Intelligent Approach for Optimal Energy Management of Chiller Plant Using Fuzzy and PSO Techniques

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***Abstract* – This paper discusses the optimal energy management of chiller plant. Two intelligent approaches have been employed. Fuzzy is used to adjust the set-point and, while PSO is utilized to optimize the objective function after setting by Fuzzy. Moreover, Fuzzy is also utilized to adjust weighting factors in order to find the best values for the PSO local and global. This will improve PSO performance. The proposed method was combined two levels as Fuzzified PSO, and the model has been simulated and validated by a real case study which consists of 5 electric-driven chillers. The results have shown that the effectiveness of the proposed method compared to the conventional one, and it also has demonstrated a better power saving.**

***Index-terms* - Chillers, Energy Consumption, Particle Swarm Optimization (PSO), Fuzzy Inference System (FIS), Fussified PSO**

I. INTRODUCTION

The energy consumption of chilled water systems reach up to 50 % of buildings energy usage [1]. Then, the cooling consumption now a day contributes to the maximum demand. The peak demand can be reduced in different ways depending on the load characteristics of building. The management of energy saving can be achieved by using load shifting technique [2]. Therefore, energy management plays a vital role for power conservation and energy efficiency in chillers plant, if these cooling machines operate properly [3].

To satisfy the cooling demand at the end users who break down the total energy consumption and reduce consumption. To manage the cooling loads, several people have conducted research on multiple-chiller, a genetic algorithm and Neuro-Fuzzy techniques have employed [4, 5]. Furthermore, a model predictive control (MPC) is used for optimal scheduling to predict the load and operating cost [6, 7]. Also, two techniques for optimal scheduling have been used in Fuzzy inference system (FIS) by [8, 9]. This paper uses optimal scheduling based on tariff rate and peak clipping techniques implementing by FPSO in order to reduce energy consumption and operating cost in chiller plant.

II. DESCRIPTION OF CHILLERS PLANT

Fig. 1 illustrates the basics system of the chillers that are connected in parallel to distribute cooling load in a building. All the chillers are the same size and can be operated in order to handle a demand load and increments of a variable load to allow the chiller system to operate at its most efficient point. The chilled-water flow through each single chiller for maintain the system reliability and stability so that each chiller-pump combination can operate independently from the others [10]. The mixing tank with amount of water in galloon per minute (*gpm*) and temperature of chilled water indicates by temperature gauge (T_i). If the flow indicates overcapacity, the chiller-pumps should be operated partially or chiller turned off. In Fig.1, a model is developed for mixing chilled-water only in order to adjust the difference between return and supply temperatures ($\Delta T = T_{CHWR} - T_{CHWS}$).

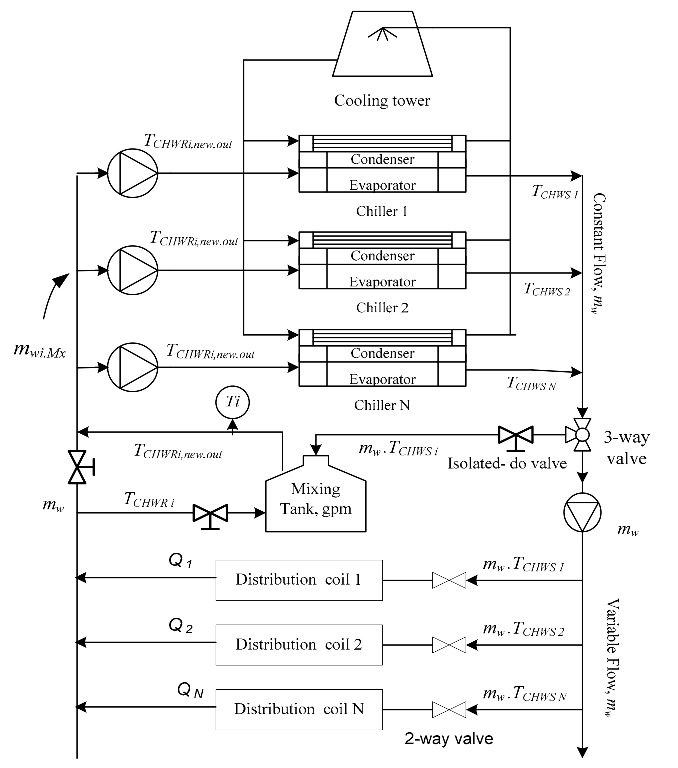

Fig. 1. The multiple-chiller decoupled

III. PROBLEM FORMULATION

Air-conditioning systems process can be modelled as steady-flow processes. It can be analyzed by applying the steady flow mass and energy balance [11],[12]. The best performance can be obtained, when the chillers are set under part load ratio (PLR). The cooling load can be modeled to satisfy the cooling demand ($Q_L = Q_{1\sim N}$) based on refrigerant tonnage (RT) of chilled water at a period *t* and can be expressed by,

