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MODEL BEHAVIOROF COOLING PLANT USING SUBTRACTIVE CLUSTERING ANFIS AT UNIVERSITY BUILDINGS

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ABSTRACT

The chiller that is used to provide cooling for buildings consumes high power, especially if not optimally operated. Thus, the use of demand response (DR); it is an important aspect of demand side management can be employed to reduce power consumption. This paper proposes cooling models to solve the complexity of chillers behavior at the demand-side using a hybrid technique. A hybrid technique of subtractive clustering adaptive neuro-fuzzy inference system (SC-ANFIS) is used to construct the model according to real operating data to manage and control the chillers cooling behavior. The obtained results demonstrate the SC-ANFIS improve system performance, tune the cooling temperature, and reduces energy consumption. The SC-ANFIS is validated with gas district cooling operating in UniversitiTeknologi PETRONAS

Keywords: Cooling Models, Subtractive Clustering (SC), Adaptive System (ANFIS)

1. INTRODUCTION

Three major concepts in demand side management which include energy efficiency (EE), energy conservation (EC), and demand response (DR). DR at a user is most important towards reducing energy consumption and increasing efficiency (Hamid, Nallagownden et al. 2014).

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It is used to change the buildings response from on-peak to off-peak to have advantage of lower billing rates (Ashrae 2011). Globally, the demand for cooling consumption in buildings account for 40% of the total energy consumption (Wei, Xu et al. 2014, Ahmad, Mourshed et al. 2016). In Malaysia, it accounts for 58% of total energy in buildings (Saidur 2009, Sadrzadehrafiei, Mat et al. 2011). This is expected to increase even more in the coming decades as a result of population growth and rising temperature of climate change. It has been observed that, the chiller(s) within a cooling system consumes the most energy than other components. Thus energy consumption be higher if the chillers are not operated optimally. This necessitate the need for optimizing the operating set points of the chillers to achieve energy conservation. This study proposes to have a multi-clustering ANFIS to simulate the cooling behavior at building demand. System description and modeling are given in section 2. Then, section 3 presented a system methodology and simulation procedure. Section 4 discussed the obtained results. Then, finally theconclusion will be drawn in section 5.

2. SYSTEM DESCRIPTION

The gas district cooling (GDC) for UniversitiTeknologi PETRONAS (UTP) is designed to produce the chilled water by chillers to cater requirements of cooling facilities to consumers. The chilled water system in the plant consists of two steam absorption chillers (SAC), four electrical air chillers (EC), and thermal storage system (TES). The total capacity of the cooling load produced by chillers about 4000 RT.

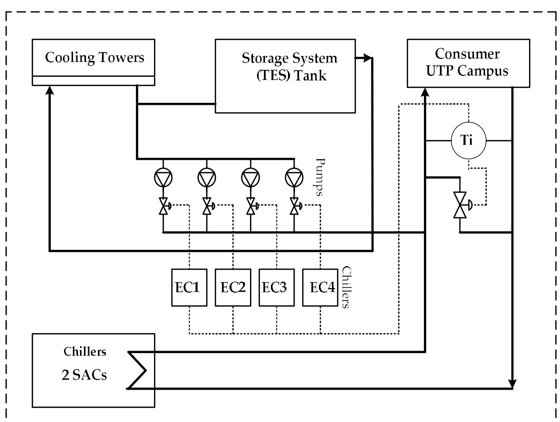


Fig.1. GDC diagram of chilled water **(May, Nor et al. 2011)**

This study in this paper is to develop cooling behavior models oftwo SAC in UTP plant for cooling facilities. The models to investigate the system operation. The modelsare energy consumption (Q_e), cooling load (Q_c), cooling water return temperature (T_{CWR}), and coefficient of performance (*COP*). Table 1 shows the standard design for parameters values for each of the SAC, while real operating data will be used for the simulation of the cooling system based on SC-ANFIS.

