A Proposed Framework for Heuristic Approaches to Resource Allocation in the Emerging Smart Grid

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Abstract—**As smart grids introduce profound changes in the operation of the electric power industry, the need for efficient and robust resource allocation (RA) algorithms arises, especially due to the increasingly stochastic nature of availability of highly dispersed resources. A framework for solving the smart grid RA (SGRA) problem using a heuristic approach such as a genetic algorithm is presented in this paper. Similar challenges exist in resource allocation in the realm of computing. A comparison is drawn between SGRA and computing RA. Its application to a multi-agent-based distribution management system, used as an environment model, is also proposed. A path forward concludes the paper.**

Keywords – distributed generation, energy storage, genetic algorithm, heuristic, multi-agent systems, plug-in electric vehicle, resource allocation, smart grid.

I. Introduction

As power systems and information technologies are converging to revolutionize the way electricity is generated, delivered, managed, and consumed, new challenges arise, such as: how to integrate storage efficiently, how to use demand-response of residential customers to mitigate peak demand, etc. [1]. Succinctly this can be surmised as: how should resources be allocated in the emerging smart grid as the stochastic nature of the availability of resources (generation, storage, and loads) becomes prevalent?

Contrary to the transmission level, where relatively few numbers of assets, albeit rated large, are used, the smart grid is expected to revolutionize the distribution side, where a multitude of smaller assets will be available for controlled deployment. Distributed and intermittent renewable energy sources, distributed storage elements such as plug-in hybrid vehicles, and the ability to schedule loads require utilities to rethink the conventional procedures of scheduling and dispatching the resources.

A similar challenge exists for computer scientists in allocating resources for computing. Several similarities can be drawn between the challenges in the domains of smart grids and computing. In computing, it is beneficial to allocate tasks to machines that they perform well on to optimize some system performance measure. Like in the emerging smart grid, the availability of the resources may be stochastic in nature. For example, this may arise due to the uncertainty in task execution times as well as the sharing of machine resources [2]. These similarities indicate the possibility of adapting some of the approaches used in the computing realm to the resource allocation problem in the emerging area of smart grids.

The main contribution of the paper is to propose a framework for addressing the large-scale distributed smart grid resource allocation problem using heuristics adapted from the computing resource allocation world. Specifically, a genetic algorithm is used to showcase the framework for the heuristic approach.

Section II describes the environment model, in which a multi-agent-based distribution system model is presented. In Section III, the resource allocation problem in smart grids is described. An example of how heuristics have been used in the field of computing is shown in Section IV. Section V proposes a framework for a heuristic approach to the resource allocation problem in the emerging smart grid. Lastly, Section VI indicates a path forward to continue with the framework proposed in the paper.

II. Multi-Agent-Based Distribution System Model

A. An Overview

Contrary to wide-area transmission systems that have long been largely automated and equipped with smart functionalities, most smart grid activities are beginning to focus on the automation of end-user distribution systems [3]. In such an emerging smart grid, a multitude of assets, including local generation sources, distributed energy sources, special loads such as plug-in hybrid electric vehicles (PHEVs), and other schedulable loads, are available for control and deployment. It is imperative to schedule and deploy such assets properly, lest there may be additional stress on the grid. These activities, usually called unit commitment and economic dispatch, are used in transmission systems [4][5], but are not suited for large distribution systems with thousands of resources. It is in that regard that a multi-agent framework for a highly distributed distribution system is presented.

B. Multi-agent modeling

Distribution systems connect the transmission system to end-users and, therefore, include a large number of

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customers with various profiles that are spread over the entire distribution network. Traditional power system modeling tools usually focus on transmission and aggregate data from distribution. However, as customers are expected to play an increasingly important role in smart grids, new tools that take into account the diversity and stochasticity associated with the end-user must be developed to comprehensively quantify and analyze the operation of the smart grid.

Multi-agent systems offer a solution to study such large systems by creating a model for each element of the system (agent) and interconnecting them to create a multi-agent system (MAS). A MAS is thus a group of agents interacting with each other and their environment [6]. This approach also enables modeling each element separately and not just the aggregated or lumped static versions of the load.

