Proceedings of the 11th World Congress on Mechanical, Chemical, and Material Engineering (MCM'25)
Paris, France - August, 2025
Paper No. ICMIE 107
DOI: 10.11159/icmie25.107

Logistical Optimization and Efficiency in Firefighter Response to Wildfires in Honduras

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Abstract **-** A model was developed to optimize the allocation of limited resources, maximizing the participation of firefighters in the Central District for forest fires. The general objective was to improve response efficiency, while the specific goal identified critical demand points and, through linear programming, created an appropriate resource allocation. Tools used included logistic regression, data analysis with Minitab, Python, and Excel, OpenSolver and interviews for process documentation. The population and sample consisted of 2,030 forest fires between January and June of 2021 and 2024. Results revealed patterns with temperatures above 22 °C, low precipitation, and winds of 7-8 km/h. 98 points with high probabilities of forest fires over 30 hectares were identified, notably San Matías and Zambrano, highlighting the need to improve firefighter preparedness for such demand. A goal based linear programming model was developed to optimize the allocation of resources among fire stations, focusing on the efficient distribution of crews and tools. This model allowed for planning tailored to the operational needs of each station, maximizing coverage based on the location and frequency of fires. The results show that, by applying linear programming, the allocation of the 98 identified critical points improved, with increased coverage in areas such as San Matías and Zambrano. The efficient allocation of the 159 fires (demand) enabled stations, particularly the Central Station and Station 8 (Tamara), to manage their resources more efficiently.

Keywords**:** Linear programming, limited resources, forest fire, occurrence prediction, firefighters

1. Introduction

The multiple forest fires that have occurred in recent years have been a consistent problem in the Distrito Central of Honduras. The fire department, being one of the organizations responsible for tackling forest fires, faces significant limitations due to lack of funding, resulting in shortages of specialized equipment and personnel. These deficiencies restrict their ability to respond to large-scale forest fires, affecting logistics, unit deployment, and the availability of essential resources, which compromises the effectiveness in controlling fires.

To address the problem in the research, a diagnosis of the current execution of the forest fire response process will be carried out using flowcharts and interviews. Then, a fire prediction tool will be developed in Python with correlation analysis, aiming to anticipate the need for fire department involvement by predicting large-scale fires (30 ha), which is when other institutions request their support. Finally, resource optimization will be proposed, focusing primarily on the crews for their allocation among Central District stations for each predicted forest fire, using goal programming. The optimization will be verified from the perspective of crew demand, which will be weighted more heavily, and tool wear based on hectares, which will be weighted less heavily.

The main objective is the optimization of crew coverage for forest fires to meet demand by assigning the crews from each station to participate in each forest fire, considering tool wear and distances discussed in this research. The specific objectives are the diagnosis of the fire department's forest fire operations, the development of a fire occurrence prediction tool, and the use of goal programming to optimize crew assignment and demand. In the Distrito Central, linear programming has already been used for optimizations, such as in a 2024 study on the distribution of limited resources like water, where a similar approach using mathematical techniques to solve allocation under various constraints is observed. Linear programming is key to optimizing resource allocation based on firefighter participation, making this study highly relevant to this research [1].

Every optimization approach manages demand according to the specifics of each investigation. When dealing with natural phenomena, it is essential to implement correlated logistic regression to analyse the behaviour of variables, facilitating decision-making within the constraints of each area involved. This methodology is key to achieving successful objectives [2]. Resource allocation methods, such as weighted scoring, including those related to participation issues. A study at the University of Carabobo in Venezuela focused on optimizing the weighted sum of variables for each objective, considering priorities a technique applicable to the fire department's resource allocation [3]. In Chile, a study combined linear programming with resource management and forest fire combat strategies, considering costs and the importance of resources. The study emphasized the wear and tear of resources during firefighting efforts, focusing on the hectares affected to determine resource needs [4].

This report is structured as follows: Chapter 2 discusses the methodology, Chapter 3 covers analysis and results, Chapter 4 presents conclusions, Chapter 5 offers recommendations, Chapter 6 explains the applicability of the research, and Chapter 7 includes the references used. The research aims to optimize resource allocation in the fire department to enhance its efficiency in forest fire responses.

2. Methodology

2.1. Approach and Scope

The study, with a quantitative and correlational approach, analysed the relationship between variables such as fire frequency and firefighter response patterns in the Central District. Using statistical tools and historical records, it identified patterns and interactions between variables to understand their correlations and optimize decision-making in forest fire management [5].

