



## Application of the Fix-and-Optimize Metaheuristic to Optimize the Allocation of Service Technicians in Electric Power Utilities

Maria Sofia Luna Delgadillo<sup>1</sup>, Vinícius Jacques Garcia<sup>2</sup>, Stéfane Dias Rodrigues<sup>3</sup>, Laura Giovanna Freitas Castro<sup>4</sup>, Karlen Maura de Souza Silva<sup>5</sup>

<sup>1,2,3</sup>Department of Production Engineering, Federal University of Santa Maria. (97.105-900, Camobi-Santa Maria, Rio Grande do Sul, Brazil) & Institute of Systems and Computer Engineering, INESC P&D. (11.055-300, Santos, São Paulo, Brazil)

<sup>1</sup>sofia.luna@acad.ufsm.br, <sup>2</sup>viniciusjg@ufsm.br, <sup>3</sup>stefane.rodrigues@acad.usfm.br

<sup>4,5</sup>Equatorial Energia Group. (90.250-020, Porto Alegre, Rio Grande do Sul, Brazil)

<sup>4</sup>laura.castro@equatorialenergia.com.br, <sup>5</sup>karlen.souza@equatorialenergia.com.br

\*correspondence: [sofia.luna@acad.ufsm.br](mailto:sofia.luna@acad.ufsm.br)

**Abstract:-** The effective allocation of technical teams to fulfill service orders is a significant challenge for electric utility companies, as balancing capacity and demand is difficult given the system's dynamic nature. As a result, operating costs and service quality, as defined by the frequency and duration of electricity supply interruptions, determine the outcomes of the operating indices measured by regulatory agencies. This paper presents a solution approach, using the Fix-and-Optimize (F&O) meta-heuristic, for a mathematical model developed based on concepts from the backlogging technique and Mixed Integer Linear Programming (MILP), to reduce the number of orders delayed by unstarted and unfinished services, through the optimized distribution of technical teams. The F&O meta-heuristic iteratively partitions the binary allocation variables, fixing 30% based on adaptive criteria and optimizing the remaining variables. For the simulation, an instance of 5,830 orders recorded over a period of 90 days was used; five capacity scenarios were analyzed using meta-heuristics, with incremental return on investment (ROI) measured. The results showed significant improvements, with costs varying from 3.8% with the initial model to 17.5% with F&O. Additionally, the trade-off analysis developed allowed us to determine the ideal configuration for the “Normal Team with 4 hours of overtime/day,” with a total cost of USD \$8600, a service rate of 92%, and an incremental ROI of 1.75. The proposed approach offers quantitative support for planning the allocation of human resources in contexts of providing technical services related to electricity.

**Keywords:** Backlog, Electricity Utilities, Fix-and-optimize, Metaheuristics, Mixed-Integer Linear Programming, Operational research.

### 1. Introduction

Energy utilities face challenges in service management, especially when balancing demand for services with limited operational resources. Dealing with delays and backlogs of pending requests requires controlling operational impacts. These impacts can lead to service delays,



longer average response times, and difficulties in meeting Service Level Agreements (SLAs), directly affecting supply reliability and customer satisfaction (Saleheen; Habib, 2022).

Factors contributing to increased delays include extreme weather conditions, power grid failures, operational constraints, and limited availability of technicians. Inadequate management of delays can compromise the utility's ability to respond to emergencies and perform preventive maintenance, thereby affecting service continuity and quality. In this context, the electric power sector strives to combine operational performance with sustainability goals. According to Al-Kuwari et al. (2025), one of the current strategic priorities is to promote a sustainable energy transition, which involves adopting more transparent practices regarding carbon emissions and gradually replacing energy matrices with renewable sources.

However, concessionaires must decide between maintaining technical teams with sufficient size and capacity to meet periods of peak demand, with high fixed costs and idleness during periods of normal demand, or operating with reduced and variable capacity, incurring an accumulation of unfulfilled orders that generate backlogs, economic penalties for delays, and a decrease in user satisfaction rates (Ribault et al., 2021). This choice between resource costs and costs is complex in different dimensions, involving interrelated decisions on fixed team sizing, use of overtime, prioritization of service according to priority level, and accumulated backlog management policies (Graf, 2020).

The economic relevance of adequate human resource sizing in the service sector has been the subject of a significant number of studies in the literature. For example, Pillac; Gueret; Medaglia (2012) emphasize that, in the context of field services characterized by dynamism, the ability to respond to emergency demands while keeping operating costs under control is a decisive competitive advantage.

Work order management systems generally operate with multiple classes or priority levels, not just emergencies, which creates a significant operational impact while requirements defined in SLAs, such as maximum response time, must be met (Gruson; Cordeau; Jans, 2018). In this study, the mathematical formulation of the model classifies orders into three sets: "Emergency," characterized by high criticality, which requires attention during the registration period; "Commercial," which allow for postponement of service in cases of limited capacity; and "Backlog," consisting of orders not fulfilled in previous periods and whose prolonged permanence in the system entails increasing costs related to penalties. This heterogeneity requires the use of dynamic and sophisticated prioritization and allocation methods that provide optimal solutions in real time, considering medium and large instances common in electricity utilities (Alvizu et al., 2017).



This article proposes an integrated methodological approach based on both Mixed Integer Programming (MIP) and the Fix-and-Optimize meta-heuristic. The mathematical model consists of a two-phase objective function to optimize the allocation of technical teams assigned to fulfill both commercial and backlog service orders. Other features adopted in the modeling include estimated service times, overtime costs, and penalty costs for delays, as well as specific technical requirements for their execution. In addition, the workday is 8 hours and allows for overtime, enabling the allocation of personnel based on estimated service times for different types of service. The analysis of human resource allocation and backlog management helps optimize service orders and the overall performance of the utility company.

The Fix-and-Optimize meta-heuristic is applied as a model resolution technique, which consists of an adaptive partitioning strategy while fixing subsets of binary allocation variables iteratively, considering sequential priority criteria, processing time, and random diversification, keeping all continuous variables free for optimization (Helber; Sahling, 2008). Thus, the algorithm defined to apply the meta-heuristic positions it as a strategy for exploiting the hierarchical structure of the problem, preserving critical decisions related to the allocation of emergency orders, while allowing flexibility for commercial order allocations and capacity adjustments through the activation of overtime.

The computer simulation was developed in the Visual Studio Code environment, using the Python programming language for instance comprising 5,830 orders recorded over a 90-day (three-month) period and involving 280 technical teams, reflecting the daily operational reality of an electric utility company. Starting from the initial optimal solution generated by the MILP model result, meta-heuristics were applied for analysis using five systematically evaluated capacity scenarios. The defined scenarios consider everything from a minimum team without overtime to a 50% expansion in nominal capacity, quantifying the incremental return on investment (ROI) for each level of expansion by analyzing delay costs versus human resource investment costs.

The content of this paper is organized as follows. Section 2 presents the Systematic Literature Review focusing on related problems and solution techniques. Section 3 details the mathematical modeling used. Section 4 describes the methodological approach employed, highlighting the configuration of the Fix-and-Optimize algorithm. Section 5 analyzes and discusses the results, and finally, Section 6 summarizes the conclusions and recommendations related to the study presented here.

## 2. Systematic Literature Review

In the areas of mathematical modeling and operational research, optimization problems related to human and technical resource logistics pose particular challenges in terms of the allocation, planning, and scheduling of available personnel for the execution of service orders (Feng; Ye,



2021). They are often classified as NP-hard and therefore require sophisticated methodological approaches that balance computational feasibility with optimal quality solutions. In this context, metaheuristic techniques have emerged as very useful tools in solving large-scale instances in practical applications (Houssein et al., 2024).

This section presents the methodology and results of the Systematic Literature Review (SLR) that explores the existing literature on the problem of accumulated orders that are unfulfilled or delayed, understood as “backlog volume,” focusing on resolution approaches related to mathematical and software programming methods that are used as a support tool in the process of allocating technical teams to execute service orders at electric power utilities.

Among these approaches, the SLR developed focused on the fix-and-optimize metaheuristic, given the solution approach to the problem described above that was chosen to be presented in this article. This approach is commonly used to break down a complex problem into manageable parts, which can be solved using exact software solvers to find good, but not necessarily optimal, local solutions efficiently.

