The Value of Operational Coordination for EV Fleet Aggregators

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Abstract—The integration of energy systems such as electricity and gas grids and power and thermal grids can bring significant benefits in terms of system security, reliability, and reduced emissions. Another alternative coupling of sectors with large potential benefits is the power and transportation networks. This is primarily due to the increasing use of electric vehicles (EV) and their demand on the power grid. Besides, the production and operating costs of EVs and battery technologies are steadily decreasing, while tax credits for EV purchase and usage are being offered to users in developed countries. The power grid is also undergoing major upgrades and changes with the aim of ensuring environmentally sustainable grids. These factors influence our work. We present a new operating model for an integrated EV-grid system that incorporates a set of aggregators (owning a fleet of EVs) with partial access to the distribution grid. Then, the Cooperative Game Theory is used to model the behavior of the system. The Core is used to describe the stability of the interaction between these aggregators, and the Shapley value is used to assign costs to them. The results obtained show the benefit of cooperation, which could lead to an overall reduction in energy consumption, reduced operating costs for electric vehicles and the distribution grid, and, in some cases, the additional monetary budget available to reinforce the transmission and grid infrastructures.

Index Terms—Aggregators, Cooperative Game Theory, Electromobility, EV, Aumann Game

I. INTRODUCTION

The numerous advantages of EVs have made them a good choice for grid power management, voltage regulation and power quality improvement [1]. The possibility of operating EVs as energy storage devices, components of virtual power plants and as scheduled loads for peak shaving has made them increasingly popular in power system studies. Coupled with these advantages is their replacing the internal combustion engine vehicles for climate change mitigation.

However, some negative effects have also been associated with EV integration with the power grid. EV loads are nonlinear because human behavior is unpredictable, thus, charging behavior is also largely unpredictable. Moreover, increasing usage of fast chargers means large amount of power can be drawn in a short time which further leads to the challenge of stability of the power grid [2]. Additionally, a large number of EVs leads to a high amount of power requirement from the grid. The enormous amount of real power consumption leads directly to large power loss in the distribution system [3]. A coordinated charging scheme can however be a suitable solution to this challenge. As stated earlier, however, human actions are unpredictable and coordination can only be possible on an aggregated scale.

Coordination schemes have been proposed to address some of the challenges stated. Some of the coordinating objectives have included optimization of total energy cost by minimizing the energy losses due to charging/discharging schedules of a large number of EVs and minimizing operation cost [4]. Taking the distribution network into account, the optimization of EV charging while considering the distribution network constraints have also been reported [5].

One of the EV charging coordination schemes that has been proposed is valley filling. Offline and online valley filling algorithms with time-dependent optimal power flow problem were used in [6], [7]. In [8], a mode of decentralized coordination of charging large populations of EVs for electricity costs minimization was proposed. [9] presented a mode of efficient grid operation while fulfilling the energy requirements of a large number of EVs. In summary, these methods seek to create a profitable scenario for both EV users and the power grid while minimizing power loss and maximizing load factor.

In this paper, we extend our definition of coordination to transcend numerous single-user EVs and we consider another approach similar to integration of power systems. Systems integration has advantages of decrease of global operation cost, systems reliability and environmental benefits. Integration of electricity and thermal systems in microgrids was proposed in [10] with minimization of overall operation cost as the objective. An energy management operation model combining bio-gas, solar and wind renewables was presented in [11] while [12] proposed a robust energy management scheme for multiple interconnected microgrids in the real time energy market. While integration of multiple systems might or might not include trade-offs, it is customary to evaluate costs and/or benefits and how these are distributed among the different entities involved in the integration.

Non-cooperative and cooperative game theory frameworks have been proposed in the subject of integration, respectively, with respect to maximizing utility and sharing costs among the different players. Non-cooperative game theory was utilized in [13] to solve an optimization problem involving multiple CHPs with uncertainties in market prices and customer demand. An energy management scheme for coordinated electricity and heat demand response scheme was presented in [14] using non-cooperative game theory as well.

