

Data-driven strategic optimization for sustainable electric last-mile delivery

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ABSTRACT

The increasing adoption of electric vehicles (EVs) in urban logistics presents unique optimization challenges that balance operational efficiency with sustainability objectives. This paper introduces a bi-objective electric vehicle routing approach specifically designed for small and medium enterprises (SMEs). Our methodology adapts the Clarke-Wright Savings algorithm with three key innovations: (1) a configurable weighted cost function balancing distance minimization and non-linear energy consumption using quadratic relationships, (2) a dynamic replanning mechanism that addresses stochastic energy consumption patterns through a random efficiency factor, and (3) a multithreaded simulation framework that concurrently tracks all vehicles in real-time, providing visibility into the temporal evolution of the logistics system and demonstrating how routes adapt dynamically to energy constraints under variable conditions. The stochasticity models real-world variability in energy consumption due to factors such as traffic conditions, weather, driving behavior, and road gradient. When the energy required for a segment would exceed energy capacity, the algorithm automatically redirects vehicles to the nearest charging station before continuing. Experiments using the E-n22-k4 benchmark instance with different configurations of efficiency demonstrate the approach's robustness while maintaining computational efficiency suitable for SME implementation. Results show that our model successfully balances operational objectives with sustainability goals, providing SMEs with an accessible entry point to sophisticated logistics optimization that can handle the inherent uncertainty of real-world EV operations.

1. INTRODUCTION

1.1 Context and motivation

The increasing adoption of EVs in urban logistics has driven the need for efficient route optimization models that balance operational efficiency with sustainability goals. While large companies have successfully implemented advanced optimization techniques and data-driven solutions, SMEs often face challenges related to cost, complexity, and accessibility of such solutions (Tengtarto, Singgih, & Siswanto, 2023; Johnson, Seyi-Lande, Adeleke, Amajuoyi, & Simpson, 2024).

This study explores an enhanced Clarke-Wright Savings (CWS) (Clarke & Wright, 1964) approach that integrates a bi-objective framework and dynamic route adaptation for EV fleets. The algorithm minimizes travel distance and energy consumption via a weighted cost function, employing a non-linear energy model to reflect real-world EV behavior. In addition, a multithreaded simulation enables concurrent, real-time vehicle tracking and automatically redirects vehicles to the nearest charging node when energy is insufficient. By structuring the problem in a computationally efficient manner with thread-based simulation, this work provides SMEs with a practical solution that doesn't require significant investment in computational resources. The approach has been tested under various efficiency scenarios, demonstrating its robustness and adaptability to different operational conditions. This implementation enables SMEs to integrate long-term sustainability objectives into their daily operational decision-making while visualizing the impact of these decisions through step-by-step route simulation.

1.2 Objectives

The primary objective of this study is to develop a bi-objective optimization model based on a modified CWS approach that simultaneously reduces travel distance and energy consumption for EV routing. This is achieved by implementing a weighted cost function with configurable parameters (α and β), which allows organizations to adjust the balance between the two objectives according to their operational priorities. A non-linear energy consumption model, proportional to the square of the distance multiplied by an efficiency factor, is used to capture realistic EV behavior. Complementing this, a dynamic replanning algorithm continuously monitors energy levels during route execution and redirects vehicles to the nearest charging node when necessary, ensuring operational feasibility despite energy constraints. The model is evaluated across multiple scenarios with varying efficiency parameters ($MIN_EFF = 0.1 / MAX_EFF = 1$ and $MIN_EFF = 1 / MAX_EFF = 2$) using the well-established E-n22-k4 benchmark instance from the Solomon dataset (Solomon, 1987), which is widely recognized in operational research for its balance between complexity and computational feasibility. A real-time simulation provides visualization of vehicle progress and route adaptation.

1.3 Contributions

This study makes several significant contributions to EV routing optimization with a focus on SME needs. First, it presents a non-linear adaptation of the CWS algorithm that minimizes both travel distance and energy consumption by using a configurable weighted cost function. Second, the dynamic replanning mechanism ensures that routes remain feasible by automatically redirecting vehicles to charging nodes when energy limitations arise, thereby addressing a critical requirement for real-world EV fleet operations. Third, the multithreaded simulation framework offers time-scaled visualization of route progression, enhancing the understanding of system behavior and facilitating informed decision-making. Finally, by incorporating a realistic non-linear energy consumption model that accounts for

quadratic relationships and variable efficiency factors, the study demonstrates the algorithm's robustness across diverse operating conditions such as traffic conditions, weather, driving behavior, and road gradient, while ensuring the solution remains computationally accessible for SMEs.

