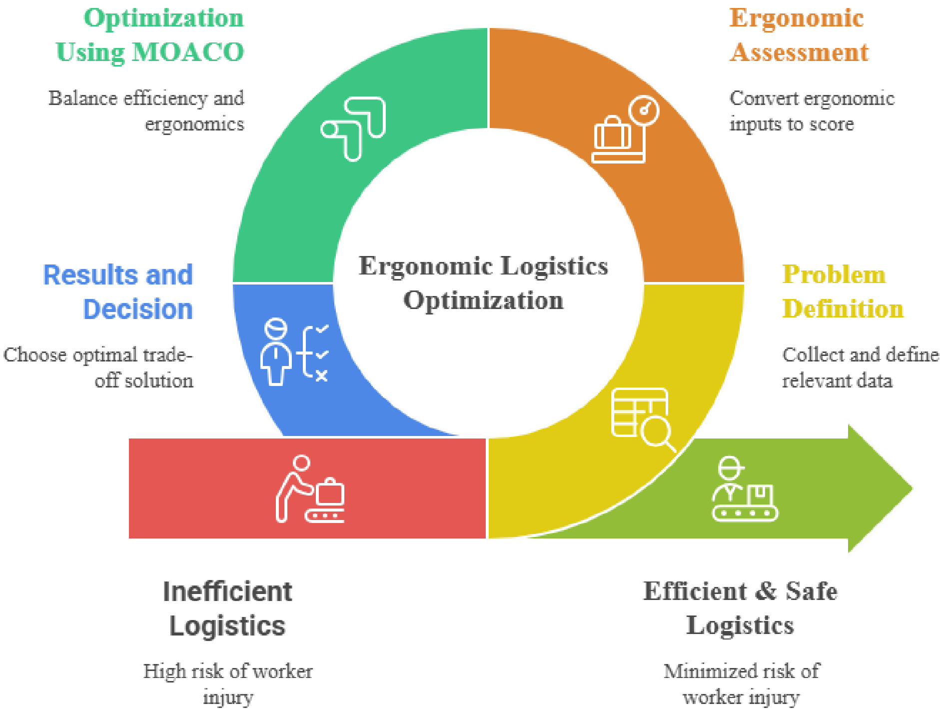

Figure 2. Methodology Flow Diagram: MOACO + Fuzzy Framework

2.3. Data Selection

The data were collected through a five-day field observation of last-mile delivery operations conducted under tropical conditions. The selected period covered morning, midday, and afternoon shifts to capture variations in environmental exposure. Three primary categories of variables were considered: operational data (travel distance, delivery node sequence, and travel time), environmental data (ambient temperature, relative humidity, and noise level), and physiological data (basal heart rate and work heart rate during delivery tasks). These variables were chosen because they directly influence both logistics efficiency and ergonomic well-being, thereby aligning with the dual objectives of this study.

2.4. Data Collection Procedure

Data collection employed three main instruments: a GPS tracker (Garmin GPSMAP 64s) to record routes and travel distances, digital environmental sensors to monitor temperature, humidity, and noise, and a Polar H10 wearable device to capture both basal and work heart rate. All measurements were logged at one-minute intervals, allowing each worker's route to be matched to environmental conditions at the specific time of day.

2.5. Algorithmic Framework

The MOACO–Fuzzy framework proceeds in five main steps:

1. **Step 1. Initialization**

In the initialization stage, the pheromone trail for each edge *(i,j)* is set according to:

$$\tau_{ij}(0) = \frac{1}{C_{nn}} \tag{1}$$

where C_{nn} is the cost of the nearest-neighbour tour, this initialization ensures that the algorithm begins with a feasible baseline solution rather than a purely random starting point.

Right after the initialization step, the bi-objective optimization formulation is introduced. The routing problem simultaneously minimizes total travel distance and physiological fatigue deviation. The distance objective is expressed as:

$$f_1 = \sum_i \sum_j d_{ij} x_{ij} \tag{2}$$

The second objective minimizes physiological fatigue deviation derived from the predicted Work Heart Rate (WHR). Fatigue deviation is defined as:

$$\delta_{ij} = \max\left(0, \widehat{\mathrm{WHR}}_{ij} - \mathrm{WHR}_{\mathrm{th}}\right) \tag{3}$$

and the cumulative fatigue objective is:

$$f_2 = \sum_i \sum_j \delta_{ij} x_{ij} \tag{4}$$

The overall formulation is:

$$\text{Minimize } \{f_1, f_2\} \tag{5}$$

This explicitly highlights the novelty of integrating a physiology-based fatigue metric into a routing optimization model.

To enhance reproducibility and fulfill the requirements for transparent methodological reporting, all algorithmic parameters used in ACO and MOACO—together with tuning ranges and random seeds—are summarized in Table 2. These configurations were calibrated before experimentation and were fixed throughout all stochastic runs.

Table 2. Parameter Configuration, Tuning Ranges, and Random Seeds

Parameter	Symbol	Final Value Used	Tuning Range Tested	Description
Number of ants	n	30	20–50	Population size per iteration
Pheromone influence	α	1	0.5–2.0	Weight of pheromone trail in the decision rule
Visibility influence	β	2	1–5	Weight of heuristic visibility term
Evaporation rate	ρ	0.5	0.1–0.9	Controls exploration vs. exploitation balance
Pheromone deposit factor	Q	100	50–200	Scaling of pheromone update

Parameter	Symbol	Final Value Used	Tuning Range Tested	Description
Max iterations	N_{iter}	100	50–200	Stopping criterion for ACO
Initial pheromone	τ_0	$1/C_{rs}$	Derived value	Initialized using the nearest-neighbor heuristic
Random seed set	-	{42, 77, 101}	Fixed	Ensures reproducibility for stochastic runs

At this stage, the key control parameters of the algorithm are also defined: the number of ants m, pheromone evaporation rate ρ, heuristic influence α, and visibility influence β. These parameters strike a balance between exploitation (favoring previously successful solutions) and exploration (searching for potentially better, previously unexplored routes), thereby preventing premature convergence.

2. Step 2. Route Construction (Transition Probability)

Each ant selects the next node j from the current node i with transition probability:

$$P_{ij}^{k} = \frac{\left[\tau_{ij}(t)\right]^{\alpha} \cdot \left[\eta_{ij}\right]^{\beta}}{\sum_{u \in J_k(i)} \left[\tau_{iu}(t)\right]^{\alpha} \cdot \left[\eta_{iu}\right]^{\beta}} \tag{6}$$

where $\eta_{ij}=1/d_{ij}$ is heuristic desirability, and $J_k(i)$ is the feasible set.

