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Numerical Analysis of Optimising Liquid Desiccant Dehumidification for Sustainable Building Cooling: A Data-Driven Method Using Response Surface Methodology

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Abstract: Leveraging data-driven methods such as Response Surface Methodology (RSM) has considerable potential for sustainable building cooling via mitigating energy consumption and environmental impacts. This research focuses on using the RSM to improve liquid desiccant dehumidification for sustainable building cooling performance using a D-optimal design. Specifically, the research intends to investigate the actual influence of the inlet air conditions and desiccant concentration on the performance of liquid desiccant dehumidification systems, i.e., the moisture removal rates and dehumidifier efficiency. To systematically conduct this research, a set of experimental data gathered from the open literature is utilised. This includes a specific set of inlet parameters of air temperature (27–34.5 °C), ratio of air humidity (20.5–25 g/kg), and solution temperature (27.5–38.5 °C) as the independent variables. Also, the feedback variables include the moisture removal rates (MRR) and efficacy (ϵ). The associated results of the analysis of variation indicate that the ratio of air humidity has the greatest influence on the moisture removal rate. However, the solution temperature and the ratio of air humidity have the most influence on efficacy. In the event of response optimisation, the result at MRR and (ϵ) are 0.54 g/s and 0.50, respectively, with a minimum desirability of 0.992 and 1.

Keywords: desiccant; dehumidification; RSM; D-optimal; desirability

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1. Introduction

Liquid desiccant dehumidifiers are effective in removing moisture from the air by using a liquid solution to absorb water vapour. The liquid desiccant dehumidifier's performance of desiccant used can be determined via allocating the flow rate of the air and solution, and the temperature and humidity of the incoming air [1–3]. One advantage of liquid desiccant dehumidifiers is that they can operate at lower temperatures and humidity levels than other dehumidification technologies. They are also more energy-efficient than refrigerant-based dehumidifiers, which require a lot of energy to cool the air and remove moisture [4]. However, liquid desiccant dehumidifiers require a source of heat to regenerate the desiccant solution and release the captured moisture [5]. This heat source can be provided by a waste heat recovery system, solar collectors, or other sources of renewable energy. Liquid desiccant dehumidifiers can also be more complex and require more maintenance than other dehumidification technologies, as the liquid desiccant solution needs to be monitored and periodically replaced. Nevertheless, they are a good option for applications where low temperature and humidity levels are required, such as in the food and pharmaceutical industries, as well as for indoor air quality control in commercial and residential buildings.

Generally, the standard symmetrical designs cannot be used when the experimental domain is irregularly in form, or when the number of experiments appointed by a classical design is large. To sort out this issue, the principal notion of D-optimality can be used to select the proper design [6]. In hot and humid climates, the humid air is dehumidified with a strong liquid or solid dry, and the warm-dry air is cooled by evaporating water into it, which results in an acceptable final humidity and temperature. Dehumidification is a process that occurs when humid air interacts with a desiccant solution. The efficacy (ϵ) of the dehumidification process is measured using two indicators: the moisture removal rate (MRR) and efficacy of (ϵ) [7]. Several systems of liquid desiccant dehumidification for sustainable building cooling were constructed and improved during the last 30 years to improve the efficiency of classical air condition systems. According to Jain et al. [8], on account of the pressure vapour between the desiccant solution and air, the liquid desiccants absorb moisture from the air. The liquid desiccants available are used at slight temperatures, roughly between 50 °C and 80 °C [9]. Thus, the heat sources with a low temperature could be used to power the regeneration process at roughly 70 °C via using several techniques such as solar energy, waste heat, and geothermal power.

The aim of the current research is to study the effects of inlet air temperature (27–34.5 °C) and humidity (20.5–25 g/kg) on the moisture removal rate (MRR) and dehumidifier efficiency (ε), as well as to assess how different desiccant amounts impact energy efficiency and environmental performance. To systematically conduct this aim, the D-optimal method is used to reduce the number of experiments, besides developing a robust mathematical model using RSM to relate input variables (air temperature, humidity, solution temperature) to output responses (MRR and ε).

The outline of this article is as follows:

Section 2 introduces a review of the existing literature on dehumidifier performance, and categorizes modelling strategies into theoretical analysis, and experimental studies. In Section 3, the definition of Response Surface Methodology and a discussion of its role in optimizing system performance through systematic input testing are detailed. In Section 4, an analysis of inlet parameters affecting performance metrics together with assessing the model accuracy with key statistical indicators is provided. Section 5 focuses on introducing a mathematical model developed from experimental data to predict performance under variable conditions. In Section 6, an explanation of regression analysis techniques and deriving accurate formulas for variable relationships is provided. In Section 7, D-optimal design implementation for response prediction including the coding of variables at three levels is ascertained. Section 8 provides an overview of components and subsystems involved in dehumidification and regeneration processes, while Section 9 provides a description of using the Design-Expert's optimization tool to enhance system performance via a desirability function. Section 10 presents experimental findings, detailing operating conditions and D-optimal optimization results. Section 11 explores the complexities of interactions between operational parameters while highlighting the significance of optimizing liquid desiccant systems. Lastly, Section 12 summarizes the key findings on temperature and humidity effects, model accuracy, and optimal conditions in addition to emphasizing implications for energy savings and sustainable cooling policies.

2. Literature Review

The performance of the dehumidifier and regenerator was experimentally and theoretically studied by a number of researchers. Modelling strategies for guess dehumidifier and regenerator performance can be grouped into three categories based on past research: models for theoretical numerical analysis, experimental analysis, and artificial intelligence.

The researchers were commonly focused on estimating the overall performance of humidity, besides evaluating the desiccant solution inlet rate of flow, temperature, and concentration [10–12]. Moon et al. [13] demonstrated the new mass transfer performance information of the flow liquid desiccant dehumidifying system by developing new statistical correlations on dehumidifying efficacy.

Sanjeev et al. [14] conducted a set of experiments to investigate the efficiency of liquid desiccant dehumidification for a sustainable building cooling method under various operation parameters. The dehumidifier and regenerator with a cooling tower are the three essential components of the system. As desiccants in the system, lithium chloride and calcium chloride were employed. The results specified that the dehumidifier's efficiency can be ranged between (0.25 and 0.44), while the regenerator's efficiency reached between (0.07 and 0.8).

Liu et al. [15] evaluated the operation of the adiabatic dehumidifier units that were internally cooled. The internally cooled dehumidifier was established to perform better in mass transfer than the adiabatic unit. By utilising mathematical analysis of variance, the consequence of intake operation elements on the dehumidifier's condensation rate and the regenerator's water evaporation was investigated. The results indicated that the ratio of humidity of intake air, the mass flow rate of the intake air, and the temperature of the inlet solution have a straight effect on the water condensation rate with a significance ($p < 0.01$). Furthermore, the rate of water evaporation in the regeneration can also be affected by the intake air mass flow rate and the inlet solution temperature ($p < 0.01$). The mass transfer of aqueous solutions comprising lithium chloride and lithium bromide was also assessed. The results exposed that the (LiCL) can perform better than the (LiBr) in terms of dehumidification at the same rate of desiccant flow.

Mc-Donald et al. [16] and Sameer et al. [17,18] utilised the regression analysis to quantify data generated from packing the tower desiccant dehumidifier. Precisely, the regression formula was used to allocate the temperature of outlet air and the ratio outlet of humidity desiccant temperature and concentration.

Although previous studies have determined the impact of distinct elements on the performance of Liquid Desiccant Dehumidification, insufficient studies have evaluated the collective impacts of these characteristics quantitatively using experimental data obtained from various sources. Previous evaluations have predominantly concentrated on theoretical models or have been restricted to particular case studies, which may not be entirely reflective of wider operational circumstances. The main purpose of the present investigation is to appraise how the input parameters can impact the critical outlet air and desiccant qualities of Liquid Desiccant Dehumidification. The D-optimal design is engaged to improve the overall performance of liquid desiccant dehumidification for sustainable building cooling while assessing the relevance of independent factors on the moisture removal rate (MRR) and dehumidifier efficacy.

3. Response Surface Methodology (RSM)

The Response Surface RSM is a statistical and mathematical practice that finds the relationship between input factors and output responses to maximise the performance of a system or process Hern et al. [19]. It is regularly used in engineering, chemistry, and other fields where it is imperative to optimise a system's performance while reducing cost or obtaining the best out of efficiency. RSM demands planning a series of tests with numerous input variable combinations and calculating the suitable output answers. By analysing the data from these experiments, RSM can help in defining the best combination of input variables to produce the intended output response. RSM typically includes fitting a mathematical model to the experimental data, which can be used to guess the response for any combination of input variables considering the range of the experiments. This model can then be used to recognize the optimal combination of input variables that will result in the desired output response. RSM is utilised for both linear and nonlinear systems and can handle interactions between input variables. It can also be utilised to signify the relative importance of each input variable on the output response and can be utilised to optimise the performance of a liquid desiccant dehumidifier by recognizing the optimal values for the input variables that maximise the output variables. It can also help to reduce the number of experiments required to optimise the process, which can save time and resources. Overall, RSM is an influential tool for optimising systems and processes and therefore can help save time and resources by determining the optimal combination of input variables without the need for in-depth testing. It is predominantly useful for systems with multiple variables that affect performance.

