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Multi-objective-optimization of process parameters of industrial-gas-turbine fueled with natural gas by using Grey-Taguchi and ANN methods for better performance

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ABSTRACT

Gas-turbines are widely utilized in the power generation sectors as these require low operational cost, have very good efficiencies among other turbines, and produce less pollution but required to improve their performances further. This study used efficient and simple optimization methods of grey Taguchi and ANN to enhance gas turbine performance. The objective was to increase η^{th}, horsepower, and to decrease SFC and heat release of the industrial gas turbine (model # T-4502) by optimizing different levels of input process parameters by gyey-Taguchi method. Finally, air inlet temperature of 28.8 °C,14400 rpm and cartridge filter were found as optimal input parameters at which gas turbine's performance improved with less consumption of natural gas. Moreover, ANOVA analysis revealed that 'air-inlet-temperature' is the dominant and 'type of air-inlet-filter' is the least effective process parameter with 71.17% and 1.40% impacts on the output parameters of the gas turbine.

Confirmatory test was carried out experimentally and by ANN at suggested optimal level of input parameters, satisfactory results obtained which validates the effectiveness of the grey-Taguchi-method.

1. Introduction

Gas Turbines have a broad range of applications in industry, which are generally used to provide electrical energy and mechanical power mainly in the natural gas sector for services such as prime movers for pipeline compression, gas lifting, gathering of gas, boosting of gas, etc. (Soares, 2015; Kurz and Brun, 2009; Bălănescu and Homutescu, 2019; Tahan et al., 2017). The gas turbine used as a mechanical driver is more efficient than the steam turbine (RK, 1995). The prime objective of a gas turbine is to run at optimal parameters to give maximum efficiency by utilizing the lower fuel consumption during operations in the prevailing environmental conditions (Cao et al., 2016).

There are a lot of ways to increase the gas turbine output. Some significant methods include control of humidity (Comodi et al., 2015), air inlet temperature (Liu et al., 2019; Alhazmy et al., 2006; Mohapatra and Sanjay, 2014a; Kwon et al., 2018) and air filtration systems (Effiom et al., 2015; Talaat et al., 2018) as well as the filter type. Such techniques have more influence on

Abbreviations: GT, Gas Turbine; SFC, Specific fuel consumption; HR, Heat Release; OA, Orthogonal array; DOE, Design of experiments; GRG, Grey relational grade; GRA, Grey relational analysis; GRC, Grey relational coefficient; QLF, quality loss function; ANOVA, Analysis of Variance; ANN, Artificial Neural Network; GP, Mixed flow two-stage turbine; PT, Mixed flow single-stage gas turbine; PLC, programmable logic controllers; SNGPL, Sui Northern Gas Pipelines Limited

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thermal efficiency, heat rate, fuel consumption, and operational availability. Hosseini et al. have reported that inlet temperature, humidity, and pressure drop have a dominant impact on the execution of the gas turbine owing to the air inlet cooling system, particularly with the evaporative cooling system (Hosseini et al., 2007).

Air quality entering the gas turbine depends upon the filtration systems, and thus erroneous choice of filters can have catastrophic consequences. Filter-effectiveness creates less fouling and less deterioration, which is the key to maintain the higher efficiency and power, as the output power of a gas turbine mostly depends on inlet air temperature and cleanliness (Effiom et al., 2015; Talaat et al., 2018)

Mohapatra and Sanjay (2014b) showed that some variables such as ambient temperature, compressor's pressure ratio, inlet temperature of compressor, the temperature at turbine inlet, and relative humidity have predominant effects on the execution of gas turbine power plant. Moreover, commercial methods adopted to cool the inlet air have also been reported as effective in improving the performance and efficiency of gas turbine (Farzaneh-Gord and Deymi-Dashtebayaz, 2011).

The presence of foreign objects may cause engine deterioration including compressor erosion and degradation of turbine components, fouling of compressor airfoils, and corrosion. Hard foreign objects are removed by proper filters which may further influence engine horse power, engine temperature, and thermal efficiency. So a gas turbine is fitted with a sophisticated complex air filter system for the proper filtration of the contaminations of the system. Such filters are made up of different media including paper, cellulose, fiber, membrane, and glass. Each of them offers its own filtration capacity, performance, and life depending on environments and applications (Effiom et al., 2015; Sennett, 2007).

Researchers have shown that gas turbine performance is measured in terms of the compressor health and environmental conditions also affect the output of the axial air flow compressor of gas turbines. Performance deterioration of a compressor can be compensated by its washing. Both on-line and off-line washings of a compressor have revealed pleasant effects on the gas turbine's performance (Ogbonnaya, 2011; Schneider et al., 2010).

Ambient air temperature at the inlet, relative humidity, and nature of fuels made a direct impact on the gas turbine. Moreover, decrease in ambient air temperature at the inlet also increases the efficiency of a plant (Alhazmy et al., 2006; Farzaneh-Gord and Deymi-Dashtebayaz, 2011). Also, the turbines working on natural gas discharge lesser pollutants when compared with those running on conventional fuels (Basha et al., 2012).

All of the above performance parameters should be optimized to increase the performance of the gas turbine with less fuel consumption. This requirement needs a comprehensive experimental testing study of gas turbine. Testing of gas turbine under all possible operating conditions is not only time consuming but also expensive. Contrary to conventional methods, some statistical and mathematical optimization techniques are available to provides the best optimal reaction conditions with minimum possible runs of the experiment as compared to the single-factor experimental design.

