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. ~~This concept of Smart Grid has become popular in the recent times. The main objective in this Smart Grid is to intelligently make use of power.~~ It involves ~~taking~~ performing optimal actions both at the production and consumption sites of ~~electricity~~ 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. ~~In this work, we consider multiple microgrids 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. ~~Depending on the current battery and renewable power information, they take a decision on number of power units to be bought or sold.~~ 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. ~~If any of the other neighboring microgrids sell the power, they can consume it. Otherwise, they can get it from the main grid. If power is bought, it is first used to meet its demand and rest of it will be stored in the battery.~~ 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. ~~We note that the future forecast demand and renewable units also impact this decision.~~ 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

Research on smartgrids can be classified into two areas - Demand-side management and Supply-side management. Demand side management (DSM) ([1], [2], [3], [4], [5], [6]) deals with techniques developed to efficiently use the power by bringing the customers into the play. The main idea is to reduce the consumption of power during peak time and shifting it during the other times. This is done by dynamically changing the price of power and sharing this information with the customers.

Supply-side management deals with developing techniques to efficiently make use of renewable and non-renewable energy at the supply side. We now discuss the papers that are close to our work. In [7], authors consider the problem of optimal energy storage management problem under dynamic cost setup. They consider a renewable generator that is equipped with a limited storage battery and capable of meeting the some local demands. It also has connection from the main grid. The decision to be taken at every instant is the number of power units to be stored in the battery. They allow this to be negative as power can be drawn from the battery. They formulate this problem as a Markov Decision Process under long run average cost. The objective is to minimize the long run average cost of power bought from the main grid.

The assumption made in this paper is that demand at all times can be met. This is facilitated by allowing the main grid as many units of power as asked by the renewable generator. In our work, we extend this MDP model to put additional constraint on the maximum number of power units that a main grid can provide. Another notable contribution is that we extend this setup to the multiple microgrids. Here, we allow the microgrids to share the power among themselves.

In [8], they consider the problem of maximizing the profits among the broker agents. These agents buy the power from the producers and sell it to the customers. They apply Reinforcement Learning (RL) algorithms to solve this problem to show that learning policies perform better than the traditional non-learning strategies.

In [9], authors propose an MDP for solving the problem of minimizing the demand and supply deficit and apply dynamic optimization methods. But when the model information (the renewable energy generation in this case) is not known, we cannot apply these techniques.

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 micrograds 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. 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 otherhand, 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 otherhand, 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

We considered the problem of electrifying a village by setting up microgrids close to the village. These microgrids have access to the renewable energy storage batteries and also electrical connections from the main grid. We identified two problems associated with the microgrid. First problem is to minimize the expected long-run discounted demand-supply deficit. We model this problem in the framework of MDP [9]. This formulation doesn't take into consideration the cost of power production at the main grid site. Finally, we formulated MDP taking the cost of power production into consideration. We applied Multi-Agent Q-Learning algorithm to solve these problems. Simulations show that, when maximum power allocation at the main site is not very less, storing the power in the batteries and using them intelligently is the better solution compared to not using the storage batteries.

V. Future Work

As future work, we would like to consider the possibility of power sharing between the microgrids. In this case, along with decision on amount of power to be used from stored batteries, microgrids also have to make decision on the amount of power that can be shared with others. We would also like to consider the heterogeneous power price system. In this scenario, the price of power production at the main grid will vary from time to time.

Acknowledgment

The authors would like to thank Robert Bosch Centre for Cyber-Physical Systems, IISc, Bangalore, India for supporting part of this work.

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