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PERFORMANCE OPTIMIZATION OF RADIATOR ENGINE PARAMETERS DURING HARD CONDITIONS BY CONTROL CHARTS MONITORING AND EVALUATING

Ali Fadhil Abduljabbar
Master of Statistics
Department of Medical Laboratory Technologies
Middle Technical University, Kut Technical Institute
Al Za'faraniya, Baghdad, Iraq, 10074

Bashra Kadhim Oleiwi
Doctor of Mechatronics Engineering/Control and Systems Engineering
Department of Control and Systems Engineering
University of Technology-Iraq
Baghdad, Iraq, 19006

Ahmad H. Sabry
Corresponding author
Doctor of Control and Automation Engineering
Department of Computer Engineering
Al-Nahrain University
Al Jadriyah Bridge, Baghdad, Iraq, 64074
E-mail: ahs4771384@gmail.com

Recently, engine design and control systems have been developed using data-driven modeling techniques to specify the in-cylinder complicated combustion process. The cooling fan performance is highly influenced by several factors that are determined based on what is called (DOE) «design of experiments». These factors include blade tip clearance, pitch angle, distance from radiator. This work presents a method to improve a cooling fan performance of an engine by designing a Six Sigma technique using Control, Improve, Analyze, Measure, and Define (CIAMD). First, let's assess the existing cooling fan performance and define its problem. Then, let's specify the parameters that affect on fan performance to be optimized. Next, let's conduct sensitivity analysis and evaluate manufacturing control of the developed cool Fan. The primary fan does not distribute air enough by the radiator to maintain the machine cool throughout hard circumstances. First, the work demonstrates how to develop an experiment to examine the influence of three performance elements: blade pitch angle, blade-tip clearance, and fan distance from the radiator. In order to improve the performance of the cooling fan, Box-Behnken design is adopted for testing quadratic (nonlinear) effects. It then indicates how to predict optimal quantities for every element, to produce a technique that makes airflows above the objective of 1486.6 m^3/h when utilizing experimental measurements. Finally, it reveals how to operate simulations to confirm that this method creates airflow based on the specifications with more additional fans manufactured performance of 99.999 %. The results of S and X-bar control charts indicate that the manufacturing process is statistically under control

Keywords: optimization, Six Sigma technique, control chart, Box-Behnken, cooling fan

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1. Introduction

An essential component of the vehicle cooling system is the engine cooling fan. The tip of the blade, which performs the majority of the fan's work, has a significant impact on the aerodynamic performance of the fan. Static pressure and shaft power are crucial indications to evaluate its aerodynamic performance. It's critical that the cooling system operate with the least amount of input energy possible because it takes a portion of the engine's power. Increased fuel efficiency from a cooling system upgrade can help engines satisfy legal mobility requirements. A diagram showing the airflow components of an engine is shown in Fig. 1.

Recently, engine design and control systems have been developed using data-driven modeling techniques to specify the in-cylinder complicated combustion process [1]. Because uncertainties or stochastic elements would significantly affect the lower system's dependability and decoupling state of the system, robustness optimization to increase the reliability of an engine mounting system (EMS) is required in the design [2].

Bill Smith introduced a quality-control system known as Six Sigma in 1986 [3]. It makes use of data-driven examination to decrease errors or flaws in a business or corporate operation. The Six Sigma model is a method for working more accurately and quickly. Six Sigma applies to various sectors such as a quality approach to robust optimization [4], for HPLC-UV method optimization [5], Performance optimization of the retail Industry [6], for production process optimization in a paper production company [7], Improving online quality control [8], for robust design optimization [9], Multi-Point Dieless Forming Process [10], Sorbitol production optimization in B2B industry [11], in the mould industry [12], for Inherent Issues in Production Shop Floor Management [13], and others. Therefore, by removing and locating the root causes of faults and reducing manufacturing variance, Six Sigma procedures aim to increase manufacturing quality. Six Sigma does this by employing Six Sigma statistical, using experimental and specialist quality control management techniques.

