Fairness-Aware Energy-Effective Electricity Technician Dispatch Problem

Haifa Zaidi[1]
hzy487@uregina.ca

Sifat E Jahan[1]
sjt588@uregina.ca

Malek Mouhoub [1]
mouhoubm@uregina.ca

***Abstract*— Combinatorial optimization problems involve identifying the best solution from a wide set of alternatives; these often arise in logistics, scheduling, and resource allocation. These problems, such as the Traveling Salesman Problem (TSP) and the Multi-Depot Vehicle Routing Problem (MDVRP), are generally NP-hard, with solution spaces that increase exponentially, making brute-force methods impractical. We address a specific application of the MDVRP: the Electricity Technician Dispatch Problem (ETDP), which involves planning and optimizing technician routes for maintenance services to customers at various geographical locations while satisfying specific constraints and objectives. We focus on a variant of the ETDP that optimizes multiple objectives, including economic, environmental, and social. Economic objectives aim to reduce operational costs, such as fuel costs and technician wages. Environmental objectives focus on sustainability, for example, by minimizing gas emissions. Social objectives include fairness of workload and customer satisfaction. We will explore the ETDP problem in single- and multi-objective contexts and solve it using nature-inspired techniques.**

Keywords: Vehicle Routing Problem, Combinatorial Optimization, Evolutionary Algorithms, Metaheuristics.

I. Introduction

Optimization is the process of finding solutions that minimize or maximize specified objectives while satisfying all constraints. A single-objective optimization problem is a problem with a single objective function, typically leading to a single optimal solution. In contrast, a multiobjective optimization (MOO) task involves simultaneously considering multiple conflicting objectives. It focuses on identifying solutions where improving one objective requires compromising another, known as Pareto-optimal or non-dominated solutions. These problems are challenging to solve due to conflicting objectives and the difficulty of finding the set of optimal solutions (Pareto solutions) that satisfy all constraints, especially in high dimensionality. MOOs are used in many domains, such as engineering and mathematics, and are utilized to solve real-world problems, such as scheduling or resource allocation. Nature-inspired techniques in MOO are methods that draw inspiration from biological and natural processes to solve complex optimization problems [13], [27]. Evolutionary techniques are population-based approaches that use processes inspired by natural evolution, such as selection, mutation, and recombination, to solve MOO problems.These techniques are effective in approximating various Pareto-optimal solutions for complex problems. They evaluate a population of potential solutions iteratively to converge towards the Pareto front while maintaining solution diversity. Some of the well-known multi-objective evolutionary algorithms include SPEA (Strength Pareto Evolutionary Algorithm), which keeps an external archive of non-dominated solutions, applies clustering techniques to retain diversity, and fitness assignment based on Pareto dominance, and NSGA-II (Non-Dominated Sorting Genetic Algorithm II), which employs fast non-dominated sorting to rank solutions and maintain diversity. By using a good trade-off between convergence and diversity, these methods balance conflicting objectives to achieve strong convergence to Pareto-optimal solutions, making them effective for solving real-world MOO problems.

We consider the ETDP, which emphasizes planning and optimizing routes for technicians providing maintenance services to customers situated in diverse geographical locations. To our knowledge, while MOO techniques have been widely used for solving VRPs, demonstrating their effectiveness in balancing conflicting objectives, only a limited number of studies have focused on the ETDP specifically.This is an emerging area of research that offers innovative possibilities to extend optimization techniques to the electricity service sector. We will explore a variant of the ETDP that focuses on the following three objectives:

1) **Economic**: seek to reduce travel distances, operational costs, and technicians' expenses, overall improving resource utilization.
2) **Environmental**: support sustainability goals such as reducing gas emissions.
3) **Social**: focus on equity and quality in utility operations, such as the fair distribution of the workload and customer satisfaction.

Considering these three objectives together facilitates the development of a more sustainable and equitable dispatch strategy that balances cost-efficiency, workload fairness, and environmental friendliness. This approach allows for the integration of multi-objective optimization (MOO) for electricity services, which can capture the trade-off between the conflicting objectives of different interrelated scopes. We will apply MOO techniques to identify Pareto-optimal solutions for various instances of ETDP. Notably, this study will compare the optimal solutions obtained by single-objective and multi-objective approaches using nature-inspired techniques.

