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AeroEP: A Logistics Route Planning Tool for Rotary-Wing Aircraft

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***Abstract*– Currently, modernizing logistics processes within the Armed Forces is a key challenge for ensuring efficient, sustainable, and adaptable operations in complex scenarios. In the Peruvian Army, the planning of helicopter supply routes is limited by manual methods, a lack of technological tools, and resource constraints, which reduce response capacity and operational efficiency. The main problem identified is the need to optimize logistics route planning in environments with multiple types of supplies and dynamic operational conditions, where traditional methods do not ensure the optimal management of time, fuel, and distance.**

The absence of an integrated system limits strategic decision-making and the optimal use of available resources. In response to this need, we propose AeroEP, a web-based tool that incorporates a heuristic method to optimize helicopter route planning for the Peruvian Army. The system was developed using the SCRUM agile methodology, structured into three phases: planning, design and development and testing. AeroEP incorporates a route optimization model based on the 2-opt algorithm, which takes into account distance, flight time, and fuel consumption, enabling the efficient simulation and reorganization of routes. Additionally, AeroEP features a modular system and an interactive web interface that ensure real-time data integration and availability.

The results demonstrate that AeroEP significantly improves operational efficiency: total distance traveled was reduced by 13.98%, flight time by 13.55%, and fuel consumption by 13.97%, achieving an average improvement in operational efficiency of 13.84%. The tool optimized routes in just 0.1658 seconds during simulations, confirming its suitability for dynamic environments with limited resources. These results validate AeroEP's effectiveness as a decision-support system for logistics planning, contributing to institutional modernization, resource optimization, and greater operational resilience for the Peruvian Army.

Keywords-- Helicopter Route Planning, Vehicle Routing Problem, Logistics Optimization, Operational Efficiency

I. INTRODUCTION

The modernization of armed forces processes is an imperative for ensuring that the country has a robust institution with a high capacity to safeguard national interests, promote national development, and preserve public peace [1], [2], [3], [4]. In [1], the need to modernize the Armed Forces is detailed so that they can effectively and efficiently fulfill their established functions. Logistical support within the Peruvian Army is undergoing a dynamic transformation, with planning serving as the cornerstone for ensuring that operational support aligns with new doctrines and regulations. Although the organization requires rapid and flexible deployment capabilities at both tactical and strategic levels, it frequently faces numerous challenges in real-world operations due to the lack of coordination mechanisms necessary to operate in uncertain environments.

This gap between speed requirements and the complexity of logistical processes highlights the urgency of optimizing management, not only to ensure overall operational safety but also to guarantee efficiency and economic sustainability [1], [5]. The discipline and coordination inherent in military organizational culture risk becoming obsolete if advanced technological tools are not integrated into decision-making automation. Therefore, modernization efforts must prioritize route planning, a critical activity that transcends operational boundaries and becomes a decisive factor in emergency response and natural disaster relief operations. The adoption of these technologies will enable the Army to overcome current limitations and ensure an adaptable, organized, and efficient response capability capable of meeting the stringent timelines and requirements imposed by constantly changing operational conditions.

In the current context, the Peruvian Army faces an urgent need to modernize its logistical operations. Due to terrain complexity and the need to manage ten different types of supplies while complying with specific processes, traditional manual methods are no longer sufficient. The lack of intelligent route-planning tools limits response speed and operational efficiency, hindering the Peruvian Army's ability to maintain its strategic advantage. Consequently, digital transformation is no longer an option but a necessity; it requires moving beyond existing regulatory frameworks and adopting technologies that ensure precise, rapid, and truly optimized use of resources within the operational area.

Under these circumstances, the development of web-based applications based on heuristic optimization emerges as an ideal solution, transforming this challenge into an opportunity for continuous improvement by shifting from experience-based planning to data-driven planning supported by predictive models. By integrating algorithms and simulating technical characteristics, this tool seeks not only to optimize the efficiency and effectiveness of transportation and distribution but also to provide a scalable solution that adapts to existing economic constraints. In this way, the implementation of this system will significantly promote institutional modernization, ensure compliance with performance indicators, and raise the quality of logistical support to current technical standards.

In this regard, this article proposes AeroEP, a logistics route planning tool for rotary-wing aircraft in the Peruvian Army, aimed at optimizing operational efficiency, driving the digital transformation of supply processes, and ensuring scalable and precise decision-making in the face of operational complexity and the diversity of supplies that can be transported by helicopters.

This paper is organized into six sections. The first section presents the introduction. The second section briefly describes the theoretical foundations. The third section reviews related research on route optimization and intelligent technologies. The fourth section details the proposed method. The fifth section presents the obtained results. Finally, the sixth section provides the conclusions of the study.

