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Multi-Objective Performance Steady State Optimization Complete Membrane-Based Liquid Desiccant Dehumidifier System

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Keywords
Steady State, Complete Membrane, Liquid Desiccant, Dehumidifier System

Abstract
This study focuses on the multi-objective performance steady state optimization of a complete membrane-based liquid desiccant dehumidifier system. The system is designed to efficiently remove moisture from the air using liquid desiccant technology. The objective of the optimization is to simultaneously maximize the dehumidification performance, minimize energy consumption, and optimize the system's operational parameters. A steady state model of the membrane-based liquid desiccant dehumidifier system is developed, and a multi-objective genetic algorithm is applied to explore the optimal solution space. The results demonstrate the trade-offs between dehumidification performance and energy consumption, providing insights into the performance and efficiency of the system. The proposed optimization approach offers a valuable tool for designing and improving the performance of membrane-based liquid desiccant dehumidifier systems in various applications.

1. Introduction

Infiltration, ventilation, and occupants all contribute to the air conditioning load of a space structure. When building heating, ventilation, and air conditioning systems for a building, thermal comfort, energy savings, and indoor air quality are key considerations. Thermal comfort varies based on what is done. *Heating ventilation air conditioning (HVAC) systems* typically must maintain an interior air temperature of 18-26°C and a relative humidity level of 40-70% to provide comfortable thermal conditions for occupants In fact, 20-40% of the energy consumption of HVAC systems is in air dehumidification. From the existing system, there are various problems such as weak ability to handle latent heat loads, and fungal and bacterial growth. *Liquid Desiccant* has recently received great attention for its good ability to remove latent heat and moisture loads. However, *Liquid Desiccant* droplets can be carried into a conditioned space so as an alternative, a semi-permeable membrane is used to avoid *carry-over problems.* Bai et. al experimentally and numerically found that the main parameters that determine the performance of the dehumidifier are NTU and mass flow rate (m) and they interact with each other (Shirazi et al., 2018). Dehumidification performance is evaluated by the parameters of *sensible effectiveness*, *latent effectiveness,* and *moisture flux rate*. In this report, an analysis will be carried out on simulation-based multi-objective optimization with *Effectiveness* and *Moisture Flux rate* as conflicting objective functions. By combining the two programs *Design Expert* and MATLAB, a multi-objective optimization model for this case is formulated, thus a set of *Optimal Pareto solutions* can be determined (Grossman, 2002).

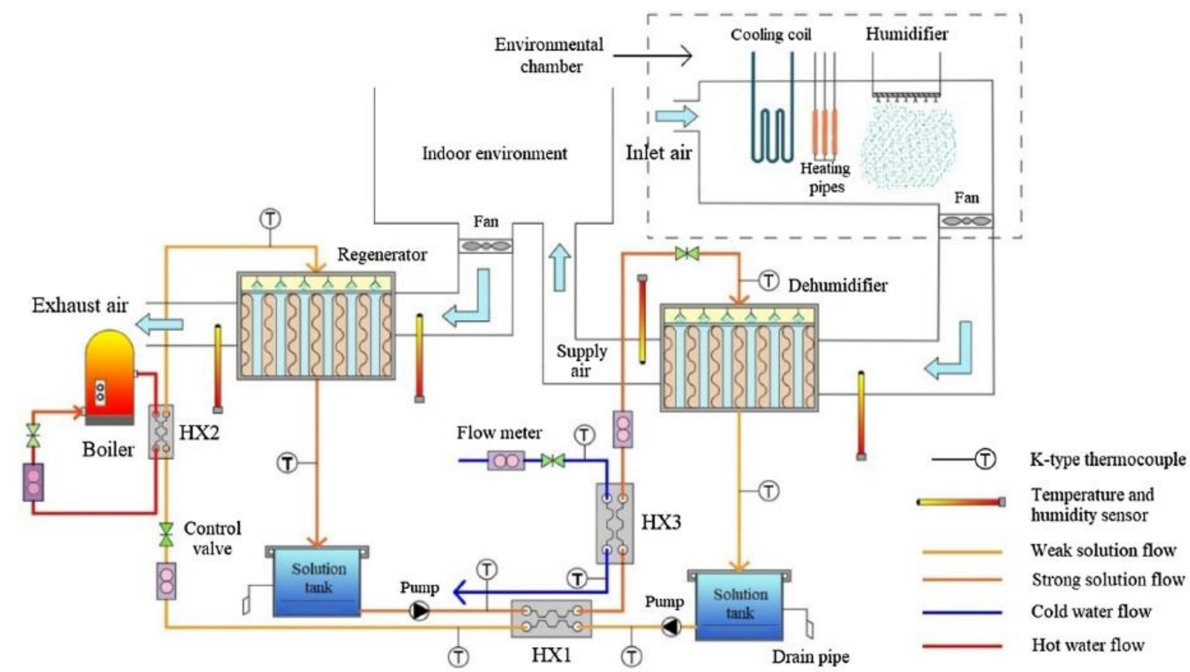
This paper aims to present comprehensive data and analysis for designing and operating liquid desiccant dehumidifier systems in the real world. Another thing is to do multi-objective system optimization and study the optimization results between Design Expert, MATLAB with Design Expert equation, and MATLAB with ANN equation (Bai et al., 2020).

- All components in this system are well isolated
- *Liquid desiccant* and *airflow* in a *dehumidifier* are considered *laminar flow*
- All thermodynamic processes operate at *steady-state conditions*

System Description

Scheme of Liquid *Desiccant Dehumidifier System.*

The *liquid desiccant dehumidifier system* mainly consists of a *dehumidifier*, *regenerator*, three *heat exchangers*, two *solution tanks*, one chilled water supply unit, and one hot water supply unit. *The liquid desiccant* used is *Lithium chloride* (LiCl). *The cooled* solution in the *Heat Exchanger* (HX3) flows to the dehumidifier, where the temperature and humidity ratio is reduced by the strong solution so that the solution becomes diluted. The air from the room is used as regenerating air in the regenerator where moist and hot air will be discharged out. *Heat Exchanger (HX1) is used for heat recovery, the dilute solution is further heated with hot water in the* Heat Exchanger *(HX2) before flowing into* the regenerator (Yuliani & Zainul, 2018). Airflow is regulated by 2 variable speed fans and calculated with *Testo Thermos anemometer* with a range of 0-10m/s with accuracy The flow of the solution is driven by 2 15W magnetic centrifugal pumps. The flow rate ±5%. *of the solution through* the dehumidifier and *regenerator is adjusted by* the flow meter *with a range of 1-15 L/min and* the accuracy of the ±5% (Li et al., 2011).*Solution* Concentration viewed from the density *sing Brannan Hydrometer* with solution and ±2%.*water* temperature *was calculated using type K Thermocouple with a range of 0-1100 C and accuracy Air Humidity was calculated with Sensiron Evaluation KIT with a range of 0-100% and accuracy* ±0,75%. ±3%. (Cheng et al., 2012)



Gambar 1 Skema *Liquid Desicccant Dehumidifier System* [1]

2. Materials and Methods

Working Flow Chart

The process undertaken to complete this study can be seen in the *flow chart* below.

