Reinforcement Learning for Model-Free Power Management of Networked Microgrids

Qianzhi Zhang, Student Member, IEEE, Kaveh Dehghanpour, Member, IEEE, Zhaoyu Wang, Member, IEEE,

Abstract—This paper presents an approximate Reinforcement Learning (RL) methodology for data-driven power management of networked Microgrids (MG) in electric distribution systems. In practice, the system operator has limited or no knowledge of the MG asset behavior and models behind the Point of Common Coupling (PCC). This makes the distribution systems unobservable and impedes a conventional optimization approach for solving the power management problem while satisfying network constraints. To tackle this challenge, we have proposed a bi-level model-free machine learning framework in a retail market environment which functions exclusively based on the exchanged signals between different entities within the market. While at the lower level, each MG provides power-flow-constrained optimal response to price and voltage signals, at the higher level, the system operator performs function approximation to predict the behavior of market participants under incomplete information of MG parametric models. This function approximation scheme is then used within an adaptive RL framework to optimize the price signal and the substation voltage as the system load and solar generation change over time. Numerical experiments have been devised to verify the performance of the proposed learning model.

Index Terms—Distribution systems; Networked microgrids; Power management; Reinforcement learning; Adaptive training;

I. INTRODUCTION

Power management and monitoring of Distributed Generators (DG), Renewable Energy Resources (RES), and Energy Storage Systems (ESS) is a critical challenge in modern distribution networks [1]. In general, these resources can be clustered into small-scale controllable self-sustaining power systems, known as Microgrids (MG) [2]. Due to privacy and data ownership concerns the extent of utility knowledge on real-time asset behavior behind the Point of Common Coupling (PCC) with MGs can be limited or null. This constraint can jeopardize the observability of the distribution system. Hence, optimal power management techniques should be able to accommodate the incomplete information of utilities and system operators on MG operation, while taking AC power flow constraints into account. This problem becomes more severe as the penetration of MGs in distribution systems grows.

A smart distribution system consisting of multiple MGs can facilitate reliable service provision to customers in future power systems [3]. A wide range of methods have been applied in the literature with the aim of economic operation of the networked MGs, including methods such as heuristic techniques [4], [5], centralized decision models [6], [7], and distributed optimization methods [8], [9]. However, many of these works have only considered aggregate power balance constraints, while the detailed operational and power flow constraints inside each MG are omitted from the power management formulation. On the other hand, hierarchical control architectures with MG power flow and operational constraints are applied in networked MG power management design [10]–[14]. In [10], an interactive and hierarchical control framework for MG operation coupling was introduced to achieve effective load sharing and guaranteed system-wide stability. In [11], a bi-level architecture for distributed-energy-resource management for multiple MGs using multi-agent systems was presented, which allows the pool members to participate in a local market.

However, the functionality of previous models [3]–[14] highly depends on the full system operator’s knowledge of MG operation behind the PCC and customers’ private data, which can compromise the data ownership and dependency of MG owners. Also, these methods can be categorized as “model-based” since the decision agents depend on detailed physical models of the distribution systems. One shortcoming of model-based solutions is their inability to adapt to constantly-changing system conditions when the amount of measurement data is limited.

In this paper, to solve the problem of decision making under limited utility information while providing decision adaptability, a bi-level model-free decision system is proposed: at the higher level of the hierarchy, a utility agent maximizes its profit by setting the locational energy price and substation voltage, in a distribution system consisting of multiple privately-owned MGs each connected to the main system at its PCC. Assuming that the utility agent has access only to active/reactive power measurements at the PCCs and aggregate load and solar information behind the PCCs, a model-free reinforcement learning (RL) framework [15] is developed to solve the energy pricing and substation voltage control problem. The strength of the RL framework is that the system operator can accurately estimate the response of MGs to input price/voltage signals through function approximation, using only a limited amount of information. Hence, the data-driven model-free aspect of the RL technique is used as an asset to optimize the pricing and voltage regulation policies by observing the response of MGs to external signals at their PCCs. Moreover, the RL framework is trained using a regularized recursive least square methodology with forgetting, which enables the system operator agent to adapt to sudden changes in system parameters. Hence, by avoiding explicit MG modeling at this level, the utility decision model becomes

Q. Zhang, K. Dehghanpour, and Z. Wang are with the Department of Electrical and Computer Engineering, Iowa State University, Ames, IA 50011 USA (e-mail: qianzhi@iastate.edu).
highly adaptable against changes in MG parameters which can be unknown. At the lower level of the hierarchy, each MG Control Center (MGCC) agent receives the price signal from the utility agent and solves the power-flow-constraint MG power management problem under the estimated PCC voltage. Thus, the MGs provide response to the input received from the utility agent from the higher level. Numerical experiments were performed to demonstrate the accuracy and adaptability of the proposed RL framework under different scenarios.

The reminder of the paper is organized as follows. Section II presents a summary of the decision hierarchy. Section III elaborates the proposed RL-based distribution system control framework. Section IV formulates the individual MG power management problem. Simulation results and conclusions are given in Section V and Section VI, respectively.

