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NON-DOMINATED SORTING GENETIC OPTIMISATION FOR CHARGING SCHEDULING OF ELECTRICAL VEHICLES WITH TIME AND COST AWARENESS

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The usage of electric vehicles (EVs) is a growing trend, but limited charging stations (CSs) and the fear of charge running out hinder confidence in relying on EVs. Optimal scheduling algorithms are needed to optimise EVs charging objectives. This paper proposes using a bi-non-dominated sorting genetic algorithm (NSGA-II) to optimise charging cost and service time jointly. NSGA-II outperforms traditional genetic algorithms (GA) regarding diversity and domination, resolving extreme solution issues. The proposed optimization algorithm based on NSGA-II, in principle, could be applied to any charging system, no matter what electrical technologies (e.g., AC-DC, DC-DC, or both) are used.

Keywords: electric vehicles, charging scheduling, multi-objectives optimisation, and genetic algorithms

1. Introduction

The emergence of electric vehicles (EVs) is a significant trend in the automotive industry. EVs offer several advantages over traditional fuel vehicles, including (reduce air pollution and gas emissions, lower operating costs, etc.) [1]. Today, many major automakers are investing heavily in EV technology to phase out their traditional fuel vehicles entirely in the coming years [2]. With continued investment in technology and infrastructure, the transition to EVs is only expected to accelerate in the future [3]. EVs are seen as a sustainable transportation option because they have the potential to use electricity generated from renewable sources like solar or wind power. This reduces dependence on fossil fuels.

A main challenge of EVs is the range of autonomy. EVs typically have a range of 100-300 miles on a single charge, which is considered too low for some long-distance trips [4]. Conversely, charging stations (CSs) still need to be improved in many areas, such as charging infrastructure coverage, charging speed and accessibility, and range anxiety [5]. Intelligent algorithms can be a solution to solve the charging problem for EV by optimising the charging schedule of EVs and

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minimising the waiting time at CSs [6]. Several types of scheduling algorithms are described in [7]. For instance, a solution is to consider the real-time demand (dynamic) for charging and the availability of CSs. This reduces EV drivers' waiting time and ensures that the CSs are utilised efficiently. Another approach is to use predictive scheduling that anticipates the charging demand based on historical data and then a forecast is performed for future demand. This can help to allocate the charging resources effectively and ensure that the CSs are available when needed.

An EV charging system can be evaluated based on several key metrics, including charging efficiency, charging speed, availability, cost, and reliability [8]. High charging efficiency and speed can minimise the charging time and reduce energy waste; the drivers expect high availability of CSs and low costs; high reliability can ensure that EV drivers can rely on the charging infrastructure for their daily needs. However, some objectives may conflict with each other, e.g., maximising charging speed while minimising cost [9]. Therefore, a multi-objective optimisation problem must be solved, where the challenge is to balance the different metrics. A multi-objective optimisation should find an optimal trade-off solution that satisfies the problem's constraints and objectives. However, this paper proposes the usage of a bi-non-dominated sorting genetic algorithm (NSGA-II) for optimising EV charging in terms of service time and charging cost. We mean by a non-dominated set of solutions that no one is superior with respect to all objectives, but it is superior to some and inferior to others. This study is clearly dedicated to simulations. So, there is no hardware implementations in this paper.

The remainder of the article is organised as follows. Section 2 summarises the state-of-the-art. Section 3 presents the methodology used in this study. The experimental evaluation of the proposed method and results are described in Section 4. Section 5 presents the conclusion and future work.

2. Related works

The work in [10], developed the diversity-maximisation non-dominated sorting genetic algorithm (DM-NSGA-II) to solve a multi-objectives function (power load profile, EV charging cost, and battery charge degradation). It is based on a flexible time scale to generate a real-time optimal schedule. It was shown that the DM-NSGA-II is wider in solution space and offers various trade-off options to decision-makers. This algorithm provides a set of solutions to the decision-maker instead of a single one, which requires an additional selection algorithm.

