Historical data based energy management in a micro-grid with a hybrid energy storage system

Ke. Jia, Y.R. Chen, T.S. Bi, *Senior Member*, Y.Q. Lin, D. Thomas and M. Sumner

Abstract [1]**—In a micro-grid, due to potential reverse output profiles of the Renewable Energy Source (RES) and the load, energy storage devices are employed to achieve high self-consumption of RES and to minimize power surplus flowing back into the main grid. This paper proposes a variable charging/discharging threshold method to manage energy storage system. And an Adaptive Intelligence Technique (AIT) is put forward to raise the power management efficiency. A battery-ultra-capacitor hybrid energy storage system (HESS) with merits of high energy and power density is used to evaluate the proposed method with onsite measured RES output data. Compared with the PSO algorithm based on the precise predicted data of the load and the RES, the results show that the proposed method can achieve better load smoothing and maximum self-consumption of the RES without the requirement of precise load and RES forecasting.**

***Index Terms*—adaptive intelligent technique (AIT), energy management, hybrid energy storage system (HESS), variable threshold**

NOMENCLATURE

P_l , P_G, P_{pv}, P_{wd}	the load demand, the grid power, the photovoltaic power and the wind power(W)
P_{HESS} P_{BESS},P_{CAP}	the total power dispatch reference, the power dispatch reference of battery and ultra-capacitor (W)
P_{sp}	the surplus power(W)
P_{CDthr}	the threshold power(W)
P_{con}	a constant power(W)
$E_{G,}$ E_{pv}, E_{wd},	the grid energy, the PV energy, the wind energy(Wh)
E_{BPG}	the adjustable energy of the ultra-capacitor(Wh)
$E_{(conv.loses+Pr(loss))}$	the energy losses(Wh)
$E_{Hess.BESS}$, $E_{Hess.CAP}$	the dispatch energy of the battery and the ultra-capacitor(Wh)
E_{BESS},E_{CAP}	the energy reserved state of the battery and the ultra-capacitor(Wh)
$E'_{CAP}(d+1)$	the energy available for re-dispatch at end of day (d+1)(Wh)
$P'_{CAP}(d+1)$	the power available for re-dispatch at end of day (d+1)(Wh)
$\Delta E_{CAP}(d)$	the energy dispatched by the ultra-capacitor in day d (Wh)
Δt, d, T	the sample interval(1s in this paper), the day number and the total count of sample time for a day (86400 in this paper)
prc	the tariff
Kx	the ultra-capacitor index
T_a	the average moving time
i, i_s	the global and local sample time count
η	the conversion efficiency

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I. INTRODUCTION

DEVELOPMENT of distributed renewable energy generators has been one of the main focuses of research and industry to reduce pollution and the consumption of fossil energy. The usage of the RES and the energy storage system in a micro-grid can guarantee the security, reliability, and efficiency of the energy distribution [1-3].

The potential benefits of energy storage system for the grid have been investigated as a mechanism to increase grid resilience since it can supply backup power and grid stabilization services. The low cost of power electronics promotes the storage technologies usage in the form of EV (Electrical Vehicle) [4] and other kinds of batteries for ancillary services such as frequency and voltage regulation and load demand optimization [5-8].

Plug-in EVs have been investigated for distribution and residential networks with charging stations, for peak shaving and loss reduction [9-10]. However, the load and power flow profile have to be well-known for this method to work well and the utilization of EVs as energy storage units will increase degradation rates in the batteries: this might not be acceptable for EV owners. A demand tracking based model is proposed in [11]. This model aims at load smoothing but has charging efficiency problems during each of the charging windows. It requires accurate predicted data of the load demand and RES output for effective energy dispatching [12]. Economic factors are considered in [13] and the optimized strategy is achieved using genetic algorithms that might not be very practical for real time industry application. A predictive control solution using neural networks for forecast the load and PV output forecasting is introduced in [14-15]. The energy management results are affected by the marginal errors between the real data and the forecasting. A Linear Programming (LP) routine is adopted to design dispatch schedules of the storage system using PV output and load forecasts [16-18]. This method considers the reasonable efficiency factors of the converters and battery. An improved method is proposed in [19-20]. It uses the generic algorithm to design the hourly dispatch schedule and is added a feedback controller to supervise the state of charge of the battery. A PSO-based algorithm is proposed in [21] which variably dispatches the energy in order to minimize the cost of generated electricity. But this method is easy to get a local optimal result. In [22], a dynamic demand scheduling scheme using the theory of optimal portfolio selection strategy is proposed. But appliances in this paper may not be true in real-life scenarios and the reliability of energy supply is needed to be reconsidered. In [23-25], the stochastic optimization and robust optimization methods using historical wind data and wind forecasts are proposed to derive storage schedules respectively. Those methods reduce the forecast errors and guarantee a smoothed output of the wind power.

