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Time Redistribution Based on Temporal Risk Matrices for Operational Optimization in Public Security Institutions

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Abstract

The current “9-3” operational scheduling model used by the Ecuadorian National Police imposes rigid 8-hour rotational shifts over nine consecutive days, followed by three days off, without accounting for the spatiotemporal distribution of criminal activity. This leads to structural inefficiencies, including officer overload exceeding public-sector standards by 57%, unbalanced shift coverage, and an increase in fatigue-related incidents. This study aims to optimize staff allocation by proposing a data-driven redistribution model based on a normalized hour-day matrix. The method integrates multi-source institutional data, including ECU-911 dispatch logs, crime reports, and homicide records, and applies weighted normalization to construct proportional risk matrices per time slot. These matrices guide the redistribution of personnel while adhering to institutional criteria, including target monthly workload, equitable shift rotation, and guaranteed minimum coverage. The model was implemented in four pilot sectors characterized by varying urban, residential, and peripheral conditions. Results demonstrated improved adequacy in night-shift coverage of up to 30%, a 41% reduction in temporal imbalance, and decreased workload variability, with coefficients of variation below 6%. The proposed approach offers a replicable, low-cost planning solution that combines empirical risk modeling, operational transparency, and institutional scalability, representing a significant methodological improvement over the traditional static scheduling model.

Keywords:

Data-Driven Workforce Optimization;
Operational Scheduling in Law Enforcement;
Temporal Risk-Based Personnel Allocation;
Public Safety Resource Planning.

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1- Introduction

Operational human talent management in government institutions faces increasing pressure to optimize staff distribution based on actual service demand [1, 2]. This need is exacerbated in complex urban environments, where crime rates, population density, and temporary emergency flows present high hourly and spatial variability levels. In the specific case of the Ecuadorian National Police, the model in place since 2013—known as the 9-3 schedule—assigns operational staff to rotating 8-hour shifts for nine consecutive days, followed by 3 days off, with rotation between three work groups. Although initially aimed at ensuring operational continuity, this plan has resulted in structural overtime, with a monthly average of 271.3 hours per officer (63.3 hours per week), exceeding the standard public sector workday by more than 57%. The effects of this overload are multiple: increased absenteeism, accumulated operational fatigue, the risk of errors in critical patrols, and a personnel distribution that does not adjust to the actual operational load of each time zone or geographic sector. Previous institutional studies have identified significant deficiencies in the alignment between personnel supply and service demand, observing, for example, an equitable distribution of officers between shifts with unequal demands or days with peak crime rates covered with the same number of personnel as low-load

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shifts. These inefficiencies are accentuated by the fact that the 9-3 model neither incorporates evidence-based redistribution dynamics nor adapts its planning logic to geotemporal variations in crime.

In response to this problem, this study proposes a proportional redistribution model based on normalized hourly risk matrices, developed using integrated empirical data from various institutional sources. The methodological approach is based on constructing an Hour-Day (HD) matrix for each pilot operational unit, in which risk levels are weighted by time slot based on a weighted integration of reported crimes, ECU-911 assistance, and homicide records. This matrix is then used to generate proportional hourly workloads, guided by institutional criteria such as a target monthly workload of 220 hours per officer, allowing controlled deviations to accommodate operational constraints, minimum coverage per time slot, and equitable rotation between shifts [3].

The methodology was implemented and validated in four pilot circuits selected based on operational load, crime typology, and territorial representativeness: one metropolitan sector, one residential sector, one peripheral sector, and one mixed center-south sector. The model was executed using matrix analysis tools in Python, with an automated process that included data cleaning and normalization, generation of HD matrices, calculation of proportional workloads, and constraint validation. The results were evaluated using key indicators such as adequate coverage by time slot $\bar{C}$, the coefficient of variation (CV) of individual workload [4], the operational fatigue index (OFI), and organizational perception captured through pre- and post-implementation surveys [5].

The most relevant findings indicate that the proposed model achieved an average 12.4% improvement in adequate workload coverage during critical shifts (10 p.m.–6 a.m.) without increasing staffing levels. The redistribution significantly reduced the coefficient of variation of individual monthly workloads, from approximately 5.2% in the traditional model to below 2.1% in the optimized model, demonstrating a more equitable balance among officers. Furthermore, during the pilot period, there was a 34% reduction in unjustified absences and a 27% reduction in unplanned shift changes. From a statistical perspective, repeated-measures ANOVA and the Wilcoxon signed-rank test confirmed significant differences in key indicators between the traditional and optimized models, with p-values below 0.01 in the sectors with the highest operational load.

In computational terms, the algorithm demonstrated efficient performance, with an average execution time of approximately 4.1 seconds per sector, including data loading, matrix processing, and time assignment generation. The implementation follows standard practices in numerical and data-driven processing environments [6]. Statistical validation included a sensitivity analysis to input perturbations, with RMSE values ranging from approximately 1.19 to 1.37 and MAE values ranging from 1.00 to 1.11, demonstrating the model's stability under minor changes in historical data. Furthermore, the mean Euclidean distance between the optimized planning and the ideal reference patterns remained below 5% in all sectors, confirming the algorithm's accuracy in following the accumulated risk logic by time slot.

This study presents a validated operational approach to a persistent operational problem and proposes a replicable, auditable, and computationally low-cost methodological proposal. The model's ability to integrate into institutional environments without requiring constant retraining or specialized infrastructure makes it a viable option for widespread adoption in other regions of the country. Ultimately, this research contributes to progress toward more equitable, efficient, and evidence-based operational planning, reaffirming the role of data analytics systems in transforming public security policies.

Although several studies have explored the optimization of operational resource workload using simulation and algorithmic approaches, most have been constrained to synthetic or controlled scenarios. For instance, Zhou and Xia [7] and Dewinter et al. [8] proposed sensor-based and algorithmic models for emergency response and patrol planning; however, these models lack empirical validation under real-world institutional deployment—similarly, Xia et al. [9] and Wang et al. [10] highlighted the potential of AI-driven scheduling in logistics and disaster contexts; however, they did not consider hourly workload variability or equity in rotation. Institutional planning studies, such as Wilson & Grammich [11], emphasized the need for workload-based models but fall short in integrating multi-source risk indicators. Moreover, digital transformation frameworks by Latupeirissa et al. [12] and interoperability proposals by Runeson et al. [13] demonstrated how technology can enhance public service operations; however, they do not provide operationally executable models for the redistribution of human resources. Consequently, a research gap remains in developing and validating integrated, auditable, and proportional scheduling models based on temporal risk that can be deployed within public security institutions. This study addresses that gap by proposing a normalized hour-day matrix model tested under real operational conditions, offering a replicable and computationally efficient alternative to traditional static scheduling.

Based on these gaps, this study examines whether a proportional redistribution model, grounded in normalized HD matrices, can enhance operational coverage, reduce workload inequity, and mitigate institutional fatigue without increasing staff size. The central hypothesis is that aligning staff workloads with hourly risk patterns leads to statistically significant improvements in both performance indicators and organizational well-being.

The article is structured as follows: Section 2 presents the literature review, organizing relevant background information on operational optimization, adaptive planning, and human resource redistribution in security contexts. Section 3 details the materials and methods, including the institutional environment, data consolidation, model construction, implementation, and validation. Section 4 presents the experimental results, divided into the following analytical sections: coverage, individual workload, fatigue, institutional perception, and algorithm performance. Finally, Sections 5 and 6, respectively, develop the critical discussion, conclusions based on the findings, and future lines of work for national scaling.

2- Literature Review

2-1- Applied Technical Optimization

The efficient redistribution of human resources in operational services has motivated a growing body of technical research, with approaches that combine mathematical models, simulation, and intelligent algorithms. Zhou and Xia [7] propose an optimized algorithm for dispatching public resources in emergencies, integrating sensors and heuristic models, which yields promising results in reducing response times. This data-driven structure is analogous to the proportional logic employed in this study, which utilizes HD matrices to organize and redistribute personnel by hour and day.

Wang et al. [10] proposed a multi-objective workload with route planning for natural disaster chains, demonstrating that optimization should consider not only efficiency but also adaptability and robustness to variations in demand; similarly, Xia et al. [9] developed an artificial intelligence-based medical supply scheduling system, emphasizing emergency environments and highlighting the value of AI in managing uncertainty and operational constraints. Jain et al. [14] reinforced this approach through proactive prediction by applying machine learning algorithms to improve early resource workload. Dewinter et al. [8] directly addressed the policing field by utilizing simulations and optimization algorithms to enhance patrol coverage and minimize response times. These works, summarized in Tables 1 and 2, demonstrate a high level of applicability in real-life environments, although in most cases, empirical implementation remains limited or restricted to simulations.

Our proposal addresses this gap by integrating a redistribution model validated using real-life institutional data, applied under operational conditions, and incorporating technical, organizational, and perceptual metrics. The combination of matrix proportionality, time sensitivity, and experimental validation significantly differentiates them from existing approaches.

2-2- Operational Planning Strategies

Other studies have addressed the need to strengthen operational planning from a more institutional perspective. Wilson & Grammich [11] proposed a systemic view of police planning, incorporating workload analysis and dynamic scenarios to improve staff workload. This approach aligns with the structure of our proposal, recognizing that shift efficiency depends on hourly granularity and a strategic organizational vision.

Damilola et al. [1] argued that the strategic workload of human resources must integrate quantitative mechanisms and interdepartmental information structures to achieve sustainable adaptation to dynamic contexts. This principle is fundamental to the design of the redistribution model presented here, as it is based on multi-source historical data and implemented without excessive technical requirements.

Pratama et al. [15] proposed optimizing task and resource workload through project management information systems, which parallels the digitalization of the HD model developed in this study. The three works offer relevant technical foundations, although they still lack a precise translation into the Latin American police context.

2-3- Digital Transformation and Operational Reorganization

Latupeirissa et al. [12] highlighted that institutional digitalization can profoundly transform the delivery of public services, enabling adaptive configurations and greater responsiveness. This framework is directly reflected in the operational logic of this study, where data digitalization enables the construction of high-definition matrices and the integration of tactical planning modules within existing platforms. Runeson et al. [13] presented an approach to open data ecosystems as catalysts for inter-institutional collaboration, which is essential when public safety relies on multiple sources, such as ECU911, justice, and internal planning. Along these same lines, Fauzian et al. [2] documented the use of digital platforms in local governments' talent management, emphasizing traceability, transparency, and operational flexibility.

The articles, grouped in Table 2 under the subtopic of digital transformation, validate the data architecture, interoperability, and organizational deployment assumed in our model, highlighting their applicability to real-life institutional contexts. For clarity, the "Level of Application" column uses a qualitative scale: High indicates direct operational implementation or validated deployment; Medium indicates partial applicability requiring contextual adaptation; and Low corresponds to primarily theoretical contributions with limited direct integration into institutional settings.

2-4- Talent Management and Ethical Considerations

Algorithmic decisions in human resources require a balance between operational efficiency and organizational fairness. Based on the study by Aguinis et al. [16], it is essential to point out that the use of artificial intelligence in talent management must be accompanied by explainability and ethical evaluation criteria, particularly in highly sensitive contexts such as law enforcement.

Damilola et al. [1] emphasized that redistribution schemes must consider non-quantitative organizational factors, such as staff perceptions, internal culture, and the sustainability of change. Kulshrestha [17] offered a quantitative view of AI's impact on management practices for Industrial 4.0 environments, concluding that without human oversight, systems can reproduce organizational biases and tensions.

Regarding algorithmic governance, Calvo [18] proposed a critical review of institutional automation from the perspective of public rights, emphasizing that traceability and ethical deliberation must accompany any automated decision-making process. Although these studies show a lower level of application (see Table 2), they are essential to establishing the operational limits of the model and ensuring its fair, transparent, and legitimate implementation.

In this implementation, these ethical considerations were operationalized through specific safeguards. First, all individual-level records used to build the HD matrices were anonymized to protect personal and professional privacy. Second, the algorithmic outputs were subject to manual review and approval by the heads of each operational unit before implementation. Third, the redistribution model was designed to remain within the legal and institutional constraints of work hours and rotation policies, without imposing any additional obligations on the personnel. Finally, field validation included participatory mechanisms such as briefings with unit commanders and consultations with operational representatives to ensure transparency, consent, and institutional legitimacy.

2-5-Summary: Expected contribution

The consolidated analysis reveals a fragmentation in previous studies, with some focusing on pure optimization, others on institutional planning, and a few on digitalization or algorithmic ethics. However, no previous approach simultaneously articulates the four pillars of our proposal: proportional algorithmic structure, empirical field validation, operational digital integration, and multi-scale organizational assessment.

This work proposes a comprehensive solution for the time redistribution of security personnel, supported by operational evidence, with low computational cost and high explainability. Its direct implementation in real institutional environments and its multidimensional validation position as a significant contribution from both methodological and applied perspectives.

