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Key words: smart grid, time-of-use, renewable energy sources, battery energy storage system, particle swarm optimization, intelligent particle swarm optimization.

ABSTRACT

With increasing development of smart grid and restructuring of the power industry, the problem of operating schedule for a time-of-use (TOU) rate industrial customer may become a more important issue due to the inclusion of the variations in the TOU rate structures. This paper develops a new algorithm, named intelligent particle swarm optimization (INPSO), to solve the operating schedule of a renewable energy based TOU rate industrial user with battery energy storage system (BESS). Adding another particle best ($P_{best_{ap}}$) item with a diversity based judgment mechanism, proposed INPSO algorithm can give a good direction to enhance its search capacity that leads to a higher probability of obtaining the global optimal solution. A TOU rate industrial customer of Taiwan Power Company (TPC) is used as an example to validate the feasibility of the INPSO algorithm for the application considered. Numerical experiments are included to understand how variations in the rate structures on the optimal operation of the TOU rate customer system. The computer program developed in this paper can also be a power tool for TOU rate industrial users to evaluate the economic benefits of the renewable energy sources (RES) and BESS.

I. INTRODUCTION

In the coming decades, global environmental issues could

significantly affect energy usage patterns around the world. Renewable energy sources will become more important due to a lack of fossil fuels, the need to control atmospheric emissions, and environmental concerns. The government in Taiwan has commissioned research on renewable energy applications under the consideration of diversifying energy sources (Chen et al., 2008; Chen et al., 2010). Among various renewable energy sources in Taiwan, wind energy systems (WES) and photovoltaic generation systems (PVGS) are promising alternatives for power generation because of their tremendous environmental and social benefits (Chang et al., 2003; Lee and Chen, 2009; Wu et al., 2011). Various WES and PVGS based hybrid power systems have received widespread attentions and applications, and are widely installed or undergoing testing in the time-of-use (TOU) rate industrial users. However, more and more renewable energy sources will penetrate into the grid, which brings challenges to operating schedule problem for a hybrid power system due to the intermittency and unpredictability of renewable power generation (Pavlos, 2006; Chen, 2007; Jabr and Pal, 2009). In the future market-based micro grid system, it can be expected that many problems will also arise in the renewable energy based TOU rate industrial user due to the inclusion of the variations in the TOU rate structures, particularly in system operation and planning (Lee and Chen, 2009; Hopkins et al., 2012; Huang et al., 2012; Mozafari et al., 2012).

Recently, both customers and electric utility companies have experienced increasing costs in energy and electric power due to the escalating cost of burning fuels and capital costs for building new generation units. Load management changes the shape of the load curve so that generation of costly peak units or capacity additions are avoided or deferred and is an effective solution to the above problem. The TOU rate is a load management policy designed to shift electricity use from peak load periods to light load periods. This shift abates the requirements of new construction projects and raises the overall efficiency of the power system. For some heavy load TOU

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Table 1. Three-section TOU electricity rate structures of TPC for high-voltage power service.

Classification	Energy Charge (NT\$/kWh)	
	Summer Season	Non-summer Season
Peak load hours (PLH) (10:00-12:00 and 13:00-17:00)	3.45	---
Medium load hours (MLH) (The hours other than PLH and LLH)	2.00	1.94
Light load hours (LLH) (00:00-07:30 and 22:00-24:00)	0.82	0.77

rate users, electricity charges play a prominent role in production costs. In order to minimize the total electricity charge of a TOU rates customer, many different energy storage devices, such as refrigeration storage (RS), compressed air energy storage (CAES), battery energy storage system (BESS), etc., have been investigated. Among them, the BESS is one of the most promising technologies to reduce the cost of electricity for TOU rate users (Lee and Chen, 1994; Lee, 2007). The importance of the scheduling problem of BESS is, thus, like to increase, and more advanced algorithms are worth developing to reach the minimum electricity charge of a renewable based TOU rate industrial customer.

With increasing of the development of smart grid and restructuring of the power industry, the efficient operation schedule for a TOU rate industrial user may become a more important problem. Several new implications will arise with respect to the traditional concepts of the TOU rate structure of the TPC system under competitive environment. Table 1 shows the pricing structure for high-voltage three-section TOU rates customers in the TPC system (Lee and Chen, 2009). The TOU rate for electrical power is the practice of implementing different prices for different times of use. The TPC confirms power peak and power valley times, and then adopts higher prices during the peak time and lower prices during the valley time. But in a market-based micro grid system, the TOU rate structure may be changed day-to-day basis by the TPC to further raise the overall efficiency of the power system. The TOU rate industrial user can adjust their operation policy on using electricity power with profit motives. In addition, the sold/purchased power from the utility grid is also another characteristic in a competitive electrical market. This mechanism can significantly reduce the electricity charges, increase the economic benefits of energy generated by BESS and RES. Therefore, the problem of efficient operation of BESS for a renewable based TOU rate industrial customer under competitive environment may lead to be more complex than the conventional dispatch.

Several optimization algorithms based on classical calculus based techniques or stochastic searching techniques (Lee and Chen, 1994; Bakirtzis and Petridis, 1996; Juste et al., 1999; Wood and Wollenberg, 1996; Lee, 2007; Gaing, 2013), in-

cluding priority list (PL), multi-pass dynamic programming (MPDP), evolutionary programming (EP), genetic algorithm (GA), and particle swarm optimization (PSO), could be used to solve the extended generation scheduling problem. Among all, the PSO approach is of particular interest because of its ability to generate a high-quality solution within shorter computation time and exhibit a more stable convergence characteristic than other stochastic methods. This paper proposes an improved algorithm, modified from PSO (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998), to solve the operating schedule of BESS for a renewable energy based TOU rate industrial user. A new index called another particle best ($P_{best_{ap}}$) is incorporated into PSO to provide parts of information guiding to the global solution and give additional exploration capacity to swarm. A novel diversity based judgment mechanism for the evaluation of $P_{best_{ap}}$ behavior is also proposed to enhance its search capacity that leads to a higher probability of obtaining the global optimal solution. Test results are provided to illustrate the merits of the proposed method and to give a good indicator to install a BESS in a renewable energy based TOU rate industrial user.