Table 1. The standard design values for each a SAC

Chiller variables	Value
CHW flow rate (m^3/hr)	504
CW flow rate (m^3/hr)	920
CHW supply/return temperature (°C)	6/13.5
CW return/supply temperature (°C)	32/39.5
Cooling load (kW)	4395
Cooling capacity (RT)	1250
Cooling rate efficiency (q_r)	3.90
Fuel gas consumption (kg/h)	4875
Cooling fan consumption (kW)	44
Coefficient of performance (COP)	1.35

3. METHODOLOGY

A 480 of sampling data (20 days) were collected for developing the models using SC-ANFIS. The model will be developed to optimize the behavior of the system. To simulate the models, four steps were implemented using the data classified and categorized into 7 groups. Each group has one cluster center assigned according to fuzzy substantive clustering method stated in the following steps:

- first set the collected data to be classified to 7 clusters, (K = 7)
- Determine a minimum and maximum value for each value
- Place or assign centroids for thecluster mean to be input to the ANFIS
- Stop when none of the cluster assigned change.

3.1 Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a logic controller introduced in 1993 by *Jang et. al.*(Jang 1993). It is a combination of artificial neural networks (ANN) and fuzzy inference system (FIS). The ANN and FIS have good capabilities and interpretability for learning methods and both are used as the expert system (Hadi Abdulwahid and Wang 2016).

The combination of these two techniques benefits a great success to overcome the limitation of ANN and FIS when used separately (Al-Hmouz, Shen et al. 2012, Moon, Chang et al. 2013, Collotta, Messineo et al. 2014, Elena Dragomir, Dragomir et al. 2015, Hadi Abdulwahid and Wang 2016). Figure 2 shows the structure of ANFIS used to simulate cooling behavior of SAC that resulted in optimal demand-side. The proposed system will be simulated based on real system data. Then, four models are developed and simulated based on 16 input variables.

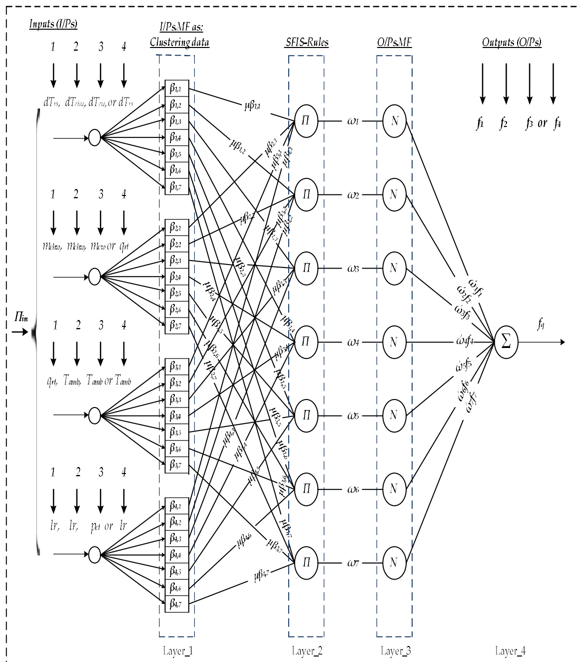


Fig.2. The structure of adaptive system (ANFIS)

3.2 Data Collection and Clustering

In order to simulate the models according to variables, the real data is provided by the GDC staff in UTP. The collected data from 5 to 25 December 2016 includes T_{CHWR}, T_{CHWS}, T_{CWS}, T_{CWR}, q_c, P_{ct}, q_u, m_{CHW},m_{CW}, l_r, T_{amb}, and *COP*. *Let,* $T_{CHW} = T_{CHWR} - T_{CHWS}$, $T_{CW} = T_{CWS} - T_{CWR}$, T_{RS}, $T_{CWR} - T_{CHWS}$. The real data were set and classified into 7 groups and then implemented with SC-ANFIS to simulate and optimize cooling behavior models for demand-side. The actual-data which have been classified into 16 input variables to represent the coolingbehavior models which can express by Eq. (1),

$$\begin{bmatrix} Model_{q\#1}^{1} \\ Model_{q\#2}^{2} \\ Model_{q\#3}^{3} \\ Model_{q\#4}^{4} \end{bmatrix} = [\pi_{in}] \begin{bmatrix} p_{qi}^{1} \\ p_{qi}^{2} \\ p_{qi}^{3} \\ p_{qi}^{4} \end{bmatrix} + \begin{bmatrix} p_{q0}^{1} \\ p_{q0}^{2} \\ p_{q0}^{3} \\ p_{q0}^{4} \end{bmatrix} \quad (1)$$

Where p^{i}_{q0} and p^{i}_{qi}(i =1, 2, …,m) are model parameters of input data and Π_{in} is input variables matrix; which is expressed by,

$$\pi_{in} = \begin{bmatrix} T_{RS} & m_{CHW}q_c & l_r \\ T_{CHW} & m_{CHW}T_{amb} & l_r \\ T_{CW} & m_{CW}T_{amb} & p_{ct} \\ & T_{RS}q_cT_{amb}l_r & \end{bmatrix} \quad (2)$$

The variable elements will be defined as T_{RS} = T_{CWR} - T_{CHWS}, q_c = cooling load rate, T_{CHW} = T_{CHWR} - T_{CHWS}, T_{CW} = T_{CWS} - T_{CWR}, and T_{amb} which is obtained from Ipoh weather data (Malaysia December 2016).

