

PAPER • OPEN ACCESS

Utilization of Response Surface Method (RSM) in Optimizing Automotive Air Conditioning (AAC) Performance Exerting $\text{Al}_2\text{O}_3/\text{PAG}$ Nanolubricant

To cite this article: A.A.M. Redhwan *et al* 2020 *J. Phys.: Conf. Ser.* **1532** 012003

View the [article online](#) for updates and enhancements.



IOP | ebooks™

Bringing together innovative digital publishing with leading authors from the global scientific community.

Start exploring the collection—download the first chapter of every title for free.

Utilization of Response Surface Method (RSM) in Optimizing Automotive Air Conditioning (AAC) Performance Exerting Al₂O₃/PAG Nanolubricant

A.A.M. Redhwan^{1*}, W.H. Azmi², M.Z. Sharif², N.N.M. Zawawi², S. Zainal Ariffin¹

¹Faculty of Manufacturing Engineering Technology, TATIUC, 24000, Kemaman, Terengganu, Malaysia

²Faculty of Mechanical and Manufacturing Engineering, Universiti Malaysia Pahang, 26600 Pekan, Pahang, Malaysia

*Corresponding author: redhwan323@gmail.com

Abstract. This manuscript examines the performance of automotive air conditioning (AAC) with the variation of the concentration of Al₂O₃/PAG nanolubricant, initial refrigerant charges, and compressor speed. Today, the response surface methodology (RSM) is one of the most commonly used optimization techniques for designing experimental work and for optimizing variables for a system. In this study, RSM was used to predict response parameters such as cooling capacity and compressor work. Besides, critical relationships between input and response factors will be identified using RSM. Independent variable optimization is carried out using a desirability approach to maximize cooling capacity and minimize the compressor. The results of the RSM analysis found that the optimum conditions with high desirability of 100% were at a concentration of 0.010%, cooling charge of 168 grams and compressive speed of 1160 rpm. At this optimum condition, the AAC system produces a cooling capacity of 1314 kW and a compressor work of 14.19 kJ/kg. The model predicted by RSM is accurate and has been validated in experiments with a deviation of less than 3.4%. Therefore, it can be concluded that RSM can predict optimization parameters that affect AAC performance.

1. Introduction

Air conditioning (AC) is an essential component in the automotive system. Modern air conditioning provides thermal comfort in the car's compartment, mostly in countries facing hot and humid atmospheres like Malaysia. Furthermore, the compressor of air conditioning turns out to be a singular major secondary load on an automotive engine. The compressor used in air conditioning loads the engine. This will result in reduced engine efficiency and increased fuel consumption and thus release excess greenhouse gases. The costs of using air conditioning (AAC) systems in terms of energy efficiency have required researchers to explore new possibilities and technologies to improve their efficiency [1]. Nanotechnology can be applied to refrigerants or compressor lubricants to improve the efficiency of the AAC system. Nanoparticles are usually added to a refrigerant or compressor lubricant to improve performance in terms of heat transfer. A systematic study was performed by Redhwan et al. [2] to study the development of nanorefrigerant and nanolubricant and different performance



advancements. The use of nanorefrigerant and nanolubricant is confirmed to have the potential to save energy, especially in cooling systems [3].

Studies on nanorefrigerant/nanolubricant have been extensively carried out by scientists to improve cooling performance in domestic refrigerators [4, 5] air conditioning (RAC) systems [6] and vapor compression refrigeration systems (VCRS) [7-9]. Researchers have been able to reduce the energy consumption of cooling systems to 26% [5], improve the coefficient of performance (COP) up to 33% [9], and increase energy efficiency ratio (EER) to 6% [6] using nanorefrigerant/nanolubricant. The addition of nanoparticles into refrigerant /lubricant can lessen the energy consumption of the cooling system by increasing the efficiency of the compressor [10].

The studies on the effect of operating parameters by employing an individual approach are done in various studies [8, 11]. Their research work is done by changing the control factor for an appropriate time only under certain circumstances. However, the method used is not suitable in this study because the performance of the AAC depends not only on compressor speed, refrigerant charge, nanolubricant concentration, but also on some of these parameters collectively. Henceforth, a systematized multifactor investigation which offer a comprehensible performance characteristic of the AAC system in comparison with an individual approach is required. In such multifactor problems, the using of non-linear method namely Design of Experiments (DoE) is suitable to examine the interaction effects of experiment variables. DoE is remarked as one of the most efficient and cost-effective technique to assess the specific and collective effects of experiment factors on output responses [12]. Numerous techniques, for example, Taguchi method, factorial design and response surface method might be utilized for experiment design purpose.

