A Dimensionless Model for Estimating the Dehumidification Effectiveness of Liquid Desiccant Dehumidifiers: Application of Least Square Support Vector Machine

A. Zendehboudi, X. Li*, P. Song
Department of Building Science
School of Architecture, Tsinghua University, Beijing 100084, China

SUMMARY
This study introduces a novel dimensionless model based on Least Square Support Vector Machine (LSSVM) that is practical and powerful for estimating the dehumidification effectiveness of liquid desiccant dehumidifiers. This model considers the number of transfer unit, thermal capacity ratio of air to desiccant, and difference between air and desiccant inlet parameters as the inputs. The performance of the aforementioned model for the estimation of the dehumidification effectiveness is further assessed against a theoretical model in the open literature. It was found that the LSSVM model is more in agreement with the actual data and further improvement is achievable compared to the theoretical model, with the coefficient of determination and mean square error values 0.998 and 5.58E-05, respectively. All the results indicate that the suggested dimensionless model is promising for accurate and reliable outcomes, which could be practical for other dehumidifiers with different geometries.

INTRODUCTION
Heating, ventilation, and air-conditioning (HVAC) systems utilize around 50% of the total energy used in buildings (Pérez-Lombard et al. 2008). The statistics indicated that the energy consumption for dehumidification process is responsible for 20-40% of the total energy utilized in HVAC systems (Huang and Zhang 2013). As a matter of fact, next-generation HVAC technologies have emerged as interesting alternatives to the conventional vapor-compression system for dehumidification and cooling. Obviously, from the previous literature, it was found that the desiccant cooling systems are one of the new technologies, which are able to control separately the latent and sensible loads, resulting in reducing energy consumption, and keeping safe the environment by removing condensed water and conventional refrigerant from the mechanism of cooling systems (Abdul-Wahab et al. 2004).

Desiccants can take on a liquid or solid form. The liquid desiccants are more preferable because of various benefits, such as need of lower regeneration temperature, pressure drop, etc (Zurigat et al. 2004). Triethylene glycol aqueous solution is regarded as the earliest desiccant in such systems, which then replaced by lithium chloride (LiCl) aqueous solution due to the benefits of the latter one (Liu et al. 2011). Dehumidifier is one of the most important components in the liquid desiccant systems, and a great deal of research has focused on the component to evaluate and model its performance. In the past years, different theoretical and empirical models for predicting the performance of the desiccant systems have been developed by different researchers, such as Gandhidasan (1994), Martin and Goswami (2000), Liu et al. (2006), Liu et al. (2007), Moon et al. (2009), and Park et al. (2016).

Nowadays, researchers pay more attention to the application of artificial neural algorithms, which are the new computational techniques for problem solving and determining optimal values. These approaches have been implemented for the prediction of the operating parameters of liquid desiccant systems to present a reliable and easy-to-use model for optimizing the design and operating the device. These models are a solution of nonlinear problems when the relation between input-output pairs are not clear. Different attempts have been made in the literature to describe the applicability of such models to liquid desiccant systems performance prediction, such as Zeidan et al. (2010), Gandhidasan and Mohandes (2011), Mohammad et al. (2013a), and Mohammad et al. (2013b). In Table 1, the summary of studies conducted on liquid desiccant systems by means of soft computing approaches is summarized.

It is clear from the literature that the previous works on the prediction of dehumidifiers using artificial intelligence techniques have mainly presented the models which are related to specific physical geometry of the component. Support Vector Machines (SVMs) are relatively a new machine learning algorithm, which have attracted ample attentions in solving different complex functions owing to the merits such as the easy implementation, robustness, and high efficiency (Zendehboudi 2016). Owning to the proven proficiency of SVMs in images retrieval (Tao et al. 2006), fault diagnosis (Tian et al. 2015), and text detection (Kim et al. 2001), this article aims to apply a modified version of SVM, i.e., Least Square Support Vector Machine (LSSVM), to develop a practical and powerful dimensionless model for estimating the dehumidification effectiveness of liquid desiccant dehumidifiers. This model takes into consideration the number of transfer unit, thermal capacity ratio of air to desiccant, and difference between air and desiccant inlet parameters as the inputs. The performance of the aforementioned model for the estimation of the dehumidification effectiveness is further assessed against a theoretical model in the open literature.

