Optimal Energy Management Strategies of Microgrids

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***Abstract*—This paper presents the optimal energy management strategies by using dynamic programming for two types of microgrids: grid-connected and island microgrids which comprise PV systems and battery energy storage systems (BESS). For the grid-connected microgrids, the objective is to minimize the cash flow of the system as well as to minimize the power exchange with the main grid. For the island microgrid, the objective is to minimize the operation cost and to reduce emissions by scheduling of DER in microgrid. In this work, adaptive observer algorithms have been developed. These battery models are used in optimization programs to be accurate and adaptive to operating conditions without being prohibitively complex. Simulations are carried out in order to evaluate the efficiency of the proposed methods.**

***Index Terms*— Battery energy storage system, Diesel, Grid, Microgrid, Optimal energy management, PV system.**

I. INTRODUCTION

Recently, the increase of fuel price and the development of renewable energy technologies give more opportunities for using the renewable sources in microgrid [1-14]. Therefore, a microgrid includes photovoltaic systems (PV), battery energy storage systems (BESS), others sources (diesel) and loads. In order to increase the economic efficiency and reliability of the microgrid, energy management system (EMS) is necessary to be taken into account. For connected-grid microgrids, the EMS is expected to minimize the cash flow of the system as well as to minimize the power exchange with the main grid. For island microgrids, the EMS is expected to minimize the operation cost and to reduce emissions.

This large-scale integration of variable, intermittent and small-size Renewable Energy Systems (RES), and more generally of Distributed Generation (DG), poses technical challenges to the operation of existing electricity grids. Microgrid present opportunities to increase the flexibility of grid. Microgrids are electricity distribution systems containing loads and distributed energy resources, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded [CIGRE]. There are two kinds of microgrids: grid-connected microgrid and island microgrid.

In microgrid when operated in parallel with RES (Fig. 1), energy storage systems (ESSs) can mitigate the volatility of the source by storing available energy and re-injecting it into the network, when the system load surpasses the available power. By the same token, they can increase the predictability of the combined system by balancing an unforeseen surplus production with an unexpected shortage at a later time. Batteries are a mature storage technology that can be readily deployed and scaled to the needs of any particular installation. In consequence, battery energy storage systems (BESSs) are already being used for the grid integration of PV power plants with requirements for operation control and production plan notification. In this work, adaptive observer algorithms have been developed. These battery models are used in optimization programs to be accurate and adaptive to operating conditions without being prohibitively complex.

II. OPTIMAL ENERGY MANAGEMENT FOR A MICROGRID

This session presents the optimal energy management strategies by using dynamic programming (DP) for two types of microgrid: grid-connected (grid, PV systems and BESS) and island microgrid (Diesel, PV systems and BESS).

A. Grid connected microgrid

In this paper, the optimal energy management of grid connected microgrid which comprises PV systems and BESS is presented. DP is used to minimize the cash flow of the system as well as to minimize the power exchange (import/export power) with the main grid (Fig. 1). The constraints of EMS are the power balance between supply and consumption, the capacity of each DER (Distributed Energy Resources) and microgrid operation.