In the present study, RSM is used to investigate the factors' effect on the response parameters. RSM is a combination of both mathematical and statistical methods that were used to establish mathematical modeling among factors and responses and recognize the cause of factors affecting response in a specific process [13]. RSM is also well-known as a practical method to evaluate engineering problems based on both modelings and optimizing the response surface, which is affected by the experimental inputs [14]. The use of RSM in designing an experiment will require less testing and less time than full factorial experimental testing. Besides, the long calculation of work can also be shortened. Therefore, the time required to determine and solve some objectives can be reduced by using RSM.

To date, research work to determine the performance evaluation of cooling systems using the RSM method is still limited. For example Costa and Garcia [15] used RSM in optimizing the efficiency of a refrigeration cycle demonstration unit using a multi-response optimization method. In their study, a statistically designed experiment using RSM was carried out to reduce the energy consumption of the cooling system and to maximize the effect of cooling. The most recent paper was presented by Redhwan et al. [16]. RSM was used to evaluate the optimization of AAC performance employing SiO₂/PAG nanolubricants. The authors considered experimental variable parameters such as refrigerant charge, compressor speed and nanolubricants concentrations. However, in their previous works Redhwan et al. [17] and Redhwan et al. [18] found that Al₂O₃/PAG lubricant show better performance in term of thermal conductivity compared to SiO₂/PAG nanolubricants. It is expected that the performance of AAC is much better when Al₂O₃/PAG nanolubricant is used. Aminullah et al. [19] and Zawawi et al. [20] also found that dispersing Al₂O₃ nanoparticle into PAG based enhance its tribology performance in term of lowering the wear rate and reducing the coefficient of friction.

Henceforth, the present work employs RSM approach to examine the effect of refrigerant charge, compressor speed and Al₂O₃/PAG nanolubricants volume concentration on the AAC performance. Design Expert software is used, while the experiments are designed utilizing Faced Centered Design (FCD) procedure. Based on the FCD design, 20 experiments were conducted. The cooling capacity (QL) and compressor work (Win) are used as the response factors in the RSM evaluation.

2. Methodology

This section presents information concerning the experimental design and desirability approach in achieving optimal conditions of the AAC experiment. The methodology of preparation and stability

investigation of Al₂O₃/PAG nanolubricant is done by following in the previous research [21-25]. The experimental setup of AAC system was designed and developed for the performance analysis of Al₂O₃/PAG nanolubricants in the previous study [26, 27]. For further evaluation, the experimental data presented by [28] are used in the present study.

Three experiment variables in the present study namely compressor speed, refrigerant charge, and volume concentration of Al₂O₃/PAG nanolubricant were believed to be as active factors on the cooling capacity (Q_L) and compressor work (W_{in}) as responses. Designs that can suit model required minimum three levels of each factors. This is satisfied by Central Composite Designs (CCD) which has three levels per parameter. Since the region of concern and area of operability are almost identical, the face-centered design (FCD) which consider the eight corners of the cube are centered and scaled to (+1, +1, +1) and = 1. FCD was used for the current study to achieve the experimental data, which would outfit full second-order polynomial models in place of the response surfaces above a reasonably wide range of parameters. In CCD, the number of experiment point is determined by using Equation 1:

$$N = 2^n + 2n + n_0 \quad (1)$$

Where N is the number of running test of experiment, n is the number of factors and n₀ is the number of central points. In the Equation 1, the “2ⁿ” term is known as factorial experiment points. These points permit apparent approximates of all major causes and 2-factors interrelations. Meanwhile, “2n” term is identified as axial points which permit the pure quadratic effects estimations. Finally, “n₀” represents the center point and can be designed to be run concurrently both as axial and factorial points.

In the recent study, FCD with three factors was noted to have a total of 20 runs of experiments which entail of eight factorial points, six axial points, and six central points. It was used to assess the data gained from the experimental work. A multiple regression analysis was used to gain the coefficients. Later, the equations were used to predict the responses. The relationship between the factors and responses was achieved by applying a statistically significant model.

Desirability approach is a favored choice amid optimization methods since it has advantageous characteristic such as unfussiness, availability in the software, flexibility in weighting and giving importance ranking for individual response [14]. The same technique was also utilized by Khoobbakht et al. [29]. Hence, the present work used desirability approach in optimizing experiment variables, namely, compressor speed, refrigerant charge and volume concentration for the response properties of cooling capacity and compressor work. In the current work, each response has its own goal, either to maximize or minimize. For example, cooling capacity required maximize goal while compressor work is set to be minimize. The response desirability is then collectively combined using the geometric approach which eventually presents the total general desirability, D.