Thus, the literature review process presented here was developed with the aim of understanding how these concepts are being applied in the management of excessive backlog volumes by improving the allocation strategies of the technical teams responsible for their respective service. It focused on the service sector, mainly electricity supply, given the context of application studied, to obtain an overview of the approaches applied in research related to the subject of this research article (Fonseca; Figueiroa; Toffolo, 2024).

To explore the available literature on the subject under study, an SLR was conducted in the main databases, Scopus, Web of Science (WoS), and IEEE Xplore, using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The PRISMA protocol, originally published in 2009 and updated in 2020, is widely recognized for providing a rigorous and transparent methodological framework for conducting systematic reviews, ensuring reproducibility and clarity at all stages of the process (Page et al., 2021).

The systematization of the study began with the formulation of the following research question: What are the main approaches identified in the literature for the application of heuristics and metaheuristics in the process of solving problems related to routing, scheduling, and allocation of service technicians?

Based on this question, the search string to be used in the databases was defined:

("scheduling" OR "routing" OR "timetabling") AND ("optimization" OR "matheuristic" OR "heuristic") AND ("maintenance" OR "service" OR "vehicle").

In addition, inclusion criteria were defined for the final selection process, which consisted of reading the title, abstract, and methodology of each document, ensuring that the selected



articles met the following requirements: (I) Human resource optimization problems applied in the service sector, in the contexts of logistics, health, manufacturing, or energy; (II) Application of mathematical, heuristic, or meta-heuristic optimization techniques; (III) Presentation of equations, algorithms, and computational results.

After defining the PRISMA protocol entries, the string was applied in the advanced search section of the Scopus and WoS databases, resulting in an initial total of 52 bibliographic records. Table 1, presented below, summarizes the filtering process adopted, followed by a description of the main findings in each of the selected documents.

**Table 1. Summary of PRISMA Protocol Application Phases and Results**

PRISMA Protocol phase	Scopus	WoS	IEEE Xplore	Total
<b>Initial search (without filters)</b>	21	20	11	52
<b>Filters addition<sup>1</sup></b>	18	15	6	39
<b>Duplicates remotion<sup>2</sup></b>	-10	-	-3	26
<b>Final selection (title, abstract and methodology reading)</b>	7	15	2	23

<sup>1</sup>Added filters: publication year (2010–2025), language (english), document type (journal paper) and open Access.

<sup>2</sup>Thirteen duplicate documents were identified and removed.

Table 1 presents a summary of the steps followed in the article selection process, according to the PRISMA protocol. Initially, applying the search string to the Scopus, WoS, and IEEE Xplore databases resulted in a total of 52 documents, 21 from Scopus, 20 from WoS, and 11 from IEEE Xplore. Next, the following filters were applied: year of publication (2010 to 2025), language (English), document type (journal article), and open access, to ensure the full availability of the texts. This step resulted in 39 selected articles, of which 18 were from Scopus, 15 from WoS, and 6 from IEEE.

Subsequently, the bibliographic data were exported in BibTeX and CSV formats. To eliminate duplicates between the databases, the records in the BibTeX files were cross-checked, resulting in the exclusion of 13 articles repeated between the Scopus and IEEE Xplore databases, totaling 26 unique documents. Finally, the titles, abstracts, and methodological sections of the articles were read in order to identify those that effectively met the previously defined inclusion criteria. At the end of this screening, 23 articles were selected to compose the SLR database.

The analysis of the works is presented below. It contains the most relevant cases through a specific review of the issues addressed in each case, contrasting them with the methodological approach proposed to solve them and with the results obtained from each application.



The study by Gamst & Pisinger (2024) presents a variation of the Technician Routing and Scheduling Problem (TRSP), by formulating a method that integrates operational and investment decisions. The proposed methodology is based on the column generation technique, in which technician routing costs are estimated iteratively rather than seeking the optimal solution, thereby significantly reducing computational time. The results were validated using real data from a telecommunications company, demonstrating an approximate 16 percentage-point reduction in service technicians' travel time.

Similarly, in the research by Dupin & Talbi (2020) A pair of meta-heuristics based on Mixed-Integer Linear Programming (MILP) was developed, integrated with machine learning techniques to solve variants of the Vehicle Routing Problem with Time Windows (VRPTW). His work addresses constraints on trip interdependence, multiple warehouses, and outsourcing costs, but the central innovation is applying machine learning techniques to stabilize the column generation algorithm. In the computational experiments, medium-sized public instances were used, demonstrating that the proposed methodology can guarantee solution quality in less restricted cases.

Moving away from the column generation technique, in Nielsen & Pisinger (2023) the tactical aspect of TRSP is investigated in a dynamic environment, with a multi-period planning horizon. This approach differs in that some tasks are known, while others arrive dynamically throughout the planning horizon. As a solution, the authors propose area-partitioning strategies using sweep-and-parallel algorithms to reduce the dynamism index. When implementing tactical planning, the computational results show a 10% reduction in travel distance, making it feasible to keep up to 70% of technicians on relatively static schedules without a significant increase in travel distance.

A variant of TRSP was proposed in the study developed by Gong et al. (2021), which addresses for the first time the problem of scheduling and routing in the context of home health care, through the integration of overtime with measurable costs and the reconciliation of caregiver and client preferences. The proposed mathematical formulation consists of an integer programming model whose objective is to minimize travel costs, overtime, preference mismatches, and financial penalties resulting from care discontinuity. In this case, the Variable Neighborhood Search (VNS) heuristic is applied with a set-covering model, enabling efficient exploration of the space of local optimal solutions. The results were validated using real instances from a healthcare provider in New York, USA, demonstrating practical applicability and extensibility to other companies in the same sector.

In the study Stalhane et al. (2019) the problem of optimal sizing of a fleet of ships that support maintenance operations in offshore wind farms is considered. In this case, the problem is formulated as a two-phase stochastic process: the first phase corresponds to ship hiring, while the second to maintenance task planning, with uncertainty arising from weather conditions and



failure occurrences. For this purpose, an ad-hoc Dantzig-Wolfe decomposition is developed, which differs from standard decomposition methods by including and maintaining parts of the second phase of the problem in the primary phase. The model is solved using a meta-heuristic that generates sets of extreme points, allowing the location of new and existing farms. As a result, the computational studies, divided into three parts, validated the model's stability in in- and out-of-sample tests and its practical applicability as a decision-making support tool for wind farm operators and manufacturers of medium- and large-sized vessels.

In the study by Ji et al. (2023), a variant of the Enhanced Adaptive Large Neighborhood Search (EALNS) heuristic was proposed for the problem of scheduling unrelated parallel machines with sequentially dependent setup times (UPMSP-SDST). The hierarchical calculation mechanism applied refines the comparison of different machinery removal/insertion strategies, capturing optimal solutions evaluated using multiple metrics. Experiments on 1640 instances demonstrate the superior performance of EALNS over other heuristic methods, particularly on large-scale problems.

In Wu et al. (2011) the multi-item lot sizing problem is considered, taking setup times into account, to minimize the sum of inventory maintenance and setup costs together. To this end, Hybrid Nested Partitions and Mathematical Programming (HNP-MP) is proposed, which applies a heuristic sampling and partitioning method with a global perspective, integrated with mathematical programming to calculate optimal solution regions and guide the partitioning of the problem. Thus, the time-dependent heuristic decomposition called Relax-and-Fix (R&F) is implemented to obtain good optimal regions and reduce computational processing time. The results, based on benchmark tests, demonstrate that the applied methodology is computationally feasible and generates adequate solutions, even surpassing other approaches in literature.

Now, focusing on the Fix-and-Optimize metaheuristic, in Oliveira & Scarpin (2021) a generalization is proposed for the Multi-Period Multi-Service Scheduling Problems (MMSSP) model using Relax-and-Fix and Fix-and-Optimize heuristic strategies, as will be applied in this article, where the problem is partitioned by fixing and/or relaxing some variables iteratively. Experimental validation was performed using 150 small, medium, and large instances, demonstrating that the heuristics employed produce high-quality solutions and validating the applicability of these strategies through structured planning periods.

