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Prediction and sensitivity analysis under different performance indices of R1234ze ORC with Taguchi's multi-objective optimization

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ABSTRACT

In this study, parametric optimization and sensitivity analysis of performance parameters were performed for the Organic Rankine Cycle (ORC) system at 120 °C heat source temperature. R1234ze, which is called the new-generation fluid, was used in the ORC design. Performance parameters have been selected considering Energy, Exergy, Economy (Turbine performance) and Environmental (Thermodynamic sustainability indices) factors. Six performance indices used in the orthogonal design with Taguchi-ANOVA. These are; thermal efficiency, turbine power, exergy efficiency, total irreversibility, Volume Flow Ratio (VFR) and Environmental Effect Factor (EEF). Such control factors as $\Delta T_{PP,e}$ - $\Delta T_{PP,c}$ -$T_{c,i}$ -T_{sup} – η_t – η_p were selected for the statistical analysis. Sensitivity levels were determined under all performance indices for the designed ORC. It has been determined that indices affect control factors differently. According to the results of the parametric optimization, it was determined that the parameter affecting the ORC performance the most was $\Delta T_{PP,e}$. The effect of $\Delta T_{PP,e}$ on ORC performance is stated as 39.72%. EES numerical analysis results were compared with the derived predictive equations using different statistical methods with regression method. When these equations obtained for all objective functions are evaluated, the average MAPE, RRMSE and R^2 values were determined as 4.1%, 4.29% and 94.1%, respectively.

1. Introduction

An Organic Rankine Cycle (ORC) technology based on a system for generating electricity from heat uses heat from the hot source to vaporize the organic working fluid in the evaporator. The pressurized organic fluid is then sent to the turbines and generates electricity when combined with the generator. Organic fluid is condensed again into a liquid in the condenser. Here, either the cooling tower, groundwater or river water is used as a cooling fluid. Then, the pump sends the organic fluid back to the evaporator and this closed cycle process repeats [1].

Imran et al. [2] compiled bibliometric studies in the ORC field by compiling the studies conducted between 2000-2016. In the study, Scopus evaluated SCI articles that he scanned using Elsevier databases. In all studies studied, the type of publication, fields of study, journal names, citations, authors and institutions were taken into consideration. Between the specified years, it was stated that

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2120 articles were written from 3443 authors from 71 countries, and China came first in the country ranking in the research articles.

In the review articles examined in the field of ORC; Tchanche et al. [3] conducted studies on ORC application areas; Bao et al. [4], organic fluid selection criteria and expander selection; Lecompte et al. [5] and Mahmoudi et al. [6], ORC configurations for waste heat applications; Pethurajan et al. [7], turbine selection and applications; Aboelwafa et al. [8], fluid selection and cycle configurations for solar ORC applications; Iglesias Garcia et al. [9], performance of low temperature ORC applications in cycles operating on different principles; Zhao et al. [10] artificial intelligence applications in ORC design.

When the literature is examined, it is seen that different artificial intelligence methods are used for parametric optimization of ORC, performance prediction and sensitivity analysis. Some of them are summarized below.

Wang et al. [11] studied the parametric optimization of geothermal origin ORC and the sensitivity level. They determined the objective function as thermodynamic and economic performance. Performance indices had been determined as net power, thermal efficiency, turbine size parameter, back work rate and total heat transfer capacity. They determined that the optimum orthogonal design results were achieved with R245fa fluid, when the superheating temperature was 10 °C, $\Delta T_{PP,e}$ and $\Delta T_{PP,c}$ were 5 °C, the evaporation temperature was 65 °C, and the pump and turbine isentropic efficiency was 75% and 85% respectively. They stated that the evaporation temperature was in the first place in the sensitivity level values of the ORC system designed using the R245fa fluid.

Liu et al. [12] determined the sensitivity level values of geothermal ORC on different parameters. System parameters are organic fluid, superheating temperature, $\Delta T_{PP,e}$ and $\Delta T_{PP,c}$, evaporation temperature and isentropic efficiency of the turbine and pump. The performance of the system is determined separately at different geothermal heat source temperatures. They stated that although the change of geothermal heat source temperature has an effect on net power, turbine size parameter and total heat transfer coefficient, they have no effect on thermal efficiency. Although $\Delta T_{PP,e}$ is the most important factor on net power at heat source temperatures below 100 °C, it is determined that the evaporation temperature is the most effective parameter at heat source temperatures above 100 °C.

Kumar et al. [13] studied the thermodynamic optimization of the ORC system using the Taguchi method. Different organic fluid, turbine inlet temperature, condenser temperature and mass flow rate are determined as factor values in Taguchi. Thermal efficiency, net power and total irreversibility are determined as performance parameters. L9 orthogonal array was used. 4 different independent variables were handled at 3 different level values; 3^4 (L9) array. They determined that the parameter that has the most impact on thermal efficiency and net power was the turbine inlet temperature, while organic fluid and mass flow rate for total irreversibility.

Yılmaz et al. [14] studied the determination of the thermal efficiency of the recuperative ORC with R410a and R407c by artificial neural networks. Thermal efficiency was estimated based on evaporation temperature, condensation temperature, cooling and superheating temperatures. When the real values and the results obtained from artificial neural networks were compared, it was determined that R^2 value was 99% for both fluids.

Bademlioğlu et al. [15] examined the parameters affecting thermal efficiency in recuperative ORC using Taguchi and Analysis of Variance (ANOVA) methods. In Taguchi, they obtained thermal efficiency values by using L27 orthogonal design. 9 different independent variables were handled at 3 different level values; 3^9 (L27) array. They determined that the thermal efficiency was affected by the evaporation and condensation temperature of 70% and the isentropic efficiency of the turbine.

Zhi et al. [16] worked on multi-parametric analysis, optimization and efficiency prediction with the artificial neural networks method for ORC designed using R1234ze fluid. They made sensitivity analyzes on the thermal efficiency and exergy efficiency of the performance parameters. They stated that turbine isentropic efficiency and heat source temperature had the most effect on ORC.

Kılıç and Arabacı [17] determined the performance of ORC using artificial neural networks and adaptive neuro-fuzzy. As organic fluid, they used R123, R125, R227, R365mfc, SES36. Performance parameters are determined as evaporation temperature, condenser temperature, cooling and superheating temperatures. It has been determined that artificial neural networks reach successful results in estimating the ORC thermal efficiency.

Bademlioğlu et al. [18] used the Taguchi-Grey Relational Analysis method to determine the parameters affecting ORC performance. They found that ORC performance affected evaporation temperature, turbine isentropic efficiency, recuperative efficiency and condensation temperature by 31.37%, 19.53%, 16.64% and 16.61%, respectively.

