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Electricity scheduling strategy for home energy management system with renewable energy and battery storage: a case study

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Abstract: With the development of smart grid, energy consumption on residence will play an important role in the electricity market, while the Home Energy Management System (HEMS) has huge potential to help energy conservation. In this study, a practical HEMS model with renewable energy, storage devices and plug-in electric vehicles, considering the battery sustainability and the full utilisation of the renewable energy, is first established. Then, according to the combinations of the genetic algorithm (GA) and the multi-constrained integer programming method, an improved GA is proposed, which goal is to minimise the electricity purchase and maximise the renewable energy utilisation. Finally, it is demonstrated by an example that the proposed method is significant in cost saving and reducing energy wastes. To verify the performances of the proposed algorithm, the numerical results indicate that the proposed algorithm has high computational efficiency and good robustness. In addition, it can avoid the disadvantages easy to trap at a local optimal point, and are insensitive to initial solutions. The effect of the storage device on system property and the sensitivity of cost savings versus demand response, size of the battery, and the electricity price sell to the grid are also analysed.

1 Introduction

1.1 Motivation and background

Recently, the energy consumption increased quickly. The energy consumption on residence and business will increase to 20–40% of the total global energy consumption in the next decade and will play a decisive role in the electricity market [1]. Driven by the concept of smart grid, the usage habit of energy for customers and metering methods of electrical energy will be radically changed. In the context of giving priority to energy-saving, it is necessary to achieve the intelligence of household appliances, which will encourage and help the customers to use electric power reasonably. The demand response (DR) is introduced to enhance the interaction between the grid and the user by the price signal and the incentive mechanism [2]. DR means that when users receive the guiding signal given by the power supply company, they will change their ingrained usage pattern. That is to say, they will reduce or delay the load to ensure the stability of power system [3], when the reliability of the power system is faced with challenges.

Energy management in household attracts more and more attention with the increasing demand of household energy. HEMS (Home Energy Management System) make full use of sensors to find superfluous energy and control household appliances to achieve the purpose of saving energy, which will take into account the trade-off between the family energy saving and the comfortable life. It has profound impact on reducing energy waste, improving energy efficiency and changing the concept of energy conservation. The HEMS utilises optimal scheduling and advanced control methods to maximise energy savings and ensure customer satisfaction. It is crucial important to seek efficient and practical intelligent algorithms to solve the optimal scheduling problem of HEMS.

1.2 Literature overview

In the HEMS, system modelling and scheduling strategy are two main research focuses [4].

Yi *et al.* [5] and Pipattanasomporn *et al.* [6] save residents' electricity bills by scheduling household appliances in the light of DR schemes. Ranjan and Thomas [7] proposed a model for HEMS which considers the customer's preferences and maintains the power consumption below the sanctioned limit such that the minimum comfort violation occurs. However, the models in [6, 7] only adopted DR as a signal to guide the user's behaviour, not provided an operating strategy considering real-time electricity price variability to minimise the daily cost. Paterakis *et al.* [8] proposed a half-hour-ahead rolling optimisation to achieve household economic benefits in response to real-time electricity price (RTP) schemes, which can optimise the schedule for home appliances and battery charging/discharging behaviour, even if the forecasted information is not accurate. The models mentioned above only use single signal (DR or RTP) to guide the scheduling, and it is obvious that both of them are helpful to the energy management of the household. The model will be excellent if two signals are combined to guide the scheduling.

Kazemi *et al.* proposed a method based on grey wolf optimisation and genetic algorithm (GA) to achieve the optimal schedule for appliances in terms of cost and peak-to-average ratio (PAR) [9]. However, in the system model, renewable energy, storage batteries and electric vehicles (EVs) are not taken into account. Kuzlu proposed a smart HEM model including renewable sources and energy storage system (ESS), which achieves the goals of resource conservation and cost saving [9]. However, in the models mentioned above the renewable energy utilisation, the battery sustainability and the power interaction costs are not considered in the process of modelling. Therefore, it is necessary to structure a more practical and comprehensive HEMS model.

The optimal scheduling is a multiple dimension, non-linear problem with various constraint conditions. There are many optimal algorithms, such as mixed-integer programming, real-time rolling optimisation, particle swarm optimisation (PSO), and dynamic priority algorithm. In [10–12], HEMS optimisation was considered as mixed-integer linear programming (MILP) problems and formulated by some mature mathematical programming optimisation procedures. Chen *et al.* [10] and Erdinc *et al.* [11]

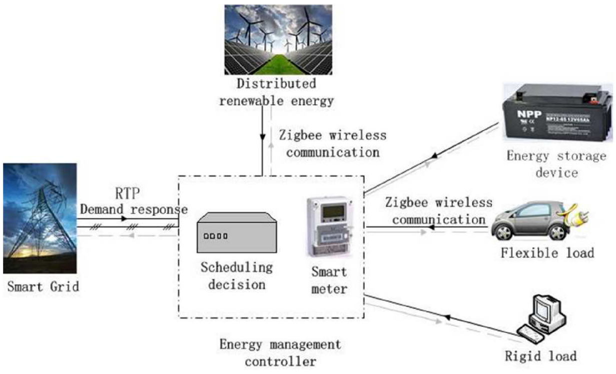

Fig. 1 *HEMS framework*

solved the problem by MILP solvers (CPLEX), while Huang *et al.* [12] solved this MILP problem by linear interactive and general optimiser. These solvers can solve the optimisation problem quickly. In some cases, the calculation only needs times in the level of milliseconds. However, the solver handles the constraints in a simple way (especially in integer programming problems). In this case, we can only get sole solution ultimately, which cannot evaluate the performance of solution comprehensively, and it is really hard to apply in the real situation. What's more, because the solving process cannot be changed, in order to improve the performance, what we can do is to optimise the model. To improve the adaptability, intelligent algorithms are adopted to solve HEMS scheduling problem. PSO is one of the heuristic algorithms, which is often used in HEMS optimal scheduling. Rehman [13] designed a binary PSO (BPSO) algorithm. It manages energy demand according to power supply, by automatically controlling the appliances or by shifting the load from peak to off peak hours. However, the PSO is suitable for solving real number optimisation problems rather than discrete optimisation problems. For discrete optimisation problems (e.g. HEMS), it is easy to fall into local optimum. Geng *et al.* [14] adopted discrete multi-objective bacterial colony chemotaxis algorithm (DMOBCC) to solve the HEMS scheduling problem. The objective function is to minimise the users' electricity costs as well as maximise the users' satisfaction. Basit *et al.* [15] proposed a Dijkstra algorithm to solve HEMS scheduling problem, which has much lower complexity. Multi-objective kinetic-molecular theory optimisation algorithm in [5] and electron drifting algorithm in [16] were also proposed, which schedule their power consumption to save energy, reduce emission, shift peak load and reduce the financial burden. Compared with the traditional heuristic algorithms, these algorithms can reduce the complexity, however, there is no definite rule for various parameter settings, and it has a large uncertainty. Furthermore, the ability to handle large quantities of variables at the same time is limited.

