A Novel Mathematical Model of the Solar Assisted Dehumidification and Regeneration Systems

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Abstract: This paper introduces a state-of-the-art modelling technique to investigate the performance of solar assisted dehumidification and regeneration cycles. The dehumidification/regeneration system investigated in this study employs a solid adsorbent bed and enables use of both solar energy and returning warm air to deliver efficient dehumidification and regeneration of the treated air. Study of literature revealed a huge gap between model results and industrial performance of such systems. Hence, the modelling work presented in this paper employs Gaussian Process Regression (GPR) technique to close the gap between model outputs and real-life operation parameters of the system. An extensive amount of laboratory tests were also carried out on the dehumidification/regeneration system and model predictions were validated through comparison with experimental results. The model predictions were found to be in good agreement with experimental results, with maximum error not exceeding 10%.

The GPR technique enables simultaneous analysis of a vast quantity of key system parameters derived from mathematical models and laboratory tests. The system parameters investigated in this study include: temperature, relative humidity and flow rate of process air, and temperature of regeneration air, solar radiation intensity, operating time, moisture extraction efficiency of the dehumidification cycle and moisture removal efficiency of the regeneration cycle. Investigation of both modelling and experimental results revealed that efficiencies of the both dehumidification and regeneration cycles decrease as relative humidity of the process air increases. The increase in regeneration temperature leads to an increase in regeneration efficiency whereas; it does not have a significant impact on the dehumidification efficiency. A similar trend was also observed when solar intensity were increased.

The proposed technique reduced the complexity of model by eliminating the need for heat and mass transfer calculations; reduced the performance gap between model results and real-life performance data, and increased the reliability of model outputs by showing a good agreement with experimental results. The GPR based mathematical model delivers an effective design and performance evaluation tool for the solar assisted dehumidification and regeneration systems and provides an unprecedented opportunity for commercializing such systems.

Keywords: *Gaussian process regression, mathematical model, solar assisted, efficiency, dehumidification*

1. INTRODUCTION

Air humidity is an important factor in both residential and industrial buildings which generally is controlled by air conditioning systems. Excessive amount of humidity can either have a negative effect on the habitants or the electronic instruments of residential and industrial buildings. Furthermore, it is a key aspect for increasing durability of products as dry air is used for improving the quality of products in large industries such as food production, pharmaceutical production, and industrial chemicals production. It is also required in goods storage, packaging rooms, organic plants, organic products and hygroscopic raw materials storage (Yadav, 2012).

The air with relative humidity (RH) between 40% and 60% is the most convenient indoor air for various purposes (Dai et al., 2017). Mechanical vapour compression refrigeration air conditioning systems are the main devices that are used to provide a comfortable residential and industrial air environment by controlling the temperature and humidity of the air. Due to their energy intensive process and low COP (Bi et al., 2018), energy efficient desiccant cooling and air-conditioning systems have attracted the attentions in past decades. In such systems, the dehumidification is done by solar energy or waste heat recovery instead of energy intensive devices (Safizadeh et al., 2014). Desiccant cooling and air-conditioning systems with solid or liquid desiccant are potential substitutes to electrically driven vapour compression cooling systems (Xiao et al., 2011; Calise et al., 2014; Ge et al., 2011).

Analysis of the desiccant systems are commonly classified into numerical, experimental and mathematical models. Literatures have investigated the heat and mass transfer processes occurring in the sorption systems in order to study the suitability of different desiccant materials for the absorbent, system configurations, component dimensions, operating conditions, and regeneration heat sources. Furthermore, development of components such as absorbers and solar regenerators and systems for air conditioning and drying applications, comparative assessment of the liquid sorbents properties and the performance comparison between indirect and direct solar regeneration unit have been carried out over the past years (Yin et al., 2014; Rafique et al., 2016; Misha et al., 2012; Gomez-castro et al., 2018; Daou, 2006). The above-mentioned literatures have led to great achievements in optimization, characterization and design of the desiccant systems.