METHODOLOGY
Least square support vector machine model
SVM theory has been first introduced by Vapkin (1998). This approach uses kernel functions to map the input variables to high-dimensional feature spaces and find a hyperplane via a nonlinear mapping. LSSVM was introduced by Suykens and Vandewalle (1999), which is considered as the modified version of SVM, along with two main advantages: (1) the inequality constraints are transferred into equality constraints; (2) a set of linear equation problems is solved instead of a convex quadratic programming (Zendehboudi 2016).
Lagrangian function as:

\[ Z = \sum_{i=1}^{n} a_i \theta(\chi_i) + b \]

To solve the optimization problem, we should define the Lagrange function as:

\[ L(\omega, a, e) = \sum_{i=1}^{n} a_i [\omega \cdot \theta(\chi_i) + b + e_i - \gamma] \]

Where \( \omega \) refers to the Lagrange multipliers. Based upon Karush-Kuhn-Tucker conditions, we can get:

In Eq. (1), \( \omega \) is the weight vector, \( b \) is the bias, and \( \theta(\chi) \) is representative of a mapping function, which maps \( \chi \) into higher dimensional feature space.

The regression equation is transformed to an optimization problem by minimizing the cost function, which can be formulated as in (2), with the constraint of Eq. (3):

In below, a summarized explanation of LSSVM theory is presented. Suppose a regression problem over data set \( Z = \{\chi_i, y_i\}_{i=1,2,3,...,n} \) where \( \chi_i \in \mathbb{R}^q \) is the input vector, \( y_i \in \mathbb{R} \) is the corresponding target value, and \( n \) refers to the training data size. The support vector regression model that fit the relationship between input-output is as follow:

\[ \hat{y} = \omega^\top \theta(\chi) + b \]

Where \( a_0 \) is the kernel function. There are different kernel functions, which are used in LSSVM model. Among which, radial basis functions (RBF) is well-known and has been repeatedly applied in various studies due to advantages such as simplicity, notable regression capability, and reliability (Zendehboudi 2016). Therefore, in this study, RBF was selected as the kernel function, as shown in Eq. (7).

\[ K(\chi, \chi_i) = \exp \left(- \frac{||\chi - \chi_i||^2}{\sigma^2} \right) \]

The approximation ability of LSSVM is seriously affected by kernel parameter \( \sigma^2 \) and regularization parameter \( \gamma \). GA, which has already proven its ability in determining the LSSVM parameters, was executed for the purpose of determining the optimal magnitudes of these two parameters so that leads to higher accuracy. The best values of \( \sigma^2 \) and \( \gamma \) were indicated as 8.608540161647952 and 3.981258374460578E+03 for the dehumidification effectiveness.

Table 1. Summary of studies on liquid desiccant dehumidifiers using soft computing.

