A Data-Driven Robust Optimal Power Flow Method for An Islanded Microgrid with Droop Control

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***Abstract* – Islanded microgrids have encountered challenges such as heavy frequency and voltage deviations, as well as impaired operational efficiency by uncertain renewables. Existing model-based optimal power flow (OPF) methods fail in estimating network operating conditions, making online decisions, and providing robust solutions. As a reinvention to islanded microgrids, this paper proposes a data-driven robust OPF method to address these emerging issues, the first in the literature. The method aims to minimize the total operating cost by economically dispatching multiple microturbines with droop control enabled. An improved islanded microgrid power flow algorithm is developed first with high convergence efficiency and then used in a deep reinforcement learning algorithm. Samples of uncertainty are generated and utilized in the training process to guarantee solution robustness. Via case study, the high efficiency of the proposed method in comparison to the existing work is validated.**

***Index Terms* – Deep reinforcement learning, droop control, islanded microgrid, optimal power flow, uncertainty.**

Nomenclature

a_n	Generation cost parameters($/kW).
$\boldsymbol{BCBV}$	Branch current to branch voltage drop matrix
$\boldsymbol{BIBC}$	Bus current to branch current matrix.
f	System frequency (per unit).
I_{branch}	Current through a branch (A).
I_n	Injection current at a bus (A).
$m_{eq}^{P/Q}$	Droop control coefficients.
n	Bus index.
P/Q_n	Active/reactive power injection (kW/kVar).
P/Q_n^{MT}	Real-time microturbine active/reactive power output (kW/kVar).
P/Q_n^{MT0}	Microturbine active/reactive power output setpoint (kW/kVar).
P/Q_n^{NL}	Net load active/reactive power, i.e., load minus distributed power generation (kW/kVar).
$S_n^{MT,cap}$	Microturbine power capacity (kVA).
V	Bus voltage (per unit).
V_r	Reference bus voltage (per unit).
V_0/f_0	Nominal voltage/frequency (per unit).
$(.)^{max/min}$	Maximum/minimum limit.
$(.)^*$	Conjugate of complex number.
$Re/Im()$	Real/imaginary part of complex number.
$\Delta(.)$	Deviation to reference or change to be updated.

Bold symbols indicate vectors/matrices.

The work was supported in part by the Discovery Early Career Research Award (DE240100059) of Australian Research Council, and in part by The University of Sydney International Scholarship (USYDIS).

I. INTRODUCTION

Microgrids, as a new form of power system, can efficiently integrate distributed energy resources and supply reliable power to local users, and they have been increasingly constructed, especially in rural areas and on islands. It is essential to economically control microgrid-owned microturbines and robustly keep network operating constraints [1].

Optimal power flow (OPF) methods for grid-connected microgrids by dispatching microturbines have been widely studied. However, advancing methods for islanded microgrids is a timely research topic. Ref. [2] developed an optimal scheduling model with a power balance equation to minimize power mismatches, while [3] proposed an OPF model with linearized distribution flow to minimize daily operating costs. Both studies did not consider the system frequency in the islanded operation mode. However, the power imbalances in the islanded microgrids can cause system frequency deviations and even system instability [4]. It is imperative to estimate and address the system frequency deviations in islanded microgrids. Microturbines are generally enabled with droop control functions to provide frequency and voltage control. The response of the microturbines to frequency and voltage deviations is expected to be considered in estimating the network operating conditions.

Ref. [5] proposed an efficient power flow calculation algorithm called direct load flow for three-phase distribution networks. Based on this algorithm, ref. [6] developed a direct backward/forward sweep (BFS) algorithm for islanded microgrids. This BFS algorithm can estimate the system frequency with consideration of microturbine frequency and voltage droop control. Later, a modified BFS algorithm was developed in [7] with load modeling. These BFS algorithms can provide an efficient numerical analytics tool for islanded microgrids, but they cannot be directly extended as operating constraints into a mathematical OPF model.

