CÁSSIO AUGUSTO USSI MONTI

OPTIMIZATION OF QUEUING COMPLEXITY IN THE FOREST TRANSPORTATION PROBLEM

LAVRAS - MG

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Tese apresentada à Universidade Federal de Lavras, como parte das exigências do Programa de Pós-Graduação em Engenharia Florestal, área de concentração em Ciências Florestais, para obtenção do título de Doutor.

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OTIMIZAÇÃO DA COMPLEXIDADE DE FILAS NO PROBLEMA DO TRANSPORTE FLORESTAL

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À minha família.

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RESUMO

A necessidade de reter custos é um desafio constante das empresas do setor florestal, tanto no Brasil quanto no mundo, e um dos fatores de maior impacto nos custos de produção do setor, sem dúvida, é a logística da colheita e transporte florestal. Sob esta ótica, o objetivo deste trabalho foi avaliar um sistema de controle operacional do transporte florestal pós otimizado utilizando sistema *fuzzy* de inferência considerando cenários reais de empresa do setor juntamente com simulação de atrasos no sistema. Um modelo clássio de programação linear inteira e um simulador de fila foram usados para validação dos resultados. O modelo *fuzzy* foi associado ao simulador de fila para proporcionar o re-roteamento dos veículos baseado em variáveis da fila durante a operação. A comparação dos métodos se deu entre o modelo *fuzzy* e o simulador de filas sem o modelo *fuzzy*. Foram adicionados tempos de atrasos para avaliar a capacidade de adaptação dos métodos. O tempo de fila se manteve constante com o aumento do atraso nos resultados do simulador de filas. O modelo *fuzzy* calculou aumento do tempo de fila mediante aumento do tempo de atraso. O modelo *fuzzy* retornou resultados plausíveis com o esperado para o comportamento de tempo de filas quando comparado com apenas o simulador de filas. Em conclusão, o modelo *fuzzy* proporciona a aderência do conhecimento de especialista na modelagem da fila e proporciona melhor entendimento do processo de transporte florestal se comparado apenas com o simulador de filas.

Palavras-chave: Transporte florestal. Otimização em redes. Suprimento de madeira. *Fuzzy Sets*.

ABSTRACT

The need to retain costs is a constant challenge for companies in the forestry sector, both in Brazil and around the world, and one of the factors with the greatest impact on the sector's production costs, without a doubt, is the logistics of forest harvesting and transport. From this perspective, the objective of this work was to evaluate a post-optimized forest transport operational control system using a fuzzy inference system considering real company scenarios in the sector together with a simulation of delays in the system. A classic integer linear programming model and a queue simulator were used to validate the results. The fuzzy model was associated with the queue simulator to provide vehicle rerouting based on queue variables during the operation. The comparison of methods was between the fuzzy model and the queuing simulator without the fuzzy model. Delay times were added to evaluate the adaptability of the methods. The queuing time remained constant with the increase in the delay in the queuing simulator results. The fuzzy model calculated an increase in queue time due to an increase in delay time. The fuzzy model returned plausible results as expected for queuing time behavior when compared with just the queuing simulator. In conclusion, the fuzzy model provides adherence to expert knowledge in queue modeling and provides a better understanding of the forest transport process compared to the queue simulator alone.

Keywords: Forest Transportation. Forest Operations. Timber Supply. Fuzzy Sets.

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PRIMEIRA PARTE

1 INTRODUÇÃO GERAL

O transporte é uma das operações florestais de maior complexidade e que resulta em custos elevados para o setor (EPSTEIN, RÖNNQVIST e WEINTRAUB, 2007). No Brasil, o transporte florestal é majoritariamente realizado pelo modal rodoviário, principalmente, devido à grande malha viária e diferentes tipos de veículos, com várias capacidades de carga (MACHADO, LOPES e BIRRO, 2009). Os modais ferroviário e aquaviário se postam como opções viáveis para o transporte secundário de madeira. Contudo, o transporte primário, que se refere ao transporte de madeira do campo até um ponto secundário de descarregamento, ainda depende do transporte rodoviário na maioria dos casos de companhias florestais (TAHVANAINEN e ANTTILA, 2011).

Sendo o custo um dos principais focos na abordagem do problema do transporte florestal, inúmeros estudos vêm tratando desta temática ao longo dos anos, por exemplo, Monti et al. (2020) desenvolveram modelo de programação linear inteira mista para minimizar número de caminhões e custo total da operação levando em consideração tempo de fila como um fator constante. Epstein, Rönnqvist e Weintraub (2007) descrevem o problema do transporte florestal e afirmam que minimizar o número de caminhões traz diversos benefícios como, otimização do custo do transporte, reduz o impacto ambiental e impacto nas estradas florestais.

As filas no carregamento, descarregamento e área de processamento de madeira tem sido um problema frequente que vem demandando atenção de pesquisadores florestais (AUDY et al., 2023). A redução de filas e de tempo de espera dos caminhões e sincronização de caminhões e gruas vem sendo objeto de estudo ao longo dos anos utilizando principalmente programação linear (WEINTRAUB et al., 1996; EL-HACHEMI et al., 2008; RIX et al., 2015; AMROUSS et al., 2016; BORDÒN et al., 2020). Contudo, com o avanço de tecnologias de rastreamento e envio de informação, a aplicação da programação linear apresenta difícil implementação devido à baixa capacidade de reprocessamento em tempo real. Para tal uso, outros métodos de tomada de decisão apresentam maior aderência, como heurísticas e métodos de inteligência computacional.

Para dar caráter analítico as decisões tomadas em tempo real, muitos métodos de inteligência artificial são testados e os sistemas fuzzy tem grande destaque nesta aplicação (NAJA e MATTA, 2014; LEITE et al., 2016; PATIL e SOMA, 2018; NTAKOLIA e LYRIDIS, 2022). Leite et al. (2012) propuseram uma abordagem de modelagem online de dados não estacionários e encontraram resultados que comprovam *Fuzzy Sets* e modelos derivados como sendo opções mais promissoras na modelagem online de dados.

O objetivo geral deste trabalho foi investigar a logística do transporte florestal com foco em redução de complexidade de filas nas áreas de carregamento e descarregamento considerando estudo de caso. Uma nova metodologia baseada em lógica *fuzzy* foi desenvolvida considerando elementos da fila como inputs do modelo. A principal contribuição deste estudo é propor um modelo baseado em simulação de filas e *fuzzy logic* para o transporte florestal. Tal abordagem é inédita na literatura florestal. Objetivos específicos deste estudo foram:

1. Entender o uso de números nebulosos (*Fuzzy Sets*) na tomada de decisão em casos de incerteza (Primeira Parte – Referencial Teórico);
2. Validar a metodologia desenvolvida utilizando *Fuzzy Sets* para a tomada de decisão no transporte florestal (Segunda Parte – Artigo).

2 REFERENCIAL TEÓRICO

2.1 Teoria dos Números Nebulosos

A Teoria dos Números Nebulosos, também chamada de Teoria *Fuzzy* or *Fuzzy Sets*, se figura dentre os métodos mais avançados de recomendação e auxílio na tomada de decisão, os sistemas fuzzy granular evolutivo tem notoriamente destaque no cenário científico e aplicado, sendo utilizados como tecnologia autônoma de recomendação de resposta nas linhas de metrô da cidade de Tóquio e em controle de temperatura em industrias, dentre outras. Sendo um sistema não linear baseado em regras linguísticas do tipo IF-THEN para modelar os aspectos humanos de conhecimento de especialista sem, no entanto, empregar análises quantitativas de precisão (POURJAVAD e MAYORGA, 2019). Segundo Leite et al. (2012), a modelagem linguística, principalmente do consequente da regra fuzzy, proporciona melhor aproximação das curvas e maior interpretabilidade dos resultados. Os sistemas fuzzy surgem como uma ferramenta funcional e têm no modelo Mandani (Mamdani e Assilian, 1975) sua forma mais simplificada, porém eficaz, de inferência com base em modelagem linguística através de funcionais chamados funções de pertinência. No sistema Mamdani, o consequente da regra fuzzy é definido pelo conhecimento de especialista (Zadeh, 1965). Por sua vez, as funções de pertinência balizam o processo de acordo com as relações definidas pelas regras linguísticas do antecedente com o consequente do sistema (Figura 1). Como exemplo de funcionais de pertinência se pode citar: Trapezoidal, Triangular e Gaussiano.