4. Evaluation of RSM Model

Additionally, a thorough analysis that systematically examines the effects of multiple inlet parameters, namely, air temperature, humidity ratio, and solution temperature, on critical performance metrics like moisture removal rates (MRR) and dehumidifier efficiency (ϵ), is often lacking in previous studies that have examined various aspects of liquid desiccant systems. To assess the accuracy of the proposed RSM model, several statistical indicators were employed to compare predicted and actual values. Key indicators considered include Mean Square Error (MSE), coefficient of determination (R^2), and absolute relative error Khoshraftar et al. [20]. The calculation of MSE value is defined by Wu et al. [21]:

The MSE is calculated as follows:

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{P}_{\mathrm{mea}} - \mathrm{P}_{\mathrm{for}})^2$$

$\mathrm{P}_{\mathrm{mea}}$ represents the measured power and $\mathrm{P}_{\mathrm{for}}$ stands for the forecasted or predicted power. The R^2 is calculated as follows:

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{m} (\mathrm{P}_{\mathrm{mea}} - \mathrm{P}_{\mathrm{for}})^2}{\sum_{i=1}^{m} P_{mea}^2 - \frac{\sum_{i=1}^{m} P_{for}^2}{m}}$$

5. Mathematical Model

By utilising the data from the experiments to figure out a mathematical model that clarifies the relationship between the variables and the performance of the dehumidifier, this model can be a simple linear relationship or a more complex polynomial equation. Utilising the mathematical model to guess the efficiency of the dehumidifier in different conditions can be achieved by inputting the values of the variables into the model and calculating the predicted performance. Adjusting the accuracy of the model is important for comparing the estimated performance to actual performance under the same conditions. The performance of the dehumidifier is predicted mathematically via computing the moisture dissipation average and its performance. Nelson and Goswami [22] and Oberg and Goswami [23] inspected the performance of dehumidifying with respect to the moisture removal rate. The moisture dissipation rate and dehumidifier effectiveness are mathematically estimated to determine its performance. The water carried from the air to the liquid desiccant was defined by Yin et al. [24], as represented below:

$$\Delta m_{con} = m_a \times (w_{in} - w_{out}) \tag{1}$$

m_a represents the rate of mass flow on the dehumidifier inlet, w_{in} the ratio of an inlet of air humidity, and w_{out} the ratio of outlet air humidity. The efficacy of the (dehumidifier/regenerator) is measured as the ratio of the change in actual humidity in the air to the greatest potential change in humidity feasible according to the following operating parameters:

$$\varepsilon = {}^{w_{in} - w_{out}}\!\Big/_{w_{in} - w_{out-eq}} \tag{2}$$

ω_{out-eq} denotes the ratio of outlet air humidity in balance with the desiccant solution with the desiccant solution under the following operational conditions of Kinsara et al. [25]:

$$w_{out-eq} = 0.62185 \times {}^{P_{wz}}\!\Big/_{(P - P_{wz})} \tag{3}$$

P signifies the total pressure of air on the solution and $P_{\omega z}$ is the partial pressure of water vapour in the solution.

The rate of moisture removal refers to the quantity of moisture extracted from the air per time unit, typically measured in grams per hour (g/h). This parameter is influenced by various factors such as the volume of air undergoing treatment, the moisture content of the incoming and outgoing air, and the duration of the process.

The moisture removal rate is commonly determined using the formula: Moisture Removal Rate = Q ($W_{in} - W_{out}$), where

- Q represents the volumetric flow rate of air (e.g., in cubic meters per hour);
- W_{in} indicates the moisture content of the incoming air (in grams of water per cubic meter);
- W_{out} signifies the moisture content of the outgoing air (in grams of water per cubic meter).

6. Regression Analysis

Regression analysis is a statistical approach that is used to analyse the association between one or more dependent variables (response) and independent variables (predictors) in order to predict the value of the response variable based on the values of the predictor variables. Finding the mathematical formula that most accurately captures the relationship between the variables is the aim of regression analysis. Three types of regression analysis are distinguished: polynomial, logistic, and linear regression. The most popular type of regression analysis is linear regression, which seeks to establish a linear relationship between predictor variables and response variables. In simple linear regression, there is only one predictor variable, while in multiple linear regression, there are multiple predictor variables. Logistic regression is used when the response variables is binary, which is significant as it only has two possible outcomes. Polynomial regression is used when the relationship between the predictor variables and the response variables is not a linear formula.

Regression analysis involves finding a mathematical correlation that best represents the association between predictor variables via a response variable. The equation depends on the type of regression analysis being used.

6.1. Simple Linear Regression

The simple linear regression correlation is:

$$Y = \beta_0 + \beta_x$$

Y is the independent variable (response), x is the independent variable (predictor), and β_x is the slope coefficient. β_x signifies the change in Y for a unit change in x, and the intercept (β_0) represents Y value when x is zero.

6.2. Multiple Linear Regression

The following correlation signifies the multiple linear regression with β_x predictor variables

$$Y = \beta_0 + \sum \beta_i x_i + \sum \beta_{ii} x_i^2 + \sum\sum \beta_{ij} x_i x_j$$

β_0 is the intercept or constant term. β_1, β_2, …, β_i are the slope coefficients; the slope coefficients represent the change in Y on a unit change in the corresponding predictor variable while keeping the other predictor variables constant.

6.3. Logistic Regression

The logistic regression equation is expressed in the following correlation

$$p = 1/(1 + exp\ (-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i)))$$

p is the probability of the dependent variable (response) being in a certain category (usually 1 or 0), and β_1, β_2, …, β_i are the slope coefficients. The slope coefficients signify the change in the log odds of the dependent variable for a unit change in the corresponding predictor variable, holding all other predictor variables constant.

7. Statistical Analysis and Experimental Design (D-Optimal)

Every variable that required optimisation was coded at three different levels.: −1, 0, and +1. For predicting individual Y variables, a quadratic polynomial regression model was adopted. The following model is projected for each response of Y,

$$Y = \beta_0 + \Sigma\beta_i\, xi + \Sigma\beta_{ii}\, x^2 + \Sigma\Sigma\beta_i j\, x_i\, x_j \tag{4}$$

In this research, the "Mini-tab INC., version 14, Pa. USA", a statistical software package data, is used. This software is widely used for data analysis for multiple regression analysis (ANOVA) and analysis of ridge maximum of data in the response surface regression (RSREG) procedure [23]. The coefficient of determination R^2 is used to assess the model's quality of fit and its statistical significance is determined using the F-test. The reaction of the moisture removal rate and the performance of the dehumidifier are studied using a three-factor D-optimal design. The primary response criteria and their values are chosen after an initial screening stage. The variables X_1, X_2, and X_3 respectively stood for temperature of inlet air (°C), and the inlet ratio of air humidity (g/kg), with the inlet solution temperature (°C). The independent variables are included in Table 1, which includes the intake air temperatures of 27 and 34 °C, inlet air humidity ratios of 20 and 25, and inlet solution temperatures of 27 and 38 °C.

Table 1. D-Optimal design requires independent variables and their levels.

Independent Variables		Variables Levels		
		−1	0	+1
Temperature of Air (°C)	X_1	27	30	34
Humidity Ratio of Air (g/kg)	X_2	20	22	25
Solution Temperature (°C)	X_3	27	33	38

Moisture analysis plays an important role in evaluating and optimising the liquid desiccant dehumidification processes for sustainable building cooling. This analysis involves estimating the amount of moisture present in the desiccant that can affect the performance of the process. The efficiency of a liquid desiccant is determined by determining the volumetric flow rate of the liquid. This is specifically conducted using liquid flow meters, which work by sensing the flow and generating a signal proportional to the flow rate. There are several types of liquid flow meters, such as the following:

1. Differential pressure flow meters: Measure the pressure difference across a primary device such as an orifice plate or Venturi tube. This is suitable for dirty liquids.
2. Positive displacement flow meters: Contain moving components that recurrently fill and displace a known volume of liquid. Highly precise and suitable for highly viscous liquids.
3. Velocity flow meters: Determine the velocity of the liquid and convert it to a flow rate. These include turbine, magnetic, and electrical.
4. Mass flow meters: Determine the mass flow rate rather than the volumetric flow rate.

There are other ways to improve the efficiency of the liquid dryer, including the following:

- Enhancing the design: The performance of the liquid dryer can be enhanced by better designing the unit. The design should be optimised to attain an even distribution of the liquid and reduce losses.
- Using advanced materials: Use advanced materials that enhance heat transfer and reduce losses.
- Monitoring and regulating the process: The dryer process should be continually monitored and attuned according to the ambient conditions. Sensors can be utilised to measure temperature, pressure, and fluid flow.

