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Hybrid Optimization for Secure and Timely Medical Logistics: A Case Study in Burkina Faso

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Abstract. Transportation logistics plays a critical role in ensuring equitable access to medical supplies in low-infrastructure and insecure environments. This paper proposes a three-stage hybrid framework to solve a Vehicle Routing Problem with Safety and Time Windows (VRP-ST) in high-risk contexts. The methodology combines a Clarke–Wright savings heuristic for rapid initialization, an Ant Colony Optimization (ACO) metaheuristic to minimize a risk-adjusted distance objective, and Google OR-Tools to strictly enforce hard constraints, including vehicle capacities and delivery time windows. The approach is evaluated on a nationwide case study involving 44 healthcare centers in Burkina Faso. The results show a 19% reduction in total risk-adjusted distance (from 10,425 to 8,280 units) relative to the initial heuristic solution, together with improved fleet utilization. Beyond this case study, the framework provides a robust and fully feasible decision-support tool for medical logistics planning in crisis-affected regions. A sensitivity analysis under ±10% demand and risk-penalty perturbations confirms the stability of the solutions.

Keywords: Clarke–Wright savings, Ant Colony Optimization, OR-Tools, Vehicle Routing Problem, medical logistics, risk-adjusted distance, Burkina Faso

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1. INTRODUCTION

Vehicle routing optimization plays a vital role in logistics, particularly in healthcare, where the efficient distribution of medical supplies directly impacts the quality of

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care. The Vehicle Routing Problem (VRP) focuses on designing optimal routes that minimize costs, reduce transport time, and improve access to healthcare services, especially in regions with limited infrastructure and security risks, such as Burkina Faso (Cipta & Hasibuan, 2023).

To address these challenges, this study adopts a hybrid optimization approach that combines classical heuristics with advanced metaheuristic and constraint-based techniques. The Clarke–Wright algorithm generates efficient initial routes (Stević & Gavranović, 2024), but it lacks the flexibility to handle dynamic constraints. To improve performance, we integrate Ant Colony Optimization (ACO), which iteratively refines routes through collective learning inspired by ant behavior (Diao, 2024). Finally, Google's OR-Tools is employed to optimize the solution further, incorporating complex constraints like time windows and vehicle capacities (Alves et al., 2021).

This study applies these three methods to the medical supply distribution challenge in Burkina Faso, with the goal of reducing transport costs and improving healthcare coverage under security and time constraints. However, most VRP studies still prioritize cost-time minimization under stable network assumptions, whereas medical deliveries in crisis-affected settings must simultaneously account for security-driven disruptions and strict service time requirements. Accordingly, this paper proposes a risk-adjusted VRP-ST formulation grounded in structured expert elicitation and develops a practical three-stage hybrid solution strategy that combines Clarke–Wright initialization, ACO-based global improvement, and OR-Tools refinement to ensure full feasibility under capacity and time-window constraints. The rest of this paper provides a literature review, outlines the methodology and data used, analyzes the results, and discusses future improvements, including integrating real-time data for adaptive routing.

2. STATE OF THE ART

2.1. VRP surveys and cost-time minimization

The Vehicle Routing Problem (VRP) is a foundational problem in distribution logistics, commonly formulated to minimize travel cost and/or travel time under operational constraints. Several survey papers provide comprehensive taxonomies of VRP variants, solution methods (exact, heuristic, and metaheuristic), and benchmarking practices. In addition to application-driven studies, several comprehensive survey papers have established the Vehicle Routing Problem as a central topic in operations research. The seminal survey by Laporte (2009) provides a unifying framework for classical VRP variants, solution methodologies, and computational benchmarks, with a strong emphasis on cost and distance minimization under capacity and routing constraints. Similarly, the monograph by Toth and Vigo (2014) offers an extensive and structured overview of exact methods, heuristics, and metaheuristics for capacitated and time-constrained VRPs and remains a foundational reference in the field.

More recently, Vidal (2020) revisited VRP solution strategies through a unifying perspective on hybrid heuristics and metaheuristics, highlighting their effectiveness for large-scale and highly constrained problems. Taken together, these surveys show that while classical VRP research has predominantly focused on cost and time minimization, real-world applications increasingly require hybrid and flexible approaches capable of accommodating additional constraints and externalities, such as service time windows, uncertainty, and safety/security considerations. This observation directly motivates the hybrid framework proposed in this study, which extends traditional cost-time optimization by explicitly incorporating safety and time-window considerations in a high-risk medical logistics context.

Building on these general insights from the VRP literature, the following subsections review the main optimization paradigms relevant to this study, with a particular focus on constructive heuristics, metaheuristics, and hybrid approaches.

2.2. Route Optimization with Clarke–Wright

The Clarke–Wright savings algorithm is a classical constructive heuristic for the capacitated VRP, originally introduced by Clarke & Wright (1964). It remains widely used due to its simplicity and strong baseline performance, and has been applied in medical logistics (Cipta & Hasibuan, 2023) and other distribution contexts (Bouraima et al., 2024). However, the method does not explicitly model dynamic factors such as demand variability, traffic conditions, or strict time windows, which limits its direct applicability in real-time and crisis-sensitive settings.

2.3. Route Optimization with Ant Colony Optimization (ACO)

ACO, inspired by ant foraging behavior, offers a dynamic approach to route optimization. The algorithm iteratively updates solutions, improving route efficiency through collective learning (Diao, 2024). ACO has been applied in various domains, including educational transportation and hazardous material delivery. However, its high computational cost and reliance on real-time data limit its practicality in large-scale systems, particularly when accurate input data is difficult to obtain in crisis contexts.

2.4. Route Optimization with OR-Tools and hybrid models

Google OR-Tools provides a flexible, open-source toolkit for large-scale VRP optimization. It integrates with mapping tools like Google Maps and the Distance Matrix API to improve real-world route planning (Alves et al., 2021). However, its reliance on simulated data and failure to incorporate real-time traffic dynamics pose limitations for practical use in dynamic environments, such as those encountered in geopolitically unstable or crisis-stricken areas.