II. Literature Review

In this review section, we highlight traditional optimization approaches and modern artificial intelligence-driven

[1]Department of Computer Science, University of Regina, Regina, Canada

strategies, providing an overview of significant methodologies, recent advances, and forthcoming developments regarding MDVRP. There are several studies that focus on different objectives [11], [22]. In [26], the authors focused on the objective of fairness of the profit for MDVRP, where they considered a bi-objective optimization problem that incorporates a fairness objective function into the traditional cost minimization objective. An adaptive large neighborhood search algorithm is used, which is integrated with an e-constraint scheme. Their findings show that the fairness in economic cost remains below 5% across different instances with varying complexity levels. In [15], the authors propose an approach to solve MDVRP that considers the minimization of energy consumption in transport and the risk of hazardous material transport. The findings show that by considering only energy consumption instead of distance as the objective, even though the distance slightly increased, a significant reduction was achieved in the number of vehicles and energy consumption. Another study considering various objectives (revenue maximization, cost, time, and CO_2 emission minimization) was proposed in [14]. They focus on a variant of MDVRP where green vehicles are known as multi-depot green vehicle routing problems (MDGVRP). The approach proposes a method using an improved Ant Colony Optimization (ACO) algorithm that shows satisfactory results when solving MDGVRP with multiple objectives. In [20], the authors discuss another variant of MDVRP known as min-max MDVRP, which is very important for time-critical applications. In their approach, they also use ACO to solve multi-depot problems and compare its results with the traditional Linear Programming (LP)-based algorithm, showing superiority in obtaining optimal results. An extensive study using genetic algorithms for the resolution of MDVRP and its variants is presented in [21]. They evaluated 23 benchmark problems and showed that GAs can provide quality solutions when solving MDVRP and, in some cases, can offer enhanced solutions. Other nature-inspired techniques have also been employed for solving MDVRP or variants, such as the Particle Swarm Optimization (PSO) algorithm. In [3], a study using PSO in a VRP variant focusing on a time constraint, known as VRP with Time Windows (VRPTW) was proposed. It showed that without a proper heuristic, it might lead to infeasible solutions with swarm intelligence.

In the context of the ETDP, the following approaches have been reported. Xu and Chiu [29] proposed a GRASP-based method to solve the problem of dispatching technicians with time windows. In another study [28], constraint programming and column generation methods were used to dispatch technicians for machine repair at Xerox in Chile. In defining this issue, each customer has distinct priorities, and their demand must be fulfilled within a period by the company's technicians. As a result, minimizing response time plays a crucial role in service delivery.In a recent study, Sadeghilalimi et al. [25] addressed ETDP using a two-phase hybrid approach that integrates clustering techniques with exact methods, heuristics, and metaheuristics for routing. The results showed promising performance compared to existing studies. In [31], this work was extended by implementing a new hybrid Genetic Algorithm-based technique to solve ETDP, which showed better results compared to the two-phase method.

There is a limited study of MDVRP using evolutionary algorithms [9], [11], [12], none of them focuses on ETDP, to our knowledge. There is a study considering the traveling distance and maximum delivery duration as objectives for MDVRP using a multi-objective evolutionary algorithm. Their approach considers GA with a fuzzy cluster-based initialization process to enhance algorithm performance and showed superior results compared to traditional approaches [1]. This study uses NSGA-II to solve multi-objective multi-period low carbon location routing problems (MMLCLRP) that demonstrate the feasibility of the algorithm with enhanced solutions considering various objectives (cost, the earliest dispatch to demand depots and CO_2 emissions) [4]. Another study focuses on emergency management using a bi-objective model to reduce overall system expenses for ambulance location, dispatch, and possible relocation [24].

Evolutionary algorithms have been used to solve other complex problems, such as combinatorial reverse auctions (CRAs), and have proven to be highly efficient [10].

