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Operating Point Estimation for an Absorption Process using Data Clustering Technique

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Abstract: As part of a tri-generation plant, an absorption process provides the means to recover the energy that otherwise would be lost to the environment. Since the overall efficiency relies on the amount of energy recovered in all subsystems, knowing the current performance of the absorption process is vital to proper management of the resources. This study proposes the use of data clustering technique to estimate the most frequent operating point experienced by the absorption system in a given year. The same technique is applied to identify operating point trajectory of the system over nine years. In order to demonstrate applicability of the proposed approach, an absorption system that is comprised of two 12 ton h^{-1} heat recovery steam generators and two 1250 RT double-effect $LiBr\text{-}H_2O$ steam absorption chillers is considered as a case study. It was observed that data clustering technique is an effective method in establishing the relationships between the supplied heat and the amount of energy recovered by each subsystem. The heat recovery steam generators were identified as operating at part load ratio of about 0.41. The clustering method clearly revealed that both chillers deteriorated in performance. The absorption systems were mostly run at part load ratio of about 0.8. As such, at this operating point the energy demand was by 43% higher than that required for a healthy system. The proposed technique is applicable for performance monitoring, optimization and multi-state reliability studies of the absorption system.

Key words: Waste heat, absorption process, data clustering, steam absorption chiller, heat recovery steam generator

INTRODUCTION

In a tri-generation plant, absorption process provides the means to recover the energy that otherwise would be lost to the environment. The use of Steam Absorption Chillers (SACs) was resorted to increase the overall thermal efficiency of a system to as high as 73 to 90% (Hordeski, 2011; Dincer and Zamfirescu, 2011). SACs are also preferred to vapor compression chillers since they use less electricity to drive the solution pumps and use waste heat to create cooling potential. They are also considered environmentally friendly as they use $LiBr\text{-}H_2O$ solution as working fluid, which is not a halocarbon-based refrigerant.

The performance of an SAC has to be monitored at all times to ensure that the system is not deteriorated severely and thus affecting economic operation of the system. Knowing the current performance is also critical to properly manage the available resources under actual operating conditions.

Performance characteristics of an absorption process can be demonstrated in different ways. One way is to use artificial neural network to describe variation of coefficient of performance, exergetic efficiencies and working fluid properties (Chow *et al.*, 2002; Sozen *et al.*, 2003; Manohar *et al.*, 2006; Sencan *et al.*, 2006; Tamiru *et al.*, 2009; Cascales *et al.*, 2011; Congradac and Kulic, 2012; Labus *et al.*, 2012). Sozen *et al.* (2004) studied application of fuzzy systems to absorption system modeling. A comparison test on alternative multivariable regression models is addressed in the study of Puig-Arnavat *et al.* (2010). It turns out that though the stated approaches are effective enough to capture characteristics of the system over the whole operating regions, they are short of

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revealing how the system deteriorates with time. The later aspect is specifically important in multi-state reliability modeling (Muhammad *et al*., 2010) and optimization of the available resource under realistic conditions.

Data clustering techniques (Jain *et al*., 1999; Fung, 2001), on the other hand, has the capacity to systematically find similarities in a given data set. It has been used successfully for object recognition, pattern segmentation and information management. In relation to thermal systems, data clustering methods was applied to optimize combustion efficiency of a coal-fired boiler (Kusiak and Zhe, 2006) and efficiency of electric-utility boiler (Song and Kusiak, 2007). To the authors' knowledge, there is no previous work on the use of clustering method in the performance analysis of an absorption process.

The objective of this study is to test the feasibility of data clustering technique in the performance monitoring of an absorption process. Non-dimensional performance parameters are first calculated and the data clustering method is applied to the resulting input-output data with the intention of identifying a cluster center that would be considered representative of the operating points.