2. LITERATURE REVIEW

2.1 Vehicle routing problem (VRP)

The VRP is a well-established combinatorial optimization problem that determines the most efficient set of routes for a fleet of vehicles serving multiple customers (Larson & Odoni, 1981). It is a generalization of the well-known Travelling Salesman Problem (TSP) and has been extensively studied in logistics and transportation research. Many VRP variations exist, including those that incorporate constraints such as time windows (VRPTW) or energy consumption for electric vehicles (EVRP) (Toth & Vigo, 2014). Recent advancements have explored robust formulations that handle demand uncertainties and travel time variations (Campos, Coelho, & Munari, 2024). In addition, (Liu, Chen, Por, & Ku, 2023) conducted a systematic literature review of VRP with time windows, highlighting the most recent methodologies and their practical applications. Existing research on VRP acknowledges the significant computational complexity of exact solution methods for large problem instances, leading to an increasing preference for heuristic approaches (Toth & Vigo, 2014).

2.2 Clarke-Wright savings (CWS) for VRP

The CWS heuristic has emerged as one of the most widely used methods for solving VRP efficiently, merging routes iteratively to minimize total transportation costs (Clarke & Wright, 1964). This approach merges routes iteratively to minimize total transportation costs. Over the years, several modifications have been introduced to improve its adaptability to real-world applications. For example, (Doyuran & Çatay, 2011) proposed a robust enhancement that significantly reduced travel distances in benchmark instances. Our bi-objective CWS adaptation aligns with recent advancements in the field, such as the multi-criteria CWS approach for humanitarian logistics that integrates fuzzy decision-making techniques (Cengiz Toklu, 2023), while maintaining computational feasibility for practical applications in SME environments.

2.3 Optimization in electric last-mile deliveries

Electric last mile delivery optimization is an emerging area that seeks to improve the efficiency and sustainability of logistics operations using electric vehicles. Recent studies have explored various optimization techniques to address the specific challenges of last mile delivery, including the need for frequent recharging and route management in urban environments (Lin, Zhou, & Wolfson, 2016; Schiffer & Walther, 2018). For example, (Lin, Zhou, & Wolfson, 2016) investigated route optimization for electric vehicles considering the

location of charging stations. Electric last mile delivery optimization has advanced significantly with the use of emerging technologies. (Özarık, Costa, & Florio, 2024) presented a machine learning framework for last-mile route optimization, highlighting its application in Amazon's last-mile routing challenge. In addition, (Hanaa, Benhra, & Ed-dehbi, 2025) proposed a novel strategy combining electric vehicles and drones to improve energy efficiency and reduce CO2 emissions in last-mile delivery. However, few studies have specifically focused on making such optimization models accessible and practical for SMEs. Our implementation specifically addresses the challenges faced by SMEs in adopting advanced optimization techniques (Tengtarto, Singgih, & Siswanto, 2023; Johnson, Seyi-Lande, Adeleke, Amajuoyi, & Simpson, 2024) offering a computationally efficient solution for practical electric vehicle routing optimization.

3. METHODOLOGY

3.1 Problem description

This research focuses on the VRP for a fleet of electric vehicles, with the aim of minimizing a bi-objective cost function that accounts for both energy consumption and travel distance. The model incorporates optional charging nodes that can be activated as needed.

3.2 Mathematic model

The proposed model is deterministic and bi-objective, integrating both distance and energy consumption into the route optimization process:

- **Sets:**
 - $V = \{0, 1, 2, \dots, n\}$: Nodes (0 is the depot, 1 to n are customers).
 - $C = \{c_1, c_2, \dots, c_m\}$: Set of charging nodes.
 - $K = \{1, 2, \dots, |K|\}$: Set of vehicles
 - $E = \{(i, j) : i, j \in V \cup C, i \neq j\}$: Set of edges
- **Parameters:**
 - d_i : Demand of customer i , $\forall i \in V \setminus \{0\}$
 - $Q = 6,000$: Vehicle capacity (6 tons)
 - $B = 2,500$: Maximum battery capacity
 - (250 kWh, where each unit = 0.1 kWh)
 - d_{ij} : Euclidean distance between nodes i and j .
 - $r_c = 2000$: Charging rate at charging node c (200 kWh), $\forall c \in C$
 - α : Weight for the distance objective, $0 \leq \alpha \leq 1$
 - β : Weight for the energy objective, $0 \leq \beta \leq 1$
 - MIN_EFF: Minimum efficiency factor
 - MAX_EFF: Maximum efficiency factor
 - η_{ij} : Efficiency factor for edge, (i, j) , $MIN_EFF \leq \eta_{ij} \leq MAX_EFF$
- **Weight Constraints:**
 - $\alpha + \beta = 1$
 - $\alpha, \beta \geq 0$

- **Decision variables:**

- $x_{ijk} \in \{0,1\}$: 1 if vehicle k travels directly from i to j , $\forall (i,j) \in E, \forall k \in K$
- $y_{ik} \in \{0,1\}$: 1 if node i is visited by vehicle k , $\forall i \in V \cup C, \forall k \in K$
- $b_{ik} \geq 0$:
 - Battery level of vehicle k upon arrival at node i , $\forall i \in V \cup C, \forall k \in K$
- $c_{ck} \geq 0$:
 - Amount of charge received by vehicle k at charging node c , $\forall c \in C, \forall k \in K$

