A Flexible Distributed Approach to Energy Management of an Isolated Microgrid

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***Abstract*—This paper studies an energy management problem for an isolated microgrid including photovoltaic panels, wind turbines, batteries and ultracapacitors. A normal form game is proposed for the energy management to maximize the energy utilization ratio of renewable energy sources, extend the battery life and keep the ultracapacitors able to compensate the dynamic variations. The solution of this game represented by Nash equillibrium is analytically derived and proved to be the existing and unique. A simulation platform using data in second is established to study the energy management approach based on probability distrubution funcions. In simulation, the game theory based approach has a comparable performance against the rule based control, while the pre-knowledge of the load demands and weather information is not required. Also the game theory based approach is more flexible than rule based approach under the influence of uncertain weather.**

***Index Terms*—Game theory, isolated microgrid, photovoltaic panel, wind turbine, Nash equilibrium.**

I. Introduction

The microgrid is a networked group consisting of different distributed energy sources, such as photovoltaic panels (PVs), wind turbines (WTs), and energy storage devices [1]. The network of microgrids can operate either in grid connected mode or in isolated mode [2]. The isolated microgrids are worth being studied because isolated microgrids have some distinct applications such as in avionic, automotive, marine industries and remote rural areas [3]. There are many problems to be solved in isolated microgrids. One of them is to find a proper energy management approach due to the existence of substantial energy sources and demand fluctuations. This paper introduces a flexible distributed approach to energy management of an isolated microgrid.

Before looking at the energy management approaches, the system configuration is first introduced clearly. The studied system includes PVs, WTs, battery pack and ultracapacitor (UC) pack, which are connected to the DC bus. The power suppliers include two renewable energy sources due to the complementary behavior of solar irradiance and wind speed patterns [4]. Since batteries have high energy density while ultracapacitors have high power density, the hybrid energy storage system (HESS) consists of a battery pack and a UC pack. Each device has its own distributed controller that can determine its power flow autonomously.

As the HESS is one important part of this isolated microgrid, the energy management approaches of HESSs can become good references. In fact, many approaches have been proposed to control the battery-ultracapacitor HESSs [5]–[7]. The multi-objective optimization is used to determine the trade-off between the energy loss minimization and the battery protection [5]. In the ideal situation, the batteries satisfy the average load demand (ALD), while the UCs meet the rest dynamic load demands [6]. To implement the ALD-based control, the load demands should be known in advance and the capacity of the UCs should meet the dynamic load requirement. In [7], the optimization problem is solved by Karush-Kuhn-Tucker conditions, whose results have a comparable performance with ALD-based control without the pre-knowledge of the load demands.

In terms of energy management approaches in isolated microgrids, many technologies have already been studied [8]–[10]. A fixed control strategy is proposed in [8] for a hybrid WT/PV reverse osmosis desalination microgrid. But only operating constraints and power balance are considered in this approach. An optimal approach for the isolated wind-diesel microgrid in [9] is used to optimize energy of the storage system and operation cost of the microgrid. However, the prediction of WT output power and load demands should be known in advance. In [10], the supervisor control is proposed to determine the power distribution between PVs, WTs and storage system. In this approach, the WTs have priority to provide power compared with PVs, and the battery will start to discharge if the renewable energy sources can not meet the load demands. This approach may be influenced by uncertain weather.

This paper is organised as follows. Section II describes the environment data, the system topology, devices modeling and sizing. To implement the normal form game, the utility functions of all the devices are defined in section III. Then, the detail normal form game is presented in section IV. In section V, the simulation is conducted under the comparison with rule based approach. Finally, the conclusion is given in section VI.

II. Isolated microgrid modeling

This section introduces the environment, system topology, the simulation models and sizings of all the devices.

A. Environment

The hourly wind speed, solar irradiance, temperature and load profiles are obtained on Feb. 2nd of San Diego Lindbergh

Field from System Advisor Model (SAM) [11]. SAM is designed by National Renewable Energy Laboratory (NREL) to facilitate decision making in the renewable energy systems.