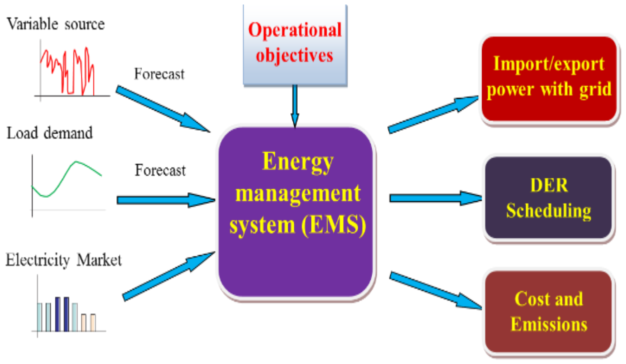

Figure 1. EMS for a grid connected microgrid

1) Configuration of a grid connected microgrid

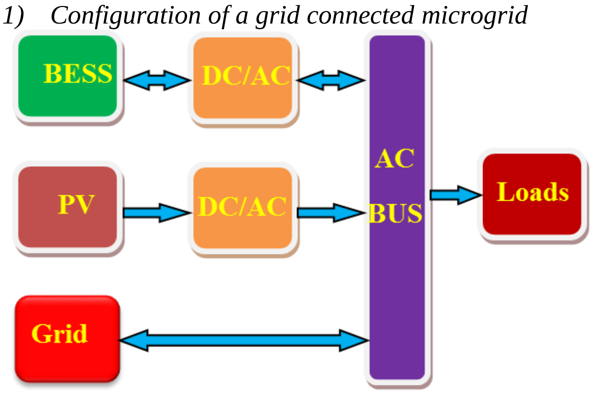

Figure 2. Grid-connected microgrid configuration

Fig. 2 shows a grid-connected microgrid that will be studied in this paper.

2) Data and hypothesis

a) Photovoltaic system

The PV system production is varied. In this paper a PV production curve shown in Fig. 3 is used [Measurements at CEA-INES].

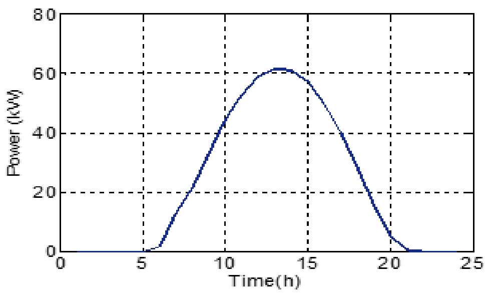

Figure 3. The daily data of PV system production

b) Battery energy storage system (BESS)

The charge and the discharge of BESS depend on the operation strategy of microgrid. If the load demand is greater than the available generated power, the BESS will discharge to cover the deficit. On the other hand, BESS will be charged when the production exceeds the consumption.

At the moment t, the state of charge SOC(t) is related to the previous SOC(t-1), the power production and power load of the system during the time from t-1 to t. During the charge process, the state of charge at the moment t can be calculated by the following equation:

$$SOC(t)=SOC(t\text{-}1)+\frac{P_{PV}(t)+P_{grid}(t)-P_L(t)}{C_{ref}}.\Delta t \qquad (1)$$

c) Loads

In this paper, the load data utilized is based on daily load curve as shown in Fig. 4 (this curve obtained for a real case).

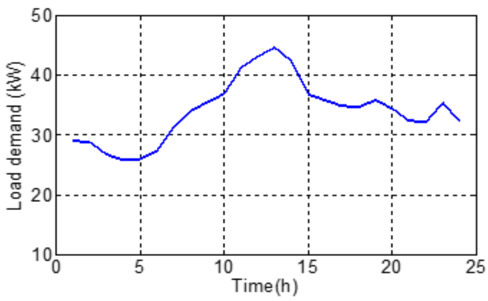

Figure 4. The daily load curve

d) Utility of power system

Electric power can be purchased from the grid whenever the PV system and BESS are not enough to meet the load demand. On the other hand, when the PV production exceeds the consumption, the power excess will be sold back to the grid (high tariff) or/and charged to the BESS (low tariff). In this paper, the simulation is considered via two scenarios of the grid tariff (dynamic tariff).

3) Adaptive Observer Techniques for On-Line Battery Model Identification

Adaptive model identification using parameter estimation and state observers can be used to overcome these limitations. They allow for a characterization of an equivalent electric circuit (EEC) model, using the operational measurement data of a BESS, directly [12]. A sequential coestimation of battery system parameters and states can be used by using a recursive least squares (RLS) filter for parameter, and a Kalman filter (KF) for state estimation. A similar approach has been shown using a normalized least mean squares (NLMS) observer. The inability to control the relative adjustment speed of system parameters and states in the coestimation has led to the development of a simultaneous gradient descent coestimation (COEST) observer. The EEC models characterized by these methods can be used in EMS optimization.

In this work, results from a comprehensive study of the RLS, NLMS and COEST observers on a BESS are presented. The goodness of the online battery voltage estimation is compared and stability concerns are addressed. Furthermore, the extraction of EEC model parameters, in particular OCV and lump internal resistance curves (Fig. 5), are demonstrated. Finally, it is shown that observer estimations are sufficient to reconstruct the OCV characteristic even when the precise curve is not known as an input to the system.