RE (2002) analyzed and optimized the gas turbine through variation of different gas turbine cycles, involving important parameters such as temperature and pressure ratio.

Some researchers used multi-objective genetic algorithms optimization and genetic algorithms optimization with Pareto approach for maximizing the efficiency of gas turbine power plant (Ahmadi and Dincer, 2011; Hajabdollahi and Fu, 2017), the efficiency of turbojet engine (Atashkari et al., 2005), cooling of inlet air of gas turbine (Shirazi et al., 2014), and exergy efficiency of biomass-based SOFC (solid oxide fuel cell) gas turbine with minimum cost (Habibollahzade et al., 2019; Bang-Møller et al., 2011; Facchinetti et al., 2012).

Juliano Pierezan et al. optimized the heavy-duty gas turbine to reduce fuel consumption by using coyote optimization algorithm (Pierezan et al., 2019).

Although the above mentioned optimized techniques are available to predict the arrangement of optimal parameters to improve the required output results and better economic performance of gas turbine but these are highly non-linear, time-consuming, less efficient, and complex. Therefore more linear, simple and efficient optimization technologies with less time should also be explored to minimize the SFC at cruise conditions, capital, and maintenance costs, as well as to maximize the performance, efficiency, and specific thrust of the gas turbines.

Boulila et al. (2019) used a simple Taguchi optimization method for designing a gas turbine blade but it requires more number of experiments. Therefore, Taguchi with grey relational analysis (GRA) based optimization methodology can be used to overcome all these drawbacks. Moreover, this grey Taguchi methodology requires less number of experiments.

Gul et al. (2016, 2019) carried out a useful multi-variable optimization technique to maximize engine performance parameters by utilizing Taguchi grey relational analysis and pointed out the influence of input factors on a particular output response.

Karnwal et al. (2011) have utilized the Taguchi based grey relation analysis for enhancing brake thermal efficiency of a diesel engine with low emanations. Similarly, multi-response grey Taguchi optimization techniques have also been widely used in the development of industrialized sectors like in turning process on CNC (Lin, 2004; Tzeng et al., 2009), hot turning process (Ranganathan and Senthilvelan, 2011), casting process (Patel et al., 2014; Anbuchezhiyan et al., 2018), machining and milling processes (Jung and Kwon, 2010; Kopac and Krajnik, 2007; Singh et al., 2004; Tsao, 2009), end milling of Al-alloy (Unnikrishna Pillai et al., 2018), laser cutting (Tsai and Li, 2009), and energy management systems (Yao and Chi, 2004), wire EDM (electric discharge machining) process (Thangaraj et al., 2020). Moreover, the artificial neural network tool can also be used significantly for optimizing and validating any experimental data (Gul et al., 2019; Nikpey et al., 2013). It is a non-linear function that develops a complex relationship between inputs and targeted outputs parameters and thus may predict the output responses accurately (Kannan et al., 2013). Thus, the said ANN technique is deemed to play a decisive role in the validation of the already developed optimal results.

Although efficient grey Taguchi based optimization techniques are successfully used for the industrial sector like in CNC, milling, casting, welding, machining, and turning, laser cutting etc., but reviewed studies showed that no one used it for the multi-objective optimization of the industrial gas turbines to get better economic performance with less fuel consumption. The purpose of this research is to find the optimal combination of input factors of industrial gas turbine (GT) model no: T-4502, which helps in reducing the specific fuel consumption (SFC), heat rate (HR), and increase horsepower & thermal efficiency of the gas turbine. Presently, grey taguchi method is used to solve and convert multiple-objective optimization parameters into a single-objective output response. In the end, output responses of the industrial gas turbine (GT) are measured experimentally at the suggested optimal arrangement of input factors and validated by the simulated results of the artificial neural network of MATLAB software. ANN simulated results also ensured the usefulness of the simple grey Taguchi method that can be used for analysis and optimization of any type of turbine of any power plant of the public or private sector.

Table 1
Performance specification of the Gas Turbine.

Configuration	Specifications ranges	
Fuel	Gas	Liquid
NGP RPM	15 000	15 000
NPT RPM	15 500	15 500
Minimum horse power (kW)	2909.72	2822.47
Heat rate (kJ/kW-h)	13 623.62	13 775.01
Minimum compression ratio	8.6	8.6
Compressor mass flow (pps)	37.5	37.5

2. Materials and methodology

2.1. Experimental setup

In the current study, experiments were performed on two shafts industrial gas turbine (GT) model no: T-4502 at public sector organization SNGPL (Sui Northern Gas Pipelines Limited) Multan, Pakistan. GT consisting of axial compressor, annular combustor liner, mixed flow two-stage turbine (GP), and mixed flow single-stage gas turbine (PT). The axial flow air compressor consists of eleven stages. In Fig. 1 station 1 indicates the location of measuring the air inlet filters differential in which there is an alarm setting mechanism through PLC, in order to observe the filter health. For the control of the air inlet ambient temperature, air inlet cooling techniques were adopted and thus the evaporative cooling system was installed in the air inlet system. Station 2 shows the inlet of the compressor, while station 3 is the exhaust of the combustor gases. The combustible gases enter into the turbines (GP + PT) at station 4, and finally, the exhaust of the gas turbine is released at location 5.