Zhao et al. [19] studied optimum empirical correlation to rapidly predict the performance of the ORC system. They stated that thermal efficiency, exergy efficiency and net power can be expressed depending on the heat source characteristics.

Yang et al. [20] used the Artificial Neural Network (ANN) for performance prediction and optimization of an ORC for diesel engine waste heat recovery. When they compared ANN models with experimental data, they found that the maximum relative error result was less than 5%.

Palagi et al. [21], Khosravi et al. [22], Herawan et al. [23], Yang et al. [24], Massimiani et al. [25] used the ANN method to predict ORC performance parameters. Zhang et al. [26] and Zhang et al. [27] used Support Vector Machine (SVM) method to predict ORC performance parameters. Dong et al. [28] used both ANN and SVM methods for ORC parametric optimization. They compared both methods. In the SVM method; Gauss Radial Basis kernelfunction (SVM-RBF) and linear function (SVM-LF) compared. The prediction performances of the three methods were compared using different statistical methods. According to the results, they stated that Back Propagation ANN and SVM-LF are more suitable.

In this study, parametric optimization of ORC was designed by using R1234ze at 120 °C heat source temperature. The aim of this study is to determine the sensitivity levels of ORC performance parameters under different objective functions. When the literature studies were examined, it was seen that sensitivity analyzes were made for 1 or 2 objective functions before. In this study, 6 different purpose functions are defined, including energy, exergy, economic (turbine performance) and environmental parameters. As can be seen from the literature studies, it is stated that the maximum turbine power is not obtained due to evaporator load, condenser heat load and mass flow rate requirement at the point where the thermal efficiency reaches the maximum. Therefore, both parameters were evaluated separately in this study.

Another aim of the study is to derive equations that allow estimating ORC performance under different objective functions. Regression analysis was done by using the factor values selected in Taguchi. Predictive equations for determining ORC performance with R1234ze for 120 °C heat source temperature are derived. The results obtained by EES numerical analysis and the regression equation were compared using different statistical methods.

2. Materials and methods

2.1. Thermodynamic analysis

The thermodynamic analysis of the ORC system, designed using different types of organic fluids, was done with Engineering Equation Solver (EES) software. The design model was created by introducing the equations required for thermodynamic analysis to EES. By determining the accepted limit values for the design model, the effect of use R1234ze as the organic fluid on the system performance was determined.

Table 1 summarizes the thermophysical and safety-environmental properties of some organic fluids [29]. R1234ze was chosen as the organic fluid because of its very low GWP value. The properties of R1234ze were compared with other categories of fluids in order to understand its features more clearly. In the comparison, it has been determined that the new-generation organic fluids exhibit thermophysical properties closer to wet fluids.

Thermodynamic analysis equations of ORC are given in Table 2. In the equations given in the table below; Isentropic efficiencies of turbine and pump, η_t and η_p, respectively. $T_{h,i}$ and $T_{h,o}$ heat source input-output; $T_{c,i}$ and $T_{c,o}$ are the cooling water inlet-outlet temperatures, respectively. T_h is the temperature of the heat source, taking the logarithmic mean temperature of the heat source inlet and outlet temperature. T_c is the temperature of the cold source, taking the logarithmic mean temperature of the cooling water inlet and outlet temperature. T_h and T_c given in Table 2 are defined in equations (1) and (2).

$$T_h=(T_{h,i}-T_{h,o})/Ln\ (T_{h,i}-T_{h,o}) \tag{1}$$

$$T_c=(T_{c,i}-T_{c,o})/Ln\ (T_{c,i}-T_{c,o}) \tag{2}$$

The reason for using EES software is that it contains the thermophysical properties of many organic fluids in the database. The effect of using different fluids on the system performance can be easily seen. EES software is also used to detect a component whose irreversibility value reaches a negative value in a certain temperature or pressure range. In this way, the compatibility of the prepared model with the second law of thermodynamics is checked.

The effect of the difference between the evaporator pinch point temperature ($T_{p,e}$) and the evaporation temperature of the organic fluid for different heat source temperatures in ORC has been determined. This difference is defined as the $\Delta T_{PP,e}$. Likewise, the difference between the condenser pinch point ($T_{p,c}$) and the condensation temperature of the organic fluid is defined as the $\Delta T_{PP,c}$. $\Delta T_{PP,e}$ and $\Delta T_{PP,c}$ can be seen from the operating principle and T-s diagram of ORC given in Fig. 1.

The evaporator and condenser energy balance relations (Eqs. (3)–(8)) are given below.

- Evaporator energy balance

$$\dot{m}_{ORC}*(h_3-h_2)=\dot{m}_h*C_p*(T_{h,i}-T_{h,o}) \tag{3}$$

$$\dot{m}_{ORC}*h_3-h_{3,f}=\dot{m}_h*C_p*(T_{h,i}-T_{p,e}) \tag{4}$$

$$\Delta T_{pp,e}=(T_{p,e}-T_{3,f}) \tag{5}$$

- Condenser energy balance

$$\dot{m}_{ORC}*h_{4a}-h_1=\dot{m}_c*C_p*(T_{c,o}-T_{c,i}) \tag{6}$$

$$\dot{m}_{ORC}*h_{1,g}-h_1=\dot{m}c*C_p*(T_{p,c}-T_{c,i}) \tag{7}$$

Table 1
Thermophysical and safety-environmental properties of some organic fluids.

Fluids/Properties	R601	R245fa	R134a	R1234ze
Type	Dry	Isentropic	Wet	**New-Generations**
Molecular mass (g/mol)	72.15	134	102	**114.04**
Normal Boiling Points (°C)	36.1	15.1	-26.1	**-18.8**
Critical Temperature (°C)	196.6	154	101.1	**109.52**
Critical Pressure (Mpa)	3.37	3.65	4.06	**3.63**
ASHRAE 34 safety group	A3	B1	A1	[a]**A2L**
ODP	0	0	0	**0**
GWP	20	1030	1430	**6**

[a] A2L; low toxicity and mildly flammable.

Table 2
ORC thermodynamic analysis equations.

