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Optimization of queueing complexity in the forest transportation problem

Cássio Augusto Ussi Monti[1], Vanessa Souza Gomes[2], Severino José Macôo[3], Kalill Jose Viana da Páscoa[4], Luciano Cavalcante de Jesus França[5], Mônica Canaan Carvalho[6], Carolina Souza Jarochinski e Silva[4], Lucas Rezende Gomide[4]✤

[1]Suzano S.A., Department of Forest Modeling, Jacareí, SP, Brazil
[2]Remsoft Ltda., São José dos Campos, SP, Brazil
[3]High Polytechnic Institute of Gaza, Division of Agriculture, Main Campus of Lionde. Chókwè, Gaza, Mozambique
[4]Federal University of Lavras, Department of Forest Science, Lavras, MG, Brazil
[5]Federal University of Uberlândia, Institute of Agricultural Sciences, Uberlândia, MG, Brazil
[6]Youx, Department of Data Analysis, Lavras, MG, Brazil

FOREST MANAGEMENT

ABSTRACT

Background: The principal challenge in forest transportation lies in minimizing the fleet of vehicles and cranes while adhering to operational constraints. Addressing this intricate operational issue yields numerous advantages. This research is dedicated to the development and evaluation of a controlling device designed to enhance timber logistics. A queue simulator is utilized to estimate prospective wait times for the optimized system. Two scenarios are analyzed: one integrating the controlling device and the other excluding it. The study underscores the advantages of vehicle type A, which, due to its higher number of wheelers and fewer cranes compared to vehicle type B, demonstrates greater efficacy in establishing a robust queuing system.

Results: Although comprehensive numerical analysis is not provided, the utilization of fewer cranes indicates potential cost reductions. The Forest Transportation Problem (FTP) model is employed to optimize the spatial allocation of trucks and cranes during loading and unloading operations. The succinct mathematical formulation of this model renders it both effective and user-friendly. The fuzzy controlling device (FCD), which emulates human decision-making processes in the allocation of wheelers to cranes, significantly enhances the comprehension of optimization outcomes. A comparative assessment reveals that scenario 1 (excluding the FCD) appears more advantageous for replicating the queuing system under the specified conditions. Notably, the integration of the FCD with the queue simulator engenders logical and coherent queue behavior within the forest transportation framework.

Conclusion: The findings of this study substantiate the effectiveness of the developed controlling device in optimizing timber logistics by augmenting the efficiency of the queuing system and potentially reducing crane utilization costs. Vehicles associated with higher crane productivity required fewer trucks to perform transportation tasks more efficiently compared to those with less productive cranes. The incorporation of the FCD refines the decision-making process and yields valuable insights into the operational dynamics of forest transportation. The study's outcomes contribute significantly to the field, offering practical implications for optimizing resource allocation and enhancing logistical performance in forestry operations.

Keywords: Decision-making; Fuzzy controlling device; Queuing system; Timber logistics; Timber trucking.

HIGHLIGHTS

Vehicle scheduling boosts efficiency, aiding economic growth and environmental goals.
Queue simulator and fuzzy device improved queuing system in the case study.
Model results support better decisions and strategic planning in transportation.
Fuzzy controller outperformed the base case in queuing system simulation.

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✤Corresponding author: lucasgomide@ufla.br
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INTRODUCTION

Transportation is a critical component of forest logistics. Effective transportation planning plays a pivotal role in reducing operational costs, optimizing resource utilization, and minimizing environmental impacts (Bordón, Montagna, & Corsano, 2018; Rönnqvist et al., 2015). Nevertheless, forest transportation encompasses considerable complexity, involving multiple interdependent criteria, including cost efficiency, queuing dynamics, vehicle capacity, and road conditions. Compounding these complexities are uncertainties and imprecisions, such as fluctuations in queuing durations at loading and unloading points, variations in travel times, degradation of forest roads, and unanticipated truck breakdowns (Amrouss et al., 2017; Malladi & Sowlati, 2017). Sibdari and Sepasi (2022) addressed these challenges by applying a simulation-optimization approach that incorporates various uncertainties, such as stochastic travel times and external disturbances including random demand and road delays at mills and forests. Their approach demonstrated scalability and practicality for real-world applications. Similarly, Han et al. (2018) developed a mixed-integer programming model integrated with a network algorithm to optimize biomass feedstock logistics within a tree-shaped road network. Their findings revealed a cost reduction of up to 11% compared to conventional logistics systems by minimizing grinding, transportation, residue loading, machine mobilization, and processing site construction costs.

The optimization of forest transportation remains a critical research domain in logistics and forest planning. It forms an integral part of the forest industry supply chain, where transport plans must incorporate diverse operational criteria to ensure sustainable and efficient transportation (Akay & Demir, 2022; Anderson & Mitchell, 2016; Malladi & Sowlati, 2017). Traditional optimization methodologies frequently assume deterministic and precise input parameters (Palander & Vesa, 2022; Santos et al., 2019). However, such assumptions may not hold true in real-world scenarios where uncertainties prevail (Rönnqvist et al., 2015). Forest transportation involves additional operational layers, such as timber loading and unloading, which generate queues throughout the planning horizon. Various studies have sought to mitigate queuing occurrences through deterministic methodologies. For instance, Rix et al. (2015) developed a mixed-integer linear programming model utilizing column generation techniques to minimize transportation costs and queuing durations over a one-year horizon. Similarly, Bordón, Montagna, and Corsano (2018) introduced a Mixed-Integer Linear Programming (MILP) model for generating cost-efficient truck routes while ensuring continuous log supply.

Alternative heuristic-based approaches have also been explored. Haridass et al. (2014) implemented simulated annealing techniques integrated with deterministic simulation models to minimize total unloaded mileage. Oliveira et al. (2022) addressed the vehicle routing problem under forest transportation constraints by testing non-exact algorithms—Simulated Annealing, Greedy, and a hybrid Greedy-Simulated Annealing approach—across multiple operational strategies. However, as Bychkov et al. (2021) highlighted, queuing problems in forest transportation are inherently stochastic, necessitating approaches that account for intrinsic uncertainties and imprecisions. Recent advancements have positioned Fuzzy Sets as a robust framework for addressing uncertainties and imprecisions in decision-making processes (Bhardwaj & Sharma, 2021; Özkir & Demirel, 2012; Sarkar & Amrita, 2012). Fuzzy inference systems, in particular, enable partial membership of elements within sets ideal for contexts where category boundaries are ill-defined (Ljubomir et al., 2019). Within forest transportation, fuzzy inference systems facilitate simultaneous consideration of multiple criteria and uncertainties. For example, Akay and Demir (2022) employed a hybrid fuzzy multi-criteria decision-making method to determine the most suitable vehicle types for forest product transportation under various operational conditions. Chen et al. (2020) developed a multi-objective, multi-period fuzzy mixed-integer programming model that integrated carbon emission considerations with cost minimization to assess uncertainties' impacts on timber supply networks' configurations. This study contributes by proposing a novel approach that employs fuzzy inference systems to control post-optimized forest transportation operations. The objective is to provide a realistic representation of queuing systems through simulation and to develop a robust controlling framework focusing on minimizing queuing times during timber trucking operations.