II. Theoretical Background

A. Logistics Planning

Logistics planning is defined as an integrated process whose primary purpose is to ensure operational sustainability through anticipation and adaptation. Its importance lies in the ability to anticipate changes in operational concepts, such as the need for new support areas, infrastructure, or transportation assets, thereby integrating requirements and priorities before a crisis occurs. In theory, sound planning can reduce reliance on costly improvised responses that negatively affect command and control, thus establishing a critical correlation between deployment planning and force employment planning [5]. From a procedural perspective, the logistics planning sequence is subordinate to the tactical mission, which in turn guides the entire support effort. This process begins with mission and course-of-action analysis, followed by a "logistics assessment" to determine operational feasibility. Once feasibility is validated, a logistics plan is developed and incorporated as an annex to the overall operational plan, taking into account key aspects such as action control, troop constraints, and force mobilization [1], [5].

B. Types of Supplies

According to the Logistics Manual of the Peruvian Army [5], the critical supplies required to sustain military operations are classified into ten categories to ensure comprehensive and efficient management. Category I covers personnel and animal subsistence needs, including food and water. Category II includes organizational supplies, ranging from clothing and personal equipment to tools and office supplies. Category III manages energy resources such as fuel, lubricants, and defensive equipment. Category IV centrally stores lethal weapons, including ammunition, explosives, and chemical agents. Category VI meets individual requirements through general merchandise. Category VII includes major end items such as combat vehicles, aircraft, and vessels. Category VIII provides all medical and hygiene supplies. Category IX focuses on maintenance, including spare parts and components. Finally, Category X allocates resources to support non-military projects and civil affairs.

C. Vehicle Routing Problem

In the field of logistics optimization, the Vehicle Routing Problem (VRP) is a fundamental approach to transportation planning, aimed at effectively organizing and coordinating delivery plans through the strategic allocation of available resources. For successful implementation, it is necessary to analyze key variables such as distances between delivery points, associated operational costs, and fleet travel times in order to determine the optimal route that meets customer requirements. This optimization process must strictly comply with fundamental operational constraints, such as vehicle load capacity [6].

$$\min Z = \sum_{i=0}^{n} \sum_{j=0, j\neq i}^{n} c_{ij} x_{ij} \qquad (1)$$

Equation 1 represents the objective function of the mathematical model, whose primary purpose is to minimize the total value Z, corresponding to the maximum possible reduction in operational costs or the total fleet mileage. To compute this total value, the formulation employs a double summation that systematically covers all origins i and destinations j within the logistics network, from the depot to the final customer, logically excluding trips from a node to itself $(j \neq i)$. The core of the calculation involves multiplying a specific travel cost c_{ij} between two nodes expressed in terms of distance, time, or monetary cost by a binary decision variable x_{ij}.

This variable acts as a switch, taking a value of 1 only when the vehicle travels along that route and 0 otherwise, thereby ensuring that only the actual travel costs included in the planned route are considered. Travel distance is a key dimension in logistics optimization, as the primary objective of this approach is to minimize the total route length without compromising service efficiency. This reduction is not only a spatial indicator but also directly affects the operational cost structure, which in turn influences the rates charged to customers or the internal budget allocated to delivery operations.

Therefore, efficient distance management represents the first step toward ensuring the economic sustainability of transportation. From a technical perspective, distance is not an isolated factor but interacts dynamically with the transported goods, jointly determining vehicle energy consumption [7]. Transportation costs represent the economic value of logistical activities that enable physical connections between suppliers and customers. This economic value constitutes compensation for goods transportation and serves as the basis for determining supply chain profitability.

The composition of these costs is complex and extends far beyond the mere physical movement of materials [8]. Transportation time is considered a key performance indicator, closely associated with efficient management in the modern business environment. This factor is used as an interdisciplinary indicator to measure fleet productivity and organizational responsiveness. By establishing time-based objectives, management can assess operational performance and identify bottlenecks, thereby transforming time into a strategic asset that must be managed with the same rigor as financial resources. In the logistics domain, transit time analysis encompasses the entire delivery cycle, from cargo loading to effective delivery at the destination [9].

The integration of the VRP model into traditional route planning can transform a process primarily based on experience and manual operation into an analytical and automated process. Traditional methods rely on the planner's subjective experience or the driver's geographical knowledge to determine which route to take. In [10], the authors explain how to systematize this decision-making process using algorithms capable of simultaneously managing all relevant dimensions. In this way, route planning ceases to be an intuitive linear process and becomes a calculated mathematical solution (see Figure 1).

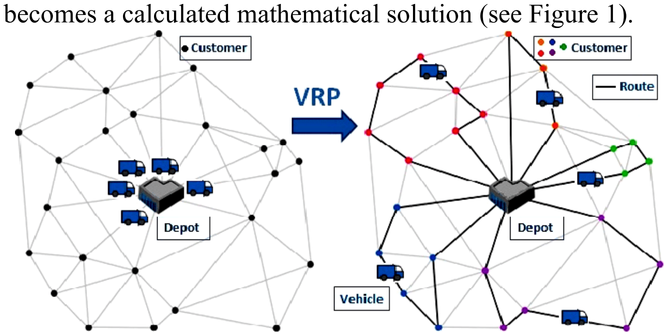

Fig. 1 Comparison of route optimization using the VRP.