II. PROBLEM FORMULATION

1. Notation

The following notation is used throughout the paper.

a_i, b_i, C_f	: cost coefficients of diesel unit i
$C_{PE}(t)$: tariff of the purchased power at hour t (NT\$/kWh)
$C_{SE}(t)$: tariff of the sold power at hour t (NT\$/kWh)
$CS_{1,t}$: penalty function for Eq. (8) at hour t
$CS_{2,t}$: penalty function for Eq. (10) at hour t
$CS_{3,t}$: penalty function for Eq. (18) at hour t
$CS_{4,t}$: penalty function for Eq. (26) at hour t
$d\%$: percentage of maximum diesel unit capacity
$FC(t)$: diesel fuel cost at hour t
$F_i(\bullet)$: operation cost function of diesel unit i
$F_{PE}(t)$: cost of the purchased power at hour t (NT\$/h)
$F_{SE}(t)$: income of the sold power at hour t (NT\$/h)
i	: index for diesel units
j	: index for non-dispatchable units
ND	: number of diesel units in system
$P_D(t)$: system load demand at hour t
$P_i(t)$: power output of diesel unit i at hour t
P_i^{\max}	: maximum generation limit of diesel unit i
P_i^{\min}	: minimum generation limit of diesel unit i
$P_{bat}(t)$: power output of battery at hour t (positive for discharging and negative for charging)
P_{bat}^{\max}	: maximum power output of battery
$P_{grid}(t)$: power output of utility grid at hour t (posi-

	tive for purchased and negative for sold)
P_{grid}^{max}	: maximum power output of utility grid
$P_{SB}(t)$: the inverter output at hour t
P_{Wj}^{max}	: upper generation limit of wind unit j
$P_{Wj}^*(t)$: available generation of wind unit j at hour t
$P_{Wj}(t)$: actual generation of wind unit j at hour t
$P_{WT}(t)$: total actual wind power generation at hour t
P_{PVj}^{max}	: upper generation limit of solar unit j
$P_{PVj}^*(t)$: available generation of solar unit j at hour t
$P_{PVj}(t)$: actual generation of solar unit j at hour t
$P_{PV}(t)$: total actual solar power generation at hour t
$r_1\%$: percentage of load demand
$r_2\%$: percentage of actual renewable power generation
r_b	: penalty factor
$rand(-1,1)$: uniform random value in the range $[-1,1]$.
$rand(0,1)$: uniform random value in the range $[0,1]$.
SD	: minimum solar radiation intensity
SU	: maximum solar radiation intensity
$S_r(t)$: solar radiation intensity at hour t
$SOC(t)$: energy left in the battery at hour t
SOC_{min}	: minimum energy left in the battery
SOC_{max}	: maximum energy left in the battery
T	: number of time intervals (hours)
t	: index for time intervals (hours)
TC	: total electricity charge
$T_r(t)$: ambient temperature at solar in hour t
$US_i(t), DS_i(t)$: up/down reserve contribution of diesel unit i at hour t
US_i^{max}, DS_i^{max}	: maximum up/down reserve contribution of diesel unit i
$US_{bat}(t), DS_{bat}(t)$: up/down reserve contribution of battery at hour t
$US_{bat}^{max}, DS_{bat}^{max}$: maximum up/down reserve contribution of battery
$US_{grid}(t), DS_{grid}(t)$: up/down reserve contribution of utility grid at hour t
$US_{grid}^{max}, DS_{grid}^{max}$: maximum up down reserve contribution of utility grid
$USR(t), DSR(t)$: system up/down reserve requirement at hour t
$v(t)$: wind speed at hour t
v_{lj}	: cut in wind speed of wind unit j
v_{Rj}	: rated wind speed of wind unit j
v_{Oj}	: cut out wind speed of wind unit j
$\varphi_j(\bullet)$: wind power curve of wind unit j
$\delta_j(\bullet)$: solar radiation/ ambient temperature power curve of solar unit j
η_B	: battery efficiency during the charging/ discharging period
Δt	: time interval

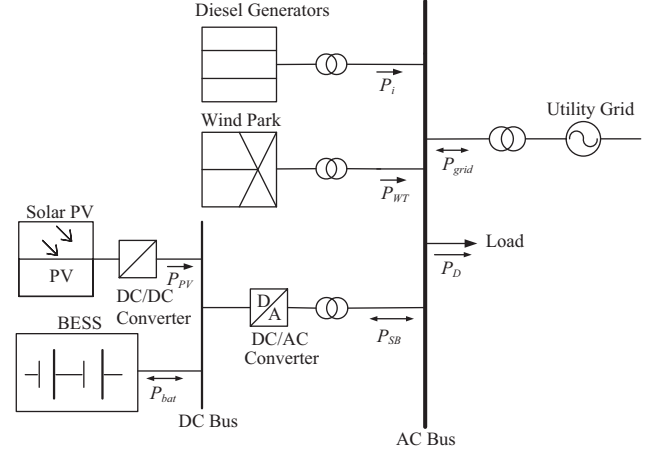


Fig. 1. TOU rate customer system.