- Enhancing thermal insulation: The performance of the liquid dryer can be enhanced by using high-quality thermal insulators to preserve the compulsory temperature inside the unit.
- Enhancing the control system: Use an advanced control system that can better alter the dryer process according to the ambient conditions.

The rate of moisture removal and efficacy of a liquid desiccant dehumidifier are investigated using a three-factor response surface methodology (RSM). Table 2 shows various responses at various experimental combinations for coding. For several experimental combinations, such as 0.259 to 0.577 for MRR and 0.318 to 0.532 for ε, there was a considerable range in all replies. The maximum and minimum values of these parameters are attained as a result of the test being pre-treated on experimental combinations (run order) of 5, 9, 12, and 17.

Table 2. D-Optimisation of optimal design of MRR and efficiency.

<table>
<tr><th rowspan="2">No. of Run</th><th colspan="3">Independent Variable Levels</th><th colspan="2">Responses</th></tr>
<tr><th>T_a (°C)</th><th>W_a (g/kg)</th><th>T_s (°C)</th><th>MRR (g s^{-1})</th><th>ε (%)</th></tr>
<tr><td>1</td><td>27.00</td><td>20.50</td><td rowspan="3">38.50</td><td>0.451</td><td>0.457</td></tr>
<tr><td>2</td><td rowspan="2">34.50</td><td>25.00</td><td>0.342</td><td>0.483</td></tr>
<tr><td>3</td><td>20.50</td><td>0.337</td><td>0.424</td></tr>
<tr><td>4</td><td rowspan="3">27.0</td><td rowspan="2">25</td><td>33.00</td><td>0.543</td><td>0.514</td></tr>
<tr><td>5</td><td>38.50</td><td>0.541</td><td>0.532</td></tr>
<tr><td>6</td><td rowspan="2">22.75</td><td>27.50</td><td>0.491</td><td>0.452</td></tr>
<tr><td>7</td><td>34.50</td><td>33.00</td><td>0.390</td><td>0.417</td></tr>
<tr><td>8</td><td rowspan="2">27.00</td><td rowspan="2">20.50
25.00</td><td rowspan="5">27.50</td><td>0.474</td><td>0.418</td></tr>
<tr><td>9</td><td>0.577</td><td>0.462</td></tr>
<tr><td>10</td><td rowspan="3">34.5</td><td>20.50</td><td>0.359</td><td>0.322</td></tr>
<tr><td>11</td><td>25.00</td><td>0.486</td><td>0.406</td></tr>
<tr><td>12</td><td>25.50</td><td>0.399</td><td>0.318</td></tr>
<tr><td>13</td><td>30.75</td><td>23.88</td><td rowspan="3">38.50</td><td>0.388</td><td>0.416</td></tr>
<tr><td>14</td><td>34.50</td><td>25.00</td><td>0.352</td><td>0.495</td></tr>
<tr><td>15</td><td>27.00</td><td rowspan="3">20.5</td><td>0.355</td><td>0.432</td></tr>
<tr><td>16</td><td>30.75</td><td>33.00</td><td>0.388</td><td>0.436</td></tr>
<tr><td>17</td><td>34.50</td><td rowspan="2">38.50</td><td>0.259</td><td>0.430</td></tr>
<tr><td>18</td><td>30.75</td><td>22.75</td><td>0.318</td><td>0.431</td></tr>
</table>

8. Explanation of the Operating System

The system and measured data are shown in Figure 1. Vapour compression (VCS), regeneration, and dehumidification are the three subsystems that make up the system. Before the solution is put into the dehumidifier and regenerator, it is first dehumidified and then regenerated using the VCS. Every subsystem for dehumidification and regeneration has installed a centrifugal fan, pump, valves, filter, eliminator, and flow meter.

The two pumps are utilised to move the solution back and forth between the regenerator and the condenser and the dehumidifier and evaporator, respectively. The ambient air at the bottom of the regenerator and the dehumidifier is moved around by two centrifugal fans.

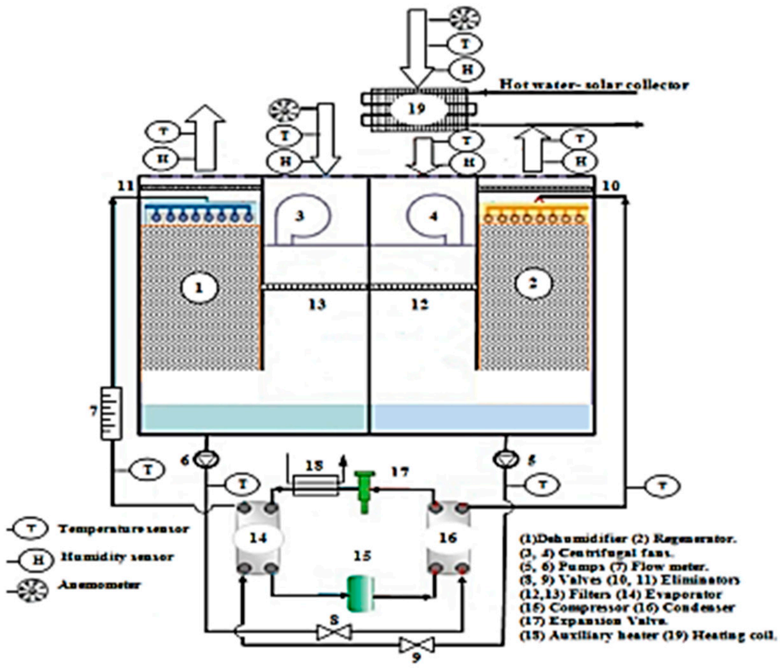


Figure 1. The diagram system of the liquid desiccant.

With an accuracy of ±0.1 °C, nine thermocouples were fitted to measure the temperature of the air and solution. The relative humidity at the input and outflow air streams was measured using five TR-RH2W humidity sensors, which have an accuracy of ±3% RH. To gather and send the recorded data to the PC system, each of these sensors is attached to a data acquisition logger. A flow meter was added to regulate the mass flow rate of the desiccant solution, with an accuracy of 2 L/h. Within the parameter ranges shown in Table 3, experimental experiments were conducted to assess the liquid adsorption dehumidification unit's performance.

Table 3. Characteristic measured data representing the monitoring period.

Air flow rate through the dehumidifier	0.125 kg/s
Air flow rate through the regenerator	0.125 kg/s
Dehumidifier/regenerator inlet desiccant flow	0.1 kg/s
Solar hot water flow rate through heating coil	0.25 kg/s
Dehumidifier air inlet temperature	27 to 34.5 °C
Regenerator air inlet temperature	39 to 57 °C
Humidity percentage at dehumidifier air inlet.	20.5 to 25 g/kg
Humidity percentage at regenerator air inlet.	18.9 to 21.8 g/kg
Dehumidifier inlet solution temperature.	27.5 to 38.5 °C
Regenerator solution inlet temperature	42 to 73 °C
Solar hot water inlet temperature	40 to 85 °C
Desiccant concentration	36.8%wt.

The simulation estimated the temperature, concentration, and mass flow rate at each state point, from P1 to P6, on the desiccant solution side of the liquid desiccant system. The air flow rate, dry bulb temperature, and humidity ratio for the process and regeneration air before and after the absorber and the regenerator were also calculated to evaluate the energy performance of both the reference and proposed systems.

9. Optimisation

Design-numerical Expert's optimisation is based on a desirability objective function. The overall desirability (D) is the multiplicative mean of all individual desirability (d_i) values between 0 and 1.

$$D = (d_1 \times d_2 \times \ldots . d_n)^{1/n} = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \quad (5)$$

D is the optimal design optimisation of moisture removal rates and effectiveness. n is the number of responses, and the total function becomes 0 if any of the answers go outside of their desirable range.

Design Optimisation of MRR

Design optimisation of moisture removal rate and efficacy can be accomplished using D-optimal design, which is a statistical optimisation technique that reduces the variance of the estimated model parameters while maximising the accuracy of the predicted response. To optimise the moisture removal rates and effectiveness, the first step is to outline the parameters that affect moisture removal, such as temperature, humidity, airflow rate, and the type and size of the moisture removal system. Then, an experimental design matrix is formed based on these factors, and the moisture removal rates and efficacy are restrained for each combination of factors. The experimental data are then analysed using statistical software to fit a model that relates the moisture removal rates and efficiency to the factors. The model can be used to forecast the moisture removal rates and efficiency for any combination of factors. The D-optimal design method is used to recognize the optimal combination of factors that maximise the moisture removal rates and effectiveness. This is conducted by selecting the factor levels that reduce the variance of the estimated model parameters while maximising the exactness of the predicted response.

10. Results and Analysis

10.1. Operating Conditions

To assess the performance of the liquid dehumidifier, experiments are directed using the parameters listed in Table 3. When conducting a D-optimal design optimisation for MRR and efficiency, it is significant to carefully consider the specific parameters and operating conditions that are most relevant to the experiments being conducted. Generally, the operating conditions for D-optimal design optimisation of MRR and efficiency depend on a diversity of factors, and a wide-ranging analysis of these factors is mandatory to select the optimal operating conditions.