Figure 1 presents the operational transformation process performed by a VRP model. The left-hand side presents the initial unstructured scenario, with multiple dispersed demand points and a vehicle fleet centralized at a depot, to which no tasks have yet been assigned. After algorithm execution, the right-hand side shows the optimized logistics solution, where demand has been strategically segmented and a specific sequential route has been planned for each vehicle.

This demonstrates how the mathematical model transforms a disordered network of nodes into an efficient delivery solution, ensuring that each vehicle completes its assigned route and returns to the central depot, thereby satisfying service demand. In [11], it is stated that the VRP formulation is of high relevance, particularly in post–natural disaster scenarios.

According to the literature reviewed, the VRP mathematical model is considered the mathematical and theoretical foundation for solving the challenges of coordinating delivery points, not only for ground vehicles but also for aerial vehicles. Specifically, the fundamental objective of VRP is to find the optimal delivery route by minimizing travel costs and the number of vehicles used for delivery, with a new value proposition being that, unlike ground or maritime vehicles that face traffic conditions, aerial vehicles can be more competitive for making deliveries based on criteria of effectiveness and efficiency [12].

D. *Web-Based Route Optimization System*

Web applications have evolved toward more robust architectures such as Progressive Web Applications (PWAs). PWAs overcome the connectivity limitations of traditional web pages by enabling background operation and push notifications, thereby eliminating the need for application installation [13]. These hybrid tools combine the usability of the web with the power of native software, offering significant advantages such as file caching, which drastically reduces load times on subsequent accesses, and ensuring normal operation even under unstable or nonexistent connectivity conditions [14].

From a technical perspective, the efficient operation of these applications in resource-constrained environments relies on the use of Service Workers. Service Workers are scripts that run in the background, independently of the visible page, to manage network requests and native data storage [15]. Various projects have been carried out to promote logistics innovation in different settings through the use of digital technology, such as the application of digital planning tools, mathematical optimization models, and web-based management platforms.

Furthermore, academic literature has found that most efforts have focused on transforming operational practices, which is considered relevant in all circumstances, regardless of whether it is necessary to improve the distribution and dispatch process, In this regard, there is a need for further research on how these technological resources can be used to reduce inefficiencies, high operating costs, and route delays [16].

Problems related to supply chain optimization are present at every level of the supply chain, and these processes involve a high degree of mathematical complexity, making it very difficult to find a viable solution quickly in a dynamic operational environment. Consequently, over the past few decades, optimization models such as the 2-opt algorithm have demonstrated exceptional performance when integrated with digital tools [17]. In logistics planning and vehicle routing, the application of heuristic algorithms such as 2-opt is crucial. These algorithms aim to optimize routing plans by eliminating unnecessary intersections, directly reducing travel distance and improving response speed [18].

In addition, the user interfaces of these solutions are built using an application shell model, which stores static visual components (HTML, CSS, and JavaScript) in the device's memory to ensure instant loading regardless of network quality [19]. This modular approach strictly separates visual presentation from dynamic content, loading information exclusively through web service calls. As a result, it simulates the fluidity of native applications and significantly optimizes resource consumption by avoiding full interface reloads with each interaction [20].

III. State of The Art

Several studies have addressed the optimization of logistical planning involving helicopters in emergencies and disaster-response scenarios. In [21], an optimization procedure for helicopter response operations to small- and large-scale disasters was developed based on a mathematical planning model and validated through interviews with personnel from the Brazilian Air Force and the Military Fire Brigade of the State of Rio de Janeiro. The results demonstrated that route-planning systems provide substantial decision-support value for logistical commanders. In [22], a framework aimed at improving the success of Maritime Search and Rescue (MSAR) helicopter missions was proposed, emphasizing the need to manage multiple sources of operational uncertainty. The study introduced the UMAD framework, which integrates a multi-agent approach with a discrete-event system. Validation through Monte Carlo simulations confirmed the model's effectiveness in supporting helicopter logistical planning. In [23] examined disaster logistics in earthquake scenarios and proposed a two-stage multi-objective optimization model based on Just-in-Time (JIT) principles and ant colony optimization. The model constructs a three-tier network consisting of helicopters, warehouses, and delivery points, demonstrating significant improvements in decision-making processes, material distribution efficiency, and aerial operations in emergency zones. In [24], the operational resilience of Helicopter Emergency Medical Services (HEMS) during the COVID-19 pandemic was assessed. A retrospective comparison of helicopter deployments during lockdown periods and the corresponding timeframe in the previous year revealed reduced demand and increased post-dispatch cancellations. These findings highlight the critical importance of adaptive logistical planning to sustain specialized medical services during large-scale health emergencies amid resource constraints. The study presented in [25] focused on initial humanitarian aid distribution following disasters through a multimodal transportation strategy. A three-level network model integrating land, maritime, and aerial (helicopter) operations was validated using data from the Yogyakarta earthquake. Results showed that intermodal transport, particularly air–sea coordination significantly enhanced supply flow in hard-to-reach areas, supporting informed decision-making in emergency logistics. In [26], disaster management in flood scenarios was analyzed from an event-logistics perspective using a VRP-based approach to optimize helicopter routes. Applying the model to the 2008 Itaí Valley floods demonstrated substantial improvements in relief capacity and notable reductions in operational costs, confirming the practical value of mathematical optimization techniques in civil defense operations. Finally, [27] explored large-scale disaster supply distribution challenges through the integration of Unmanned Aerial Vehicles (UAVs). By formulating a multi-objective routing problem solved using reinforcement learning algorithms (Q-learning), the study demonstrated that autonomous aerial systems can effectively complement traditional helicopter operations and enhance supply stability at evacuation centers during crisis situations.