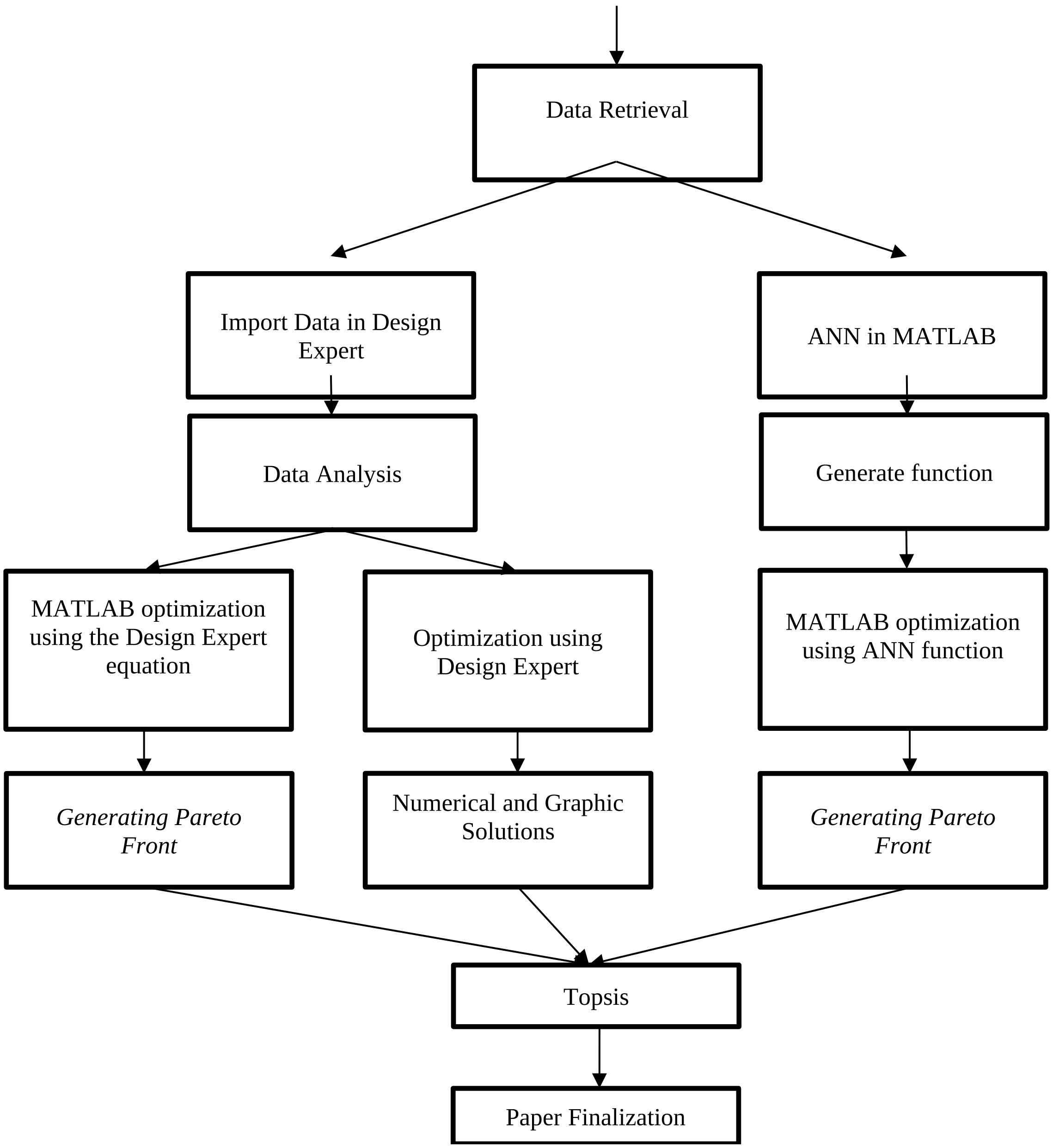


Figure 2. Research flowchart

Data Retrieval

The experimental data used in this study is taken from tables contained in reference journals and can be seen in table 1. (Abdel-Salam et al., 2016)

Table 1 Experiment data

Factor 1	*Factor 2*	*Factor 3*	*Response 1*	*Response 2*
NTU de	*NTU re*	*m solution* (kg/s)	*e laten*	*m flux rate*
1	4	0.009	0.251	0.0073
1	4	0.012	0.249	0.0068
4	4	0.0056	0.689	0.0049
6	6	0.0037	0.79	0.0038
4	4	0.0224	0.667	0.0046
8	4	0.012	0.833	0.0029
4	4	0.0112	0.718	0.0051
6	6	0.0074	0.831	0.0039
4	8	0.009	0.678	0.0049
4	1	0.009	0.702	0.0049
4	4	0.009	0.698	0.0048
8	4	0.009	0.85	0.0031
4	4	0.012	0.702	0.0046
4	8	0.012	0.676	0.0045
4	4	0.009	0.708	0.0048
4	4	0.012	0.682	0.0046
6	6	0.0148	0.807	0.0034
4	1	0.012	0.699	0.0048

Response Surface Methodology Modelling

The response plot is generated from experimental data. Where there are 3 factors as input, namely NTU *dehumidifier*, NTU *regenerator*, *mass solution*. And 2 *responses* as output, namely *latent effectiveness (latent)*∈ and *Moisture Flux Rate. Where the goal of optimization is* to get the maximum possible ∈*latent* value and the maximum *possible moisture flux rate* value. The statistically significant model p-value ($p < 0.05$) was developed using ANOVA, *Design Expert software* (Al-Abidi et al., 2013). For the results of the *response analysis* from *Design Expert* can be seen in the table below.