2. Formulation

The objective of the algorithm presented in this paper is to reach the minimum electricity charge while satisfying all operational constraints in a renewable energy based TOU rates industrial customer with a BESS. The operation policy on using electricity power for the TOU rate industrial user can be adjusted properly according to the modified TPC rate structures in the future market-based micro grid system. Fig. 1 shows a typical industrial customer in the TPC system. The components of the system include diesel generators, wind farm, solar PV array, BESS and utility grid. Utilized extra spinning reserves for the intermittency and unpredictability of renewable power generation are considered to ensure the security and reliability of a power system (Chen, 2007). The mathematical model of the generating scheduling problem can be stated as follows.

Objective function:

$$\text{Minimize } TC = \sum_{i=1}^T \{FC(t) + F_{PE}(t) - F_{SE}(t)\} \quad (1)$$

$$FC(t) = \sum_{i=1}^{ND} F_i(P_i(t)) \quad (2)$$

$$F_i(P_i(t)) = C_f \times (a_i \times P_i(t) + b_i \times P_i^{max}) \quad (3)$$

$$F_{PE}(t) = \begin{cases} (P_D(t) - \sum_{i=1}^{ND} P_i(t) - P_{WT}(t) - P_{SB}(t)) \times C_{PE}(t), & \text{if } P_{grid}(t) \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

$$F_{SE}(t) = \begin{cases} (\sum_{i=1}^{ND} P_i(t) + P_{WT}(t) + P_{SB}(t) - P_D(t)) \times C_{SE}(t), & \text{if } P_{grid}(t) \leq 0 \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

subject to the following constraints.

1) System Constraints

- Power balance constraint

$$\sum_{i=1}^{ND} P_i(t) + P_{WT}(t) + P_{grid}(t) + P_{SB}(t) = P_D(t) \quad (6)$$

- System up spinning reserve constraints

$$USR(t) = r_1 \% \times P_D(t) + r_2 \% \times [P_{PV}(t) + P_{WT}(t)] \quad (7)$$

$$\sum_{i=1}^{ND} US_i(t) + US_{grid}(t) + US_{bat}(t) \geq USR(t) \quad (8)$$

- System down spinning reserve constraints

$$DSR(t) = r_1 \% \times P_D(t) + r_2 \% \times [P_{PV}(t) + P_{WT}(t)] \quad (9)$$

$$\sum_{i=1}^{ND} DS_i(t) + DS_{grid}(t) + DS_{bat}(t) \geq DSR(t) \quad (10)$$

2) Diesel Unit Constraints

- Unit generation limits

$$P_i^{\min} \leq P_i(t) \leq P_i^{\max} \quad (11)$$

- Unit's maximum up/down reserve contribution constraints

$$US_i^{\max} = d \% \times P_i^{\max} \quad (12)$$

$$DS_i^{\max} = d \% \times P_i^{\max} \quad (13)$$

- Unit's up/down reserve contribution constraints

$$US_i(t) = \min \{ US_i^{\max}, P_i^{\max} - P_i(t) \} \quad (14)$$

$$DS_i(t) = \min \{ DS_i^{\max}, P_i(t) - P_i^{\min} \} \quad (15)$$

3) Non-Dispatchable Unit Constraints

- Wind power curve constraints

$$P_{Wj}^*(t) = \begin{cases} 0 & v(t) \leq v_{lj} \text{ or } v(t) > v_{Oj} \\ \varphi_j(v(t)) & v_{lj} \leq v(t) \leq v_{Rj} \\ P_{Wj}^{\max} & v_{Rj} \leq v(t) \leq v_{Oj} \end{cases} \quad (16)$$

- Solar radiation/ambient temperature power curve constraints

$$P_{PVj}^*(t) = \begin{cases} 0 & S_r(t) \leq SD \\ \delta_j(S_r(t), T_r(t)) & SD \leq S_r(t) \leq SU \\ P_{PVj}^{\max} & S_r(t) \geq SU \end{cases} \quad (17)$$

4) Battery Constraints

- Charge/discharge power limits

$$-P_{bat}^{\max} \leq P_{bat}(t) \leq P_{bat}^{\max} \quad (18)$$

- State of charge limits

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max} \quad (19)$$

$$SOC(0) = SOC_S \quad \text{initial state of charge} \quad (20)$$

$$SOC(T) = SOC_E \quad \text{final state of charge} \quad (21)$$

- State of charge balance equation

$$SOC(t) = SOC(t-1) - P_{bat}(t) \times \eta_B \times \Delta t \quad \text{if } P_{bat}(t) < 0 \quad (22)$$

$$SOC(t) = SOC(t-1) - P_{bat}(t) \times \frac{\Delta t}{\eta_B} \quad \text{if } P_{bat}(t) \geq 0 \quad (23)$$

- Battery's up/down spinning reserve contribution constraints

$$US_{bat}(t) = \min \left\{ P_{bat}^{\max} - P_{bat}(t), P_{bat}^{\max}, \frac{SOC(t) - SOC_{\min}}{\Delta t} \times \eta_B \right\} \quad (24)$$

$$DS_{bat}(t) = \min \left\{ P_{bat}^{\max} + P_{bat}(t), P_{bat}^{\max}, \frac{SOC_{\max} - SOC(t)}{\eta_B \times \Delta t} \right\} \quad (25)$$

5) Utility Grid Constraints

- Sold/purchased power limits

$$-P_{grid}^{\max} \leq P_{grid}(t) \leq P_{grid}^{\max} \quad (26)$$

- Grid's up/down spinning reserve contribution constraints

$$US_{grid}(t) = \min \{ US_{grid}^{\max}, P_{grid}^{\max} - P_{grid}(t) \} \quad (27)$$

$$DS_{grid}(t) = \min \{ DS_{grid}^{\max}, P_{grid}(t) + P_{grid}^{\max} \} \quad (28)$$

