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A method for obtaining performance correlations of absorption machines

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Abstract

Several authors have developed models to be implemented in building thermal simulation programs for modelling absorption machines. Some anarchy has been detected related to the order of these models and the variables they consist of. In this paper, specific statistical tools were employed to establish regression models for the *COP* and the capacity of a water-lithium bromide single-effect absorption chiller. Experimental designs were used to obtain the data (values of *COP* and capacity) utilized to estimate the model parameters. The hypotheses initially adopted in the formulation of the models were modified at the sight of the results of subjecting the values obtained for the response variables to a variance analysis.

Keywords: Absorption; Model; Experimental designs; ANOVA

1. Introduction

The development of simulation tools for estimating the energy consumption in air conditioning systems is getting more and more importance. Several models of absorption machines have been developed in order to be implemented in building thermal simulation programs like TRNSYS [1].

The absorption machine model that TRNSYS includes in its standard library corresponding to a water-lithium bromide single-effect machine driven by hot water was developed by Blinn [2]. In this model, second order functions were fitted to describe the relationship between the dependent variables *COP* and capacity, and the generator and the cooling water inlet temperatures, the two independent variables chosen by Blinn.

$$Capacity = \sum_{i=1}^{3}\sum_{j=1}^{3} a_{ij}(T_{\mathrm{cw,i}})^{j-1}(T_g)^{i-1}$$

$$COP = \sum_{i=1}^{3}\sum_{j=1}^{3} b_{ij}(T_{\mathrm{cw,i}})^{j-1}(T_g)^{i-1}$$

The a and b coefficients were obtained by fitting the second order functions to performance data provided by the manufacturer of the machine, a WF-36 ARKLA chiller. Blinn proposed the addition of two new independent variables, the inlet chilled water temperature and the hot water mass flow rate, in order to improve his model.

Instead of using the operation data provided by the manufacturer, the performance of an absorption machine can be obtained by means of thermodynamic models. Koeppel [3] developed a mechanistic model of a water-lithium bromide double-effect direct-fired absorption machine in the environment of EES [4]. From this model, another one was derived to be implemented in the TRNSYS program.

The cooling load met by this TRNSYS model was calculated from the chilled water mass flow rate, inlet temperature and setpoint temperature (given inputs).

$$Q_{\mathrm{load}} = m_{\mathrm{chw}} \cdot Cp_{\mathrm{w}} \cdot (T_{\mathrm{chw,i}} - T_{\mathrm{chw,s}})$$

If the cooling load met by the model was lower than the nominal capacity of the machine then the outlet chilled water temperature was equal to the chilled water setpoint. If not, the cooling load was set equal to the nominal capacity and the outlet chilled water recalculated. The part-load factor was given by

$$PLF = Q_{\mathrm{load}}/Q_{\mathrm{load,nom}}$$

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Nomenclature

COP	coefficient of performance	
Cp	specific heat	$kJ \cdot kg^{-1} \cdot K^{-1}$
Df	degrees of freedom	
m	mass flow rate	$kg \cdot s^{-1}$
PLF	part load factor	
Q	heat transfer rate	kW
T	temperature	K
X	standardised factor value	

Subscripts

cw	cooling water
chw	chilled water
g	generator
hw	hot water
i	inlet
o	outlet
s	setpoint
w	water

This model calculated *COP* as function of four variables using curve fits (fourth order polynomials) obtained by Koeppel from the EES model.

$$COP = f(PLF, T_{\mathrm{chw,s}}, T_{\mathrm{cw,i}}, m_{\mathrm{cw}}/m_{\mathrm{cw,nom}})$$

The EES code developed by Koeppel was a system specific one for a double-effect absorption machine in parallel flow configuration. However, there exist modular nature programs for simulating absorption cycles in different cycle configurations and with different working fluids, like the ABSIM program [5]. In ABSIM, the user has to convey to the program the components that constitute the cycle, how they are interconnected, their heat and mass transfer characteristics, and the cycle operating parameters.

ABSIM was employed by Gommed and Grossman [6] to analyse the performance of a water-lithium bromide single-effect absorption machine driven by hot water. The cycle response to changes in some of its working parameters was investigated following the traditional method, that is, just one parameter was varied while the others were kept constant. However, this way of conducting the study has several disadvantages. First, it demands a high number of simulations; second, the results obtained from the study of each parameter have a restricted validity, since the rest of parameters were kept constant at fixed levels and besides, it does not allow to detect the existence of interactions between the factors.

