

Smart Grid work for PES GM

A, B, C

Abstract—One of the key challenges of Smart Grid management is ensuring to meet the demand while having control on the supply cost. It involves performing optimal actions both at the production and consumption sites of electric grid. In this work, we consider the problem of managing multiple microgrids attached to a central smart grid. Each of these microgrids are equipped with batteries to store renewable power. At every instant, each of them receive a demand to meet. Depending on the supply (i.e., currently available battery energy, power drawn either from the central grid or from the peer microgrids), each of the microgrids take a decision on from where to draw the energy to meet the demand. When a microgrid buys energy either from the central grid or from the peer microgrids, it can use that energy either to meet the current demand or to store in the battery storage for future use. Hence, there is a control decision problem at each microgrid on the number of power units to be bought or sold at every time instant. We note that both the forecasted demand and predicted renewable supply impact this decision by each microgrid. Further, we consider some amount of the forecasted demand to be adjustable in terms of the time when it can be met by the microgrid. Such an adjustable demand is attributed due to the activities of daily living pertaining to Smart Homes connected to the microgrid networks. Hence, we formulate this problem in the framework of Markov Decision Process and apply Reinforcement Learning algorithms to solve this problem. Through simulations, we show that the policy we obtain performs an significant improvement over traditional techniques.

I. INTRODUCTION

The smart grid is a distributed energy network composed of intelligent nodes (or agents) that can either operate autonomously or communicate and share energy [1]. The purpose of a smart grid is to efficiently deliver energy to consumers as well as store and convert energy produced, e.g., according to prices, supply and demand.

A microgrid is a networked group of distributed energy sources with the goal of generating, converting and storing energy. While the main power stations are highly connected, micro-grids with local power generation, storage and conversion capabilities, act locally or share power with a few neighboring micro-grid nodes [2]. This scenario is being envisaged as an important alternative to the conventional scheme with large power stations transmitting energy over long distances.

In order to take full advantage of the modularity and flexibility of micro-grid technologies, smart control mechanisms are required to manage and coordinate these distributed energy systems so as to minimize the costs of energy production, conversion and storage, without jeopardizing grid stability.

The implementation of such smart controls is by no means easy for the following reasons: (i) Small scale energy production and storage is intrinsically related to intermittency of wind/solar energy and to variability in the load profile. So an important challenge is to increase resilience and reliability

under stochastic supply and demand. (ii) Micro-grids can operate in two different modes: (a) when they are connected to the main power grid, and (b) in the isolated or island mode. Moreover, they can share energy with other microgrids that require energy. Thus, one needs to make dynamic decisions on (a) when to operate in the connected (to the power grid) or isolated modes, (b) when to share energy with other microgrids and when to store energy for future use, and (c) which form to store energy given that storage management itself involves heterogeneous storage technologies with different operating characteristics.

In this paper, we address two problems. First, energy sharing among the microgrids under stochastic supply and demand (mentioned above as (i) and (ii)) along with the optimal battery scheduling of a microgrid from the supply-side management (SSM) perspective. Second is from the demand-side management (DSM) perspective, which is efficiently scheduling the time adjustable demand from smart appliances in the smart home environment, called as an ADL (activity of daily living) demand along with the normal demand. Our goal here is to reduce the energy demand and supply deficit in the long-run. We address this learning and scheduling problem by modeling them as a Markov decision process (MDP) [3], [4].

A. Supply-side management problem

Supply-side management (SSM)[1] deals with developing techniques to generate, transmit and distribute energy efficiently at supply-side. Cooperative energy exchange among microgrids is a popular technique in SSM for efficient energy distribution. Local energy sharing/exchange between microgrids has the following advantages: (a) it can significantly reduce power wastage that would otherwise result over long-distance transmission lines, and (b) it helps satisfy demand and reduce reliance on the main grid. Figure 1 shows a cooperative energy exchange model with multiple microgrids (on the distribution side of the network) that can cater to their individual local loads. Each microgrid controls its local sub-network through its controller (labelled C_1 , C_2 etc.) that mainly has access to its local state information.

