Artificial Intelligence for Load Management Based On Load Shifting in the Textile Industry

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Abstract—The target of any load management is to maintain a constant level of load. The important benefits of load management are reduction in maximum demand, reduction in power loss, better equipment utilization and saving through reduced maximum demand charges. Load shifting, one of the simplest methods of load management, is to reduce customer demand during the peak period by shifting the use of appliances and equipment to partial peak and on-peak periods. This paper proposes an application of artificial intelligent (AI) optimization methods i.e. genetic algorithm (GA), particle swarm optimization (PSO) and bee algorithm (BA) to develop the load shifting and the same has been tried with the actual load data collected from the textile industry plant. The objective is to minimize the total electricity tariff cost. The methodology proposed can be used for determining the optimal response for textile industry under time varying tariffs such as flat rate and time of use (TOU).To show its efficiency, the AI methods are applied to solve the case studies in case of single process multi-jobs (SPMJ). The results show that the proposed methods are able to achieve the best solution efficiently and easy to implement.

Keyword- Artificial Intelligent, Bee algorithm, Load management, Time of use, Textile industry.

I. INTRODUCTION

The textile industry is one of the most convoluted contemporary industries because it is a fragmented and heterogeneous sector dominated by small and medium enterprises (SMEs) [1]. Characterizing the textile manufacturing industry is composite because of the wide variety of substrates, processes, machinery and apparatus used, and finishing steps undertaken. Different types of fibres or yarns, methods of fabric production, and finishing processes (preparation, printing, dyeing, chemical/mechanical finishing, and coating), all correlate in producing a finished fabric. Electrical energy is one of the main cost factors in the textile industry. Especially in times of high energy price volatility, improving energy-efficiency should be a primary concern for textile plants. There are various energy-efficiency opportunities that exist in every textile plant, many of which are cost-effective. However, even cost-effective options are not often implemented in textile plants mostly because of limited information on how to implement such energy-efficiency measures, especially given the fact that a majority of textile plants are categorized as SMEs and hence they have limited resources to acquire this information. Know-how on energy-efficiency technologies and practices should, therefore, be prepared and disseminated to textile plants. An extensive literature review was conducted in this study to collect information on the energy use in and energy efficiency measures/technologies for the textile industry [2].

In recent years; various load management (LM) programs are used by electric utilities to tackle the peak load problem [3]. LM is the strategies, reported with potential reduction in system peak demand with different LM [4]. Many the utility, have the reduction in peak demand improves the utilization of base load generating stations and avoids costly peaking stations and other device in their service area [5]. The customer benefits, as there is reduction in the energy cost bill. To promote LM, utilities offer incentives like time of use (TOU) rates [6]. The textile plants being the bulk consumers, the contact of LM action like load scheduling under TOU tariff on peak demand reduction is high. The textile industries can also control their energy costs by optimal load schedule under TOU tariff [7]. The production-scheduling problem in textile manufacturing, as a multi-stage job shop scheduling problem, is also reported [8]. Most of the models for textiles are centred on process scheduling to achieve the targeted production subject to production constraints and do not give the impact on peak electricity-demand reduction. The optimal schedule to reduce the peak utility load is reported for production processes considering cost worker and process constraints. Extending this work, a production process model coupled with an optimization formulation for process industries with jobs and continuous type loads is presented here to prescribe optimal load-schedule strategies under different tariff structures. The industries can also control their electricity costs by optimal load schedule under TOU tariff.

Load shifting (LS) is a basic method for adapting load curves so as to reduce marginal costs of electric power supply. Load shifting within textile industry is based on their inhabitant behaviour and in their equipment. Thus, we have to account for both [9] the practice of managing electricity supply and demand so that peak energy use is shifted to off-peak periods. Properly done, load shifting helps meet the goals of improving energy efficiency and reducing emissions by smoothing the daily peaks and valleys of energy use and optimizing existing generation assets. Load shifting may be accomplished in several ways. Demand response programmers shift load by controlling the function of machine production, water heaters, heat pumps, and similar electric loads at maximum demand times.

The goal of this paper is to develop the artificial intelligent optimization methods i.e. genetic algorithm (GA), particle swarm optimization (PSO) and bee algorithm (BA)[10] for solving the load shifting problem in textile industry. The load scheduling problem consisting of small jobs, medium jobs and large jobs which considers the applied to determine the start time of the process in order to minimize the total electricity cost under varying tariffs such as flat rate and time of use (TOU) [11] . To show its efficiency, the case studies in case of single process multiple jobs (SPMJ) are studied. The results optimized by the BA are compared to those obtained by the conventional approaches, i.e. GA and PSO in terms of solution quality and computational efficiency. The paper is organized as follows: Section II problem formulation deals with the design principles of LS job scheduling on machine production. Section III describes the basics of artificial intelligence. Section IV demonstrates the experimental setup deals with the results and discussions and conclusions are drawn in Section V.

II. OVERVIEW AND PROBLEM FORMULATION

A. *Textile Process*

Fig. 1 is a generalized flow diagram depicting the various textile processes that are involved in converting raw materials in to a finished product. All of these processes do not occur at a single facility, although there are some vertically integrated plants that have several steps of the process all in one plant. There are also several niche areas and specialized products that have developed in the textile industry which may entail the use of special processing steps that are shown in Fig. 1.

- Spun yarn spinning
- Weaving
- Wet-processing (preparation, dyeing, printing, and finishing)
- Man-made fiber production

B. *Type of Energy Used in Textile Industry*

In general, energy in the textile industry is mostly used in the forms of: electricity, as a common power source for machinery, cooling and temperature control systems, lighting, office equipment, etc.; oil as a fuel for boilers which generate steam; liquefied petroleum gas; coal; and city gas. The rational use of energy calls for a broad application of energy conservation technologies in the various industrial sectors where energy is wasted. One of these energy intensive industrial sectors to be considered to improve efficiency through the introduction of modern energy conservation technologies is the textile industry. In the textile industry, appreciable amounts of energy could be saved or conserved by regulating the temperature in the steam pipes, adjusting the air/fuel ratio in the boilers, and installing heat exchangers using warm waste water.