At the sight of the stated above, it is clear that there are differences between the regression models implemented by the authors in system simulation programs for modelling absorption machines. These discrepancies are related to the order of the models and the variables they consist of.

Several questions arise from the literature review. Is the effect of the two improving independent variables proposed by Blinn really significant? Why did Koeppel fit a fourth order model for *COP*? Which independent variables and which model would choose Gommed and Grossman to represent the performance of the machine they investigated in [6]?

The purpose of this paper is to show the use of specific statistical tools to establish the models that represent the performance of an absorption machine. Experimental designs are used to obtain the data (values of *COP* and capacity) utilized for estimating the model parameters.

The hypotheses initially adopted in the formulation of the models are verified by subjecting the values obtained for the response variables to a variance analysis. Both the effect of the independent variables on the *COP* and the capacity of the machine are investigated, including the presence of interactions between them.

Although this paper is focused on a water-lithium bromide single-effect absorption machine driven by hot water, the applied method is valid for any absorption cycle.

2. Method

A lithium bromide-water single-effect absorption chiller driven by hot water was selected as reference case for this study [6]. Its heat transfer characteristics are shown in Table 1, and its operating parameters at the design point in Table 2.

At the first stage of the study, a set of independent variables (factors) was chosen to build the regression models for the *COP* and the capacity of the absorption machine. Then, preliminary studies were carried out in order to detect

Table 1
Heat transfer characteristics of the absorption chiller

Component	UA ($kW \cdot K^{-1}$)
Evaporator	11.93
Absorber	6.11
Solution heat exchanger	2.03
Generator	8.48
Condenser	17.88

Table 2
Temperatures and mass flow rates at design point of the absorption chiller

	Mass flow rate ($L \cdot s^{-1}$)	Inlet temperature (°C)
Condenser (cooling water)	2.96	29.4
Absorber (cooling water)	3.65	29.4
Evaporator (chilled water)	2.27	12.0
Generator (hot water)	3.14	82.2
Weak solution	0.45	

linear effects and remove from the models those factors that did not have a significant effect on the response variables capacity and *COP*.

The region to be explored was defined by varying the considered factors in a specific interval corresponding to their habitual range of existence. When signs of the presence of second order effects were found, advanced designs were employed in order to build the models.

2.1. Preliminary design for capacity

At this first stage of the study, four independent variables were selected to establish the capacity model, the two employed by Blinn [2], and the two he proposed with the aim to improve his model. Factorial designs were used in order to study the effects that the variation of these factors had on the performance of the machine. Experimental designs are an efficient method, which allows detecting interactions between the factors. These designs employ the analysis of variance (ANOVA) as statistical support [7].

The simplest factorial designs are those in which each factor is studied at two levels. They can only detect linear effects (trends). As we had four factors, the preliminary design was composed of 2^4 treatments (combination of factors at their different levels).

To simulate the treatments that build up each design, a computer code developed by Martínez and Pinazo [8] in the environment of the TRNSYS program was used. The thermodynamic model implemented in TRNSYS to simulate absorption systems is essentially the same as that employed by ABSIM. Slight differences can be found such as using different correlations for the thermodynamic properties of the water-lithium bromide fluid par.

Like ABSIM, this code has a modular nature and allows the calculation of absorption systems in different cycle configurations and with different working fluids. It has been tested against ABSIM for several cycles in a wide range of operating conditions and against measured data from a single-effect absorption machine, with good agreement in both cases [8]. The study presented in this paper can be replicated by simulating the treatments that build up each design with the ABSIM program. The results should be almost identical.

Table 3 shows the study interval of the considered factors. The values of these variables were standardised.

$$X(F) = \frac{F - F_{\text{centre}}}{\Delta F/2}$$

Table 3
Levels and values of the considered factors for the capacity preliminary design

Level	$T_{\text{cw,i}}$ (°C)	$T_{\text{chw,i}}$ (°C)	$T_{\text{hw,i}}$ (°C)	m_{hw} (kg·s^{-1})
−1	24	12	75	1.57
+1	31	16	100	4.72

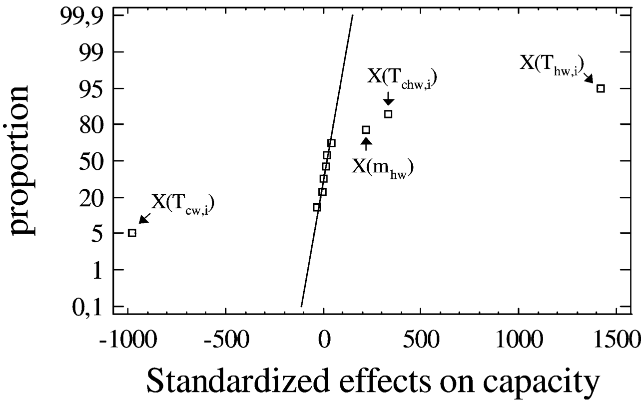

Fig. 1. Normal probability plot for capacity.