Air inlet temperature was controlled through an evaporative cooling system to make an essential modification for a hot climate, as air inlet temperature is the primary parameter that affects the performance characteristics of the machine (Sanaye et al., 2011; Zadpoor and Golshan, 2006).

Pressure transmitters, thermocouple, pressure gauges, lube oil flow meter and fuel flow meters were used during the experimentation.

The GP and PT are not mechanically coupled to each other, GP runs independent of the PT, and PT runs by using the exhaust of the GP. The other performance description of the gas turbine is given in Table 1.

In a gas turbine, both liquids, as well as gas, can be used as fuel but in this study natural gas was used as fuel. The experiments were performed on the performance testing facility of the SNGPL Multan, Pakistan. PT was coupled with a dynamometer through flexible coupling fully equipped with the instrumentation gadgetry as well as mechanical equipment.

A dynamometer is used for torque measurement. This is then used for the calculation of the horsepower of the gas turbine. While the load variation on the power turbine during experimentation was done with the pressurized water controlled through pressure control valve impinging on a dynamometer. The fuel control valve was used for measuring, and thus controlling the supply of the fuel during ramping and accelerating the engine. For the measurement of gas turbine speed in rpm, magnetic picks were used to send signals in terms of frequency to control the system for subsequent calculation.

2.2. Grey Taguchi methodology

The grey Taguchi method categorizes the important factors which give the best contributions to the variation. The output parameters can be determined at the various sets of input factors.

Table 2
Experimental input variables and their levels.

Control variables	Code	Levels			Output to be observed
		1	2	3	Horse Power (HP)
Temp (°F)	A	28.8	13.66	15.5	Thermal efficiency (η_{th})
Speed (RPM)	B	15 000	14 700	14 400	Specific Fuel Consumption (SFC)
Filter types	C	Conical	Cartridge	Barrier	Heat Rate (HR)

Table 3
Orthogonal array L_9 (3^3).

Run No	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

So L_9 OA (orthogonal array) design was adopted to design experiments and output responses were evaluated on OA suggested combinations of given input parameters.

The grey Taguchi technique shows the connections between actual and desired experimental data and converts numerous quality characteristics into a single grey relational grade (GRG) (Jung and Kwon, 2010). It allows knowing the optimal arrangement of input factors that may influence the execution of the gas turbine. The changing of the levels of input factors is required to be specified. No of experiments to be performed increases with the increase of levels of variation of input factors.

In the grey Taguchi method, suitable orthogonal array OA was selected to investigate all parameters with their three different levels. All these levels of variation for each input parameter are shown in Table 2. An OA was used for the DOE on the basis of L_9 (3^3).

Table 3 shows the L_9 (3^3) OA for the experimental work.

2.3. Normalization of experimental data

As the main objective of current research is to increase the thermal efficiency and horse Power keeping the heat rate as well as SFC at their minimum values, so experimental data were normalized by using higher the better & smaller the better criteria (Lin, 2004). The considered criterion was completed with respect to better quality aspects of interest (Ranganathan and Senthilvelan, 2011).

Let the actual and comparable series are represented by $R_o(l)$ & $R_i(l)$. While $i = 1, 2, 3, 4, 5, 6 \ldots m$ and $l = 1, 2, 3, 4 \ldots n$. Here m represents the total no of conducted experiments and n represents the total no of observations of the given data.

The normalization of the original comparable series for maximizing the required outputs follows Eq. (1) i.e "larger the better" criteria.

$$R_i^*(l) = \frac{R_i(l) - \min R_i(l)}{\max R_i(l) - \min R_i(l)} \tag{1}$$

For the objective to minimize the output, "smaller the better" criterion is as follows as Eq. (2),

$$R_i^*(l) = \frac{\max R_i(l) - R_i(l)}{\max R_i(l) - \min R_i(l)} \tag{2}$$

Grey relational coefficient (GRC) is utilized to find relation among actual $R_o(l)$ and comparable series $R_i(l)$. The value of GRC will be

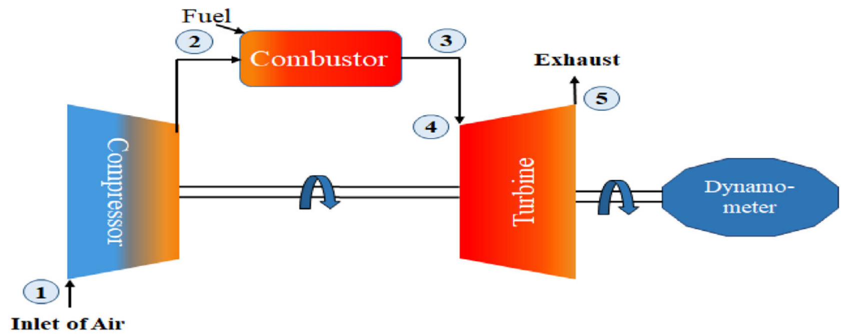

Fig. 1. Schematic workbench of the gas turbine.

unity if these two series are the same. The GRC is formulated as

$$\lambda_i = \frac{\Delta_{\min} + \gamma \cdot \Delta_{\max}}{\Delta_{oi(l)} + \gamma \cdot \Delta_{\max}} \qquad 0 \leq \gamma \leq 1 \tag{3}$$