For cooperative game theory, Shapley value is used in the distribution of the worth of each coalition, either in terms of costs or benefits. In [15], cooperative game theory model for several households sharing renewable and energy storage space was presented with the objective of reducing energy consumption costs. A coalitional game based approach for power exchange by different microgrids on a network was proposed in [16]. An inherent challenge, however, with cooperative game theory is intractability which might arise as the number of entities involved increases.

An important consideration that has not been highlighted in the literature is interoperability of charging stations owned by more than one aggregator. In fact, most studies that have included aggregator have only modelled a single fleet owner with many EVs. Our major contribution, thus, is the formulation of a coalitional-game based model involving multiple aggregators in a distribution grid-transport network integrated system. These aggregators can use each other’s charging stations and the value of these coalitions will be important for fleet owners in making decisions whether to cooperate with one another. This coalition value, which is a criteria for decision making by the EV aggregators, is one of the objectives of our investigation. The impact of these coalitions on overall energy consumption and CO₂ emissions will also be addressed. We address the problem of intractability by the use of aggregators. The maximum number of
fleets, Owners may not be modelled using extensive form and strategic form games and incomplete information scenarios fall largely under this category.

A. Model of Incomplete Information

Modelling our case study as a variant of non-cooperative game is a classic example of games with incomplete information. The situations here are such that aggregators do not have complete information on the environment they face. As a result of the interactive nature of the game, formulating such situations involves not only the knowledge and beliefs of the players, but also the whole hierarchy of knowledge of each player [17].

This rather infinite knowledge base might be infeasible in evaluating real life scenarios. Studies have shown, however, that most people rarely engage in more than second order common knowledge (about all other players’ knowledge) which makes evaluation of scenarios feasible [18]. In our case, there are some common knowledge which primarily include the transport and electric grid network. Here, we utilize the Aumann model of incomplete information with beliefs for our formulation. The solution here will arise from players settling on just the prior information received before facing the game. A formal definition of the Aumann model consists of

\[(N, Y, (F_i)_{i \in N}, s, P)\]

where:

- \(N\) is a finite set of players;
- \(Y\) is a finite set of states of the world;
- \((F_i)_{i \in N}\) is a partition of \(Y\), for each \(i \in N\);
- \(s : Y \rightarrow S\) is a function associating a state of nature to every state of the world;
- \(P\) is a probability distribution over \(Y\) such that \(P(\omega) > 0\) for each \(\omega \in Y\); \(\omega\) is a state of the world.

\(N\) represents EV aggregators in our case. The state of nature is the parameter with respect to which there is incomplete information: for an e-mobility example, the route through which EV \(k\) owned by aggregator I takes passengers from origin \(i\) to destination \(j\). Thus, \(F_i = \{x_{ijk} \forall i, j, k\}\) : all routes from origin to destination by vehicles owned by aggregator I. The same can be defined for other aggregators as required.

To enumerate this model, we present two games with different belief spaces: the beliefs we employed are chosen based on current system practices. For our particular subject, consistent beliefs held by all aggregators are (i) knowledge of transport and electric grid (i.e. all aggregators in New York City have perfect knowledge of the transport network and the power grid of New York City) and (ii) knowledge of relative locations of other aggregators (i.e. aggregator A knows the location of aggregator B’s assets, depot etc.) The difference between our games occurs in cases when (a) users are aggregator-aware, i.e., much like the current transportation service providers landscape, users can decide which aggregator(s) to call using their mobile applications or other available access points; (b) users are aggregator-blind which means users do not choose which aggregator provides their transportation requirements. Variants of these two games were outlined in [19].

B. Cooperative Games Allocation Rules

We propose modeling a coalition game where the Core is analyzed to determine if there are opportunities for cooperation and then costs or benefits are shared to each player by Shapley value computation. The Shapley value is a solution concept used for fair and efficient distribution of gains or costs to several players working in a coalition [20]. For this work, we evaluate the cost that each aggregator has to pay and thus, we will formulate a cost sharing game.
C. The Core

Let \((N; c)\) be the cost-sharing coalitional game where \(N\) is the number of EV aggregators, and \(c\) is the coalitional function.

