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Research Article

TRIPLE-OBJECTIVE OPTIMIZATION OF SUPERCRITICAL CO_2 RECOMPRESSION BRAYTON CYCLE IN SOLAR TOWER SYSTEMS WITH ENERGY, EXERGY AND EXERGOECONOMIC ANALYSIS

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Abstract: *This study addresses the energy, exergy and exergoeconomic analyses of the supercritical CO_2 recompression Brayton cycle used in solar tower systems. In the study, a three-objective optimization model was developed using artificial neural networks (ANN) to optimize the system performance. The model provides information for the development of sustainable solar energy systems by providing analyses on key factors such as energy efficiency, environmental impact and economic viability. The results show that the supercritical CO_2 cycle provides higher thermal efficiency compared to conventional systems and offers cost advantages by reducing the size of system components. In addition, the analyses show that energy and exergy losses can be minimized and the cost effectiveness of the system can be increased, providing important findings in terms of the efficiency and economic viability of solar energy systems.*

Keywords*: Energy Analysis, Exergy Analysis, Multi-Objective Optimization, Artificial Neural Networks (ANN), Innovative Energy Solutions*

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1. Introduction

Solar energy stands out as an important resource in response to the global energy crisis and environmental problems. Solar tower systems are one of the most promising ways to take advantage of these resources, thanks to their high efficiency and scalability. Supercritical CO_2 has many advantages over conventional fluids; such as higher thermal efficiency, smaller system size, and improved heat transfer properties.

Some studies in the literature: Abdelghafar et al. [1] conducted an energy, exergy, and exergoeconomic analysis of combined power cycles powered by sCO_2-based concentrated solar energy. Abid et al. [2] compared the solar-powered supercritical CO_2 power and hydrogen production cycle in terms of energy, exergy and exergoeconomic aspects. Adibhatla and Kaushik. [3] conducted an energy, exergy and economic analysis for a combined cycle power plant powered by an integrated solar steam generator. Almutairi et al. [4] presented a review examining the use of solar energy in power plants for preheating purposes. Al-Sulaiman and Atif. [5] compared performance by integrating different supercritical CO_2 Brayton cycles with the solar tower system. Atif and Al-Sulaiman. [6] performed energy and exergy analyses of solar tower-powered supercritical CO_2 recompression cycles at six different locations. Bai et al. [7] analyzed the use of CO_2-SF_6 mixing fluid in solar power plants in the supercritical Brayton cycle from a thermodynamic point of view. Bashan and Gümüş. [8] performed the energy and exergy analysis according to the optimal design parameters for the recovered supercritical CO_2 power cycle. Bejan et al. [9] presented a wide range of resources on thermal design and optimization. Cengel and Boles. [10] discussed gas-steam mixtures and air conditioning systems with a thermodynamic approach. Citaristi. [11] provides information on the International Energy Agency (IEA). Dincer and Rosen. [12] discussed the relationship between energy, environment and sustainable development. Ehsan et al. [13] evaluated the commercial potential and research status of supercritical

CO_2 power cycles. Guelpa and Verda. [14] conducted an exergoeconomic analysis on the supercritical CO_2 cycle design for concentrated solar power plants. Guo et al. [15] presented a comprehensive review on the use of supercritical CO2 cycles in energy industries. Heller et al. [16] analysed the technical and economic selection of supercritical CO_2 cycles for concentrated solar plants based on particle technology. Hinkley et al. [17] provide a roadmap on concentrated solar fuels. Kalogirou. [18] studied the development of solar collectors and their applications. Khan et al. [19] compared the recovery and exergoeconomic analysis of waste heat for two solar-powered supercritical CO_2 Brayton cycles. Kulhanek and Dostal. [20] conducted thermodynamic analysis and comparison on supercritical CO_2 cycles. Li et al. [21] examined the applications of supercritical CO_2 power cycles in nuclear power, solar power, and other energy industries. Liang et al. [22] performed simultaneous optimization of supercritical CO_2 Brayton and organic Rankine cycles integrated with a concentrated solar power plant. Liu et al. [23] compared the integration of coal-fired power plants with supercritical CO_2 Brayton cycles with steam Rankine cycles. Mehos et al. [24] presented a roadmap for concentrated solar power. Mohammadi et al. [25] performed advanced exergy analyses for recompression supercritical CO_2 cycles. Montes et al. [26] evaluated recent developments on pressurized central receivers and solar power plants operating with supercritical power cycles. Okonkwo et al. [27] conducted a second-law analysis and exergoeconomic optimization of solar tower-powered combined-cycle power plants. Osorio et al. [28] performed dynamic analysis of supercritical CO_2-based closed cycles powered by concentrated solar energy. Shah. [29] provides information on advanced power generation systems and thermal resources. Sun et al. [30] analyzed two supercritical CO_2 cycles in terms of recovery of gas turbine waste heat. Xin et al. [31] performed a thermodynamic analysis on a novel supercritical CO_2 Brayton cycle based on the thermal cycle division analysis method.