In classical power grids, system level optimization is done based on a centralized objective function, where as microgrid network has heterogeneous nature right from the manner in which electricity is generated such as from wind turbines, solar farms and diesel generators to energy storage devices such as batteries and capacitors. Because of this heterogeneity and the fact that energy can be shared between microgrids depending on requirements, one needs to consider asynchronous distributed techniques to control and optimize a smart grid system with a microgrid distribution network.

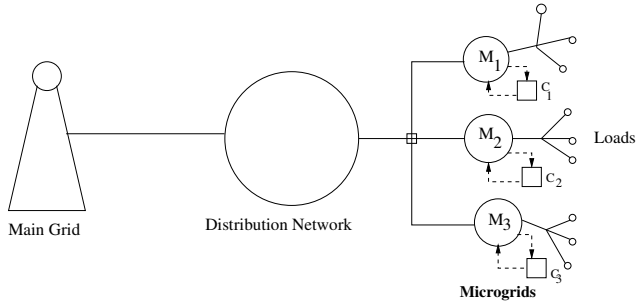


Fig. 1: Cooperative Energy Exchange Model

Related work : [5] provides a survey on game theoretic approaches for microgrids where both cooperative energy sharing models as well as non-cooperative game models for distributed control of microgrids are examined when the system model is known. Since models for energy dynamics are very unreliable [6], one has to use model-free algorithms to address these problems. Because of their model-free nature, reinforcement learning [7] approaches that are primarily data-driven control techniques are playing a significant role in these problems.

In [8], distributed reinforcement learning algorithm for coordinated energy sharing and voltage restoration in a islanded DC microgrid is proposed. In [9], reinforcement learning algorithm for optimal battery scheduling under the dynamic load environment and solar power is proposed with the goal of reducing energy consumption from the main grid. In this paper, we consider the coordinated energy sharing among the grid connected microgrids with optimal battery scheduling problem when stochastic supply and adjustable stochastic demand is available.

B. Demand-side management problem

Load shifting is a popular technique used in demand-side management (DSM) [10]. It involves moving the consumption of load to different times within an hour, or within in a day, or even within a week. It doesn't lead to reduction in net quantity of energy consumed, but simply involves changing the time when the energy is consumed. Advantage due to load shifting for the customer is reduction in the energy consumption cost, and the advantage for the smart grid is in managing the peak load consumption. Hence load shifting is beneficial for both the consumers and the smart grid.

With the increased use of the smart appliances and smart home environments, the concept of load shifting is becoming increasingly handy for the smart grid as the demand from smart appliances is time adjustable in general. One or more of these smart appliances collectively achieve some activity in the smart home environment, called as an ADL (activity of daily living). It's possible to monitor and identify the ADLs in the smart home environments [11], [12]. When an ADL is active, the smart appliances associated with that ADL are switched on to perform the activity defined by the ADL thus adding load on the smart grid. With the help of the smart home technology, it's possible to find the amount of load each ADL puts on the

grid, and also the allowed time window during which the ADL would perform the activity (e.g., washing machine running for an hour to clean the cloths anytime between 3PM to 6PM). If the time window for the ADL lets the smart grid have more than one possible way of scheduling the load, it's considered as flexible ADL. On the other hand, if the time window for the ADL lets the smart grid have exactly one possible way of scheduling the load, it's considered as non-flexible ADL (e.g., washing machine running for an hour to clean the cloths anytime between 3PM to 4PM, is not flexible since there is only one option of switching on the washing machine at 3PM). Thus the demand from the flexible ADLs need not be met at a fixed time period, instead could be met at any time period within a flexible time window. With the help of the advanced metering infrastructure (AMI) [13] that provides a two-way communication between the utility and customers, it's possible to take the decision of when to schedule the ADL demand at the smart grid and convey the same to the customer's smart meter.

There is other regular demand that needs to be met at fixed time periods, apart from the zero or more ADL related demand associated with any customer. This regular demand along with the zero or more non-flexible ADL demand of a smart home is considered to be non-ADL demand for the rest of the paper. Similarly, the demand due to zero or more flexible ADLs of the smart home is considered to be ADL demand.

There is prior art around scheduling the ADL-demand using the load shifting technique for handling the peak load scenarios [14]. However, they precisely know the supply profile while doing such a scheduling of the ADL-demand. In this paper, we propose scheduling of ADL-demand using the load shifting technique with uncertainty in the supply profile generated (e.g., renewable energy sources like solar or wind being the primary sources of power generation).