IV. Proposed Method

The AeroEP tool was developed iteratively using the Scrum agile framework, which made it possible to effectively manage the system's complexity through a phased development cycle. For better organization, the process was divided into three main phases: planning, design and development, and testing (see Figure 2).

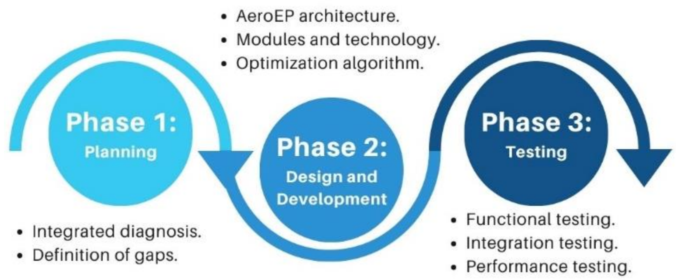

Fig. 2 Phases for the development of the AeroEP tool.

A. *Phase 1: Planning*

This phase focused on defining the operational status and system requirements for AeroEP. This included analyzing current logistics practices, identifying technical limitations, and ensuring alignment with the Peruvian Army's operational objectives.

A.1 Integrated diagnosis and gap identification

An analysis was conducted of current logistics route planning practices within the Peruvian Army. This analysis examined existing tools, organizational guidelines, and operational procedures to identify weaknesses and areas for improvement.

As shown in Table I, although a systematic set of rules exists, there is a lack of specific technical support for route optimization. This deficiency led to the development of AeroEP, a decision-support system designed to improve the efficiency of route planning and reduce operational time and resource expenditure.

TABLE I
DIAGNOSIS AND GAPS IN LOGISTICS ROUTE PLANNING

Analyzed Dimension	Current Situation	Identified Gap
Planning systems	No integrated route planning system	Need for an integrated planning platform
Tools in use	Administrative software	Lack of specialized route optimization tools
Technological approach	Route planning performed using traditional methods	Optimization techniques are not applied
Regulatory support	Logistics manuals and directives.	Limited technological support.

A.2 Functional requirements derived from the diagnosis

Based on the identified shortcomings, the system's functional requirements were defined to ensure direct alignment with actual operational needs. These requirements were derived from an analysis of existing logistics processes and serve to support critical decision-making processes in route planning.

As shown in Table II, the requirements are formulated as operational capabilities rather than as individual technical characteristics to ensure their relevance in real-world military logistics scenarios.

TABLE II
FUNCTIONAL REQUIREMENTS AND OPERATIONAL PURPOSE OF AEROEP

Functional component	Operational purpose
Geospatial visualization	Provides situational awareness of the logistics environment.
Coordinate management	Enables structured definition and management of distribution points.
Route definition	Supports initial route configuration based on operational inputs
Route optimization	Minimizes distance, travel time, and fuel consumption.
Plan persistence	Allows storage, retrieval, and comparison of route plans.
Environment control	Enables scenario reset and evaluation of different operational conditions.

A.3 Operational Alignment and System Objectives

The AeroEP system was developed to support key operational objectives in military logistics by optimizing route planning and ensuring more efficient use of resources. Its capabilities contribute to improved logistics coordination, shorter response times, and optimized fuel consumption.

As summarized in Table III, the system aligns with the organization's overall objectives, such as operational readiness, disaster relief, and digital transformation, demonstrating its applicability in real-world military scenarios.

TABLE III
OPERATIONAL CONTRIBUTION OF AEROEP

Institutional Strategic Objective	System Contribution
S.O. 1: Increase military capabilities for Army employment	Optimization of logistics route planning.
S.O. 2: Strengthen Army participation in Disaster Risk Management	Improved response through efficient routing.
S.O. 3: Strengthen Army participation in support of Peru's Sustainable Development	Reduction in fuel consumption.
S.O. 7: Strengthen research, development, and innovation within the Army	Application of optimization algorithms.
S.O. 12: Strengthen digital transformation within the Army	Digitalization of route planning processes.

B. Phase 2: Design and Development

B.1 Technology Stack

Table IV presents the main technologies used in the development of AeroEP, supporting both backend and frontend functionalities.