II. OVERALL DECISION HIERARCHY

Fig. 1 gives a general overview of the proposed bi-level power management scheme for a distribution system with multiple MGs. The two levels of the model are described as follows:

- **Level I - Distribution System Control:** The utility agent employs an adaptive model-free RL framework, developed using a regularized recursive least square function approximation methodology, to find the optimal locational price signals for the MGs and the voltage at the substation based on the latest system states. The price signals are then transmitted to MGCC agents. At this level, each MG is modeled as an aggregate controllable load which is price/voltage-sensitive. The task of the RL framework is to discover the complex relationship between locational price/voltage and exchanged power with MGs at PCCs, without direct knowledge of details of system operation behind the PCCs and only with access to estimations of the aggregate solar and fixed loads for each MG. Renewable and load power uncertainty are represented within the learning model continuous state set. The RL framework is updated by the utility agent through repeated interactions with the MGCC agents. To facilitate adaptive conformation to changes in un-modeled system parameters, such as fuel price, a forgetting mechanism has been integrated into the training process to assign higher importance levels to the latest observed data, compared to older observations.

- **Level II - MG Power Management:** At the lower level, the MGCC agents receive the price signal for a look-ahead decision window. Based on the voltage level at the PCC and the received price signal, each MGCC agent solves a constrained Mixed Integer Nonlinear Program (MINP) to dispatch their local generation/storage assets to maximize their revenue (or equivalently minimize their cost) in the market, subject to full three-phase AC power flow constraints. Based on the solution to this problem, each individual MGCC agent determines the exchanged active and reactive power with the distribution system at PCC.

III. LEVEL I: ADAPTIVE RL-BASED DISTRIBUTION SYSTEM CONTROL

At the higher level of the hierarchy, a utility company is in charge of setting the locational price of electricity and substation voltage at different times to maximize its income from power exchange between wholesale and retail sectors. The difficulty in solving this problem is that the utility has almost no knowledge of MGs’ asset control and management data. This implies that the lower-level entities cannot be directly modeled at the higher level of the decision model, which makes the distribution system unobservable. To solve this problem, a RL approach is adopted, in which the decision making utility agent observes the response of its environment, consisting of networked MGs, to its actions at different states. Based on the received reward/cost signals from its environment and without explicit modeling, the agent searches for actions that optimize its expected accumulated received rewards at different system states. Hence, a RL framework consists of a Markov decision process including a set of states ($S \in S$), a set of actions ($a \in A$), a reward function ($r : S \times A \rightarrow \mathbb{R}$), and a state-action value function corresponding to each state-action pair $(Q : S \times A \rightarrow \mathbb{R})$. These components are defined for the problem at hand, as follows:

1) **State set definition:** In this paper, the system state, which is denoted by $S(t) = (S_1(t), \ldots, S_N(t))^\top$ at time $t$, is a concatenation of MGs’ local state vectors $(S_n(t)$ for the $n^{th}$ MG) defined as:

$$S_n(t) = \{\hat{P}_{PV}(t,n), \hat{P}_{D}(t,n)\}$$

where, $\hat{P}_{PV}(t,n), \hat{P}_{D}(t,n)$ are the vectors of aggregate solar power generation estimation, and aggregate active load power estimation for the $n^{th}$ MG at time $t$, respectively. Hence, to define the global state, the utility agent needs to estimate or predict the uncertain aggregate renewable power and load at the PCC for each MG. To represent the uncertainty of the prediction process, Gaussian noise values are added to the actual underlying solar and load values:

$$\hat{P}_{PV}(t,n) = \sum_{i} P_{PV,i,t,n} + e_{PV}(t)$$

$$\hat{P}_{D}(t,n) = \sum_{i} P_{D,i,t,n} + e_{D}(t)$$

where, $e_{PV}$ and $e_{D}$ are zero-mean Gaussian random numbers with standard deviations selected according to [16] and [17]. Also, $P_{PV,i}$ and $P_{D,i}$ denote the active solar power and active load at the $i^{th}$ bus of the $n^{th}$ MG at time $t$, respectively.

2) **Action set definition:** Given the definition of model states, the global action vector is similarly defined by the locational retail price signals at the PCCs with MGs, denoted as $\lambda_{R,n}$ for the $n^{th}$ MG, and the substation voltage magnitude, $V_{i,\text{Sub}}$, $a(t) = (\lambda_{R,1,n}, \ldots, \lambda_{R,N,n}, V_{i,\text{Sub}})^\top$.