In the study of Hashemi-Petroodi et al. (2022) investigated the impact of the task assignment technique on a lot-sizing assembly line system, using a Mixed-Integer Linear Programming (MILP) model that considers both the reconfiguration of the available workforce and the duplication of mixed assembly lines. The production lines of the manufacturing system studied are rhythmic and process different product models that require different sets of tasks and precedence interrelationships and, therefore, require variable combinations, depending on the



configuration of each takt, to satisfy the specific conditions of each line at a given moment. Hence, the proposed MILP model aims to minimize both labor and equipment costs by efficiently redesigning using dualization and robust optimization. For the treatment of large-scale instances, constructive metaheuristics (CM) and fix-and-optimize were used, demonstrating that the model dependent on the fix task assignment technique significantly reduces equipment costs and costs associated with the labor force used, when compared to classic lines.

After analyzing the main sources found in the SLR process, it can be stated that the existing literature consolidates metaheuristics, particularly the Fix-and-Optimize technique, as validated methodologies for scheduling human resources or equipment in multi-period and/or multi-item contexts. However, four persistent gaps were identified in the literature explored for the construction of this article, which are described below. There are gaps regarding the dynamic nature of the arrival of new orders and their online registration, as well as the updating of the status of existing orders in the system; there are no analyses of the explicit trade-offs between efficiency and staff satisfaction; few studies incorporate uncertainty in terms of distance and travel times between orders; there is a lack of applied studies in the electricity distribution sector, as the literature found focuses on purely industrial applications, such as machinery, equipment, and production line reconfiguration.

These gaps are consistent with the operational challenges faced by electricity utilities, particularly with regard to reducing delayed service orders, understood as backlog volume, by planning the optimized distribution of technical teams, addressing dynamic demand, variable capacity and availability, penalties for order expiration, and efficient use of overtime, among other specific conditions of the system studied. Therefore, the research proposed in this article through the development of the Fix-and-Optimize meta-heuristic adapted to the Mixed Integer Linear Programming -Mixed (MILP) model based on the backlogging technique for optimizing team scheduling in electric power utilities, represents a unique opportunity to fill a percentage of the gaps defined above, offering validation of this meta-heuristic technique in the service sector, with a focus on electric power and potential replication for telecommunications, gas, water supply.

### **3. Mathematical Model**

The proposed mathematical model is based on Mixed-Integer Linear Programming (MILP) and structured to efficiently address the assignment of service orders to technical teams with variable availability, considering different levels of prioritization of existing service orders in the pending list, composed of both unmet demands and new orders registered in the current analysis period.



In addition, the model simulates a context that represents the actual operating conditions of electric utilities and can be applied to optimize the allocation of technical resources in contexts that require agile responses and careful prioritization of work orders. The optimization strategy adopted is a sequential approach with an objective function segregated into two phases, which, according to the analysis presented in this article, was applied over a planning horizon of one quarter (90 days).

The formulations of the sets, variables, parameters, objective function, and mathematical constraints of the model are detailed in the following subsections. Tables 2, 3, 4, and 5 present the mathematical elements used in the model: indices, sets, parameters, and variables.

**Table 2. Model Index and Sets**

Symbol	Description
$i$	Technician teams, $i = 1, 2, 3, \dots, I$
$j$	Service orders, $j = 1, 2, 3, \dots, J$
$E$	Subset of emergencial service orders (priority $P_j \leq 2$ ), $e = 1, 2, 3, \dots, E \subseteq J$
$B$	Subset of backlog service orders, $b = 1, 2, 3, \dots, B \subseteq J$
$C$	Subset of comercial service orders (priority $P_j \geq 2$ ), $c = 1, 2, 3, \dots, C \subseteq J$
$t$	Analysis periods (Days), $t = 1, 2, 3, \dots, T$

**Table 3. Model Variables**

Symbol	Description	Dominium
$x_{ij}^E$	Equals 1 if $i$ attends $e$ (emergencial service order), 0 otherwise	$\{0, 1\}$
$x_{ij}^B$	Equals 1 if $i$ attends $b$ (backlogged service order), 0 otherwise	$\{0, 1\}$
$x_{ij}^C$	Equals 1 if $i$ attends $c$ (comercial service order), 0 otherwise	$\{0, 1\}$
$y_{it}$	Equals 1 if $i$ uses overtime at $t$ period, 0 otherwise	$\{0, 1\}$
$he_{it}$	Amount of overtime worked by technician $i$ in period $t$ (hours)	$R \geq 0$
$z_{ij}$	Auxiliary variable for linearization of the product $x_{ij} \times T_j$ (hours)	$R \geq 0$



$w_{ij}$	Auxiliary variable for linearization of weighted allocation cost (dimensionless)	$R \geq 0$
$PA_j$	Attention period of order j (day)	$R \geq 0$
$TB_j$	Backlog residence time of order j (periods)	$R \geq 0$
$at_j$	Accumulated delay of order j relative to generation period (periods)	$R \geq 0$
$p_j^{adj}$	Dynamically adjusted priority of order j (points)	$R \geq 0$
$atp_j$	Priority-weighted delay of order j (dimensionless)	$R \geq 0$

**Table 4. Model Parameters**

Symbol	Description	Unity	Typical Value
$C_{it}$	Available capacity of technician i in period t	Hours	8
$T_j$	Estimated execution time of order j	Hours	1,8
$P_j$	Base priority of order j	Dimensionless	1,9
$PG_j$	Generation period of order j	Period (day)	1,t
$\theta$	Overtime cost multiplier factor	Dimensionless	1,5
$\gamma$	Backlog penalty factor	Dimensionless	2,0
$\beta$	Weighted delay adjustment factor	Dimensionless	0,5
$\alpha_B$	Daily priority increment in backlog	Points/day	0,7
$\rho$	Minimum capacity proportion for backlog	Dimensionless	0,6
$M_{max}$	Maximum number of orders per technician	Orders	8
$HE_{maxday}$	Daily overtime limit per technician	Hours	4
$HE_{maxweek}$	Weekly accumulated overtime limit	Hours	12
$C_{hour}$	Unit cost of regular work hour	USD/hour	10
$C_{ov}$	Unit cost of overtime ( $\theta \times C_{hour}$ )	USD/hour	15
$C_{delay}$	Cost per day of delay	USD/day	20
$C_{emerg}$	Cost per unattended emergency order	USD/order	100



$C_{loss}$	Cost per unattended commercial order	USD/order	40
M	Sufficiently large constant (Big-M)	Dimensionless	10000

### 3.1. Objective Function Definition

This subsection defines the two-phase objective function (equation 1) that seeks to minimize the total cost of the system, expressed as the weighted sum of delay costs and resource costs. Thus, the first phase or main optimization phase, represented by equation 2, calculates the delay cost in fulfilling orders, where term 1 penalizes backlog orders in proportion to the execution time and weighted accumulated delay. Additionally, the backlog penalty factor, included in this first term, amplifies the backlog cost while encouraging its priority reduction. Term 2 of equation 2 applies a fixed penalty to each emergency order not fulfilled during the generation period, reflecting the criticality of this priority level, as well as potential regulatory penalties. Term 3 applies the penalty to unfulfilled commercial orders, representing lost revenue or customer dissatisfaction.