Previous models or algorithms are investigated using mostly predicted data and designs are made on the assumption of accurate predictions. However, the accurate forecasts are almost impossible in reality. Thus, this paper proposes a management method which does not depend on accurate forecasting. The innovations of the proposed method are: 1) It can reduce the deviation of the load shaving caused by the forecast errors via calculating the variable dispatch threshold power. 2) It can achieve maximum utilization of the stored energy to smooth the load demand as much as possible since the dispatch power of the energy storage system can track the load demand and the RES output variation.

The method proposed in this paper aims at achieving energy management of a hybrid energy storage system which consists of a battery and an ultra-capacitor to shave the load demand. The management is divided into two steps for each sample point. The first step is to reasonably distribute the load shaving task between those two devices generally according to the load fluctuant condition. The second step is to manage the energy of the ultra-capacitor to regulate the surplus load demand as much as possible by the real-time controllable AIT. The onsite measured RES output data are used to test the proposed method in this paper. The results show that this method can achieve load shaving and maximum self-consumption of RES without the requirement for precise predicted load and RES data. Compared with the standard method using the PSO algorithm, the proposed method provides a variable power regulation and the simulation results verify its improvement.

The details will be clarified in the later sections. Section II discusses the model of the hybrid energy storage system and gives out the dispatch principle of the battery. Section III proposes the dispatch principle of the ultra-capacitor. Section IV investigates the AIT which is the essence of the proposed method. Section V is the testing result which shows the advantages of the AIT by comparison. The last Section VI is the conclusion of the whole paper.

II. The Model Of Hybrid Energy Storage System

The system structure of a micro-grid consists of the RES, load demand, the storage system and other variable factors for the grid as shown in the Fig.1. A hybrid energy storage system (HESS) is used to verify the proposed energy management algorithm.

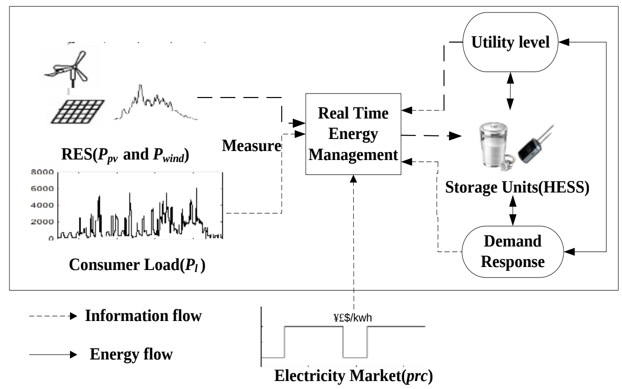

Fig. 1. Structure of Energy Management System

The HESS consists of the Li-ion-battery and the ultra-capacitor in order to integrate the merits of these two energy storage devices to achieve higher energy utilization efficiency. The dispatch principles of two storage devices in load shaving are different according to their own characteristics since it is beneficial to assure the full potential use of two devices to shave load.

The Li-ion-battery is characterized by high energy density and short cycle span. The ultra-capacitor has high power density, quick response and fast charge/discharge speed. Thus, the HESS is a system with high energy and power density and long life cycle span. In addition, the life span of the battery is influenced by the depth of discharge (DOD) largely while that of the ultra-capacitor will not be impacted. Therefore, the Li-ion battery is used to smooth the flat part of the load demand and the ultra-capacitor can be used to shave the large-amplitude part of the load demand. This section will discuss the general energy dispatch principle between the battery and the ultra-capacitor.

The total dispatch power (P_{HESS}) including the capacitors (P_{CAP}) and the batteries (P_{BESS}) is calculated as shown in the (1). For these variables, the positive value means the storage devices are in the discharging mode and the negative value means in the charging mode.

$$P_{BESS}(i) + P_{CAP}(i) = P_{HESS}(i) \tag{1}$$

During operation, the calculation of dispatch power should obey some constraints. The values of P_{BESS} and P_{CAP} cannot exceed their limitations ($P_{BESS.lim}$ and $P_{CAP.lim}$). These limitations should be constrained to match the surplus power of the HESS and the maximum values of dispatchable power of the ultra-capacitor and the battery.

When charging:

$$\left|P_{BESS/CAP.\lim}(i)\right| = Min\begin{Bmatrix} P_{BESS/CAP.\max}, \\ \dfrac{(E_{BESS/CAP.\max} - E_{BESS/CAP}(i-\Delta t))\times 3600}{\Delta t} \end{Bmatrix} \quad (2)$$

Where, Δt is the time interval between two sample points and the $E_{BESS/CAP}$ is the energy reserved state of the battery and the ultra-capacitor. The equation (2) is used to make sure the charging power and energy within the battery and capacitor maximum limitation. The lower option quantifies the maximum energy limitation in the charging window (The energy is summation of power over a period of time).