Three AAC system design parameters with their constraints are investigated: design parameter A is the compressor speed, B is the volume concentrations of Al₂O₃/PAG nanolubricants, while C is the refrigerant charge. The range for compressor speed is set to 900 to 2100 rpm. The volume concentrations vary from 0.006 to 0.014% while the refrigerant charges from 90 to 170 g were selected. Table 1 shows the suitable levels of the factors used to design the parameters of the AAC system. From the design of experiment, the experimental work on the AAC systems was run. The responses of 20 runs in the design matrix along with their corresponding points on the fitted models are based on the RSM demonstrated in Table 2.

Table 1. The AAC system design parameter and its level for central composite design

Parameter	-1	0	1
A- Compressor Speed, (rpm)	900	1500	2100
B- Volume Concentration, ϕ (%)	0.006	0.010	0.014
C- Refrigerant charge, (g)	90	130	170

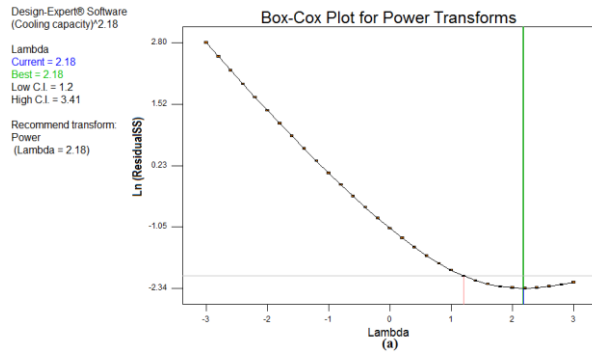
Table 2. The un-coded experimental design and result of experiment

Run	Process parameter settings			Experimental	
	A-Speed (rpm)	B- ϕ (%)	C-Ref. Charge (g)	Q _L (kW)	W _{in} (kJ/kg)
1	1500	0.014	130	0.956	25.100
2	1500	0.010	130	1.301	20.400
3	2100	0.006	170	1.199	23.100
4	1500	0.010	130	1.210	22.000
5	2100	0.014	90	0.682	46.300
6	1500	0.010	130	1.230	23.200
7	900	0.014	90	0.363	30.700
8	1500	0.010	130	1.220	19.400
9	1500	0.010	130	1.121	18.700
10	900	0.006	90	0.461	25.200
11	2100	0.010	130	1.235	24.800
12	1500	0.010	90	1.030	23.400
13	1500	0.010	170	1.225	19.000
14	900	0.014	170	1.162	16.100
15	1500	0.010	130	1.123	19.100
16	900	0.010	130	1.066	15.400
17	2100	0.006	90	0.647	39.200
18	900	0.006	170	1.059	14.700
19	2100	0.014	170	1.208	25.900
20	1500	0.006	130	0.912	23.400

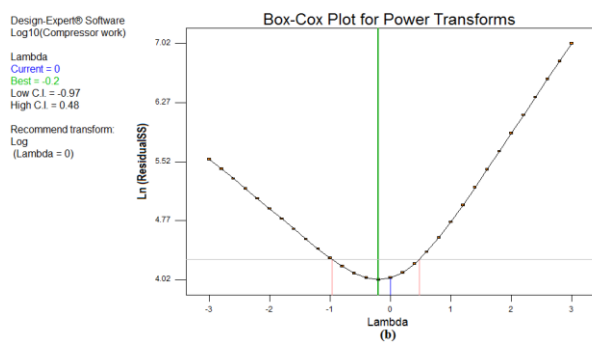
3. Results and discussion

3.1. ANOVA Analysis on the Responses

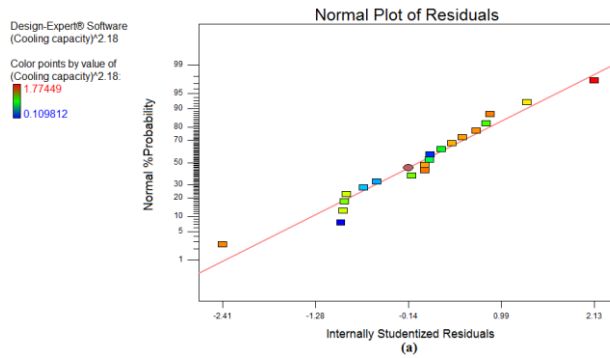
The analysis of response, namely cooling capacity and compressor work was performed using variance analysis (ANOVA) and RSM by utilizing Design-Expert software. The results attained are applied in the software for statistical accuracy and to develop a model equation for the responses. The Box-Cox power transformation evaluation was used to check the suitability of the polynomial equations suggested. If the results are not correctly predicted, the power of the polynomial for the model will be increased to achieve reasonable accuracy. Figure 1(a) & (b) represented the Box-Cox power transformation, which was done on to the cooling capacity and compressor work to obtain higher accuracy of the prediction. While the normal probability plots depicted in Figure 1(c)&(d) are the results of normality testing for the experimental results. The figures depict the predicted versus actual values for the design matrix. The normal probability plot should be verified for the range of residuals, which should lie close to the mean line. It was found that the values of residuals are minimal and tightly fitted to the mean line depicted in the graph since it is normally fitted for all responses after power altered was done on both responses.