The GA can deal with either linearly or non-linearly, discrete or continuous objective functions and constraints. The ergodic properties of evolutionary operators make it possible to effectively perform global optimisation in a probabilistic sense. Javaid *et al.* [17] adopted GA for HEMS scheduling, the coding method can handle more different types of variables at the same time, which overcome the drawback mentioned above. However, traditional GA is easy to trap in a local optimal and sensitive to give initial solutions. In order to avoid these shortcomings, the performance of the traditional GA needs to be improved, and it is the focus of this paper.

In summary, there exist some problems that need to be addressed suitably:

i. Although the models mentioned above can achieve the purpose of reducing electricity costs or increasing user's satisfaction, the renewable energy utilisation, the battery sustainability and power interaction costs are still not addressed in the previous works, which can cause energy wastage and extra cost.
ii. Considering the calculation time and complexity, the above algorithms have weak convergence performance and are easy to plunge into local optima. Moreover, they are sensitive to given initial solutions.

1.3 Contributions and organisation

The main contribution of this paper can be represented as follows:

i. We incorporate the battery sustainability and the full utilisation of the renewable energy into the system, and establish a more comprehensive and practical model, which was not mentioned in the previous work.
ii. Combining the GA and the multi-constrained integer programming method, an improved GA named multi-constrained integer programming genetic algorithm (MCIP–GA) is proposed, which goal is to minimise the electricity cost and maximum the utility of renewable energy. The proposed algorithm can avoid the disadvantages which are easy to trap in a local optimal and are sensitive to given initial solutions. We also prove that the algorithm generates solution significantly shorter than the previous methods.

The paper is organised as follows: Section 2 establishes the system model, including the mathematical model of all devices. Section 3 presents the HEMS scheduling objectives. Section 4 gives the design of MCIP–GA. Section 5 gives the analysis of the simulation experiment. Section 6 summarises the full text.

2 System model

In this paper, the model contains household appliances, distributed power generation (DG), EV and energy storage devices. Combined with the RTP and DR (the upper limit of electric power) information provided by the grid, the surplus energy can be sold to the grid.

The framework of HEMS is shown in Fig. 1, where the information of the next scheduling cycle in the family, the output power of DG, RTP and DR, will transmit to the energy management controller before scheduling. RTP adopts the forecast data. Each device is equipped with smart sockets, and the scheduling controller will communicate with each endpoint through wireless ZigBee network so as to achieve fully automatic control of household appliances.

2.1 Electric devices models

According to the flexibility of scheduling time, the load can be divided into the rigid load (such as lighting, television, and computer) and flexible load. For the rigid load, when being requested, it should be served immediately. The user's satisfaction will decrease if the rigid load participates in the scheduling. The flexible load has little effect on user's satisfaction and has time elasticity, which is sensitive to RTP and DR.

The household appliance is modelled according to the properties of the device. H is defined as the scheduling space. In this paper, one day is divided into 48 continuous time slots Δh, $\Delta h = 1, 2, \ldots, 48$. All appliances are represented by a collection of A, each of them is represented by a, $a \in A$. The power of the device is expressed as P_a, and $P_a(h)$ represents the power in per slots. The d_a is the length of time to complete the task of a, and $[\alpha_a, \beta_a]$ is the allowable operation time range set by the user, which is the slots user expects device to work. An auxiliary binary variable S_a is introduced to indicate the state of the appliance, and $S_a(h) = 0$ indicates that $\boldsymbol{a}$ is closed during the h, and $S_a(h) = 1$ is on.

The device $\boldsymbol{a}$ should satisfy the basic time constraints shown as follows:

$$\begin{cases} \sum_{\alpha_a}^{\beta_a} S_a(h) = d_a \\ 1 \le \alpha_a \le H - d_a + 1 \\ \mathrm{d}_a \le \beta_a \le H \end{cases} \tag{1}$$

$$S_a(h) = 0, \quad h \in H \setminus [\alpha_a, \beta_a] \tag{2}$$

$$E_a = P_a \times d_a \tag{3}$$

The above constraints are for all flexible loads, where E_a and P_a in (3) are the total power consumed and the sum of power consumed in the unit slot, respectively.

2.2 Load models

The flexible load can be divided into interruptible load (such as EVs) and non-interruptible load (such as washing machines and dishwashers).

(i) Interruptible loads

$$S_a(h) = \{0, 1\}, \quad h \in [\alpha_a, \beta_a] \tag{4}$$

$$\sum_{h = \alpha_a}^{\beta_a} S_a(h) \times P_a = E_a \tag{5}$$

(ii) Non-interruptible loads: Some device cannot be interrupted from start working to the completion of the task. Regarding the above situation, new constraints should be added to

$$\begin{gathered} \sum_{h = \tau + 1}^{\tau + d_a} S_a(h) \ge J_a \cdot [S_a(\tau + 1) - S_a(\tau)] \\ \tau \in [\alpha_a - 1, \beta_a - d_a] \end{gathered} \tag{6}$$

where J_a indicates the number of time slots required for device operation, and if the device is started at $\tau + 1$, it will last for at least d_a hours.

(iii) Air conditioner system

$$\begin{aligned} T_{\text{in}}(h) = {} & T_{\text{in}}(h) \cdot \mathrm{e}^{-(\Delta h/\xi)} + R_{\text{eq}} \cdot P_{\text{a}}(h) \cdot K_{\text{airc}} \cdot \left(1 - \mathrm{e}^{-(\Delta h/\xi)}\right) \\ & + T_{\text{out}}(h) \cdot \left(1 - \mathrm{e}^{-(\Delta h/\xi)}\right) \end{aligned} \tag{7}$$

where T_{in} is the indoor temperature, T_{out} is the outdoor temperature, $P_{\text{a}}(h)$ is the power of air conditioner, R_{eq} is the equivalent thermal resistance of room, K_{airc} is the power conversion coefficient, constant $\xi = M_{\text{air}} \cdot C \cdot R_{\text{eq}}$, M_{air} is the indoor air quality, and C is the atmospheric heat capacity at atmospheric pressure ($C = 0.525\,\text{kWh/}^\circ\text{C}$).

$$T_{\text{in}}^{\min} \le T_{\text{in}}(h) \le T_{\text{in}}^{\max} \tag{8}$$

The indoor temperature should be kept within the pre-set range $\left([T_{\text{in}}^{\min}, T_{\text{in}}^{\max}]\right)$.