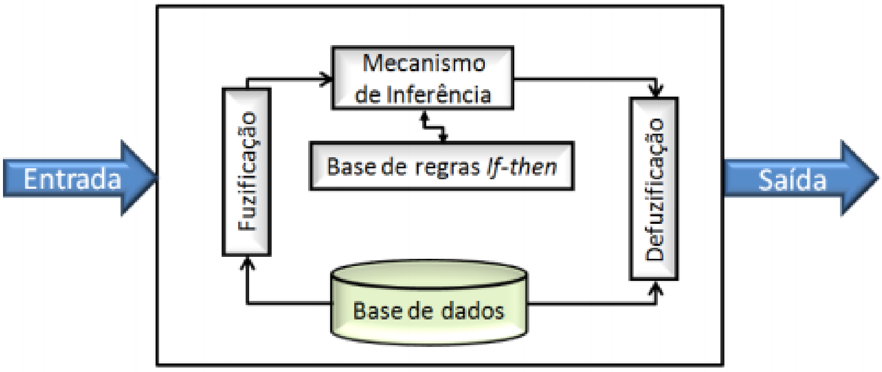

Figura 1. Esquema de um sistema de inferência fuzzy do tipo Mamdani. Fonte: Zimmermann (1991)

O modelo Takagi-Sugeno é uma forma mais sofisticada do modelo Mamdani de inferência fuzzy, tendo o consequente da regra fuzzy como uma série de equações, comumente lineares, definidas a partir do conjunto de regras linguísticas e sendo ativadas de acordo com as entradas do sistema (POURJAVAD e MAYORGA, 2019). O modelo Takagi-Sugeno proporciona conexão mais precisa do modelo linguístico com os dados de entrada, tendo a subjetividade do conhecimento de especialista mitigada pela atualização do conjunto de regras do consequente com base nos dados de treinamento. Tanto o sistema Mamdani quanto ao Takagi-Sugeno são normalmente utilizados nos sistemas fuzzy evolutivos (LEITE et al., 2012).

Um sistema fuzzy granular evolutivo modifica o sistema Takagi-Sugeno e Mamdani, podendo atuar concomitantemente dando conhecimento de especialista e ao mesmo tempo aderindo aos dados, de forma a agrupar as informações de entrada e considerando o conceito de similaridade matemática (LEITE et al., 2012). Uma série de métodos de cálculo de distância proporcionam diferentes interpretações de similaridade que, por sua vez, são entendidas como limites de separação dos dados para a criação dos grupos ou grânulos fuzzy. A função de pertinência gaussiana tem demonstrado eficiência e eficácia representando a distância esperada entre instâncias incertas pertencentes a dois grânulos diferentes (LEITE et al., 2012), sendo este funcional um dos mais utilizados na geração dos grânulos durante a dinâmica do processo fuzzy granular evolutivo. Durante o processamento online, ou seja, de maneira que os dados entram no sistema fuzzy, eles atuam na atualização dos grânulos, tanto em tamanho quanto em forma funcionando como um método não supervisionado de tomada de decisão em tempo real (LEITE et al., 2016). O Quadro 1 ilustra um exemplo de regra fuzzy contendo o consequente linguístico e funcional, sendo que x_i é a variável de entrada, A_n é a função de pertinência criada de acordo com os dados de entrada e *pm* é o polinômio de aproximação.

IF (x_1 is A_1) AND... AND (x_n is A_n) THEN (y_1 is B_1) AND $y_1 = pm(x_j \forall j)$

Quadro 1. Exemplo geral de regra fuzzy do tipo Takagi-Sugeno evolutivo.

2.2 Aplicações de Teoria de Números Nebulosos no Transporte

O uso de *Fuzzy Sets* para tomada de decisão no transporte é amplamente abordado em diversos estudos. Patil e Soma (2018) desenvolveram um sistema de tomada de decisão que usa regras *fuzzy* baseado no volume de trafego em rodovias para veículos evitarem congestionamento. O sistema proposto apresenta uma rede de comunicação de veículos para que eles troquem informação ao longo do deslocamento em rodovias (VANETs). Os autores concluem afirmando que o tempo de espera no transito é reduzido com o uso do sistema proposto. Adicionalmente, eles dizem que o sistema desenvolvido promove o re-roteamento dos veículos para que eles não entrem em congestionamento. Naja e Matta (2014) apresentam solução similar ao estudo anterior, contudo, descrevem um método baseado em regras *fuzzy* aplicado a entrada de rodovias de grande movimento com auxílio de sistema inteligente de transporte com monitoramento em tempo real dos veículos. Os resultados demonstram redução de tempo de viagem e que seu sistema é capaz de caracterizar as condições de trafego com eficiência.

Fuzzy Sets proporcionam grande flexibilidade nas aplicações em diversas áreas do conhecimento sob diversas ópticas. Shelke, Malhortra e Mahalle (2019) desenvolveram um sistema de controle inteligente de trafego *fuzzy*. O modelo desenvolvido é baseado no funcionamento dos sinais de transito para otimizar o deslocamento por centros urbanos a fim de evitar longos congestionamentos. Sensores monitoram as informações de transito e define prioridades *fuzzy* para mudança de sinal de transito. Os autores concluem recomendando seu sistema de controle de trafego devido à capacidade de redução de tempo de espera e de número de veículos em espera baseado em dados simulados.

Métodos heurísticos de otimização de problemas combinatórios ou não-lineares também são amplamente utilizados para tratamento de problemas de logística e transporte. *Fuzzy Sets* também são adaptáveis nos procedimentos internos de heurística para resolução de problemas de otimização, por exemplo, Ntakolia e Lyridis (2022) criaram um método híbrido combinando algoritmo de colônia de formigas com *fuzzy logic* para o problema de trafego aéreo. Os autores propões uma formulação inteira não-linear mista do chamado Air Traffic Flow Management (ATFM) baseado em trajetórias 4-D dos voos. O objetivo do modelo foi minimizar o custo total dos atrasos causados durante os voos, como variações de velocidade, alteração de rotas e políticas de cancelamento. O algoritmo híbrido foi desenvolvido para resolver este problema utilizando regras *fuzzy*. Os autores reportam resultados positivos em favor do algoritmo híbrido quando comparado com métodos tradicionias e concluem notando que *fuzzy sets* permitem a avaliação quantitativa das rotas geradas pelo algoritmo e isto favorece a melhoria das soluções.

2.3 Aplicações de Teoria de Números Nebulosos na Modelagem Florestal

Dentro das diversas aplicações dos modelos fuzzy possíveis de serem citados na literatura florestal, alguns se destacam pela adaptabilidade do método e tratamento da incerteza associada à problemas mais complexos (KANGAS e KANGAS, 2004).

O uso de *Fuzzy Sets* para melhor abordar objetivos contrastantes como sustentabilidade, equidade e saúde de ecossistema proporciona uma ferramenta flexível e robusta ao mesmo tempo (DUCEY e LARSON, 1999). Embora as necessidades de incorporação de práticas concretas sobre sustentabilidade são crescentes, a falta de clareza em que este conceito se refere é evidente (O'LAUGHLIN et al., 1994). Decisões acerca de sustentabilidade frequentemente se conflitam com múltiplos interesses, o que dificulta a quantificação pelos métodos tradicionais (IVERSON e ALSTON, 1993). Ducey e Larson (1999) propuseram uma abordagem *fuzzy* para tratar a modelagem de sustentabilidade através de uma técnica tabular usando *fuzzy sets* para a comparação de alternativas de manejo incorporando multiplex objetivos. Esta tabela desenvolvida consiste em proporções associadas a decisões florestais hipotéticas tomadas por um indivíduo ou grupo de indivíduos. Os autores definiram níveis de satisfação maior do que 0.5 como send o critério de aceitação da alternativa de manejo. Ducey e Larson (1999) compararam seu modelo com dois métodos tradicionais, processo de hierarquia analítica e técnica de matriz simples. Os autores concluem que os métodos tradicionais são mais complexos e não proporcionam a flexibilidade necessária para o tratamento de tais problemas. Contudo, *fuzzy sets* possibilita a tomada de decisão racional para objetivos incertos ou imprecisos com relativa simplicidade computacional.

Os problemas florestais clássicos de tomada de decisão são relacionados ao agendamento da colheita florestal. O uso de *Fuzzy Sets* proporciona flexibilidade no tratamento de incerteza e imprecisão (PASALODOS-TATO et al., 2013). Pickens e Hof (1991) implementaram *fuzzy goal programming* para o problema de agendamento de colheita florestal com o objetivo de maximizar o mínimo valor presente líquido (VPL) periódico. Os autores reportam fluxo aproximadamente constante de colheita no horizonte de planejamento e significativo aumento do VPL. Bare e Mendoza (1992) notaram frequentes estudos com resultados excessivamente otimistas e a necessidade de satisfazer restrições com baixa flexibilidade. Portanto, eles implementaram uma metodologia *fuzzy* para reconhecer as incertezas inerentes do problema de agendamento florestal. Os resultados indicaram que níveis adicionais de exploração dos recursos foram atingidos, proporcionando melhoria considerável na função objetivo. Contudo, o modelo *fuzzy* apresentou limitação na restrição de fluxo constante de colheita.