3.3 ANFIS Simulation and Optimization

After data classification, ANFIS was used to carry out the simulation with a system configuration given in Table 2.

Table 2. The ANFIS configuration for each model

Configuration	Value
Type	Sugeno
No. of inputs	4
No. of outputs	1
And method	Prod
Membership functions	Gaussmf
Or method	Sum
Implication	Prod
Aggregation	Sum
Defuzzification	wtaver

The simulation was executed in two parts; the training data and the checking datausing Fuzzy Logic Toolbox. The 480 of the data which is 65% of data sample points are used as training data selected randomly from the UTP GDC recoding. The remaining 35% of the data sample points is used as checking data to validate the ANFIS models. There are 4 input parameters for each model as shown in Figure 2 and the construction of the fuzzy memberships based on the 4-7-7 Gaussian inputs shown in Figure 3. The SC-ANFIS for the training data used a hybrid learning algorithm, epochs, and root mean square error (RMSE) to identify consequent parameters of first order Sugeno Fuzzy Inference System for optimizing Q_e, Q_c, T_{CWR}, and *COP*. After training process, the checking data was used to validate the models. To determine the fitness performance, the RMSE for training and checking data must be as little as possible of the required SFIS model (Q_e, Q_c, T_{CWR}, *COP*). In both cases, a minimization error used to obtain training/checking data up to 165 epochs.

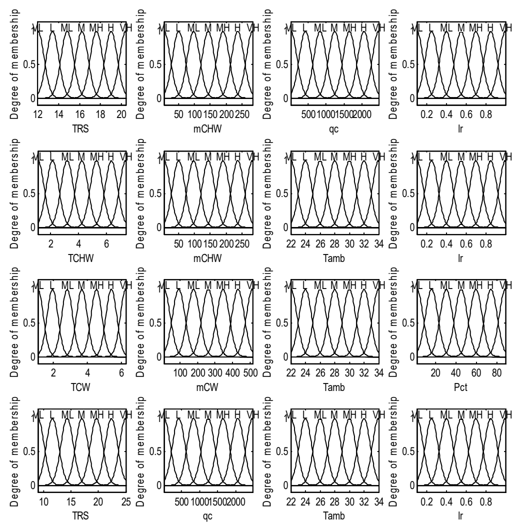


Fig.3. The MFs sets of S-FIS; Model#1: Energy consumption, Model#2: Cooling load capacity, Model#3: Cooling water return temperature, and Model#4: Coefficient of performance.

The flow chart of the SC-ANFIS algorithm was used to implement the cooling system is presented in Figure 4.

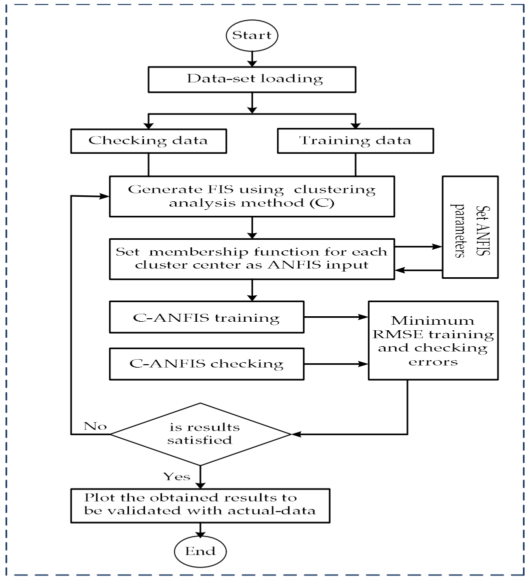


Fig.4. The SC-ANFIS chart

The models confidence of the SC-ANFIS compared to the ANFIS using real data have been verified with the standard deviation (STD) and standard mean error (STR). Thus, it can be expressed by,

$$STD = \sqrt{\frac{\sum(data\ points - data\ mean)^2}{No.of\ data\ points}} \tag{3}$$

$$STR = \frac{STD}{\sqrt{No.of\ data\ points}} \tag{4}$$

4. RESULTS AND DISCUSSION

The system was implemented in MATLAB Environment using Fuzzy Logic Toolbox. Two techniques were implemented based on ANFIS (Franco, Dall'Agnol et al. 2011)and SC-ANFIS. The ANFIS was based on 6 MFs, while SC-ANFIS used 7 MFs. After implementation these two techniques, the parameters values for models arepresented in Tables 3 - 4.