The energy consumption of the air conditioning in a time slot should meet the following constraints:

$$0 \le P_a(h) \le P_a^{\max} \cdot S_a(h) \tag{9}$$

where $P_a^{\max}$ is rated power.

(iv) Water heater system: The temperature of hot water is related to water temperature, environmental temperature, flow rate of hot water, structure of water heater, rated power and so on

$$\begin{aligned} T_{\text{water}}(h + 1) = {} & T_{\text{water}}(h) \cdot \mathrm{e}^{-((1/R'(h) \cdot C)) \cdot \Delta h} + \left[1 - \mathrm{e}^{-((1/R'(h) \cdot C)) \cdot \Delta h}\right] \\ & \times \left\{ \begin{array}{l} G^{\text{EWH}} \cdot R'(h) \cdot T^{\text{EWH,env}}(h) \\ + B(h) \cdot R'(h) \cdot T^{\text{EWH,in}}(h) + Q(h) \cdot R'(h) \end{array} \right\} \end{aligned} \tag{10}$$

where T_{water}, $T^{\text{EWH,env}}$, $T^{\text{EWH,in}}$ are the temperature of the hot water, the ambient temperature, and the water temperature of the inlet valve in the time slot h, respectively.

The significance of other parameters is given in [18].

The water temperature should be kept within the pre-set range $\left([T_{\text{water}}^{\min}, T_{\text{water}}^{\max}]\right)$.

$$T_{\text{water}}^{\min} \le T_{\text{water}}(h) \le T_{\text{water}}^{\max} \tag{11}$$

2.3 Storage battery model

The storage battery dynamically adjusts charge or discharge behaviour according to the system energy, which can bring more flexibility to the optimisation. The storage state should be considered, this paper characterises it with the state of charge (SOC). SOC reflects the ratio of the battery's remaining capacity to its rated capacity. An auxiliary binary variable S_{batt} is introduced to indicate the state of the battery ($S_{\text{batt}}(h) = 1$ indicates the state of charging and $S_{\text{batt}}(h) = 0$ indicates the state of discharging). And the dynamic process is as follows:

$$\text{SOC}(h + 1) = \text{SOC}(h) + \frac{(P_{\text{batt}}^{\text{ch}}(h) - P_{\text{batt}}^{\text{dch}}(h)) \cdot h}{E_{\text{batt}}} \tag{12}$$

where $P_{\text{batt}}^{\text{ch}}(h)$ and $P_{\text{batt}}^{\text{dch}}(h)$ denote charging and discharging powers of the battery, respectively, and E_{batt} is the rated capacity of the battery.

In order to prolong the lifetime of the battery, it is necessary to limit the SOC to a certain range, the constraint conditions are described as follows:

$$\text{SOC}^{\min} < \text{SOC}(h) < \text{SOC}^{\max} \tag{13}$$

where $\text{SOC}^{\max}$ and $\text{SOC}^{\min}$ denote the upper and lower limits of battery's SOC, respectively.

Considering the charging and discharging efficiencies of the battery, the charging and discharging limits of the battery are as follows:

$$0 \le \frac{P_{\text{batt}}^{\text{ch}}(h)}{\eta_{\text{ch}}} \le P_{\text{ch}}^{\max} \cdot S_{\text{batt}}(h) \tag{14}$$

$$0 \le P_{\text{batt}}^{\text{dch}}(h) \cdot \eta_{\text{dch}} \le P_{\text{dch}}^{\max} \cdot (1 - S_{\text{batt}}(h)) \tag{15}$$

where η_{ch}, η_{dch} are the battery's charging and discharging efficiencies, respectively, $P_{\text{ch}}^{\max}$, $P_{\text{dch}}^{\max}$ are the battery maximum charging and discharging powers, respectively.

$P_{\text{batt}}(h)$, the output power of the battery (positive value for charging and negative value for discharging), is calculated as

$$P_{\text{batt}}(h) = \frac{P_{\text{batt}}^{\text{ch}}(h)}{\eta_{ch}} \cdot S_{\text{batt}}(h) - P_{\text{batt}}^{\text{dch}}(h) \cdot \eta_{\text{dch}} \cdot (1 - S_{\text{batt}}(h)) \tag{16}$$

2.4 EV model

The model of EV is similar to a storage battery, but the performance of the EV's battery will get worse. In order to prolong the lifetime of the EV, as far as possible to reduce the battery discharge operation, so in this paper, the EV can only be charged. The dynamic process is described as follows:

$$\text{SOC}_{\text{EV}}(h + 1) = \text{SOC}_{\text{EV}}(h) + \frac{P_{\text{EV}}^{\text{ch}}(h) \cdot h}{E_{\text{EV}}} \tag{17}$$

Equation (17) indicates that the EV is a flexible load in the system, EV can only accept the power $\left(P_{\text{EV}}^{\text{ch}}(h)\right)$.

$$\text{SOC}_{\text{EV}}^{\min} \le \text{SOC}_{\text{EV}}(h) \le \text{SOC}_{\text{EV}}^{\max} \tag{18}$$

Constraints (18) limits the scope of SOC between $\mathrm{SOC}_{\mathrm{EV}}^{\min}$ and $\mathrm{SOC}_{\mathrm{EV}}^{\max}$.

$$0 \le \frac{P_{\mathrm{EV}}^{\mathrm{ch}}(h)}{\eta_{\mathrm{ch}}} \le P_{\mathrm{ch}}^{\max} \cdot S_{\mathrm{EV}}(h) \tag{19}$$

Constraints (19) impose a limit on the charging power of the EV

$$\forall h \in \left[T^a, T^b\right] \tag{20}$$

where T^a, T^b represent the arrival time of the EV to household and the departure timing of the EV from household, respectively. The scheduling must be performed in this interval

$$P_{\mathrm{EV}}(h) = \frac{P_{\mathrm{EV}}^{\mathrm{ch}}(h)}{\eta_{\mathrm{ch}}} \cdot S_{\mathrm{EV}}(h) \tag{21}$$

where $P_{\mathrm{EV}}(h)$ is the output power of the battery (positive value for charging and negative value for discharging), is calculated as

$$\mathrm{SOC}_{\mathrm{EV}}^{\mathrm{ini}} = \mathrm{SOC}_{\mathrm{EV}}(T^a) \tag{22}$$

Equation (22) limits the SOC of EV at the arrival time ($\mathrm{SOC}_{\mathrm{EV}}(T^a)$), which coincides with the initial state-of-energy of the EV $\left(\mathrm{SOC}_{\mathrm{EV}}^{\mathrm{ini}}\right)$.

$$\mathrm{SOC}_{\mathrm{EV}}(h) = \mathrm{SOC}_{\mathrm{EV}}^{\mathrm{ini}}, \quad \forall h \notin \left[T^a, T^b\right] \tag{23}$$

If it is not in the scheduling range, the state-of-energy of the EV will remain the initial state.