Our contributions : We summarize our contributions as follows :

- (i) To the best of our knowledge, we are the first one to integrate both the Demand-side and Supply-side management problems in a single Markov decision process framework. We used reinforcement learning algorithms which do not require knowledge of the underlying model to address these problems. Our algorithms are easy to implement and also scalable.
- (ii) The Optimal scheduling of ADL demand at microgrid level, where both the demand and power generation is stochastic is first time introduced through this work.

ORGANIZATION OF THE PAPER

The rest of the paper is organized as follows. The next section describes the important problems associated with the microgrids and solution techniques to solve them. Section III presents the results of experiments of our algorithms. Section IV provides the concluding remarks and Section V discusses the future research directions.

II. PROBLEM FORMULATION AND MDP MODEL

We consider N microgrids denoted by $\{1, \dots, N\}$, which are inter-connected through distribution network. In this paper, we consider the case when microgrids are connected to the main grid (i.e, they are operated in grid connected mode). Each microgrid comprise of the distributed small scale renewable power generating sources and also equipped with energy storage devices. Let B_i be the maximum energy storage capacity of microgrid i . At every time step t of a day, i th microgrid controller C_i is having the following information:

- Total generated energy from all its distributed renewable energy sources denoted by r_t^i .
- Accumulated non-ADL demand denoted by d_t^i , from every load in the i th microgrid.
- Set of all ADL jobs at microgrid i denoted J_t^i . J_t^i is of the form $\{\gamma_1^i, \dots, \gamma_n^i\}$, where j th ADL job γ_j^i , is a tuple consists of number of units of energy required to finish that job denoted by a_j^i and an integer f_j^i , which denotes number of future time slots remaining by which one can schedule that job without incurring the penalty. Let it be represented as follows $\gamma_j^i = (a_j^i, f_j^i)$. Let the total ADL demand be denoted by $A_t^i = \sum_{j=1}^n a_j^i$.
- Total energy available in the storage device of microgrid i , denoted by b_t^i .

In this paper, we are considering the cooperative energy exchange model under which microgrids can share energy among themselves. From the above available information, microgrid controller C_i at every time step t has to decide on the following choices: (a) Amount of energy it needs to buy/sell from the main grid, (b) Amount of energy it needs to buy/sell from the neighboring microgrids, (c) Amount of the energy it needs to store/take from the storage device, and (d) Sub-set of ADL jobs it needs to schedule. Both the demand and energy generated at microgrid i is uncertain/random due to random nature of loads (d_t^i and A_t^i) and renewable energy generation (r_t^i).

Markov decision process (MDP) is a general framework for modeling problems of dynamic optimal decision making under uncertainty. *****Need to write about MDP*****. In the next sub-section we provide the details of our MDP model.

A. MDP model

1) *State space*: The state s_t^i at time instant t for microgrid i is as follows:

$$s_t^i = (t, nd_t^i, p_t, J_t^i), \quad (1)$$

where the net demand $nd_t^i = r_t^i + b_t^i - d_t^i$ and p_t, J_t^i denotes the price of a unit of energy and set of all ADL jobs at time instant t . Net demand nd_t^i , if positive implies there is excess of power after meeting the Non-Adl demand and if negative, there is a deficit in power even to meet the Non-adl demand. *****Note that we include the current time also in the state space. This is because for the same $, nd_t^i, p_t, J_t^i$, the decision taken can be different at different times. For example, a microgrid operating on solar renewable will be able to sell

the power during the morning time as they may still receive the solar power during the afternoon. But they may not want to sell the power during the evening as they will be no solar power in the night. Instead they store the excess power in the battery*****.

2) *Action space*: At each time instant t microgrid controller needs to take two decision u_t^i and v_t^i . The first action u_t^i , if positive, denotes the number of units that the microgrid is willing to sell and if negative, represents the number of units that the microgrid is willing to buy.