MATERIAL AND METHODS

Forest tranportation instance

The dataset utilized in this study comprises machinery production data collected over a six-month period through a comprehensive time and motion study. In the forest industry, such studies are instrumental in orchestrating weekly transportation operations, encompassing timber trucking, loading, and unloading activities. For the purposes of this research, the company implemented an independent loading system tailored to two distinct vehicle types (A and B). This system accounts for the specific daily production capacities of each vehicle type, as well as the corresponding crane productivity. Under this operational framework, each vehicle type is paired with a dedicated crane type for loading operations. Conversely, during unloading operations, both vehicle types compete for access to all available cranes. This competition inherently generates queuing times during loading and unloading cycles. The number of operational cycles a vehicle can complete per day is contingent upon various delays encountered throughout the process. Notably, significant delays at any stage, either the vehicle displacement, loading, or unloading, can severely disrupt operational flow, necessitating effective queuing management strategies. This study addresses the outlined logistical operations by evaluating two distinct strategic scenarios, designated as Scenario 1 and Scenario 2. A detailed exposition of these scenarios is provided in the corresponding "Scenario and Simulations" section, wherein their respective impacts on queuing dynamics and overall operational efficiency are thoroughly analyzed.

The machinery allocation model

The Machinery Allocation Model (MAM), applied to vehicle fleets (trucks and cranes) in forestry, is based on the Transportation Problem and requires specific adaptations. It must account for crane loading and unloading capacities, vehicle transportation capacities, and the number of cycles per vehicle. This information ensures accurate modeling of timber trucking operations to meet target timber volumes from harvested stands to processing mills at unloading yards (Figure 1).

The proposed integer programming (IP) model, outlined in Equations 1–9, aims to minimize the total number of equipment - vehicles (*Y*) and cranes (*X*) - required for transport operations (Equation 1). The model does not specify which cranes or trucks are activated but assumes that operations occur wherever loading and unloading cranes are available, allowing a block of stands to be considered for the operation. This problem is further detailed in Monti et al. (2020). Here, Y_i represents the number of vehicles of type *i*, where $i \in \{A, B\}$, and X_i denotes the number of cranes assigned to vehicle type *i* during loading. Loading cranes are truck-type-specific, meaning each vehicle type has a designated crane type. The decision variable *W* represents the number of cranes available for unloading operations, which serve all vehicle types, introducing competition among them. In contrast, loading cranes are exclusive to their corresponding vehicle types, eliminating such competition between vehicle types. The constant Q_i indicates the required timber volume each vehicle must deliver to the mill. The parameters Ll_i and UL_i define the lower and upper bounds for the number of vehicles per type. The model's time components, V_i and H_i, measured in hours/day, represent the time needed for each vehicle type to complete a cycle and the total operational hours allowed per day, respectively. A cycle, in this context, comprises the sequence of departing empty from the unloading station, traveling to the loading station, completing the loading, returning to the unloading station, and completing the unloading operation.

$$Minimize \sum_{i=1}^{N} (Y_i + X_i) + W \quad (1)$$

Subject to

$$\sum_{i=1}^{N} CAP_i Y_i \geq 6,750\, tons / day \ \ (Mill's\, specification) \quad (2)$$

$$CAP_i Y_i \geq Q_i \ , \quad \forall i \in 1,\ldots,N \quad (3)$$

$$Y_i \geq LL_i \ , \quad \forall i \in 1,\ldots,N \quad (4)$$

$$Y_i \leq UL_i \ , \quad \forall i \in 1,\ldots,N \quad (5)$$

$$V_i Y_i \leq H_i \ , \quad \forall i \in 1,\ldots,N \quad (6)$$

$$CAP_i Y_i - C_i X_i \leq 0 \ , \quad \forall i \in 1,\ldots,N \quad (7)$$

$$CAP_i Y_i - C_w W \leq 0 \ , \quad \forall i \in 1,\ldots,N \quad (8)$$

$$Y_i \ , X_i , W \in Z \quad (9)$$

The model incorporates key production parameters, including the daily production capacity of each vehicle type (CAP_i, in tons/day), the loading capacity of cranes assigned to each vehicle type C_i, in tons/hour/day, and the unloading capacity of cranes *Cw*, in tons/hour/day. Equations 2 ensure that the mill's target volume is met. Equations 3–5 establish the minimum daily production requirements and the upper and lower production bounds for each vehicle type. Equations 6 address the total daily transportation time, while Equations 7–8 define the relationship between the number of cranes required and the number of trucks to be loaded or unloaded per vehicle type. Finally, Equations 9 specify the decision variables related to the integer set. The productivity yield data for each vehicle and crane type, along with operational time and target volumes required by the mill, are summarized in Table 1. According to machinery specifications, loading crane type A operates at 36.63 tons/hour, while type B achieves 65.85 tons/hour. The unloading cranes exhibit a production capacity of 160.97 tons/hour.

Fuzzy Controlling Device

The proposed fuzzy controlling device (FCD) utilizes queuing time and the proportion of vehicles served by each crane as key variables to streamline the transportation operation. The fuzzy system developed for this study adopts the classical Mamdani approach, employing trapezoidal membership functions. The trapezoidal function was selected due to its resemblance to classical set theory in decision-making processes. In classical set theory, a measured value falling within a defined threshold is classified as belonging entirely to that category, represented by a step function. In contrast, fuzzy theory assigns a degree of membership to multiple categories

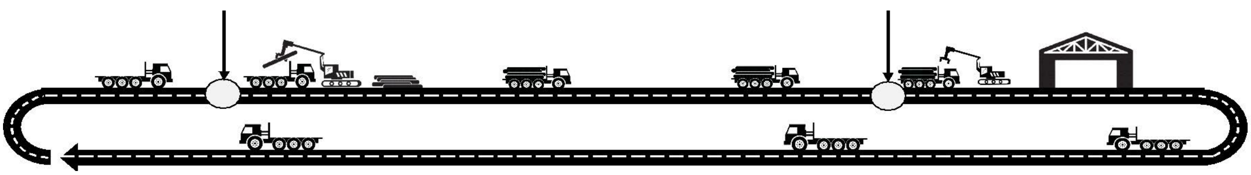

Figure 1: Basic representation of forest logistics of timber trucking.

simultaneously, represented by trapezoidal functions. This allows for a more nuanced classification when boundaries between categories are not clearly defined. For this model, three classes—Low, Medium, and High—were established for each input variable (Figure 2), representing queuing time (in hours) and the proportion of vehicles being loaded or unloaded by specific cranes.

The thresholds for the High, Medium, and Low classes were defined based on the Medium class. Specifically, the Medium class was set to represent half the range of each input's support. For instance, the proportion of vehicles falls within the interval [0, 1], meaning the Medium class encompasses the value 0.5. The trapezoidal membership function's legs were initially determined through expert opinion and refined via sensitivity tests. The fuzzy output represents the proportion of vehicles allocated to each crane at the moment they begin moving toward it. To enhance control over this allocation, five output classes were established: very low, low, medium, high, and very high (Figure 3).

