COMPUTATIONAL RESEARCH PROGRESS IN APPLIED SCIENCE & ENGINEERING (CRPASE)

CRPASE: TRANSACTIONS OF APPLIED SCIENCES

Journal homepage: http://www.crpase.com

CRPASE: Transactions of Applied Sciences 11 (1) Article ID: 2925, 1–9, March 2025

ISSN 2423-4591

Research Article

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Optimization of Operating Conditions of Beta-Type Stirling Engine with Regenerator Using Artificial Neural Network and Response Surface Method

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Keywords

Optimization, Artificial Neural Network, Response Surface Method, Box-Behnken Method, Stirling Engine.

Abstract

The aim of this study is to determine the optimal operating conditions of a beta-type Stirling engine and the main factors affecting these conditions. The main factors affecting the engine power are engine speed (750-900 rpm), pressure (6-8 bar) and temperature (600-700 °C). Experimental design was conducted applying Box-Behnken Design, to obtain engine power values via selected factors. In addition, these experiments were carried out on a beta-type Stirling engine with a regenerator, which has not been previously studied in the literature. The engine power was analyzed using the Response Surface Method and Artificial Neural Network, and the most appropriate model was achieved. The desirability function approach was used to determine the optimal engine operating conditions and the optimum values of the main factors of pressure, engine speed and temperature were determined to be 8 bar, 900 rpm and 650 °C, respectively. Under optimal engine operating conditions, the engine power was determined to be 56.736 W. Besides, the Determination Coefficient (R^2) and Mean Square Error values for the Response Surface Method were 0.898 and 6.47, respectively, while for the Artificial Neural Networks method, they were 0.975 and 2.11, respectively. The results obtained indicate that the developed Artificial Neural Network model is an acceptable and more powerful modeling technique than the Response Surface Method for predicting power values of the beta-type Stirling engine.

1. Introduction

The world's energy demand is increasing day by day with the increase in population density in the world, and most of this demand is still met by fossil fuels. Fossil fuels are the primary source of CO2 and greenhouse gas emissions into the atmosphere. Greenhouse gases, exhaust gases and carbon dioxide emissions from the use of fossil fuels cause human health and environmental concerns. At the same time, these gases increase the temperature by trapping heat in the atmosphere and cause climate change [1], [2].

The World Health Organization (WHO) has stated that climate change is the biggest threat to human and environmental health in the 21st century [3], [4]. For this reason, instead of fossil fuels, the use of renewable, clean systems that can work with solar energy, geothermal energy, etc., which are available in the world, has increased considerably. Stirling engines, which can work with all kinds of heat energy and use clean energy sources, are one of these systems. The basic principle of Stirling engines is based on obtaining mechanical energy through temperature difference at low pressures. Thus, with Stirling engines, high energy

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Received: 09 November 2025; Revised: 02 December 2025; Accepted: 12 December 2025
https://doi.org/10.61186/crpase.11.1.2925

Academic Editor: **Kamelia Sepanloo**

Please cite this article as: E. Ozgoren Unlu, B. Yazici, Y. Onder Ozgoren, Optimization of Operating Conditions of Beta-Type Stirling Engine with Regenerator Using Artificial Neural Network and Response Surface Method, Computational Research Progress in Applied Science & Engineering, CRPASE: Transactions of Applied Sciences 11 (2025) 1–9, Article ID: 2925.

production can be achieved by using alternative resources by reducing the use of environmentally harmful fuels [5], [6].

Stirling engines are a focal point of research due to their remarkable energy conversion efficiency. The interest in these engines is on the rise, driven by the escalating costs and dwindling reserves of fossil fuels. Stirling engines have the versatility to operate with various working fluids, including air, helium, nitrogen, and hydrogen. They are theorized to possess superior thermal efficiency and emit lower levels of pollutants, thereby reducing environmental damage [7], [8]. Furthermore, throughout literature, the Stirling engine stands out for its high level of performance [2], [9]. Correspondingly, the use of fossil fuels such as gas, oil and coal in the world in terms of terawatt-hours of electricity capacity obtained in the places where energy production is made according to years is given in Figure 1 below. As can be seen from this figure, it is clear that it is very important to develop new engine designs in terms of statistical and energy conversion systems.

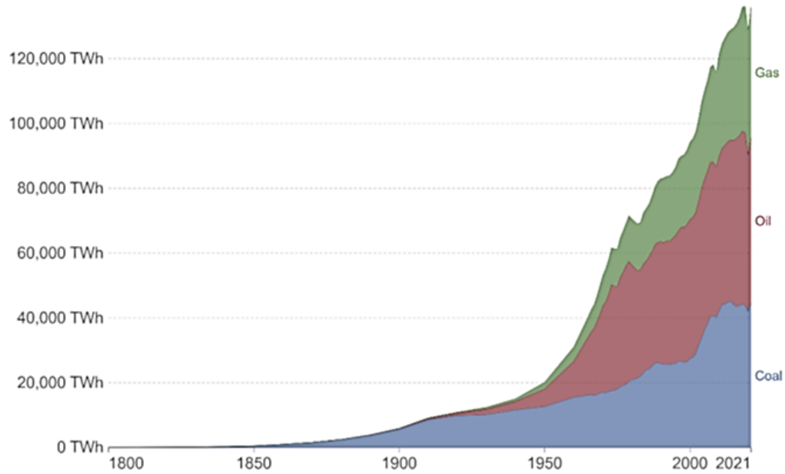

Figure 1. Fossil fuel consumption in the world by years [10].