3 Scheduling objective

The scheduling objective is to minimise the electricity purchase from grid and maximise the renewable energy utilisation, the power consumed during per slot is shown as

$$P_{\mathrm{total}}(h) = \sum_{a=1}^{m+n} S_a(h) \cdot P_a(h) + P_{\mathrm{must}}(h) + P_{\mathrm{batt}}(h) - P_{\mathrm{DG}}(h) \tag{24}$$

where the first term represents the power consumption of flexible load, $P_{\mathrm{must}}(h)$ is the rigid load's consumption, $P_{\mathrm{batt}}(h)$ indicates the battery output (positive charge, negative discharge), and $P_{\mathrm{DG}}(h)$ indicates the DG output. The objective function is shown as

$$\begin{aligned} &\min \sum_{h=1}^{48} [P_{\mathrm{total}}(h) \cdot \mathrm{RTP}(h)] \\ &\mathrm{s.t.}\ P_{\mathrm{total}}(h) \le D(h) \\ &\sum_{h=1}^{48} \sum_{a=1}^{m+n} S_a(h) = \sum_{a=1}^{m+n} d_a \end{aligned} \tag{25}$$

The constraint indicates that the power consumption of perslot should not exceed the maximum power limit.

4 MCIP–GA design

The GA can deal with either linearly or non-linearly, discrete or continuous objective functions and constraints. But it is easy to trap in a local optimal and sensitive to given initial solutions. In order to improve the performance of the traditional GA, initialisation operator, repair operator and dynamic mutation are introduced to the algorithm.

4.1 Algorithm design

A large number of invalid chromosomes are generated in the iterative process, which reduce the valid evolution mode of the population. It is necessary to design reasonable initialisation, crossover and mutation operator to make it 'valid,' where 'valid' means that the solution space generated by the genetic operators satisfies the equation constraint.

(i) *Chromosome coding*: The chromosomes of GA has binary encoding, which can represent the working state of the devices at different time slots, and 0/1 indicates that the device is turned off/on. The chromosome of a can be expressed as $X_a = \left\{X_a^h,\ h = 1, 2, \ldots, 48\right\} = \left[X_a^1, X_a^2, \ldots, X_a^{48}\right]$. For the non-interruptible device, the start time is X_a^{τ}, and the end time is $X_a^{\tau + d_a}$. All conditions of the non-interruptible device can be expressed by the start time with one code. The total number of '1' can express the number of total working periods, and the allowable working range can be set by limiting the beginning and the end range of the '1'. There are m non-interruptible devices, and n interruptible devices, all the devices state composed an individual as follows:

$$X = \{X_a, a \in 1, \ldots, m+n\} = \begin{bmatrix} X_1^1 & X_1^2 & \cdots & X_1^{48} \\ \vdots & \vdots & \vdots & \vdots \\ X_m^1 & X_m^2 & \cdots & X_m^{48} \\ \vdots & \vdots & \vdots & \vdots \\ X_{m+n}^1 & X_{m+n}^2 & \cdots & X_{m+n}^{48} \end{bmatrix} \tag{26}$$

(ii) *Initial population generating*: Initial population randomly generated is the start of search, and it is necessary to ensure all individuals are valid in the groups. The initialisation operator can generate solutions in d_a, any solution randomly generated is an individual which meets the constraints. The initialisation operator can directional and randomly generate population with a uniformly distributed. Therefore, it can effectively overcome the sensitivity of given initial solutions, and the convergence performance of the algorithm is improved. For example, the initial solution of a device can be randomly generated under the scheduling interval $[\alpha_a, \beta_a]$, and the working time $d_a = 5$, where the genotype is shown as follows:

$$X_a = 0000000\underbrace{0100100111000}_{[\alpha_a, \beta_a]}\ldots 00000.$$

(iii) *Fitness function*: The fitness is the basis of measuring the individual quality, which drives the evolution process, and gives the quality degree of each individual. Then objective function is shown as

$$\mathrm{objvalue}(h) = \sum_{h=1}^{48} \left\{ \begin{bmatrix} \displaystyle\sum_{a=1}^{m+n} S_a(h) \cdot P_a(h) + P_{\mathrm{must}}(h) \\ + P_{\mathrm{batt}}(h) - P_{\mathrm{DG}}(h) \end{bmatrix} \cdot \mathrm{RTP}(h) \right\} \tag{27}$$

where $p_{\mathrm{must}}(h)$ is the rigid load.

The GA is based on the fitness degree to determine how much the individual in the current group has the chance to pass on to the next generation, and it requires that the fitness value must be non-negative. It is necessary to convert the target function from the minimum cost to the maximum cost. Therefore, the fitness is the reciprocal of the objective function

$$\mathrm{fitness}(h) = \frac{1}{\mathrm{obivalue}(h) + c} \tag{28}$$

where c is the threshold, which depends on the initial value.

(iv) *Selection*: The roulette wheel selection is used to select the excellent individuals from the current population, so they have the opportunity to be the father to multiply the descendants for the next generation. Strong-adaptability individuals make a contribution to a large probability of one or more offspring for the next generation.

(v) *Crossover:* The individuals $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ are two-dimensional matrices, which are selected by the crossover probability P_c, and each row will be crossed. Since the non-interruptible device is represented by only one bit, it has no practical meaning to cross, so