2.2. Population, Sampling, and Sample

The study covered 2030 recorded data of historical forest fires in the Central District between January to June 2021 to 2024, these being an open database belonging to the Institute for Forest Conservation (ICF) along with the National Office of Oceanic and Atmospheric Administration (NOAA) climate database from 2021 to 2024 detailing various fire characteristics such as wind speed, hectares, vegetation, cause of the fires, month of occurrence, start time, and other information required for the investigation. The study utilized 100% of the available data, making it a census rather than a sample. This approach allows for the consideration of all possible variations in the study and ensures that the analysis reflects the actual conditions and correlations of the variables under consideration. [5].

2.3. Variables

For this study, two research instruments were used, each based on a specific set of variables: OpenSolver for goal programming, optimizing resource allocation for forest fire response, and logistic regression in Python for fire occurrence prediction. The OpenSolver model is used to evaluate various factors related to fire management, including fire station (i), fire demand (j), fire area (Haj), terrain conditions (Tj), squad numbers (Ci), tool kits, vehicles, distances (Dij), tool kit wear (Kij), and firefighting capacity (CAPij), with squad assignment (xij) as the dependent variable. The logistic regression model in Python, on the other hand, uses fire ID, coordinates, cause, vegetation, time, affected area, and climate factors (temperature, precipitation, wind speed), with fire occurrence (1 or 0) as the dependent variable. A more detailed description of each variable can be found in Section 3.3.

2.4. Instruments and Techniques

Various instruments and techniques were used to achieve the study's objectives. OpenSolver Excel facilitated linear programming and resource optimization for fire stations, while Python's logistic regression (using pandas, numpy, and scikit-learn) predicted forest fires based on historical data [6]. Interviews with firefighters provided insights into response challenges, and Minitab was used for statistical analysis to identify correlations and improve the model. Data cleaning and analysis ensured accuracy, with performance evaluated through precision, recall, and K-Fold cross-validation to assess real-world applicability [7].

2.5. Data Collection

Data collection for this research involved interviews with key fire department members, including a lieutenant in charge charge of the academy and a captain responsible for operations. The fire incident database from the Instituto de Control Forestal (ICF) was also used. Interviews were chosen to gain in-depth insights into the department's experiences, decisions, and challenges, as performance data on forest fire responses are not typically documented at the stations. Informal conversations were also conducted to provide a more comprehensive understanding of the department's operations and response strategies.

2.6. Diagnosis of the current situation of the Fire Department in the Distrito Central of Honduras

To analyze the response process without existing documentation, a flowchart and technical sheet for forest fire response were developed, providing a structured visualization of stages, identifying critical points, and standardizing procedures. A detailed stage analysis assessed time and operational efficiency impacts. Data was collected through interviews on internal performance measurement, using a methodology from an Ecuadorian study on KPIs [8]. Operational effectiveness, resource management, and a SWOT analysis were conducted, revealing insights from firefighters' collaboration with other institutions, as noted in a similar study of Ecuador's capital fire department [9].

2.7. Predictive Modelling

This study utilized historical forest fire data from January to June 2021 to 2024, provided by the Instituto de Control Forestal (ICF), to analyse the relationship between climatic variables (temperature, precipitation, wind speed), vegetation type, and fire occurrences. Minitab and Python were employed to calculate correlations and identify patterns that influence fire behaviour. This analysis followed methodologies commonly used in studies like those in Peru [10], helping to understand how environmental factors, including vegetation type and climate change, affect fire dynamics. The results align with findings from Ecuador [11], indicating that these fire patterns will persist beyond 2021 due to ongoing climate changes.

To predict fire occurrences, a logistic regression model was developed using Python, incorporating a 10-fold cross-validation process to prevent overfitting, especially given the imbalance in fire occurrence and non-occurrence data. This approach was inspired by similar predictive models used in Cuba [12]. Feature selection included dynamic variables like fire causes, vegetation type, and coordinates, along with static variables such as month, hour, temperature, precipitation, and wind speed. A pilot test, using 20 known fire occurrences not part of the main dataset, confirmed the model's accuracy. The model's performance was then evaluated through precision, recall, and F1-Score, with successful results supporting its effectiveness for predicting future forest fires.

