V2G Optimization for Dispatchable Residential Load Operation and Minimal Utility Cost

Rosemary E. Alden[1], Ashutosh Timilsina[2] , Simone Silvestri[2], and Dan M. Ionel[1]
[1]SPARK Lab, Department of Electrical and Computer Engineering, University of Kentucky, Lexington, KY, USA
[2]CPS Lab, Department of Computer Science, University of Kentucky, Lexington, KY, USA
rosemary.alden@uky.edu, ashutosh.timilsina@uky.edu, simone.silvestri@uky.edu, dan.ionel@ieee.org

***Abstract*—Electric Vehicles (EVs) are gaining popularity among consumers and are expected to play a significant role in the future of transportation. Within this paper, a reverse auction is formulated through an optimization problem to minimize the utility energy cost using Vehicle-to-Grid (V2G) operation, as well as transition residential communities to dispatchable aggregate constant load profiles for demand response (DR). The *evolutionary V2G Auction (eV2GA)*, including the non-dominated sorting genetic algorithm (NSGA-II), is proposed for the formulated problem. It uses co-simulation with OpenDSS for power flow analysis as part of the objective function to account for physical constraints of infrastructure on the cost analysis. The results are verified against a greedy method in two case studies on the IEEE 123 test feeder with modified residential load showing over 20% reduction in cost from no v2G. It is demonstrated that physical power system constraints, such as line active power flow limits, may be implemented into the optimization through the proposed approach and do affect the V2G design solution by placing influence on location of the selected EVs in the distribution system.**

***Index Terms*—Electrical vehicle (EV), Vehicle-to-Grid (V2G), Reverse Auction, Optimization, Electrical Infrastructure, Smart and Micro Grid, Distribution, OpenDSS**

I. Introduction

The problem of selecting the optimal set of electric vehicles (EVs) to engage in grid services while considering physical constraints on the power system is gaining attention in literature as EVs grow in popularity. A recent study on the topic of EV integration includes the optimization of grid flexibility from the adjustment of EV charging and PV utilization for maximum power availability using OpenDSS distribution system models [1]. The authors of [2] concluded vehicle-to-grid (V2G) and smart charging lead to cost savings with consideration to battery health in six scenarios of smart charging, demand side management, and V2G distributed energy with a variable electricity cost. Day-ahead EV scheduling was assessed in a grid impact study with distribution system modeling & cost minimization, voltage violations, and discharge period maximization [3].

To expand upon previous studies, a utility cost minimization and residential aggregate load dispatch problem for V2G operation is formulated and solved using a reverse auction bidding system with a population-based metaheuristic algorithm in this paper. The first main contribution is using V2G operation to change the aggregate residential load shape to a constant, i.e. “dispatching" it, at minimum cost to the utility. The second main contribution is the co-simulation of a power system in Open-DSS, an open-source distribution system modeling software, and the optimization of bids using a non-dominated sorting genetic algorithm (NSGA-II) in Python to consider grid impact from power flow calculations in the objective function. This allows for the impact of EV discharging on aggregate power at the main feeder, active power of individual lines, thermal overloading of transformers based on rated and simulated power, voltage level across the system, etc. as simulated by OpenDSS on a particular distribution system to be considered between each V2G status candidate design.

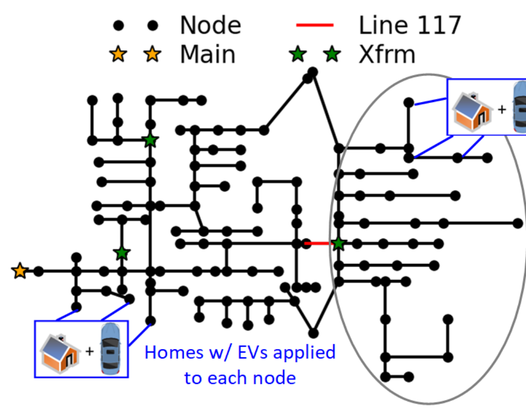

Fig. 1: IEEE 123 Bus System one line diagram for the case study with residential load. Line 117 represents a line constraint as physical limitation in eV2GA w/ 117 case study.