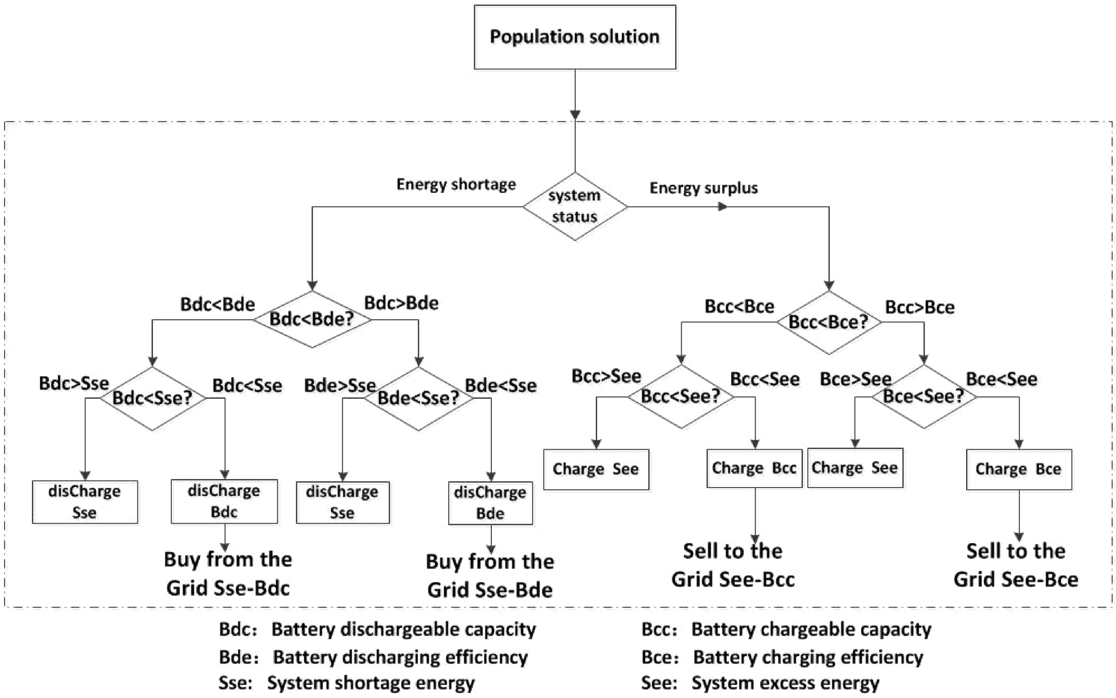

Fig. 2 *Battery decision process*

it does not participate. Interruptible device cross by a single point, which cross at random position produced in the allowable operation time range. It is necessary to detect chromosomes after crossover. For the infeasible chromosomes, the repair operator fixes it to a feasible solution. The repair method is to detect the degree genotype deviate from the constraint (dBite, be dBite $= X_{\mathrm{da}(a)} - X_{\mathrm{constraint}}$), and then select the correct genotype randomly, at last reverse the gene value.

(vi) *Mutation*: All individuals with less than the mutation probability P_{m1} participate in the mutation, evidently. When approaching the optimal solution (the fitness of the optimal solution has not changed for a long time), the mutation rate is improved to P_{m2} so as to prevent solution from falling into the local optimal solution. The mutated chromosome may be infeasible and also needs to be repaired.

Due to the operations of crossover, mutation cooperate, and compete with each other, the GA has the search capability of balancing both the global and the local. Mutation operation is to repair some genetic genes that may be lost in the process of crossover. The mutation reflects the local search ability of GA meanwhile maintains the diversity of the population. If the crossover rate and mutation rate are selected appropriate, the GA will avoid prematurely.

The proposed MCIP–GA can effectively avoid premature convergence mainly because of the following three points: (a) The initialisation operator can generate directional and randomly population with a uniformly distributed. (b) The repair operator can jump out of local solutions to improve the diversity of the population when the population falls into local optimal or suboptimal solutions (super individual). (c) Dynamic mutation rate. In the early stage of GA, mutation rate is larger to improve the search ability in the entire search space. In the late stage, when GA approaches the optimal solution, the smaller value of mutation rate should be made to prevent the destruction of the superior structure.

4.2 Constraint processing

4.2.1 Energy storage processing: The action of battery depends on the energy delta(h) and the SOC(h) in the intra-system, and the delta(h) represents the power difference between the total consumption power and distributed power. If the output of photovoltaic (PV) is still surplus after providing for all loads, the battery will store excess energy, which relies on the relationship between the rechargeable capacity of the battery and charging rate of the per slot. If there is still excess power, then sell it to the grid to obtain economic benefits. On the contrary, if the distributed output is not enough to supply for all load (delta(h) > 0), the system needs to use the battery power. The more times of battery charging/discharging, the shorter life of the battery will be. So we convert the charging/discharging loss to the power consumption. The price sell to the grid in this paper is lower than RTP, which is 50% of the RTP. Battery decision process is shown in Fig. 2.

4.2.2 DR processing: The total consumption also needs to satisfy the limit of DR. The penalty function is a simple and effective method in dealing with the constraint, which is used to convert the power constraint to the fitness

$$p(h) = \begin{cases} \mu \cdot \sum_{i=1}^{m+n} p(i), & p_{\mathrm{total}}(h) > p_{\mathrm{demand}}(h) \\ \sum_{i=1}^{m+n} p(i) & p_{\mathrm{total}}(h) < p_{\mathrm{demand}}(h) \end{cases} \quad (29)$$

where μ is the penalty parameter, which can effectively reduce the solution fitness whose power exceeds the DR.

Through the decision, if the total power exceeds the limit of DR, the actual power at this slot will multiply by a penalty value μ. Then the target value will be large while the fitness will be small. In the selection process of each generation, these individuals will be gradually eliminated.

5 Example analysis

In this paper, we adopt RTP data on March 1, 2017 in Queensland provided by the Australian energy market operators (AEMO) [19]. Power output of PV generation is from an open source database [20]. Algorithm parameters: NIND = 40, MAXGEN = 500, PRECI = 48, $mm = 6$, $nn = 24$, GGAP = 0.9, $P_c = 0.7$, $P_{m1} = 0.005$, $P_{m2} = 0.01$. A lead-acid battery with a capacity of 6.68 kWh is applied. The maximum power of charging/discharging in each time slot is 3 kW. SOC of the battery should be maintained between 0.3 and 0.9. The initial state is a random number generated within [0.3, 0.6], $\mathrm{SOC}(1) = 0.3 + 0.6 * \mathrm{rand}(1, 1)$. The charge/discharge efficiency $\eta_{\mathrm{ch}} = \eta_{\mathrm{dch}} = 0.8$, and charge/discharge loss is a random number generated within [0, 1]. The load parameters are shown in Table 1 .

5.1 Simulation results analysis

First, in order to highlight the impact of each module on the user's cost, the simulation is divided into five cases. From the traditional family to the smart family, individually add the conditions of PV module, battery module, and the ability to sell electricity. The results are shown in Table 2.'Y/N' means that the system in the corresponding case uses the module (PV or battery) and has the ability to sell electricity or not. STG indicates whether the system has the ability to sell electricity or not, and CD indicates that the extent each factor affects the reduction of cost, which can provide guidance for the next decision. The calculation of the CD is as

$$\mathrm{CD}_i = \frac{\mathrm{cost}_{\mathrm{case}(i-1)} - \mathrm{cost}_{\mathrm{case}(i)}}{\mathrm{cost}_{\mathrm{case}(i-1)}} \tag{30}$$

It can be observed from Table 2 that the cost of traditional families (584.6568 cent) is far more than smart households (187.2734). And the existence of renewable energy plays an important role in saving electricity costs, whose cost is reduced by 48.46% compared with case 1. Then, the other two factors also contribute to cost saving, with little difference in effectiveness (8.10 and 11.02%). Therefore, the model designed in this paper has great potential in energy and cost saving. This paper focuses on the system of case 5, which will be discussed in detail in the following section.