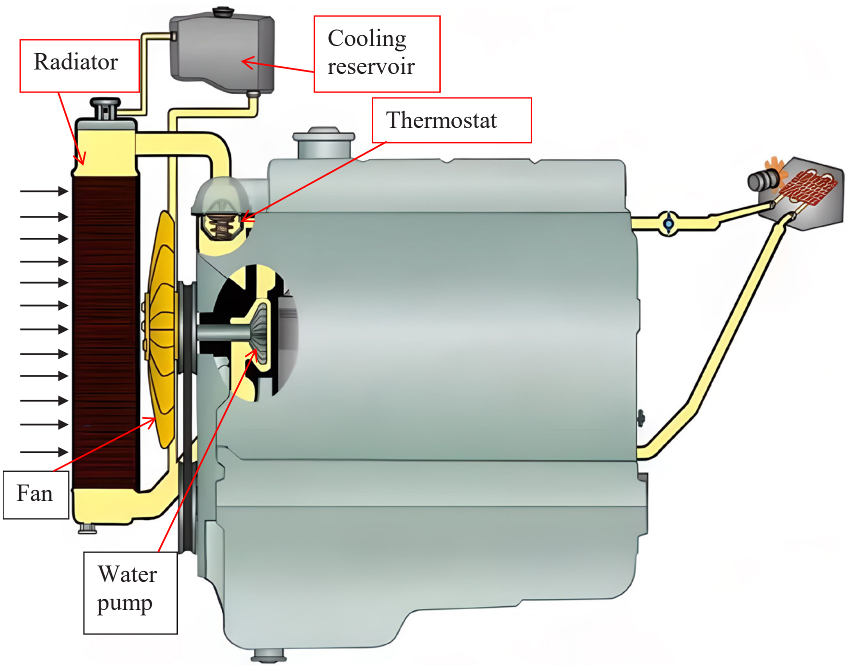

Fig. 1. Airflow components of an engine

Therefore, optimizing fan's parameters has a significant impact on the aerodynamic performance of the fan and is essential to improve the performance of radiator engine parameters during hard conditions.

2. Literature review and problem statements

Using fan's associated elements such as shroud provide space for the fan, which in turn distributes air across the radiator as is required for efficient cooling system of various engines. The study [14] discussed the use of Six Sigma technique on the fan shroud as one of the significant cooling components across the heat exchangers of an engine that assists to achieve optimum airflow, where the key challenges are on designing such a shroud that meets harshness, vibration and noise requirements but with no compromising on airflow goals. This study used A CFD simulation. Although this study proposed two operation modes pumping and flexible to optimize parameters such as structural embossing, number of ribs, and wall thickness as control factors, the method was not easy to understand with complexity. Under the double heating effects of high-power electronic apparatus and aerodynamic, the power demand and heat sink of superior high-speed aircraft have been rising exponentially, which seriously restricts the aircraft performance. A thermal/power management system (TPMS) was used to improve system cooling [15]. However, the optimization variables were not consisting of the fan duct heat exchanger structure size, cooling air flow rate, and compressor outlet temperature.

The high-pressure turbine cooling of a fan-shaped hole was discussed for performance optimization by [16]. A deep learning architecture was designed to estimate the cooling airflow rate for the cooling-hole location. Although the model optimization was conducted to recover the temperature uniformity and the film cooling effectiveness on the vane surface with several fan-shaped holes, their results were only applicable on the film cooling model. The authors of study [17] also discussed the cooling issue of engines of internal combustion type to remove waste heat using the radiator fan(s), radiator, thermostat valve, and water pump to reject heat to the local environment and flow cooling fluid throughout the engine block. Although this study utilized compound matrix of radiator fan to reduce energy usage, the forced convection heat transmit process and the mathematical model was missing. Implementation of cooling system on diesel engine to predict system parameters based on deep learning network based algorithm was presented by [18]. However, their experimental results showed no significant difference compared to the traditional neural network one. The optimization technique of blade tip parameters and a calculation technique of aerodynamic performance of the fan such as tip arch height, tip length, and tip mounting angle were studied by [19].