2.8. Resource Optimization

The methodology involved formulating and solving a mathematical model to optimize resource allocation and maximize efficiency in forest fire response. Using weighted goal programming, the weighted sum of undesired deviations was minimized, as proposed in a Venezuelan study [3], with weights ranging from 1 to 2 to prioritize objectives [13]. Weights were assigned: 2 for minimizing distances and 1 for minimizing tool kit wear, implemented via linear programming in OpenSolver. This balanced priorities and normalized them in separate objective functions [14]. The model included decision variables, constraints, and an objective function to optimize the two goals. OpenSolver was selected for its capacity to handle high-demand distance minimization, aligning with findings from Colombian research on coverage and allocation optimizations [15].

3. Results and Analysis

3.1. Diagnosis of the fire station operations in the Distrito Central

The forest fire response process is generally well-structured, but delays occur due to coordination through unofficial channels like messaging groups. The lack of specialized tools and equipment reduces operational efficiency and poses risks to personnel. Firefighters typically intervene in large fires or difficult terrains when other institutions, like the Armed Forces or Instituto de Control Forestal (ICF), cannot manage the situation, especially for fires over 30 hectares or when the fire department is closest. Although performance indicators related to time and cost are used to evaluate responses, these are not consistently recorded or accessible, hindering effective analysis. While the trucks are equipped with necessary tools and no significant operational impediments were found, personnel shortages become an issue when crews are dispatched. Delays in confirming additional support and poor inter-institutional communication further complicate the response process, risking delays and compromising safety.

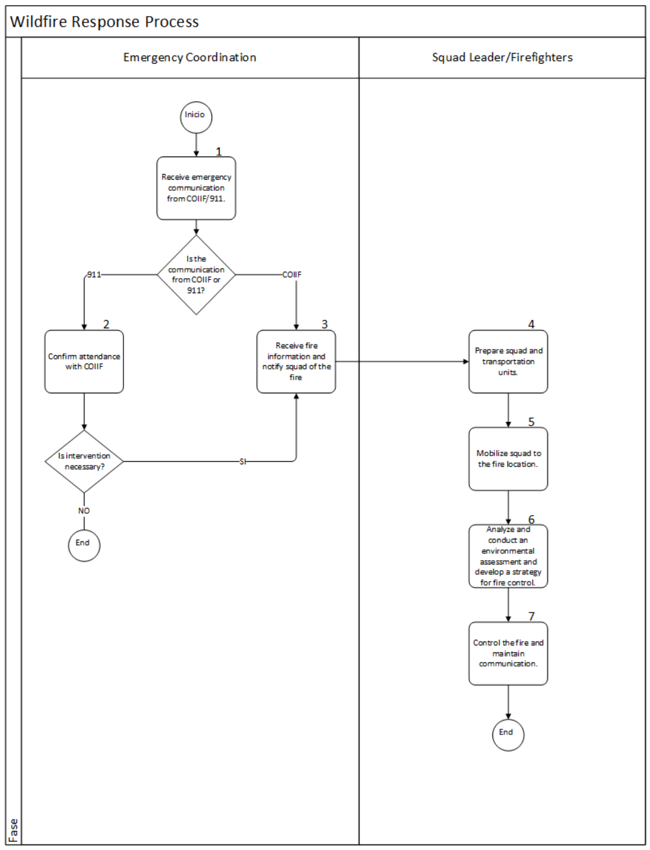

Fig. 1: Flowchart of the forest fire response process of the Fire Department in the Distrito Central in Honduras.

3.2. Design of predictive tool for forest fire to anticipate firefighter participation in the Distrito Central

The analysis identified activity peaks and patterns in fire occurrences during March and April, which share similar characteristics in their forest fires. Minitab results reveal that grass areas (correlation of +0.405) and pine (correlation of +0.395) are most prone to fires, primarily in the early afternoon hours from 12:00 to 14:00. Climatic factors show that temperatures between 25 to 29.99 °C are associated with a higher occurrence of fires, while low precipitation of 0 to 1.99 mm along with wind speeds between 6 to 11.99 km/h are correlated with an increase in fire magnitude.

In Figure 2, a concentration of fire occurrences and susceptibility in the Central District is observed, particularly concentrated in the southern area of the region. From the selection of 98 high-probability points, specific characteristics were considered. The first step involved grouping points that were 0.1 km apart. After forming these groups of nearby points, a representative point from each group was selected. The frequency of points within the same group and the area in hectares were analysed to test in the occurrence model.