3) **Reward function definition:** The reward function at time $t$ represents the discounted accumulated profit of the utility over the decision window $T$:

$$R(t) = \sum_{t=1}^{T} \gamma^t (\lambda_{W,t} P_{W,t} - \sum_{n=1}^{N} \lambda_{R,n} P_{PCC,n}^{t,n})$$

where, $P_{PCC,n}^{t,n}$ is the exchanged power between the MG and the utility at the substation at time $t$ and for MG $n$. The discount factor $\gamma$, typically chosen as $0 < \gamma < 1$, reduces the importance of future rewards compared to current rewards.
where, $\gamma$ is a discount factor ($\gamma \leq 1$) that defines the agent’s preference for the immediate reward, defined as the profit at time $t$, $\pi(t) = \lambda_t W - \sum_{n=1}^{N} \lambda_t \lambda_t P_{PCC}$. Also, $\lambda_t W$ denotes the wholesale energy price, $P_{PCC}$ is the exchanged power with the wholesale market, where $P_{PCC} \leq 0$ represents power import from the wholesale market. Note that $P_{PCC} \leq 0$ implies export to grid.

4) State-action value function parameterization: To optimize the utility agent’s action, an auxiliary state-action value function is formed, denoted as $Q(S, a)$, which can be thought of as a replacement for the explicit system model. The state-action value function determines the long-term accumulated expected reward given the current state and action vectors:

$$Q_t(S, a) = E\{\sum_{t'=t+1}^{T} \gamma^{t'} \pi(t') | S = S(t), a = a(t)\}$$  

where, the expectation operator $E\{\} \text{ is calculated with respect to the future expected action-states, which in this case are in turn functions of the solar-load uncertain powers. The goal of RL is to learn an optimal state-action value function, } Q_t(S, a) \text{, that satisfies the Bellman optimality equation [15], as follows:}$$

$$Q_t(S, a) = E\{\pi(t+1) + \gamma \cdot \max_{a'} Q_{t'}(S(t+1), a')\}$$  

Since solving (5) directly is not possible, RL provides a framework to obtain the optimal state-action value function which satisfies (5) using an iterative episodic learning environment. To implement this framework for the utility agent interacting with multiple MGs, the state-action value function is parameterized employing a multiple linear regression function approximation technique, defined by $\hat{Q}_t$, which is stated as follows:

$$\hat{Q}_t(S, a) \approx \hat{Q}_t(S, a; \theta) = Q_{SS-a}(\theta) + Q_S(t; \theta) + Q_a(t; \theta)$$  

Given the regression parameter vector $\theta$, $Q_{SS-a}$, $Q_S$, and $Q_a$ are the parameterized sub-components that capture the effect of state-action interaction, state values, and action values, respectively. These regression sub-components are defined as follows:

$$Q_{SS-a}(t; \theta) = \sum_{n=1}^{N} \theta_{1,n} \lambda_{t,n} \hat{P}_{PV}(t, n) + \sum_{n=1}^{N} \theta_{2,n} \lambda_{t,n} \hat{P}_D(t, n) + \sum_{n=1}^{N} \theta_{3,n} \hat{V}_{Sub} \hat{P}_{PV}(t, n) + \sum_{n=1}^{N} \theta_{4,n} \hat{V}_{Sub} \hat{P}_D(t, n)$$  

$$Q_S(t; \theta) = \sum_{n=1}^{N} \theta_{5,n} \hat{P}_{PV}(t, n) + \sum_{n=1}^{N} \theta_{6,n} \hat{P}_D(t, n)$$  

$$Q_a(t; \theta) = \sum_{n=1}^{N} \theta_{7,n} \lambda_{t,n} + \theta_{8} \hat{V}_{Sub} + \theta_{9}$$  

where, $\theta = \{\theta_{1,n}, \theta_{2,n}, \ldots\}$ constitute the parameters of the approximate state-action value function that have to be learned by the agent through repeated interaction with the MGs. To achieve this task we have adopted an adaptive episodic learning mechanism, which is shown in Fig. 2. Each episode in the learning process corresponds to an online decision instant. Hence, as the decision window rolls along time new episodes are perceived by the utility agent. The learning process has the following steps:

Step 1. Initialization: The time index is initialized as $t = t_0$, representing the first episode. The parameters of the state-action value function are initialized, $\theta \leftarrow \theta(t_0)$. The initial
state of the system, corresponding to aggregate solar power and load of all the MGs for the decision window \([t_0, t_0 + T]\) is predicted, \(\bar{S}(t_0), ..., \bar{S}(t_0 + T)\). Note that these predicted states, while representing system uncertainty, are updated continuously as the decision window rolls along time.

Step 2. Greedy Action Selection: Based on the latest state-action value function defined by parameter \(\theta\), the optimal actions are estimated for the decision window \([t, t + T]\) to maximize the agent’s accumulated reward, as follows:

\[
a_{opt}(t') = \arg \max_{a'} Q_t(S(t'), a') \\
\quad s.t. \quad a' = (\lambda^{R}_{t',1}, \ldots, \lambda^{R}_{t',N}, V_{t'}^{Sub})^T \\
\quad \lambda^{R}_{min} \leq \lambda^{R}_{t',i} \leq \lambda^{R}_{max}, \forall i = \{1, \ldots, N\} \\
\quad V_{min}^{Sub} \leq V_{t'}^{Sub} \leq V_{max}^{Sub}, \forall t' = \{t, \ldots, t + T\}
\]