In addition, Response Surface Methodology (RSM), which is one of the methods of design of experiments, is used in many fields such as engineering, technology, medicine, food, chemistry, etc. with the aim of optimization, that is, obtaining the most appropriate working conditions of the created systems and ensuring maximum efficiency. RSM is very important in terms of determining the experimental variables in research, knowing what effects these variables, which are thought to be effective on the response variable, have, and creating mathematical model designs appropriate to the results. As a result of the analysis made with this method, considerable savings can be achieved in terms of time, product and cost [11]. In addition, the Artificial Neural Network (ANN) method, which has been shown as an alternative to this method in recent years, has attracted considerable attention. Although ANN does not require the assumptions required in the RSM, it has a working system similar to the nerve cells in the human brain and its ability to learn has become more used by researchers than alternative techniques [12].

The aim of integrating statistics with engineering principles is to enhance the power output of the beta-type Stirling engine developed by researchers, utilizing parameter values derived from operational conditions through statistical techniques. This endeavor seeks to engineer more potent engines functioning under ideal conditions, thus encouraging the adoption of eco-friendly technologies. RSM presents several benefits over traditional full factorial design experiments, including a reduction in the number of tests required and decreased time consumption [13]. Furthermore, an effective statistical mathematical approach known as RSM, which employs the Box-Behnken Design (BBD) based on RSM, is deployed for optimizing experimental conditions. This is achieved by determining the analytical relationships and interactions between dependent (response) and independent (factor) variables. Notably, this technique encompasses 3 to 7 factors at three levels (low, medium, and high), facilitating the generation of comprehensive data sets through fewer experimental combinations. This approach enables researchers to easily acquire response variables [14], [15]. Another category that has recently been used to characterize various processes in terms of mathematical relationships is modeling using ANN. Polynomial regression-based modeling approaches such as RSM that model complex nonlinear relationships can be effectively replaced by ANN. Also, ANN models incorporate all experimental data points and are therefore theoretically more accurate [16], [17]. The modeling process of an ANN involves selecting the network architecture, determining the hidden layers and the number of neurons in each layer, learning, training, and final stage, verification, and validation of the model. However, there are studies using these two methods on Stirling engines. Masoumi et al. [18] constructed a genetic-fuzzy control scheme for an active free-piston Stirling engine (AFPSE) and obtained a hybrid intelligent converter that is robust to parameter changes. The main factors for the optimal operating condition with respect to the power piston in the open-loop engine system were selected as the sink and source temperatures, the power piston mass, and the stiffness of the power piston's spring. First, a brief description of the mathematical equations governing the open-loop AFPSE was given. Then, an optimal fuzzy controller for the engine is derived. At the end of the study, simulation and practical results demonstrated the feasibility of designing a new intelligent AFPSE (IAFPSE). Moreover, based on the obtained practical results, it was shown that the

IAFPSE was robust to changes in the power piston mass and the operating frequency was intelligently tuned between 5.4 Hz and 4.3 Hz, respectively, while the power piston mass varies between 0.6 kg and 1 kg. Ozgoren et al. [8] used an Artificial Neural Network to predict the power (P) and torque (T) values obtained from a beta-type Stirling engine using air as the working fluid. The closest neural network results to the experimental torque and power values were obtained with two hidden layers 5-13-9-1 and 5-13-7-1 network architectures, respectively. The best prediction values were obtained using the Levenberg-Marquardt learning algorithm. The Determination Coefficient (R^2) for torque values were 0.998331 and 0.997231 for the training and test sets, respectively, while the R^2 values for power values were 0.998331 and 0.997231 for the training and test sets, respectively. The R^2 values obtained showed that the developed neural network is an acceptable and powerful modeling technique for predicting the torque and power values of the beta-type Stirling engine. Besides, Solmaz et al. [2] developed a statistical model to evaluate the effect of engine operating parameters on the performance characteristics of a beta-type Stirling engine. The aim of the study was to increase the specific power of the engine by increasing the compression ratio of the engine designed and manufactured in a previous study. The independent variables selected were charge pressure (2-9 bar), heating temperature (500-700 °C) and engine speed (550-750 rpm). The engine was analyzed using a design of experiments based on the Response Surface method and the optimal model was obtained. The optimum engine speed, charge pressure and heating temperature were determined as 700 rpm, 8 bar and 700 °C, respectively, and their desired value was found to be 0.86. At the optimum engine operating conditions, the brake torque and brake power were found to be 11.95 Nm and 868.13 W, respectively. The optimized parameters were then validated by comparing with the experimental data of the Stirling engine and found to be 4%. The specific power of the engine was found to be 1100 W/L, which is 13% higher than the previous design.

