Deep Learning-based Real-time Switching of Reconfigurable Microgrids

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***Abstract*—This paper proposes a new approach for finding the optimal switchings of reconfigurable microgrids (MGs) based on a deep learning technique. As the load and power generation of units vary with time, the network reconfiguration depends on both the current and previous status of load demand and generation units. To this end, the gated recurrent unit (GRU) algorithm, a time series model, is employed to solve the network reconfiguration. The GRU architecture is designed to learn the network topology characteristics, e.g., power injection and line impedance. Finally, the proposed technique is examined with the IEEE 33 microgrid test system. Results show that the deep learning-based technique is able to make accurate reconfiguration decisions in real time.**

***Index Terms*—Deep learning, gated recurrent unit, microgrid, reconfiguration.**

NOMENCLATURE

Sets/Indices

i/Ω^{DG}	Index/Set of the generation unit
k/Ω^{S}	Index/Set of switches
nm/Ω^{L}	Index/Set of MG distribution lines
$n,m/\Omega^{N}$	Index/Set of MG node
RCS	Index of the remote control switches
t/Ω^{T}	Index/Set of time
$\underline{(.)}/\overline{(.)}$	Indices of minimum and maximum values

Parameters and variables

C_i	Generation cost of ith unit
C_M	Cost of purchased power from the main grid
I_{it}	Status of ith unit. 1: if it is ON; otherwise it is 0.
$I^{L}_{nm,t}$	MG distribution line current flow at tiem t
$N_{RCS,k}$	Number of reconfiguration switching actions of kth RCS
N_{loop}	MG network main loops
N_{branch}	MG branch number
N_{bus}	MG bus number
P^{M}_{t}	Purchased power from the main grid at time t
P^{G}_{it}/Q^{G}_{it}	Active/reactive power of unit i at time t
P^{D}_{t}/Q^{D}_{t}	Active/reactive power demand
$P^{L}_{nm,t}$	MG distribution lines active power flow at time t
$Q^{L}_{nm,t}$	MG distribution lines reactive power flow at time t
$R/X/Z$	Resistance/reactance/impedance
SU/SD	Startup/shutdown cost
V_{mt}	Voltage of bus m at time t
$\Delta_{mn,t}$	Auxiliary variable
λ_{RCS}	Reconfiguration switching cost
θ_{nt}	Angle of bus n at time t

I. INTRODUCTION

A microgrid (MG) is the aggregation of distributed energy resources (DERs) and load in a small electricity grid, which can operate in both grid-connected and islanded modes [1]. During the past decades, MG has been attracting lots of attention due to its significant benefits, e.g., higher reliability and resiliency, voltage profile, and load balancing, as well as lower power losses and operation costs [2] [3] [4]. However, along with these benefits, there still exist challenges in MG protection, control, and energy management [5].

The energy management of MG has been widely studied in the literature. For instance, the energy management of a renewable-based MG has been investigated in [6]. The authors used a hybrid energy storage system to compensate the uncertainty associated with renewable energy resources. In [7], a robust optimization technique was proposed for MG energy management. The authors used a fuzzy prediction interval model to manage the complexity of the problem. A market-based energy management of MG was studied in [8], where the correlation between the MG and the main utility grid was modeled. Energy management of a MG with electric vehicles has been investigated in [9]. It should be noted that compared to the conventional bulk power grids, distribution lines of a MG are more willing to be overloading and voltage fluctuation due to the higher Thevenin impedance, particularly in the islanded mode. To this end, using the reconfiguration technique as a fast, reliable, and effective response can enhance the reliability and performance of the MG network.

By definition, reconfiguration is to change the MG topology through pre-located and tie switches [10]. Using the reconfiguration technique for the optimal energy management of MG has been widely investigated in the literature. For example, in [11] a reconfiguration technique was developed for MG operation by considering the uncertainties from renewable energy generation. The authors used a mixed-integer linear programming (MILP) technique to solve the problem. In [12] a reconfigurable MG was studied by modeling the effect of the dynamic line rating constraint. The authors adopted a heuristic technique known as the collective decision optimization algorithm (CDOA), to overcome the nonlinearity and complexity of the problem. A reconfigurable hybrid AC/DC MG was studied in [13], where the authors developed a reconfiguration technique for both AC and DC parts.