The work in [11], a new model is presented that integrates multi-objective optimisation and multi-criteria decision-making (MCDM) to determine the optimal electric vehicle supply equipment (EVSE) configuration. This method combines the benefits of multi-objective optimisation, which provides Pareto solutions, with an improved MCDM model. The model evaluates the Pareto frontier and identifies the best solution by allowing CSs owners to use linguistic variables to weigh decision-making factors. The proposed model enhances the conventional weighted aggregated sum product assessment (WASPAS) method by incorporating Dombi Bonferroni functions, making it more adaptable than other alternatives.

The work in [12], presented a multi-objective whale optimisation algorithm (MWOA-PFLF) that incorporates particle filters and Levy Flights to minimise total distribution costs and maximise average battery utilisation simultaneously. The use of particle filters allows for the prediction of near-optimal solutions in each iteration. At the same time, the combination of Levy Flights helps to escape local optima and speed up convergence. The work in [13], proposed a solution to minimising energy consumption and travel time for EVs based on intelligent heuristic mechanisms, which is a multi-objective optimisation problem. A graph-based multi-objective heuristic algorithm (MoHA) is proposed to obtain the desired solutions quickly. MoHA ensures that EVs are always routed through a path that minimises energy consumption and total travel time.

The work in [14], proposed a multi-objective optimisation model for the design problem of urban electric transit networks. This model simultaneously determines the transit routes, service frequency, and charging depot locations while minimising costs for passengers and operators. Constraints regarding bus routes, charging depots, vehicle operation, and charging schedules are considered to ensure the feasibility of the electric transit network's design and operation. The solution approach is based on a Pareto artificial fish swarm algorithm (PAFSA), which utilises crossover and mutation operators.

The work in [15], the charging optimisation model considered various charging options such as peak demand of depot charging, time-of-use (TOU) tariffs, partial recharging, waiting times, and characteristics of public stations. TOU tariffs is a pricing mechanism used to charge customers with different rates for electricity based on the time of day or day of the week. The authors break down the electric vehicle routing problem with time window constraint (EVRP-TW) and optimal charging problem into sub-problems. The overall optimal solution is achieved by solving all the sub-problems hierarchically. The developed optimisation algorithm (DOA) utilises ant colony optimisation (ACO) and grey wolf optimisation (GWO) algorithms in addition to the CPLEX solver, which is used for solving the optimisation problem by the simplex algorithm.

The work in [16], examined the practical use of fast-charging and slow-charging modes at CSs for EVs. A dynamic speed control for EVs is implemented to alleviate CS congestion and reduce waiting times. The system scalability, including various electric vehicle charging station (EVCS) solutions, is also explored. To solve the EVCS problem, the authors proposed a hybrid approach that combines particle swarm optimisation (PSO) and the firefly algorithm (FFA) with a Levy Flights search strategy.

The work in [17], the grey sail fish optimisation (GSFO) algorithm is proposed for optimal charging scheduling. This algorithm integrates the GWO and sail fish optimisation (SFO) techniques to determine the EV demand when charging and compute the path decision factor for each EV's travel to the CS. Meanwhile, the work in [18], solved an individual EV routing problem using a multi-objective optimisation approach to minimise the total trip time and cumulative charging cost. The problem formulation considered real-world elements such as traffic at CSs, detour distances to reach the station, and variable electricity costs. A genetic algorithm (GA) and PSO were employed to obtain the most optimal route.

Overall, it is found that the literature has used different formulations and proposed various algorithms for solving the problem of charging electric vehicles (CEVs) using meta-heuristic-based searching algorithms such as PAFSA, PSO, FFA, GWO, ACO, and others. Some have included the travelling cost, waiting time, charging cost and other criteria. Furthermore, multi-objective optimisation is effective due to its capability of handling self-confliction caused by the multi-objective nature of the problem. However, the issue of exploration and exploitation balancing is still an open issue and should be studied. To handle it, we propose the usage of the NSGA-II for solving this problem. This algorithm behaves with exploration and exploitation balancing by integrating non-dominated sorting and crowding distance, i.e., the distance between one solution and an adjacent one in the Pareto front. The Pareto front is a set of non-dominated solutions generated by multi-objective optimisation.