Outra comum aplicação de *Fuzzy Sets* é na abordagem de habitat para vida selvagem devido ao elevado nível de incerteza e subjetividade oriunda de conhecimento de especialista (US FISH AND WILDLIFE SERVICE, 1981). Diversos estudo vem sendo desenvolvidos para criação de índices de habitat, por exemplo, Yi et al. (2014) compararam modelos de índice de habitat para uma espécie de peixe esturjão. Dentre as abordagens utilizadas os modelos *fuzzy* foram testados e comparados com métodos tradicionais. Duas estratégias *fuzzy* foram comparadas, baseada em conhecimento de especialista e baseada nos dados. Os autores concluem afirmando que na presença de dados, a metodologia *fuzzy* baseada em dados é ligeiramente superior ao método tradicional; contudo, na ausência de dados de campo, a metodologia *fuzzy* proporciona uso mais eficiente de informações. Jorde et al. (2001) desenvolveu melhorias no software CASIMIR de predição de índices de habitat através do uso de regras *fuzzy*. Eles compararam dados amostrais e modelos tradicionais com o modelo *fuzzy* testado e encontraram alta correlação das predições geradas pelo modelo *fuzzy* em relação ao modelo tradicional.

3 CONSIDERAÇÕES FINAIS

O planejamento florestal apresenta várias vertentes de atuação e o planejamento da logística do transporte de madeira se enquadra dentro da gama problemas de difícil resolução no setor florestal. Para execução de tal tarefa, técnicas matemáticas e probabilísticas são comumente usadas. Como demonstrado nesta Primeira Parte, Teoria *Fuzzy* pode ser utilizada em várias aplicações florestais, porém nenhum estudo ainda foi realizado na área de logística florestal abordando o problema de filas nas áreas de carregamento e descarregamento. Quando o problema de filas se faz presente no transporte floresta, a utilização de sistemas mais robustos para tratamento das filas se faz necessário.

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SEGUNDA PARTE - ARTIGO

Optimization of Queueing Complexity in the Forest Transportation Problem

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ABSTRACT

To minimize the fleet of vehicles and cranes while taking operational limits into account, the focus of this work is on developing and evaluating a controlling device for timber logistics. To determine prospective wait times for the optimized system, a queue simulator is used. One scenario includes the controlling device, whereas the other does not. The study emphasizes the benefits of vehicle type A, which has more wheelers and fewer cranes than vehicle type B, making it more effective at constructing a queuing system. Although a numerical analysis is not given, the use of fewer cranes also suggests possible cost reductions. The Forest Transportation Problem model was used by the researchers to optimize the placement of trucks and cranes during loading and unloading operations. This model's concise mathematical formulation made it effective and easy to use. The fuzzy controlling device (FCD), which simulates human decision-making in allocating wheelers to cranes, improves understanding of the optimization outcomes. When comparing scenario 2 with it to scenario 1 without it, the latter seems to be more beneficial in replicating the queuing system for the particular study situation. In the forest transportation scheme, the combination of FCD and the queue simulator provides logical behavior of queues. The study findings show how the created controlling device may effectively optimize timber logistics, resulting in in- creased queuing system efficacy and potential crane utilization cost savings.

The FCD application improves decision-making and offers insightful information on forest transportation operations.
Keywords: Fuzzy controlling device, Queuing system, Decision-making, Timber logistics, Timber trucking.

1 INTRODUCTION

Transportation is a critical component of forest logistics. Efficient transportation planning can reduce transportation costs, increase the utilization of transportation resources, and minimize the environmental impact (BORDÓN, MONTAGNA and CORSANO, 2018; RÖNNQVIST et al., 2015). However, forest transportation is a complex problem that involves multiple criteria, including transportation costs, queuing issues, vehicle capacity, and road conditions. In addition, the transportation problem in forest logistics is often complicated by uncertainties and imprecisions, such as variations in queues of loading and unloading points travel times, degradation of forest roads, and truck breakdowns (AMROUSS et al., 2017; MALLADI and SOWLATI, 2017). SIBDARI; SEPASI (2022) solved a forestry logistics problem, using a simulation-optimization approach that allows the incorporation of different uncertainties, such as stochastic travel time and occurrence of external factors, such as random demand and external delay in roads, mills, and forests. The authors suggested a solution approach to this complex problem in real-world problem size. HAN et al. (2018) developed a mixed integer programming model coupled with a network algorithm that optimizes biomass feed stock logistics on a tree-shaped road network. The model minimizes the total cost of the operation including grinding, transportation, residue loading, machine mobilization, and processing site construction. The authors found that the optimized solution reduced the cost of logistics by up to 11% compared to the conventional system.

The optimization of forest transportation is an essential research topic in logistics and forest planning. Transport planning is an important part of the forest industry supply chain and aims to ensure more efficient and sustainable transportation. Therefore, the transport plan must consider the various criteria involved in the transportation problem (AKAY and

DEMIR, 2022; ANDERSON and MITCHELL, 2016; MALLADI and SOWLATI, 2017). However, the traditional optimization techniques used in forest transportation planning often assume that the input parameters are precise and deterministic (PALANDER and VESA, 2022; SANTOS et al., 2019), which is not always the case in real-world situations, since different problems deal with sources of uncertainty (RÖNNQVIST et al., 2015). The forest transportation has other operations embed to it such as loading and unloading of timber and the queue that these operations generate over the planning horizon of the transportation. Many publications attempted to mitigate the occurrence of queues in forest transportation by using the deterministic approach. Rix, Rousseau and Pesant (2015) developed a mixed integer linear programming model based on column generation and solved a transportation planning problem over a 1-year time horizon that incorporates log truck scheduling elements to minimize transportation costs and queuing times. Bordón, Montagna and Corsano (2018) presented a Mixed-Integer Linear Programming (MILP) model for generating truck routes at minimum cost and guaranteed a logs supply. Some other publications attempted to address the issue via heuristics. Haridass et al. (2014) used simulated annealing that interacts with a deterministic simulation model of the log transport system to minimize the total unloaded miles traveled by trucks. Oliveira et al. (2022) solved the vehicle routing problem under forest transportation constraints and daily wood demand by testing three non-exact algorithms (Simulated Annealing, Greedy and Greedy-Simulated Annealing) into four operational strategies. However, the queue problem is purely stochastic (BYCHKOV et al., 2021), and there is a need to address the uncertainty and imprecision intrinsic to it. In their studies Yoshida and Takata (2019) simulated the daily chip production using a mobile chipper based on queuing theory and stochastic modeling. They quantified the influence of three uncertainties on the wood chip production and they noted that the uncertainty reduced the production by 14% to 27% compared to the production of deterministic simulation.

In recent years, Fuzzy Sets have emerged as a powerful tool for dealing with uncertainties and imprecisions in decision-making processes (BHARDWAJ and SHARMA, 2021; ÖZKIR and DEMIREL, 2012; SARKAR and AMRITA, 2012). Fuzzy inference systems allow for partial membership of an element in a set, which is particularly useful in situations where the boundaries between categories are not well- defined (LJUBOMIR et al., 2019). In the context of forest transportation, fuzzy inference systems can be used to optimize the transportation plan by considering multiple criteria and uncertainties simultaneously. Several studies have applied fuzzy sets in logistics transportation planning, such as Akay and Demir (2022) proposed a hybrid fuzzy multi-criteria decision-making method to reveal the weight values of the criteria that are effective in selecting the most suitable vehicle types in forest product transportation and in addiction, determine which vehicle alternative is the most suitable in given conditions. Chen et al. (2020) developed a multi-objective and multi-period fuzzy mixed-integer programming model that incorporates carbon emissions along with cost minimization to assess the impacts of uncertainty and environmental objectives on the configuration of timber supply networks. The contribution of this study lies in proposing an approach for controlling the post-optimized forest transportation problem using fuzzy inference systems. The main focus of the proposed approach is to provide realistic simulation of the queue system, via a developed queue simulator, and control the queuing time during the timber trucking operation, via the proposed fuzzy controller.

2 METHODOLOGY

2.1 The Machinery Allocation Model

The machinery allocation model (MAM) in terms of vehicle fleet (trucks and cranes) in the forestry context, on the basis of the Transportation Problem, must consider a sequence of adaptations. The loading and unloading capacity of cranes should be considered as well as the number of cycles executed by each vehicle and transportation capacity of each vehicle. This information is necessary to consistently mimic the timber trucking operation in order to meet a target timber volume to be transported from harvested-hauled stands to the processing mills, at unloading yards (Figure 1).

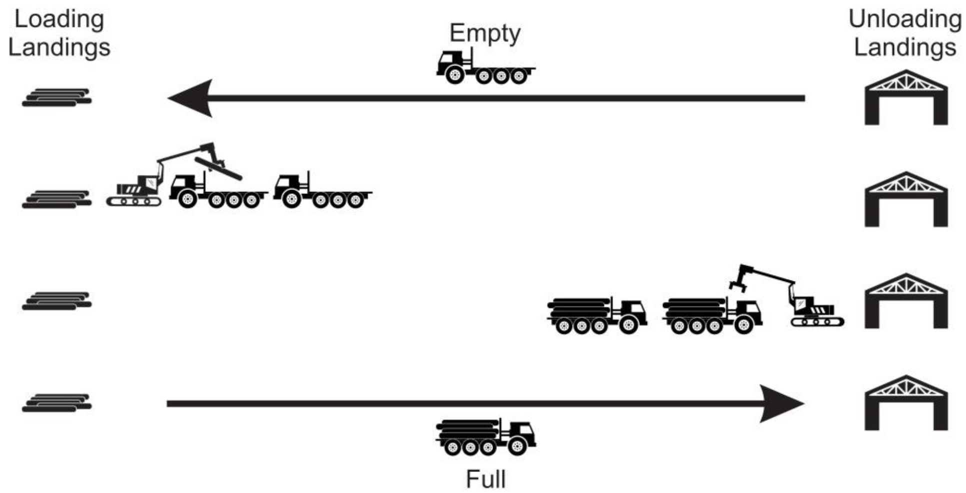

Figure 1: Basic representation of forest logistics of timber trucking.

