

Operational Optimization of a Stand-alone Hybrid Renewable Energy Generation System based on an Improved Genetic Algorithm

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Abstract—In a hybrid renewable energy power generation system, optimization and control is a challenging task because the behaviors of the system are becoming unpredictable and more complex. After the system is built, optimization and control of its operation is important for utilizing the renewable energy efficiently and economically. In the paper, an improved genetic algorithm is developed for achieving the optimization of the hybrid RE system by considering its operation during its life-time. The proposed algorithm is validated by performing a scenario simulation and the results show that the improved genetic algorithm has better convergence speed or accuracy than those of the standard genetic algorithm.

Index Terms—Hybrid RE Generation System, Operational Optimization, Optimal Control, Improved Genetic Algorithm.

I. INTRODUCTION

All around the world there is increasing use of renewable energy sources and more efficient use of energy. These are motivated by a will to reduce green-house gases (GHG) emissions and the increase of fuel prices that drives up the prices of energy. At the same time the role of electricity as an energy carrier is increasing and the construction of new transmission lines and large central power plants is becoming more and more difficult. Energy policies are promoting distributed energy resources such as energy efficiency, distributed generation (DG), energy storage devices, and renewable energy resources (RES), increasing the number of DG installations and especially variable output sources like wind power, solar and small hydro which are partially controllable. Intermittent generation like wind can cause problems in grids, in physical balances and in the adequacy of power. Thus, the goal for integrating distributed energy

resources locally and globally has to be achieved via energy and network management by which feasible ways to decrease the problems caused by the variable output of intermittent resources include adding energy storages into the system, creating more flexibility on the supply side to mitigate supply intermittency and load variation, and increasing flexibility in electricity consumption. In this paper, the integrated power generation system is formed by interconnecting small and modular generation sources (wind turbine, PV arrays) and storage devices (battery bank) which can be operated in the island or grid connected mode. However, optimizing its control can be a challenging task simply because the behavior of the system is becoming unpredictable and more complex.

It has been shown in references [1-4] that the optimal control mainly focuses on the initial setup design and not much thereafter during its life-time operation. In fact, after the system is put into operation, optimization of the system setup and operation by matching various contingency factors is proven to be significant. This is not difficult to see from the fact that a hybrid RE system is often over designed in size so as to meet the intermittent and uncontrollable characteristics of the RE sources. Unnecessary stresses are put on equipment by putting them on track for maximum power output irrespective of the loading condition. Hence, 50% more energy is recovered [5] and maximizing its time of usage economic value is achieved after optimizing its run time operation. Also, the life span of the system is prolonged through proper maintenance.

Regarding the energy management of the hybrid renewable energy generation system, Distributed Artificial Intelligence (DAI) is envisaged in the paper for managing and optimizing the system performance by making use of its basic properties, such as heterogeneity, self-adaptive, distribution, autonomous, openness and dynamism[6][7]. There are different types of problems to be resolved, including communication among devices, distributed control algorithms, and multi-objectives on the optimization process, and in this paper the focus is on the optimization process of the system.

Since John Holland introduced the use of the Genetic Algorithm in 1975 as functional optimizers, it has been widely researched and applied in different fields [8]. Being regarded as a family of computational tools, an improved genetic algorithm is developed for optimizing the hybrid RE system as a global system process. It requires optimization of the stand-

This work is supported by the RGC Hong Kong (GRF Project: PolyU 526208), the National Natural Science Foundation of China (No. 60904078) and the State Key Program of National Natural Science Foundation of China (No.60534040).

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alone hybrid renewable energy power generation system. The rest of the paper is organized as follows: Section 2 introduces the energy management system in a hybrid renewable energy generation system, including the framework and the basic characteristics of the components. The standard genetic algorithm is introduced briefly in Section 3 for analyzing the system operation based on the proposed global optimization functions. Then an improved genetic algorithm is developed to meet the characteristics of the optimization functions. Section 4 presents a scenario simulation and shows the results of the analysis. Finally, section 5 provides the conclusions.