At the same time, MASs help define the interactions between the individual elements (agents) of the system. This facilitates estimating the required communication infrastructure, enabling faster real-scale deployment, and is particularly relevant as smart grids rely on a highly dispersed and efficient communication.

C. Multi-agent distribution system architecture

A multi-agent model of a distribution system is thus proposed and serves as an environment model for the resource allocation (RA) problem. In this model, each market player of the system is modeled as an agent. The independent system operator (ISO) is a non-profit entity that maintains the balance between supply (generation) and demand (system load) at the transmission level. Distribution system operators (DSOs) are connected to the ISO, and are responsible for distributing power to their customers. Each DSO has several physical assets, such as substations and feeders, that help transfer electric energy to the end user (residential, commercial, or industrial). Each of these customers has traditional loads, and may also have specialized assets such as PHEVs, and local distributed generators (DG) such as photovoltaic panels.

Every asset in the distribution system is expected to be under the control of an agent. A typical smart distribution system can be represented by the hierarchical structure of communication flow shown in Figure 1. Aggregators can act as interfaces between end-users and DSOs, notably for PHEVs charge-recharge scheduling and for provision of certain ancillary services [7]. Additionally, large DGs and storage units may also be connected directly to substations.

Each agent is in charge of controlling the actuators of the asset associated with it, using inputs from other agents and from local measurements, and subscribing to local goals. A local goal for an agent may include maximization of the availability of the associated asset for demand response events. Inputs from other agents may include set point requests from a central controller; upon receipt, the agent can decide to implement certain actions based on local objectives. Although this approach might seem contrary to traditional MAS concepts, it enables the developed system to account for communication aspects that are an essential topic in smart grids. Based on the environment model shown in Figure 1, algorithms to allocate resources (generation, storage, loads) efficiently need to be developed.

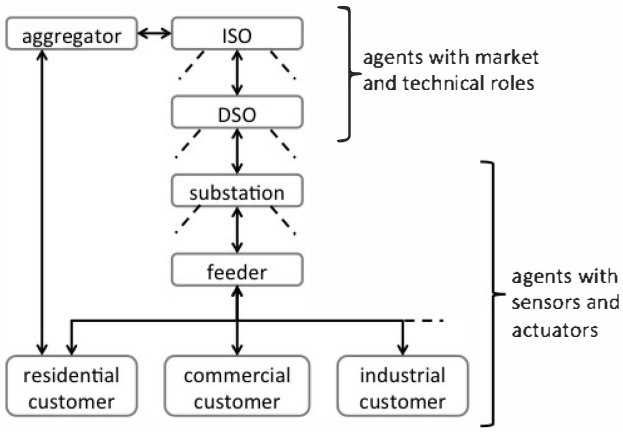

Figure 1: Architecture of the agent-based distribution system model. Dashed lines indicate connections with more agents of the same kind [8].

III. Resource Allocation in Smart Grids

A. Resource allocation in present day power grids

Resource allocation methods such as unit commitment (i.e., scheduling the use or non-use of generators a day in advance) and economic dispatch (i.e., optimizing the scheduled generator outputs) have been used for decades in electric grids at the transmission level for centralized assets [4]. As present day power grids evolve to include highly dispersed assets at the end-user domain available for control and deployment, the RA problem may require some departures from the traditional techniques of optimization, such as heuristic optimization methods like genetic algorithms [9-12] and particle swarm optimization [13], for solving unit commitment and economic dispatch.

B. Smart grid resource allocation problem complexity

The RA problem in smart grids is more complex than in traditional grids for the following reasons: 1) the number of schedulable assets in the decentralized distribution system is exceptionally large compared to the traditional centralized model of the grid; and 2) the stochastic nature of loads, generation, and storage. Load (demand) varies in real-time with customers' activity, but can be forecast using well-known artificial intelligence techniques that have been used by utilities for decades [14]. However, the capacity to manage demand through various mechanisms introduces yet another degree of uncertainty, as demand can be influenced, for example, through a utility contract such as time-of-use (ToU) billing [1]. The increase of distributed renewable energy sources (RES) in the electric grid, especially those with intermittent inputs as wind and solar, introduces a shift from the status quo, where a smaller number of high-rated centralized generators are dispatched concomitantly with greater certainty in output than RES.