As $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and maximum estimations of $\Delta_{oi(l)}$ series. $\Delta_{oi(l)}$ is known as quality loss function & calculated by subtracting estimated comparable series values of given data from the actual values. The quality loss function is utilized to examine that specific features are within the given specific limits or not. γ is the distinguishing coefficient whose value is selected as $\gamma = 0.5$.

$$\Delta_{oi(l)} = (\text{Quality Loss}) = [R_\circ^*(l) - R_i^*(l)] \tag{4}$$

$$\therefore R_\circ^*(l) = 1.0$$

Then GRG is evaluated by using Eq. (5). The overall multi-response optimization of the turbine depends on the GRG i.e the average of GRC.

$$\zeta = \frac{1}{n}\sum_{l=1}^{n} \varepsilon_l \lambda_i \tag{5}$$

Here,

$$\left[\sum_{l=1}^{n} \varepsilon_l = 1\right]$$

2.4. ANOVA (analysis of variance) technique

The ANOVA can be executed on 'Minitab' statistical software to find out the numerical implication of the performance affecting optimized parameters. The percentage contribution of all the input factors was measured to evaluate their significance. It is revealed that input factors with greater F-value have a substantial influence on multiple output parameters.

2.5. Validation of results by Artificial Neural Network (ANN)

MATLAB 'nntool' command was used to develop an artificial neural network (ANN) that will revalidate the output responses at optimum combination of input parameters (A1 B3 C2 in this case), obtained from grey Taguchi optimization method. If the ANN predicted and experimental values at optimal combination are close to each other, then the effectiveness of the optimal combination can be ensured. This will lead to the investigation of performance of gas turbine experimentally at optimum combination of input parameters.

Three input (temperature, speed, filter type) and four output (horse power, thermal efficiency, SFC, heat release) factors of the network were represented by neurons, which works in a similar manner as human brain neurons works.

Each neuron of ANN collects and stores the information during their training from experimental data. Then, this trained network was utilized to simulate the output responses at the optimal set of input parameters suggested by the grey Taguchi method. Neurons of each layer of ANN are connected with each other by the transfer function (like logsis tansig or purelin) of synaptic weights which helps in predicting the output response for any desired combination. The structural model of the artificial neural network is described in Fig. 2.

Table 4
Experimental results based on OA.

Run No	Orthogonal array			Horse power (kW)	Thermal efficiency	Heat rate (kJ/kW-h)	SFC (kg /kW h)
	A	B	C				
1	1	1	1	3725	27.41	9284	37.5
2	1	2	2	3629	27.6	9212	35.1
3	1	3	3	3850	28	9165	36.3
4	2	1	2	3501	26.01	9782	40.1
5	2	2	3	3436.8	25.52	9594	38.25
6	2	3	1	3590	26.7	9440	37.03
7	3	1	3	4102	27.35	9300	35.67
8	3	2	1	3780	26.5	9245	34.02
9	3	3	2	3629	27.83	9145	36.9

3. Results and discussions

3.1. Output response based on OA

Experimental results were obtained after experimentation carried out according to orthogonal array DOE L_9 (3^3). Nine experiments were performed by taking three input variables with the three different levels to tabulate the output parameters i.e. horse power, heat rate, SFC, and thermal efficiency as shown in Table 4.

The experimental results show the output responses, which are changing with input factors such as ambient temperatures. The increase of ambient temperature at inlet & air density reduces the mass flow rate and ultimately causes a decrease in horse power and thermal efficiency (Sanaye et al., 2011).

When air inlet filters were replaced, the changes in the inlet pressure of the gas turbine were observed due to the different efficiencies of air inlet filters. This loss in the input pressure reduces thermal efficiency and increases the SFC. Inefficient air filters caused a decrease in inlet pressure which in turn decreased the density and air inlet mass. The decreased mass flow rate further reduced the output power and output pressure of the axial compressor. As the exhaust pressure remained unchanged, so the gas turbine pressure ratio decreased, and ultimately thermal efficiency was also reduced. The decrease in horse power means the reduction in fuel flow and heat rate caused by the behavioral changes of the cartridge filter. This pressure loss has the same effect as lower barometric pressure. It reduces air inlet mass,

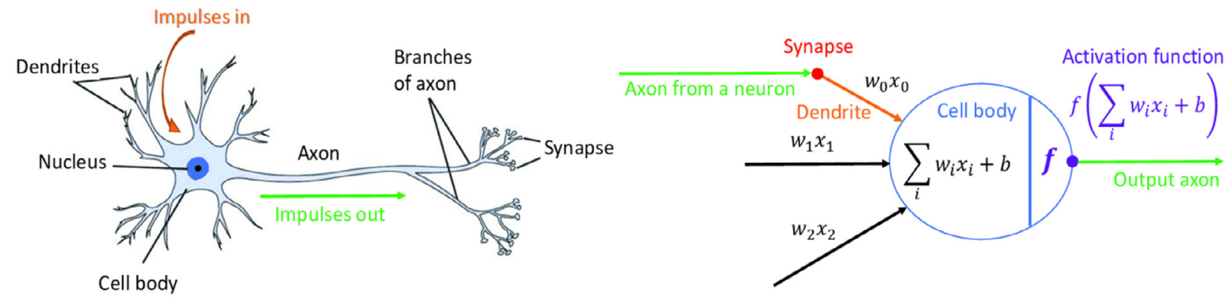

Fig. 2. Natural and structural ANN model.