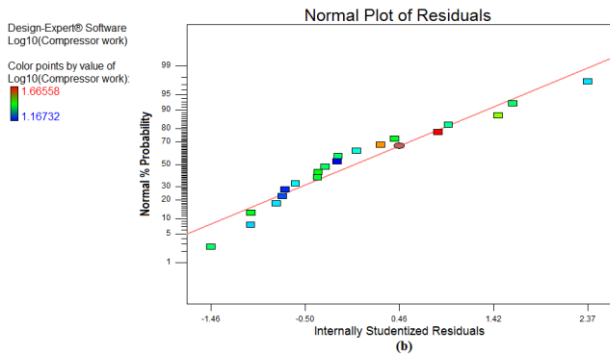
a) Box-Cox plot for Cooling Capacity



(b) Box-Cox plot for Compressor Work



(c) Normal probability plot for Cooling Capacity



(d) Normal probability plot for Compressor Work

Figure 1. Box-Cox and Normal probability plots for Cooling Capacity and Compressor work.

The model summary of a quadratic model (with power transformation) for cooling capacity and compressor work was carried out and represented in Table 3. Table 3 shows that the model fit is expressed as the coefficient of R-squared. The values show 0.9108 and 0.9291 for cooling capacity and compressor work of the variability in response that can be elucidated by the model for the responses mentioned. The closer the R2 value to 1, the better the model fits the experimental data [30]. Table 3 also shows the Predicted R-Squared value of 0.8586 and 0.8839 for cooling capacity and compressor work, respectively, which is in reasonable agreement with the Adjusted R-squared value of 0.8870 and 0.9102 in which the difference between these values is less than 0.2 as desired. The adequate precision values for these responses are 20.710 and 25.314, as depicted in Table 3, where this parameter reflects the signal-to-noise ratio. A value higher than four is sought. Both responses show values higher than four, meaning that they are sufficient signals and can be used to navigate the design space as indicated from the table.

Table 3. Model summary for AAC system response surface model

Source	Q _L (kW)	W _{in} (kJ/kg)	Remarks
R- squared	0.9108	0.9291	-
Adjusted R-squared	0.8870	0.9102	-
Predicted R-squared	0.8586	0.8839	Closed to Adj. R2
Adequate precision	20.710	25.314	> 4

3.2. Cooling Capacity ANOVA Analysis

Further analysis of variance (ANOVA) for the cooling capacity was carried out as depicted in Table 4.

Table 4. ANOVA analysis for cooling capacity response surface quadratic model

Source	Sum of Squares	df	Mean Squares	f-value	p-value Prob > f	Significant
Model	4.390	4	1.100	38.30	<0.0001	✓
A-Speed	0.210	1	0.210	7.24	<0.0168	✓
B- ø	0.012	1	0.012	0.41	<0.5324	X
C-Chg	2.390	1	2.390	83.43	<0.0001	✓
B ²	1.780	1	1.780	62.12	<0.0001	✓
Residual	0.430	15	0.029	-	-	-
LoF	0.260	10	0.026	0.73	0.6864	X
Pure Error	0.170	5	0.035	-	-	-

Table 4 shows that this model is statistically significant, with a sum of squared models of 4.39 and a f-value of 38.30. P-values are values that are commonly used to assess the importance of each coefficient. A "Prob> f" value of less than 0.05 indicates that the model terms are significant and better. The term of the model is not significant if the value of "Prob> f" is greater than 0.1. In the case of this study, the p-value for the model is less than 0.0001. This means that there is a maximum probability of 0.01% that "Model f-value" occurs due to noise. Factors such as speed (A), initial cooling charge (C), and combined squared concentration (B₂) show values with "Prob> f" values less than 0.05. Apart from the concentration (B) term, other non-significant factor model combinations with values of "Prob> f" greater than 0.100 were excluded in the model reduction. Model reductions are made by removing non-

significant factors that will improve the model. Therefore, the cooling capacity is $Q_L = f(A, b, C, B^2)$. Unlike model values, the value of "LoF" (standing for Lack of Fit) is not important, and the value of "Prob> f" is greater than 0.100. The f-value was 0.73 for cooling capacity indicating that "LoF" was not significant due to pure error. A non-significant "LoF" is desired to make certain models fit.