Although the study analyzed the feasibility of the optimization method, blade velocity vector diagram, blade pressure diagram and fan performance curve, the optimization and analysis of fan parameters were not accurate enough for the engine cooling fan design. These issues have been discussed by [20], where a vehicle cooling system with front-end intake air volume was found to be affects directly on the aerodynamic resistance and heat dissipation performance of engine compartment, but the computational fluid dynamics (CFD) used method was not able to optimize the fan speed.

All this allows asserting that it is expedient to conduct a study on improving a cooling fan performance of an engine when the primary fan does not distribute air enough by the radiator to maintain the machine cool throughout hard circumstances.

3. The aim and objectives of research

The aim of research is to determine the optimal operating parameters of the radiator engine under hard conditions. This will make it possible to maintain the machine cool throughout hard circumstances.

To achieve this aim, the following objectives are accomplished:

– to assess the existing cooling fan performance and define its problem;

– to specify the parameters that affect on fan performance to be optimized;

– to conduct sensitivity analysis and evaluate manufacturing Control of the developed cool Fan.

4. Methods and materials

4. 1. Object and research hypothesis

This work discusses the radiator circulating flow of cooling air issue of an engine fan model to maintain the engine cool during variation conditions including hot weather and stop-and-go traffic. Let's assume that airflow must be 1486.63 m^3/h at least, to maintain engine cooling during such hard circumstances.

A diagram showing the main methodology steps is demonstrated in Fig. 2.

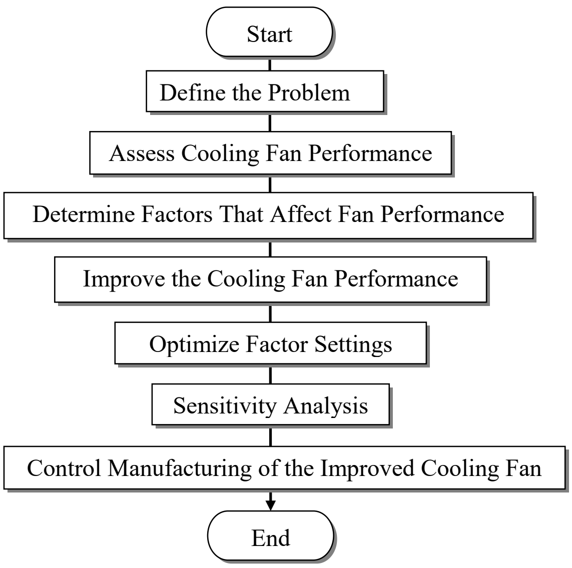

Fig. 2. The main methodology steps

Therefore, it is required to assess the existing model and expand an alternative one that is capable of reaching the goal of circulating flow of air.

4. 2. Methodology steps

In order to evaluate the performance of the engine cooling fan, let's initially load a sample of historical production measurements includes 5000 of observations of the performance of the engine cooling fan. The cooling fan performance is influenced by several factors that are determined based on what is called (DOE) «design of experiments».

These factors include the followings:

– blade tip clearance;

– pitch angle;

– distance from radiator.

Let's assume that these factors can control and modify. The airflow rate is the response of the cooling fan (m^3/h). Since, the airflow is a fluid process and has a nonlinear behavior as usual; let's adopt a surface design based response to predict the nonlinearity relations amongst these factors. Box-Behnken Design, which is introduced in [21], is used to create the experimental attempts in normalized (coded) variable range [–1, 0, +1].

The Coded-Value matrix is a (15×3)=[–1–10; –110; 1–10; 110; –10–1; –101; 10–1; 101; 0–1–1; 0–11...

Where the column to the left represents the distance values of the fan from the radiator, the pitch angle values are shown in the second column, and the last column includes the blade clearance tip. Let's assume that the effects of the parameters on the following maximum and minimum values are required to be tested:

– blade tip clearance: 2.5 to 5 cm;

– pitch angle: 14 to 36 degrees;

– distance from radiator: 2.54 to 3.8 cm.