According to the user's expected time, the task is randomly arranged and the result is shown in Fig. 3. It can be found that there are some time slots that substantially exceed the limit of DR (e.g. 7:00–7:30). In addition, people use appliances without any planning, a lot of load work in the higher price time slot (as 7:00–10:00, 16:00–20:00), which result in massive waste of energy. In the simulation period, the user needs to pay 493.1588 cents.

In Fig. 4, the optimised result is shown that RTP and PV played a regulatory role and the power consumption is always below the limit of DR. The load curve is smooth, and the grid guides the user's decision through DR. In this case, the user needs to pay 187.2734 cents, which save 62% compared with Fig. 3.

The power transmitted between the HEMS and the grid is shown in Fig. 5. The HEMS can sell the electricity to the grid in exchange for profit. In the low price period, HEMS get electricity from the grid. When the output of PV is little, it is supplied by the grid and the battery (e.g. 00:00–8:00). In the high price period (e.g. 8:00–16:30), it is supplied by PV and the battery, and the excess power is sent to the grid.

5.2 Comparison of different working patterns

According to system energy situation (excess or deficiency), the battery exists two patterns of simulations. Pattern I is direct act, while pattern II act after judging the RTP level.

5.2.1 Battery act directly (pattern I): This case means that as long as the system needs energy, the battery willd is charge directly without considering RTP.

5.2.2 Battery act based on RTP (pattern II): When the system needs energy, the controller judges RTP to decide whether to use the battery or not. When the RTP is higher than the average, the battery discharges first. Otherwise, the system gets electricity from the grid.

The simulation results are shown for Figs. 6–9. It can be found that pattern I needs to pay 191.8308 cents to the grid, while the pattern II gains 18.6109 cents profit. That is to say pattern II is more economical.

First, compared with the power exchange under two working patterns in Figs. 6 and 8, positive indicates the grid output power to HEMS, and negative vice versa. HEMS send more power to the grid in pattern II when the PV output is large (e.g. 11: 00–13: 00). The price is higher at this period, although the price sell to the grid is just a half of RTP, it is still a considerable income.

Second, the SOC of the battery is shown in Figs. 7 and 9. Comparing these two patterns, the advantage of the latter is that only when the system needs energy severest (high RTP, heavy rigid load), will the battery discharge, such as 7:00–8:00, 18:00–20:00. In the pattern I, there is already no reservation in the battery, but RTP is still high and PV output almost zero (e.g. 17:00–19:00). At this time, HEMS is forced to get power from the grid. While with pattern II, the battery at this stage has the available energy for HEMS, which avoids the peak RTP period and large variation charge of battery effectively. The pattern can maintain the spare capacity in any cases and benefits battery life in the long run.

The essence of the two battery patterns is the game between the economic benefits of selling electricity to the grid and potential economic battery benefits. When there is surplus energy in the system, charging power to the battery will gain a temporary profit against selling power to the grid. Due to the energy deficiency of the battery, the system needs other power supply, and the battery faces the risk of limited available capacity in the high RTP case. If there is not sufficient energy in the system, the battery is used only when RTP is larger than the average value. Otherwise, we buy electricity from the grid. When the RTP is relatively low, we can get energy from the grid directly. It can reserve a certain backup capacity for battery. So this pattern is more economical.

5.3 Performance of algorithm

The performance of algorithm is measured by two indices: computational efficiency and robustness.

5.3.1 Computational efficiency: One of the key challenges to implement the proposed algorithm is the computational efficiency. The simulation experiments are performed in an Intelcore i3 PC with the following hardware configurations: processor @ 3.40 GHz, RAM 4 GB. In order to show the efficiency of the proposed MCIP–GA, the calculation time to make the decision is evaluated. The CPU times needed by MCIP–GA are shown in Table 3. For comparison, the calculation time of PSO reported in [15] and BPSO reported in [21] is also shown.

From the results, it can be found that the proposed method is superior to other mentioned methods. The proposed MCIP–GA requires the least time (12.70 s) to achieve the optimal value compared to the other two heuristic algorithms (18.58 and 39.28 s). With the same hardware configurations, the calculation time depends on the algorithm's efficiency. The proposed algorithm has superiority on efficient program coding, which can handle large number of variables at the same time. Consequently, the proposed algorithm has high efficiency.

Fig. 10 shows the convergence curve of the algorithm. In the evolutionary process, the deviation between the mean value and the optimal value is very large before the early 20 generations, which indicates that population exists a large number of useless schemas. The deviation becomes smaller after 50 generations, which means that all solutions in the population are excellent. That is to say, solutions not conforming to this habitat have been eliminated in the process of 'survival of the fittest,' while the high fitness schema is retained. It can be observed that the reduction of the electricity price is steady in the 100 iterations. This fact indicates that the number of iterations for GA is sufficient.

To further evaluate the convergence performance and accuracy of the proposed MCIP–GA, the value of StdDev is also calculated. For comparison, the other five optimisation algorithms described in [5] are also evaluated, whose objective function, constraint condition and algorithm complexity are approximately the same as MCIP–GA.

The calculation of the StdDev is as follows:

$$\mathrm{StdDev} = \frac{\text{Average value} - \text{Optimal value}}{\text{Average value}} \tag{31}$$

where Average value and *Optimal* value are the mean value and the optimal solution in the last generation population, respectively.

It can be seen from Table 4 that the MCIP–GA gets the optimal value in the 70 generations. The iterations of MCIP–GA are less than those of the others. MCIP–GA has a great advantage in searching for the optimal solution quickly by finding the excellent patterns among the chromosomes. For the heuristic algorithm, all the solutions in the last generation should be quite good. If StdDev is too large, the solution obtained has a risk of falling into the local optimum. For MCIP–GA, the gap between the optimal solution and mean value is controlled at 6.38%. While for other algorithms, the gap is huge, even up to 49.26% (DSKMTOA algorithm). Thus, a series of solutions obtained by the improved algorithm are generally excellent, which has higher accuracy.

5.3.2 Robustness: In this paper, the optimisation is based on the forecast data (RTP, renewable energy output etc.). Due to the deviation between the predicted value and true value, the performance of scheduling may be different. Therefore, we replace the forecast data by real data to verify the anti-disturbance ability of the optimisation (robust optimisation). Our aim is to study the relationship between the cost and PV utilisation versus the uncertainties of the PV. The sensitivities of the electricity bill cost and the robustness with respect to different optimisations are depicted in Table 5.