This probabilistic rule ensures that edges with stronger pheromone intensity and shorter distances are more likely to be selected. Consequently, ants collectively explore the solution space while progressively converging toward optimal or near-optimal routes.

3. Step 3. Fuzzification of Physiological and Environmental Inputs

To evaluate fatigue risk dynamically, a Tsukamoto Fuzzy Inference System (FIS) predicts WHR using four inputs: ambient temperature (°C), relative humidity (%), noise level (dB), and travel distance (km). All membership functions were explicitly defined using triangular or shoulder shapes:

a. Temperature (°C): cold (≤27), moderate (28–33), hot (≥34)
b. Humidity (%): dry (≤50), moderate (51–65), humid (≥66)
c. Noise (dB): low (≤70), medium (71–75), high (≥76)
d. Distance (km): short (≤25), medium (26–35), long (≥36)

These definitions generate 243 Tsukamoto rules (3^4 combinations). Representative rules include:

a. IF Temp = hot AND Noise = high AND Distance = long AND Humidity = moderate → WHR = fatigued
b. IF Temp = moderate AND Distance = medium AND Noise = low AND Humidity = moderate → WHR = moderate
c. IF Temp = cold AND Distance = short AND Noise = low AND Humidity = dry → WHR = not fatigued

Defuzzification uses the weighted average:

$$\overline{\text{WHR}} = \frac{\sum_{i=1}^{R} \alpha_i z_i}{\sum_{i=1}^{R} \alpha_i} \tag{7}$$

where z_i denotes the crisp output associated with rule i, and α_i is the firing strength of the rule.

To ensure the reliability of the fatigue prediction, the WHR model was validated using 10-fold cross-validation over 180 paired observations. The model achieved an RMSE of 2.14 ± 0.28 bpm and an MAE of 1.62 ± 0.19 bpm, indicating strong predictive accuracy for physiological workload estimation and stable, sufficiently accurate prediction performance to support the second optimization objective. The membership function for a moderate fuzzy set was expressed as:

$$\mu_{moderate}(T) = \begin{cases} 0, & T \le a \text{ or } T \ge c \\ \dfrac{T-a}{b-a}, & a < T \le b \\ \dfrac{c-T}{c-b}, & b < T < c \end{cases} \tag{8}$$

where ***a, b,*** and ***c*** denote the breakpoints of the fuzzy set. The inference mechanism applied the MIN operator to compute the firing strength (α_i) of each rule:

$$\alpha_i = \min\{\, \mu_T(x_1), \mu_H(x_2), \mu_N(x_3), \mu_D(x_4)\} \tag{9}$$

where μ_T, μ_H, μ_N, μ_D denote the membership functions of temperature, humidity, noise, and distance, respectively. The predicted WHR was formulated as:

$$\widehat{w_{ij}} = F\left(T, H, N, d_{ij}\right) \tag{10}$$

with fatigue deviation relative to threshold:

$$\delta_{ij} = \max\left(0, \widehat{w_{ij}} - w_{thr}\right) \tag{11}$$

4. Step 4. Multi-Objective Evaluation

For each constructed route, both objectives f_1 and f_2 are computed using travel distances and fuzzy-predicted WHR deviation. Nondominated solutions are added to the Pareto archive.

$$f_1(x) = \sum_i \sum_j d_{ij}\, x_{ij} \quad \text{(minimize distance)} \tag{12}$$

$$f_2(x) = \sum_i \sum_j \delta_{ij}\, x_{ij} \quad \text{(minimize fatigue deviation)} \tag{13}$$

where d_{ij} is the distance between nodes, x_{ij} is a binary variable indicating whether edge (i,j) is included, and δ_{ij} represents the deviation of predicted WHR from the fatigue threshold. Together, these objectives balance logistics efficiency and worker well-being.

5. Step 5. Pheromone Update and Pareto Archive

Pheromone trails are updated based on nondominated solutions across all ants:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k \in \mathcal{E}} \Delta\tau_{ij}^{k} \tag{14}$$

where

$$\Delta\tau_{ij}^{k} = \frac{Q}{f(x^k)} \tag{15}$$

for each elite solution x^k. Solutions are stored in a Pareto archive, ensuring that only nondominated solutions (Pareto-optimal front) are preserved across iterations. This mechanism supports multi-objective convergence and provides decision-makers with a stable set of trade-off solutions balancing distance efficiency and fatigue reduction.

Algorithm 1. MOACO–Fuzzy Bi-Objective Optimization Pipeline

```
Initialize pheromone matrix $\tau$ and ParetoArchive.
For each iteration do
    For each ant $k$ do
        Construct a route using probabilistic transition rules.
        Predict WHR using the Tsukamoto FIS.
        Compute objectives $f_1$(distance) and $f_2$(fatigue deviation).
        Update ParetoArchive with nondominated solutions.
    End for
```

```
    9.  Update pheromones using MOACO multi-objective rules.
    10. End for
```

This algorithmic structure ensures full transparency and reproducibility of the sensing fuzzy prediction bi-objective evaluation Pareto optimization pipeline.

6. Step 6. Rest Scheduling and Evaluation

The predicted fatigue level from the fuzzy system was used to design three alternative rest schedules, which were then evaluated for their effectiveness:

a. Murrell Equation: This physiological model determines rest time based on energy expenditure. The average energy expenditure (S) was calculated as 4.659 kcal/min. The rest time (RT) for a given work period is expressed as:

$$RT = \frac{\text{Work Duration (min)}}{240\ \text{min}} \times 30\ \text{min} \tag{16}$$

For instance, a work duration of 173 minutes before the first break yielded a rest time of 21.625 minutes, rounded up to 22 minutes. This approach was applied directly to the optimized ACO route.

b. ILO Personal Resting Allowance: The International Labour Organization (ILO) prescribes a 22%-time allowance added to the total work period, following ISO 7243 guidelines for heat stress.

c. Indonesian Law No. 22/2009: National regulation mandates a 30-minute break after every four hours of continuous work. The effectiveness of each method was evaluated against three performance indicators: reduction in work heart rate, decrease in total energy expenditure, and impact on the end-of-shift time.