$$Q_L(i,t) = \sum_{t=1}^{T}\sum_{i=1}^{N}(PLR_1, \quad PLR_2,..., \quad PLR_N).RT_i,t \qquad (1)$$

$$s.t,\ PLR_i^{LOWER} \leq PLR_i \leq PLR_i^{UPPER} \qquad (2)$$

where 1 RT = 3.517 kW [8, 13-15], PLR_i^{LOWER} and PLR_i^{UPPER} are PLR the minimum and maximum values of *i*th chiller, respectively. The chillers produce a mass flow of chilled-water (kg/Sec) at supply temperature (T_{CHWSi} ° K) by evaporator to the distribution coils (load) in order to serve cooling utilities. The flow of chilled-water will return to enter evaporator under a certain return temperature (T_{CHWRi} ° K). This chilled water must meet the cooling load demand in kW according to,

$$Q_{evap\ i} = Q_{L\ i} = \{m_w c_w (T_{CHWRi} - T_{CHWSi})\}, \qquad (3)$$

where $Q_{evap,i}$ is the cooling load by evaporator, c_w is the specific heat of chilled water (4.197 kJ/kg.°K), and $m_{w,i}$ is the flow rate of chilled water. The cooling consumption can be increased or decreased based on flow rate and temperature difference. In Eq. (3), if m_w increases consumption will increase, whilst increasing of ΔT will be resulted to the increasing of cooling load.

IV. CHILLER COOLING LOAD MODELING

Hybrid model will be developed by mixing supply and return chilled-water based on energy balanced steady-state condition. The amount of flowing chilled water supplied by *i*th chiller for cooling load only can be expressed in,

$$m_w i = \sum_{t=1}^{T} n_i * m_w \qquad (4)$$

where, n_i number of *i*th chiller. If the T_{CHWRi} is greater than the setting value, amount of supply chilled water will be mixed with return in a tank to minimize T_{CHWRi}. Therefore, the amount of flowing chilled water will be,

$$m_{w \cdot Mx} = \sum_{t=1}^{T} n_i * m_{w \cdot Mx} \qquad (5)$$

By assuming balance mass of water flow (m_w) on value of specific heat (c_w) [12], the mass flow of fluid in Eq. (5) can be re-written as,

$$\sum_{t=1}^{T}\sum_{i=1}^{N} m_{w.Mx.\,input\,,i} = \sum_{t=1}^{T}\sum_{i=1}^{N} m_{w.Mx\,.output\,,i} \qquad (6)$$

In Fig. 1, the energy balance of fluid flow rate at a given temperature can be modeled as,

$$m_{ws.in}T_{CHWSi} + m_{wr.in}T_{CHWRi} = m_{w.Mx}T_{CHWRi.new.out} \qquad (7)$$

where, $m_{ws.in}T_{CHWSi}$ is the mass flow rate of chilled water entering to the tank at supply temperature, $m_{wr.in}T_{CHWRi}$ is the mass flow rate of entering chilled water to the tank at return temperature, and $m_{w.Mx}T_{CHWRi.new.out}$ is the mass flow rate of leaving chilled water to the chiller at a certain return temperature of time *t*. Therefore, the new T_{CHWRi} which enters to the evaporator once again which can be calculated from Eq. (7), is

$$T_{CHWRi\ .new\ .out} = \frac{m_{ws\ .in\ TCHWSi} + m_{wr\ .in} T_{CHWRi}}{m_{w.Mx}} \qquad (8).$$

$$\text{where, } \Delta T_i = T_{CHWRi\ .new\ .out} - T_{CHWSi} \qquad (9)$$

To determine the cooling load, Eq. (8) substitutes in Eq. (3) as,

$$Q_{evap}\,,_i = m_w c_w \Delta T_i \qquad (10)$$

$$s.t,\ \ Q_{evap,i}^{Minimum} \leq Q_{evap,i}, t \leq Q_{evap,i}^{Maximum} \qquad (11)$$