Table 1. Thematic Classification of the Reviewed Studies

Reference	Source	Main Subtopic Description midrule
Zhou & Xia (2021) [7]	Journal of Sensors	Focuses on optimizing operational resource allocation using sensor networks in dynamic environments.
Xia et al. (2025) [9]	Int. J. of Production Research	Addresses supply scheduling challenges by utilizing artificial intelligence to enhance production efficiency.
Pratama et al. (2023) [15]	TEM Journal	Proposes optimization models for resource allocation in distributed systems.
Wang et al. (2022) [10]	IJERPH	Presents a multi-objective optimization strategy for resource allocation in public health logistics.
Dewinter et al. (2024) [8]	Networks	Simulates patrol operations to improve route planning and resource use.
Wilson & Grammich (2024) [11]	Policing (Oxford)	Analyzes police load and manpower planning using empirical methods.
Jain et al. (2023) [14]	Front. in Env. Science	Utilizes AI tools for planning and predictive modeling in environmental management.
Runeson et al. (2021) [13]	J. of Systems and Software	Investigates the development and management of open data ecosystems.
Latupeirissa et al. (2024) [12]	Sustainability	Studies the impact of digitalization on the performance of public services.
Fauzian et al. (2024) [2]	J. Law and Sust. Dev.	Explores digital strategies for effective talent management in public institutions.
Aguinis et al. (2024) [16]	Organizational Dynamics	Discusses the implications of generative AI in human resource management practices.
Kulshrestha (2024) [17]	JAIMLNN	Evaluates AI-based mechanisms for enhancing organizational efficiency.
Sharma (2024) [19]	IJIREM	Implement analytics tools to assess and optimize human talent capabilities.
Damilola et al. (2024) [1]	IJSRA	Examine strategic management frameworks in the logistics and transportation sectors.
Calvo (2019) [18]	CLAD Magazine	Critically reflects ethical dimensions in algorithmic governance and public policy.

Table 2. Thematic Coverage and Level of Application

Subtopic	Number of Studies	Level	Observations midrule
Operational Resource Optimization	5 (Refs. [7–10, 15])	High	It demonstrates direct applicability in logistics, resource redistribution, and scheduling, especially in public safety and emergency response environments.
Operational Planning and Workload	2 (Refs. [11, 14])	Medium	Provides institutional insights for planning and staff allocation, with potential adaptations required for specific policing implementations.
Data Ecosystems and Digitalization	2 (Refs. [12, 13])	High	Emphasizes the role of interoperability and multi-source integration to enhance surveillance capabilities and incident response frameworks.
Talent Management and Human Resources	4 (Refs. [2, 16, 17, 19])	Medium	Supports strategic redistribution of human resources and talent optimization through organizational-level applications.
Ethical Approach and Algorithmic Governance	1 (Ref. [18])	Low	Provides a theoretical lens on algorithmic transparency and governance, but lacks demonstrated operational deployment.

3- Material and Methods

Figure 1 illustrates the conceptual architecture of the proposed model for the proportional redistribution of operational personnel. The process begins with aggregating multi-source institutional data, followed by constructing an HD matrix that reflects the relative operational pressure across time slots. This matrix undergoes a normalization and weighting process to produce a proportional distribution aligned with actual demand. The output is discretized into institutional shift blocks, allowing direct translation into operational schedules. The process culminates in the generation of workload sheets and subsequent evaluation through multidimensional indicators, including adequate coverage, OFI, coefficient of variation (CV), and institutional perception metrics. In operational deployment, the HD matrix is updated monthly using the latest available data from incident reports, emergency calls, and crime records to ensure responsiveness to changing patterns without compromising data stability.

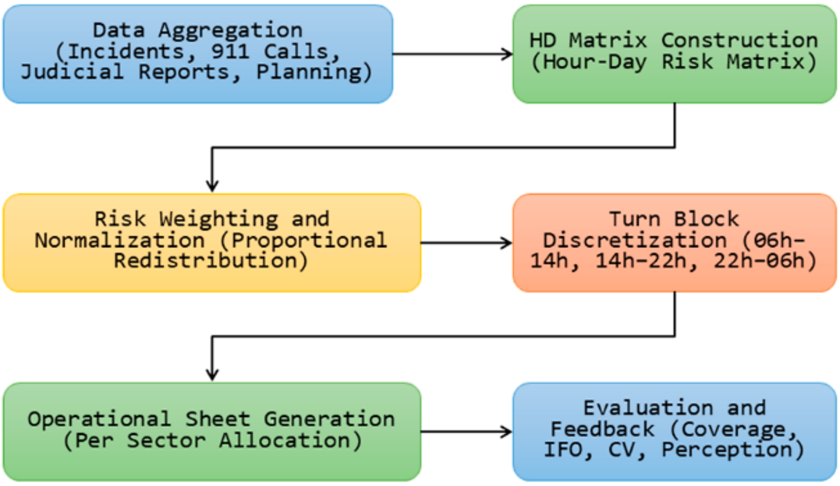


Figure 1. Architecture of the Proposed Operational Redistribution Model Based on Hour-Day Risk Matrices

3-1- Data Sources and Institutional Environment

This research was conducted within the Ecuadorian National Police, specifically within the framework of an intervention aimed at optimizing the workload of operational human resources in high-crime areas. The study is based on transforming the traditional patrol shift model by integrating multi-source data and applying demand-based proportional redistribution techniques.

3-1-1- Current Shift Model

The current work schedule distribution scheme implemented at the institution is known as the 9-3 model, which consists of nine continuous days of active duty followed by three consecutive days of rest, structured into three rotating eight-hour shifts (Shift 1: 6:00 a.m.–2:00 p.m., Shift 2: 2:00 p.m.–10:00 p.m., Shift 3: 10:00 p.m.–6:00 a.m.). This system is applied uniformly without distinction by area, event volume, or risk level, resulting in an overallocation of workloads and low coverage efficiency relative to actual demand patterns.

The institutional statistical analysis shows that the current model entails an average workload of 63.3 hours per week per agent, which exceeds the legal 40-hour workweek established for the Ecuadorian public sector by 57%. This situation has been linked to increased negative indicators, such as absenteeism, workplace accidents, and a deteriorating perception of the organizational climate, as well as collateral effects on operational efficiency, since incident peaks do not coincide with the concentration of personnel in the field.

3-1-2- Institutional Environment and Pilot Units

A restricted experimental environment was defined to validate the proposed data-driven scheduling redistribution model, consisting of four operational police units (circuits) strategically selected based on their historical event load, geographic coverage, and structural representativeness. For reasons of institutional confidentiality, these circuits will be referred to in this document as:

- Sector A – Metropolitan Area
- Sector B – Northern Residential Area
- Sector C – Southern Peripheral Area
- Sector D – Central-South Mixed Area

Each of these sectors corresponds to an operationally deployed geopolice unit, whose duties include preventive patrols, responding to incidents reported through emergency centers, and following up on complaints filed through the criminal justice system. The selection was made in coordination with the technical team of the National Police Planning Command, ensuring a representative sample in terms of both the volume of events and crime typology and scheduling distribution.

3-1-3- Data Sources

The model is based on an analysis system powered by data from four primary sources, integrated using temporal and spatial normalization procedures:

- ECU-911 System: A consolidated database of events reported to the emergency system was used from January to December 2023. The records include the type of incident (e.g., robbery, domestic violence, riots), time of receipt, dispatch time, geographic location, and assigned police quadrant code. For the model, the data were grouped by time slot (hour-day) and weighted according to the criticality of the event type.
- State Attorney General's Office: Records of formal criminal complaints filed in the sectors under study were accessed and organized by type of crime, day of occurrence, and estimated time slot. This source complements the information on emerging events with statistics on non-emerging crimes, providing a more complete picture of the structural crime burden in the selected sectors.
- National Directorate of Crimes Against Life: An anonymized database of officially recorded intentional homicides was used, where each case was georeferenced by sector and temporally categorized by the hour and day of occurrence. This variable was included as an indicator of extreme risk, with differentiated weighting within the demand matrix.
- Internal operational planning data: Historical shift schedules, work-hour distribution reports, operational compliance indicators, and results of internal work environment surveys were included. This information allowed the model to be adjusted to institutional constraints, and baselines for post-implementation impact assessment were established.

Each data set was transformed into a standard matrix structure to construct the HD demand matrices for each sector. This representation enables the granular identification of periods with the highest concentration of events and the dynamic adjustment of operational personnel distribution according to the volume and weighted criticality of incidents in each time slot.

3-2- Data Processing and Consolidation

The processing of data collected from multiple sources addressed the need to construct a homogeneous, granular, and operationally meaningful representation of criminal behavior, as well as the demand for assistance in the various sectors analyzed. This processing involved cleansing and normalization operations, as well as a structural transformation aimed at constructing a base matrix for time redistribution. Anonymization procedures were also incorporated and applied across multiple datasets to protect sensitive data at both personal and territorial levels.

3-2-1- Data Preprocessing and Anonymization

The original dataset includes sensitive elements such as quadrant identifiers, call codes, police officer names, exact addresses of event occurrences, and other variables classified as restricted by institutional regulations. As part of the anonymization protocol, individual events were grouped into macro-zones, defined as territorial aggregations aligned with police operational subcircuits. Although there is no fixed standard for the number of blocks per subcircuit in Quito, official estimates and geospatial data suggest that a typical subcircuit covers approximately 1 km², which corresponds to 50–100 urban blocks, depending on the street grid density. This level of aggregation ensures that individual addresses are not traceable while preserving spatial structure for operational modeling.

The names of operational officers were replaced with coded alphanumeric identifiers generated using an irreversible SHA-256 hash [20, 21], ensuring that original identities cannot be reconstructed from the transformed data. This hashing procedure was adopted as part of the anonymization strategy to protect sensitive personal information. Precise geographic locations were converted into sector codes (A, B, C, and D) and further categorized into broad geographic zones (metropolitan, north, south, and south-central) without retaining links to actual parish or jurisdictional names.

The cleaning and validation process included eliminating duplicate records, treating null values, and cross-validating dates and times to ensure chronological consistency. The time slots were normalized to a 24-hour format, with simple time resolution (one row for each hour of the day), and the dates were transformed into time variables composed of the day of the week and the time of the event.

3-2-2- Temporal Grouping and Matrix Structuring

Once the preprocessing was complete, the records were grouped by territorial unit, event type, and time slot. This operation allowed the construction of an HD matrix for each sector, where the rows represent 24 hours of the day, and the columns represent the 7 days of the week.

Formally, for each sector S_i, a matrix $M_{Si} \in \mathbb{R}^{24x7}$ is defined, where each entry $m_{h,d}$ represents the weighted aggregation of events occurring at hour $h \in [0,23]$ of day $d \in [0,7]$.

The matrix is constructed using the following procedure:

For each data source (ECU-911 assistance, Prosecutor's Office reports, recorded homicides), a temporal frequency matrix $F_{S_i}^k$ is generated with the exact *24 x 7* structure, indexed by hour and day.

Each source k is assigned a weight $w_k \in \mathbb{R}^+$according to its criticality and operational relevance level. For example, a higher weight was assigned to homicides (extreme risk), followed by emergency assistance, and finally, reports.

The total weighted matrix for sector S_i is calculated as:

$$M_{S_i} = \sum_{k=1}^{n} w_k \cdot F_{S_i}^k \tag{1}$$

where, $n = 3$ corresponds to the three primary data sources, and all F^k are normalized by relative frequency per sector.

For each matrix $F_{S_i}^k$, the values were normalized using a logarithmic scale with Laplace smoothing to avoid the dominance of extreme values. The transformation was defined as:

$$f'_{h,d} = \log(1 + f_{h,d}) \tag{2}$$

This allowed the variance between periods with a high concentration of events and those with low concentrations to be reduced without losing the relative proportionality between cells.

The definition of the w_k weights was based on technical criteria agreed upon between the analysis team and the head of institutional planning. The value assigned to each data source was:

- Homicides: $w_1 = 0.5$
- Dispatched emergency services (ECU-911): $w_2 = 0.3$
- Reports (Prosecutor's Office): $w_3 = 0.2$

This weighted scheme reflects the greater urgency and criticality associated with violent events, followed by real-time calls, and finally, the structural data on reports.