2.5. Metaheuristics and hybrid approaches

Other metaheuristics, like Simulated Annealing (SA) and Tabu Search (TS), have also been applied to optimize vehicle routes in constrained environments. These methods perform well in reducing operational costs and improving route efficiency (Prayoga & Mardiana, 2023; Salsabila, 2023), but they often ignore dynamic real-world factors such as traffic congestion or weather conditions, which are crucial in crisis situations.

2.6. VRP models with risk factors and security constraints

The optimization of Vehicle Routing Problems (VRP) is a well-established research field. However, real-world applications, especially in high-risk environments such as humanitarian logistics or distribution in insecure areas, require a modeling approach that goes beyond traditional cost and distance minimization objectives. This literature review focuses on approaches that integrate risk factors and security constraints to address these complex challenges.

A key issue is incorporating risk into the objective function. In their literature review, Fröhlich et al. (2023) highlight that risk can be defined as the probability of an undesirable event occurring. They describe several methods to integrate risk, notably the weighted multi-objective approach, where risk is combined with classical cost in a minimization function. This principle is directly relevant to our study, as it justifies the use of a weighted distance (Equation (2)) to reflect the impact of risk on the total cost. The factors r_{ij} we use can be considered as weights or proxies that reflect the probability and severity of threats on a given arc, similar to multiplying the risk of an accident by the exposed population, as mentioned in the review.

Moreover, the integration of security constraints goes beyond accident risks. Bigdeli et al. (2023) propose a robust VRP model designed to operate in the presence of a proactive attacker. Their work emphasizes the need to plan routes that maximize delivery success while minimizing costs, a problem that is particularly relevant in regions where insecurity is a major factor, such as Burkina Faso. Bigdeli et al.'s (2023) approach provides a theoretical justification for incorporating risk factors into our model, associating them with the success probability of delivery missions. This strengthens our decision to penalize risky routes, as it increases the robustness and reliability of the solution in the face of potential threats.

Finally, Omidvar et al. (2017) specifically examine the road safety problem. They present a model that identifies the safest routes by considering the probability of collisions and traffic congestion. Their results show that selecting safer routes may sometimes lead to an increase in distance and travel time, but this trade-off is justified by the improved safety. This validates our method, which, by using risk multipliers ($r_{ij} > 1$), increases the cost of dangerous roads, thus encouraging the algorithm to prioritize longer but safer routes, a crucial balance in a context where the safety of drivers and cargo is paramount.

By combining the ideas from these three studies, our hybrid methodology, which adjusts distance based on risk factors, presents itself as a rigorous and justified approach to VRP in environments with security and infrastructure constraints.

2.7. Research positioning

Most studies on VRP primarily focus on minimizing costs and time, but very few integrate security constraints in a crisis context. Our VRP-ST (VRP with Safety and Time Windows) model addresses this gap by incorporating critical security constraints, specifically tailored for environments like Burkina Faso, where route management must not only be optimized for costs but also ensure the safety of teams and cargo.

By combining Clarke–Wright, ACO, and Google OR-Tools into a hybrid model, this study addresses the limitations of individual approaches. It aims to optimize medical supply routes in Burkina Faso, where infrastructure and security constraints demand a highly adaptive and scalable solution. The following section presents the methodology used to collect and integrate data into the hybrid optimization framework.

3. METHODOLOGY

Our methodology for optimizing Vehicle Routing Problems (VRP) is structured around a hybrid approach that combines multiple algorithms to maximize efficiency while addressing real-world challenges. The process begins with the collection and preparation of data, as illustrated in Figure 1, which serves as the foundation for the mathematical modeling of the problem. To model the optimization problem, we formulated a specific variant called the VRP with Safety and Time Windows (VRP-ST), which extends the classic VRP by integrating safety constraints and time windows. The resulting mathematical model is directly fed by geographical data, client information, and collected risk factors. This formulation serves as the foundation of our hybrid approach, establishing the framework within which the algorithms will operate to find the optimal solution.

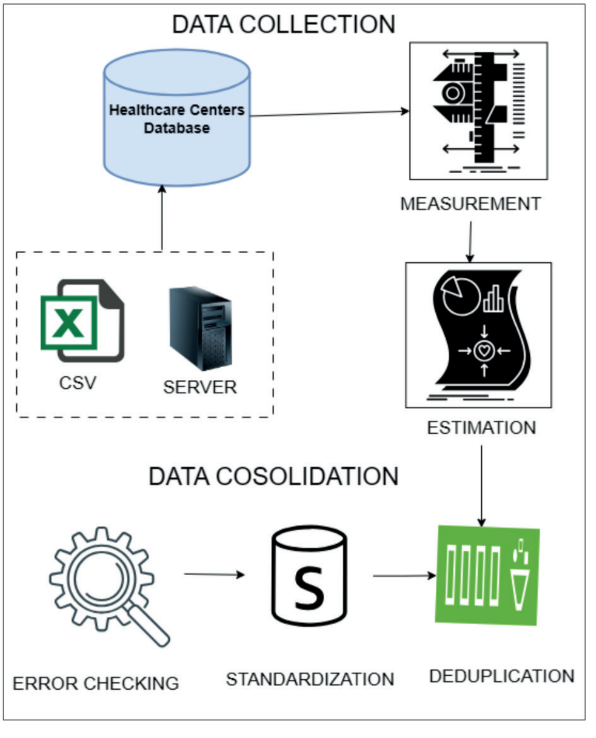

Fig. 1. *Data collection and consolidation process*

3.1. Data collection

Data collection from healthcare services in Burkina Faso (Directorate General of Studies and Sectoral Statistics, 2024) was a crucial first step in understanding the dynamics of healthcare access and optimizing resource allocation for medical supply distribution. This study systematically gathered data from various healthcare centers to assess their logistical and medical supply needs. We identified relevant healthcare centers and measured the distances between them in kilometers. We also estimated the demand volumes for medicines and medical equipment and analyzed constraints related to transportation, accessibility, vehicle availability, road conditions, and safety. Certain data were either unavailable or could not be directly collected. To address these gaps, we generated or estimated specific values. For example, vehicle capacities, demand at specific centers, and the number of vehicles in operation were approximated based on available data and reasonable assumptions. The generated data were then integrated into our medical routing optimization model to improve resource allocation and optimize logistical costs.