The deployment of storage in the grid – from PHEVs to large utility-scale storage – enables new energy management possibilities. However, maintaining the state-of-charge (SOC) of battery energy storage system (BESS) units introduces a time-dependence; e.g., to be able to provide power during a demand peak, a unit has to charge as much as possible several hours in advance. In the case of PHEVs, the need for maintaining a certain SOC for enabling the primary function (transportation) of the asset introduces yet another constraint in the energy management scheme. Only PHEVs will be considered for storage in this paper, due to their distributed nature and relatively lower capital cost for the end-user arising from the dual use of this asset compared to dedicated energy storage devices.

While the end-user sector of the grid is undergoing unprecedented transformation through the "Smart Grid Initiative" [15], the transmission sector, which forms the backbone of the interconnected grid, is seeing reduced investments. Concomitantly, projected demand for electricity is expected to grow. This dichotomy is expected to result in reduced available transmission capacity (ATC) in the electrical grid [16] which may impact the system in the following ways: 1) inflated prices of electricity; and 2) reduced reliability and security of supply to the end-users.

One of the ancillary services that the PHEV fleet could provide when functioning in the vehicle-to-grid (V2G) mode is the ability to locally supply the demand, thus alleviating the congestion scenario; however, this ancillary service to be achieved for the purpose of congestion relief relies on several things: 1) high penetration of the PHEV fleet; 2) the willingness of end-user to engage in demand response (DR) actions; 3) an infrastructure built on information exchange via control and communication; and 4) the evolution of a fully deregulated retail electricity market that recognizes this ancillary service. DR refers to programs that provide incentives to consumers for deferring or curtailing the local demand during peak system periods [17]. This is usually triggered by the service provider (i.e., the utility) based on information related to system reliability or market conditions. As a consequence of this evolution in the operation of emerging smart grids, newer algorithms for unit commitment and economic dispatch must be explored.

IV. Heuristic Based Approaches to Resource Allocation in Computing

In a heterogeneous computing environment, a collection of machines that have different computational capabilities are utilized to execute tasks that have diverse computational requirements [18]. Because the environment is heterogeneous, each task will perform differently on each of the different machines. It is beneficial to allocate tasks to machines that they perform well on to optimize some system performance. In general, the problem of optimally allocating tasks to machines in a heterogeneous environment is known to be NP-Complete [19-21], which leads to the use of heuristics.

The characteristics of each task, such as execution time, on each machine can be modeled either deterministically or stochastically. In the deterministic model, each task characteristic on each machine is given as a discrete value. In the stochastic model, the characteristics are represented as a probability mass function (PMF) [22]. In both models the information for each task on each machine is assumed to be known beforehand.

Using the information about each task, the scheduling heuristics are used to optimize some system performance metric, such as minimize energy consumed or minimize system completion time. In the stochastic model, the resulting optimization would be a probability based on the PMFs of each task. Like in the unit commitment problem, both genetic algorithms [18], [23] and particle swarm optimizations [23] have been used. In addition, many other heuristics have been used such as Tabu [18], [23], simulated annealing [18], and k-percent best [24], [25].

Given the similarities between resource allocation in the realms of heterogeneous computing and the smart grid (which also involves heterogeneous resources), it makes sense to adopt similar heuristics to the emerging smart grid problem. The large, distributed nature of the smart grid matches well with the high complexity of previously solved heterogeneous computing resource allocation problems. The stochasticity of resources in heterogeneous computing has been modeled as well [22] and could be adapted to the stochastic nature of resource availability in the smart grid.

