Genetic Algorithms as an Optimization Approach for Managing Electric Vehicles Charging in the Smart Grid

Sergiy Korotunov [1][0000-0001-5184-4455], Galyna Tabunshchyk [2][000-0003-1429-5180], Vyacheslav Okhmak [3][0000-0003-1969-6063]

[123] National University "Zaporizhzhia Polytechnic", Zhukovsky str., 64, Zaporizhzhia, 69063, Ukraine
skorotunov@yahoo.com, galina.tabunshchik@gmail.com, slavas490@gmail.com

Abstract. Usage of the genetic algorithms for solving electric vehicles optimization problem in the scope of smart grid is an extremely actual problem nowadays. Electric vehicles are modern and promising alternative to conventional vehicles. They are characterized by lower operation cost and environment-friendly ability to use renewable sources of energy. Smart grids can be used in order to avoid undesirable impact of electric vehicles. Such grids require optimization and correct scheduling to handle growing number of electricity consumers. This can be achieved with implementation of specifically designed genetic algorithms. The goal of the paper is to select optimal method and propose it for using for optimization of the digital twin of the electric vehicles charging infrastructure. As a result of paper such method is proposed. Moreover, as a scientific novelty, genetic algorithm functions are compared and analyzed applying to the problem in consideration.

Keywords. Genetic algorithm, optimization, electric vehicle, smart grid, crossover, selection, mutation.

1 Introduction

Electric vehicles (EVs) can be viewed as an eco-friendly and cost-effective alternative to conventional vehicles with internal combustion engines (ICE). EVs are produced and designed by number of different manufacturers and their production amount is expected to grow rapidly in the coming years [1]. EVs have lower operating costs with respect to ICE vehicles and can be charged with locally produced renewable energy sources (RESs) [2]. However, number of challenges to wide spreading of EVs exist. Although their operating costs are less, EVs are still more expensive to buy than ICE vehicles. In addition, access to charging stations is limited, and large capital investment is required for developing a public charging infrastructure [2]. More than that, EVs consume comparatively high power from the grid during charging. Therefore, uncoordinated charging of a large number of EVs can have an adverse impact on the grid operation (power outages, unacceptable voltage fluctuations) [3]. Power generation can be increased in order to handle the peak demand of EVs. However, this will lead to significant infrastructure cost. As an alternative cost-effective solution, smart grid allows EVs to coordinate their charging operations, which can improve frequency regulation [4], smooth out intermittent power generation from RESs, and make the electric power usage efficient [5].

2 Formal problem statement

Smart grid [6, 7] is a concept aimed at providing the next generation electricity network that stands out by high configurability, reactivity and self-control capability. This is a complex infrastructure that characterizes by following attributes [8]:

- multidisciplinary character,
- spatial distribution,
- network systems heterogeneousness,
- implementation of evolutionary development,
- functioning and controlled separation of its elements.

Smart grid is expected to be a key part of the global system of interacting actors, which in its turn will lead to improved management of available resources and increased energy efficiency. Precise monitoring and management are needed to achieve this goal [9]. Smart grid is created on the basis of advanced information and two-way digital communication technologies. Therefore, it cannot just intelligently deliver electricity but also manage power facilities taking advantage of real-time information exchange and interaction between providers and consumers [10].

Meanwhile, EVs are new and important targets for the smart grid to manage. EVs are equipped with batteries having high energy-storage capacity, so EV charging imposes large electric load on the power system [11]. EVs are forced to be equipped with an electronic interface for grid connection to allow controlled energy exchanges. Despite high number of the researches in area, EVs still need to be charged more often and it takes at least tens of minutes [12]. That makes it necessary to build a large charging infrastructure which embraces fast charging stations, battery swapping stations, and individual charging points for slower charging [11].

Different types of interactions are possible between the power grid and an EV:

- grid to vehicle (G2V),
- vehicle to grid (V2G).

In G2V, an EV's battery can be charged from the grid using stored electricity from external power sources. That means that the power flow is always unidirectional In V2G, the power flow is bidirectional, i.e., from the grid to an EV while charging and from an EV to the grid while discharging. V2G-enabled EVs may earn incentives and sell power while discharging to the grid and make payments while charging batteries from the grid. Therefore, V2G-enabled EVs can facilitate the supply/demand balance by discharging during peak hours (peak clipping) and charging during off-peak hours (valley filling) as can be seen at Fig. 1.