For OPF methods, [8] directly involved the frequency and voltage calculation equations of droop control and formulated a mixed-integer linear programming model. Ref. [9] designed controllers for frequency and voltage regulation, and it applied a genetic algorithm (GA) for an optimization model with Simulink estimating microgrid operating conditions. Recently, OPF methods with the BFS algorithm as a separate tool for estimating network operating conditions have been developed. In ref. [10], an OPF model was formulated to address tie-line switching conditions and then solved by applying the BFS algorithm to update the system frequency and voltages. A GA-based OPF method was proposed in [11] by involving the BFS

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algorithm in evaluating the solutions of each generation. The computing burdens of the above methods are heavy, due to the non-convex programming model, the involvement of microgrid operation simulation, the low GA convergence, or the iterative update from a separate power flow model, leaving the research gaps. Besides, the uncertainty of renewables and loads is to be addressed in the OPF methods, exacerbating the burdens.

On the other hand, power systems are being reinvented when deep reinforcement learning (DRL) is employed to optimize non-convex power system problems, especially considering complex operating conditions and constraints. Ref. [12] adopted a soft actor-critic (SAC) algorithm for a volt/var control problem, and a multi-agent deep deterministic policy gradient (DDPG) algorithm was adopted in [13] for optimizing inverter reactive power outputs in a large-scale distribution network in a distributed manner. Recently, [14] proposed a tuning friendly DRL method with various algorithms for power system control. All these studies demonstrate DRL algorithms' effectiveness and high efficiency in solving power system problems. As uncertainties can be addressed via a neural network well-trained by a DRL algorithm, DRL algorithms are expected to be effective for the OPF of islanded microgrid. The challenges to be addressed include estimating system dynamics with an efficient power flow algorithm, involvement of microturbine droop control, and training process for islanded microgrid operating constraints.

The literature review reveals that the OPF challenges in islanded microgrids have yet to be effectively addressed. This is primarily attributed to the limited practical applicability of the existing methods because of the substantial computing burdens. With emerging data-driven computing environments, this paper proposes *a data-driven robust OPF method for an islanded microgrid* where multiple droop-controlled microturbines are economically dispatched. This OPF method can be conducted in real time with online decision making. *An improved BFS algorithm* is first developed to enhance convergence efficiency and then used in a SAC algorithm. Samples of net load uncertainty are generated and utilized in the training process to guarantee the solution robustness. Note that other DRL algorithms, including DDPG, can be applied when necessary. The superior efficiency of the proposed method is confirmed via case study in comparison to the existing work.

II. Optimal Power Flow for Islanded Microgrid

An OPF model for an islanded microgrid to minimize the operating cost while keeping operating constraints is formulated, and an improved BFS algorithm is developed to fast estimate microgrid operating conditions.

A. Objective Function and Operating Constraints

1) Objective Function

The OPF aims to minimize the total operating cost of all microturbines below.

$$\min F = \sum a_n P_n^{MT} \tag{1}$$

A linear function is used for the fuel cost [10], and quadratic functions can be applied when necessary.

2) Microturbine Operating Constraints

Given an apparent power capacity for each microturbine, the power outputs are constrained as follows.

$$0 \le P_n^{MT} \le S_n^{MT,cap}, \forall n \tag{2}$$

$$-S_n^{MT,cap} \le Q_n^{MT} \le S_n^{MT,cap}, \forall n \tag{3}$$

$$(P_n^{MT})^2 + (Q_n^{MT})^2 \le (S_n^{MT,cap})^2, \forall n \tag{4}$$

3) Microgrid Operating Constraints

Microgrid operating constraints, including the limits for system frequency and (reference) bus voltages, are applied.

$$f^{min} \le f \le f^{max} \tag{5}$$

$$V_r^{min} \le V_r \le V_r^{max} \tag{6}$$

$$V^{min} \le V_n \le V^{max}, \forall n \tag{7}$$

It is worth noting that the microgrid operating conditions, including the system frequency and bus voltages, are estimated by an accurate power flow algorithm.

B. Improved BFS Algorithm

Ref. [7] proposed a modified BFS algorithm for islanded microgrid power flow. This paper further improves the convergence efficiency by updating the power injections in the inner loop of bus voltage iteration.