III. INTELLIGENT PARTICLE SWARM OPTIMIZATION (INPSO)

PSO is a population-based optimization approach first

proposed by Kennedy and Eberhart in 1995 (Kennedy and Eberhart, 1995). In a physical N-dimensional search space, the position and velocity of particle q are represented as the vectors $X_q = \{x_{q1}, x_{q2}, \dots, x_{qN}\}$ and $V_q = \{v_{q1}, v_{q2}, \dots, v_{qN}\}$ in the PSO algorithm. Let $Pbest_q = \{x_{q1}^{Pbest}, x_{q2}^{Pbest}, \dots, x_{qN}^{Pbest}\}$ and $Gbest = \{x_{1,Gbest}, x_{2,Gbest}, \dots, x_{N,Gbest}\}$ be the best position of particle q and the best position that has been achieved so far by any particles, respectively. By tracking two best values, i.e. $Pbest_q$ and $Gbest$, the global optimal might be reached by this optimization technique. In the traditional PSO, it should be noted that the social behavior models the memory of the particle (fish) about the best position among the particles (the experience of its neighbors; $Gbest$). However, it is not reasonable for social behavior to only employ the $Gbest$ which is not normally the global optimal solution, containing parts of non-optimal information. The influence of social behavior to the next movement of the fish (particle) often is affected not only by the location of the fish (particle) which is in the best position of all, but also by the location of the fish (particle) which it randomly looked at when fish schools start looking for food. To increase the possibility of exploring the search space where the global optimal solution exists, we follow a slightly different approach about the social behavior to further provide a selection of the global best guide of the particle swarm. The social behavior consists of two phases, the best particle position ever obtained ($Gbest$) and the random another particle best position ($Pbest_{ap}$), namely, another behavior. After increasing another behavior to the social behavior, the $Pbest_{ap}$ provides parts of information guiding to the global solution and gives additional exploration capacity to swarm. The new velocity update equation is given by:

$$\begin{aligned} V_q^{k+1} = & \omega \times V_q^k + c1 \times rand \times (Pbest_q^k - X_q^k) + c2 \\ & \times rand \times (Gbest^k - X_q^k) + c3_q^k \times rand \\ & \times (Pbest_{ap}^k - X_q^k) \\ q = & 1, 2, \dots, Q; \quad ap \neq q \end{aligned} \quad (29)$$

where $c1$ and $c2$ represent the weighting of the stochastic acceleration terms that pull each particle toward $Pbest_q$ and $Gbest$ positions, $rand$ means a random variable between 0.0 to 1.0, and ω is the inertia weight factor. $Pbest_{ap} = \{x_{ap1}^{Pbest}, x_{ap2}^{Pbest}, \dots, x_{apN}^{Pbest}\}$ is the best position of a random another particle, called particle ap . $c3_q = \{c3_{q1}, c3_{q2}, \dots, c3_{qN}\}$ is the weight factor of another behavior. In general, the initial candidate solutions are usually far from the global optimum and hence the larger $c3_q$ may be proved to be beneficial to explore globally. However, the difference of global best guide between $Gbest$ and $Pbest_{ap}$ is gradually decreasing during successive iterations. Therefore, the value of $c3_q$ will be em-

ployed the linearly decreasing and is calculated using the following expression.

$$\begin{aligned} c3_q = & c3_{\max} - (c3_{\max} - c3_{\min}) \times \frac{iter}{iter_{\max}} \\ q = & 1, 2, \dots, Q; \quad i = 1, 2, \dots, N \end{aligned} \quad (30)$$

where $c3_{\max}$ and $c3_{\min}$ are the initial and final weights, respectively, $iter_{\max}$ is the maximum iteration count, and $iter$ is the current number of iterations.

Adding the $Pbest_{ap}$ item in PSO, it makes the search space much effectively and has a good robustness. However, the information guiding to the global solution from the random another particle best position ($Pbest_{ap}$) may contain in the best particle position ever obtained, $Gbest$. The random another particle best position cannot normally present a positive guidance. For maintaining population diversity, an intelligent judgment mechanism for the evaluation of the $Pbest_{ap}$ behavior is developed to give a good direction to identify the near global region. The new velocity and position of each particle can be calculated as shown in the following formulas.

$$\begin{aligned} V_q^{k+1} = & \omega \times V_q^k + c1 \times rand \times (Pbest_q^k - X_q^k) + c2 \\ & \times rand \times (Gbest^k - X_q^k) - c3_q^k \times rand \\ & \times (Pbest_{ap}^k - X_q^k), \text{ if } (x_{Gbest}^k - x_q^k) \times (x_{ap}^k - x_q^k) \geq 0 \end{aligned} \quad (31)$$

$$\begin{aligned} V_q^{k+1} = & \omega \times V_q^k + c1 \times rand \times (Pbest_q^k - X_q^k) + c2 \\ & \times rand \times (Gbest^k - X_q^k) + c3_q^k \times rand \times (Pbest_{ap}^k - X_q^k), \\ & \text{if } (x_{Gbest}^k - x_q^k) \times (x_{ap}^k - x_q^k) < 0 \end{aligned} \quad (32)$$

$$X_q^{k+1} = X_q^k + V_q^{k+1} \quad q = 1, 2, \dots, Q; \quad ap \neq q \quad (33)$$

As shown in (31) and (32), the novel diversity-based judgment mechanism for evaluating $Pbest_{ap}$ behavior is used to maintain population diversity, which facilitates identification of the near-global region. The weight factor $c3_q$ maintains a wide spread of nondominated solutions. From (31), if $(x_{ap}^k - x_q^k)$ and $(x_{Gbest}^k - x_q^k)$ move in the same direction, the information guiding to the global solution from $Pbest_{ap}$ and $Gbest$ is similar. Compared with $Gbest$, x_{ap}^k is a bad position, and the influence of particle ap to the movement of particle q is negative. Conversely, the information guiding to the global solution from $Pbest_{ap}$ and $Gbest$ differs largely if $(x_{Gbest}^k - x_q^k)$ and $(x_{ap}^k - x_q^k)$ do not move in the same direction. As shown in (32), the influence of particle ap on the movement of particle q is positive. The most attractive feature of the intelligent judgment mechanism for evaluating the aforementioned $Pbest_{ap}$

behavior is its ability to maintain population diversity, which increases the possibility of escaping local optimal solution traps.