Considering the intermittent nature of renewable energy sources, the environment data was randomized according to the probability distribution functions given in [12], as shown in Fig. 1. Also, the 24 hours was compressed into 24 minutes in order to shorten the simulation and experiment time, i.e., each minute in this figure represents one hour in the real world.

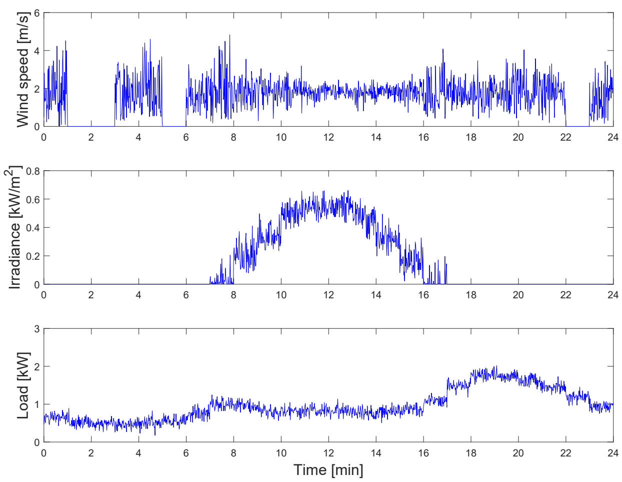


Fig. 1. Randomized environment data.

B. System topology

The topology of studied isolated microgrid is shown in Fig. 2. The voltage of DC bus is stabilized by an extra capacitor which is not shown in the figure. The four control variables are i_w, i_p, i_c and i_b. These variables are chosen according to the requirement of the future experiment. The PV panels and WTs are emulated by Hardware-In-the-Loop emulations, while the battery pack, UC pack and corresponding DC-DC converters are real devices [13]. i_l is obtained from the load profile in each time instant.

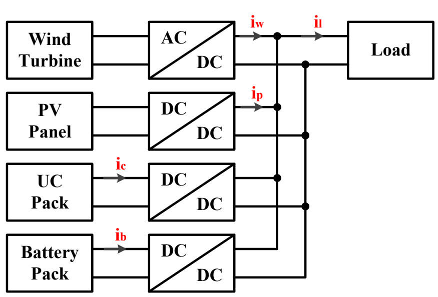
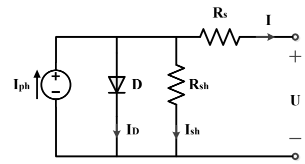


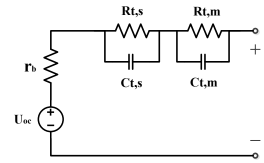
Fig. 2. System topology.

C. Models of devices

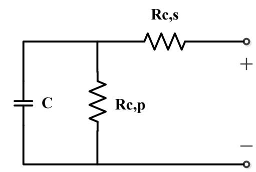
1) Photovoltaic panels: The equivalent circuit model of single PV cell is shown in Fig. 3(a). The relationship between



(a) Single PV cell.



(b) Battery pack.



(c) UC pack.

Fig. 3. The equivalent circuit models.

I and U can be expressed as

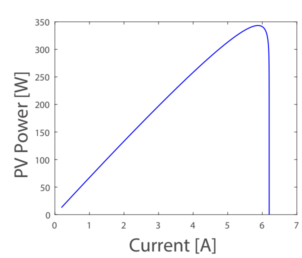
$$I = I_{ph} - I_S \left\{ exp\left[\frac{q(U + R_s I)}{kT}\right] - 1 \right\} - \frac{U + R_s I}{R_{sh}}, \quad (1)$$

where I_{ph} is photocurrent, I_S is diode saturation current, q is electron charge $(1.60217646 \times 10^{-19} C)$, k is Boltzmann Constant $(1.3806503 \times 10^{-23} J/K)$, T is temperature, R_s is series resistance and R_{sh} is shunt resistance. The real module used in the simulation is SunPower SPR-X21-335-BLK, whose specifications can be obtained from SAM as listed in Table I. The relationship between the output power and output current of single PV panel is depicted in Fig. 4(a).