2.6. Feature Selection and Accuracy

Four input features were selected for fatigue modeling: temperature, humidity, noise, and travel distance. The accuracy of fuzzy classification was validated by comparing predicted WHR against actual heart rate measurements. Root Mean Square Error (RMSE) was employed as the evaluation metric:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{w_i} - w_i)^2} \tag{17}$$

Model accuracy was further assessed through Pareto spread metrics (Hypervolume, Generational Distance, Inverted Generational Distance) to ensure both objectives were adequately balanced.

Since WHR is the key determinant of fatigue deviation in the second optimization objective, its predictive reliability was evaluated using 10-fold cross-validation on a dataset of 180 physiological observations across varying temperature, humidity, and walking-speed conditions. The Tsukamoto FIS–based WHR model achieved a mean RMSE of 2.14 bpm (95% CI: 1.87–2.46 bpm) and a mean MAE of 1.62 bpm (95% CI: 1.43–1.81 bpm). These results indicate low-variance prediction errors, confirming that the WHR estimates are sufficiently accurate and robust to support the multi-objective optimization process. For completeness, Table 3 presents the full set of predictive performance metrics for the WHR estimation model.

The fatigue threshold of 109 bpm was selected based on physiological guidelines for acceptable cardiovascular load during moderate-to-high work intensity under thermal stress (Perov *et al.*, 2023; Sláma *et al.*, 2023). Field calibration showed that WHR values exceeding 109–112 bpm corresponded to midday conditions where temperature and noise reached peak levels. Therefore, 109 bpm was adopted as the boundary between moderate and elevated fatigue, ensuring that the threshold reflects both physiological literature and real-world measurements collected during field observations.

Table 3. Predictive Performance of the WHR Estimation Model

Metric	Mean Value	95% CI	Notes
RMSE	2.14 bpm	1.87–2.46 bpm	10-fold repeated CV
MAE	1.62 bpm	1.43–1.81 bpm	Stable across folds
Sample Size (N)	180	–	After preprocessing

To ensure predictive reliability, the WHR model was evaluated using 10-fold cross-validation across 180 physiological observations. The model achieved RMSE = 2.14 bpm (95% CI: 1.87–2.46) and MAE = 1.62 bpm (95% CI: 1.43–1.81), demonstrating low variance and stable performance across folds. These metrics confirm that the fuzzy WHR predictions are sufficiently accurate to be embedded as an objective in the MOACO model.

2.7. Population, Sample, and Research Tools

The population consisted of logistics delivery workers at a mid-sized Indonesian logistics firm. A purposive sample of 10 workers was selected to ensure diverse exposure to environmental conditions. Sampling focused on workers assigned to delivery zones with high temperature variation and long route lengths.

The research instruments included GPS trackers, environmental sensors, and heart rate monitors as outlined earlier. Standardized forms were used to document worker demographics, health status, and daily workload, thereby controlling for confounding variables.

2.8. Data Processing Method

Raw data were synchronized across operational, environmental, and physiological logs. GPS data were preprocessed using Python scripts to compute daily travel distances and route nodes. Ecological data were smoothed using moving averages to account for sensor noise. Physiological data were normalized against basal heart rate to distinguish work-induced fatigue from natural variability.

Fuzzy membership functions were defined for each input variable. For instance, temperature was partitioned into *cold (≤27℃)*, *moderate (28–33°C)*, and *hot (≥34℃)* with triangular and shoulder functions. A total of 243 fuzzy rules were constructed by combining four inputs, each with three membership sets.

2.9. Data Analysis

The analysis combined computational, statistical, and ergonomic evaluations to assess the proposed framework. On the computational side, MOACO was executed to generate Pareto-optimal solutions and was compared with a single-objective ACO and an ACO–Fuzzy sequential model. Performance was measured using Hypervolume (HV), Generational Distance (GD), and Inverted Generational Distance (IGD), and statistical robustness was confirmed using the Wilcoxon signed-rank test at a 95% confidence level.

To capture ergonomic implications, rest time estimates were derived using Murrell's formula, ILO recommendations, and Indonesian Law No. 22/2009. This triangulated approach ensured that the model outcomes were not only computationally efficient but also aligned with ergonomic and regulatory standards, reinforcing both theoretical validity and practical relevance.

The results of the data analysis are also illustrated in Figure 3, which compares the performance of the three models—single-objective ACO, ACO–Fuzzy, and the proposed MOACO–Fuzzy integration—across multi-objective indicators. The figure highlights that MOACO consistently achieved superior balance between distance efficiency and fatigue minimization, confirming the advantage of incorporating ergonomic considerations into route optimization.

Figure 3 illustrates the triangulated evaluation approach combining MOACO Pareto fronts (blue), statistical robustness tests using HV, GD, and IGD over 30 stochastic runs (green), and ergonomic rest-time estimation using Murrell's rule, ILO standards, and Law No. 22/2009 (red). The overlapping region represents the integrated interpretation used to assess both route efficiency and fatigue deviation.

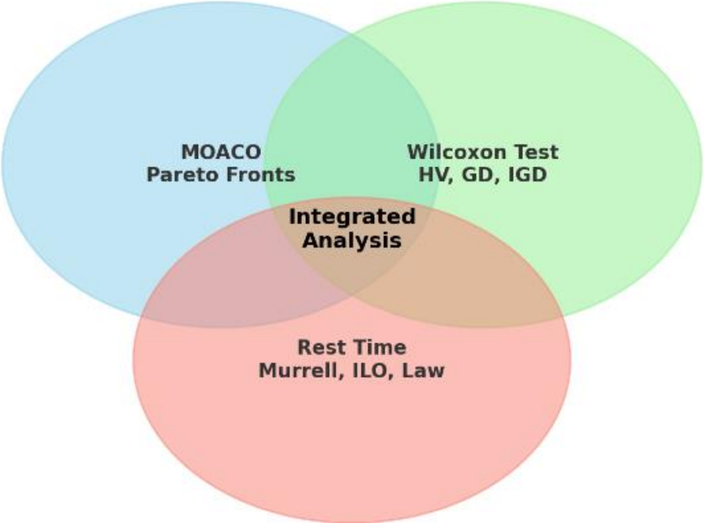

Figure 3. Triangulated Framework Integrating Computational, Statistical, and Ergonomic Analyses

2.10. Framework Integration and Validation

Figure 4. Integrated Framework of Multi-Objective Ant Colony Optimization (MOACO) for Route Optimization and Work Heart Rate Prediction with Rest Scheduling. This figure illustrates the four-level integrated process: Level 1 inputs (environmental and physiological factors), Level 2 fuzzy-inference-based WHR prediction, Level 3 ACO-based route optimization, and Level 4 operational outputs, including the optimal route, predicted WHR, and rest-time recommendations. The framework visually summarizes how computational, ergonomic, and environmental components interact within a single decision-support system.