Reconfigurable MG is mixed-integer nonlinear programming (MINLP) problem, due to the binary variable of the switches and nonlinear AC power flow. Up to now, a number of mathematical and heuristics techniques have been already developed to solve the optimal operation of the reconfigurable MG. However, mathematical approaches, e.g., linearing the problem to a MILP problem, are suffering from optimality of the solution. On the other hand, hueristic algorithms generally converge slowly. To this end, in this paper for the first time, the gated recurrent unit (GRU) learning-based technique is developed to find the optimal switchings of the reconfigurable MG for both grid-connected and islanded modes. Using GRU to find the optimal switchings of the reconfigurable MG has two advantages: *(i)* high convergence speed, and *(ii)* being flexible and extendable to different sizes of networks. It should be noted that machine/deep learning techniques have been widely used in MG operations to forecast the load demand [14], solar power [15], and wind power [16]. However, to the best of authors' knowledge, this paper is the first to utilize deep learning for solving the reconfigurable MG operation problem.

The rest of this paper is organized as follows: Section II explains the mathematical formulations of the reconfigurable MG. Section III describes the proposed GRU model. Section IV presents the simulation results, followed by the conclusion in Section V.

II. Reconfigurable Microgrid formulations

The proposed reconfigurable MG includes an objective function and constraints as follows.

$$\begin{aligned} Minimize \quad & \sum_{i\in\Omega^{DG}}\sum_{t\in\Omega^{T}}[C_iP^G_{it}+SU_{it}I_{it}+SD_{it}I_{it}]+ \\ & \sum_{t\in\Omega^T}[C_M(P^M_t-P_{loss,t})]+\sum_{k\in\Omega^S}N_{RCS,k}\lambda_{RCS} \end{aligned} \quad (1)$$

subject to

$$\begin{aligned} \sum_{nm\in\Omega^L}[P^L_{nm,t}-R_{nm}(I^L_{nm,t})^2]-\sum_{nm\in\Omega^L}P^L_{nm,t} \\ +P^G_{it}=P^D_t \quad \forall i\in\Omega^{DG},\forall t\in\Omega^T \end{aligned} \quad (2)$$

$$\begin{aligned} \sum_{nm\in\Omega^L}[Q^L_{nm,t}-X_{nm}(I^L_{nm,t})^2]-\sum_{nm\in\Omega^L}Q^L_{nm,t}+ \\ Q^G_{it}=Q^D_t \quad \forall i\in\Omega^{DG},\forall t\in\Omega^T \end{aligned} \quad (3)$$

$$\begin{aligned} (V_{mt})^2-(V_{nt})^2=2(R_{nm}P^L_{nmt}+X_{nm}Q^L_{nmt}) \\ -(Z_{nm})^2(I^L_{nmt})^2+\Delta V_{nmt} \\ \forall nm\in\Omega^L,\forall n,m\in\Omega^N,\forall t\in\Omega^T \end{aligned} \quad (4)$$

$$\begin{aligned} (V_{mt})^2(I^L_{nmt})^2=(P^L_{nmt})^2+(Q^L_{nmt})^2 \\ \forall nm\in\Omega^L,\forall m\in\Omega^N,\forall t\in\Omega^T \end{aligned} \quad (5)$$

$$\underline{P^G_i}I_{it}\le P^G_{it}\le\overline{P^G_i}I_{it}\quad \forall i\in\Omega^{DG},\forall t\in\Omega^T \quad (6)$$

$$\underline{Q^G_i}I_{it}\le Q^G_{it}\le\overline{Q^G_i}I_{it}\quad \forall i\in\Omega^{DG},\forall t\in\Omega^T \quad (7)$$