The runs order is randomized, then let's change the coded model quantities into actual-world values, next let's execute the experimentation in a particular order. In order to improve the performance of the cooling fan, Box-Behnken model has been adopted to inspect the quadratic (nonlinear) effect. The nonlinear model can be formed in terms of the airflow rate (A_F) by:

$$A_F = \beta_0 + \beta_1 * D + \beta_2 * P + \beta_3 * C + \beta_4 * D * P + \\ + \beta_5 * D * C + \beta_6 * P * C + \beta_7 * D^2 + \beta_8 * P^2 + \beta_9 * C^2, \qquad (1)$$

where D is the distance, P is the pitch angle, and C is the clearance, while β_i represents the formula coefficients that their normalized magnitudes in a bar chart representation.

To verify the optimal obtained factor settings, it is possible to make the task of finding the optimum factor settings automatic by considering the Problem-Based Optimizing method as demonstrated in the flow diagram of Fig. 3.

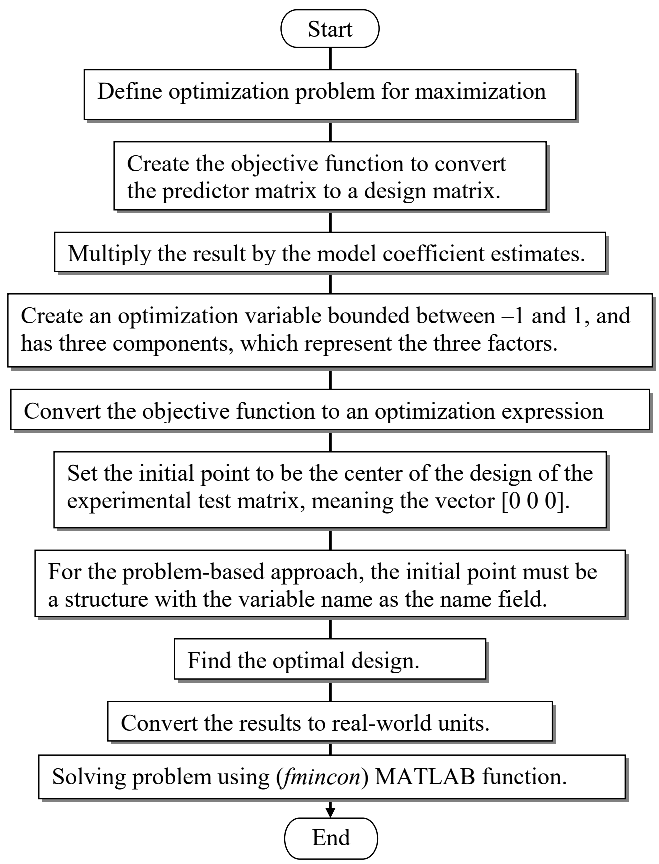

Fig. 3. The main steps of Problem-Based Optimizing method

The required airflow is met by the upgraded cooling fan design. Based on the design-tunable factors, the derived model can accurately predict the fan performance. However, let's conduct a sensitivity analysis to make sure that the performance of the fan is resilient to variation in manufacture and setting up. For sensitivity examination, let's assume that the manufacturing uncertainties are as listed in Table 1 based on historical experience.

Table 1

List of the manufacturing uncertainties based on historical records

Coded Values	Real Values	Factor description
–2.5+/–0.25 cm	2.5+/–0.25 cm	Blade tip clearance
0.227+/–0.028 degrees	27.3+/–0.25 degrees	Blade pitch angle
2.5+/–0.20 cm	2.5+/–0.1 cm	Distance from radiator

It is crucial to establish that these variances in components will allow for the maintenance of a sturdy design focusing on the desired airflow. A defect rate of just 3.41 per 1,000,000 fans is the goal of the Six Sigma philosophy. In other words, the fan must consistently reach the aim of 1486.63 m^3/h airflow.

A Monte Carlo simulation can be used to verify the design by creating 5,000 arbitrary numbers through the given tolerance for the three parameters. Let's also incorporate a noise variable that is inversely correlated with the fitted model's RMS error, or noise in the data.

To evaluate the manufacturing control of the developed cool fan, control charts can be used to track and assess the creation and installation of the new fan. Analyze the new cooling fan's first 30 days of production. At first, five cooling fans were made each day. Let's initially load the test data from the new process. Then, plotted S and X-bar charts. Next, the data is reshaped to a daily representation.