II. Problem Formulation for Dispatachable Residential Load using V2G

The proposed V2G control methodology is based on utility-bidirectional level 2 charger communication through CTA-2045 [4] or other methods. With this communication bridge, utilities may request EV owners in a distribution system to submit bids during demand response time periods using a reverse auction mechanism [5] for payment compensation in exchange for discharging power. Two decision stages are proposed: (S1) EV owners submit bids [$\$/kWh$ and kW] for the next discharge period, Δt in [h] and (S2) an optimization problem is solved to select the winning bids by minimizing

Algorithm 1: Evolutionary V2G Auction (eV2GA)

Input : List of EVs $\mathcal{EV}$, fitness function $f(.)$, max generations G_{max}, population size NP
Output: best identified feasible solution $\mathbf{q}^*$

Update set of EVs at time t $\mathcal{EV}_t$ and their SOC;
Collect bids $\langle a_i, b_i \rangle$ from each interested EV, ev_i;
Generate initial population $\mathcal{Q} = \{\mathbf{q_k} | \ k = 1, \dots, NP\}$;
while *termination criteria is not met* **do**
  for *each* $\mathbf{q_k} \in \mathcal{Q}$ **do**
    Create candidate $\bar{\mathbf{q}}_\mathbf{k}$ via mutation & crossover;
    Run OpenDSS and solve power flow for $\bar{\mathbf{q}}_\mathbf{k}$;
    Check power and other circuit constraints based on OpenDSS simulation;
    /* **Compare fitness** */
    if $(f(\bar{\mathbf{q}}_\mathbf{k}) < f(\mathbf{q_k}))$ *& constraints satisfied* **then**
      $\mathcal{Q} = (\mathcal{Q} \setminus \{\mathbf{q_k}\}) \cup \{\bar{\mathbf{q}}_\mathbf{k}\}$;
    end
  end
end
/* **Find the best solution from pool** */
Let $\mathbf{q}^* = \arg \max_{\mathbf{q_k} \in \mathcal{Q}} f(\mathbf{q_k})$;
Execute V2G operations for winning EV owners as per $\mathbf{q}^*$;

utility cost considering power system constraints, i.e. lines, equipment, and voltage levels (0.95-1.05 p.u.).

In stage (S1), an EV owner, $ev_i \in \mathcal{EV}(t)$, is defined as $ev_i \stackrel{\text{def}}{=} \langle k_i, SOC_i \rangle$ where k_i is the node to which ev_i is connected on the circuit as modeled in OpenDSS and SOC_i is the EV state of charge (SOC) upon arriving home. Interested EV owner, ev_i, with SOC_i higher than a minimum threhold SOC_{min}, submits the bid $\langle a_i, b_i \rangle$, i.e. their respective asking price, a_i in $\$/kWh$ to discharge at power level, b_i in kW, for the duration of the next discharge period. Let $q_i \in \{0,1\}$ be a set of binary decision variables that correspond to whether or not each $ev_i \in \mathcal{EV}$ is selected for V2G in the next time step.

In stage (S2), an optimization problem is defined to select the winning bids of the auction. The problem minimizes overall cost for the utility to meet the residential load. It also constrains the aggregate power at the circuit main feeder, P_l, to be below a selected threshold, P_T, for dispatchable constant residential load operation, which is of high interest to utilities. The problem is formally defined as follows:

$$\text{minimize } f(q)\text{: } \overbrace{\Big(P_l \Delta t\Big) \cdot b_o(t)}^{C_o} + \overbrace{\sum_{i \in \mathcal{EV}} a_i b_i q_i}^{\sum C_i^{EV}}$$

$$\text{s.t.} \quad \alpha P_T \leq P_l \leq P_T, \quad SOC_i \geq SOC_{min}, \quad q_i \leq \frac{SOC_i}{SOC_{min}},$$

$$\mathrm{q}_i \in \{0,1\}, \quad abs\left(1 - \frac{V_{k_i}}{V_{rated}}\right) q_i \leq \ 0.05 \text{ [p.u.]},$$

where C_o is total utility cost from generation, C_i^{EV} is total utility cost for V2G payment to selected EV owners, $b_o(t)$ is utility rate of generation in $\$/kWh$ at time t, and V_k is voltage at each node.

OpenDSS simulates P_l using internal Nodal Admittance formulation of the power system and Newton–Raphson power flow calculations, which are co-simulated through Python API. It is important to note that the individual EV discharging powers, b_i, residential load, line losses, and other distribution system parameters are considered by OpenDSS in the power flow simulation. The proposed algorithm for optimization is presented in Alg. 1, called *evolutionary V2G Auction (eV2GA)*. It adopts population-based Non-dominant Sorting Genetic Algorithm-II (NSGA-II) optimization to find a design solution matching the requested dispatch aggregate power by adjusting P_T.