IV. SOLUTION METHOD AND IMPLEMENTATION OF INPSO

The main computational processes of the algorithm presented in this paper to solve the operating schedule problem of a TOU rate industrial user are discussed in the following steps. This algorithm is an implementation of INPSO.

Step 1: Initialize the INPSO parameters.

Set up the set of parameters of INPSO, such as number of particles Q , weighting factors ω , $c1$, $c2$, $c3_{\max}$, $c3_{\min}$, and maximum number of iterations $iter_{\max}$.

Step 2: Calculate the available output of RES.

The available renewable power generation can be obtained from the wind speed, solar radiation intensity, and ambient temperature by applying Eqs. (16) and (17). Once the amount of actual renewable power generation is determined, the system up/down spinning reserve requirements can be calculated properly by applying Eqs. (7) and (9).

Step 3: Generate the energy stored in a BESS randomly.

Electrical energy stored in the BESS is used as the state variable in the study. The initial energy stored of BESS is generated randomly by Eqs. (34)-(36). Once the amount of $SOC(t)$ is determined, the charge/discharge power output ($P_{bat}(t)$) of BESS can be calculated properly by applying state of charge balance equations (Eqs. (22) and (23)).

- Charge balance equation

$$SOC(t) = SOC(t-1) + rand(-1, 1) \times P_{bat}^{\max} \times \eta_B \times \Delta t$$

$$if \quad rand(-1, 1) \geq 0 \quad (34)$$

- Discharge balance equation

$$SOC(t) = SOC(t-1) + rand(-1, 1) \times P_{bat}^{\max} \times \frac{\Delta t}{\eta_B}$$

$$if \quad rand(-1, 1) < 0 \quad (35)$$

$$SOC(t) = \begin{cases} SOC_{\max} & if \quad SOC(t) > SOC_{\max} \\ SOC_{\min} & if \quad SOC(t) < SOC_{\min} \end{cases}$$

$$t = 1, 2, \dots, T \quad (36)$$

Step 4: Generate the initial power outputs of ND diesel generating units randomly.

The initial power outputs of ND diesel generating units are

generated randomly by Eqs. (37) and (38).

$$P_i(t) = rand(0, 1) \times P_i^{\max} \quad t = 1, 2, \dots, T \quad (37)$$

$$P_i(t) = \begin{cases} P_i(t) & if \quad P_i(t) \geq P_i^{\min} \\ 0 & if \quad P_i(t) < P_i^{\min} \end{cases} \quad t = 1, 2, \dots, T \quad (38)$$

Step 5: Create an initial population randomly.

Each particle contains the energy stored in the BESS at every time stage, and the real power generation of diesel generators. Eq. (39) shows a particle q . The initial power outputs of BESS and ND diesel generating units are generated randomly by Step 3-4. To satisfy the power balance equation, the output of grid generation $P_{grid}(t)$ is determined by applying Eq. (40).

$$X_q^k = \begin{bmatrix} SOC(1) & SOC(2) & \dots & SOC(T) \\ P_1(1) & P_1(2) & \dots & P_1(T) \\ P_2(1) & P_2(2) & \dots & P_2(T) \\ \vdots & \vdots & \ddots & \vdots \\ P_{ND}(1) & P_{ND}(2) & \dots & P_{ND}(T) \end{bmatrix}, q = 1, 2, \dots, Q \quad (39)$$

$$P_{grid}(t) = P_D(t) - \sum_{i=1}^{ND} P_i(t) - P_{SB}(t) - P_{WT}(t) \quad t = 1, 2, \dots, T \quad (40)$$

Step 6: Evaluate the fitness of the particles.

For each particle, calculate the value of the fitness function. The fitness function is an index to evaluate the fitness of the particles. Eq. (1) shows the fitness function of the generating scheduling problem. To account for up-reserve requirement violations (8), down-reserve requirement violations (10), battery's charge/discharge power limit violations (18), and sold/purchased power limit violations (26), the total electricity charge is augmented by nonnegative penalty terms $CS_{1,t}$, $CS_{2,t}$, $CS_{3,t}$, and $CS_{4,t}$, respectively, penalizing constraint violations. Thus, the augmented cost function TC is formed

$$TC_A = TC + \sum_{b=1}^4 (r_b \sum_{t=1}^T CS_{b,t}) \quad (41)$$

The penalty factor (r_b) is selected as 1.0E5. The penalty terms ($CS_{1,t}$ - $CS_{4,t}$) are proportional to the corresponding violations and zero in case of no violation. There are chosen high enough as to make constraint violations prohibitive in the final solution.

Step 7: Record and update the best values.

The two best values are recorded in the searching process. Each particle keeps track of its coordinate in the solution space that is associated with the best solution it has reached so far. This value is recorded as P_{best} . Another best value to be recorded is G_{best} , which is the overall best value obtained so far by any particle.