5. Results of the results of the proposed optimization process

5. 1. Results of the performance assessment of the cooling fan and define its problem

A Plotting of the historical production measurements of the engine cooling fan is shown in Fig. 4.

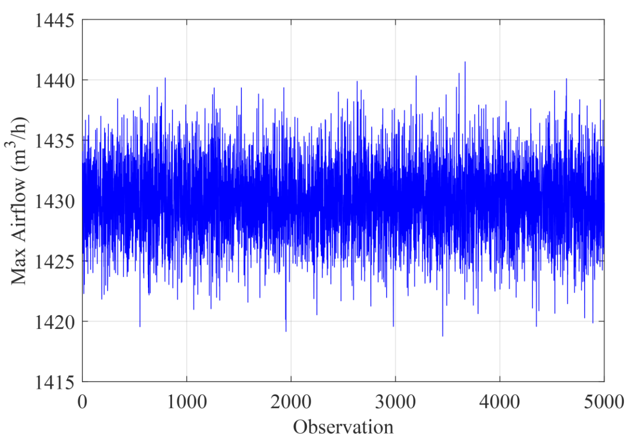

Fig. 4. The historical production measurements of the engine cooling fan

The plotting of the histogram with fitting the data to a normal distribution is shown in Fig. 5.

The values of mean (μ) and the standard deviation (σ) for the normal distribution are: μ=1429.98[1429.91, 1430.04], and σ=3.1887[3.14511, 3.23352].

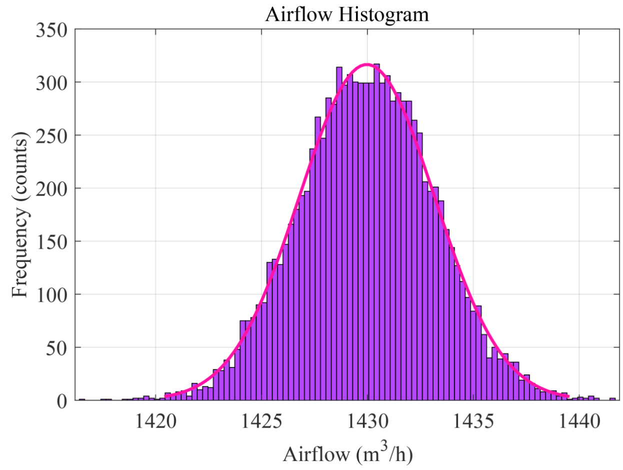

Fig. 5. The histogram based on normal distribution fit for the measurements of the engine cooling fan

The plot fits the measured data into a normal distribution to estimate the data parameters. The predicted 95 % confidence interval of the mean speed of the fan airflow is (1429.91, 1430) and the mean value of the airflow speed is 1429.976 m^3/h. This prediction provides clear insight that the current airflow value of the fan is not reach to the target value 1486.63 m^3/h. Therefore, it is required to develop a design for the fan to fulfill the goal airflow. This algorithm produces the response and design parameter values that are listed in Table 2.

Table 2

Design parameter values

Run_Number	Airflow	Clearance	Pitch	Distance
6	1422	0	–1	–1
3	1468	0	1	–1
11	1408.5	0	–1	1
7	1454.3	0	1	1
14	1495	–1	0	–1
8	1493.4	1	0	–1
5	1481.5	–1	0	1
15	1484.9	1	0	1
1	1417	–1	–1	0
2	1415.3	1	–1	0
4	1461	–1	1	0
13	1459.4	1	1	0
9	1485	0	0	0
10	1488	0	0	0
12	1486.6	0	0	0

According to the mode design test outcomes, the changing factors values are directly affect airflow rate. Furthermore, it is unclear how resilient the design is to changes in the factors. Therefore, using the existing experimental data, let's built a model to optimize the settings of its factors.

5. 2. Results of specifying parameters that affect on fan performance to be optimized

The formula coefficients that their normalized magnitudes in a bar chart representation are shown in Fig. 6.