This study aims to explore the potential of supercritical CO_2 recompression Brayton cycles in solar tower systems that concentrate solar energy. With the integration of energy, exergy, and exergoeconomic analyses, this study provides valuable insights into optimizing the performance and economic viability of solar tower systems.

2. Materials and Methods

2.1. Solar Tower Systems and the Supercritical CO_2 Brayton Cycle

Solar tower systems generate high-temperature thermal energy by concentrating sunlight into a receiver using mirrors or heliostats. This energy can be converted into electricity through various thermodynamic cycles. The supercritical CO_2 cycle operates above the critical temperature and pressure of CO_2; In this way, a fluid that combines liquid and gas properties is obtained. This feature is important to improve thermal efficiency and make the system more compact. Figure 1 shows the general configuration of the solar tower system.

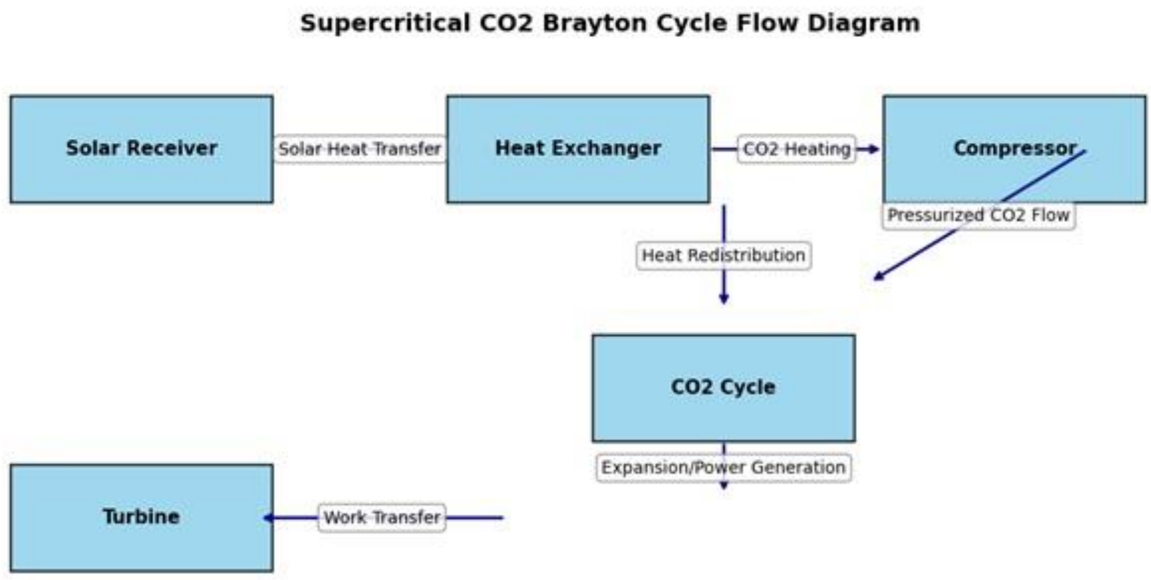

Figure 1. Solar Tower System Configuration

This graph shows the flow diagram of the supercritical CO_2 Brayton cycle. The diagram clearly reveals the energy flow and processes between the main components of the system. Solar Receiver: It is the first component that collects energy from the sun and transfers it to the CO_2 fluid. This is where the transfer of energy begins. Heat Exchanger: Increases the efficiency of the system by further heating the hot CO_2 fluid from the solar receiver. Heat transfer takes place here. Compressor: The heated CO_2 is pressurized here. This pressure increase is critical to improving the energy efficiency of the system. Turbine: Pressurized CO2 is expanded here to produce mechanical work. This process ensures the energy output of the system. CO_2 Cycle: The CO_2 coming out of the turbine completes the cycle in the system. At the end of the process, the CO_2 returns to the solar receiver and the cycle starts over. The graph has arrows that show the flow of energy between the components. Each arrow represents a specific process: Energy Transfer: From solar receiver to heat exchanger, Heating CO_2: Heat exchanger to compressor, Heat Transfer: Compressor to turbine, Pressurization: Turbine to CO_2 cycle, Work Production: Reconversion from CO_2 cycle to solar receiver. The diagram provides a visual representation of the operation of the system, providing an important reference for the energy efficiency and performance analysis of the supercritical CO_2 Brayton cycle.

2.2. Energy Analysis

Energy analysis evaluates energy efficiency by calculating energy flows, inputs, outputs and losses in the system. In this analysis, the energy equations in each component of the system, such as compressors, turbines, heat exchangers, etc., should be written in detail. In addition:

Energy equations: Energy equations should be written in each component where energy conservation is achieved.