Let $P_t^i = \{\Gamma_1^i, \dots, \Gamma_N^i\}$ be the power set of J_t^i , which consists of all possible combinations of the ADL jobs that can be scheduled at time instant t at microgrid i . Let $A_t^i = \{A(\Gamma_1^i), \dots, A(\Gamma_N^i)\}$, where $A(\Gamma_j^i) = \sum_{\gamma_k^i \in \Gamma_j^i} a_k^i$. Then the action u_t^i is bounded as follows. For ease of understanding, we drop the subscripts.

$$-\min(M, B - nd + \max_{1 \leq j \leq N} A(\Gamma_j^i)) \leq u \leq \max(0, nd - \min_{1 \leq j \leq N} A(\Gamma_j^i)) \quad (2)$$

The intuition behind the bounds is as follows. A microgrid can sell atmost the excess power. That is, the power remaining after meeting the demand. While buying, it can buy to meet the demand and also to fill its battery.

Now after getting u_t^i , we construct the feasible set F_t^i , which is a subset of P_t^i . Each element Γ_j^i in the F_t^i has to satisfy the following condition $A(\Gamma_j^i) \leq u_t^i$. Agent has to pick the action $v_t^i = \Gamma_j^i \in F_t^i$. Now ADL jobs in Γ_j^i will get scheduled. Let J_{t+1}^i be the new ADL jobs at time instant $t + 1$. $J_{t+1}^i = J_{t+1}^i \cup \tilde{J}_t^i$, where $\tilde{J}_t^i = J_t^i - v_t^i$ and $\tilde{J}_t^i = \{(a_1^i, y_1^i - 1), \dots, (a_n^i, y_n^i - 1)\}$, where $(a_j^i, y_j^i) \in J_t^i$.

The battery information is updated as follows:

$$b_{t+1}^i = \max(0, nd_t^i - u_t^i) \quad (3)$$

3) *Single stage cost function*: We formulate the single stage cost function as follows :

$$g^i(s, u) = p_t * u_t^i + c * (\min(0, nd_t^i - u_t^i)) + c * \sum_{k=1}^n I_{y_k^i=0} a_k^i. \quad (4)$$

The first term represents the cost of buying or selling the power and the second term represents the demand and supply deficit. For every unit of demand that is not met, the microgrid incurs a cost of c .

B. Average cost setting

Finally, the objective of the microgrid i is to maximize the following [?]:

$$\limsup_{n \rightarrow \infty} 1/n \sum_{k=0}^n E(g^i(s_k, u_k)), \quad (5)$$

where $E(\cdot)$ is the expectation.

We also consider the long run discounted cost formulation. The objective here is to maximize the following:

$$\limsup_{n \rightarrow \infty} \sum_{k=0}^n \gamma^k * E(g^i(s_k, u_k)), \quad (6)$$

where γ is the discount factor.

III. EXPERIMENTAL RESULTS

The following experimental results are desired to be observed:

- With different ADLs being scheduled along with the non-ADL demand, few of the ADLs are expected to be scheduled at the beginning of the allowed execution time window of the ADL, few other ADLs are expected to be scheduled at the end of the allowed execution time window of the ADL, while some other ADLs get scheduled at the mid of the allowed execution time window. This ensures that the MDP learning agents exploit the fact that the ADL demand is flexible to meet in a given range of time window. On the other-hand, it is not desired that the learning agent schedules all the ADLs either at the beginning or at the end of the allowed time window of execution.
- With surplus energy available at a microgrid at any moment, it is desired not to sell this surplus to other microgrids if there is more demand than supply in the near future. For example, if the renewable energy source for a microgrid is solar energy, then if there is surplus energy (i.e., excess energy available after meeting the demand at some moment) at the microgrid during the midday, the microgrid could sell that surplus energy to the other microgrids (because it is expected to generate more supply as the day progresses); on the other-hand, if there is surplus energy at the microgrid during the end of the day, the microgrid might not want to sell that surplus energy to the other microgrids (because there may not be much supply possible for the rest of the day).
- How are we ensuring this? If there is 5 units of surplus at time t . If the demand at time $(t+1)$ is 5 units, it's possible to meet that demand by storing 5 units at time t . Other possibility is, sell the 5 units in time t , and buy 5 units in time $t + 1$ from some other microgrid. However the first option is most desired. How are we ensuring this in our experiments? One possible way to implement this is by ensuring the buying cost to be more than the selling cost for one unit of energy.

IV. CONCLUSION

V. FUTURE WORK

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