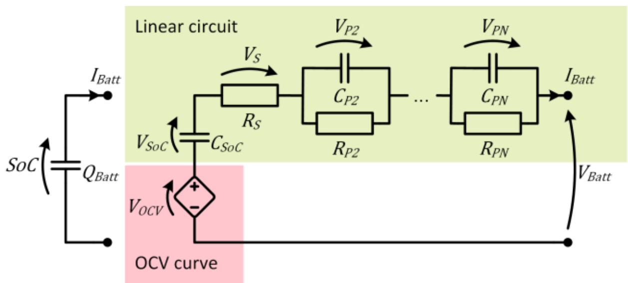

Figure 5. Dynamic EEC battery model

The three observer algorithms investigated in this work are used to identify model parameters and system states of a dynamic EEC battery model as illustrated in Fig. 5.

The model contains of a voltage source V_{OCV} controlled by the state-of-charge (SoC) of the battery, i.e. the voltage over the capacitor C_{Batt}, and representing the a priori open-circuit voltage (OCV) estimate using a predetermined characteristic $V_{OCV}(SoC)$ as shown in Fig. 6.

The observer determines the parameters and states of the remaining linear circuit whose dynamics can be described by:

$$\vec{x}_{k+1}=\mathbf{A}\cdot\vec{x}_k+\mathbf{B}\cdot u_k\,, \qquad y_k=\mathbf{C}\cdot\vec{x}_k+\mathbf{D}\cdot u_k$$

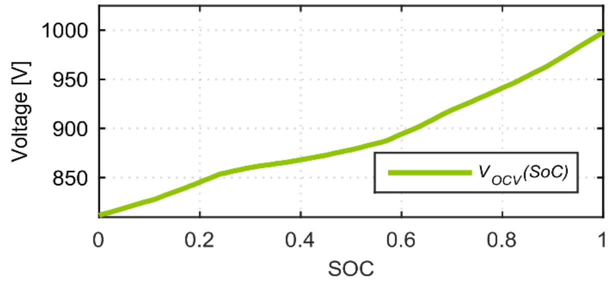

Figure 6. OCV curve of a BESS

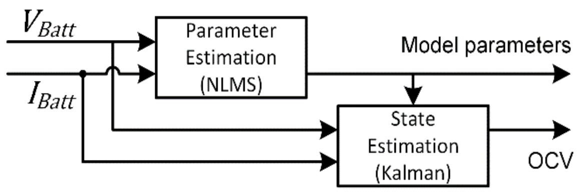

Figure 7. a) Sequential system parameter and state coestimation using adaptive filter and Kalman filter

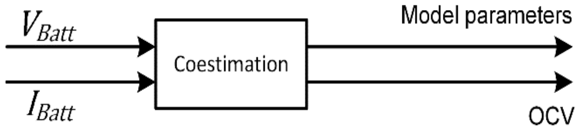

Figure 7. b) Simultaneous system parameter and state coestimation

The output of the observed system at time step k is the difference between the measured battery voltage V_{bat_k} and the a priori estimate of the OCV voltage $V_{OCV}(SoC)$. The system state $\vec{x}_k$ contains the transient over-voltages across the capacitors that model diffusion and porosity phenomena, as well as the voltage V_{SoC}. The capacitance C_{SoC} is assumed to be infinite such that $\alpha_1 = 1$ (where α is diagonal of A) and $b_1 = 0$. In consequence, V_{SoC} can be interpreted as the instantaneous error of the a priori OCV estimation that is excluded from the system dynamics and only adjusted by the state estimation. The physical parameters can be obtained:

$$C_{Pj} = -\frac{b_j}{T}, \qquad R_{Pj} = -\frac{b_j}{1-\alpha_j}. \tag{2}$$

Figs. 7a and 7b present the sequential system parameter and state coestimation using adaptive filter and Kalman filter and the simultaneous system parameter and state coestimation, respectively.

These battery models are used in optimization programs to be accurate and adaptive to operating conditions without being prohibitively complex.

4) *Methodology*

This section presents the optimal energy management of a grid-connected microgrid.

a) *Objective function*

The objective function is to minimize the final value of the cash flow "CF" during the entire studied period. There are two parts of the cash flow: the cash received "CR" and the cash pay "CP". The received cash is expressed as a negative value and the cash pay is given as a positive value.