Where F is the factor value, F_{centre} the centre of the study interval, and ΔF the extent of that interval. For the inlet hot water temperature, the standardised variable takes value +1 for the high level of the variable (100 °C) and −1 for the low level of the variable (75 °C).

Once the 16 treatments were simulated, the values obtained for the response variable were subjected to a variance analysis. Fig. 1 is a normal plot where those estimated effects considered large with respect to noise in the experiment, are identified. The normal probability plot consists of a horizontal axis scaled for the data and a vertical axis scaled so the cumulative distribution function of a normal distribution plots as a straight line. The closer the data are to the reference line, the more likely they follow a normal distribution.

Suppose that the values obtained for capacity from the experiment had occurred simply as the result of random (roughly normal) variation about a fixed mean, and the changes in levels of the factors had no real effect at all on this response variable. Then the main effects and interactions would have been roughly normal and would have been distributed about zero. They would therefore plot on normal probability paper as a straight line. The effects that do not fit on the reference line are not easily explained as generated by the noise.

As it can be seen, all the main effects significantly contribute to the variance of the response (capacity) since they fall away from the line that defines unimportant effects. All interactions fall on this straight line. According to these results, a first order model was fitted for the capacity.

$$\begin{aligned} \textit{Capacity} = {} & 57.3012 - 10.42X(T_{\text{cw,i}}) + 3.5625X(T_{\text{chw,i}}) \\ & + 15.14X(T_{\text{hw,i}}) + 2.34375X(m_{\text{hw,i}}) \end{aligned}$$

This model explained the variability observed in the experiment to a 99.8886% (R-squared statistic). In contrast with the quadratic function employed by Blinn for the capacity, a first order model was considered appropriate.

2.2. Preliminary design for the COP

A 2^4 factorial design was also used to estimate the effects of the four selected factors on the response variable *COP*. Fig. 2 shows those effects plotted on normal probability paper.

Note that only the main effects of the cooling and chilled water inlet temperatures appeared as significant, while those of the hot water inlet temperature and mass flow rate did not.

A further study was necessary because of the presence of the significant interaction between the hot and cooling water inlet temperatures (AC), which indicated that both factors did not behave additively. Therefore, a first order model was no longer valid for the *COP*.

At the sight of the preliminary study results, the factors included in the advanced model should have been the cooling and chilled water inlet temperatures, as they were the only ones with significant main effect. However, there exists an aphorism in experimental design that says a factor must never be neglected if it takes part of a significant interaction, although its main effect is not significant. The reason for this rule is that, sometimes, the effect of a factor can be negligible because its optimum level is located in the middle of the interval defined by the essayed high and low ones. This situation is especially possible if the levels below and above the nominal operating condition are essayed.

Therefore, even though the main effect of the hot water inlet temperature obtained from the preliminary design was negligible, this factor was included in the advanced study as its interaction with the inlet cooling water temperature was significant.

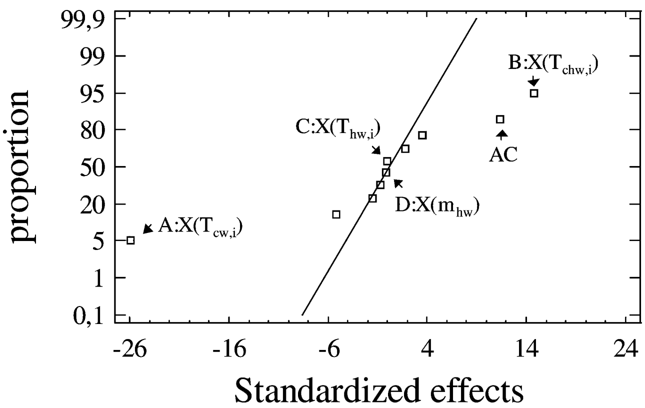

Fig. 2. Normal probability plot for *COP*.