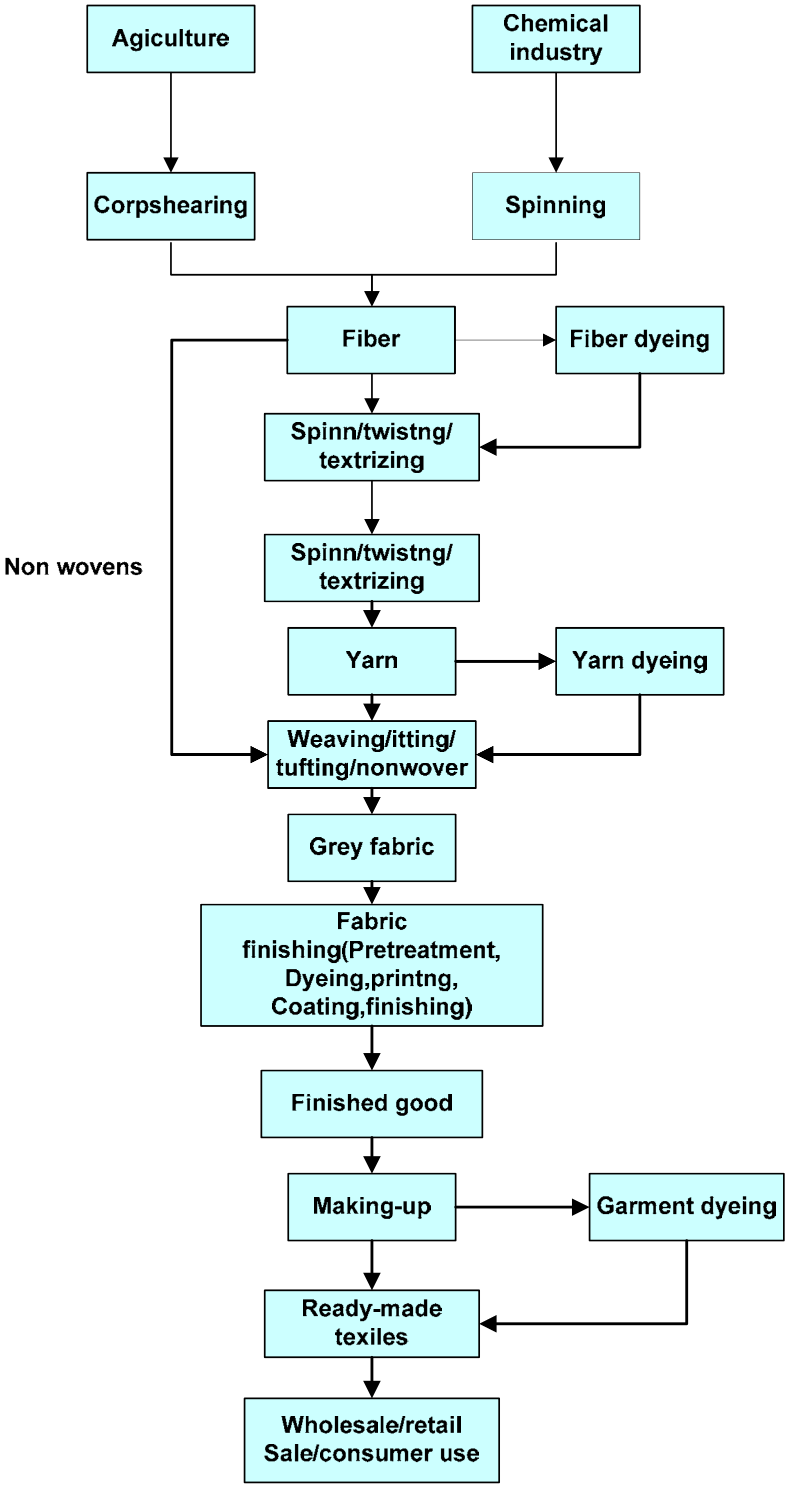

Fig. 1. Textile Process [7]

C. Load Pattern and Electrical Trariffs in Thailand

Domestic consumption in 1991 could be divided into three periods of time, i.e. during the evening time hours of 6:30 to 9:30 pm when the power consumption was highest (peak period), during the daytime hours of 8:00 am to 6:30 pm when the consumption was moderate (partial-peak period), and during the night-time and early morning hours of 9:30 pm to 8:00 am when the consumption was low (off-peak period). During the peak period, the Electricity Generating Authority of Thailand (EGAT) had to use its full generation capacity until the minimum reserve margin was reached; the Provincial Electricity Authority (PEA) had to use its full dispatching capacity in the same period, whereas the Metropolitan Electricity Authority (MEA) had to maximize its dispatching capacity in the afternoon when the consumption nationwide was at moderate level. Therefore, if the demand had increased during the peak period, the power sector would have been required to increase the investment in power generation and distribution. Both from an energy efficiency perspective and from equity of rates perspectives, large consumers during the peak period should pay a higher tariff than small consumers during the off-peak period of the system. One way to determine a fair tariff was to use a formula to automatically adjust the electricity charges in different periods of a day, i.e., implement a Time-of-Day (TOD) Rate. However, this method could not be applied to all individual consumers because the expense for meter installation was rather high.

1) The TOD Rate or Flat rate

The TOD Rate is the electricity tariff rate that varies with the time-period during which electricity has been used during the day. Its objective is to shift consumption from the peak to off-peak periods. The TOD Rate was first used in Thailand in 1964 as an alternative rate applied to the industrial sector. In 1966 it became one of the alternative rates for customers that were served directly by EGAT. In practice, only a few customers opted into this rate.

2) Time-of-Use (TOU) Rate

The Time-of-Use Rate (TOU) was established as an alternative for users who currently use the TOD rate so that the tariff structure would reflect the costs and load curve of the system. As of September 1998, 167 customers were on TOU rates, of which 11 were in MEA and 156 in PEA. The TOU rate differs from the TOD rate in the following: TOU will increase tariff categories for consumers whose consumption is at or greater than 115 kV; the tariff will be lower than that of the previous 69 kV.TOU will be divided into two periods of time, i.e. peak, from 9 am to 10 pm on Mondays through Saturdays and off-peak during all other hours. Under the TOU rate, the energy charge varies according to voltage levels and periods of time. Under the TOU rate, there is no demand charge during the Off-Peak period. The newly established TOU rate will be compulsory for new consumers who have to use the TOD rate. The TOU rate best reflects actual costs of the current power system. This will provide more incentives for consumers to change their consumption behaviour, whereas those whose consumption is consistent and who do not change their consumption behaviour will not be harmed. The research for electrical tariff to major industrial sector may consist of a charge for the total kWh consumed, a power factor charge and a KW maximum demand charge. The costs of the total electrical energy before shifting and after shifting are calculated with the TOU tariff rate applying by the MEA rated voltage is 24 kV connected grid. The tariff for the industrial sector is TOD rate or flat rate as shown TABLE I and TOU rate shown in TABLE II

TABLE I
The Time-of-Day (TOD) Rate in Thailand

Time of Day Rate (Tariff)		**Demand Charge(Baht / kW)**			**Energy Charge (Baht /kWh)**
		1*	2*	3*	
1	69 kV.and over	224.30	29.91	0	1.6660
2	12 – 24 kV.	285.05	58.88	0	1.7034
3	Below 12 kV.	332.71	68.22	0	1.7314

Flat rates or Time-of-Day (TOD Tariff), Demand charge: 1.7034 Baht /kWh or (0.052 $/kWh)), Energy charge: 58.88 Baht/kW or (1.84 $/kWh))(Note: present transaction rate 1 US$:Baht. 32.0

1* On Peak: Everyday from 06.30 PM to 09.30 PM,2* Partial Peak: Everyday from 08.00 AM to 06.30 PM (only the amount of maximum demand that is out of the On -Peak period will be charged at this rate).