II. HYBRID RE GENERATED SYSTEM AND STANDARD GENETIC ALGORITHM

A. System Configuration

The hybrid RE generated system referred in this paper as shown in Fig. 1 is one which has multi sources of renewable energy for supplying power to a building, village, district, or

other places where the power grid cannot be accessed. It is a modular system comprising wind turbine generators and PV generators as the primary sources of power with batteries as an energy storage device. The function of the main separator acts to leave the system as an island or connect it to the power grid. The wind turbine generators are connected to the AC-bus via the separators. The PV generators and batteries are connected to the DC-bus, and interfaced to the AC-bus via the DC/AC converters. The feeders have two kinds of loads, one is the vital load which should be supplied uninterruptedly, and the other is the ordinary load. The energy management units and demand control units are the essential components of the Energy Management System (EMS). The purpose of the EMS is to make decisions to optimize the system in response to changes in the contingency factors for meeting the load demand, optimizing overall benefits and efficiency, and evaluating the system performance based on the best use of the multi energy sources.

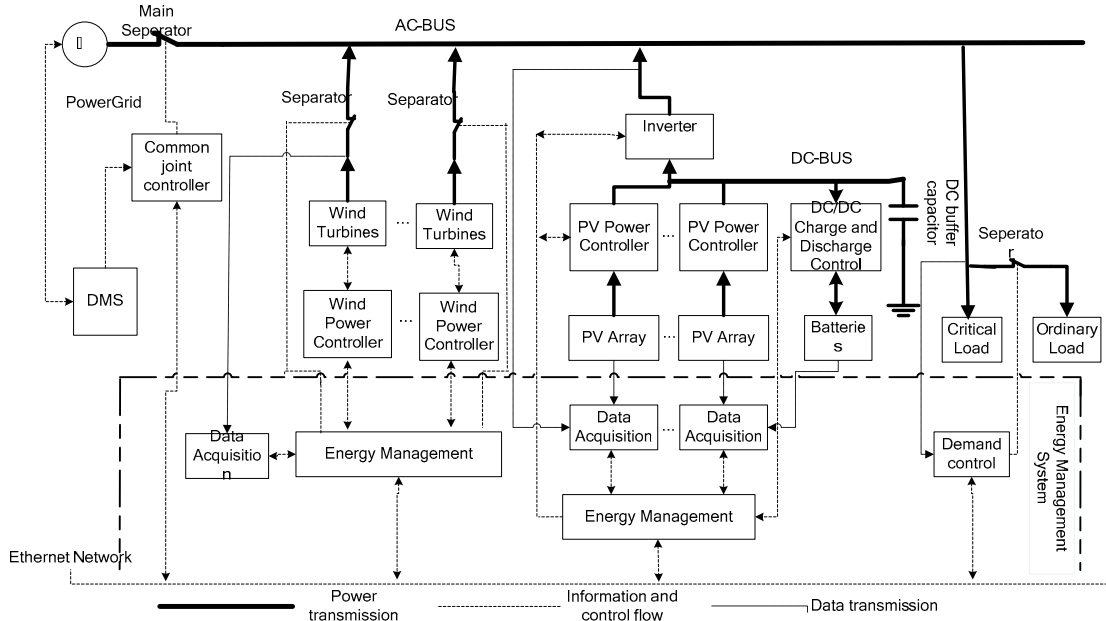


Fig.1 A typical RE hybrid power system

B. Basic Model of system components

(1) Wind Turbine

One simplified model to simulate the power output of a wind turbine [9] is used in this paper and described in (1).

$$P_w(v) = \begin{cases} P_R \cdot \frac{v - v_{ci}}{v_R - v_{ci}} & (v_{ci} \leq v \leq v_R) \\ P_R & (v_R \leq v \leq v_{co}) \\ 0 & (v \leq v_{ci} \text{ or } v \geq v_{co}) \end{cases} \quad (1)$$

Where, P_R is the rated power of the wind turbine; v_{ci} is the cut-in wind speed; v_R is the rated wind speed; and v_{co} is the cut-off wind speed.

(2) PV Array

The rated power output of the PV cell is computed at the

standard condition (1000w/m^2 , 25°C cell temperature). The real power output varies according to various factors. Two main factors, solar irradiation and ambient temperature, are taken into account in this model [10].

$$P_{PV} = \begin{cases} P_{stc} \frac{G_{ING}}{G_{STC}} (1 + k(T_c - T_r)) & (G_{ING} > C) \\ 0 & (G_{ING} \leq C) \end{cases} \quad (2)$$

Where P_{PV} is the output power of the module at irradiance G_{ING} ; P_{stc} is the module maximum power at the standard condition; G_{ING} is the incident irradiance; G_{STC} is the standard irradiance of 1000w/m^2 ; k is the temperature coefficient of power; T_c is the cell temperature; T_r is the reference temperature 25°C ; and C is a threshold value constant according to the performance of the PV cell.