V. Proposed Heuristic Framework for Use in Smart Grids

A. Problem formulation

The smart grid resource allocation (SGRA) problem can be summarized as an optimization problem with the following objectives and constraints. The main objective is usually to minimize costs for design (for planning applications) and/or operations and maintenance (for demand-response applications). In the latter case, these costs usually only include fuel costs, which do not apply for RES. Additional objectives can include any subset of the following: 1) maximizing the share of RES; 2) minimizing the total greenhouse gases emissions; 3) optimizing customer preferences; 4) maximizing the reliability of the system. The system reliability may also be used as a constraint to meet, and can be considered as a robustness metric for the system [26]. Let C_{tot} and E_{tot} be the total cost and total emissions for the system, respectively, $c_i(P_i)$ and $e_i(P_i)$ be the cost and the emissions, respectively, for the ith asset producing an electrical power output of P_i, and n be the total number of assets where an asset is either a conventional generator, a storage unit in the form of a PHEV, a renewable energy source, or a schedulable load. Equation 1 describes an example with two such objectives: minimizing C_{tot} and E_{tot}.

$$\min \begin{cases} C_{tot} = \sum_{i=1}^{n} c_i(P_i) \\ E_{tot} = \sum_{i=1}^{n} e_i(P_i) \end{cases} \quad (1)$$

These additional objectives can be handled either using a multi-objective Pareto-optimality based approach, in which each objective is a dimension of the Pareto front [27], or as a single-objective problem in which the additional objectives are transformed into constraints (e.g., by setting emissions or stability limits).

Several constraints need to be met for the system to operate properly:

- Let P_g, P_s, P_{ls}, P_{lf}, P_{res}, and P_{cong} be the asset power for conventional generators, PHEVs, schedulable loads, fixed loads, renewable energy sources, and congestion needs, respectively. Similarly, let n_g, n_s, n_{ls}, n_{lf}, and n_{res} be the number of conventional generators, PHEVs, schedulable loads, fixed loads, and renewable energy sources, respectively. A balance between generation (supply) and the load (demand) has to be maintained at all times, as shown in Equation 2.

$$\sum_{n_g} P_g + \sum_{n_s} P_s - \sum_{n_{ls}} P_{ls} = \sum_{n_{lf}} P_{lf} - \sum_{n_{res}} P_{res} + P_{cong} \quad (2)$$

- Let $P_{g,max}$, $P_{s,max}$, and $P_{ls,max}$ be the maximum power output of the conventional generators, PHEVs, and schedulable loads. Spinning reserve requirements should be met, as shown in Equation 3.

$$\sum_{n_g} P_{g,max} + \sum_{n_s} P_{s,max} - \sum_{n_{ls}} P_{ls,max} \geq \sum_{n_{lf}} P_{lf} - \sum_{n_{res}} P_{res} + P_{cong} \quad (3)$$

- Let $P_{i,min}$ and $P_{i,max}$ be the minimum and maximum output for asset i. The minimum and maximum operation range for each asset must be respected, as shown in Equation 4 [5].

$$P_{i,min} \leq P_i \leq P_{i,max} \quad (4)$$

- Let Rd_i and Ru_i be the ramp up and ramp down rates for asset i. Let $\frac{dP_i}{dt}$ be the current ramp rate for asset i. The ramp rates of all conventional generators and PHEVs must be respected, as shown in Equation 5 [5].

$$Rd_i \leq \frac{dP_i}{dt} \leq Ru_i \quad (5)$$

- Let Tu_i and Td_i be the current up and down times for conventional generator i, respectively. Let $Tu_{i,min}$ and $Td_{i.min}$ be the minimum up and down times for generator i, respectively. The minimum up and down times for each generator must be met, as shown in Equations 6 and 7, respectively [5].

$$Tu_i \geq Tu_{i,min} \quad (6)$$

$$Td_i \geq Td_{i,min} \quad (7)$$

- For the energy storage elements considered here, i.e., the PHEVs, in addition to the power operation and ramp ranges, as shown in Equations 4 and 5, they also have a few additional constraints. Let SOC be the usable state-of-charge, N_c be the number of daily battery cycles, and T be the charging target (i.e., the PHEV should be charged when the customer wants to use it, at time T). The constraints on SOC bounds, battery cycling, and charging are shown in Equations 8-10, respectively.