<table>
<thead>
<tr>
<th>Author</th>
<th>Material</th>
<th>Method</th>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Air and desiccant temperature</td>
<td>2. Desiccant vapor</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Air specific humidity</td>
<td>3. Mass of evaporated water</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Desiccant inlet concentration</td>
<td></td>
</tr>
<tr>
<td>Gandhidasan and Mohandes (2011)</td>
<td>LiCL</td>
<td>ANN</td>
<td>1. Air humidity</td>
<td>1. Water condensation rate</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Air and desiccant flow rates</td>
<td>2. Desiccant concentration</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Air and desiccant temperatures</td>
<td>3. Desiccant temperature</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4. Desiccant concentration</td>
<td></td>
</tr>
<tr>
<td>Mohammad et al.</td>
<td>TEG</td>
<td>ANN</td>
<td>1. Air and desiccant temperatures</td>
<td>1. Water condensation rate</td>
</tr>
<tr>
<td>(2013a)</td>
<td></td>
<td></td>
<td>2. Air and desiccant flow rates</td>
<td>2. Dehumidifier effectiveness</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Desiccant concentration</td>
<td></td>
</tr>
<tr>
<td>Mohammad et al.</td>
<td>LiCL</td>
<td>ANN</td>
<td>1. Air and desiccant flow rates</td>
<td>1. Moisture removal rate</td>
</tr>
<tr>
<td>(2013b)</td>
<td></td>
<td></td>
<td>2. Air humidity</td>
<td>2. Dehumidification effectiveness</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Air and desiccant temperatures</td>
<td></td>
</tr>
<tr>
<td>Current study</td>
<td>LiCL</td>
<td>GA-LSSVM</td>
<td>1. Number of transfer unit</td>
<td>1. Dehumidification effectiveness</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2. Thermal capacity ratio of air to desiccant</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3. Difference between air and desiccant inlet parameters</td>
<td></td>
</tr>
</tbody>
</table>
Data collection and construction of datasets

To construct and develop a reliable predictive mode, the experimental data samples were extracted from the report of Park et al. (2016). According to the analytical solution results of Liu et al. (2007), the dehumidification effectiveness is as a function of $m^*$, $K$, and $NTU_m$, which is shown as Eqs. (8-10). Therefore, the dimensionless input and output parameters could be obtained, as shown in Table 2.

$$m^* = \frac{m_a C_{p,a}}{m_s C_{p,s}}$$  \hspace{1cm} (8)

$$K = \frac{\omega_{a,in} - \omega^*}{\omega_{a,in} - \omega_{a,eq}}$$  \hspace{1cm} (9)

$$NTU_m = \frac{\alpha m}{A}$$  \hspace{1cm} (10)

where $m^*$ is the thermal capacity ratio of air to desiccant, $m_a$ and $m_s$ are for respective the mass flow rate of air and desiccant, $C_{p,a}$ and $C_{p,s}$ are the specific heat of air in equilibrium with desiccant and desiccant, $K$ is the dimensionless humidity ratio difference between air and desiccant inlet parameters, $\omega_{a,in}$ and $\omega_{a,eq}$ are the humidity ratio of inlet air and air in equilibrium with desiccant, $\omega^*$ is the humidity ratio of intersection point of inlet desiccant in concentration line and inlet air isenthalpic line, $NTU_m$ is the number of mass transfer unit, $\alpha_m$ is the mass transfer coefficient, and $A$ is the heat and mass transfer area.

RESULTS AND DISCUSSION

In this investigation, MATLAB 2015b has been used to construct the model network architecture. To develop and check the validity of the constructed model, the dataset was randomly divided to two sets of training and testing data, which are 70% and 30% of the total data, respectively. The testing data were not introduced to the network during the training process. After the training process, the validity and over fitting of the network was checked with the testing data.

Likewise, after developing the model, to examine the suggested model’s accuracy and predictability, Liu et al. (2007) model was developed considering the same data set and input variables. This model has an expression as follows:

$$\varepsilon = \frac{1 - e^{-NTU(1-m)}}{m} - e^{-NTU(1-m)}$$  \hspace{1cm} (11)

To visualize the performance of the developed models in a better way, regression plots between the predicted and actual values, scatter plots of error distribution as a function of the actual data, and contrast between the actual and predicted versus the number of data points are presented. Additionally, two statistical error tests, the coefficient of determination ($R^2$) and the root mean squared error (RMSE), were utilized in this study. The statistical error tests were used to demonstrate the deviation between the estimated data samples using the introduced models and the observed data samples. It is worth to mention that the method consists of the lowest values of RMSE as well as the highest values of $R^2$ is chosen as the best-fit technique in this contribution. These parameters can be calculated through Eqs. (12) and (13).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\text{actual} - \text{predicted})^2}{\sum_{i=1}^{n} (\text{actual} - \text{average(actual)})^2}$$ \hspace{1cm} (12)
The values of $R^2$ and RMSE of these two different predictive approaches are presented in Table 3. Indeed, it is noticeable that a favorable agreement exists between the estimations using the GA-LSSVM and the actual data. The results show that Liu et al. (2007) model cannot be practical to precisely model the dehumidification effectiveness.