The developed actual quadratic models of cooling capacity Q_L as fitted based on RSM in terms of the experimental factors is presented in Equation 2.

$$Q_L^{2.18} = -4.333 + 2.401(10)^{-4} A + 754.682B + 0.0122C - 37306.3210B^2 \quad (2)$$

Where Q_L is the cooling capacity (kW), A is the speed (rpm), B the volume concentration of Al_2O_3/PAG nanolubricant (%), and C is the refrigerant charge (g). Negative signs indicate that they have antagonistic effects, while positive coefficients in the equation reflect synergistic results, on the responses analyzed [29]. The predicted value of the cooling capacity, Q_L determined through Equation 2, is close to the experimental value.

Based on the ANOVA analysis, the refrigerant charge (C) and concentration-squared (B^2) show significant interaction effects. It can be seen that the cooling capacity increases with the increase in refrigerant charges. This is mainly due to the increase in the mass flow rate due to the increase in cooling charges. Figure 2 shows the interaction between the refrigerant charge and volume concentration.

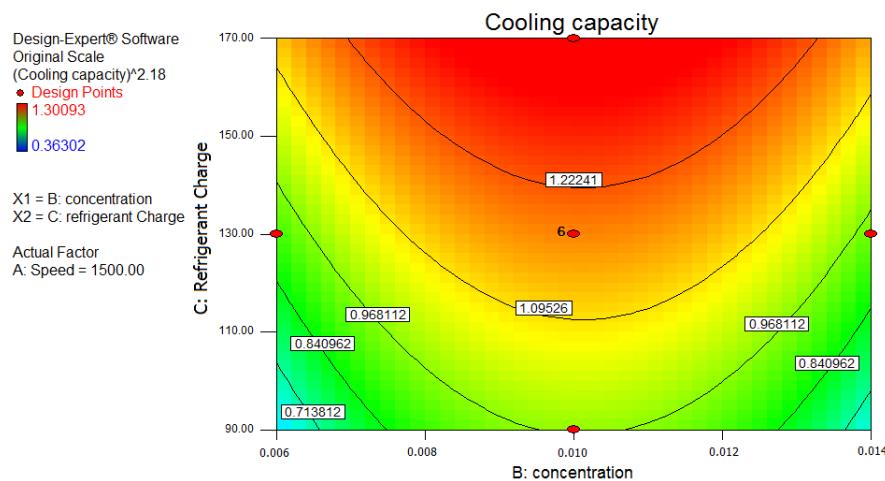


Figure 2. Cooling capacity as the function of Refrigerant charge and Nanolubricant Concentration

Figure 2 shows the curvature of the plot indicating the interaction between the variables. The increase in the refrigeration charges has led to a significant increase in cooling capacity, especially at a volume concentration of 0.006%. Furthermore, increasing the volume concentration will increase cooling capacity up to 0.010% volume concentration. This can be seen at 0.010% volume concentration, where across the refrigerant charge, the cooling capacity value is decreasing. The figure also shows that cooling capacity is optimum at 0.010% volume concentration.

3.3. Compressor Work ANOVA Analysis

Table 5 shows the analysis of variance (ANOVA) for compressor work was carried out. The table shows that the f-value is 49.15, which confirms that the model is significant. In terms of factors, Speed (A), volume concentration (B), the refrigerant charge (C), and a combination of B_2 show significance with "Prob > f" values of less than 0.05. Other combinations of factor models are not significant with "Prob > f" values to be more than 0.100. Therefore, compressor work is given by $W_{in} = f(A, B, C, B_2)$.

Furthermore, for the “LoF” value for compressor work, the f-value is 0.5408, which means that the lack of fit is not significant relative to the pure error.

Table 5. ANOVA compressor work quadratic model

Source	Sum of Squares	df	Mean Squares	f-value	p-value Prob > f	Significant
Model	0.270	4	0.067	49.15	<0.0001	✓
A-Speed	0.096	1	0.096	69.98	<0.0001	✓
B- ϕ	0.008	1	0.008	5.62	<0.0316	✓
C- Chg	0.120	1	0.120	86.06	<0.0001	✓
B ²	0.048	1	0.048	34.93	<0.0001	✓
Residual	0.021	15	0.001	-	-	-
LoF	0.014	10	0.001	0.99	0.5408	X
Pure Error	0.007	5	0.001	-	-	-

analysis for response surface

The developed actual quadratic model of compressor work (W_{in}) as fitted based on RSM in terms of the experimental factors corresponded to Equation 3. The predicted value of w_{in} determined by Equation 3 was adequately close to the experimental values.

$$\log_{10} w_{in} = 1.9596 + 1.6333(10)^{-4} A - (115.4567) B - 2.7170(10)^{-4} C - 6119.944B^2 \quad (3)$$

Based on ANOVA analysis, speed (A), concentration (B), refrigerant charge (C) and concentration-squared (B^2) show a significant interaction effect. Interaction of AAC parameters between compressor speed and volume concentration and its effects toward the compressor work is shown in Figure 3.