Table 5
Grey relation generation of output responses.

Horse power	Thermal efficiency	Heat rate	SFC
0.566	0.238	0.218	0.572
0.71	0.161	0.105	0.178
0.378	0	0.031	0.375
0.902	0.802	1	1
1	1	0.705	0.696
0.769	0.524	0.463	0.495
0	0.262	0.243	0.271
0.483	0.605	0.157	0
0.71	0.069	0	0.329

Table 6
Taguchi QLF ($\Delta_{0\ i}$) of each response.

Larger-the-better (Xi*)		Smaller-the-better (Xi*)	
Horse power	Thermal efficiency	Heat rate	SFC
0.434	0.762	0.782	0.428
0.29	0.839	0.895	0.822
0.622	1	0.969	0.625
0.098	0.198	0	0
0	0	0.295	0.304
0.231	0.476	0.537	0.505
1	0.738	0.757	0.729
0.517	0.395	0.843	1
0.29	0.931	1	0.671

Table 7
The estimation of GRC and GRG for various arrangement.

Run No	OA			Grey relational coefficients (Distinguishing coefficient $\gamma = 0.5$)				GRG
	A	B	C	Horse power	Thermal efficiency	HR	SFC	
1	1	1	1	0.469	0.678	0.696	0.466	0.577
2	1	2	2	0.413	0.756	0.826	0.738	0.683
3	1	3	3	0.569	1	0.941	0.571	0.77
4	2	1	2	0.357	0.384	0.333	0.333	0.351
5	2	2	3	0.333	0.333	0.415	0.418	0.374
6	2	3	1	0.394	0.488	0.519	0.502	0.475
7	3	1	3	0	0.656	0.673	0.648	0.494
8	3	2	1	0.508	0.453	0.761	1	0.68
9	3	3	2	0.413	0.879	1	0.603	0.701

compressor discharge pressure, shaft horse power, and fuel flow rate.

Moreover, it has a secondary effect of making the inlet pressure lower than the exhaust pressure, thus reducing the engine pressure ratio as well. The lower pressure ratio causes a reduction in both horse power (HP) and thermal efficiency. A reduction of 1% in engine inlet pressure due to barometric pressure causes exactly a 1% reduction in output air inlet mass, shaft horse power, compressor discharge pressure, and fuel flow. However, a reduction of 1% in engine inlet pressure due to inlet duct pressure loss causes a 1% loss of thermal efficiency and almost 2% reduction in power. Inlet pressure loss lowers the pressure (and thus the density and mass flow rate) at the air inlet. The lower mass flow rate lowers output power and compressor discharge pressure, but the exhaust pressure remains unchanged so the engine pressure ratio and thus thermal efficiency are lowered. Higher air inlet temperature causes an effect on the power to be reduced due to the low mass flow rate and results in the increase of fuel consumption and heat rate. But the increase of horsepower (HP) & thermal efficiency along with the decrease of specific fuel consumption & heat release can be achieved simultaneously by the grey Taguchi optimization technique.

3.2. Grey Taguchi scheme

3.2.1. Grey relational generation

As experimental results consist of the different units/dimensions, their comparative analysis cannot be made. So, it was necessary to convert them into non-dimensional values. Normalization of the experimental output data in comparable units was done through grey relational generation by using "higher the better" and "smaller the better" criteria for maximizing and minimizing the output parameters and mentioned in Table 5.

Data is normalized between 0 and 1, and thus the value closer to 1 indicates better performance (Kopac and Krajnik, 2007).

3.2.2. Estimation of GRC and average GRG

A grey relational coefficient (GRC) has the ability to build up a connection between the actual series and comparable series formed during the grey relational generation of the output normalized data. Grey relational coefficient is calculated from the quality loss function (QLF). QLF is the immediate measurement of the level of variation among the actual and comparable series (Gul et al., 2016; Jung and Kwon, 2010) and for optimization, this is a specific target that needs to be achieved.

The target is a specified upper and lower limit, with the focal point to be the middle point. Taguchi QLF provides a decent approach to analyze the costs related to variability even within the limits and consequently prompts to the decrease of the variability of gas turbine output performance parameters towards a particular target value. Table 6 showing the QLF values, QLF is a measure of the level of variation, a smaller value indicating an approach towards an ideal target with a smaller loss. As the objective was to maximize horsepower and thermal efficiency so "larger the better" criteria was adopted for normalization. Similarly, the target was to minimize heat rate and specific fuel consumption so these are normalized by "smaller-the-better" criteria

Conversion of multi-objective cases to the single-objective case can be made through GRC as shown in Table 7, which is further used to determine the performance affecting parameters (Jung and Kwon, 2010).

Table 8
Average grey relational grade.

Levels	Input factors		
Sr No:	A	B	C
1	**0.677**	0.474	0.578
2	0.401	0.58	**0.586**
3	0.633	**0.657**	0.547
Delta	0.276	0.174	0.0323
Rank	1	2	3

Based on OA and Grey relational coefficient, Grey relational grade is evaluated as shown in Table 7. GRG is required to find an optimal arrangement of input factors that would be suitable for optimizing all output parameters (Ma et al., 2010). A parametric arrangement with higher GRG shows that it is nearer to the optimal values, and ensures better performance (Gul et al., 2016).