Due to mixing chilled water, the total consumption of cooling load can be reduced to according to,

$$R = Minimize \sum_{t=1}^{T}\sum_{i=1}^{N}(n_i.Q_{evap}(i,t)) \qquad (12)$$

According to Tenaga National Berhad (TNB) for Electricity in Malaysia. The electricity bill is basically depending on two tariff rates in the industrial buildings. The electricity cost can be represented by,

$$C_i = \delta_{on-off} * \sum_{t=1}^{T}\sum_{i=1}^{N} R(i,t) \qquad (13)$$

where $\delta_{on\text{-}off}$ is the tariff rate, it is 0.304 RM/kWhr at peak hours and 0.187 RM /kWhr during off-peak hours, and the maximum demand is RM 31.70 according to TNB.

V. CASE STUDY

A case study of 5 chillers at Industrial Building at Perak, Malaysia. The power consumption and electricity bill for the whole period have shown in Fig. 2. An empirical data were taken in a period of March 2014 to February 2015. These data include the chilled water flow rate, supply chilled water temperature (T_{CHWS}) and return chilled water temperature (T_{CHWR}). The average T_{CHWS} of above period is 12 °C which is 285.15 °K and T_{CHWR} varies between (287.85 – 291.35) °K. The operating conditions of fluid flow rate and temperature were taken from the existing system using Ultrasonic Flow Meter as shown in Table. 1.

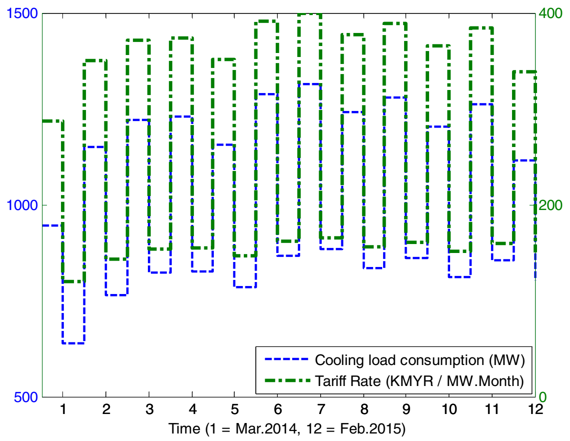

Fig. 2. The cooling consumption with tariff rate

Table 1. The operating conditions for chilled-water system

Chiller	1	2	3	4	5
Flow rate, (m^3/hr)	105	105	105	105	105
Average T_{CHWSi} (°C)	12	12	12	12	12
Average T_{CHWRi} (°C)	T_{CHWR} at On-Peak and Off-Peak hours				
On Peak, Mar.2014	16.0	16.4	16.2	16.3	16.1
Off Peak, Mar.2014	14.7	15.0	14.8	14.9	14.8
On Peak, Apr.2014	17.0	17.3	17.1	17.2	17.0
Off Peak, Apr.2014	15.2	15.7	15.4	15.4	15.3
On Peak, May.2014	17.2	17.7	17.4	17.5	17.3
Off Peak, May.2014	15.4	16.0	15.7	15.9	15.3
On Peak, Jun.2014	17.1	17.9	17.7	17.4	17.2
Off Peak, Jun.2014	15.3	16.2	15.9	15.7	15.2
On Peak, Apr.2014	16.9	17.3	17.2	17.1	17.2
Off Peak, Apr.2014	15.1	15.8	15.6	15.5	15.4
On Peak, Aug.2014	17.4	18.0	17.8	17.9	17.5
Off Peak, Aug.2014	15.4	16.3	15.8	16.0	15.7
On Peak, Sept.2014	17.5	18.2	17.8	18.1	17.6
Off Peak, Sept.2014	15.5	16.4	16.0	16.2	15.6
On Peak, Oct.2014	17.2	17.8	17.6	17.7	17.3
Off Peak, Oct.2014	15.4	16.1	15.7	15.8	15.5
On Peak, Nov.2014	17.3	18.0	17.7	17.8	17.6
Off Peak, Nov.2014	15.4	16.2	15.9	16.0	15.6
On Peak, Dec.2014	17.2	17.5	17.4	17.4	17.2
Off Peak, Dec.2014	15.3	16.0	15.6	15.7	15.4
On Peak, Jan.2015	17.4	17.9	17.6	17.6	17.5
Off Peak, Jan.2015	15.6	16.0	15.9	16.0	15.5
On Peak, Feb.2015	17.0	17.5	17.3	17.4	17.1
Off Peak, Feb.2015	15.1	15.9	15.7	15.8	15.3