$$\underline{V_n}\le V_{nt}\le\overline{V_n}\quad \forall n\in\Omega^N,\forall t\in\Omega^T \quad (8)$$

$$-\pi\le\theta_{nt}\le\pi\quad \forall n\in\Omega^N,\forall t\in\Omega^T \quad (9)$$

$$N_{RCS,k,t}\le\overline{N_{RCS}}\quad \forall k\in\Omega^S,\forall t\in\Omega^T \quad (10)$$

$$N_{loop}=N_{branch}-N_{bus}+1 \quad (11)$$

Equation (1) is the objective function, which seeks to minimize the total operation cost of the MG, including the generation unit cost, exchanging power from the main grid cost (in the grid-connected mode), and reconfiguration switching cost of the network. Equations (2)-(11) are constraints of the problem. More specifically, the active and reactive load balances of each bus are guaranteed by constraints (2) and (3), respectively. Constraints (4) and (5) apply the Kirchhoff's Voltage Law (KVL) to the MG distribution lines. Here, ΔV_{mn} is the auxiliary variable, which is zero if line nm operates (the switch is ON); otherwise, it can be positive or negative, which depends on the difference between the sending and receiving voltages of the line mn. The active and reactive powers of the distributed generators (DGs) should be within limits as (6) and (7), respectively. Furthermore, the voltage and angle of buses should be constrained as (8) and (9), respectively. The remote control switches (RCSs) actions per day are limited as (10). Finally, constraint (11) assures the rediality of the MG network.

III. Gated Recurrent Units for Microgrid Reconfiguration

As mentioned above, the load and output power of DGs vary with time. Hence, the network reconfiguration is related to both the current and previous status of the load and DGs. To this end, a time series deep learning algorithm, i.e., gated recurrent unit (GRU), is adopted to find the optimal reconfiguration switchings of the MG network. GRU was developed by Chung et al. [17] in 2014, with the aim to reduce the complexity and improve the performance of the long short-term memory (LSTM). Similar to LSTM, GRU includes gates that control the data flow from the input to the output. Fig. 1 depicts the block diagram of the GRU technique. It is shown that the activation h_t at the time t is a function of the candidate activation $\tilde{h}_t$ and the previous activation h_{t-1}. That means

$$h_t=(1-z_t)h_{t-1}+z_t\tilde{h}_t \quad (12)$$

where z_t is an update gate that determines the updates of the unit for its activation or content. Hence, this gate can be calculated as:

$$z_t=\sigma(U_zh_{t-1}+W_zx_t+b_z) \quad (13)$$

where σ is a smooth and differentiable activation function; W_z, U_z and b_z are the input constant, previous activation constant, and the bias of the update gate (z), respectively. Moreover, the candidate activation in (12) can be calculated as:

$$\tilde{h}_t = tanh(U(r_t \bigodot h_{t-1})Wx_t \tag{14}$$

Here, $\bigodot$ denotes as the element-wise multiplication. Also, the parameter r_t is the reset gate that can be updated as:

$$r_t = \sigma(U_r h_{t-1} + W_r x_t + b_r) \tag{15}$$

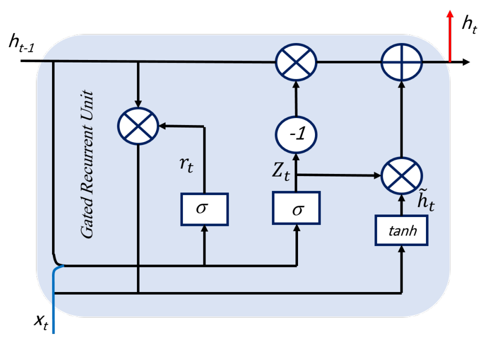

Fig. 1. The GRU block diagram.