Assumptions and data handling. Vehicle capacities were estimated based on typical fleet data available for similar healthcare logistics operations. Demand estimates were derived from historical trends and expert consultations within the healthcare system. For missing data, particularly the number of vehicles in certain regions, proportional allocation based on available regional data was used to make inferences.

3.2. Data consolidation

After the initial data collection, it was essential to ensure that the data were consistent, accurate, and ready for analysis and optimization. This process involved checking for errors, correcting inconsistencies, and standardizing the formats to ensure compatibility with optimization tools.

The collected data were cleaned by correcting errors and inconsistencies in the files, standardizing the data formats for uniformity, and using estimation or cross-referencing methods to fill in missing data. Duplicate entries were also removed to ensure that each healthcare center was uniquely represented.

Two tables summarize the key data used in our model: Table 1 lists the risk indices for routes between various locations, adjusting distances based on road safety levels and guiding routing decisions toward safer paths. Table 2 presents the demand levels for medical supplies at each healthcare center, which is essential for organizing an equitable and efficient distribution system. To further validate our dataset, we visualized the distance matrix. Figure 2 (on the interleaf) shows this matrix as a heatmap, where each cell represents the distance between two centers. This visualization helped confirm the symmetry of the distances $d_{ij} = r_{ji}$, identify any anomalies, and ensure the integrity of the data before proceeding with the optimization phase. The final dataset consisted of a symmetric distance matrix with 44 rows and 44 columns, reflecting the distances between the healthcare centers.

Risk classes versus optimization penalties. Table 1 reports the discrete expert-based risk classes $c_{ij} \in \{1, 2, 3\}$ assigned to the road segments. In the VRP-ST

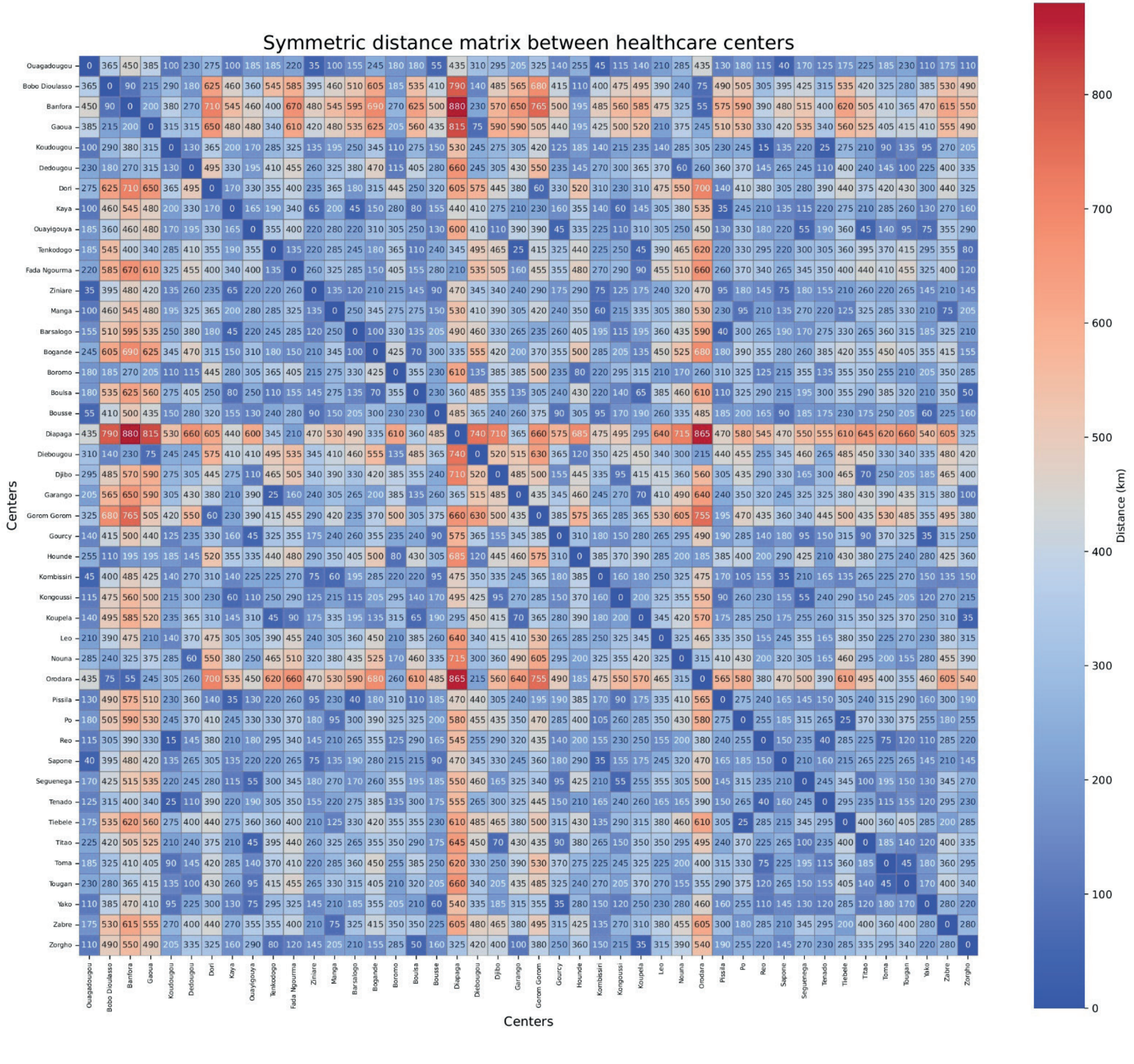

Fig. 2. *Symmetric distance matrix between healthcare centers*

optimization model, these classes are mapped to multiplicative penalties r_{ij} used as follows:

$$\boldsymbol{r}_{ij} = \begin{cases} 1.5, & \text{if} \quad c_{ij} = 1 \text{ (moderate risk)}, \\ 3, & \text{if} \quad c_{ij} = 2 \text{ (high risk)}, \\ 5, & \text{if} \quad c_{ij} = 3 \text{ (strongly discouraged)}. \end{cases} \tag{1}$$