In general, when the literature is examined, there are studies that have been carried out with ANN and RSM method using Stirling engine experimental data. However, these studies have been carried out exclusively ANN and RSM method. In this study, unlike these studies, which have separate examples in the literature, both methods are used and statistical comparisons of these methods are included. Besides, due to the applicability of the analyses and the need for fewer experiment observation values, it has been revealed that they very functional methods in determining the optimum operating conditions of the Stirling engine. In this way, it has been determined that less costly conditions and statistical models can be created during the development phase of the newly produced regenerator engine. This research focuses on maximizing the performance metrics for the power output of the beta-type Stirling engine using the RSM with BBD and ANN. The objective is to optimize the engine's performance, compare the effectiveness of these two methods, develop the most accurate mathematical model, and identify which method yields the lowest error rate. To achieve this, variables believed to influence engine power, such as engine speed (rpm), pressure (bar), and temperature (°C), were assigned to different levels. Experiments were carried out on a Stirling engine equipped with a regenerator, and the values of the response variables were collected and analyzed using statistical techniques.

2. Materials and Methods

In this research, the effect of the specified factors on the power output of a beta-type Stirling engine equipped with a regenerator is investigated experimentally. In addition, the experimental setup and operation of the Beta Type Stirling engine are visually explained in Figure 2. The methodologies used to analyze the data obtained from the experiments using the Stirling engine are described in detail in the following sections.

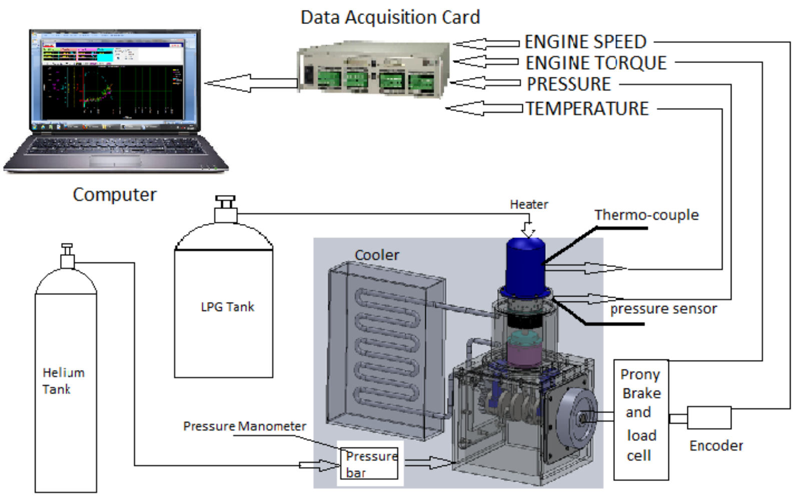

Figure 2. Schematic illustration of the experimental setup.

2.1. Response Surface Method (RSM)

This section discusses determining optimal engine power conditions to maximize performance. Optimization of independent parameters (factors) was performed using RSM based on BBD [2], [19]. Design of experiment model was carried out according to BBD that involves three independent variables (engine speed, pressure, and temperature), each with three levels, and engine power was chosen as the response variable (see Table 1). The resulting design matrix consists of 17 experimental runs and is shown in Table 2. In addition, the experiments were carried out in one replicate.

Table 1. Factors and factor levels

No.	Factor	Name	Factor Level		
			-1	**0**	**+1**
1	**A**	Pressure (bar)	6	7	8
2	**B**	Engine Speed (rpm)	750	825	900
3	**C**	Temperature (°C)	600	650	700

In BBD, each factor has three levels. BBD are more economical than Central Composite Designs (CCD) because they theoretically require fewer factors and fewer factor levels. One of the advantages of BBD is that they are global and have only three levels of data. BBD are the result of combining an incomplete block design with an appropriate two-level multifactor design [20], [21]. One of the advantages of the BBD plan is that it is a global design and has only three levels of data. BBD are created by appropriately combining incomplete block designs and two-stage multifactor designs [19]. In this context, the second order polynomial regression equation is used in the BBD method in order to theoretically form the regression equation and the relationship between engine power and independent variables is expressed according to Eq. (1).

$$y_{engine\ power} = \beta_0 + \sum_{a=1}^{k} \beta_a x_a + \sum_{a=1}^{k} \beta_{aa} {x_a}^2 + \sum \sum_{a<b}^{k} \beta_{ab} x_{ab} + \cdots + \varepsilon \quad (1)$$

where β_a, β_i, and β_{ab} are the model coefficients, k is the number of independent variables, x_a, x_{ab}, and ${x_a}^2$ represents linear and quadratic terms, respectively. Statistical analyses such as ANOVA, lack of fit, model graphs and summary statistics were applied to determine the suitability and accuracy of the model to be obtained [22], [23].