The power flow model of an islanded microgrid where microturbines are enabled with frequency and voltage droop control is formulated as follows.

$$P_n^{MT} = P_n^{MT0} + \frac{f^i - f_0}{m_n^P}, \forall n \tag{8}$$

$$Q_n^{MT} = Q_n^{MT0} + \frac{|V_n^i| - V_0}{m_n^Q}, \forall n \tag{9}$$

$$P_n + jQ_n = (P_n^{NL} + jQ_n^{NL}) - (P_n^{MT} + jQ_n^{MT}), \forall n \tag{10}$$

$$I_n = \frac{P_n - jQ_n}{V_n^{i*}}, \forall n \tag{11}$$

$$\boldsymbol{I_{branch}} = [\boldsymbol{BIBC}]\boldsymbol{I_n} \tag{12}$$

$$\Delta \boldsymbol{V}^{i+1} = [\boldsymbol{BCBV}]\boldsymbol{I_{branch}} \tag{13}$$

$$\boldsymbol{V}^{i+1} = \boldsymbol{V_r^i} - \Delta \boldsymbol{V}^{i+1} \tag{14}$$

$$\Delta f^{i+1} = (m_{eq}^P)\left[P_r^{NL} - P_r^{MT} + Re\left(\sum_{n \in N_r} V_r^i I_{rn}^*\right)\right] \tag{15}$$

$$\Delta V_r^{i+1} = (m_{eq}^Q)\left[Q_r^{NL} - Q_r^{MT} + Im\left(\sum_{n \in N_r} V_r^i I_{rn}^*\right)\right] \tag{16}$$

$$f^{i+1} = f^i + \Delta f^{i+1} \tag{17}$$

$$V_r^{i+1} = V_r^i + \Delta V_r^{i+1} \tag{18}$$

Eq. (8) and (9) calculate the active and reactive power outputs of the microturbines with the frequency and voltage droop control functions, respectively. Equation (10) computes the power injections considering the net loads and the microturbine power generation. It is worth noting that the net load of each bus, which equals the total load consumption minus the local distributed power generation, is uncertain and varying. Thus, OPF solutions are expected to be updated online in real time to follow the uncertainty realization efficiently. Eq. (11)-(14) compute the current injection, the branch current, the voltage drop and the updated bus voltage for each bus or branch. Eq. (15) and (16) calculate the changes in the frequency and the reference bus voltage, respectively. The frequency and the reference bus voltage are updated by (17) and (18). The equiva-

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lent droop coefficients [6] in (15), (16) can be calculated below.

$$m_{eq}^{(.)} = (\sum_{n} \frac{1}{m_{eq}^{(.)}})^{-1} \tag{19}$$

With this model, *a BFS Algorithm for Islanded Microgrid Power Flow* is developed below. There are two loops, where the inner loop updates the bus voltages $\boldsymbol{V}^i$ while the outer loop updates the system frequency f^i and reference bus voltage V_r^i.

Remark: The system-wide bus voltages are sensitive to the power flows that are directly changed by bus power injections, while the system frequency and reference bus voltage are impacted by power imbalance. Calculating bus power injections is involved in the inner loop to first obtain stable system-wide bus voltages and thus enhance the convergence rate. The improvement on the convergence efficiency is validated in the case study.

Algorithm I – Improved BFS Algorithm

Step 0 Initialize iteration index i as 0, f^0 as f_0, V_r^0 as V_0, and $\boldsymbol{V}^0$ as **1** p.u.

Outer Loop starts.

Inner Loop starts.

Step 1 Calculate bus power injections $P_n + jQ_n$ by (8) - (10) with f^i and $\boldsymbol{V}^i$.

Step 2 Calculate bus voltages by (11) - (14) with $\boldsymbol{V}^i$.

Step 3 If the maximum bus voltage drop is greater than the preset threshold ε^{in}, update the bus voltages $\boldsymbol{V}^i$, and go to **Step 1**; otherwise, set the obtained bus voltages as $\boldsymbol{V}^{i+1}$, and go to **Step 4**.

Inner Loop ends.

Step 4 Calculate frequency change as Δf^{i+1} by (15), reference bus voltage change as ΔV_r^{i+1} by (16). Then, Update frequency as f^{i+1} by (17) and reference bus voltage as V_r^{i+1} by (18).

Step 5 If the ΔV_r^{i+1} is greater than the preset threshold ε^{out}, set $i = i + 1$, and go to **Step 1**; otherwise, terminate the algorithm.

Outer Loop ends.

In the OPF model with the improved BFS algorithm, the microturbine active and reactive power output setpoints, i.e., P_n^{MT0} and Q_n^{MT0} are control variables. The power injections, currents, voltages, and system frequency are state variables.