The proposed integer programming (IP) model is represented in Equations 1-9. In this IP step, the goal is to minimize the total number of equipment (vehicles - Y and cranes - X) used in the transport operation (Equation 1). Therefore, the information about what crane or truck are activated is not assessed. The model was developed so that where there are loading/unloading cranes, the operation is executed. Therefore, a block of stands can be considered. This problem was described in more details on Monti et al. (2020).

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

Subject to

$$\sum_{i=1}^{N} CAP_i\, Y_i \; \geq 6750\; tons/day\; (Mill's\; specification) \qquad (2)$$

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

$$Y_i \;\geq\; LL_i\,, \quad \forall i \;\in 1, \dots, N \qquad (4)$$

$$Y_i \;\leq\; UL_i\,, \quad \forall i \;\in 1, \dots, N \qquad (5)$$

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

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

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

$$Y_i\,, X_i, W \;\in\; \mathbb{Z} \qquad (9)$$

Where Y_i is the number of vehicles of the class i, for i = {A and B}, X_i is the number of cranes belonging to the machinery list of vehicles i in the loading operation. In the loading operation, the cranes are truck-type-specific, which means that each vehicle type has a particular type of crane for the loading operation. The decision variable W represents the number of cranes in the unloading operation, which can serve all vehicle types. Therefore, the vehicle types compete with each other for cranes in the unloading operation, because they all can be served by all cranes available in the unloading station. However, for the loading operation, the cranes are truck-type-specific and in that operation the truck types do not compete for cranes with each other. The constants Q_i represents the expected amount of timber with which each vehicle must arrive at the mill. LI_i and UL_i are the lower and upper limits regarding the number of vehicles within vehicle type i. The time component of the model is defined by some constants V_i and H_i, both in hours/day, and they represent the time each vehicle type executes all possible cycles in a day, and the total hours allowed by vehicle type in one day, respectively. A cycle in this context is defined as the time it takes for the vehicle to complete the sequence: departs empty from unloading station, travels to the loading station, finishes the loading, travels back to the unloading station, finishes the unloading.

The production of each vehicle type, in tons/day (CAP_i), the loading capacity of the crane associated with vehicle type i, in tons/hour/day (C_i), and the unloading capacity associated with unloading cranes, in tons/hour/day (C_w) were considered in the model.

Equation 2 ensures that the mill's target volume is supplied. The Equations 3 - 5 guarantee the minimum production capacity for each vehicle per day and the upper and lower bounds of volume production for each vehicle per day. Equation 6 accounts for the total timing of the transportation per day and Equations 7-8 account for the link between the number of cranes necessary to load or unload the number of trucks of each type. Equation 9 defines the decision variables pertaining to the integer set.

The production yield related to each vehicle type, crane type, times, and target volumes corresponding to the mill daily operation requirements (Table 1) were collected.

Vehicle Type (i)	Q_i (tons/day)	LL_i (vehicles)	UL_i (vehicles)	H_i (h/day)	V_i (h/day)	CAP_i (tons/day)
A	1500	10	50	14.59	7.29	74
B	6000	10	50	16.13	5.38	351

Table 1: Yield metrics by vehicle type.

The production by crane type is defined at the machinery specifications. Loading crane type A produces 36.63 tons/hour and crane type B produces 65.85 tons/hour. For the unloading cranes, the production is 160.97 tons/hour.

2.2 Fuzzy Controlling Device

In the proposed fuzzy controlling device (FCD), the queuing time and proportion of vehicles being served by each crane are the variables that narrowed the process of controlling the transportation operation. The fuzzy system built for this study used the classical *Mamdani* system, with trapezoid membership functions. The trapezoid function was chosen due to its similarity with the classical set theory for decision making. For example, under the classic set theory, if a measured number is in a particular threshold interval, then you classify that number as belonging to the corresponding class of that interval (represented by a step-function in the classical set theory). Under the fuzzy theory, the same measured number has a degree of membership to distinct classes and not necessarily belong to a single class (represented by a trapezoid in the fuzzy theory).

Three classes (LOW, MEDIUM, HIGH) for each input variable (Figure 2) were created representing the status of the queuing time, in hours, and the proportion of vehicles being loaded/unloaded by specific cranes.

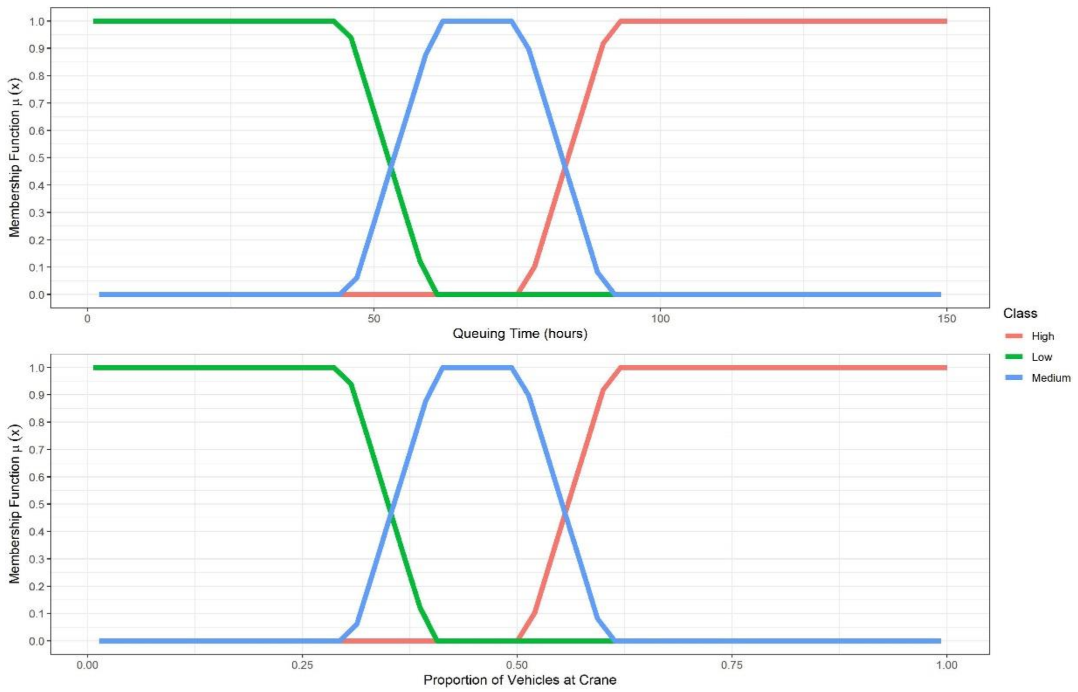

Figure 2: Membership functions of input variables: Queuing Time and Proportion of Vehicles at Crane

The definition of thresholds for the classes High, Medium, and Low was based on the Medium class. The Medium class was set to be proportional to the half of the range of each input’s support. For example, the Proportion of Vehicles exist within the interval [0,1], thus the Medium class should contain the 0.5. The legs of the trapezoid were defined based off expert opinion initially and previous sensitivity tests.

The fuzzy output is the proportion of vehicles allocated to each crane at the moment the vehicles begin the movement toward the crane. Aiming to have more control over the proportion of vehicles allocated (output), 5 classes (Figure 3) were designed for the fuzzy output (VERY LOW, LOW, MEDIUM, HIGH, VERY HIGH).