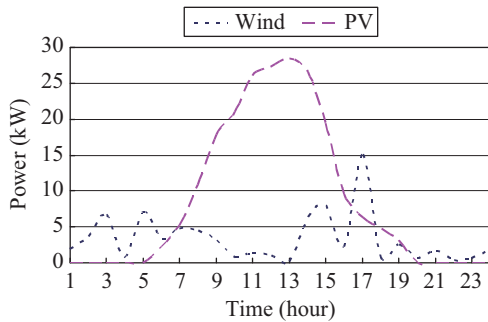


Fig. 2. Available generation of RES for a typical day in the summer season.

Step 8: Update the velocity and position of the particles.

Eqs. (31) and (32) are applied to update the velocities of particles. The velocity of a particle represents a movement of the elements in a particle. Eq. (33) is applied to update the position of the particles. The position of a particle is defined in Eq. (39).

Step 9: End conditions.

Check the end condition. If it is reached, the algorithm stops, otherwise, repeat steps 6-8 until the end conditions are satisfied. In this study, the “end conditions” of INPSO are

- (1) The total operating cost between two consecutive iterations is unchanged or the variation of operating cost is within a permitted range.
- (2) The variation of G_{best} is within a permitted range.
- (3) The maximum number of iterations is reached.

V. NUMERICAL EXAMPLES

To show the applicability and effectiveness of the proposed algorithm, an industrial customer in the TPC System is used as an example. Fig. 1 shows the TOU rate customer system which includes wind farm, solar PV array, BESS, diesel generators and utility grid. The wind farm includes two wind turbine generators (WTGs) and the total capacity of wind power installed is 40 kW. The capacity of solar-PV models is 37.8 kW. The available renewable power generation for all time periods, which can be calculated from the Eqs. (16) and (17), is given in Fig. 2. A simulated BESS with a capacity of 180 kWh/30 kW is integrated into this system. The minimum SOC is limited to 20% and the charging/discharging efficiency is 0.9. The initial/end state of charge is set to be 120 kWh. There are three identical diesel generators. The generation cost coefficients of a diesel generator are $a_i = 0.264$, $b_i = 0.08415$, and $C_f = 26.0$ NT\$/liter. The maximum and minimum generation limits of a diesel generator are 100 kW and 40 kW, respectively. As illustrated in Fig. 1, the solar-PV modules and BESS are connected to a step-up transformer via an inverter. The efficiency of the inverter is 0.95. The minimum and maximum loads for the study period of 24 h are 125 kW and 250 kW, respectively. Ignoring the renewable power generation, the system emergency up/down reserve is assumed

to be 20% of the forecasted load in the coming hours ($r_1\% = 20\%$). In this study, the increased up/down spinning reserve requirement is calculated as a simple fraction ($r_2\% = 20\%$) of the predicted renewable power generation to compensate for possible fluctuations in power of the renewable sources. The maximum up/down spinning reserves of the diesel generator (or utility grid) could not contribute more than 20 percent of its rated capacity. Like other stochastic methods, the proposed INPSO has a number of parameters that must be selected. The solutions obtained from the INPSO largely depend on the number of particles Q and control parameters (e.g., ω , c_1 , c_2 , $c_{3_{max}}$, $c_{3_{min}}$). Unfortunately, the appropriate selection of these parameters justifies the preliminary efforts required for their experimental determination. From our experience, the value of population size Q is an important parameter of INPSO and must be determined experimentally depending significantly on the problem being solved. The recommended value of weighting factor is: $\omega = 0.2\sim 0.4$, $c_1 = 0.8\sim 2.5$, $c_2 = 0.8\sim 2.5$, $c_{3_{max}} = 0.2\sim 0.4$, $c_{3_{min}} = 0.01\sim 0.05$. In the studied cases, the parameters of INPSO are selected as follows: $Q = 1000$, $\omega = 0.3$, $c_1 = 1.2$, $c_2 = 0.8$, $c_{3_{max}} = 0.4$, $c_{3_{min}} = 0.05$, $iter_{max} = 2000$. All the computation is performed on a PC Intel Core(TM) 2 Quad Q8300 2.5 GHz CPU computer with 3.49 GRAM size, and computer programs were developed in FORTRAN. Different scenarios are considered and the studied cases are stated in detail as follows:

1. Case 1: Evaluation of operating policy of the TOU rate customer system

The first study case is to illustrate the optimal operating policy of the next time stage for the TOU rate customer system in real-time application. The maximum purchased power of the utility grid is assumed to be 350 kW and the pricing structures for high-voltage three-section TOU rate customers in the TPC system is shown in Table 1. To illustrate the effects of incorporating the RES and BESS into the TOU system on the existing generation scheduling problem, Fig. 3 shows the electrical energy changes in the BESS, whose power outputs are shown in Fig. 4. The results show that the BESS was fully charged during the light load hours (hour 1-4) when the price of electricity is cheaper (0.82 NT\$/kWh). The BESS then discharged during peak load hours (hour 10-12 and hour 13-17) when electricity charges are high (3.45 NT\$/kWh). Optimal amount of energy purchased from utility grid during period can be determined by using the proposed software. The final power outputs of the utility grid during a typical 1-day load are also shown in Fig. 4. In this study case, it is found that these three diesel generators are shut down for all time periods due to their high prices. As a result, the function of the intelligent optimizer developed can shave the peak of the load curve by the output of the BESS to save on energy costs and reduce the risk of the BESS running out of energy in a peak-demand reduction application. The numerical results of the developed software can also be summarized to develop expert knowledge for BESS controller design.

