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Power Loss Minimization in Microgrids Using Bayesian Reinforcement Learning with Coalition Formation

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***Abstract*—Energy trading among microgrids has been emerging as a promising solution to implement community microgrids, also known as energy sharing communities. The key idea behind these communities is to share the surplus energy in one microgrid with another microgrid that has higher demand than its generation. The objective of these transactions can be monetary as well as optimizing a system parameter. In this paper, we focus on energy trading for the purpose of power loss minimization. We assume microgrids form coalitions to avoid exporting energy from the utility grid or a distant microgrid which might cause higher line losses due to increased distance. We propose a novel Bayesian Reinforcement Learning (BRL) based algorithm, which allows the microgrids to reduce the overall power loss. We compare this scheme with a coalitional game theory-based approach, Q-learning based approach, random coalition formation approach, as well as with a case that has no coalitions. Our results show that more than 50% reduction in power loss compared to no coalitions and less power loss than the other approaches is achieved. We also show power loss can be further reduced by proper sizing of the storage unit.**

***Index Terms*—machine learning, Bayesian reinforcement learning, microgrid, smart grid.**

I. Introduction

Recently, the centralized-unidirectional system of electric power transmission, distribution and demand-driven control systems have been gradually evolving into a massive heterogeneous mix of the utility grid and microgrids along with including renewables into energy generation mix and residential demand-response for smart homes [1], [2]. These groundbreaking technologies impose increasing pressure for higher quality and reliability in electricity distribution. Along with these requirements, to enhance the self-healing capability of smart grids, microgrids have been studied in the literature [3]. Microgrids are power system components that are defined as small-scale electricity distribution systems with loads, generation capacity and islanding capability.

The need to cope with this rapid transformation of conventional electrical grid towards future smart grid with connected multiple microgrids has led to an investigation of optimal smart grid architectures. While the main components of the future smart grid, such as generators, substations, controllers, smart meters, collector nodes are coming to maturity, truly harmonic integration of those in a microgrid context to guarantee intelligent and dynamic functionally across the whole smart grid remains as an open issue. This challenge can be best addressed using machine learning techniques or more broadly Artificial Intelligence (AI) across the grid infrastructure and microgrids [4].

Machine learning algorithms are definitely the critical tools to enable many applications that range from computer vision to sentiment analysis, self-organized systems and robotics. However, an AI-enabled smart grid calls for machine learning techniques that are different from those developed for conventional application areas. Thus, novel machine learning techniques that are exclusively designed to meet the unique challenges of the smart grid and microgrids are needed.

In the literature, several prior works have introduced machine learning to address various challenges of microgrids. In [5], the authors propose a dynamic demand response and distributed generation management method for a residential microgrid community. In [6], a fully distributed learning approach is proposed for optimal reactive power dispatch. In [7], temporal difference reinforcement learning approach is used to achieve the optimal control policy for the residential energy storage. In [8], a reinforcement learning based algorithm is presented for the problem of distributed energy management with wireless networks in microgrids.

To further enhance the utilization of microgrids and to make use of surplus energy in one microgrid to supply loads in another microgrid, energy trading among microgrids has been recently studied. The advances in small-scale renewable energy generators and affordable battery solutions are the main drivers for energy trading. Among the many advantages of energy trading for consumers, power loss minimization is one of the significant advantages on the utility side. In the transmission and distribution system, power is lost due to heating dissipation in power lines and the amount of loss is proportional to

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distance and power. Therefore, minimizing the distance between interconnections reduces power loss which can be realized by interconnecting several microgrids and allowing peer-to-peer energy trading between microgrids. In the literature, energy trading has been modeled using various techniques, including game theory. In [9], the problem of energy trading among microgrids is considered with the aim to minimize the power loss over the line. The authors have proposed a coalitional game theory approach which allows microgrids to transfer energy inside a coalition.

In this paper, we propose a Bayesian reinforcement learning approach to form coalitions to effectively address uncertainty in generation and demand. In our approach, each microgrid agent assumes a prior density function over the states of the system. As the agents interact through the iterations of reinforcement learning, they update their estimations, finally reaching coalitions that minimize power loss. Our results show more than 50% reduction in power loss with respect to having no coalitions and improvement over other compared techniques. In addition, we show the improvement of power loss reduction with respect to battery size.