The aggregation operator used was the "min" function for the "and" connections between fuzzy rules. All nine possible combinations were considered as the antecedents of the fuzzy rules (Table 2). The consequent of fuzzy rules was defined based on the assumption that a higher queuing time and a greater proportion of vehicles being served by a crane should result in fewer vehicles being directed to that crane. The centroid method was chosen for defuzzification due to its ability to return the average value of the geometric shape formed by the interaction between the fuzzy rules and the distribution classes of each input variable. In the context of queuing control, this method ensures that the average vehicle allocation reflects the integrated relationship between the input variables.

Each crane type (both loading and unloading) was assigned a unique fuzzy inference system designed to determine the proportion of vehicles associated with that crane during each cycle. The controller device makes decisions based on an integrated analysis of each crane

Table 1: The overall daily information about vehicle type to solve the forest optimization problem.

Vehicle type	Q (tons/day)	Number of vehicles		H (h/day)	V (h/day)	CAP (tons/day)
		Lower	Upper			
A	1,500	10	50	14.59	7.29	74
B	6,000	10	50	16.13	5.38	351

Where: Q – daily demand of timber supply to the mill, H- daily work hours; V- time to complete a cycle; CAP- vehicle capacity.

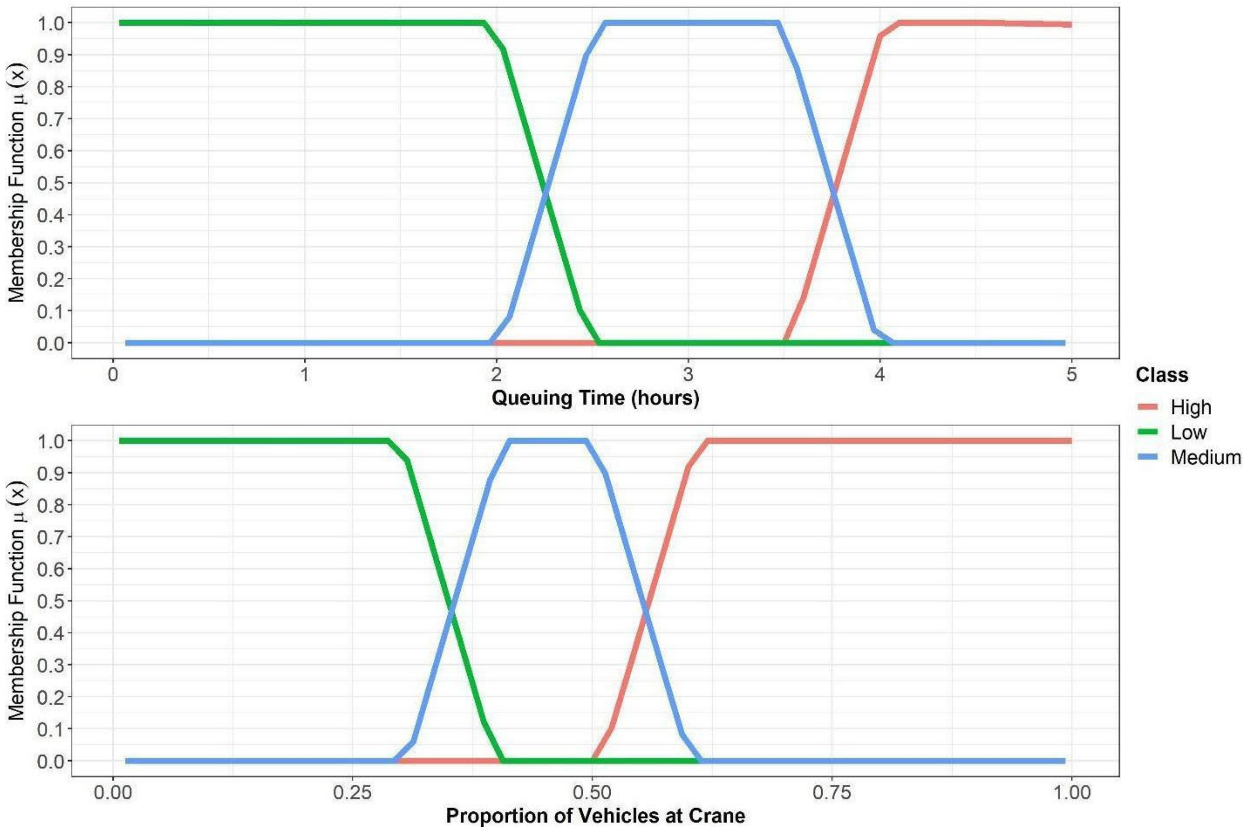

Figure 2: Membership functions of input variables: Queuing Time (hours) and Proportion of Vehicles at Crane.

type independently during the loading operation, ensuring no cross-association between crane types at this stage. For the unloading operation, the process is repeated; however, unlike the loading operation, the fuzzy controller device imposes no restrictions on which vehicle type is served by the cranes. As a result, all vehicle types compete for any available crane during unloading. This proposed approach extends the framework described by Monti (2020) by incorporating a controlling device specifically designed to manage the queuing system, thereby enhancing operational efficiency and reducing queuing delays.

Scenarios and Simulation

For this study, the optimal number of trucks per vehicle type and cranes per crane type was determined by using the proposed Machinery Allocation Model (MAM). A queue simulator was developed to replicate the queuing times associated with forest transportation operations. To evaluate the controlling capacity of the developed Fuzzy Controlling Device (FCD), the FCD was integrated with the queue simulator (QLsim), allowing for an optimal distribution of vehicles throughout the timber trucking process, thereby