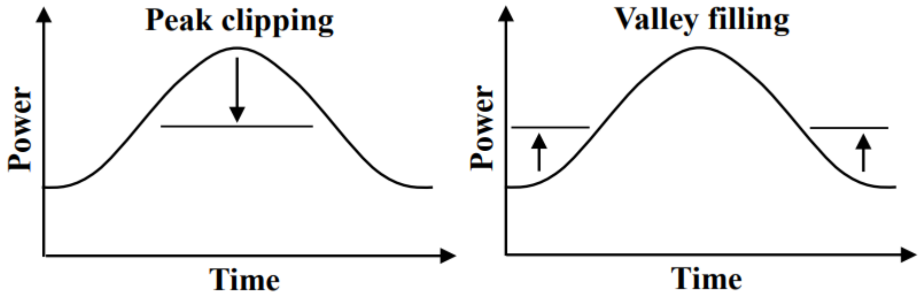

Fig. 1. Peak clipping and valley filling (Adapted from [13])

The impact of EVs on the power grid has been studied [14]. One solution to decrease the impact of EVs on the grid is to schedule their charging/discharging profiles. This can be done by aggregating different sets of EVs for charging or discharging with different start times and durations such that grid constraints are maintained. However, the aggregation of EVs differs from the aggregation of more traditional power resources [15]. In particular, the temporal availability of EVs along with their location information is an important parameter to consider while aggregating EVs for possible grid overload planning and management. Thus, determining and optimizing the appropriate charge and discharge times of EVs that do not violate grid constraints while maintaining acceptable degrees of user satisfaction is a challenging problem.

3 Literature review

The EV charge scheduling problem formulates as following. It takes a set of EVs, grid, user, and aggregator-side parameters as input and outputs a charging schedule. By charging schedule, it is meant the starting and ending times of charging of each EV in the set. It is an optimization problem that optimizes some grid, user, or aggregator-side parameters (or a mix of them) subject to different number of constraints. No single mathematical formulation exists for the problem in general, forming different optimization problems.

The optimization intends to provide the best local or global solutions. Generally, the mathematical formulation of an optimization problem is to maximize or minimize an objective function while satisfying all considered constraints related to the integrated components in the model [16].

Depending on the complexity and the difficulty, optimization can be addressed by means of exact or approximate methods.

The exact mathematical methods can generate an optimal solution when they are specified in a feasible region. There are two basic categories: linear and non-linear model. They are based on all implemented constraints and the objective functions. The linear models are divided in three types: linear programming, integer programming and mixed integer linear programming, according to the variables if they are real, integer, or both variable types, correspondingly.

The approximate methods have an advantage that can simply manage the nonlinear constraints and objective functions. In the same time, they cannot always guarantee the quality of the obtained results because they generally employ random search methods [17]. More than that, the possibility to find the global solution decreases as soon as the size of the considered problem increases [18].

In this paper we consider the genetic algorithms (GAs) as a part of approximate methods [19]. We study those for the modeling of the EV scheduling problem because it generally permits to employ the characteristics of the integrated distributed energy resources with employing integer and binary variables to make a decision on the operation status of the production systems, battery storage system, EVs and smart appliances of the microgrid.

3.1 Analyze GA approaches for EV optimization problem

GA are becoming one of the most popular search techniques for the problems having large search space [20]. One of such problems can be EV charging scheduling GA can create a reasonable quality solution within a controllable time bound by means of a population-based directed search, which is inspired by biological evolution principles.

In the description of GA, the workflow is a sequential change of populations consisting of a fixed number of individuals corresponding to the trial points of the solution space. Individuals who respond to high-quality (more appropriate) solutions receive the advantage of producing offspring in the next population [21].

From the population consisting of feasible solutions called chromosomes, the next-generation population is created through genetic operations such as selection, crossover, and mutation. This evolution process continues for the given number of iterations or until a termination condition is met [22].

Authors in [23] integrated vehicular networks with smart grid and designed a charge scheduler for EVs based on heuristic-based approaches and GAs, which minimizes the load at a charging station. Each request consists of:

- vehicle type,
- estimated arrival time,
- desired service completion time (deadline),
- current battery charge.

On receiving the request, the power consumption profile of the vehicle is retrieved from the repository of vehicular information. Then, the charging station verifies whether it can satisfy the new request along with the other requests already submitted to the scheduler. The result is communicated back to the vehicle. On receiving the result, the driver may accept the schedule, initiate a renegotiation session, or choose another charging station.