MATERIALS AND METHODS

Overview: The block diagram representing a generic absorption system is illustrated in Fig. 1. The SAC is connected to the Heat Recovery Steam Generator (HRSG) through the Steam Header (SH). Each HRSG uses exhaust gas from a gas turbine. The HRSG is critical to increase the cogeneration efficiency. The absorption system was considered operated by the steam produced by the HRSG. It was further assumed that the steam absorption chillers were all driven by the saturated steam tapped from the steam header. The SAC was responsible for the cooling effect needed to cool the water required for cooling of academic buildings. Since each component involved energy and mass transfer, the equation for a Steady State Steady Flow (SSSF) system was applied to each subsystem.

The steps, used to achieve the objectives are as follows:

- **Step 1:** Preparation of a database for the working fluid properties that could be accessed at ease during model simulation. The whole system involved exhaust gas, steam, saturated water and LiBr-H_2O solution. Hence, it was necessary that a suitable database was arranged either in terms of look-up tables or regression equations. In the present study, set of empirical equations were used
- **Step 2:** Reliable hourly data was selected corresponding to peak hour operations. Absorption chillers were ideally suitable for base load applications. However, they were not used to charge a thermal storage system because of the limitations in the lower temperature they achieved. In most cases, they were operated starting at around 6:00 a.m. and stopped at about 7:30 p.m. On a daily basis, they experienced transient conditions in the first 45 min and the last 30 min of the operation duration. For the reason that the system did not stay longer in transient conditions as compared to the steady state region, it is not important to consider the transient data in the evaluation of the system performance over a long period of time

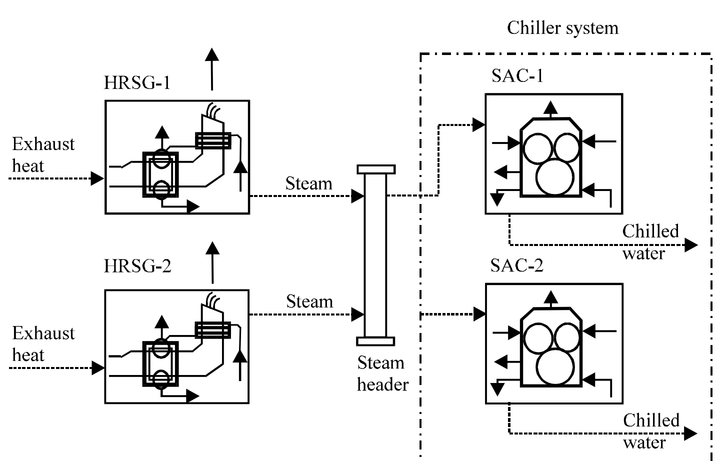

Fig. 1: Flow sheet for steam and absorption process

Table 1: Excerpt of actual data collected from SAC monitoring system

Hour	RT	m_{st} ($M^3 h^{-1}$)	P_{st} (kPa)	m_{ch} ($M^3 h^{-1}$)	$T_{ch,in}$ (°C)	$T_{ch,out}$ (°C)	$T_{co,in}$ (°C)	$T_{co,out}$ (°C)
0:00	0	0	80	0	7	6	31	31
1:00	0	0	66	0	7	6	31	31
2:00	0	0	57	0	8	7	30	31
3:00	0	0	51	0	8	7	30	30
4:00	0	0	41	0	9	7	30	30
5:00	0	0	35	0	9	8	29	30
6:00	496	77	334	66	10	8	28	29
7:00	620	5435	785	300	13	8	28	32
8:00	643	5460	806	301	13	6	29	34
9:00	932	5493	806	399	13	7	30	35
10:00	737	5614	804	504	13	9	30	36
11:00	707	5584	804	504	13	9	30	36
12:00	727	5562	805	504	13	9	30	36
13:00	716	5583	804	504	13	9	30	36
14:00	708	5563	805	504	13	9	30	36
15:00	719	5566	805	504	13	9	31	36
16:00	698	5542	805	504	13	9	31	37

RT: Ton of refrigeration, m_{st}: Mass flow rate of steam, P_{st}: Steam pressure, m_{ch}: Mass flow rate of chilled water, $T_{ch,in}$: Chilled water inlet temperature, $T_{ch,out}$: Chilled water outlet temperature, $T_{co,in}$: Cooling water inlet temperature, $T_{co,out}$: Cooling water outlet temperature