When discharging, the similar regulation is required and the minimum energy reversed in the HESS is used in the lower option of the equation (3):

$$\left|P_{BESS/CAP.\lim}(i)\right| = Min\begin{Bmatrix} P_{BESS/CAP.\max}, \\ \dfrac{(E_{BESS/CAP}(i-\Delta t) - E_{BESS/CAP.\min})\times 3600}{\Delta t} \end{Bmatrix} \quad (3)$$

The equation (3) is used to make sure the discharging power and energy within the battery and capacitor minimum limitation.

It is assumed that the dispatch power during each sample period (1s) is constant. The numeric conversion between P (kW) and E (kWh) in 1s is shown in the equation (4).

$$P(i)\times 1 = E(i)\times 3600 \quad (4)$$

After confirming the constraint conditions, the next step is to distribute the dispatch power between the battery and the ultra-capacitor.

Firstly, a fixed average moving time parameter T_a (in seconds) is used to calculate the dispatch power of the battery. In order to make the battery in the low-discharging mode and used to smooth the relatively flat part of the load demand, the dispatch power of the battery is the average power during this average moving time as shown in the equation (5). This computing method is referred to the [26]. i_s (in seconds) is a local variable to mark the sample points' serial time number and is numbered consecutively during one day. That means i_s is labeled from 1 to 86400 (There are 86400 sample time every day since the sample interval is 1 second in this paper.) each day. When i_s is less than T_a, the battery does not work since there are not enough sample points to calculate an average value. Otherwise, the calculated dispatch reference of the battery is the average power of the HESS during the past T_a period. Also, the practical dispatch power of the battery will be subjected to some other constraint conditions.

When $i_s \le T_a$

$$P_{BESS}(i) = 0$$

When $i_s > T_a$

$$P_{BESS}(i) = \frac{1}{T_a}\sum_{t=i-T_a}^{t=i-\Delta t} P_{HESS}(t) \quad (5)$$

In addition, the electrical-power conversion losses should be considered. The conversion efficiency of converters in both the $DC/AC_{(DC/AC)}$ and $AC/DC_{(AC/DC)}$ side and the battery are about 95% and 85% respectively. Thus, the final efficiency of the storage-generation system is:

$$\eta_{AC/DC}\times\eta_{battery}\times\eta_{DC/AC} = 0.95\times 0.85\times 0.95 = 0.77 \quad (6)$$

After determining the calculation of the required dispatch energy, the control process will be described for three conditions. Considering the battery power dispatching regulations described above, the HESS power dispatching process can be classified into three conditions:

Condition 1 when $i_s \le T_a$

In this condition, the dispatch power of the battery is zero as shown in the equation (5) and only the ultra-capacitor works. And the specific dispatch power calculation process of the ultra-capacitor will be clarified in the section III and IV (The following two conditions are the same.).

$$P_{Hess}(i) = P_{CAP}(i) \quad (7)$$

Condition 2 when $i_s > T_a$ and meets the condition of

$$\frac{\frac{1}{Ta}\sum_{t=i-T_a}^{t=i-\Delta t} P_{HESS}(t)}{P_{BESS}(i-\Delta t)} > 0 \quad or \quad \begin{cases} \dfrac{\frac{1}{Ta}\sum_{t=i-T_a}^{t=i-\Delta t} P_{HESS}(t)}{P_{BESS}(i-\Delta t)} \le 0 \\ \dfrac{SoC_{CAP}(i) - SoC_{CAP.0}}{P_{CAP}(i-\Delta t)} \le 0 \end{cases}$$

SoC_{CAP} is the ultra-capacitor's state of charge. This condition means that the current operating mode of the battery does not change comparing with the last operating mode (the former condition) or it changes but the ultra-capacitor cannot supply the required grid power alone (the latter condition). It balances the battery and ultra-capacitor's working power: the battery and ultra-capacitor work together as shown in the equations (1)-(5).

Condition 3 when $i_s > T_a$ and meets the condition of

$$\begin{cases} \dfrac{\frac{1}{Ta}\sum_{t=i-T_a}^{t=i-\Delta t} P_{HESS}(t)}{P_{BESS}(i-\Delta t)} \le 0 \\ \dfrac{SoC_{CAP}(i) - SoC_{CAP.0}}{P_{CAP}(i-\Delta t)} > 0 \end{cases}$$

This condition means that the operating pattern of battery changes and the ultra-capacitor can work alone. In order to reduce the charge and discharge times of the battery, it should maintain its previous state with a constant power P_{con}. As for the ultra-capacitor, it has enough reserved energy in this situation and is controlled to dispatch power.

If previous second state is discharging

$$P_{BESS}(i) = P_{con}$$

If previous second state is charging,

$$P_{BESS}(i) = -P_{con} \quad (8)$$

These three conditions described above can make sure that the battery will be used to shave the flat part of the load demand whereas the ultra-capacitor will reduce the large-amplitude part of the load demand especially when the EV load occurs. Section III and IV will describe the specific energy management method of the ultra-capacitor.

III. Algorithm For Energy Dispatch For The Ultra-capacitor

This section will introduce the specific dispatch power calculation process of the ultra-capacitor. Independent of the precise forecast data, the calculation process focuses on the real-time correction step. Under this circumstance, the ultra-capacitor can achieve the maximum energy utilization especially when large fluctuations (forecast errors) occur.