- **Bi-Objective function:**

$$\text{Minimize } Z = \alpha \sum_{k \in K} \sum_{i \in V \cup C} \sum_{\substack{j \in V \cup C \\ j \neq i}} d_{ij} x_{ijk} + \beta \sum_{k \in K} \sum_{i \in V \cup C} \sum_{\substack{j \in V \cup C \\ j \neq i}} e_{ij} x_{ijk}$$

Where:

- d_{ij} is the energy consumption modeled as:
 - $e_{ij} = \beta \cdot \eta_{ij} \cdot d_{ij}^2$

- **Constraints:**

- Flow Conservation:

$$\sum_{\substack{j \in V \cup C \\ j \neq i}} x_{ijk} = \sum_{\substack{j \in V \cup C \\ j \neq i}} x_{jik} = y_{ik}, \quad \forall i \in V \cup C, \forall k \in K$$

- Customer Service Requirement:

$$\sum_{k \in K} y_{ik} = 1, \quad \forall i \in V \setminus \{0\}$$

- Vehicle depot Constraints:

$$\sum_{\substack{j \in V \cup C \\ j \neq 0}} x_{0jk} = \sum_{\substack{i \in V \cup C \\ i \neq 0}} x_{i0k} = 1, \quad \forall k \in K$$

- Capacity Constraints:

$$\sum_{i \in V \setminus \{0\}} d_i y_{ik} \leq Q, \quad \forall k \in K$$

- Battery Dynamics:

$$b_{jk} \leq b_{ik} - e_{ij} x_{ijk} + B(1 - x_{ijk}), \quad \forall (i,j) \in E, \forall k \in K$$

$$b_{ik} + c_{ck} \leq B, \quad \forall c \in C, \forall k \in K$$

$$b_{0k} = B, \quad \forall k \in K$$

$$b_{ik} \geq 0, \quad \forall i \in V \cup C, \forall k \in K$$

- Charging Constraints:

$$c_{ck} \leq r_c y_{ck}, \quad \forall c \in C, \forall k \in K$$

3.3 Proposed Algorithm

The algorithm is designed to optimize routes for a fleet of vehicles, ensuring that each vehicle can complete its route without exceeding its energy capacity while minimizing the total cost, which includes both distance and energy consumption. The algorithm begins by defining several key classes: *Node*, *ChargingNode*, *Edge*, *Route*, and *Solution*. *Nodes* represent customer node's locations in the network, and *ChargingNodes* represent charging stations. *Edges* represent the paths between nodes, with associated costs in terms of distance and energy consumption. *Routes* are sequences of edges that a vehicle will travel, and the *Solution* is a collection of routes that cover all nodes.

The algorithm incorporates several key configuration parameters that influence its performance and behavior. These parameters are designed to be adjustable, allowing for fine-tuning to favor the dynamic insertion of charging nodes and optimize the overall routing solution. The *CAPACITY* parameter is set to 6,000 (6 tons) (according to instance E-n22-k4 requirements), representing the maximum load that a vehicle can carry, and the same value from standard CWS problems. This constraint ensures that the total demand on any given route does not exceed the vehicle's capacity, maintaining feasibility in terms of load management. The α parameter represents the weight assigned to the distance component in the cost calculation. This parameter allows the algorithm to prioritize minimizing the distance traveled, which can be crucial for reducing travel time and associated costs. The β parameter represents the weight assigned to the energy consumption component in the cost calculation. By adjusting this parameter, the algorithm can shift its focus towards minimizing energy consumption, which is particularly important for electric vehicles with limited battery capacity. The *BATTERY* parameter is set to 2,500 units, representing a 250-kWh maximum energy capacity for the electric delivery vehicle (where each unit equals 0.1 kWh). This parameter plays a crucial role in both the initial route planning and dynamic execution phases. During route construction, potential merges are evaluated against this constraint to ensure energy feasibility. More importantly, during the multithreaded simulation, the algorithm continuously monitors the predicted energy consumption for upcoming segments, calculating an energy threshold that includes worst-case efficiency scenarios (*MAX_EFF*). When this threshold exceeds the battery capacity, the vehicle is automatically rerouted to the nearest charging station, where it receives a 2,000-unit (200 kWh) charge before continuing

to its destination. This dynamic energy management ensures routes remain feasible even when encountering unexpected variations in energy consumption.