TABLE IV
TECHNOLOGY STACK OF AEROEP

Component	Technology
Backend framework	FastAPI
Programming language	Python
Database	SQLite
Server	Uvicorn
Frontend	HTML, CSS, JavaScript
Mapping tool	Leaflet.js
Optimization algorithm	2-opt

The AeroEP system was implemented using a lightweight web architecture. The backend was developed using FastAPI due to its high performance and support for asynchronous processing. Python was chosen for its flexibility and extensive ecosystem. SQLite was employed for data storage, and Uvicorn was adopted as the application server.

The frontend was implemented using standard web technologies (HTML, CSS, JavaScript) to enable user interaction and visualization. Leaflet.js was employed for the geospatial visualization of delivery locations and routes due to its efficiency and optimized design.

The 2-opt heuristic algorithm was selected for route optimization, providing a balance between computational efficiency and solution quality in real-time applications.

B.2 Architecture of the AeroEP Tool

Figure 3 illustrates the architecture of the AeroEP system, which consists of three main components: the user interface, the backend, backend and the optimization module.

The user interacts with the system through a web interface, while the backend manages data processing and communication via API endpoints. The optimization module implements the 2-opt heuristic to calculate optimized routes based on the input coordinates.

This modular structure ensures scalability and the efficient integration of the optimization process within the system.

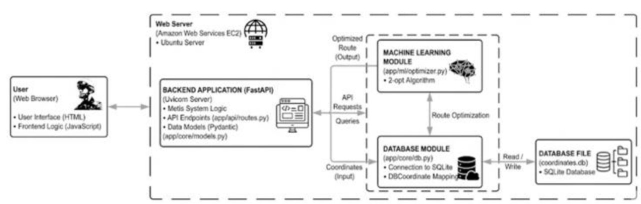

Fig. 3 AeroEP Architecture.

B.3 Optimization Model and Algorithm

Route optimization problems are modeled as VRP, whose objective is to minimize the total route cost. Let G = (V, E) be a graph, where V represents the set of nodes (delivery points) and E the set of edges.

The objective function is defined as follows:

$$\min_{x_{ij}} \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \tag{2}$$

where c_{ij} represents the cost (distance, time, or fuel) between nodes i and j, and x_{ij} is a binary decision variable that indicates whether the route contains an edge from i to j. This model satisfies standard routing constraints and ensures that each node is visited only once and that path continuity is maintained.

To solve this problem, a 2-opt heuristic algorithm is used. This method iteratively improves the initial route by reducing the total cost through the exchange of edge pairs. The cost change for possible exchanges is evaluated as follows:

$$\Delta C = (c_{ij} + c_{kl}) - (c_{ik} + c_{jl}) \quad (3)$$

If $\Delta C < 0$ the swap is accepted, the total cost decreases. This process is repeated until no further improvements can be made, resulting in a locally optimized route.

The algorithm used for route optimization in AeroEP is described as follows:

Algorithm 1: 2-opt Route Optimization

Input: Set of coordinates V
Result: optimized route

1. Generate an initial feasible route.
2. Compute distance matrix.
3. Repeat:
   - Select two edges.
   - Compute cost variation ΔC.
   - If $\Delta C < 0$, the swap is accepted
4. Until no improvement is found.
5. Return optimized route.

The 2-opt heuristic provides a locally optimal solution with polynomial-time complexity, making it suitable for real-time applications.

C. *Phase 3: Testing*

In Algorithm 2, the three types of tests conducted on the AeroEP system are combined into a single, unified workflow. First, the system functionality is verified by initializing the FastAPI application, starting the Uvicorn server, and creating the required database tables, ensuring that the platform is ready to process user requests. Next, the modular integration is tested by registering individual coordinates and batch lists, confirming that all modules interact correctly and that the data is consistently stored in the database. Finally, the computational performance of the 2-opt algorithm is assessed using a simulated scenario of logistics distribution, calculating distances between points, applying the 2-opt heuristic, and generating the optimized route. Metrics such as processing time and percentage savings in distance are recorded. This consolidated approach ensures that AeroEP is fully operational, that all modules are correctly integrated, and that the optimization algorithm performs efficiently in real-time logistical planning scenarios.

Algorithm 2: Unified Testing Procedure for AeroEP

Input: User access to system (coordinates, API requests)
Result: Verified functionality, modular integration, and algorithm performance
Procedure TEST_AEROEP( )

1. Start Server and System Functionality Test
   Start session (uvicorn app.main:app)
   Create FastAPI instance (APP = FastAPI())
   Mount static (/static) and templates (/templates) directories
   Include API routes under /api
   Call create_db_tables() to ensure database and tables exist
2. Modular Integration Test
   Obtain database session (SESION_DB)
   For each coordinate:
      Create coordinate object (DB_COORD)
      Add to session
      Commit and refresh session
   Return confirmation of registered coordinates
3. 2-opt Algorithm Performance Test
   Load list of coordinates for simulation
   Calculate distance matrix between points
   Apply 2-opt optimization iteratively
   Generate optimized route (opt_route)
   Record processing time and distance savings

The fuel consumption of the Mi-17 helicopter is calculated using the following formula:

$$f_{ij} = 0.30 \times d_{ij} \quad \text{(liters)} \quad (4)$$

Where 0.30 l/km corresponds to the fuel consumption during cruise flight at an altitude of 2000 m, as described in [5] and d_{ij} is the distance between nodes.