On the other hand, equation 3 calculates the cost associated with the use of human resources, including overtime. In it, term 1 accounts for the fixed cost of maintaining the team, which is proportional to the available nominal capacity. Term 2 adds the variable cost for overtime activation, multiplied by the factor  $\theta$ , which reflects the salary addition attributed to this time, equivalent to 50% of the basic hourly wage.

$$\min Z = Z_{delay} + Z_{technicians} \quad (1)$$

Where:

$$Z_{delay} = \sum_{j \in B} \gamma \cdot [T_j + (1 + \beta) \cdot atp_j] \cdot \left( \sum_{i \in I} x_{ij}^B \right) + \sum_{\{j \in E\}} C_{emerg} \cdot \left( 1 - \sum_{i \in I} x_{ij}^E \right) + \sum_{j \in C} C_{loss} \cdot \left( 1 - \sum_{i \in I} x_{ij}^C \right) \quad (2)$$

$$Z_{technicians} = \sum_{i \in I} \sum_{t \in T} C_{hour} \cdot C_{it} + \sum_{i \in E} \sum_{t \in T} C_{ov} \cdot he_{it} \quad (3)$$

### 3.2. Constraints Determination

The restrictions given by equations 4 to 6 ensure that orders classified as emergency (equation 4), backlog (equation 5), and commercial (6) are handled by a maximum of one technical team during the current analysis period. For emergency orders, this reflects the criticality and contractual requirements inherent to this priority level. In the case of backlog orders, the corresponding restriction also allows



for non-fulfillment, leading to an extension or additional backlog formation if capacity is insufficient. According to restriction 6, commercial orders can be fulfilled during the current analysis period or postponed, with higher-priority orders prioritized when capacity is limited.

$$\sum_{i \in I} x_{ij}^E = 1, \forall j \in E \quad (4)$$

$$\sum_{i \in I} x_{ij}^B \leq 1, \forall j \in B \quad (5)$$

$$\sum_{i \in I} x_{ij}^C \leq 1, \forall j \in C \quad (6)$$

The set of constraints corresponding to equations 7 through 9 represents the linearization of the expression.  $z_{ij} = x_{ij} \times T_j$ , which makes up a non-linear product, given that when  $x_{ij} = 1$ , the restrictions force  $z_{ij} = T_j$  and when  $x_{ij} = 0$ , forces  $z_{ij} = 0$ . So, to linearize the expression, add the constant M with a value of 10,000.

$$z_{ij} \geq T_j - M(1 - x_{ij}), \forall i \in I, \forall j \in J \quad (7)$$

$$z_{ij} \leq T_j, \forall i \in I, \forall j \in J \quad (8)$$

$$z_{ij} \leq M \cdot x_{ij}, \forall i \in I, \forall j \in J \quad (9)$$

Similarly, equations 9 to 12 are responsible for linearizing the expression  $w_{ij}$ , which is equivalent to the weighted cost of allocating delayed orders (in backlog), simultaneously capturing the order execution time and the economic penalty for delay.

$$w_{ij} \geq \text{weight}_j - M(1 - x_{ij}), \forall i \in I, \forall j \in J \quad (10)$$

$$w_{ij} \leq M \cdot x_{ij}, \forall i \in I, \forall j \in J \quad (11)$$

$$w_{ij} \geq 0, \forall i \in I, \forall j \in J \quad (12)$$

Where:

$$\text{weight}_j = \gamma \cdot [T_j + (1 + \beta) \cdot \text{atp}_j]$$



Equations 13 to 16 are associated with the use of overtime. First, the restriction given by equation 13 sets the total working time limit for each technical team to the sum of regular capacity, standard 8-hour working day, and overtime, preventing human resources from being overworked.

$$\sum_{j \in J} z_{ij} \leq C_{it} + he_{it}, \forall i \in I, \forall t \in T \quad (13)$$

Complementary to the previous one, restriction 14 represents the activation of overtime, linking its use to the activation of the binary Variable  $y_{it}$ , thus ensuring that the variable  $he_{it} > 0$  and, in consequence,  $y_{it}$  assumes the value of 1 when activated. This restriction also limits the use of daily overtime to the maximum allowed.

$$he_{it} \leq HE_{maxday} \cdot y_{it}, \forall i \in I, \forall t \in T \quad (14)$$

Restriction 15 limits the accumulation of overtime in a 7-day rolling window, ensuring compliance with legal limits under international labor law, with the aim of preserving the well-being of technicians.

$$\sum_{t'=\max(1,t-6)}^{he_{it}} he_{it} \leq HE_{maxweek} \quad \forall i \in I, \forall t \in T \quad (15)$$

Additionally, restriction 16 requires that overtime only be activated if regular capacity is fully utilized, avoiding idleness with simultaneous use of overtime, which could lead to additional costs.

$$\sum_{j \in J} z_{ij} \geq C_{it} - M(1 - y_{it}), \forall i \in I, \forall t \in T \quad (16)$$

The set of equations between 17 and 19 consists of operational constraints. Starting with constraint 17, which limits the number of orders with different classifications allocated to each technician, allowing for the identification of shifts between orders and the management of multiple tasks.

$$\sum_{j \in J} x_{ij}^E + x_{ij}^B + x_{ij}^C \leq M_{max}, \forall i \in I \quad (17)$$

Restriction 18 defines the minimum proportion of total capacity (regular + overtime) that must be used to fulfill backlog orders, avoiding chronic accumulation of delays. This is where the dynamic prioritization policy is implemented.

$$\sum_{i \in I} \sum_{j \in B} z_{ij}^B \geq \rho \cdot \left( \sum_{i \in I} C_{it} + \sum_{i \in I} he_{it} \right) \quad (18)$$



To support the previous restriction, equation 19 represents weekly intensification by increasing the minimum daily proportion of total capacity that must be used to fulfill backlog orders. This update, which can be called “cleaning,” is performed weekly (every 7 days) by implementing at least 20% more capacity, seeking to reduce accumulated delays.

$$\begin{cases} \rho_{effective} = \rho_{intensive} = 0,8 \text{ if } t \equiv 0 \pmod{7} \\ \rho = 0,6 \text{ otherwise} \end{cases} \quad (19)$$

The constraints presented in equations 20 to 25 relate to temporal variables. Starting with constraint 20, which records the period in which each order  $j$  was effectively fulfilled, allowing the calculation of temporal metrics, such as queue waiting time.

$$PA_j = t, \text{ if } \sum_{i \in I} x_{ijt} = 1, \forall j \in J \quad (20)$$

Equation 21 calculates the order's dwell time within the system, interpreted as backlog time, based on the difference between the service period and the generation period.

$$TB_j = PA_j - PG_j, \forall j \in J \quad (21)$$

Similarly, equation 22 ensures that the backlog time for orders classified as urgent is zero, ensuring that immediate service is mandatory during the generation period, as per equation 4.

$$TB_j = 0, \forall j \in E \quad (22)$$

Constraint 23 quantifies the delay time as the number of periods elapsed since the generation of order  $j$  until the current analysis period, used for dynamic priority adjustment.

$$at_j = \max(0, t - PG_j), \forall j \in J \quad (23)$$

For its part, equation 24 performs dynamic priority adjustment of orders that remain on hold within the backlog, implementing an aging mechanism that increases the prioritization level of delayed orders.

$$p_j^{adj} = P_j + \alpha_B \cdot at_j + 0,5 \cdot T_j, \forall j \in J \quad (24)$$

Complementing the previous restriction, equation 25 defines the lower bound for weighted delay, capturing interaction between waiting time and order priority level.

$$atp_j \geq at_j \cdot P_j, \forall j \in J \quad (25)$$



Finally, equations numbered 26 and 27 ensure, respectively, the binary nature and non-negativity of the variables defined for this model.

$$x_{ij}^E \in \{0,1\}, \forall i \in I, \forall j \in E \quad x_{ij}^B \in \{0,1\}, \forall i \in I, \forall j \in B \quad x_{ij}^C \in \{0,1\}, \forall i \in I, \forall j \in C, y_{it} \in \{0,1\}, \forall i \in I, \forall t \in T \quad (26)$$

$$he_{it} \geq 0, \forall i \in I, \forall t \in T \quad z_{ij} \geq 0, \forall i \in I, \forall j \in J \quad w_{it} \geq 0, \forall i \in I, \forall j \in J \quad PA_j \geq 0, \forall j \in J \quad TB_j \geq 0, \forall j \in J \quad at_j \geq 0, \forall j \in J \quad p_j^{adj} \geq 0, \forall j \in J \quad atp_j \geq 0, \forall j \in J \quad (27)$$