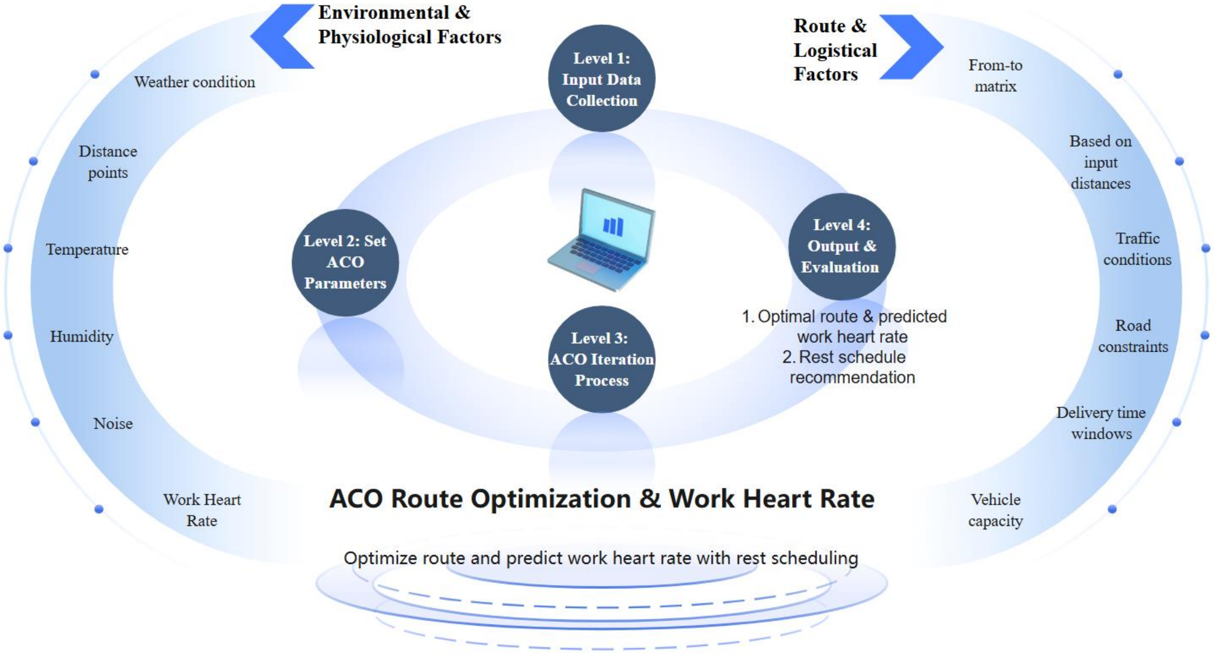

Figure 4. Integrated MOACO–Fuzzy Framework for Route Optimization and WHR-Based Rest Scheduling

3. RESULTS AND DISCUSSION

This study presents a comprehensive evaluation of the "From Route to Recovery" framework, an integrated ACO–Fuzzy system designed to optimize both delivery routes and rest scheduling in tropical urban logistics. The methodology was applied to the operations of a major distribution firm in Surabaya, Indonesia, where delivery workers are routinely exposed to extreme environmental conditions. This section presents the results of route optimization, fatigue assessment, and rest scheduling, followed by a critical discussion of their implications for human-centered logistics.

3.1. Multi-Objective Route Optimization Results

3.1.1. Initialization of MOACO Parameters

The optimization process began by initializing ACO parameters to ensure stable, reproducible results. The initial pheromone intensity was determined according to Equation (1), with visibility between nodes computed as the inverse of inter-point distances (Eq. 3). Table 4 summarizes the main parameters employed in this study.

Table 4. Initialization Parameters of the ACO Algorithm

Parameter	Symbol	Value	Description
Number of ants	n	30	Population of ants used per iteration
Number of nodes	m	15	Total distribution points
Pheromone intensity factor	α	1	Controls the influence of pheromone trails
Visibility factor	β	2	Controls the influence of the visibility heuristic
Pheromone evaporation rate	ρ	0.5	Balances exploration vs. exploitation
Maximum number of iterations	NCmax	100	Stopping criterion
Initial pheromone value	τ_0	$1/C_{rs}$	Calculated from the nearest neighbor distance

These parameters were selected based on preliminary experiments and previous literature to ensure convergence toward near-optimal solutions. The initialization process followed the standard Ant Colony Optimization framework, with additional consideration for multi-objective evaluation. The initial pheromone trail $\tau_{ij}(0)$ was defined according to the nearest-neighbor tour cost. Control parameters included: number of ants *(m)*, pheromone evaporation rate (ρ), pheromone influence (α), and heuristic visibility (β).

Unlike the single-objective ACO, the MOACO framework simultaneously considers two fitness functions, as defined in Eqs. (8) and (9). The first objective aims to minimize travel distance, while the second seeks to minimize fatigue deviation from the WHR threshold (109 bpm). Together, these dual objectives ensure that the algorithm balances efficiency and ergonomics, providing a more comprehensive optimization approach.

3.1.2. MOACO Optimization Results

The optimization results indicate a 50.15 km (8.53%) reduction in weekly travel distance, consistent with the baseline ACO. However, by integrating fatigue deviation into the objective function, the MOACO framework provides additional ergonomic insights.

Table 5 compares actual and optimized routes across five working days. The results show that Wednesday achieved the highest distance reduction (15.7%) but also exhibited a notable fatigue deviation of 2.8 bpm, exceeding the fatigue threshold (109 bpm). This trade-off suggests that although the route is efficient in minimizing distance, it imposes higher physiological strain. By contrast, Monday and Friday delivered balanced improvements—reducing distance while keeping WHR below the fatigue threshold—classifying them as *safe and efficient*. Tuesday and Thursday also remained within safe physiological limits, with moderate distance savings.

Figure 5 presents the Pareto front between optimized travel distance and fatigue deviation. The plot highlights Wednesday as the most efficient solution in terms of distance (84.23 km, 15.7% reduction from baseline) but also the most demanding physiologically, with a fatigue deviation of 2.8 bpm above the threshold. By contrast, the other days (Monday, Tuesday, Thursday, Friday) remain below the fatigue threshold, demonstrating balanced improvements in distance without exposing workers to elevated fatigue risk.