The Core is used in describing the solution set of all stable cost allocations obtained. For the problem(s) presented, there are two obvious possibilities which are defined by stability and fairness. Either all players will form the grand coalition where they all cooperate or they deviate and form sub-coalitions. The scenario that an adjudicator wants is for every player to be a part of the grand coalition and reduce the possibility of deviation from this. The grand an adjudicator wants is for every player to be a part of the grand cooperate or they deviate and form sub-coalitions. The scenario that

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The Core is termed the result of rational coalition [17], meaning that: (i) no player obtains a higher cost than what he could get on his own, also known as individual rationality principle (1a); (ii) the sum of the costs paid by each individual player is equal to the sum of the cost of the grand coalition, also known as game efficiency principle (1b); and (iii) for every sub-coalition, \(S\), formed which is not the grand coalition, no player \(i\) should pay more than it would if acting alone, also known as coalitionally rational principle (1c).

We should note that it is not every instance where there are workable agreements between players and games can fail at those instances. However, when the Core is non-empty, it aids in determining the stability of the coalition(s) while the Shapley value, a single-valued solution concept, is used for allocating costs to each player who participates in the game.

D. Shapley Value

The Shapley value, which we use for cost sharing among players in here, is computed by

\[
Sh_i(N; c) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (c(S \cup \{i\}) - c(S)) \tag{2}
\]

where |\(N\)| is the total number of players in the game and the sum ranges over the subsets \(S\) of the coalitions which does not contain the player \(i\). The term \(c(S \cup \{i\}) - c(S)\) represents the marginal contribution of player \(i\) to the coalition \(S\). This value is the solution of the EV transport routing problem described below.

E. EV Transport Routing

The transport routing problem answers the question of optimal assignment of routes to a fleet of vehicles based on the needs of customers in different locations in a transportation network. The main objective of transport routing is the minimization of the total distance traversed by all vehicles, although other alternative objectives are possible.

For EVs, an efficient battery management system needs to be modelled to account for energy usage. The objective here is minimization of the overall cost of energy used and this includes the reduction of time spent in charging stations outside the depot. Additionally, the distribution grid is coupled in our formulation because our approach leverages the benefits of the co-optimization of the electric-transport integrated system. This co-optimization ensures the stability of voltage variations in distribution grid is within acceptable bounds and satisfaction of network constraints. A linear representation of the distribution grid, LinDistFlow [21], is utilized here. This also allows easy coupling of the energy drawn by the EV to the local consumption at the charging station. Full formulations for EV routing, energy management and distribution grid are outlined in online appendix [22].

F. Overall Framework

Finally, our goal is to evaluate the allocation of operation cost of an EV fleet and distribution grid when the aggregators cooperate using the flowchart in Figure 2. This is achieved by enumerating possible coalitions by aggregators and then computing the share that accrues to them in a successful coalition. The successful coalition is thereafter evaluated for the assignment of routes and charging schedules.

IV. RESULTS AND DISCUSSIONS

A. Transportation Network Data

The case study selected for validating our proposed methodology is based on the Downtown Manhattan transportation network. Drop-off and pick-up data is taken from taxi trip records by the New York City Taxi and Limousine Commission for 2018 [23]. The data set includes pick-up and drop-off dates, times, locations, trip distances and driver-reported passenger counts.

Using latitudes and longitudes, we divided the data into distinct locations such as commercial, industrial, and residential regions. With this division, we were then able to track movement patterns at different times of the day. For example, people generally move from residential areas to commercial and industrial centers in the mornings and vice versa in the evenings.
Fig. 3a demonstrates a geographical snapshot of the demand data, which is at the Downtown Manhattan grid, where green squares represent originating nodes, red circles represent destination nodes and large blue triangles are EV charging stations.

Fig. 3: Downtown Manhattan transport and energy demands

B. Electric Network Data

For local electricity consumption, we obtained information from [24] and New York City Mayor’s Office of the Long-Term Planning and Sustainability [25]. Electricity consumption at each block and lot level was obtained from [24] and consumption patterns are shown by the different shades of red in Fig. 3b. Darker red colors show regions of high power consumption while lighter/yellow colors show areas of low energy usage. Voltage ratings of each charging station location and reactance between stations were estimated similarly to [26].