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (8)$$

$$N_c \leq N_{c,max} \quad (9)$$

$$SOC_{t=T} = 100\% \quad (10)$$

- Let V_j be the voltage magnitude on bus j. Let V_{min} and V_{max} be the minimum and maximum bounds on the bus voltage magnitudes. The proper operation of the system with regard to the bounded bus voltage magnitudes must be respected, as shown in Equation 11.

$$V_{min} \leq V_j \leq V_{max} \quad (11)$$

- Let f be the frequency of the system. Let f_{min} and f_{max} be the minimum and maximum system frequencies. The proper operation of the system with regard to the bus frequency must be respected, as shown in Equation 12.

$$f_{min} \leq f \leq f_{max} \quad (12)$$

- Let S_k be the power flow on cable k. Let S_{max} be the maximum power flow. The proper operation of the system with regard to the maximum power flow on cables, as shown in Equation 13, must be met.

$$S_k \leq S_{max} \quad (13)$$

- The constraints resulting from the preferences set by customers for their assets, such as: the time for enabling demand-response (DR) and the set of loads available of scheduling should be met.

- The impact of DR on the customer should be as low as possible, i.e., it should ideally be as transparent as possible.

The problem at hand is thus non-linear, and the solution space may potentially reach unmanageable sizes for distribution systems [26]. Heuristics, such as genetic algorithms, are well suited for this kind of problem.

B. Genetic algorithm approach to smart grid resource allocation

To show how a heuristic approach to solving the resource allocation and scheduling problem in the smart grid could be used, a possible setup for a genetic algorithm is presented. As shown in Sections III.A and IV, a genetic algorithm has already been shown to solve both the unit commitment problem and the heterogeneous resource allocation and scheduling problem for computing. As such, the genetic algorithm is thought to be an apt choice to showcase the framework for a heuristic approach to resource allocation in the smart grid.

To properly utilize a genetic algorithm in different domains, the encoding mechanism of the genetic algorithm must be created to represent the optimization problem's variables. In the case of the smart grid, the variables in question are the on/off states of each of the assets, as well as their power output. The assets that we are modeling as controllable in this problem are the conventional generators, the PHEVs, and the schedulable loads. These represent the left hand side of Equations 2 and 3. The values that we are assuming are fixed are the fixed loads, the renewable energy sources, and the congestion needs as requested by the ISO. The reason we are assuming the renewable energy sources cannot be controlled is because we are making the assumption that they do not have a storage unit associated. The three fixed values represent the right hand side of the same equations.

At the lowest level in the genetic algorithm exists the gene. To model the SGRA problem, each gene represents an asset that is controllable, i.e. the values on the left hand side of Equations 2 and 3. Let $\boldsymbol{u_i}$ be a vector whose j^{th} element is a binary value representing the on/off value of asset i at hour $j * 0.25$ (i.e., the vector elements represent a 15 minute block of time). Let $\boldsymbol{o_i}$ be a vector whose j^{th} element is a real value representing the discrete output power of asset i at hour $j * 0.25$. The gene of each asset is then comprised of a $96\ x\ 2$ matrix, $[\ \boldsymbol{u}\ \boldsymbol{o}\ ]$, representing the on/off state and the output values for an asset over a 24 hour period. Additionally, each asset has a fixed availability vector, $\boldsymbol{a_i}$, associated with it whose j^{th} element is a binary value representing whether or not a given asset is available at hour $j * 0.25$. The availability vector is separate from the asset gene and is assumed to be provided by the consumer for each asset. Thus, the power output for asset i at time j is given by Equation 14.

$$P(i,j) = \boldsymbol{a_i}[j] \times \boldsymbol{u_i}[j] \times \boldsymbol{o_i}[j] \tag{14}$$

One entire solution to the SGRA problem is represented in a chromosome. The chromosome is made up of $n_g + n_s + n_{ls}$ genes, each representing one asset of the system. Let $\boldsymbol{G_i}$ be the gene for a conventional generator i, $\boldsymbol{S_i}$ be the gene for PHEV i, and $\boldsymbol{LS_i}$ be the gene for schedulable load i. One chromosome, or solution, is shown in Figure 2.

$$\left[\boldsymbol{G_1} \cdots \boldsymbol{G_{n_g}}\ \boldsymbol{S_1} \cdots \boldsymbol{S_{n_s}}\ \boldsymbol{LS_1} \cdots \boldsymbol{LS_{n_{ls}}}\right]$$

Figure 2: Chromosome representation for a solution in the SGRA problem.