III. Problem Formulation

The ETDP is a variant of the MDVRP and can be represented as a graph $G = (V, E)$ in which $V = V_c \cup V_d$ is a set of nodes that includes V_c customer locations ($|V_c| = n$) and V_d technician depots $|V_d| = m$. The set of edges E represents the distance between customers/depots. The cost of traveling between the vertices i and j is defined as c_{ij}. Each depot has a maximum of K technicians, each with a capacity of P_k. Each customer requires a service with a specific service time q_i. Additionally, each customer $i \in V_c$ has a soft time window $[e_i, l_i]$, representing the earliest and latest preferred start times for service. Technicians are encouraged to begin service within this time window. Early arrivals are permitted; however, starting service after the window is considered a violation of the time window.Three categories of objectives are involved: the first is economic, focusing on minimizing the total operational cost required to serve all customers. The second objective is environmental, with the aim of reducing CO_2 emissions. The third is social, ensuring fairness in workload between technicians and maximizing customer satisfaction. We formally define the ETDP as follows.

Decision Variables. We define a binary decision variable, x_{ij}^k, which is equal to 1 if the nodes i and j are on technician k's route from the depot p, and 0 otherwise, and y_{pk}, which is equal to 1 if technician k, belonging to depot p, is assigned to a route.

$$x_{ij}^k = \begin{cases} 1, & \text{if technician } k \text{ travels directly from node } i \\ & \text{to node } j \text{ (after serving customer } i) \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

$$y_{pk} = \begin{cases} 1, & \text{if technician } k \text{ from depot } p \text{ is assigned to a} \\ & \text{route in that depot} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

$$S_i = \begin{cases} 1, & \text{if customer } i \text{ is served within its time window} \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

Constraints. Each customer must be visited exactly once by an assigned technician k from depot p. These requirements are expressed through Equations 4 and 5. Equation 4 states that each customer location j is reached from exactly one other location (including a depot). Equation 5 requires that from each location i there is a departure to exactly one other location (including a depot).

$$\sum_{k=1}^{K} \sum_{i=1, i\neq j}^{n+m} x_{ij}^k = 1 \qquad 1 \leq j \leq n \tag{4}$$

$$\sum_{k=1}^{K} \sum_{j=1, j\neq i}^{n+m} x_{ij}^k = 1 \qquad 1 \leq i \leq n \tag{5}$$

Every technician should start at a service center p and return to the same service center exactly once after completing the mission. This requirement is expressed using Equation 6.

$$\sum_{j=1}^{n} x_{pj}^k + \sum_{i=1}^{n} x_{ip}^k = 2y_{pk}, 1 \leq k \leq K, 1+n \leq p \leq n+m \tag{6}$$

Each customer i has a non-negative demand q_i (number of hours needed to service customer i), which must be satisfied by technician k: $0 < q_i \leq P_k$, where P_k is the number of hours available to technician k. Equation 7 expresses the fact that technician k has enough hours to serve its customers.

$$\sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n+m} q_i \cdot x_{ij}^k \leq P_k \qquad 1 \leq k \leq K \tag{7}$$

Each depot p has a maximum number of technicians that cannot be exceeded.

$$\sum_{k=1}^{K} \sum_{i=1}^{n} x_{jp}^k = \sum_{k=1}^{K} y_{pk} \leq K \quad n+1 \leq p \leq n+m \tag{8}$$

Economic objective. The objective function (9) consists of minimizing the total operational cost. The first and second terms, respectively, define the fuel cost and the wages of the technicians. c_{ij} is the distance (cost) between nodes i and j.

$$\begin{aligned} \min f_1 = {} & \underbrace{c_{\text{fuel}} \cdot FC}_{\text{Fuel Cost}} + \underbrace{c_{\text{emissions}} \cdot E}_{\text{Carbon Emission Cost}} \\ & + \underbrace{w \cdot T_{\text{tot}}}_{\text{Labor Cost}} + \underbrace{c_v \cdot T_{\text{tot}}}_{\text{Vehicle Usage / Depreciation Cost}} \\ & + \underbrace{\sum_{i=1}^{n} c_{\text{early}} \cdot \max(0, e_i - a_i)}_{\text{Early Arrival Cost}} \\ & + \underbrace{\sum_{i=1}^{n} c_{\text{late}} \cdot \max(0, a_i - l_i)}_{\text{Late Arrival Cost}} \end{aligned} \tag{9}$$

$$FC = \frac{\alpha}{v} + \beta\, m_{\text{curb}} + \gamma\, v^2 \tag{10}$$

$$\alpha = \frac{\xi F N V D_{\text{tot}}}{k\, \psi}, \quad \beta = \frac{\xi g \sin\phi + g C_r \cos\phi\, D_{\text{tot}}}{1000\, \varepsilon\, \omega\, k\, \psi}, \tag{11}$$