- **Step 3:** For each hourly operation, energy balance was applied to calculate for Part Load Ratio (PLR) and Part Load Factor (PLF)
- **Step 4:** Tabulate the hourly data over a year. Excerpt from one day operation is demonstrated in Table 1. Similar set of data were collected for each operating day and arranged in a matrix to make it suitable for the data clustering process
- **Step 5:** Data clustering technique was applied to the input-output data in order to determine the cluster centers. The cluster centers would be considered to characterize the system in a given year
- **Step 6:** Steps, 1 to 5 were repeated for each year in the considered time span

Properties of working fluids: In applying the energy conservation equation to the components of the absorption process, specific enthalpy at the inlet and outlet, respectively, of each component was calculated. The enthalpy is a function of stagnation temperature T and pressure P and Air and combustion product are mixtures of such gases as N_2, O_2, Ar, CO_2 and Ne. Hence, for the i-th specie in air mixture or combustion product, the specific enthalpy was calculated by:

$$h^{(i)} = \int_{T_0}^{T} C_p^{(i)}(T)dT + h_0^{(i)} \tag{1}$$

where, T_0 and $h_0^{(i)}$ represent temperature and specific enthalpy, respectively, at the reference point or dead state, $C_p^{(i)}(T)$ is the specific heat at constant pressure. In Eq. (1), the empirical equations for $C_p^{(i)}(T)$ that correspond to air and combustion products were taken from the literature (Walsh and Fletcher, 2004). For the combustion product, $C_p^{(i)}(T)$ is a function of Fuel-to-Air Ratio (FAR). The empirical equation for the combustion gases were also adopted from the same literature. Using Eq. 1, specific enthalpy of the working fluid were approximated by Eq. 2:

$$h = \sum_i n_i h^{(i)} \tag{2}$$

where, n_i is the mass fraction for i-th specie. Empirical equations applicable for estimation of steam properties for a given temperature and pressure are adapted from standard gas tables (Irvine and Liley, 1984).

Heat recovery steam generator (HRSG): The exhaust gas from a Gas Turbine Generator (GTG) is used as energy source to run the HRSG. The purpose of the HRSG is to produce saturated steam at 0.85 MPa by taking feed water at a temperature of about 90°C. A diverter damper at the inlet controls the amount of exhaust gas admitted to the HRSG. For loads higher than 30% of nominal capacity, a three-element controller is used to ensure constant water level in the steam drum. The pressure in the steam drum is made stable by controlling the position of the diverter damper in response to the pressure feedback. Assuming multiple HRSG in the absorption process, for i th HRSG, the energy transferred to the feed water was calculated by:

$$\dot{Q}_{H,st}^{(i)} = \dot{m}_s^{(i)}(h_g - h_f), \quad i = 1,2,...,n_h \tag{3}$$

where, $m_s^{(i)}$ is the steam flow rate, h_g is enthalpy of saturated vapor at 0.85 MPa, h_f is enthalpy of saturated liquid at 90°C, n_h is the number of HRSG in the system. Heat energy of the exhaust gas, which otherwise would have been lost to the environment, is recovered at the evaporator and economizer. Since, the part of the energy in the blow-down-steam is exchanged to the feed water, the energy balance in Eq. 3 is the combination of all that. Disregarding the effect of the diverter damper, the energy available to the system that includes the gas turbine generator is:

$$\dot{Q}_{total}^{(i)} = \dot{m}_{f,gas}^{(i)} LHV_{gas} \tag{4}$$

where, $m_{f,gas}$ is flow rate of gas fuel, LHV is lower heating value in kJ kg $^{-1}$ K.