Table 1. *Risk table between localities*

Start	End	Risk class
Banfora	Gaoua	1
Gaoua	Banfora	1
Dori	Kaya	2
Kaya	Dori	2
Titao	Ouahigouya	3
Ouahigouya	Titao	3
Fada Ngourma	Diapaga	3
Diapaga	Fada Ngourma	3
Kaya	Barsalogo	2
Barsalogo	Kaya	2
Bogande	Dori	3
Dori	Bogande	3
Dori	Djibo	3
Djibo	Dori	3
Djibo	Gorom Gorom	3
Gorom Gorom	Djibo	3
Kaya	Pissila	2
Pissila	Kaya	2
Ouahigouya	Seguenega	2
Seguenega	Ouahigouya	2
Toma	Tougan	2
Tougan	Toma	2

Table 2. *Demand table by center*

Part 1			Part 2		
Node	Center	Demand	Node	Center	Demand
0	Ouagadougou	0	1	Bobo Dioulasso	50
2	Banfora	30	3	Gaoua	40
4	Koudougou	35	5	Dedougou	45
6	Dori	25	7	Kaya	30
8	Ouayigouya	50	9	Tenkodogo	20
10	Fada Ngourma	40	11	Ziniare	15
12	Manga	25	13	Barsalogo	35
14	Bogande	30	15	Boromo	20
16	Boulsa	15	17	Bousse	40
18	Diapaga	25	19	Diebougou	30
20	Djibo	45	21	Garango	20
22	Gorom Gorom	15	23	Gourcy	30
24	Hounde	50	25	Kombissiri	25
26	Kongoussi	40	27	Koupela	35
28	Leo	30	29	Nouna	45
30	Orodara	50	31	Pissila	20
32	Po	30	33	Reo	25
34	Sapone	15	35	Seguenega	35
36	Tenado	30	37	Tiebele	25
38	Titao	20	39	Toma	40
40	Tougan	50	41	Yako	30
42	Zabre	20	43	Zorgho	15

This mapping preserves the ordinal expert assessment while allowing the solver to trade off safety and distance through risk-adjusted distance.

3.3. Vehicle Routing Problem with Security and Time Constraints (VRP-ST) formulation

This section presents the mathematical formulation of the Vehicle Routing Problem with Safety and Time Windows (VRP-ST), which extends the classical capacitated VRP by incorporating route-dependent security penalties and delivery time constraints.

Indices and notations

Let:

- $V = \{0, 1, ..., n\}$ denote the set of nodes, where node 0 represents the central depot and nodes 1, ..., n correspond to healthcare centers,
- $A = \{(i, j) \mid i, j \in V, i \neq j\}$ be the set of directed arcs between nodes,
- $K = \{0, 1, ..., m\}$ be the set of available vehicles,
- d_{ij} denote the physical distance between nodes i and j,
- r_{ij} denote the security-related risk factor associated with arc (i, j),
- d'_{ij} denote the risk-adjusted distance, defined as:

$$d'_{ij} = d_{ij} \cdot r_{ij}, \tag{2}$$

- q_i be the demand at node i,
- Q denote the vehicle capacity,
- $[a_i, b_i]$ be the allowable delivery time window at node i,
- t_{ij} be the travel time between nodes i and j,
- T_{max} denote the maximum allowable working duration for each vehicle,
- $x_{ijk} \in \{0, 1\}$ be a binary decision variable equal to 1 if vehicle k travels directly from node i to node j, and 0 otherwise,
- u_{ik} be the arrival time of vehicle k at node i.

Risk classes versus optimization penalties. Security levels were elicited through structured interviews with logistics managers from the five major health-supply distribution organizations operating in Burkina Faso, including the national public procurement agency (CAMEG) and four private distributors. In total, five domain experts (one per organization) were consulted, each with direct operational experience delivering to security-challenged areas. Experts were asked to identify road segments recurrently affected by security incidents or access restrictions and to classify each segment into one of three ordered categories (moderate, high, strongly discouraged), based on empirical observations of disruption likelihood and operational consequences (e.g., escorts, detours, postponed missions, or temporary suspension of deliveries). When multiple opinions were available for a segment, the majority class was retained; in case of a tie or uncertainty, a conservative rule was applied by selecting the higher-risk class. The class-to-multiplier mapping $r_{ij} \in \{1.5, 3, 5\}$ was chosen to ensure a monotonic and sufficiently separated penalization across categories while avoiding excessive scaling that could dominate the objective function. In particular, 1.5 (rather than 2) reflects that moderate-risk segments remain operationally usable without systematically forcing detours, while still internalizing additional precautionary costs (reduced speed, waiting time, and coordination overhead). Conversely, 3 and 5 represent progressively stronger deterrence that is consistent with high-risk and strongly discouraged routes and preserve a clear ordinal gap within the risk-adjusted cost $d'_{ij} = d_{ij} \cdot r_j$. This modeling choice is consistent with risk-weighted routing approaches reported in the literature (Bigdeli et al., 2023; Fröhlich et al., 2023).