Energy efficiency: Energy efficiency is defined as the ratio of the output energy of the system to the energy entering the system. By calculating this ratio on each component, the overall energy efficiency of the system can be achieved.

$$\eta_{energy}=\frac{E_{output}}{E_{input}} \tag{1}$$

In equation 1, E_{output} is the output energy and E_{input} is the input energy.

2.3. Exergy Analysis

Exergy analysis more comprehensively evaluates a system's efficiency, energy quality, and environmental impact. This analysis is important for a better understanding of energy losses and offers more in-depth information when compared to energy efficiency. Exergy is calculated by taking into account environmental energy losses and entropy. Exergy loss is associated with the fact that heat energy becomes less efficient in a given environment.

Exergy loss: Exergy loss can be calculated by considering the entropy changes for each component.

Exergy efficiency: Exergy efficiency, like energy efficiency, is defined as the ratio of output exergy to input exergy.

$$\eta_{exergy} = \frac{Ex_{output}}{Ex_{input}} \tag{2}$$

In equation 2, Ex_{output} is the output exergy and Ex_{input} is the input exergy.

2.4. Exergoeconomic Analysis

Exergoeconomic analysis evaluates the economic performance of an energy system by relating it to exergy losses. In this analysis, the costs of each component in the system are combined with the efficiency analyses. That is, the points where energy and exergy losses are linked to their costs should be detailed.

Cost calculations: The investment cost, operating costs and maintenance costs of each component, e.g. heat exchanger or turbine, can be calculated.

Exergoeconomic efficiency: This efficiency is often defined as a parameter that evaluates the ratio between exergy loss and costs. In this way, it can be optimized for cost minimization.

$$\eta_{exergoeconomic} = \frac{C_{exergy}}{C_{total}} \tag{3}$$

In Equation 3, C_{exergy} is the cost for exergy loss and C_{total} is the total cost.

2.5. Advanced Technical Details

Temperature and pressure dependence: Exergy and energy calculations often vary depending on the temperature and pressure in the system. It is necessary to calculate these parameters for components and study their effect on each component.

$$Ex = (h - h_0) - T_0 \cdot (s - s_0) \tag{4}$$

In equation 4, h is enthalpy, s is entropy, T_0 is ambient temperature, and h_0 and s_0 are the reference enthalpy and entropy at environmental conditions.

Dynamic simulations: Energy, exergy and exergoeconomic analyses, more realistic results can be obtained by using dynamic simulations. Such simulations allow to analyze variable parameters in the system (temperature, pressure, flow rate, etc.) over time.

2.6. Energy Efficiency Calculator

Energy efficiency (η) is calculated as follows (5):

$$\eta = \frac{W_{\text{exit}}}{Q_{\text{input}}} \tag{5}$$

- W_{exit}: The net work produced by the system, i.e. the difference between turbine and compressor.
- Q_{input}: The total energy transferred to the solar receiver.