3.2.3. Determination of average GRG

The orthogonal design of experiments ensures the independent impact of input factors on GRG at various levels. An average GRG helps in defining the best parametric arrangement from all other types of parametric arrangements, that will give the desired results of output parameters.

Average GRG was established to convert a multi-objective variable into a single-objective variable. The average GRG measured for each level of input factors is summarized in Table 8.

The graphical response of average GRG of every input factor at different selected levels shown in Fig. 3 and it is used for choosing an appropriate combination of input factors. This graphical representation gives information about the more influence of input factor on the output results. As the highest point on the graph is temperature rather than speed and air inlet filter which indicates that inlet temperature is a more important and sensitive parameter and thus is placed at 1st rank position, as shown in Table 8. It has been proved practically that air inlet temperature is the most influencing and significant factor for the process parameters of gas turbine (Singh et al., 2004). Subsequently, the optimal parametric arrangement at which the required output consequences are achieved is given as **(A1, B3, C2)** = 28.8 as a temperature, 14 400 rpm as speed, and Cartridge as a filter type level. Air inlet ambient temperature of 28.8 °C, GT speed of 14 400 rpm and use of cartridge filter is the optimal arrangement at which gas turbine offers maximum efficiency and more horse power, together with decreased heat rate and SFC.

3.3. ANOVA analysis

Table 9 shows the ANOVA analysis, which was executed on a statistical problem-solving tool called Minitab 16. This showed the most significant input factor in the form of the relative percentage of influencing factors, and thus concluded the most substantial input factor of optimal arrangement (Zębala and Kowalczyk, 2015).

ANOVA results showed that air inlet temperature is 71.17% has the most significant impact on the performance of the gas turbine, while the type of air inlet filter is the factor that has the least effect on performance. From ANOVA analysis, Table 9 reveals that the factor A. Air inlet temperature with 71.16% is the most significant factor for the optimization of the gas turbine, while turbine speed contributes 27.43% to optimization. Air inlet filter shares only about 1.4% contribution in the optimization of GT, which has obviously a very limited impact on the performance of the turbine.

From the ANOVA analysis, it is clear that the air inlet temperature has the most substantial impact on the performance of the gas turbine. As low ambient air entering the axial flow compressor has a high volume which is directly proportional to the horse power and the turbine's pressure ratio due to which its thermal efficiency increases.

ANOVA analysis also cleared that optimal parameter air inlet filter has a very minimum impact, while the cartridge filter causes no pressure losses, thus pressure ratio as a whole remained the same leading to no significant impact on the thermal efficiency of the turbine. A gas turbine is not consuming much fuel due to the lower ambient temperature. It is evident that the grey taguchi method improves multiple responses in the optimization of gas turbine performance parameters.

3.4. Validation of results by experimentation and ANN

After getting an optimal combination of input factors from the grey Taguchi method the next step was to verify and validate the output responses experimentally and also by an artificial neural network. A1B3C2 optimal parameters were used for the confirmation of the experiment. ANN model was consisted of three input, hidden and output layers with 3, 14 and 4 neurons respectively. These input, hidden and output layers have transfer functions as logsig, tansig and purelin, as given in Fig. 4.

ANN model was trained by importing experimental data from Table 5. During training, the number of neurons in the central hidden layer was changed until the mean square error reduces to 0.0527. Then this trained artificial neural network was used to calculate output performance responses on the suggested optimal combination (A1B3C2). Screenshots of ANN simulation are presented in Fig. 5.

Results obtained from the experiment and ANN are shown in Table 10. Fig. 6 illustrates that experimental results and artificial neural networking predicted results at the optimal combination of input factors suggested by grey Taguchi are very close to each other. This ensures the effectiveness and efficiency of the grey Taguchi method in optimizing the input factors of the gas turbine.

These experimental and ANN results showed that a combination of the temperature of 28.8 °C and speed of 14 400 rpm along with cartridge filters offers sufficient power. With the increase in speed, the power also increases because air inlet ambient temperature is lower which means air entering the axial flow compressor is dense and has large air volume.

Conclusion

In this study, the grey taguchi scheme was applied to optimize the performance parameters of the gas turbine. The impact of process parameters including inlet temperature, type of air inlet filters, and rotor speed on power, heat rate, SFC and thermal efficiency was investigated. Following are the key findings of the study:

1. A1B3C2 (28.8 °C, 14 400 rpm, cartridge filter) is the best optimal input parameter's combination predicted by grey taguchi method. The said optimal arrangement had improved the performance of gas turbine in terms of higher thermal efficiency, higher horse power, lower heat rate, and low SFC of natural gas.
2. ANOVA analysis revealed that among input parameters, air inlet ambient temperature is the most influential parameter with a 71.16% impact, while the type of air filter is the least effective one with 1.4% impact on the performance of the gas turbine. Although the air inlet filter is a necessary accessory of the gas turbine, but it does not matter which type of filter to be used, the main concern is only maintenance of the air inlet filtration system.