The initialization phase involves reading node data and setting up initial edges between the depot and other nodes. The cost of these edges is calculated based on the Euclidean distance between nodes and the energy consumed to travel that distance, considering the vehicle's efficiency and battery consumption parameters. Initial routes are created by assigning each node to its own route, ensuring that the demand and battery constraints are respected. This results in a set of routes where each route consists of a single customer node and the depot. To optimize the routes, the deterministic algorithm calculates potential savings for merging routes by evaluating direct connections between nodes. Savings are calculated based on the reduction in total cost that would result from merging two routes. If the energy is insufficient for a direct connection it will skip to next saving until finish with the savings list. The process for the deterministic algorithm is shown in points 1, 2 and 3 in the Algorithm Pseudocode in Figure 2.

Once the deterministic algorithm is ready, the simulation phase begins. In this phase, each route from the proposed solution, which already balances distance and energy considerations, is evaluated using Python 3.13.2 (Van Rossum & Drake, 2024). We selected Python for this implementation due to its enhanced performance features, extensive scientific computing ecosystem, and improved concurrency support introduced in the 3.13.x series (Python Steering Council, 2024). For each route, a separate thread is executed using Python's threading module, part of the standard library which received significant updates in recent versions (Python Software Foundation, 2025).

This multithreaded approach simulates concurrent vehicle movements, where each vehicle follows its assigned path independently. Time delays are implemented using *time.sleep()* proportional to edge distances, creating a time-scaled visualization of route progress. Every certain time interval, depending on the distance of the edge being traversed, the simulation shows whether the vehicle reaches the next node or requires recharging. The energy threshold calculation continuously monitors both previously consumed energy and the required energy for the upcoming segment, considering up to a maximum efficiency factor (MAX_EFF) that could potentially prevent route completion.

When this threshold exceeds the battery capacity (BATTERY = 2500), the algorithm automatically identifies the nearest charging station and dynamically updates the route—inserting a detour to the charging node before continuing to the original destination. Upon reaching the charging station, the vehicle's energy level is updated with the received charge (2000 units), and the journey continues until eventually returning to the depot (node 0). This dynamic energy management corresponds with points 4 and 5 of the Pseudocode illustrated in Figure 2, with the complete simulation process depicted in Figure 3.

The threading module was chosen over alternatives like asyncio or multiprocessing due to its lightweight nature and suitability for I/O-bound simulations that benefit from the improved thread scheduling introduced in Python 3.13, where the primary goal is concurrent execution rather than CPU-intensive parallel computation (Viafore, 2024).

Algorithm 1: Bi-objective CWS with Dynamic Replanning
 Input: Nodes V , Charging nodes C , Parameters α, β, B, Q
 Output: Optimized routes R

1. Initialize:

- Create initial routes connecting each customer to depot
- Calculate edge costs: $cost(i, j) = \alpha \cdot d_{ij} + \beta \cdot d_{ij}^2$
- Calculate savings:
 $savings(i, j) = cost(0, i) + cost(j, 0) - cost(i, j)$

2. Sort savings in descending order

3. While savings list is not empty:

- a. Get highest saving e_{ij}
- b. Get routes r_i and r_j containing nodes i and j
- c. If merge conditions are satisfied:
 - Check capacity: $\sum_{i \in V \setminus \{0\}} d_i y_{ik} \leq Q$
 - Check battery feasibility
 - If feasible, merge routes r_i and r_j
- d. Remove e_{ij} from savings list

---- Determinist Model Ready ----
 (From now on, MIN_EFF & MAX_EFF will be affecting the energy)

4. For each route r in routes:

- a. Create thread to simulate route execution
- b. While route not completed:
 - Calculate new energy needed for next segment
 - If $energy_required > remaining_battery$:
 - Find nearest charging node c
 - Insert c before next segment
 - Update battery level
 - Move to next node

5. Return optimized routes R

Fig. 2 – Bi-objective CWS with Dynamic Replanning (no determinist).

This part of the process visualizes each of the steps that have been simulated as in the following two examples. Figure 4 represents one of the trips between nodes that does not need extra energy to continue. In contrast, Figure 5 shows when the destination node cannot be reached, and a load node is needed.