## 4. Methodological Approach

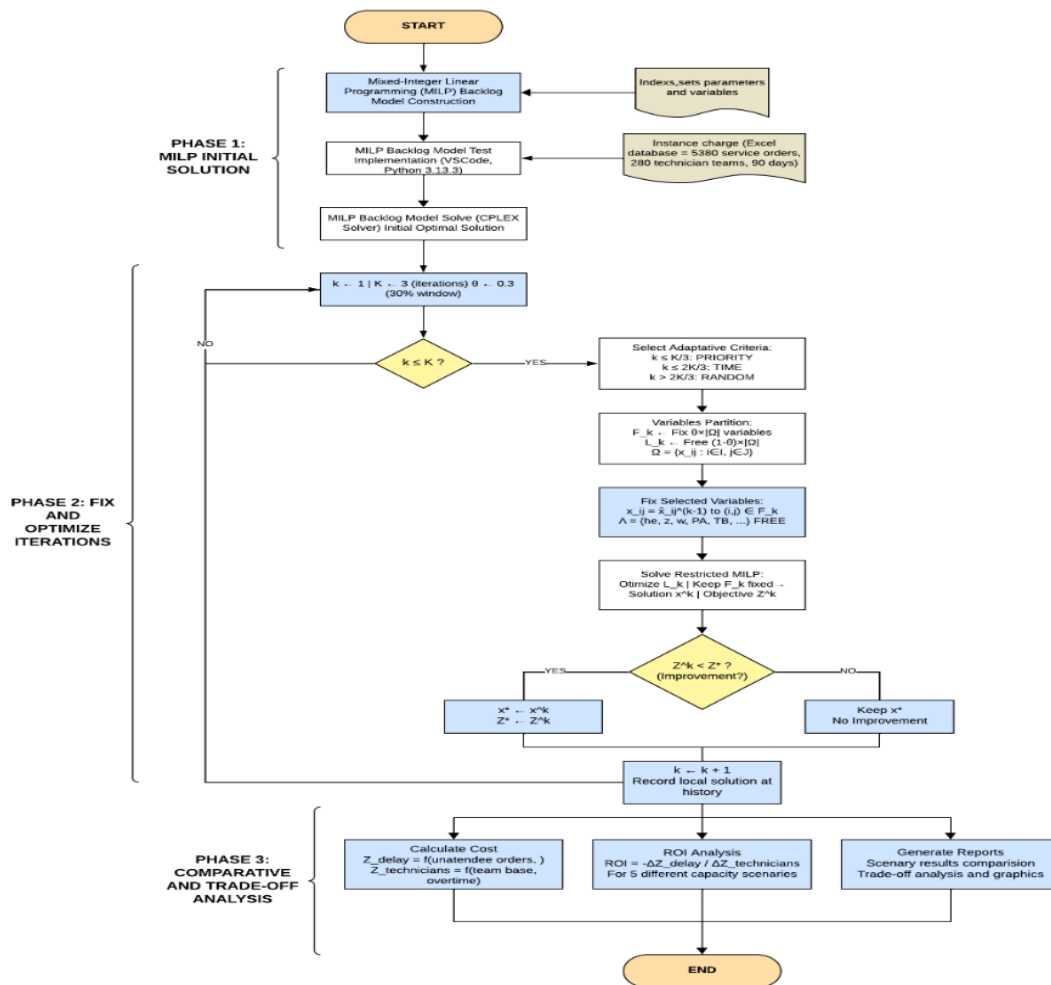


Fig.1. Flow diagram – Solution Approach



Fig.1 illustrates the flow of the methodological approach proposed in this study to address the problem of technical team allocation using a Mixed Integer Linear Programming (MILP) model solved through the Fix-and-Optimize meta-heuristic. This approach was chosen due to the NP-hard computational complexity of the problem, where exact methods become impractical for realistic instances. The methodology is structured in three sequential phases: Initial Solution, Fix-and-Optimize Iterations, and Trade-off Analysis. The First Phase consists of constructing and solving the complete MILP model

without variable fixations, obtaining a feasible reference solution. The mathematical model incorporates three categories of orders (emergency, commercial, and late), individual and collective capacity constraints, daily and weekly overtime limits, and dynamic prioritization mechanisms. The mathematical model was developed based on the methodology proposed by Hillier and Lieberman (2013), which is structured in six iterative steps. The first stage of Hillier and Lieberman's approach corresponds to problem definition, data collection, and analysis, which, for the case studied here, corresponds to an Excel database extracted from the report "Projection of demand and maximum electricity and power 2024-2028" prepared by the Mining and Energy Planning Unit of the Colombian Ministry of Mines and Energy, selected because it contains a representative volume of variable demand and capacity that are useful for the proposed simulation. For the study presented in this article, a dataset containing 5,830 work orders with different classifications and priority levels, 280 technical teams, and an operational planning horizon of 90 days (one quarter) was chosen. Subsequently, in the second stage, a mathematical model was constructed based on MILP, whose objective function is defined as biphasic and focuses on the allocation of technicians to service orders and seeks to maximize service efficiency, prioritizing emergency orders and those accumulated in the order book, as well as adequately fulfilling "new" orders that are not emergency orders and do not belong to the order backlog. The model's constraints ensure that each order is assigned to only one technician, that individual working hours are respected, and that specialization requirements are met, among others, as described in the section on the formulation of the mathematical model.

In the Second Phase, the operational conditions of the Fix-and-Optimize metaheuristic were defined, which iteratively divides binary decision variables into fixed and free subsets, solving reduced MILP subproblems in each iteration. This strategy exploits the structure of the problem, preserving high-quality decisions while exploring improvements in flexible allocations. At each iteration  $k$ , variables are partitioned, where the set of binary allocation variables given by  $\Omega = \{x_{ij}: i \in I, j \in J\}$  is divided in:

$$\Omega = F_k \cup L_k, \text{ where } F_k \cap L_k = \emptyset \quad (28)$$



$F_k$ : Fixed variables ( $|F_k| \approx \theta \times |\Omega|$ , with  $\theta = 0.3$ )

$L_k$ : Free variables ( $|L_k| \approx (1 - \theta) \times |\Omega|$ )

For variables in set  $F_k$ , the constraint  $x_{ij} = \bar{x}_{ij}^{k-1}$  is added, where  $x_{ij} = \bar{x}_{ij}^{k-1}$  represents the value equivalent to the best solution from the previous iteration. All continuous variables, given by the set  $A = \{he_{it}, y_{it}, z_{ij}, w_{ij}, PA_j, TB_j, at_j, p_j^{adj}, atp_j\}$  remain free through all iterations of the meta-heuristic. Additionally, three sequential criteria were defined for the adaptive variable partitioning strategy for the set  $F_k$ . The first criterion consists of priority (iterations 1 to  $\lfloor K/3 \rfloor$ ) and fixes allocations of orders with a higher priority level (lower  $P_j$ ), preserving the critical structure of the solution and ensuring that emergency orders are fulfilled in the generation period itself. The second criterion is related to processing time, in iterations  $\lfloor K/3 \rfloor + 1$  to  $\lfloor 2K/3 \rfloor$ , fixing the binary allocation variable starting with the largest orders (higher  $T_j$ ) and stabilizing the structure of the solution, since these orders have limited flexibility for reallocation due to capacity constraints. Finally, the third adaptability criterion corresponds to randomness (iterations  $\lfloor 2K/3 \rfloor + 1$  to  $K$ ), selected and setting random allocations  $\theta \times |A|$ , which introduces diversification to escape local optima, which is one of the main slogans of the heuristic used.

On the other hand, the stopping criterion defined for the heuristic is given by equation 29, which establishes that the execution of the algorithm ends after  $K = 3$  predefined iterations or when the relative improvement becomes insignificant.

$$\frac{(Z^{k-1} - Z^k)}{Z^{k-1}} < \varepsilon, \text{ where } \varepsilon = 10^{-4} \quad (29)$$

Finally, for the Third Phase of the proposed methodological approach, a comparative trade-off analysis was developed between the cost associated with delayed orders and that associated with different configurations of the available technical teams. To this end, five analysis scenarios were defined with different configurations of technical team capacity, and for each of them, the costs of delays, resource costs, and incremental return on investment (ROI) were quantified for each level of expansion (equation 30).

$$ROI_{\{s \rightarrow s'\}} = - \frac{(Z_{\text{delay}}^{\{s'\}} - Z_{\text{delay}}^s)}{(Z_{\text{resources}}^{\{s'\}} - Z_{\text{resources}}^s)} \quad (30)$$

If the ROI result is  $> 1$ , this indicates that the reduction in delay costs exceeds the increase in resource costs, justifying the investment under the conditions given by the respective scenario.



In contrast, if the ROI result is  $< 1$ , this signals a negative marginal return, so investing in this scenario (or scenarios) is not recommended.