The calculation process is based on the data of the day before which acts as the references for the initial calculation. These references will be compared with the practical data to calculate the real-time discharging threshold at each sample time and manage the energy of the ultra-capacitor precisely. This senction will mainly give out some calculation criterias and the essence of the algorithm will be clarified in the section IV.

The first step of the algorithm is to determine the operating mode (charging or discharging) of the ultra-capacitor from the surplus power for the ultra-capacitor (P'_{sp}) related to tariff (*prc*). Then the limitation of dispatch power and the efficiency of energy conversion should be calculated. If the ultra-capacitor operates in discharge mode, the most important part is calculating the discharge threshold.

The whole system's surplus power (P_{sp}) in any sample interval equals to the load demand minus the summation of power available from the HESS. During the low-tariff period, the energy storage units are regarded as the load and the main gird is compelled to charge for the energy storage units (P_G). During the high-tariff, the main gird does not extra charge for the energy storage units. Since the grid power (P_G) changes with tariff, the calculation of the surplus power falls into two cases as shown in the equation (9).

If $prc(i)$=1

$$P_{sp}(i) = P_l(i) - [P_{pv}(i) + P_G(i) + P_{wd}(i)]$$

If $prc(i)$=2

$$P_{sp}(i) = P_l(i) - [P_{pv}(i) + P_{wd}(i)] \tag{9}$$

Where, P_l is the load demand, P_G is the grid power, P_{pv} is the photovoltaic output, P_{wd} is the wind power. These variables are non-negative. "1" represents the low-tariff and "2" represents the high-tariff. P_{SP} is the surplus power. Its negative value means the energy supply is less than the demand and the positive value means the energy supply is larger than the demand.

The power (P'_{sp}) required from the ultra-capacitor shown in the equation (10) is the surplus power after subtracting the dispatch power by the battery according to the equations (5)-(8).

$$P'_{sp}(i) = P_{sp}(i) - P_{BESS}(i) \tag{10}$$

After confirming the operation mode, it is easy to calculate the discharge power for the ultra-capacitor (P_{CAP}). This value is modified according to the electrical-power conversion losses. The discharge power is related to the threshold power P_{CDthr} for the discharging of the ultra-capacitor shown in the equation (11).

$$P'_{sp}(i) - P_{CDthr}(i) = P_{CAP}(i) \tag{11}$$

The conversion efficiency of converters is 95%. Different with the battery, losses due to ultra-capacitor internal resistance can be ignored for the comparable small values. Thus, the final efficiency of the storage-generation is:

$$\eta_{AC/DC} \times \eta_{DC/AC} = 0.95 \times 0.95 = 0.90 \tag{12}$$

The proposed method regulates the ultra-capacitor dispatch power intelligently based on the data of the day before. In this case, the proposed method cannot be used in the first day (the fixed-threshold method is used for the first day).

For the first day (*d=1*), the value of the P_{CDthr} is fixed comparing the surplus power and the limit of discharge power and checking the rest power of the ultra-capacitor. For the following days, the P_{CDthr} for each current sample is related to the previous day's data and the discharge threshold will be calculated using the method below.

The total available energy of the micro-grid is the summation of the measured PV output (E_{pv}), wind turbine output (E_{wd}) and grid energy (E_G) at low tariff. Then considering the losses and the energy dispatched by the battery, the energy that can be used by the ultra-capacitor is shown below.

$$\begin{aligned} E_{BPG(d)} = &\sum_{i=1}^{T} E_{pv}(i,d) + \sum_{i=1}^{T} E_{wd}(i,d) + \sum_{i=1}^{T} E_G(i,d) - \\ &\sum_{i=1}^{T} E_{(conv.loses+P_r(loss))}(i,d) - \sum_{i=1}^{T} E_{HESS.BESS}(i,d) \end{aligned} \tag{13}$$

In order to change the real-time threshold power in day (*d*+1), the total energy dispatched by the ultra-capacitor in day *d* (ΔE_{CAP}) should be calculated first. It is the difference between the adjustable energy and the final reserved energy of the ultra-capacitor in day *d*.

$$\Delta E_{CAP}(d) = E_{CAP}(T \times (d-1)) + E_{BPG}(d) - E_{CAP}(T \times d) \tag{14}$$

Where, E_{CAP} is the reserved energy of the ultra-capacitor and E_{BPG} is available energy for the ultra-capacitor.