From the vehicle-side viewpoint, entering the station, the vehicle is assigned and plugged to a charger. The controller connects or disconnects power to each vehicle according to the schedule generated by either a scheduler within a charging station or a remote charging server running in the Internet.

In [24] same authors evaluated the performance of a charging task scheduler for EV, aiming at reducing the peak load and improving the service ratio in charging stations. They try to achieve better results by making the initial population include both heuristic-generated schedules for fast convergence and randomly generated schedules for diversity loss compensation. The performance measurement result obtained from that work reveals that scheme in consideration can reduce the peak load for the given charging task sets by up to 4.9%, compared with conventional schemes.

Authors in [25] established a stochastic procedure for modeling and analyzing an EV fleet to generate an accurate charging and discharging profiles. They focused on the uncertainties that may affect EV charging/discharging profiles:

- EV type – battery electric vehicle (BEV) which is supplied by an electrical source to feed its energy storage unit and plug-in hybrid electric vehicle (PHEV) which has ability to utilize ICE along with electric one,
- EV battery capacity – authors assumed that the battery pack for a BEV has a 20-30 kWh pack and for a PHEV, 5-15 kWh,
- time duration availability and scheduling time – authors hypothesized that 50% of EV of the fleet were plugged-in to be charged at the workplace in the parking lots and the other EV were connected to the grid to be charged at home in the evening.

Comparing described previously works it can be said that in first two works authors presented a chromosome as a single feasible schedule. It was represented by a fixed-length string of an integer-valued vector. The charging task could be started, suspended, and resumed at a slot boundary. They used the roulette wheel as selection method, random operation as crossover method. Due to the fact that each element has a different permissible range, the mutation was prohibited.

In contrast, authors of third work used number of selection methods. Namely, stochastic universal selection, roulette-wheel selection, tournament selection and ranking selection [26]. Like the first group of authors they used random operator as crossover method. But, unlike them they used mutation operator that would change randomly the genes of the chromosomes which could also change their characteristics.

Another important distinction is that the proposed by last group of authors GA algorithm allows to make the optimal trade-off between V2G and G2V operations cost to highly increase benefits from EV batteries by scheduling the charging mode in the low power price periods and discharging mode in the high-power price periods. This contradicts to first two works were authors only utilize and optimize charging faze of the EV, ignoring discharging ability.

Therefore, it can be concluded that after analyzing and comparing GA approaches one can be selected as optimal. It is the third work which has critical advantages above other ones.

- it allows and supports usage of the mutation operator which should help in creating better GA and prevent falling into local minimums,

- it provides support both for V2G and G2V, which can be critical in modern EVs and smart grids.

4 Model selection

After analyzing, following method can be used for the future optimization of the EV charging infrastructure along the horizon T with t time steps. The aim of the EV charging/discharging scheduling is to minimize the smart grid total cost and to minimize the overall cost of the power in the G2V operations of EVs. Which is given by following function:

$$\min f_{cost} = \sum_{t=1}^{T} \left\{ \sum_{n=1}^{EV_{Char}} \eta_{Char} \times E_n \times C(t) - \sum_{n=1}^{EV_{Disch}} \eta_{Disch} \times E_n \times C(t) \right\} \tag{1}$$

Here:

- EV_{Char} and EV_{Disch} are number of charging and discharging EVs respectively,
- η_{Char} and η_{Disch} are charging and discharging efficiency respectively,
- E_n is the power received or delivered from vehicle n,
- $C(t)$ is the hourly price of electricity.

From that model, EV can be in one of the following states:

- in the charging state,
- in the discharging state,
- not charging or discharging (battery is in idle mode).

Number of constraints need to be defined in order to achieve complete model of the charging process.

$$SoC_n^t = SoC_n^{t-1} + \eta_{Char} \times E_n \tag{2}$$

$$SoC_n^t = SoC_n^{t-1} - \eta_{Disch} \times E_n \tag{3}$$

$$\eta_{Char} \times E_n \le SoC_n^{\max} \tag{4}$$

$$-\eta_{Disch} \times E_n \le -SoC_n^{\min} \tag{5}$$

$$\sum_{t=1}^{T} \eta_{Char} \times E_n + \sum_{t=1}^{T} \eta_{Disch} \times E_n = SoC_n^{need} \tag{6}$$

The (2) constraint describes the cost of the power delivered to the EV battery, while the (3) describes the cost of the power supplied from the EV battery to the grid. Constraints (4) and (5) ensure that the state-of-charge (SoC) is scheduled within a predefined range between $SoC_n^{\min}$ and $SoC_n^{\max}$ (generally the customer can pre-set this range). Constraint (6) guarantees that the system meets each single EV's energy need at the unplugging time (SoC_n^{need}) at any recharging cycle.