The rest of this paper is organized as follows. In Section II related work is summarized. In Section III, the system model is described. In Section IV, the Bayesian reinforcement learning scheme is explained. Numerical results are provided in Section V and finally, the conclusion is presented in Section VI.

II. Related work

Although machine learning has been used in several smart grid applications, their use in energy trading among microgrids is limited. In [10], the authors proposed two learning automata-based methods for optimal power management in smart grids. These methods aim to control the power consumption by different grid users and identify the needed energy for various distribution substations. In [11], a set of connected microgrids are considered, which can transfer energy to each other and the macrogrid. Each microgrid is equipped with a battery to store energy and local energy generators such as wind turbine and photovoltaic panels. The energy trading between microgrid is modeled as a noncooperative distributed game, in which each microgrid aim to maximize its own utility function. A hotbooting Q-learning approach is implemented to achieve the Nash equilibrium of the dynamic repeated game. In [12], the authors enhanced [11] by adding a deep Q-network based approach. Deep Q-network estimates the values of Q-table and therefore improves the convergence rate and system performance.

In addition, energy trading problem has been studied with game theoretical approaches. In [13], a set of interconnected microgrids aims to exchange energy with each other and also with the macrogrid. Microgrids with surplus energy can choose to sell part of their energy and store the rest for the future. Likewise, microgrids that suffer from the shortage of energy or wish to store energy for future can buy energy. In this paper, two level continuous kernel Stackelberg game is employed in which seller and buyer microgrids are classified as leaders and followers players, respectively. In [14], a priority based energy trading game is proposed in which buyers are prioritized to eliminate the difficulty of energy pricing. Although the game theory results are promising, they do not address the uncertainties. Therefore, joint implementation of learning and game theory algorithms can result in a more autonomous and distributed system and at the same time enhance the efficiency.

III. System Model

In this paper, we consider a network of N interconnected microgrids (MG) which are also connected to the utility grid or the macrogrid. The microgrids can trade energy among each other or with the utility grid. The simple block diagram of the system is demonstrated in Fig. 1. In a specific time slot, each MG $i \in N$, generates power g_i and has demand denoted by d_i. We also consider that the microgrids are equipped with a battery having capacity of b_i and they can store some of their generated energy in the battery. The surplus energy is defined as: $q_i = g_i - d_i - b_i$ and it corresponds to the amount of energy that the microgrid is willing sell. We assume that for an interval T, some microgrids have surplus energy and are able to export energy (seller MGs) while others need to import energy (buyer MGs). At each iteration a microgrid can move from the seller group to the buyer group depending on the interplay between its generation and demand. Power trading among the microgrids, as well as selling power to the utility grid results in power loss over the distribution lines. The amount of this power loss can be expressed as follows [9]:

$$P_{i0}^{loss} = R_{i0} \frac{{P_i}^2 (q_i)}{U_0^2} + \rho P_i (q_i) \tag{1}$$

where R_{i0} is the resistance of line per km which formulates the power loss in correlation to the distance between MGs and macrogrid. ρ denotes the fraction of power loss that occurs in the transformer at the macrostation which sits at the interconnect between the MGs and the macrogrid. $P_i(q_i)$ is the power flowing over the power line and the U_0 represents the power which flows among the macrogrid and microgrid i computed according to:

$$P_i (q_i) = \begin{cases} q_i & q_i > 0 \\ L_i^* & q_i < 0 \\ 0 & o.w \end{cases} \tag{2}$$

L_i^* demonstrate the power that should be generated or transferred and can be obtained solving:

$$L_i = R_{i0}\frac{L_i^2}{U_0^2} + \rho L_i - q_i \tag{3}$$

The above equation may have zero, one, or two solutions, for any given parameters. In the case of two positive solutions, the smallest root is considered. Whenever (2) does not have solution , we consider that the energy of $\frac{(1-\beta)U_0^2}{2R_{i0}}$ transmitted from macrogrid [9].