A. ∈laten

Fit Summary:

Table 2 *Fit Summary.*

Source	**Sequential p-value**	**Lack of Fit p-value**	**Adjusted R^2**	**Predicted R^2**	
Linear	< 0.0001	0.0140	0.7280	0.5951	
2FI	0.9984	0.0105	0.6548	0.2787	
Quadratic	**< 0.0001**	**0.4651**	**0.9941**	**0.9310**	**Suggested**
Cubic	0.6579	0.2320	0.9928		**Aliased**

Anova:

Table 3 Anova

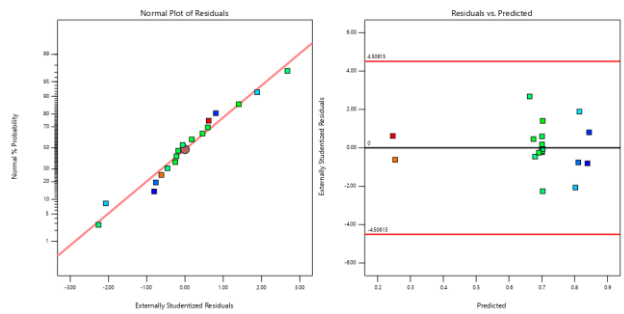
Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	0.4760	9	0.0529	318.56	< 0.0001	significant
A-NTU de	0.1096	1	0.1096	660.42	< 0.0001	
B-NTU re	0.0003	1	0.0003	1.81	0.2154	
C-m solution	0.0004	1	0.0004	2.25	0.1723	
AB	0.0002	1	0.0002	1.45	0.2624	
AC	0.0001	1	0.0001	0.3530	0.5689	
BC	0.0000	1	0.0000	0.0620	0.8096	
A^2	0.0903	1	0.0903	543.74	< 0.0001	
B^2	0.0003	1	0.0003	1.77	0.2198	
C^2	0.0008	1	0.0008	4.86	0.0585	
Residual	0.0013	8	0.0002			
Lack of Fit	0.0011	6	0.0002	1.44	0.4651	not significant
Pure Error	0.0002	2	0.0001			
Cor Total	0.4773	17				

Actual Equation:

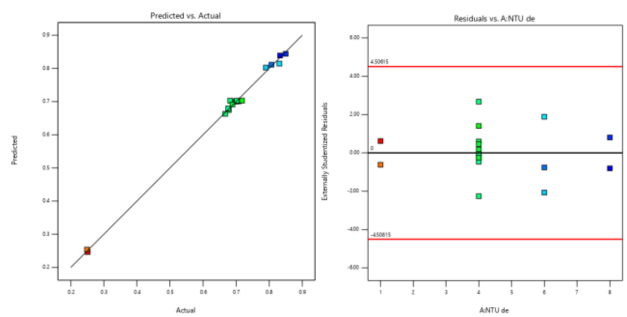
For A = NTU *dehumidifier*; B = NTU *regenerator*; C = *m solution.*

∈laten = -0.078686 + 0.251718A + 0.014844B + 9.03603C - 0.003080AB 0.591858AC + 0.248142BC - 0.016520A^2 - 0.000943B^2 - 333.91460C^2

Diagnostic:



(a) (b)



(c) (d)

Figure 3. *Normal plot* (a); *residual vs predicted* (b); *predicted vs actual* (c); *residual vs A: NTU de* (d)

Table 4 *Report*

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	0.2510	0.2464	0.0046	0.688	0.644	0.619	0.092	0.919	1
2	0.7080	0.7008	0.0072	0.181	0.620	0.594	0.008	0.279	2
3	0.8500	0.8441	0.0059	0.689	0.825	0.806	0.151	1.201	3
4	0.2490	0.2536	-0.0046	0.688	-0.644	-0.619	0.092	-0.919	4
5	0.6820	0.7027	-0.0207	0.234	-1.837	-2.261	0.103	-1.250	5
6	0.8330	0.8389	-0.0059	0.689	-0.825	-0.806	0.151	-1.201	6
7	0.7020	0.7006	0.0014	0.688	0.189	0.177	0.008	0.262	7
8	0.6980	0.7008	-0.0028	0.181	-0.238	-0.223	0.001	-0.105	8
9	0.6780	0.6745	0.0035	0.689	0.482	0.458	0.052	0.681	9
10	0.6990	0.7004	-0.0014	0.688	-0.189	-0.177	0.008	-0.262	10
11	0.7020	0.7027	-0.0007	0.234	-0.064	-0.060	0.000	-0.033	11
12	0.6760	0.6795	-0.0035	0.689	-0.482	-0.458	0.052	-0.681	12
13	0.6890	0.6913	-0.0023	0.565	-0.271	-0.254	0.010	-0.290	13
14	0.7180	0.7028	0.0152	0.209	1.327	1.406	0.046	0.722	14
15	0.6670	0.6629	0.0041	0.975	2.011	2.676	16.026(1)	16.843(1)	15
16	0.7900	0.8024	-0.0124	0.697	-1.743	-2.069	0.699	-3.139(1)	16
17	0.8310	0.8144	0.0166	0.388	1.642	1.886	0.171	1.501	17
18	0.8070	0.8112	-0.0042	0.827	-0.783	-0.762	0.293	-1.665	18

Moisture Flux Rate

Fit Summary:

Table 5 *Fit Summary*

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	**< 0.0001**		**0.9315**	**0.9005**	**Suggested**
2FI	0.8686		0.9181	0.8363	
Quadratic	**0.0121**		**0.9693**	**0.6939**	**Suggested**
Cubic	0.7200		0.9585		**Aliased**

Anova:

Table 6 Anova

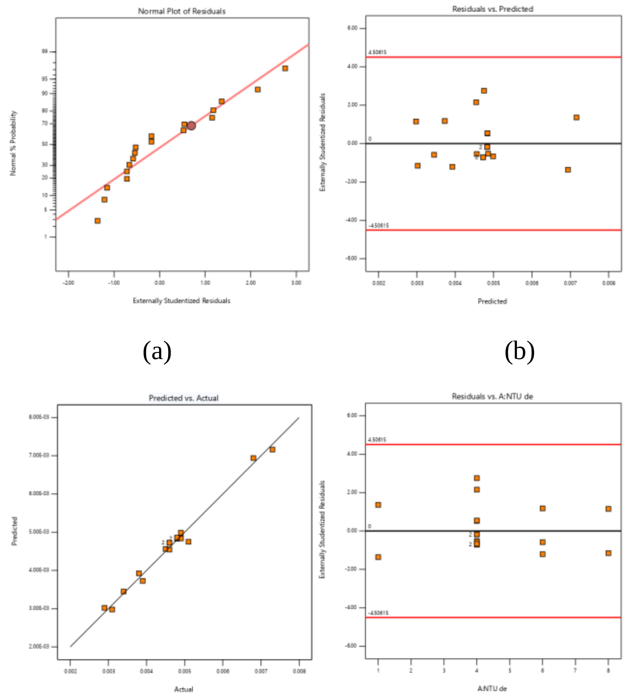
Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.0000	9	2,24E-03	60.54	< 0.0001	significant
A-NTU de	5,11E-03	1	5,11E-03	138.09	< 0.0001	
B-NTU re	7,36E-05	1	7,36E-05	1.99	0.1961	
C-m solution	2,20E-04	1	2,20E-04	5.94	0.0408	
AB	8,87E-06	1	8,87E-06	0.2400	0.6374	
AC	2,64E-05	1	2,64E-05	0.7146	0.4225	
BC	3,33E-05	1	3,33E-05	0.8991	0.3708	
A^2	6,59E-04	1	6,59E-04	17.81	0.0029	
B^2	1,08E-07	1	1,08E-07	0.0029	0.9582	
C^2	1,47E-05	1	1,47E-05	0.3974	0.5460	
Residual	2,96E-04	8	3,70E-05			
Lack of Fit	2,96E-04	6	4,93E-05			
Pure Error	0.0000	2	0.0000			
Cor Total	0.0000	17				

Actual Equation:

For A = NTU *dehumidifier*; B = NTU *regenerator*; C = *m solution*.