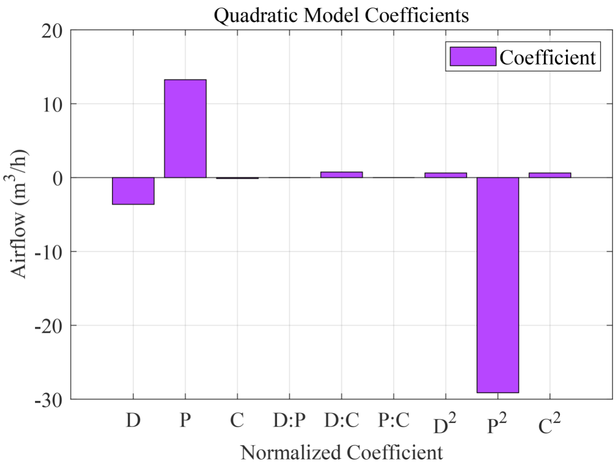

Fig. 6. Equation (A_F) coefficients' normalized magnitudes in a bar chart representation

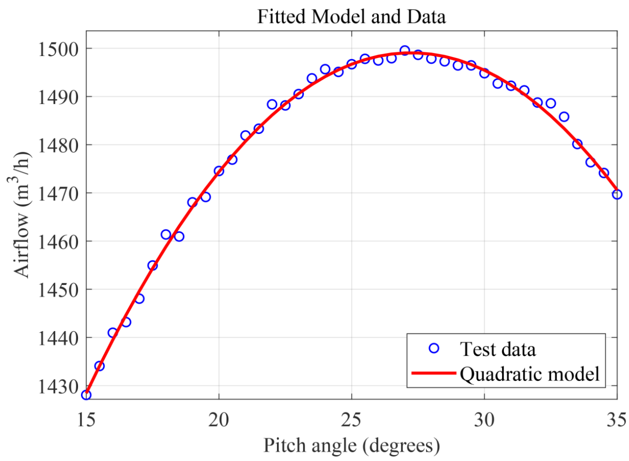

Fig. 8. The measured/tested data against airflow with the developed fitting model

The dominant factors in the bar chart representation are the Pitch^2 and Pitch and the association between one output variable and multiple input variables is represented by creating a surface response plot. Let's employ the MATLAB function (*plotSlice*) to produce the model surface response plots as shown in Fig. 7.

5. 3. Results of sensitivity analysis and manufacturing Control evaluation

A histogram data representation is used to evaluate the model deviation for the predicted airflow, and a normal distribution fitting of the data is used to estimate the standard deviation and the mean. Fig. 9 shows Monte Carlo model representation of the data including the related mean and standard deviation.

The S and X-bar control charts are shown in Fig. 10.

The predicted value of 1.73 and the *Cp* value of 1.75 are extremely similar. The *Cp* value is greater than the *Cpk* value, which is 1.66. Merely the *Cpk* value lower than 1.35, which shows that the method drastically deviated in the direction of the limits of the process, raises suspicions, though. The procedure operates fine within the parameters and delivers the desired airflow 1486.6 (m^3/h) more than 99.999 % of the time.