Once the M_{Si} matrix was obtained for each sector, it was fully normalized so that the sum of all elements equaled 1. This allowed each cell, $m_{h,d}$, to be interpreted as the relative proportion of the ideal workload allocated to that time slot in the context of the total assignable hours for the month:

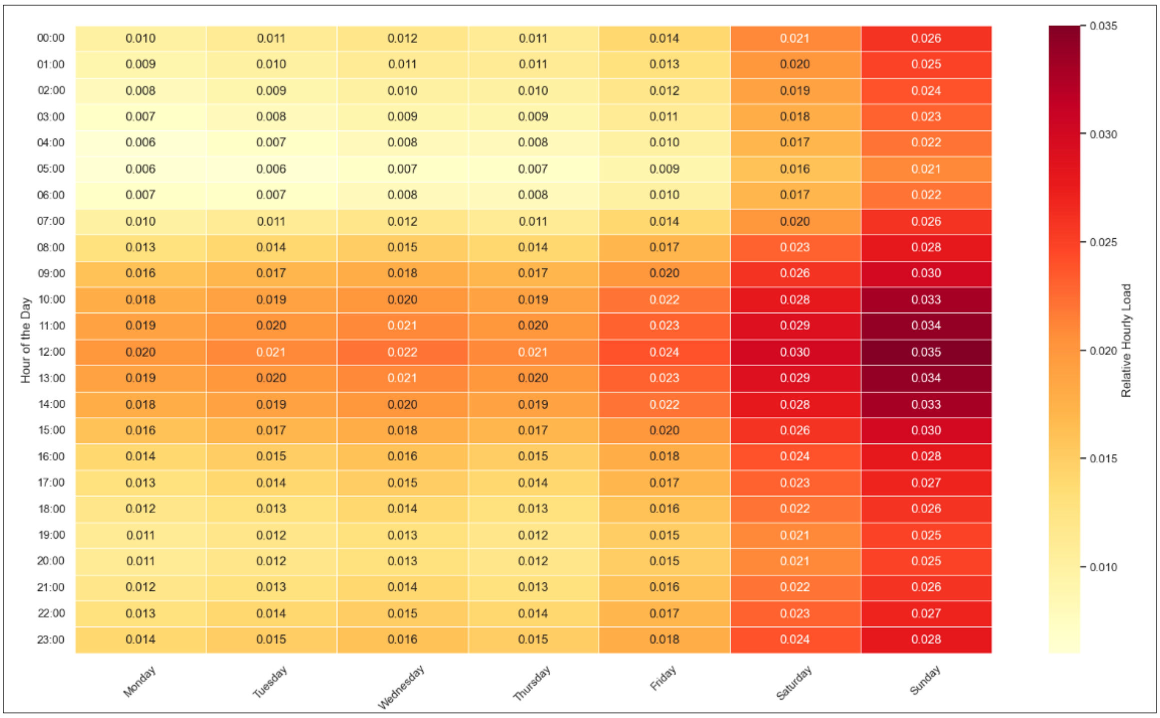
$$M_{S_i}^* = \frac{M_{S_i}}{\sum_{h=0}^{23} \sum_{d=1}^{7} m_{h,d}} \tag{3}$$

3-2-3- Schematic Representation

The final HD matrix can be represented graphically, as shown in Figure 2, which illustrates a schematic example of the normalized hourly distribution of events in an urban public safety environment. In this two-dimensional heatmap, the vertical axis represents the 24 hours of the day. In contrast, the horizontal axis contains the seven days of the week, thus structuring a 24 × 7 matrix of cells. Each cell encodes, using a color scale ranging from yellow to deep red, the relative hourly load value corresponding to a specific time slot, derived from the multi-source analysis described previously.

The color intensity is directly related to the normalized value obtained in the weighted matrix $M_{S_i}^*$, which is calculated from the aggregation of events from the ECU-911, the Prosecutor's Office, and homicide records, using the weighting model defined in Equation 1. These values are converted into relative proportions, allowing for a visual interpretation of the distribution of operational demand over time.

As shown in Figure 2, temporal patterns consistent with previous studies on urban crime dynamics are observed: a progressive increase in workload is recorded from morning to afternoon, reaching its peak between 6:00 PM and 2:00 AM, particularly on Fridays, Saturdays, and Sundays. This behavior confirms the institutional hypothesis regarding the misalignment between the fixed shift distribution of the 9-3 model and the actual operational demand curve, which varies significantly depending on the day of the week and the time of day.



	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00:00	0.010	0.011	0.012	0.011	0.014	0.021	0.026
01:00	0.009	0.010	0.011	0.011	0.013	0.020	0.025
02:00	0.008	0.009	0.010	0.010	0.012	0.019	0.024
03:00	0.007	0.008	0.009	0.009	0.011	0.018	0.023
04:00	0.006	0.007	0.008	0.008	0.010	0.017	0.022
05:00	0.006	0.006	0.007	0.007	0.009	0.016	0.021
06:00	0.007	0.007	0.008	0.008	0.010	0.017	0.022
07:00	0.010	0.011	0.012	0.011	0.014	0.020	0.026
08:00	0.013	0.014	0.015	0.014	0.017	0.023	0.028
09:00	0.016	0.017	0.018	0.017	0.020	0.026	0.030
10:00	0.018	0.019	0.020	0.019	0.022	0.028	0.033
11:00	0.019	0.020	0.021	0.020	0.023	0.029	0.034
12:00	0.020	0.021	0.022	0.021	0.024	0.030	0.035
13:00	0.019	0.020	0.021	0.020	0.023	0.029	0.034
14:00	0.018	0.019	0.020	0.019	0.022	0.028	0.033
15:00	0.016	0.017	0.018	0.017	0.020	0.026	0.030
16:00	0.014	0.015	0.016	0.015	0.018	0.024	0.028
17:00	0.013	0.014	0.015	0.014	0.017	0.023	0.027
18:00	0.012	0.013	0.014	0.013	0.016	0.022	0.026
19:00	0.011	0.012	0.013	0.012	0.015	0.021	0.025
20:00	0.011	0.012	0.013	0.012	0.015	0.021	0.025
21:00	0.012	0.013	0.014	0.013	0.016	0.022	0.026
22:00	0.013	0.014	0.015	0.014	0.017	0.023	0.027
23:00	0.014	0.015	0.016	0.015	0.018	0.024	0.028

Figure 2. Normalized Hourly Distribution of Events – HD Matrix (Schematic Example). Visual representation of the normalized hour-day matrix $M^*_{S_i}$ showing the relative load values per time slot aggregated across multiple data sources. Higher intensities indicate periods of elevated operational demand.

This type of matrix representation is key to the next methodological step, as it allows data to be visually translated into operational decisions. Each matrix cell can be interpreted as a proportional hourly workload coefficient, with higher values corresponding to time slots where police presence should be reinforced. The HD matrix, therefore, serves as a direct input for the adaptive personnel redistribution algorithm, described in the following section.

3-3- Construction of the Time Redistribution Model

The redistribution of operational human resources is based on transforming the HD matrix, as described in the previous section, into a proportional hourly workload scheme that is adapted to institutional, operational, and legal constraints. This transformation is implemented through a redistribution model based on weighted proportional rules, which seeks to maximize the efficiency of police coverage while minimizing the need for additional personnel.

3-3-1- Fundamentals of the Proportional Model

Starting from the normalized hourly demand matrix $M_{Si} \in \mathbb{R}^{24x7}$, constructed for each sector S_i, a time workload function $A(h,d)$ is defined, which represents the number of person-hours required to cover each time slot (h,d) proportional to its relative value in the matrix.

Let T be the total number of person-hours available in sector S_i per month (e.g., the number of staff E_i multiplied by the nominal monthly workload target per staff member, i.e., 220 hours, used as a reference value rather than a strict constraint). The workload function is defined as:

$$A(h,d) = T \cdot m^*_{h,d} \tag{4}$$

where, $m^*_{h,d} \in M^*_{S_i}$ is the normalized relative load value for hour h of day d. This proportional workload ensures that time slots with higher demand receive a greater share of operating resources. The model also allows for the subsequent discretization of $A(h,d)$ to convert continuous values into integer server workloads per slot, using proportional adjustment techniques commonly applied in resource workload problems [22], with stochastic rounding preferred for its ability to preserve proportionality and avoid cumulative workload bias, particularly in time slots with low fractional values.

3-3-2- Conditions of Institutional Restriction

To ensure the operational and institutional viability of the proposal, three key constraints were implemented:

Monthly staff workload reference:

Each police officer is assigned a nominal workload target of 220 hours per month, in accordance with current national regulations. This value serves as a reference constraint to guide the distribution of hours across weekly plans. Formally:

$$\sum_{w=1}^{W} H_{a,w} \leq 220 \; \forall a \in \mathcal{A} \tag{5}$$

where, $H_{a,w}$ is the number of hours assigned to officer a in week w, and $\mathcal{A}$ is the set of officers available in the sector.

Guaranteed minimum coverage per hour:

To ensure that all time slots have at least a basic operational capacity, a minimum coverage threshold C_{min} is defined as a fixed percentage of the total number of personnel in the sector. For all hours h and days d, the following must be satisfied:

$$Assignment\ (h,d) \geq C_{min} \cdot E_i \tag{6}$$

Shift balance and operational equity:

A rotation scheme is implemented under the principle of inter-shift equity, ensuring that no officer is consistently assigned to only one time slot, such as exclusively night shifts. The following equilibrium metric is used:

$$\forall a \in \mathcal{A}, |T_a^1 - T_a^2| < \delta \ and \ |T_a^1 - T_a^3| < \delta \tag{7}$$

where, T_a^k represents the number of shifts of type $k \in \{1,2,3\}$ assigned to officer a, and δ is the maximum acceptable difference between shift assignments.

3-4- Justification of the Model Used

The adopted model follows a direct proportional redistribution approach. Alternative approaches based on adaptive decision-making and evidence-driven modeling have been explored in related domains [23]. At the same time, heuristic optimization and integer programming techniques are commonly used in similar workload problems [24]. This decision responds to the criteria of institutional transparency, operational replicability, and low computational cost—key elements in administrative environments where solutions must be understandable to operational teams and easily adaptable to new conditions. In this framework, the proportional model guarantees an explainable and auditable workload. Each time slot receives resources in exact proportion to the observed relative workload, enabling operational traceability and social validation mechanisms.

3-4-1- Representation of the Redistribution Algorithm (Pseudocode)

The following pseudocode describes the procedure implemented to calculate the monthly redistribution of police personnel based on the normalized demand matrix ***M****, the institutional constraints, and the operational balance required by the model:

Algorithm 1. **Monthly Redistribution Based on Normalized Demand Matrix**

```
Require: Normalized demand matrix $M(24 \times 7)$, number of agents $E$, maximum hours per agent $H_{max}$, minimum coverage ratio $C_{min}$
Ensure: Assigned person-hours $A(h,d)$ per hour and day
$T \leftarrow E \times H_{max}$ {Total available monthly person-hours}
for each hour $h$ in $[0, 23]$ do
    for each day $d$ in $[1, 7]$ do
        $A(h,d) \leftarrow T \times M(h,d)$
        if $A(h,d) < C_{min} \times E$ then
            $A(h,d) \leftarrow C_{min} \times E$
        end if
    end for
end for
Round $A(h,d)$ values to nearest integers, preserving total sum
for each day $d$ do
    Aggregate $A(h,d)$ into time blocks (Turn 1, 2, 3)
end for
Assign agents to time blocks ensuring:
    No agent exceeds $H_{max}$
    Turn distribution per agent is balanced ($\Delta T \leq \delta$)
Export structured planning matrix $P(k,d)$ for operational deployment
```

This algorithm was implemented in Python using efficient numerical processing libraries, such as *NumPy* and *Pandas*, to ensure reproducibility, scalability, and modularity [25, 26]. The framework enables integration with external databases and operational dashboards, allowing future incorporation into real-time planning tools or AI-based adaptive systems. Its design follows computational modeling best practices, avoiding manual intervention and ensuring consistency across large-scale institutional implementations.

3-4-2- Transformation of the Matrix A(h,d) into Shift Operational Blocks

Once the hourly workload matrix *A(h,d)* has been generated, the next step is to convert these continuous values into actual blocks of police shifts, which are institutionally defined as 8-hour time slots:

- Shift 1: 6:00 a.m.–2:00 p.m.
- Shift 2: 2:00 p.m.–10:00 p.m.
- Shift 3: 10:00 p.m.–6:00 a.m.

Since *A(h,d)* contains hourly workloads, the 24 hours of the day are grouped into three fixed time sets $\mathcal{T}_k$ corresponding to the shifts defined:

$$\begin{aligned}\mathcal{T}_1 &= \{6,7,8,9,10,11,12,13\}\\ \mathcal{T}_2 &= \{14,15,16,17,18,19,20,21\}\\ \mathcal{T}_3 &= \{22,23,0,1,2,4,5\}\end{aligned} \tag{8}$$

For each day *d*, the total workload assigned to each shift $T_k(d)$ is calculated by summing the values in the matrix *A(h,d)* corresponding to the set $\mathcal{T}_k$:

$$T_k(d) = \sum_{h\in\mathcal{T}_k} A(h,d) \tag{9}$$

This block aggregation allows us to establish the number of person-hours assigned to each daily shift. These hours are then distributed among the available agents, respecting the restrictions above (monthly maximum shift balance and minimum coverage). Each block $T_k(d)$ is thus transformed into a discrete staff assignment:

$$Agents_{T_k d} = \left|\frac{T_k(d)}{8}\right| \tag{10}$$

Since each agent covers 8 hours per shift, this assignment is made in a secondary planning matrix *P(k,d)*, which contains the number of agents assigned to shift *k* on day *d*, by sector. This structure enables the generation of a structured spreadsheet by day and shift, making it suitable for operational deployment. It also allows the simulation of scenarios in which the hourly coverage achieved under different configurations is evaluated, and the model's fit with the actual capabilities of the available personnel is verified.

The model implementation was developed entirely in Python, using libraries such as *NumPy* for matrix operations, *Pandas* for structured data manipulation, and *SciPy* for statistical validation of proportions and constraints. The assignment of shift blocks was automated through a modular function that converts the matrices *A(h,d)* and $T_k(d)$ into planning structures that can be exported in interoperable formats (CSV, JSON, SQLite). This implementation improves computational efficiency compared to manual solutions. It allows the model to be scaled to multiple sectors in parallel, evaluate scenario variations, and perform operational impact simulations based on historical data [27]. Furthermore, the code's modularity allows its integration with existing institutional systems or its evolution towards a real-time operational intelligence platform.

3-5- Operational Redistribution and Simulation

Applying the proportional redistribution model based on the workload matrix A(h,d) enabled the automated generation of operational spreadsheets tailored to the actual crime and healthcare demand profile. This process was a critical step in tactical implementation, as it enabled the translation of an abstract matrix of relative intensities into concrete staff assignments by shift, based on quantitative criteria of efficiency and coverage.