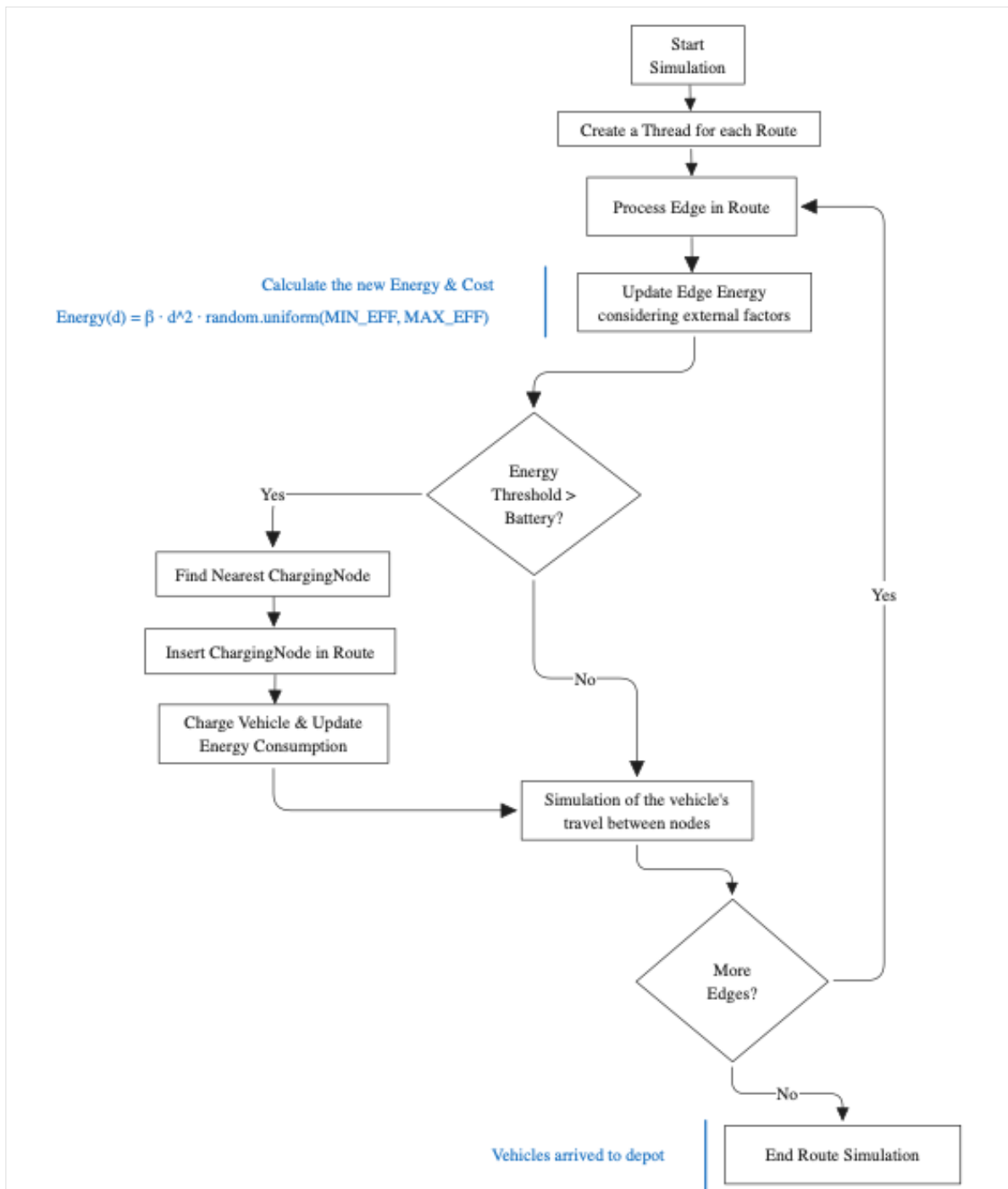


Fig. 3 - Flowchart of the algorithm in the simulated phase.

--- Vehicle 2 Segment 1: Node 0 -> Node 14 ---

Updated parameters: Edge Distance = 7.07, Edge Energy = 41.20, Route Energy = 550.21

Previous Edge Energy: 25.00

Previous Route Energy: 534.00

Energy Threshold (worst case scenario): 559.00

Battery Limit: 2,500.00

Vehicle can continue its journey

Fig. 4 - Example of simulation of one of the vehicle's travels between nodes

--- Vehicle 0 Segment 7: Node 7 -> Node 0 ---

Energy limited - Passes through recharge node 56

--- Vehicle 0 Segment 7: Node 7 -> Node 56 ---

Updated parameters: Edge Distance = 19.10, Route Energy = 345.98

--- Vehicle 0 Segment 8: Node 56 -> Node 0 ---

Updated parameters: Edge Distance = 19.70, Route Energy = 356.89

--- Node 0 has been reached from Vehicle 0.

Vehicle 0 has arrived at the depot.

Fig. 5 - Example of simulation in which a charging node is needed

4. EXPERIMENTAL EVALUATION

4.1 Description of benchmarking instances

To evaluate our approach's effectiveness, we conducted experiments using the E-n22-k4 benchmark instance (22 nodes, 4 vehicles), extended with 9 strategically placed charging nodes.

4.2 Experimental configuration

We tested three scenarios:

1. Balanced parameters ($\alpha=0.5$, $\beta=0.5$) with standard efficiency (MIN_EFF=0.1, MAX_EFF=1.0), as shown in Figure 6.
2. Balanced parameters with reduced efficiency (MIN_EFF=1.0, MAX_EFF=2.0), as shown in Figure 7.
3. Distance-focused parameters ($\alpha=1.0$, $\beta=0.0$) with standard efficiency.
4. Energy-focused parameters ($\alpha=0.1$, $\beta=0.9$) with standard efficiency.