3. Methodology

This section presents our proposal for solving the CEVs problem.

3.1. System high-level architecture

In this study, the optimisation algorithm NSGA-II for EV charging schedule is considered to act in a centralised scheme. The system architecture includes EVs, CSs, and a central control unit (CCU), all interconnected through vehicle-to-infrastructure (V2I) communication (e.g., see Fig. 1).

1. EVs: communicate their charging requirements to the CCU, such as the current state of the charge (SOC), EV battery capacity, charging mode, and current location of the vehicle.
2. CSs: they inform the CCU about their locations, capacities (number of charging points), availability status, and pricing structure. They also continuously update any changes in their current data and pricing structure. Additionally, the peak and off-peak pricing rates and the time frames for each should be provided.

3. Travel Information: travel times or distances between EVs and CSs. In this study, we considered this information available and fed the optimisation algorithm NSGA-II. This information can be delivered by an external complex navigation system that accounts for different factors such as road lengths, traffic jam, speed limits on the road, and other factors which is out of the scope of this research.
4. CCU: it processes the information from EVs and CSs in a centralised way. It runs the NSGA-II algorithm to optimise the scheduling of EV charging while trying to minimise the charging cost and service time. After the optimisation algorithm runs, the CCU communicates the charging schedule to the involved EVs and CSs (when and where each EV should be charged).
5. V2I: it supports the EVs, CSs, and CCU communication based on different wireless technologies (cellular networks, dedicated short-range communications (DSRC), or other internet of things (IoT) communication protocols), ensuring reliable and secure message exchange.

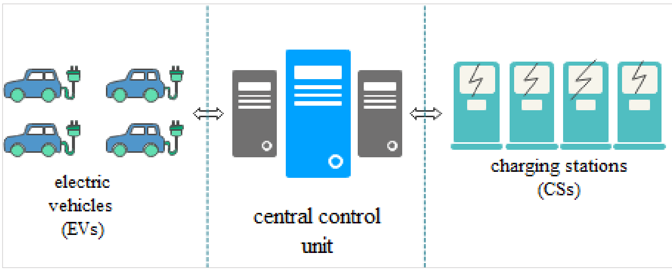


Fig. 1. The system architecture of charging scheduling in the centralised scheme

3.2. Problem statement

The optimisation in this system minimises the total cost (in terms of time and price) of EVs charging while ensuring adequate service levels. The CEVs problem has two major objectives:

Service Time: consists of three components, travelling time, waiting time, and charging time. The service time can be reduced by minimising the waiting time for charging, maximising the utilisation of CSs, and ensuring that the charging process is completed within a certain time frame. It can be written as follows:

$$T_{v,c}^{service} = T_{v,c}^{travelling} + T_{v,c}^{waiting} + T_{v,c}^{charging} \quad (1)$$

The value of $T_{v,c}^{travelling}$ denotes the time required for EV to travel to the station. The EV indexed by v and CS by c. $T_{v,c}^{travelling} = \sum_i \frac{D_i}{S_i}$, where D_i denotes the distance of particular road segment i (the way from the current position of the EV to the CS) and S_i denotes the average speed in the i. Note that, in this study, we supposed the charging system operator knows all road segments followed by the vehicle and its speed on each segment.

However, the speed values could depend highly on the traffic. Also, the EV could stop for a while at some points of the route for whatever reasons, which will modify the time spent travelling. Knowing all these parameters is very difficult in a dynamic vehicular traffic context. Therefore, some simplifying assumptions are necessary in this study. For instance, we assume the average speed for EVS is 60k/h. The system could determine a minimal travelling time for an EV by proposing an available and closer CS considering the current position of that vehicle.