C. Battery Bank

The battery plays two different roles in the system. When

the renewable energy is insufficient to supply the load, the battery is discharged to meet the load demand as an energy supplier. When the supply from the renewable energy exceeds the load demand, the battery is charged and viewed as a load. Usually, there are two effects related to the performance of the system, i.e., state of charge (SOC) and the float charge current.

Firstly, the maximum SOC and the minimum SOC are confined at 100% and 20% of its Ah capacity, respectively. SOC is the index which would prevent the battery from overcharging and undercharging. So, the charged quantity of the battery is subjected to the following constraints:

$$SOC_{\min} \leq SOC(t) \leq SOC_{\max} \quad (3)$$

Secondly, the maximum allowable charging and discharging currents must be less than 10% of the battery AH capacity and are given by the following constraints [10].

$$\begin{aligned} P_+ &\leq (0.1 \times V_{\text{sys}} \times U_{\text{batt}}) / \Delta t \\ P_- &\leq (0.1 \times V_{\text{sys}} \times U_{\text{batt}}) / \Delta t \end{aligned} \quad (4)$$

Where P_+ and P_- are the charging and discharging power, respectively; V_{sys} is the system voltage at the DC bus; Δt is the time step; and U_{batt} is the battery capacity in AH. According to the P_+ and P_- , the SOC can be obtained by the following equation:

$$SOC(t) = SOC(t-1) - P_- + P_+ \quad (5)$$

C. Operational Optimization of the Hybrid RE System

According to the requirements of the system as analyzed above, the approaches of optimization should be built with three layers: individual layer, colony layer and system layer. The optimization is carried out from bottom to top, and the decision making is followed from top to bottom. The framework is shown in Fig.2. This paper focuses on the optimization and scheduling algorithms in the system layer.

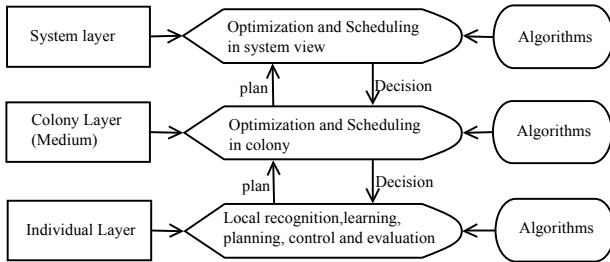


Fig.2 The framework of optimization

D. Basic standard genetic algorithm

Genetic algorithm (GA) is a global optimization technique, which loosely resembles biological evolution based on Darwin's theory of natural selection. The specific mechanisms of the algorithm involve the language of microbiology and mimic genetic operations in developing new potential solutions. A population represents a group of potential solution points [11]. Reference [12] gives a comprehensive study of the genetic algorithms. In GA, each variable is encoded by a gene using an appropriate representation (e.g.,

real number or a string of bits). The corresponding genes for all variables form a chromosome capable of describing an individual design solution. A set of chromosomes representing several individual design solutions comprises a population where the fittest are selected to reproduce. Mating is performed using crossover to combine genes from different parents to produce children. The children are inserted into the population and the procedure starts over again. The flow chart of the standard GA is presented in Fig.3.

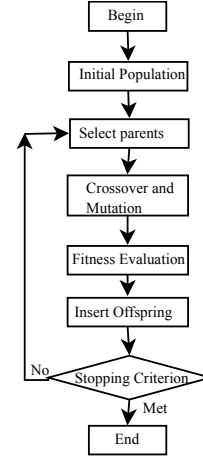


Fig.3 Flow Chart of Standard Genetic Algorithm

In the standard GA, fitness is defined by f_i / \bar{f} , where f_i is the evaluation associated with string i and \bar{f} is the average evaluation of all the strings in the population. Fitness is also designed by rank or tournament selection. After the fitness value is calculated, the parents are selected from the current population by designed strategies, including rank, proportional and top. Then, the next population is created by crossover and mutation. Crossover is applied to randomly pair with a probability called p_c , and the strategies include a single point, two points and uniform crossover ways. Then, typically the mutation rate is applied with less than 1% probability.