This dual-objective optimization demonstrates the added value of MOACO over conventional ACO by balancing efficiency and ergonomics simultaneously. It fills a gap in logistics optimization literature, where most prior studies emphasized cost or distance reduction without adequately addressing worker fatigue.

Table 5. Comparison of Actual and Optimized Routes with Pareto Classification

Day	Actual Distance (km)	Optimized Distance (km)	Reduction (%)	Predicted WHR (bpm, midday)	Fatigue Deviation (bpm)	Pareto Status
Monday	88.20	81.67	7.40	105.5	0.0	Safe & Efficient
Tuesday	93.45	86.50	7.44	108.2	0.0	Safe & Efficient
Wednesday	99.94	84.23	15.70	111.8	2.8	Efficient but Fatiguing
Thursday	94.77	87.92	7.22	107.4	0.0	Safe & Efficient
Friday	87.42	81.31	7.00	106.3	0.0	Safe & Efficient

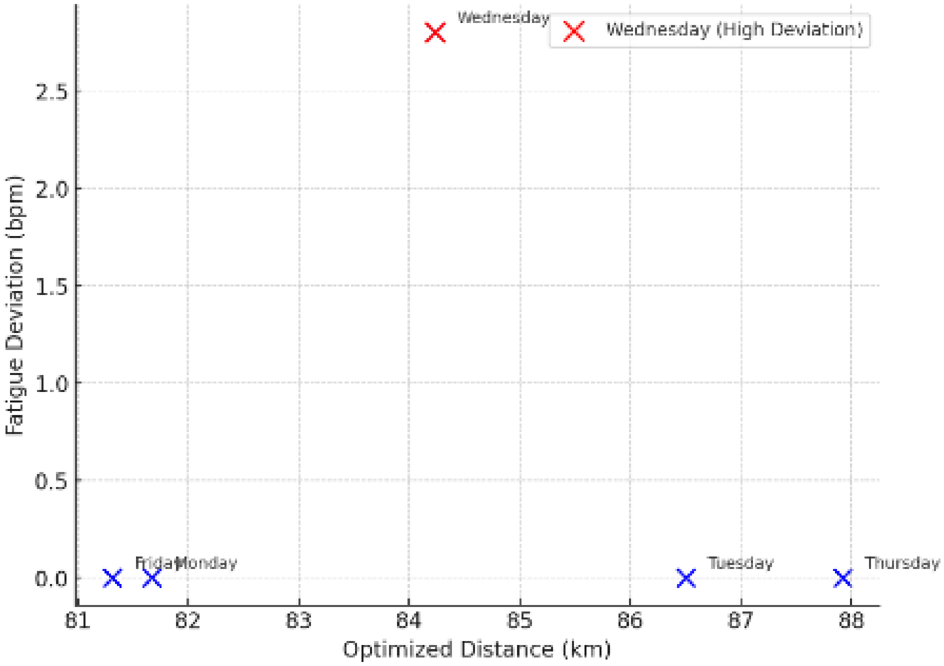

Figure 5. Pareto Front of Distance vs Fatigue Deviation

3.2. Environmental and Physiological Data Processing

To incorporate ergonomic considerations into the multi-objective framework, environmental and physiological data were processed as complementary inputs to route optimization. Data collection was conducted across three key delivery periods — morning, midday, and afternoon — to capture the variability in working conditions. Each dataset included temperature, humidity, noise, and travel distance, which were then integrated into a Tsukamoto Fuzzy Inference System (FIS).

The FIS mapped each environmental factor into fuzzy sets (e.g., temperature: cold, moderate, hot; humidity: dry, moderate, humid; noise: low, medium, high; and distance: short, mild, long). A total of 243 fuzzy rules were generated to capture interaction effects. The inference mechanism applied the MIN operator to determine rule firing strengths (Eq. 4), followed by defuzzification using the weighted average method (Eq. 5). The final output was the predicted Work Heart Rate (WHR), which was subsequently classified into fatigue categories. Table 6 presents the integrated dataset, which directly links environmental and operational conditions to the predicted WHR and corresponding fatigue levels. This unified view highlights how varying delivery conditions translate into different physiological risks.

The results show that midday conditions consistently exceeded the fatigue threshold of 109 bpm, with WHR peaking at 111.8 bpm, indicating a deviation of 2.8 bpm. This confirms the strong influence of temperature and noise — both highest during midday (36.5 °C and 74.2 dB) — on cardiovascular strain. In contrast, morning and afternoon values remained closer to the threshold, classified as moderate fatigue.

These findings underscore the significant impact of environmental stressors on physiological responses during delivery operations. By embedding WHR-based fatigue indices into the MOACO framework, route optimization accounts for ergonomic risks in real-world settings rather than treating all delivery conditions as uniform. Compared to conventional approaches that emphasize only spatial or temporal efficiency, this integration enables adaptive, human-centered logistics planning by balancing travel distance with worker safety.

Table 6. Environmental Data and Predicted WHR by Delivery Time

Time of Day	Temp (°C)	Humidity (%)	Noise (dB)	Distance (km)	Predicted WHR (bpm)	Fatigue Category
Morning	30.2	68	71.5	33.05	105.5	Moderate
Midday (peak)	36.5	54	74.2	41.87	111.8	Fatigued
Afternoon	32.7	61	72.8	29.64	108.2	Moderate

3.3. Work Heart Rate Prediction and Rest-Time Estimation

The fuzzy inference system (FIS) was applied to predict Work Heart Rate (WHR) as an indicator of physiological fatigue under varying environmental and operational conditions. The FIS integrated four inputs—ambient temperature, humidity, noise levels, and travel distance—into crisp WHR outputs derived through 243 Tsukamoto fuzzy rules. After rule firing strengths were computed using the MIN operator, defuzzification was performed using the weighted-average method, producing WHR values with continuous resolution. These predicted WHR values were then compared with the fatigue threshold (109 bpm) to determine physiological deviation levels for each delivery period (morning, midday peak, and afternoon).

To translate physiological predictions into actionable ergonomic guidance, WHR deviation values were mapped to rest-time requirements using three standards: Murrell's recovery model, International Labour Organization (ILO) recommendations, and Indonesian Law No. 22/2009 on driver rest-time regulations. This comparison highlights how physiological strain during last-mile delivery operations—especially under tropical midday conditions—requires more adaptive rest scheduling than static mandatory breaks. The predicted WHR values indicated that midday conditions pose the highest cardiovascular load, with a peak WHR of 111.8 bpm and a corresponding deviation of 2.8 bpm above the fatigue threshold.