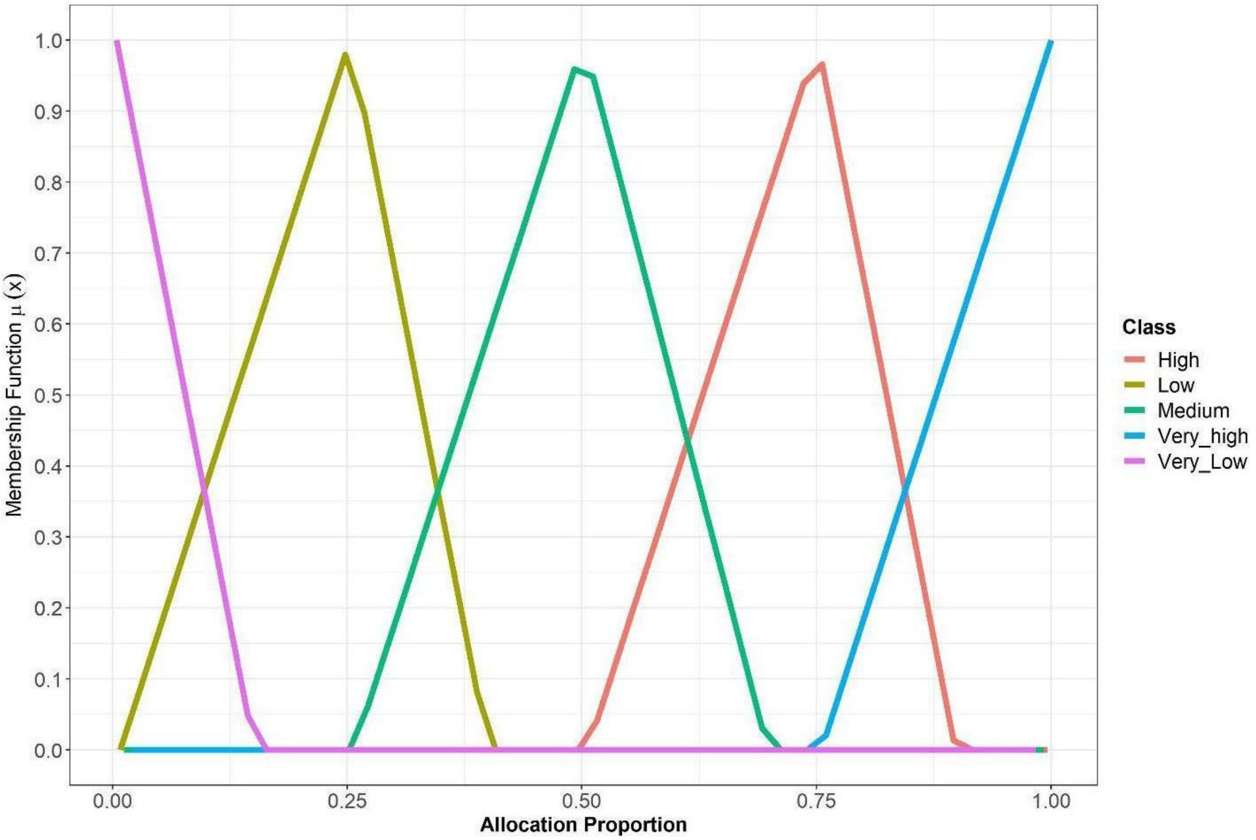

Figure 3: Membership function for the fuzzy output.

Table 2: Fuzzy rules for the antecedent (queuing time and proportion of vehicles) and the corresponding rules for the consequent (vehicle allocation).

ID	Queuing time	Proportion of vehicles	Vehicle allocation
1	High	High	Very low
2	Medium	High	Low
3	Low	High	Medium
4	High	Medium	Low
5	Medium	Medium	Medium
6	Low	Medium	High
7	High	Low	Medium
8	Medium	Low	High
9	Low	Low	Very high

providing a more accurate representation of queuing times. The model's performance was assessed by comparing queuing time results from two scenarios: (1) MAM + QLsim (base scenario) and (2) MAM + FCD + QLsim (Figure 4). In the base scenario, the number of machinery units was optimized following the methodology outlined in Section 2.1, after which the queue simulator was applied to simulate the queuing system based on this optimal configuration. To introduce realism into the simulation, various delay times—0h, 1h, 2h, and 3h—were incorporated, simulating road delays commonly encountered in logistical operations. For each scenario, the long-run average queue time and the probability of crane idleness were computed using an appropriate queuing model. Additionally, the effective work time for each vehicle type and the corresponding average queue time were calculated based on the outputs generated by the queue simulator.

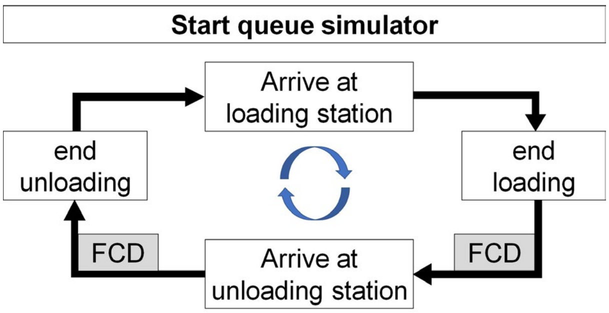

Figure 4: Dynamics of scenario 2 with the queue simulator (QLsim) and FCD operators.

The queue simulator algorithm was developed using the R environment, while the Forest Transportation Problem (FTP) model was solved with the "lpSolve" package (Berkelaar et al., 2022). The Queue Logistic Simulator (QLsim) replicates the company's logistics system through the following four steps:

1. Simultaneous Arrival: All vehicles arrive at the loading station at 5 AM and are served following the "first-in, first-out" (FIFO) scheme;
2. Queue Computation: Queues are calculated by aligning the production rates of cranes with the capacities of the corresponding vehicle types;
3. Sequential Processing: After a vehicle is served, the next vehicle in the queue begins loading, while the loaded vehicle proceeds to the unloading station;
4. Unloading Competition: At the unloading station, vehicle types A and B compete for crane availability under the FIFO scheme. Upon completion, the cycle restarts with the next batch of vehicles.

The QLsim is a heuristic designed to align timber production yields for various vehicle types and cranes during loading and unloading operations, following the four steps outlined previously. The simulator generates queues for each truck based on crane and vehicle production rates; however, it does not optimize truck-to-crane scheduling for queue time minimization. An illustrative example of queue time computed by QLsim is presented in Figure 5. Suppose two type A trucks (A_1 and A_2) begin service at 5 AM and require one hour to reach the loading station, arriving simultaneously at 6 AM. With only one crane available at the station, a queue forms with the second truck (A_2) waiting. Truck A_1 requires one hour for loading, causing A_2 to wait for one hour before its turn. A_1 departs the loading station at 7 AM and proceeds to the