The predictive model identified 98 points, presented in Figure 3, with a high probability of forest fires from January to June under the average climatic conditions of that season for the year 2025. Notable points of occurrence include areas such as San Matías, Zambrano, San Mateo, Las Moras, Ciudad España, Tamara, and Recizapa. These points are based on fire frequency and magnitude, particularly those with probabilities of greater than 30 hectares.

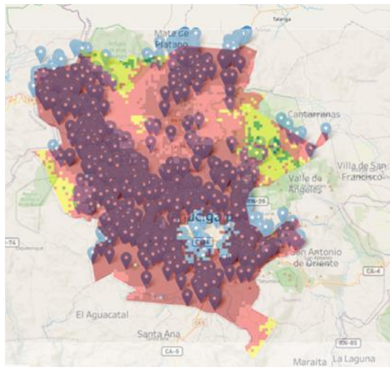

Fig. 2: Forest fire susceptibility in the Distrito Central from 2021 to 2024.

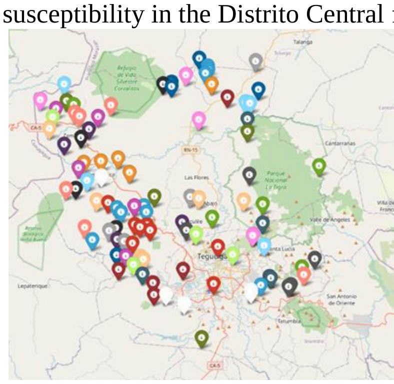

Fig. 3: 98 Selected points with high probability of large-scale forest fires based on average climate conditions for 2025 in the Distrito Central.

3.3. Optimization of squad coverage at each fire station for forest fire combat in the Distrito Central

Data from 98 fire points, including their probabilities per month, were analysed, with each point representing a series of nearby points. By conducting an analysis by month and year, and considering the probability of occurrence each month, it was found that there was a high probability of occurrence mainly in March and April, but other months also showed probabilities. This confirmed the possible occurrence of fires each month, but the historical frequency of each fire-prone point helped determine the demand. A forecasted demand of 159 forest fire events was identified from January to June for the year 2025.

To optimize the allocation of crews at each fire station in the Central District for forest fire combat, the OpenSolver model was employed. The 159 forecasted fire events were used as the demand to be covered, along with the stations and their available resources. The most restricted resource was the available crews, which were allocated to cover each forest fire. Considering the general percentage of 1% of the fire area as the demand to cover by capacity in hectares across all crews (3 ha per crew). The covered area and the demand to be addressed by the fire department when providing support to other institutions for large-scale forest fire management, including the type of terrain at each point, but with a classification to consider the wear and tear of the toolkits each crew must carry when attending to a forest fire, along with the distances from each station to each fire event point, were incorporated into the goal programming model using the weighting method to optimize crew allocation.

In goal-based linear programming, the application and development revealed significant advancements in optimizing the coverage of assigned crews (1) and resources in wildfire management, aiming for a complementary objective of mutual optimization. The mathematical model was successfully adapted with a focus on 2 integrated goals using OpenSolver software, considering all process constraints as detailed below:

$$x_{ij} = \text{Number of crew assigned from station i to fire j.} \qquad (1)$$

$$\sum_i x_{ij} \leq C_i \tag{2}$$

$$\sum x_{ij} \leq Vehicles\ at\ station\ i. \tag{3}$$

$$\sum x_{ij} \leq Kits\ available\ at\ station\ i. \tag{4}$$

$$\sum_j (x_{ij} \times CAP_{ij}) \geq Ha_{ij}. \tag{5}$$

$$min \sum_{i,j} (D_{ij}\ \times x_{ij}) \tag{6}$$

$$min \sum_{i,j} (K_{ij}\ \times x_{ij}) \tag{7}$$

$$Normalized\ distance = \frac{\text{Total distance traveled in km}}{5871.8\ km} \tag{8}$$

$$Normalized\ wear = \frac{\text{kit wear}}{1.0369\ global\ wear} \tag{9}$$

$$Combined\ objective\ function = \alpha \times \text{Normalized distance} +\ \beta \times \text{Normalized wear.} \tag{10}$$