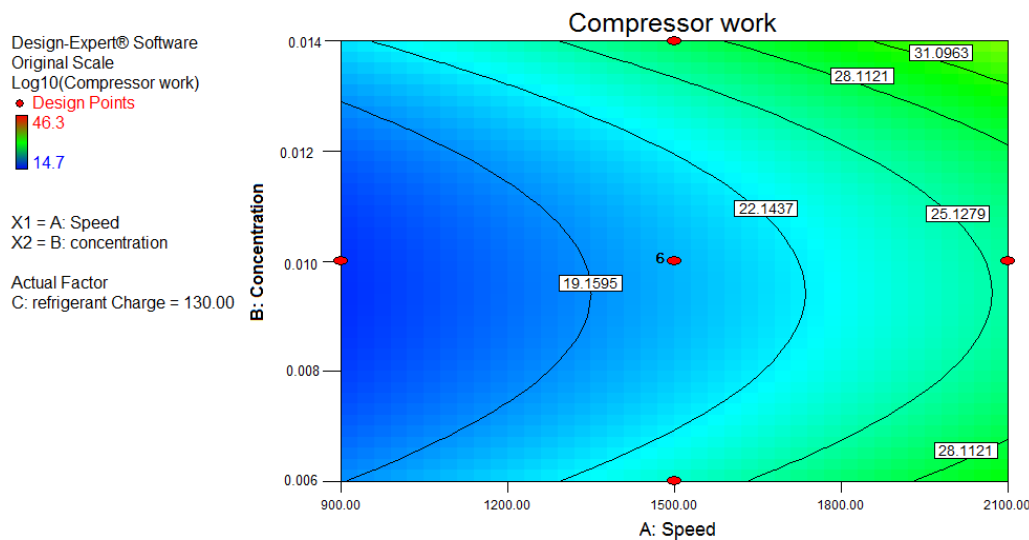


Figure 3. Compressor Work as the function of compressor speed and Nanolubricant Concentration

Compressor work is high at low nanolubricant concentrations. Increasing the volume concentration will reduce the compressor work before it increases again after the volume concentration of 0.010%. Besides, the figure shows that the compressor work also increases with increasing speed. This is mainly due to the increase in mass flow rate as the compressor speed increases. Figure 3 indicates that the compressor work is minimal at 0.010% volume concentration and low compressor speed. The compressor work will decrease with the increasing volume concentration up to 0.010% volume concentration. Above 0.010% volume concentration, the compressor work is again increased. Hence,

from Figure 3, it can be concluded that the minimum compressor work occurs when the volume concentration of $\text{Al}_2\text{O}_3/\text{PAG}$ nanolubricant is at 0.010% and at 900 rpm compressor speed.

3.4. Optimization of the Responses

The optimization of the responses was done according to the desirability approach. In the desirability analysis, the total desirability (D) is the geometric (multiplicative) mean of all individual desirability. The individual desirability is ranging from 0 (least) to 1 (most). Table 6 The best combination of parameters was selected via the highest desirability value.

Table 6. Optimum response target value and limit for optimization of AAC performances

Factors		Responses			Desirability
Speed	ϕ	Ref. Charge	Q_L	w_{in}	
1160.29	0.010	167.78	1.314	14.19	1.000

The highest desirability value is 1.000 which reflected the maximum cooling capacity of 1.314 kW and minimum compressor work of 14.19 kJ/kg. This can be attained by employing the AAC parameters of 1160.29 rpm of compressor speed, $\text{Al}_2\text{O}_3/\text{PAG}$ nanolubricant with concentration of 0.010% and refrigerant charge of 167.78 g, represented in ramp form as shown in Figure 4. The highest desirability value is also best portrayed in graphical form as shown in contour and 3D view in Figure 5.

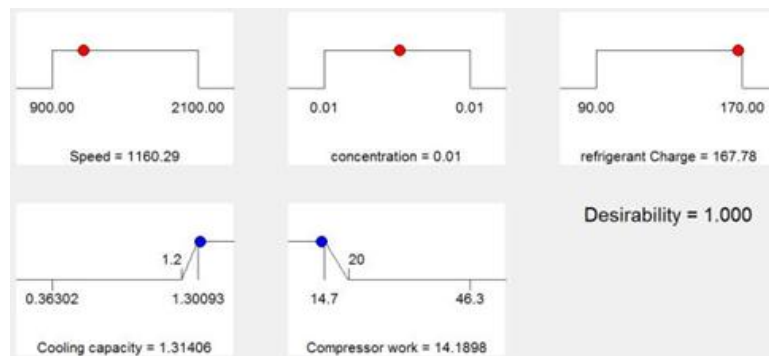


Figure 4. Ramp solution for desirability approach

Table 7 represents the predicted results of desirability were then validated through the experiment. The parameter, namely compressor speed rounded to 1160 rpm, volume concentration of 0.010%, and 168 g initial refrigerant charge (rounded value), are used in the experiment for validation. It can be concluded that the predicted result with certain desirability is compared, as shown in Table 7. Considering all responses, these are the outcomes of the optimum conditions of the AAC system. The results show a close agreement between the predicted and experimental results with a maximum deviation of 3.35%.