IV. Power Loss Minimization using Bayesian Reinforcement Learning

In this paper, we propose a Bayesian Reinforcement Learning (BRL) scheme that aims to facilitate energy trading among microgrids with minimum power loss.

To reduce the power loss due to transmission of electricity from the distant macro grid, we consider that MGs can participate in energy trading by joining a coalition. Forming cooperative groups and trading energy among close by microgrids (coalitions) is a promising approach to reduce the transmission power loss since the line loss depends on the distance and the power. A coalition is determined with a pair (C, v) where C denotes set of players that agree to form a coalition and v is a function that assigns for every coalition the total benefit achieved by that coalition as described in [9]. In our case, a coalition can have several values for v according to internal energy trading policy. Scheduling internal energy trading in an optimized way can result in an optimal coalition value. The coalition value is defined as:

$$v(C) = \max\left[-\left(\sum P_{ij}^{loss} + \sum P_{i0}^{loss} + \sum P_{j0}^{loss}\right)\right] \tag{4}$$

where P_{ij}^{loss} shows the loss due to energy trading among seller MG i and buyer MG j and loss due exchange with the macrogrid. P_{i0}^{loss} and P_{j0}^{loss} represents the situation that the coalition has an overall surplus generation (MG i selling energy to macrogrid) or demand (MG j buying energy from macrogrid) respectively. We assume each MG is equipped with a battery and stores the surplus generation partially. The amount of energy to be stored is associated with the defined utility function. The proposed Bayesian Reinforcement Learning approach aims to optimize the decision to join a coalition and the amount of energy to be stored at the battery for each MG in a distributed way. For simplicity, we assume that only one coalition has variation in the amount of generation and demand, which triggers new coalition formation.

Energy trading among microgrids is a dynamic process that can be formulated as a Markov Decision Process (MDP) in which each agent decides on the battery level as well as the desirable coalition to join.

The MDP with the infinite horizon is modeled with the following elements. We denote $s_t = \{P_i, B_i\}$ as the state of the system which is limited to possible states set $S = P \times B$ for the MG i which includes the battery level P_i (which corresponds to the state of charge) and coalition number B_i for the agent to join. An action $a_t = \{k, b_i\}$ chosen from possible actions set $A = K \times B_b$ includes the decisions about the coalition to join and the level of energy to be stored in the battery. The state transition function $T(s, a, s')$ is selected from $T : S \times A \times S \Rightarrow [0, 1]$ and defined as the transition probability from current state s to next state s' taking action a by the MG. The reward function $R(s, a, r)$ is expressed as the immediate reward r when action a is chosen at the state s and computed in (5) . The goal of each MGs is to obtain the optimal policy $\pi : S \times T \times R \Rightarrow A$ which result in maximized long term expected reward.

Equation (4) formulates the total benefit of the coalition. Each user in the coalition should have its own share from this benefit. To share the total benefit of a coalition, we use the proportional fair division algorithm which divide the total value among the members of a coalition as relative loss to energy exchange with the macrogrid and can be expressed as (5). This is also the immediate reward of the i-th MG (known as transfer function):

$$r_i = \zeta_i\left(v(C) - \sum_{j\in C} v(\{j\})\right) + v(\{i\}) \tag{5}$$

where ζ_i is the relative ratio of their contribution equals to $\frac{v(\{i\})}{\sum_{j\in C} v(\{j\})}$ and $v(\{j\})$ represents the coalition with single member MG j.