The value of $T_{v,c}^{waiting}$ denotes the waiting time , required for an EV to wait in the queue. The $T_{v,c}^{waiting} = \frac{L_{q,c}}{\lambda_{c,t}}$, where $L_{q,c}$ denotes the queue length and $\lambda_{c,t}$ denotes the arrival rates of EVs to the station. The queue length depends on $\lambda_{c,t}$ and the average time a vehicle spends to charge its battery. The formulas are derived from basic queue theory for a M/M/c model [19], where the equivalent formulas: $L_q = \rho^2/(1-\rho)$, and traffic intensity $\rho = \lambda/\mu$. The value of $T_{v,c}^{charging}$ denotes the charging time which is required for EV to complete the charging. The $T_{v,c}^{charging} = \frac{B^{size}(\sigma - B^{soc}(t))}{\partial_c^o}$, where B^{size} denotes the battery full size capacity and $B^{soc}(t)$ denotes the battery SOC. ∂_c^o is the charging rate followed by charging mode o (o = slow or fast). σ denotes the expected full percentage level of the battery.

Charging Cost: refers to the expense of electricity consumed when recharging an EV battery. The charging cost of an EV can vary based on factors such as the energy prices, and the total amount of energy required to charge the battery. In order to reduce the charging cost, this work uses the TOU tariffs. This means EV owners are charged differently, depending on the time of day they charge their vehicle. Here, the electricity price varies over time, with higher prices during peak hours and lower prices during off-peak hours. This encourages EV owners to charge their vehicles during off-peak hours and reduce the strain on the grid during peak hours. The charging cost with applying TOU can be expressed as follows:

$$C_{v,c} = \begin{cases} p_{off-peak,class(i)}\ E_{v,c} \\ p_{peak,class(i)}\ E_{v,c} \end{cases} \quad (2)$$

Where $C_{v,c}$ denotes the charging cost. $E_{v,c}$ is the amount of energy of the EV requires to be charged. $p_{class(i),off-peak}$ and $p_{peak,class(i)}$, respectively, denote the pricing rates of charging in off-peak period and peak period for CS with a $class(i)$. Where $class(i)$ is the charging power rate for CS (e.g., fast, slow, regular).

In this study, the proposed algorithm operates in collective optimisation mode. In this mode, the CCU collects charging requests from EVs over a certain period or until a certain number of requests are received, and then it processes all the requests in a single run of the optimisation algorithm. This approach may lead to more efficient use of computational resources, but it might result in slightly outdated solutions if the system's state changes significantly during the collection period. Hence, the collection period should be tuned. Depending on the vehicular traffic conditions, it may change during the days of the week, during the day, etc. Optimising the collection period value could be another topic for future study.

3.3. The propose of multi-objective optimisation

Typically, the user desires a low charging cost and a low service time, which are conflicts. A higher cost will be associated with shorter service time, and low cost will lead to longer service time. Hence, optimising them requires adopting one of the meta-heuristic multi-objective optimisation algorithms. Therefore, this research proposes the usage of NSGA-II for optimising charging scheduling [20]. As a multi-objective optimisation algorithm, NSGA-II identifies trade-offs between minimising charging cost and service time by providing a set of Pareto-optimal solutions that cater to different decision-maker preferences. The algorithm's Pareto-based ranking converges towards the true Pareto front, ensuring optimal solutions for the given problem. NSGA-II maintains diversity among solutions through the crowding distance metric, ensuring a wide spread of solutions representing various trade-offs between conflicting objectives. Its scalability, adaptability, and proven performance across various domains make it a suitable choice for tackling the complexities and self-conflicting nature of the CEV optimisation problem.