Table 4
Levels and values of the considered factors for the *COP* advanced design

Level	$T_{\mathrm{cw,i}}$ (°C)	$T_{\mathrm{chw,i}}$ (°C)	$T_{\mathrm{hw,i}}$ (°C)
−1	24	12	75
0	27.5	14	87.5
+1	31	16	100

2.3. Advanced design for the COP

In this design, each factor was studied at three levels (low, median and high) in order to detect second-order effects. The high and low levels remained the same as in the preliminary design, and the midpoint between them was selected as the median level. The levels and values for the three studied factors are shown in Table 4.

Table 5 shows the results of the analysis of variance for *COP*. All the effects, excluding the squared term corresponding $T_{\mathrm{chw,i}}$, have p-values less than 0.05, indicating that they are significantly different from zero at the 95.0% confidence level. The equation of the fitted model is

$$\begin{aligned} COP = {} & 0.74867 - 0.02089X(T_{\mathrm{cw,i}}) + 0.0121X(T_{\mathrm{chw,i}}) \\ & - 0.00184X(T_{\mathrm{hw,i}}) - 0.00387X^2(T_{\mathrm{cw,i}}) \\ & + 0.00271X(T_{\mathrm{cw,i}})X(T_{\mathrm{chw,i}}) \\ & + 0.00978X(T_{\mathrm{cw,i}})X(T_{\mathrm{hw,i}}) \\ & - 0.00424X(T_{\mathrm{chw,i}})X(T_{\mathrm{hw,i}}) - 0.00424X^2(T_{\mathrm{hw,i}}) \end{aligned}$$

The model as fitted explains 98.9949% of the variability in *COP* (R-squared statistic).

3. Results

Besides the estimation of the regression models for the response variables capacity and *COP*, the applied method provides interesting results.

Table 5
Analysis of variance for *COP*

Source	Sum of squares	*Df*	Mean square	*F*-ratio	*p*-value
A: $T_{\mathrm{cw,i}}$	0.0078584	1	0.0078584	1087.47	0.0000
B: $T_{\mathrm{chw,i}}$	0.00263538	1	0.00263538	364.69	0.0000
C: $T_{\mathrm{hw,i}}$	0.0000608672	1	0.0000608672	8.42	0.0099
AA	0.0000899646	1	0.0000899646	12.45	0.0026
AB	0.0000880208	1	0.0000880208	12.18	0.0028
AC	0.00114856	1	0.00114856	158.94	0.0000
BB	0.0000010696	1	0.0000010696	0.15	0.7052
BC	0.000215901	1	0.000215901	29.88	0.0000
CC	0.000107809	1	0.000107809	14.92	0.0012
Residual	0.000122847	17	0.000122847		
Total	0.0123288	26	0.0123288		

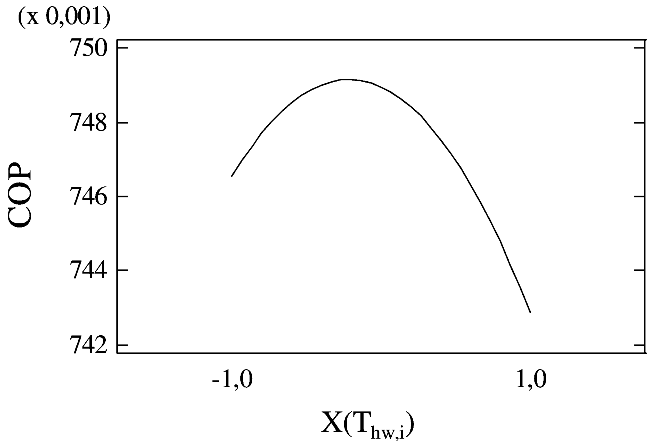

Fig. 3. Main effect of hot water inlet temperature.

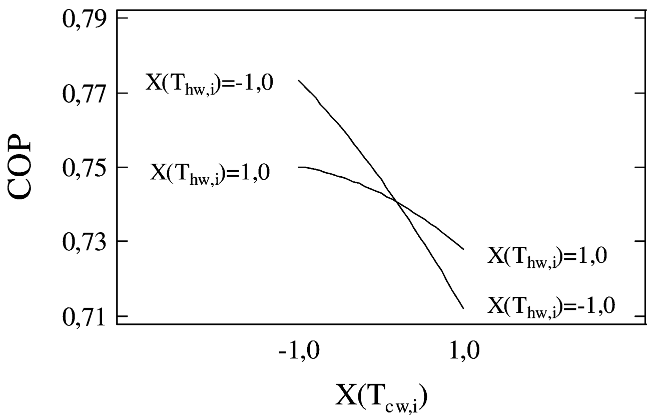

Fig. 4. Interaction plot for *COP*.