ORC Thermodynamic Analysis		
Components	Energy Analysis	Exergy Analysis
Pump	Pump Work (kJ/kg) w_p=h_2-h_1=(h_{2s}-h_1)/η_p	Pump Irreversibility (kJ/kg) i_p=T_0(s_2-s_1)
Evaporator	Evaporator Duty (kJ/kg) q_e=h_3-h_2	Evaporator Irreversibility (kJ/kg) i_e=T_0[s_3-s_2- h_3-h_2/T_h]
Turbine	Turbine Work (kJ/kg) w_t=(h_3-h_4)=(h_3-h_{4s})η_t	Turbine Irreversibility (kJ/kg) i_t=T_0(s_4-s_3)
Condenser	Condenser Duty (kJ/kg) q_c=(h_4-h_1)	Condenser Irreversibility (kJ/kg) i_c=T_0[s_1-s_4+ h_4-h_1/T_c]
System	Net Work (kJ/kg) w_{net}=q_e-q_c Thermal Efficiency η_{th}=w_{net}/q_e	Total Irreversibility (kJ/kg) i_{total}=i_p + i_e + i_t + i_c Exergy Expended (kJ/kg) $e_{expended}$=(1-T_0/T_h)q_e + w_p Exergy Efficiency η_{II}=1- i_{total}/$e_{expended}$

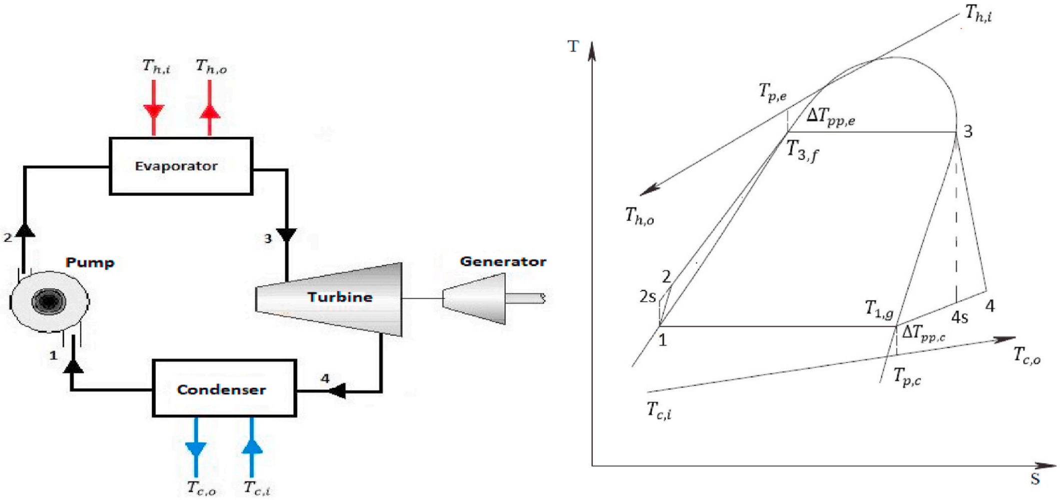

Fig. 1. ORC Working Principle and Demonstration of $\Delta T_{PP,e}$ and $\Delta T_{PP,c}$ in T-s diagram.

$$\Delta T_{pp,c}=(T_{1,g}-T_{p,c}) \tag{8}$$

Equations related to Volume Flow Ratio (VFR), turbine Size Parameter (SP) and turbine Pressure Ratio (PR) which are indicated as turbine performance indicators, are given below (Eqs. (9)–(13)). Since there is certain proportion between the SP and the actual turbine size, SP, being regarded as an indicator of turbine dimensions, given by Eq. (12), can be used to evaluate the actual turbine size in place of a detailed design calculation. This can be used to compare different turbine sizes and is an appropriate indicator of its relative cost. Larger size parameter means bulkier and more expensive turbines [30].

$$\dot{m}_{ORC}=\rho_3 V_3 \tag{9}$$

$$\dot{m}_{ORC}=\rho_4 V_4 \tag{10}$$

$$VFR=V_4/V_3 \tag{11}$$

$$SP=\frac{\sqrt{\dot{V}_4}}{[(h_3-h_{4S})\eta_{+}]^{\frac{1}{4}}} \tag{12}$$

$$PR=P_3/P_4 \tag{13}$$

The waste exergy ratio (WER) is described as the ratio of the net exergy waste of the cycle to the total input exergy (WER: Total exergy waste/Total input exergy). Environmental effect factor (EEF) of an ORC is an important parameter to indicate whether or not it damages the environment because of its unusable waste exergy output and exergy destruction (EEF: Waste exergy ratio/Exergy efficiency). EEF is used directly to determine the environmental damage caused by the working fluid. Exergy Sustainability Index (ESI) is an important parameter for exergetic sustainability of the ORC in terms of the second-law of thermodynamics. The exergetic sustainability index can be written to be reverse of the environmental impact factor [31].

WER, EEF and ESI equations used in determining thermodynamic sustainability indices are also specified (Eq. (14)–(16)).

$$WER = I_{total}/E_{Expended} \tag{14}$$

$$EEF = WER/\eta_{II} \tag{15}$$

$$ESI = 1/EEF \tag{16}$$

For the thermodynamic analysis of ORC, the following assumptions are employed.

- All processes are under steady state.
- Pressure losses in the evaporator and condenser are neglected. Losses in pipelines are neglected.
- In the analysis, all equipment is considered adiabatic and it is assumed that there is no heat transfer between its surfaces and the environment.
- Potential and kinetic energy changes have been neglected.
- Organic fluid: R1234ze
- Heat source temperature: 120 °C
- Heat source mass flow rate is 0.27 kg/s.
- Isentropic efficiency of the turbine and the pump are 75%.
- Dead point pressure and temperature, respectively, P_0: 100 kPa and T_0:25 °C

2.2. Parametric optimization with Taguchi-ANOVA

Taguchi Method is a statistical approach to optimize the process parameters. This method uses an orthogonal array, consisting of factors and levels, to classify the results. In data analysis, signal-to noise (S/N) ratios are used to calculate the response of the experimental trials. There are three types of analysis of the objective functions, smaller the better (SB), nominal the better (NB) and larger the better (LB). By introducing a parameter of S/N ratio, the sensitivity of the parameters on the physical behavior can be comprehend clearly. In the S/N ratio, the signal refers to the desired real value, whereas the noise refers to the undesired factors in the measured values. The S/N ratio in the Taguchi method is a measure used in science and engineering to compare the level of a desired signal to the level of the background noise [32].

In this study, the system was examined in terms of 6 different objective functions. Accordingly, the principle of "LB" for thermal efficiency, turbine power and exergy efficiency maximization; "SB" principle has been applied in total irreversibility, volume flow rate and environmental impact factor minimization. The S/N equations for SB and LB are given below (Eq. (17)–(19)).

- Smaller the better (SB):

$$S/N = -10\,log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right)\Bigg) \tag{17}$$

- Larger the better (LB):

$$S/N = -10\,log\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{18}$$

$$\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$$

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{19}$$

(y_i: The *i*th observation value of the performance response, n: number of tests in one experiment/simulation, y: Average of the observation value and S^2: Variance of observation values).

While the optimum parameters for the objective functions were determined from the S/N ratio obtained by the Taguchi method, the relationship between the performance parameters was also determined by ANOVA. This analysis was carried out a 5% significance level and a 95% confidence level. The significance of control factors in ANOVA is determined by comparing the F values of each control factor. Contribution rate percentages of the performance parameters above the objective functions were determined.