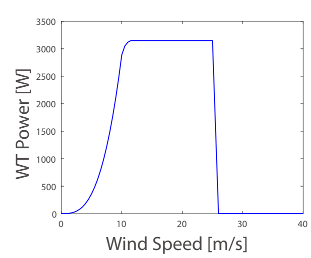
TABLE I
PARAMETERS OF SINGLE PV PANEL UNDER STANDARD TEST CONDITION

Number of cells	96	Open circuit voltage	67.9 V
Maximum power	335.2 W	Short circuit current	6.2 A
Max power voltage	57.3 V	R_s	0.5 Ω
Max power current	5.8 A	R_{sh}	457.1 Ω

2) Wind Turbines: Similarly, the real module is Kestrel e400i chosen from SAM. The power curve of single WT is depicted in Fig. 4(b).



(a) PV power curve.



(b) WT power curve.

Fig. 4. The characteristic curves.

3) Battery Pack: As shown in Fig. 3(b), the parameters U_{oc} and r_b in the equivalent circuit model for battery pack can be calculated using six-ordered polynomial functions [14]. The transient response in minute and second of the battery pack can be modelled by different time constants, i.e., $\tau_m = R_{t,m}C_{t,m}$ and $\tau_s = R_{t,s}C_{t,s}$, respectively.

$$U_{oc} = a_{oc,0} + a_{oc,1}x + a_{oc,2}x^2 + \cdots + a_{oc,6}x^6, \quad (2)$$
$$r_b = a_{r,0} + a_{r,1}x + a_{r,2}x^2 + \cdots + a_{r,6}x^6, \quad (3)$$

where x is the state-of-charge (SOC) of battery. All the coefficients are listed in Table II.

TABLE II
PARAMETERS OF ONE LI-ION BATTERY CELL

$a_{oc,0}$	2.30	$a_{oc,1}$	15.96	$a_{oc,2}$	-99.35
$a_{oc,3}$	295.20	$a_{oc,4}$	-446.49	$a_{oc,5}$	331.41
$a_{oc,6}$	-95.56	$a_{r,0}$	0.02	$a_{r,1}$	-0.24
$a_{r,2}$	1.69	$a_{r,3}$	-5.66	$a_{r,4}$	9.67
$a_{r,5}$	-8.13	$a_{r,6}$	2.67		
$R_{t,s}$	5.60 mΩ	$C_{t,s}$	12200 F		
$R_{t,m}$	2.87 mΩ	$C_{t,m}$	45300 F		

TABLE III
PARAMETERS OF UC PACK

C	1.76 kF	$R_{c,p}$	3 kΩ
$R_{c,s}$	2.50 mΩ	I_{cmax}	20 A

4) Ultracapacitor Pack: Fig. 3(c) shows the equivalent circuit model of UC pack. C is the capacitance of UC pack. $R_{c,s}$ is the internal resistance, while $R_{c,p}$ is used to model the leakage current. The detail values of these parameters are listed in Table III, where I_{cmax} is the maximum permitted current amplitude of the UC pack.

D. Sizing

The sizings of PV panels and WTs are determined to meet the load demands of the whole day [15]. In Fig. 5, the PV power and WT power are the maximum output power under the environment data in Fig. 1, which is calculated based on (1) and Fig. 4(b) respectively. The capacity of UC pack is determined based on the maximum difference between supplied power and load power, because the function of UC pack is to deal with transient huge power. The cumulated energy is the integration of these differences and can represent the cumulated energy of the whole system without storage devices. The capacity of battery pack is determined according to the maximum value of the cumulated energy. If the SOC of battery pack is zero at the beginning, then the battery pack should be able to store the maximum amount of cumulated energy so that the system can be self-balancing during this day.

III. FORMULATION OF UTILITY FUNCTIONS

In order to implement the normal form game, appropriate utility functions must be defined, which can quantify the degrees of preference across alternatives. This section gives the definitions of specific utility functions for all the devices in the system.