In this propose, NSGA-II begins by initialising a population of random solutions *P(0)* to find a solution for the CEV problem. Each solution represents the assignment of EVs at a specific CS and is determined by a set of decision variables (e.g., travelling time, waiting time, charging time, and pricing rate) based on formulas (1) and (2). The fitness of a solution is evaluated based on the objectives of charging cost and service time. The objective values are calculated for each solution to determine its fitness. This propose aims to find solutions that offer a superior trade-off between charging cost and service time, identifying a set of non-dominated solutions known as the Pareto front.

To generate the offspring population *Q(t)*, the algorithm selects parent solutions from *P(t)* based on their dominance rank and crowding distance. Crossover and mutation operators are applied to the decision variables of the parent solutions to create offspring solutions, which inherit characteristics from their parents while also introducing diversity. The objective values of the offspring solutions are evaluated and added to *Q(t)* until the desired population size *(N)* is reached. At the end of each generation, the current population *P(t)* is replaced by the offspring population *Q(t)*, and the process continues until the maximum number of generations *(G)* is reached. The final population *P(G)* contains a set of Pareto-optimal solutions representing various trade-offs between the conflicting cost and service time objectives.

Algorithm – Pseudocode of optimisation CEV problem using NSGA-II

Input: *N, G,* P_c, P_m
Output: *Pareto-optimal solutions*
1: *Initialise population P(0) of size N with random solutions*
2: *Evaluate the objective values of each solution in P(0)*
3: *t ← 0*
4: *While t < G do*
5: *Perform non-dominated sorting on P(t) to rank solutions based on dominance*
6: *Calculate the crowding distance for each solution in P(t)*
7: *Create an empty offspring population Q(t)*
8: *While*
10: *Apply crossover with probability* P_c *to generate two offspring solutions*
11: *Apply mutation with probability* P_m *to each offspring solution*
12: *Evaluate the objective values of the offspring solutions*
13: *Add offspring solutions to Q(t)*
14: *End while*
15: *P(t+1) ← Q(t)*
16: *t ← t + 1*
17: *End while*
18: *Return Pareto-optimal solutions from the final population P(G)*

The NSGA-II algorithm is well-suited for the CEV optimisation problem due to its ability to efficiently handle multiple conflicting objectives and provide high-quality Pareto-optimal solutions. Its diversity preservation and convergence towards the true Pareto front make it a suitable choice for tackling the complexities of the problem, ultimately offering decision-makers a range of solutions that cater to different preferences and requirements.

4. Experimental results and analysis

This study's experimental evaluation was conducted using MATLAB 2020b, a widely used numerical computing software known for its built-in optimisation and algorithm development tools. The setup encompassed a grid size of 10, with 100 EVs having battery capacities ranging from 40 to 100. We placed 20 CSs at random locations, each varying in their charging rates, namely, slow (3.7 kW), regular (22 kW), and fast (50 kW). The number of EVs waiting in the queue was set at 10. We devised a scenario wherein EVs were allocated during two distinct periods: off-peak and peak. Pricing was determined by the charging rate preference, setting rates at [0.10, 0.15, 0.20] for off-peak and [0.30, 0.35, 0.40] for peak periods.

We employed multiple genetic parameters from the MATLAB toolbox for our case study. The study set varying mutation probabilities (0.08 and 0.1) and crossover fractions (0.7 and 0.9) combined with different population sizes (50, 100, and 200). The aim was to analyse the sensitivity of both NSGA-II and GA to these parameters. The result was six distinct Pareto fronts corresponding to six individual experiments, as illustrated in Fig 2. This evaluation was chiefly to compare the efficiency of NSGA-II with the conventional GA, focusing primarily on charging cost and service time. Our findings revealed that increasing the population size from 50 to 200, with other parameters constant, yielded no significant alterations in average charging cost or service time. The NSGA-II presented diverse, non-dominated solutions regarding the two optimisation goals: charging cost and service time. Conversely, the conventional GA typically produced a singular solution with reduced service time and charging cost. The NSGA-II consistently offered more optimised solutions than GA, a limitation in the latter stemming from its predisposed objective weighting.