Comprehensive overview of the conducted literature for the desiccant systems (Yang et al., 2017; Li et al., 2015; Das et al., 2015; Yamaguchi & Saito, 2013) , which only few of them are listed in this paper, has revealed there is an apparent gap between the research findings and engineering application of this energy efficient technology. This paper pioneers in developing the Gaussian Process Regression (GPR) as a predictive mathematical model for the novel solar/waste energy driven dehumidification/ regeneration cycle to fill the outstanding gaps.

Gaussian process regression (GPR) is a powerful predictive tool to model, explore and predict the performance of the system. The GPR, as a non-parametric Bayesian approach towards regression problems, explores various considered operating scenarios in a huge dataset for the proposed system and then predicts the behaviour of the system for unforeseen scenarios by a fitting function. The GPR is non-parametric as the form of the fitted function depends on the number of data points in the dataset. The GPR has been applied to a wide range of fields such as engineering, finance, education, medicine, and law (Li et al., 2018; Shepero et al., 2018; Wang et al., 2008). For instance, Gray et al. (2016) analysed the suitability of Gaussian processes for thermal building modelling by comparing the day-ahead prediction error of the internal air temperature with a grey-box model. Wu et al. (2018) presented a new application of Gaussian process regression methods for the modelling and forecasting of human mortality rates. Liu et al. (2018) presented an accurate Gaussian process regression soft sensor with the sum of squared-exponential covariance function and periodic covariance function to capture the time varying and periodic characteristics in the subway IAQ data. Yuan et al. (2018) employed the Gaussian process regression to predict the ship fuel consumption for different scenarios.

An extensive literature review of the desiccant based dehumidification systems has disclosed the outstanding gap between the research findings and engineering application of the desiccant systems, since the current numerical and experimental models are limited to the narrow data scales. This situation has significantly obstructed the wide and rational application of the desiccant based dehumidification systems in practical engineering in which key operating parameters vary simultaneously during the different operational conditions. Additionally, the experimental models are slow and cost intensive, and the numerical models are cumbersome as the energy balance and mass transfer phenomenon must be simulated and lots of iterations makes the modelling time consuming. Lack of one by one and direct correlations between the main operating and performance parameters in the previously proposed models has apparently obstructed the analysis of the dehumidifier systems.

To fill the above mentioned gaps between the research findings and practical engineering application of the desiccant technology, this paper has pioneered in bringing the Gaussian Process Regression (GPR) into a solar/waste energy driven dehumidification/regeneration system which bridges the identified gap by enabling the performance analysis of the system by using the key parameters only. The GPR has been employed to convert thousands of numerical and experimental data to a practical engineering equation which enables the engineering scale and characterization of the solar/waste energy driven dehumidification/regeneration cycle. The equation correlates the key operating parameters with the performance parameters, and thus enables the performance analysis of the system by predicting the unforeseen operating conditions. The outstanding features of the GPR based mathematical model for the solar/waste energy driven dehumidification/regeneration cycle are:

- Directly correlates the main operating parameters i.e. temperature, relative humidity and flow rate of process air, temperature of regeneration air, length of the desiccant bed, solar radiation intensity and operating time with performance parameters i.e. moisture extraction efficiency for the dehumidification cycle and moisture removal efficiency for the regeneration cycle.
- Needless of the energy and mass balance equations, and associated initial and boundary conditions and iteration processes.
- Practical, swift, accurate and cost-effective method that make it suitable for studying any critical operating conditions without any danger and is appropriate for commercializing.
- Valid to predict system performance for any unforeseen operating conditions within the real operating ranges.

2. METHODS: GAUSSIAN PROCESS REGRESSION

Gaussian process regression (GPR) is a vigorous method to predict the value of the unforeseen points by observing some known data. Practically, GPR goes through the collected inputs (independent variables) and outputs (dependent variables) and accurately predicts the value of outputs for any new possible inputs by a fitted function and correspondent coefficients. The objective of this function is to find the accurate value of the output as quickly and accurately as possible. Moreover, the function can express and explore the direct and one by one relationship between any inputs and outputs. A detailed description of the GPR has been presented in (Rasmussen, 2004). Here a brief review of the fundamentals is provided.