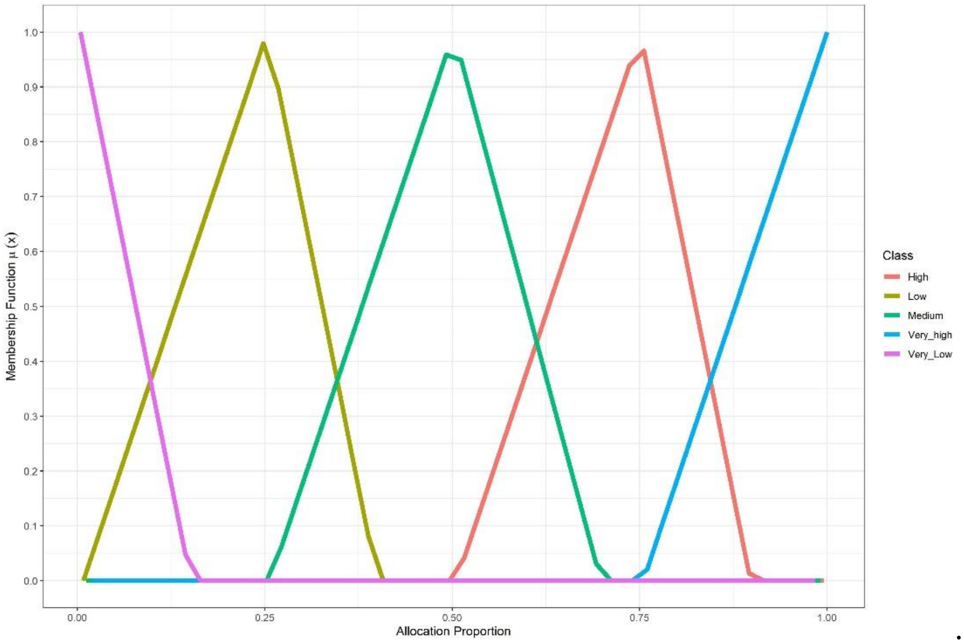

Figure 3: Membership function for the fuzzy output

The aggregation operator utilized was the *Min* function for the *AND* connections between fuzzy rules. All the 9 combinations were considered for the antecedent of fuzzy rules (Table 2). The consequent of fuzzy rules was defined based on an assumption: The larger the queuing time and proportion of vehicles being served by a crane; the smaller number of vehicles must be directed to this crane. The Centroid Method was selected as defuzzification method.

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

Table 2: Fuzzy rules for the antecedent (Queuing Time and Proportion of Vehicles) and the corresponding rules for the consequent (Vehicle Allocation).

Each crane (loading and unloading) was assigned to an unique fuzzy inference system aiming to make decision about the proportion of vehicles associated with that crane at each cycle. The controller device makes the decision upon integrated analysis of each crane type individually in the loading operation, which guarantees no association between crane types for the decision in this step. For the unloading operation, the process is repeated and the fuzzy controller device applies no restriction on which vehicle should be served by the cranes dissimilar to the loading operation. Therefore, for the unloading operation the decision making accounts for all vehicle types to being served by any available crane, which introduces the competition between vehicle type for available crane.

2.3 Study Case

The database for this study consists of machinery production data obtained from a time and motion study during 6 months. The forest industry uses the time and motion study to plan its weekly transportation operations, which, in this study case, consist of timber trucking, loading, and unloading operations. The company designed an independent loading system for the two vehicle types (A and B) that considers specific daily vehicle production as well as crane production. In this system, each vehicle type is served by a specific crane type in the loading operation. For the unloading operation, the two vehicle types compete for all cranes to be served. This strategy produces queuing time during the loading and unloading operations in a normal cycle. Each vehicle can complete a limited number of cycles per day, depending on the delays associated. However, in cases when there is a significant delay in any step of the process (vehicle displacement, loading, and unloading), the queuing time can be disruptive of the operation and needs to be better administered. In this study, the above description of the logistic operation is addressed under two different strategies, the scenario 1 and 2. Both scenarios were described in the Scenario and Simulations Section.

2.4 Scenarios and Simulation

For this study, the optimal number of trucks per vehicle type and cranes per crane type were allocated via the proposed machinery allocation model (MAM). A queue simulator was developed to simulate the queuing times associated with the forest transportation operation. In order to investigate the controlling capacity of the developed device (FCD), the FCD was applied in conjunction with the queue simulator (QLsim) so that the optimal number of vehicles can be well distributed across the timber trucking operation aiming to better represent the queuing time in the operation.

The model performance was computed by comparing the results regarding queuing time obtained from two scenarios: 1) MAM + QLsim (base scenario); and 2) MAM + FCD + QLsim (Figure 4). Delays were added to the simulation to investigate the disparity between scenarios 1 and 2. Each scenario was tested on 4 different delay magnitudes (0h, 1h, 2h, 3h) and the simulated long-run average queue time and the probability of idleness of the cranes were computed using a pertinent queue model. The effective working time of each vehicle type was also obtained based on the queue simulator computations as well as the average queuing time.

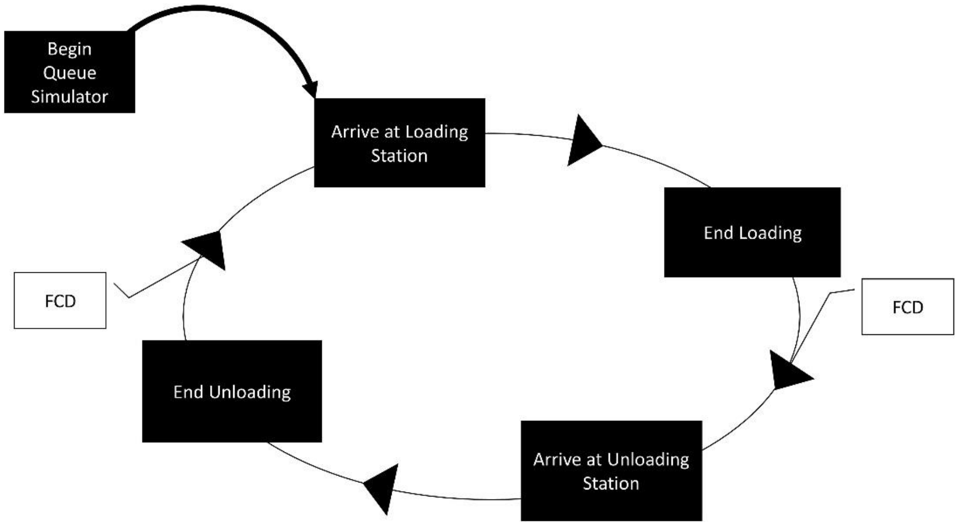

Figure 4: Dynamics of scenario 2 with the queue simulator (QLsim) and FCD operators.

The queue simulator algorithm was developed on the R environment and the FTP model was solved using the package "lpSolve" (BERKELAAR et al., 2022). The queue logistic simulator (QLsim) mimics the logistic system of the company and it is composed of 4 steps:

1. All vehicles arrive at the same time (5 AM) to the loading station and get served in the "first-in, first-out" (FIFO) scheme.
2. The queues are computed by matching production rates of cranes and vehicle types;
3. Once the vehicle is served, the next in line starts being served and the loaded vehicle heads to the unloading station;
4. At the unloading station, vehicle types A and B compete for crane availability under the FIFO scheme (The queues are formed following FIFO). When done, the cycle is complete and the next cycle initiates.

The QLsim is a heuristic of deterministic nature and was developed so that the timber production yields for the vehicle types and cranes, for loading and unloading operations, were matched according to the 4 steps outlined above. Therefore, the simulator produces the queues referring to each truck based on cranes and vehicle production yields, but it does not optimize the scheduling of trucks to cranes to compute the queue time. An example of queue time by the QLsim is provided (Figure 5). Suppose two trucks of the type A begin the service at 5 AM and take 1 hour to displace to the loading station. Thus, both arrive at the same time, 6 AM. Assume there is a single crane loading the trucks at that station, so a queue is formed with one truck on it (A2). If the truck A1 takes one hour to be fully loaded, the waiting time for A2 is one hour. Then, A1 departs from the loading station at 7 AM a displaces to unloading station, while A2 is loaded by the crane. The final time of both trucks are different due to the waiting time at the loading station at the beginning of the service. At the unloading station, there is no detected waiting time. The QLsim is only allowed to compute the waiting time during the loading and unloading operation. The delays introduced to the system as a the above described scenarios are injected to the loading and unloading stations.

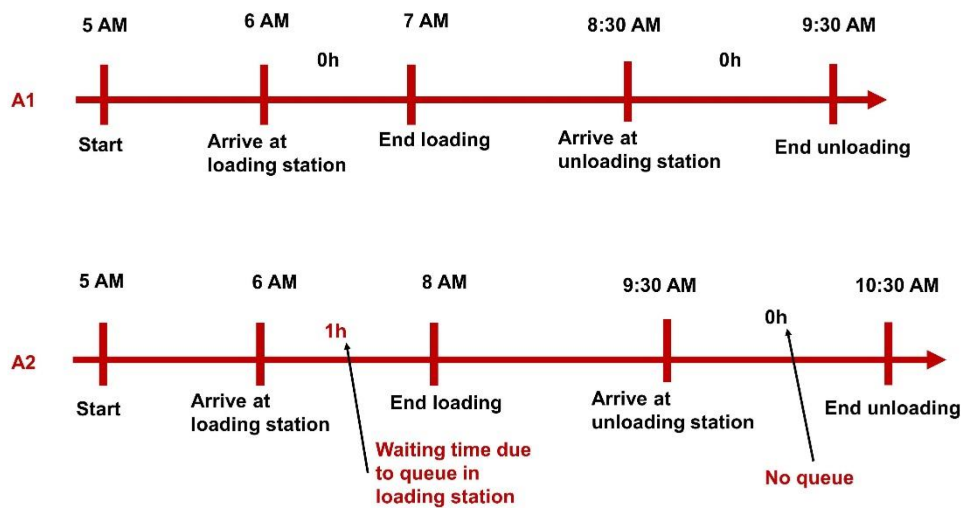

Figure 5: Example of computation of queue time by the QLsim for two trucks of the same type.