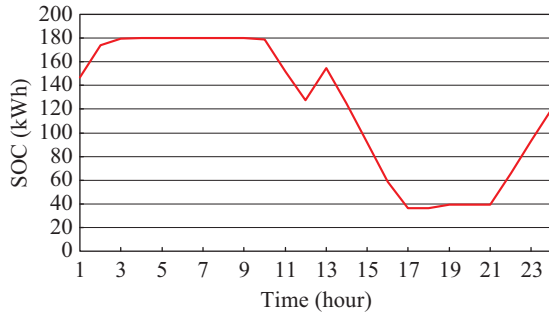


Fig. 3. Electrical energy changes in the BESS (Case 1).

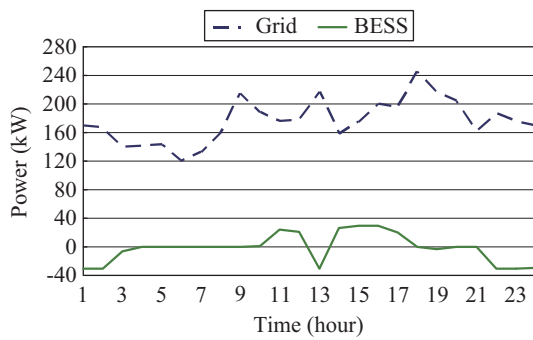


Fig. 4. Outputs of BESS and Grid during a typical daily load (Case 1).

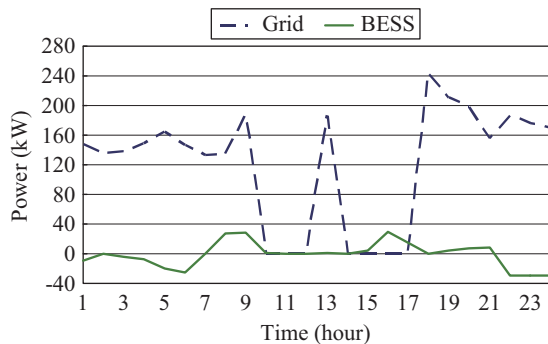


Fig. 5. Outputs of BESS and Grid during a typical daily load (Case 3).

2. Case 2: Prediction of electricity cost savings from the expected new customer system

To evaluate the impact and economic benefits of the installation of RES/BESS, the developed INPSO software, described in section 5, is a useful tool for the TOU rate industrial users to predict the energy cost and the cost savings from the expected new customer systems in off-line application. Table 2 gives a good indicator to understand the effects of the RES/BESS on the total electricity cost savings from the expected new customer system in the second study case. For the previous TOU system, if RES and BESS were excluded in the system, the total electricity cost is NT\$ 9718.17 in case 2.1. Because of the RES/BESS integration, it is necessary to update the energy flow control strategies from each component to fully explore the TOU rate customer system benefits. From

Table 2. Comparison of electricity cost saving under various simulation cases.

Case	RES	BESS	TC (NT\$)	Saving (%)
2.1	Without	Without	9718.17	---
2.2	With	Without	8964.93	7.75%
2.3	With	With	8677.84	10.70%

the results in Table 2, the significant benefits of electricity cost savings from the new TOU rate customer system are expected. As shown in case 2.2, a 7.75% electricity cost saving is achieved when the TOU system includes the RES. Obviously, the installation of the BESS creates a further electricity cost saving of 10.70% in case 2.3. Numerical results give a good indicator to provide valuable information for installation of the RES and the capacity of BESS as electricity cost savers in the TOU system. Thus, different amounts of the RES/BESS can be added to the original system to evaluate the significant benefits of annual electricity cost savings. In this way, the economic penetration limit of the RES and optimal capacity of the BESS into a given TOU system can be determined.

3. Case 3: Further study with higher three-section TOU rate structures scenario

Further study with higher three-section TOU rate structures scenario is considered in the third study case to understand how variations in the pricing structures on the operation of the TOU customer system. In the Table 1, the energy costs of peak load, medium load and light load periods are assumed to be 10.45, 7.00 and 2.82 NT\$/kWh, respectively. Fig. 5 shows the final power outputs of the utility grid and BESS during a typical 1-day load. With the low purchasing price (2.82 NT\$/kWh) of the energy, most of load demand is provided by the utility grid during the off-peak load periods (hour 1-6). However, the power outputs of the utility grid decreases very rapidly during peak-load periods when the prices of purchased power are very high (10.45 NT\$/kWh). Note that the average full load cost (AFLC) of a diesel generator is about 8.58 NT\$/kWh that is lower than the energy costs (10.45 NT\$/kWh) of peak load periods. It is found to be more cost-effective to start up two diesel generators during peak load hours (hour 10-12 and hour 13-15). Switching on three diesel generators in parallel results in operating the units at lower efficiencies compared to the two units since they generate a higher percentage of power based on their ratings. As a result, the developed INPSO software is a useful tool for the TOU rate industrial user to maximize the contribution of diesel generators, RES and BESS for reducing the electricity cost of grid dispatch.

4. Case 4: Evaluation of operating policy considering sold/purchased power from utility grid

In the last study case, the simulation includes test runs for the previous TOU system to describe the sold/purchased power from utility grid in the future market-based micro grid system.

Table 3. Performance of different algorithms after ten runs.