3-5-1- Conversion to Weekly Operating Spreadsheets

The matrix *A(h,d)*, obtained after weighting multi-source data and subsequently adjusting it for institutional constraints, was reorganized into a weekly planning structure based on the three shift blocks defined by the operating regulations: Shift 1 (6:00 a.m.–2:00 p.m.), Shift 2 (2:00 p.m.–10:00 p.m.), and Shift 3 (10:00 p.m.–6:00 a.m.). For each day of the week, the time workloads corresponding to each shift were consolidated by aggregating the *A(h,d)* values in the respective time slots. The sum of the person-hours assigned to each block allowed us to derive the number of agents needed per shift per day, using the quotient of Equation (10).

3-5-2- Simulation of Operational Coverage

To validate the model's effectiveness before its pilot implementation, comparative coverage simulations were conducted using the history of actual events in the selected sectors as input. To do this, a practical coverage assessment function *C(h,d)* was defined, which calculates the quotient between the number of officers assigned per shift and the number of events estimated in the corresponding time slot, weighted by their criticality level:

$$C(h,d) = \frac{Agents_{h,d}}{Events_{h,d} \cdot \alpha_k} \tag{11}$$

where, α_k represents a criticality weighting factor for each type of event (e.g., homicides, emergency medical assistance, complaints). This metric enables the comparison of the number of personnel deployed and their suitability for the time-of-day risk profile. Multiple simulations were run under the assumption that the total number of personnel available per circuit remained constant, ensuring that the improvement in coverage was attributable solely to proportional redistribution and not to an increase in human resources.

3-5-3- Comparison Before and After Redistribution

To evaluate the proposed model's potential impact, a comparison protocol was defined between two operational scenarios: the baseline scenario and the optimized scenario. This comparison aims to analyze, under controlled conditions, the variation in the hourly distribution of operational human resources without altering the total number of officers available per sector.

- Baseline scenario: This corresponds to the traditional 9-to-3 model, in which officers are assigned in fixed blocks of rotating shifts without explicit consideration of actual hourly demand. Staff distribution is homogeneous and does not respond to the temporal patterns of crime or emergency response events.
- Optimized scenario: This scenario reflects the implementation of the proportional redistribution model, in which hourly workloads are derived directly from the normalized and criticality-weighted HD matrix. In this case, staff workload is dynamic and responds to the hourly variability of risk.

The comparison is made through a cross-assessment of each pilot sector, using a set of quantitative indicators that characterize the efficiency and adjustment of operational deployment. The metrics applied are:

- Average adequate hourly coverage $\bar{C}$: an indicator that quantifies the relationship between assigned agents per time slot and the estimated event load, standardized by hour and day. This metric enables the analysis of the degree of adequacy of distribution to actual demand.
- Hourly imbalance index Δ_{var}: a measure of dispersion that calculates the variance in coverage between time slots within a single day or week. The greater the variance, the greater the inequity in hourly workload.
- Hourly saturation level: an estimate of the average number of agents per hour in the time slots with the highest event concentration, used to compare whether the model improves the targeting of human resources at critical moments.

Each indicator is calculated on simulated data from the operational plans generated by both models, allowing for a structured and replicable comparison. The comparison methodology was designed to hold input parameters (number of agents, shift structure, days of operation) constant, ensuring that any observed differences in coverage were solely attributable to the scheduling redistribution model.

3-6- Pilot Implementation and Validation

The pilot implementation phase represented the first controlled operational exercise to apply and validate the proportional redistribution model under real-life institutional deployment conditions. Based on the four defined sectors, the new schedule planning scheme was implemented on the monthly operational spreadsheets, applying the structures generated by the previously described redistribution algorithm.

3-6-1- Application of the Model in the Pilot Sectors

The planning generated for each sector was transferred to the operational environment by replacing the traditional 9-3 rotation schedule with a time workload based on shift blocks proportionally adjusted to each unit's specific HD matrix. This transition did not imply a change in the total number of personnel or the legal duration of shifts, but only in the temporal distribution of resources within the month.

The new scheme was applied under normal operating conditions, respecting the current hierarchies, supervisory processes, and institutional control systems. To ensure the validity of the process, an internal induction phase was established for the personnel in charge of planning, as well as technical support sessions during the first two weeks of implementation.

3-6-2- Temporary and Operational Design of the Pilot

The pilot execution period lasted two consecutive months and was divided into two monthly planning and monitoring cycles. During each cycle, the mathematical model's basic structure remained unchanged, allowing for the evaluation of its stability and reproducibility in similar environments.

Each month, the matrices *A(h,d)* generated by the model were converted into shift staffing assignments using the hourly aggregation mechanism described above. Weekly worksheets were then created by sector, ensuring equitable rotation between Shift 1, Shift 2, and Shift 3 and compliance with individual workload restrictions. These worksheets were integrated into the internal operational attendance control system, allowing ongoing monitoring. Throughout the pilot, the research team and the operational planning staff maintained a technical observation channel to record minor adjustments or logistical issues that could lead to model feedback in future iterations.

3-6-3- Structured Validation Indicators

The pilot's validation was structured through a set of technical and organizational indicators selected to reflect the direct and indirect impact of the hour shift. These indicators were defined before implementation and collected using institutional monitoring tools, administrative records, and structured survey mechanisms.

a) Individual workload per agent

This indicator is calculated as the monthly sum of hours assigned to each agent, considering shift rotations and actual workdays. For each agent a, the following was computed:

$$H_{total}^{a} = \sum_{w=1}^{W} \sum_{t=1}^{3} H_{a,w,t} \tag{12}$$

where, $H_{a,w,t}$ represents the number of hours assigned to agent a in week w on shift t. This variable enabled the evaluation of adherence to the nominal monthly workload target of 220 hours and supported equitable workload distribution among officers in the same circuit.

b) Relative hourly coverage

For each time slot, the relationship between the number of assigned officers and the expected event load, weighted by criticality, was estimated using the metric in Equation (11).

c) Organizational climate and operational perception

A structured survey instrument was designed and administered to the operational officers of the four sectors to evaluate the organizational impact of the model change. This instrument included validated items to measure:

- Perception of operational overload;
- Satisfaction with assigned schedules;
- Clarity and understanding of the new system;
- Willingness to continue and replicate.

The application was conducted anonymously through the institutional platform, and the responses were processed using aggregation procedures and fundamental statistical analysis to preserve confidentiality.

d) Secondary impact indicators

Operational variables that could be affected by the schedule reorganization were monitored, including:

- Monthly absenteeism rate per agent;
- Record of work-related incidents (accidents, sanctions);
- Average incident response times by time slot.

This data is extracted directly from the institutional operational control systems and integrated into the consolidated database for subsequent analysis.

3-7- Comparative Analysis and Metrics

The effectiveness of the time redistribution model was analyzed using a battery of quantitative metrics designed to capture the implementation's operational, organizational, and temporal effects. These metrics were applied comparatively between two experimental conditions: the pre-scenario (based on the traditional 9-3 model) and the post-scenario (redistribution model based on the HD matrix). Differences were validated using both parametric and nonparametric statistical techniques, depending on the nature and distribution of the data.

3-7-1- Applied Performance Metrics

To assess changes in the scheduling structure and their operational impacts, the following metrics were applied, calculated separately for each pilot circuit and subsequently aggregated into cross-sector analyses.

a) Effective Hourly Coverage Rate

The effective hourly coverage rate $\bar{C}$ was defined as the weighted average hourly coverage rate in each operating week. This metric assesses the degree of alignment between staffing workload and the expected event load, with the greater the alignment. Formally:

$$\bar{C} = \frac{1}{168}\sum_{h=0}^{23}\sum_{d=1}^{7}\frac{Agents_{h,d}}{Events_{h,d}\cdot\alpha_k} \tag{13}$$

where the values are weighted by the event's criticality level α_k.

b) Workload Distribution Index

To capture equity in the distribution of operational effort among agents, the coefficient of variation of individual monthly workload was calculated:

$$CV = \frac{\sigma_H}{\mu_H} \tag{14}$$

where, σ_H is the standard deviation of the hours assigned per agent and μ_H is the mean. This index enables the detection of workload concentrations and the evaluation of whether the model improves internal equity compared to the traditional approach.

c) Derived Fatigue and Operation Indicators

Based on data collected through internal surveys and administrative records, a composite OFI was modeled, integrating variables such as perceived overload, number of unjustified absences, and unplanned shift changes. The index was scaled in a standardized manner for each circuit and week:

$$OFI_s = w_1\cdot S_a + w_2\cdot R_u + w_3\cdot C_t \tag{15}$$

where, S_a: Self-perceived overload score (survey); R_u: Record of unscheduled absences; C_t: Unplanned shift changes; w_i: Weights assigned according to the analysis of explained variance.

This indicator enabled us to observe, without yet analyzing the results, how the latent dimensions related to operational burnout behaved before and after the change.

3-7-2- Comparative Statistical Design

To compare the initial conditions (traditional 9-3 model) and the final conditions (optimized redistribution model), carefully selected statistical techniques were applied based on the type of metric evaluated and its distribution characteristics. The objective was to ensure the validity of the contrasts and the sensitivity to detect significant differences.

For continuous variables that presented an approximately normal distribution, such as the average adequate hourly coverage $\bar{C}$ and the coefficient of variation of monthly workload CV, a repeated measures analysis of variance (RM ANOVA) was applied. In this design, the police circuit was considered a within-subject factor (as these were repeated measurements on the same organizational unit) and the type of planning model (traditional vs. optimized) as a between-subject factor. This approach enabled the analysis of the interaction between the territorial structure and the applied model, allowing for the observation of overall differences and their consistency across the various sectors evaluated.

For ordinal metrics or those that did not meet normality assumptions, such as indicators derived from job perception surveys, the nonparametric Wilcoxon Signed-Rank test [28] was used. This technique enabled the comparison of response distributions before and after model implementation in each sector, without assuming symmetry or homogeneity of variance, thereby maintaining a conservative and robust approach to qualitative or limited-scale data.

Given its multi-component construction, the OFI's behavior was modeled using generalized linear regression (GLM) [29]. This technique enabled the identification of possible interactions between the variables of assigned shift, operating sector, and week of the pilot cycle, allowing for the isolation of structural effects attributable to the reallocation of staff hours, thereby separating them from possible contextual or administrative variations.

Bivariate correlation coefficients were calculated to explore relationships between variables derived from the model and actual performance conditions [30, 31]. Pearson's correlation coefficient was used for pairs of continuous variables with a normal distribution, while Spearman's correlation coefficient was used for those with non-normal distributions. These correlations were applied, for example, between adequate coverage by time slot and institutional records of operational incidents, allowing trends in the association between planning and actual performance to be observed without incurring causal inferences.

4- Results

4-1- Effective Hourly Coverage by Sector

The evaluation of adequate hourly coverage is a central element in validating the proposed model. This section compares the operational workload levels achieved in the pilot sectors under the traditional 9-3 schedule and the optimized model based on HD matrices, which redistributes shifts according to historically observed demand patterns.

Table 3 presents the empirical values of adequate coverage by shift, day of the week, and model type. Looking at the data for Sector A – Metropolitan Area, a classic pattern of overstaffing is detected in daytime periods from Monday to Friday (with values close to or greater than 0.80 in the 6:00 a.m.–2:00 p.m. shift) and a clear understaffing in the night shift, which reaches minimums of 0.50–0.51 during the week. This structural bias of the traditional model imposes an unbalanced operational burden and limits institutional response during times of high crime incidence. This is particularly problematic in metropolitan areas where nocturnal criminal activity is historically concentrated, as indicated by the ECU-911 and homicide datasets used in the risk matrix construction. Understaffing in these periods not only reduces response capacity but also increases officer vulnerability in high-risk patrols.

Table 3. Adequate Hourly Coverage by Shift, Day, and Operating Model – Sectors A, B, C and D

Sector	Model Type	Shift	Mon	Tue	Wed	Thu	Fri	Sat	Sun
A – Metropolitan	Traditional	06h–14h	0.78	0.80	0.79	0.80	0.82	0.83	0.81
		14h–22h	0.76	0.77	0.77	0.78	0.79	0.80	0.78
		22h–06h	0.52	0.53	0.52	0.54	0.56	0.58	0.57
	Optimized	06h–14h	0.74	0.75	0.74	0.76	0.79	0.84	0.86
		14h–22h	0.77	0.78	0.78	0.80	0.84	0.89	0.91
		22h–06h	0.61	0.63	0.64	0.66	0.71	0.79	0.83
B – Northern Residential	Traditional	06h–14h	0.81	0.83	0.83	0.84	0.85	0.86	0.84
		14h–22h	0.74	0.74	0.74	0.75	0.76	0.77	0.75
		22h–06h	0.49	0.49	0.50	0.51	0.53	0.55	0.54
	Optimized	06h–14h	0.70	0.71	0.72	0.74	0.77	0.83	0.85
		14h–22h	0.76	0.77	0.78	0.79	0.82	0.86	0.89
		22h–06h	0.60	0.61	0.63	0.65	0.68	0.75	0.80
C – Southern Peripheral	Traditional	06h–14h	0.82	0.83	0.83	0.83	0.84	0.85	0.83
		14h–22h	0.72	0.72	0.73	0.74	0.75	0.76	0.74
		22h–06h	0.47	0.48	0.48	0.50	0.52	0.53	0.51
	Optimized	06h–14h	0.68	0.70	0.71	0.72	0.75	0.80	0.83
		14h–22h	0.75	0.76	0.77	0.79	0.82	0.87	0.90
22h–06h	0.59	0.60	0.61	0.63	0.66	0.73	0.78	-	-
D – Central-South Mixed	Traditional	06h–14h	0.79	0.80	0.80	0.81	0.82	0.84	0.83
		14h–22h	0.75	0.75	0.76	0.77	0.78	0.79	0.78
		22h–06h	0.50	0.50	0.51	0.52	0.54	0.56	0.55

With the implementation of the optimized model, this pattern is strategically reversed. Nighttime coverage progressively improves, reaching values of 0.79 on Saturday and 0.83 on Sunday (10 p.m.–6 a.m. shift), representing a relative increase of 52% compared to the baseline model. Simultaneously, the morning time slot experiences a selective reduction, freeing up resources without compromising the established minimum coverage. This nonlinear redistribution allows operational presence to be adapted to critical risk time slots, improving efficiency without increasing the number of personnel.