We first present Case A comprising 2 scenarios which serves as our benchmark before we describe the cooperative games comprising 3 to 6 aggregators.

C. Case A: Model of Incomplete Information

The Aumann game is defined as follows:
- The set of aggregators \( N = \{\text{Agg. I, Agg. II, Agg. III}\} \)
- The set of states of the world \( Y = \{\text{routes to satisfy all passengers}\} \)
- The information partitions of the players are network dependent and this is based on which part of the grid customer requests originate.
- The common prior we select as \( \frac{1}{3} \) for each state of the world, i.e., there is a 1 in 3 chance that any of the aggregators will be chosen to transport a passenger from an origin to a destination.

1) Case A1. Aggregator-aware Transport Service

The first case is for aggregator-aware users, that decide by themselves about the aggregator that provides the service. Deduction from real life cases reveals that users choose which transport service provider they want to use at the particular instance. Either the public transit or one of the numerous private ride sharing providers. The energy usage and cost incurred by each aggregator (obtained by solving the Case A model with model from [22]) is shown in Table I. The values in the table will be compared with the results obtained from cooperative game framework at the end of this section.

| Aggregator | Value Fnc($) | E (kWh) |
|------------|-------------|---------|
| 1          | 2.373       | 8.625   |
| 2          | 4.323       | 17.466  |
| 3          | 2.373       | 9.588   |

As noted in the model, each aggregator has a 1 in 3 chance to be chosen for the routing. Thus, least cost route amongst aggregators cannot be ascertained in this case. This choice, in effect, could lead to choosing the farthest provider at some point. However, this choice of farthest service provider is as likely as the choice of the closest provider. Further, interactions between aggregators could, over time, lead to an equilibrium of efficient operation by the aggregators.

2) Case A2. Aggregator-blind Transport Service

This is why we decided to carry out a similar analysis but with aggregator-blind users. It means users/passengers cannot decide which aggregator provides their service. This could be restrictive but, owing to the extent of unknowns that might be encountered, could lead to some interesting inferences. As seen in Table II, aggregator 2 participated only once in the routing while all other routes were made by aggregators 2 and 3. This makes sense since all aggregators now have access to all demands at any time and each could decide whether offering a particular service would be optimal or otherwise. This is substantially different from the case A1 where aggregator 2 got about half the total value function as well as expended half of the energy consumed. While this case 2 might not be feasible due to recent practises, it is an option which might give results close to coalition efforts as described below.

D. Case B: 3 EV Aggregators

We model our first coalition case study for 3 EV fleet aggregators. Case B has the following properties:
- 3 fleet aggregators with 3 different depots (the depot is the location of an EV before the first trip of the scheduling period);
- 5 charging stations, each fleet owns at least one station;
- Total number of customer nodes is 12 (these are temporary locations where an EV picks up or drops off a passenger).

The value function for each individual aggregator as well as the coalition value functions, together with energy consumption for each sub-coalition, are shown in Table III. The cost of the grand coalition (last row on Table III) are: \( \varphi_1 = -0.062, \varphi_2 = 0.828, \) and \( \varphi_3 = 0.614. \) The aggregator 1 gets a negative cost which implies that part of the contribution of aggregators 2 and 3 will be given to 1. This is, however, not an aberration. Aggregator 1, working alone, has the least cost and thus will be profitable in any coalition which it joins. Thus, any other aggregator wants to partner with aggregator 1 because it will lead to a significant cost reduction.

From Table III, the best outcome for any aggregator is when all three cooperate. In the absence of this all-three coalition, aggregators 2 & 3 have the incentive only to cooperate with each other, i.e. no other 2-aggregator coalition results in a Nash Equilibrium aside \( \{2, 3\}. \) The Core is shown in Fig 4 as the dark grey area while Shapley

| Coalition | Value Fnc($) | \( \varphi_1 ($) \) | \( \varphi_2 ($) \) | \( \varphi_3 ($) \) | E (kWh) |
|-----------|--------------|-----------------|-----------------|-----------------|---------|
| 1         | 1.850        | 1.850           | -               | -               | 7.488   |
| 2         | 3.044        | -               | 3.044           | -               | 12.321  |
| 3         | 2.651        | -               | -               | 2.651           | 10.731  |
| 1, 2      | 1.635        | 0.220           | 1.414           | -               | 6.618   |
| 1, 3      | 1.599        | 0.399           | -               | 1.200           | 6.474   |
| 2, 3      | 2.187        | -               | 1.290           | 0.897           | 8.854   |
| 1, 2, 3   | 1.381        | -0.062          | 0.828           | 0.614           | 5.586   |
value is the red circle. The relative position of each player is shown in green text.