Objective function

The objective is to minimize the total risk-adjusted distance across all vehicles:

$$\min \sum_{k\in K} \sum_{(i,j)\in A} d'_{ij} x_{ijk} \tag{3}$$

Flow conservation constraints

Each healthcare center must be visited exactly once:

$$\sum_{k\in K} \sum_{j\in V, j\neq i} x_{ijk} = 1, \quad \forall i \in V \setminus \{0\} \tag{4}$$

Each vehicle must depart from and return to the depot:

$$\sum_{j\in V, j\neq 0} x_{0jk} = 1, \quad \forall k \in K \tag{5}$$

$$\sum_{i\in V, i\neq 0} x_{i0k} = 1, \quad \forall k \in K \tag{6}$$

Flow continuity must be preserved at each node:

$$\sum_{i\in V, i\neq j} x_{ijk} = \sum_{l\in V, l\neq j} x_{jlk}, \quad \forall j \in V, \forall k \in K \tag{7}$$

Capacity constraint

The total demand served by each vehicle must not exceed its capacity:

$$\sum_{i\in V} q_{ik} \leq Q, \quad \forall k \in K \tag{8}$$

Time window constraints

Each delivery must occur within its specified time window:

$$a_i \leq u_{ik} \leq b_i, \quad \forall i \in V, \forall k \in K \tag{9}$$

Travel time consistency is enforced as:

$$u_{jk} \geq u_{ik} + t_{ij} - M\left(1 - x_{ijk}\right), \quad \forall (i,j) \in A, \forall k \in K \tag{10}$$

where M is a sufficiently large constant.

The total working duration of each vehicle is limited by:

$$u_{0k} + \sum_{(i,j)\in A} t_{ij} x_{ijk} \leq T_{max}, \quad \forall k \in \text{ K} \tag{11}$$

3.4. Hybrid solution approach

To improve medical supply distribution, we implemented a three-step optimization strategy. First, we used the Clarke–Wright algorithm to obtain an initial solution that minimizes the travel distance. We then applied Ant Colony Optimization (ACO), which explores multiple delivery routes using pheromone-based learning. Finally, Google OR-Tools refined the solutions by incorporating real-world constraints such as delivery deadlines and regional security concerns.

Phase 1: Clarke–Wright initialization

The Clarke–Wright algorithm generates a feasible initial solution by merging routes iteratively. It is computationally efficient ($O(n^2 \log n)$) and provides a baseline for ACO refinement.

Phase 2: Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is used to improve the initial feasible solution generated by the Clarke–Wright heuristic. The objective of this phase is to explore alternative routing configurations while minimizing the total risk-adjusted distance and strictly preserving feasibility with respect to vehicle capacity and time-window constraints.

In the proposed implementation, each ant constructs a complete VRP-ST solution by sequentially building routes that start and end at the depot (node 0). At each construction step, an ant located at node i selects the next node j from an admissible candidate set consisting of unvisited clients whose insertion does not violate capacity or time-window constraints. If no admissible client remains, the ant returns to the depot and starts a new route. As a result, all solutions generated by the ACO procedure are feasible by construction; infeasible solutions are not accepted.

Solution evaluation. Each ant a produces a complete solution S^a, evaluated through its total risk-adjusted distance:

$$C(Sa) = \sum_{(i,j)\in S^a} d'_{ij} \tag{12}$$

where d' is the risk-adjusted distance defined in Equation (2). This cost function serves as the unique solution quality metric guiding pheromone updates.

Pheromone update mechanism. Let τ_{ij} denote the pheromone intensity associated with arc (i, j). After all ants have constructed their solutions, pheromone trails are updated according to:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{a=1}^{A} \Delta\tau_{ij}^{a} \tag{13}$$

with:

$$\tau_{ij}^{a} = \begin{cases} Q \ / C(S^a) & \text{if} \quad arc(i,j) \text{ is used in } S^a \\ 0 & \qquad \text{otherwise} \end{cases} \tag{14}$$

where A is the number of ants, Q is a pheromone scaling constant, and $\rho \in (0, 1)$ is the pheromone evaporation rate. This mechanism reinforces arcs belonging to high-quality (low-cost) solutions while maintaining exploration through evaporation.

Transition probability. During solution construction, the probability that an ant moves from node i to an admissible node j is given by:

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{l \in Ni}(\tau_{il})^{\alpha}(\eta_{il})^{\beta}} \quad \text{with}\, \eta_{ij} = \frac{1}{d'_{ij}} \tag{15}$$

Where N_i denotes the admissible neighborhood of node i, and parameters α and β control the relative influence of pheromone intensity and heuristic desirability, respectively.

Parameter tuning via DOE. A Design of Experiments (DOE) approach was employed to calibrate the ACO parameters by analyzing their individual and interaction effects on solution quality and computational time. The final parameter set retained for all experiments is reported in Table 3. The DOE results highlight non-trivial synergies between parameters. In particular, the combination of a moderate evaporation rate (ρ) with a relatively high heuristic weight (β) proved effective in the VRP-ST context, enabling strong search intensification while avoiding premature convergence.

Table 3. *ACO parameters determined through DOE*

Parameter	Optimal value
Colony size	50
Maximum iterations	200
α (pheromone influence)	1.35
β (heuristic influence)	2.80
ρ (evaporation rate)	0.43

Phase 3: OR-Tools refinement and feasibility enforcement

The third optimization phase relies on Google OR-Tools to refine the best solution achieved by ACO and to strictly enforce hard operational constraints. While the Clarke–Wright and ACO phases focus on constructing and improving the routing structures, certain constraints (notably time windows and maximum working duration) are handled in a relaxed or heuristic manner during these stages. OR-Tools is therefore employed to guarantee full feasibility and to further reduce the objective value.

The problem is modeled using the OR-Tools Routing Solver, with capacity and time dimensions explicitly defined. OR-Tools then enforces feasibility through its constraint-based routing framework and performs a constrained local search to re-optimize the routing plan under hard constraints. In particular, the vehicle capacity limits, delivery time windows, and maximum route duration are strictly enforced at this stage. As a result, all final solutions produced by OR-Tools are fully feasible with respect to the VRP-ST formulation. Starting from the best ACO solution as an initial assignment, OR-Tools performs a constrained local search within its routing framework to re-optimize the plan under hard constraints. This hybridization combines ACO's stochastic exploration with OR-Tools' deterministic feasibility enforcement for capacity, time windows, and route duration.

Compared to the ACO solution, the OR-Tools refinement yields an additional cost reduction of about 3% while preserving full feasibility. Table 4 summarizes the performance of the three optimization stages in terms of risk-adjusted distance, computation time, and feasibility.