2.2. Artificial Neural Network (ANN)

The architecture of Artificial Neural Networks basically consists of three main points. İnitially, the number of layers should be decided, then the optimal number of neurons in each layer should be selected, afterwards the model should be created by deciding on the training algorithm and transfer function. In this research, the neural network examined includes three inputs, i.e., pressure, engine speed and temperature and one output the engine power [24]. In this research, a feed-forward, back-propagation multilayered perceptron (MLP) network architecture was created, the Levenberg-Marquardt (LM) algorithm was selected and the tangent sigmoid transfer function (Tanh), which is widely used in the literature, was utilized as the transfer function. Besides, since there are three independent variables and one dependent variable, the ANN design was formed as 3-4-4-1 with two hidden layers and four neurons as a result of the experiments. The mean square error (MSE) and determination coefficient (R^2), given in Eq. 2 and Eq. 3, were used to evaluate the performance of the ANN and BBD [19].

$$Mean\ Square\ Error(MSE) = \frac{1}{n} \sum_{i=1}^{n} (y_{i,ex} - y_{i,pr})^2 \quad (2)$$

$$Determination\ Coefficient(R^2) = 1 - \frac{\sum_{i=1}^{n} (y_{i,pr} - y_{i,ex})^2}{\sum_{i=1}^{n} (y_{i,pr} - y_{average})^2} \quad (3)$$

where, $y_{i,pr}$ represents the predicted value of the i.th experiment calculated by model, $y_{i,ex}$ stands for the target value of the i.th experiment (or experimental value), n is the total number of experiments, and $y_{average}$ denotes the average of values from the model [25], [26].

3. Results and Discussion

3.1. Optimization and Modelling of Beta-Type Stirling Engine Using RSM

The BBD method was used to obtain the optimal operating conditions of Stirling engine according to the selected factors. The response variable values obtained by using the BBD design matrix, and the prediction values found for ANN and BBD methods are given in Table 2. In addition, the quadratic regression equation obtained by the experimental design method is given in Eq. 4 and the ANOVA results are presented in Table 3.

Table 2. BBD and ANN values for engine power

No.	Pressure (bar)	Engine Speed (rpm)	Temperature (℃)	Engine Power (Actual)	Predicted Values with RSM	Predicted Values with ANN
1	7	825	650	44.73	43.97	44.24
2	6	825	700	45.59	43.81	45.71
3	8	825	600	51.17	52.95	55.80
4	7	825	650	43.52	43.97	44.24
5	7	825	650	44.28	43.97	44.24
6	8	825	700	52.38	52.69	52.48
7	7	750	700	41.34	40.24	41.30
8	7	900	700	38.62	41.18	38.43
9	6	825	600	46.62	46.31	43.83
10	7	750	600	40.63	38.07	40.56
11	7	900	600	45.02	46.12	44.51
12	7	825	650	42.18	43.97	44.24
13	8	750	650	41.32	42,10	41.48
14	7	825	650	45.16	43.97	44.24
15	6	750	650	41.61	44.48	41.62
16	6	900	650	39.62	38.84	42.23
17	8	900	650	59.61	56.74	59.58

$$y_{engine\ power} = 43.97 + 3.88A + 2.25B - 0.69C + 5.07AB + 0.56AC - 1.78BC + 4.55A^2 - 2.99A^2 + 0.41C^2 \quad (4)$$

Table 3. ANOVA results for engine power

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	401.45	9	44.61	6.89	0.0093
A-Pressure	120.44	1	120.44	18.61	0.0035
B-Engine Seed	40.37	1	40.37	6.24	0.0411
C-Temperature	3.80	1	3.80	0.5865	0.4688
AB	102.82	1	102.82	15.89	0.0053
AC	1.25	1	1.25	0.1939	0.6730
BC	12.64	1	12.64	1.95	0.2049
A^2	87.24	1	87.24	13.48	0.0079
B^2	37.54	1	37.54	5.80	0.0469
C^2	0.7225	1	0.7225	0.1117	0.7480
Error	45.29	7	6.47		
Lack of Fit	39.80	3	13.27	9.65	0.0265
Pure Error	5.50	4	1.37		
Total	446.74	16			
R^2	0.898				
Adj.-R^2	0.768				