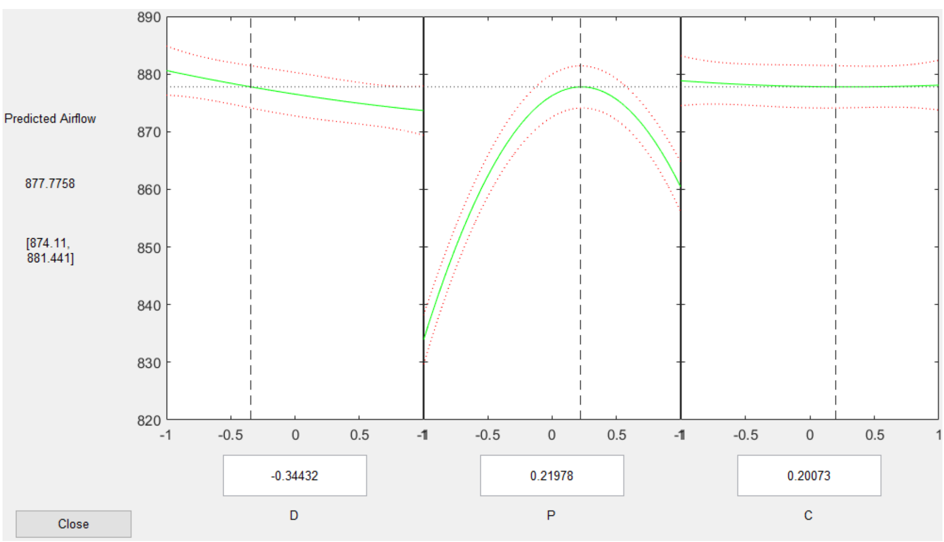

Fig. 7. The parameters of the model surface response plots

The results here demonstrates that the relation between the pitch and airflow has a nonlinear form, and the dashed blue bound lines show the result the other factors over the airflow.

Let's perform extra investigation to confirm that a 27.27-degree pitch angle is the ideal value because pitch angle has a major impact on airflow. The R square value of the fitting model is found to be 0.9963, which show that the nonlinear/quadratic design clarifies the well influence of airflow by pitch angle.

The result of plotting the airflow with pitch angle and developed proposed fitting Quadratic model is shown in Fig. 8.

With a simple substitution, the pitch angle value that equivalents to the highest airflow was found to be 27 degree, and the further analysis supports the conclusion that the ideal pitch angle is 27.3 degrees.

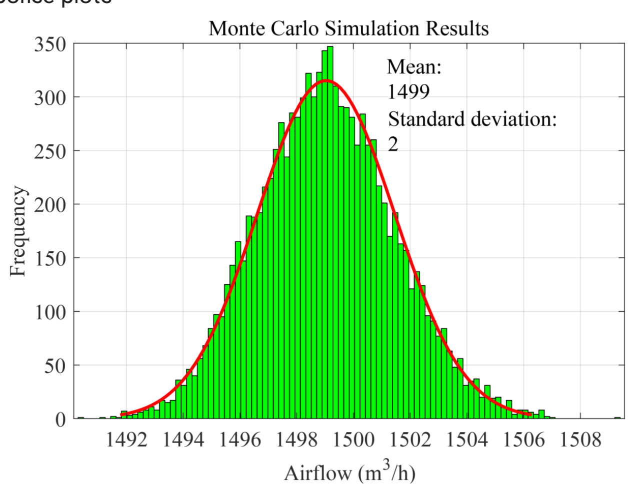

Fig. 9. Monte Carlo simulation representation of the data with the related mean and standard deviation

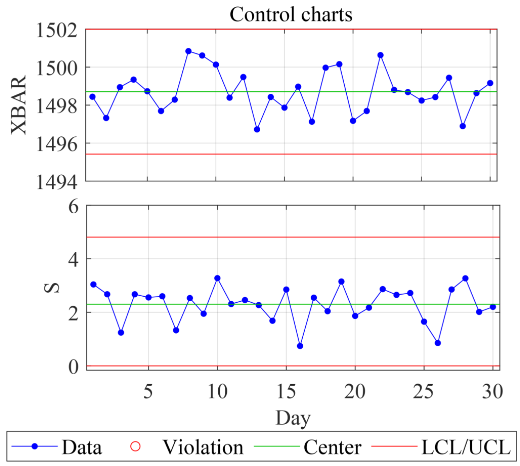

Fig. 10. S and X-bar control charts

6. Discussion of the results of optimization process and evaluation for the radiator engine parameters

Based on the historical production measurements of the engine cooling fan shown in Fig. 4, the majority values are clearly fall inside the range of about 13.59 m^3/h and the data is centered on 1430.57 m^3/h. However, the plot does not reveal a lot about the original data distribution. The histogram result that is based on normal distribution fit for the measurements provides clear insight that the current airflow value of the fan is not reach to the target value (1486.63 m^3/h). Therefore, it is required to develop a design for the fan to fulfill the goal airflow. This algorithm produces the response and design parameter values that are listed in Table 2. According to the mode design test outcomes, the changing factors values are directly affect airflow rate. In addition, there is four experiment attempts exceed or meet the goal airflow rate with a value of 1486.63 m^3/h (runs 14, 12, 4, and 2). Yet, which of these runs, if any, is the best is unclear. Furthermore, it is unclear how resilient the design is to changes in the factors. Therefore, using the existing experimental data, a model to optimize the settings of its factors is built.