$$\gamma = \frac{0.5 C_d A \rho D_{\text{tot}}}{1000\, \varepsilon\, \omega\, k\, \psi} \tag{12}$$

$$E = \eta \cdot FC \tag{13}$$

$$T_{\text{tot}} = \frac{D_{\text{tot}}}{v} + \sum_{i=1}^{n} q_i + \sum_{i=1}^{n} \max(0, e_i - a_i) \tag{14}$$

$$D_{\text{tot}} = \sum_{k=1}^{K} \sum_{i=1}^{n+m} \sum_{j=1, j\neq i}^{n+m} c_{ij}\, x_{ij}^k \tag{15}$$

Environmental objective. This objective considers CO_2 emission minimization expressed by CO_2 factor η representing the environmental impact expressed by Equation 16

$$\min f_2 = E \tag{16}$$

Social objective Equation 17 defines the third objective function, f_3, which represents the social objective. The first term is the Gini coefficient, which expresses the equitable distribution of workload and fairness among all technicians and depots, while the second term expresses the maximization of customer satisfaction. Both terms are assigned equal weights of 0.5, which can be adjusted according to the decision-maker's preferences.

$$\begin{aligned} \min f_3 = \frac{1}{2} \Bigg(& \underbrace{\frac{1}{2K^2 \bar{W}} \sum_{k=1}^{K} \sum_{k'=1, k'\neq k}^{K} |W_k - W_{k'}|}_{\text{Gini coefficient: workload fairness}} \\ & + \underbrace{\left(1 - \frac{1}{n} \sum_{i=1}^{n} S_i\right)}_{\text{Customer Dissatisfaction}} \Bigg) \end{aligned} \tag{17}$$

$$W_k = \sum_{i=1}^{n} \sum_{j=1, j\neq i}^{n} q_i\, x_{ij}^k$$

$$\bar{W} = \frac{1}{K} \sum_{i=1}^{K} W_k$$

IV. Solving Methodology

A. Genetic Algorithm

Initial Population Generation. Initially, each customer is assigned to the closed depot based on Euclidean distance. Then, clusters corresponding to each depot are split into routes using a combination of the *Sweep method* [8], *Clarke and Wright Savings* [5], and *random assignment*, while respecting the technicians' capacity constraint to ensure that the initial population consists of feasible individuals (possible solutions). We also distinguish between two types of customers: Borderline and non-borderline. A *borderline customer* is a customer who is almost as close to another depot as to their currently assigned one. This is determined by checking if the relative difference between the distance to a non-assigned depot and the distance to the assigned depot is below a predefined threshold. Mathematically, this is expressed as:

$$\frac{\text{distance} - \text{shortestDistance}}{\text{shortestDistance}} < \text{borderlineThreshold}$$

where *distance* is the distance from the customer to a non-assigned depot, *shortestDistance* is the distance to the assigned (nearest) depot, and *borderlineThreshold* is a tolerance value that defines how close a customer must be to another depot to be considered borderline. These customers are later considered for the inter-depot mutation.

Tournament Selection. Two individuals are randomly selected as competitors from the population. This ensures diversity and helps us explore different parts of the solution space. A random factor r influences whether the fittest or a random individual is selected for the crossover. If the random factor is less than the fitness bias, the individual with the higher fitness (better solution) is selected. Otherwise, a random individual is chosen.

Best Cost Route Crossover. This type of crossover begins by randomly selecting a depot for reproduction. Then, a route r_1 is randomly selected from parent p_1, and a route r_2 is randomly selected from parent p_2. To avoid duplicates, customers in r_1 are removed from p_2, and customers in r_2 are removed from p_1. Finally, each customer of r_1 is inserted into the best feasible location in p_2, and each customer from r_2 is inserted into the best feasible location in p_1.

Intra-depot mutation occurs within the same depot to increase diversity and help the genetic algorithm escape local minima. Three types of intra-depot mutation are applied. The first is reversal mutation, where two cut points are randomly selected and the customer sequence between them is reversed. The second is single-customer rerouting, where a customer is removed from its route and reinserted at the best feasible location within another route of the same depot. The third is customer swapping, in which two routes are randomly selected and a customer is swapped between them.