From Table 5, it is shown that total energy consumption has little difference in the three cases. That is to say, the scheduling strategy has little effect on the total energy consumption. However, the PV utilisation, the power to the grid and the cost have large differences in the three cases. The PV utilisation of the stochastic scheduling (35.28%) is significantly less than the other two cases, while the robust optimisation (95.31%) is close to the MCIP–GA optimisation (100%). That is to say, the robust optimisation and MCIP–GA optimisation almost have the same PV utilisation. In addition, it can also be found that the former has slightly lower PV utilisation than the later. The reasons are as follows. If the actual power of PV is lower than the forecast value, then utilisation of PV is 100%. However, if the actual power of PV is higher than the forecast value, according to the previous strategy, the extra power will not be used. At this time, the utilisation of PV will be <100%, which is the reason the PV utilisation of robust optimisation is less than that of MCIP–GA. Similarly, the power to the grid of the stochastic scheduling (58.1 kW) is significantly less than the other two cases, while the robust optimisation (100.5 kW) is close to the MCIP–GA optimisation (103.4 kW). The reason is the same as the PV utilisation above. Due to the existence of prediction error, the actual electricity cost is inevitably higher than the predicted value. It is gratifying that the gap of electricity cost between robust optimisation and MCIP–GA optimisation is small (198.3102 and 187.2734), only 11.0368 cents. Thus, the data error between the true value and predict value is insensitive to electricity cost saving. The cost accuracy is calculated based on (32), which is 94.43%. Even if the existence of the prediction deviation, the optimisation results of the proposed algorithm still can achieve the high accuracy. Consequently, the results indicate the algorithm has a strong robustness under the disturbance of prediction error.

Table 1 Parameters of deferrable loads

Appliance	$[\alpha_a, \beta_a]$	Duration, *h*	Rated power, kW
dish washer[a]	08:00–12:00	1.5	0.73
	20:00–23:00		
washing machine[a]	06:00–07:30	1.0	0.80
	15:00–17:00		
humidifier	00:00–09:00	4.0	0.15
	14:00–20:00		
laundry drier	09:00–12:00	2.0	1.26
	20:00–23:00	1.5	
floor cleaning robot	06:00–12:00	3.0	0.74
	08:00–18:00	2.5	0.70
	20:00–23:30	1.5	0.64
water heater	04:00–08:30	3.0	0.74
	16:00–20:00	2.0	0.70
	21:00–24:00	1.5	0.64
air conditioner	0:00–8:00	—	0.75
	19:00–24:00	—	0.75
electric kettle	06:00–07:30	0.5	1.50
	16:00–20:00		
	21:00–23:00		
water pump	00:00–08:00	3.0	1.00
	07:00–18:00	4.0	1.80
	16:00–24:00	4.0	1.00
	18:00–24:00	4.0	1.10
pool pump	06:00–15:00	6.0	1.60
oil press	09:00–18:00	3.5	0.35
floor waxing	14:00–18:00	3.0	0.42
electric oven	00:00–08:00	4.0	1.10
	12:00–17:00	2.5	2.00
	13:00–18:00	2.0	1.30
PHEV	00:00–08:00	3.5	2.40

[a]- Non-interruptible loads.

Table 2 Sensitivity analysis of various models

Case	PV	Battery	STG	Electric cost	CD, %
1	N	N	N	584.6568	—
2	Y	N	N	301.3263	48.46
3	Y	Y	N	276.9132	8.10
4	Y	N	Y	246.3951	11.02
5	Y	Y	Y	187.2734	—

STG – sell electricity to the grid and CD – correlation degree.

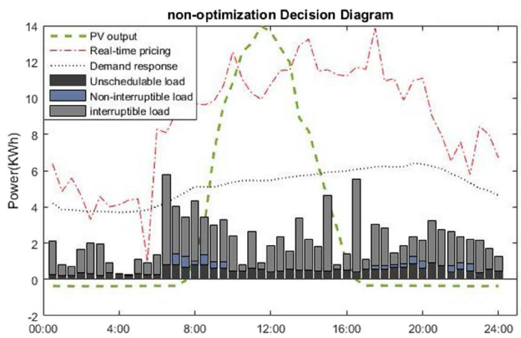

Fig. 3 *Results of the stochastic decision making*

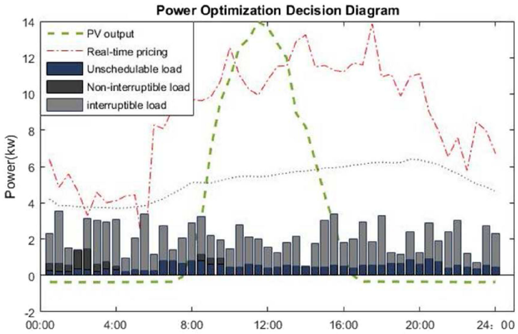

Fig. 4 *Results of the algorithm optimisation*

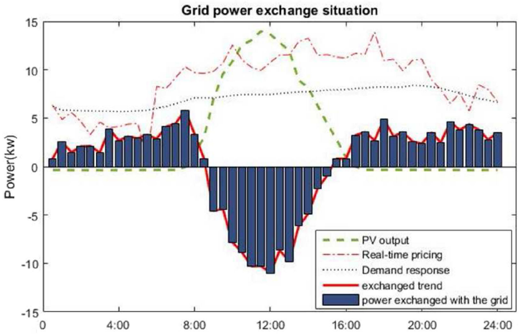

Fig. 5 *Power exchange between HEMS and the grid*

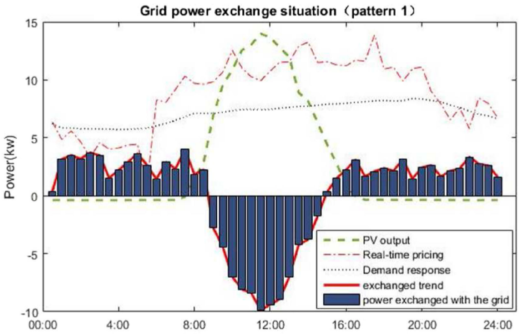

Fig. 6 *Power exchange between HEMS and the grid in pattern I*

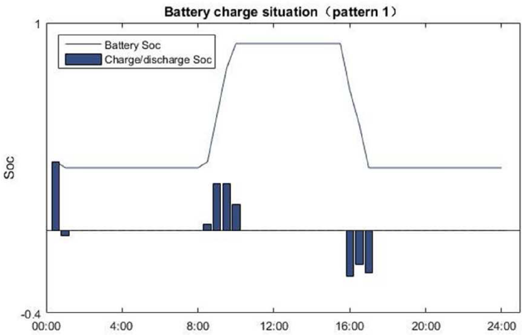

Fig. 7 *Battery SOC in pattern I*

Table 3 CPU time comparison between different algorithms

Algorithm	CPU time, s
PSO [15]	18.58
BPSO [21]	39.28
MCIP–GA	12.70

The calculation of the cost accuracy is as follows:

$$\zeta_{\text{cost}} = \frac{\text{cost}_{\text{robust}} - \text{cost}_{\text{MCIP-GA}}}{\text{cost}_{\text{robust}}} \tag{32}$$