Table 4. *Performance comparison of optimization stages (risk-adjusted cost)*

Method	Risk-adjusted cost	Time [s]	Feasibility
Clarke–Wright	10,425	5	partial
ACO	8,500	150	full
OR-Tools	8,280	200	full

4. RESULTS

This section presents the computational results obtained for the medical supply distribution problem in Burkina Faso. The objective is to minimize the total risk-adjusted distance while satisfying vehicle capacity, security, and time-window constraints. Figure 3 provides an overview of the complete optimization workflow.

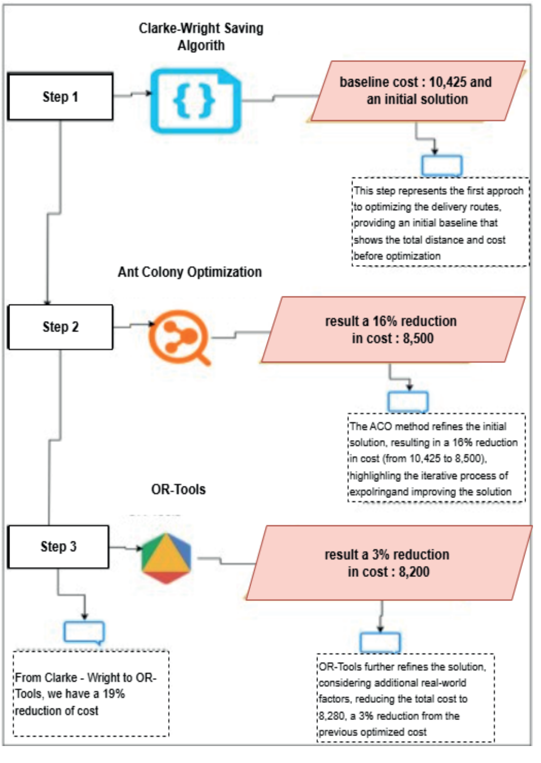

Fig. 3. *Visualization of Clarke–Wright vs. ACO results*

4.1. Optimization stages and solution quality

The optimization process was carried out sequentially using three methods: Clarke–Wright, Ant Colony Optimization (ACO), and OR-Tools. Unless otherwise stated, all reported costs correspond to the risk-adjusted distance defined in Equation (2).

Clarke–Wright initialization. The Clarke–Wright savings heuristic produced an initial feasible routing plan with a total risk-adjusted distance of 10,425 units. This solution satisfies vehicle capacity constraints and serves as a baseline, but handles time-window constraints in a heuristic manner.

ACO improvement. Starting from the Clarke–Wright solution, ACO significantly improved the routing structure through stochastic exploration. Using the calibrated parameters $\alpha = 1.35$, $\beta = 2.8$, and $\rho = 0.43$ (Table 3), the total risk-adjusted distance was reduced to 8,500 units, corresponding to an improvement of approximately 16%. All solutions generated during the ACO phase were feasible by construction with respect to capacity and time-window constraints.

OR-Tools refinement. In the final stage, Google OR-Tools was applied to strictly enforce all hard constraints and further refine the best ACO solution. By leveraging the OR-Tools Routing Solver with explicit capacity and time dimensions, OR-Tools guarantees full feasibility with respect to vehicle capacity, delivery time windows, and maximum route duration. This refinement yielded an additional reduction of about 3%, resulting in a final risk-adjusted distance of 8,280 units. Overall, the hybrid approach achieved a total cost reduction of 19% compared to the initial Clarke–Wright solution.

4.2. Cost reduction analysis

Table 5 summarizes the incremental cost reductions obtained at each optimization stage.

Table 5. *Risk-adjusted cost reduction across optimization stages*

Method	Reduction [%]	Final cost
Clarke–Wright	0	10,425
ACO	16	8,500
OR-Tools	3	8,280

These results highlight the complementary roles of ACO and OR-Tools. ACO provides substantial global improvements through exploration of the solution space, while OR-Tools performs deterministic refinement and strict feasibility enforcement.

4.3. Fleet utilization and resource efficiency

Beyond cost reduction, the proposed hybrid approach improves fleet utilization. Both Clarke–Wright and ACO required 16 vehicles to serve all healthcare centers. After OR-Tools refinement, the same demand was satisfied using only 15 vehicles, corresponding to a 6% reduction in fleet size. This reduction translates into lower fuel consumption, maintenance costs, and operational staffing requirements.

4.4. Feasibility and constraint satisfaction

All final routes produced by OR-Tools strictly satisfy vehicle capacity limits, delivery time windows, and maximum route duration constraints. In particular, no vehicle exceeded the capacity limit of 100 units, ensuring operational safety and reliability. These feasibility guarantees are critical in the context of Burkina Faso, where road conditions and vehicle availability impose strong operational constraints.

The average computation time for the ACO phase was between 150 and 155 seconds using 50 ants and 200 iterations, providing a balanced trade-off between solution quality and computational effort. The OR-Tools refinement required additional computation time but ensured full feasibility and improved solution robustness.

4.5. Sensitivity analysis

To evaluate the robustness of the proposed VRP-ST framework under plausible data uncertainty, a sensitivity analysis was performed on two inputs that are both operationally critical and partially uncertain in crisis-affected settings: healthcare-center demands and the security-related risk multipliers applied to road segments. The analysis follows the perturbation range announced in the abstract and tests whether moderate variations affect feasibility and the qualitative routing patterns produced by the three-stage pipeline.

Demand perturbation. Demands at healthcare centers were perturbed by $\pm 10\%$ around their nominal values while keeping the vehicle capacities, time windows, and all solver settings unchanged. For each scenario, the complete hybrid procedure (Clarke–Wright initialization, ACO improvement, and OR-Tools refinement) was re-executed. Across the tested demand scenarios, the OR-Tools stage consistently returned solutions satisfying the capacity and time-window constraints, and the resulting routing plans remained qualitatively similar to the baseline, with only limited variations in the final risk-adjusted objective value. These observations suggest that the proposed framework is not overly sensitive to moderate demand fluctuations.