$Moisture\ Flux\ Rate$ = +0.008254 - 0.001037A + 0.000196 B – 0.060048C - 0.000019AB + 0.012569AC – 0.014098BC + $0.000045A^2$ + $0.0000005712B^2$ + $1.42484C^2$

Diagnostic:



(a) (b)

(c) (d)

Figure 5. *Normal plot* (a*); residual vs predicted* (b); *predicted vs actual* (c); *residual vs A: NTU de* (d)

Table 7. *Report*

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	0.0073	0.0072	0.0001	0.688	1.295	1.362	0.370	2.023	1
2	0.0048	0.0048	-0.0000	0.181	-0.191	-0.179	0.001	-0.084	2
3	0.0031	0.0030	0.0001	0.689	1.129	1.152	0.283	1.716	3
4	0.0068	0.0069	-0.0001	0.688	-1.295	-1.362	0.370	-2.023	4
5	0.0046	0.0047	-0.0001	0.234	-0.740	-0.717	0.017	-0.396	5
6	0.0029	0.0030	-0.0001	0.689	-1.129	-1.152	0.283	-1.716	6
7	0.0049	0.0048	0.0001	0.688	0.550	0.525	0.067	0.779	7
8	0.0048	0.0048	-0.0000	0.181	-0.191	-0.179	0.001	-0.084	8
9	0.0049	0.0048	0.0001	0.689	0.569	0.544	0.072	0.810	9
10	0.0048	0.0049	-0.0001	0.688	-0.550	-0.525	0.067	-0.779	10
11	0.0046	0.0047	-0.0001	0.234	-0.740	-0.717	0.017	-0.396	11
12	0.0045	0.0046	-0.0001	0.689	-0.569	-0.544	0.072	-0.810	12
13	0.0049	0.0050	-0.0001	0.565	-0.690	-0.665	0.062	-0.759	13
14	0.0051	0.0048	0.0003	0.209	2.040	2.756	0.110	1.416	14
15	0.0046	0.0045	0.0001	0.975	1.786	2.154	12.632[1]	13.557[1]	15
16	0.0038	0.0039	-0.0001	0.697	-1.176	-1.210	0.318	-1.835	16
17	0.0039	0.0037	0.0002	0.388	1.151	1.178	0.084	0.938	17
18	0.0034	0.0034	-0.0000	0.827	-0.608	-0.583	0.177	-1.273	18

3.4 *Multi Objective Genetic Algorithm* (MOGA) uses RSM equations .

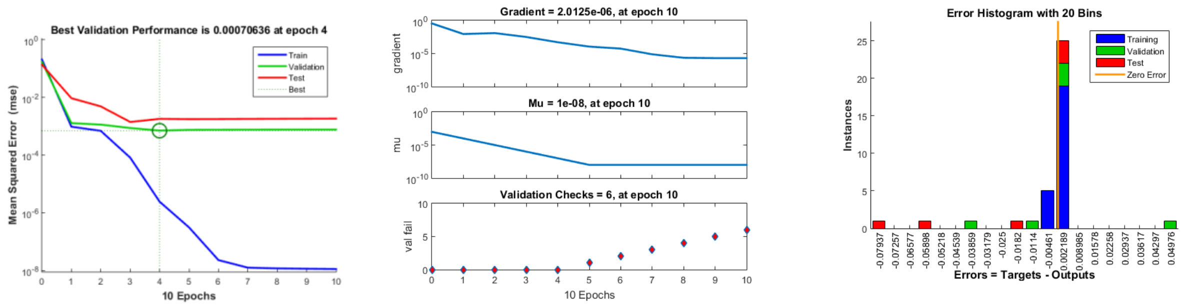
Optimization using MATLAB R2015a Software. By inputting variables x1, x2, x3 as input. And f1 and f2 as objective functions of *the actual equations RSM.* For Optimization using *the Optimization tool*, *choose* solver "gamultiobj", the number of variables "3", Lower Bounds "1 1 0.0037", Upper Bonds "8 8 0.0224", choose Pareto front plot, then *"start".* Then you will get the *pareto front plot,* the number of iterations, and the *final point table.*

3.5. *Multi Objective Genetic Algorithm* (MOGA) uses *the ANN equation.*

Randomize the data first for the type of *training, validation, testing.* Where training *must have the* largest range while *testing* and *validation* are included in the *range* of *training.* After input the *data factor* and *response* into the *workspace.* Select "Neural Network Pattern Recognition Tools". Number of *hidden neurons* = 10, dividing the data as 70% *training, 15%* validation, *15%* testing. Choose *Levenberg-Marquard* as the *training algorithm* (Factor & Grossman, 1980). Then the results of *Performance*, Training State, Error Histogram, Regression *are obtained.* After that, use the *Optimization tool* to optimize the *ANN equation* that has been generated.

Table. 8 Randomized Experiment Data

	NTU de	*NTU re*	*m solution* (kg/s)	*e laten*	*m flux rate*
Training	1	4	0.009	0.251	0.0073
	1	4	0.012	0.249	0.0068
	4	4	0.0056	0.689	0.0049
	6	6	0.0037	0.79	0.0038
	4	4	0.0224	0.667	0.0046
	8	4	0.012	0.833	0.0029
	4	4	0.0112	0.718	0.0051
	4	8	0.012	0.676	0.0045
	4	8	0.009	0.678	0.0049
	4	1	0.009	0.702	0.0049
	4	1	0.012	0.699	0.0048
	8	4	0.009	0.85	0.0031
Validation	4	4	0.012	0.702	0.0046
	6	6	0.0074	0.831	0.0039
	4	4	0.009	0.708	0.0048
Testing	4	4	0.012	0.682	0.0046
	6	6	0.0148	0.807	0.0034
	4	4	0.009	0.698	0.0048



(a) (b) (c)

Gambar 6. *Performance* (a); *Training State* (b); *Error Histogram* (c)

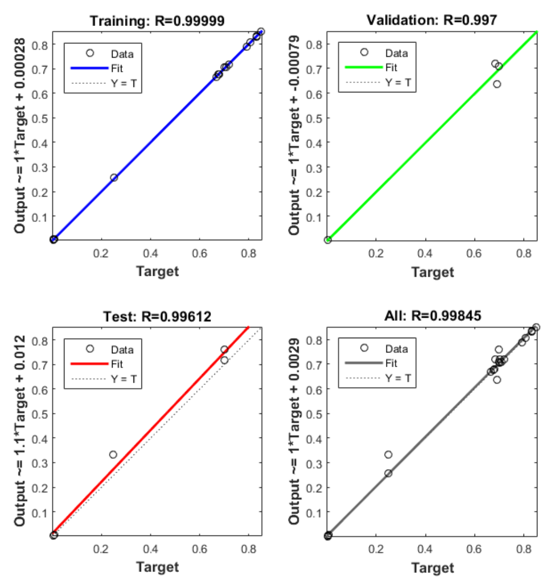


Figure 7. *Regression*

3.6 TOPSIS

By using the results of objective function 1 and objective function 2 from *MOGA-RSM and* MOGA-ANN, *TOPSIS will be carried out using Microsoft Excel 2019 software with the following steps:*(Chen et al., 2014)