Inter-depot mutation occurs between different depots and aims to improve the quality of the solution by allowing customer exchanges between depots. It is applied every 10 generations and is controlled by the *Swapping Mutation Rate* parameter. This mutation is only applied to borderline customers who were previously identified during the initial clustering phase and have a candidate list of alternative depots.

B. Pareto-Dominance Evolutionary Algorithm

The Pareto-dominance technique is a popular approach in MOO that ensures the preservation of non-dominated or Pareto-optimal solutions while maintaining diversity within the solution space. In each iteration, the Pareto-optimal solutions are identified and stored, which improves the robustness of the solutions and trades off the conflicting objectives. The Pareto-dominance approach reduces the tendency of GAs to prematurely converge on local optima, allowing a wide exploration of the solution space. Moreover, it facilitates the identification of solutions closest to the true Pareto front, while allowing the parallel exploration of multiple alternative solutions, enhancing the efficiency and effectiveness of MOO. To solve the ETDP using Pareto dominance, the algorithm begins with a randomly generated population. After that, non-dominated solutions are found by considering the three objectives (economic, environmental, and social) to minimize, and the dominated solutions are removed from the population. The Pareto dominance relation ($\prec$) between two candidate solutions A and B is defined in Equation 18.

$$A \prec B \iff \begin{cases} f_i(A) \leq f_i(B) & \forall i \in \{1,2,3\} \\ f_i(A) < f_i(B) & \exists i \in \{1,2,3\} \end{cases} \tag{18}$$

C. Non-Dominated Sorting Genetic Algorithm (NSGA-III)

NSGA-III is an evolutionary algorithm designed to handle MOO problems, particularly those with three or more objectives. It extends the classical NSGA-II technique by introducing a set of well-distributed reference points, which guide the population towards a diverse and uniform spread along the Pareto front. The algorithm starts by creating an initial population of candidate solutions, which are then evaluated based on the previously defined objectives. These solutions are then classified into different Pareto fronts using non-dominated sorting. Individuals belonging to lower-ranked fronts are given higher priority due to their superior trade-offs among objectives. When the last admissible front exceeds the population limit, reference points are generated across the objective space, and individuals are associated with the nearest reference points, forming niches or clusters. Selection favors less crowded niches (those with fewer members) to maintain diversity across the Pareto front. Once selection is complete, variation operators, such as crossover and mutation, are applied to generate new offspring, which are added to the population. The combined population is re-evaluated, and the process is continued until a maximum number of generations is reached.

D. Strength Pareto Evolutionary Algorithm (SPEA)

Another popular evolutionary algorithm to solve complex MOO problems is SPEA. This technique is recognized for its effectiveness in identifying Pareto-optimal solutions while dealing with conflicting objectives [32]. It employs an external archive to store non-dominated (Pareto-optimal) solutions and uses a fitness strategy based on the dominance concept, where the strength of a solution is measured by the number of solutions it can dominate. A clustering technique is incorporated into the algorithm to avoid overcrowding the external archive with similar solutions, thereby ensuring solution diversity. Through an iterative approach, several operators (selection, crossover, and mutation) are used by SPEA to evolve the population towards better trade-offs among the conflicting objectives. This technique effectively balances exploration and exploitation while preserving high-quality solutions and population diversity. To solve the ETDP using SPEA, we maintain two separate populations: an archive (limited-capacity external storage) and a randomly created population. The fitness function is based on the dominance concept, and it is defined in equation 18. The archive stores the non-dominated solutions generated so far, and we consider half of the population size as its capacity. To preserve the uniqueness of high-quality solutions while maintaining the diversity of the population in the archive without diverging from the Pareto front, we employ a clustering technique; specifically, k-means is used here. Later, crossover and mutation are applied to obtain the next generation of individuals, which undergo a binary tournament among the individuals in the archive to select the best-fit individuals for the next iteration and continue until convergence. The fitness of the candidate solution K is the number of solutions in the archive that dominate K.

E. Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D)

MOEA/D is particularly suited for solving the ETDP, as it can handle multiple conflicting objectives simultaneously. The main idea is to decompose the multi-objective optimization problem into a set of scalar optimization subproblems, each associated with a weight vector $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_m)$, where m is the number of objectives. In our case, the objectives include minimizing the total operational cost (economic objective $f_1(x)$), reducing the CO_2 emissions (environmental objective $f_2(x)$), and addressing the workload distribution and customer dissatisfaction due to time window violations (social objective $f_3(x)$). Each subproblem is defined by a scalarization function, such as the weighted Tchebycheff approach, $g(x \mid \lambda, z^*) = \max_{1 \leq i \leq m} \lambda_i \, |f_i(x) - z_i^*|$, where z^* is the reference point composed of the best-known values for each objective. The algorithm begins by generating a set of weight vectors that uniformly cover the objective space and initializing a population where each solution is assigned to a subproblem. During the evolutionary process, neighboring subproblems with similar weight vectors exchange information, and variation operators (crossover and mutation) are applied to generate offspring. An offspring solution replaces the current solution of a subproblem (and its neighbors) if it yields a better scalarized value according to the decomposition function. By iteratively evolving the population in this manner, MOEA/D guides the search toward a well-distributed set of Pareto-optimal solutions for the ETDP.

V. Experimentation

To evaluate the performance of the proposed solution approaches, we performed a set of experiments using Cordeau benchmark MDVRP instances [6]. The experiments are implemented in Python and executed on an Intel(R) Core(TM) i7 CPU with a 2.40 GHz processor speed and 16 GB RAM running on Windows 11 with 64 bit. The experiments reported in this section aim to assess the practical performance of the multi-objective evolutionary techniques employed to solve the ETDP, specifically Pareto-dominance EA, NSGA-III, MOEA/D and SPEA. Additionally, three variants of the GA-based approach have been considered to tackle the single-objective EDTP, namely Eco minimizing economic cost as per equation 9, Env minimizing environmental cost (as per equation 16), and Soc minimizing social cost (as per equation 17), respectively. In Table I, the parameters associated with each instance are defined as follows: n is the number of customers, k is the number of technicians, and m is the number of depots. The execution time (in seconds) and the number of Pareto solutions for each EDTP instance are listed for GA with a single objective, Pareto Dominance, NSGA-III, MOEA/D, and SPEA. It also shows. All techniques use GA as the underlying algorithm with a population size of 90, and we evaluated eleven instances of varying complexity for ETDP over 200 generations. The execution times for single objectives (Eco, Env and Soc) are average. For instances pr01 and pr07 Eco variant achieved the best results. However, for the remaining instances, Pareto Dominance is the best performer, except for pr09, where SPEA had the best timing. The Env variant achieved the average timing overall, whereas the Soc variant had the worst timing for most instances, such as pr04, pr09, and pr10; for pr05, it couldn't find a feasible solution. Among the MOO techniques, there are variations where MOEA/D shows the worst results, and Pareto Dominance is the best one, followed by SPEA, while NSGA-III achieves average performance. Tables II and III show the quality of the solutions achieved by different techniques as a solution tuple (Eco, Env, Soc). For single-objective cases, the solution achieves optimal performance for the targeted objective; however, improvements in the remaining objectives are not always observed. Thus, the quality of the solution is not always the best with single objectives. However, multi-objective algorithms have better performance and provide quality solutions. All MOO algorithms obtained overall good results, but Pareto Dominance and NSGA-III provided the most balanced solutions for most instances, except for instance pr11, where MOEA/D achieved the best performance, and for pr04, SPEA performed the best. The size of the obtained Pareto fronts, reported in Table I, highlights the diversity of trade-off solutions generated by the multi-objective methods. Since these methods produce a set of non-dominated solutions rather than a single solution, the final dispatch plan is selected randomly or based on the decision-maker's preferences among the Pareto-optimal solutions.