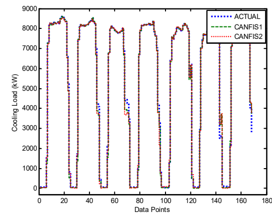
Table 3. ANFIS parameter for models based 6 rules and memberships (Franco, Dall'Agnol et al. 2011)

ANFIS	**Q_e**	**Q_c**	**T_{CWR}**	**COP**
No. of nodes	67	67	67	67
No. of LP	30	30	30	30
No. of n-LP	48	48	48	48
Total No. of P	78	78	78	78
No. of inputs	4	4	4	4
No. of rules	6	6	6	6
No. of epoch	165	165	165	165
RSME for TD	143.6710	12.1535	0.9846	0.0765
RSME for CD	173.4917	16.8286	1.0163	0.0702

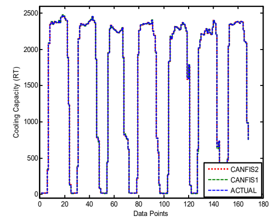
Table 4. SC-ANFIS parameter for models based 7 rules and memberships

SC-ANFIS	Q_e	Q_c	T_{CWR}	COP
No. of nodes	77	77	77	77
No. of LP	35	35	35	35
No. of n-LP	56	56	56	56
Total No. of P	91	91	91	91
No. of inputs	4	4	4	4
No. of rules	7	7	7	7
No. of epoch	165	165	165	165
RSME for TD	125.1266	10.4900	0.9334	0.0657
RSME for CD	172.0349	14.3621	0.8778	0.0578

The obtained results of models and their error using SC-ANFIS as shown in Figure 5. Figure 5 (a) shows the energy consumption Q_e,from the results,Q_e has good agreement with the real plant data after adjusting the four input variables. The actual energy consumption was about 906255.7 kW, while SC-ANFIS was about 901882.3 kW with a saving of 4373.4 kW. Figure 5 (*b*) shows the obtained results of cooling load capacity $Q_c$model. The Q_c model was consistently similar and typical to the real data. The actual cooling capacity was 254682.7 RT, while using SC-ANFIS was about 254655.6 RT with negligible error 27.2 RT (0.011%) and it was able to maintain the requirement of daily UTP demand for the cooling facilitiesduring a period of 07:00 to 23:00 hr.



(*a*)



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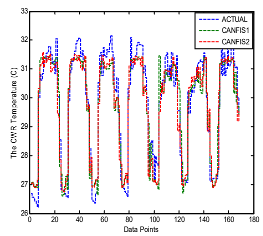
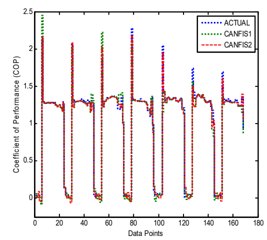


(*c*)



(*d*)

Fig.5. SC-ANFIS Results for SAC cooling behavior ; (*a*) Energy consumption; (*b*) Cooling load capacity; (*c*) Cooling water return temperature; (*d*) COP (per unit)

The temperature T_{CWR} considers one of the most influential variable for increasing efficiency in chillers. As reported in (Browne and Bansal 1998, Avery 2001, Lu and Cai 2001, Wang 2001,Lu, Cai et al. 2004) the reducing T_{CWR} was resulted in improving performance and reducing consumption. Therefore, Figure 5 shows (c) the real plant data of T_{CWR} were ranged between 30.6 to 32.2°*C*. Meanwhile, the proposed SC-ANFIS showed better for the cooling temperature results ranged between 30.65°C-31.24°C.