Risk-penalty perturbation. To assess the impact of uncertainty in expert-based security assessment and potential temporal variability of security conditions, risk multipliers r_{ij} were uniformly perturbed by $\pm 10\%$. As expected, the absolute magnitude of the risk-adjusted objective changes with the scaling of r_{ij}. However, the relative behavior of the three optimization stages and the overall structure of the final routing plans remained stable, indicating that the method does not hinge on a single finely tuned risk-penalty setting. Importantly, the OR-Tools refinement maintained strict feasibility under all tested perturbations.

Overall, the sensitivity analysis supports the stability of the proposed VRP-ST framework under moderate variations in both demand and risk-penalty parameters. This robustness is desirable in low-data, high-uncertainty environments, where demand estimates and security conditions may evolve and cannot always be measured precisely.

4.6. Routing structure visualization

For clarity and interpretability, the evolution of the routing structures across the optimization stages is illustrated graphically. Figure 4 compares the initial Clarke–Wright solution with the ACO-improved routes, highlighting the reduction in route length and structural reorganization. Figure 5 presents the final OR-Tools solution, which strictly satisfies all capacity and time-window constraints.

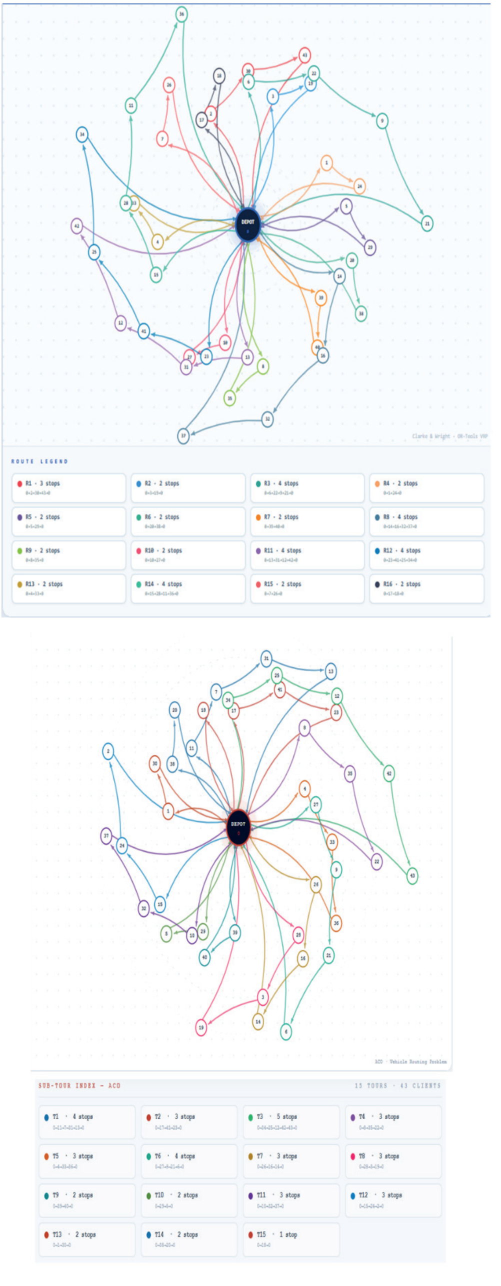

Fig. 4. *Visualization of Clarke–Wright vs. ACO results*

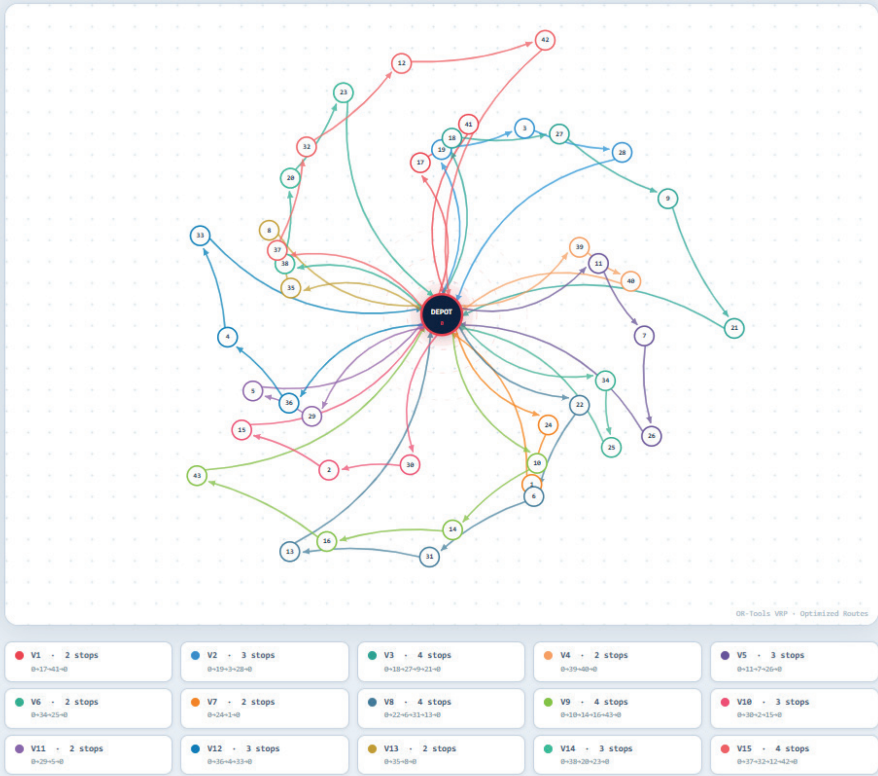

Fig. 5. *Final routing solution obtained with OR-Tools*

5. CONTRIBUTIONS

This work makes three main contributions to the literature on vehicle routing under security and operational constraints.

First, it introduces a formally defined Vehicle Routing Problem with Safety and Time Windows (VRP-ST), which explicitly integrates route-dependent security considerations through risk-adjusted distances. Unlike classical VRP formulations that focus solely on cost or time minimization, the proposed model incorporates expert-elicited security penalties while preserving full feasibility with respect to vehicle capacity, time windows, and route duration constraints.