For each scenario, we performed 10 independent runs with randomized efficiency factors to ensure statistical validity. Performance was measured through:

- Total Static distance traveled (km) – From Deterministic Model
- Total Dynamic distance traveled (km) – From Flexible Model
- Total Static energy consumed (0.1 kWh units) – From Deterministic Model
- Total Dynamic energy consumed (0.1 kWh units) – From Flexible Model
- Percentage of charging visits required in Flexible Solutions (%)
- Computational time (seconds)
- Solution feasibility rate (%) – Deterministic approach vs. Flexible approach

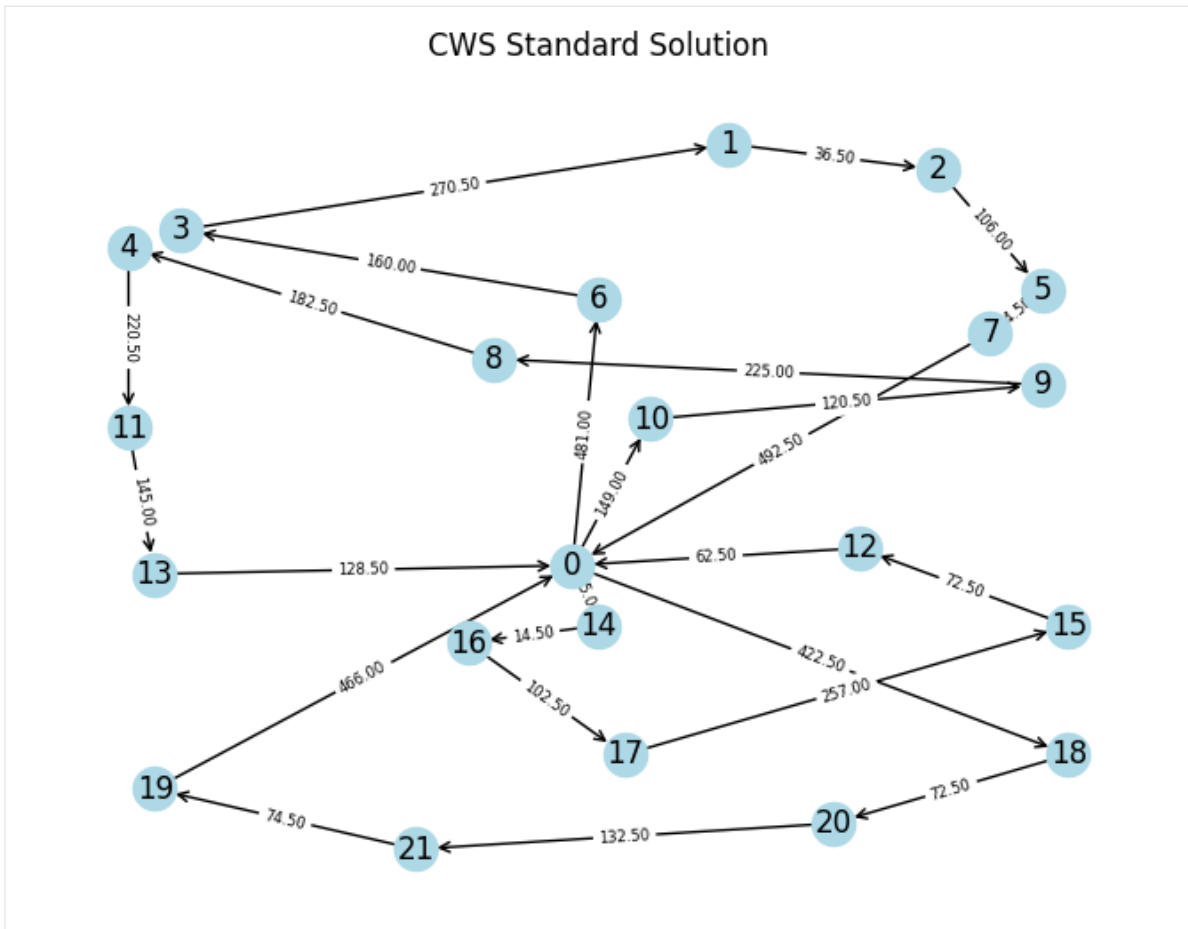


Fig. 6 - Example deterministic solution taking energy into account ($\alpha = 0.5$ and $\beta = 0.5$) and better efficiency ($MIN_EFF = 0.1, MAX_EFF = 1$) for the E-n22-k4 benchmark instance.

4.3 Results and comparative analysis

We compared our approach against two baselines:

1. Standard CWS algorithm optimizing only distance
2. Static energy-aware routing without dynamic replanning capability

All experiments were conducted on standard desktop hardware (Intel Core i5, 16GB RAM) representative of SME computing resources.