1. Calculates a normalized matrix using the following equation:.

$$X_{ij}{}^{*} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} X_{ij}{}^{2}}}$$

Table 9. results for MOGA-RSM $X_{ij}{}^*$

data ke	e laten	moisture flux rate
1	0,300573394	0,181443685
2	0,349367776	0,090721842
3	0,248851349	0,226804606
4	0,32692236	0,181443685
5	0,197129304	0,226804606
6	0,291302461	0,181443685
7	0,280079753	0,181443685
8	0,314723765	0,181443685
9	0,124425674	0,272165527
10	0,209327899	0,226804606
11	0,178099495	0,226804606
12	0,114178854	0,317526448
13	0,098076708	0,317526448
14	0,228845652	0,226804606
15	0,132720719	0,272165527
16	0,340584787	0,136082763
17	0,094661101	0,317526448
18	0,094661101	0,317526448

Table 10. results for MOGA-ANN$X_{ij}{}^*$

data ke	e laten	moisture flux rate
1	0,364700655	0,181071492
2	0,290493574	0,181071492
3	0,364700655	0,181071492
4	0,140269483	0,271607238
5	0,232575852	0,181071492
6	0,18280281	0,271607238
7	0,118550337	0,271607238
8	0,283253859	0,181071492
9	0,310402791	0,181071492
10	0,069682259	0,271607238
11	0,091401405	0,271607238
12	0,114025515	0,271607238
13	0,218096422	0,271607238
14	0,336646759	0,181071492
15	0,166513451	0,271607238
16	0,204521956	0,271607238
17	0,262439678	0,181071492
18	0,161988629	0,271607238

1. Calculate the weight of a normalized matrix

$$V_{ij} = X_{ij}{}^* \; x \; w_j$$

Table 11. results for MOGA-RSM

data ke	e laten	moisture flux rate
1	0,150286697	0,090721842
2	0,174683888	0,045360921
3	0,124425674	0,113402303
4	0,16346118	0,090721842
5	0,098564652	0,113402303
6	0,145651231	0,090721842
7	0,140039877	0,090721842
8	0,157361882	0,090721842
9	0,062212837	0,136082763
10	0,10466395	0,113402303
11	0,089049747	0,113402303
12	0,057089427	0,158763224
13	0,049038354	0,158763224
14	0,114422826	0,113402303
15	0,06636036	0,136082763
16	0,170292394	0,068041382
17	0,047330551	0,158763224
18	0,047330551	0,158763224

Table 12. results for V_{ij} MOGA-ANNV_{ij}

data ke	e laten	moisture flux rate
1	0,182350328	0,090535746
2	0,145246787	0,090535746
3	0,182350328	0,090535746
4	0,070134741	0,135803619
5	0,116287926	0,090535746
6	0,091401405	0,135803619
7	0,059275169	0,135803619
8	0,141626929	0,090535746
9	0,155201396	0,090535746
10	0,03484113	0,135803619
11	0,045700702	0,135803619
12	0,057012758	0,135803619
13	0,109048211	0,135803619
14	0,168323379	0,090535746
15	0,083256725	0,135803619
16	0,102260978	0,135803619
17	0,131219839	0,090535746
18	0,080994314	0,135803619

2. Calculate ideal best and ideal worst value. Because both objective functions want to be maximized, the maximum value for the ideal best value and the minimum value for the ideal worst value

Table 13. V+ and V- for *MOGA-RSM*

	e laten	moisture flux rate
V+	0,174684	0,158763224
V-	0,047331	0,045360921

Table 14. V+ and V- for *MOGA-ANN*

	e laten	moisture flux rate
V+	0,18235	0,135803619
V-	0,034841	0,090535746

3. Calculate Euclidean distance from ideal best and ideal worst with the following equation.

$$S_i{}^{+} = \left[\sum_{j=1}^{m} (V_{ij} - V_j{}^{+})^2\right]^{0.5}$$

$$S_i{}^{-} = \left[\sum_{j=1}^{m} (V_{ij} - V_j{}^{-})^2\right]^{0.5}$$

Table 15. Si+ and Si- for *MOGA-RSM*

Si+	Si-
0,072283142	0,112505916
0,113402303	0,127353337
0,06770156	0,102826493
0,068960705	0,124675323
0,088610108	0,085173721
0,073976515	0,10828005
0,07635337	0,10321159
0,070211691	0,119014735
0,114735089	0,091934407
0,083429041	0,088976111
0,096906239	0,079813038
0,117594461	0,11382143
0,125645534	0,113415162
0,075425518	0,095556282
0,110672445	0,092696204
0,090828068	0,125036067
0,127353337	0,113402303
0,127353337	0,113402303

Table 16. Si+ and Si- for *MOGA-ANN*

Si+	Si-
0,045267873	0,147509198
0,058530787	0,110405657
0,045267873	0,147509198
0,112215586	0,057400517
0,080083839	0,081446796
0,090948923	0,072444773
0,123075159	0,051441254
0,060889864	0,1067858
0,052784892	0,120360266
0,147509198	0,045267873
0,136649625	0,046552236
0,12533757	0,050405966
0,073302117	0,086924515
0,047391303	0,13348225
0,099093602	0,066281598
0,08008935	0,081207243
0,068289876	0,096378709
0,101356013	0,064647481

4. Calculate performance with the following equation and determine the ranking.

$$Performance = \frac{S_i{}^{-}}{S_i{}^{-} + S_i{}^{+}}$$

Table 17. *Performance MOGA-RSM*

Pi	Ranking
0,608834298	3
0,528973432	9
0,602988725	4
0,643864288	1
0,490113041	12
0,594107817	5
0,574786917	7
0,628954093	2
0,444837815	18
0,516087307	10
0,451637417	17
0,491847944	11
0,474419943	13
0,558868149	8
0,455803806	16
0,579235023	6
0,471026568	14
0,471026568	14

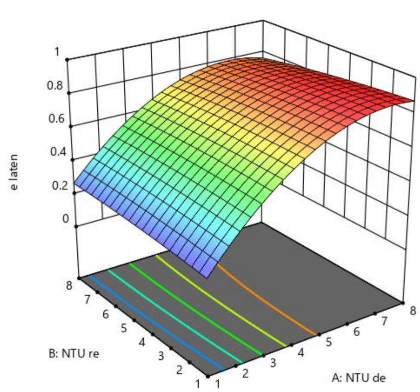
Table18. *Performance MOGA-ANN*

Pi	Ranking
0,765180201	1
0,653533686	5
0,765180201	1
0,338414313	14
0,504218883	9
0,443375569	11
0,294764561	15
0,636859265	6
0,695140813	4
0,234819799	18
0,254103509	17
0,286815476	16
0,54250978	8
0,737986553	3
0,400795269	12
0,503465333	10
0,585288984	7
0,389434458	13