One of the parameters commonly used to evaluate the performance of HRSG is efficiency of steam generation $\eta_{H,st}$. This parameter is related to $Q_{H,st}^{(i)}$ and $Q_{total}^{(i)}$ as:

$$\eta_{H,st}^{(i)} = \frac{\dot{Q}_{H,st}^{(i)}}{\dot{Q}_{total}^{(i)}} \tag{5}$$

$\eta_{H,st}^{(i)}$ is being used by the Supervisory Control And Data Acquisition (SCADA) system. Equation 5 is suitable to quantify the amount of input energy recovered by the gas turbine and HRSG. However, it hides the exact amount of energy made available to HRSG. The actual mass and energy experienced by the HRSG are:

$$\dot{m}_g^{(i)} = \dot{m}_{exh}^{(i)} - \dot{m}_{g,bypass}^{(i)} \tag{6}$$

and:

$$\dot{Q}_g^{(i)} = \dot{m}_g^{(i)} (h_{g,in}^{(i)} - h_{g,out}^{(i)}) \tag{7}$$

where, $m_g^{(i)}$ is mass flow rate of the exhaust gas passing through the HRSG, $\dot{m}_{exh}^{(i)} = \dot{m}_{air} + \dot{m}_f$ and m_{air} are mass flow rate of exhaust gas and air, respectively, $h_g = C_{p,g} T_g$ is enthalpy of the exhaust gas, T_g is temperature of exhaust gas in K; $C_{g, g}$ is specific heat of the exhaust gas in kJ kg $^{-1}$ K and at constant pressure.

To calculate the performance parameters, the following relation was used:

$$\dot{Q}_{H,in}^{(i)} = [1 - \eta_{GTG}(1-a)]\dot{Q}_{total}^{(i)} \tag{8}$$

where, η_{GTG} is efficiency of the GTG connected to the HRSG; α is a constant assumed to account for the energy lost in the GTG. Note that Eq. 8 assumed all the lost energy in the GTG was available to run the HRSG. η_{GTG} varies in the range of 0.15 to 0.29 depending up on the electric load.

Steam absorption chiller (SAC): The steam produced by the HRSG was used in the SAC to produce cooling potential. The cooling was used for air-conditioning. SAC worked by exchanging heat between the steam, cooling water and refrigerant. In part of the whole cycle, an absorbent, LiBr, was used to drive the refrigerant vapor. The performance of an SAC was evaluated by applying:

$$\dot{Q}_{S,st}^{(i)} = \dot{m}_s^{(i)} (h_g - h_f), \quad i = 1,2,\ldots,n_s \tag{9}$$

and:

$$\dot{Q}_{S,co}^{(i)} = \dot{m}_{chw}^{(i)} (h_{in} - h_{out}), \quad i = 1,2,\ldots,n_s \tag{10}$$

where, $\dot{Q}_{S,st}^{(i)}$ is the steam energy available to drive the SAC; $\dot{Q}_{S,co}^{(i)}$ is the cooling effect actually available from the system; $\dot{m}_s^{(i)}$ and $\dot{m}_{chw}^{(i)}$ are the mass flow rate of steam and chilled water, respectively and n_s is the number of SAC in the system.

Models in terms of non-dimensional parameters: The performance of the sub-systems in the absorption process was evaluated by using the non-dimensional parameters called Part Load Factor (PLF) and Part Load Ratio (PLR) (Treado *et al*., 2011). The PLR is defined as the ratio between assumed load and rated capacity. The PLF is given by the ratio between the current input energy and the energy needed at the design point, also known as rated demand. In terms of PLF, for i th (I = 1,2,...,n_s) subsystem, the energy usage was calculated by:

$$\dot{Q}_{in}^{(i)}(k) = \left(\frac{\dot{Q}_{rated}^{(i)}}{K_{rated}^{(i)}}\right).PLF^{(i)}.\gamma^{(i)}(k) \tag{11}$$

where, $\dot{Q}_{rated}^{(i)}$ is rated capacity of the subsystem; $\dot{Q}_{in}^{(i)}(k)$ is hourly, weekly or yearly energy consumption; $PLF^{(i)}$ is the part load factor; $\gamma^{(i)}{(k)}$ is the control variable and takes a value in the range of zero to one; $K^{(i)}_{rated}$ is performance at the rated condition. For HRSG and SACs, $K^{(i)}_{rated}$ is equivalent to the thermal efficiency and coefficient of performance (COP), respectively.