As per Equation (A_F), which is plotted in Fig. 6, the dominant factors in the bar chart representation are the Pitch^2 and Pitch and the association between one output variable and multiple input variables is represented by creating a surface response plot. The result of applying Problem-Based Optimizing method shows the following indicators:

1. When the constraints are satisfied and the objective function is non-reducing in practicable directions inside the optimality tolerance value, the optimization is said to be complete.

2. Finding a local minimum that complies with the restrictions.

3. A lower value for the objective function that has feasible point.

4. The optimum values of the design factors were 1499 for the airflow, 2.5 for the clearance, 27.2747 for the pitch and 2.5 for the distance.

According to the optimization outcome, the developed fan should be installed 2.5 cm away from the radiator, with a pitch angle of 27.3, and with 2.5 cm between the fan blade tips and the shroud. The result of the Monte Carlo simulation (Fig. 9) seems promising, where it shows that the airflow is better than 1486.63 m^3/h for the majority of data and average airflow is 1498.528 m^3/h. The probability of 1486.63 m^3/h or less of the airflow can be found using the MATLAB function (*cdf* (1486.63)), which was 1.454e-07. Then, computing of (1–1.454e-07)*100=99.999 indicates that the airflow of at least 1486.63 m^3/h appears to be attained by the design 99.99 % of the time. Therefore, the process capability factors can be estimated using the simulation results, where *Cpk* was with a value of 1.709768, *Cpu* was 1.804268, *Cpl* was 1.709768, *Cp* was 1.757018, *Pu* was 3.1022444e-08, *Pl* was 1.45407686e-07, *P* was 0.99999982, σ was 1.42286513, and μ was 8.82298307e+02.

Cp is valued at 1.75. When *Cp* is equal to or greater than 1.62, a process is deemed to be of excellent quality. The process is centered because the *Cpk* value resembles the *Cp* value. Now it is possible to put this plan into action and Check to make sure the cooling fan performs to a high standard and to confirm the design process.

The results of S and X-bar control charts, shown in Fig. 10, indicate that the manufacturing process is statistically under control, as shown by non-random patterns in the data or the absence of violations of control limits over time. For further process assessment, let's also perform a data capacity analysis, which generates the values such that *Cpk* was 1.663, *Cpu* was 1.8479, *Cpl* was 1.6635, *Cp* was 1.75575, *Pu* was 1.47906e-08, *Pl* was 3.00893e-07, *P* was 0.9999, σ was 1.423887, and μ was 8.821061e+02.

The presented approach was capable to specify and optimize the parameters that affect engine fan performance as well as conduct sensitivity analysis and evaluate manufacturing control of the developed cool fan, which is not presented previously in the literature in such an application.

The only limitation of this approach is that the optimum values of the design factors are obtained according to the assumed airflow particular value to maintain engine cooling during such hard circumstances. The use of Box-Behnken model to test the quadratic (nonlinear) effects was time consume. This disadvantage may require more analytical attempts to select the appropriate nonlinear model for solving the effects of the physical system nonlinearity.

7. Conclusions

1. The assessment for the existing cooling fan performance and definition of its problem has been performed by analyzing the historical measurements and its histogram based on normal distribution fit for the engine cooling fan. The predicted 95 % confidence interval provides clear insight that the current airflow value of the fan was not reach to the target value 1486.63 m^3/h.

2. The cooling fan parameters (Blade tip clearance, Blade pitch angle, Distance from the radiator) have been identified and shown their affect. This method created airflow based on the specifications with more additional fans manufactured performance of 99.999 %.

3. The proposed approach analyzed the cooling fan sensitivity and evaluated manufacturing control to show that the process operates fine under the optimized parameters and delivers the desired airflow. Furthermore, the predicted value (1.73) and the value due to the evaluation process of *Cp* (1.75) were extremely similar, where the process is supposed high quality when *Cp* is equal to or greater than 1.6.

Conflict of interest

The authors affirm that they do not have any conflicts of interest with this research financial, authorship, personal, or otherwise that would have

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Data availability

Data will be made available on reasonable request

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