Flow rate m_w $(kg/Sec) = 0.28 * m^3/hr$ $\quad T_{(°K)} = T_{(°C)} + 273.15$

VI. PSO TECHNIQUES

PSO is an optimization technique that it depends on the movement behavior of birds and fish according to,

$$V_i^{k+1} = \{WV_i^k + c_1r_1(Pbest_i^k - X_i^k) + c_2r_2(Gbest_i^k - X_i^k)\} \quad (14)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} i = 1, 2, \ldots, M_{swarm} \quad (15)$$

where, V_i^{k+1}: particle's updated velocity at $(k+1)^{th}$ iteration, W: inertia weight factor, c_1 and c_2: the weighting factors which are used to accelerate PSO performance to find $Pbest_i^k$ and $Gbest_i^k$, also r_1 and r_2 are the random (0-1), and X_i^{k+1} is the updated particle's current position. The best particle's velocity V_i^{k+1} and its position X_i^{k+1}can be calculated according to (14) & (15) [16]. To ensure the convergence characteristics, the velocity cannot exceed the set of specific range. These equations are to find the process search for optimum best local and global values accurately [17]. The inertia weight (W) is expressed as,

$$W = W_{max} - [(W_{max} - W_{min})/iter_{max}]*iter \quad (16)$$

where, inertia weight initial value, W_{max}, inertia weight final value, W_{min}, current iteration number, iter, and maximum iteration, $iter_{max}$. W should dynamically be changed in order to balance between global and local search process, whilst the velocity should be modified by a constriction factor (CF) as,

$$V_i^{k+1} = CF\{WV_i^k + c_1r_1(Pbest_i^k - X_i^k) + c_2r_2(Gbest_i^k - X_i^k)\} \quad (17)$$

$$where, CF = \frac{2}{\mathrm{abs}(2-2\varepsilon-\sqrt{4\varepsilon-\varepsilon^2})} \quad (18),$$

where ε is constant = $c_1 + c_2$, $\varepsilon \leq 4$, it's used to control the convergence characteristic of the system [18, 19].

VII. FUZZY SYSTEM

Fuzzy inference systems (FIS) has four blocks each one with a certain functionality. These are [1] fuzzification which is used to transform the crisp inputs into degrees of match with linguistic values, [2] knowledge base consists of a rule base and a database. A rule base contains a number of fuzzy if-then rules, while the database is used to define the membership functions (MFs) of Fuzzy sets used in the fuzzy rules, [3] fuzzy inference engine is employed to perform the inference operations on the rules, and [4] defuzzification is used to transform the Fuzzy results of the inference into a crisp output [20].

VIII. FUZZIFIED PARTICLE SWARM OPTIMIZATION

Two Fuzzy systems (FIS 1 & FIS 2) are used in this work. FIS 1 is used as a mixer for the chilled water as explained Fig. 3. This technique is used to reduce T_{CHWR} at daytime, and subsequently, FIS 1 is used as valve to prevent mixing for the rest of the day. Because the T_{CHWR} is closed to the manufacturer setting. According to Eqs. (7, 8), the structure of fuzzified is employed to control the subsystem output. FIS 1 inputs with supply/return chilled water flow rate, change of supply chilled water, and supply/return temperature difference. Where, the

Fuzzy output is return temperature and chilled water control valve. The system provides with two sensors for temperature (T_i) and fluid flow in tank (*gpm*).