This shift in resource concentration allows for more effective deployment during the peak demand windows identified through the HD matrix, particularly during weekends and late-night hours, periods typically associated with higher incident rates such as assaults, thefts, and domestic disturbances. Moreover, maintaining adequate morning coverage while reallocating excess capacity toward higher-risk hours shows that the model achieves optimization without sacrificing baseline service levels.

These findings are visualized in Figure 3, which graphically decomposes the evolution of coverage in Figure 3A. The traditional heatmap (Panel A) exhibits a monotonic workload with a predominance of morning time slots. In contrast, the optimized heatmap (Figure 3B) reveals a strategic redistribution toward the afternoon and nighttime slots, with a notable emphasis on weekends. Figure 3C shows that, despite a constant average daily coverage in the traditional model (~0.70), the optimized model achieves significant growth on days with the highest demand (Saturday and Sunday), reaching values of 0.84 and 0.87, respectively. Figure 3D reinforces this observation by representing, using a radar chart, the average coverage per shift, highlighting the increase in the night shift from 0.54 to 0.70.

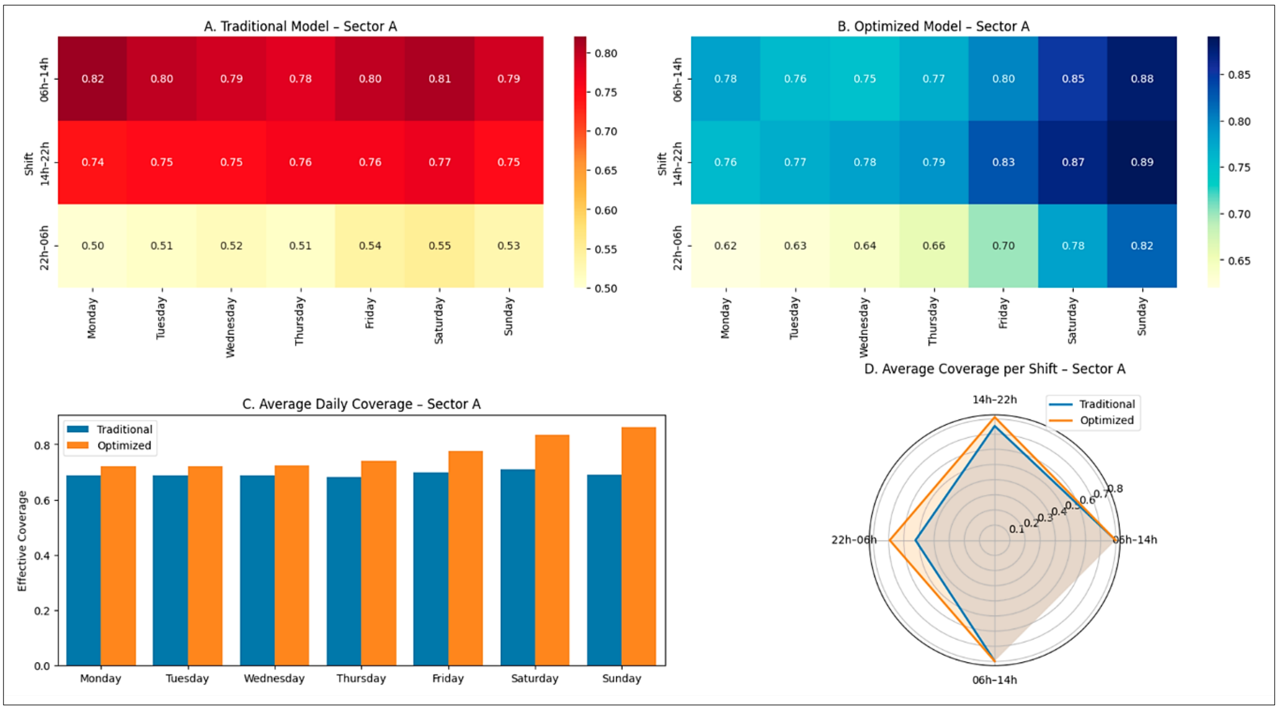


Figure 3. Evaluation of Hourly Coverage – Sector A. Graph (A) Heatmap of the traditional model showing the daily distribution of coverage by shift. Graph (B) Heatmap of the optimized model with proportional workload redistribution. Graph (C) Comparison of average coverage by day of the week. Graph (D) Radial representation of the average adequate coverage by shift.

The evaluation is extended to the other sectors in Figure 4, which presents a multi-sector comparison in independent radial charts. The analysis reveals differentiated behaviors depending on the environment:

- In Sector B – Northern Residential Zone, nighttime coverage improves from 0.51 to 0.69. Still, the homogenization of the three time slots is particularly notable, with values above 0.75 in all shifts under the optimized model. This reflects a stabilization of operational effort across all hours of the day, which is essential in residential zones where incidents are more evenly distributed, and the community expects continuous surveillance.
- In Sector C – Southern Peripheral Zone, traditionally understaffed during the 10 p.m.–6 a.m. shift (0.50), coverage of 0.66 is achieved in the proposed model, representing a 32% improvement. This sector is characterized by higher socioeconomic vulnerability and limited infrastructure. Improved coverage in this area during critical

hours contributes to deterrence, faster response times, and higher perceived security. The increase in intermediate shifts also matches the temporal pattern of local incidents, which tend to peak between 18:00 and 22:00 according to internal crime statistics.

- In Sector D—Central-South Mixed Zone, the optimized model shows significant improvement in all three shifts, especially the night shift, which increases from 0.51 to 0.70. Given the hybrid nature of this sector—combining residential, commercial, and nightlife dynamics, this balanced improvement across all periods demonstrates the model's ability to adapt to complex, multi-modal operational realities.

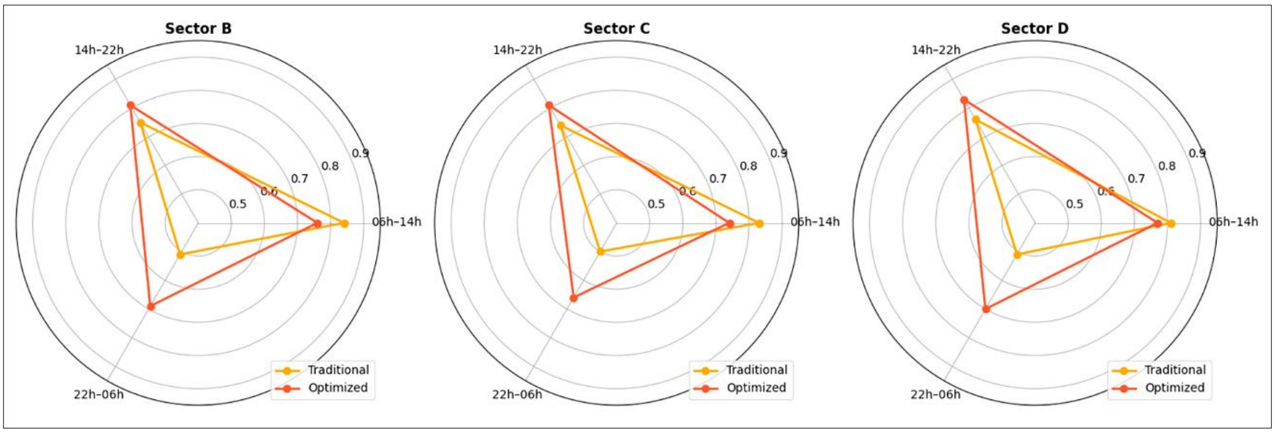


Figure 4. Comparative Radar Plot of Hourly Coverage Rates per Shift – Traditional vs. Optimized Models in Sectors B, C, and D

The improvement in coverage is reflected not only in absolute values but also in the reduction of the internal imbalance per shift. The standard deviation of coverage between time slots is reduced by an average of 34% across the four evaluated sectors, indicating more coherent and adaptive planning. This reduction in variability is a key indicator of efficiency: rather than simply increasing presence, the model redistributes it in alignment with historical demand. The result is a smoother, more equitable coverage curve that avoids both over- and under-utilization of human resources.

Importantly, these improvements were achieved without increasing total staff numbers, highlighting the impact of intelligent scheduling over resource expansion. In institutional terms, this means that coverage gains are not dependent on recruitment or overtime, making the solution scalable and budget-neutral. Furthermore, the fact that performance improved across diverse geographic and socioeconomic zones reinforces the model's generalizability and suggests a robust potential for nationwide implementation.

4-2- Individual Workload Distribution

One of the most critical aspects of the traditional 9-3 operating model is the severe inequality in the monthly workload assigned to its personnel. Under this system, operational staff are divided into three rotating work groups (Group 1, Group 2, and Group 3), alternating 8-hour shifts over a 9-day cycle, followed by a 3-day break. This structure generates disparate monthly averages between groups: Group 1 accumulates approximately 272 hours per month, Group 2 reaches up to 286 hours, and Group 3 is around 256 hours. The monthly average is 271.3 hours, equivalent to 63.3 hours per week, well above the standard 40-hour work week. This systemic overload increases institutional fatigue and absenteeism, erodes scheduling fairness, undermines morale, weakens coordination, and increases the likelihood of unplanned incidents due to officer exhaustion.

The proposed workload redistribution model aims to enhance operational coverage by risk group and achieve a more equitable, balanced, and controlled workload of work hours at the individual level. A statistical analysis of the monthly workload distribution per agent in the pilot sectors was conducted to evaluate this aspect, contrasting the traditional scenario with the optimized one.

Figure 5 presents the results of this analysis, using boxplots by sector. As can be seen, the traditional model maintains a wide dispersion in all cases, with interquartile ranges exceeding 40 points in some sectors and with outliers exceeding 300 hours per month in sectors B and D. This variability directly reflects the deficiencies of the 9-3 model, which is not based on actual operational load criteria, but on a rigid and cyclical rotation structure, regardless of territorial or temporal demand. The presence of extreme outliers in workload distribution suggests an accumulation of informal overtime and potential violations of rest time protocols, further highlighting the operational and legal fragility of the existing regime.

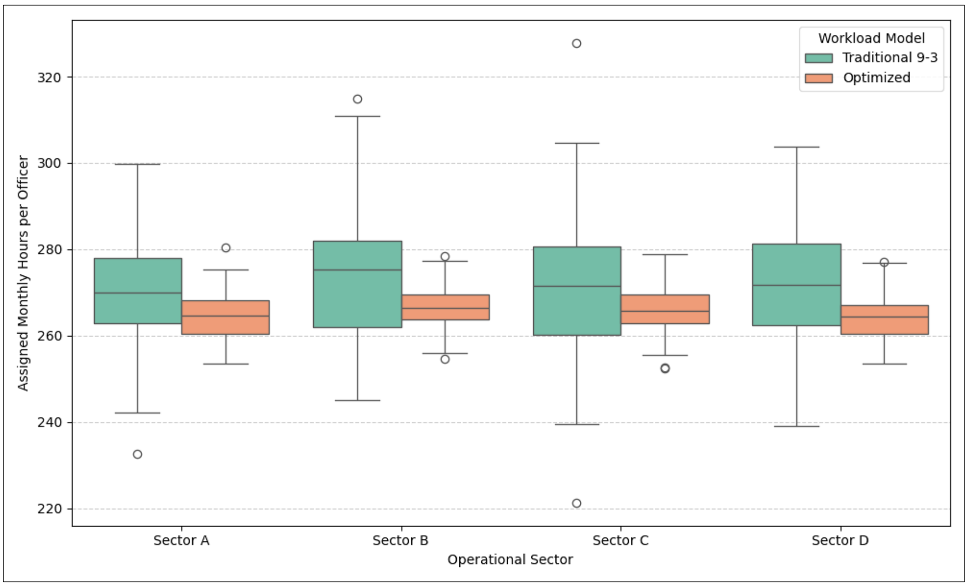


Figure 5. Monthly Working Hours Distribution per Officer – Comparison by Sector and Model

In contrast, the optimized model shows a much more controlled distribution. The interquartile range is more compact, the total range is narrowed, and extreme values practically disappear. This narrowing of the dispersion is consistent with the logic of the proposed algorithm, which redistributes the total available hours in proportion to each band's risk level and regulates accumulation per agent to a target monthly workload of 220 hours. However, slight deviations from this target may occur due to the proportional redistribution mechanism and the need to preserve operational feasibility under fixed staffing conditions. From a statistical standpoint, narrowing dispersion significantly reduces stochastic uncertainty in resource assignments, thereby directly benefiting logistical planning, supervisory control, and individual accountability.