where, \(\rho_{\lambda} = [\lambda^{R}_{min}, \lambda^{R}_{max}]\) and \(\rho_{V} = [V_{min}^{Sub}, V_{max}^{Sub}]\) define the minimum/maximum range of action for retail price and substation voltage, respectively. Note that given the parameterization for \(Q_t(S, a)\) in (7)-(9), (10) is basically a set of linear solvers, which can be solved efficiently using off the shelf solvers. A critical aspect of (10) is that the obtained optimal action, \(a_{opt}(t)\), is calculated with respect to the latest state-action value function, which could be far from being accurate in the early stages of training. Hence, to reduce the risk of sub-optimality and to strike a balance between exploration and exploitation in decision making, an \(\epsilon\)-greedy action selection method is adopted, with \(0 \leq \epsilon \ll 1\), to select the utility agent action at time \(t\) [15]:

\[
a(t) = \begin{cases} 
    a_{opt}(t) & \text{if } r \geq \epsilon \\
    \lambda^{R}_{i,t} \sim U(\rho_{\lambda}) & \forall i, V_{t}^{Sub} \sim U(\rho_{V}) \text{ if } r < \epsilon 
\end{cases}
\]

where, \(r\) is a random number selected uniformly, \(r \sim U([0, 1])\), with \(U(A)\) representing uniform probability distribution over the set \(A\). The randomization (11) promotes continuous exploration of action space to improve the outcome of the learning process. Upon obtaining the action vector \(a(t)\), retail price signals are sent to each MGCC agent and the voltage at the substation is modified.

Step 3. Networked MG Power Management: Based on the received price signals and the estimated PCG voltages, \(V_{t}^{PCG}, \forall n, t' = \{t, \ldots, t + T\}\), each MGCC agent solves its optimal energy management problem (Section IV). Based on the solutions at this stage, the aggregate power injection/withdrawal to/from the grid are obtained at the PCCs with the MGs, denoted as \(P_{t'}^{PCG}\) and \(Q_{t'}^{PCG}\), \(\forall n, t' = \{t, \ldots, t + T\}\).

Step 4. Accumulated Reward Calculation: Based on the outcomes of the MG power managements and the AC power flow, the net power exchange with the wholesale market, \(P_{t}^{W}\), is determined and used to calculate the discounted accumulated utility agent profit for the decision window \([t, t + T]\), using (5).

Step 5. Adaptive Model Training: Using the observed reward signal, the regression models defined in (7)-(9) are updated. The update process is based on a gradient descent approach to modify the parameters in the direction of improving the generalization capacity of the state-action value function [15]:

\[
\theta(t + 1) \leftarrow \theta(t) + \delta \{ R(t) - Q_t(S, a|\theta) \} \nabla_{\theta} Q_t(S, a|\theta) \quad (12)
\]

where, \(\delta\) is the step size that defines the rate of learning. Note that ideally we require \(Q_t(S, a|\theta) = R(t)\), which implies that the approximate state-action value function is able to accurately predict the accumulated reward. Accordingly, (12) is devised to reduce this prediction error over time. To implement (12), two points have to be taken under consideration: 1) since data acquisition and the training process both depend on agent action selection, approximate RL algorithms are known to be prone to overfitting and over-estimation of the values of state-action pairs [18]. Hence, a regularization mechanism has to be adopted to reduce the risk of overfitting, 2) the distribution system parameters are subject to change over time. These time-varying parameters, such as price of fuel, are not directly captured in the Markov decision process’s state definition. This makes the learned model susceptible to failure in case considerable changes occur in the values of these parameters. Hence, the training process needs to be adaptive to enable utility agent to quickly conform to new system conditions. To implement (12) while considering the above-mentioned points, a regularized recursive least squares algorithm with exponential forgetting is designed [19]. The regression parameters are updated recursively, as follows:

\[
\theta(t + 1) \leftarrow \theta(t) + \Delta(t) x(t) \{ R(t) - Q_t(S, a|\theta) \} \\
\Delta(t + 1) \leftarrow \Delta(t + 1) \left(1 + \mu \hat{\Delta}(t + 1) \right)^{-1} \\
\Delta(t + 1) \leftarrow \frac{1}{1 - \phi} \Delta(t) - \frac{\Delta(t) x(t)x^T(t)}{1 + x^T(t) \Delta(t)x(t)}
\]

where, \(x(t) = (S(t), a(t))^T\) represents the latest utility agent observation, \(\Delta\) is an auxiliary matrix mimicking the regression pseudo-inverse matrix, \(\mu\) is the regularization factor which is used for re-scaling the model covariance, and \(0 \leq \phi < 1\) is the forgetting factor. The regularization factor acts as a weight for penalizing the Euclidean norm of parameter vector (i.e., ||\(\theta||_2\)) in a ridge regression setting to prevent overfitting. The forgetting factor enables the utility agent to “forget” its earlier experiences in favor of the newer observations by assigning lower weights to the previously learned parameters. Hence, the forgetting factor introduces an exponential extinction of data history over time.