Algorithms	PSO-IW	CNPSO	INPSO
Parameter setting	$Q = 1000; Iter_{max} = 2000;$ $\omega_{max} = 0.8; \omega_{min} = 0.3;$ $c1 = 1.2; c2 = 0.8$	$Q = 1000; Iter_{max} = 2000;$ $\omega = 0.3;$ $c1 = 1.2; c2 = 0.8$ $c3_{max} = 0.4;$ $c3_{min} = 0.05$	$Q = 1000; Iter_{max} = 2000;$ $\omega = 0.3;$ $c1 = 1.2; c2 = 0.8$ $c3_{max} = 0.4;$ $c3_{min} = 0.05$
Average cost (NT\$)	27752.34	26258.62	26095.72
Worst cost (NT\$)	28260.45	26347.46	26173.07
Best cost (NT\$)	27195.75	26157.67	26055.37
Average computing time (sec)	50.27	60.51	67.29

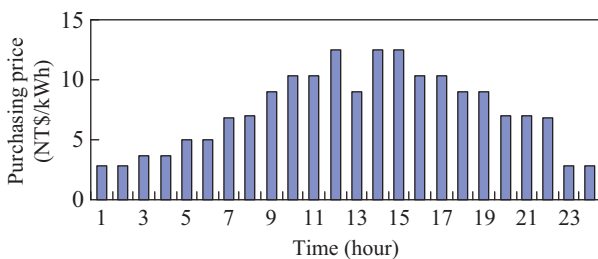
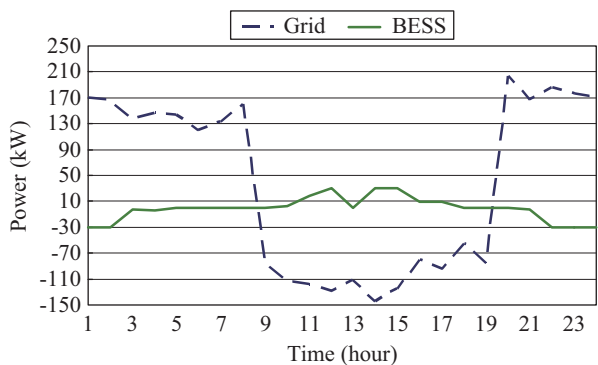
**Fig. 6. The prices of purchased power from grid utility at each time period in the Case 4.****Fig. 7. Outputs of BESS and Grid during a typical daily load (Case 4).**

Fig. 6 shows the prices of purchased power from grid utility at each time period in the case 4. The prices of sold power at each time period are identical to those of purchased power. As shown in Fig. 7, the optimal operating schedule of customer system is very sensitive to TOU rate pricing structures. In the study case, the battery capacity was not large enough to supply the load for the period of time. Most of load demand is provided by the utility grid (or diesel generator). Since the low purchasing price of the energy provided by the utility grid, the BESS can store electrical power during the off-peak load periods (hour 1-4). The BESS system then discharge rapidly during peak-load periods (hour 10-12 and hour 15-17) when the prices of sold/purchased power are very high. It is found that all of the three diesel generators produce more power to cover the load during peak load hours (hour 9-19) and the excess power is sold back to the utility grid. This mechanism

Table 4. Comparison of TC under various Q in the case 3 by using INPSO algorithm.

Particle numbers	Best cost (NT\$)	Average cost (NT\$)
20	26859.73	27485.47
50	26180.00	26418.62
100	26122.68	26239.47
200	26079.36	26148.59
400	26063.17	26130.43
600	26059.84	26115.49
800	26056.80	26102.28
1000	26055.37	26095.72

can significantly reduce the electricity charges, increase the economic benefits of energy generated by the diesel generators and provide the necessary flexibility for smoothing of renewable power generation. Numerical results give a good indicator to provide valuable information for TOU rate industrial users in the future market-based micro grid system to reach the minimum electricity charge.

5. Comparative Study of PSO-IW, CNPSO and INPSO

To evaluate the performance of the proposed algorithm, several computer programs, including PSO-IW (Particle swarm optimization with inertia weight), CNPSO (PSO-IW using common another particle behavior) and INPSO (CNPSO with an intelligent judgment mechanism), were developed to solve the case 3. Owing to the randomness of the heuristic algorithms, their performance cannot be judged by a single run result. Many trials with different initial conditions should be made to acquire a useful conclusion about the performance. Table 3 shows the worst cost, average cost, and best cost achieved for 10 trial runs. From the results, the superiority of the INPSO and CNPSO algorithms over basic PSO-IW can be noticed. Although multiple local minimum solutions exist in this studied case, the proposed INPSO can still find a better solution than PSO-IW, by 4.37 percent equivalent to 1140.38 (refer to Table 3: Best cost). Furthermore, the solution reached by the proposed INPSO is also better than CNPSO, by 0.39 percent equivalent to 102.3. The above results demonstrated the merits of the proposed algorithm. Table 4 shows the so-

lution of INPSO after ten runs under different particle numbers. From this result, the average cost of ten runs decreased when the particle number increased. It is also observed that the total operation cost is not sensitive to the particle number. In fact, several different cases were studied and the results show that the final results of INPSO are better than those of PSO-IW and CNPSO. The success of the proposed INPSO algorithm to 'jump' out of the local optimal solution is, thus, confirmed.

VI. CONCLUSIONS

With increasing of the development of smart grid and restructuring of the power industry, more and more renewable energy sources will penetrate into the grid, which brings challenges to operating schedule problem for a TOU rate industrial user. This paper proposes a novel approach to solving the operating schedule of a renewable energy based TOU rate industrial user using INPSO. Based on the load condition of the TOU user, the available renewable power generation, and the energy left in the BESS, the proposed INPSO can be used to determine the optimal operating schedule of the TOU rate customer system, and that the results are reasonable. The results show that the algorithm can be used to determine the optimal operating policy of the next time stage in real-time application. This function can save on energy costs and reduce the risk of the BESS running out of energy in a peak-demand reduction application. In off-line application, the results from the simulation exercise will also be a useful tool to aid decisions regarding the capital investment for using RES/BESS for the customer system. The INPSO can be used to test the users system in many load conditions under different seasons, summarizing test results to develop expert knowledge for BESS controller design. The computer program developed in this paper can therefore be a powerful tool for TOU rate industrial users in the future market-based micro grid system.

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