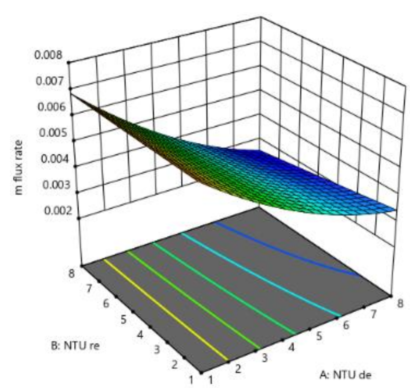
3. Results and Discussions

3.1 *RSM*

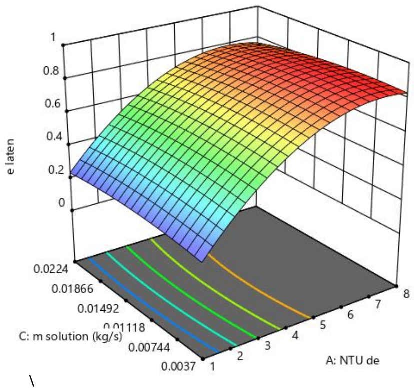
RSM results show the largest response value and the smallest response value due to input factors. In figure (a), namely with the input factor *NTU dehumidifier and NTU regenerator*, for the response, namely *e latent* and *moisture flux rate.* If the *NTU dehumidifier* is larger, the *latent e* will tend to be larger, while *the moisture flux rate* tends to be smaller. In figure (b), namely with the input factor *NTU dehumidifier* and *mass solution.* In figure (c), namely with the input factor *NTU regenerator* and *mass solution*(Elsayed et al., 1993).



(a) NTU *dehumidifer* dan NTU *regenerator*



(a) NTU *dehumidifer* dan NTU *regenerator*



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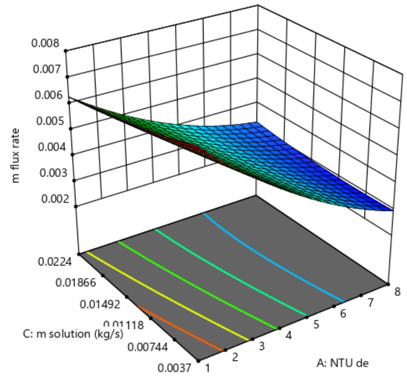
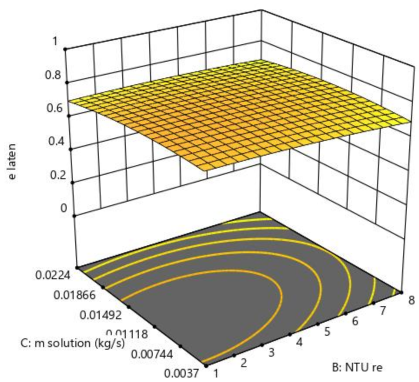
(b) NTU *dehumidifier* dan *mass solution*

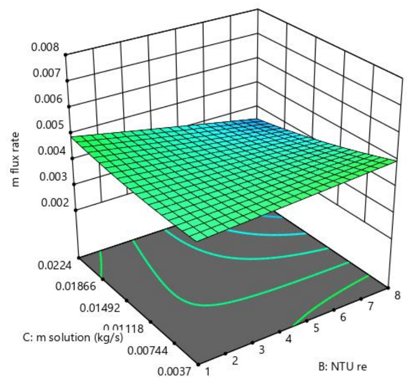


(b) NTU *dehumidifier* dan *mass solution*



(c) NTU *regenerator* dan *mass solution*

Figure 8. *Response surface contours* from factors against latent. (a) NTU ∈*de* and NTU re, (b) NTU de and m solution, *(c)* NTU *re* and *m solution.*



(c) NTU *regenerator* dan *mass solution*

Figure 9. *Response surface contours* of factor - factor against *moisture flux rate*. *(a) NTU de and NTU* re, *(b)* NTU de *and m solution*, (c) NTU re and *m solution.*

The results of Design Expert Optimization can also be in the form of tables. Design Expert has a large selection of optimization goals. Because in the liquid desiccant dehumidifier system is to get the largest possible response, we can choose "maximize" for response and *"in range"* for *factors*(Elsayed et al., 1993). The results of Design Expert optimization can be seen in table 19. There are 32 types of choices and the best choice is at number one.

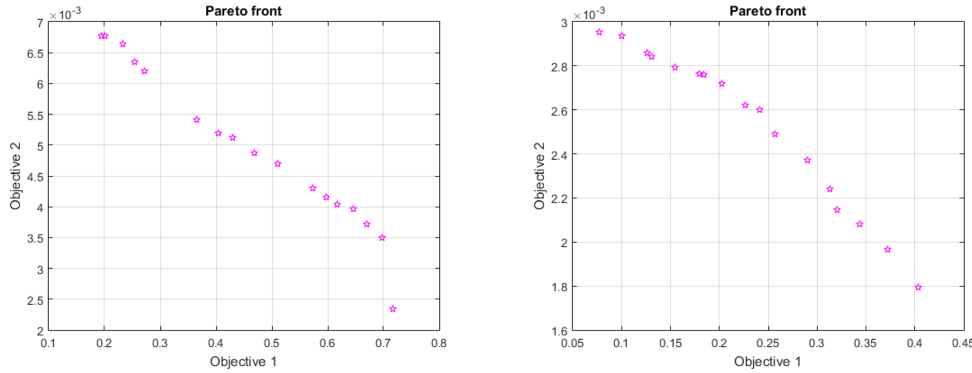
Table 19. *Design Expert optimization results*