In equation 1, f denotes the unknown function, y represents the dependent variable, x represents the independent variable and ϵ represents the measurement error.

Equation 1: Error, dependent and independent parameters function
$$y = f(x) + \epsilon$$

Gaussian process describes the distribution over functions and it needs a covariance or kernel function and mean function as shown in equation 2 to be fully specified.

Equation 2: Covariance, kernel function and mean function
$$f(x) \sim GPR(m(x), k(x, \acute{x}))$$

Generally, the covariance function, defines the degree of correlation between the outputs of two input sets (x and $\acute{x}$), and plays a key role as the backbone on which the relationships between input variables are found.

The mean covariance and the kernel functions can be defined as equations 3 and 4 respectively:

Equation 3: Mean function
$$m(x) = E\ [\ f(x)\ ]$$

Equation 4: Covariance function
$$k(x, \acute{x}) = E\ [\ \big(f(X) - m(x)\big)\big(f(\acute{x}) - m(\acute{x})\big)\ ]$$

Where $E\ [\ f(x)\ ]$ means expected value of $f(x)$.

An appropriate kernel is chosen on basis of the assumptions such as smoothness and likely patterns to be expected in the data. One common kernel function is the radial basis function kernel, which can be defined as:

Equation 5: Radial basis function kernel
$$k(x, \acute{x}) = \sigma_f^2 \exp(-\sum_{i=1}^{i=n} \frac{\|x(i) - \acute{x}(i)\|^2}{2\theta(i)^2})$$

Where σ_f^2 is called the signal variance and ϴ is called the length-scale.

The covariance matrix for any two matrices (X=[$x_1, \ldots, x_n$] and $\acute{X}$=[$\acute{x}_1, \ldots, \acute{x}_n$]) is defined as:

Equation 6: Covariance matrix

$$K(X, \acute{X}) = \begin{bmatrix} k(x_1, \acute{x}_1) & k(x_1, \acute{x}_2) & \ldots & k(x_1, \acute{x}_n) \\ k(x_2, \acute{x}_1) & k(x_2, \acute{x}_2) & & k(x_2, \acute{x}_n) \\ & \vdots & \ddots & \vdots \\ k(x_n, \acute{x}_1) & k(x_n, \acute{x}_2) & \cdots & k(x_n, \acute{x}_n) \end{bmatrix}$$

Once the prior kernel and mean functions are chosen, the GPR can be implemented to update the kernel and mean functions using the observed new data points to obtain the posterior estimation function.

3. DESCRIPTION OF THE DEHUMIDIFICATION/REGENERATION CYCLE

Schematic of the solar/waste energy driven dehumidification/regeneration cycle is shown in Figure 1. In such system, a desiccant bed which is illustrated in Figure 2, is located inside a channel and is constructed by a porous and visible-light LiCl-Sillicon-Gels material.

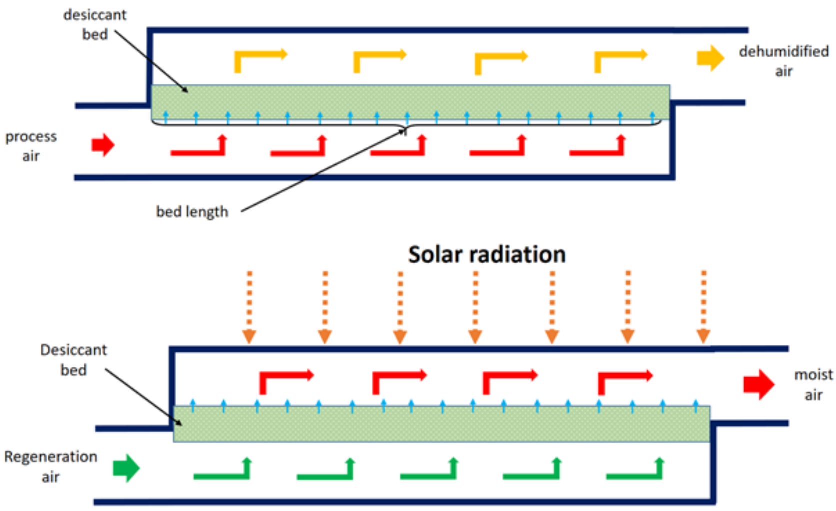

Figure 1: Solar/waste energy driven dehumidification and regeneration cycle: (upper) dehumidification process; (lower) regeneration process.