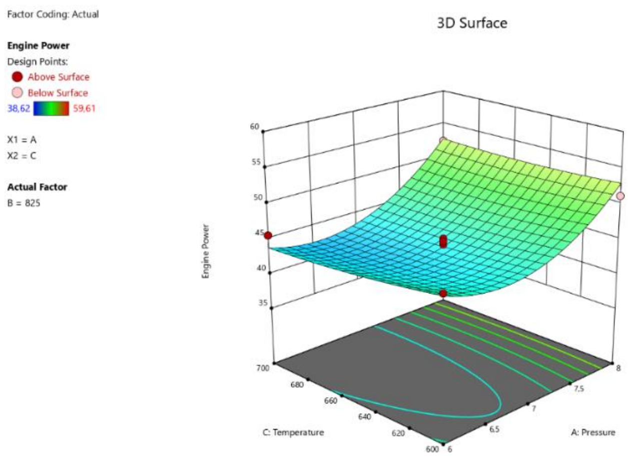

Figure 3. (a) Effect of temperature and pressure parameters on engine power

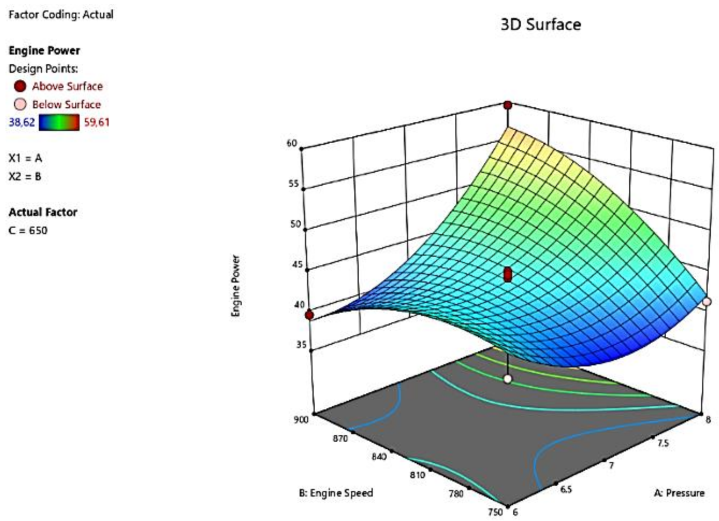

Figure 3. (b) Effect of engine speed and pressure parameters on engine power

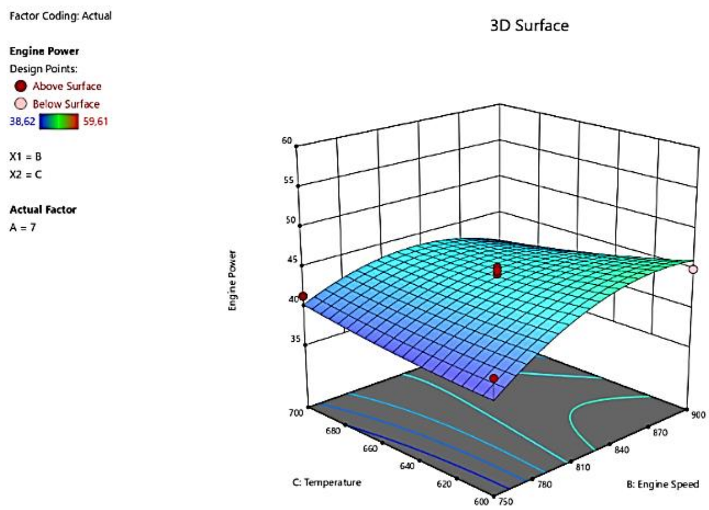

Figure 3. (c) Effect of temperature and engine speed on engine power

Initially, tests for lack of fit, along with summary statistics for linear, quadratic, and cubic models concerning variables A, B, and C were conducted. This was to identify the model that, due to its insignificant lack of fit and the highest values of R^2 and adjusted R^2, best represented the quadratic model's response. Subsequently, ANOVA (Analysis of Variance) for the quadratic models was utilized to determine the statistically significant factors impacting the model. Table 3, focusing on engine power as the response variable, revealed an impressive model F-value of 446.74, indicating that the models were in excellent agreement with the experimental data.

On the other hand, p-values of independent variables are explanatory and not significant relative to the pure error. Therefore, a not-significant lack of fit is good and model is a fit for all responses. Finally, based on these, according to Table 3, it can be observed that the variables pressure and engine speed have a significant effect on engine power, with high F-values and low p-values. However, the temperature variable is not statistically significant due to its p-value (p=0.4688).

Moreover, given the p-values of 0.0079 and 0.0469, it's evident that the quadratic effects of variables A and B significantly impact engine power, as both values fall below the threshold of 0.05. Furthermore, the presence of a high F-value of 18.61 and 6.24 indicates that the main effects of pressure and engine speed, as well as their interaction, significantly contribute to the engine's power output.

The experimental results and the predicted values obtained from the model showed that predicted values matched the experimental values reasonably well with R^2=0.898 for engine power (see Table 3). It can be concluded that the high R^2 value indicating that model was appropriate for predicting the exact correlation between both response and significant factors. Additionally, response surface plots (3D plot) that represent two variables at once while keeping all other variables at their center points are a more effective tool for understanding both the main effects and the interactions of these two variables. In order to understand how the variables interact and to determine the optimal level of each variable for the maximum response, the response surface curves (Figure 3) were plotted [27]. When Figure 3(a). is examined, it is seen that the temperature has no effect on the engine power, but it is concluded that the engine power decreases with increasing pressure value. However, at 7 bar and 650 degrees, which are the center points of the temperature and pressure variables, the engine power reached approximately the optimum value of 45.16 W. According to Figure 3(b), it is concluded that the engine power decreases with the increase in the values of the engine speed and pressure variables. Approximately and similarly, at a pressure of 7 bar and a temperature of 650 degrees, the engine power was 44.28 W. Finally, according to Figure 3(c), it is concluded that the engine power increases with the increase of the engine speed, but the power starts to decrease at the maximum engine speed. At this point, the engine power reached 45.68 W. In conclusion, when the results of the analysis are examined in light of optimization, it can be interpreted that the maximum engine power is achieved with a pressure variable value of an 8 bar, engine speed of 900 rpm, and a temperature value of 650 degrees, reaching 56.736 W.