In order to form the coalitions, the agents use BRL as the lack of information regarding the state of MGs in other coalitions imposes uncertainties to the system and accordingly coalition values. Therefore employing a method that allows MGs to learn about each coalition to remove uncertainties and refine the coalition formation process is critical. BRL is a method that aid agents to overcome the uncertainties through repeated interactions with other agents. In the proposed Power Loss Minimizing BRL, each MG considers a prior density function over the state T of the system. MGs keep updating their information about the state of the system using Bayes rule. Note that assigning prior density function will not affect the long-term learning process of each MG since after a large number of iterations the effect of assigned prior density function will be insignificant. Therefore, we assume that the state T of the system follows widely used Dirichlet function [15]. Considering the method proposed in [15] and adopting Bayesian Exploration Bonus method (BEB) [16] we can derive optimal value function as follows:

$$\begin{aligned} V_H(s) = \max_a \Bigg\{ & r(s,a) + \frac{\beta}{1+\lambda_0\,(s,a)} \\ & + \sum_{s'} P\,(s'\,|s,a)V_{H-1}(s') \Bigg\} \end{aligned} \tag{6}$$

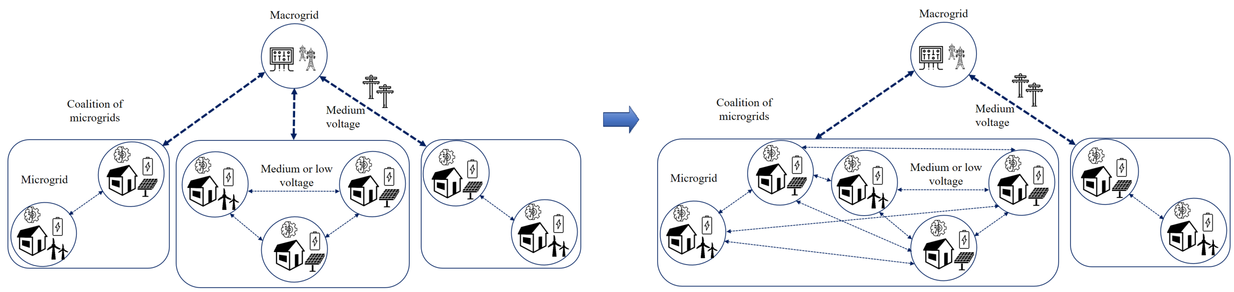

Fig. 1. Block diagram of a system of microgrids.

β denotes a fixed value that determines the effect of the additional bonus. $\lambda_0(s,a)$ is expressed as the times that action a has been taken in state s and can be calculated as $\lambda_0\left(s,a\right) = \sum\limits_{s'} \lambda\left(s,a,s'\right)$. BEB algorithm chooses the actions greedily taking into account both state transitions mean estimate and an additional bonus for state and action which comparatively less been experienced. It means that, at each state, this scheme solves an MDP using the mean of the current belief state for the probability of transition, and an extra exploration bonus equal to $\beta/(1+\lambda_0(s,a))$. The summary of this approach is provided in algorithm 1. The algorithm is divided into an initialization step and main loop. In the initialization, each MGs randomly is being assigned to a coalition and set the state pair $\{P_i, B_i\}$ equal to current surplus or shortage level of energy and desired battery level to initial surplus/needed energy and zero respectively and broadcasting current coalition formation, C, to all MGs afterwards. The algorithm includes two parts: learning and forming the coalition. In the learning stage, MGs update current rewards, estimate transition probability and bonus gain and finally update the value function $V_H(s)$. In coalition formation step, a proposer MG_i is selected from the set of all MGs, M, randomly. Then the chosen proposer takes the optimum action considering (6). The proposer is the MG which is randomly selected and proposes to join a coalition. As MGs decide on the action that results in the maximized sum of current and future expected utility, it can be claimed that (6) maximizes long-term expected reward of the considered energy trading system.

A. Q-Learning Approach

Similar to the BRL algorithm, Q-Learning is a type of Reinforcement Learning algorithm where the objective is to obtain a sub-optimal policy by choosing actions that maximize the expected current and future rewards. In Q-learning, the Q-Value should be updated considering the Bellmans equation as follows [17]:

$$Q(s,a) = \left(1-\alpha\right) Q_{t-1}(s,a) + \alpha \left[r(s,a) + \gamma \max Q_{t-1}(s,a)\right] \tag{7}$$

α and γ are the learning rate and a discount factor that shows the significance of future rewards, respectively.