5 EV charging infrastructure in consideration

Considered optimization method can be applied to the developed EV charging station. From the perspective of the EV, the global smart grid can be separated into smaller EV systems. The EV system has three levels: device level, communication level and application level as shown in Fig. 2 [27].

Micro-grid was developed in order to consider EV-charging system [28] as a part of ISRT (Interactive platform for Embedded Software Development Study, developed in Zaporizhzhia Polytechnic National University [29]) infrastructure. The ISRT-server is a platform for remote laboratories, in order to train students in IoT-tasks. It is ideal for the scalability of the charging station case. A ready-made black-box charging station module is available in the ISRT so that students can work on the communication and client layer.

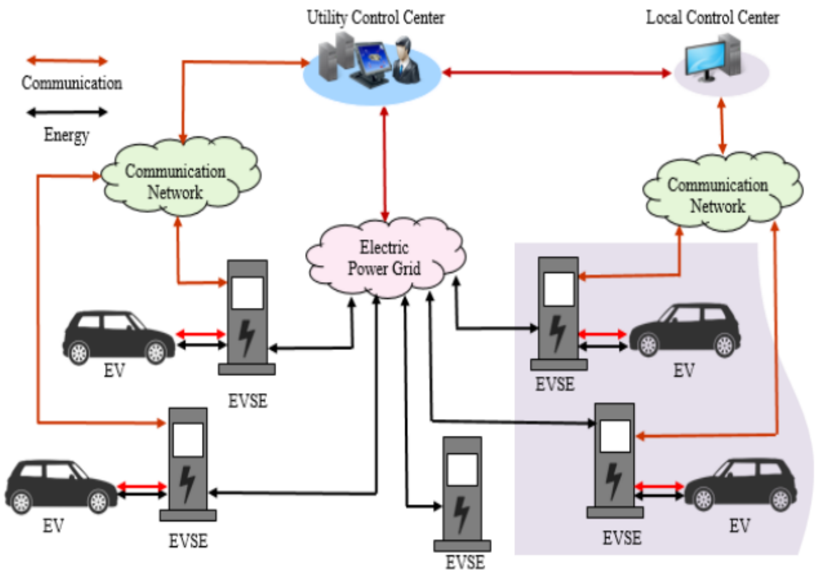

Fig. 2. Cyber-physical nature of EV system [27]

The hardware part is emulated with a simple electronic circuit to charge 1.25V Li-ion-batteries. Energy input side represented with following elements:

— net-powered,
— wind-powered,
— solar energy.

The charging system itself is both a consumer on the net and an energy provider in a V2G setup. For simulation purposes of the micro grid system users can variate input variables such as:

— the battery charge level,
— turn on and off different sources of energy;
— decide to start selling energy to the smart grid.

This system is displayed at Fig. 3. Where power sources noted as the letter A, the load as a letter B, the sale of surplus shown in the form of LED as letter C, battery and charge controller as letter D. With digits 1 – 8 different relays are depicted.