For calculating the next day's P_{CDthr} (d>1), it is assumed that the total dispatch energy and the available energy for day (*d+1*) and day *d* are equal as shown in the equation (15). Under this initial assumption, the final state of charge of the ultra-capacitor (E'_{CAP}) in day (*d+1*) can be calculated by the equation (16) which represents the energy available for re-dispatch at end of day (*d+1*). These are just the initial reference values and will be corrected comparing the current practical surplus power and the *SoC* of the ultra-capacitor with the previous day's data at the same time which will be clarified in the Section IV.

$$\begin{cases} \Delta E_{CAP}(d+1) = \Delta E_{CAP}(d) \\ E_{BPG}(d+1) = E_{BPG}(d) \end{cases} \tag{15}$$

$$E'_{CAP}(d+1) = E_{BPG}(d+1) + E_{CAP}(T \times d) - \Delta E_{CAP}(d) \tag{16}$$

Analyzing and processing the available energy are the fundamental basis of the variable-threshold method for this study. Section IV will introduce an Adaptive Intelligence Technique (AIT) to regulate the threshold power to dispatch those available excess energies.

IV. Adaptive Intelligent Technique

This section will discuss an Adaptive Intelligence Technique (AIT) which is the essential step to calculate the variable discharge threshold power of the ultra-capacitor to control its energy dispatch. This technique can make the discharge power of the ultra-capacitor track the load demand variety to maximize the utilization efficiency of the ultra-capacitor. In addition, the load demand with large fluctuation can be shaved as much as possible.

Firstly, in order to judge the ultra-capacitor's discharge state, an ultra-capacitor index Kx is applied.

$$\frac{E'_{CAP}(d+1)}{SoC_{CAP.\min}\times E_{CAP.e}}=Kx \tag{17}$$

Where, $E_{CAP.e}$ is the rated capacity of the ultra-capacitor.

This index is the ratio of the final state of charge of the ultra-capacitor under the assumption equation (15) and the minimum state of charge allowed for the ultra-capacitor. The minimum SoC is set to guarantee the stable operation of the ultra-capacitor for a long time. It is to measure whether the ultra-capacitor storage energy is above the minimum or not. It is also a boundary of energy level at where a decision is made to either draw in more energy or dispatch more energy. If $Kx>1$, it means that the ultra-capacitor can discharge more energy; otherwise, the ultra-capacitor should discharge less energy to ensure it does not go below the lower limit.

Since the real-time dispatch result depends largely on the previous day's data, this paper establishes an optimal trend target that the difference between the load gradient r_1 and the discharge rate r_2 is better to be small to fully track the load deviation. For current point i, r_1 and r_2 of the same time of the day before are calculated firstly as shown in the equation (18). Then, the objective target is established to make the current and future regulation results tend to be optimum as shown in the equation (19).

$$\begin{cases} r_1=\dfrac{P_l(i-T)}{\sum\limits_{t=T\times(d-1)+1}^{t=T\times d} P_l(t)} \\ r_2=\dfrac{P_{CAP}(i-T)}{\Delta E_{CAP}(d)\times 3600} \end{cases} \tag{18}$$

$$ot=\min\left|r_1-r_2\right| \tag{19}$$

For every sample point (i) two conditions are classified.

Condition 1 If $Kx>1$

Check the condition: whether the ultra-capacitor reserved energy in the previous sample is larger than the required minimum reserved energy and whether the current surplus power is larger than the amount in the previous day at the same sample period ($E_{CAP}(i-\Delta t)>SoC_{CAP.min}\times E_{CAP.e}$, $P'_{sp}(i)>P'_{sp}(i-T)$).

If the condition is true, the threshold P_{CDthr} is reduced. During this process, the optimal condition $r_1=r_2$ is setting and the value of r_2 (equal to r_1) is used to calculate the new threshold to make the result tend to be the optimum.

$$\begin{aligned} P_{CDthr}(i)&=P_{CDthr}(i-T)\text{-}\frac{P_{CAP}(i-T)}{\Delta E_{CAP}(d)\times 3600}\times P'_{CAP}(d+1) \\ &=P_{CDthr}(i-T)\text{-}\frac{P_{CAP}(i-T)}{\Delta E_{CAP}(d)}\times E'_{CAP}(d+1) \end{aligned} \tag{20}$$

With a lower threshold, the ultra-capacitor can discharges more energy at time i (applying with the equation (11)) which leads to a decrease in $E'_{CAP}(d+1)$. Thus, $E'_{CAP}(d+1)$ and Kx should be recalibrated:

$$\begin{aligned} E'_{CAP}(d+1)_{new}=E'_{CAP}(d+1)_{old}\,- \\ \frac{E_{CDthr}(i-T)}{\Delta E_{CAP}(d)}\times E'_{CAP}(d+1)_{old} \end{aligned} \tag{21}$$

$$Kx_{new}=\frac{E'_{CAP}(d+1)_{new}}{SoC_{\min}\times E_{CAP.e}} \tag{22}$$

Condition 2 If $Kx<1$

Check the condition: $E_{CAP}(i-\Delta t)>SoC_{CAP.min}\times E_{CAP.e}$, $P'_{sp}(i)<P'_{sp}(i-T)$ and if the condition is true the threshold P_{CDthr} is increased as:

$$\begin{aligned} P_{CDthr}(i)&=P_{CDthr}(i-T)+\frac{P_{CAP}(i-T)}{\Delta E_{CAP}(d)\times 3600}\times P'_{CAP}(d+1) \\ &=P_{CDthr}(i-T)+\frac{P_{CAP}(i-T)}{\Delta E_{CAP}(d)}\times E'_{CAP}(d+1) \end{aligned} \tag{23}$$