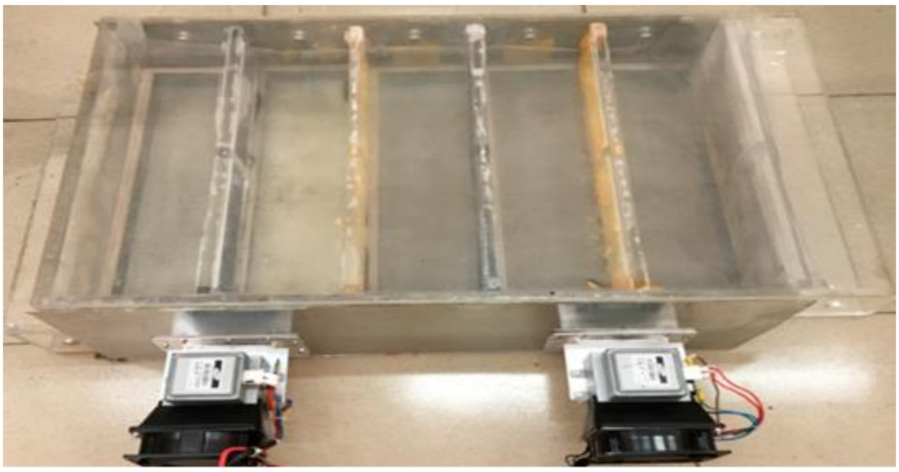

Figure 2: Image of the solar solid dehumidification/regeneration bed. [17]

The bed specifications such as its dimensions and material play a key role in the performance of both dehumidification and regeneration cycles. The size of the bed for the selected system in this study is 700 mm × 500 mm × 250 mm and the thickness of the silica gel layer was chosen at 50 mm [17]. In the dehumidification process, the humid air which is called process air, flows inside the channel and passes through the bed. The moisture of the process air is absorbed by the absorbent material in the desiccant bed owing to the vapour partial pressure difference between the solid absorbent surface of the bed and the process air. By passing the process air through the desiccant bed, the absorbent material gradually will reach its saturation state and regeneration process must be started to regenerate the saturated absorbent material for the next dehumidification cycle.

During the regeneration process, either a warm regeneration air with a temperature more than 70oC or a low temperature regeneration air with the solar radiation, which is brought into the channel through the upper side solar-visible glasses, passes through the saturated absorbent. As the regeneration air passes through the channel, the heat is transferred from the regeneration air to the water sorted inside the absorbent voids and get the water evaporated. Eventually, the evaporated water is taken out by the regeneration air and the regenerated absorbent is ready for another dehumidification cycle. When the solar radiation is not available, the regeneration air is firstly heated by an available waste heat sources as the heat play a key role in evaporating the water that is sorted in the absorbent bed.

Moisture extraction efficiency is the ratio of the inlet humidity ratio of the process air as a performance parameter of dehumidification cycle can be expressed as [3]:

Equation 7: Moisture extraction efficiency

$$\eta_{me} = \frac{d_{p,in} - d_{p,out}}{d_{p,in}}$$

Where $d_{p,in}$ is moisture content of inlet air and $d_{p,out}$ is the moisture content of outlet air.

And the moisture removal efficiency for the regeneration cycle is given as:

Equation 7: Moisture removal efficiency

$$\eta_{mr} = \frac{W_0 - W}{W_0}$$

Where W_0 is initial water content of desiccant and W is the final water content of desiccant.