Finally, regression equations are derived using data from Taguchi and ANOVA for different objective functions. The reliability of these equations is determined by the error rates obtained by using 3 different statistical methods.

These relations are given by Equation (20)–(22) [33].

- Mean Absolute Percentage Error-MAPE

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{\gamma_{i,pred}-\gamma_{i,act}}{\gamma_{i,act}}\right|\right)\times 100 \tag{20}$$

- Relative Root Mean Squared Error-RRMSE

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\gamma_{i,pred}-\gamma_{i,act}\right)^2}}{\frac{1}{n}\sum_{i=1}^{n}\gamma_{i,act}}\times 100 \tag{21}$$

- Determination of Coefficient-R^2)

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(\gamma_{i,pred}-\overline{\gamma}_{i,pred}\right)^2 \times \sum_{i=1}^{n}\left(\gamma_{i,act}-\overline{\gamma}_{i,act}\right)^2}{\sqrt{\sum_{i=1}^{n}\left(\gamma_{i,pred}-\overline{\gamma}_{i,pred}\right)^2}\times\sqrt{\sum_{i=1}^{n}\left(\gamma_{i,act}-\overline{\gamma}_{i,act}\right)^2}}\right)^2 \tag{22}$$

(γi,pred: Predicted value, γi,act: Real value, n: number of tests in one experiment/simulation, y: Average of the relevant value).

Such control factors as $\Delta T_{PP,e}$, $\Delta T_{PP,c}$, $T_{c,i}$, T_{sup}, η_t and η_p were selected for the statistical analysis. Sensitivity analysis was carried out by determining the order of importance of the factor value under 6 different performance indices for 120 °C heat source temperature. In Taguchi, 6 different indices were handled at 5 different level values and L25 (5^6) orthogonal array design was used. The parameters and their ranges (levels) used for statistical analysis are shown in Table 3.

Flow diagram determined for parametric optimization and sensitivity analysis of Taguchi and ORC performance parameters is given in Fig. 2.

3. Model validation

In order to determine the accuracy of the data obtained using Taguchi-ANOVA, two experimental studies investigated within the scope of literature research were used. To verify the model, the Taguchi model was created by examining the parameters in experimental studies. Thermal efficiency values determined by using R245fa under the same design parameters were compared for two different studies in Table 4. Although the Taguchi model was compared with experimental studies, the error rate was found below 10%. When Table 4 is examined, it is seen that the thermodynamic model prepared can be used successfully.

4. Result and discussion

4.1. Sensitivity analysis and contribution rate results with Taguchi-ANOVA

In this study, parametric optimization and sensitivity analysis were performed for the ORC designed using R1234ze for 120 °C heat source temperature. The effect of factor values on ORC performance was determined under different six performance indices.

For ORC designed using R1234ze, L25 (5^6) orthogonal array was applied to determine thermal efficiency, net power, exergy efficiency, total irreversibility, volumetric flow rate and environmental impact factor. In the Taguchi method, the 'larger is better (LB)' S/N equation for thermal efficiency, net power and exergy efficiency maximization; The 'smaller is better (SB)' S/N equation was used for total irreversibility, volume flow rate and environmental impact factor minimization.

Such control factors as $\Delta T_{PP,e}$ (A), $\Delta T_{PP,c}$ (B), $T_{c,i}$ (C), T_{sup} (D), η_t (E) and η_p (F) were selected for the statistical analysis. In Figs. 3–8, graphs of factor levels determined under R1234ze's 6 different performance indices are given. Below the figures, it is stated which equation to use signal to noise (S/N) according to the objective function.

The order of importance can be understood from the difference between the maximum and minimum values of S/N ratios of the parameters in the figure. It is seen that η_t (E) and $\Delta T_{PP,e}$ (A) are more effective in thermal efficiency maximization, exergy efficiency maximization and EEF minimization. It has been determined that the $T_{c,i}$ (C) is much more effective than other parameters in the turbine power maximization. It is seen that the most important parameter in total irreversibility minimization is $\Delta T_{PP,e}$ (A). In VFR minimization, $\Delta T_{PP,e}$ (A) and $T_{c,i}$ (C) are more effective.

Table 3
Performance parameters and level values determined for ORC Taguchi optimization.

Parameters/Levels	Unit	1	2	3	4	5
$\Delta T_{PP,e}$ (A)	(°C)	2	4	6	8	10
$\Delta T_{PP,c}$ (B)	(°C)	2	4	6	8	10
$T_{c,i}$ (C)	(°C)	10	15	20	25	30
T_{sup} (D)	(°C)	0	5	10	15	20
η_t (E)	-	0.65	0.70	0.75	0.80	0.85
η_p (F)	-	0.65	0.70	0.75	0.80	0.85

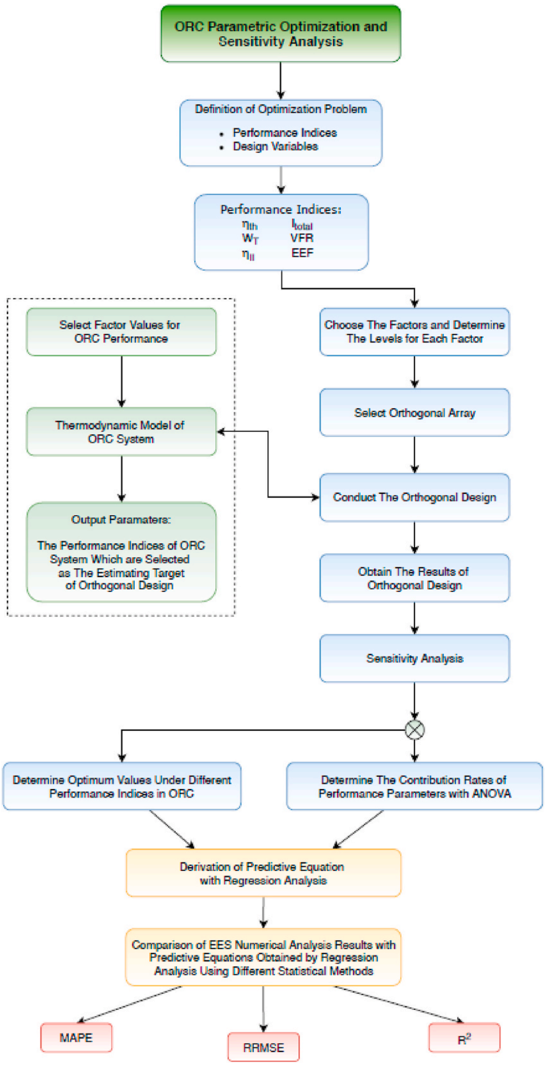

Fig. 2. ORC taguchi optimization flow chart.

Table 4
Comparison of important Taguchi predict results with experimental study literature under same design parameters.