Step 6. State Transition: The decision window is moved forward to the new episode, \(t \leftarrow t + 1\). The new system state for the decision window, \([t, t + T]\) is predicted and denoted as \(\bar{S}(t), ..., \bar{S}(t + T)\). Go back to Step 2.

IV. LEVEL II: MGCC AGENT ENERGY MANAGEMENT

We assume that each MG is comprised of diesel generators as local DGs, ESS, solar Photo-Voltaic (PV) panels and a number of loads. Each MGCC solves the power management model formulated in (16)-(19) upon receiving the price signal and estimated voltage at the PCC. This optimization problem is solved over a moving look-ahead decision window \([t, t + T]\), using the latest estimates of solar and load power
at different instants. In this formulation, \( n \) is the MG index \((n \in \{1, \ldots, N\})\), \( i \) and \( j \) define the bus numbers for each MG \((V_i, j \in \Omega_I)\), and \( k \) denotes the line index \((\forall k \in \Omega_K)\).

\[
\min_{\mathbf{x}_p, \mathbf{x}_q} \sum_{i=1}^{T} (\lambda_R^{i, t,n} P_{PCC}^{i, t,n} + \lambda_F^{i, t,n} F_{i, t,n}) \tag{16}
\]

\[
\text{s.t. } F_{i, t,n} = a_f(P_{i, t,n}^{DG})^2 + b_f P_{i, t,n}^{DG} + c_f \tag{17}
\]

\[
|P_{PCC}^{i, t,n}| \leq P_{PCC,M}^{i, t,n} \tag{18}
\]

\[
|Q_{PCC}^{i, t,n}| \leq Q_{PCC,M}^{i, t,n} \tag{19}
\]

\[
0 \leq P_{DG}^{i, t,n} \leq P_{DG,M}^{i, t,n} \tag{20}
\]

\[
0 \leq Q_{DG}^{i, t,n} \leq Q_{DG,M}^{i, t,n} \tag{21}
\]

\[
P_{DG}^{i, t,n} - P_{DG,R}^{i, t,n} \leq P_{DG,R}^{i, t,n} \tag{22}
\]

\[
P_{i, t,n}^{ij} = V_{i, t,n}^{ij}(G_{i, t,n}^{ij} \cos(\theta_{i, t,n}^{ij}) + B_{n}^{ij} \sin(\theta_{i, t,n}^{ij})) \tag{23}
\]

\[
Q_{i, t,n}^{ij} = -V_{i, t,n}^{ij}(G_{i, t,n}^{ij} \cos(\theta_{i, t,n}^{ij}) - B_{n}^{ij} \sin(\theta_{i, t,n}^{ij})) \tag{24}
\]

\[
(P_{i, t,n}^{ij})^2 + (Q_{i, t,n}^{ij})^2 \leq (S_{ij,M}^{i, t,n})^2 \tag{25}
\]

\[
\sum_{i,j,k} P_{i, t,n}^{ij} = \sum_{i,j,k} Q_{i, t,n}^{ij} - q_{i, t,n} \tag{27}
\]

\[
p_{i, t,n} = P_{i, t,n}^{D,e} - P_{DG}^{i, t,n} - P_{PV,e}^{i, t,n} + P_{Ch}^{i, t,n} - P_{Dis}^{i, t,n} \tag{28}
\]

\[
p_{i, t,n}^{D,e} = P_{i, t,n}^{D,e} - \xi_{i, t,n}^{D} \tag{29}
\]

\[
p_{i, t,n}^{PV,e} = P_{i, t,n}^{PV,e} - \xi_{i, t,n}^{PV} \tag{30}
\]

\[
q_{i, t,n} = Q_{i, t,n}^{D,e} - Q_{DG}^{i, t,n} - Q_{PV}^{i, t,n} + Q_{ESS}^{i, t,n} \tag{31}
\]

\[
V_{i, t,n}^{PCC,E} = V_{i, t,n}^{PCC} \tag{32}
\]

\[
V_{i, t,n}^{m} \leq V_{i, t,n}^{l} \leq V_{i, t,n}^{M} \tag{33}
\]

\[
|Q_{PV}^{i, t,n}| \leq Q_{PV,M}^{i, t,n} \tag{34}
\]

\[
S_{i, t,n}^{m} \leq S_{i, t,n} \leq S_{i, t,n}^{M} \tag{36}
\]

\[
0 \leq u_{CH}^{i, t,n} \leq u_{CH}^{i, t,n} \tag{37}
\]

\[
0 \leq u_{CH}^{i, t,n} \leq u_{CH}^{i, t,n} \tag{38}
\]

\[
0 \leq u_{CH}^{i, t,n} + u_{Dis}^{i, t,n} \leq 1 \tag{39}
\]

\[
u_{CH}^{i, t,n} + u_{Dis}^{i, t,n} \in \{0, 1\} \tag{40}
\]

\[
|Q_{ESS}^{i, t,n}| \leq Q_{ESS,M}^{i, t,n} \tag{41}
\]