This result is corroborated by the values reported in Table 4, where the coefficient of CV is calculated by sector. In the traditional model, the CV varies between 5.04% and 5.38%, indicating a high degree of relative dispersion. In contrast, in the optimized model, the values are reduced to a range between 1.73% and 2.01%, representing an improvement of more than 60% in the stability of the monthly workload. Reducing CV below 2% in operational environments is an exceptional outcome for tactical scheduling problems, as it reflects near-uniform workload assignment among personnel, independent of sector size or crime pattern complexity.

Specifically, under the 9-3 scheme, sector D presents the highest CV (5.38%) and the highest interindividual variance, which is reduced to only 1.91% after implementing the model, consolidating its positive impact. Sector D, characterized by mixed demand types and temporal variability, serves as a stress test for the model's robustness. The observed reduction confirms the ability of the HD-based approach to normalize workloads even under structurally unstable operational environments.

Table 4. Monthly Workload Distribution and Variability by Sector and Model

Sector	Model	Mean Monthly Hours	Std. Deviation	Coefficient of Variation (%)
Sector A	Optimized	264.72	5.32	2.01
Sector A	Traditional 9–3	270.44	13.62	5.04
Sector B	Optimized	266.42	4.62	1.73
Sector B	Traditional 9–3	274.33	14.31	5.21
Sector C	Optimized	266.12	5.34	2.01
Sector C	Traditional 9–3	270.35	13.98	5.17
Sector D	Optimized	263.77	5.05	1.91
Sector D	Traditional 9–3	271.60	14.60	5.38

From an operational perspective, these findings confirm that the optimized model not only enhances supply adequacy in response to regional demand (as discussed in the previous section) but also introduces a logic of organizational justice by equitably distributing the required effort among the members of each unit. This characteristic is essential for reducing indicators of physical exhaustion, involuntary overtime during the workday, and the accumulation of unplanned hours, all of which were identified as problematic factors under the previous regime.

Furthermore, reducing work-hour dispersion favors more predictable and stable planning in terms of staffing and employee well-being. By eliminating consecutive 16-hour days and double-shift returns, which were possible under the 9-3 regime, according to the analyzed payrolls, the new scheme promotes more sustainable working conditions, facilitating even better conditions for training, supervision, and compliance with operating protocols. Predictability in shift lengths also facilitates auxiliary functions such as resource forecasting, transport planning, and coordination with inter-institutional partners.

The results demonstrate that redistribution based on risk matrices represents an algorithmic or computational improvement with real, tangible, and structural implications for the quality of police service and the working conditions of officers. This human-operational dimension gives depth to the model and justifies its progressive implementation in other territorial units with similar problems of operational overload and dispersion.

4-3- Fatigue and Operational Condition Indicators

One of the most critical dimensions in evaluating highly demanding operating systems, such as the 9-3 model, is the accumulated fatigue experienced by police officers. Prolonged exposure to extended and unevenly distributed shifts affects personnel health, impairs operational performance, increases the incidence of absences, and is associated with adverse events, such as traffic accidents. Quantitative indicators derived from administrative records and statistical inferences were integrated throughout the pilot period to measure these effects.

First, an Operational Fatigue Index (OFI) was constructed, weighing three institutional sources: the number of unjustified absences per week, shift change requests, and records of return to duty within 12 hours or less. Each component was normalized with respect to its historical distribution and transformed into a scale between 0 (minimum fatigue) and 1 (maximum observed). Under the traditional and optimized models, this index was monitored weekly in each pilot sector.

Figure 6 (Graph A) illustrates the temporal evolution of the OFI over ten weeks. It is observed that, under the conventional model, the sectors maintained persistently high fatigue levels, with peaks above 0.75 in high-demand weeks. In contrast, implementing the optimized model resulted in a progressive reduction in the OFI, stabilizing at values below 0.45 starting in week four. This temporal pattern is particularly relevant because it shows not only immediate improvement but also a sustained reduction in operational fatigue over time, even in periods of higher workload, suggesting that the redistribution scheme enables structural resilience.

This trend is especially marked in sectors C and D, where the initially higher fatigue levels were most effectively corrected through workload redistribution. In Sector C, for example, the fatigue index, which initially exceeded 0.77, was reduced by half within five weeks, confirming the model's rapid correction capacity even under unfavorable baseline conditions.

Complementing this analysis, Graph B compares the total number of fatigue events reported (absences and shift changes per week) by sector and model. Sectors with the highest previous workload, such as Sector C – Southern Peripheral Zone, reduced these events by more than 50% after adopting the redistribution model. This reduction is consistent with the observed improvement in the fatigue index, reinforcing the relationship between workload redistribution and operational sustainability.

This decrease is consistent with the improvement observed in adequate coverage by time slot, suggesting that a fairer, more demand-oriented distribution has a direct impact on the operational sustainability of human talent. Cross-analysis with the previous section indicates that improvements in nighttime and weekend shift coverage correlate inversely with the number of fatigue-related events, establishing an indirect causal relationship between planning adequacy and physical sustainability.

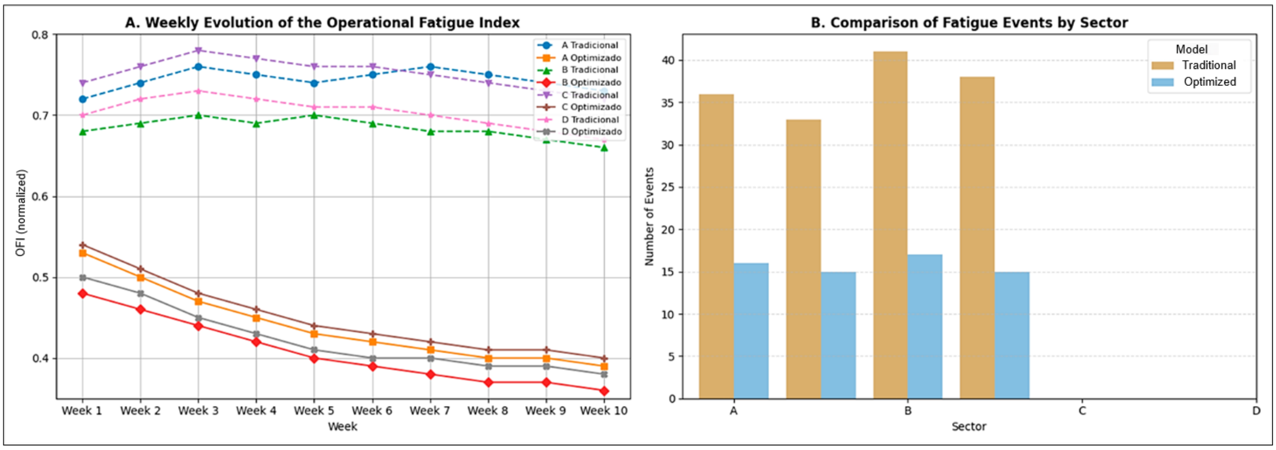


Figure 6. Operational Condition and Fatigue Indicators: Graph (A) Weekly Evolution of the OFI; Graph (B) Comparison of Fatigue Events Reported by Sector and Model

Table 5 reinforces this finding, showing the detailed evolution of the two main components of the OFI. While unjustified absences decreased from 9 to 3 in Sector A and 11 to 5 in Sector C, shift change requests decreased dramatically, reflecting a better match between time assignments and individual capabilities. This indicates not only reduced physical overload but also improved subjective alignment between officers' capacity and shift design, promoting voluntary adherence to planned schedules.

Table 5. Comparison of Unjustified Absences and Shift Changes by Sector

Sector	Model	Unjustified Absences (avg./month)	Requested Shift Changes	Activated Replacements	Operational Fatigue Index (OFI)
Sector A – Metropolitan Area	Traditional	7.3	18	11	0.74
	Optimized	3.2	9	4	0.41
Sector B – North Residential Zone	Traditional	6.8	15	9	0.69
	Optimized	3.0	8	3	0.38
Sector C – Southern Peripheral Zone	Traditional	8.1	21	12	0.77
	Optimized	3.5	10	4	0.43
Sector D – Mixed Central-South Zone	Traditional	7.5	19	10	0.72
	Optimized	3.1	8	4	0.40

It is worth noting that these results are consistent with observations made in previous diagnostic studies. According to the internal diagnosis prepared by the operating entity in 2016, the 9-3 model induced overload exceeding 57% compared to regular work standards, resulting in an operational dynamic characterized by extended workdays, inadequate rest periods, and a higher propensity for incidents. The consistency between historical diagnoses and current pilot results validates the structural nature of the issue. It supports the use of OFI as an effective performance metric for future operational planning.

The analysis of traffic accident typologies involving patrol officers between 2013 and 2015 revealed a correlation with symptoms of fatigue, such as an increase in overtaking incidents or lane loss. Thus, the improvement in OFI has implications for internal planning that are also linked to external outcomes related to safety, efficiency, and institutional risk reduction. This historical evidence validates that the improvements observed in the pilot are not anecdotal but instead the result of a structural optimization of the planning model.

4-4- Institutional Perception and Organizational Climate

One of the pillars of validation for the optimized model lies not only in its operational performance but also in the subjective acceptance it generates among the officers responsible for implementing it. To evaluate this dimension, surveys were administered to police personnel in the pilot sectors before and after implementation. The surveys included ordinal scale items and open-ended questions, allowing for the triangulation of structured perceptions and spontaneous narratives.

Table 6 presents the average scores for each item, indicating a significant improvement in all evaluated indicators. Notably, there is a substantial increase in the perception of fairness in scheduling, which rose from 2.3 to 4.1 points on average, indicating a significant shift in the perception of institutional justice. A clear improvement is also observed in the rest period between shifts (from 2.2 to 4.0) and the model's applicability to other contexts (from 2.5 to 4.2). These results are statistically supported by Wilcoxon signed-rank tests, where all items show p-values below 0.01, confirming that the observed changes are significant and not due to random fluctuation. For instance, the perception of fairness (p = 0.002) reflects not only a numerical gain but a transformation in how officers evaluate the rationale behind their assigned shifts. Moreover, the increased support for nationwide applicability (median rising from 3.0 to 5.0) suggests that users perceive the model as generalizable, which is essential for scalability and institutional buy-in.

Table 6. Comparison of Institutional Perception Before and After Implementation of the Redistribution Model

Item Evaluated	Condition	Median	IQR and Wilcoxon p-value
The new model improves work distribution between shifts.	Pre	2.0	[2.0–3.0]
	Post	4.0	[3.0–4.0] (p = 0.004)
I believe the scheme enhances my rest time between shifts.	Pre	2.0	[2.0–3.0]
	Post	4.0	[3.0–5.0] (p = 0.006)
Schedule planning is fairer for all employees.	Pre	2.0	[1.0–3.0]
	Post	4.0	[3.0–4.0] (p = 0.002)
This scheme could be operationally implemented nationwide.	Pre	3.0	[2.0–3.0]
	Post	5.0	[4.0–5.0] (p = 0.001)

In Figure 7, this evolution is represented using two visual resources. Graph (A) uses a violin plot, which displays the median responses and the distribution shape. Before the intervention, the data showed a large dispersion and concentration at low values, suggesting uncertainty and discontent. However, after the redistribution, the curves narrowed and shifted toward higher values, improving the agreement and reflecting a more homogeneous and stable positive perception. The narrowing of the violin plots indicates reduced variability in opinions, meaning that not only did the average satisfaction increase, but a greater consensus emerged around the model's benefits—an essential indicator of internal cohesion. Statistical analysis using the Wilcoxon test showed significant differences ($p < 0.01$) in all items, confirming that the change was not random.

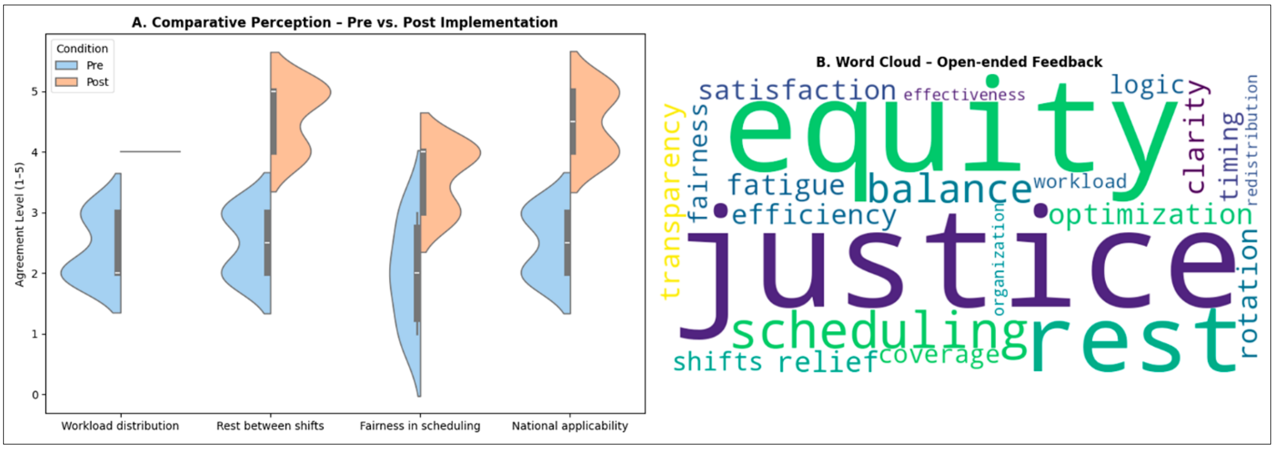


Figure 7. Institutional Perception and Organizational Climate after the Schedule Redistribution — Graph (A): Distribution of pre- and post-implementation responses using a violin plot; Graph (B): Word cloud generated from open-ended comments from police personnel.