3.2. Modelling of Beta-Type Stirling Engine Using ANN

In addition to its ability to create mathematical models of linear relationships, the ANN is also a tool that is actively used for modeling and optimization of non-linear process variables [28]. In this research, as mentioned in Chapter 2.2, 3-4-4-1 network architecture was created. In addition, the subsistence dataset was divided into training, validation, and test sets of 15%, 15% and 70% respectively. Figure 4 illustrates the neural network structure used to analyze the Stirling engine, featuring an input layer that includes pressure, engine speed, and temperature, a hidden layer with 4 neurons, and an output layer with a single neuron representing Stirling engine power. The regression coefficient values for training, validation, and testing phases, with respective R values of 0.978, 0.957, and 0.975, are also depicted in Figure 4. These R^2 values suggest a strong correlation between the experimental and estimated power outputs, indicating a good fit of the model [19]. Additionally, the ANN model's predicted R^2 and MSE values of 0.975 and 0.81, respectively, further affirm the model's accuracy in predicting the engine's power output.

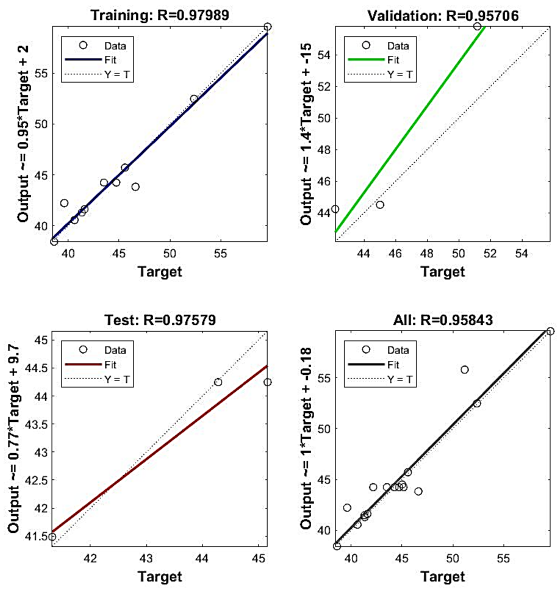

Figure 4. ANN predicted model

Both BBD and the ANN models were compared regarding their predictive capability engine power. The statistical parameters that measure and compare the accuracy of both models were estimated in Table 4.

Table 4. BBD and ANN performance criteria values for Engine Power

Methods	**BBD**	**ANN**		
		Training	Validation	Test
R^2	0.898	0.979	0.957	0.975
MSE	6.47	0.21	1.09	0.81

The use of artificial neural networks (ANN) in energy conversion systems has become an important research topic in recent years. ANN has proven to be an effective tool in modeling and optimization of nonlinear process variables. For instance, in studies comparing RSM and ANN methods, it has been found that ANN generally provides higher accuracy. Patil et al. [29] used RSM and ANN methods to estimate and predict building energy performance. In this study, simple relationships were developed with the RSM method and more complex models were created with ANN. The results showed that ANN provides higher accuracy in predicting energy performance. Similarly, Dadrasi et al. [30], the energy absorption behavior of thin-walled steel columns was modeled using RSM and ANN. In the study, it was found that ANN provides higher accuracy than RSM in predicting energy absorption parameters. Correlatively, Rai et al. [31], RSM and ANN methods were used in the hydrolysis process of lignocellulose residues. In this study, ANN was found to have a better fit with experimental data and a higher R^2 value.

Examining RSM and ANN separately in the literature, Arevalo et al. [32] used RSM in the optimization of thermal energy storage systems and found that this method was very effective in increasing energy efficiency. In addition, Khazaee et al. [33] used direct methods to evaluate the stability of power systems and these methods have been shown to be effective in energy systems. However, Michailidis et al. [34] examined the use of ANN in building energy management systems and found that this method was effective in energy optimization, Yin et al. [35] examined the use of ANN in building energy consumption prediction models and emphasized the accuracy and reliability of this method. Lastly, Wan et al. [36] created a health index using vibration signals to predict the remaining life of bearings and combined convolutional neural network and bidirectional long short-term memory models, a method similar to the ANN used in this study, to estimate this index. Additionally, the probability density function (PDF) of remaining life was estimated using the Wiener process. In the study, the validity and superiority of the method was verified using the PHM 2012 bearing data set.

In this context, as evident from the data presented in the above table, the use of ANN in the performance prediction of Stirling engines emphasizes the accuracy and generalization ability of this method, in line with other studies in literature. In our study, the accuracy and generalization ability of ANN were found to be higher compared to RSM. These results show that ANN is an effective tool in modeling and optimization of nonlinear process variables.

