Smart Grid work for PES GM

A, B, C

Abstract—**One of the key challanges 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 microgirds), each of the microgrids take a decision on from where to draw the energy to meet the demand. When a microgrids 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 pertraining 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)[] 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.

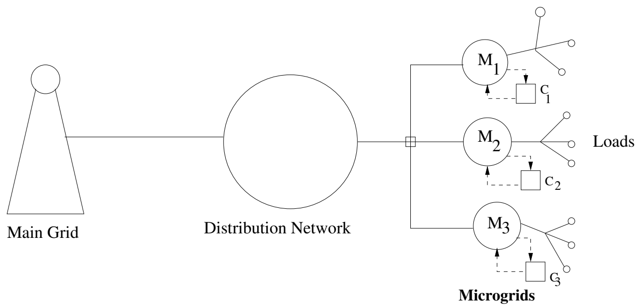

Fig. 1: Cooperative Energy Exchange Model

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 sloar 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 out 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 and Model

Consider multiple microgrids deployed at the sites where renewable energy is available. They are provided with the limited storage batteries that can store the power. Note that they do not have power generation capabilities. They have electrical connections from neighboring microgrids and also from the main grid. But the sharing of power among the microgrids is the most preferred mode as it results in the minimum dissipation loss of power. Only if the sharing among the microgrids is not possible, the main grid connection comes into play.

At the beginning of every time instant (For ex. every hour of a day), each microgrid obtains the demand that they need to meet. They also obtain the renewable power generated in that instant. Based on these two information, along with the battery information, the microgrids need to take a decision on number of power units to be bought/sold. If the power is bought, it is first used to meet the demand and the remaining will be stored in the battery. One may think of a simple greedy policy to solve this problem. That is, the microgrids sells the excess units and buys when there is deficit of demand. But this behaviour may not result in the optimal behavior in a long-run. For example, consider a situation where a microgrid have an surplus of power. But the forecasted demand in the future is very high and the forecasted renewable energy is very low. In this case, having power in its battery will be very helpful. Otherwise, it has to buy the power from the main grid which can be very high. Hence the microgrid needs to balance the current and future rewards. Mathematically, we can formulate this problem in the framework of Markov Decision Process (MDP).

*** Write about MDP, Infinite horizon and Average cost MDP *******

Now we formally present the MDP model for our problem. Let us denote $x_t^i = (d_t^i, r_t^i, b_t^i)$ as the demand, renewable generation and battery information of the microgrid i at time instant t. Let the maximum size of the battery be B. We assume that the Demand is a Markov Process. That is, the demand in the next time period depends only on the current demand. Renewable generation is assumed to be a stochastic process. As described earlier, the microgrids can share the power among themselves. This is done at the price decided by the main grid. We denote the price of a unit of power at time instant t as p_t. The price is also modeled as a Markov Process. Thus the state space is denoted by $s_t^i = < t, x_t^i, p_t >$. Note that we include the current time also in the state space. This is because for the same x_t^i and p_t, 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.

The decision taken by the microgrid i at the time t is denoted as u_t^i. This can be positive or negative. Positive action denotes the number of units that the microgrid is willing to sell. Negative units represents the number of units that the microgrid is willing to buy. If a microgrid needs power, it first accepts it from the neighboring microgrids. Then the remaining units (if any) will be bought from the main grid. If any microgrid has a surplus power that is not consumed by any other, it sells it to the main grid. To maintain the stability at the main grid, We impose a constraint on the number of units of power M that a main grid can give to each microgrid.

We observe that the action to be taken depends only on the net demand. That is we can further simplify the state space to be $s_t^i = (t, nd_t^i, p_t)$ where $nd_t^i = r_t^i + b_t^i - d_t^i$. If this is negative, it means there is a deficit in demand and positive implies there is excess of power.

Then the action is bounded as follows. For ease of understanding, we drop the subscripts.

$$-min(M, B - nd) \leq u \leq max(0, nd) \tag{1}$$

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.

The battery information is updated as follows:

$$b_{t+1}^i = max(0, nd_t^i - u_t^i) \tag{2}$$

We formulate the single stage cost function as follows :

$$g^i(s, u) = p_t * u_t^i + c * (min(0, nd_t^i - u_t^i). \tag{3}$$

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.

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

$$limsup_{n\to\infty} 1/n \sum_{k=0}^{n} E(g^i(s_k, u_k)), \tag{4}$$

where $E(.)$ is the expectation.

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

$$limsup_{n\to\infty} \sum_{k=0}^{n} \gamma^k * E(g^i(s_k, u_k)), \tag{5}$$

where γ is the discount factor.

III. Problem formulation and MDP model

A. MDP model

The decision taken by the microgrid i at the time t is denoted as u_t^i and v_t^i. Let the set of ADL jobs at microgrid i at time t be J_t^i. And $J_t^i = \{\gamma_1^i, \ldots, \gamma_n^i\}$, where jth ADL job $\gamma_j^i = (a_j^i, y_j^i)$ consists of the number of units of power required to finish the job (denoted by a_j^i) and number of time slots remaing to shedule the job (denoted by y_j). The state space be $s_t^i = (t, nd_t^i, p_t, J_t^i)$ where $nd_t^i = r_t^i + b_t^i - d_t^i$. If this is negative, it means there is a deficit in demand and positive implies there is excess of power. Let $P_t^i = \{\Gamma_1^i, \ldots, \Gamma_N^i\}$ be the power set of J_t^i, which consists of all possible combinations of the ADL jobs that can be sheduled at time instant t at microgrid i. Let $A_t^i = \{A(\Gamma_1^i), \ldots, A(\Gamma_N^i)\}$, where $A(\Gamma_j^i) = \sum_{\gamma_k^i \in \Gamma_j^i} a_k^i$.

Then the action is bounded as follows. For ease of understanding, we drop the subscripts.

$$-min(M, B - nd + \max_{1 \leq j \leq N} A(\Gamma_j^i)) \leq u \leq max(0, nd - \min_{1 \leq j \leq N} A(\Gamma_j^i)) \quad (6)$$

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 sheduled. Let J_{t+1}^i be the new ADL jobs at time instatant $t+1$. $J_{t+1}^i = J_{t+1}^i \cup \widetilde{J}_t^i$, where $\overline{J}_t^i = J_t^i - v_t^i$ and $\widetilde{J}_t^i = \{(a_1^i, y_1^i - 1), \ldots, (a_n^i, y_n^i - 1)\}$, where $(a_j^i, y_j^i) \in \overline{J}_t^i$.

The battery information is updated as follows:

$$b_{t+1}^i = max(0, nd_t^i - u_t^i) \quad (7)$$

We formulate the single stage cost function as follows :

$$g^i(s, u) = p_t * u_t^i + c * (min(0, nd_t^i - u_t^i)) + c * \sum_{k=1}^{n} I_{y_k^i = 0} a_k^i. \quad (8)$$

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

IV. Experimental Results

The following experimentals 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 microgirds if there is more demand than supply in the near feature. 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.

V. Conclusion

VI. Future Work

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