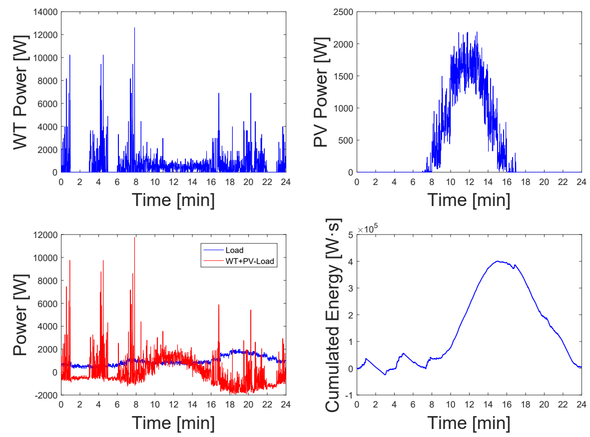


Fig. 5. Data analysis for sizing.

A. Photovoltaic panels

The PV panels want to maximize their energy utilization. The utility function of PV panels is defined as follows.

$$u_p = 1 - n_p(i_p - I_p^*)^2, \quad (4)$$

where I_p^* is the corresponding current when PV panels have the maximum output power and n_p is a normalization factor which can be defined as follows.

$$n_p = \frac{1}{(I_p^*)^2}. \quad (5)$$

The normalization factor is used to normalize the range of u_p into $[0, 1]$. The maximum output power of PV panels can be obtained from Fig. 5. Then the range of output current $[0, I_p^*]$ can be derived through dividing the power by the DC bus voltage.

B. Wind Turbines

Similarly with PV panels, the utility function of WTs is defined as follows.

$$u_w = 1 - n_w(i_w - I_w^*)^2, \quad (6)$$

where I_w^* is the corresponding current when WTs have the maximum output power and n_w is a normalization factor.

C. Battery Pack

The battery pack wants to extend its cycle life, which can be achieved by minimizing the amplitude and the variation of the battery current i_b [16]. To minimize the amplitude, the utility function is defined as

$$u_{b1} = 1 - n_{b1}(i_b - \mu_{ib})^2, \quad (7)$$

where μ_{ib} is the mean value of i_b from the beginning of the operation to the current control instant and n_{b1} is a normalization factor which can be defined as follows.

$$n_{b1} = min\left\{\frac{1}{(I_{bmax} - \mu_{ib})^2}, \frac{1}{(I_{bmin} - \mu_{ib})^2}\right\}, \quad (8)$$

where I_{bmax} and I_{bmin} are the maximum and minimum values of i_b in the current record. Also, in order to minimize the variation, the utility function is defined as

$$u_{b2} = 1 - n_{b2}(i_b - I_{blast})^2, \tag{9}$$

where I_{blast} is the battery current in the last control instant and n_{b2} is a normalization factor which can be defined similarly with n_{b1}. The two objectives are combined together using weighted sum method. Thus the utility function of battery pack is defined as

$$u_b = w_{b1}u_{b1} + w_{b2}u_{b2}, \tag{10}$$

where w_{b1} and w_{b2} are two weights.

D. Ultracapacitor Pack

The UC pack aims to become an energy buffer of the whole system to compensate the dynamic current variation and improve the overall performance of the HESS. Thus, the stored energy should stay at half of the energy capacity as much as possible to ensure the energy adjustment ability for the next control instant. In terms of the current, the desired current can be formulated as

$$I_c^* = \left(2\frac{v_c^2 - V_{cmin}^2}{V_{cmax}^2 - V_{cmin}^2} - 1\right) \cdot I_{cmax}, \tag{11}$$

where V_{cmax} and V_{cmin} are the upper and lower bounds of the UC pack voltage. I_c^* wants to keep the stored energy at the desired value and its magnitude is proportional to the rest energy in UC pack. When the difference between the rest energy and desired energy becomes larger, the magnitude of I_c^* will become greater. The desired energy can be represented as

$$V_c^* = \sqrt{\frac{V_{cmax}^2 + V_{cmin}^2}{2}}. \tag{12}$$

The utility function of the UC pack is defined as

$$u_c = 1 - n_c(i_c - I_c^*)^2, \tag{13}$$

where n_c is the corresponding normalization factor.