The objective function \([16]\), with decision vector \((\mathbf{x}_p, \mathbf{x}_q)\), minimizes each MG’s total cost of operation, which is composed of two terms: the income/cost from power transfer with the utility agent and cost of running local diesel generator. Here, \(\lambda_R^{i, t,n}\) is the DG fuel price, \(Q_{PCC}^{i, t,n}\) denotes the reactive power transfer between grid and MG through the PCC. The fuel consumption cost of diesel generator can be expressed as a quadratic polynomial function, \([17]\), with coefficients adopted from \([20]\). Constraints \([18]-[19]\) describe the power exchange limit between the MG and the upstream utility grid with the maximum active/reactive power exchange limits, \(P_{PCC,M}^{i, t,n}/Q_{PCC,M}^{i, t,n}\). Constraints \([20] - [22]\) ensure that the DG active/reactive power outputs, \(P_{DG}^{i, t,n}/Q_{DG}^{i, t,n}\), are within the DG power capacity \(P_{DG,M}^{i, t,n}/Q_{DG,M}^{i, t,n}\), and \([22]\) enforces the maximum DG ramp limit, \(P_{DG,R}^{i, t,n}/Q_{DG,R}^{i, t,n}\). Internal AC power flow model of the MG is considered here with the network topology constraints \([21]\), with \([23]\) and \([24]\) determining the active and reactive power flows of each branch \(i - j\), where \(G_{ij}^{ij}\) and \(B_{ij}^{ij}\) are the corresponding real and imaginary parts of the bus admittance matrix, and \(V_{i, t,n}^{ij}\) and \(\theta_{i, t,n}^{ij}\) are the nodal voltage magnitude and phase angle difference, respectively. Constraint \([25]\) denotes the power flow limits for each branch. Equations \([26] - [31]\) are the nodal active/reactive power balances at MG buses. The uncertainties of active load and PV power are represented by Gaussian random variables for active load and PV power prediction error. Accordingly, each MGCC agent predicts the active load and available nodal PV power over the decision window. Due to the uncertainties of active load and PV power in real-time, the predicted values are different from the actual active load and PV power. The differences are modeled using Gaussian error variables as shown in equations \([29]\) and \([30]\), where \(P_{i, t,n}^{PV,e}\) denotes the estimated active load, and \(P_{i, t,n}^{PV}\) is the estimated active power output of PV. Also, \(\xi_{i, t,n}^{PV} \sim N(0, \sigma)\) denote the Gaussian estimation errors for active load and PV power, respectively. The standard deviation of the error variables, is adopted from \([16] \text{ and } [17]\). Constraint \([32]\) sets the voltage at the PCC of the MG according to the estimated input voltage, \(V_{i, t,n}^{PCC}\). Constraint \([33]\) sets the limits for nodal bus voltage amplitude, \(V_{i, t,n}^{m}, V_{i, t,n}^{M}\). PV reactive power output, \(Q_{PV}^{i, t,n}\), is constrained by its maximum limit \(Q_{PV,M}^{i, t,n}\) per \([34]\). Operational ESS constraints are described by \([35] - [41]\), where \([35]\) determines the state of charge (SOC) of ESSs, \(S_{i, t,n}\). To ensure safe ESS operation, the SOC and charging/discharging power of ESS, \(P_{ESS}^{i, t,n}/P_{Dis}^{i, t,n}\), are constrained as shown in \([36] - [38]\). Here, \(S_{i, t,n}^{m}, S_{i, t,n}^{M}\), \(P_{Ch,M}^{i, t,n}\) and \(P_{Dis,M}^{i, t,n}\) define the permissible range of SOC, and maximum charging and discharging power, respectively. Constraint \([39]\) indicates that ESSs cannot charge and discharge at the same time instant, with \(u_{CH}^{i, t,n}/u_{Dis}^{i, t,n}\) denoting the charge/discharge binary indicator variables, and \(\eta CH/\eta Dis\) representing the charging/discharging efficiency. \(E_{Cap}^{i, t,n}\) denotes the maximum capacity of ESSs. The reactive power of ESS, \(Q_{ESS}^{i, t,n}\), is kept within maximum limit, \(Q_{ESS,M}^{i, t,n}\), through \([41]\).

V. NUMERICAL RESULTS

The proposed method is tested on a modified medium voltage IEEE 33-bus network \([22]\), which consists of four MGs as shown in Fig. 3 Each MG is modeled as a modified IEEE
13-bus network at a low voltage level [23]. Hence, the system has a total number of 85 nodes.

A. System Operation Outcomes

The aggregate hourly active load profiles of all the MGs are presented in Fig. 4. These load profiles are selected based on typical residential/commercial customer behavior using real smart meter data.

The optimal locational price signals for the MGs are presented in Fig. 5. It can be observed that higher price values are set at the intervals with higher load levels. Power exchange between MGs and the main grid under optimal price actions are shown in Fig. 6. In general, as expected, the MGs sell power to the utility agent during peak load period when the price of electricity is set higher and buy power from the utility agent during off-peak load period. The overall power exchange between the utility agent and the wholesale market and the hourly wholesale electricity price are presented in Fig. 7. It is observed that the utility exports more power to the market at times of higher price, which leads to an increase in utility’s revenue from sales of power. The utility hourly profit is shown in Fig. 8. It can be seen that the utility buys power from MGs during peak load hours, which leads to negative reward values. The reason for this is that higher retail prices at this interval incentivize the MGs to generate more power, which leads to a drop in utility’s revenue.