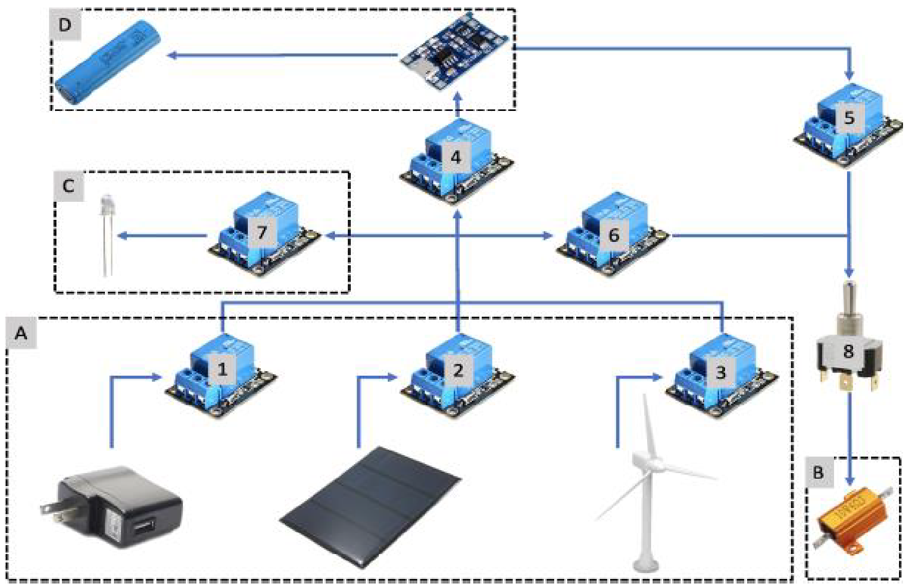

Fig. 3. Different power supplies for the charging station in a smart grid

The developed model of a charging station allows to:

— choose a power source (any separately or 2-3 sources at a time),
— control the process of battery charging (protection against undercharge or over-charge),
— "sell" residual energy and switch load.

The power source is indicated by letter A, load – B, surplus sales are indicated by LED – C, battery and charge controller – D.

As can be seen, developed digital twin of the EV charging infrastructure can be used by students to design optimal smart grid.

6 Experiments and results

Considered optimization method is simulated in the scope of the discussed charging station microgrid. To check efficiency of the specific GA some test data are used. Task of the optimization is slightly simplified because of the lack of SoC needed data for the set of EVs.

Therefore, goal of optimization can be formulated as to minimize cost of charging and discharging profiles of the set of EVs during given number of time slots.

Price of the electricity is also given for each time period. As well as charging and discharging efficiency. Each EV is characterized by state-time vector which represents if specified EV is charging, discharging or idle.

Input data for GA is matrix that contains EVs power for each time slot in given boundaries.

Number of available selection, scaling, mutation and crossover functions are compared in order to find optimal set for specified optimization problem. There are 200 iterations for each experiment.

First set of experiments has the goal to determine optimal scaling function. Fitness scaling converts the raw fitness scores that are returned by the fitness function to values in a range that is suitable for the selection function. Following functions are considered:

- rank function,
- proportional function,
- top function with quantity 0.4,
- top function with quantity 0.6.

Results can be seen at Fig. 4.

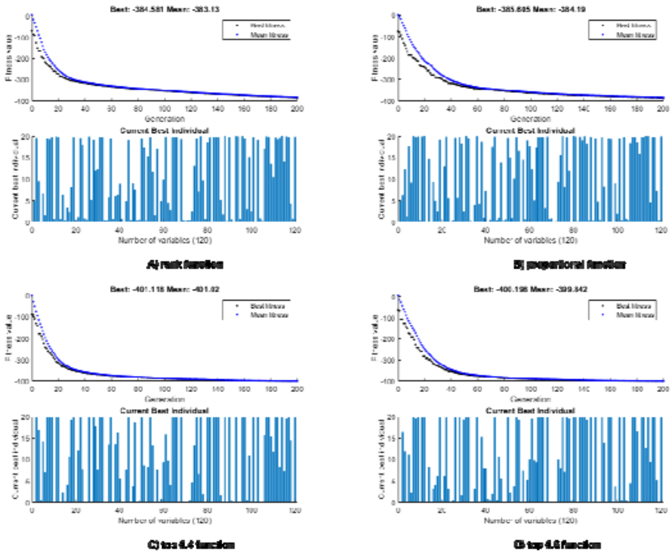

Fig. 4. Comparison of the different scaling functions:
A) rank, B) proportional, C) top 0.4, D) top 0.6

As can be seen, best optimization result is achieved using top scaling function with quantity of 0.4. Top scaling assigns 40 percent of the fittest individuals to the same scaled value and assigns the rest of the individuals to value 0. That means that only 40 percent of the fittest individuals can be selected as parents.

Next step is to determine selection GA function. Selection function specify how the GA chooses parents for the next generation. Following functions are considered:

- stochastic uniform function,
- roulette function,
- tournament function,
- uniform function.

Results can be seen at Fig. 5.