Table 7. The predicted result versus the validation result through experiment

	Factors			Response	
	Speed	ϕ	Ref. Charge	Q_L	w_{in}
Prediction	1160.29	0.010	167.78	1.314	14.19
Validation	1160	0.010	168.00	1.280	14.40
Deviation (%)				3.35	1.48

4. Conclusion

The optimization of operating factors for automotive air-conditioning (AAC) systems was performed in the present study by changing the compressor speed, refrigerant charge and Al₂O₃/PAG nanolubricant volume concentration. RSM has been used as DOE to assist in designing experiments and statistical analysis. As a result, important variables that contribute to the AAC system performance coefficient can be identified. The experimental design predicted by the RSM reduces the time required. The reduction of time is assisted by reducing the number of experiments to be performed and representing a statistically proven model for all reactions. Therefore, the method required in RSM is effective in this study. A highest desirability of 100% was achieved at the compressor speed of 1160 rpm, refrigerant charge of 167 gram and nanolubricant volume concentration of 0.010%. This situation was regarded as the optimum parameter for the AAC system having cooling capacity (QL) of 1.314 kW and compressor work (Win) of 14.19 kJ/kg. The validation via experiment found that the prediction by RSM is valid with deviation is less than 3.4%.

Acknowledgement

The authors are grateful to the TATI University College University and Malaysia Pahang (UMP) for financial support. This work was supported by grant No RDU 151311 and TATIUC STG 9001-1902.

References

- [1] Di Battista D and Cipollone R 2016 High efficiency air conditioning model based analysis for the automotive sector *international journal of refrigeration* **64** 108-22
- [2] Redhwan A A M, Azmi W H, Sharif M Z and Mamat R 2016 Development of nanorefrigerants for various types of refrigerant based: A comprehensive review on performance *International Communications in Heat and Mass Transfer* **76** 285-93
- [3] Azmi W H, Sharif M Z, Yusof T M, Mamat R and Redhwan A A M 2017 Potential of nanorefrigerant and nanolubricant on energy saving in refrigeration system—A review *Renewable and Sustainable Energy Reviews* **69** 415-28
- [4] Bi S, Guo K, Liu Z and Wu J 2011 Performance of a domestic refrigerator using TiO₂-R600a nano-refrigerant as working fluid *Energy Conversion and Management* **52** 733-7
- [5] Bi S-s, Shi L and Zhang L-l 2008 Application of nanoparticles in domestic refrigerators *Applied Thermal Engineering* **28** 1834-43
- [6] Wang R, Wu Q and Wu Y 2010 Use of nanoparticles to make mineral oil lubricants feasible for use in a residential air conditioner employing hydro-fluorocarbons refrigerants *Energy and Buildings* **42** 2111-7
- [7] Kumar D S and Elansezhian R 2012 Experimental study on Al₂O₃-R134a nano refrigerant in refrigeration system *International Journal of Modern Engineering Research* **2** 3927-9
- [8] Sabareesh R K, Gobinath N, Sajith V, Das S and Sobhan C 2012 Application of TiO₂ nanoparticles as a lubricant-additive for vapor compression refrigeration systems—An experimental investigation *international journal of refrigeration* **35** 1989-96
- [9] Subramani N and Prakash M J 2011 Experimental studies on a vapour compression system using nanorefrigerants *International Journal of Engineering, Science and Technology* **3** 95-102
- [10] Nair V, Tailor P and Parekh A 2016 Nanorefrigerants: A comprehensive review on its past, present and future *International journal of refrigeration* **67** 290-307
- [11] Sharif M Z, Azmi W H, Redhwan A A M, Mamat R and Yusof T M 2017 Performance analysis of SiO₂/PAG nanolubricant in automotive air conditioning system *international journal of refrigeration* **75** 204-16
- [12] Pandian M, Sivapirakasam S and Udayakumar M 2011 Investigation on the effect of injection system parameters on performance and emission characteristics of a twin cylinder compression ignition direct injection engine fuelled with pongamia biodiesel—diesel blend using response surface methodology *Applied Energy* **88** 2663-76