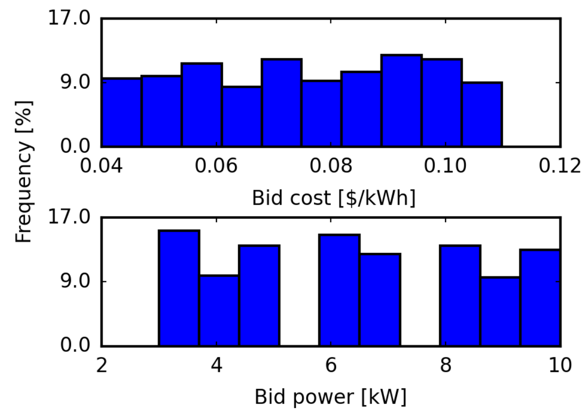

Fig. 2: Reverse auction distribution of bid cost based on experimental net-metering prices in CA and power rating between 2-10kW for level 2 bi-directional charger.

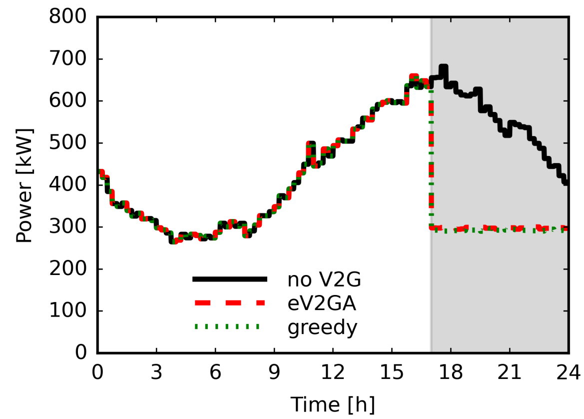

Fig. 3: Aggregate residential power at the main feeder is operated as a dispatchable load using V2G operation and the eV2GA algorithm.

III. Computational Case Study for Modified IEEE 123 Bus System

A future smart grid community with 100% EV penetration, i.e. an EV per house, is considered in the following study to showcase potential for grid savings. A modified model of the IEEE 123 Bus test feeder supplies 353 homes with residential load profiles based on minutely experimental results from a large community rural field demonstrator located in Glasgow, KY [6]. Each EV is assumed to have a round trip efficiency of 85% [7] and has a unique daily driving profile, home arrival time, and calculated SOC at home arrival time based on the 2017 National Household Travel Survey (NHTS) [8].

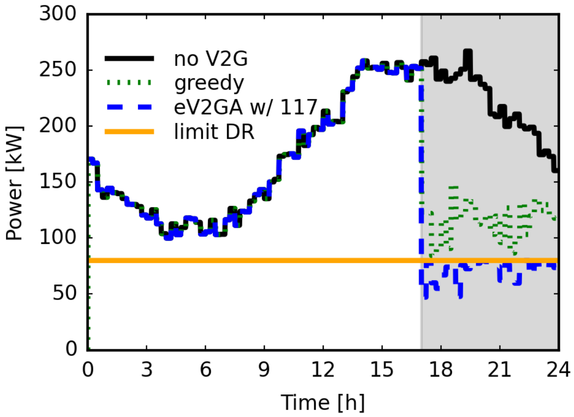

Fig. 4: Active power through line 117 between node 160 and 67 of the IEEE 123 Bus during no V2G, the greedy method, and eV2GA w/ 117 cases. The DR line limit of 80kW approximately one-third the peak load is visualized.

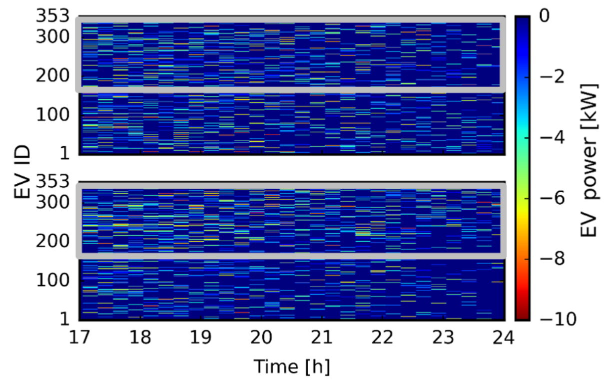

Fig. 5: Greedy algorithm (top) and eV2GA w/ 117 (bottom) EV discharging power selected. Highlighted by the gray boxes are EVs that discharge more frequently and at higher power levels in the eV2GA w/ 117 case as a result of the line constraint.