3* Off Peak: Everyday from 09.30 PM to 08.00 AM (No demand charge)

TABLE II
Time of use tariff (TOU tariff)

Time of Use (Tariff)		**Demand Charge (Baht /kW)**	**Energy Charge (Baht / kWh)**		**Service Charge (Baht/month)**
		1*	**1***	**2***	
1	69 kV and over	74.14	2.6136	1.1726	228.17
2	12 - 24 kV.	132.93	2.6950	1.1914	228.17
3	Below 12 kV.	210.00	2.8408	1.2246	228.17

Time of use tariff (TOU tariff), Demand Charge: 132.93 Baht/kW or (4.15 $kW), Energy Charge: 1.1914 Baht/kWh or (0.037 $/kWh), 1* On Peak: Monday – Friday from 09.00 AM to 10.00 PM.2*Off Peak: Monday – Friday from 10.00 PM to 09.00 AM, Saturday – Sunday and normal public holiday (excluding substitution holiday) from 00.00 AM to 12.00 PM.

D. Load Shifting Problem Formulation

In this section, the load management based on load shifting for the textile process is presented. The problem can explain in 3 parts; systematic model, feasible solution structure, and fitness function.

1).Systematic model Systematic model of load shifting for the textile process can be explained in four parts which are input parameters, decision variables, constraints and system output as shown in Fig. 2.

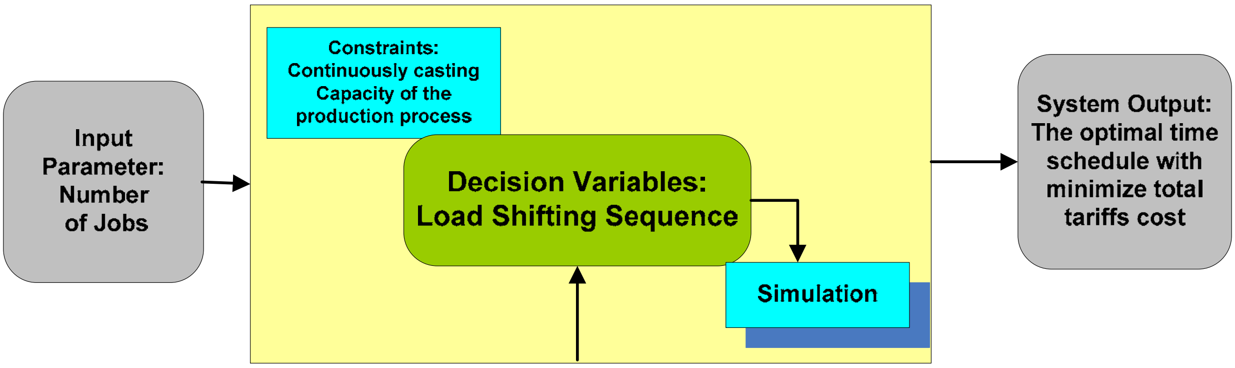

Fig.2. Systematic model of load shifting problem

1.1) Input parameters: The input parameters consist of the step of textile production process, process and transfer time, number of machine and man power of each step, rated power each of machines. The input varies depending on the of production process type.

1.2) Decision variables: The starting time of each job are assigned to decision variable .This variable will be used to determine the time schedule to minimize total energy cost.

1.3) Production Constraints: Normally, the textile industries have the specific machine and man power .The process cannot operate if the machine and man power are not available. Therefore, the constrains of time schedule are limited by the of machine and manpower of industry.

1.4) System output: The objective of load shifting scheduling is to minimize the total energy cost of process time schedule.

2).Structure and Feasible solution

In this paper, the structure of an solution for load shifting problem is composed of a set of starting time number each job .Therefore, size of solution is $1 \times n$ matrix where n is number of jobs. Note that it is very important to create a set of solution satisfying the constraints. it is called a feasible solution.

The feasible solution of candidate solution is related to the of possible jobs, which can be found by

$$FS = T^n \tag{1}$$

where *FS* is number of feasible solution, *T* is number of time periods.

3). Fitness function

In order to evaluate fitness function of load shifting problem, firstly define indices, parameters and decision variables as follows.

Indices

i : Index of job, $j \in \{1, n\}$

j : Index of the production process, $j \in 1, m\}$

t : Index of load shifting time schedule from job i to production process j , t $\in \{1, n\}$

Variables

m : Number machine of production process.

n : Number of job.

PT_j : Process time of production process j

NM_j : Number of machines of production process j

NE_j : Number of manpower of production process j

TT_j : Transfer time of production process j

MP_j : Rated power machine of production process j

ST_j : Start time of job i

STj_{j-1} : Stop time of job$_{j-1}$

$Start\_time_{ij}$: Start time of job i and process j

$Stop\_time_{ij}$: stop time of job i and process j

T: Time interval

R_T: Tariffs cost rate of time interval

The $Start\_time_{ij}$ of m_n machines are set as operational

$$Start\_time_{ij} = \begin{cases} ST_i & j = 1 \\ Stoptime_{ij-1} + TT_j & j = 2 \dots m \end{cases} \quad \begin{matrix} i = 1 \dots n \\ j = 2 \dots m \end{matrix} \tag{2}$$

The $Stop\_time_{ij}$ of m_n machines are set as operational

$$Stop_{time_{ij}} = Start_{time_{ij}} + PT_j \tag{3}$$

Total energy consumption of machines is obtained by summing the energy consumptions of all machines operating in the textile manufacturer. Certain machines processes have the feature of having multiple duty cycles. These machines have the capability to operate for different levels of power consumption. Energy consumption of given equipment for a particular period of time can be stated as:

$$E_{NMj} = P_{NMj} \times T \times R_T \tag{4}$$

where E_{NMj} is the energy consumption of the NM_{ij} machines P_{NMJ} is its power consumption at T time interval is the time at which the NM_j machines are set operational. The cost of electricity consumption of given equipment is dependent on various factors including locality, watts, time of consumption and the cost-rate (peak versus non-peak hour) for that particular time of the day.

The procedure of fitness function is given as follow. The information data for load shifting management problem is shown in TABLE III. Here, the production process has 10 processes for plant textile in Thailand. This information will be used to convert a feasible solution or sequence to a time schedule for reduces energy power consumption.

Step 1: Determine starting time and stop time of job *i* and process j .The step to find starting time of job i start with the computing equation (2) and to find stop time as equation (3)

Step 2: Determine time interval of each process and evaluate rate of tariff based on Tariff of use.