E. Modification of utility functions

The four control variables must satisfy the Kirchhoff's current law which is formulated as follows.

$$i_c = \frac{i_l - i_w - i_p - (1 - D_b)i_b}{1 - D_c}, \tag{14}$$

where D_b and D_c are duty cycles of the two corresponding bidirectional DC-DC converters. To combine this equality constraint with the utility functions, the utility function of UC pack is added to the other three functions because the UC pack is working as an assistive device in this system. The utility functions of PV panels, WTs, and battery pack are modified by adding several weights as follows.

$$u_{pc} = w_p u_p + w_{cp} u_c \tag{15}$$

$$u_{wc} = w_w u_w + w_{cw} u_c \tag{16}$$

$$u_{bc} = w'_{b1} u_{b1} + w'_{b2} u_{b2} + w_{cb} u_c \tag{17}$$

The determination of these weights is discussed in the next section.

IV. Normal form game process

This energy management problem can be solved using a normal form game $G = [3, (i_p, i_w, i_b), (u_{pc}, u_{wc}, u_{bc})]$ [17]. The PV panels, WTs and battery pack are treated as self-interested players. At each time instant, each player needs to determine its strategy, i.e., the value of the corresponding current. As all of them want to maximize their own profits, the final solution of the game is given by Nash equilibrium. No one wants to deviate from the Nash equilibrium individually, otherwise its utility will be minished.

A. Nash Equilibrium

The Nash equilibrium can be obtained by the best response process which is to choose the strategy to maximize its own utility given the strategies of the others are fixed [18]. The reaction functions are obtained by taking the partial derivatives of utility functions as follows.

$$\frac{\partial u_{wc}}{\partial i_w} = 0, \frac{\partial u_{pc}}{\partial i_p} = 0, \frac{\partial u_{bc}}{\partial i_b} = 0, \tag{18}$$

which give us

$$i_p = k_p + k_{pw} i_w + k_{pb} i_b, \tag{19}$$

$$i_w = k_w + k_{wp} i_p + k_{wb} i_b, \tag{20}$$

$$i_b = k_b + k_{bp} i_p + k_{bw} i_w. \tag{21}$$

Here the explicit reaction functions are easily derived due to the benefits of quadratic utility functions. That is also the reason why the utility functions are chosen to be quadratic functions. The explicit form is also of benefit to the computer programming and future experiment implementation. The first three constants in the reaction functions are

$$k_p = \frac{2w_p n_p I_p^* + \frac{2w_{cp} n_c i_l}{(1-D_c)^2} - \frac{2w_{cp} n_c I_c^*}{(1-D_c)}}{2w_p n_p + \frac{2w_{cp} n_c}{(1-D_c)^2}}, \tag{22}$$

$$k_{pw} = \frac{-\frac{2w_{cp} n_c}{(1-D_c)^2}}{2w_p n_p + \frac{2w_{cp} n_c}{(1-D_c)^2}}, \tag{23}$$

$$k_{pb} = \frac{-\frac{2w_{cp} n_c (1-D_b)}{(1-D_c)^2}}{2w_p n_p + \frac{2w_{cp} n_c}{(1-D_c)^2}}. \tag{24}$$

Other constants can be represented similarly. Combining (19),(20) and (21), the Nash equilibrium is calculated as

$$i_p = \frac{(1 - k_{wb}k_{bw})(k_p + k_{pb}k_b) + (k_{pw} + k_{pb}k_{bw})(k_w + k_{bw}k_b)}{(1 - k_{pb}k_{bp})(1 - k_{wb}k_{bw}) - (k_{wp} + k_{wb}k_{bp})(k_{pw} + k_{pb}k_{bw})}, \tag{25}$$

$$i_w = \frac{(1 - k_{pb}k_{bp})(k_w + k_{wp}k_p) + (k_{wb} + k_{wp}k_{pb})(k_b + k_{bp}k_p)}{(1 - k_{pw}k_{wp})(1 - k_{pb}k_{bp}) - (k_{wb} + k_{wp}k_{pb})(k_{bw} + k_{bp}l_{pw})}, \tag{26}$$

$$i_b = \frac{(1 - k_{pw}k_{wp})(k_b + k_{bp}k_p) + (k_{bw} + k_{bp}k_{pw})(k_w + k_{wp}k_p)}{(1 - k_{pw}k_{wp})(1 - k_{pb}k_{bp}) - (k_{wb} + k_{wp}k_{pb})(k_{bw} + k_{bp}l_{pw})}. \tag{27}$$

This also proves the existence and uniqueness of the pure strategy Nash equilibrium of this normal form game. The Nash equilibrium can also be solved in a distributed manner using (19),(20) and (21), which helps to build distributed controllers in real application.