The behavior of MG generation/storage assets under the optimal price signal are shown in Fig. 9 to Fig. 11. The ESS SOC's and charge/discharge powers are presented in Fig. 9 and Fig. 10. In Fig. 9, it is seen that the ESS SOC's are kept within their minimum/maximum ranges at all times. It can be observed that ESS units of the MGs are in charging state during off-peak interval under lower prices, and are in discharge mode as the retail prices increase during peak hours. The DG power outputs of the MGs are depicted in Fig. 11. Generally, DG units generate more power under higher retail price signals when the cost of buying power from the utility agent is higher compared to the local DG generation costs.

A numerical comparison between a centralized solver versus the proposed method for the multiple MGs power management problem is shown in Table I. In this table, the total social welfare is defined as the summation of the utility accumulated
reward and the operational cost of all the MGs. Compared to the centralized optimization method, the proposed RL-based method leads to an improvement of 4.9% in social welfare. Note that while the initial RL training stage can be time-consuming (depending on the value of the forgetting factor), the decision time is much smaller than that of a centralized optimization method, upon convergence. This is due to the fact that the proposed RL-based method is able to receive continual updates over time, which enables the decision framework to reach a solution in real-time without the need to solve a large-scale optimization problem at each time instant. Moreover, these advantages are complemented by the RL’s capability to maintain the data privacy of MGs.

### B. Adaptive RL Results

To verify the functionality of the RL framework, the estimated reward obtained from the multiple linear regression is compared with the actual reward at each episode, as shown in Fig. 12. As can be seen, at the earlier stages of the learning process, the difference between the predicted utility reward and the real utility agent reward is relatively high. However, as the number of episodes increases, this difference drops to within an acceptable range (less than 2%), which implies that the utility agent is able to accurately predict the response of MGs to control actions. Hence, using the proposed RL approach the utility agent is able to track the behavior of market participants and maximize its reward through continuous interactions.

To test the adaptability of the learning framework against changes in un-modeled parameters, a numerical scenario is devised. At a point in time (episode $t = 1500$ h), the DG fuel price is doubled. The reward estimation Mean Absolute Percentage Error (MAPE) is shown in Fig. 13. As can be seen, upon the occurrence of the sudden change in fuel price, the learning error percentage jumps to a very high value since the utility agent is now facing a new unknown environment, as the price of fuel is not included within the agent’s Markov decision process. However, as the learning process with forgetting proceeds, the error percentage drops to within acceptable range once more. The actual and estimated reward corresponding to this scenario are shown in Fig. 14. As can be seen here, the utility agent is able to track the actual underlying reward signal as the number of episodes increases and the RL model converges to its optimal action-state value function. In addition, due to the sudden increase in the fuel price, the utility reward increases. This is due to the fact that the cost of local DG power generation rises.

| TABLE I | COMPARISON RESULTS BETWEEN PROPOSED METHOD AND CENTRALIZED OPTIMIZATION |
|---------|-------------------------------|
| RL-based method | Centralized opt. |
| Social welfare ($) | 1227.45 | 1221.60 |
| Computational time (s) | 9.64 | 116.35 |
| MG privacy maintenance | Yes | No |
linearly with the price of fuel, which leads to higher power imports from the main grid for the MGs. In Fig. 15, the impact of forgetting factor on the convergence of the RL framework is demonstrated. This figure shows the RL-based reward estimation error for the utility agent under two different forgetting factor values. As the forgetting factor increases from 0.01 to 0.1 the speed of convergence of the RL framework has been improved. However, a trade-off exists between the rate of convergence and the accuracy of the solution. As observed in this figure, higher forgetting factors also lead to higher variances in the estimation error signal.

VI. CONCLUSIONS

Smart distribution systems with networked MGs can facilitate reliable power delivery to customers in future power grids. However, utilities have limited knowledge about MG operational parameters due to privacy and data ownership concerns, which is an obstacle in the way of optimal decision making in these systems. Motivated by the shortcomings of model-based multiple MG power management in distribution systems with limited observability, this paper presents a model-free RL-based methodology for data-driven power management of multiple networked MGs. Using the proposed model, a utility agent is able to accurately track the behavior of MGs under incomplete knowledge of operation behind the PCCs. This can be used to indirectly control the response of participants in a retail market environment. The framework is shown to be adaptive against the changes happening to unmodeled variables. The learning model has been tested and verified using extensive numerical scenarios. The proposed decision model shows better adaptability, solution quality, and computational time compared to conventional centralized optimization methods.