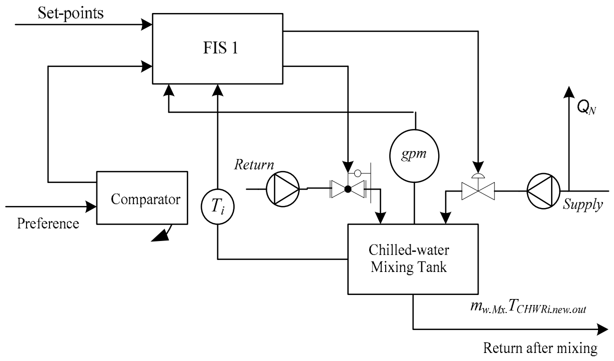

Fig. 3 Control system for cooling loop by FIS1

At peak load hours, the chilled-water flow rate mixes with a σ_i % to reduce $T_{CHWR.new}$ and ΔT based on Eqs. (8, 9), while at off-peak hours the flow rate is constant. In Figures 1 & 3 the isolated do-valve allows to mix about σ_i% of total chilled-water supply at 12 ^{O} C, and should be at off position at load below average according to,

$$\mu_i = \begin{cases} 1-\sigma_i, & m_{w.Mx}, t \quad peak \quad hours \\ 1, & m_{w.Mx}, t \quad off.peak \quad hours \end{cases} \tag{19}$$

where σ_i is the ratio of flow rate through control valve to the tank at the supply side. The subsystem contains a module which opens (valve) only when the flow under 2200 gpm (500 m^3/hr, 140 kg/Sec) and T_{CHWRi} above 16 °C at peak loads. Therefore, after mixing the cooling load consumption and electricity cost in Eqs. (12, 13) will be re-written as,

$$R = Minimize \sum_{t=1}^{T} \sum_{i=1}^{N} (\quad (1-\sigma_i)\, n_i . Q_{evap}(i,t)) \tag{20}$$

$$C_i = \delta_{(ON-OFF)} . \sum_{t=1}^{T} \sum_{i=1}^{N} R(i,t) \tag{21}$$

In Fig. 3 two inputs are provided with comparator where it is used to compare chilled-water and return temperature with a reference. The sensors (detectors) are used to differentiate between the previous and updated return temperature and mass of fluid according to its setup for that. The comparator output along with the sensor signal is fed to fuzzy logic controller. For instance, if the chilled-water flow rate above capacity a control valve will open to pass water through piping to the evaporator chilled water return. To evaluate Fuzzy output, the FIS 1 inputs with quantities that are fuzzified or converted to Fuzzy, the conversion of Fuzzy is represented by membership function, and they give the required outputs.

Fuzzy MFs are needed for all inputs and outputs variables to define the linguistic rules that govern the relationships between them. FIS1 inputs/outputs, mixed supply/return chilled-water, change of chilled-water supply, and change of temperature difference, where the required output are $T_{CHWR.out}$ and control valve position for chilled-water at set points as shown in Fig. 4.

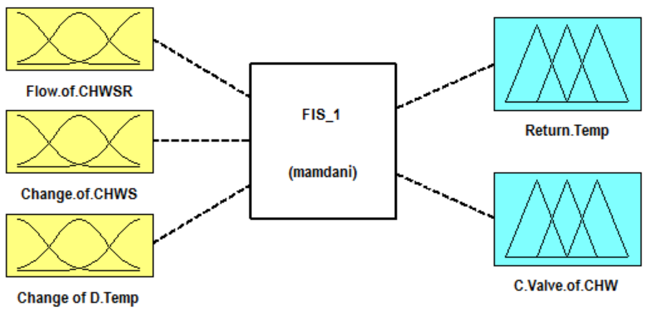

Fig. 4 Fuzzy inputs/outputs

The inputs memberships of controller include these values which are Low, Medium, and High in Figures (5, 6, 7), and Fig. 8 shows the outputs memberships with these constraints which are low, medium low (M. Lw), medium (Med), medium high (M. Hi), and high temperature. While Fig. 9 shows control valve for chilled-water with slowly open (SO), normally open (NO), slowly close (SC), normally close (NC), and at off position (OFF).