The queue model for the simulated problem can be shortly described as M/M/c under the “First-in Fist-out” (FIFO) scheme, in which the first M represents the assumption that the interarrival time follows the exponential distribution, the second M represents the assumption that the service time also follows an exponential distribution, and the term c represents the number of servers (cranes) in the queue system. The queue model functions as a poisson process with exponential service time distribution executed by the cranes loading/unloading the vehicles. The following probability density function was assumed for the FIFO scheme, $f(t) = (\mu - \lambda)e^{-(\mu-\lambda)t}$ for $t > 0$, and zero otherwise.

3 RESULTS

3.1 Fleet Minimization: MAM Assessment

The machinery allocation model optimized fleet size for vehicle type and cranes (Table 3). The integer programming model found the optimal solution in 2.3 seconds. The timber production in one day optimized by the model for the transportation operation was slightly higher than the minimum required tonnage per truck due to the requirements on the unloading operation. The unloading cranes must produce greater than or equal timber in comparison to the transported timber.

Vehicle Type	Number of Vehicles	Number of Cranes	Production (tons/day)
A	21	3	1554
B	18	6	6318

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

For the unloading operation, 3 cranes were allocated as the global optima. The total volume produced by the optimized set of cranes and vehicles was 7872 tons/day. The total number of vehicles to complete the transportation operation was optimized at 51, composed by 21 vehicles type A, 18 vehicles type A, 9 cranes for loading, and 3 cranes for unloading operation (Table 3).

3.2 Scenario Assessment

3.2.1 Base Scenario: MAM + QLsim

The base scenario composed by the MAM associated with the QLsim produced the queuing plan for the fleet of vehicle types A and B along with the respective crane service for loading and unloading operations. The effective working time under no simulated delay presented averages for vehicle type A and B equals 23.93 and 24.6 hours. The simulated delays presented decreasing pattern of effective working time as the delay increased (Table 4). The average queuing time kept constant across the delays within vehicle type for the loading operation due to the effect of the delays on the subsequent cycles shifts the time at which the vehicles are in the queue, but it does not affect the queue time itself within vehicle type. A fixed delay value mistakenly uniforms the simulation of the queue system when there is no control over the assignment between cranes and vehicles on a one-by-one basis

Delay (hours)	Vehicle Type	EWT	AQT
0	A	23.93	2.4
1	A	21.51	2.4
2	A	25.51	2.4
3	A	16.81	2.4
0	B	24.6	1.1
1	B	21.3	1.1
2	B	25.3	1.1
3	B	16.2	1.1
0	Unloading	24.26	3.24

1	Unloading	21.41	2.78
2	Unloading	25.41	2.78
3	Unloading	16.51	2.26

Table 4: Summary of effective working time and average queuing time for each vehicle type and trucking operation for scenario 1. Note: EWT - Effective Working Time; and AQT - Average Queuing Time.

For the unloading operation, the queuing time was decreasing with the increase of delay, which is the logical behavior taking into account that all vehicles arrived in the first loading operation on the first cycle at the same time. With the increase in delay, the vehicles spent more time on the road and less time forming queues.

The queue model described as M/M/c under the “First-in Fist-out” (FIFO) scheme has the term c as the number of cranes in the queue system. For the loading operation, $c = 3$ for vehicle type A and $c = 6$ for vehicle B. For the unloading operation, $c = 3$. Based on the outlined queue system on scenario 1, the probability that the cranes are idle (Figure 6) was computed. Vehicle type B presented the highest probability of idleness among the working cranes across the delay options, having its minimum probability at 3 hours and its maximum at 2 hours. This result indicates that with 2 hours of delay the vehicle B presented the most efficient transportation operation system with regard to the independent queuing structure. The fleet for vehicle type B was optimized with 18 vehicles, therefore the interarrival time, i.e., the interval of time in which the vehicles arrive, optimizes the queue system for this vehicle type around 7 minutes (2 hr * 60 min/hr / 18 vehicles).

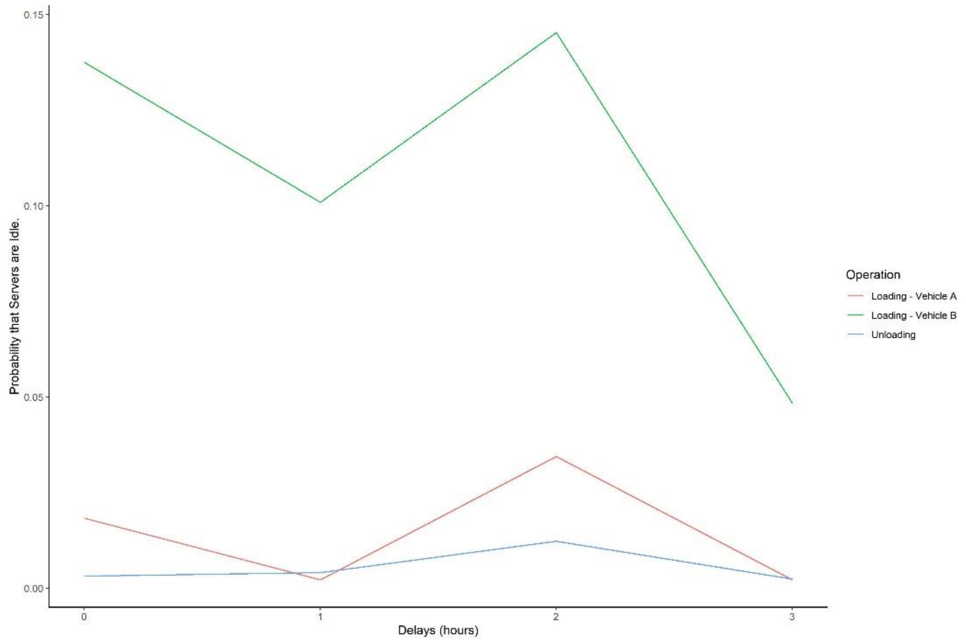

Figure 6: Probability of idleness of the cranes for each simulated delayed time for scenario 1 (base scenario).

Vehicle type A and the unloading operation presented smaller probability of idle cranes, which increase the chance of queues in the long-run. For vehicle type A, the interarrival time can be approximated to around 6 minutes. In the unloading operation there is no interarrival time computed due to the effect of the delay on the unloading operation. This happens because the transportation process is a connected, i.e., the unloading operation derived time absorbs the effects from the loading operation derived time in the cycle, therefore, the interarrival time applied to loading operation has shifting effect on the unloading operation.

The long-run average queue time for each vehicle type on loading and unloading operations was computed (Figure 7) and vehicle type A showed a major variation across the delay options, presenting its minimum value with delay of 2 hours. Vehicle type B presented small effect of delay options on the long-run analysis, as well as for the unloading operation. For vehicle type B and unloading operation the minimum long-run average queue time was with 2 hours of delay, which corroborates with the probability of cranes being idle during the operation with the same delay time option.

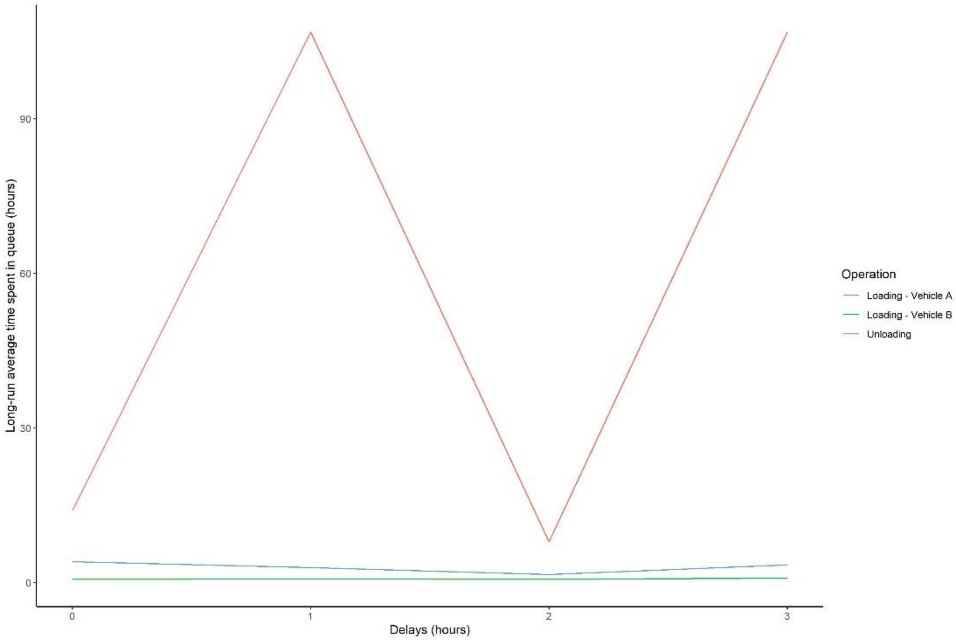

Figure 7: Long-run simulation of the average time spent in the queue for scenario 1 (base scenario).