4. Conclusions

In this research, it is aimed to optimize the Stirling engine operating conditions by using the engine speed, pressure and temperature variables selected as the main factors and different levels related to these variables, the engine power is maximized and modeling is performed with ANN and BBD methods. As a result, the determination coefficient (R^2=0.898) obtained with the BBD method was obtained as a very high value and the accuracy of the model and optimization was proved. This implies that the second-order response model matches the experimental data in an acceptable way. The ANN model was also established from the design of experiment and its results were compared via those of the BBD model. The ANN model exhibited better accuracy and generalization ability than BBD even in a limited number of experiments with R^2 of 0.975. As a result, the point difference between the actual response and the ANN predicted value became significantly smaller. The Stirling engine operating conditions process model created by ANN had high accuracy and substantial performance and was widely accepted. In general, when the literature is examined, it is determined that ANN and RSM methods give better and acceptable results in creating of model and predicting the data. However, in terms of time and cost, it is concluded that the RSM method is practical in the field of engineering. Unlike literature, both methods are included in the applied study and evaluated in terms of their applicability. It was determined that the RSM method is more relevant for design of experiments, while the ANN method is more appreciable for statistical modeling.

The higher performance of the ANN method, which has gained popularity and widespread use in recent years compared to classical methods, makes it a more suitable choice for modelling and predicting the response variable. Furthermore, the application of the aforementioned analyses to a variety of data sets obtained from the field of automotive engineering represents a future goal of the study. The ability to conduct a statistical analysis of data sets obtained from a different discipline has enabled the identification of important and significant factors, thereby allowing the use of different variables in the subsequent phase of the study.

Acknowledgements

This work was financially supported by the Unit of the Scientific Research Projects of Eskisehir Technical University under grant number [22ADP306].

References

[1] M. Aghbashlo, M. Tabatabaei, E. Khalife, T. R. Shojaei, A. Dadak, Exergoeconomic analysis of a DI diesel engine fueled with diesel/biodiesel (B5) emulsions containing aqueous nano cerium oxide, Energy 149 (2018) 967–9780.

[2] H. Solmaz, S.M.S Ardebili, F. Aksoy, A. Calam, E. Yılmaz and M. Arslan, Optimization of the operating conditions of a beta-type rhombic drive Stirling engine by using response surface method, Energy 198 (2020) 117377.

[3] US EPA, OA. Climate Impacts on Ecosystems, Available: https://web.archive.org/web/20170226212351/https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-ecosystems_.html#Extinction (accessed 24 May 2023).

[4] World Health Organization, "WHO calls for urgent action to protect health from climate change – Sign the call", Available: https://web.archive.org/web/20151008113710/http://www.who.int/globalchange/globalcampaign/cop21/en/. (accessed 24 May 2023).

[5] D.J. Shendage, S.B. Kedare, S.L. Bapat, An analysis of a beta type Stirling engine with rhombic drive mechanism, Renewable Energy 36 (2011) 289–97.

[6] D.G. Thombare, S.K. Verma, Technological development in the Stirling cycle engines, Renewable and Sustainable Energy Reviews 12 (2008) 1–38.

[7] Y.Ö. Özgören, S. Çetinkaya, S. Sarıdemir, A. Çiçek, and F. Kara, Artificial neural network based modelling of performance of a beta-type Stirling engine, Process Mechanical Engineering 227 (2012).

[8] Y. Özgören, S. Çetinkaya, S. Sarıdemir, A. Çiçek, F. Kara, Predictive modeling of performance of a helium charged Stirling engine using an artificial neural network, Energy Conversion Management 67 (2013) 357-368.

[9] F. Aksoy, H. Solmaz, H. Karabulut, C. Cinar, Y.O. Ozgoren, S. Polat, A thermodynamic approach to compare the performance of rhombic-drive and crank-drive mechanisms for a beta-type Stirling engine, Applied Thermal Engineering 93 (2016) 359–367.

[10] Our World in Data, Global Fossil Fuel Consumption", Available: https://ourworldindata.org/grapher/global-fossil-fuel-consumption (accessed:24 May 2023).

[11] D.C. Montgomery, Design and Analysis of Experiments, Wiley & Sons, New York, 2013.

[12] E. Öztemel, Yapay Sinir Ağları, Papatya Yayınları, Ankara, 2006.

[13] H. Pour, S.M.S. Ardebili, M.J. Sheikhdavoodi. Multi-objective optimization of diesel engine performance and emissions fueled with biodiesel- fuel oil blends using response surface method, Environmental Science and Pollution Research 25 (2018) 35429-35439.

[14] B.K. Kilinc, S., Malkoc, A.S. Koparal, B. Yazıcı, Using multivariate adaptive regression splines to estimate pollution in soil, International Journal of Applied Sciences 4 (2017) 10–16.

[15] H. Wang, W. Luan, L. Sun, Z. Zeng, W. Xue, Y. Bai, Study on polyvinyl butyral purification process based on Box-Behnken design and artificial neural network, Chemical Engineering Research and Design 184 (2022) 291–302.

[16] J. Shafi, Z. Sun, M. Ji, Z. Gu, W. Ahmad, ANN and RSM based modelling for optimization of cell dry mass of *Bacillus* sp. Strain B67 and its antifungal activity against *Botrytis cinerea*., Agriculture and Environmental Biotechnology 32 (2018) 291-302.

[17] J. P. Maran, V. Sivakumar, K. Thirugnanasambandham, and R. Sridhar, Artificial neural network and response surface methodology modeling in mass transfer parameters predictions during osmotic dehydration of *Carica papaya* L., Alexandria Engineering Journal 52 (2013) 507–516.