Accepted assumptions:

- The isentropic efficiencies of turbines, compressors, and other components have been accepted as constant.
- The CO_2 fluid is constantly operating under supercritical conditions (above critical temperature and pressure).
- The input energy comes from a constant heat source obtained from solar radiation.

2.7. Exergy Loss Calculator

Exerge loss (Ex_{loss}) evaluates energy losses and irreversibility in the system. The calculation is made by the formula (6):

$$Ex_{\text{loss}} = Q_{\text{input}} \text{ x } (1 - \frac{T_{\text{enviroment}}}{T_{source}}) \tag{6}$$

Here:

- $T_{\text{enviroment}}$: Ambient temperature.
- T_{source}: Source temperature, that is, the temperature reached in the solar receiver.
- Q_{input}: The total energy transferred to the solar receiver.

Accepted assumptions:

- System irreversibility (such as friction, heat transfer losses) was taken into account.
- The exergy loss of each component in the cycle is calculated individually based on their isentropic efficiency.
- The ambient temperature is considered constant, that is, no changes in the external environment are taken into account.

2.8. ANN (Artificial Neural Networks) Methodology

Artificial Neural Networks (ANNs) are a powerful artificial intelligence (AI) methodology used to model complex and nonlinear relationships by mimicking the functioning of biological neural networks. These networks use various algorithms to learn the relationships between input data and output, and direct the training data and optimization processes. Below is a detailed explanation of the ANN algorithm used, input/output parameters, and learning processes.

2.8.1 Artificial Neural Network Algorithm

Artificial neural networks are generally used with multi-layer (MLP - Multi-Layer Perceptron) structures. These structures contain multiple layers (input layer, hidden layers, and output layer). The neurons present in each layer receive the signals from the previous layer, producing output using activation functions.

Learning Algorithm: ANN's learning algorithm is generally based on backpropagation and gradient descent methods. This algorithm updates the weights of each neuron according to the difference in error between the output and the actual value.

Activation Functions: Activation functions such as ReLU (Rectified Linear Unit), Sigmoid or Tanh are generally used in neural networks. These functions help neurons solve nonlinear problems by enabling them to make decisions.

2.8.2 Input/Output Parameters

The input parameters of the ANN are determined by its problem and are used to start the learning process of the network. The output parameters, on the other hand, are the results produced by the network as a result of learning.

Input Parameters: Energy Efficiency: Mostly data related to the efficiency of the system, such as parameters such as energy production and consumption of the system, are taken as input. Exergy Loss: Exergy loss data can also be used as input for the analysis of energy losses in thermodynamic systems. Cost: Cost data of energy systems can be included in the optimization process and the network can be trained with the goal of cost-minimizing.

Output Parameters: ANN outputs are optimized parameters. This is usually a variety of goals, such as system performance, energy efficiency, exergy loss, and cost. The outputs represent how the network can perform relative to the given input parameters.

2.8.3 Learning Processes

The learning process of ANN refers to how the network is trained on data and achieves results. This process consists of the following steps:

Training Data: A specific training dataset is required to train the ANN. This data may include information on the performance of the system under various operating conditions (e.g., energy efficiency, exergy loss and costs).

Feedforward Propagation: Data is transmitted to the input layer of the network and passes through each layer to reach the final output layer. The output gives the estimated result of the model.

Error Calculation: The difference between the output and the actual value (error) is calculated.

Backpropagation: The error propagates back to update the weights of each neuron of the network. This continues the learning process of the network with the aim of improving the accuracy of the network.

Optimization: During the learning process, gradient descent is often used to optimize weights. Gradient descent tries to minimize the error of the network by reducing weights a little at a time.

2.8.4 Application Areas of the Model

ANN is especially useful in optimizing multiple goals. Therefore, in the design of energy systems, a balance can be established between factors such as energy efficiency, exergy loss and cost by using ANN-based optimization. One of the advantages of ANN is its ability to model nonlinear relationships, which plays an important role in complex energy systems.