4. MATHEMATICAL MODEL

In order to develop the mathematical model, a comprehensive data points comprising the key operating parameters and corresponding performance parameters have been provided. These data points have constructed a single comprehensive dataset which has been analysed by Gaussian process regression in R programing language. The Gaussian process regression (GPR) has been presented by an applicable engineering equation. In this section model development process which is divided into three main sub-sections, is explained.

4.1. Determination of the dependent and independent variables

To carry out the mathematical model, the solar/waste energy driven dehumidification/regeneration cycle's main operating parameters, which are also called independent variables, and proper operating parameters, which are also called dependent variables, have been identified. In this study, seven main operating parameters as shown in Figure 3, including three main flow characteristics i.e., temperature, relative humidity and flow rate which can change continually during the system operation, have been selected for both dehumidification and regeneration cycles. Additionally, based on the previous numerical and experimental models [3, 17], length of the desiccant has been selected as the main geometric characteristics because it has the dominant effect on the performance of the system among other geometric characteristics. Solar radiation intensity for the regeneration cycle and operating time of both dehumidification and regeneration cycle are considered as the operating parameters. For dependent variables, moisture extraction efficiency as a performance factor of dehumidification process and moisture removal efficiency as a performance factor of regeneration process have been selected to fulfil the performance analysis of the desiccant system.

To make the model more concentrated on the real operating conditions of the described system in section 2, and also to avoid the model from considering the unrealistic operating conditions, proper ranges for each independent variables are defined and thus the values of each variable has been narrowed to real operating conditions. Appropriate ranges have been set by a meticulous investigation of real operating conditions, numerical and experimental literatures as listed in Table 1 [3, 17]. Flow rate and relative humidity of the air stream in both cycles are considered to be same [3].

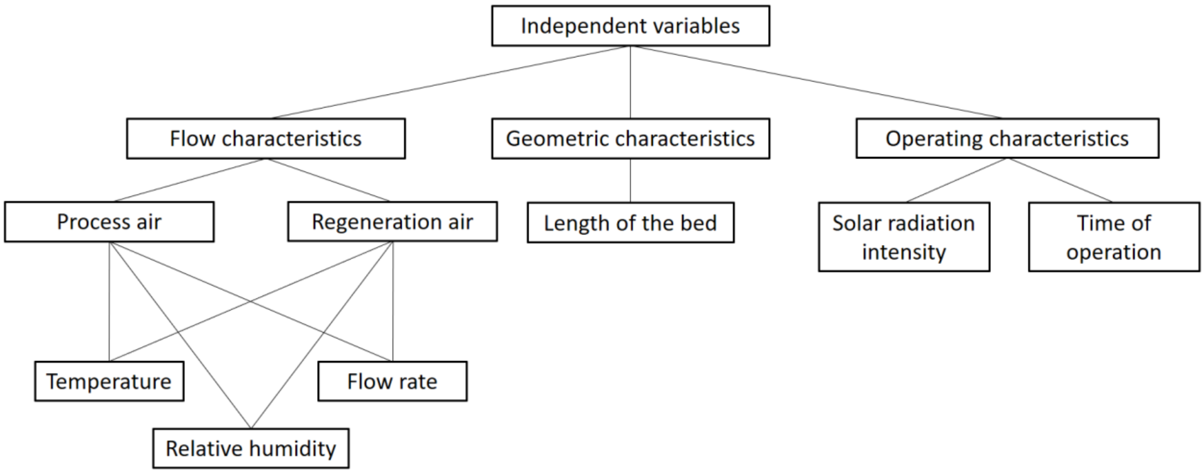

Figure 3: Independent variables diagram

Table 1 : Range of operating parameters

Operating parameters	**Ranges**
Temperature of the process air, °C	25 – 40
Relative humidity of the process air, -	0.6 – 0.9
Temperature of the regeneration air, °C	70 – 80
Flow rate air stream, m/s	1 – 4
Length of the desiccant bed, m	1 – 5
Solar radiation intensity, W/m^2	0 – 1800
Operating time of each cycle, hr	1 – 5

A comprehensive dataset as a principal of statistical modelling which must be created to trigger the data exploration. The dataset is composed of two parts: 1) Independent variables 2) Dependent variables. To construct the independent (operating parameters) section, firstly, discrete values for each independent variable are chosen by considering the defined ranges listed in Table 2. Different discrete values could have been selected because the values in Table 2 are randomly chosen to construct the dataset only and validity of the model are not restricted to these specific values.