III. Data-Driven Robust Optimal Power Flow

To efficiently apply a DRL algorithm, the optimization problem is first converted into a Markov decision process (MDP) model. Then, a DRL algorithm can be adopted to train the neural network for real-time decision-making. This paper adopts a SAC algorithm [15], considering its advantages of wider exploration and capture of multiple near-optimal behaviors. Samples of uncertain net loads are generated and utilized in the training process, thus making a neural network robust against uncertainty. Finally, the overall procedure of the proposed data-driven OPF method is introduced in this section.

A. Formulation of OPF into MDP model

A MDP model has four tuples, i.e., state space, action space, reward function, and transition function, denoted as $\{\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{T}\}$. For a state $s \in \mathcal{S}$, it is defined as a vector $[f; V_r; \boldsymbol{V}]$ as one specific microgrid operating condition. For an action $a \in \mathcal{A}$, it is defined as a vector $[\boldsymbol{P}^{MT0}; \boldsymbol{Q}^{MT0}]$. A reward function is defined below to minimize costs and avoid violating microgrid operating constraints.

$$\mathcal{R}: r = -F - Pen \tag{20}$$

Here, F is the objective function (1), and Pen is a penalty function for the constraint violations. In this paper, when the variables are out of the ranges given by (2)-(7), the deviations to the limits are calculated and penalized. Since the reward is to be maximized, minus signs are used.

The transition function can be described below, meaning a new state, $\mathcal{S}'$, can be generated based on the current state and the action. In this paper, the developed BFS algorithm is used as the transition function to update the microgrid operating condition, as follows.

$$\mathcal{T}: s \times a \rightarrow s' \tag{21}$$

With the above tuples, further, a state-action value function, i.e., the Q function $Q(s, a)$, can be derived with the Bellman equation as,

$$Q(s, a) = r + \gamma \max_{a'} Q(s', a'), \tag{22}$$

where γ is the discount factor and a' denotes the next action.

With this MDP model, the Q function is to be optimized for obtaining the OPF solution without constraint violation.

B. Soft Actor-Critic Algorithm

This paper adopted a SAC algorithm [15], an off-policy actor-critic DRL algorithm based on the maximum entropy reinforcement learning framework.

A critic network C^{θ} with θ as the parameters evaluates the Q value by (22), while an actor network A^{ϕ} with ϕ as the parameters generates the action set $\mathcal{A}$ according to the input state set $\mathcal{S}$. A policy network is defined as $J(A^{\phi})$, which considers the expected entropy of the policy over the distribution of state. The parameters ϕ are trained via updating the gradient of the policy network, $\nabla_{\phi} J(A^{\phi})$. The parameters θ are trained via minimizing the loss function of temporal difference error.

The SAC algorithm iteratively updates the environment, which can be conducted by applying the improved BFS algorithm for islanded microgrid power flow, calculates the gradient and the loss function, and optimizes the parameters. Details of the SAC algorithm can be found in [15].

C. Data-Driven Robust OPF Method

Firstly, samples of uncertain net loads (active and reactive power) are randomly generated. They are used in the training process to allow the SAC algorithm to generate feasible OPF decisions without microgrid operating constraint violations, thus ensuring solution robustness. The control variables, i.e. microturbine output setpoints, are initialized within the given ranges. The data, containing the system parameters, the initial control decisions and the random samples, is normalized.

In each episode of the SAC training process, the improved BFS algorithm is conducted for each sample to obtain an initial power flow result. If the algorithm converges, the corresponding state variables can be used for training; otherwise, the control variables are re-initialized until feasible state variables are obtained.

In the training process, the SAC algorithm interacts with the simulation environment that is implemented by the improved BFS algorithm, to accumulate successful decisions and save them with the corresponding state variables in the experience reply. Once the uncertain load condition (net loads) and the OPF decisions (microturbine output setpoints) are obtained, the improved BFS algorithm is conducted to update the microgrid operating states (power flows, system frequency and bus voltages), thus system transiting from the current state to the next one. Then, noises are added to the control variables, and thus, the rewards of full exploration can be checked to select efficient control decisions. Note that if non-convergence of the BFS algorithm or microgrid operating constraint violations occur, the reward is penalized. The penalty is expected to be eliminated during the training process, thus indicating robust solutions which do not cause constraint violations.