Flight time was estimated assuming an average operating speed of 60 km/h (1 km/min), considering the maneuvers required for approach, landing, and cargo drop at each destination.

C.1 System Functionality Test

It was validated that the web server (FastAPI + Uvicorn) and the database start correctly, including the creation of the necessary tables (DBCoordinate) and the proper display of the user interface. This ensures that the AeroEP engine is operational and ready to process requests. Table 7 shows a summary of the tests conducted, indicating the type of test, the input used, the expected result, the obtained result, and the final status of each test.

TABLE V
SUMMARY OF SYSTEM FUNCTIONALITY TEST

Test	Input	Expected Result	Obtained Result	Status
Server and application start	PuTTY initiates session	Server operational and FastAPI running	Server started at 0.0.0.0:8000	Correct
Database table creation	PuTTY initiates session	Tables created correctly	Tables created in coordinates.db	Correct
Interface visualization	User accesses URL	Interface available and functional	Interface loaded and accessible	Correct

C.2 Modular Integration Test

It was verified that the application modules work together correctly: registering individual and batch coordinates, managing sessions, and interacting with the database. Table 8 summarizes the modular integration test, showing that data is correctly registered in the database and that the modules interact consistently.

TABLE VI
SUMMARY OF MODULAR INTEGRATION TEST

Test	Input	Expected Result	Obtained Result	Status
Individual registration	Lat/Lng coordinates	Coordinate saved in DB with ID	Coordinates registered with assigned ID	Correct
Batch registration	List of 50 coordinates	All coordinates saved correctly	50 coordinates saved with confirmation	Correct
Data verification	Query DB	Matches input data	Matches	Correct

C.3 2-opt Algorithm Performance Test

A simulation was conducted for an emergency scenario with 50 delivery points along the Peruvian coast using a Mi-17 helicopter. The 2-opt algorithm calculated the optimized route in 0.1658 seconds, reducing the total distance from 2,603.59 km to 649.87 km, achieving 75.04% savings. Table 9 summarizes the performance metrics of the algorithm, showing the efficiency and speed of the route calculations.

TABLE VII
2-OPT ALGORITHM PERFORMANCE METRICS

Metric	Value
Initial distance	2,603.59 km
Optimized distance	649.87 km
Processing time	0.1658 s
Percentage savings	75.04 %

V. RESULTS AND DISCUSSION

A. Results

This section presents the results of a two-stage comparative evaluation of logistics performance. First, we analyze the delivery routes generated using conventional planning methods prior to optimization. Next, we present the results following the application of the AeroEP system, which optimizes routes using a heuristic algorithm based on the 2-opt method. The analysis focuses on three key performance indicators: distance traveled, travel time, and fuel consumption for routes between delivery points.

These indicators are directly related to the operational efficiency of route planning and correspond to the objectives of the VRP. To evaluate system performance, we created simulated logistics scenarios with randomly selected delivery coordinates reflecting operating conditions in Peru. Several scenarios with varying numbers of delivery points were tested to assess scalability and performance.

In each scenario, an initial route was first generated, followed by the application of a two-opt algorithm, and the performance metrics were recorded.

All experiments were conducted in a controlled environment, and improvements in processing time, distance, time expenditure, and fuel consumption were measured.

A.1 Results prior to optimization

The first simulation was conducted using the original data loaded into the AeroEP tool, before applying the 2-opt algorithm. Figure 4 illustrates the route planning, where the tool generates pop-up windows for each segment, displaying the distance, estimated travel time, and fuel consumption, allowing operators to fully understand the resources required at each stage of the supply chain. Table 10 presents the results of the first simulation using the Mi-17 transport helicopter.

The table shows the distance traveled, flight time, and fuel consumption for each delivery point, allowing observation of how these resources are distributed across the route. Before applying the optimization algorithm, the logistic delivery route required covering a total of 214.45 kilometers across six delivery points, with a flight time of approximately 214 minutes and a fuel consumption of 64.34 liters. This data serves as a baseline reference to assess the improvements generated by the AeroEP tool.

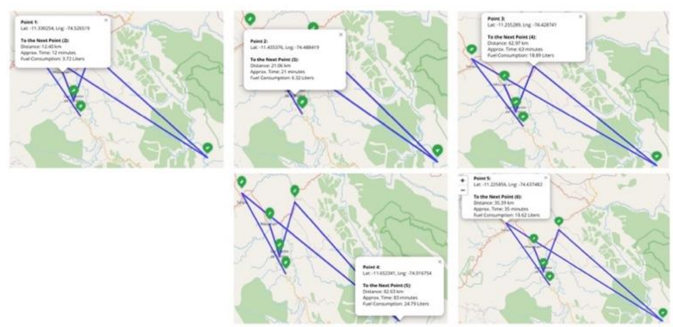

Fig. 4 Route planning prior to optimization with the AeroEP tool.