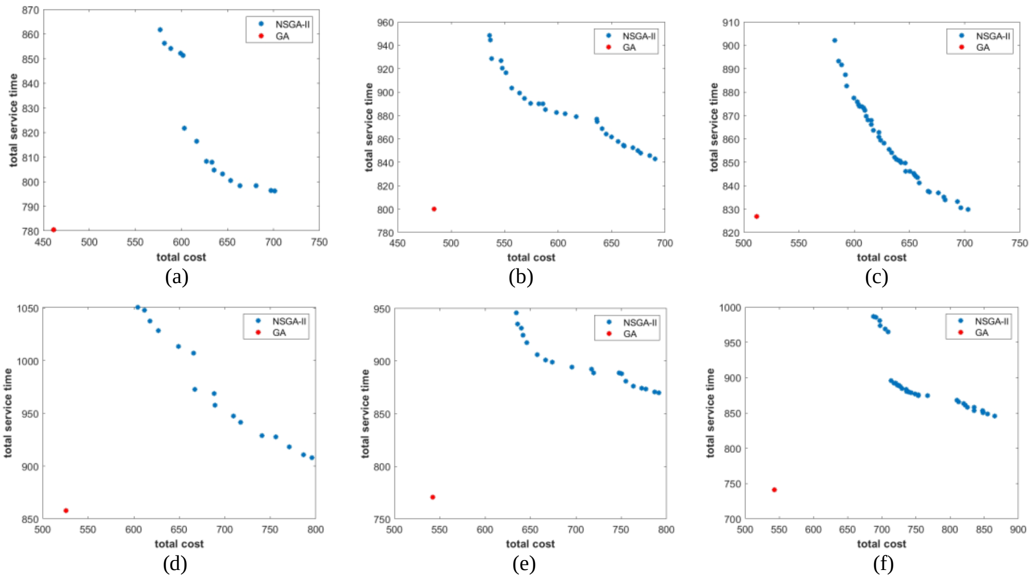


Fig. 2. The Pareto front for the six experiments generated from NSGA-II and traditional GA with crossover fraction 0.7, mutation probability 0.08, and population size (a) 50 (b) 100 (c) 200 and crossover fraction 0.9, mutation probability 0.1, and population size (d) 50 (e) 100 (f) 200.

Further clarity is provided through three histograms derived from our initial experiment. Fig. 3 showcases the solution from the conventional GA, with the majority of EVs allocated to stations 5 and 6 and the least (two EVs) spread across other stations. This uneven distribution is symptomatic of GA's inherent restrictions, revealing its inadequacy in optimising assignments evenly. The significant imbalance highlights the inherent challenge of fairly distributing EVs across CSs in a real-world scenario.

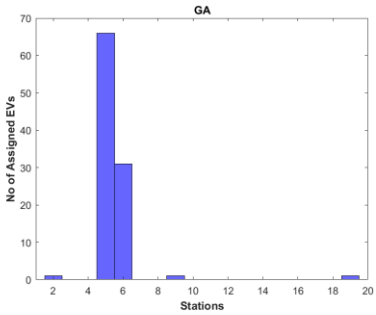
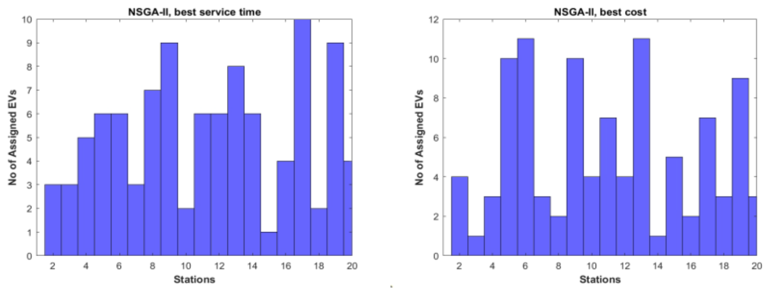


Fig. 3. The assignment of 100 EVs over 20 CSs generated by GA with crossover fraction 0.7, mutation probability 0.08, and population size 50 in terms of service time and cost.