Number	NTU de	NTU re	m solution	e laten	m flux rate	Desirability	
1	**3.605**	**8.000**	**0.004**	**0.612**	**0.006**	**0.621**	**Selected**
2	3.580	8.000	0.004	0.609	0.006	0.621	
3	3.602	7.957	0.004	0.612	0.006	0.621	
4	3.600	7.942	0.004	0.612	0.006	0.621	
5	3.648	8.000	0.004	0.616	0.006	0.621	
6	3.604	7.897	0.004	0.613	0.006	0.621	
7	3.642	7.945	0.004	0.616	0.006	0.621	
8	3.610	7.851	0.004	0.614	0.006	0.621	
9	3.585	7.824	0.004	0.612	0.006	0.621	
10	3.681	7.999	0.004	0.620	0.006	0.621	
11	3.613	7.740	0.004	0.615	0.006	0.621	
12	3.556	7.797	0.004	0.609	0.006	0.621	
13	3.526	7.897	0.004	0.604	0.006	0.621	
14	3.580	7.996	0.004	0.610	0.006	0.620	
15	3.566	7.364	0.004	0.614	0.006	0.620	
16	3.618	6.436	0.004	0.627	0.006	0.618	
17	3.981	7.522	0.004	0.655	0.005	0.616	
18	3.679	5.772	0.004	0.639	0.005	0.615	
19	3.594	5.689	0.004	0.630	0.006	0.614	
20	3.621	4.887	0.004	0.637	0.005	0.610	
21	3.729	2.630	0.004	0.656	0.005	0.592	
22	4.574	1.000	0.022	0.707	0.005	0.588	
23	4.523	1.000	0.022	0.702	0.005	0.588	
24	4.496	1.015	0.022	0.700	0.005	0.587	
25	4.636	1.022	0.022	0.712	0.005	0.587	
26	4.524	1.031	0.022	0.703	0.005	0.587	
27	4.506	1.063	0.022	0.701	0.005	0.586	
28	4.194	1.000	0.020	0.690	0.005	0.584	
29	4.150	1.000	0.018	0.699	0.005	0.582	
30	4.089	1.000	0.018	0.693	0.005	0.582	
31	3.885	1.000	0.017	0.675	0.005	0.581	
32	3.843	1.000	0.013	0.681	0.005	0.580	

3.2 Multi Objective Genetic Algorithm (*MOGA*)

For MOGA Optimization, use the equation from Design Expert and the EN equation. The results *of pareto front optimization MOGA* with RSM *equation and* optimization MOGA *with* ANN equation are presented in the form of *pareto front* in figure 10 and *presented in table* 20 *and* table 21. For pareto a and b have similarities in form but differ in value. (FACTOR & GROSSMAN, n.d.)

Pareto Front:



(a) MOGA - RSM (b) *MOGA - ANN*

Figure 10. *Pareto Front.* (a) *MOGA – RSM*, (b) *MOGA - ANN*

Tabel:

f1 = *ϵ laten*; f2 = *moisture flux rate*; x1 = *NTU dehumidifier*; x2 = *NTU regenerator*; x3 = *mass solution.*

Tabel 20. *MOGA - RSM*

data ke	f1	f2	x1	x2	x3
1	0,616	0,004	3,603	7,904	0,022
2	0,716	0,002	7,944	7,942	0,022
3	0,51	0,005	2,641	7,601	0,022
4	0,67	0,004	4,221	7,835	0,022
5	0,404	0,005	1,883	7,814	0,022
6	0,597	0,004	3,412	7,892	0,022
7	0,574	0,004	3,185	7,809	0,022
8	0,645	0,004	3,9	7,4	0,022
9	0,255	0,006	1,151	3,363	0,022
10	0,429	0,005	2,058	7,321	0,022
11	0,365	0,005	1,636	7,468	0,022
12	0,234	0,007	1,194	1,03	0,022
13	0,201	0,007	1	1	0,021
14	0,469	0,005	2,337	7,7	0,022
15	0,272	0,006	1,205	4,127	0,022
16	0,698	0,003	4,643	7,855	0,022
17	0,194	0,007	1	1	0,022
18	0,194	0,007	1	1	0,022

Tabel 21. *MOGA - ANN*

data ke	f1	f2	x1	x2	x3
1	0,403	0,002	1,687	4,246	0,004
2	0,321	0,002	1,055	5,541	0,006
3	0,403	0,002	1,687	4,246	0,004
4	0,155	0,003	1,016	7,902	0,012
5	0,257	0,002	1,097	6,735	0,008
6	0,202	0,003	1,042	7,491	0,009
7	0,131	0,003	1,021	7,96	0,013
8	0,313	0,002	1,115	5,97	0,006
9	0,343	0,002	1,194	5,43	0,006
10	0,077	0,003	1	7,995	0,016
11	0,101	0,003	1,011	7,972	0,014
12	0,126	0,003	1,013	7,96	0,013
13	0,241	0,003	1,099	6,816	0,009
14	0,372	0,002	1,306	5,156	0,004
15	0,184	0,003	1,139	7,812	0,011
16	0,226	0,003	1,063	7,106	0,009
17	0,29	0,002	1,051	5,905	0,007
18	0,179	0,003	1,106	7,828	0,011

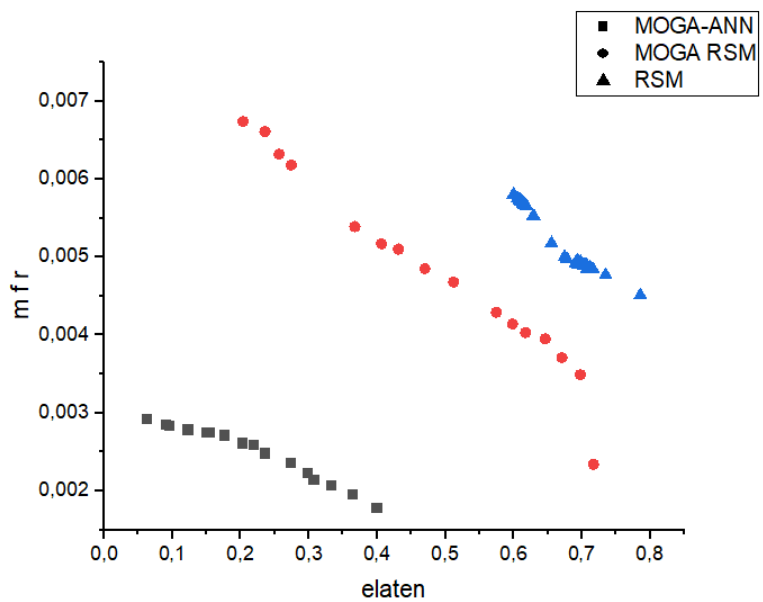


Figure 11. *Pareto Front* for 3 types of optimization. *RSM, MOGA – RSM, MOGA – ANN*

From figure 11 shows the most optimal objective function is through the RSM Design Expert method. Where to get the maximum possible value is *latent e* of 0.006 and moisture flux rate *of 0.006.* The input factor is NTU *Dehumidifier* of 3.605, NTU *Regenerator of 8, and mass solution of* 0.004.

3.3 TOPSIS.

The purpose of *TOPSIS* is to determine the most optimal point generated by the equation RSM - DE, MOGA - *equation* DE, MOGA - *equation* ANN. In optimizing the *RSM – DE equation*, topsis is not done because the value of the most optimal solution can be determined from *desirability*(Ru & Yan, 1992). The results of *the TOPSIS MOGA* equation *DE* can be seen in table 22.

The results of *the TOPSIS MOGA* ANN equation can be seen in table 23.