Data clustering methods: There are alternative approaches for data clustering. Among them are Principal Component Analysis (PCA), K-Means Clustering, Fuzzy C-Means, Mountain Clustering, Subtractive Clustering, possibilistic clustering and rough set theory. The present study is based on K-means clustering (Wu, 2012) as it is the simplest to apply. The algorithm works first by calculating cluster centers for a given number of clusters. Once the cluster centers are known, the classification of a data point to a cluster is decided based on shortest distance formula. The Euclidian distance form (Babbar *et al*., 2009) is given by:

$$d = (x - \mu_i)^T S^{-1} (x - \mu_i) \tag{12}$$

where, x is the data vector; μ_i is the cluster center; Σ is the covariance matrix.

RESULTS

Application of the proposed method is demonstrated by considering an absorption system having two HRSG and two SAC. The design specifications of the sub-systems are shown in Table 2. The two HRSG were identical in design. Each of them was intended to generate saturated steam at 0.85 MPa by using the exhaust gas from a single-shaft GTG rated 5.2 MW at ISO condition. Details about the GTG are not included for the scope is limited to the absorption system only. The feed water flowing into the evaporator section of the HRSG was preheated by the blow-down steam and exhaust gas at the blow-down heat exchanger and economizer, respectively. The steam, after passing through a steam header, was used to operate the SAC.

Operating points: As stated in the methodology, PLR and PLF were calculated for each HRSG. The clusters were then estimated by using K-means clustering. The program used for K-means was from MATLAB R2008a.

Plots of the operating points and cluster centers calculated for HRSG-1 and HRSG-2 are shown in Fig. 2 and 3, respectively. As can be seen, two clusters seem reasonable to characterize all the operating points. For each HRSG, one cluster seems containing more than 70% of the operating points in a year (Table 3). It can be implied that, based on the percentage of operating points (τ) residing to each cluster, the operating point trajectory can be constructed by choosing the cluster with the highest density.

For both HRSGs, the available energy slightly changes about part load factor of 0.6238. For HRSG-1, 70% of the operating points are featured by a part load ratio of 0.4345 while the rest 30% indicates operating points with a part load ratio of 0.8012. Based on the locations of the clusters, in 70% of the total operating points, about 0.3667 of the PLR that is potentially convertible to steam is lost to the environment. In Fig. 2 and 3, a shift in the operating point from left to right is due to the admission of more exhaust gas into the HRSG.

Considering a two-month data of year 2006, 95% of the operating points indicate that HRSG-1 wasted 47.54% of the input energy to the environment. For HRSG-2, 89% of the operating points are featured by 49.24% of the supplied energy released to the environment.

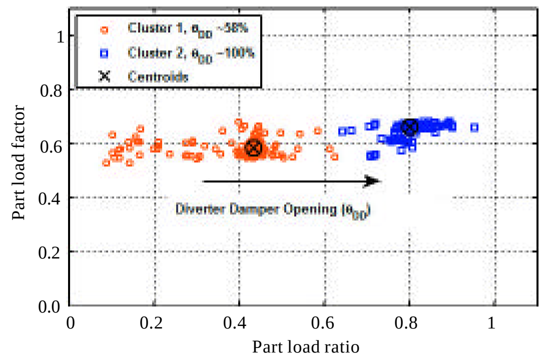

Fig. 2: Performance map for HRSG-1 (Year 2004)

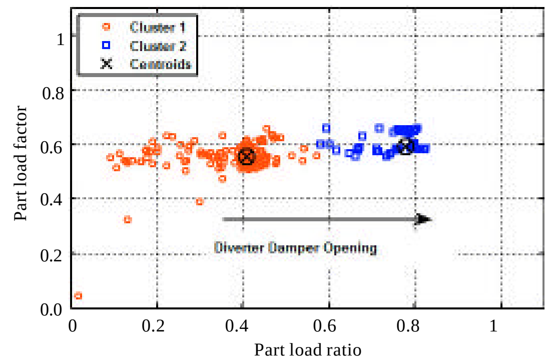

Fig. 3: Performance map for HRSG-2 (Year 2004)