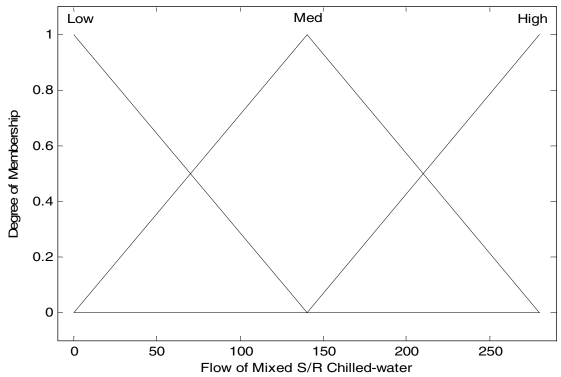

Fig. 5 Fuzzy membership input of mixing chilled water (kg/Sec)

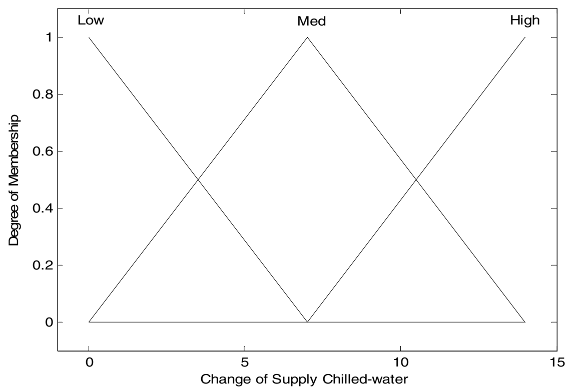

Fig. 6 Fuzzy membership input of change of supply CHW (kg/Sec)

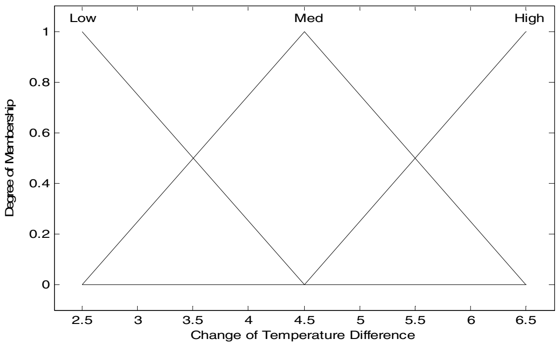

Fig. 7 Fuzzy membership input of change temperature difference

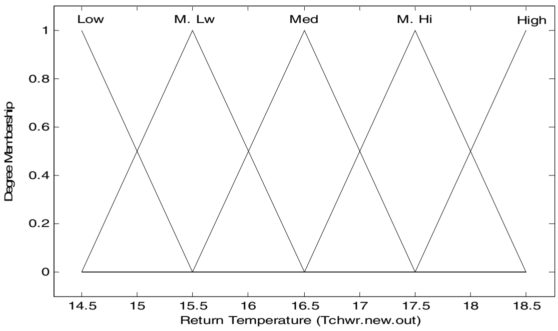

Fig. 8 Fuzzy membership output of return temperature

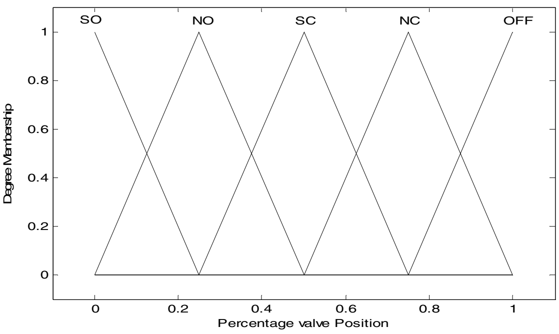

Fig. 9 FIS 1 memberships output of flow change by control valve

The rules for FIS1 are 27 rules, a few of them are;

If (Flow of CHWSR) is Low and (Change of CHWS) is Med and (Change of D.Temp) is Med, then the (Return Temp) is M. Lw and (C. valve of CHW) is NO,
If (Flow of CHWSR) is Med and (Change of CHWS) is High and (Change of D.Temp) is High, then the (Return Temp) is M. Hi and (C. valve of CHW) is SC,
If (Flow of CHWSR) is High and (Change of CHWS) is Med and (Change of D.Temp) is Low, then the (Return Temp) is Med and (C. valve of CHW) is Normally Close,

After implementing Fuzzy, the supply chilled water has been mixed with return (return is 140 kg/Sec, 2200 gpm) by $\sigma_i = 4.76$ % which is 110 gpm (7 kg/sec) for 5 chillers. Fuzzy Timer (FT) starts to reduce cooling consumption at daytime, but during off-peak $\sigma_i = 0$, so the FT does not be scheduled the sequence of time, and therefore Fuzzy does not allow isolated-do valve to be opened at all.