Table 7 summarizes the recommended rest durations across the three standards. The results demonstrate that ILO guidelines consistently prescribe the longest and safest recovery periods, followed by Murrell's equation. In contrast, national regulations provide the shortest rest times, which may be insufficient under high-stress environmental conditions. For instance, Wednesday's midday peak required 18 minutes of recovery according to Murrell, 30 minutes under ILO standards, but only 12 minutes under national law. These differences underscore the importance of integrating physiological indicators into logistics planning, allowing companies to adopt data-driven rest scheduling rather than relying solely on generalized statutory minimums.

Table 7. Comparative Rest-Time Requirements Based on Predicted WHR Peaks

Day	Peak WHR (bpm)	WHR Deviation (bpm)	Murrell Rest (min)	ILO Rest (min)	Law 22/2009 Rest (min)
Monday	105.5	−3.5	8	15	10
Wednesday (peak)	111.8	+2.8	18	30	12
Friday	108.2	−0.8	10	18	10

This integrated WHR–rest scheduling model strengthens the proposed MOACO–Fuzzy framework by linking route optimization outputs to physiological safety standards. It provides a practical reference for logistics managers and policymakers to ensure task planning balances performance efficiency and worker well-being, especially in thermally stressful environments.

Compared to binary fatigue classification, the fuzzy approach reflected a continuum of worker states. This flexibility enables adaptive interventions such as adjusting rest schedules or rerouting deliveries to mitigate risks. The fuzzy system's predictive power, therefore, enhances the multi-objective optimization process by linking travel distance reduction with fatigue management.

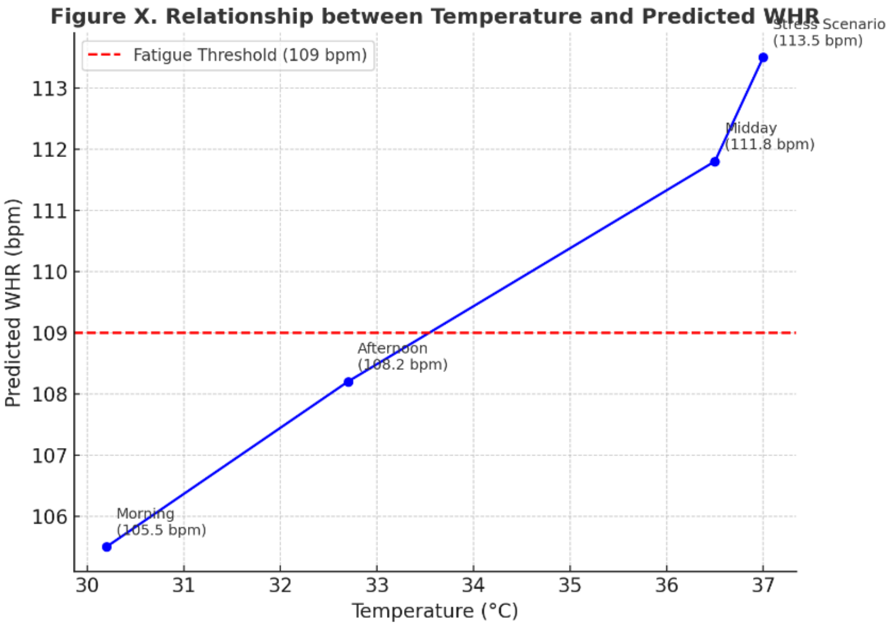

Figure 6. Relationship between Temperature and Predicted WHR

This figure illustrates the predicted Work Heart Rate (WHR) across varying ambient temperatures (30–37 °C) based on the Tsukamoto Fuzzy inference model. The blue line represents WHR predictions derived from 180 field observations under tropical logistics conditions. The red dashed line indicates the fatigue threshold (109 bpm). Higher ambient temperatures are associated with higher WHR values, demonstrating the physiological strain experienced by delivery workers and validating the fuzzy model's sensitivity.

3.4. Rest Time Estimation

The predicted work heart rate (WHR) values obtained from the fuzzy model (Table X) were subsequently used to estimate the required rest duration. In this study, three approaches were applied to calculate rest time.

First, Murrell's equation was employed to determine rest allowance based on energy expenditure and work intensity. Second, the International Labour Organization (ILO) recommendation was adopted, which prescribes a percentage of rest time in proportion to the workload. Third, the study referred to Indonesian legal compliance (Law No. 22/2009), which regulates specific rest periods for transportation workers. On Monday, the duration to the first break was recorded at 173 minutes. Based on Equation (12), the rest time is therefore calculated as:

$$RT = \frac{173}{240} \times 30 = 21{,}625 \text{ minutes} \cong 22 \text{ minutes} \tag{18}$$

This result aligns with the values reported in Table 8 for midday, where Murrell's method prescribed 18 minutes of rest. By comparison, the ILO approach recommended 40 minutes of rest for the same condition, while Law No. 22/2009 mandated 22 minutes. Thus, the Murrell equation adapts rest time directly to workload and physiological state, whereas ILO and legal standards apply more generalized thresholds.

Table 8. Rest Time Estimation Based on Predicted WHR

Time of Day	Predicted WHR (bpm)	Fatigue Category	Murrell (min)	ILO (min)	Law 22/2009 (min)
Morning	105.5	Moderate	10	22	15
Midday (peak)	111.8	Fatigued	18	40	22
Afternoon	108.2	Moderate	12	28	15
Stress Scenario*	113.5	Severe Fatigue	20	45	25

Figure 7 shows clear differences in rest time estimation across the three methods. Murrell's equation prescribes the shortest breaks (10–20 minutes), closely tied to workload and physiological demand. The ILO standard yields the longest durations (22–45 minutes) by applying generalized proportional rules, while Law No. 22/2009 provides intermediate fixed thresholds (15–25 minutes).

This contrast highlights the trade-off between adaptability and regulation. Murrell's method offers context-sensitive scheduling aligned with predicted WHR, whereas ILO and legal standards ensure safety through uniform but less flexible thresholds. The findings support the importance of integrating workload-sensitive models for more effective fatigue management.