III. OVERALL OPTIMIZATION WITH IMPROVED GENETIC ALGORITHMS

In this paper, the cost and power quality are taken into account in the optimization. The overall optimization is formulated by observing the following objective function and constraints.

$$\min f = \sum_{i=1}^3 \sum_{j=1}^n (\beta_1 C_i + \beta_2 Perf_{ij}) P_{ij} \quad (6)$$

$$\begin{aligned} s.t. \quad & \sum_{i=1}^3 \sum_{j=1}^n P_{ij} = P_{\text{load}} \\ & 0 \leq P_{ij} \leq P_{ij \text{ max}} \end{aligned} \quad (7)$$

Where, β_1 and β_2 are the weights for the economic and quality index, respectively, which vary with the different aim of the system optimization stage. C_i is the per-cost of each generator power output. $Perf_{ij}$ is the assessment value of power quality for each generator. P_{ij} is the real power output

of each power supplier. $i=1,2,3$ stands for the types of energy sources, including wind, PV and battery. The constraint is shown in equation (9), which assures balance between supply and demand. Where P_{load} is the sum of the load demand, and $P_{ij\max}$ is the maximum capability of each energy sources' power output under the environmental conditions at that time, which is calculated according to the model of each component.

For simplicity of computation, let,

$$Z_i = (\beta_1 \frac{C_i}{\sum C_i} + \beta_2 \frac{Perf_i}{\sum Perf_i}) P_{i\max} \quad (8)$$

Where, $\beta_1=0.7$ and $\beta_2=0.3$; C_i and $Perf_i$ are normalized to $[0,1]$ as shown to avoid the difference of their dimensions.

Then, the objective function is rewritten as follows.

$$\min f = \sum_{i=1}^n Z_i \cdot Y_i \quad (9)$$

$$\begin{aligned} s.t. \quad & \sum_{i=1}^n P_{i\max} \cdot Y_i = P_{load} \\ & 0 \leq Y_i \leq 1 \end{aligned} \quad (10)$$

By embedding the characteristics of the system into the objective function there are several points to be taken into account. On one hand, the system does not prefer the amplitude to be too large in the operation during the running time regardless of the exciting mechanism, the environmental changes or the device default. Further more, many statistic parameters are taken into account in the initial design of the system as shown in reference [1][2][3][4]. As a result, the operation incurs a change in the small amplitude. On the other hand, the changed amplitude of the variable is not large as shown in the constraint (10). So, the standard GA is improved according to this aspect. In effect, the improvement focuses on the strategy of the crossover. Other steps and parameters are set according to the standard GA. A new way, called single-point crossover on each variable, is defined as follows.

Assuming that the objective function contains m variables, and the variable is encoded with binary code, its length is l_1, l_2, \dots, l_m , respectively. The single-point crossover on each variable is shown in Fig.4, which takes into account the two chromosomes A and B for example. Then, the points of hyper-plane can be expressed as,

$$\begin{aligned} A(x_1, \dots, x_m) & \xrightarrow{\text{crossover}} A'(x'_1, \dots, x'_m) \\ B(y_1, \dots, y_m) & \xrightarrow{\text{crossover}} B'(y'_1, \dots, y'_m) \end{aligned} \quad (11)$$

Where, $x_k \rightarrow x'_k$ and $y_k \rightarrow y'_k$, ($k=1,2,\dots,m$), which has a relationship of increase-decrease, respectively. If $x'_k = x_k \pm \varepsilon$, then $y'_k = y_k \mp \varepsilon$, and among them,

$\varepsilon = (string_2)_{10} \cdot ((2^{(l_k - t_k)} - 1) / (2^{l_k} - 1))$, l_k is the encoding

length of the kth variable, t_k is the crossover position of the corresponding variable through random selection, $string_2$ is

the difference of the two strings code behind t_k . In the algorithm programming, the change range of t_k is controllable, which can ensure small-scale changes around the original position after the variable carries out the crossover operation as shown in Fig.5.