TABLE I

COMPUTATIONAL TIME COMPARATIVE RESULTS

Time Comparison											
Inst No.	n	k	m	Eco	Env	Soc	Pareto Dom.	NSGA-III	MOEA/D	SPEA	Pareto Size
pr01	48	2	4	**20.69**	27.98	80.73	26.40	36.60	114.93	92.86	65
pr02	96	3	4	144.60	187.94	687.03	**130.74**	263.23	611.38	215.48	52
pr03	144	4	4	802.30	560.88	3111.84	**313.21**	1246.23	2011.23	536.18	28
pr04	192	5	4	902.03	1025.35	6755.92	**620.48**	949.65	5022.08	786.01	20
pr05	240	6	4	1088.56	1138.26	-	**743.53**	1265.39	5762.76	1187.38	46
pr07	72	7	4	**21.18**	39.07	130.16	43.81	49.34	147.22	77.51	50
pr08	144	3	6	198.86	271.94	1350.02	**153.79**	788.56	1162.40	217.56	22
pr09	216	6	3	518.77	617.38	2939.45	351.77	1796.88	1333.75	**344.06**	35
pr10	288	5	6	1862.41	1169.55	7240.45	**593.76**	2230.85	2799.92	644.96	9
pr11	48	1	4	39.29	22.53	**20.27**	27.15	72.12	100.28	70.85	69
pr13	96	2	4	438.82	540.05	563.95	**302.75**	1193.95	942.58	511.83	46

TABLE II

SOLUTION QUALITY (ECONOMIC, ENVIRONMENTAL, SOCIAL)

Inst.	Single Objective		
	Eco	**Env**	**Soc**
pr01	$(103493.87 \mid 411.62 \mid 0.35)$	$(120909.02 \mid 339.44 \mid 0.16)$	$(148484.23 \mid 529.28 \mid 0.08)$
pr02	$(212746.08 \mid 665.17 \mid 0.32)$	$(245790.51 \mid 534.40 \mid 0.28)$	$(299311.01 \mid 1259.28 \mid 0.19)$
pr03	$(270130.90 \mid 860.10 \mid 0.32)$	$(319473.16 \mid 722.85 \mid 0.20)$	$(444139.78 \mid 1806.83 \mid 0.15)$
pr04	$(356603.60 \mid 976.40 \mid 0.29)$	$(408111.31 \mid 839.23 \mid 0.19)$	$(555602.99 \mid 2243.80 \mid 0.14)$
pr05	$(508804.48 \mid 1251.56 \mid 0.31)$	$(556887.99 \mid 1005.97 \mid 0.22)$	-
pr07	$(89758.01 \mid 461.94 \mid 0.13)$	$(90707.01 \mid 457.92 \mid 0.13)$	$(130504.62 \mid 833.70 \mid 0.08)$
pr08	$(159808.18 \mid 693.65 \mid 0.08)$	$(158567.52 \mid 667.62 \mid 0.09)$	$(276795.48 \mid 1751.05 \mid 0.02)$
pr09	$(215958.69 \mid 897.98 \mid 0.12)$	$(214111.45 \mid 875.43 \mid 0.12)$	$(361346.29 \mid 2258.87 \mid 0.04)$
pr10	$(300201.00 \mid 1241.78 \mid 0.10)$	$(298256.13 \mid 1220.09 \mid 0.09)$	$(497215.38 \mid 3085.17 \mid 0.04)$
pr11	$(86297.73 \mid 403.16 \mid 0.43)$	$(94431.97 \mid 339.45 \mid 0.37)$	$(115472.85 \mid 509.56 \mid 0.23)$
pr13	$(220288.36 \mid 756.36 \mid 0.44)$	$(249033.84 \mid 716.56 \mid 0.36)$	$(295460.33 \mid 1154.37 \mid 0.26)$

TABLE III

SOLUTION QUALITY (MULTI-OBJECTIVE)