10.2. Analysis of Response Surface

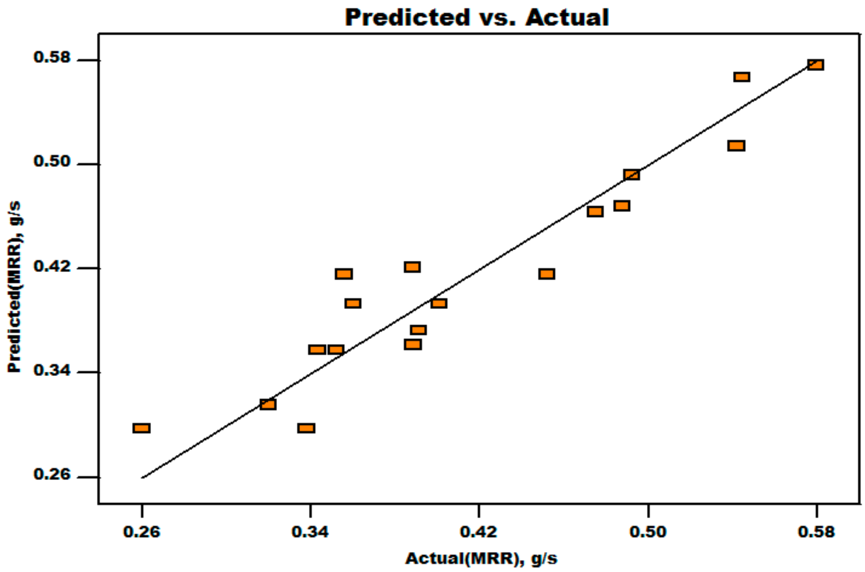
Quadratic regression equations are improved to anticipate the moisture removal rate and validation under the designated experimental condition using *RSM*. The regression Equations (6) and (7) of the response properties are developed as a function of three input parameters examined in the experiment:

$$\begin{aligned} MRR = +0.38 - 0.057 \times X_1 + 0.043 \times X_2 - 0.039 \times X_3 + 0.052 \times X_1^2 + 0.028 \times X_2^2 - 0.022 \times X_3^2 + \\ 0.009419 \times X_1 \times X_2 - 0.00364 \times X_1 \times X_3 - 0.00364 \times X_2 \times X_3 \end{aligned} \quad (6)$$

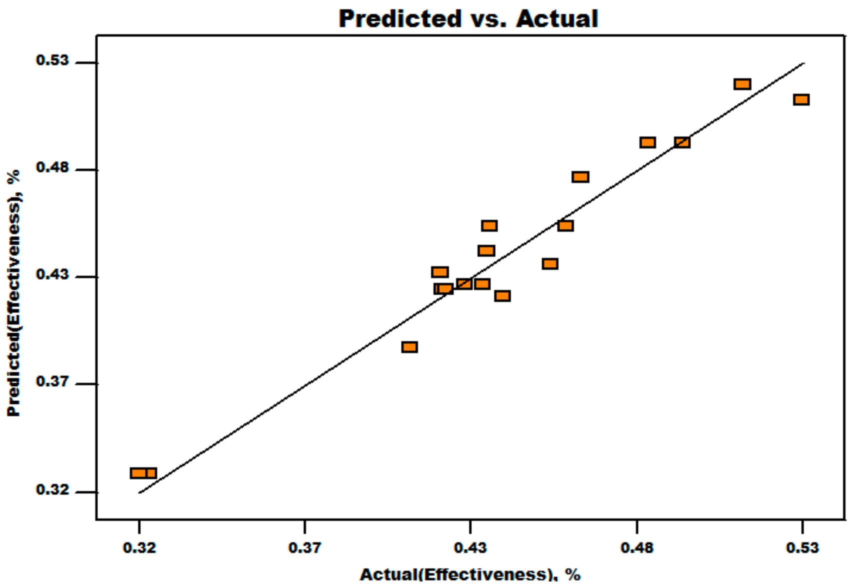
$$\begin{aligned} \varepsilon = +0.43 - 0.029 \times X_1 + 0.032 \times X_2 + 0.033 \times X_3 + 0.016 \times X_1^2 + 0.016 \times X_2^2 - 0.027 \times X_3^2 + \\ 0.001879 \times X_1 \times X_2 + 0.016 \times X_1 \times X_3 - 0.001883 \times X_2 \times X_3 \end{aligned} \quad (7)$$

X_1 represents the air temperature (Ta), X_2 represents the air humidity (W_a), and X_3 represents the solution temperature (Ts). It should be noted that (Ta) and (Ts) have a negative effect, while (Wa) has a positive effect on (MRR). The ratio of air humidity to solution temperature has a positive effect and a negative effect on air temperature (ϵ). Based on the associated results of Figure 1 for the predicted and actual values, it can be ascertained that the predicted values are statistically similar to the actual measured values.

In this regard, Figure 2 illustrates that the predicted and actual values are approximately linear; i.e., the errors are evenly distributed.



(**a**)



(**b**)

Figure 2. Plot of predicted response Y versus actual response: (**a**) MRR, (**b**) ϵ.

To assess the regression coefficients and statistical indication of type variables, the numerical analysis of variance was performed by fitting the experimental data (Equation (4)). The F-ratio was used to determine the importance of the model components at a probability (P) of 0.01. The adequacy model was assessed via the analysis model, the test for lack of fit, the coefficient of calculated R^2, the sum of the squares of the expected error, and the coefficient of variation (CV). The ANOVA findings for several runs of the experiment are shown in Tables 4 and 5.

Table 4. The anticipated quadratic polynomial model's regression coefficients for the response variables Y MRR and ϵ.

Predictors	Coefficients (β) MRR (g/s)	T	Prob.	Nota.	Coefficients (β) ε (%)	T	Prob.	Nota.
Intercept	+0.38	8.01	0.0037	*	+0.43	17.27	0.0003	*
Linear								
X_1	−0.058	27.58	0.0008	*	−0.029	36.69	0.0003	*
X_2	+0.044	14.39	0.0053	*	+0.032	40.49	0.0002	*
X_3	−0.040	12.07	0.0084	*	+0.033	45.32	0.0001	*
Quadratic								
X_{11}	+0.053	2.84	0.1309	**	+0.017	1.36	0.2796	**
X_{22}	+0.029	1.00	0.3478	**	+0.017	1.62	0.2405	**
X_{33}	−0.023	0.60	0.4595	**	−0.028	4.84	0.0592	**
Interaction								
X_{12}	+0.009419	0.66	0.4425	**	+0.001879	0.15	0.7218	**
X_{13}	−0.013	1.06	0.3360	**	+0.017	9.62	0.0148	**
X_{23}	−0.00365	0.090	0.7724	**	−0.001884	0.14	0.7322	**
R^2	0.91				0.96			

* $p < 0.01$; ** $p < 0.1$; Nota. = Notability.

Table 5. The ANOVA of models optimally MRR and ε.

Variable and Source	df	Sum of Squares	F-Value	*p*-Value
		MRR, g/s		
Model	9	0.13	8.02	0.0038
Residual	8	0.015		
Lack of fit	4	4.712×10^{-3}	1.56	0.7093
Pure error	4	8.502×10^{-3}		
R^2	0.90			
CV,%	9.82			
ε, %				
Model	9	0.048	17.28	0.0004
Residual	8	2.522×10^{-3}		
Lack of fit	4	2.130×10^{-3}	5.43	0.0654
Pure error	4	3.929×10^{-4}		
R^2	0.95			
CV,%	4.09			

For the model presented in Table 4, a probability > F less than 0.01 indicates that the model is significant in the linear model. This is desirable because it signifies that the parameters significantly affect the responses. In this case, the important terms in the model are X_1, X_2, and X_3.