Step 3: Evaluate tariff cost by equation (4) and energy cost of process at time interval.

TABLE III
The dyeing machines of production process for 10 proceses.

No	Process	Process time (min)	Machine/process	No. Machine plant	Manpower/Process.	No. Manpower plant	Transfer Time	Machine kW/No.
1	Fabrics Prepare	75	1	2	2	2	15	84
2	Dye, Thies	60	1	3	2	6	10	105
3	Preset	100	1	4	2	8	15	123
4	Fabric Prepare	90	1	2	2	10	10	94
5	Dying	150	1	4	2	8	20	117
6	Ring Spinning	130	1	2	2	4	10	100
7	Rewinding	60	1	2	2	4	15	94
8	Heat setting	100	1	4	3	12	20	134
9	Inspection	60	1	3	4	12	10	78
10	Packing	95	1	4	3	9	15	85

(TABLE III. Shown the textile process in Thailand)

E. Case study

To illustrate the model proposed, a case study has been worked out for a typical the dyeing machines of production process for 10 steps of textile process Samutsakorn province in Thailand. The connected load of the plant is 22 kV and transformer rated power is 2500 kVA, .400/230 V. Average daily electricity consumption is 3500 kWh. The plant has an automatic power factor correction unit which maintains the power factor nearly unity.

For Example, assumed a solution is [8, 8, 8], Step 1, from in Table II column number of machines of plant defined as [2, 3,4,2,4,2,2,4,3,4] transform given by matrix 4 *10.

$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \end{bmatrix}$$

Checked condition, If the total status of machine job $_i$ and process the column shown status is $1 \geq 1$,status is available ,but the total status of machine job $_i$ and process is = 0 ,defined the machine cannot operated.

Step 2: determine starting time and stop time of job *i* and process j .The step to find starting time of job *i* start with the computing equation

$$Start\_time_{ij} = \begin{cases} ST_i & j = 1 \\ Stoptime_{ij-1} + TT_j & j = 2 \dots m \\ & i = 1 \dots n \\ & j = 2 \dots m \end{cases}$$

If process can not available to find stop time as equation, minimize

$$\{Stop\_time_{ki}\}, i = 1 \dots n, k \neq i$$

TABLE IV
Time Scheduled of jobs 1, 2, 3 after load shifting technique

Job process	1	2	3	4	5	6	7	8	9	10
Job1										
Start time	8:00	9:30	10:40	12:35	14:15	17:05	19:25	20:40	22:40	23:50
Stop time	9:15	10:30	12:20	14:05	16:45	19:15	20:25	22:20	23:40	01:25
Job2										
Start time	8:00	9:30	10:40	12:35	14:15	17:05	19:25	20:40	22:40	23:50
Stop time	9:15	10:30	12:20	14:05	16:45	19:15	20:25	22:20	23:40	01:25
Job3										
Start time	9:30	11:00	12:10	14:15	15:55	19:25	21:45	23:00	01:00	02:10
Stop time	10:45	12:00	13:50	15:45	18:25	21:35	22:45	00:40	02:00	03:45

Step3: Evaluate tariff cost by equation (4) and energy cost of process at interval time.

TABLE V
The Result of energy cost power consumptions load-shifting technique for case study

Job process	1	2	3	4	5	6	7	8	9	10	Total energy cost (Baht)
Job1	155.6762	282.9750	552.4750	379.9950	788.2875	583.9167	253.3300	534.7225	92.9292	160.3426	3,785.6
Job2	155.6762	282.9750	552.4750	379.9950	788.2875	583.9167	253.3300	534.7225	92.9292	160.3426	3,785.6
Job3	282.9750	282.9750	552.4750	379.9950	788.2875	583.9167	147.3262	266.0793	92.9292	160.3426	3,537.3
Total energy cost (Baht)											11,109.5

III. ARTIFICIAL INTELLIGENCE OPTIMIZATION TECHNIQUES

Swarm Intelligent is the one of artificial intelligence, it is affected from a wide diversity study of social animals in nature discovered their interesting behaviours. In particular, the researches focus on collective behaviours that result from the local interactions of the individuals with each other and with their environment. Agents in a swarm act relatively independently from all others in order to achieve the goal of swarm they belong without following commands or rules. For this paper, GA, PSO and BA algorithm are focused.

A. Genetic Algorithm

Genetic algorithms (GA) [13-16] are numerical optimization algorithms inspired by natural selection and natural genetics. The concept of GA was developed by Holland. In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones. Unsuccessful changes are eliminated by natural selection. In GA terminology, a solution vector is called a chromosome. Chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome. In the original GA, genes are assumed to be binary digits. In later implementations, more varied gene types have been introduced. Normally, a chromosome corresponds to a unique solution in the solution space. This requires a mapping mechanism between the solution space and the chromosomes. This mapping is called an encoding. GA operates with a collection of chromosomes, called a population. The population is normally randomly initialized. Generally, the components of GA are following:

1) Representation

In genetic algorithms, the design variable or features that characterize an individual are represented in order list called string. Each design variable corresponds to gene and the string of design variables.

2) Initialization

GA operates with a set of strings instead of a single string. This set or population of string goes through the process of evolution to produce new individual strings. The initial population is chosen at random. The initial population should contain a wide variety of structures.

3) Evaluation function

Fitness is the value of the only objective function to be optimized. Evaluation is a procedure to determine the fitness of each string in the population and is very much application oriented. The performance of the algorithm is highly sensitive to the fitness values because GA proceeds in the direction of evolving better fit strings and the fitness value is the only information suitable to the GA.

4) Genetic operator

Genetic operators are the stochastic transition rules employed by GA. These operators are applied on each string during each generation to generate a new improved population from old one. GA consists of following three basic operators.

4.1) Reproduction

Reproduction involves selection of chromosomes for the next generation. In the most general case, the fitness of an individual determines the probability of its survival for the next generation. There are different selection procedures in GA depending on how the fitness values are used. Proportional selection, ranking, and tournament selection are the most popular selection procedures.

4.2) Crossover

The crossover operator is the most important operator of GA. Crossover mechanism is depicted on Fig. 3. In crossover, generally two chromosomes, called parents, are combined together to form new chromosomes, called offspring. The parents are selected among existing chromosomes in the population with preference towards fitness so that offspring is expected to inherit good genes which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution.