Algorithm 1 Coalition formation with BRL for distributed energy trading among MGs

Initialization: Initialize a discount rate and β .
At time $t=0$:
for MG i = 1 to M **do**
  randomly select coalition C_k, set the state $\{P_i, B_i\} = \{P_i, 0\}$.
  Broadcast C to all MGs and set the $V = 0$
end for
Main loop:
for Each time slot t = 1 to T **do**
  for MG i = 1 to M **do**
    update current reward $u_i(t)$
    Estimating the probability of transition and update value function (6)
  end for
  BR Coalition formation with the probability of $1/M$ the proposer MG_i is selected from the set M;
  For MG_i**:**
  take a action $a = \{k, b_i\}$ that maximise $V_H(s)$
  Sends a to all MG_m, $m \in C_k / \{i\}$
  if $u\{i \in C_k\} \geq u\{i \notin C_k\}$ for all $m \in C_k / \{i\}$ then set $i \in C_k$ and update the u for $m \in C_k / \{i\}$.
end for

Agents, reward function and states are considered to be the same as the previous section. The Q-Learning policy is to choose actions maximizing the Q-value. In order to consider action exploration, Q-Learning uses the ϵ-greedy method which randomly selects the actions with probability ϵ (known as the Exploration phase), or choosing the action which maximizes the Q-value with probability $1-\epsilon$ (Exploitation).

B. Game Theoretical Approach

In order to compare our proposed method with other techniques, in this section we introduce a coalitional game based method similar to what is proposed in [9]. When one coalition has variation in the amount of generation and demand. Then MGs will be randomly chosen and propose to join a new coalition. The new coalition will accept new member if, there is an old member which will be able to achieve higher payoff within the new formation without hurting any of the other MGs payoff (known as Pareto order [18]). Consecutive merge and split iterations happen until the system of MGs reach a coalition formation, from whereon no MG has any incentive to further merge to a new coalition. The summary of this scheme is demonstrated in Algorithm 2.

Algorithm 2 Game Theoretical Coalition formation for distributed energy trading among MGs

Initialization:
for MG i = 1 to M **do** randomly select coalition C_k
end for
Main loop:
for Each time slot t = 1 to T **do**
  for MG i = 1 to M **do**
    update current utility $u_i(t)$
  end for
  Game Theoretical Coalition formation with the probability of $1/M$ the proposer MG_i is selected from the set M;
  For MG_i**:**
  Sends a to all MG_m, $m \in C_k/\{i\}$
  if $u\{i \in C_k\} \geq u\{i \notin C_k\}$ for all $m \in C_k/\{i\}$ then set $i \in C_k$ and update the u for $m \in C_k/\{i\}$.
end for

V. Performance Evaluation

For the numerical evaluation, we set up a network of microgrids where N is between 4 and 10 within an area of 10 km by 10 km where macrogrid is located at the middle of considered area and microgrids are located at random. A full day is divided to 24 time slots where load and generation patterns are generated randomly according to a Gaussian random variable and periodically repeat after a day with slight variations as in [9]. We compare the proposed BRL method with non-cooperative method (no coalition formation), random coalition formation scheme, coalitional game (CG)-theory based method and Q-learning based algorithm. The results are obtained over 10 runs and the average results are plotted.

TABLE I
Summary of Parameters

parameter	value
Number of MGs	4 to 10
Number of coalitions	4
Number of battery levels	4
Considered area	10km*10km
R_{i0}	0.2
U_0	50 kv
ρ	0.02
β	0.8

In Fig. 2, we present the average loss per user versus the number of microgrids ranging from 4 to 10. We have compared five different schemes in this evaluation. In the no coalition scheme we considered that each MG just transfer energy with macrogrid and there is no coalition formation included. In the random scheme, we considered a random scenario for coalition formation, in which MGs are assigned to coalitions randomly. Next three schemes, CG based, QL and proposed BRL schemes were introduced in Section III. As it is expected, when the number of microgrids increases it results in less power loss. As the system has more adaptation capability with the variations in the environment, there is less power loss. BRL scheme has less power loss compared to QL and CG based schemes.