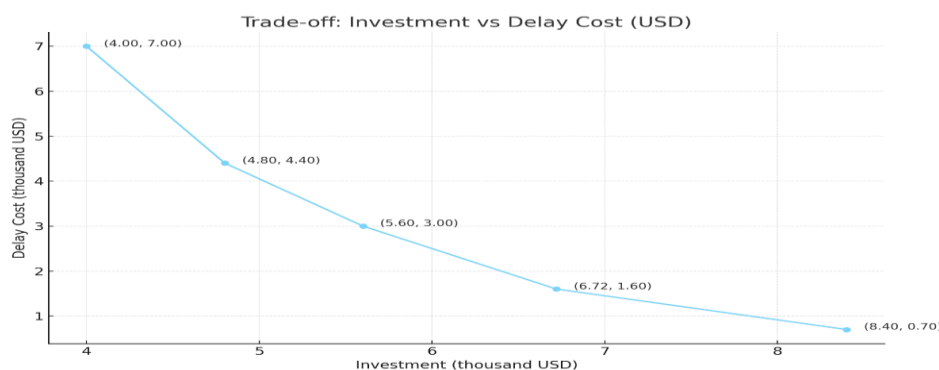
The five capacity scenarios established range from configurations with capacity constraints to configurations with abundant resources. Scenario 1, named “Minimum Team”, has no overtime. In scenario 2, “Limited Overtime”, up to 2 hours of overtime per day are allowed. For scenario 3, “Standard Overtime”, up to 4 hours of overtime per day are considered as a baseline. In scenario 4, “Expanded Team”, there was a nominal 20% increase in capacity, and finally, in scenario 5, “Maximum Team”, capacity was increased by 50%. This configuration allows for the systematic identification of the optimal break-even point, at which incremental returns on investment exceed the break-even threshold.

## 5. Results and Analysis

**5.1. Trade-off Analysis.** This subsection presents a comprehensive analysis of the trade-off between investment in human resources and the costs resulting from delayed service requests. The scatter plot reveals a clear inverse relationship between these variables, demonstrating that increased investment in operational capacity results in an exponential reduction in delay costs. Each point on the diagram represents a distinct capacity scenario, color-coded for easy visual identification of performance characteristics.

The “Standard Team (4 hours’ overtime/day)” scenario, highlighted in green with a star-shaped marker, represents the ideal balance point in this multidimensional trade-off space, with an investment in resources of \$5,600 and a delay cost of \$3,000, totaling \$8,600. This configuration achieves a superior balance between operational efficiency and service quality, as evidenced by its position at the inflection point of the efficiency curve.

Fig.2 presents the comprehensive trade-off analysis. The trade-off frontier, represented by the dashed line connecting all scenarios, suggests nonlinear behavior characteristic of mixed-integer programming problems, where marginal gains decrease as installed capacity increases.



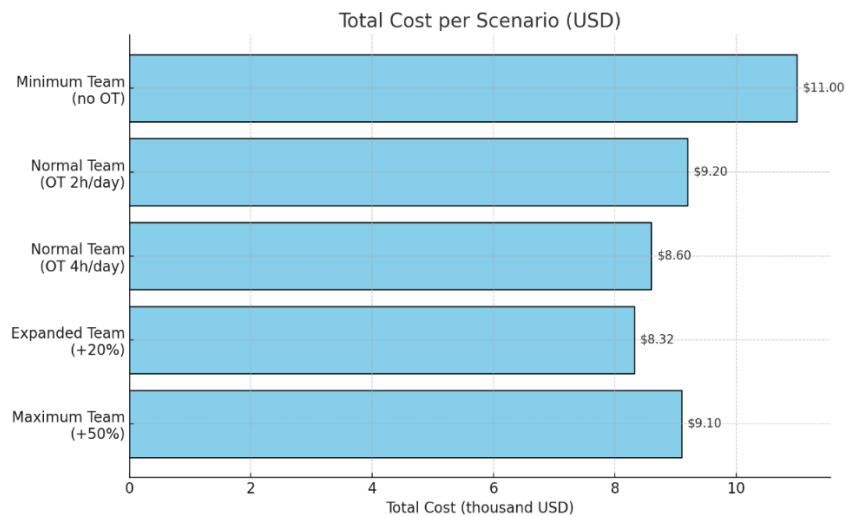
**Fig.2. Trade-off Analysis: Investment vs Delay Cost (USD)**



This behavior is consistent with established literature on capacity sizing in service delivery systems and reflects fundamental economic principles of diminishing returns. The curvature of this frontier indicates that initial investments in capacity generate substantial reductions in delay costs, while subsequent investments produce progressively smaller benefits (Helber; Sahling, 2008).

Notably, the frontier exhibits a clear inflection point in the standard overtime scenario, beyond which additional investments in capacity begin to generate negative marginal returns, as evidenced by the upward trajectory of total costs in the Expanded and Maximum Team scenarios.

**5.2. Cost Assessment per Scenario.** Fig.3 presents a horizontal analysis of the total consolidated costs for each team configuration evaluated, breaking down the economic impact of different resource allocation strategies. The results show that the minimum team scenario, despite having the lowest resource cost (\$4,000), generates the highest total cost (\$11,000) due to high penalties for absences and the systematic accumulation of delays. This represents an additional cost of 28% compared to the ideal configuration, highlighting the economic inefficiency of operations with limited capacity.



**Fig.3. Total Cost Analysis per Scenario (USD)**

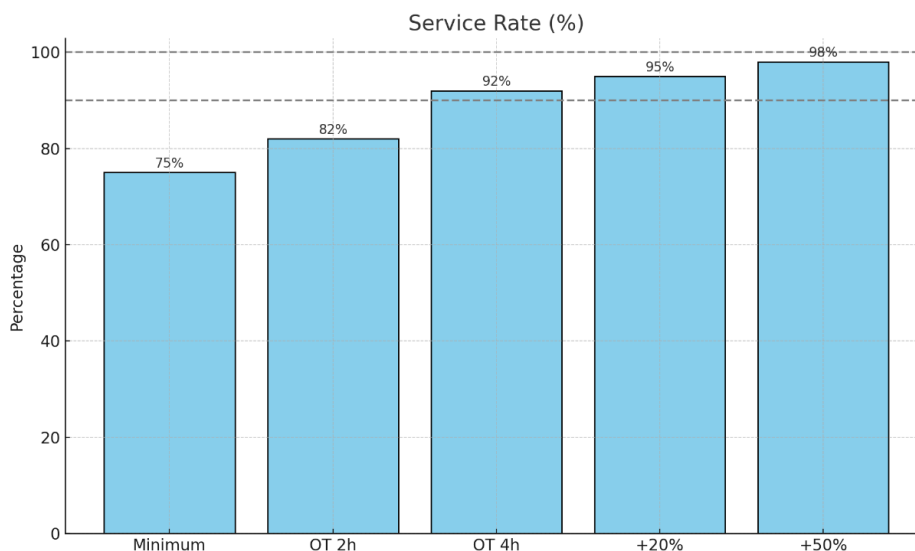
The “Expanded team (+20%)” scenario has the lowest absolute cost (\$8,320), but with a marginal difference of only 3.7% compared to the “Standard team (4 overtime hours)” scenario, which costs \$8,600. This small difference suggests that expanding beyond the standard configuration offers limited marginal returns, as will be rigorously quantified through ROI analysis in subsection 5.5. The near equivalence of these two configurations indicates that the



sweet spot lies within a relatively narrow range, requiring careful analysis rather than an obvious choice.

Particularly noteworthy is that the maximum capacity scenario (+50%) has a total cost of \$9,100, actually exceeding the +20% scenario by \$780. This result highlights a clear inflection point beyond which additional investments in capacity deteriorate the objective function due to the disproportionate increase in fixed costs without a corresponding reduction in delay costs, which approach zero (most orders are fulfilled), making further additions to capacity economically unproductive. The cost curve that emerges from this analysis provides strong empirical evidence for the existence of an optimal level of capacity, validating the theoretical framework underlying workforce sizing decisions in service operations.

**5.3. Service Level and Response Rate.** Fig.4 shows the service rates achieved in the scenarios evaluated, a critical metric for assessing the quality of service provided to customers. The results indicate a strong positive correlation between installed capacity and service rate, with performance ranging from 75% (minimum staff) to 98% (maximum staff), covering a variation of 23 percentage points.