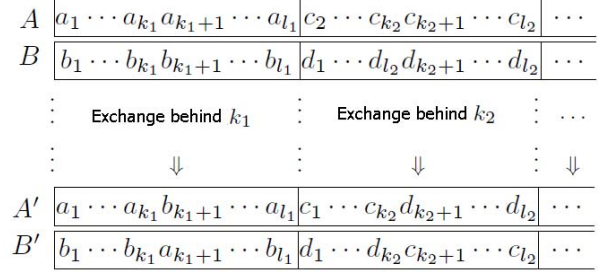


Fig.4 The illustrator of single-point crossover on each variable

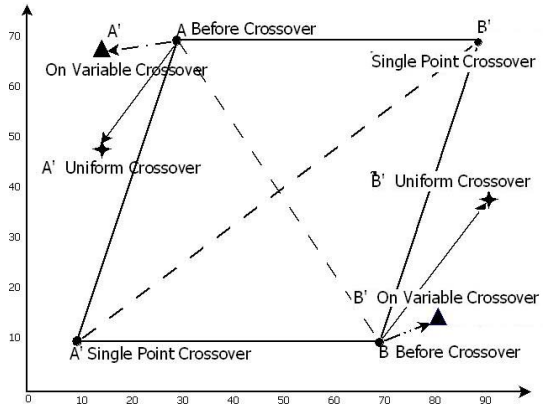
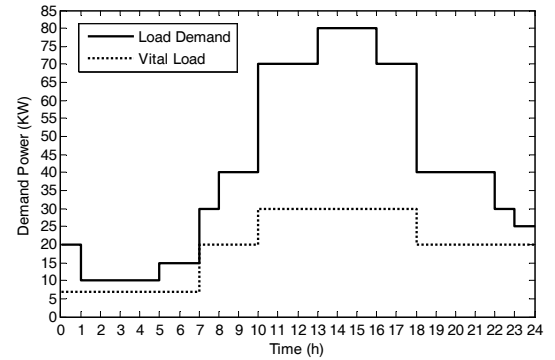


Fig.5 The comparison among the new way and the standard way

IV. SCENARIO SIMULATION AND RESULTS

The scenario simulation and experiment are presented as shown in Fig.6. Versus the time for a typical day in summer, Fig. 6 (a) shows load demand and vital load demand, and Fig.6 (b) shows the wind speed and sun irradiance. The wind speed data and sun irradiance come from the real measurement data of the lab-building in the New Energy Research Center at the South China University of Technology.



(a)

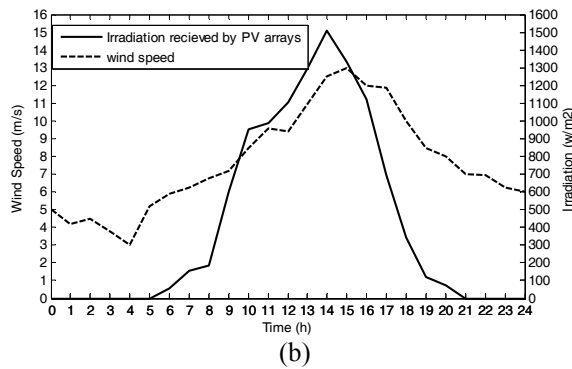


Fig. 6 Load demand, wind speed and sun irradiance versus the time for a typical day in summer

The hybrid RE power system includes six wind turbines, four PV arrays and a set of batteries (170Ah, 12V). Their key parameters are shown in table 1.

TABLE I
PARAMETERS OF WIND TURBINES AND PV MODULES

Parameters	PV1	PV2	PV3	PV4	WT1
Optimum operating voltage (v)	30.2	33.2	31.6	37.7	4
Optimum operating current (A)	6.63	4.52	4.75	7.95	12
Maximum power at STC (w)	200	150	150	300	8
Total rate power (kw)	10	7.5	7.5	15	15
Parameters	WT2	WT3	WT4	WT5	WT6
Cut-in speed (m/s)	3	4	4	4	3.5
Rate wind speed (m/s)	11	10	11	10	10
Rotor diameter (m)	7	6	5	10	6
Rate power (kw)	10	7.5	5	15	7.5

For performing the simulation, there are several rules constructed as follows.

Rule 1: If $\sum(P_w + P_{pv}) \geq P_{load}$, then the energy sources do not include the battery, and the battery is viewed as a load. So there are ten energy nodes as the supplier. The battery is the lowest priority to obtain the energy.

Rule 2: If $\sum(P_w + P_{pv}) < P_{load}$, then the battery will serve as the power supplier.

Rule 3: Simplification is used in the optimization process. The strategies about charging and discharging the battery are not considered. In the whole process, the battery is discharged according to its maximum discharging current, and is charged according to its maximum charging current.

The final results are shown in Fig.7. In Fig.7, the black line shows the maximum power output of each component according to the environmental condition and their model. And the blue block shows the real power output of each component after optimization.