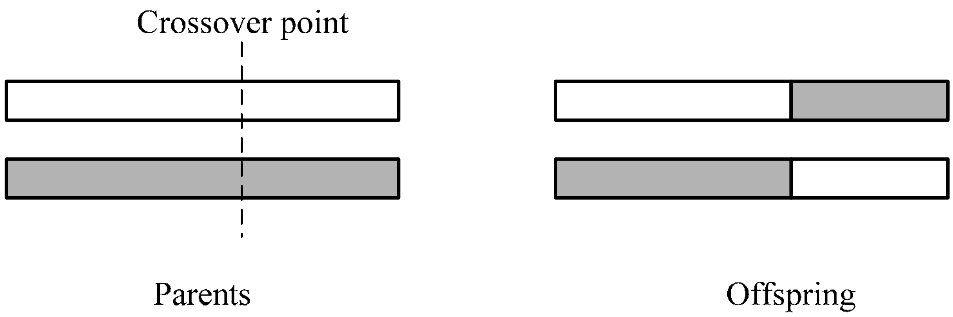

Fig.3. Example of one-point crossover

The crossover rate is the parameter that affects the rate at which the crossover operator is applied. A high crossover rate introduces new strings more quickly into the population. If the crossover rate is too high performance strings are eliminated faster that selection can produce improvements. A low crossover rate may cause stagnations due to the lower exploration rate. An operation rate (p_c) with typical value between 0.6 and 1.0 is normally used as the probability of crossover.

4.3) Mutation

The mutation operator introduces random changes into characteristics of chromosomes. Mutation is generally applied at the gene level. In typical GA implementations, the mutation rate (probability of changing the properties of a gene) is very small and depends on the length of the chromosome. Therefore, the new chromosome produced by mutation will not be very different from the original one. Mutation plays a critical role in GA. As discussed earlier, crossover leads the population to converge by making the chromosomes in the population alike. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima. Mutation mechanism is explained in Fig.4.

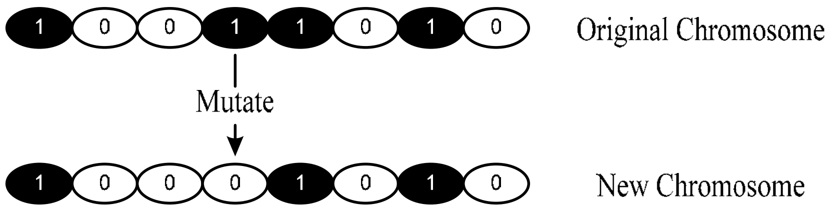

Fig.4. Example of mutation (bit mutation on the fourth bit)

The procedure of a conventional GA is given as follows:

Step 1: Set $t = 0$. Randomly generate N initial population of chromosomes.

Step 2: Evaluate the fitness of initial population of chromosomes.

Step 3: Check the stopping criterion. If satisfied, terminate the search, else $t = t + 1$

Step 4: Select mating pair of chromosomes called parent chromosomes.

Step 5: Create two child chromosomes from the parent chromosomes by applying genetic operator (crossover and mutation)

Step 6: Evaluate the fitness of population of chromosomes. Go to Step 2.

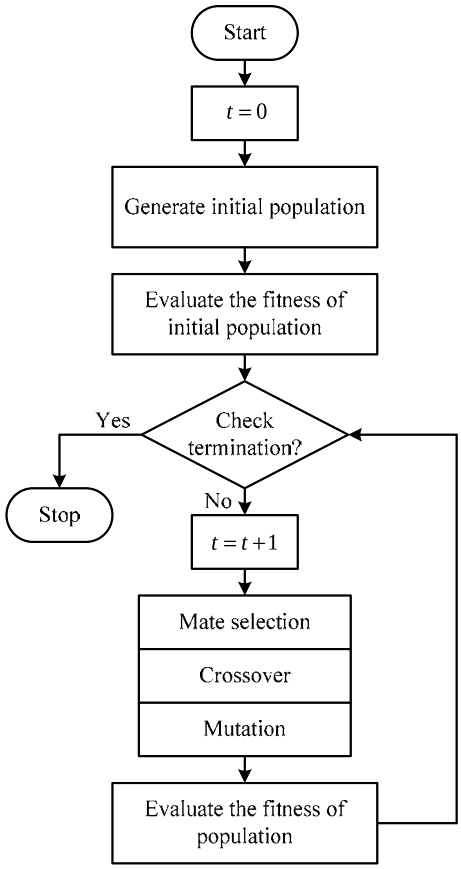

Fig.5.flow chart genetic algorithm

B. *Particle Swarm Optimization*

In 1995, Kennedy and Eberhart first introduced the particle swarm optimization (PSO)[17] method. The PSO method is an optimization technique which is motivated by social behaviours of organisms such as fish schooling and bird flocking. PSO provides a population-based search procedure in which individuals called "particles" change their positions (states) with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighbouring particles, making use of the best position encountered by itself and its neighbours. The swarm direction of a particle is defined by the set of particles neighbouring the particle and its history experience. particle is recorded and represented as $pbest_i = \left(pbest_{i1}, pbest_{i2}, \ldots, pbest_{id}\right)$. The index of the best particle among all the particles in the group is represented by the $gbest_d$. The rate of the velocity for particle i

is represented as $v_i = (v_{i1}, v_{i2}, \ldots, v_{id})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $pbest_{id}$ to $gbest_{id}$ as shown in the following formulas:

$$v_{id}^{t+1} = w \cdot v_{id}^{t} + c_1 * rand(\cdot) * \left(pbest_{id} - x_{id}^{t}\right) + c_2 * rand(\cdot) * \left(gbest_d - x_{id}^{t}\right) \quad (5)$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1},\ i = 1,2,\ldots,n,\ d = 1,2,\ldots,m \quad (6)$$

where

n is number of particles in a group

m is number of members in a particle

t is pointer of iterations (generations)

w is inertia weight factor

c_1, c_2 are acceleration constants

$rand(\cdot)$ is uniform random value in the range [0,1]

v_i^t is velocity of particle i at iteration t, $V_d^{\min} \le v_{id}^t \le V_d^{\max}$; x_i^t is current position of particle at iteration.Figure 3.10 shows the concept of searching mechanism of PSO using the modified velocity and position of individual i based on (5) and (6).

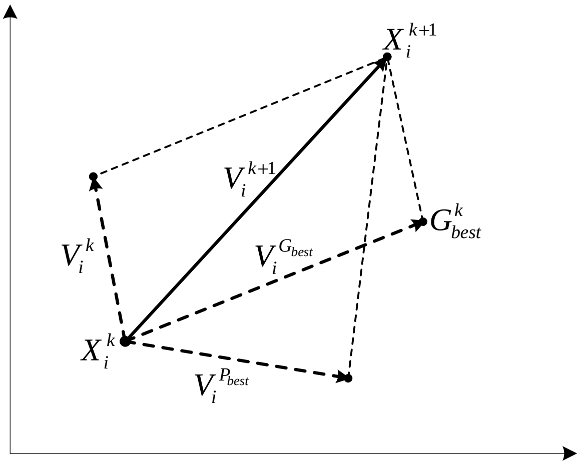

Fig.6. the search mechanism of particle swarm optimization

In the above procedures, the parameter $V^{\max}$ determined the resolution, or fitness, with which regions are to be searched between the present position and the target position. In many experiences, $V^{\max}$ was often set at 10–20% of the dynamic range of the variable on each dimension. The constants c_1 and c_2 represent the weights of the stochastic acceleration terms that pull each particle toward the $pbest$ and $gbest$ positions. Hence, the acceleration constants c_1 and c_2 were often set to be 2.0 according to past experiences. As originally developed, w often decreases linearly from about 0.9 to 0.4 during a run. In general, the inertia weight is set according to the following equation:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \quad (7)$$

where

$iter_{\max}$ is the maximum number of iterations

$iter$ is the current number of iterations.