Table 22. Result *TOPSIS MOGA* - *RSM*

data ke	f1	f2	x1	x2	x3	*ranking*
1	0,616	0,004	3,603	7,904	0,022	3
2	0,716	0,002	7,944	7,942	0,022	9
3	0,51	0,005	2,641	7,601	0,022	4
4	0,67	0,004	4,221	7,835	0,022	1
5	0,404	0,005	1,883	7,814	0,022	12
6	0,597	0,004	3,412	7,892	0,022	5
7	0,574	0,004	3,185	7,809	0,022	7
8	0,645	0,004	3,9	7,4	0,022	2
9	0,255	0,006	1,151	3,363	0,022	18
10	0,429	0,005	2,058	7,321	0,022	10
11	0,365	0,005	1,636	7,468	0,022	17
12	0,234	0,007	1,194	1,03	0,022	11
13	0,201	0,007	1	1	0,021	13
14	0,469	0,005	2,337	7,7	0,022	8
15	0,272	0,006	1,205	4,127	0,022	16
16	0,698	0,003	4,643	7,855	0,022	6
17	0,194	0,007	1	1	0,022	14
18	0,194	0,007	1	1	0,022	14

Table 23. Result *TOPSIS MOGA* - *ANN*

data ke	f1	f2	x1	x2	x3	ranking
1	0,403	0,002	1,687	4,246	0,004	1
2	0,321	0,002	1,055	5,541	0,006	5
3	0,403	0,002	1,687	4,246	0,004	1
4	0,155	0,003	1,016	7,902	0,012	14
5	0,257	0,002	1,097	6,735	0,008	9
6	0,202	0,003	1,042	7,491	0,009	11
7	0,131	0,003	1,021	7,96	0,013	15
8	0,313	0,002	1,115	5,97	0,006	6
9	0,343	0,002	1,194	5,43	0,006	4
10	0,077	0,003	1	7,995	0,016	18
11	0,101	0,003	1,011	7,972	0,014	17
12	0,126	0,003	1,013	7,96	0,013	16
13	0,241	0,003	1,099	6,816	0,009	8
14	0,372	0,002	1,306	5,156	0,004	3
15	0,184	0,003	1,139	7,812	0,011	12
16	0,226	0,003	1,063	7,106	0,009	10
17	0,29	0,002	1,051	5,905	0,007	7
18	0,179	0,003	1,106	7,828	0,011	13

Table 24. The optimum point in each optimization method.

Metode	*e laten*	*moisture flux rate*	*NTU dehumidifier*	*NTU regenerator*	*mass solution*
RSM (Design Expert)	0,612	0,006	3,605	8	0,004
MOGA - RSM	0,67	0,004	4,221	7,835	0,022
MOGA - ANN	0,403	0,002	1,687	4,246	0,004

3.4. Discussion

Based on the results of optimization that has been carried out and TOPSIS as a decision support, the multi-objective optimization method that produces the most optimal objective function value is optimization with *Design Expert (RSM*) software. The most optimal objective function value through the *Design Expert software* optimization method is ϵ *latent* of 0.612 and moisture flux rate *of* 0.006. Both objective function values have fulfilled the optimization goal, namely the ϵ *maximum latent value possible with the maximum* possible moisture flux rate *value* (GROSSMAN, 2002). For the *MOGA optimization method with* the RSM , *quation* has an optimum objective function value that is close to optimization with *Design Expert software*, namely ϵ *latent* value of 0.67 and *a moisture flux rate* of 0.004. While *MOGA optimization with the* ANN *equation* has the optimum objective function value that is most different from the other two optimization methods, namely ϵ *the latent* value of 0.403 and the moisture flux rate *of 0.002*. This may be due to differences between *the ANN-generated equations and the* Design Expert-generated equations. Errors in data randomization can also affect the ANN equation produced by MATLAB, so the pareto front also experiences differences.

4. Conclusion

From the optimization of *RSM, MOGA – RSM, MOGA – ANN* that has been carried out in a *complete membrane-based liquid desiccant dehumidifier system, the following conclusions can be drawn:*

1. The *RSM* method has the most optimal objective function value compared to the other two methods.
2. The *MOGA – ANN method* has the most different objective function value from the other 2 optimization methods.

Errors in the data randomization method can affect the results of the generated ANN equation .

5. References

Abdel-Salam, A. H., McNevin, C., Crofoot, L., Harrison, S. J., & Simonson, C. J. (2016). A field study of a low-flow internally cooled/heated liquid desiccant air conditioning system: Quasi-steady and transient performance. *Journal of Solar Energy Engineering*, *138*(3), 031009.

Al-Abidi, A. A., Mat, S., Sopian, K., Sulaiman, M. Y., & Mohammad, A. T. (2013). Experimental study of PCM melting in triplex tube thermal energy storage for liquid desiccant air conditioning system. *Energy and Buildings*, *60*, 270–279.

Bai, H., Zhu, J., Chen, X., Chu, J., Cui, Y., & Yan, Y. (2020). Steady-state performance evaluation and energy assessment of a complete membrane-based liquid desiccant dehumidification system. *Applied Energy*, *258*, 114082.

Chen, Y., Yin, Y., & Zhang, X. (2014). Performance analysis of a hybrid air-conditioning system dehumidified by liquid desiccant with low temperature and low concentration. *Energy and Buildings*, *77*, 91–102.

Cheng, Q., Zhang, X.-S., & Li, X.-W. (2012). Double-stage photovoltaic/thermal ED regeneration for liquid desiccant cooling system. *Energy and Buildings*, *51*, 64–72.

Elsayed, M. M., Gari, H. N., & Radhwan, A. M. (1993). Effectiveness of heat and mass transfer in packed beds of liquid desiccant system. *Renewable Energy*, *3*(6–7), 661–668.

FACTOR, H. M., & GROSSMAN, G. (n.d.). A PACKED BED DEHUMIDIFIER/REGENERATOR FOR SOLAR AIR CONDITIONING WITH LIQUID DESICCANTS. *Solar Energy*, *24*, 541–550.

Factor, H. M., & Grossman, G. (1980). A packed bed dehumidifier/regenerator for solar air conditioning with liquid desiccants. *Solar Energy*, *24*(6), 541–550.

Grossman, G. (2002). Solar-powered systems for cooling, dehumidification and air-conditioning. *Solar Energy*, *72*(1), 53–62.

GROSSMAN, G. (2002). Solar-powered systems for cooling, dehumidification and air-conditioning. *Solar Energy*, *72*(1), 53–62.

Li, X.-W., Zhang, X.-S., & Quan, S. (2011). Single-stage and double-stage photovoltaic driven regeneration for liquid desiccant cooling system. *Applied Energy*, *88*(12), 4908–4917.

Ru, Y., & Yan, W. J. (1992). Simulation study for an open-cycle absorption solar-cooling system operated in a humid area. *Energy*, *17*(7), 649–655.

Shirazi, A., Taylor, R. A., Morrison, G. L., & White, S. D. (2018). Solar-powered absorption chillers: A comprehensive and critical review. *Energy Conversion and Management*, *171*, 59–81.

Yuliani, F., & Zainul, R. (2018). *Analisis Termodinamika Molekul Magnesium Sulphate (MgSO4)*.