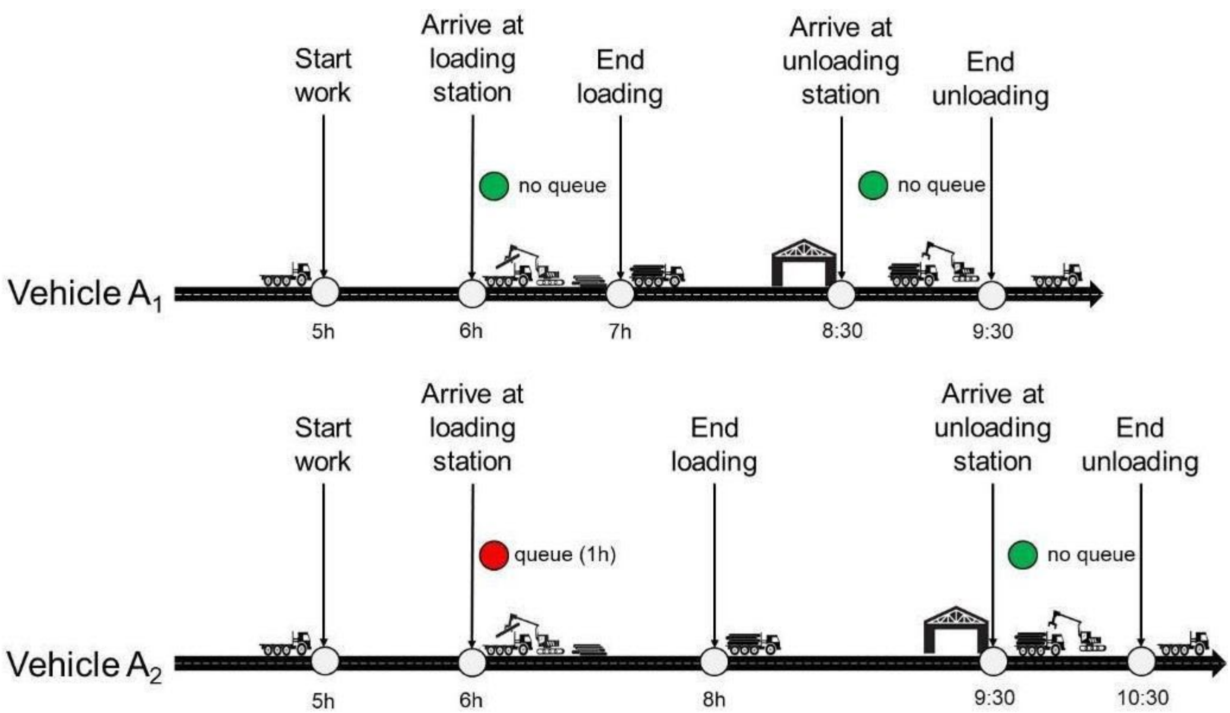

Figure 5: Example of computation of queue time by the QLsim for two trucks of the same type.

unloading station, while A_2 begins loading. The completion times for both trucks differ due to A_2's initial waiting period. At the unloading station, no waiting time is observed. The QLsim exclusively calculates waiting times occurring during loading and unloading operations. Delays simulating real-world disruptions are introduced at both the loading and unloading stations, affecting overall queuing performance.

The queue model for the simulated problem is characterized as an M/M/c model under the "First-in, First-out" (FIFO) scheme. In this context, the first M denotes the assumption that interarrival times follow an exponential distribution, while the second M indicates that service times also follow an exponential distribution. The term c represents the number of servers (cranes) operating within the queue system. This queue model operates as a Poisson process, with cranes performing loading and unloading tasks under an exponential service time distribution. The probability density function (PDF) assumed for the FIFO scheme, $f(t) = (\mu - \lambda)e^{-(\mu-\lambda)t}$ for $t > 0$, and zero otherwise.

RESULTS

Fleet Minimization: MAM Assessment

The Machinery Allocation Model (MAM) optimized the fleet size for both vehicle types and cranes, as presented in Table 3. The integer programming model identified the optimal solution in 2.3 seconds. The daily timber production optimized by the model slightly exceeded the minimum required tonnage per truck, accommodating the unloading operation's constraints. Specifically, unloading cranes were required to handle an amount of timber equal to or greater than the transported volume. For the unloading operation, three cranes were allocated as the global optimum. The total volume produced by the optimized combination of cranes and vehicles reached 7,872 tons per day. The optimized fleet consisted of 51 vehicles, comprising 21 type A vehicles, 18 type B vehicles, nine cranes for loading, and three cranes for unloading operations (Table 3).

Scenario Assessment

Base Scenario: MAM + QLsim

The base scenario, combining the MAM with the QLsim, generated the queuing plan for the fleet of vehicle types A and B, along with their corresponding crane services for loading and unloading operations. Under conditions without simulated delays, the effective working times averaged 23.93 hours for vehicle type A and 24.60 hours for vehicle type B. Simulated delays revealed a decreasing trend in effective working time as delay duration increased (Table 4). Despite these delays, the average queuing time remained constant within each vehicle type during the loading operation. This consistency occurs because delays in earlier cycles shift the timing of vehicles entering the queue without altering the queue time itself. However, applying a fixed delay value introduces uniformity in the simulation, which can misrepresent the queuing system when individual truck-to-crane assignments are not explicitly managed.

Table 3: Optimized number of vehicles and cranes. Note: Cranes belonging to the loading operation only.

Vehicle Type	Number of Vehicles	Number of Cranes	Production (tons/day)
A	21	3	1,554
B	18	6	6,318

Table 4: Summary of effective working time and average queuing time for each vehicle type and trucking operation in scenario 1.

Vehicle Type	Delay (h)	Effective working time (h)	Average queuing time (h)
A	0	23.93	2.40
A	1	21.51	2.40
A	2	25.51	2.40
A	3	16.81	2.40
B	0	24.60	1.10
B	1	21.30	1.10
B	2	25.30	1.10
B	3	16.20	1.10
Unloading	0	24.26	3.24
Unloading	1	21.41	2.78
Unloading	2	25.41	2.78
Unloading	3	16.51	2.26

In the unloading operation, queuing time decreased as delay duration increased. This behavior is expected, considering that all vehicles initially arrived simultaneously at the loading station during the first cycle. With longer delays, vehicles spent more time traveling and less time forming queues. The queuing system follows an M/M/c model under the "First-in, First-out" (FIFO) scheme, where c represents the number of cranes available. For the loading operation, c equals 3 for vehicle type A and 6 for vehicle type B. In the unloading operation, c equals 3. Based on the queuing system outlined in scenario 1, the probability of crane idleness (Figure 6) was calculated. Vehicle type B exhibited the highest probability of crane idleness across the different delay scenarios, with the lowest probability at a 3-hour delay and the highest at a 2-hour delay. This suggests that a 2-hour delay results in the most efficient transportation operation for vehicle type B concerning its independent queuing structure. The fleet for vehicle type B was optimized to 18 vehicles. Consequently, the interarrival time, defined as the interval between consecutive vehicle arrivals, was optimized at approximately 7 minutes (calculated as 2 hours × 60 minutes/hour ÷ 18 vehicles).

Vehicle type A and the unloading operation exhibited a lower probability of crane idleness, which increases the likelihood of queuing over the long term. For vehicle type A, the interarrival time is approximately six minutes. In contrast, no interarrival time is calculated for the unloading operation due to its dependency on delays affecting the loading process. Specifically, the unloading operation absorbs timing shifts from the loading operation, causing the interarrival time at the unloading stage to reflect changes originating from earlier cycles. The long-run average queue time for each vehicle type during loading and unloading operations was computed (Figure 7). Vehicle type A displayed significant variability across delay scenarios, with the shortest queue time occurring at a two-hour delay. Vehicle type B demonstrated minimal sensitivity to delay variations in both loading and unloading operations. For both vehicle type B and the unloading operation, the lowest long-run average queue time corresponded to a two-hour delay. This outcome aligns with the observed probability of crane idleness, confirming that the two-hour delay scenario optimizes queuing efficiency for these operations.