5. RESULTS, DISCUSSION AND CONCLUSIONS

5.1 Results analysis

Empirical evidence indicates that the modified CWS model successfully balances distance and energy consumption while providing flexibility through optional charging stations. The experimental results demonstrate the algorithm's ability to adapt to different scenarios and efficiency conditions across multiple operational contexts. In the balanced scenario with standard efficiency parameters ($\alpha = \beta = 0.5$), the model maintains consistent distance

measurements (431.99 km) for both static and dynamic approaches. However, the dynamic approach exhibits slightly higher energy consumption (4705.88 ± 604.2 units) compared to the static approach (4649.99 units), which can be attributed to the stochastic nature of efficiency factors during real-time simulation.

Simulation (random MIN_EFF & MAX_EFF per edge)

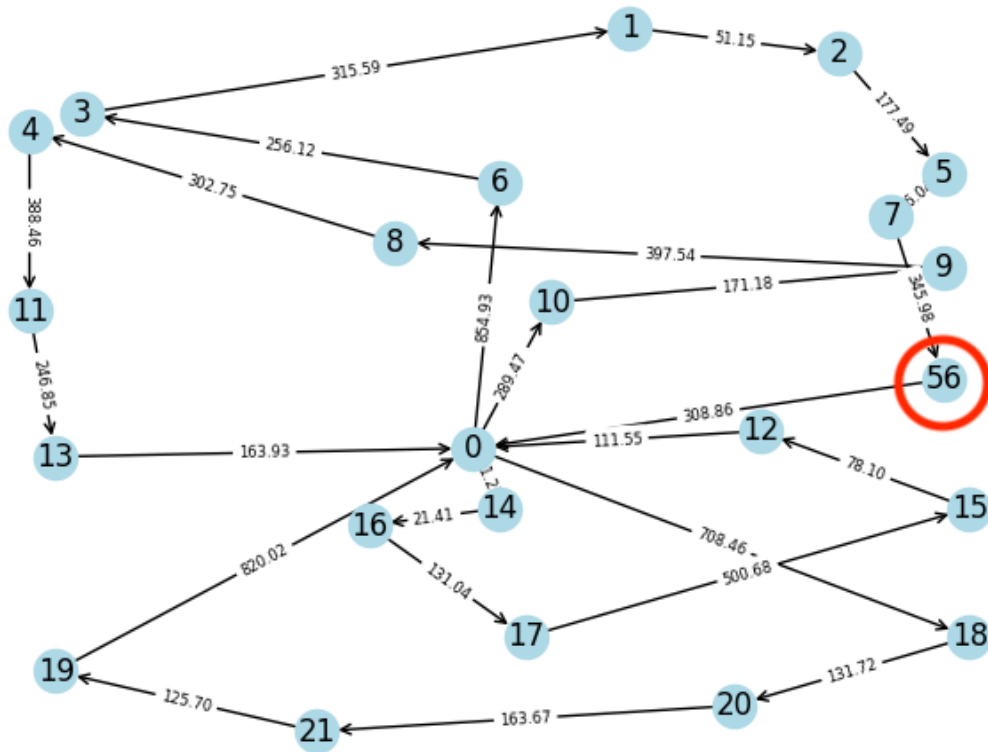


Fig. 7 - Example simulated solution taking energy into account ($\alpha = 0.5$ and $\beta = 0.5$) and worst efficiency ($MIN_EFF = 1, MAX_EFF = 2$) for the E-n22-k4 benchmark instance.

When efficiency parameters are reduced in the balanced scenario, the dynamic approach implements a modest increase in distance (435.7 ± 3.71 km) to accommodate more frequent charging requirements, resulting in elevated energy consumption (5677.4 ± 956.9 units). This scenario demonstrates the algorithm's adaptability to energy constraints, with 50% of solutions incorporating charging visits to maintain operational feasibility. The distance-focused scenario ($\alpha = 1, \beta = 0$), which serves as a baseline for comparison, achieves the shortest routes (388.77 km) but necessarily omits energy consumption considerations from the optimization process.

The energy-focused scenario prioritizes efficiency through parameter adjustments, consequently producing longer routes (637.45 km static, 680.96 km dynamic) but significantly reduced energy consumption in the dynamic implementation (9134.41 ± 632.8

units) compared to the static approach (17463.6 units). All solutions in this energy-prioritized scenario incorporate charging visits.

Computation times remain remarkably consistent across all tested scenarios (1.83 to 2.15 seconds), providing substantive evidence that the addition of charging options and dynamic replanning capabilities does not significantly increase computational complexity. Furthermore, the dynamic approach ensures complete feasibility (100%) across all scenarios, representing a measurable improvement upon the static approach which achieved only 90% feasibility in the energy-focused case. These findings align with previous research emphasizing the importance of flexibility in electric vehicle routing paradigms (Schiffer & Walther, 2018). The model's demonstrated ability to effectively balance competing objectives and adapt to varying efficiency conditions illustrates its considerable potential for practical application in electric vehicle fleet management, particularly for SMEs with limited computational resources seeking to implement sustainable logistics solutions.