Design Parameters	Condensing temperature: 33,8 °C; Turbine inlet pressure: 995 kPa; Turbine inlet temperature: 89.7 °C, Turbine and pump isentropic efficiency: 84.9% and 79.7%		Condensing temperature: 30 °C; Turbine inlet pressure: 1250 kPa; Turbine inlet temperature: 102.5 °C, Turbine and pump isentropic efficiency: 60%	
Organic Fluids	R245fa		R245fa	
Performance Parameters	Present Study **Taguchi-Predict**	Experimental Study Literature [34]	Present Study **Taguchi-Predict**	Experimental Study Literature [35]
Thermal Efficiency (%)	9.64	9.28	8.5	7.8
MAPE (%)	9.6		9.1	

S/N ratio table and sensitivity levels of the parameters are given in Tables 5–10 for 6 performance indices for 120 °C heat source temperature.

Optimum orthogonal arrays and sensitivity levels determined according to Taguchi results for 120 °C heat source temperature with R1234ze is summarized in Table 11.

Following the determination of the sensitivity level ranking, the contribution rates were determined by using ANOVA in order to see how much effect the parameters had on the ORC performance. ANOVA is a statistical method which is used to determine the

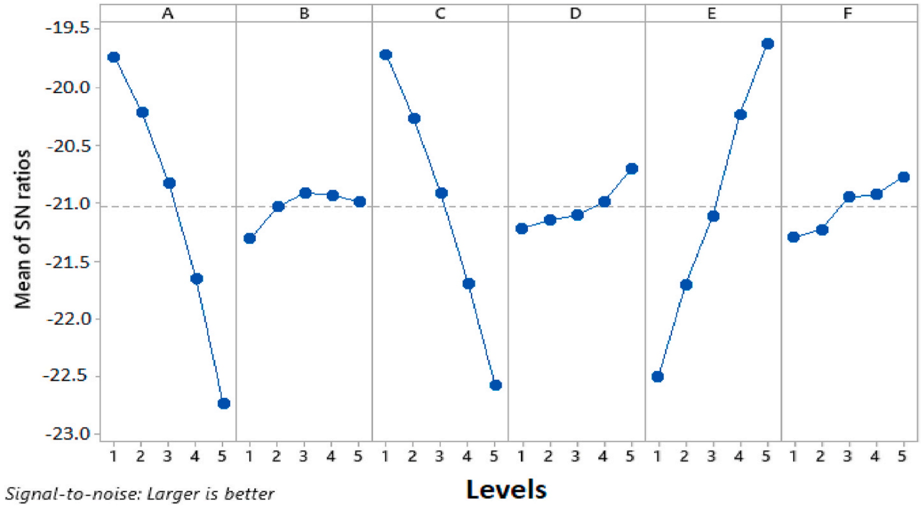

Fig. 3. Effect of process parameters on LB S/N ratio for thermal efficiency maximization.

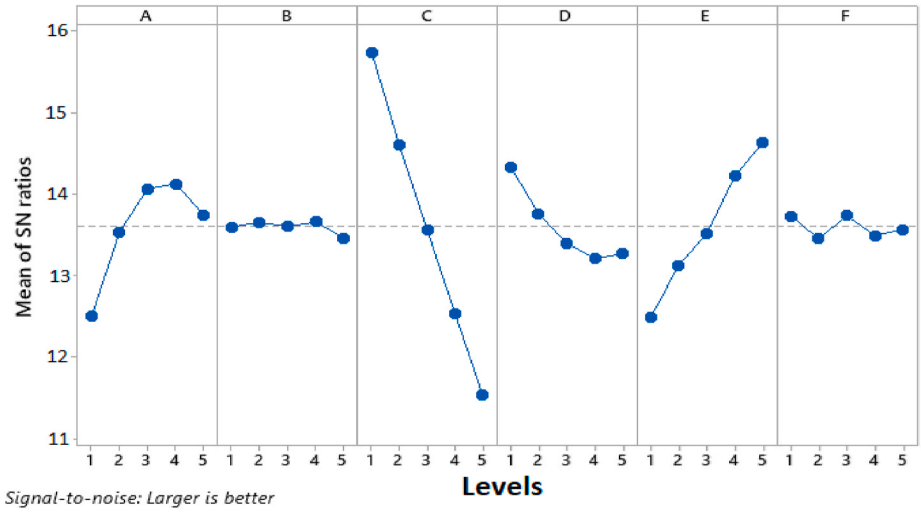

Fig. 4. Effect of process parameters on LB S/N ratio for turbine power maximization.

individual interactions of all the control factors in the test design. In this study, ANOVA was used to analyze the effects of $\Delta T_{PP,e}$ (A), $\Delta T_{PP,c}$ (B), $T_{c,i}$ (C), T_{sup} (D), η_t (E) and η_p (F). Contribution rates according to ANOVA results are given in Fig. 9. When this figure is examined;

- η_t (E), $\Delta T_{PP,e}$ (A) and $T_{c,i}$ (C) have an effect of approximately 30% on thermal efficiency.
- It is stated that $T_{c,i}$ (C) has a significant effect (65%) on the turbine power.
- It is seen that the most important parameters for exergy efficiency and EEF are η_t (E) (51–56%) and $\Delta T_{PP,e}$ (A) (37–39%).
- It is stated that $\Delta T_{PP,e}$ (A) has a 57% and 60% effect on VFR and total irreversibility value, respectively.
- When all performance parameters are considered together, it is seen that $\Delta T_{PP,e}$ (A), and η_t (E) are the ones that affect ORC performance the most. It was determined that $\Delta T_{PP,e}$ (A) and η_t (E) values affect ORC performance by 39.72% and 29.52%, respectively.

Table 12 summarizes the two most sensitive parameters and contribution rates in achieving the objective functions set in the low temperature ORC. When the table is examined, the importance of $\Delta T_{PP,e}$ value is seen in all low temperature applications. The effect of $\Delta T_{PP,e}$ on thermal efficiency, turbine power, exergy efficiency, total irreversibility, VFR and EEF is 33.39%, 10.62%, 37.70%, 60.05%, 57.05%, 39.51%, respectively. When averaged, $\Delta T_{PP,e}$'s effect on ORC performance was found to be 39.72%.