[18] S A.P. Masoumi, A.R. Tavakolpur-Saleh, A. Rahideh, Applying a genetic-fuzzy control scheme to an active free piston Stirling engine: design and experiment, Applied Energy 268 (2020) 115045.

[19] V.A. Raj, R.P. Kumar, B. Vijayakumar, E. Gnansounou, B. Bharathiraja, Modelling and Process Optimization for Biodiesel Production from *Nannochloropsis Salina* Using Artificial Neural Network, Bioresource Technology 329 (2021) 124872.

[20] R. H. Myers, D. C. V. Montgomery, C. M. Anderson-Cook, Response Surface Methodology: Process and Product Optimization Using Designed Experiments, John Wiley & Sons, New York, 2016.

[21] M. Demircioğlu, Mısır bitkisinin genetiği değiştirilmiş organizma (gdo) analizinde gerçek zamanlı pcr (polimerase chain reaction) parametrelerinin merkezi kompozit tasarım ile optimizasyonu, Doktora Tezi, İstanbul Üniversitesi, Sosyal Bilimler Enstitüsü, İşletme Anabilim Dalı, İstanbul (2022).

[22] K.R. Reddy, Green synthesis, morphological and optical studies of CuO nanoparticles, Journal of Molecular Structure 1150 (2017) 553–557.

[23] T. Suresh, N. Siverajasekar, K. Balasubamani, Enhanced ultrasonic assisted biodiesel production from meat industry waste (pig tallow) using green copper oxide nanocatalyst: comparison of response surface and neural network modelling, Renewable Energy 164 (2021) 897–907.

[24] A.A. Meybodi, A. Ebadi, S.Shafiei, A. Khataee, R. Rostampour, Modeling and optimization of antidepressant drug Fluoxetine removal in aqueous media by ozone/H2O2 process: Comparison of central composite design and artificial neural network approaches, Journal of the Twain Institute of Chemical Engineers 48 (2015) 40–48.

[25] J. Jawad, A.H. Hawari, S.J. Zaidi, Modeling and sensitivity analysis of the forward osmosis process to predict membrane flux using a novel combination of neural network and response surface methodology techniques, Membranes 11 (2021).

[26] M. Nouioua, M.A. Yallese, R. Khettabi, S. Belhadi, M.L. Bouhalais, F. Girardin, Investigation of performance of the mql, dry, and wet turning by response surface methodology (RSM) and artificial neural network (ANN), The International Journal of Advanced Manufacturing Technology 93 (2017) 2485–2504.

[27] E. Karimi, F. Yousefi, M. Ghaedi, K. Dahstian, Back propagation artificial neural network and central composite design modeling of operational parameter impact for sunset yellow and azur (II) adsorption onto MWCNT and MWCNT-Pd-NPs: Isotherm and kinetic study, Chemometrics and Intelligent Laboratory Systems 159 (2016) 127–137.

[28] R. Selvaraj, I.G. Moorthy, R.V. Kumar, V. Sivasubramanian, Microwave mediated production of FAME from waste cooking oil: modelling and optimization of process parameters by RSM and ANN approach, Fuel (2019) 237 40–49.

[29] S. R. Patil, M. K. Sinha, M. A. Deshmukh, S. Thenmozhi, A. Sujatha, Predicting and forecasting building energy performance using RSM and ANN, Asian Journal of Civil Engineering 25 (2023) 159–165.

[30] A. Dadrasi, A. R. Albooyeh, S. Fooladpanjeh, M. D. Shad, M. Beynaghi, RSM and ANN modeling of the energy absorption behavior of steel thin-walled columns: a multi-objective optimization using the genetic algorithm, Journal of the Brazilian Society of Mechanical Sciences and Engineering 42 (2020) 563.

[31] V. Rai, K. Sandesh, P. Ujwal, V. B. Shet, RSM- and ANN-based modeling for a novel hydrolysis process of lignocellulose residues to produce cost-effective fermentable sugars, Biomass Conversion and Biorefinery 14 (2024) 24181–24196.

[32] P. Arevalo, D. Ochoa-Correa, E. Villa-Avila, Advances in Thermal Energy Storage Systems for Renewable Energy: A Review of Recent Developments, Processes 12 (2024) 1844.

[33] Khazaee, S., Hayerikhiyavi, M., Kouhsari, S. A direct-based method for real-time transient stability assessment of power systems, Computational Research Progress in Applied Science & Engineering 6 (2020) 108–113.

[34] P. Michailidis, I. Michailidis, S. Gkelios, E. Kosmatopoulos, Artificial Neural Network Applications for Energy Management in Buildings: Current Trends and Future Directions, Energies 17 (2024) 570.

[35] Q. Yin, C. Han, A. Li, X. Liu, Y. Liu, A Review of Research on Building Energy Consumption Prediction Models Based on Artificial Neural Networks, Sustainability 16 (2024) 7805.

[36] Wan, J., Yang, Y., Guo, J., Dai, L. A Hybrid CNN-BiLSTM and wiener process-based prediction approach of remaining useful life for rolling bearings, Computational Research Progress in Applied Science & Engineering 8 (2023) 1–12.