Scenario	Static Distance (km)	Dynamic Distance (km)	Static Energy Units	Dynamic Energy Units	Charging Visits in Solution	Comp. Time (s)	Feasibility Static vs. Dynamic
Balanced, Standard Eff.	431.99	431.99	4649,99	4705.88 ± 604.2	0%	2.15 ± 0.1032	100% 100%
Balanced, Reduced Eff.	431.99	435.7 ± 3.71	4649,99	5677.4 ± 956.9	50%	2.14 ± 0.04	100% 100%
Distance-focused, Standard	388,77	388,77	-	-	0%	1.89 ± 0.06	100% 100%
Energy-focused, Standard Eff.	637,45	17463,6	680,96	9134.41 ± 632.8	100%	1.83 ± 0.05	90% 100%

Table 1 - Performance comparison across experimental scenarios (mean ± std. dev. over 10 runs).

5.2 Study limitations & Future research directions

The present study, while demonstrating promising results for electric vehicle routing optimization in SMEs, exhibits several limitations that warrant discussion and provide opportunities for future research.

A clear limitation is that the study begins with a relatively simple known algorithm (Clarke-Wright Savings). There are more sophisticated algorithms that could potentially better

address the complexities of electric vehicle routing problems with recharging considerations. However, the decision to start with CWS was deliberate, aiming to demonstrate to SMEs that by properly contextualizing the problem, optimization strategies can be implemented with positive return on investment without requiring major financial commitments or specialized expertise. This approach supports the educational dimension of the research, illustrating how external conditions can influence planning decisions. While acknowledging this algorithmic limitation, beginning with a well-established heuristic provided accessibility and transparency that more complex methods might obscure.

Another significant limitation is the focus on a single benchmark instance (E-n22-k4) rather than testing across multiple diverse datasets. Expanding the testing to additional instances would provide greater insight into how the algorithm performs under different spatial distributions and demand patterns. This limitation also necessitated establishing charging nodes specific to the single instance used; a more comprehensive approach would require developing automated methods for optimal charging station placement across varied geographic distributions.

The stochastic element of the model captures energy consumption variability through a random efficiency factor between predefined boundaries (MIN_EFF=1, MAX_EFF=2). While this approach introduces realism compared to deterministic models, it employs a simplistic uniform distribution rather than more sophisticated probability distributions that might better represent real-world energy efficiency variations. The model also does not account for temporal factors such as traffic congestion patterns or time-dependent energy costs, which significantly impact operational decisions in practice.

The battery dynamics in the model employ a straightforward representation where energy consumption follows a quadratic relationship with distance. However, real-world EV battery behavior exhibits more complex characteristics influenced by factors such as temperature, battery age, driving behavior, and elevation changes. Additionally, the charging process is modeled as instantaneous with a fixed rate (2000 units), whereas actual charging exhibits nonlinear patterns with diminishing rates as the battery approaches full capacity.

While the multithreaded simulation approach effectively demonstrates dynamic replanning capabilities, its computational scalability may present challenges for larger problem instances. The current implementation uses basic threading with `time.sleep()` for visualization purposes, but commercial applications would require more efficient concurrent processing methods to handle fleet sizes beyond the small-scale example presented. This limitation could impact the applicability of the approach to larger logistics operations.

The model does not address several practical considerations essential for real-world implementation, including driver scheduling constraints, vehicle maintenance requirements, and operational disruptions. The simulation assumes perfect information about energy

consumption patterns before replanning occurs, whereas real-world systems would need to incorporate predictive models and real-time data streams to anticipate potential energy constraints before they become critical.

6. CONCLUSIONS

This research introduces a bi-objective optimization approach for electric vehicle routing in last-mile delivery, specifically designed for SMEs through adaptation of the Clarke-Wright Savings algorithm. Our three key innovations—a configurable weighted cost function, dynamic energy-based replanning, and multithreaded simulation—create a framework that effectively adapts to real-world energy consumption variability. The stochastic efficiency factor (η) captures unpredictable variations in energy consumption that electric vehicles encounter in practice, advancing beyond deterministic models.

Despite employing a straightforward algorithmic foundation, consistent computation times (~ 2 seconds) across all scenarios demonstrate that basic optimization methods yield substantial benefits when adapted to electric vehicle routing. Our experimental results confirm 100% solution feasibility across scenarios, showing that modest distance increases (435.7 ± 3.71 km vs. 431.99 km) can accommodate charging requirements while maintaining route feasibility.

While future research should expand to diverse instances and enhance battery dynamics modeling, the current implementation provides a practical starting point for SMEs transitioning to electric delivery fleets. The approach demonstrates that sustainable logistics optimization can be democratized through thoughtful adaptation of established algorithms, making sophisticated decision support accessible without specialized expertise or substantial investment.

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