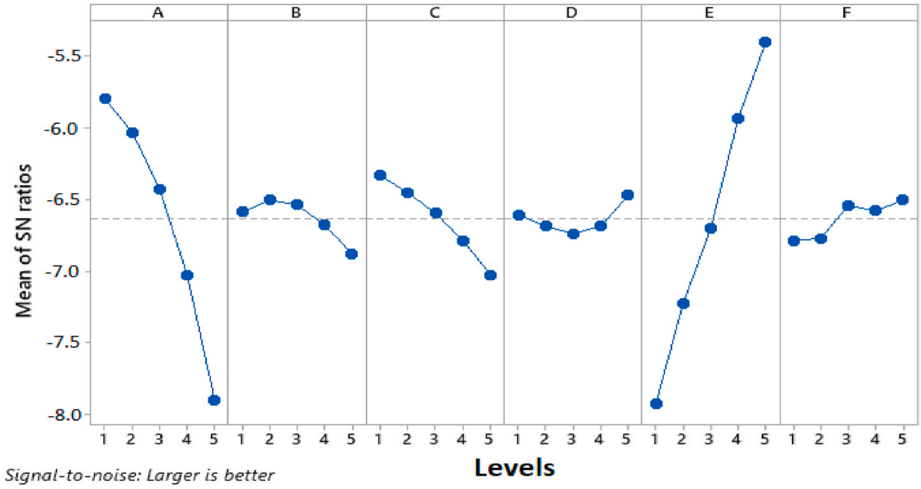

Fig. 5. Effect of process parameters on LB S/N ratio for exergy efficiency maximization.

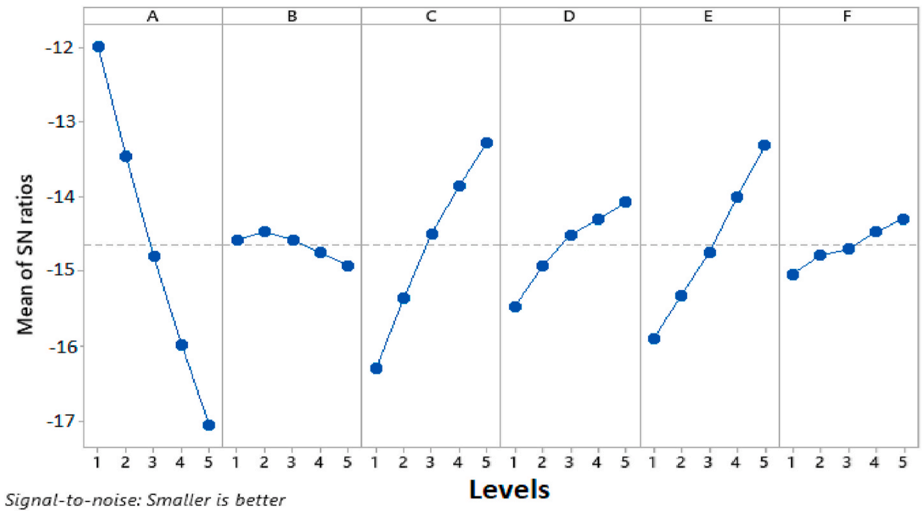

Fig. 6. Effect of process parameters on SB S/N ratio for total irreversibility minimization.

4.2. Performance prediction with regression analysis

In the last part of the study; regression analyses are used for the modeling and analyzing of several variables where there is relationship between a dependent variable and one or more independent variables. In this study, the dependent variables are thermal efficiency, turbine power, exergy efficiency, total irreversibility, VFR and EEF. The independent variables are $\Delta T_{PP,e}$, $\Delta T_{PP,c}$, $T_{c,i}$, T_{sup}, η_t and η_p. In obtaining predictive equations for the dependent variables, regression analysis was used. These predictive equations were made for linear regression models. Details about the procedure regression analysis can be found in Refs. [36].

The predictive equations which were obtained by the linear regression model of dependent variable are given Table 13 for 120 °C heat source temperature. Validation ranges for $\Delta T_{PP,e}$ and $\Delta T_{PP,c}$ is 1 °C–10 °C; for $T_{c,i}$ 10 °C–30 °C; for T_{sup} 0 °C–20 °C and for η_t and η_p are 65–85%

For ORC with R1234ze at 120 °C heat source temperature, EES numerical analysis results and predicted values obtained by using regression equations were compared using different statistical methods at optimum and random levels. These are, MAPE, RRMSE and R^2.

Table 14 summarizes the average error rates determined by comparing EES analysis and predictive values for 120 °C heat source temperatures. It is seen that the lowest R^2 value is determined as 95.6%.

The predicted values and the EES analysis values are very close to each other. As a result, the linear regression model was shown to be successfully for the predict ORC performance.

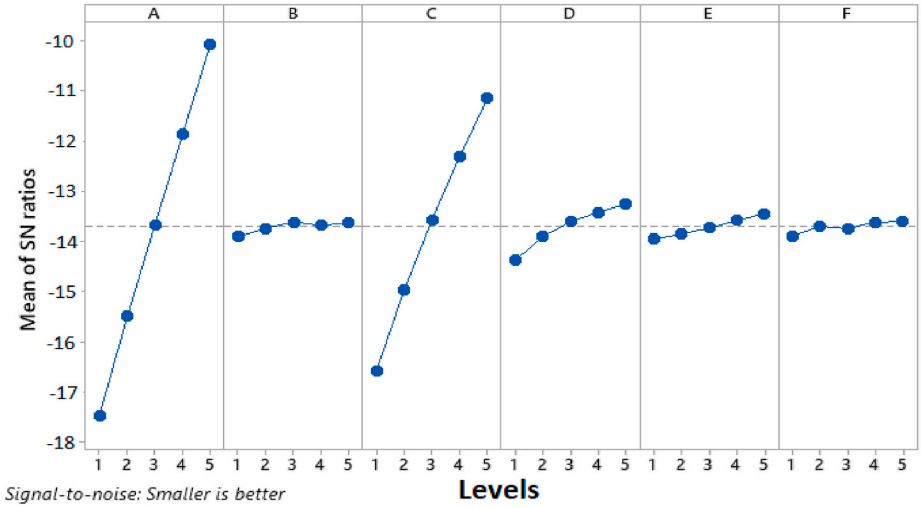

Fig. 7. Effect of process parameters on SB S/N ratio for VFR minimization.

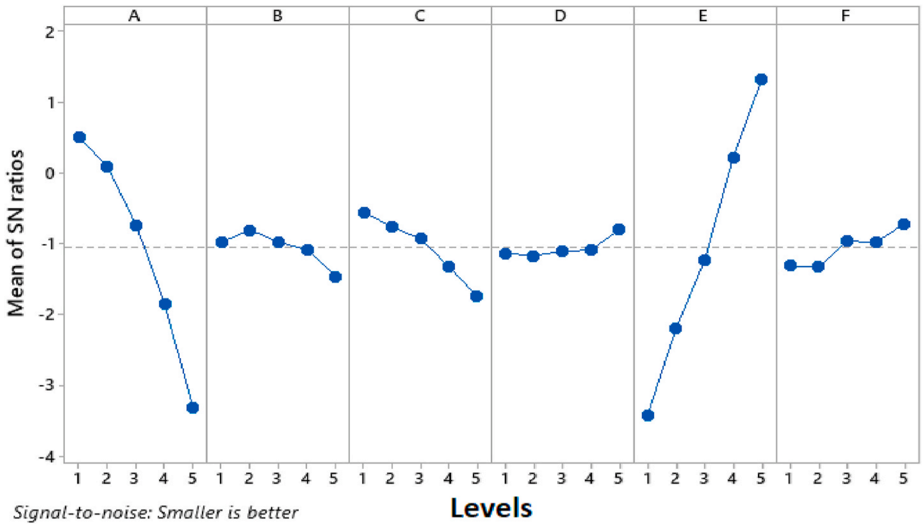

Fig. 8. Effect of process parameters on SB S/N ratio for EEF minimization.