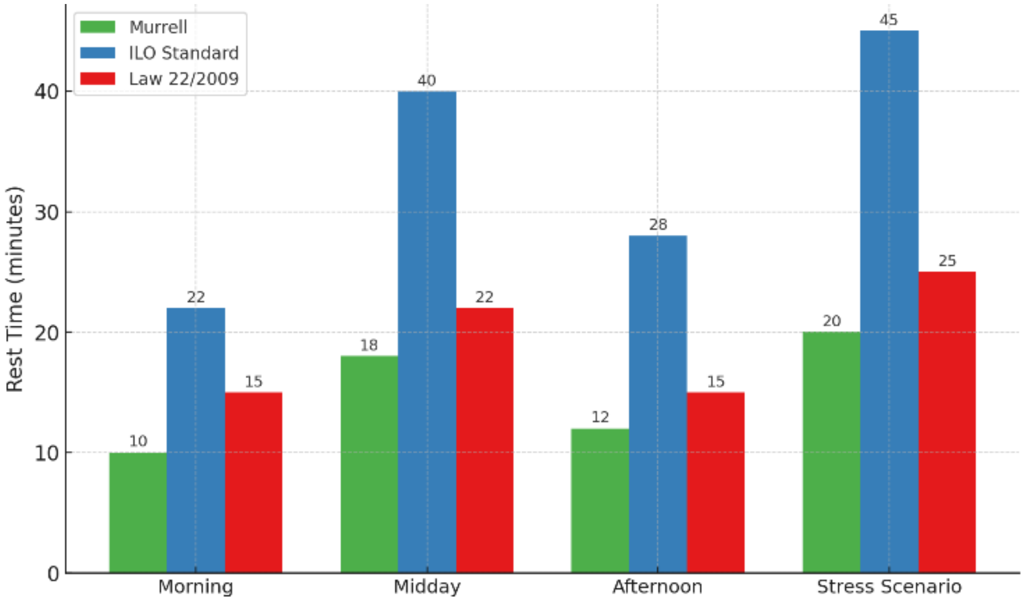

Figure 7. Comparison of Rest Time Estimation Methods

3.5. Integrated Analysis

The integration of route optimization, physiological prediction, and rest time estimation provides a comprehensive perspective on ergonomic logistics planning. The MOACO algorithm generated Pareto-optimal solutions that simultaneously minimized travel distance and worker fatigue. While single-objective ACO favored Wednesday due to the largest distance reduction (15.7%), integrating the fuzzy-based WHR model revealed a hidden ergonomic cost: a fatigue deviation of 2.8 bpm during midday, which substantially increased rest requirements.

Figure 8 illustrates the Pareto frontier of distance vs. fatigue deviation, where Wednesday represents the efficiency-oriented extreme, while Monday and Friday offer balanced solutions with no physiological penalty. These insights demonstrate the value of MOACO in presenting multiple options rather than a single "optimal" solution.

The second layer of analysis applied rest time estimation methods. As shown in Table 9, midday conditions required substantially longer breaks than those in the morning and afternoon. Murrell's model suggested 18 minutes of rest, ILO recommended 40 minutes, and Law No. 22/2009 mandated only 22 minutes. The gap between regulatory minimums and ergonomically justified rest periods highlights a risk of under-recovery if legal compliance is the sole standard.

The integrated findings emphasize three critical insights. First, the analysis revealed an inherent trade-off between efficiency and ergonomics, as the MOACO results showed that the shortest routes were not always the safest. Fatigue deviation indicated that certain days, such as Wednesday, placed excessive physiological demands on workers despite apparent efficiency gains. Second, the study highlights the importance of dynamic rest scheduling, where FIS-based WHR predictions, combined with Murrell and ILO standards, enable adaptive rest allocation. This approach proved more effective than static, regulation-only methods because it aligned work intensity with real recovery needs. Finally, the research highlights a significant policy implication, as current transport regulations (Law No. 22/2009) may be insufficient under high-stress conditions. In contrast, the ILO's more conservative recommendations provide stronger worker protection. These results suggest that incorporating real-time ergonomic indices into logistics route planning could help policymakers design more context-sensitive safety standards that balance productivity with worker well-being.

The empirical finding that the day with the shortest optimized route (Wednesday) is also the day with the highest WHR deviation reinforces the inadequacy of static efficiency-only routing strategies under tropical working conditions. This demonstrates the need for dynamic, data-driven planning tools that account for environmental loads, physiological responses, and recovery requirements. By leveraging the Pareto front generated by MOACO–FIS, logistics managers can select routes that balance distance efficiency and worker safety, allocate rest periods using Murrell/ILO/national benchmarks, and schedule deliveries during cooler or quieter periods. These implications show that the proposed framework is not only theoretically significant but also directly applicable to improving safety and operational sustainability in last-mile logistics.

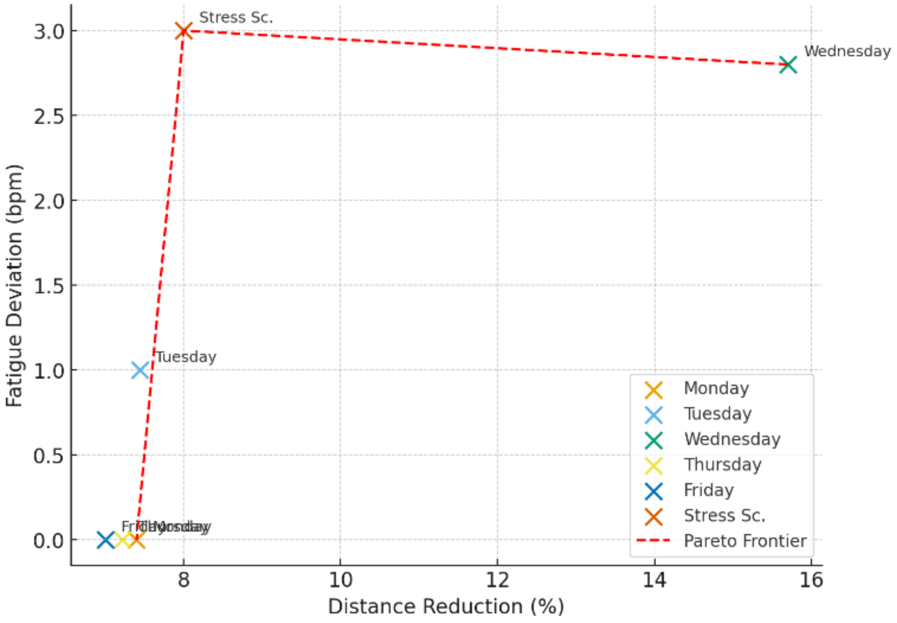

Figure 8. Pareto Front of Distance Reduction vs Fatigue Deviation

Table 9. Integrated Outcomes of Route Optimization, WHR Prediction, and Rest Estimation