Table 2: Design point data for the main sub-systems in the absorption process

Subsystem	Capacity	Properties of working fluid
HRSG	12 ton h^{-1}	Saturated steam at 0.85 MPa
HRSG-pump	15.5 m^3 h^{-1} and 11kW	Water at temperature less than 100°C
SAC	1250 RT, 5500 kg h^{-1} Steam consumption	Saturated steam at 0.78 Mpa
SAC-pump	920 m^3 h^{-1} and 7.5 kW	Water at temperature less than 100°C

RT: Ton of refrigeration; HRSG: Heat recovery steam generator; SAC: Steam absorption chiller

Table 3: Operating points and percent classification (year 2004)

Cluster parameter	HRSG-1	HRSG-2	SAC-1	SAC-2
μ_{11}	0.4345	0.4081	0.2631	0.9353
μ_{12}	0.5859	0.5569	0.2404	0.9428
μ_{21}	0.8012	0.7793	0.8802	0.2812
μ_{22}	0.6616	0.5920	0.9062	0.2368
τ_1(%)	69.9600	73.5100	14.1800	83.8200
τ_2(%)	30.0400	26.4900	85.8200	16.1800

μ_{11}, μ_{12}, μ_{21}, μ_{22}: Coordinates of cluster centers, τ_1 and τ_2: Percentage of points to each cluster

If the comparison is based on data of year 2009, HRSG-1 operated almost all the time with 42.86% of the input heat lost to the surrounding. Regarding HRSG-2 the energy loss amounts to 43.97% of the input energy. Similar behaviors were observed in the data of other years too.

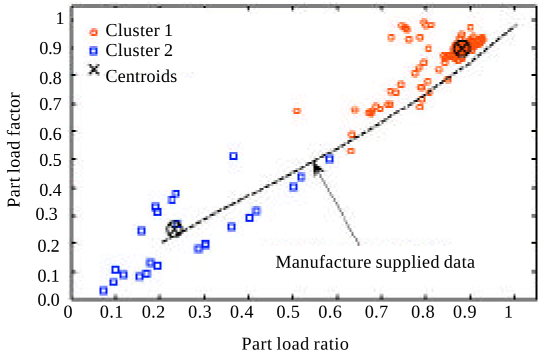

Fig. 4: Performance map for SAC-1 (Year 2004)

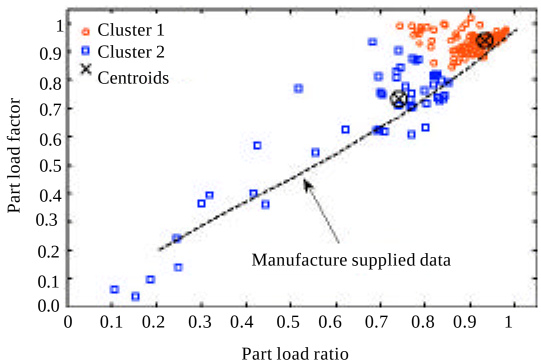

Fig. 5: Performance map for SAC-2 (Year 2004)

Table 4: Cluster location for each year and percent of total data in the cluster

	SAC-1		SAC-2	
Year	Cluster location	τ(%)	Cluster location	τ(%)
2004	0.8802, 0.9061	85.82	0.9353, 0.9427	83.82
2005	0.8126, 0.8087	83.57	0.8656, 0.8763	82.21
2006	0.8030, 0.8306	87.64	0.8188, 0.8285	84.93
2007	0.8139, 0.9840	87.29	0.8552, 0.8810	86.97
2008	0.8051, 1.1071	86.66	0.8037, 0.9287	85.84
2009	0.7624, 1.1233	86.45	0.7606, 1.0543	87.26
2010	0.7575, 1.1770	88.64	0.7059, 1.0236	79.83
2011	0.7478, 1.1702	87.85	0.6745, 1.1535	78.83
2012	0.7255, 1.1639	90.39	0.5594, 0.9881	92.07

τ_1 and τ_2: Percentage of points to each cluster

The SAC considered in the case study were both of double-effect, LiBr-H_2O, absorption chillers. For SAC-1, 88% of the operating points indicated that the system was run at part load ratio of 0.8835. In case of SAC-2, 80% of the operating points were located at part load ratio of 0.93. The scatter plots for the two cases are shown in Fig. 4 and 5, respectively. The two figures also illustrate a trend supplied by the manufacturer. The cluster centers were close to the manufacturer supplied trend since the SACs were still new.