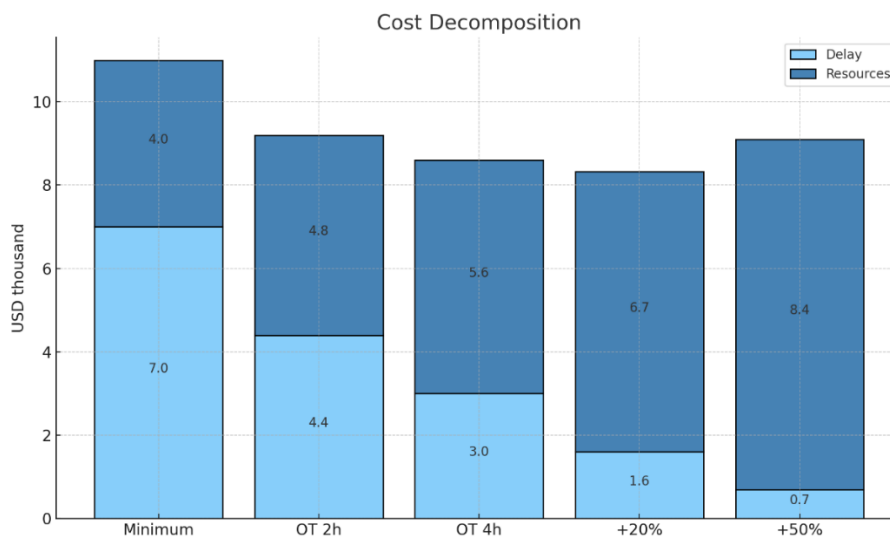
**Fig.4. Service rate per Scenario**

The “Standard Team (OT 4h)” scenario achieves a service rate of 92%, successfully exceeding the 90% threshold established as acceptable (orange reference line) and approaching the ideal target of 100% (green reference line). This performance positions the scenario in a region of high operational reliability, suitable for contracts with demanding Service Level Agreements (SLAs). The safety margin of 2 percentage points above the minimum requirement provides operational resilience against demand variability and unforeseen circumstances.



**5.4. Cost Breakdown: Backlog vs. Investment in Resources.** Fig.5 shows the breakdown of total costs into their main components: delay costs (represented in light blue) and resource costs (represented in navy blue). This stacked bar visualization reveals a consistent pattern of gradual substitution between these components as operational capacity increases, providing insights into the fundamental economic trade-off that drives optimal workforce sizing decisions.

In the minimum staffing scenario, delay costs are overwhelmingly predominant (\$7,000, corresponding to 63.6% of total costs), contrasting sharply with relatively low resource costs (\$4,000, representing 36.4%). This configuration characterizes the operation under a regime of chronic undercapacity, resulting in the systematic formation of delays and the progressive deterioration of service levels. The organization essentially saves on workforce costs but pays much more in fines, customer dissatisfaction, and possible contract violations.



**Fig.5. Cost Decomposition (delay/resources) per Scenario**

As capacity gradually increases, a gradual reversal of this ratio is observed. In the “Standard Team (OT 4h)” scenario, the cost distribution reaches a more favorable balance, with delay costs of \$3,000 (34.9%) and resource costs of \$5,600 (65.1%). This configuration represents a transition point between regimes dominated by different cost components, where neither delay costs nor resource costs exhibit excessive dominance. The ratio of approximately 2:1 between resource costs and delay costs appears to be characteristic of efficient service operations.

In the maximum capacity scenarios (+20% and +50%), resource costs dominate almost entirely (81.0% and 92.3%, respectively), with delay costs becoming practically residual. Although such configurations ensure higher service rates (95% and 98%), they imply high operational idleness and low economic efficiency, as evidenced by total costs that exceed the optimized scenario. These configurations essentially represent insurance against delays through massive



redundancy of resources, a strategy that proves economically inefficient given the cost structure of this problem. The decomposition analysis provides clear visual evidence that optimal workforce sizing should balance these competing cost forces rather than minimizing any of the components individually, reinforcing the multi-objective nature of the optimization problem.

**5.5. Incremental ROI Analysis per Scenario.** Fig.6 presents a critical analysis of the incremental return on investment (ROI), calculated using equation 31, for each proposed capacity expansion, a key metric for resource sizing decisions that quantifies the relationship between the reduction in delay costs and the increase in capacity investment. This analysis transforms the abstract optimization problem into actionable management insights by explicitly calculating the financial return on each incremental capacity addition.

$$ROI = -\frac{\Delta C_{delay}}{\Delta C_{resources}} \quad (31)$$

where:

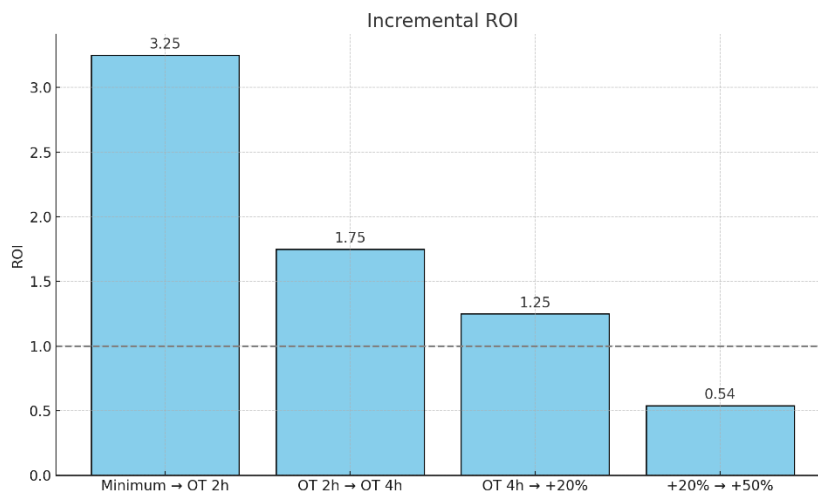
$\Delta C_{delay}$  = Variation in delay cost between consecutive scenarios

$\Delta C_{resources}$  = Variation in resource cost between consecutive scenarios

ROI values greater than 1.0 (dashed break-even line) indicate that the reduction in delay costs outweighs the additional investment in resources, economically justifying the expansion. On the other hand, an ROI of less than 1.0 signals a negative marginal return, where incremental costs exceed incremental benefits. This metric provides direct and interpretable guidance for capacity investment decisions.

The results show a systematic decrease in ROI with successive expansions, revealing the structure of decreasing returns on capacity investments. The first two capacity investments show highly favorable economic returns. The expansion from the minimum to the 2-hour overtime scenario generates an ROI of 2.43×, representing the highest efficiency among all scenarios evaluated, considering that each monetary unit invested saves 2.43 units in delay costs. Moving to OT 4h, the ROI drops to 1.75×, remaining economically attractive, although demonstrating the principle of diminishing marginal returns.

The third stage. Corresponding to the scenario with 4 hours of overtime and a 20% increase, it presents an ROI of only 1.25×, dangerously approaching the limit of economic viability. At this point, marginal benefits approach marginal costs, making the decision sensitive to parameter variations and the organization's risk preferences.



**Fig.6. Incremental ROI Analysis per Scenario**

Finally, expanding to +50% capacity is clearly unfavorable, with a negative ROI of 0.54 $\times$ . This \$1,680 investment generates only \$900 in delay cost savings, resulting in a value destruction of \$780. This scenario should be avoided, as the incremental costs (salaries and overhead) far exceed the already minimal benefits at high service levels. The incremental ROI analysis strongly supports the selection of the standard scenario with the addition of 4 hours of overtime as the optimal configuration, representing the last point on the investment curve where additional investments still generate returns substantially above the break-even point. Expansions beyond this point result in progressively decreasing and eventually negative returns, as demonstrated empirically. This finding provides clear and quantitative guidance for managerial decision-making: invest up to 4 extra hours/day, but avoid permanent expansion of the workforce unless other strategic factors (not captured in this cost model) justify the economically negative ROI.

## 6. Conclusions

This research presented a comprehensive methodology based on mixed integer linear programming (MILP) and Fix-and-Optimize heuristics for optimizing the sizing of technical teams in service order management contexts characterized by multiple priority classes. The main methodological contribution consists of a systematic analysis of the trade-off between delay costs and investment in human resources, rigorously quantifying the incremental return on investment in capacity expansion scenarios.