Vehicle type A exhibited significant variability in projected queuing times, with optimal performance observed under scenarios with no delay and a two-hour delay. However, this outcome may be misleading, as a no-delay scenario would typically result in queuing times comparable to or exceeding those observed with a one-hour delay. Specifically, in the no-delay scenario, total queuing time for all 21 type A vehicles was approximately 15 hours, averaging less than one hour per vehicle. In the two-hour delay scenario, the intervals between vehicle arrivals were well distributed during the unloading operation, contributing to reduced queuing times. Conversely, scenarios involving one-hour and three-hour delays yielded the highest long-run average queuing times. One plausible explanation for this discrepancy is the interaction between the crane production yield during loading and unloading operations and the production capacity of vehicle type A. This interaction may have contributed to the distinct behavior observed for vehicle type A compared to vehicle type B. These findings underscore a critical limitation of scenario 1 (base scenario), which only matches the aggregate production rates of vehicles and cranes without assigning specific vehicles to designated cranes. Such an approach overlooks individual scheduling dynamics, leading to unrealistic queuing patterns under certain delay conditions. Addressing this limitation by incorporating more granular control over vehicle-to-crane assignments is essential to achieve more accurate and reliable queuing performance outcomes.

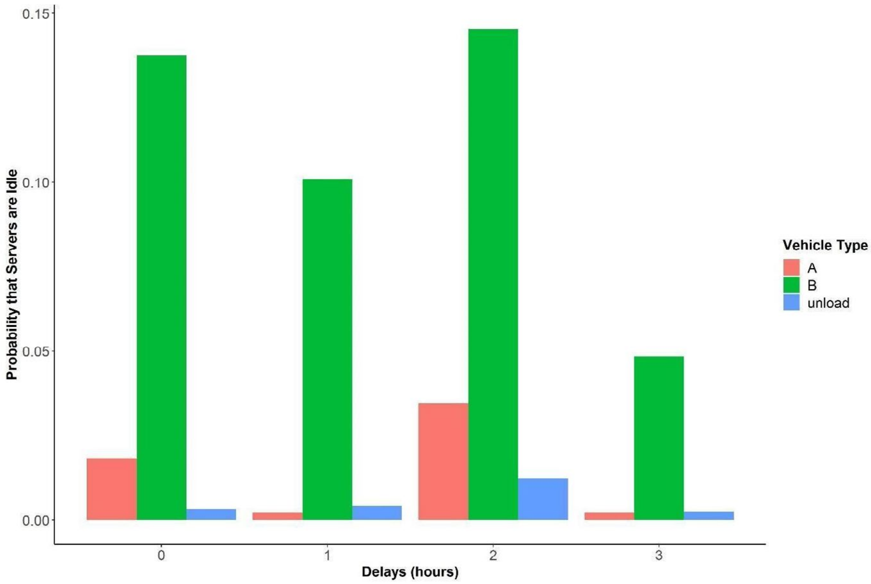

Figure 6: Probability of idleness of the cranes for each simulated delayed time for scenario 1 (base scenario).

Scenario 2: MAM + FCD + QLsim

In scenario 2, the FCD serves as an intermediary between the Machinery Allocation Model (MAM) and the queue simulator. The primary function of the FCD is to allocate vehicles of types A and B to the appropriate cranes during both loading and unloading operations. When the FCD is incorporated as an intermediate step, the queuing time (Table 5) follows a logical pattern, increasing proportionally with the delay time for both vehicle types during the loading process. For the unloading operation, queue time is observed only in the no-delay scenario. This occurs because delays introduced during the loading phase affect the unloading schedule, allowing the unloading operation to adjust vehicle group schedules in accordance with crane availability and dynamics. Consequently, when delays are present in the loading phase, they help distribute vehicle arrivals more evenly during unloading, reducing queuing times.

The effective work hours were proportionally influenced by delays, with longer delays resulting in increased work hours. Assigning vehicles individually to cranes enhanced operational control and mimicked human decision-making, effectively reducing queue times even under high-delay scenarios. The probability of crane (server) idleness during loading operations varied across tested delay options, with vehicle type A exhibiting a higher likelihood of idle cranes (Figure 8). Although vehicle type A operated with 21 wheelers and three cranes, it showed greater idle crane probability due to the shorter time required to load its vehicles. Despite the lower productivity of cranes assigned to vehicle type A

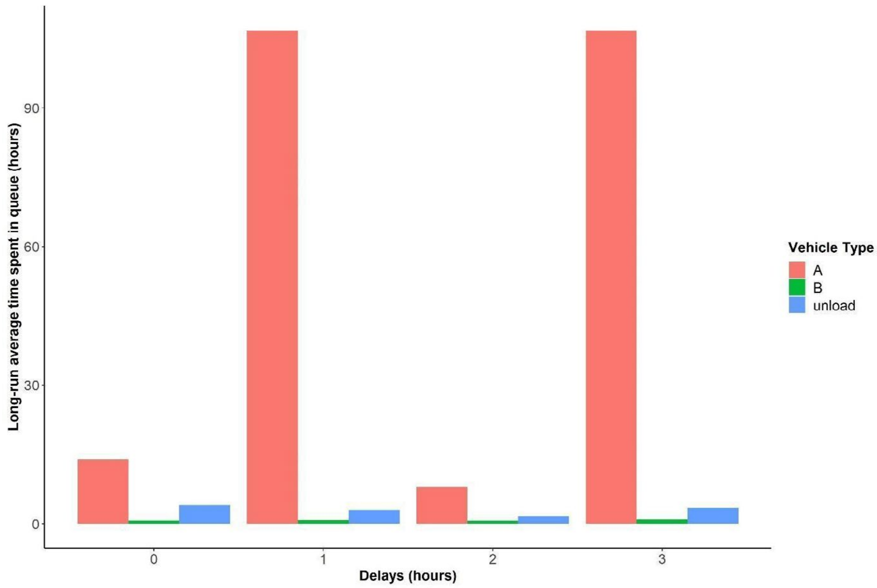

Figure 7: Long-run simulation of the average time spent in the queue for scenario 1 (base scenario).

Table 5: Summary of effective working time and average queuing time for each vehicle type and trucking operation in scenario 2.

Delay (h)	Vehicle Type	Effective working time (h)	Average queuing time (h)
0	A	27.30	1.00
1	A	29.63	1.33
2	A	31.97	1.67
3	A	34.30	2.00
0	B	23.90	3.60
1	B	28.61	3.94
2	B	33.33	6.09
3	B	38.04	8.23
0	Unloading	26.32	1.73
1	Unloading	29.35	0.00
2	Unloading	32.79	0.00
3	Unloading	36.41	0.00

compared to those assigned to vehicle type B, the idleness probability remained higher for vehicle type A. This outcome aligns with the Forest Transportation Problem (FTP) model, which optimized the allocation of 21 type A vehicles to three cranes and 18 type B vehicles to six cranes. The integration of the Fuzzy Controlling Device (FCD) with the FTP model provided deeper insights into the transportation process, highlighting the dynamics between crane productivity, vehicle allocation, and queuing behavior.