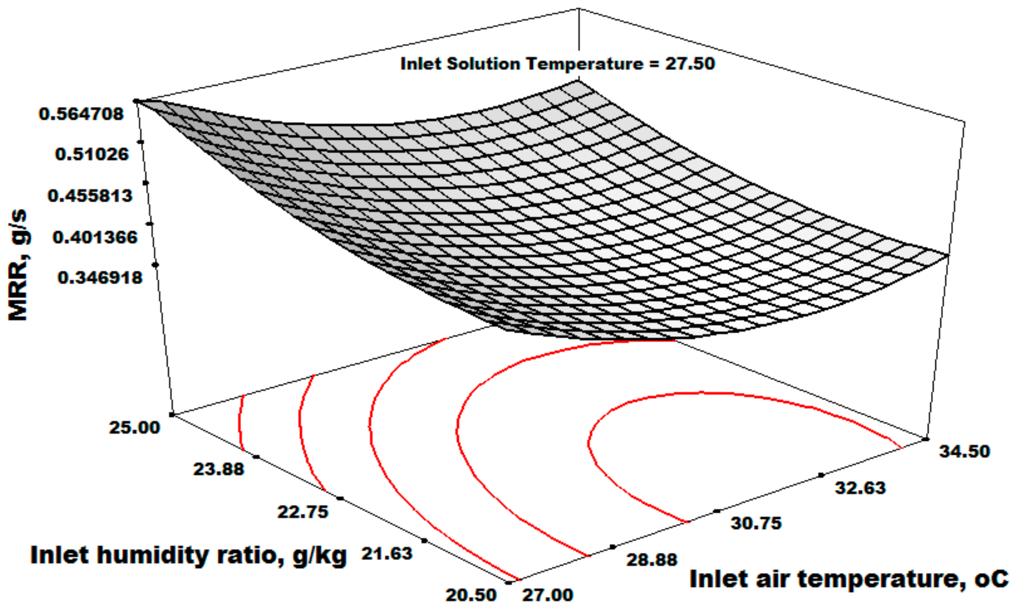
The most significant linear order effect of air humidity ratio (X_2) is the most significant factor associated with MRR, while the most significant linear order effect of air humidity ratio (X_2) and solution temperature (X_3) is the most significant factor related to ϵ. It is clear from Table 5 that the discrepancy and impurity of MRR and ϵ are small with the sum of squared errors of 4.712 × 10^{-3}, 8.502 × 10^{-3}, 2.129 × 10^{-3}, and 3.928 × 10^{-4}, respectively. The residual is in the variance and the CV is relatively small. The most significant component was the linear order main effect of air humidity ratio (X_2) on MRR, followed by the linear order main effect of air humidity ratio and solution temperature X_3, which are the most significant aspect ratios with ϵ. The lack of fit and impurity of MRR and ϵ appear to be minimal in Table 5, with the sum of squared errors of 4.712 × 10^{-3} and 8.502 × 10^{-3}, 2.129 × 10^{-3}, and 3.928 × 10^{-4}, respectively, leading to residual contrast and relatively low coefficient of variation.

The obtained results of Table 4 indicate that our model is compatible with the data of the experiment on R^2 values greater than 0.91 for the MRR model and 0.96 for the ε model.

A regression model with RSM may be tested and its statistical significance evaluated via the ANOVA table displayed in Table 5. The suggested regression model is considered statistically significant with an F-value of 8.02 and a *p*-value of 0.0038, allowing for successful generation power prediction under the examined operational circumstances. In particular, for the relevant model terms X_1, X_2, X_3, X_1X_2, X_1X_3, and X_2X_3, the probability value (*p*-value) is less than 0.0004, which shows that the coefficients in Table 5 are significant. The model terms are not critical if the values are higher than 0.05. Model reduction may improve the overall design if many model terms (apart from those needed to sustain hierarchy) are deemed to be unimportant. The Adjusted R^2 of 0.95 and the Predicted R^2 of 0.90 diverge by less than 0.05, which is a reasonable alignment. The experimental design and findings are assessed by choosing the proper linear, quadratic, etc., models.

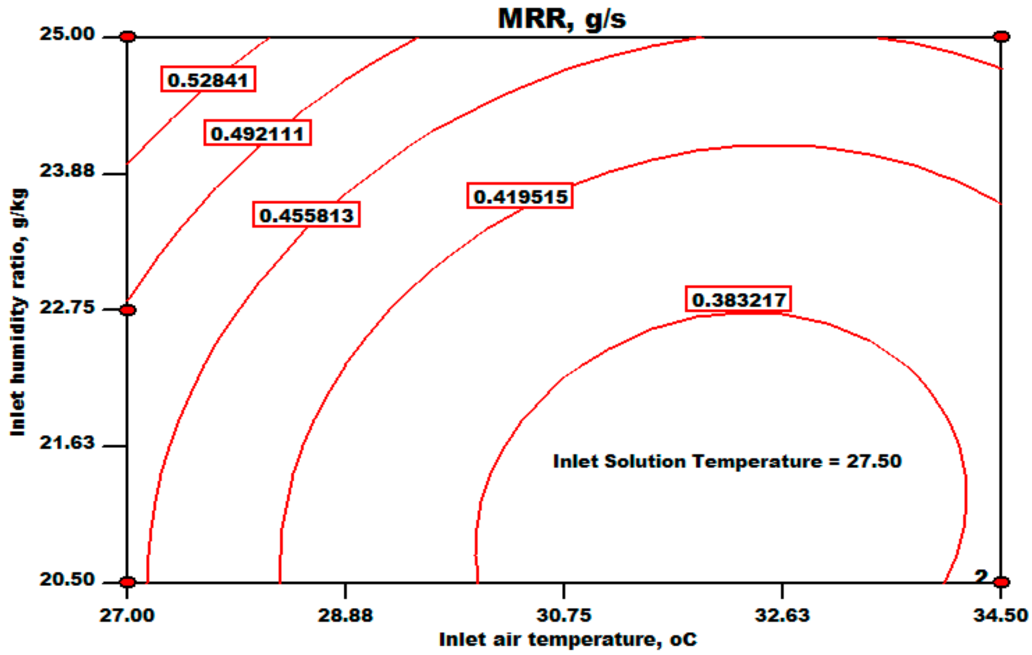
10.3. Influence of Operational Parameters on MRR and ε

The relationships between independent and dependent variables can be exhibited in the 3D exemplification as response surfaces. Curves with similar response values are constructed on a plane whose coordinates signify the levels of the contour plot's independent components. For a given set of factor levels, every contour appears with a surface value that is significantly higher than the stated level. Three-dimensional surface diagrams with contour graphs to the MRR verses ε are illustrated in Figures 3 and 4 and Figures 5–8, respectively.



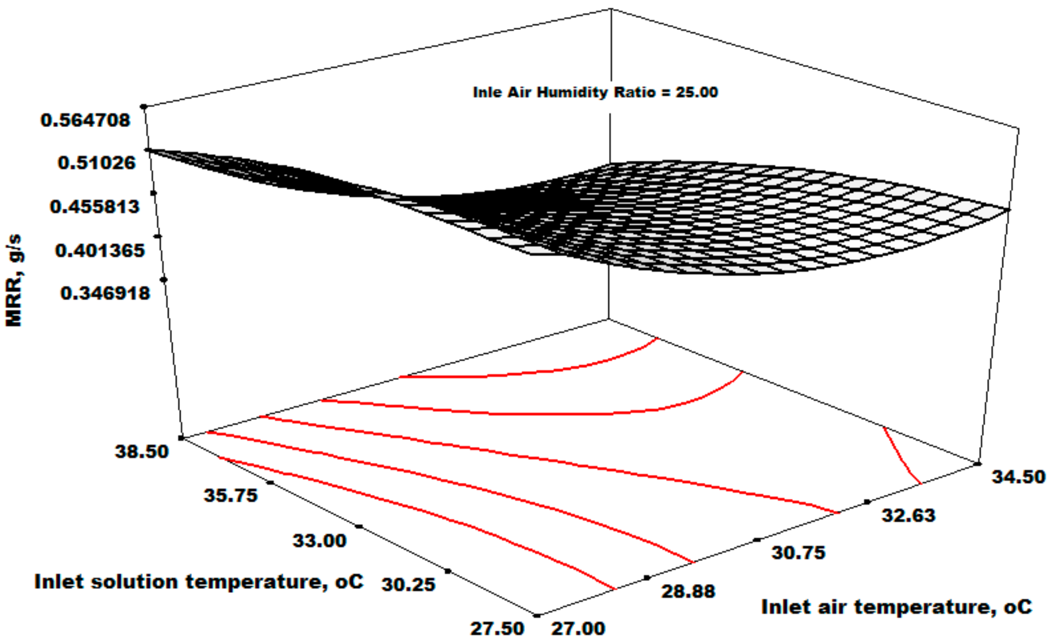
(**a**)

Figure 3. *Cont.*



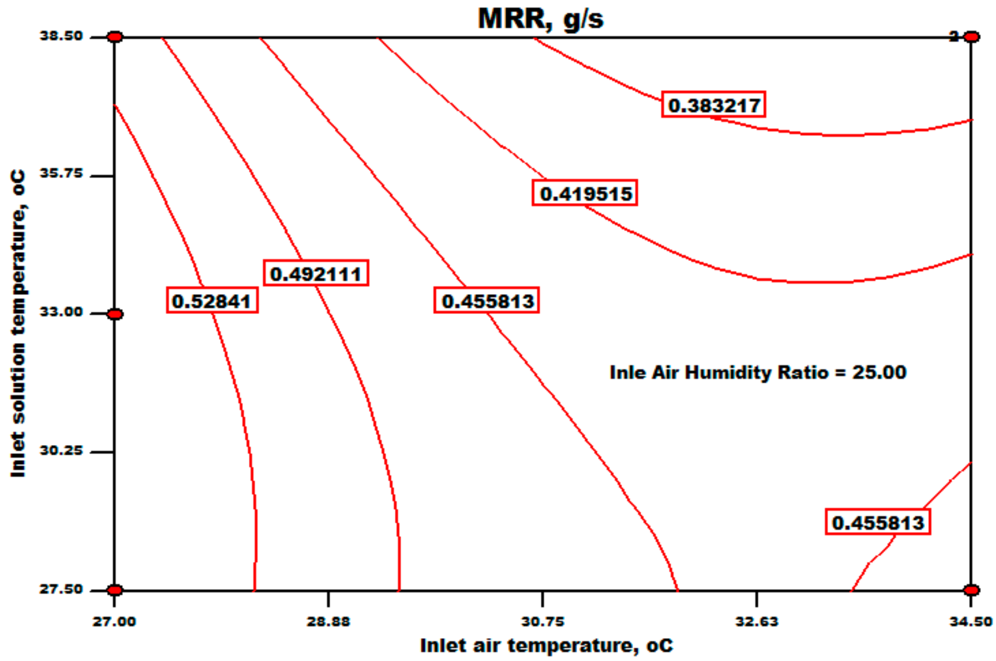
(**b**)

Figure 3. Effect of the inlet air temperature vs. ratio of humidity MRR: (**a**) response surfaces, (**b**) contour plot.