Algorithm 1 GRU Algorithm

for *t=1:24* **do**
  for *t=1: Number GRU cells* **do**
    1. Update gate Z_t based on the weights and biases to decide the ratio of input data that can be passed.
    2. The reset gate r_t is updated to forget some range of input data.
    3. A memory unit $\tilde{h}_t$ is obtained based on the amount of data that is forgotten.
    4. From the memory unit $\tilde{h}_t$, update gate Z_t, and previous cell output h_{t-1}, the next output h_t is selected and applied to the next GRU unit based on the derived equations.
  end
end

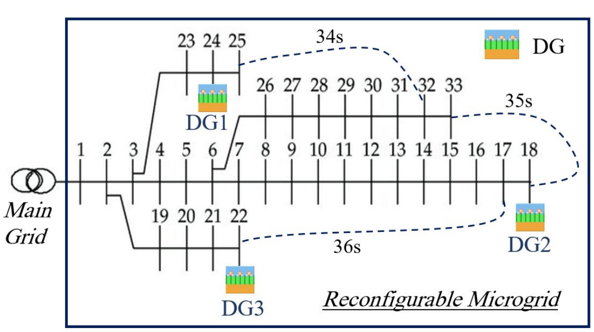

Fig. 2. Modified IEEE 33 bus test system.

It is worth noting that the load and DGs power are inputs, the GRU units are in the hidden layer, and the status of the switches is the output. The procedure of the GRU technique is explained in Algorithm 1. Moreover, to prepare the training data, the network reconfiguration is solved by CDOA under different load conditions [12]. Different load curves have been selected according to real data from both the California Independent System Operator (CAISO) [18] and the Electric Reliability Council of Texas (ERCOT) [19].

IV. Simulation Results

To validate the effectiveness of the proposed technique, the IEEE 33 reconfigurable MG bus test system is selected in our case study. The single line diagram of the proposed network is depicted in Fig. 2. The network contains 3 tie switches, 33 sectionalized switches, and 3 DGs. Table I summarizes the characteristics of DGs within the network. Also, Fig. 3 shows the hourly load demand and market price. The proposed MG reconfiguration is tested on both grid-connected and islanded modes.

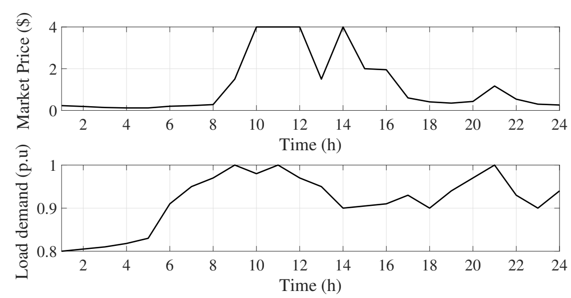

Fig. 3. Hourly market price and load demand

TABLE I
Generation units capacity and cost

Generation Type	$\underline{P_i^G}$ (kW)	$\overline{P_i^G}$ (kW)	C_i ($\$/kWh$)	SU/SD ($)
Fuel cell	80	1000	0.294	0.96
Microturbine 1	100	1500	0.457	1.65
Microturbine 2	100	1500	0.457	1.65

A. Grid-connected mode

In this part, the MG is in the grid-connected mode; that means, it can exchange power with the main grid. Fig. 4 depicts the optimal switchings of both the conventional (CDOA) and the proposed learning-based techniques. According to the simulation results, there exist slight differences between the optimal reconfiguration switchings (that should be opened to ensure the radiality of the network) of both the conventional and the proposed techniques. For instance, at hour 3, the first switch number between the conventional and proposed techniques (see S1 in Fig. 4) are different. However, in the majority of the time horizon, the switching numbers are the same between both techniques. Slight differences between the optimal reconfiguration switchings can affect not only the output power of DGs within the network but also the exchanging power with the main grid. Fig. 5 shows the optimal output power of DGs in the grid-connected mode. It is shown that the output power of the DGs is varying, due to the different reconfiguration switchings.