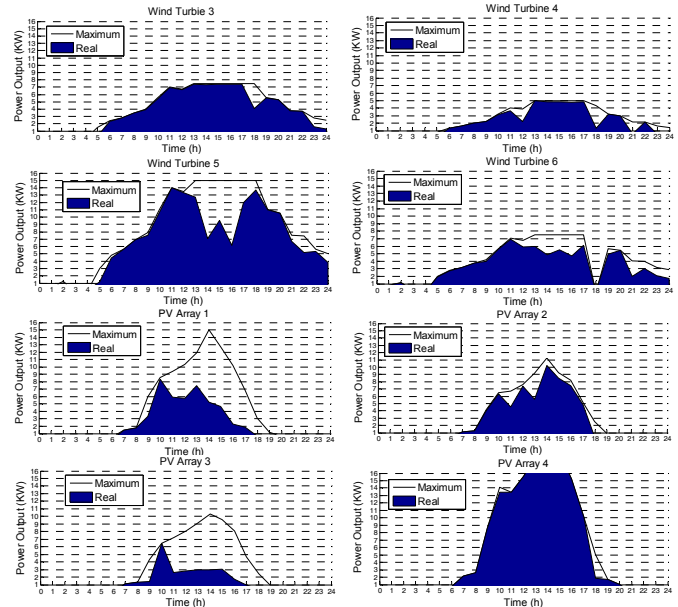
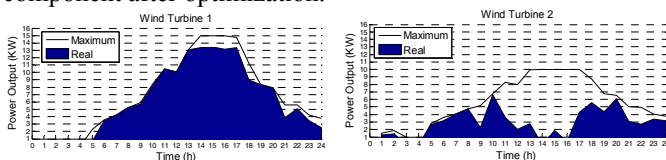


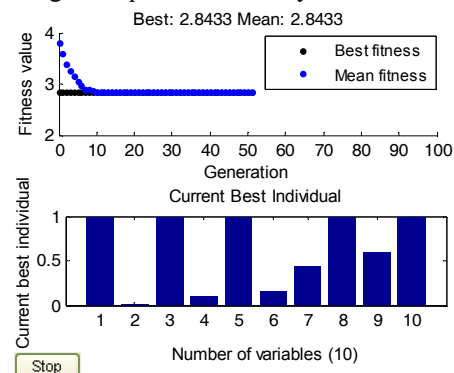
Fig. 7 The optimization results of the hybrid power system

From Fig.7, we can get:

(1) Over sizing to a certain degree is shown in the hybrid RE system from the gap between the maximum power and real output power. By means of the optimization, the equipment and elements in the system can avoid working at the maximum power point all the time, which can prolong the device life time.

(2) The performance of each device can be analyzed in a qualitative aspect. For example, the performance of wind turbine 1 is better than that of wind turbine 2 because the former has a higher probability to be selected. The performance of PV array 4 is better than the performance of PV array 3 for the same reason. If the parameters are computed statistically, the alarm from the machine fault can be used for determining the requirement of system maintenance.

Compared to the standard GA and improved GA over 24 hours with the same initial condition, the results show that the improved GA is better than the former in all conditions. As a limitation of the paper, Fig.8 shows the comparison of the standard GA and the improved GA at 15:00, which is selected randomly. From Fig.8, the fitness value obtained in the improved GA is better than that of the standard GA in terms of either convergence speed or accuracy.



(a) The standard GA

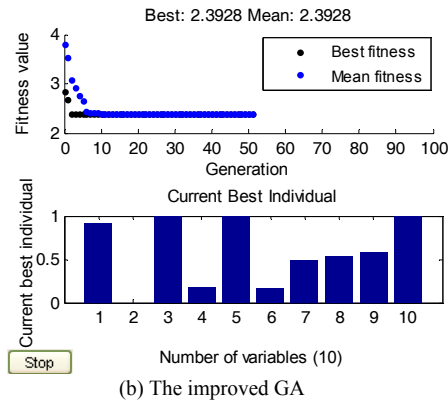


Fig.8 The comparison between the standard GA and improved GA at 15:00

V. CONCLUSIONS

The usage of renewable energy has been steadily increasing over the past few years to help solve acute problems of energy and environmental concerns. Efforts have been spent to exploit renewable energy, such as wind and photovoltaic. To overcome their intermittent, unpredictable and uncontrollable control characteristics, the hybrid power generation system is widely adopted as a new way to improve the power system reliability and make it more flexible and cost effective. Optimization of its control is a challenging task. It is shown in the paper that the envisaged operation of the hybrid RE system allows the renewable energy be used efficiently and economically. Aiming for achieving the best power quality and lowest cost, the improved genetic algorithm developed and applied for the system operational optimization is proven to work accordingly. It has been shown that the optimization produces a small amplitude change decided by the characteristics of the system, and the major improvement rests on the crossover strategies in the evolution process. The simulation results show that that the improved genetic algorithm has better convergence speed and accuracy than those of the standard genetic algorithm all the time.

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