The search procedures of the PSO method were as shown below.

Step 1: Specify the lower and upper bounds of all parameters and initialize randomly the individuals of the population including individual dimensions, searching points, velocities, $pbests$, and $gbest$. These initial individuals must be feasible candidate solutions that satisfy the constraints.

Step 2: Calculate the evaluation value of each individual in the population using the evaluation function.

Step 3: Compare each individual's evaluation value with its $pbest$. The best evaluation value among the $pbest$ is denoted as $gbest$.

Step 4: Modify the member velocity (v) of each individual according to (5)

Step 5: If $v_{id}^{t+1} > V_d^{\max}$, then $v_{id}^{t+1} = V_d^{\max}$. If $v_{id}^{t+1} < V_d^{\min}$, then $v_{id}^{t+1} = V_d^{\min}$.

Step 6: Modify the member position of each individual according to (6). x_{id}^{t+1} must satisfy the constraints. If x_{id}^{t+1} violates the constraints, then x_{id}^{t+1} must be modified toward the near margin of the feasible solution.

Step 7: If the evaluation value of each individual is better than the previous $pbest$, the current value is set to be $pbest$. If the best $pbest$ is better than $gbest$, the value is set to be $gbest$.

Step 8: If the number of iterations reaches the maximum, then go to Step 9. Otherwise, go to Step 2.

Step 9: The individual that generates the latest $gbest$ is the optimum solution with optimum cost.

C. *Bee Algorithm Optimization*

Bee Algorithm Optimization (BA) algorithm was proposed by Karaboga for optimizing numerical problems in 2005[18]. The algorithm mimics the food foraging behaviours of swarms of bees. Bees algorithm use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms. It is a very simple, robust and population based stochastic optimization algorithm. In BA algorithm, the colony of artificial bees contains two groups of bees are scout and employed bees. The scout bees have the responsibility is to find a new food source. The responsibility of employed bees is to determine a food source within the neighbourhoods of the food source in their memory and share their information with other bees within the hive.

The procedure of the BA algorithm is given as below:

Step 1: Generate randomly the initial populations of *n* scout bees. These initial populations must be feasible candidate solutions that satisfy the constraints. Set *NC=0*.

Step 2: Evaluate the fitness value of the initial populations.

Step 3: Select *m* best sites for neighbourhood search.

Step 4: Separated the *m* best sites to two groups, the first group has *e* best sites and another group has *m-e* best sites.

Step 5: Determine the size of neighbourhood search of each best size (patch size, *ngh*).

Step 6: Recruit bees for selected sites (more bees for the best *e* sites).

Step 7: Select the fittest bees from each patch.

Step 8: Check the stopping criterion. If satisfied, terminate the search, else $NC = NC + 1$.

Step 9: Assign the $n-m$ remaining bees to random search.

Step 10: New population of scout bees. Go to Step 2.

where *NC* is number of iteration, *n* is number of scout bees, *m* is number of the best selected sites, *e* is number of the best site, *ngh* is neighbourhood size**.**

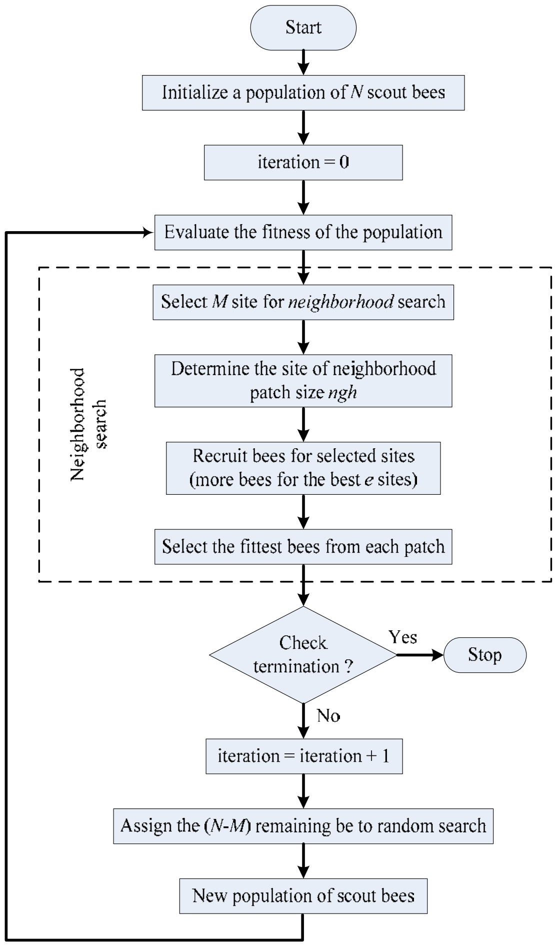

Fig.7. Flow chart of BA algorithm

IV. EXPERIMENT AND RESULT

To assess the feasibility solution of the swarm intelligence techniques i.e. GA, PSO and BA, three take load sizes problems (small, medium and large problems) are applied. All optimization methods (GA,PSO, and BA) were implemented in MATLAB® package and the simulation cases done on a Intel Core i5-430M, 2.26GHz laptop computer with 4 GB RAM under Windows 8.Each studied systems was run 30 times with differential random initial solutions. In order to evaluate the performance of each technique, the best, worst, average, and standard deviation of the generation costs and the average of computational time to get near optimum solution are used for evaluation. Unfortunately, the number of initial solutions and the computational time for an iteration of these techniques are different. Therefore, the execution of search was done by the same iterations. This method is not suitable for comparison. Consequently; this work uses the time limit as the stopping criterion. The search processes of all techniques are executed by the same time period; therefore, the maximum iteration of each technique depends on the time limit. When the search satisfies the stopping criterion, the best, worst, average, and standard deviation of the generation costs and the average of computational time to get near optimum solution are reported.

A. *Case studies*

There are 3, 7 and 10 jobs of dyeing production process of a textile industry. These processes consist of 10 steps as shown in Table 1. That needs to find the starting time of each job. So, the number of the feasible solutions is

$1.3824 \times 10^4, 4.5865 \times 10^9$ and 6.3403×10^{13}, respectively.