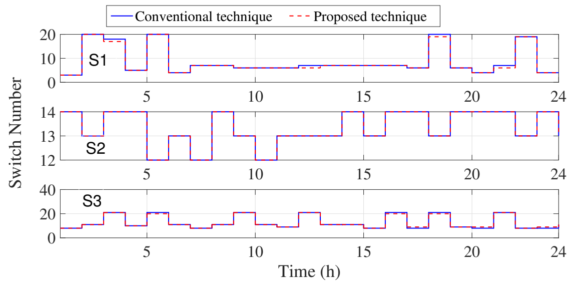

Fig. 4. Optimal reconfiguration switchings of the grid connected mode for both the conventional (solid lines) and proposed techniques (dashed lines).

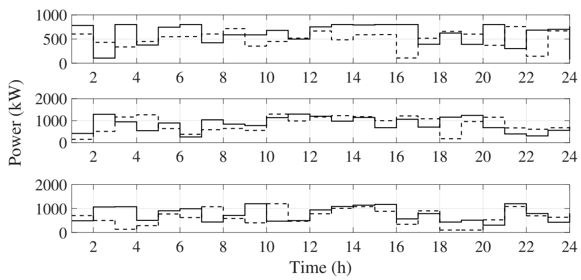

Fig. 5. Generation units power outputs in the grid-connected mode for both conventional (solid lines) and proposed (dashed lines) techniques.

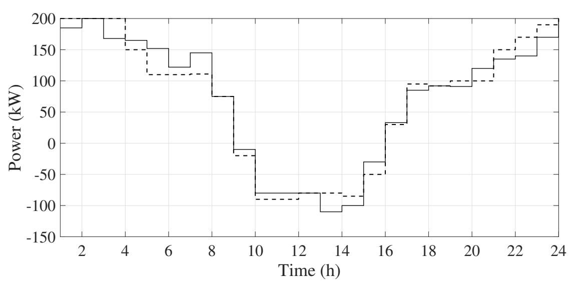

Fig. 6. Exchanged power with the main grid for both conventional (solid lines) and proposed (dashed lines) techniques.

TABLE II
COMPARISON OF THE TOTAL OPERATION COST

Mode	Method	Cost ($)
Grid-connected	Conventional Optimization-based	21,074
Grid-connected	Proposed Learning-based	21,127
Islanded	Conventional Optimization-based	25,295
Islanded	Proposed Learning-based	25,470

Fig. 6 shows the exchanging power with the main grid for both the conventional and the proposed techniques. It should be noted that the negative power means selling power to the grid, while the positive power means purchasing power from the main grid. As can be seen, there exist slight differences between the conventional and proposed techniques. However, they have almost the same pattern. Indeed, more power is purchased from the main grid with decreasing the market price.

Although the contributions of DGs and exchanging power are different, the optimal operation cost of the proposed and conventional techniques are very close. Table II compares the total MG operation cost between the conventional and proposed techniques. The operation cost of the proposed technique is slightly higher than that of the conventional technique. However, the learning-based method can converge within milliseconds as shown in table III.

TABLE III
COMPARISON OF THE CONVERGENCE TIME

Mode	Method	Convergence speed
Grid-connected	Optimization-based	15.3 (s)
Grid-connected	Learning-based	1.4 (ms)
Islanded	Optimization-based	16.6 (s)
Islanded	Learning-based	1.5 (ms)

The per unit (p.u) voltage magnitude of buses after the reconfiguration switching, considering the proposed learning-based technique is depicted in Fig. 7. Based on the figure, all of the voltages of buses are within the permissible ranges, which validates the effectiveness of the learning-based technique.

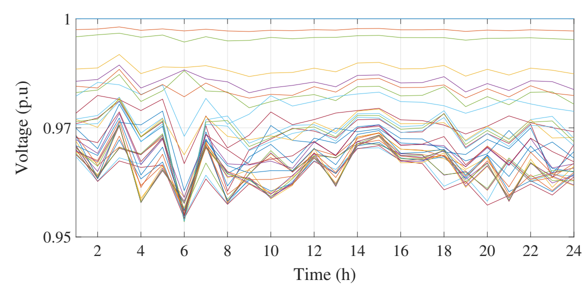

Fig. 7. The per unit (p.u) voltage magnitude of buses in the grid-connected mode.