Objective function is :

$$\min CF = \min \sum_{o}^{24} CR(t) + CP(t) \tag{3}$$

The received cash is defined as the profit from the selling power excess to the main grid:

$$CR(t) = P_{grid}(t) * Fit(t) * t \tag{4}$$

Where P_{grid}: power exchange with the main grid (in this equation: $P_{grid}(t) \leq 0$);

Fit: Feed-in tariff

There are two parts of the cash pay: the cost of electricity purchase from the grid and the replacement cost of battery:

$$CP(t) = (P_{grid}(t) * EgP(t) * t + BrC(t)) \tag{5}$$

Where P_{grid}: power exchange to the main grid (in this equation: $P_{grid}(t) \geq 0$);

EgP: electricity grid price

BrC: replacement cost of baterry

Thus, the objective function of this problem is rewritten as the following equation:

$$\min \sum_{0}^{24} (P_{grid}(t) * FIT(t) * t) + (P_{grid}(t) * EgP(t) * t + BrC(t)) \tag{6}$$

- The replacing cost of batteries

From the adaptive model presented as preceding part, the battery ageing model is obtained [12]. The state of health variation (ΔSOH) can be expressed as a function of the SOC variation (ΔSOC) and the ageing coefficient (Z) [12].

$$\Delta SOH(x_i, x_j, t) = Z * (SOCx_i(t-\Delta t) - SOCx_j(t)) \tag{7}$$

The replacement cost is calculated as follows:

$$BrC(t) = BiC \frac{\Delta SOH(t)}{1 - SOH_{min}} \tag{8}$$

where

BiC : the investment cost of battery
SOH_{min} : the minimum state of health.

b) *Constraints*

* Constraint related to the power balance

* Constraint related to the BESS power output

* Constraint related to the battery state of charge

* Constraint related to the battery ageing

* Constraint related to the grid power.

B. *Island microgrid*

In this paper, optimal energy management of an island microgrid which comprises PV systems, Diesels and BESS is presented. A dynamic programming is used to minimize the operation cost and emissions. The power balance between supply and load demand in each time-interval, the capacity of each DER and microgrid operation are viewed as the constraints.

1) *Configuration of an island microgrid*

Fig. 8 shows an island microgrid that will be studied in this paper.

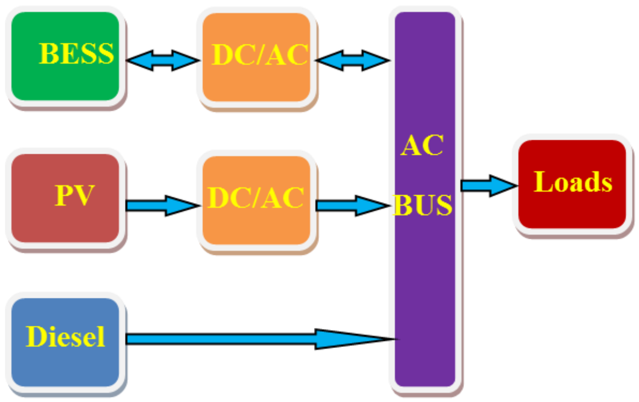

Figure 8. Island microgrid configuration

2) Data and hypothesis

The daily data of PV system production is the same as the preceding part (II.A.2). The load data utilized is the same as the preceding part. For battery energy storage system, the same as the preceding part, the state of charge (SOC) can be calculated as (1). During the charge process, the state of charge at the moment t can be calculated by the following equation:

$$SOC(t)=SOC(t-1)+\frac{P_{PV}(t)+P_{Diesel}(t)-P_L(t)}{C_{ref}}.\Delta t \quad (9)$$

The diesel genset is used to cover the entire load in case of insufficient PV system and BESS production. Diesel is started to meet the load demand and may be shut off whenever the PV system and BESS production are sufficient to supply the load.