The proposed eV2GA algorithm including co-simulation with OpenDSS is applied to the residential community during a demand response (DR) time window of 17:00 - 24:00 with discharge periods, Δt, of 15 minutes to match smart meter data resolution. The P_T is set to 300kW, representing a 50% reduction in load from the circuit peak on the summer test day. The individual bids for payment, a_i, from the reverse auction were selected randomly between \$0.04-\$0.11/kWh, i.e. twice the cost of net metering from an example utility, due to increased cost to the user from EV battery degradation [9]. The bid discharge power, b_i, is also determined randomly between 2-10kW for residential bi-directional chargers as illustrated in Fig. 2. For each vehicle, an SOC_{min} of 50% was assumed for participation to ensure usability the following day. The utility generation rate, $b_o(t)$, per Δt is randomly sampled from a normal distribution of 50%-80% of average retail cost in CA, USA of \$0.18/kWh [10].

With these specified parameters, the optimization problem is formulated and solved 28 times in a minutely time series co-simulation. The aggregate power at the main feeder is reduced to meet the P_T using the energy distributed in EV across the distribution system (Fig. 3). The optimization procedure is validated against the true minimum cost without circuit constants as found by the greedy method [11], where the minimum bids are sorted and selected individually until the required V2G power per time step is met to reduce the aggregate power at the main feeder to below the threshold.

After 50 generations, the average reduction in cost as compared to no V2G operation in the DR time window from the NSGA-II based optimization solution is 23.04%. This is within 2% of the greedy method solution average reduction of 24.98% and is assumed satisfactory for minimizing cost while considering line constraints. While the NSGA-II completes in a small number of generations on this case study, its benefit is scalability with the current framework and bid system for larger distribution systems with thousands of homes and EVs.

IV. V2G Optimization including Line Power Constraints

The IEEE 123 Bus system is a robust and stable test-bench without line or voltage violation issues under residential load and with V2G operation, as expected. To emulate a distribution system that has not yet been updated to meet load growth or has limited line capacity, a reality for many distribution circuits undergoing a smart grid transition, a line power limit has been introduced onto bus 117 of the IEEE 123 Bus system, as indicated by the red line in Fig. 1. Line 117 represents a connection between two sub-circuits in the distribution circuit, and a capacity limit of 80kW is applied to reduce the allowed power flow between circuits to $\sim 30\%$ of the peak (Fig. 4).

The optimization algorithm is applied to the community of 353 homes with the same bids and an additional penalty constraint for the DR limit placed on line 117. The resulting design solution, termed eV2GA w/ 117, meets the line power limit and is compared to the reference true minimum solution from the greedy algorithm also in Fig. 4. The eV2GA w/ 117 solution shows a clustered group of EVs selected for V2G that were not not selected with out the line constraints. These vehicles with ID 210-353 are located after line 117 and are encircled in gray in Fig. 1. The power discharged from vehicles 210-353 is now much higher in Fig. 5 than for the greedy algorithm, showcasing the impact of physical line constraints and location of homes on the selection of EVs for V2G.

The location of these EVs influenced the market and V2G design selection more than user compensation cost as the bids selected in the eV2GA w/ 117 case are significantly higher for vehicles 210-353 than the greedy algorithm (Fig. 6). The competition to sell power in the sub-circuit before line 117 increased as a preference was placed on vehicles 210-353 due to their location, driving the bids for all other cars to be lower. The impact of physical line constraints on distribution system

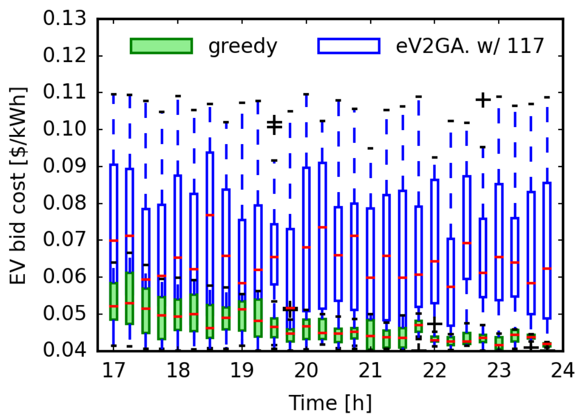

Fig. 6: Selected bids for EVs 210-353 located in the circled region of Fig. 1. The eV2A w/ 117 solution selects higher bids to meet line power limit due to the influence of the location on the market.