REFERENCES

[1] M. Manbachi and M. Ordonez, “AME-based energy management of islanded ac/dc microgrids utilizing energy conversion and optimization,” to appear in IEEE Trans. Smart Grid.
[2] R. Lasseter, A. Akhil, C. Marnay, J. Stephens, J. Dagle, R. Guttromson, A. S. Meliopoulos, R. Yinger, and J. Eto, Integration of distributed energy resources. The CERTS Microgrid Concept. California, USA: Lawrence Berkeley National Laboratory, 2002.
[3] S. A. Areffifar, Y. A. . J. Mohamed, and T. H. M. El Fouly, “Optimum microgrid design for enhancing reliability and supply-security,” IEEE Trans. Smart Grid, vol. 4, no. 3, pp. 1567–1575, Sept. 2013.
[4] N. Mohsen, M. Braun, and S. Tenbohlen, “Optimization of unit commitment and economic dispatch in microgrids based on genetic algorithm and mixed integer linear programming,” Applied energy, vol. 210, pp. 944–963, Jan. 2018.
[5] N. Nikmehr and S. N. Ravadanegh, “Optimal power dispatch of multi-microgrids at future smart distribution grids,” IEEE Trans. Smart Grid, vol. 6, no. 4, pp. 1949–1657, Sept. 2015.
[6] S. A. Areffifar, M. Ordonez, and Y. A. I. Mohamed, “Energy management in multi-microgrid systems development and assessment,” IEEE Trans. Power Syst., vol. 32, no. 2, pp. 910–952, March 2017.
[7] O. Ouni, H. Dagdougui, and R. Sacile, “Optimal control of power flows and energy local storages in a network of microgrids modeled as a system of systems,” IEEE Trans. Control Syst. Tech., vol. 62, no. 4, pp. 2551–2559, April 2015.
[8] P. Kou, D. Liang, and L. Gao, “Distributed empc of multiple microgrids for coordinated stochastic energy management,” Applied energy, vol. 185, pp. 939–952, Nov. 2017.
[9] D. Gregoratti and J. Matamoros, “Distributed energy trading: The multiple-microgrid case,” IEEE Trans. Ind. Electron., vol. 62, no. 4, pp. 2551–2559, April 2015.
[10] Y. Zhang, L. Xie, and Q. Ding, “Interactive control of coupled micro-grids for guaranteed system-wide small signal stability,” IEEE Trans. Smart Grid, vol. 7, no. 2, pp. 1088–1096, March 2016.
[11] H. S. V. S. K. Nunna and S. Doolla, “Multiagent-based distributed energy-resource management for intelligent microgrids,” IEEE Trans. Ind. Electron., vol. 60, no. 4, pp. 1678–1687, April 2013.
[12] Z. Wang, B. C. J. Wang, and J. Kim, “Decentralized energy management system for networked microgrids in grid-connected and islanded modes,” IEEE Trans. Smart Grid, vol. 7, no. 2, pp. 1097–1105, March 2016.
[13] Z. Wang, B. C. J. Wang, M. Begovic, and C. Chen, “Coordinated energy management of networked microgrids in distribution systems,” IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 45–53, Jan. 2015.
[14] B. Zhao, X. Wang, D. Lin, M. Calvin, J. Morgan, R. Qin, and C. Wang, “Energy management of multiple-microgrids based on a system of systems architecture,” To appear in IEEE Trans. Power Syst.
[15] R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction. London, England: The MIT Press, 2017.
[16] C. Yang, A. A. Thatte, and L. Xie, “Multitime-scale data-driven spatiotemporal forecast of photovoltaic generation,” IEEE Trans. Sustain. Energy, vol. 6, no. 1, pp. 104–112, Jan. 2015.
[17] C. Guan, P. B. Luh, L. D.Michel, Y. Wang, and P. B. Friedland, “Very short-term load forecasting: wavelet neural networks with data pre-filtering,” IEEE Trans. Power Syst., vol. 28, no. 1, pp. 30–41, Feb. 2013.
[18] W. D. Smart and L. P. Kaelbling, “Practical reinforcement learning in continuous spaces,” ICML, pp. 903–910, Jun. 2000.
[19] I. Houtzager, J. W. van Wingerden, and M. Verhaegen, “Recursive predictor-based subspace identification with application to the real-time closed-loop tracking of flutters,” IEEE Trans. Control Syst. Technol., vol. 20, no. 4, pp. 934–949, Jul. 2012.
[20] A. Pourmousavi, H. Nehrir, and R. K. Sharma, “Multi-timescale power management for islanded microgrids including storage and demand response,” IEEE Trans. Smart Grid, vol. 6, no. 3, pp. 1185–1195, May 2015.
[21] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, “Matpower: Steady-state operations, planning, and analysis tools for power systems research and education,” IEEE Trans. Power Syst., vol. 176, pp. 12–19, Feb. 2011.
[22] M. E. Baran and F. F. Wu, “Network reconfiguration in distribution systems for loss reduction and load balancing,” IEEE Trans. Power Del., vol. 4, pp. 1401–1407, Apr. 1989.
[23] W. Kersting, “Radial distribution test feeder,” in Proceedings of 2001 IEEE Power Engineering Society Winter Meeting, vol. 2, pp. 908–912, 2001.