TABLE VIII
LOGISTIC ROUTE RESULTS BEFORE 2-OPT OPTIMIZATION

Indicators	Distance Traveled	Travel Time	Fuel Consumed
P1	0 km	0 min	0 liters
P2	12.40 km	12 min	3.72 liters
P3	21.06 km	21 min	6.32 liters
P4	62.97 km	63 min	18.89 liters
P5	82.63 km	83 min	24.79 liters
P6	35.39 km	35 min	10.62 liters
Total	**214.45 km**	**214 min**	**64.34 liters**

A.2 Results after optimization

The second set of results was obtained using the data generated by the AeroEP 2-opt algorithm. Figure 5 shows the optimized route planning, with pop-up windows detailing the distance, flight time, and fuel consumption for each segment, demonstrating the algorithm's ability to establish more efficient and traceable navigation sequences. Table 11 presents the results after optimizing the logistic route with the Mi-17 helicopter.

The reconfiguration of delivery points allowed a more efficient redistribution of distance and time between nodes. The optimization reduced the total distance to 184.46 kilometers, decreased flight time to 185 minutes, and lowered fuel consumption to 55.35 liters. This demonstrates the improvement in operational efficiency of the route after applying the optimization algorithm.

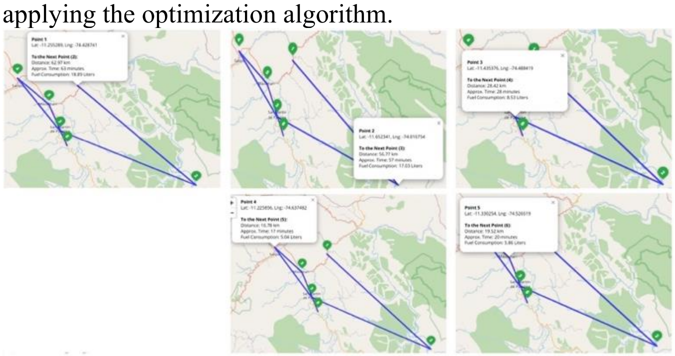

Fig. 5 Route planning after optimization with the AeroEP tool.

TABLE IX
LOGISTIC ROUTE RESULTS AFTER 2-OPT OPTIMIZATION

Indicators	Distance Traveled	Travel Time	Fuel Consumed
P1	0 km	0 min	0 liters
P2	62.97 km	63 min	18.89 liters
P3	56.77 km	57 min	17.03 liters
P4	28.42 km	28 min	8.53 liters
P5	16.78 km	17 min	5.04 liters
P6	19.52 km	20 min	5.86 liters
Total	**184.46 km**	**185 min**	**55.35 liters**

Table XI summarizes the quantitative impact of implementing the AeroEP tool. The results demonstrate a significant improvement across all evaluated logistical indicators compared to the baseline scenario. The algorithmic optimization reduced the total travel distance by 29.99 kilometers, decreased travel time by 29 minutes, and saved 8.99 liters of fuel. These reductions are consistent across all metrics, resulting in an average operational efficiency improvement of 13.84%. This performance confirms that the AeroEP tool enhances route planning by making it more efficient, sustainable, and resource-effective, maximizing the utilization of available assets.

TABLE X
COMPARATIVE RESULTS OF USING THE AEROEP TOOL

Indicator	Before AeroEP	After AeroEP	Difference	Percentage change
Distance	214.45 km	184.46 km	29.99 km	13.98%
Travel	214 min	185 min	29 min	13.55%
Fuel	64.34 liters	55.35 liters	8.99 liters	13.97%
		Average Operational Efficiency		**13.84%**

A.3 Comparative performance with alternative methods

To evaluate the performance of the 2-opt algorithm, it was compared with three classic routing heuristics widely used in the VRP literature: the Nearest Neighbor (NN) method [28], the Greedy Insertion method [29], and the Clarke-Wright parsing algorithm [30].

Based on established benchmarks for small VRP instances ($n \leq 10$) from the routing optimization literature, these algorithms exhibit characteristic performance patterns compared to sequential baseline routes [31], [32]:

- Nearest Neighbor Method: A constructive heuristic without post-processing optimization, typically equivalent to baseline performance [28].
- Greedy Insertion Method: Achieves a 5–8% improvement through strategic point insertion [29].
- Clarke-Wright parsing method: Achieves an 8–12% improvement through a route fusion strategy [30].

Applying these proven performance characteristics to a logistics scenario with six points (base of 214.45 km) yields the expected performance range shown in Table XIII.