The training process updates all the neural network parameters until a convergence threshold is reached. Note that the exploration noises are gradually reduced. The well-trained neural network is saved for online decision-making, which takes the net loads as inputs and provides the microturbine setpoints in real time.

IV. Case Study

The proposed method is validated on a 33-bus islanded microgrid, and system parameters are given by [16]. Considering renewable generation, the net load range is set from 70% to 100% of the given load values. Five microturbines are operated, and their parameters are given in Table I. Note that other parameters can be applied without affecting the effectiveness of the case study.

Table I Microturbine Parameters

Microturbine No.		1	2	3	4	5
Bus No.		1	6	13	25	33
Power Capacity (kVA)		3000	2000	1000	2000	1200
Generation Cost ($/kW)		0.05	0.08	0.06	0.08	0.065
Droop	m^P	-0.05	-1.00	-0.1	-1.00	-0.20
Coefficients	m^Q	-0.05	-1.00	-0.1	-1.00	-0.20

The nominal voltage and frequency are set as 1 p.u. The bus voltage range is set as [0.9, 1.1] p.u., and the frequency range is set as [0.94, 1.06] p.u.

For the SAC algorithm, the discount factor is 0.97, the learning rate is 0.001, the batch size is 64, the replay capacity is 10^5 and Adam Optimizer [17] is utilized.

Numerical simulations are conducted on a 64-bit PC with 1.80-GHz CPU and 32 GB RAM using MATLAB platform.

A. Validation of Improved BFS Algorithm

The proposed power flow algorithm is validated in comparison with the modified BFS algorithm. The results, including the microturbine active power outputs, frequency, reference (ref.) bus voltage, voltages at two feeder ending buses, as well as iteration numbers, are shown in Table II. The relative errors are calculated for validation.

Table II Power Flow Results

Method		Modified BFS	Proposed	Relative Error
Micro-turbine Active Power (kW)	***No. 1***	1251.212	1251.207	4.15E-06
	No. 2	490.061	490.060	5.30E-07
	No. 3	850.606	850.604	3.05E-06
	No. 4	490.061	490.060	5.30E-07
	No. 5	650.303	650.302	2.00E-06
System Frequency		0.919879	0.919879	2.83E-07
Voltage (p.u.)	***Ref. Bus***	0.996651	0.996618	3.32E-05
	Bus 18	0.993736	0.993709	2.71E-05
	Bus 33	0.990144	0.990116	2.81E-05
Inner Iterations		26	16	-
Outer Iterations		12	4	-

The table shows that the improved BFS algorithm is highly accurate, with all relative errors less than 0.01%. Moreover, this improved BFS algorithm can reduce the iteration numbers of both inner and outer loops, thus improving the convergence efficiency.

B. Convergence of SAC Algorithm

The reward of each episode in the SAC training process is recorded to demonstrate the convergence, and it can be separated into fuel cost and constraint violation penalties. The convergence results of SAC are shown in Figure 1.

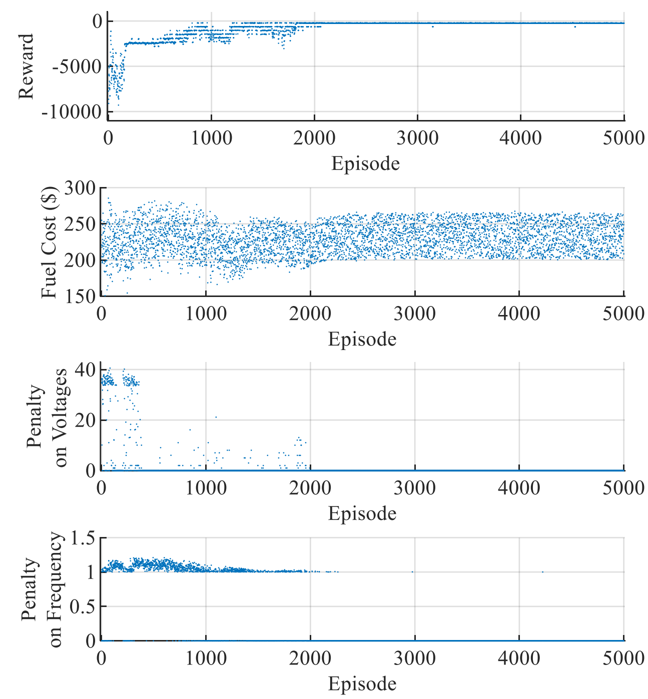

Figure 1. Convergence of SAC.