- [13] Myers R H, Montgomery D C and Anderson-Cook C M 2016 *Response surface methodology: process and product optimization using designed experiments*: John Wiley & Sons)
- [14] Karimi F, Rafiee S, Taheri-Garavand A and Karimi M 2012 Optimization of an air drying process for Artemisia absinthium leaves using response surface and artificial neural network models *Journal of the Taiwan Institute of Chemical Engineers* **43** 29-39
- [15] Costa N and Garcia J 2016 Using a multiple response optimization approach to optimize the coefficient of performance *Applied Thermal Engineering* **96** 137-43
- [16] Redhwan A A M, Azmi W H, Najafi G, Sharif M Z and Zawawi N N M 2019 Application of response surface methodology in optimization of automotive air-conditioning performance operating with SiO₂/PAG nanolubricant *Journal of Thermal Analysis and Calorimetry* **135** 1269-83
- [17] Redhwan A A M, Azmi W H, Sharif M Z and Zawawi N N M 2017 Thermal conductivity enhancement of Al₂O₃ and SiO₂ nanolubricants for application in automotive air conditioning (AAC) system. In: *MATEC web of conferences*: EDP Sciences) p 01051
- [18] Redhwan A A M, Azmi W H, Sharif M Z, Mamat R and Zawawi N N M 2017 Comparative study of thermo-physical properties of SiO₂ and Al₂O₃ nanoparticles dispersed in PAG lubricant *Applied Thermal Engineering* **116** 823-32
- [19] Aminullah A R M, Azmi W H, Redhwan A A M, Sharif M Z, Zawawi N N M, Kadirgama K and Ashraf M N S 2018 Tribology investigation of automotive air condition (AAC) compressor by using Al₂O₃/PAG nanolubricant *J Mech Eng* 49-61
- [20] Zawawi N N M, Azmi W H, Redhwan A A M and Sharif M Z 2017 Coefficient of friction and wear rate effects of different composite nanolubricant concentrations on Aluminium 2024 plate. In: *IOP Conference Series: Materials Science and Engineering*: IOP Publishing) p 012065
- [21] Sharif M Z, Azmi W H, Redhwan A A M and Mamat R 2016 Investigation of thermal conductivity and viscosity of Al₂O₃/PAG nanolubricant for application in automotive air conditioning system *international journal of refrigeration* **70** 93-102
- [22] Zawawi N N M, Azmi W H, Redhwan A A M, Sharif M Z and Samykano M 2018 Experimental investigation on thermo-physical properties of metal oxide composite nanolubricants *International Journal of Refrigeration* **89** 11-21
- [23] Redhwan A A M, Azmi W H, Sharif M Z, Zawawi N N M and Mamat R 2018 Sonication time effect towards stability of Al₂O₃/PAG and SiO₂/PAG nanolubricants *J Mech Eng* 14-27
- [24] Sharif M Z, Azmi W H, Redhwan A A M, Zawawi N N M and Mamat R 2017 Improvement of nanofluid stability using 4-step UV-vis spectral absorbency analysis *J Mech Eng* **4** 233-47
- [25] Zawawi N N M, Azmi W H, Sharif M Z and Najafi G 2019 Experimental investigation on stability and thermo-physical properties of Al₂O₃-SiO₂/PAG nanolubricants with different nanoparticle ratios *Journal of Thermal Analysis and Calorimetry* **135** 1243-55
- [26] Redhwan A A M, Azmi W H, Sharif M Z and Hagos F Y 2017 Development of nanolubricant automotive air conditioning (AAC) test rig. In: *MATEC web of conferences*: EDP Sciences) p 01050
- [27] Sharif M Z, Azmi W H, Redhwan A A M, Mamat R and Najafi G 2019 Energy saving in automotive air conditioning system performance using SiO₂/PAG nanolubricants *Journal of Thermal Analysis and Calorimetry* **135** 1285-97
- [28] Redhwan A A M, Azmi W H, Sharif M Z, Mamat R, Samykano M and Najafi G 2019 Performance improvement in mobile air conditioning system using Al₂O₃/PAG nanolubricant *Journal of Thermal Analysis and Calorimetry* **135** 1299-310
- [29] Khoobbakht G, Najafi G, Karimi M and Akram A 2016 Optimization of operating factors and blended levels of diesel, biodiesel and ethanol fuels to minimize exhaust emissions of diesel engine using response surface methodology *Applied Thermal Engineering* **99** 1006-17
- [30] Oh B-R, Seo J-W, Choi M H and Kim C H 2008 Optimization of culture conditions for 1, 3-propanediol production from crude glycerol by *Klebsiella pneumoniae* using response surface methodology *Biotechnology and Bioprocess Engineering* **13** 666-70