For the unloading operation, the probability of crane idleness increases with simulated delays. This occurs because delays shift the truck schedule, reducing queuing times in subsequent cycles. The FCD results corroborate the logical expectation that queuing times decrease as transportation delays increase. As a result, trucks take longer to reach unloading stations, spend less time in queues, and crane idleness becomes more pronounced. This behavior is particularly evident in the abrupt change observed between the no-delay and one-hour delay scenarios (Figure 8). The queuing system simulation for vehicle type A showed a higher average time spent in queues compared to vehicle type B in the long-term analysis (Figure 9). The delay scenarios highlight differences between the two vehicle types during the loading operation. For vehicle type B, the average queuing time increased almost linearly with delays. In contrast, vehicle type A exhibited a non-linear increase in queuing time as delays grew. This suggests that vehicle type B faces operational challenges in aligning wheeler-to-crane assignments, despite being allocated more cranes (six cranes) in the optimization process.

The lower probability of idle cranes for vehicle type B (Figure 8) supports this conclusion, indicating intensive crane utilization but higher queuing times. In scenario 2, the unloading operation displayed behavior more consistent with queuing theory expectations, particularly when the number of clients (wheelers) exceeded the number of servers (cranes). As delay times increased, the long-term average queuing time decreased, reaching its minimum. This outcome is attributed to the higher productivity rates of cranes during unloading compared to loading operations. The queue system analysis validates this characteristic of the transportation strategy, confirming the operational efficiency gains in the unloading process under extended delay scenarios.

DISCUSSION

Vehicle scheduling systems enhance efficiency in forestry industries, contributing to both economic and environmental benefits (Monti et al., 2020; Weintraub et al., 1996). Analyzing truck-crane interactions helps identify bottlenecks and idle periods within the forest transportation system, which can be optimized to lower transportation costs (Monti et al., 2020). Operational delays disrupt transportation flow, leading to queues at loading and unloading stations (Ghaffariyan, 2021). The FTP model, combined with a queue simulator, effectively generated a queuing plan for vehicle types A and B and their respective loading and unloading cranes. The FTP model optimized resource allocation by considering the total effective operating time for each vehicle type. However, it was not designed to predict the interactions among vehicles of the same type during loading, nor the queues formed throughout the operation. The queue simulator addressed this gap by simulating queuing schedules without controlling truck-to-crane assignments (scenario 1). In contrast, the FCD refined operational control in scenario 2, resulting in more logical outcomes through reduced queuing times and improved allocation of wheelers to their designated cranes.

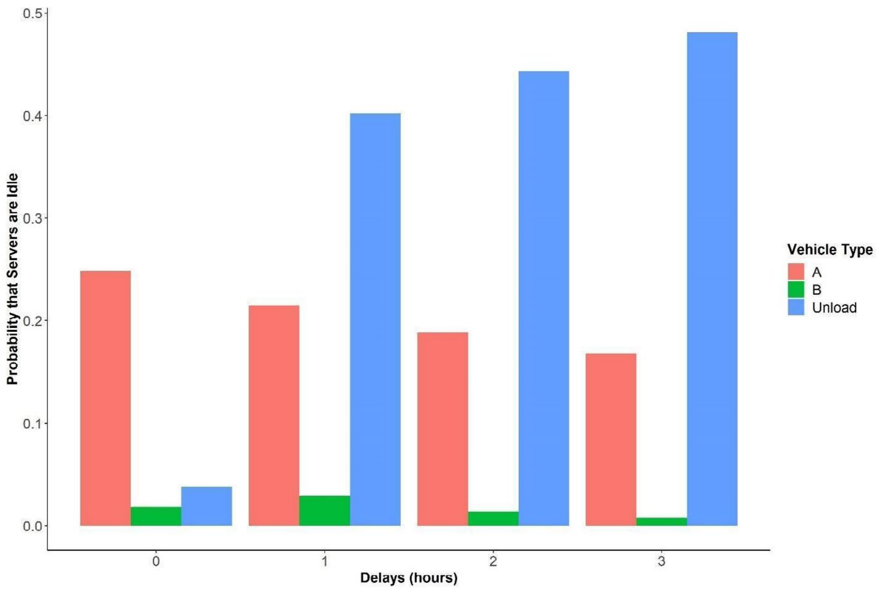

Figure 8: Probability of idleness of the cranes for each simulated delayed time for scenario 2.

Kogler and Rauch (2020) developed a discrete event simulation (DES) tool for operational planning within an interconnected timber supply chain. This tool allocates resources under multiple objectives, aiming to minimize equipment use and maximize production while controlling queue formation. The FCD + FTP approach mirrors this methodology by reducing both queueing and equipment use, ultimately lowering transportation costs. The dynamic crane allocation strategy enabled by the FCD significantly enhances process efficiency. The FTP model optimizes timber transportation logistics through a simple yet effective framework. When integrated with the queue simulator and FCD, it offers post-optimization improvements that enhance the queuing system. Scenario 2 demonstrated a notable reduction in machinery requirements, optimizing the fleet to 51 units, and improving overall queuing performance. This finding highlights the FCD's effectiveness in minimizing operational queues and improving resource utilization within forest transportation systems. The optimization model's results provide substantial support for transportation industry decision-makers. By determining the ideal number of trucks and cranes, businesses can streamline operations, reduce costs, and enhance overall efficiency. Additionally, the successful application of transportation-based optimization models underscores the critical role of mathematical optimization techniques in addressing real-world logistical challenges (Figure 10).

The second key finding of this study is the effectiveness of the Fuzzy Controlling Device (FCD) in reducing queue times. Simulation results revealed that the fuzzy controller significantly lowered queuing times compared to scenarios relying solely on the queue simulator, even when critical delays were introduced. This highlights the capability of fuzzy logic controllers to manage dynamic, complex, and unpredictable transportation scenarios. The FCD proved effective across various delay conditions (0h, 1h, 2h, 3h), underscoring the

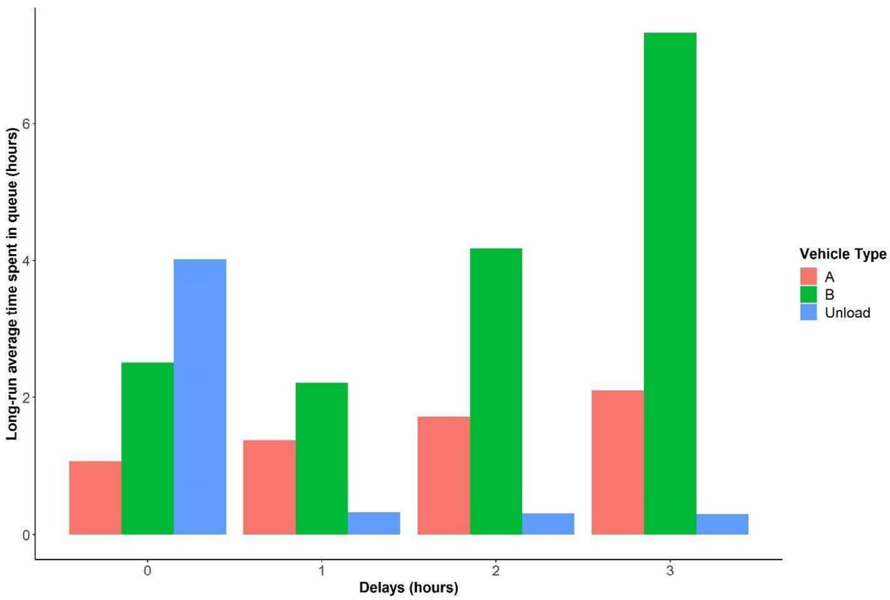

Figure 9: Long-run simulation of the average time spent in the queue for scenario 2.