Table 5
S/N response table and sensitivity level of parameters for thermal efficiency maximization.

$T_{h,i}$= 120 °C; R1234ze; max ($\eta_{ısıl}$)						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	-19.74	-21.31	-19.72	-21.22	-22.50	-21.29
2	-20.21	-21.03	-20.27	-21.15	-21.70	-21.22
3	-20.83	-20.91	-20.92	-21.11	-21.11	-20.95
4	-21.65	-20.93	-21.69	-20.99	-20.23	-20.93
5	-22.73	-20.99	-22.57	-20.70	-19.62	-20.77
$\mathbf{\Delta_{max-min}}$	3.00	0.40	2.85	0.51	2.88	0.52
Sensitivity level	**1**	**6**	**3**	**5**	**2**	**4**

5. Conclusions

In this study, parametric optimization and sensitivity analysis of ORC designed using R1234ze were performed for 120 °C heat source temperature. In addition, regression equations are derived for performance prediction of ORC. The sensitivity levels of the

Table 6
S/N response table and sensitivity level of parameters for turbine power maximization.

$T_{h,i}$= 120 °C; R1234ze; max (W_T)						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	12.50	13.60	15.74	14.34	12.49	13.73
2	13.54	13.66	14.60	13.76	13.13	13.46
3	14.07	13.61	13.56	13.40	13.52	13.74
4	14.13	13.66	12.55	13.22	14.22	13.50
5	13.75	13.47	11.54	13.27	14.63	13.57
$\Delta_{max-min}$	1.63	0.20	4.20	1.12	2.15	0.28
Sensitivity level	**3**	**6**	**1**	**4**	**2**	**5**

Table 7
S/N response table and sensitivity level of parameters for exergy efficiency maximization.

$T_{h,i}$= 120 °C; R1234ze; max (η_{II})						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	-5.801	-6.586	-6.331	-6.608	-7.921	-6.791
2	-6.033	-6.506	-6.452	-6.687	-7.222	-6.770
3	-6.431	-6.538	-6.594	-6.737	-6.701	-6.543
4	-7.029	-6.678	-6.786	-6.685	-5.937	-6.580
5	-7.895	-6.880	-7.026	-6.472	-5.408	-6.505
$\Delta_{max-min}$	2.093	0.374	0.695	0.264	2.513	0.286
Sensitivity level	**2**	**4**	**3**	**6**	**1**	**5**

Table 8
S/N response table and sensitivity level of parameters for total irreversibility minimization.

$T_{h,i}$= 120 °C; R1234ze; min (I_T)						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	-11.99	-14.57	-16.30	-15.47	-15.90	-15.03
2	-13.45	-14.46	-15.36	-14.93	-15.31	-14.78
3	-14.80	-14.57	-14.49	-14.50	-14.74	-14.70
4	-15.97	-14.74	-13.86	-14.30	-14.00	-14.47
5	-17.05	-14.92	-13.27	-14.07	-13.31	-14.29
$\Delta_{max-min}$	5.06	0.46	3.03	1.39	2.58	0.74
Sensitivity level	**1**	**6**	**2**	**4**	**3**	**5**

Table 9
S/N response table and sensitivity level of parameters for VFR minimization.

$T_{h,i}$= 120 °C; R1234ze; min (VFR)						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	-17.45	-13.90	-16.56	-14.38	-13.95	-13.89
2	-15.49	-13.74	-14.97	-13.90	-13.85	-13.70
3	-13.66	-13.61	-13.57	-13.60	-13.73	-13.75
4	-11.87	-13.68	-12.31	-13.41	-13.58	-13.61
5	-10.07	-13.62	-11.15	-13.25	-13.44	-13.61
$\Delta_{max-min}$	7.38	0.29	5.41	1.12	0.51	0.28
Sensitivity level	**1**	**5**	**2**	**3**	**4**	**6**

parameters that have an impact on ORC performance were determined. Six performance indices used in the orthogonal design. Such control factors as $\Delta T_{PP,e}$ (A), $\Delta T_{PP,c}$ (B), $T_{c,i}$ (C), T_{sup} (D), η_t (E) and η_p (F) were selected for the statistical analysis. It was observed that the sensitivity levels changed under different performance indices. Significant results achieved under different performance indices are summarized below.

- It has been determined that three parameters are effective on thermal efficiency. The sensitivity level ranking for thermal efficiency maximization was realized as η_t (E) (33.64%) > $\Delta T_{PP,e}$ (A)(33.39%) > $T_{c,i}$ (C) (29.77%).
- It has been determined that $T_{c,i}$ (C) has a significant effect on achieving maximum turbine power. The sensitivity level ranking for turbine power maximization was realized as $T_{c,i}$ (C) (65.21%) > η_t (E) (19.40%) > $\Delta T_{PP,e}$ (A) (10.62%).

Table 10
S/N response table and sensitivity level of parameters for EEF minimization.

$T_{h,i}$= 120 °C; R1234ze; min (EEF)						
Level	$\Delta T_{PP,e}$ (A)	$\Delta T_{PP,c}$ (B)	$T_{c,i}$ (C)	T_{sup} (D)	η_t (E)	η_p (F)
1	0.50437	-0.97337	-0.55565	-1.13117	-3.41537	-1.30657
2	0.08894	-0.80527	-0.76346	-1.16738	-2.18452	-1.32644
3	-0.73375	-0.97284	-0.92834	-1.10476	-1.22909	-0.96297
4	-1.84647	-1.08622	-1.31553	-1.08707	0.21863	-0.97451
5	-3.30722	-1.45644	-1.73115	-0.80375	1.31622	-0.72364
$\boldsymbol{\Delta}_{\mathbf{max\text{-}min}}$	3.81159	0.65118	1.17549	0.36363	4.73159	0.60280
Sensitivity level	**2**	**4**	**3**	**6**	**1**	**5**

Table 11
Determination of optimum orthogonal arrays and sensitivity level obtained for different performance indices at 120 °C heat source temperature with R1234ze.