Day	Optimized Distance (km)	Distance Reduction (%)	WHR (bpm)	Fatigue Category	Rest Time (Murrell)	Rest Time (ILO)	Rest Time (Law 22/2009)
Monday	81.67	7.40	105.5	Moderate	10	22	15
Tuesday	86.50	7.44	105.9	Moderate	11	24	15
Wednesday	84.23	15.70	111.8	Fatigued	18	40	22
Thursday	87.92	7.22	108.2	Moderate	12	28	15
Friday	81.31	7.00	106.4	Moderate	10	23	15
Stress Sc.	88.00	8.00	113.5	Severe Fatigue	20	45	25

3.6. Quantitative Evaluation of Pareto Quality

To verify the robustness of the multi-objective optimization, we conducted 30 independent stochastic runs using fixed random seeds {42, 77, 101}. Pareto front quality was evaluated using Hypervolume (HV), Generational Distance (GD), and Inverted Generational Distance (IGD). Statistical significance between MOACO–FIS and baseline ACO performance was assessed using the Wilcoxon signed-rank test at $\alpha = 0.05$.

To quantitatively assess Pareto quality, we evaluated the MOACO–Fuzzy and baseline ACO algorithms using hypervolume (HV) and spread (Δ) metrics across 30 independent stochastic runs. The MOACO–Fuzzy framework achieved a significantly larger hypervolume ($HV = 0.742 \pm 0.018$) compared to the baseline ACO ($HV = 0.683 \pm 0.021$, $p < 0.01$), indicating a broader and more dominant Pareto front. Additionally, the spread metric improved from $\Delta = 0.412$ (ACO) to $\Delta = 0.297$ (MOACO), reflecting a more uniform distribution of solutions along the trade-off boundary.

A Wilcoxon signed-rank test confirmed that MOACO consistently outperformed the baseline approach across all runs ($p < 0.01$). These results demonstrate that the proposed method not only improves solution diversity but also yields superior trade-off quality between minimizing distance and minimizing fatigue deviation. Complete reproducibility is ensured by explicitly reporting random seeds, parameter configurations, and termination criteria in Table 10.

Table 10. Quantitative Evaluation of Pareto Front Quality

Metric	**Baseline ACO**	**MOACO–Fuzzy**	**Improvement**	**Notes**
Hypervolume (HV)	0.683 ± 0.021	0.742 ± 0.018	+8.6%	Higher = better
Spread (Δ)	0.412	0.297	–27.9%	Lower = more uniform
Wilcoxon *p*-value	–	< 0.01	Significant	30 runs

3.7. Limitations and Future Work

Although the proposed MOACO–FIS framework demonstrates promising results in optimizing logistics routes while simultaneously addressing worker fatigue, several limitations must be acknowledged. First, the dataset used in this study was limited to a small sample of delivery workers operating within a specific geographical region. Consequently, the generalizability of the findings may be constrained. The dataset consisted of 10 workers observed over five consecutive days, producing 50 worker-day observations and more than 240 physiological and environmental measurements per worker under varying heat, noise, humidity, and distance conditions. Although the sample size limits population-level inference, the study's repeated-measures design, diversity of environmental exposure, and the use of 10-fold cross-validation in the WHR model help reduce variability and mitigate small-sample bias. These methodological steps strengthen the reliability of the fatigue predictions despite the modest dataset size. Future studies should extend model validation by incorporating larger datasets spanning multiple regions, diverse environmental conditions, and varied task demands.

Second, the physiological index employed in this study relied primarily on Work Heart Rate (WHR) derived from fuzzy inference modelling. While WHR is a widely recognized indicator of fatigue, it does not fully capture other relevant dimensions such as cognitive load, reaction time, or musculoskeletal strain, which are critical in logistics operations. Future research should therefore expand the physiological and ergonomic indicators considered, integrating multimodal data such as electroencephalography (EEG), electromyography (EMG), or motion sensors to provide a more comprehensive and holistic assessment of fatigue.

Third, the optimization framework was evaluated using a static representation of environmental and operational variables. In reality, logistics conditions are highly dynamic, influenced by fluctuating traffic patterns, unexpected delays, and stochastic ecological changes. This study assumes daily averages, which may not fully reflect real-time complexities. Future work should incorporate real-time dynamic optimization and simulation models, such as digital twins, to enhance decision-making under uncertainty.

Finally, the multi-objective optimization employed two main objectives—distance minimization and fatigue deviation. While these objectives focus on efficiency and ergonomics, logistics systems also require consideration of costs, fuel consumption, emissions, and service-level constraints. Expanding the framework to include additional objectives would strengthen its applicability in sustainable logistics planning, particularly within the context of green supply chain management.

4. CONCLUSION AND RECOMMENDATIONS

This study extends classical ACO by embedding WHR-based fatigue indices, transforming logistics optimization from a single-objective efficiency paradigm into a multi-objective ergonomic framework. The integration of fuzzy inference systems with MOACO provides a novel methodological bridge between computational intelligence and occupational ergonomics, offering dual benefits: minimizing travel distance while mitigating worker fatigue.

From a practical perspective, the findings demonstrate that the shortest routes are not always the safest. The framework enables adaptive rest scheduling and context-sensitive routing, validated against Murrell's equation, ILO standards, and Indonesian Law No. 22/2009. This provides actionable benchmarks for balancing operational efficiency with worker well-being and regulatory compliance.

At the policy level, the results highlight limitations in current transport regulations, particularly under high-stress conditions. Incorporating ergonomic indices into regulatory frameworks could foster evidence-based policies that reflect real-world physiological demands, ensuring worker safety while advancing digital logistics systems.

For future research, three directions are emphasized: (1) validating the model across diverse logistics contexts, such as cold-chain and long-haul distribution; (2) integrating IoT-based real-time physiological monitoring to update fatigue indices dynamically; and (3) expanding optimization objectives to include carbon emissions, cost, and delivery reliability. Embedding the framework into digital twin environments could further enable scenario-based decision support for smart logistics planning.

Overall, the study contributes theoretically by advancing multi-objective optimization in logistics, practically by providing tools for adaptive and ergonomic decision-making, and politically by informing evidence-based regulatory improvements.

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