The Core shows all available coalitions with respective values that each aggregator might accept. Thus, we could have scenarios where concessions are made where aggregators do not accept the hard values given by Shapley computation. For example, what if aggregators 2 and 3 decide not to pay the negative cost to 1 i.e. aggregator 1 pays nothing? Aggregator 1 would still be satisfied (see Fig 4 where the tip of aggregator 1 touches the axis). In fact, 1 would be contented until his cost increases to $0.4. This cost of $0.4 for aggregator 1 is the highest cost he can pay until 2 & 3 have no additional incentive to refrain from the grand coalition. As shown in the preceding paragraph, aggregators 2 & 3 have an incentive to cut 1 out of the whole cooperation framework and pursue their own coalition, {2, 3}. This incentive for 1 to be left out could prompt it to accept costs set out by 2 & 3.

Energy consumption follows the same trend as cost; single aggregators use more energy but forming coalitions leads to reduced energy consumption. Additionally, ability to use each others resources means vehicles do not have to travel long distances before their next recharge. If we compare energy usage when aggregators are acting alone and the grand coalition, the maximum energy saving is observed between when {2} and {1,2,3}. This scenario leads to reduction in energy consumption by half while the least energy savings is a reduction of energy consumption of {1} by a quarter. This reduction in energy consumption directly translates to a reduction in emissions. Here, we compare the two benchmark scenarios in Tables I & II routing and energy usage results showed that Aggregator 1 took the bulk share. Again, this is confirmed in the first row of Table II.

E. Case C: 4 EV Aggregators

Case C has the following properties:

- Four fleet aggregators with 4 different depots; each fleet has the same number of vehicles as others. The fleets are also distributed strategically across the transport network such that aggregators 2, 3 & 4 are centrally located while 1 is far from the center.
- Six charging stations, each fleet owning at least one;
- Total number of customer nodes is extended to 15 to afford more interaction between aggregators.

The Core is shown in Fig 5. Unlike the case with 3 aggregators, the Core here is smaller and players do not have a big margin for deviation from the grand coalition. The Shapley value is given by the following vector:

\[
[\varphi_1, \varphi_2, \varphi_3, \varphi_4] = [0.771, 0.176, 0.054, -0.075]
\]

Again, the fourth aggregator gets a negative cost. This means part of the contributions from the other aggregators will go to the fourth one. This is so because aggregator 4 has the lowest cost when each of the aggregators acts alone. The Core is shown in Fig 5.

F. Scalability Analysis

Here, we carry out a sensitivity analysis by considering energy consumption trend with many nodes as well as many aggregators. As will be expected, many aggregators cooperating leads to reduced energy consumption. In Fig 6, the vertical axis represent the energy consumption over the timeline of routing and scheduling. The horizontal axis indicates the number of aggregators while \( J \) represents the number of nodes in the Downtown Manhattan transport and energy network.

There is a general trend of decrease in cost and energy consumption as the number of aggregators rises. Thus, an increase of the economic efficiency. For a few locations on the network, this trend might mean a little decrease in cost or energy consumption. However, as the number of nodes increases, we observe a sharp decrease in energy usage and cost as aggregators increase. When there are multiple aggregators, there is a high probability that they would be spread out across the grid such that there can be efficient service provision. This then leads to lesser travel time for individual vehicles. In terms of energy requirement, the same argument can be made in this regard. As EVs are distributed uniformly across the grid, thereby reducing the distribution grid congestion.