B. Weight coefficients determination

The Nash equilibrium can be calculated after all the weight coefficients are determined. To determine the weights, some requirements should be clarified firstly. The summation of all the weights in the same equation should be equal to one, i.e.,

$$w_p + w_{cp} = 1, \tag{28}$$

$$w_w + w_{cw} = 1, \tag{29}$$

$$w'_{b1} + w'_{b2} + w_{cb} = 1. \tag{30}$$

According to the function of the UC pack which is an assistive device in this system, the corresponding weights are determined based on the current stored energy. When the difference between stored energy and desired energy becomes larger, the weights should also becomes larger. Meanwhile, the utility of UC pack is not very important to the whole system when the difference is very small. Thus, the weights for the UC pack are determined in an adaptive way as follows.

$$w_{cp} = w_{cpmin} + \frac{1 - w_{cpmin}}{(V_c^*)^2 - V_{cmin}^2} \left|(V_c^*)^2 - v_c^2\right|, \tag{31}$$

$$w_{cw} = w_{cwmin} + \frac{1 - w_{cwmin}}{(V_c^*)^2 - V_{cmin}^2} \left|(V_c^*)^2 - v_c^2\right|, \tag{32}$$

$$w_{cb} = w_{cbmin} + \frac{1 - w_{cbmin}}{(V_c^*)^2 - V_{cmin}^2} \left|(V_c^*)^2 - v_c^2\right|. \tag{33}$$

Then the problem is transformed to determine $w_{cpmin}, w_{cwmin}, w_{cbmin}$ and $\frac{w'_{b1}}{w'_{b2}}$. These four parameters can be determined by finding the Pareto frontier, which is regarded as the future work.

V. Simulation

The simulation is conducted under the environment shown in Fig. 1. The time step is one second and the total control instants is $N = 24*60+1 = 1441$. In order to do experiment in the future, the PV power, WT power and load power are scaled down for 100 times. The DC bus voltage is chosen as 24 V.

A. Evaluation criteria

Five parameters are used to evaluate the performance of the energy management, including the energy utilization ratio of the PV panels η_p, the energy utilization ratio of the WTs η_w, the average battery current μ_{ib}, the variance of the battery current σ_{ib}^2 and the average energy difference between the energy stored in the UC pack and the desired energy μ_{Ec}. They are formulated as follows. Because the DC bus voltage is stabilized by an extra capacitor and is regarded as a constant, the energy utilization is calculated only based on the current records.

$$\eta_p = \frac{\sum i_p}{\sum I_p^*}, \tag{34}$$

$$\eta_w = \frac{\sum i_w}{\sum I_w^*}, \tag{35}$$

$$\mu_{ib} = \frac{1}{N} \sum i_b, \tag{36}$$

$$\sigma_{ib}^2 = \frac{1}{N} \sum (i_b - \mu_{ib})^2, \tag{37}$$

$$\mu_{Ec} = \frac{1}{N} \sum \left| \frac{1}{2} C v_c^2 - \frac{1}{2} C (V_c^*)^2 \right|. \tag{38}$$