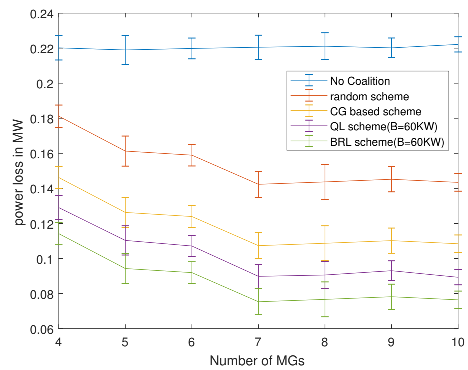

Fig. 2. Average loss per user versus the number of microgrids.

In Fig. 3 to evaluate the effect of battery capacity, we demonstrate the average loss per user versus the number of microgrids ranging from 4 to 10 for three different scenarios with different battery capacities. It is shown that when the battery capacity of microgrids increase, the average power loss decreases as expected. Also, when we have more MGs we will have less power loss in the system. This is expected since more energy can be stored for future use and power is not lost during transmission.

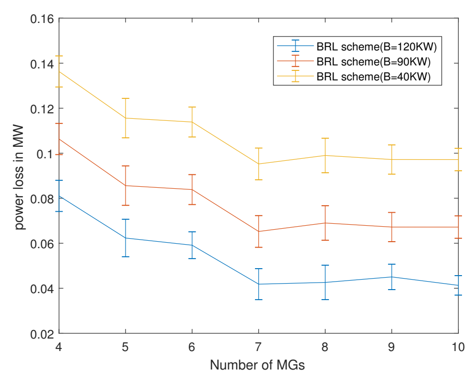

Fig. 3. Average loss per user versus the number of microgrids.

In Fig 4, we show the convergence of the average power loss per user versus the number of iteration. In this figure, we demonstrated the accumulative average power loss in time for BRL scheme with different battery capacities. As it is seen in the figure, power loss (which also indicates the negative of the average utility of the MG) converges over time.

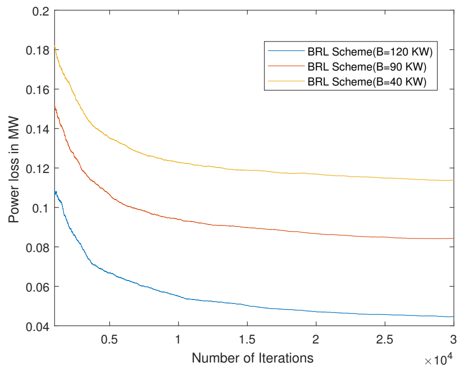

Fig. 4. Average power loss per user versus number of iteration.

To demonstrate the complexity of our method in comparison with the CG based method, in Fig 5 we show the simulation run time for both schemes. The results demonstrate that the proposed scheme completes in less time than colaitional game theory approach. The results are obtained with a PC with Intel(R) Core(TM)15-6500 CPU and 8192MB RAM.

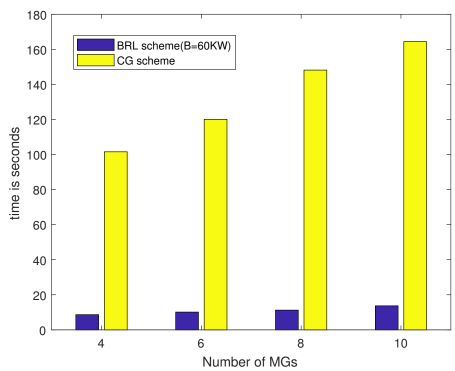

Fig. 5. Run time of proposed learning method and CG based scheme.

VI. Conclusion

Energy trading among microgrids is a key to achieve community microgrids, also known as energy sharing communities. In this context, micrgrids with surplus energy share/trade energy with other microgrids that suffer from higher demand than their generation. In this paper, we visited the problem of energy trading with the aim of power loss minimization. BRL has been used to form coalitions of microgrids to avoid exporting energy from the utility grid or distant microgrids which might cause higher line losses. BRL allowed microgrids to learn the pattern of energy generation and take the optimal coalition decisions. Comparing our proposed scheme with the Q learning and coalitional game theoretical method, significant reduction in power loss has been achieved.

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