Organic fluid: R1234ze	f(x)	Optimum Orthogonal Array	Sensitivity Rank
$T_{h,i}$=120 °C	max (η_{th})	A_1 B_3 C_1 D_5 E_5 F_5	E > A > C > F > D > B
	max (W_T)	A_4 B_2 C_1 D_1 E_5 F_3	C > E > A > D > F > B
	max (ηII)	A_1 B_2 C_1 D_5 E_5 F_5	E > A > C > B > F > D
	min (I_T)	A_1 B_2 C_5 D_5 E_5 F_5	A > C > E > D > F > B
	min (VFR)	A_5 B_3 C_5 D_5 E_5 F_4	A > C > D > E > B > F
	min (EEF)	A_1 B_2 C_1 D_5 E_5 F_5	E > A > C > B > F > D

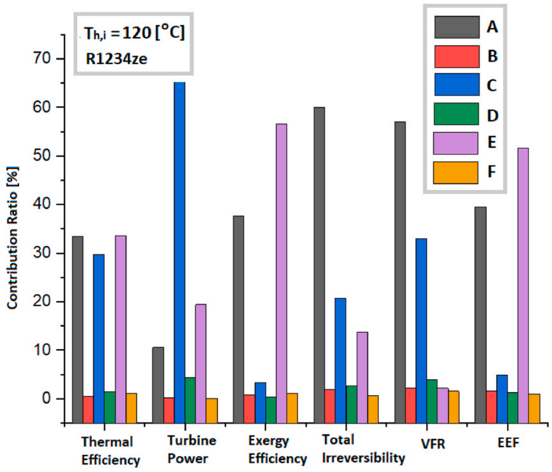

Fig. 9. Contribution ratio of each parameter ORC with R1234ze at 120 °C heat source temperature for six different performance indices [$\Delta T_{PP,e}$ (A), $\Delta T_{PP,c}$ (B), $T_{c,i}$ (C), T_{sup} (D), η_t (E) and η_p (F)].

- It is seen that $\Delta T_{PP,e}$ (A) and η_t (E) are effective on exergy efficiency and EEF. The sensitivity level ranking for exergy efficiency maximization was realized as η_t (E) (56.60%) > $\Delta T_{PP,e}$ (A) (37.70%). For EEF minimization; η_t (E) (51.59%) > $\Delta T_{PP,e}$ (A) (39.51%).
- It has been determined that $\Delta T_{PP,e}$ (A) has a significant effect on achieving minimum total irreversibility. The sensitivity level ranking for total irreversibility minimization was realized as $\Delta T_{PP,e}$ (A) (60.05%) > $T_{c,i}$ (C) (20.77%) > η_t (E) (13.73%).
- It is seen that $\Delta T_{PP,e}$ (A) and $T_{c,i}$ (C) are effective on VFR. The sensitivity level ranking for VFR minimization was realized as $\Delta T_{PP,e}$ (A) (57.05%) > $T_{c,i}$ (C) (32.95%).

When all performance parameters are considered, it is determined that the parameter that most affects ORC performance is $\Delta T_{PP,e}$. The effect of $\Delta T_{PP,e}$ on ORC performance was determined to be 39.72%. After $\Delta T_{PP,e}$, it was determined that η_t influenced ORC performance with 29.52%.

In the last part of the study, ORC performance prediction equations are derived by using regression method. The dependent variables are selected as thermal efficiency, turbine power, exergy efficiency, total irreversibility, VFR and EEF. The independent variables are $\Delta T_{PP,e}$, $\Delta T_{PP,c}$, $T_{c,i}$, T_{sup}, η_t and η_p. The results obtained by EES numerical analysis and the regression equation were compared using different statistical methods. When the errors that occur in the equations derived for all performance parameters are examined, the results of MAPE, RRMSE and R^2 were determined as 4.1%, 4.29% and 94.1%, respectively. It has been determined that ORC performance can be determined significantly without the need of any software.

Table 12
Two parameters with maximum sensitivity and contribution ratios under different objective functions.

f(x)	$T_{h,i}$=120 °C R1234ze
max (η_{th})	33.64%; η_t 33.39%; $\Delta T_{PP,e}$
max (W_T)	65.21%; $T_{c,i}$ 19.40%; η_t
max (η_{II})	56.60%; η_t 37.70%; $\Delta T_{PP,e}$
min (I_T)	60.05%; $\Delta T_{PP,e}$ 20.77%; $T_{c,i}$
min (VFR)	57.05%; $\Delta T_{PP,e}$ 32.95%; $T_{c,i}$
min (EEF)	51.59%; η_t 39.51%; $\Delta T_{PP,e}$
Average;	**39.72%; $\Delta T_{PP,e}$** **29.52%; η_t**

Table 13
The predictive equations based on dependent variables of different performance parameters of ORC designed at 120 °C heat source temperature.

$T_{h,i}$	Dependent Variables	Predictive Equations – **Organic Fluid: R1234ze**
120 °C	η_{th}	$0.01239 - 0.003608*\Delta T_{pp,e} + 0.00039*\Delta T_{pp,c} - 0.001372*T_{c,i} + 0.000271*T_{sup} + 0.14607*\eta_t + 0.02716*\eta_p$
	WT (kW)	$2.119 + 0.0941*\Delta T_{pp,e} - 0.0021*\Delta T_{pp,c} - 0.11723*T_{c,i} - 0.02643*T_{sup} + 6.4*\eta_t - 0.214*\eta_p$
	η_{II}	$0.0446 - 0.013468*\Delta T_{pp,e} - 0.00172*\Delta T_{pp,c} - 0.001612*T_{c,i} + 0.000417*T_{sup} + 0.6727*\eta_t + 0.0872*\eta_p$
	I_{total}(kW)	$10.56 + 0.3794*\Delta T_{pp,e} + 0.0667*\Delta T_{pp,c} - 0.08891*T_{c,i} - 0.03039*T_{sup} - 7.265*\eta_t - 1.074*\eta_p$
	VFR	$19.9 - 0.561*\Delta T_{pp,e} - 0.0834*\Delta T_{pp,c} - 0.1701*T_{c,i} - 0.06*T_{sup} - 4.27*\eta_t - 3.44*\eta_p$
	EEF	$3.04 + 0.0672*\Delta T_{pp,e} + 0.01113*\Delta T_{pp,c} + 0.00979*T_{c,i} - 0.00089*T_{sup} - 3.182*\eta_t - 0.353*\eta_p$

Table 14
Prediction performance of the ORC using statistical indicators.

Dependent Variables	MAPE (%)	RRMSE (%)	R^2 (%)
η_{th}	4.2	4.36	93.7
W_T	3.6	3.89	94.3
η_{II}	3.3	3.51	95.5
I_T	4.4	4.52	93.8
VFR	4.3	4.67	93.9
EEF	4.8	4.81	93.7
Average	**4.1**	**4.29**	**94.1**

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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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