Inst.	Multi-Objective			
	Pareto Dom.	**NSGA-III**	**MOEA/D**	**SPEA**
pr01	$(103801.83 \mid 439.13 \mid 0.35)$	$(\mathbf{118912.69} \mid \mathbf{347.91} \mid \mathbf{0.18})$	$(94687.07 \mid 404.72 \mid 0.25)$	$(107755.08 \mid 382.83 \mid 0.25)$
pr02	$(\mathbf{200284.81} \mid \mathbf{581.77} \mid \mathbf{0.32})$	$(215274.17 \mid 554.20 \mid 0.30)$	$(207244.88 \mid 620.86 \mid 0.29)$	$(210097.82 \mid 579.19 \mid 0.31)$
pr03	$(268605.22 \mid 846.67 \mid 0.32)$	$(\mathbf{297448.48} \mid \mathbf{770.31} \mid \mathbf{0.17})$	$(319823.78 \mid 977.14 \mid 0.21)$	$(289715.76 \mid 803.71 \mid 0.24)$
pr04	$(356599.66 \mid 977.24 \mid 0.26)$	$(388627.07 \mid 879.33 \mid 0.24)$	$(413405.36 \mid 1253.32 \mid 0.20)$	$(\mathbf{382090.77} \mid \mathbf{944.22} \mid \mathbf{0.22})$
pr05	$(\mathbf{491419.64} \mid \mathbf{1219.09} \mid \mathbf{0.32})$	$(545042.70 \| 1034.80 \mid 0.20)$	$(545016.50 \mid 1324.11 \mid 0.25)$	$(517839.92 \mid 1143.47 \mid 0.26)$
pr07	$(90206.79 \mid 461.56 \mid 0.13)$	$(\mathbf{89080.03} \mid \mathbf{451.71} \mid \mathbf{0.12})$	$(91337.13 \mid 468.99 \mid 0.16)$	$(90883.42 \mid 462.65 \mid 0.13)$
pr08	$(\mathbf{157023.70} \mid \mathbf{661.70} \mid \mathbf{0.07})$	$(159449.55 \mid 674.83 \mid 0.08)$	$(168465.21 \mid 770.37 \mid 0.07)$	$(159538.04 \mid 679.62 \mid 0.08)$
pr09	$(217149.48 \mid 910.58 \mid 0.11)$	$(\mathbf{214741.96} \mid \mathbf{883.07} \mid \mathbf{0.10})$	$(235280.00 \mid 1071.48 \mid 0.12)$	$(222992.39 \mid 963.74 \mid 0.08)$
pr10	$(294212.69 \mid 1202.33 \mid 0.10)$	$(\mathbf{292921.27} \mid \mathbf{1173.32} \mid \mathbf{0.09})$	$(396728.00 \mid 2165.75 \mid 0.07)$	$(297063.62 \mid 1224.81 \mid 0.10)$
pr11	$(86010.14 \mid 384.73 \mid 0.42)$	$(91042.45 \mid 348.32 \mid 0.38)$	$(\mathbf{83084.83} \mid \mathbf{384.24} \mid \mathbf{0.43})$	$(85786.36 \mid 354.49 \mid 0.40)$
pr13	$(\mathbf{222645.81} \mid \mathbf{794.90} \mid \mathbf{0.41})$	$(252049.23 \mid 756.60 \mid 0.29)$	$(242364.49 \mid 844.89 \mid 0.39)$	$(236815.71 \mid 789.31 \mid 0.40)$

VI. CONCLUSION AND FUTURE WORKS

The study presents an approximate solution to the MD-VRP problem, especially the ETDP, using a GA approach. In contrast to the traditional MDVRP, which focuses on minimizing the total distance traveled only, we present three objectives that consider several aspects of the electricity market, including its economic, environmental, and social components. We investigate the effectiveness of various MOO methods regarding the quality of the solution and time performance for the ETDP problem. The findings in this study indicate that both nature-inspired techniques and multi-objective evolutionary algorithms provide near-optimal solutions with considerably low computational time. In this context, we conducted a series of experiments comparing GA with single-objective and multi-objective optimization algorithms (Pareto dominance EA, NSGA-III, MOEA/D and SPEA) to evaluate the effectiveness of optimal solutions in terms of computational time and solution quality. Overall, all approaches demonstrated satisfactory performance; however, the Pareto dominance EA approach outperforms other techniques in terms of both solution quality and computational time.

As future work, we plan to extend the proposed framework to address the dynamic version of the EDTP with time windows, where customer requests, traffic conditions, travel times, and operational constraints may change in real time [7], [23]. Such an extension would better reflect real-world logistics and transportation environments characterized by uncertainty and continuously evolving conditions [16]–[18]. In addition, future investigations will consider the integration of additional socio-economic and environmental objectives, including fairness, equity of service distribution, energy consumption, carbon emissions, workload balancing, and service reliability. Another promising direction is to explore other nature-inspired and evolutionary multi-objective optimization techniques, such as Ant Colony Optimization (ACO), Differential Evolution (DE), and hybrid metaheuristic frameworks, in order to identify improved trade-offs among conflicting objectives [2], [13], [19], [30]. These investigations may contribute to the development of more adaptive, scalable, sustainable, and socially responsible routing strategies for complex dynamic transportation systems.

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