The second reason for Fuzzy (which is FIS 2) in this work is to combine with PSO. This is in order to adjust dynamically learning factors based on [21]. The normal PSO parameters have been setting as $c_1 = 1.882$, $c_2 = 1.764$, CF = 0.311, iteration = 100, max iter = 200, swarm size = 30, $W_{min} = 0.45$, and $W_{max} = 0.95$. The FPSO has same parameters except c_1 and c_2 [21] and with weight inertia (W) have been adjusted dynamically.

IX. Fuzzified PSO Results and Discussion

The procedures of implementing FPSO to solve the optimal problem, the following steps should be taken:
Step 1 define and generate the PSO initial parameters *i.e* initial position and velocity for each particle (0,0).
Step 2 generate the initial parameters for position and velocity for each particle randomly.
Step 3 adjust the set-points using FIS 1 according to Eqs. (7, 8, and 9).
Step 4 evaluate the objective function of each an individual particle based on Eqs. (20, 21)
Step 5 adjust the learning factors (c_1, c_2) [21], and weight inertia (W) dynamically using FIS 2.
Step 6 select the best local position (Bbest) of each individual particle with a minimum value.
Step 7 select the best global position (Gbest) of particles with the minimum objective function.
Step 8 update velocity for each individual particle that should be calculated according to Eq. (14).
Step 9 modify velocity Eq. (17) for each individual particle that should be calculated in based on Eq. (18).
Step 10 update position for each individual particle that should be calculated based to Eq. (15).
Step 11 update the weight inertia (W) according to equation (16).
Step 12 check the stopping criteria if satisfied to stop else repeat from step 4 until to be satisfied.

In algorithm steps, FIS acts as estimator for return temperature and a dynamic adjuster for the learning factors and inertia. The cooling capacity by FIS is optimized by PSO with a minimum of cooling load consumption. Matlab simulation has conducted for three methods and carried out compared to the existing system (a case study).

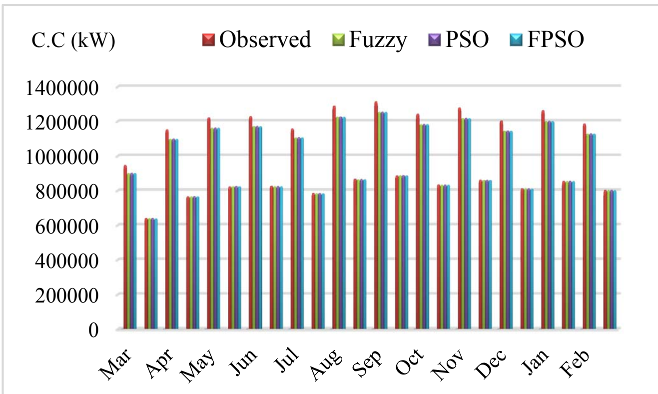

Fig. 10 The comparison of chillers cooling capacity (C.C)

The results of the comparison have shown in Fig. 10. However, the FPSO has demonstrated the effectiveness for saving cost and reducing consumption by 3.61 % of total energy consumption. While the saving of PSO and FIS are 3.56 % and 3.54 %, respectively. The present work also has reduced the electricity cost (bill) by *RM* 264482 of the total cost per-year. Compared to computational time (CT) and saving using Intel (R) Core ™ i5-3470 CPU@3.20 GH, three programs have conducted, 200 iter each and the outcomes shown in Table 3.

Table 3. Comparison for saving and computational time

Method	Fuzzy	PSO	FPSO
Saving bill (*%*)	3.54	3.56	3.61
Saving (*kW/yr*)	671026.7	674817.8	682400.0
CT (*in Second*)	13.98972	12.68447	12.37536

X. CONCULSION

The work in this paper formulates a PSO problem to find an optimal energy set-points for chiller plant management. This suggests Fuzzified particle swarm optimization (FPSO) in order to; overcome the PSO deficiency which is represented in C1 & C2 [21] and weight inertia. Then, optimal energy management is gotten at each step hours to fix the cooling load at off-peak hours, whilst it mitigates at peak hours using Fuzzy control and then optimize using PSO. Using Matlab, simulation results have shown the significant of FPSO for reducing by 3.61 % of the total both energy consumption and electricity cost. Also, it has met the cooling demand after operating conditions set-points.

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