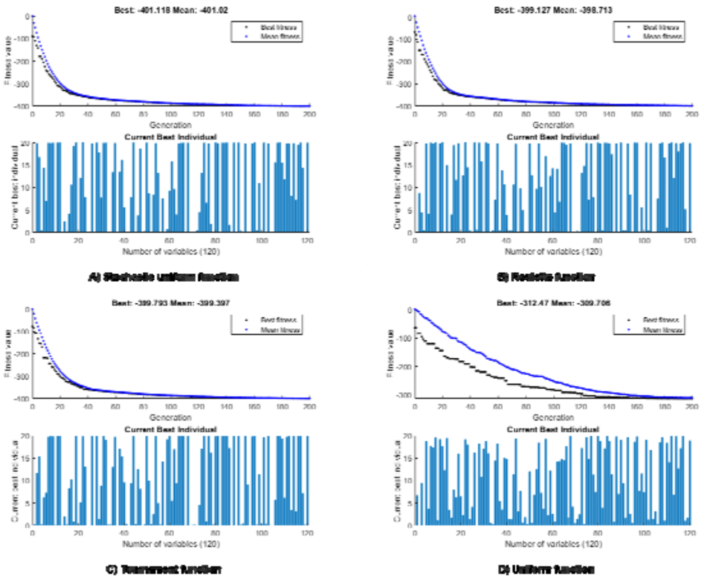

Fig. 5. Comparison of the different selection functions:
A) stochastic uniform, B) roulette, C) tournament, D) uniform

From results, best optimization result is achieved using stochastic uniform selection function. Stochastic uniform function creates a line in which each parent corresponds to a section of the line of length proportional to its scaled value. The algorithm moves along the line in steps of equal size. At each step, the algorithm allocates a parent from the section it lands on. The first step is a uniform random number less than the step size.

Following set of experiments is related to selection of the best mutation function for specified problem. Mutations specify how the GA makes small random changes in the individuals in the population to create mutation children. Mutation provides genetic diversity and enables the GA to search a broader space and does not allow it to fall into local minimum. Following functions are considered:

- adaptive feasible function,
- uniform function.

Comparison of those can be seen at Fig. 6.

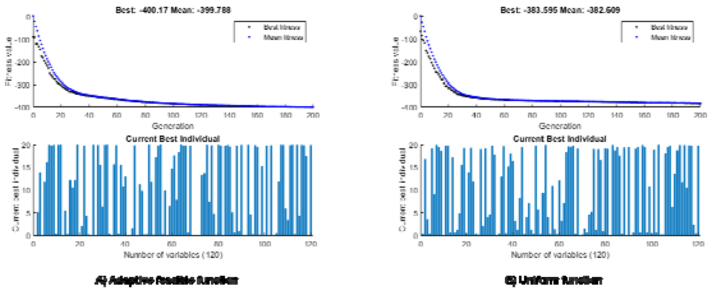

Fig. 6. Comparison of the different mutation functions:
A) adaptive feasible and B) uniform

It can be seen that best optimization result is achieved using adaptive feasible mutation function. Adaptive feasible randomly generates directions that are adaptive with respect to the last successful or unsuccessful generation. The mutation chooses a direction and step length that satisfies bounds which are defined.

Last set of experiments has as its goal to determine the best crossover function for specified problem. Crossover functions specify how the GA combines two individuals, or parents, to form a crossover child for the next generation. Following crossover functions are considered:

- two-point function,
- constraint dependent function,
- heuristic function.

They can be seen at Fig. 7.

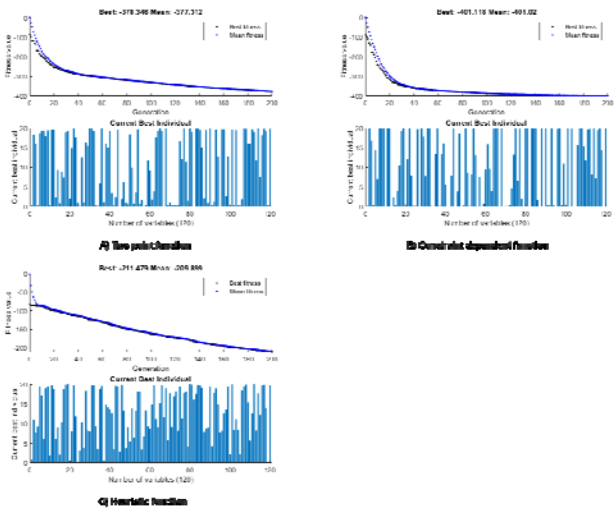

Fig. 7. Comparison of the different crossover functions:
A) two-point, B) constraint dependent, C) heuristic