Vehicle type A presented high variation for projection of queuing time and the optimal delay times tested were no delay and 2 hours of delay. This result can be misleading since "no delay" should yield queuing time similar to or higher than 1 hour of delay. For "no delay", the total queuing time was around 15 hours for all vehicles of type A, which produced less than 1 hour of queue on average for the 21 vehicles. In the case of the 2-hour delay, the gaps of time between vehicles were well distributed on the unloading operation. However, for 1 hour and 3 hours of delay, the long-run average queue time was maximum. One of the plausible hypothesis is the combination between crane production yield on the loading and unloading operations and the production yield of vehicle type A happened to produce this discrepancy when compared to the vehicle type B. This result highlights the misleading factor intrinsic to scenario 1 (base scenario), which integrates the transportation with loading/unloading operations only by numerically matching the production rates of the vehicles and cranes and not individually, by assigning each vehicle to specific cranes during the operations. There is a clear need for addressing the control of the queues in the base scenario (scenario 1) due to the unrealistic results obtained with the analysis of the considered delays.

3.2.2 Scenario 2: MAM + FCD + QLsim

In scenario 2, the FCD intermediates the process between MAM and the queue simulator. The role of FCD is to assign the MAM from vehicle type A and B to cranes in the loading operation and in the unloading operation. When using the FCD as intermediate step, the queuing time (Table 5) presented a logical behavior of increasing as the delay time increases for both vehicle type during the loading operation. For the unloading operation, only the "no delay" condition presented queuing time due to the effect of the delays during the loading operation on the unloading operation. As the delay is different than zero on the loading operation, the unloading operation is effected such that the schedule of each group of vehicles is adjusted to fit to the crane dynamics.

Delay (hours)	Vehicle Type	EWT	AQT
0	A	27.3	1
1	A	29.63	1.33
2	A	31.97	1.67
3	A	34.3	2
0	B	23.9	3.6
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
2	Unloading	32.79	0
3	Unloading	36.41	0

Table 5: Summary of effective working time and average queuing time for each vehicle type and trucking operation for scenario 2. Note: EWT - Effective Working Time; and AQT - Average Queuing Time

The effective working time was also proportionally affected by the delays such that as the delay increases, the effective working time also increases. The assignment of vehicles individually to cranes promotes greater control over the operations and mimics the human decision making to reduce the queuing time even when there are high delay rates associated with the operation. The chance of cranes (servers) being idle during the loading operation across the tested delay options is higher for the vehicle type A (Figure 8), which shows a clear change of behavior compared to scenario 1. Despite vehicle type A has 21 wheelers and 3 cranes in use during the operations, it presented higher probability that the cranes are idle during the process due to the lesser time required to load the vehicles of type A. Even though the cranes corresponding to vehicles of type A are less productive than cranes of vehicles of type B, the chance of cranes belonging to vehicles of type A being idle is higher. This corroborates with the FTP model which optimized the 21 wheelers of vehicle type A to only 3 cranes, while 6 cranes to 18 vehicles of type B. The FCD provided more understanding of the transportation operation when associated with the FTP in this sense.

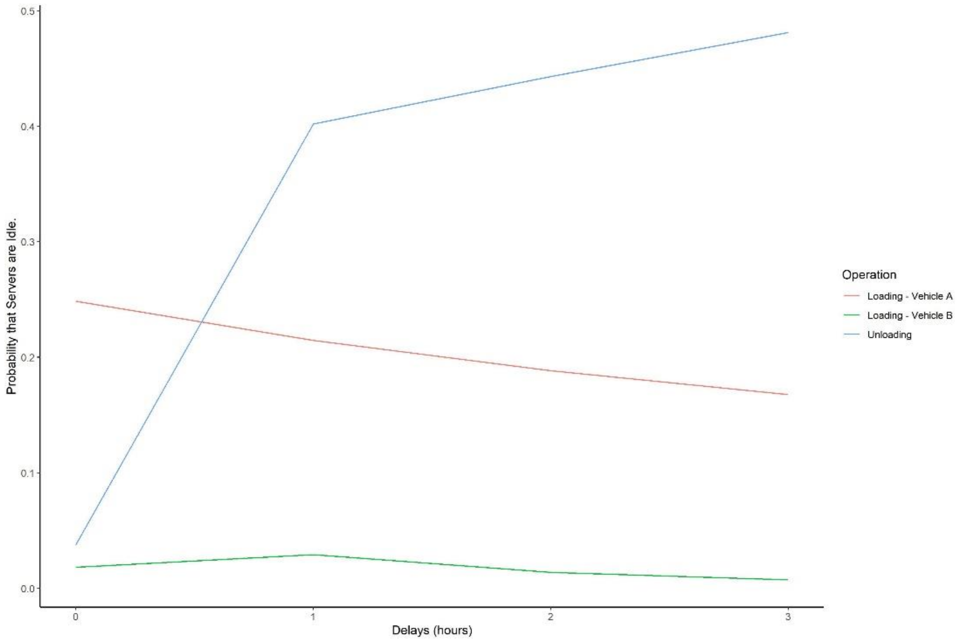

Figure 8: Probability of idleness of the cranes for each simulated delayed time for scenario 2.

For the unloading operation, the probability of cranes being idle increases with the simulated delays due to the fact that as the delay occurs, the truck schedule is shifted so that the queuing times are lessen in the subsequent cycles. The result obtained on FCD corroborates with the logical behavior of queues being minimized as there is delays during the transportation. Therefore, the trucks take more time to arrive at the unloading stations and, as consequence, they stay less time in queues and the idleness of cranes is accentuated. The abrupt change from “no delay” option to 1 hour delay demonstrates this behavior quite well (Figure 8).

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The queue system simulated for vehicle type A produced more average time spent in the queue (Figure 9) when compared to vehicle type B in the long-run analysis. The delay options accentuate the discrepancy between vehicle types in the loading operation. As the delay increases for vehicle type B, the average time spent in the queue increases approximately linearly, while vehicle type A presented nonlinear rate of increase in the time spent in the queue as the delay time increases. For vehicle type B, this result indicates the operational difficulty of adjusting the assignment of wheelers to cranes during the operation. Even with more cranes being optimized to vehicle type B (6 cranes), the queue system for this vehicle indicate more time in the queue. The lower probability of cranes being found in idle (Figure 8) reinforces this statement for vehicle type B.

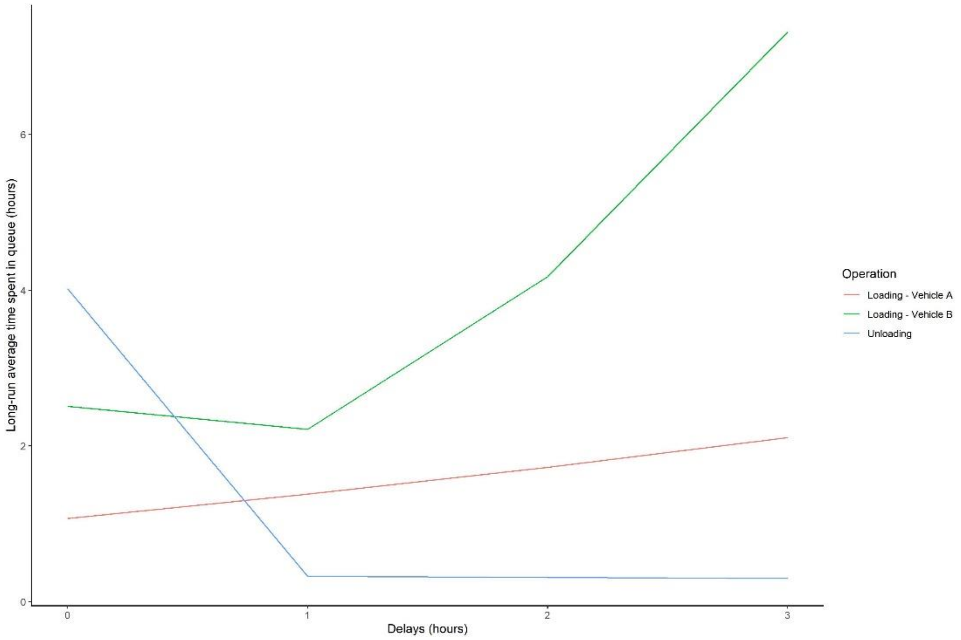

Figure 9: Long-run simulation of the average time spent in the queue for scenario 2.

The unloading operation in scenario 2 presented more inline coercion with the logical behavior of the queuing system when there is an overpopulation of clients (wheelers) in comparison with servers (cranes). As the delay time increases, the average time spent in queue, on the long-run, is reduced to its minimum. The productivity rate of cranes in the unloading operation is far more efficient than for the loading operation, and this characteristic of the transportation strategy (study case) is validated in the queue system by the long-run queue time analysis.