With a higher threshold, the ultra-capacitor discharges less energy at time i to increase $E'_{CAP}(d+1)$.Thus, $E'_{CAP}(d+1)$ and Kx should be recalibrated(the Kx is recalibrated with the equation (22))

$$\begin{aligned} E'_{CAP}(d+1)_{new}=E'_{CAP}(d+1)_{old}\,+ \\ \frac{E_{CDthr}(i-T)}{\Delta E_{CAP}(d)}\times E'_{CAP}(d+1)_{old} \end{aligned} \tag{24}$$

Based on the analysis and functions above, the flow chart for implementation is presented in Fig.2.

The AIT works when provided with real time information of load demand, distributed generation, supply from main grid, converter rating and system efficiencies. The system reads measured load demand and distributed generation data first. Initially, values for threshold power are manually fixed after being subject through techno-economic conditions mentioned above. The threshold power gauges the amount of energy that should be dispatched at every point i for day d. After error checking of total energy dispatched plus ultra-capacitor state at end of day d using (25), the algorithm moves to the next process flow where it modifies the current threshold power based on the power which is calculated using the previous day's information. The AIT process helps determine the actual threshold power for day ($d+1$).

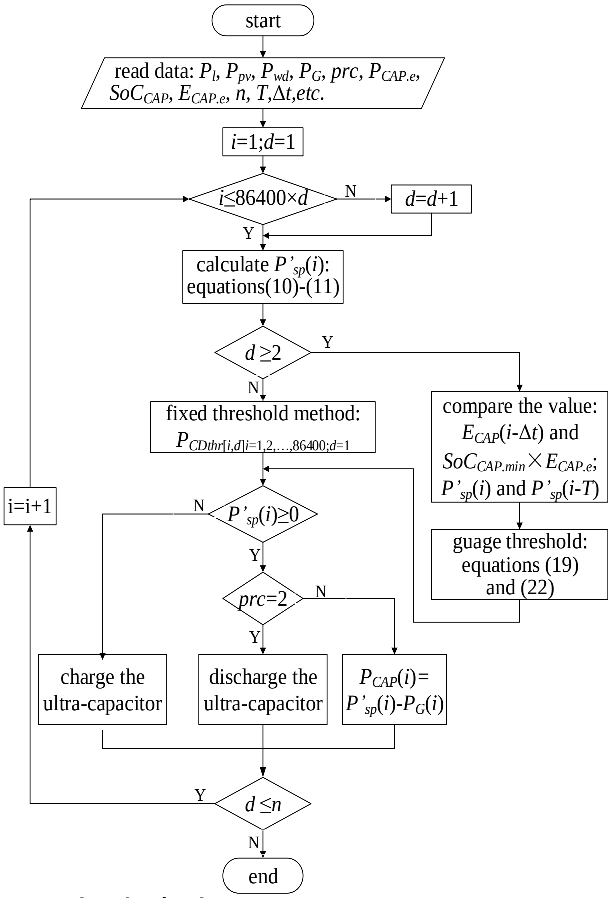

Fig. 2. Algorithm for ultra-capacitor Management System

$$\sum E_{Hess.CAP(discharge)}(d) + E_{CAP}(T\times d) \leq \sum E_{Hess.CAP(charge)} \quad (25)$$

V. RESULTS

This paper utilizes the on-site measured data as the input data for the proposed method to test the operation efficiency. The RES data are generated from a 3kW wind turbine and a 3kW PV panel. The load demand data is from a load simulation model--the CREST Domestic Electricity Demand Model [27]. The electricity price is referred to the Economy 7 tariff policy. The storage system consists of a 65kWh/5kW Li-ion battery and a 35kWh/50kW ultra-capacitor. The Wind turbine, PV, storage system and three households are formed as a community micro-grid.

The Fig.3 shows the RES output and the load demand during 3 days. The PV output reaches its peak in the middays and the wind turbine output reaches the peak in the late nights and early mornings. The output distribution of RES is a reverse profile with the load demand.

The Fig.4 shows the surplus power calculated by the equation (9). The negative value indicates that the output of the RES is larger than the load and is better to be stored in order to be effectively discharged during the load peak period.