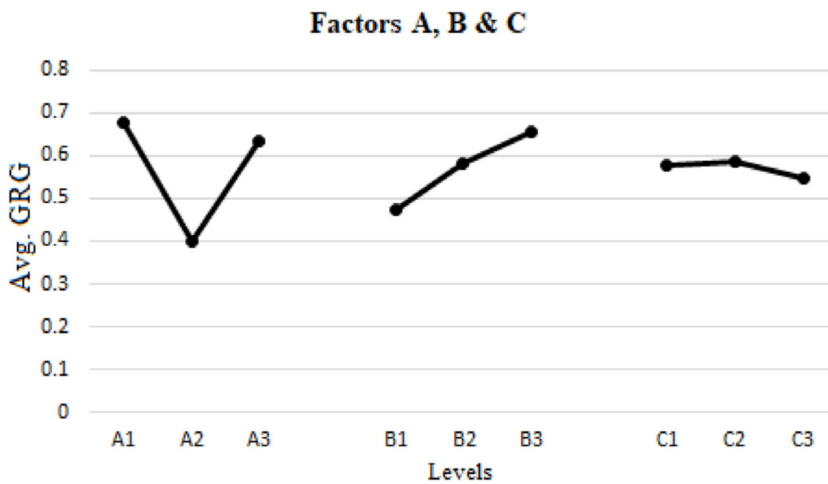

Fig. 3. Graph between average GRG and level of factor.

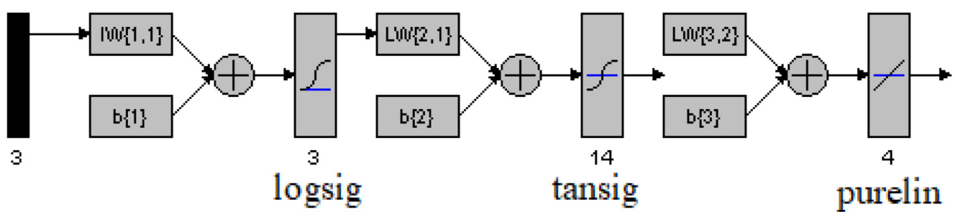

Fig. 4. ANN model.

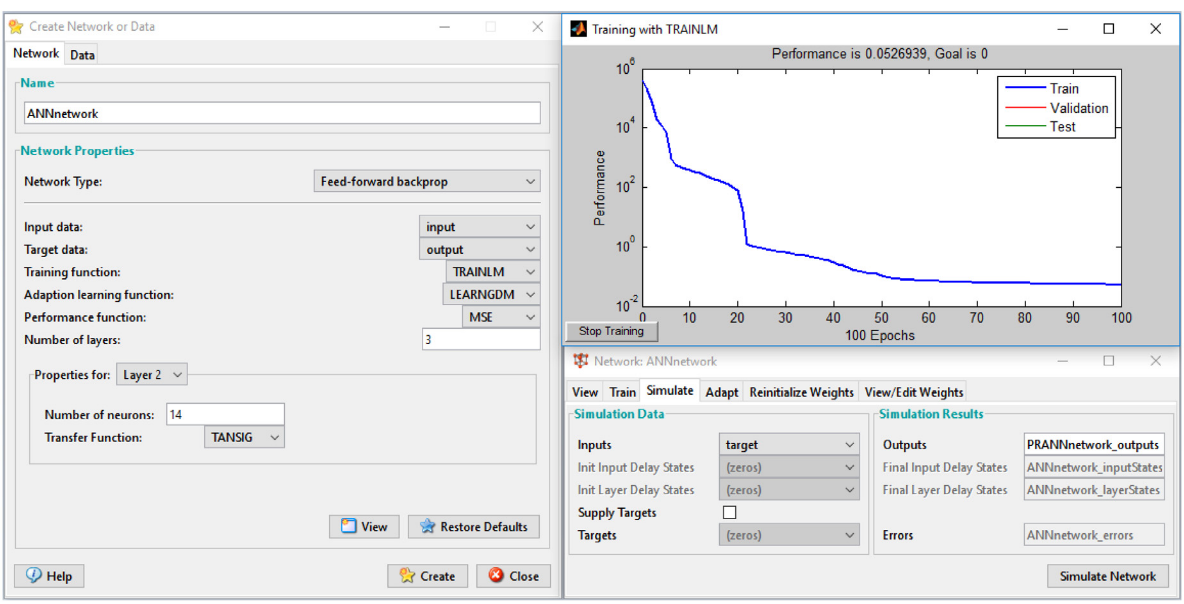

Fig. 5. Development and training of ANN for simulation of results.

Table 9
ANOVA analysis.