It can be seen that best optimization result is achieved using constraint dependent function. Constraint dependent chooses scattered function when there are no linear constraints, and chooses intermediate function when there are linear constraints. These choices ensure that feasible parents give rise to feasible children, where feasibility is with respect to bounds and linear constraints. Scattered function is used externally because there are no linear constraint functions. Scattered crossover function creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

After executing specified experiments, best GA functions for specified EV charging problem can be selected. Thus, best optimization results achieved using top scaling function with quantity 0.4, stochastic uniform selection function, adaptive feasible mutation function and scattered crossover function.

7 Conclusion

In the paper the authors considered the possibility of utilization of the GAs for developed in the previous researches EV charging infrastructure. Review of the main characteristics of the EVs, charging, smart grid and GAs was carried out by the authors. Current researches related to implementing GAs for managing EV s charging are considered and analyzed. After investigation and executing simulation experiments it is possible to make an assumption that utilization of the GAs for EVs charging problem is promising optimization approach. As the future work, it is planned to develop own GA which will handle optimization of the developed EV charging infrastructure.

Scientific novelty of the work is that number of GA scheduling techniques were considered and analysed. One optimization method on the basis of GA was selected as optimal after comparison. Simulation experiments were executed for that method using different GA options. Those were compared and selected optimal options for specified problem. This method is proposed to use for later researches to provide optimization of the developed EV charging infrastructure.

8 References

1. Global EV Outlook 2019 – Analysis - IEA, https://www.iea.org/reports/global-ev-outlook-2019
2. Sortomme, E., El-Sharkawi, M.: Optimal Charging Strategies for Unidirectional Vehicle-to-Grid. IEEE Transactions on Smart Grid. 2, 131-138 (2011). doi: 10.1109/tsg.2010.2090910
3. Clement-Nyns, K., Haesen, E., Driesen, J.: The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid. IEEE Transactions on Power Systems. 25, 371-380 (2010). doi: 10.1109/tpwrs.2009.2036481
4. Sekyung Han, Soohee Han, Sezaki, K.: Development of an Optimal Vehicle-to-Grid Aggregator for Frequency Regulation. IEEE Transactions on Smart Grid. 1, 65-72 (2010). doi: 10.1109/tsg.2010.2045163