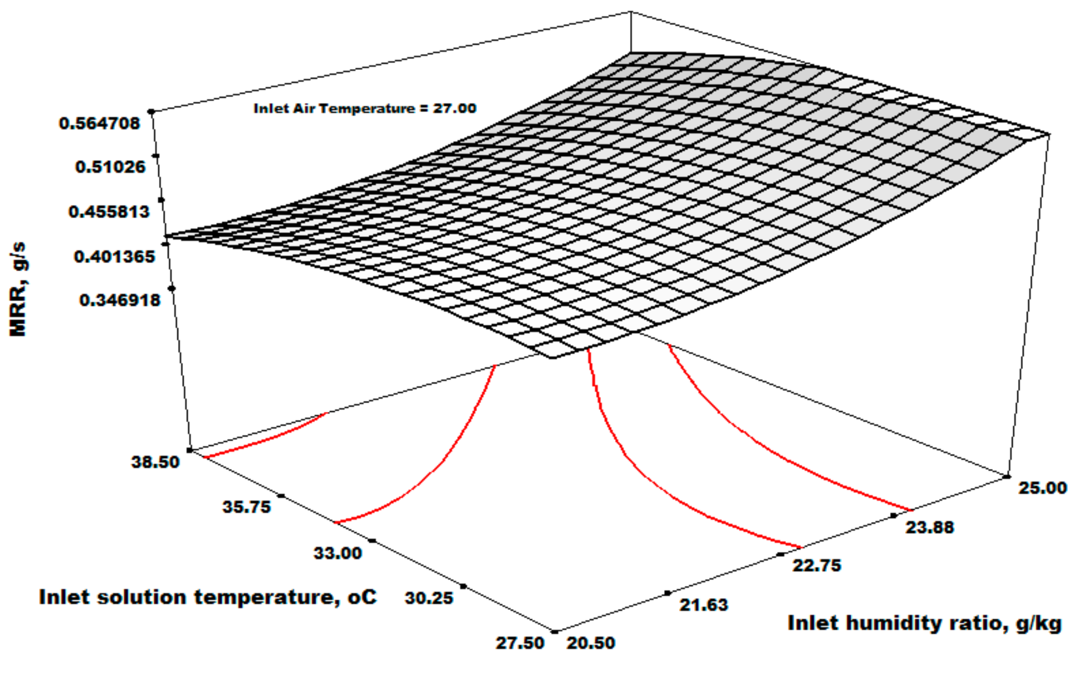
(**a**)

Figure 4. *Cont.*



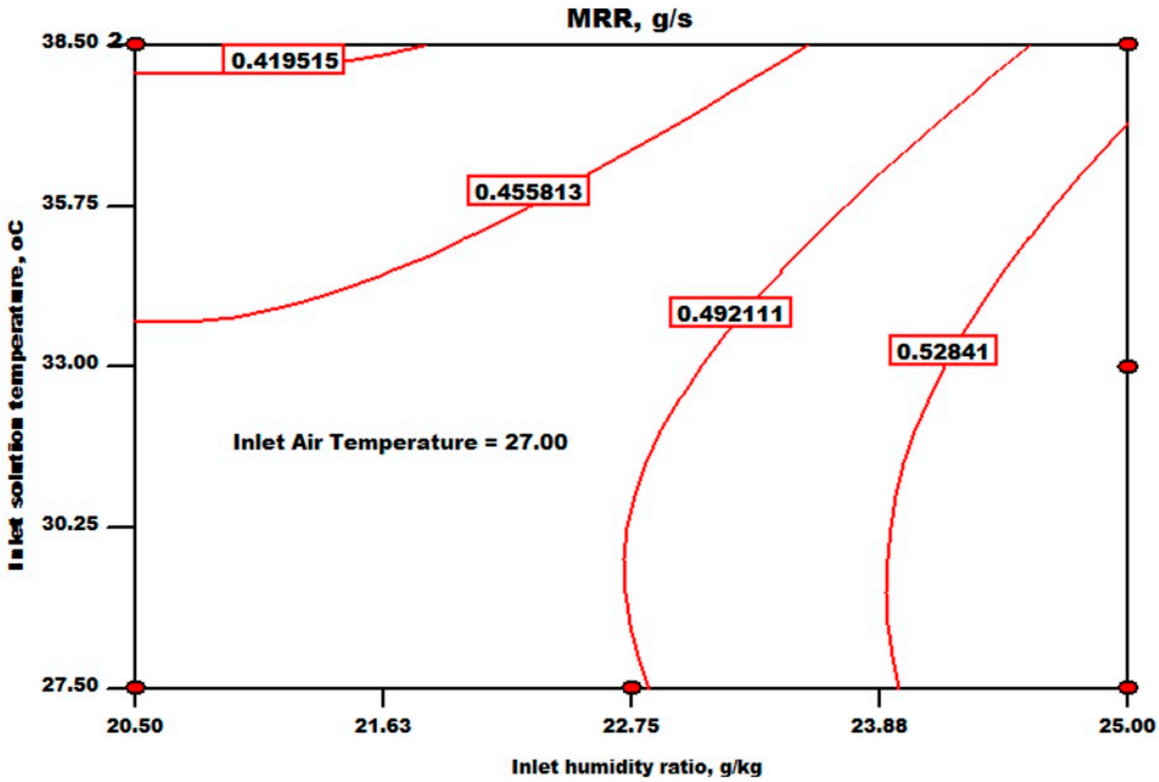
(**b**)

Figure 4. Influence of inlet air temperature vs. solution temperature on the MRR: (**a**) response surface, (**b**) contour plot.



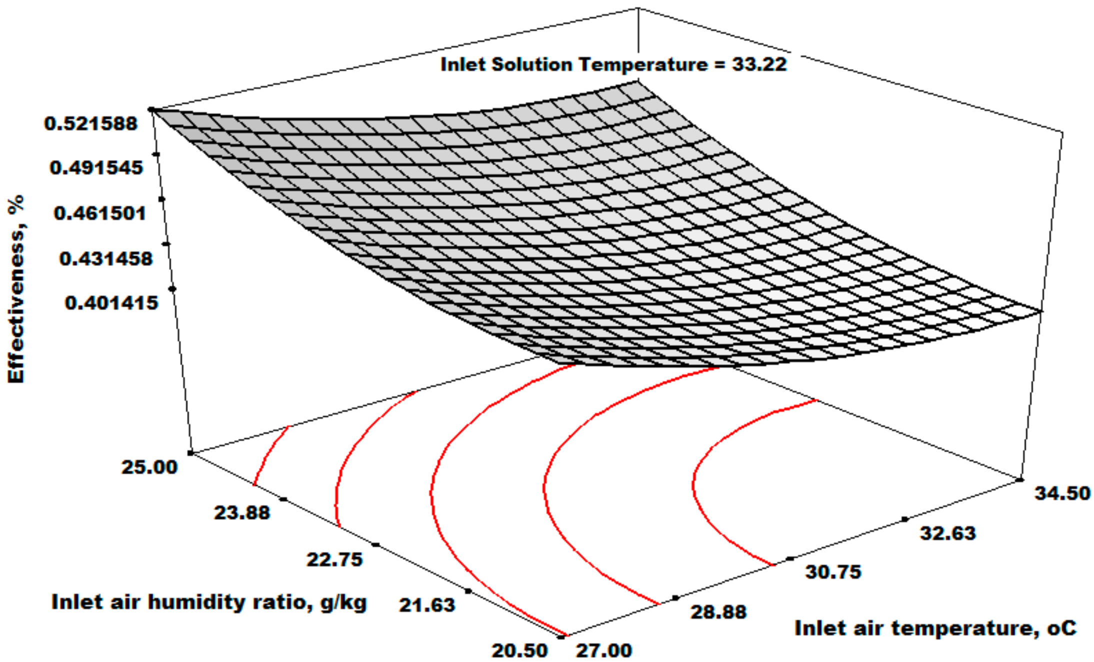
(**a**)