The goal-based linear programming (GLP) model developed with OpenSolver optimizes crew and resource allocation for wildfire management, minimizing travel distance and tool kit wear. Key variables include:

- **x_ij**: Number of crews assigned from station *i* to fire *j* (Equation 1). This decision variable determines how many crew members are allocated to a specific fire event.
- **Ha_j**: The area of fire *j* in hectares, representing the total area that needs to be covered by firefighting efforts (Equation 5).
- **T_j**: Terrain condition of fire *j*, categorized as smooth, moderate, or rocky, which affects the resources and strategies for firefighting.
- **C_i**: Number of available crews at station *i*. Each station, except Central Station, has one crew. Central Station has additional crews to cover larger demands (Equation 2).
- **Kits**: The number of firefighting tool kits available at station *i*. Each crew requires one kit for operations. Central Station has 10 kits, while others have 4 kits each (Equation 4).
- **Vehicles**: The number of firefighting vehicles available at station *i*. Each vehicle can accommodate one crew and one kit (Equation 3).
- **D_ij**: Distance from station *i* to fire *j* in kilometers, which impacts the response time and the overall efficiency of deployment (Equation 6).
- **K_ij**: Wear factor for firefighting kits at station *i* when deployed to fire *j*, quantifying the degradation of the kit as it is used (Equation 7).
- **CAP_ij**: Firefighting capacity in hectares for a crew from station *i* assigned to fire *j*. It is calculated as the area of fire *j* divided by the coverage capacity of one kit (3 hectares per crew) (Equation 5).

Constraints ensure feasible resource allocation: Crew assignments do not exceed available crews (Equation 2), vehicles (Equation 3), kits (Equation 4), or coverage capacity (Equation 5). The objective function combines two goals:

1. Minimizing travel distance (D_ij, weight $\alpha = 2$) (Equation 6); 2. Minimizing tool kit wear (K_ij, weight $\beta = 1$) (Equation 7). Values are normalized using maximum values: Total distance normalized by 5871.8 km (Equation 8), and

kit wear normalized by 1.0369 global wear (Equation 9). The combined objective function (Equation 10) balances these goals, ensuring efficient fire coverage while respecting resource limitations.

Table 1: Optimal distribution of crews based on participation months to cover forecasted wildfire demand.

Station (i)		Number of Forest Fire Responses per Month	Times Each Squad Participates in a Forest Fire
Main Station	Central	1.April = 25 3.March = 12 2.February = 2	39
Station 1	Col. Mayangle	1.April = 11 3.March = 6 2.February = 2	19
Station 2	Kennedy	1.April= 7 2.March = 5	12
Station 3	La Vega	1.April = 7	7
Station 4	El Carrizal	1.January = 2 4.April = 38 2.February = 2 5.May = 2 3.March = 8	52
Station 5	Nueva Capital	1.February = 5 3.April = 9 2.March = 8 4.May = 2	24
Station 6	El Chimbo	1.April = 8 2.March = 4	10
Station 7	Hatillo	1.April = 8 2.March = 4	12
Station 8	Tamara	1.February = 13 3.April = 40 2.March = 14 4.May = 8	75

4. Conclusion

The analysis identified significant operational limitations in the fire department, including insufficient personnel, financial support, and deficiencies in information management. These issues hinder internal operations and inter-institutional coordination, relegating the department to a support role in large-scale situations. Poor documentation and transparency further impede collaboration, weakening wildfire response efforts. Resource scarcity limits coverage to 3 hectares at a time, complicating planning and management.

The predictive model highlighted wildfire concentration in eastern Distrito Central (Zambrano, San Matías, Amarateca, La Tigra), with key conditions being temperatures above 22°C, low precipitation, grass/pine vegetation, and wind speeds of 7–8 km/h, peaking in March–April. This trend is expected to continue into 2025, necessitating ongoing preparedness.

Linear programming optimized crew coverage, effectively addressing 98 fire points (January–June 2025) and projected demand for 159 fires. Central Station and Station 8 (Tamara) demonstrated effective response and coverage, ensuring readiness for future fires under similar conditions.

Acknowledgements

We thank our project advisors, Eng. Mendel Nelson, Eng. Dulce Raudales, Eng. Nelbren Cuellar, Eng. Paola Pascua, and Firefighter Captain Reinaldo Vargas, for their invaluable guidance, expertise, and support in the research.

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