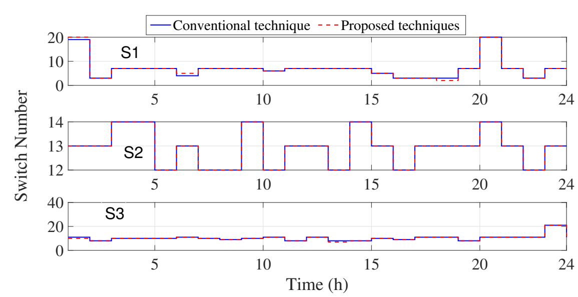

Fig. 8. Optimal reconfiguration switchings of the islanded mode for both the conventional (solid lines) and proposed techniques (dashed lines).

B. Islanded mode

In the second scenario, the MG is disconnected from the main grid; that means the DGs within the network should satisfy the load demand of the network. Fig. 8 depicts the optimal reconfiguration switchings of both conventional and the proposed techniques. Similar to the previous gird-connected mode, there exist slight differences between the optimal reconfiguration switchings of the proposed and conventional techniques. For instance, at hour 1, the switching number of S1 and S2 are different between the conventional and proposed techniques. This difference leads to the different contributions of DGs, as shown in Fig. 9. However, same as the previous case, the total operation cost of the conventional and proposed techniques are very close. It is worth noting that in both techniques, the total operation cost of the islanded mode is higher than the grid-connected mode. These extra costs are known as islanded costs. Table III compares the computational efficiency between the conventional and proposed techniques, showing that the deep learning-based method is able to gain the optimal network switchings within milliseconds. It is should be noted that since the islanded MG is more prone to be overloaded due to the higher Thevenin impedance, a fast and accurate reconfiguration technique plays a significant role in MG operation. Therefore, the security of the network could be increased by leveraging the fast deep learning-based reconfiguration technique in MG operations.

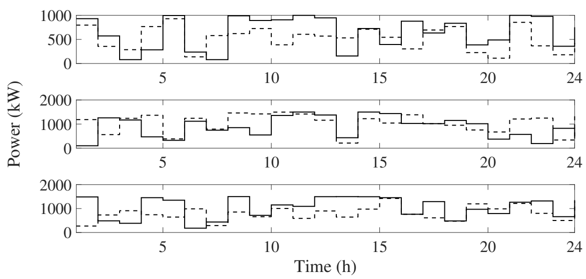

Fig. 9. Generation units power outputs in the islanded mode for both conventional (solid lines) and proposed (dashed lines) techniques.

Fig. 10 depicts the voltage magnitude (p.u) of buses after the reconfiguration switching, considering the proposed learning-based technique. Similar to the grid-connected mode, all of the voltages of buses are within the permissible ranges.

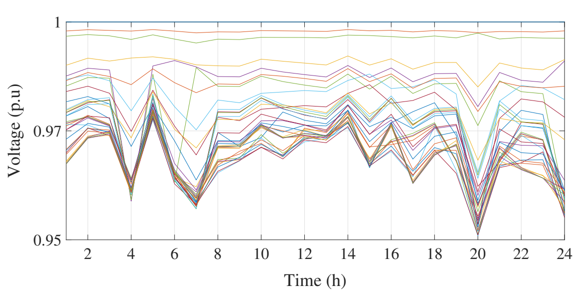

Fig. 10. The per unit (p.u) voltage magnitude of buses in the grid-connected mode.

V. Conclusion

In this study, the gated recurrent unit learning-based method was utilized for obtaining the optimal switchings of the reconfigurable MG. Results of both grid-connected and islanded modes showed that although there exist some differences in the output power of DGs and switchings, the total operation costs are almost the same between the conventional and proposed learning-based techniques. Results also showed the high computational efficiency of the deep learning-based technique, which could be helpful under emergency conditions (e.g., attacks, contingency, and natural disasters) when a fast MG reconfiguration is desired.

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