Table 5. T_{CWR} average values during running hours

T_{CWR}	Actual	ANFIS	SC-ANFIS
Day#1	31.07	31.19	30.96
Day#2	31.11	31.00	30.98
Day#3	31.28	30.76	30.83
Day#4	31.24	30.94	30.90
Day#5	30.65	30.72	30.54
Day#6	30.69	30.54	30.66
Day#7	31.14	30.88	30.92

GDC plant at UTP (Lemma and Hashim 2011) not only increased chillers efficiency, but also committed MSB for excellence to the OHSE in Malaysia. The COP results obtained from the simulation represented daily energy efficiency of the chillers which is given in Table 6.

Table 6. COP average values during running hours

COP	Actual	ANFIS	SC-ANFIS
Day#1	1.26	1.26	1.26
Day#2	1.30	1.28	1.30
Day#3	1.32	1.34	1.31
Day#4	1.28	1.28	1.27
Day#5	1.36	1.33	1.33
Day#6	1.32	1.31	1.30
Day#7	1.30	1.27	1.28

The COP ranged from 1.26 to 1.33 which obtained from Figure 5 (*d*) based SC-ANFIS. Compared to the actual data, ANFIS, and recommended, the SC-ANFIS was better.It can be concluded that the lower COP means higher cooling rate efficiency (qr). The actual and simulation results were shown in Figure 5 (*d*) where a transient case occurred because of the first moment of SAC operation. Then, the fuel gas consumed gradually and could not give enough heating until reach to a maximum supply of fuel gas. Therefore, after supplying a 4875 kg/h, each SAC produces a cooling capacity of 1250 RT, then it operates at full load with a COP of 1.35.

5. PERFORMANCE AND VALIDATION

The models have been simulated using SC-ANFIS which was compared with ANFIS (Franco, Dall'Agnol et al. 2011) using the real plant data. To do this, a comparison is made in Table 7 based on a statistical analysis software (SAS). The SAS was used to analyze the simulation results using the analytical equations in (3 – 4). The obtained results showed that the SC-ANFIS is a compromising techniques and superior compared to other AI methods. Based on the findings, the proposed model demonstrated based SC-ANFIS with 7 MFs was better in terms of good agreement. The performance analysisdemonstrates that compared to the ANFIS in Table 7which used 6 fuzzy rules and memberships.

Table 7. The statistical analysis measures for the SAC models

Method	Model	STD.DEV	STD.ERR
Actual	Q_e	3459.00	266.867
ANFIS	Q_e	3477.79	268.317
SC-ANFIS	Q_e	3772.57	267.914
Actual	Q_c	1015.87	78.3760
ANFIS	Q_c	1016.22	78.4031
SC-ANFIS	Q_c	1015.99	78.3861
Actual	T_{CWR}	1.87126	0.14437
ANFIS	T_{CWR}	1.71766	0.13252
SC-ANFIS	T_{CWR}	1.72387	0.13300
Actual	COP	0.57899	0.04466
ANFIS	COP	0.58070	0.04480
SC-ANFIS	COP	0.57896	0.04468

6. CONCLUSION

Recently, adaptive neuro-fuzzy inference system became one of the most dominant technique in energy management, control, and system modeling. This paper developed ANFIS models for investigating UTP SAC cooling behavior with real plant data. The real data were categorized into clustering sample points used as the input variables (16) to ANFIS. The 4 developed models were optimized using 7 fuzzy rules with memberships function. The simulation of the ANFIS was compared with using 6 fuzzy rules in (Franco, Dall'Agnol et al. 2011). The obtained results showed that the proposed study better in terms of accuracy and efficient tool in terms of simulation. The cooling behavior models have reduced energy consumption by 4373.4 kW of total energy GDC consumption at UTP demand-side. The testing models based SC-ANFIS wereverified according to the SAS which showed an excellence agreement as presented in the validation section.

LIST OF SYMBOLS

T_{amb} Ambient temperature

T_{CHWS} Chilled water return temperature

T_{CHWS} Chilled water supply temperature

q_{rt} Cooling load rate

q_cCooling load

m_{CHW} Chilled water flow arte

lr Partial load ratio

T_{CWS} Cooling water supply temperature

T_{CWR} Cooling water return temperature

m_{CW} Cooling water flow arte

Q_e Energy consumption

P_{ct} Input power to the tower fan

RSME Root square mean error

No. of LP Number of linear parameters

No. of nLPNumber of nonlinear parameters

To. No. of P Total number of parameters

TD Training data

CD Checking data

MSB MakhostiaSdnBhd, Malaysia

OHSE Standard, Health, Safety and Environment

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