Each solution has a fitness value, or values, associated with it. These values are used to evaluate the chromosome in the dimensions that are trying to be optimized. For example, if trying to optimize for the values in Equation 1 there would be a fitness value associated with both the C_{tot} and E_{tot} objectives (if using a multi-objective Pareto-optimality based approach). As stated before, the multi-objective optimization problem can be turned into a single objective optimization problem by optimizing over one objective and placing constraints on the others. Another way to accomplish this is to place weights on each of the objectives and combine them into a single fitness value.

To accommodate for the constraints in the SGRA problem, penalty functions will be used. If a constraint is violated, a penalty will be included in the chromosome's fitness value. The penalty value is a function of the magnitude of violation and the current generation of the genetic algorithm. The reason that the penalty is a function of the generation is because at earlier generations it is beneficial to keep a variety of genetic material. Even if a chromosome violates a constraint, it might have a partial solution that performs well with respect to the objectives. We keep a chromosome in the population even though it may violate a constraint because it might be able to produce a child that performs well and fixes the constraint violation as it evolves. As the number of generations increases, however, the genetic algorithm is less likely to keep a chromosome that violates any of the constraints. In the final Pareto front (if multi-objective), none of the solutions should contain any constraint violations.

Let $F_a(x)$ be the fitness function associated with objective a for chromosome x, $F'_a(x,t)$ be the fitness function, including penalty weights, associated with objective a for chromosome x in generation t, n_c be the number of constraints, v_b be a binary value representing whether or not constraint b is violated, m_b be the magnitude that constraint b is violated, and $p_b(t)$ be the penalty weight associated with constraint b in generation t. The fitness value being optimized with the genetic algorithm is shown in Equation 15. Note that $F'_a(x,t) = F_a(x)$ if no constraints are violated (i.e., $v_b = 0\ \forall\ b = 1, \ldots, n_c$).

$$F'_a(x,t) = F_a(x) + \sum_{b=1}^{n_c} v_b m_b p_b(t) \tag{15}$$

In the initial population, it is usually beneficial to have some type of genetic preconditioning in the form of seeding. This seeding uses some number of solutions in the initial population that are not generated at random. This can be done by running less computationally intensive heuristics to generate some initial seeds. In the case of the SGRA, it

might be beneficial to precondition the population with some initial seeds that do not violate any constraints.

There are many different ways to perform crossover selection (such as tournament selection [28] or linear bias [29]), crossover, and mutation. For the purpose of the framework, these will be left as generic genetic operators in the scope of this paper. It is important to note that the crossover and mutation operators should take into account the change in power outputs from the changed assets to meet the power balance constraint in Equation 2. It should be noted that this would most likely not be a trivial matter to produce crossover and mutation operators that will respect the power balance constraint.

A genetic algorithm is a valid heuristic approach to solving large-scale optimization problems and as such was used as an example. In addition to the ability to find near-optimal solutions, in one run of the genetic algorithm many solutions are found (equal to the population size) with different characteristics. In the SGRA problem, solutions might have similar fitness values, but one might have, for example, a much larger spinning reserve that might be beneficial to the system in question.

VI. PATH FORWARD

Going forward there are many aspects of the proposed framework to be explored. Perhaps, the most obvious one is to implement the proposed genetic algorithm and obtain results. In this light, other heuristics will be implemented as comparisons to the genetic algorithm. For practical purposes as a day-ahead scheduler, the performance of the different heuristics should be explored as well as how their execution time scales with the size of the problem. It would also be interesting to explore the temporal and spatial stochasticity of the renewable energy sources, PHEVs, schedulable loads, and conventional generators. With this added stochasticity, metrics of robustness (as defined in [22]) would be useful for characterizing the system.

As the applicability of any RA algorithm to the smart grid domain has to be tested using power systems analysis software, a co-simulation framework introduced in [8] may be used. Such a unique test bed enables coordinated simulation of communication, control, and power system aspects of energy management systems.

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