1) *Simulation Results*

After performed 30 trials, the best solutions of three methods are given in Tables 8, 9 and 10. The results of the BA method in comparison with those of GA and PSO in terms of maximum, average, minimum generation cost, the standard deviation, and average computational time are provided in Table 8, 9 and 10 clearly, the BA method has always better solutions than other methods.

TABLE VI
Time Scheduled of jobs 1, 2, 3 after load shifting technique

Job process	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Job 1										
Start time	16:00	17:30	18:40	20:35	22:15	01:05	03:25	04:40	06:40	07:50
Stop time	17:15	18:30	20:20	22:05	00:45	03:15	04:25	06:20	07:40	09:25
Job 2										
Start time	17:00	18:30	19:40	21:35	23:15	02:05	04:25	05:40	07:40	08:50
Stop time	18:15	19:30	21:20	23:05	01:45	04:15	05:25	07:20	08:40	10:25
Job 3										
Start time	23:00	00:30	01:40	22:15	23:55	02:45	05:05	06:20	08:20	09:30
Stop time	10:45	12:00	03:20	23:45	02:25	04:55	06:50	08:00	09:20	11:05

Step3: Evaluate tariff cost by equation (4) and energy cost of process at interval time.

TABLE VII
The Result of energy cost power consumptions load-shifting technique for case study

Job & process	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total energy cost (Baht)**
Job 1	282.9750	282.9750	552.4750	368.2168	348.4845	258.1367	111.9916	266.0973	92.9292	281.1078	2,845.4
Job2	282.9750	282.9750	552.4750	368.2168	348.4845	258.1367	111.9916	266.0973	92.9292	408.9138	2,831.8
Job3	125.0970	125.0970	244.2370	167.9874	348.4845	258.1367	111.9916	266.0793	193.9756	362.7021	2,203.8
Total energy cost (Baht)											7,811.0

TABLEVIII
Best results obtained 10 processes for small jobs (3jobs) production process system using GA, PSO, and BA

Methods	**Max cost (Baht)**	**Average cost(Baht)**	**Min cost(Baht)**	**SD(Standards Deviation)**	**CPU time (sec)**	**%Get optimum**
GA	7,836.41	7,836.41	7,836.41	0.0000000000027751	1.892	100
PSO	7,836.41	7,836.41	7,836.41	0.0000000000027751	1.382	100
BA	7,836.41	7,836.41	7,836.41	0.0000000000027751	1.069	100

TABLE IX
Best results obtained 10 processes for medium jobs (7 jobs) production process system using GA, PSO, and BA

Methods	**Max cost (Baht)**	**Average cost (Baht)**	**Min cost (Baht)**	**SD (Standard Deviation)**	**CPU time (sec)**	**% Get optimum**
PSO	18,950.20	18,321.20	18,066.20	272.30	96.666	33.33
GA	18,192.50	18,078.70	18,066.20	0.00213168	26.922	90.00
BA	18,066.20	18,066.20	18,066.20	0.0000000000074003	10.8348	100

TABLE X
Best results obtained 10 processes for large jobs (10 jobs) production process system using GA, PSO, and BA

Methods	**Max cost(Baht)**	**Average cost(Baht)**	**Min cost(Baht)**	**SD(Standard Deviation)**	**CPU time(sec)**	**%Get optimum**
PSO	27,962.90	27,027.30	26379.00	568.84	121.34	0
GA	26,717.00	26,268.00	26,054.00	0.00856645	302	0
BA	26,232.40	26,035.10	25,912.50	0.003246387	78.50	43.33

TABLE XI
The Result for 3, 7 and 10 jobs of load-shifting technique for case study

Job process	**Flat rate cost (Baht)**	**After shifting with TOU tariffs cost(Baht)**	**% Saving**
3 jobs	11,085	7,836.41	29.306
7 jobs	24,127	18,066.20	25.120
10 jobs	33,040	25,912.50	21.57

B. *Comparison of three Methods*

1) Solution Quality

For three size production cost process system, the best solutions of three methods are given in Tables 8,9,10 after performed 30 trials. The results of the BA method are compared with those obtained by GA, and PSO in terms of maximum, average, minimum tariffs cost, the standard deviation, and average computational time, as provided in Table 8,9,10. Obviously, all methods have succeeded in finding the near optimum solution presented in with a high probability of satisfying the equality and inequality constraints. In order to demonstrate the efficiency of the BA method, the distribution outlines of the best solution of each trial are considered. Fig. 8,9,10 shows the distribution outlines of the best solution of each trial in case of 3, 7 and 10 number of jobs. Almost all tariffs costs obtained by the BA method are lower. This verifies that the BA method has better quality of solution. For the Tables 11 are result after load shifting 3,7,10 jobs comparative flat rate for 3, jobs more than 3jobs TOU tariffs cost 29.306%;7jobs saving is 25.120 % and 10 jobs to be saving 21.57%. Fig. 8, 9 and 10 shows the distribution outlines of the best solution of each trial in case of 3,7,10 jobs for production process 10 processes.

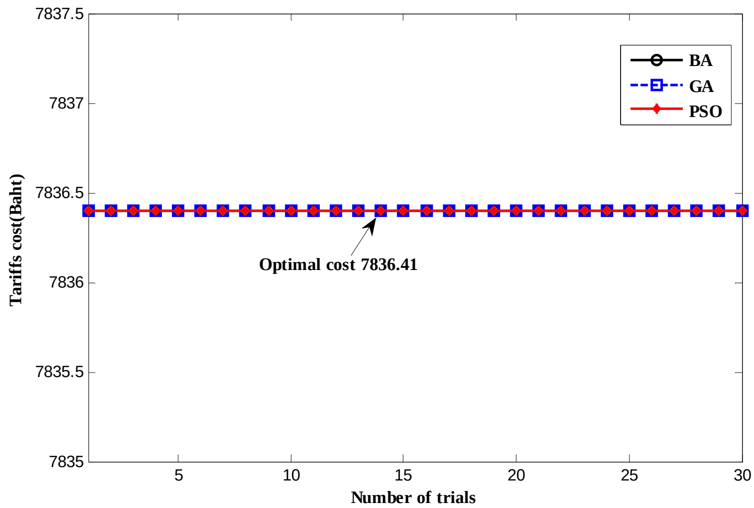

Fig.8. Distribution of tariffs cost of three methods of 3 jobs for 10 processes of production process system