5. Sundstrom, O., Binding, C.: Flexible Charging Optimization for Electric Vehicles Considering Distribution Grid Constraints. IEEE Transactions on Smart Grid. 3, 26-37 (2012). doi: 10.1109/tsg.2011.2168431
6. Internet of Energy: ICT for energy markets of the future, https://www.iese.fraunhofer.de/content/dam/iese/en/mediacenter/documents/BDI_initiative_IoE_us-IdE-Broschuere_tcm27-45653.pdf
7. Smartgrids: Strategic deployment document for europe's electricity networks of the future, https://ec.europa.eu/research/energy/pdf/smartgrids_en.pdf
8. Maier, M.: Architecting principles for systems-of-systems. Systems Engineering. 1, 267-284 (1998). doi: 10.1002/(sici)1520-6858(1998)1:4<267::aid-sys3>3.0.co;2-d
9. Karnouskos, S.: Cyber-Physical Systems in the SmartGrid. 2011 9th IEEE International Conference on Industrial Informatics. (2011). doi: 10.1109/indin.2011.6034829
10. Gellings, C.: The smart grid. The Fairmont Press, Lilburn (2009)
11. Lopes, J., Soares, F., Almeida, P.: Integration of Electric Vehicles in the Electric Power System. Proceedings of the IEEE. 99, 168-183 (2011). doi: 10.1109/jproc.2010.2066250
12. Tribioli, L., Barbieri, M., Capata, R., Sciubba, E., Jannelli, E., Bella, G.: A Real Time Energy Management Strategy for Plug-in Hybrid Electric Vehicles based on Optimal Control Theory. Energy Procedia. 45, 949-958 (2014). doi: 10.1016/j.egypro.2014.01.100
13. Lampropoulos, I., Kling, W., Ribeiro, P., van den Berg, J.: History of demand side management and classification of demand response control schemes. 2013 IEEE Power & Energy Society General Meeting. (2013). doi: 10.1109/PESMG.2013.6672715
14. Gong, Q., Midlam-Mohler, S., Marano, V., Rizzoni, G.: PEV charging impact on residential distribution transformer life. IEEE 2011 EnergyTech. (2011). doi: 10.1109/energytech.2011.5948498
15. Jansen, B., Binding, C., Sundstrom, O., Gantenbein, D.: Architecture and Communication of an Electric Vehicle Virtual Power Plant. 2010 First IEEE International Conference on Smart Grid Communications. (2010). doi: 10.1109/smartgrid.2010.5622033
16. Iqbal, M., Azam, M., Naeem, M., Khwaja, A., Anpalagan, A.: Optimization classification, algorithms and tools for renewable energy: A review. Renewable and Sustainable Energy Reviews. 39, 640-654 (2014). doi: 10.1016/j.rser.2014.07.120
17. Chen, Y., Wu, Y., Song, C., Chen, Y.: Design and Implementation of Energy Management System With Fuzzy Control for DC Microgrid Systems. IEEE Transactions on Power Electronics. 28, 1563-1570 (2013). doi: 10.1109/tpel.2012.2210446
18. Lin, M., Tsai, J., Yu, C.: A Review of Deterministic Optimization Methods in Engineering and Management. Mathematical Problems in Engineering. 2012, 1-15 (2012). doi: 10.1155/2012/756023
19. Leoshchenko, S., Oliinyk, A., Subbotin, S., Shylo, S., Shkarupylo, V.: Method of Artificial Neural Network Synthesis for Using in Integrated CAD. 2019 IEEE 15th International Conference on the Experience of Designing and Application of CAD Systems (CADSM). (2019). doi: 10.1109/cadsm.2019.8779248
20. Sivanandam S, Deepa S.: Introduction to Genetic Algorithms. Springer-Verlag Berlin Heidelberg, Berlin, Heidelberg (2008)
21. Desprez, C., Chu, F., Chu, C.: Minimising the weighted number of tardy jobs in a hybrid flow shop with genetic algorithm. International Journal of Computer Integrated Manufacturing. 22, 745-757 (2009). doi: 10.1080/09511920902810938
22. Subbotin, S.: THE NEURO-FUZZY NETWORK SYNTHESIS WITH THE RANKING AND SPECIFIC ENCODING OF FEATURES FOR THE DIAGNOSIS AND AUTOMATIC CLASSIFICATION ON PRECEDENTS. Radio Electronics, Computer Science, Control. 0, (2016). doi: 10.15588/1607-3274-2016-1-6

23. Lee, J., Kim, H., Park, G., Jeon, H.: Genetic Algorithm-Based Charging Task Scheduler for Electric Vehicles in Smart Transportation. Intelligent Information and Database Systems. 208-217 (2012). doi: 10.1007/978-3-642-28487-8_21
24. Lee, J., Park, G.: Genetic algorithm-based demand response scheme for electric vehicle charging. International Journal of Intelligent Information and Database Systems. 7, 535 (2013). doi: 10.1504/ijiids.2013.057420
25. Elmehdi, M., Abdelilah, M.: Genetic Algorithm for Optimal Charge Scheduling of Electric Vehicle Fleet. Proceedings of the 2nd International Conference on Networking, Information Systems & Security - NISS19. (2019). doi: 10.1145/3320326.3320329
26. Goldberg, D., Deb, K.: A Comparative Analysis of Selection Schemes Used in Genetic Algorithms. Foundations of Genetic Algorithms. 69-93 (1991). doi: 10.1016/b978-0-08-050684-5.50008-2
27. Ahmed, M., Kim, Y.: Performance Analysis of Communication Networks for EV Charging Stations in Residential Grid. Proceedings of the 6th ACM Symposium on Development and Analysis of Intelligent VehicularNetworks and Applications - DIVANet '17. (2017). doi: 10.1145/3132340.3132352
28. Arras, P., Tabunshchyk, G., Okhmak, V., Korotunov, S.: Modeling and Simulation of the Services for Vehicle Charging Infrastructure Interaction. 2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS). (2019). doi: 10.1109/idaacs.2019.8924449
29. Arras, P., Tabunshchyk, G., Korotunov, S., Okhmak, V.: Cost Optimization Simulation for Electric Vehicle Charging Infrastructure. 2020 IEEE European Technology & Engineering Management Summit. (2020)