3) Methodology

This section presents the optimal energy management of an island microgrid.

a) Objective function

The objective is to minimize the system cost (CS) considering the CO_2 emissions. The system cost includes the fuel cost (FC), the emission cost (EC) and the replacement cost of battery (BrC). In this session, the day-ahead cost of system can be determined as following:

$$\text{Min } CS=\sum_{t=1}^{24} FC(t)+EC(t)+BrC(t) \quad (10)$$

- The fuel cost is expressed as following:

$$FC=\sum_{t=1}^{24} C_f.F(t) \quad (11)$$

where

C_f: the fuel price

F(t): the hourly consumption of diesel generator. F(t) is characterized as:

$$F(t)=0.246.P_{DG}(t)+0.08415.P_R \quad (12)$$

where

P_R : the rated power of diesel generators

P_{DG} (t): the diesel power at time t

- The emission cost (EC) is estimated as follows:

$$EC=\sum_{t=1}^{24}\frac{E_f.E_{cf}P_{DG}(t)}{1000} \quad (13)$$

where

E_f: the emission function (kg/kWh)

E_{cf} : the emission cost factor

- The replacing cost of battery

b) Constraints

* Constraint related to the power balance
* Constrains related to BESS
* Constraint related to the diesel generator.

4) Dynamic programming for energy management based on SOC

The state of the system at each time is estimated by a set of variables of SOC. It is discretized with a step size "ΔSOC". The initial state of charge (SOC_0) is given as initial node without the previous node. Similarly, one sets for the final state of charge (SOC_T). All edges are oriented in one direction from t to t+Δt. Thus, the change of SOC process is seen as a directed graph with initial node (SOC_0) and the final node (SOC_T). Hence, the Bellman algorithm for the searching SOC is used (Fig. 9).

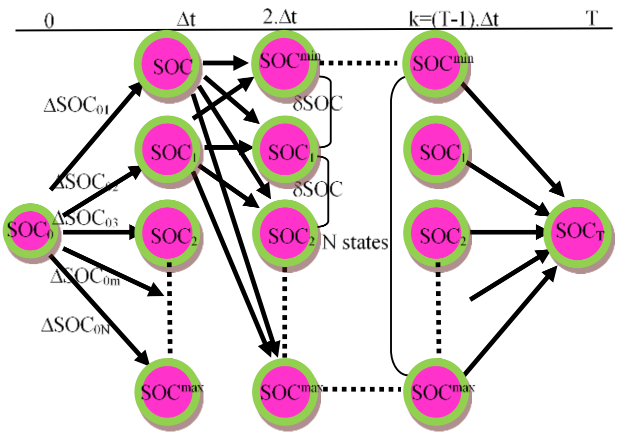

Figure 9. Application of DP algorithm for battery's SOC space

III. Simulation and Results

From the optimal energy management strategies developed in the preceding part, this session presents simulations and results for two types of microgrid: grid-connected (grid, PV systems and BESS) and island microgrid (Diesel, PV systems and BESS).

A. Grid-connected microgrid

The loads and PV production are random variables. The stochastic approach is used to simulate. To facilitate explaining, in this paper, two scenarios are simulated (with different limits of power exchange: 500 and 300 kW). The sample day-ahead forecast values of load and PV production are taken for a day in the preceding section. The simulation parameter values are presented in Table I.

TABLE I. SIMULATION PARAMETER VALUES

Name	Value	**Unit**
T	24	h
Δt	1	h
SOC(to)	0.5	pu
SOCmin	0.2	pu
SOCmax	0.9	pu
Ppeakload	1000	kW

In order to optimize the schedule of sources, as well as the power exchange with the main grid in dynamic tariff, the simulation for 24h is performed to determine the minimum of cash flow. The simulation is terminated when the SOC variable reaches its final state.

In this scenario, the power is sold/bought to/from the main grid with dynamic tariff for a day. The dynamic tariff is shown in Fig. 10.

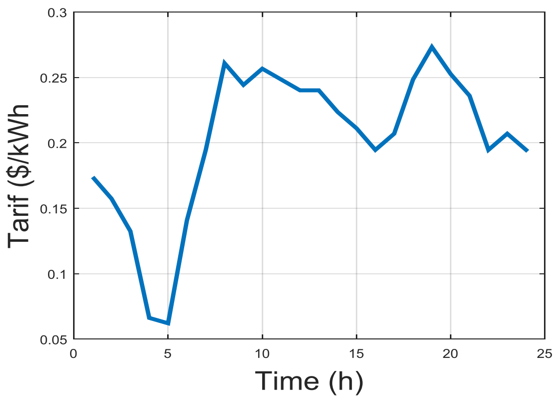

Figure 10. Dynamic tariff

The optimal power schedule is shown in Fig. 11. If the maximal limit of power exchange with grid is fixed by 500 kW, the power from the main grid is supplied for the demand loads and charged for BESS in the beginning of the day. This can be explained that the tariff is very slow in this period time. After that, the demand loads are supplied from the PV system and the BESS from 7 AM to 5 PM. The BESS plays the main role to provide the demand loads.