B. Simulation results

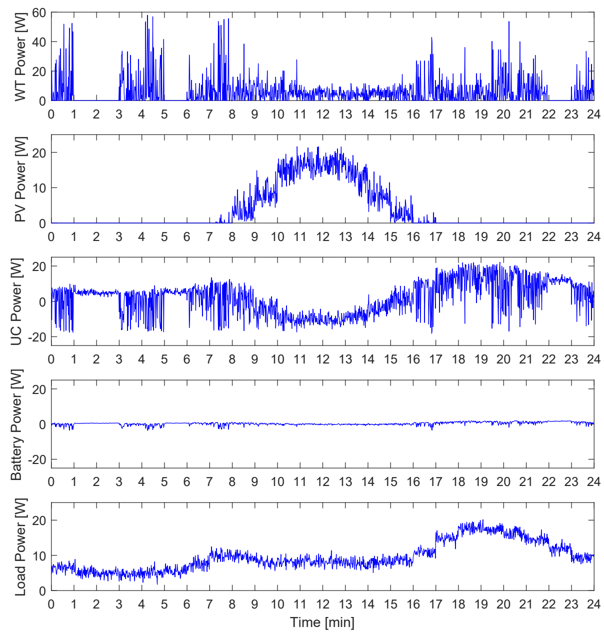


Fig. 6. Simulation results.

The four parameters are chosen by experience, as $w_{cpmin} = 0.1, w_{cwmin} = 0.1, w_{bmin} = 0.1$ and $\frac{w'_{b1}}{w'_{b2}} = 0.3$. The power profiles are shown in Fig. 6 in the simulation. The evaluation criteria values are compared with the rule based control, as listed in Table IV in the first case. In this rule based control, the power distribution between power supply and storage system is determined by supervisor control , while the power distribution within the storage system is determined by ALD-based control. The two mentioned rule based approaches have been briefly introduced in the introduction section. The game theory based approach has a comparable performance against that of the rule based approach. The rule based approach can achieve 100% energy utilization ratio and zero average battery current due to the proper predictions, i.e., it requires good pre-knowledge about the environment data and load demands. However, the game theory based approach does not need these pre-knowledge.

TABLE IV
EVALUATION CRITERIA COMPARISON

Case	Approach	η_p (%)	η_w (%)	μ_{ib} (A)	σ_{ib} (A^2)	μ_{Ec} (J)
1	Game theory based	99.23	91.66	0.04	0.06	251.59
	Rule based	100	100	0	0	337.98
2	Game theory based	98.99	92.12	0.06	0.06	187.42
	Rule based	76.08	100	0	0	334.59
3	Game theory based	99.75	92.46	0.13	0.07	136.16
	Rule based	100	100	0.3	0	332.62

C. Flexibility

To illustrate the influences of uncertain weather to two different energy management approaches, other two cases are considered as shown in Table IV and analysed below individually. Case 2 represents when there is more energy generated by the renewable energy sources than expected, which means that the weather is better than expected so that more energy can be generated by PV panels and WTs. The game theory based approach maintains the similar performance compared with case 1 in terms of the first four criteria and achieves even smaller μ_{Ec} (the smaller the better), while the rule based approach performs obviously worse in terms of η_p. These differences are because the game theory based approach can utilize those unexpected extra energy to undermine the fluctuations in E_c. The η_w is not affected in rule based approach because the energy generated by WTs have priority to be utilized compared with the energy generated by PV panels under supervisor control.

Meanwhile, case 3 represents when there is less power generated by renewable energy sources than expected so that the HESS needs to provide more power to meet load demands. In this case, the increment of μ_{ib} under game theory based approach is smaller (the smaller the better), accompanied with smaller μ_{Ec}. The increment of μ_{ib} under rule based control is larger because the UC pack will always deal with all the fluctuations under ALD-based control while the batteries and UC packs can share the fluctuations in game theory based approach. All in all, it can be concluded that game theory based approach is more flexible than rule based approach under the influences of uncertain weather.

VI. CONCLUSIONS

In this paper, a game theory based approach is proposed for the energy management of an isolated microgrid using normal form game. The utility functions for all the devices are clearly defined to maximize the energy utilization ratio of the renewable energy sources, extend the battery life and improve the ability of ultracapacitors to compensate the dynamic load. The solution of this normal form game is analytically derived whose solving process can be used to build distributed controllers. The randomized environment data is used to test the prosed approach, and the data in second is compressed to 24 minutes to represent the operation during the whole day which can shorten the simulation time without losing the characteristic. In simulation, the proposed approach has a comparable performance against the rule based approach which combines the supervisor control and ALD-based control, while the proposed approach does not require to get the load profile and weather information in advance. Also the game theory based approach is more flexible than rule based approach under the influence of uncertain weather. In the future, more appropriate weights should be determine by finding Pareto fronts.

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