The reward becomes almost steady after the 2060th episode. The fuel cost eventually varies between $200.40 and $266.24, for the droop control adjusts the microturbine active power outputs, leading to the varying cost. All the voltage violations are removed within 1992 episode. The training process takes 2263 episodes to address the frequency violation, while the penalty of frequency violation still occurs twice after that.

It can be concluded that in the training process, more effort is required in eliminating the frequency violation, which is an important finding from this work.

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C. Validation of Data-Driven Robust OPF Method

The well-trained neural network for OPF is conducted under two extreme cases, i.e., the maximum load case (100% load) and the minimum load case (70% load). The frequencies are obtained as 0.9696 p.u. and 1.0248 p.u., respectively. The bus voltages in these two cases are shown in Figure 2. All the frequencies and bus voltages are kept within the allowed ranges, validating the effectiveness of the neural network in keeping network operating constraints.

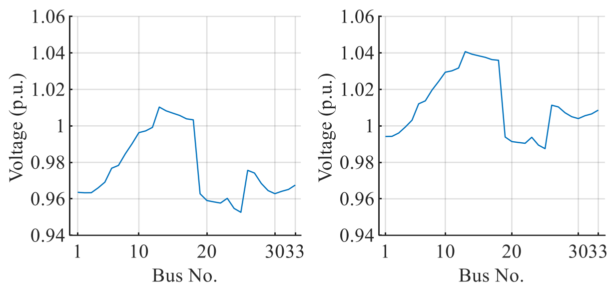

Figure 2. Bus voltages: a) maximum load case; b) minimum load case.

To comprehensively check the solution robustness of the proposed method, the well-trained neural network is conducted under 1000 net load scenarios generated via Monte Carlo sampling. The average time of conducting the neural network for OPF is only 1.920 seconds, including data processing time.

For comparison, a conventional GA method with a single mean case of net load (named GA-Deterministic) and another GA method with 4 representative cases (two are the extreme cases) (named GA-Stochastic) are applied. Both GA methods involve the improved BFS algorithm to update network operating conditions. The solution time of GA-Deterministic is 124.155 seconds, and that of GA-Stochastic is 487.436 seconds. Then, the OPF results of GA methods are tested under the same 1000 scenarios. The average fuel cost, absolute frequency deviations, absolute voltage deviations, and constraint violation rate are analyzed, shown in Table III.

TABLE III OPTIMAL POWER FLOW RESULTS

Optimization Method		**GA-Deterministic**	**GA-Stochastic**	**Proposed**
Average Fuel Cost ($)		170.50	162.84	232.56
Absolute Frequency Deviation (p.u.)	*Maximal*	0.0894	0.0434	0.0350
	Average	0.0583	0.0134	0.0088
Absolute Voltage Deviation (p.u.)	*Maximal*	0.0605	0.0985	0.0791
	Average	0.0226	0.0537	0.0172
Constraint Violation Rate (%)		43.90	0	0

Compared to the conventional GA-Deterministic method, the proposed data-driven method can provide fully robust OPF solutions against uncertainty without constraint violation. The proposed method is superior in reducing the frequency and the voltage deviations to the GA-Stochastic method. Only the proposed data-driven robust OPF method can make online decisions, though it compromises on the fuel cost minimization. This is because the proposed method prioritizes eliminating operating constraint violations, thus providing robust online solutions under uncertainty. Note that if the penalty terms for constraint violations are allowed to be non-zero, a trade-off between the solution robustness and the fuel cost minimization can be made, i.e. further minimizing the fuel cost with limited constraint violations.

V. CONCLUSION AND FUTURE WORK

This paper proposes the first data-driven robust OPF method for an islanded microgrid with an improved BFS algorithm for power flow. Via comprehensive case studies, the high accuracy and convergence efficiency of the improved BFS algorithm are verified, and the convergence of the SAC algorithm is demonstrated. Moreover, compared to the existing model-based work, the proposed data-driven robust OPF method is superior in terms of solution robustness. It can effectively promote the reinvention of islanded microgrids.

In future work, convex relaxations, chance-constrained formulations and MPC-based approaches can be involved in the proposed method. Emerging DRL algorithms can be adopted to improve the optimization performance.

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