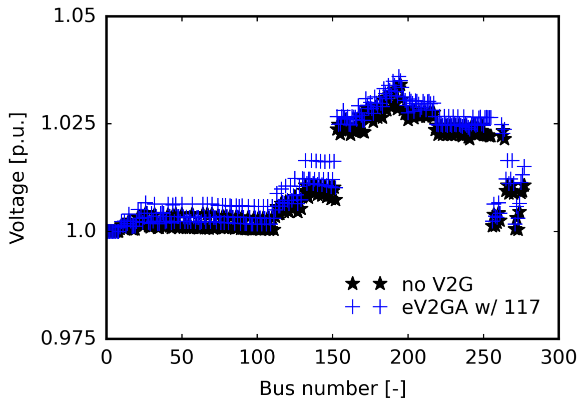

Fig. 7: A voltage rise is caused by the distributed V2G power injection. An additional application of eV2GA includes constraint from voltage violations caused by V2G at high penetrations on more unstable circuits.

V2G planning and the market between owners and utilities is exemplified on a benchmark system in this paper. Additional case studies with other physical constraints such as voltage across the system (Fig. 7), thermal overloading, and power losses may be considered through the proposed methodology.

The eV2GA w/ 117 solution appears more expensive for the utility with an average reduction in cost of 20.39%. Only a 4.59 % reduction in savings occurs from than the greedy method, and system limitations from physical equipment are considered, which may cost the utility significantly from damages if violated. The importance of including physical constraints into V2G optimizations and controls is highlighted.

V. Conclusion

The newly proposed eV2GA algorithm ensures dispatchability of aggregate residential load in a future smart grid community with high EV penetration while minimizing the cost paid by the utility to meet the load for the DR time period. Within the eV2GA, co-simulation of OpenDSS and Python allows for detailed power flow calculations in the objective function that consider line equipment and physical constraints of the distribution system.

The first case study on the modified IEEE 123 Bus test feeder with over 300 hundred homes, EVs, and no additional distribution system constraints validates the eV2GA algorithm against the greedy method and true minimum average reduction in cost solution to within 2% after 50 generations. The benefit of the NSGA-II algorithm is that additional constraints and parameters may be considered with the proposed framework on more complex circuits of thousands of nodes.

The second case study includes a power flow limit on a key line connecting two sub-circuits, and it documents the influence of EV location on the reverse auction system. Preference was placed on vehicles whose discharging alleviates strain on parts of the distribution system over cheaper vehicles in other places. The eV2GA algorithm is scalable to additional circuits and constraints including thermal overloading, voltage violations, and power losses.

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References

[1] M. Müller, Y. Blume, and J. Reinhard, "Impact of behind-the-meter optimised bidirectional electric vehicles on the distribution grid load," *Energy*, vol. 255, p. 124537, 2022.

[2] J. Thakur, C. Martins Leite de Almeida, and A. G. Baskar, "Electric vehicle batteries for a circular economy: Second life batteries as residential stationary storage," *Journal of Cleaner Production*, vol. 375, p. 134066, 2022.

[3] T. Boonseng, A. Sangswang, S. Naetiladdanon, and S. Gurung, "A new two-stage approach to coordinate electrical vehicles for satisfaction of grid and customer requirements," *Applied Sciences (Switzerland)*, vol. 11, no. 9, 2021.

[4] C. Thomas, "Performance test results: Cta-2045 electric vehicle supply equipment," Electric Power Research Institute (EPRI), Palo Alto, California (United States), Tech. Rep. 3002011757, 2017.

[5] H. Liu, Y. Zhang, S. Zheng, and Y. Li, "Electric vehicle power trading mechanism based on blockchain and smart contract in v2g network," *IEEE Access*, vol. 7, pp. 160 546–160 558, 2019.

[6] H. Gong, R. E. Alden, and D. M. Ionel, "Stochastic battery soc model of ev community for v2g operations using cta-2045 standards," in *2022 IEEE Transportation Electrification Conference & Expo (ITEC)*, 2022, pp. 1144–1147.

[7] J. Sears, D. Roberts, and K. Glitman, "A comparison of electric vehicle level 1 and level 2 charging efficiency," in *2014 IEEE Conference on Technologies for Sustainability (SusTech)*, 2014, pp. 255–258.

[8] "National Travel Household Survey," https://nhts.ornl.gov/, accessed: 2020-5-13.

[9] "SDGE True Up Monthly Rate Table," https://www.sdge.com/residential/savings-center/solar-power-renewable-energy/net-energy-metering/billing-information/excess-generation, accessed: 2022-10-10.

[10] "Us electricity profile 2021," https://www.eia.gov/electricity/state/, accessed: 2022-10-10.

[11] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to algorithms*. MIT press, 2022.