Table 3. Statistical parameters of the developed models.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model</th>
<th>$R^2$</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GA-LSSVM</td>
<td>0.9980</td>
<td>5.586E-05</td>
</tr>
<tr>
<td></td>
<td>Liu et al. (2007)</td>
<td>0.7961</td>
<td>0.0058</td>
</tr>
</tbody>
</table>

Figure 1. Regression plot between the predicted and actual dehumidification effectiveness: (a) GA-LSSVM; (b) Liu et al. (2007) model.

Figure 2 represents the relative deviation for both models. As it is clear from this figure, the relative deviations of the model of Liu et al. (2007) are higher than those of the developed GA-LSSVM presented in the current study. The predicted data samples using the developed GA-LSSVM fall within an error band of $-4.63\%$ and $+3.07\%$. This fact highlights that the predicted values by the GA-optimized approach are more reliable and accurate. The results generated by the correlation predicted results and the related actual data for the dehumidification effectiveness. In these plots, the vertical axis represents the estimated values and the horizontal axis is the actual values. This figure indicates the degree of agreement between the actual data and predicted values using both the GA-LSSVM and the model of Liu et al. (2007). By sketching the diagonal line, it is observed that the predicted and actual values are in great consistency using the suggested GA-LSSVM model because the distribution of the predicted points around the unit slop line is lower, proving the ability of the model to reproduce the actual data samples with high accuracy. Results are found to be less scattered for low dehumidification effectiveness values than for high ones using Liu et al. (2007) model.
of Liu et al. (2007) was presented to have a better understanding about the suggested model in the current study. It is observed that this model generally underpredicts the experimental data samples as the data points are below the zero line. Comparison of the relative deviations of these two approaches for the prediction of this problem highlighted that the GA-LSSVM method is a good solution by presenting accuracy improvements in comparison with the other one. Figure 3 shows the contrast plot where the predicted and actual data samples are plotted as a function of the number of data samples. This evaluation shows truthfully of a model and provides the tendency of a predictive method in terms of overestimation and underestimation. This figure shows that, for all data samples, there is a high overlap between the estimated and the actual trends and the developed GA-LSSVM outcomes excellently follow the trend of actual samples. Once again, these result shows high integrity of the suggested model in prediction of the dehumidification effectiveness based on the given data and proves that the actual samples are precisely modeled using the designed network.

![GA-LSSVM Model](image)

![Liu et al. Model](image)

**Figure 3. Contrast plot of the actual and predicted data versus the number of samples:** (a) GA-LSSVM; (b) Liu et al. (2007) model.

**CONCLUSIONS**

A LSSVM approach was developed to offer a novel dimensionless model for the accurate estimation of the dehumidification effectiveness of liquid desiccant dehumidifiers by considering the number of transfer unit, thermal capacity ratio of air to desiccant, and difference between air and desiccant inlet parameters as the input vectors. Genetic Algorithm was implemented to optimize the tuning parameters of the LSSVM method. Meanwhile, to visualize the robustness and reliability of the suggested novel model, a well-known reported model in the literature was developed by utilizing the same data set and inputs. Based on a comparative analysis via various graphical and statistical error analyses, it was concluded that the performance of the GA-LSSVM highly outperforms the another one and presents predictions with reasonable errors. The maximum generalization error of the developed LSSVM, according to all data samples, was within -4.63% and +3.07% error band with an MSE=5.586E-05 and $R^2=0.9980$. The suggested model is highly valuable to industries, which could be used for other dehumidifiers with different geometries in the reported dimensionless ranges to determine and monitor the outcomes with a favorable precision.

**ACKNOWLEDGEMENT**

This study was supported by the Innovation Research Groups of the National Natural Science Foundation of China (Grant No. 51521005).

**REFERENCES**