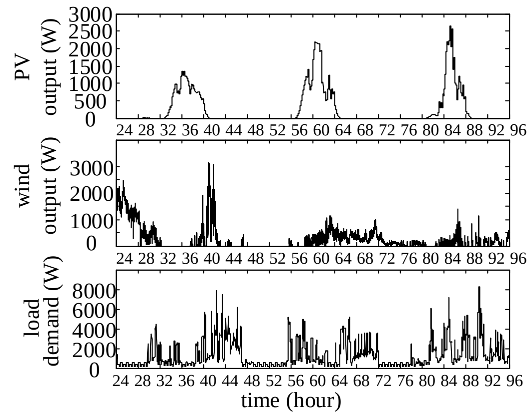

Fig. 3. RES output and Load demand

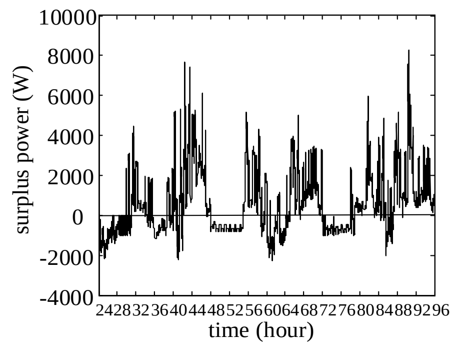

Fig. 4. Surplus power curve

A. Particle Swarm Optimization Algorithm

The particle swarm optimization (PSO) algorithm [28] is based on the precise forecast data.

Fig.5 shows the dispatch power of the HESS and the new load demand after being regulated by the HESS management using the PSO algorithm. Compared with the surplus power in the Fig.4, PSO algorithm shows the load shaving ability. However, this load shaving effect of the PSO is not obvious since the operation result is associated with the number of particles, the dimensionality of the particle swarm and other parameters. Also, the value of those parameters influences the algorithm operation speed. Therefore, the PSO algorithm has the shortage of long operation time and unstable results.

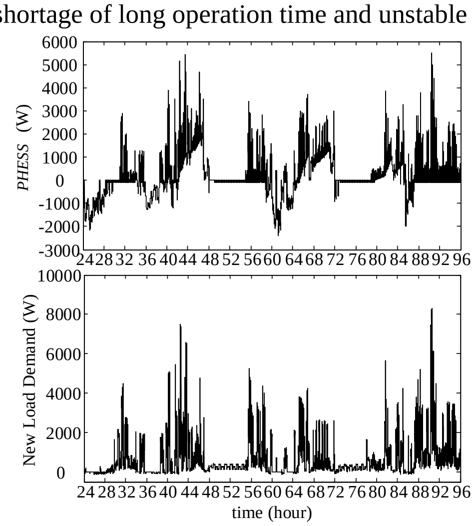

Fig. 5. The dispatch power and New Load Demand with PSO

In addition, if a sudden fluctuation ΔP_{error} appears during the practical condition, the load shaving result may be affected seriously since the instability characteristics of the PSO algorithm.

Fig.6 shows the New Load Demand (NLD) with and without $\Delta P_{l.error}$ (this fluctuation appears during the 44th to 45th hours and it is used to simulate the demand of the Electric Vehicle with 2000W). The blue dashed line is the result under the circumstance that the forecast data is very precise and the green line is the result under the circumstance that a sudden load fluctuation appears. The result shows that the PSO algorithm based on forecast data cannot deal with the condition of sudden fluctuation very well.

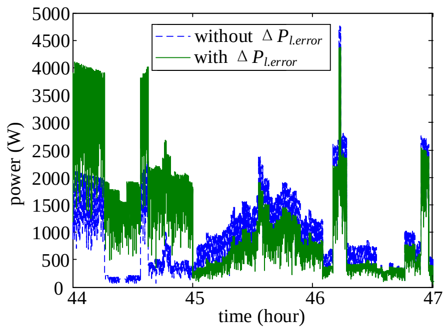

Fig. 6. New Load Demand (NLD) with or without $\Delta P_{l.error}$ (PSO)

According to the testing results, the PSO algorithm based on forecast data requires a precise load consumption and RES output forecast to calculate the dispatch power of the HESS at the beginning of each day. However, it's not always the case that consumer load demand and RES are accurately forecasted in reality. Therefore, the whole system might dispatch inefficiently most times by the PSO algorithm.

B.AIT Algorithm.

Fig.7 shows the New Load Demand with or without $\Delta P_{l.error}$ applying with the AIT (using the same data as the PSO algorithm). Comparing Fig.6 with Fig.7, it is obvious that the magnitude of the demand fluctuation with and without $\Delta P_{l.error}$ of the PSO algorithm is larger than that of the variable threshold method. This result shows that the load fluctuation has less impact on the HESS's power dispatch when the AIT is employed. Compared with the PSO algorithm, the AIT not only improves the efficiency of HESS, but also reduces the influence of data fluctuation on HESS's power dispatch.