Figure 5. *Cont.*



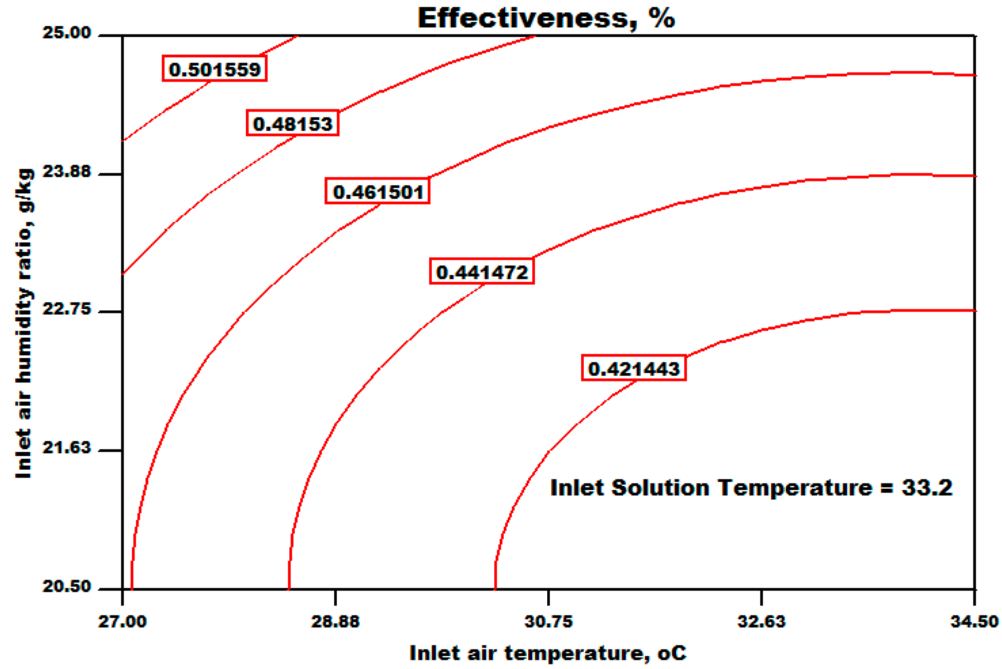
(**b**)

Figure 5. Influence ratio of air temperature vs. solution temperature on the MRR: (**a**) response surface, (**b**) contour plot.



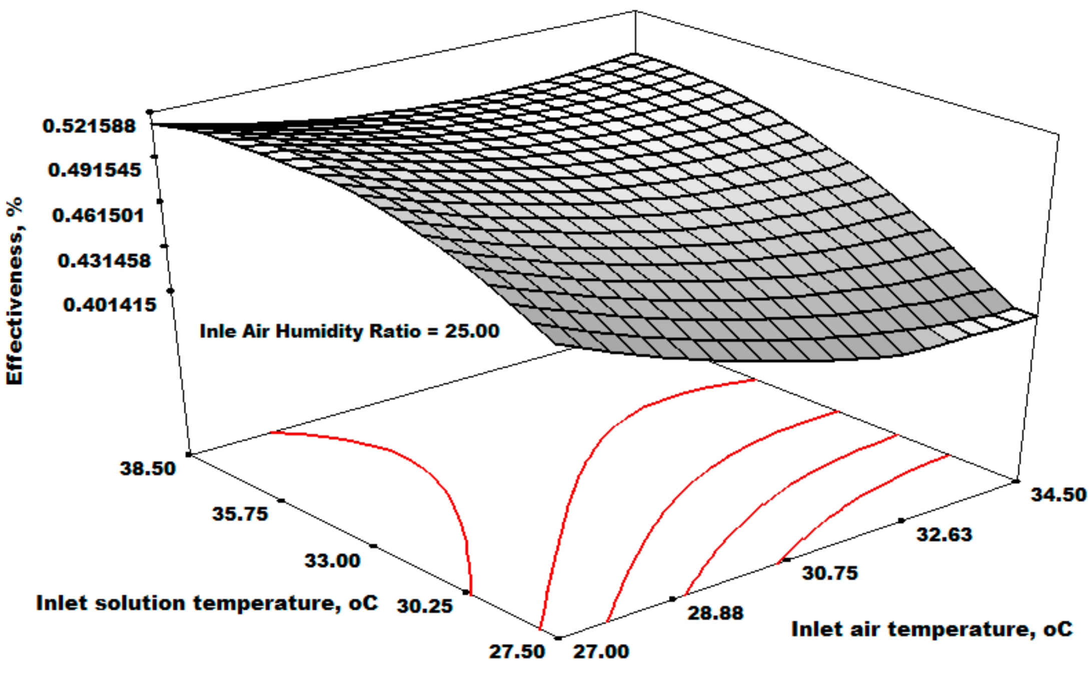
(**a**)

Figure 6. *Cont.*



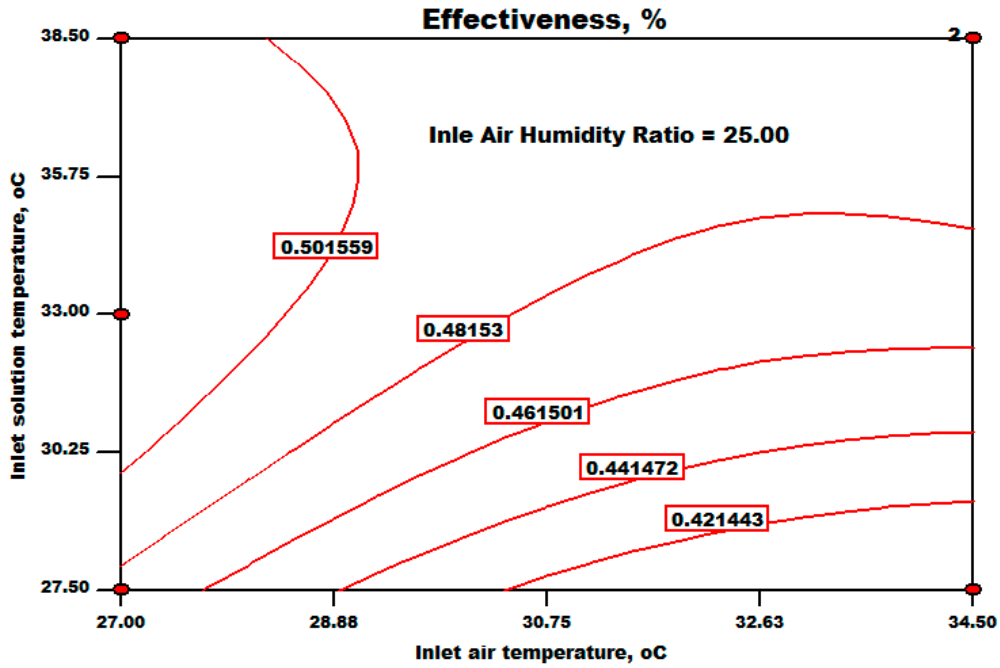
(**b**)

Figure 6. Effect of the inlet air temperature vs. the ratio of humidity on the ε: (**a**) response surface, (**b**) contour plot.



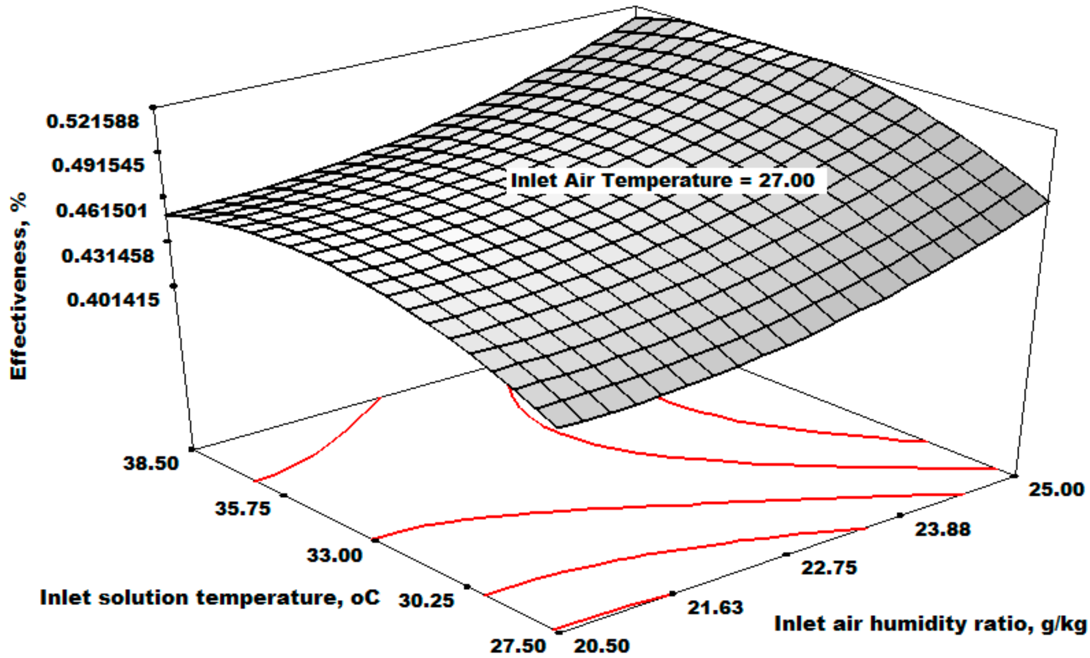
(**a**)