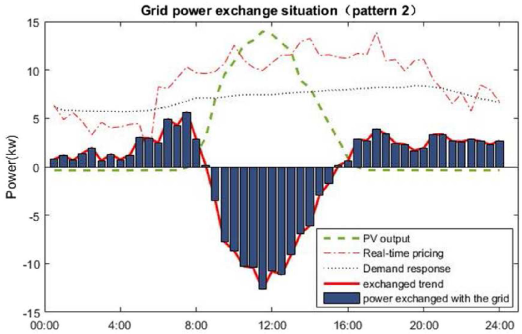

Fig. 8 *Power exchange between HEMS and the grid in pattern Ⅱ*

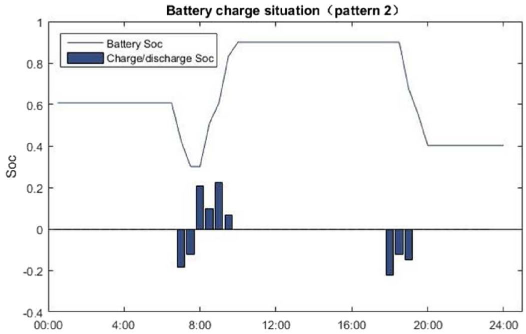

Fig. 9 *Battery SOC in pattern Ⅱ*

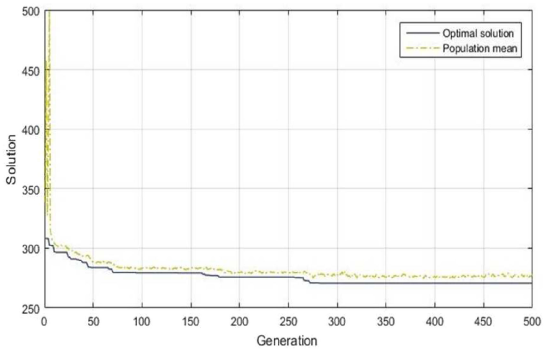

Fig. 10 *Change of optimal solution and population mean*

Table 4 Algorithm comparison

Algorithm	Convergence algebra	StdDev, %
BPSO	300	8.63
DSDE	600	17.6
BKMTOA	750	6.28
DSPSO	950	16.44
DSKMTOA	890	49.26
MCIP–GA	70	6.38

StdDev – standard deviation of best values.

where ζ_{cost} is the cost accuracy between the robust optimisation and MCIP–GA optimisation, $\text{cost}_{\text{robust}}$, $\text{cost}_{\text{MCIP-GA}}$ are the cost of the robust optimisation and MCIP–GA optimisation, respectively.

5.4 Sensitivity analysis

To further study the impact of various factors on cost savings, we make sensitivity analysis on DR, size of the battery, and the electricity price sell to the grid.

The simulation results are shown in Table 6. First, with the decrease of DR, the user's electricity cost increases. When the DR <5, the electricity cost increase to 403.1536 cents. Therefore, it is difficult to perform the schedule under an extremely low power limit. However, when the DR = 8, DR almost cannot guide the user's behaviour, so DR = 7 is more appropriate. Second, increasing

Table 5 Influence of predictor deviation on optimisation

Terms	Stochastic scheduling	Robust optimisation	MCIP–GA optimisation
total energy	146.6	140.3	135.9
PV utilisation, %	35.28	95.31	100
power to grid	58.1	100.5	103.4
cost	493.1588	198.3102	187.2734

Table 6 Sensitivity analysis of battery size and DR

Case	DR, kWh	Size of battery, kWh	Electric cost, cents
1	8	6.68	153.9658
2	8	3.68	160.3265
3	7	6.68	181.3891
4	7	3.68	215.3665
5	6	6.68	240.3267
6	6	3.68	260.7154
7	5	6.68	403.1536
8	5	3.68	432.6211
9	4	6.68	512.6314
10	4	3.68	526.3383

Table 7 Sensitivity analysis of Pr

Case	Pr, cents	$\Delta SOC_{batt}^{total}$	$\Delta Power_{tras}$, kW	Electric cost, cents
1	30%RTP	2.28	72	181.3891
2	50% RTP	1.31	95	100.9645
3	AvRTP	1.52	83	120.3856
4	6	1.85	77	186.8493
5	5	2.03	70	226.5142
6	4	2.46	68	286.3621

Pr –- the electricity price sell to the grid.

AvRTP – average of RTP, which is 8.8208 cents.

$\Delta SOC_{batt}^{total}$ – total variation of battery's SOC.

$\Delta Power_{tras}$ – total electric energy sent to the grid.

the capacity of the battery is also helpful to reduce the electricity cost. Thus, for the users, it is more economical to install large capacity batteries as much as possible. Although the cost of investment in the early stage is large, the long-term return is obvious.

From Table 7 we can see that the electricity price sell to the grid (Pr) play a decisive role. The Pr in cases 1 and 2 is related to RTP. The advantage of these two modes is that the user can sell electricity to the grid with a high price. Because the high RTP always means the load peak, more power is needed in the grid at this time. If the users sell electricity in this period, it will benefit both the user and the grid (to slow down the load pressure). While the low RTP always means the load valley. When the Pr is low, the user gains little benefit, which drives the user to find another way to seek greater economic value. By comparing cases 1 and 2, the higher the Pr, the more HEMS will send power to the grid, and the greater benefit will be made. The lower the Pr, the more HEMS will use the battery first. The price is constant from cases 3 to 6. We can see that with the decrease of Pr, the usage frequency of battery increase accordingly. Meanwhile, it can reduce the power sent to the grid and increase the user's costs.

6 Conclusion

In this paper, a HEMS model aiming to minimise the electricity cost and maximise the renewable energy utilisation is proposed. A novel improved MCIP–GA, according to the combinations of the GA and the MCIP method, is designed to perform the scheduling strategy. The initialisation operator, repair operator and dynamic mutation rate are designed in the improved algorithm to avoid the disadvantages which are easy to trap in a local optimal and are sensitive to given initial solutions.

From the results of the example used, the following can be observed: (i) The existence of renewable energy plays an important role in saving electricity cost. (ii) The proposed method is significant in cost saving and reducing energy wastes. (iii) The MCIP–GA can generate a solution with high efficiency and has good robustness under the disturbance of prediction error, which can provide a reference for similar optimisation problems. (iv) The battery will discharge only when the system needs energy severest, which is more economical. (v) For the users, it is more economical to install large capacity batteries as much as possible. Although the cost of investment in the early stage is large, the long-term return is obvious. (vi) The dynamic Pr is beneficial for both user and the grid, which can provide a reference for the power company.

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