Table 2 : Discrete values for operating parameters

T_p [°C]	RH_p [-]	T_r [°C]	U [m/s]	L_d [m]	I [W/m^2]	t [hr]
25	0.6	20	1	1	0	1
27.5	0.7	70	2	2	300	2
30	0.8	80	3	3	600	3
32.5	0.9	90	4	4	900	4
35	0.99	-	-	5	1200	5
37.5	-	-	-	-	1500	-
40	-	-	-	-	1800	-

Having identified the discrete values, to finalize the construction of the independent section of dataset, all possible combinations of the discrete values are created. All possible combinations allow the GPR model to be aware of all possible operating conditions of the system and thus accredits the model under any random operating conditions. Figure 4 illustrates three operating conditions out of n possible conditions. In each condition, single values for each independent variable is selected and then a set of all selected values is located in the independent part of the dataset as one operating condition. Once all possible sets are selected, the model will be aware of all possible combinations during the data analysis process.

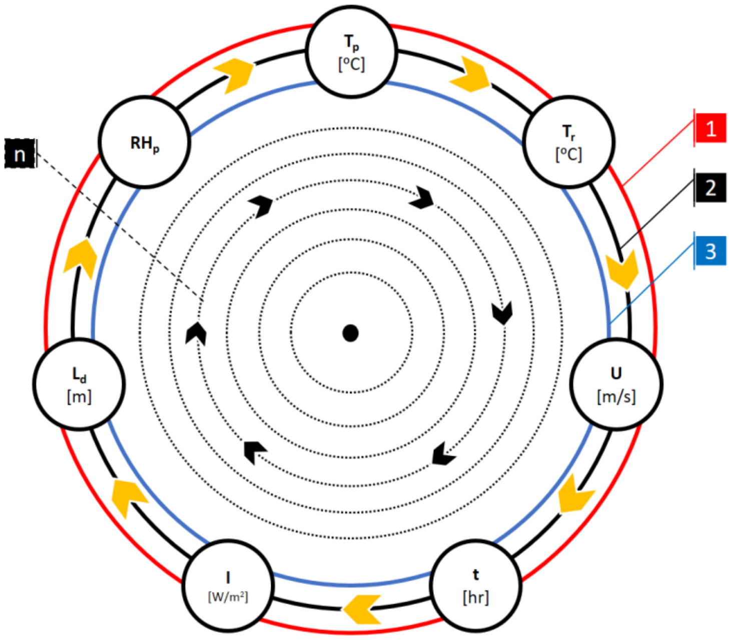

Figure 4: Illustration of three operating conditions out of n operating conditions

To build the dependent part of the dataset, all corresponding performance parameters for each created operating condition have been calculated through an experiment [17] and constructed the comprehensive dataset as shown in Table 3. In this study, 4320 set of operating conditions are analysed by a GPR based mathematical model to provide the generalized model.

Table 3: Comprehensive dataset

Operating conditions	T_p [°C]	RH_p [-]	T_r [°C]	U [m/s]	L_d [m]	I [W/m²]	t [hr]	η_{sorp}	η_{desorp}
1	25	0.6	20	1	1	600	2	0.277561778	0.518653866
2	25	0.6	1	3	20	600	1	0.368264439	0.692065835
3	25	0.6	20	1	1	1800	2	0.277561778	0.936875303
4	25	0.6	20	1	3	600	2	0.275255819	0.903544548
5	25	0.6	1	3	20	1200	2	0.275255819	0.999996842
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
4325	40	0.9	4	3	80	0	5	0.01325928	0.999999932
4326	40	0.9	4	3	90	0	5	0.01325928	1
4327	40	0.9	4	5	70	0	5	0.013555742	0.999972234
4328	40	0.9	4	5	80	0	5	0.013555742	0.999999935
4320	40	0.9	4	5	90	0	5	0.013555742	1

4.2. Gaussian process regression model

The GPR analysis has been carried out in R programing tool 3.5.1 using the DiceKriging package. The detailed information about the DiceKriging package can be found in (Roustant, 2012). The Gaussian covariance kernel has been selected in GPR because it is the standard choice for obtaining a smooth interpolating function.