The hot water mass flow rate was eliminated from the *COP* model because its effect was not significant on this variable. Note, however, that the effect of the same factor resulted significant on capacity. In fact, a common form of part-load control in large air conditioning systems is to reduce the firing water flow rate to maintain a constant water chilled delivery temperature. These results are in agreement with the well-known fact that the nominal *COP* of the absorption machines hardly varies at part-loads.

Fig. 3 shows the effect of the inlet hot water temperature on the *COP*, which is quite similar to that obtained by Gommed and Grossman [6]. In this reference, the authors qualitatively explain this effect in terms of the absorption cycle losses. A quantitative explanation for this effect in terms of the entropy generation in the absorption cycle is given in [8].

Fig. 4 shows the interaction between the inlet cooling water temperature and the inlet hot water temperature. By far, it is the most significant double interaction. It indicates to what extent both factors do not behave additively, and how the effect of each one depends on the value of the other.

We can appreciate how, although the effect of the inlet cooling water temperature on *COP* is always negative, that is, the *COP* diminishes as the inlet cooling water

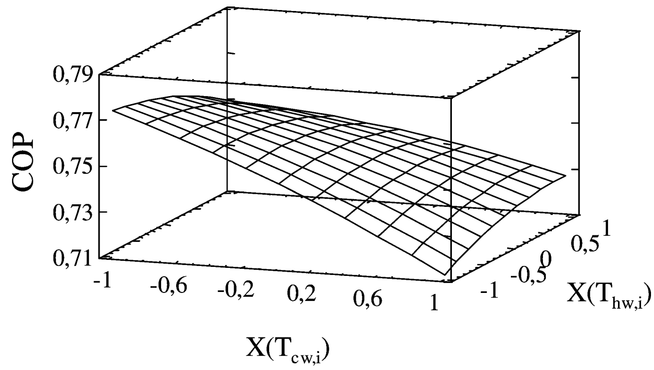

Fig. 5. Estimated response surface.

temperature increases, the effect is smaller at high inlet hot water temperatures.

This is valuable information for designing control strategies applicable to the air conditioning system where the absorption machine operates. At high inlet hot water temperatures, the improvement achieved in the *COP* by maintaining low the inlet cooling water temperature will be of little importance. Therefore, it could have no point to spend energy, for example, for driving the cooling tower fans, in order to keep the inlet cooling water temperature low. On the contrary, at low inlet hot water temperatures this measure could be effective for energy savings.

Fig. 5 shows a three-dimensional plot of the relationship between the *COP* and the hot and cooling water inlet temperatures. Based on the derived model, it helps in locate optimal values for the response variable.

4. Conclusions

The purpose of this paper was to show the use of experimental design and ANOVA techniques to establish the models that represent the performance of an absorption machine. These techniques were used to investigate the effect of the considered factors on the *COP* and the capacity of the machine, including the presence of interactions between them, and to verify the hypotheses initially adopted in the formulation of the models for both response variables.

First-order models were initially considered for the *COP* and the capacity of the absorption machine selected as reference case for the study. This model resulted to be appropriate for the capacity, whereas for the *COP*, it was necessary to adopt a second-order model after getting the ANOVA results.

Something similar happened with the independent variables initially considered for the *COP* and the capacity. All the considered variables had a significant effect on the capacity, while for the *COP* the hot water mass flow rate could be excluded from the model.

The use of experimental design and ANOVA techniques provided well-known information, like the small variation of *COP* at absorption machine part-load operation and information not so evident a priori, like the interaction between the hot and cooling water inlet temperatures. This knowledge is important both for the construction of the model and for the selection of the control to be applied to the system.

Note that the model for the capacity was obtained by carrying out only 16 simulations of the reference absorption cycle with the tool developed in the environment of TRNSYS, and that the model for the *COP*, a second order one, needed only 43 simulations (16 for preliminary design and 27 for the advanced one). The resulting models, as fitted, explained 99.8886% of the variability in capacity and 98.9949% in *COP* within the studied region.

In the conducted study, the regression models were initially expressed in terms of four independent variables following the indications given by Blinn [2]. However, the preliminary stage (two level factorial designs) should be used to include any factor that, in the researcher's opinion, could have a significant effect on the response variables.

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