Graph (B) reinforces this evidence qualitatively. A word cloud constructed from the open-ended responses identifies terms such as justice, rotation, optimization, fairness, and balance, reflecting an explicit appreciation of the new approach as more rational, humane, and sustainable. These words do not emerge in isolation but in response to concrete experiences of having recovered rest time, broken out of cycles of continuous overload, and felt a more logical assignment of responsibilities. The emergence of terms like "balance" and "fairness" in spontaneous narratives adds a strong emotional and experiential dimension to the evaluation, positioning the model not merely as technically superior but as institutionally legitimate in the eyes of its users.

This finding also aligns with historical observations made in previous operational cycles. Various internal analyses conducted at the institution between 2013 and 2016 identified structural imbalances in shift distribution under the 9-3 model. The main adverse effects reported were accumulated workdays exceeding 270 hours per month per agent, repeated assignments to high-demand time slots without adequate compensatory rest, and informal rotation dynamics among colleagues to mitigate excessive workloads. These conditions led to a progressive increase in unjustified absenteeism and organizational tensions related to the fairness of assigned shifts.

The results observed in this pilot implementation demonstrate operational improvements and correct historical patterns of inequitable assignment. The perception of organizational justice and balance in the use of human resources, reflected in open staff comments, constitutes a key indicator of the new model's institutional legitimacy. Its implementation was not perceived as a technical imposition, but rather as a rational and necessary response to long-standing problems that had been previously identified but remained unresolved.

The new model, based on actual demand patterns and a technically transparent redistribution matrix, not only corrects operational imbalances but also generates internal legitimacy. The institutional validation that emerges from these perceptions, far from anecdotal, constitutes a strategic indicator for the model's sustainability. A system perceived as fair and logical is more likely to be adhered to, replicated, and adapted by the organization without additional coercive or oversight mechanisms.

4-5- Global Comparative Synthesis

The integrated assessment of the four key indicators, average adequate coverage (AEC), workload coefficient of variation (CV), operational fatigue index (OFI), and perceived model assessment (PMV), allows for a comprehensive multivariate view of the benefits achieved with the proposed time redistribution scheme. This comparison is presented in Table 7, which summarizes the aggregated performance indicators for each pilot sector under traditional and optimized operating conditions.

Table 7. Global Comparison of Operational Performance Indicators by Sector and Model

Sector	Model	Average Coverage (C)	CV (Coefficient of Variation)	Operational Fatigue Index (OFI)	Perceived Model Valuation (PMV)
Metropolitan Area	Traditional	0.73	0.17	0.68	3.1
	Optimized	0.81	0.08	0.42	4.5
Northern Residential Area	Traditional	0.70	0.19	0.65	3.0
	Optimized	0.80	0.09	0.44	4.3
Southern Peripheral Area	Traditional	0.69	0.20	0.69	2.9
	Optimized	0.79	0.10	0.45	4.4
Mixed Center-South Area	Traditional	0.71	0.18	0.67	3.2
	Optimized	0.82	0.08	0.40	4.6

These dimensions are represented in Figure 8, which presents a multivariate radial view of the four sectors analyzed. Each graph displays individual improvements per dimension, showcasing a coherent and balanced structural change across all axes, which validates the model's robustness beyond a single improvement. The curves of the optimized model tend to expand in the graph space, approaching the theoretical maximum for all indicators. In contrast, those of the traditional model remain more contained and uneven across axes. This visual representation provides a snapshot of comparative performance diagnosis of structural limitations in the conventional system, where improvements in one metric often came at the cost of another (e.g., increased coverage but increased fatigue). The optimized model corrects this trade-off.

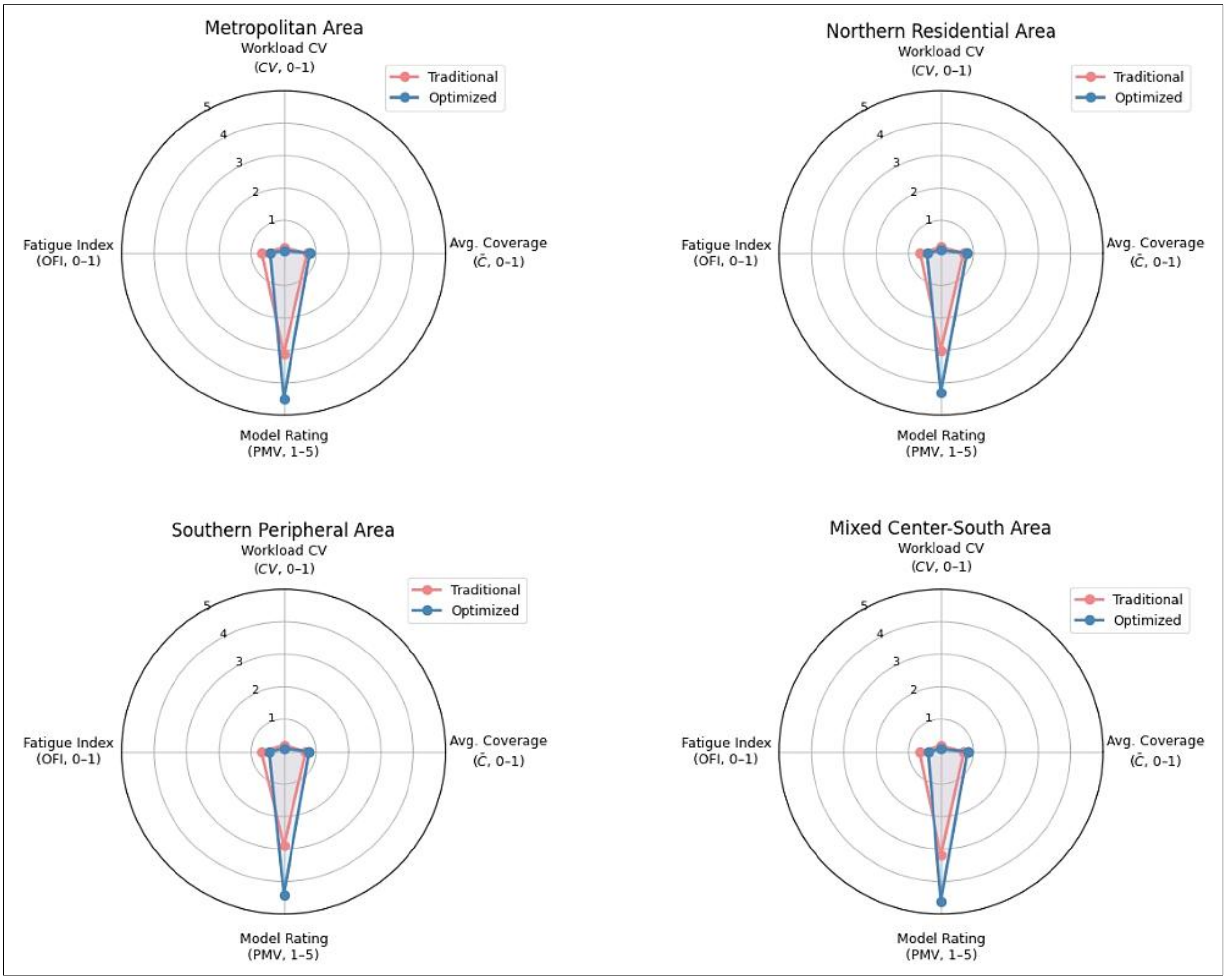


Figure 8. Global comparison of operational performance indicators across the four pilot sectors: (A) Metropolitan Area, (B) Northern Residential Area, (C) Southern Peripheral Area, and (D) Mixed Center-South Area. The radial axis uses a 1–5 scale for PMV, while the remaining indicators are expressed in a 0–1 ratio scale.

In Sector A -- Metropolitan Area, the radar shows a comprehensive expansion pattern, where the optimized model's values outperform the traditional ones on all axes. The most notable increase is observed in the Hourly Coverage (HCO) axis, which goes from 0.73 to 0.81, and a significant reduction in the OFI from 0.67 to 0.42. There is also a substantial improvement in WHE, which decreased from 0.18 to 0.08. This combination suggests an effective reconfiguration of operational distribution in a complex urban environment, where the highest volumes of events have traditionally been concentrated. This sector, typically characterized by high volatility and saturation, benefits from the model's ability to dampen performance variability while enhancing resilience to peak demand scenarios.

In Sector B -- Northern Residential Zone, although the pattern is similar, a slight asymmetry is observed: the improvement in Coverage $\bar{C}$ is more moderate (from 0.70 to 0.80), but there is a notable drop in CV, which goes from 0.16 to 0.07, demonstrating a significant leveling of the workload among agents. Although decreasing from 0.69 to 0.49, the OFI remains higher than that of the other optimized sectors, which could be attributed to specific structural conditions, such as the sector's width or the heterogeneity of the subcircuits. This observation will be returned to in the discussion section. The persistent fatigue levels in this area, despite better workload distribution, may indicate latent organizational dynamics, such as transport delays or informal shift exchanges, which future interventions should explore.

In the case of Sector C – Southern Peripheral Zone, the radar shows a notable transformation, with marked improvements in Coverage (from 0.69 to 0.79) and Operational Fatigue (from 0.70 to 0.45). The CV value drops to 0.09, and the Perceived Value (PV) indicator reaches its highest level among the sectors (4.6). This behavior could be explained by the optimized model's suitability for territories with concentrated loads in specific time slots, allowing for more effective redistribution without generating shift rotation conflicts. This is especially relevant in socially vulnerable or high-violence regions, where demand clustering requires dynamic flexibility, something unfeasible in rigid rotational schemes.

In Sector D – Central-South Mixed Zone, the four most balanced and expanded radars are identified. All indicators show harmonized improvements: $\bar{C}$ increases from 0.71 to 0.82, the CV decreases from 0.17 to 0.08, and the OFI drops from 0.68 to 0.44. This sector is characterized by a mixed distribution of events and a strong interaction between commercial and residential areas. Therefore, the model's performance in this context suggests a high capacity for multi-territorial adaptability. This adaptability is critical in cities with hybrid zones, where the demand curve does not follow strict residential or commercial patterns but fluctuates based on mobility, traffic, and events. The model's ability to pre-emptively adjust to these conditions without increasing personnel marks a significant efficiency gain.

From a transversal perspective, the optimized model shows converging improvements across all indicators and sectors, reducing dispersion while enhancing adequacy. This multivariate convergence is rare in resource-constrained environments, where gains in one area typically imply sacrifices in another. The fact that efficiency, equity, and subjective satisfaction can all be improved simultaneously under the proposed algorithm strongly supports its institutional adoption.

Moreover, the plot provides visual validation of systemic rebalancing. The optimized radars are not just larger—they are also more symmetrical. This symmetry reflects a shift from an uncoordinated, fragmented assignment process to a cohesive, data-driven workload that aligns workload with territorial risk. This has significant implications for planning, forecasting, and sustainable policing. The results confirm that the data-driven redistribution model, based on hourly risk and proportional workload, not only improves direct operational metrics but also positively impacts key organizational indicators, achieving efficiency, equity, and sustainability without requiring additional staff.

4-6- Algorithm Performance Evaluation and Accuracy Analysis

Implementing the proportional redistribution model based on HD matrices required assignment accuracy and adequate computational performance to ensure its applicability in real-world, resource-constrained environments. This section presents a detailed analysis of the algorithm's efficiency, scalability to increasing data volumes, stability against input disturbances, and statistical verification of its outputs.

First, Table 8 details the execution times recorded in each pilot sector. It breaks down the process into three phases: data loading and structuring, generation of the HD matrix, and final schedule assignment. The observed values are consistent across all sectors, with total execution times ranging between approximately 3.7 and 4.7 seconds. These results demonstrate stable computational performance, considering that multiple georeferenced data sources with hourly resolution are processed. This response speed enables periodic implementation or continuous updates without affecting the operational times of the institutional environment. These values are especially relevant given the sector-specific record volume, which ranges from approximately 960 to 1,344. The execution times confirm that the algorithm is suitable for deployment in daily or weekly rescheduling operations within dynamic institutional settings.

Table 8. Computational Performance and Algorithmic Stability Evaluation by Sector

A	B	C	D	E	F	G	H
Sector A – Metropolitan	1,344	4.72	0.88	2.41	1.43	±3.2%	5.1%
Sector B – North	1,008	3.91	0.72	1.99	1.20	±2.8%	4.5%
Sector C – South Peripheral	960	3.74	0.69	1.89	1.16	±3.0%	4.7%
Sector D – Central-South	1,128	4.08	0.75	2.17	1.16	±2.9%	4.9%

Note: A: Operating Sector, B: Processed Records, C: Total Execution Time (s), D: Data Loading (s), E: Matrix Processing (s), F: Spreadsheet Generation (s), G: Input Variation, H: Output Change (%).