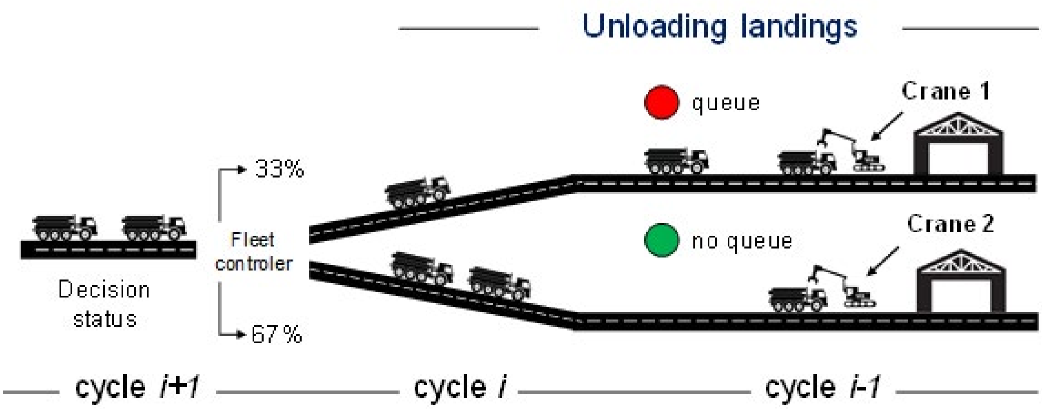

Figure 10: Decision making process under forest transportation dynamics and fleet controlling.

importance of real-time monitoring for improving timber logistics efficiency. Amrouss et al. (2017) demonstrated a real-time optimization approach for forest transportation that uses online communication and positioning devices, enabling rapid responses to random disturbances. However, this method requires rerunning the model with each disruption. In contrast, the FCD autonomously responds to such events, emulating expert decision-making and narrowing the gap between planned and actual operational costs. Similarly, Malladi, Quirion-Blais, and Sowlati (2018) reported a 12% reduction in transportation costs through optimized scheduling. Teodorovic (1999) emphasized the relevance of fuzzy logic in modeling complex traffic and transportation systems, citing its ability to handle subjectivity, ambiguity, uncertainty, and imprecision in human decision-making. Traditional linear programming models often fail to accommodate these uncertainties, as they assume constant travel times and require recalculations upon disruptions. Fuzzy controllers, however, address these challenges by using linguistic variables and fuzzy rules, enabling quicker system responses and streamlined transportation operations.

The green supply chain represents a frontier for addressing environmental, social, and economic challenges (Paul et al., 2021). The fuzzy system presented in this study enhances forest transportation by optimizing vehicle assignments, reducing costs, minimizing greenhouse gas emissions, lowering resource consumption, and improving job safety. Integrating the proposed method with larger fleets could further validate its efficiency. Sun and Li (2024) explored green logistics optimization using a hybrid algorithm combining greedy and genetic algorithms, showing that while such methods can help achieve environmental goals, queue-related inefficiencies may hinder emission reduction efforts. Many studies focus on aligning forest transportation models with real business cases, often evaluating model efficiency post-operation rather than in real time. Essghaier et al. (2023) support the view that deterministic optimization may be inadequate for real-world conditions, advocating for fuzzy optimization due to its adaptability. The third major finding is the comparison between scenarios involving the LP model alone and those incorporating both the LP model and FCD. The integration of fuzzy logic along with LP-based models led to shorter queuing times and enhanced system performance. This demonstrates that adding intelligent controllers like fuzzy logic significantly improves traditional optimization models. Other relevant research includes Minh and Noi (2023), who implemented a multi-server queuing model combined with genetic algorithms, reducing operating costs by 30–50%. Oliveira et al. (2022) identified the hybrid greedy-simulated annealing algorithm as the most effective for forest vehicle routing. Sarkar et al. (2015) used queuing theory to optimize machinery and personnel, achieving reduced idle and waiting times. The combination of the FTP model, queue simulator, and FCD in this study yielded similar improvements.

Forestry 4.0 integrates advanced technologies such as AI, IoT, big data analytics, precision forestry, and climate change mitigation strategies. Feng and Audy (2020) emphasized the importance of integrating digital technologies and automated systems for smart decision-making. Many forest vehicles now feature web-based allocation and GPS tracking systems, allowing real-time operations management. The methodology presented here contributes to this digital transformation by demonstrating how automated controllers can optimize forest transportation processes. In conclusion, this study provides key insights for enhancing transportation infrastructure and minimizing queuing times. The optimization model identified an optimal number of trucks and cranes, while the fuzzy controller effectively managed uncertainties, reducing queuing times and operational costs. Combining fuzzy logic with optimization models offers a promising approach for addressing complex transportation challenges. Future research should explore the integration of additional intelligent control techniques to further optimize transportation systems.

CONCLUSION

We have developed a fuzzy controlling device (FCD) for timber logistics, optimizing vehicle and crane fleets based on operational constraints to minimize queuing times. The integration of the Machinery Allocation Model (MAM), FCD, and the queue simulator (QLsim) resulted in logical queuing behavior within forest transportation operations. While the MAM effectively optimized truck and crane fleets for loading and unloading through an integer programming model under a deterministic framework, the FCD enhanced the interpretation of optimization results by replicating human decision-making. Specifically, the FCD assigned more vehicles to cranes with lower queuing tendencies, effectively addressing the queuing problem in forest logistics. Simulation results demonstrated that vehicles paired with higher-productivity cranes required fewer trucks to achieve efficient transportation compared to those with less productive cranes. The dynamic nature of vehicle queues in forest logistics highlighted the necessity of strategic interventions to improve operational efficiency. Our findings indicate that adopting automation and optimization approaches can lead to more efficient and sustainable practices in forest operations.

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AUTHORSHIP CONTRIBUTION

Project Idea: C. A.U. M.; L. R. G.

Funding: C. A. U. M.; L. R. G.

Database: C. A. U. M; L. R.G.

Processing: C. A. U. M; L. R. G.

Analysis: C. A. U. M.; V. S. G.; S. J. M.; L. R. G.

Writing: C. A. U. M.; V. S. G.; S. J. M.; L. R. G.

Review: C. A. U. M.; V. S. G.; S. J. M.; L. C. J. F.; K. J. V.P; M. C.C.; C. S. J. S.; L. R. G.

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