4 DISCUSSION

Vehicle scheduling systems improve efficiency in forestry industries and promote economic and environmental gains (MONTI et al., 2020; WEINTRAUB et al., 1996). The analysis of truck-crane components makes it possible to identify bottlenecks and idleness in the forest transport system (MONTI et al., 2020), that can be optimized to reduce the transportation costs. The existence of delays in the operation can compromise the transportation flux, generating queues in the loading and unloading stations (GHAFFARIYAN, 2021).

The FTP associated with the queue simulator was able to produce the queuing plan for the fleet of type A and B vehicles along with the respective cranes for loading and unloading. The FTP produced the resource allocation for the fleet while accounting for the total effective time each vehicle type operates. However, the FTP was not designed to predict the interaction between the vehicles of the same type in the loading operation respective to the formed queues along the operation. The queue simulator provided the simulated queuing schedule for when there is no control over the assignment of trucks to cranes (scenario 1). The FCD provided refinement in the control over the timber trucking operation (scenario 2) and clearly provided more logical outcome with mitigation of queuing time and better allocation of wheelers of each vehicle type to their particular cranes.

Kogler and Rauch (2020) introduced a tool based on a models of discrete event simulation (DES) to the operational planning level to an interconnected timber supply chain. This tool simulates the allocation under different multi-objective scenarios, seeking minimizing the use of equipment and maximizing the production while containing the formation of queues. The FCD + the FTP presents similar approach of minimizing the queueing and the use of equipment with the overall goal of minimizing the operating cost of transportation. The dynamic approach promoted by FCD in terms of crane allocation improves the efficiency of the process substantially.

The FTP models the transportation forestry-based problem by optimizing the logistics of timber transportation with efficiency due to its simplicity. The queue simulator + FCD provided the post- optimization capacity to enhance the queuing system for the considered case study when comparing to the scenario 1. The achieved arrangement found by scenario 2 significantly reduced the overall machinery resource via FTP, resulting in 51 total, and the queuing system of the overall operation. The significance of using the FCD on the forest transportation problem in lowering operational queues and improving resource utilization is shown by this finding.

The optimization model's results offer the transportation industry's decision-makers a great deal of support. Businesses may optimize their operations, reduce expenses, and boost overall effectiveness by determining the ideal number of trucks and cranes needed to handle transportation jobs. The use of models based on transportation issues also highlights the significance of mathematical optimization methods in resolving logistical problems encountered in the real world (Figure 10).

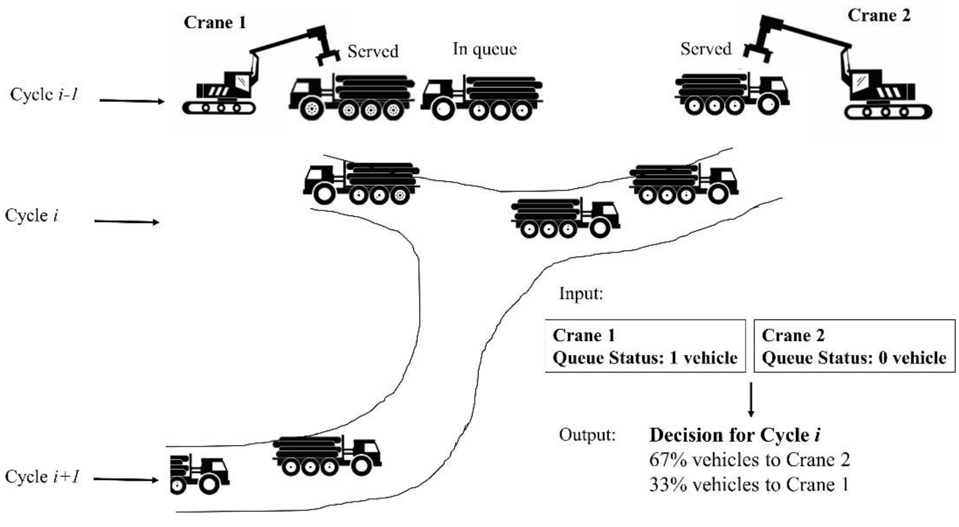

Figure 10: Decision making process under forest transportation dynamics.

Fuzzy controller for reducing queue times is the second result. The simulation's use of a fuzzy controller considerably cut down on queue time. When the fuzzy logic-based controller was in charge of the online simulation, it showed significantly less queue time than the scenario using only the queue simulator even when there are critical delays introduced to the system. This discovery emphasizes the capability of fuzzy logic controllers to manage dynamic, complicated, and unpredictable scenarios typical of transportation systems.

This result denotes the importance of online monitoring for improving the timber logistics efficiency. AMROUSS et al. (2017) adopted the real-time optimization strategy of the forest transportation activities through use of online communication and positioning device, which allows complete or partial re-planning of the operations at the moment of a random disturbance is identified. That methodology allowed the reduction random events impacts through the reduction of the response time to the event, which includes delays and queueing formation. The inconvenient of that method is the need to rerun the model every time there is a random event. The FCD, on the other hand, responds to random events automatically by mirroring the human decision of an expert in forest transportation while mitigate the gap between the actual cost and the planned cost of operation generated by the FTP. Malladi, Quirion-Blais, and Sowlati (2018) showed a reduction of 12% in the transportation operating costs by optimizing the overall cost of the timber transportation.

To handle uncertainty in transportation systems, fuzzy logic controllers provide a reliable and flexible method. The controller effectively uses linguistic variables and fuzzy rules to make decisions based on ambiguous and incomplete information. With this capacity, the controller may speed up the system's processing time and cut down on queuing, making the transportation process more streamlined and effective.

LP Model with Queue Simulator as opposed to LP Model, Fuzzy Controller, and Queue Simulator is the third outcome. The comparison of the two scenarios showed that the integration of a fuzzy controller with the LP model and the queue simulator (scenario 2) led to shorter queuing times than utilizing just the LP model and the queue simulator (Scenario 1), which was the case in the first example. This study suggests that the fuzzy controller improves decision-making, which enhances the performance of the transportation system.

The contrast between the two situations shows how well LP-based models may be improved by adding fuzzy logic controllers. Reducing queue times is made possible by the fuzzy controller's capacity to adjust to dynamic and uncertain conditions. This shows that combining established optimization methods like LP models with cutting-edge controllers like fuzzy logic can produce superior outcomes in terms of reducing wait times and boosting system effectiveness when dealing with complicated transportation problems.

Minh and Noi (2023) implemented the multi-server queuing model (Mt/G/nt) for cost minimization encompassing the formation of queues through genetic algorithm. The authors introduced a scheduling system considering minimization of number of wheelers while accounting for a constraint on the queue time. The results showed the model was capable of reducing from 30% to 50% of operating costs. The combination of methods as intelligent controllers assists improving the solution. Oliveira et al. (2022) tested different heuristics to solve vehicle routing problem in the forest framework and concluded that the hybrid greedy-simulated annealing presented best performance overall. Sarkar et al. (2015) applied queuing theory for reducing idleness and waiting time by optimizing the number of machinery and personnel. Their results showed efficient mitigation of the idle and waiting time. The queue simulator + FCD (both associated with FTP) showed similar result by promoting efficiency in obtaining the solution (online analysis) and mitigated the queuing time in the forest transportation framework.

In summary, the study offers important insights for improving transportation infrastructure and cutting wait times. The transportation problem's optimization model produced a global optimal solution that minimized costs by using a certain number of trucks and cranes. The online simulation's use of a fuzzy controller also showed how well it could handle uncertainty in transportation networks by successfully reducing queuing times. In addition, the use of fuzzy controllers in conjunction with queue simulation demonstrated improved performance in reducing queuing times compared to the use of the LP model alone. These findings emphasize the value of adopting cutting-edge optimization methods and sophisticated control systems to raise the efficacy and cost-effectiveness of transportation networks. Future studies can investigate how to combine additional intelligent control techniques with optimization models to further enhance transportation system performance.

5 CONCLUSION

In this study, a controlling device was developed for the timber logistics after optimized fleet of vehicles and cranes according to operational constraints and a queue simulator produced the associated potential queuing times. Two scenarios were compared for the output queuing system: with and without (base scenario) the fuzzy controlling device.

The vehicle type with higher crane production needed less trucks to execute the transportation task more efficiently in comparison to the vehicle type with less productive cranes.

The Machinery Allocation Model efficiently optimized the truck and crane fleets to loading and unloading operations using a simple and efficient integer programming model. The fuzzy controlling device provided better understanding of the results obtained from the optimization step in relation to the base scenario. The FCD mimics the human decision-making process in allocating the vehicles to cranes during the loading and unloading operations by logically assigning more vehicles to cranes with less indication of queue formation. The use of the fuzzy controller showed more advantageous than the base scenario in simulating the queuing system for the presented study case. MAM + FCD + Qlsim provided logical behavior of queues in the forest transportation scheme. The base scenario highlighted the queues are not static in the forest logistics and a treatment is necessary to promote improvement of the operation. The outcomes of this study demonstrates that the fuzzy controller is significant for understanding the queue system in the forest logistics.

The link to access the code that generated in this project is available here.

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