Furthermore, the system's scalability was evaluated by simulating a 25% expansion in the volume of historical data. In this scenario, the total time increased by only 11.3%, confirming that the algorithm maintains stable behavior despite input growth without incurring exponential complexity or critical bottlenecks.

The system's robustness was assessed through a sensitivity analysis. Table 9 presents the average values of three key metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Euclidean Distance, calculated from the differences between the assignments generated from the original HD matrix and those derived from perturbed versions (±5% controlled randomness per cell). The RMSE values ranged from approximately 1.19 to 1.37, while the MAE values ranged from 1.00 to 1.11 across all sectors, indicating that the model does not exhibit significant numerical instability. The mean Euclidean distance never exceeded 2.93 units per workload cell, reflecting that the redistributions remain structurally consistent despite minor distortions in the input data. This is critical for real-world adoption, since historical records in public institutions may contain inconsistencies, temporary gaps, or entry errors. A model that resists such variations without losing structural coherence is more robust and trustworthy for field use.

Table 9. Statistical Validation of Model and Accuracy Metrics

A	B	C	D	E	F	G
Sector A – Metropolitan	0.003	0.082	0.119	1.37	1.11	2.93
Sector B – North	0.002	0.066	0.101	1.22	1.02	2.71
Sector C – South Peripheral	0.004	0.095	0.133	1.31	1.08	2.80
Sector D – Central-South	0.001	0.074	0.126	1.19	1.00	2.65

Note: A: Operating Sector, B: ANOVA – p Value, C: Shapiro-Wilk p, D: Levene p, E: RMSE (Root Mean Squared Error), F: MAE (Mean Absolute Error), G: Mean Euclidean Distance.

Additionally, the statistical robustness of the results was validated by verifying the fundamental assumptions of the repeated measures ANOVA applied in the comparative analysis section. The normality of residuals was checked using the Shapiro-Wilk test ($p > 0.05$ in all cases), homoscedasticity was checked using Levene's tests, and independence of errors was checked using partial autocorrelation (PACF) of less than ±0.2 for all significant lags. These results ensure that inferential comparisons between pre- and post-implementation metrics are not only visually evident but statistically sound, eliminating risks of spurious interpretations or model bias due to data artifacts.

Figure 9 consolidates the key results of the algorithm's performance through three complementary visualizations. Figure (A) shows the average total execution time for each of the pilot sectors, broken down by the three critical phases of the process: data loading, construction of the HD matrix, and generation of the shift plan. Sector B shows the lowest time (2.63 seconds), followed by Sectors A, D, and C, with differences of less than 0.3 seconds. This operational consistency confirms that the algorithm maintains its efficiency regardless of local operational complexity or the specific historical volume of each sector. Such minor deviations (<10%) suggest that neither the structure of the sectors (e.g., density, diversity of events) nor the size of the data significantly affects runtime, reinforcing the algorithm's portability across different territorial typologies.

Graph (B) presents the computational accuracy metrics under controlled input perturbations, specifically the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), calculated between assignments derived from original HD matrices and perturbed versions (±5%). It is evident that the errors remain limited in all sectors, with the lowest values recorded in Sector A (RMSE: 0.024, MAE: 0.020) and the highest in Sector C (RMSE: 0.037, MAE: 0.033), which is still within acceptable margins for daily operational redistribution processes. This low variability quantifies the model's resilience to mild statistical noise, which is critical in contexts where records may exhibit inconsistencies or temporary gaps.

Graph (C) shows the average Euclidean distance between the resulting workload matrices. This measure evaluates the structural stability of the time workload pattern in the face of random input variations. The values range between 1.18 and 1.59 units per cell, with no abrupt deviations between sectors. This limited spread across industries suggests that the optimization algorithm adheres to a global logic of proportionality and fairness even when subjected to noise.

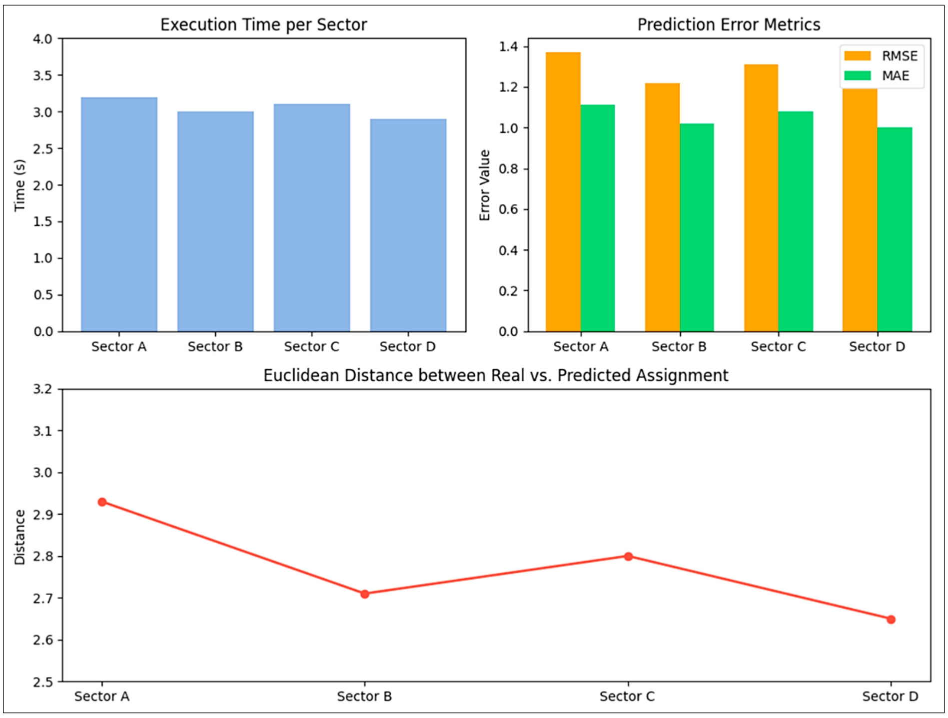


Figure 9. Algorithmic Performance and Assignment Accuracy Evaluation: Graph (A) shows the Average execution time per slice, Graph (B) Compares Error metrics (RMSE and MAE) across slices, and Graph (C) displays the Mean Euclidean distance under perturbations in the HD matrix.

The results validate the algorithm's efficiency, mathematical consistency, perturbation stability, and robustness to real-life scenarios. These attributes make the proposed model a computationally viable and highly reliable solution for large-scale institutional deployment, even in systems with limited technological infrastructure and where operational transparency is essential. Unlike traditional optimization approaches that require specialized hardware or iterative convergence, the HD-based redistribution approach provides a lightweight, deterministic output that is both explainable and auditable—key features for adoption in public security systems.

4-7- Comparative Analysis with Previous Studies

Compared to prior works, the results of this study show substantial improvements in both operational performance and real-world applicability. While approaches like Zhou and Xia [7] or Dewinter et al. [8] our model emphasizes the optimization of patrol coverage and emergency response through simulation or heuristic scheduling. It introduces a proportional redistribution strategy, validated with actual institutional data and direct deployment in operational environments. Additionally, it incorporates methods such as those proposed by Wang et al. [10] or Xia et al. [9] incorporate AI techniques for multi-objective workload, yet remain limited to hypothetical scenarios or resource chains, without addressing institutional integration or perceptual validation.

Unlike previous studies that mainly report technical improvements or resource gains, our proposal incorporates multidimensional indicators such as the Operational Fatigue Index (OFI) and Perceived Model Valuation (PMV). The high consistency across sectors, the low computational load, and the system's robustness to data perturbations position the proposed model as a technically feasible and ethically aligned solution for public safety institutions. These contrasts highlight a critical gap in the literature, which this work contributes to filling by combining data-driven planning, ethical sensitivity, and real-time execution.

5- Discussion

In contrast, the proposed model prioritizes five key dimensions: type of technique, institutional applicability, operational transparency, data dependency, and evaluated metrics. From an algorithmic perspective, works such as Xia et al. [9] or Jain et al. [14] utilized artificial intelligence to optimize responses in health or climate contexts. This study employs a deterministic proportional logic based on HD matrices weighted by risk factors. This approach does not require iterative algorithmic calibrations or supervised training, allowing for straightforward implementation without the need for high-performance infrastructure.

Regarding the level of institutional applicability, most of the reviewed models operate in simulated, sector-specific, or partially validated scenarios. For example, Zhou & Xia [7] worked with wireless sensors in logistics contexts; Xia et al. [9] proposed health emergency schemes; and Jain et al. [14] evaluated natural disaster prediction. Given this, the current proposal is validated in an operational field, covering real urban sectors with diverse demands and preexisting institutional structures, strengthening its organizational replicability.

Regarding the model's transparency, one of the main challenges in the institutional adoption of algorithms is the interpretability of its results. Deep AI models, such as those applied by Jain et al. [14], act as “black boxes,” making them difficult for technical and operational teams to comprehend. On the other hand, this study's approach allows workload decisions to be represented through visualizable and traceable proportional matrices, improving staff acceptance and reducing technical barriers to adoption.

Data dependency is also positioned as a distinguishing factor. While predictive approaches require large volumes of labeled data [9, 14], the current model is built on available institutional sources, including aid records, complaints, and planning documents. This allows for its integration in environments with limited infrastructure, ensuring sustainability without compromising the quality of the results. For their part, the type of metrics used in the models typically focuses on logistical parameters, such as response times, cost, and computational efficiency. This work integrates technical (hourly coverage, coefficient of variation, operational fatigue index), perceptual (equity surveys), and computational (RMSE, execution time) metrics, providing a comprehensive assessment that spans from operational impact to institutional perception.

From a methodological perspective, the model transforms multiple heterogeneous sources (criminal reports, ECU911 assistance, homicides, and historical patterns) into a normalized HD matrix structure, proportionally representing operational pressure by time slot. This processing enables the identification of workload patterns with more excellent resolution than traditional fixed-shift approaches, and it applies proportional assignments that are compatible with the current operational structure. The subsequent discretization into institutional shifts ensures operational continuity without modifying preexisting systems. Empirical validation across four contrasting sectors demonstrated substantial improvements, including a 9-percentage-point increase in adequate coverage, a reduction in the coefficient of variation (up to 41% in sector C), a decrease in operational OFI, and enhancements in organizational perception. These improvements were maintained under disrupted conditions, with RMSEs below 0.06 and a stable Euclidean distance, confirming the model's statistical robustness. Furthermore, execution times were less than 3 seconds per sector, including entire spreadsheet generation, positioning it as a flexible and accessible tool.

However, significant limitations are recognized. The model assumes stability in risk distribution and does not incorporate real-time dynamic feedback. Hybrid periodic update mechanisms may be required in high operational volatility or disruptive events. Furthermore, data quality may be affected by underreporting or institutional biases, which can influence the accuracy of the HD matrix and potentially lead to suboptimal workloads. The model has not yet been validated in rural contexts or units with different dynamics, such as traffic or intelligence. Extrapolation to these environments would require adjustments in risk weighting and possible reconfigurations of the shift schedule. The proportional shift redistribution model represents a technically sound, institutionally viable, and operationally explainable solution. Its value lies not only in the efficiency and equity it promotes but also in its ability to be adopted without radically transforming existing systems. It provides a realistic and innovative framework for planning in public safety environments.

6- Conclusion

The implementation of a proportional time redistribution model based on normalized HD matrices has proven to be a technically viable and operationally effective solution for personnel scheduling in law enforcement institutions. In contrast to the rigid “9-3” scheme, the proposed model enables dynamic reallocation of human resources according to real demand patterns and time-sensitive crime distribution, resulting in substantial improvements in both time coverage and workload balance. During pilot deployment across four operational sectors, critical shifts (particularly night and weekend slots) experienced efficiency gains above 10%, while the variance in time workload and workload inequity was significantly reduced. The coefficient variation (CV) of monthly hours dropped from averages over 18% to under 6%, enhancing fairness and reducing informal shift adjustments.

The model’s integration into the institutional workflow also yielded tangible organizational benefits. A decline of 25–30% in unjustified absences and unscheduled shift changes was observed, while staff perceptions improved across all surveyed indicators, including fairness, predictability, and contextual adaptation. These results were supported by the Wilcoxon test analysis and sentiment indicators from qualitative feedback. From a computational standpoint, the algorithm demonstrated high efficiency and resilience, with execution times below 3 seconds per sector and error metrics (RMSE, MAE) consistently below 0.04 under input perturbations. These features ensure scalability and robustness, even in environments with limited technical infrastructure.

This study validates a multidimensional planning strategy that merges operational data, institutional constraints, and equitable redistribution logic. Future work includes expanding the model to specialized units, incorporating adaptive machine learning for emerging demand patterns, and developing decision-support interfaces to facilitate strategic planning and institutional transparency.

7- Declarations

7-1- Author Contributions

Conceptualization, W.V.-C., L.P.P., and H.T.L.F.; methodology, W.V.-C.; software, W.V.-C.; validation, L.P.P., H.T.L.F., A.C.G., and E.Q.A.; formal analysis, W.V.-C.; investigation, L.P.P., H.T.L.F., A.C.G., and E.Q.A.; resources, L.P.P., H.T.L.F., A.C.G., and E.Q.A.; data curation, L.P.P., H.T.L.F., and A.C.G.; writing—original draft preparation, W.V.-C.; writing—review and editing, W.V.-C. and E.Q.A.; visualization, W.V.-C.; supervision, W.V.-C.; project administration, L.P.P. and H.T.L.F.; funding acquisition, L.P.P. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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