Input factors	Levels			DOF	Sum of square (SS)	Mean square (MSS)	F-value	Contribution (%)
	1	2	3					
A	0.679	0.474	0.578	2	0.131	0.065	0.065	71.17%
B	0.401	0.58	0.586	2	0.05	0.025	0.025	27.43%
C	0.625	0.657	0.547	2	0.003	0.001	0.001	1.40%
Total				8	0.184	0.092	0.092	100%

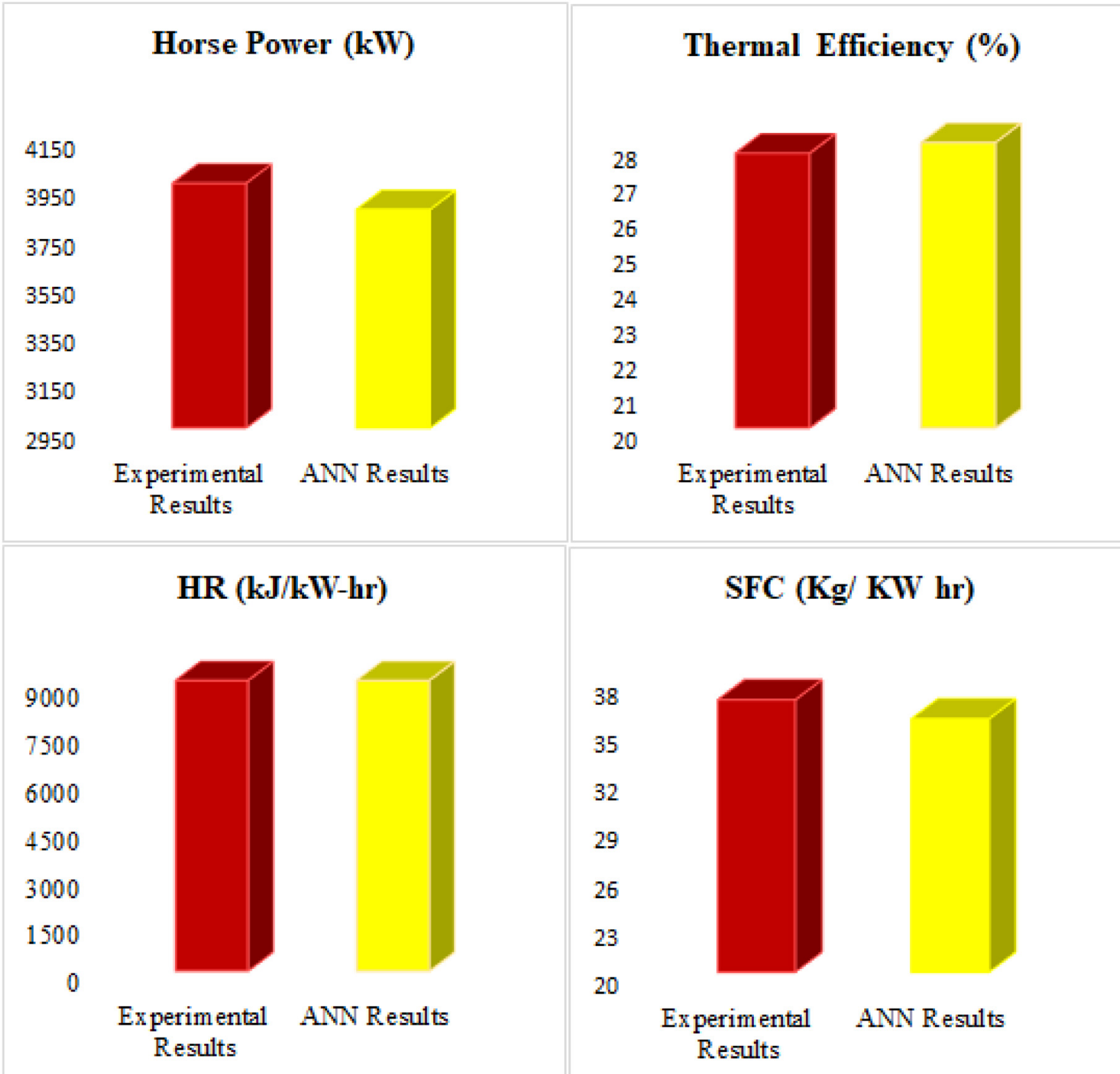

Fig. 6. Validation of results by experimentation and artificial neural networking.

Table 10
Validation of results.

Optimal combination of input factors: A1B3C2 (28.8 °C, 14 400 rpm, cartridge filter)		
Control variables:	Experimental results	ANN results
Horse power (kW)	3956	3847.81
Thermal efficiency (%)	27.78	28.08
HR (kJ/kW-h)	9267	9165.42
SFC (kg/ kW h)	36.92	35.74

3. Validation of results experimentally and by ANN suggests that the grey Taguchi methodology is more efficient for the optimization of any type of gas turbine.
4. This efficient and simple optimization methodology can be utilized for optimization of any process parameters of gas turbines used in power generation sectors to improve its performance and efficiency.

Future recommendations

Optimization of gas turbine can also be done by using other technologies like PSO, NSGA-II and AI based algorithms. Very little research is available on these techniques.

CRediT authorship contribution statement

M. Gul: Develop optimization model, Wrote results and discussion portion in this manuscript. **M.A. Kalam:** Supervise the project/ research, Approve of the final version. **M.A. Mujtaba:** Wrote introduction portion, Check overall formatting and bench marking aspects of manuscript. **Saira Alam:** Design of experiments, Run the testing on gas turbine. **M. Nasir Bashir:** Did and Wrote literature review. **Iqra Javed:** Wrote abstract, Draw figures and graphs. **Umair Aziz:** Analysis on ANN, Validated the results. **M. Rizwan Farid:** Grey-Taguchi analysis on MINITAB. **M. Tahir Hassan:** Write the conclusion, Critically evaluate the technical results. **Shahid Iqbal:** Worked on methodology of experimentation work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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