The backlogging based mathematical model integrates tactical decisions (nominal workforce sizing) and operational decisions (daily allocation and overtime policy) within a unified MILP formulation that incorporates 25 equations and multiple classes of variables. The Fix-and-Optimize heuristic employs an adaptive partitioning strategy, iteratively fixing 30% of the binary allocation variables according to a multi-criteria approach (priority, processing time, randomization), while keeping the continuous



variables free for optimization. This strategy reduces computational complexity, allowing for the practical solution of realistic instances.

Systematic trade-off analysis across five capacity scenarios revealed that the optimal configuration (“Standard team with 4 hours of overtime per day”) has a total cost of \$8,600, a service rate of 92%, and an incremental ROI of 1.75×, decisively outperforming the undersized and oversized alternatives. This configuration achieves a superior balance between economic efficiency (only 3.4% above the absolute minimum cost), service quality (exceeding 90% of the contractual limit), cost balance (35% delay, 65% resources), and operational feasibility (compliance with labor regulations).

On the other hand, sensitivity analysis showed systematically decreasing marginal returns for successive capacity expansions, with a clearly identified inflection point in the standard overtime configuration. The incremental ROI analysis rigorously quantified this phenomenon: highly favorable returns (2.43×) for initial expansions; positive but decreasing returns (1.75×) at the optimal point; marginal viability (1.25×) for moderate oversizing; and negative returns (0.54×) for aggressive oversizing. This performance curve provides strong empirical evidence for the existence of an optimal capacity level, validating the theoretical framework underlying workforce sizing decisions.

Additionally, the proposed methodology provides robust quantitative support for resource sizing decisions, applicable to various technical service delivery contexts characterized by capacity constraints, multiple priority classes, and flexible overtime policies. The integration of the optimization model, the efficient heuristic solution method, and the systematic trade-off analysis framework represents a significant contribution to operational research applied to service operations management.

## Acknowledgments

The authors would like to thank the Laboratory for Modeling and Optimization of Systems (LaMOS – UFSM). This study was funded by the Coordination for the Improvement of Higher Education Personnel (CAPES) - Financial Code 001. Additionally, the research was developed within the scope of ANEEL's Research, Development, and Innovation Projects (PDI), under code PD-00037-0053/2024, in conjunction with INESC P&D Brasil and the Eqt<sup>x</sup> Lab of the Equatorial Energia Group, Porto Alegre.

## References

- [1] Al-Kuwari, A. *et al.* Life cycle sustainability assessment of electricity production technologies: a structured review and future research perspectives. Elsevier Ltd, 2025. <https://doi.org/10.1016/j.esr.2025.101939>
- [2] Alvizu, R. *et al.* Energy Efficient Dynamic Optical Routing for Mobile Metro-Core Networks Under Tidal Traffic Patterns. *Journal of Lightwave Technology*, vol. 35, n° 2, p. 325–333, 2017. <https://doi.org/10.1109/JLT.2016.2638739>
- [3] Dupin, N. & Talbi, E.G. Machine learning-guided dual heuristics and new lower bounds for the refueling and maintenance planning problem of nuclear power plants. *Algorithms*, vol. 13, n° 8, 2020. <https://doi.org/10.3390/a13080185>
- [4] Feng, B. & Ye, Q. Operations management of smart logistics: A literature review and future research. Higher Education Press Limited Company, 2021. <https://doi.org/10.1007/s42524-021-0156-2>



- [5] Fonseca, G.H.G., Figueiroa, G.B., Toffolo, T.A.M. A fix-and-optimize heuristic for the Unrelated Parallel Machine Scheduling Problem. *Computers and Operations Research*, vol. 163, 2024. <https://doi.org/10.1016/j.cor.2023.106504>
- [6] Gamst, M. & Pisinger, D. Decision support for the technician routing and scheduling problem. *NETWORKS*, vol. 83, n° 1, p. 169–196, 2024. <https://doi.org/10.1002/net.22188>
- [7] Gong, X. *et al.* A Matheuristic Approach for the Home Care Scheduling Problem with Chargeable Overtime and Preference Matching. *IEEE Transactions on Automation Science and Engineering*, vol. 18, n° 1, p. 282–298, 2021. <http://dx.doi.org/10.1109/TASE.2020.3026484>
- [8] Graf, B. Adaptive large variable neighborhood search for a multiperiod vehicle and technician routing problem. *Networks*, vol. 76, n° 2, p. 256–272, 2020. <https://doi.org/10.1002/net.21959>
- [9] Gruson, M., Cordeau, J., Jans, R. The impact of service level constraints in deterministic lot sizing with backlogging. *Omega*, vol. 79, p. 91–103, 2018. <https://doi.org/10.1016/j.omega.2017.08.003>
- [10] Hashemi-Petroodi, S. *et al.* Model-dependent task assignment in multi-manned mixed-model assembly lines with walking workers. *OMEGA-INTERNATIONAL JOURNAL OF MANAGEMENT SCIENCE*, vol. 113, 2022. <https://doi.org/10.1016/j.omega.2022.102688>
- [11] Helber, S. & Sahling, F. A fix-and-optimize approach for the multi-level capacitated lot sizing problem. 2008. <https://doi.org/10.1016/j.ijpe.2009.08.022>
- [12] Hillier, F.S. & Lieberman, G.J. *Introdução à Pesquisa Operacional*. 8. ed. São Paulo - SP: McGraw-Hill Interamericana do Brasil Ltda. 2013.
- [13] Houssein, E.H. *et al.* *Metaheuristics for Solving Global and Engineering Optimization Problems: Review, Applications, Open Issues and Challenges*. Springer Science and Business Media B.V., 2024. <https://doi.org/10.1007/s11831-024-10168-6>
- [14] Ji, B. *et al.* An Enhanced Adaptive Large Neighborhood Search for Unrelated Parallel Machine Scheduling with Sequence Dependent Setup Times. *IEEE ACCESS*, vol. 11, p. 16735–16748, 2023. <https://doi.org/10.1109/ACCESS.2023.3245825>
- [15] Nielsen, C. & Pisinger, D. Tactical planning for dynamic technician routing and scheduling problems. *Transportation Research Part E: Logistics and Transportation Review*, vol. 177, 2023. <https://doi.org/10.1016/j.tre.2023.103225>
- [16] Oliveira, J.D. & Scarpin, C.T. Multi-Period Service\_Scheduling Problems: A new model and heuristic approaches of relax-and-fix and fix-and-optimize. *IEEE Latin America Transactions*, vol. 19, n° 9, p. 1528–1536, 2021. <https://doi.org/10.1109/TLA.2021.9468446>
- [17] Page, M.J. *et al.* The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ Publishing Group*, 2021. <https://doi.org/10.1136/bmj.n71>
- [18] Pillac, V., Gueret, C., Medaglia, A. On the dynamic technician routing and scheduling problem. *ODYSSEUS 2012-5th International Workshop on Freight Transportation and Logistics*. 2012. Available at: <https://dumas.ccsd.cnrs.fr/EC-NANTES/hal-00739781v1>
- [19] Ribault, A. *et al.* Economic optimisation of cold production: a matheuristic with artificial neural network approach. *INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH*, vol. 59, n° 22, p. 6941–6962, 2021. <https://doi.org/10.1080/00207543.2020.1831705>



- [20] Saleheen, F. & Habib, M.M. Global Supply Chain Disruption Management Post Covid 19. American Journal of Industrial and Business Management, vol. 12, n° 03, p. 376–389, 2022. <https://doi.org/10.4236/ajibm.2022.123021>
- [21] Stalhane, M. *et al.* Optimizing vessel fleet size and mix to support maintenance operations at offshore wind farms. EUROPEAN JOURNAL OF OPERATIONAL RESEARCH, vol. 276, n° 2, p. 495–509, 2019. <https://doi.org/10.1016/j.ejor.2019.01.023>
- [22] Wu, T. *et al.* An optimization framework for solving capacitated multi-level lot-sizing problems with backlogging. European Journal of Operational Research, vol. 214, n° 2, p. 428–441, 2011. <https://doi.org/10.1016/j.ejor.2011.04.029>