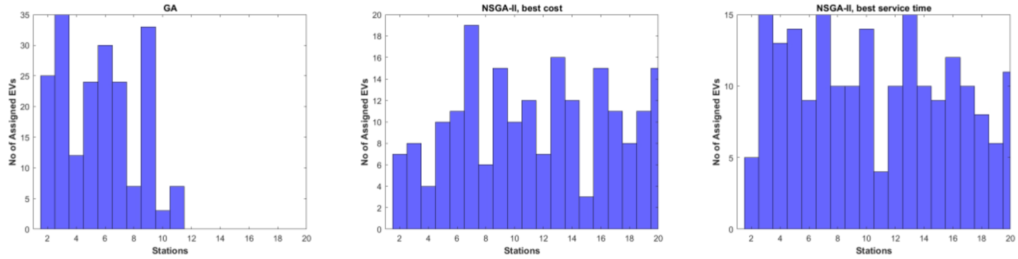
Fig. 4 represents the solution generated from NSGA-II. The assignments, in terms of service time (a) and charging cost (b), show a more balanced EV distribution across CSs. Multiple stations, for instance, stations 9, 17, and 19 in (a), received the highest EV count. The minimal EV count at station 15 could be influenced by factors like travel time or charging time, affecting service duration. In practical scenarios, the system follows assignment (a) for EVs preferring to charge during peak periods, typically EVs prioritising reduced service time. Conversely, for those requesting off-peak charging to reduce the costs, the system follows assignment (b). However, this equitable distribution of EVs and maintaining the charging system stability, achieved by NSGA-II, highlights its capability to consider various factors when making assignments, including charging rate and price rate preferences.



(a) (b)

Fig. 4. The assignment of 100 EVs over 20 CSs generated by NSGA-II with crossover fraction 0.7, mutation probability 0.08, and population size 50 in terms of (a) service time and (b) charging cost.

Ultimately, we expanded the number of EVs to 200 to assess the efficacy of our proposed solution with a larger vehicle count. Fig. 5 (a) showcases the solution produced by GA, indicating noticeable improvements with the increased EV assignments. In contrast, solutions from NSGA-II are represented in Fig. 5 (b) for service time and in Fig. 5 (c) for charging cost. The NSGA-II solutions demonstrate a more even distribution than GA, ensuring a more efficient and sustainable charging infrastructure. This underscores the superiority of NSGA-II in handling increased complexity and optimising multiple objectives simultaneously, particularly when scaling to real-world scenarios with a larger number of vehicles. This balance not only enhances the overall efficiency of the CSs but also aligns with the EV user's preferences, whether prioritising service time or charging cost.



(a) (b) (c)

Fig. 5. The assignment of 100 EVs distributed over 20 CSs during the off-peak period generated from GA and NSGA-II.

5. Conclusions and future work

This paper has presented the problem of CEVs from the perspective of multi-objective optimisation. It has formulated the problem as a bi-objective optimisation problem with two objectives, namely, service time and charging cost. We proposed the usage of NSGA-II as an optimisation algorithm. Unlike traditional GA optimisation, which uses a weighted average for more than one objective optimisation, NSGA-II brings several distinct advantages. Firstly, it offers decision-makers a set of non-dominated solutions known as the Pareto front. It uses non-dominated sorting and crowding distance for both exploitation and exploration. Comparing NSGA-II with traditional GA has shown its superiority in diversity and optimality. This leads to more flexibility for the decision-maker in assigning the EVs to the CS. Future work is to explore the usage of reinforcement learning, which is more capable of operating in a dynamic environment and being trained on the variable conditions of the environment.

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