Figure 7. *Cont.*



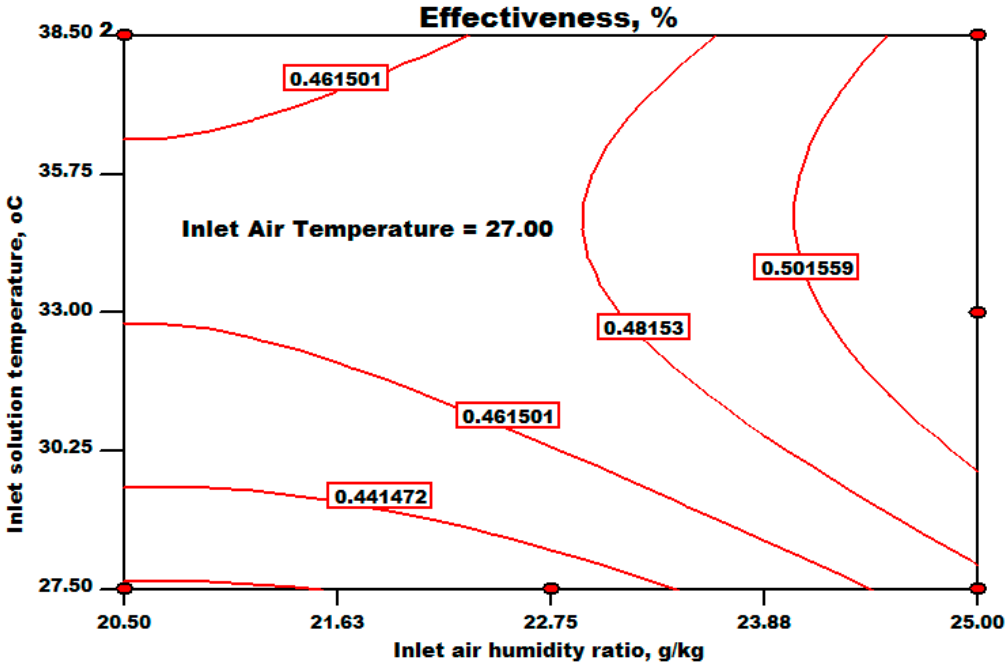
(**b**)

Figure 7. Influence between inlet air and solution temperature on the ε: (**a**) response surface, (**b**) contour plot.



(**a**)

Figure 8. *Cont.*



(**b**)

Figure 8. Influence of the inlet air humidity ratio and solution temperature on the ϵ: (**a**) response surface, (**b**) contour plot.

Response surfaces are 3D representations of the relationships between independents and dependents. Curves with the same response values are plotted on a plan whose coordinates indicate the levels for the independent components in a contour plot. Each contour indicates a distinct height from the surface over the plane formed by a combination of the factors' levels. Figures 2–4 and Figures 5–7, respectively, exhibit 3D surface graphs and contours for the MRR and ε.

The responses as MRR and ε are shown in the figures as a function of air temperature, the ratio of air humidity, and solution temperature. The fitted quadratic model accounts for the curved profile in the figure. MRR rises with decreasing air temperature to its minimum level (27 °C), as shown in Figures 2–4. Also, the input air temperature raises the solution temperature, which boosts the desiccant solution's partial pressure. As a result, the MRR of the dehumidifier is lowered. When the ratio is changed from (20 to 25 g/kg), the MRR is 0.577 gs^{-1} when the ratio of air humidity was 25 g/kg. This can be explained as when the humidity ratio rises, the partial water vapour pressure of the air rises, increasing the mass transfer potential. These results suggest that the air humidity ratio has a significant role in liquid desiccant dehumidification for sustainable building cooling. As the temperature of the solution rises, the MRR drops fast. The vapour pressure of the solution as the temperature rises lessons the mass transfer potential between the humid air and the liquid desiccant.

Figures 6–8 show that when the air temperature drops, the ε rises, indicating that raising the input temperature of air lowers the solution temperature, and this raises the partial pressure of the desiccant solution. As a result, the dehumidifier's efficacy is diminished. On the other hand, raising the inlet ratio of air humidity marginally reduces the efficacy. As the humidity ratio rises, the partial pressure of the water vapour of air rises, increasing the mass transfer potential. The inlet humidity ratio, furthermore, does not influence the dehumidifier's efficacy. As the solution increases in temperature, the equilibrium ratio of humidity at the solution surface and the humidity ratio of air outflow from the dehumidifier increase. The dehumidifier's efficacy increased marginally as a consequence of the offsetting effects between the numerator and denominator and denominator in (Equation (2)).

10.4. Optimisation of Operational Variables for MRR and ϵ

The mathematical optimisation approach gives the conditions of operation optimization whereby the optimum moisture removal rate and efficacy range from about 0 to 1. Each independent variable and response had a desired outcome indicated. The independent variables for both MRR and ϵ were kept within the range, while the response was set to maximum. Table 6 displays the optimum conditions for maximizing MRR obtained (27.4 °C, 24.5 g/kg) and (27.5 °C). Similarly, the maximized ϵ of the set of optimum conditions obtained was (27.4 °C, 24.8 g/kg) and (38.5 °C). Individual optimization yielded MR and ϵ responses of (0.54/s) and (0.5), respectively, with minimal desirability of (0.992) and (1). The optimal circumstances for maximum MRR achieved were (27.4 °C), (24.5 g/kg) (27.5 °C), and (27.5 °C), as indicated in Table 6. Similarly, the set of the best circumstances obtained to maximize the ϵ were (27.4 °C, 24.8 g/kg), and (38.5 °C). In the instance of individual optimisation, the MRR and ϵ responses were (0.54 g/s) and (0.5), respectively, with minimum desirability (0.992) and (1).

Table 6. Individual and multiple optimizations for maximum/minimum responsiveness.

Response Parameters	Coded Optimum Value			Uncoded Optimum Value			Responses	
	X_1	X_2	X_3	Ta	Wa	Ts	MRR, g/s	ε, %
MRR, g/s	−1	1	−1	27.4	24.5	27.5	0.54	0.48
ε, %	−1	1	1	27.4	24.8	38.5	0.52	0.50

11. Discussion

The results of this study highlight the complexity of interactions between operational parameters of dehumidification processes. The positive correlation between air humidity and the moisture removal rate (MRR) highlights that higher humidity levels promote mass transfer. By increasing humidity, water vapour is more likely to move from the air to the drying solution, improving dehumidification efficiency, especially when ambient humidity varies greatly.

Conversely, the negative impact of temperatures on MRR highlights the importance of optimal thermal conditions, as high temperatures can reduce the moisture absorption capacity of the dryer. This phenomenon illustrates the need for balanced temperature control to maintain system efficiency.

Statistical analysis, including analysis of variance, demonstrates the robustness of the regression model, with high R^2 values indicating a good explanation of the variance in the data. Specific interactions, particularly between air temperature and humidity, open the door to future research to refine these variables and optimize performance. Response surface methodology (RSM) provides a useful framework to visualize the complex interactions between variables, helping engineers make informed decisions when configuring systems. Moving forward, additional studies could evaluate the performance and durability of dehumidifiers under various environmental conditions, taking into account dust accumulation or corrosion. Exploring new materials or hybrid systems could also lead to significant improvements in performance and durability.

Overall, this research enriches the understanding of liquid desiccant systems and provides practical insights to optimize the design of energy-efficient refrigeration systems in the context of sustainable construction, paving the way for reduced energy consumption and improved indoor air quality.

12. Conclusions

The influence of temperature (air, ratio of air humidity and solution temperature) on the desiccant dehumidifier rate and performance was determined using response surface analysis. The most important conclusions can be made in the following:

1. With R^2 more than 0.90 for the moisture removal rate for the developed model and greater than 0.95 for the ϵ model, the model was able to reflect the experimental data.
2. Due to the examination of variation, the air humidity ratio has the greatest influence on the moisture removal rate. However, the ratio of air humidity to solution temperature has the greatest influence on efficacy.
3. Based on the table of D-optimal design optimisation, this model projected the highest moisture removal rate of 0.54 g/s. This is conducted within an optimal air temperature of 27.4 °C, humidity ratio of 25 g/kg, and solution temperature of 27.5 °C. Furthermore, the maximum effectiveness was approximated to be 0.50 below the optimum levels of air temperature of 27.4 °C, humidity ratio of 24.8 g/kg, and 38.5 °C of solution temperature.

Referring to the above conclusions, it is fair to ascertain that the optimisation of inlet parameters of liquid desiccant dehumidifiers via data analysis can attain substantial energy savings and lessen greenhouse gas emissions. Indeed, this would pave the way toward more sustainable building cooling policies.

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