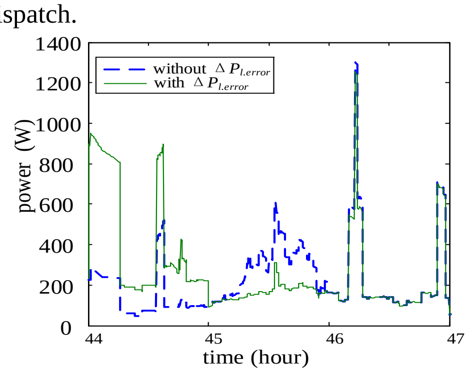

Fig. 7. New Load Demand (NLD) with or without $\Delta P_{l.error}$ (AIT)

The figures below only show zoom in part of data in order to make clear comparison. The Fig.8 shows the actual charging and discharging power of the HESS with PSO algorithm and the AIT algorithm respectively. Compared with the PSO algorithm (dashed blue line), the proposed AIT algorithm (red line) provides more power from the HESS during the high-tariff period.

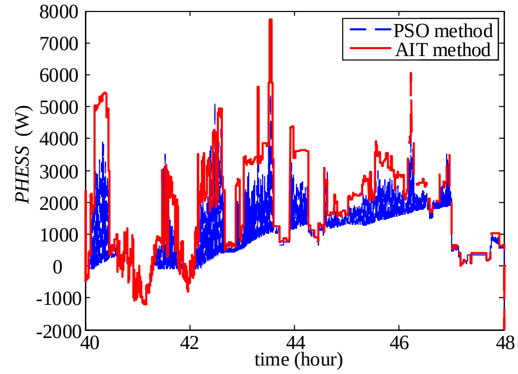

Fig. 8. Power output of HESS with PSO and with AIT

The load demand seen from the grid side (the suppliers) has been reduced as shown in Fig.9. Compared with the PSO algorithm (dashed blue line), the AIT algorithm offers much less peak demand since it can discharge more power to shave the peak load as shown in the Fig.8.

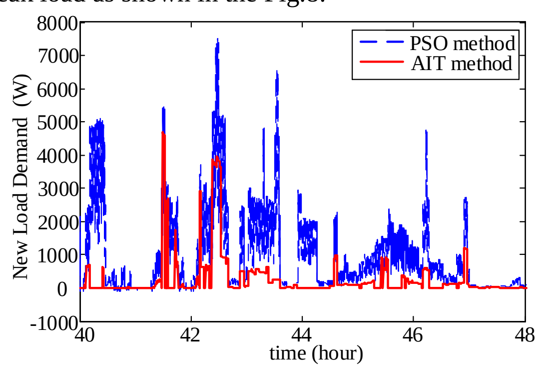

Fig.9. New Load Demand (NLD) before and after applied with AIT

Overall improvements of the AIT for 8 weeks are demonstrated in the Table I.

TABLE I.
Weekly Improvement by AIT technique

week	New Load Demand with PSO (E+04, wh)	New Load Demand with AIT (E+04, wh)	HESS efficiency with PSO	HESS efficiency with AIT
1	9.88	3.34	26.02%	78.56%
2	8.16	0.84	25.46%	95.03%
3	10.68	8.12	42.68%	82.70%
4	10.72	12.00	64.76%	64.14%
5	12.29	11.20	38.11%	55.48%
6	9.06	2.70	26.38%	78.12%
7	9.65	3.19	37.63%	94.19%
8	1.31	1.11	25.80%	59.00%

The Table I shows the improvement in the load smoothing and efficiency of the energy system when the proposed AIT is applied. Comparing the results from the second row to the third row, it is obvious that the AIT can get much lower load demand than the PSO algorithm. The HESS efficiency is the ratio of discharge energy and the available energy in the HESS (from the fourth to the fifth row) indicating that the efficiency of HESS is raised and more stored energy is discharged to smooth the load applied with the AIT. However, there is an unconformable data. In the week 4, the AIT algorithm shows better result than the AIT. The reason of this condition is that during the week 1-3, the PSO algorithm does not fully utilize the stored energy which means it has larger accessible energy to dispatch in the week 4. As a result, it gets better load shaving effect with larger HESS efficiency. Considering the unstable characteristics of the PSO algorithm, it is not easy to achieve this result always. Then the proposed program was utilized in a one year data and the overall energy saved from the grid is about 8.56% and the renewable energy local utilization had been improved by 20.12%. From all the results, the AIT proposed in this paper shows better effect in load shaving and the utilization efficiency of the storage unit.

VI. Conclusion

This paper proposes a variable-threshold methodology for control of energy storage unit within a micro-grid. With each stage of the decision making for energy distribution, an Adaptive Intelligence Technique (AIT) is used to calculate the current power management reference and adaptively update current HESS state to adjust to the fast changed consumer demand pattern. The AIT is tested in a micro-grid system used onsite measured data and simulated load demand. According to the results, compared with the traditional PSO algorithm, the AIT improves the efficiency of renewable energy utilization. Compared with the method which relies on forecasting information, the proposed AIT can regulate the threshold power and discharging power without precise forecasting. This can reduce the deviation effect of the load shaving result caused by the sudden fluctuation of the load demand and improve the accuracy of the control strategy. Therefore, the proposed algorithm is more practical for real time implementation and can bring benefit to both the local customers and the power suppliers by achieving maximum RES local utilization and load smoothing.

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