Second, the paper proposes and validates a three-stage hybrid optimization framework that combines a constructive heuristic (Clarke–Wright), a metaheuristic (Ant Colony Optimization), and a constraint-based solver (Google OR-Tools). This hybridization is designed to separate global exploration from strict feasibility enforcement, thereby addressing both solution quality and operational realism in high-risk logistical environments.

Third, the study provides empirical evidence from a nationwide medical supply distribution case in Burkina Faso, demonstrating that risk-aware hybrid routing can simultaneously reduce transportation costs, improve fleet utilization, and maintain full feasibility under security and time constraints. Beyond the specific case study, the proposed framework constitutes a transferable decision-support methodology for medical logistics planning in crisis-affected and resource-constrained regions.

6. DISCUSSION

This study proposes a hybrid optimization framework that combines the Clarke–Wright savings heuristic, Ant Colony Optimization (ACO), and Google OR-Tools to address a Vehicle Routing Problem with Safety and Time Windows (VRP-ST) in a high-risk logistical context. The results demonstrate that this hybridization is not merely algorithmic but functional, as each component contributes distinctly to the observed performance gains.

6.1. Role of hybridization and performance interpretation

The Clarke–Wright heuristic plays a constructive role by rapidly generating a feasible baseline solution. While this solution is not optimal, it provides a structured starting point that significantly reduces the search space for subsequent optimization stages. ACO then exploits this structure through stochastic exploration, enabling global improvements that account for the risk-adjusted objective function. This explains the substantial reduction (approximately 16%) observed during the ACO phase. Finally, OR-Tools acts as a deterministic refinement layer, strictly enforcing all hard constraints and performing local improvements, which leads to an additional 3% reduction while guaranteeing full feasibility.

These complementary roles help explain why the proposed framework achieves a total cost reduction of 19% without sacrificing constraint satisfaction. This finding is consistent with prior studies showing that hybrid approaches can outperform standalone heuristics or exact methods in complex VRP settings (Borowski et al.; 2020, Liu et al., 2023).

6.2. Risk-aware routing in insecure environments

A central feature of the proposed VRP-ST formulation is the explicit integration of security considerations through route-dependent risk factors. By adjusting travel distances using multiplicative penalties $r_{ij} \in \{1.5, 3{,}5\}$, the model discourages unsafe routes while preserving overall feasibility. This formulation aligns with recent trends in VRP research that incorporate real-world externalities such as risk, safety, or environmental impact (Liu et al., 2023; Nunna, 2017).

The results indicate that accounting for security constraints does not merely increase costs but leads to more robust routing plans that are better suited to crisis-affected regions. In the context of Burkina Faso, where road insecurity and infrastructure degradation are significant concerns, this trade-off is operationally justified.

6.3. Comparison with learning-based optimization approaches

Recent advances in Learning-Based Optimization (LBO) have shown promise for large-scale and stochastic VRPs (Li et al., 2022). While our framework does not rely on machine learning, the use of OR-Tools provides comparable flexibility in handling complex constraints. Unlike LBO approaches, which often require large volumes of high-quality training data, the proposed method remains applicable in data-scarce environments. This characteristic is particularly important in low- and middle-income countries, where comprehensive historical data are rarely available.

However, as noted in the literature, no single optimization paradigm dominates across all VRP variants (Li et al., 2022). The effectiveness of the proposed hybrid approach should therefore be interpreted as context-dependent rather than universally optimal.

6.4. Limitations and robustness considerations

Despite its encouraging performance, the proposed framework has several limitations. First, part of the input data, including demand levels and risk factors, relies on expert judgment or estimated values, which may introduce bias. Second, the risk modeling is static and does not capture the temporal variability of security conditions, which can evolve rapidly in practice. Third, although computational times remain acceptable for strategic and tactical planning, real-time re-optimization for large fleets would require further efficiency improvements.

These limitations highlight the need for cautious interpretation of the results and underline the importance of future validation using real-time and longitudinal data.

6.5. Practical implications and future research directions

From a practical perspective, the proposed VRP-ST framework offers a decision-support tool for medical logistics planners operating in insecure and resource-constrained environments. The observed reductions in risk-adjusted distance and fleet size translate directly into operational savings and improved service reliability.

Future research could focus on integrating dynamic risk information, such as real-time security alerts or weather conditions, to enhance adaptability. Machine learning techniques could also be explored to improve demand forecasting rather than route optimization itself. Finally, emerging paradigms such as quantum optimization may offer long-term opportunities for scaling large VRP instances, although their practical applicability remains an open research question.

7. CONCLUSION

This paper proposes a hybrid optimization framework to address a Vehicle Routing Problem with Safety and Time Windows (VRP-ST) in a high-risk logistical context. By combining the Clarke–Wright savings heuristic, Ant Colony Optimization (ACO), and Google OR-Tools, the proposed approach leverages the complementary strengths of constructive heuristics, metaheuristics, and constraint programming.

Applied to a nationwide medical supply distribution case in Burkina Faso, the framework achieved a total reduction of 19% in risk-adjusted distance while strictly satisfying vehicle capacity, time-window, and route-duration constraints. In addition, the optimized solution reduced the required fleet size from 16 to 15 vehicles, illustrating tangible operational benefits beyond cost reduction. These results confirm that hybrid optimization strategies can provide effective and feasible solutions for complex VRP variants in insecure and infrastructure-constrained environments.

Despite these encouraging outcomes, several limitations must be acknowledged. Part of the input data, including demand levels and route risk factors, relies on expert judgment and estimated values, which may introduce uncertainty. Moreover, the risk modeling remains static and does not capture the temporal variability of security conditions. Finally, although the computational effort is acceptable for strategic and tactical planning, real-time re-optimization at a large scale remains challenging.

Future work will focus on strengthening the robustness and applicability of the proposed framework. In particular, integrating dynamic data sources related to security conditions, traffic, or weather could enable adaptive routing decisions. Machine learning techniques may also be explored to improve demand forecasting and scenario analysis rather than replacing optimization itself. Overall, this study highlights the practical relevance of hybrid VRP approaches as decision-support tools for medical logistics in crisis-affected and resource-limited settings.

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