The analysis is done in four major steps:

i. The constructed comprehensive dataset is imported.
ii. The GPR analysis is carried out by a fitted function for the imported dataset.
iii. Report of the analysis is printed with all calculated coefficients.
iv. Final exponential equation is produced.

5. RESULTS AND DISCUSSION

In this section, the model is firstly validated in model verification subsection and then generalized in order to accredit the model validity for any operating conditions within the defined ranges. Eventually, the constructed equation and its correspondent coefficients are presented for both dehumidification and regeneration processes. Finally, to illustrate the applicability and contribution of the model to the proposed system, effect of four operating parameters are discussed.

5.1. Model verification

The developed mathematical model by GPR have been verified by experimental results [17]. Figure 5 gives the dehumidification efficiency for both experiment and GPR based mathematical models. The comparison has been done with listed values in Table 4 and for five hours of system operation for each cycle. Dehumidification efficiency decreases as the cycle continues and the desiccant bed absorbs more water. It can be seen that the results are almost overlapped where the maximum relative error is 9.7%.

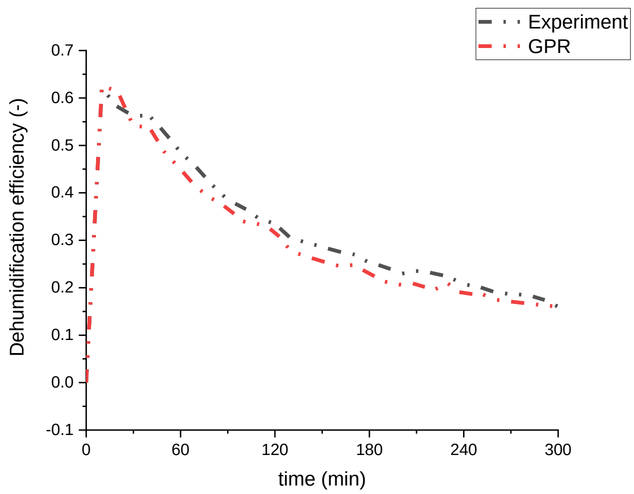

Figure 5: Validation of the mathematical model

Table 4: Parameters value for model verification

Parameters	Values
Relative humidity of the process air, -	0.81
Temperature of the regeneration air, °C	27.69
Flow rate air stream, m/s	0.62
Length of the desiccant bed, m	0.7
Solar radiation intensity, W/m^2	300
Relative humidity of the process air, -	0.81

5.2. Model generalization

Once the model was verified, the cross verification is conducted to generalized the model and to show the independency of the model to the created dataset in Table 3 and thus to express the validity of the proposed model for any new operating condition within the defined ranges. For this purpose, ten unforeseen operating conditions are chosen to investigate the generalization of the model as shown in Table 5. Figure 6 shows the comparison results for both experimental and GPR based mathematical models which indicates the good agreement of both models for random operating conditions in which the maximum relative errors for dehumidification and regeneration cycles are 2.14% and 9.96% respectively.