Cluster centers corresponding to nine years data and for SAC-1 and SAC-2 are shown in Fig. 6 and 7, respectively. The calculated values for each cluster

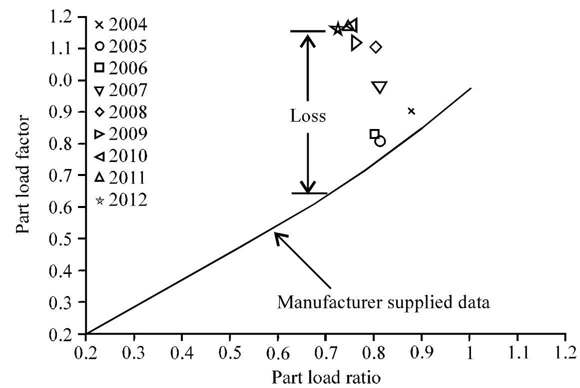

Fig. 6: Performance based on nine years data for SAC-1

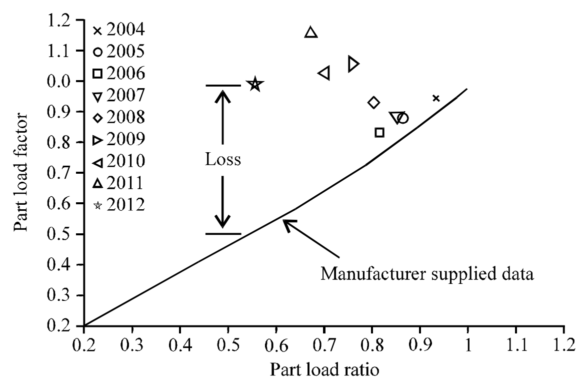

Fig. 7: Performance based on nine years data for SAC-2

centers shown in Fig. 6 and 7 are listed in Table 4. As can be observed from Fig. 6 and 7, both chillers were operated at reduced capacity due to malfunctions. In 2012, the steam consumed by SAC-2 was as high as that needed to run a new chiller at full capacity. Utilizing high quantity of steam, it was able to provide about 0.55 PLR only. SAC-2 needed more than one PLF to operate at 0.75 PLR. This was true for years 2008 to 2012. It can be said that, as compared to SAC-1, SAC-2 deteriorated the most.

DISCUSSION

In general, the use of a heat recovery steam generator increases the overall efficiency to about 80% (Horkdeski, 2011). In the present study, the efficiencies were lesser than expected for most of the energy in the exhaust gas was lost to the environment. The average efficiency of steam generation for each system was about 45%, which made the overall efficiency reduced to 65%. Both SACs demonstrated higher steam consumption for a reduced cooling potential. The deteriorated performance could be attributed to fouling in the cooling water loop, crystallization due high temperature in the generators and air leak into the system. It can be concluded that, direct use of a performance map supplied by a manufacturer to study the SAC that had served for more than three to nine years may lead to erroneous result. To overcome the problem, models need to be developed based on recent actual operation data. In the multiple input multiple output cases, neural network and fuzzy approach could be an ideal solution.

CONCLUSION

The feasibility of data clustering method for the estimation of operating trajectory of an absorption process was tested in this study. By adopting K-means clustering, the objective was successfully achieved. Through analysis of the results, the following conclusions can be made:

In a situation where plenty of measured data are available, K-means is an effective method to clearly demonstrate the most repeated operating points. By using K-means, the operating trajectories of the SACs over the course of nine years clearly demonstrated feasibility of the method.

The HRSG and SAC are all seen deteriorated in performance. Hence, a multivariable regression or artificial neural network model developed on the bases of data from a new engine could not be used directly to optimize operating strategies of the same system served more than three years.

The method presented in the present study can be extended to other parts of the tri-generation plant. Future study will focus on extending the proposed method to thermo-economic and environmental load assessment.

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