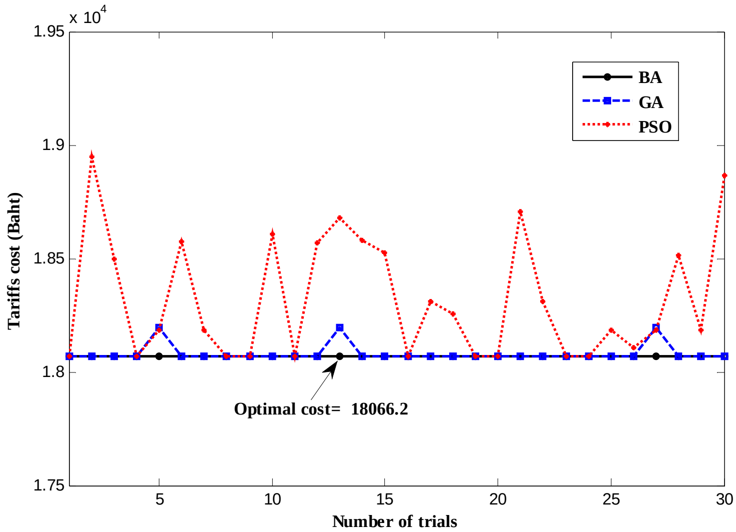

Fig. 9. Distribution of tariffs cost of three methods of 7 jobs for 10 processes of production process system

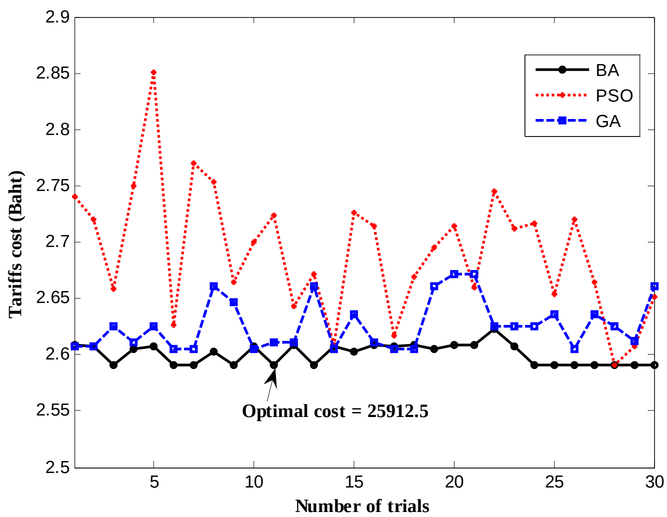

Fig.10. Distribution of tariffs cost of three methods of 10 jobs for 10 processes of production process system

2) Computation Efficiency: the convergent characteristics of the BA compared with other methods for three case studies are shown in Fig. 11, 12, and13. Clearly, the BA converges to the optimum solution much faster than other methods. Furthermore, the comparisons of computation time of five methods for three studies system are already given in Table 8,9 and10 .The BA method has better quality of solution.

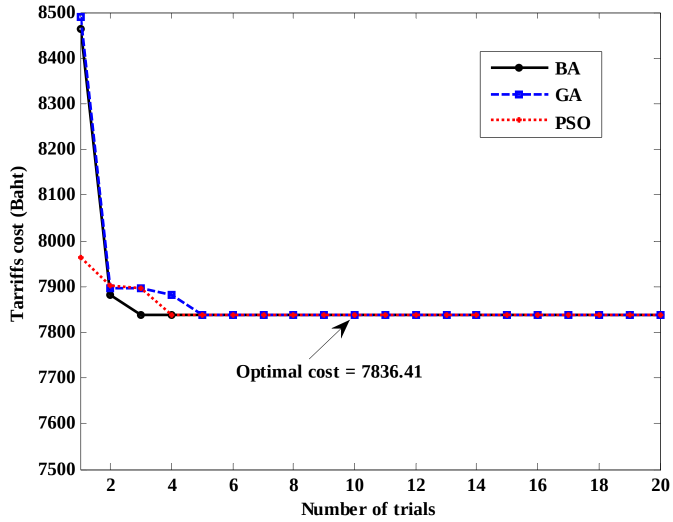

Fig.11.Convergence curve three methods of 3 jobs for 10 processes of production process system

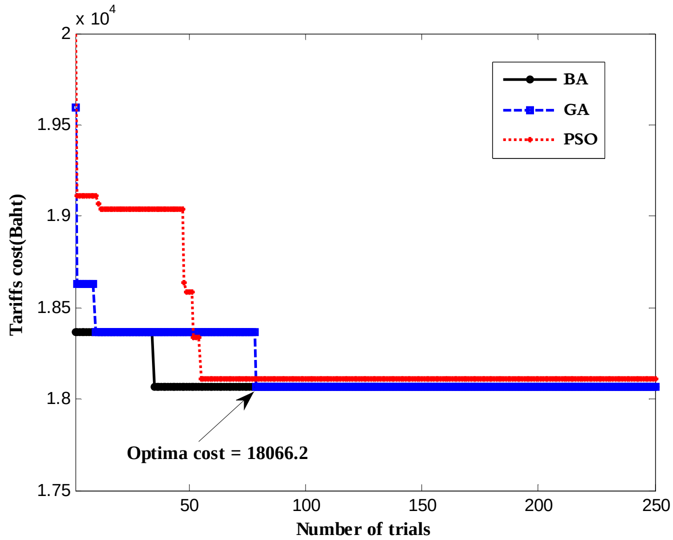

Fig. 12. Convergence curve three methods of 7 jobs for 10 processes of production process system

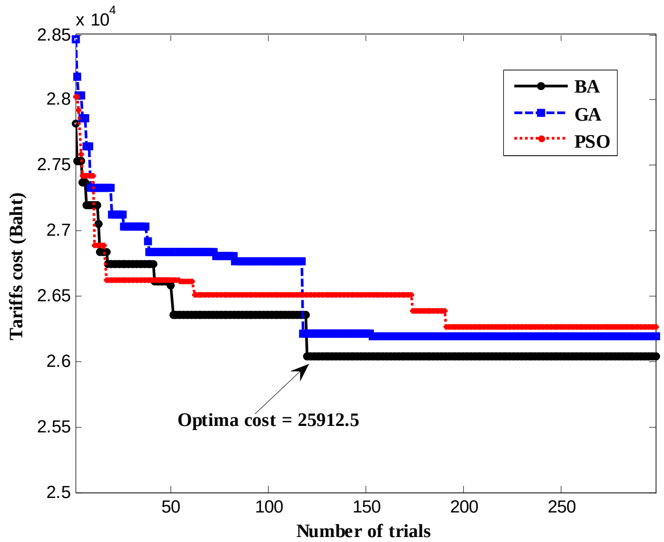

Fig. 13. Convergence curve three methods of 10 jobs for 10 processes of production process system

V. CONCLUSION

The artificial intelligent optimization methods i.e. genetic algorithm (GA), particle swarm optimization (PSO) and bee algorithm (BA) are proposed for solving the LS problem by taking the three size problem (small, medium and large scale) and load shifting effects into the case studies in case of single process multiple jobs (SPMJ) to minimize the total electricity cost under varying tariffs such as flat rate and time of use (TOU) consideration. Numerical testing and a comparative analysis show that the BA algorithm outperforms other methods i.e. GA, and PSO in terms of high-quality solution, stable convergence characteristic and good computation efficiency.

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