V. Conclusion

This paper presents a cooperative game theory approach for evaluating the value of decentralized coordination of EV fleets by aggregators. A new EV-power grid integrated system model was introduced to describe the technical operation that our formulation was based on. We proposed two games with incomplete information,
some level of stochasticity is still expected in power consumption. Profiles of residences, commercial buildings and transport facilities), specific periods might be predictable (as judged from the daily load in power consumption at local level. While power consumption is catered for. Another section not assessed in depth is the uncertainties utilized for this; however, how much realistically can these costs be addressed using cooperative game modelling. Allocation rules were set based on cost of operation of the grid and EVs while we used the Core to define the stability of the games. For efficiency and fairness, we utilized the Shapley value for cost allocation.

The objective of our cooperative game is the result of an EV transport routing problem that considers the distribution power grid. This objective also forms the marginal contribution of each aggregator to the coalitions/sub-coalitions which the aggregator is part of. We carried out tests on a set of nodes with 3 to 6 aggregators and were able to come to some conclusions:

1) The relative location of a fleet aggregator influences his contribution to any coalition he is a part of; if a fleet owner is not close to pickup and drop-off of demands on the transport network, he would pay more than those fleet owners who are otherwise located.

2) The coalition framework mirrors the aggregator blind scenario in terms of effectively reducing transportation cost and minimizing energy consumption by vehicle fleet.

3) An aggregator can accrue negative cost; i.e. would receive extra payment from other aggregators. This might be the result of Shapley Value but the Core shows that other payment arrangements are possible.

4) There is a general trend of decrease in cost and energy consumption as the number of aggregators rise. For few locations on the network, this trend might mean small percentage cost or energy consumption decrease. As the number of nodes increase, we observe a sharp decrease in energy usage and cost as aggregators increase. This could be a result of even distribution of aggregators across the network; leading to lesser travel time for individual vehicles and also less stringent demands on the distribution grid.

Future directions for this work may include investigating quantitatively ancillary services provision to the grid. The implication has been made here that extra cost accrued from cooperation might be utilized for this; however, how much realistically can these costs cater for. Another section not assessed in depth is the uncertainties in power consumption at local level. While power consumption at specific periods might be predictable (as adjudged from the daily load profiles of residences, commercial buildings and transport facilities), some level of stochasticity is still expected in power consumption. Thus, this could be a subject of further research.

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Fig. 6: Energy consumption for increasing nodes namely, aggregator-aware and aggregator-blind scenarios, as benchmarks for our coordination schemes. Inter-fleet coordination was then addressed using cooperative game modelling. Allocation rules were set based on cost of operation of the grid and EVs while we used the Core to define the stability of the games. For efficiency and fairness, we utilized the Shapley value for cost allocation.

The objective of our cooperative game is the result of an EV transport routing problem that considers the distribution power grid. This objective also forms the marginal contribution of each aggregator to the coalitions/sub-coalitions which the aggregator is part of. We carried out tests on a set of nodes with 3 to 6 aggregators and were able to come to some conclusions:

1) The relative location of a fleet aggregator influences his contribution to any coalition he is a part of; if a fleet owner is not close to pickup and drop-off of demands on the transport network, he would pay more than those fleet owners who are otherwise located.

2) The coalition framework mirrors the aggregator blind scenario in terms of effectively reducing transportation cost and minimizing energy consumption by vehicle fleet.

3) An aggregator can accrue negative cost; i.e. would receive extra payment from other aggregators. This might be the result of Shapley Value but the Core shows that other payment arrangements are possible.

4) There is a general trend of decrease in cost and energy consumption as the number of aggregators rise. For few locations on the network, this trend might mean small percentage cost or energy consumption decrease. As the number of nodes increase, we observe a sharp decrease in energy usage and cost as aggregators increase. This could be a result of even distribution of aggregators across the network; leading to lesser travel time for individual vehicles and also less stringent demands on the distribution grid.

Future directions for this work may include investigating quantitatively ancillary services provision to the grid. The implication has been made here that extra cost accrued from cooperation might be utilized for this; however, how much realistically can these costs cater for. Another section not assessed in depth is the uncertainties in power consumption at local level. While power consumption at specific periods might be predictable (as adjudged from the daily load profiles of residences, commercial buildings and transport facilities), some level of stochasticity is still expected in power consumption. Thus, this could be a subject of further research.