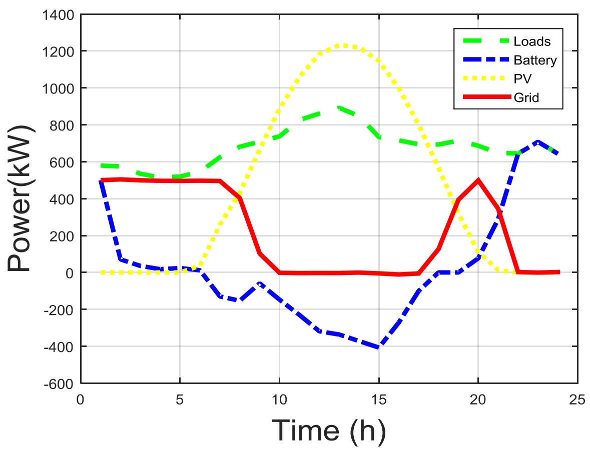

Figure 11. The power schedule

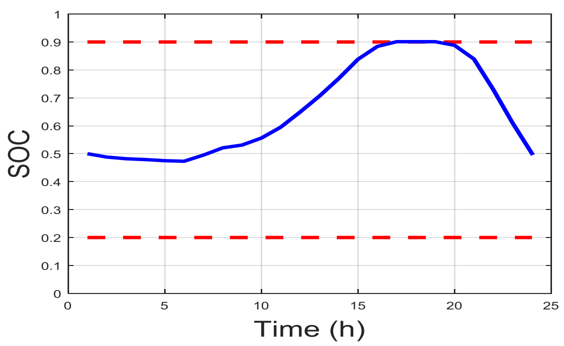

Figure 12. SOC variation

Fig. 12 shows the variation of SOC of battery. The final cost for the DP optimization is 932.43 $/day.

If the maximal limit of power exchange with grid is fixed by 300 kW (Fig. 13), the final cost for the DP optimization is 1022.1 $/day. The SOC variation is shown in Fig. 14.

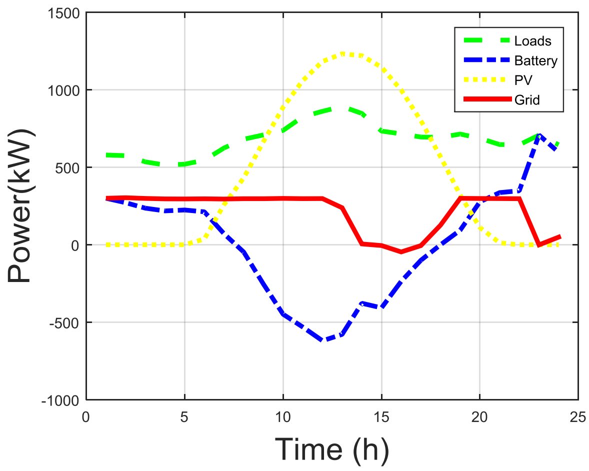

Figure 13. The power schedule

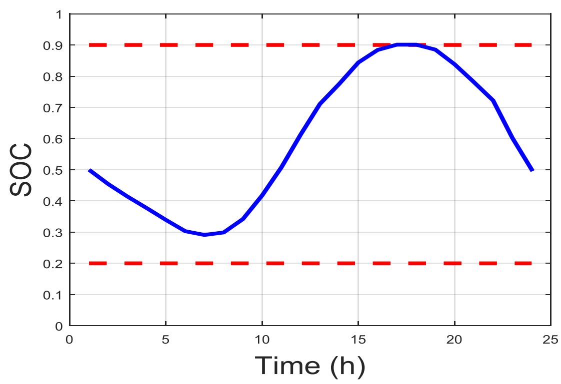

Figure 14. SOC variation

B. *Island microgrid*

The optimal energy management of isolated PV-diesel-BESS hybrid system is to be presented in this subsection. The day-ahead simulation is carried out to minimize the system cost, the CO_2 emission as well as to determine the optimal schedule of diesels and BESS.