Table 5: New random independent parameters

Random operating conditions	T_p [°C]	RH_p [-]	T_r [°C]	U [m/s]	L_d [m]	I [W/m²]	t [hr]
1	26.9	0.7	3.7	1.4	20	600	1
2	26.9	0.87	3.7	4.6	20	600	1
3	33.2	0.65	1.25	4.6	20	600	1
4	33.2	0.7	1.25	4.6	20	600	1
5	38.5	0.65	2.85	4.6	20	600	1
6	38.5	0.7	1.25	4.6	20	600	1
7	38.5	0.87	3.7	4.6	20	600	1
8	26.9	0.7	1.25	1.4	90	0	1
9	26.9	0.87	3.7	4.6	90	0	1
10	33.2	0.65	3.7	4.6	90	0	1

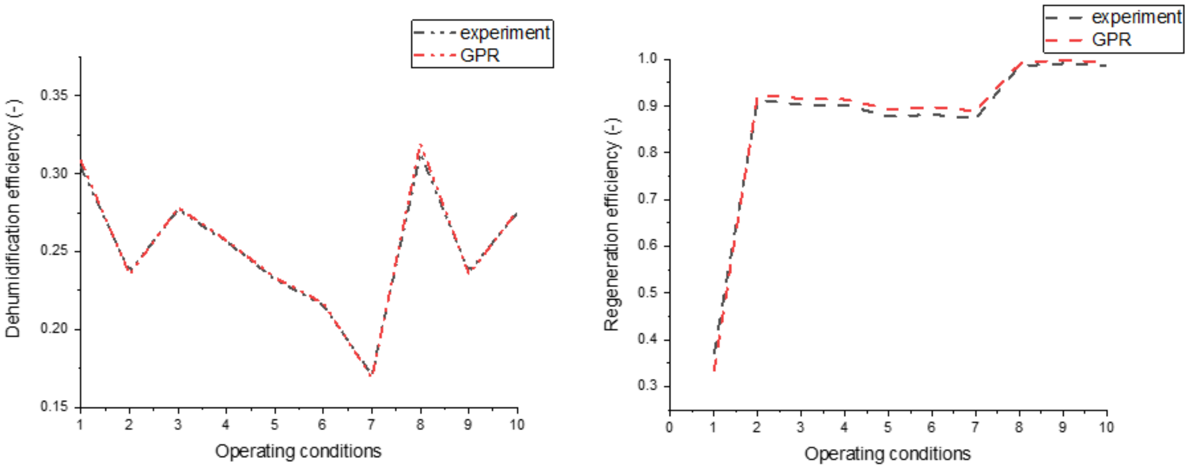

Figure 6: Cross validation of the mathematical model: (left) dehumidification efficiency (right) regeneration efficiency

6. CONCLUSION

A new application of Gaussian Process Regression (GPR) is presented in this paper which enables the performance analysis of the novel solar/waste energy driven dehumidification/ - regeneration cycle. Such effort adds important scientific values to the characterization and engineering design of the solar/waste energy driven dehumidification/regeneration cycle by correlating the main parameters of the system. The existed gap in previous literatures between the research and engineering application of the system is now filled as the engineering scale design and characterization of the desiccant system is now achievable. This approach offers an invaluable contribution to the commercialization and market viability of the novel solar/waste energy driven dehumidification/regeneration cycle technology, and thus makes the analysis process of the system environmentally friendly.

The GPR based mathematical model has been developed by exploring thousands of numerical and experimental data into an exponential equation which directly correlates the main operating parameters of the desiccant system i.e. temperature, relative humidity and flow rate of process air, temperature of the regeneration air, length of the desiccant bed, solar radiation intensity and operating time of the system to the performance parameters, i.e. moisture extraction efficiency for the dehumidification cycle and moisture removal efficiency for the regeneration cycle. Additionally, the model enables analysis of the parameters and their effects on the performance of the system directly. The extraction process of the equation has been carried out in R programing language using the Dice Kriging package, and then the model is validated by experimental data with maximum relative error of 9.7%. Furthermore, the cross validation has been presented to illustrate the validity of the model for any new operating parameter with maximum relative errors of 2.14% and 9.96% for dehumidification and regeneration cycles respectively.

The presented GPR based mathematical model is simple, practical, accurate and swift in operation as no iteration, energy or mass transfer equations are needed to analyse the system. Thus, the GPR based mathematical model provides an effective design and performance evaluation tool for the solar/waste energy driven dehumidification/regeneration cycle to commercialize and explore the product.

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