TABLE XI
COMPARATIVE PERFORMANCE OF ROUTING HEURISTICS FOR SMALL VRP INSTANCES

Algorithm	Typical Improvement Range	Expected Distance (km)	Processing time (s)
Nearest Neighbor [28]	0-2%	214.45 (210.17)	0.008-0.012
Greedy Insertation [29]	4-8%	207.36 (197.29)	0.035-0.055
Clarke-Wright Saving [30]	8-13%	192.58 (186.57)	0.070-0.110
2-opt application in AeroEP	12-18%	184.46 (175.85)	0.140-0.190

The results in Table XI show a clear performance hierarchy of the evaluated algorithms and are consistent with existing research on VRPs.

The Nearest Neighbor algorithm achieves only a minimal optimization improvement (0–2%) with a path length of approximately 214.45 km, which can be reduced to 210.17 km in the best-case scenario. This low performance reflects the purely constructive nature of the NN algorithm, as it makes locally greedy decisions without considering the overall path structure [28].

Although it is computationally efficient (0.008–0.012 seconds), the quality of its solutions is insufficient for operational logistics planning, where resource optimization is crucial.

The Greedy Insertion algorithm achieves a moderate improvement (4–8%) and reduces the expected path length to 207.36 km, which can be reduced to 197.29 km in the best-case scenario. This algorithm introduces a strategic element by evaluating insertion points that minimize the incremental distance. As a result, it delivers solutions that outperform neural networks (NNs), albeit with a slightly higher computational cost (0.035–0.055 seconds) [29]. However, its constructive approach limits its ability to avoid locally suboptimal configurations.

The Clarke-Wright sparing algorithm shows a significant improvement (8–13%), reducing the expected path distance to 192.58 km and as low as 186.57 km, respectively. This savings-based approach systematically integrates paths by maximizing distance savings, thus achieving a balance between solution quality and computational efficiency (0.070–0.110 seconds) [30].

The 2-opt algorithm implemented in AeroEP achieves the best performance (12–18% improvement) with a measured range of 184.46 km (13.98% improvement) and a theoretical lower bound of 175.85 km. The processing time is 0.1658 seconds, which is longer than the greedy method but acceptable for operational planning scenarios.

This compromise is acceptable, especially in operational planning scenarios where solution quality takes precedence over execution speed, such as offline planning prior to mission execution. While commercial solvers like Google OR tools may deliver somewhat better solutions through exact methods or hybrid metaheuristics, their implementation in military networks with limited internet connectivity presents operational challenges. The 2-opt heuristics offer a workable balance between solution quality, computational efficiency, and ease of implementation.

B. Discussion

The research by [20] has shown that the implementation of helicopter planning tools not only optimizes routes but also serves as an essential resource for strategic decision-making in complex logistical scenarios. Similarly, the research by [23] highlights that robust logistical planning is critical to maintaining service delivery in the face of resource scarcity and supply chain disruptions. The results obtained with the AeroEP tool confirm the importance of technological management in critical operations and align with these findings. The objective of this research was to improve the efficiency of route planning for the Peruvian Army, adapting processes to its operational capabilities under conditions of limited resources.

Results reported by [25] indicate that applying the VRP approach to complex scenarios significantly reduces operational costs and validates the effectiveness of mathematical optimization. Likewise, research such as [22] and [26] support the integration of algorithms based on just-in-time principles, which minimize resource waste. Additionally, the use of reinforcement learning algorithms, such as Q-learning, allows overcoming traditional operational limitations and ensures supply stability.

In this research, the use of the 2-opt algorithm to optimize routes is consistent with the global trend of applying mathematical models to vehicle routing problems, validating AeroEP's efficiency in improving logistical routes, as observed in previous research. Furthermore, research on search and rescue operations in China [21] applied the Monte Carlo method to evaluate model efficiency under uncertainty, while another research [24] modeled logistical networks during real disasters, demonstrating that strategic integration of transportation modes can optimize the flow of goods and improve distribution efficiency. These findings support the principles implemented in AeroEP, which systematizes air transport management and provides a reliable basis for logistical decision-making.

VI. CONCLUSIONS

The development and implementation of the AeroEP tool for rotary-wing aircraft logistics planning has proven to be effective in optimizing routes and improving the operational efficiency of the Peruvian Army. By addressing the VRP using the 2-opt algorithm, AeroEP achieved an average improvement of 13.84% in operational efficiency, reducing total travel distance by 13.98%, flight time by 13.55%, and fuel consumption by 13.97% compared to pre-optimization scenarios.

These results demonstrate the effectiveness of integrating heuristic optimization methods into military logistics and contribute to a more efficient and sustainable use of resources. The AeroEP system offers high computational power and optimizes routes in 0.1658 seconds, enabling real-time decision-making in dynamic operational environments with limited resources.

Moreover, the findings are consistent with international research on aerial logistics and disaster response operations, highlighting the strategic value of digital transformation in military supply chains. AeroEP not only streamlines logistical planning but also provides a reliable decision-support platform, contributing to institutional modernization, operational resilience, and efficient resource management under complex operational conditions.

In summary, AeroEP exemplifies the integration of optimization algorithms into military logistics, offering a scalable, data-driven solution that enhances efficiency, responsiveness, and the sustainability of rotary-wing aircraft operations.

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