The simulation parameter values are presented in Table II. The simulation is finished when the state of charge SOC variable reaches its final state. In this part, the initial state of charge SOC(t_0) is fixed by 0.5.

TABLE II. SIMULATION PARAMETER VALUES

Name	Value	Unit
T	24	h
Δt	1	h
SOCmin	0.2	pu
SOCmax	0.9	pu
Minimum power of diesel	100	kW
Maximum power of diesel	900	kW

The power schedule of the studied island microgrid is shown in Fig. 15. It can be seen the load demand is satisfied by DER (diesel and BESS). At the beginning of the day, when the load is low, the load demand is supplied by the diesel. After that the BESS discharges to meet the load, the diesel does not work at 6 AM. The diesel stops the operation in 13 hours (from 6 AM to 7 PM) estimated by using the DP method. In this period, the consumption is supplied by the PV system production. When the PV power is sufficient to meet loads, the BESS is charged by the power excess. It shows that the diesel is cooperated with the BESS and PV in order to satisfy the load in DP method.

The simulation results show that the diesel generation is stopped for a period of 13 hours per day and the diesel is operated a constant power. Thus it leads to make good operating condition, reduce the cost fuel as well as the CO_2 emission and increase the lifetime of diesel generators. Furthermore, the final SOC equal with the initial one; thus the charge operation will be easily performed in the beginning of next day (Fig. 16).

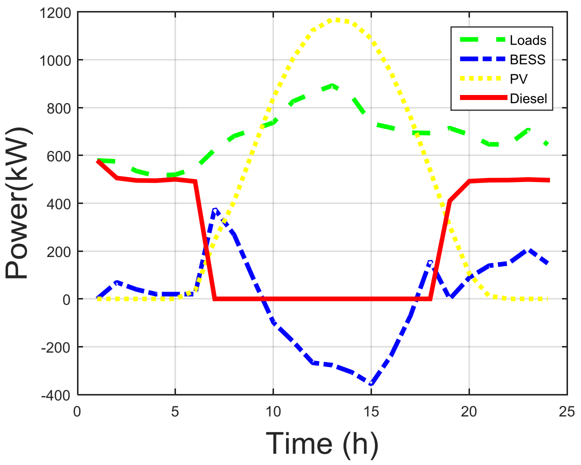

Figure 15. The power schedule

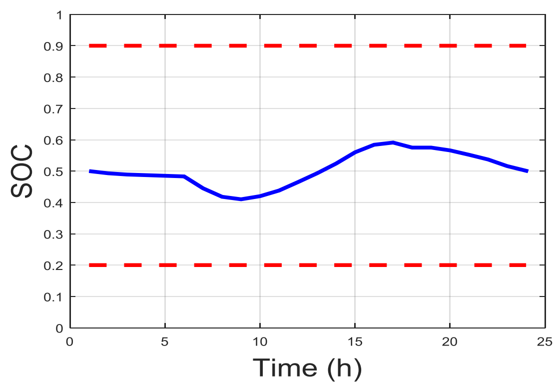

Figure 16. SOC variation

If the initial SOC is 0.5, the final cost for the DP optimization is 2065.4$/day. The SOC variation is shown in Fig. 16.

IV. CONCLUSIONS

In this paper, the optimal energy management of a grid-connected microgrid which comprises PV system and BESS has been proposed. Dynamic programming technique is used to find the minimum of cash flow in order to optimize the schedule of sources (Grid and BESS), as well as the power exchange with the main grid for a dynamic tariff. The simulation results show that the proposed solution not only gives the global optimal of energy management but also to find the minimum value of power exchange with the main grid.

The optimal energy management of an island microgrid which comprises PV system, Diesel and BESS has been also proposed. To find the optimal schedule of power sources (Diesel and BESS), to minimize operation cost and CO_2 emissions, the same as preceding part, dynamic programming technique has been used. The simulation results show that the proposed solution gives the global optimal of energy management for an island microgrid.

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