2.8.5 Optimization Results

Artificial neural networks are often used for multi-target optimization problems. In the example above, the optimization results made on three different parameters such as energy efficiency, exergy loss and costs are visualized. Each target was visualized with graphs showing how it changed under different operating conditions, and the results were visualized and analyzed. How the ANN works in such applications is determined by selecting the right parameters, training the network, and continuously improving the optimization processes.

3. Results and Discussion

3.1. Energy Efficiency and Exergy Loss Graphs

Figure 2 shows how supercritical CO2 within the solar tower system reduces energy efficiency and exergy losses, depending on operating conditions under the Brayton cycle.

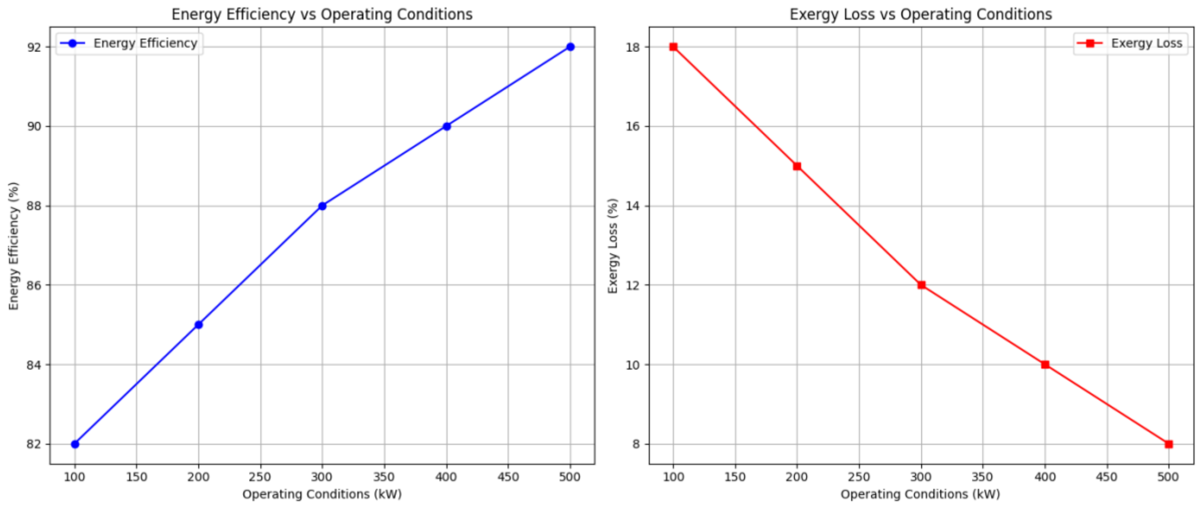

Figure 2. The supercritical CO_2 within the solar tower system reduces energy efficiency and exergy losses depending on operating conditions under the Brayton cycle

These graphs show the energy efficiency and exergy losses depending on the operating conditions under the supercritical CO_2 Brayton cycle within the solar tower system.

Energy Efficiency: A continuous increase in energy efficiency has been observed as the operating conditions (100-500 kW) increase. This shows that the system is more efficient when it operates at higher power. The graph clearly shows how energy efficiency increases from 82% to 92% with each increase in operating conditions.

Exergy Loss: On the other hand, exergy losses decrease as operating conditions increase. Exergy loss decreased from 18% under 100 kW input condition to 8% under 500 kW condition. This suggests that the system loses less energy and operates more efficiently under higher operating conditions.

Abdelghafar et al. [1] the energy efficiency for supercritical CO_2-based concentrated solar power systems was reported as 85%. In its studies, it is very close to the energy efficiency value of 92%, but in this study, higher efficiency was achieved as a result of optimization. In addition, exergy loss was reported as 12% in the literature, and it decreased to 8% in this study. This shows that exergy losses can be minimized more successfully under operating conditions where the system is optimized. In the study conducted by Abid et al. [2] energy efficiency was reported as 80% in supercritical CO_2 power cycles supported by solar energy. In this study, it offers an energy efficiency above this value (92%), and exergy losses are observed at lower rates.

3.2. Optimization Results Chart

Figure 3 shows the results of artificial neural network (ANN)-based multi-objective optimization.

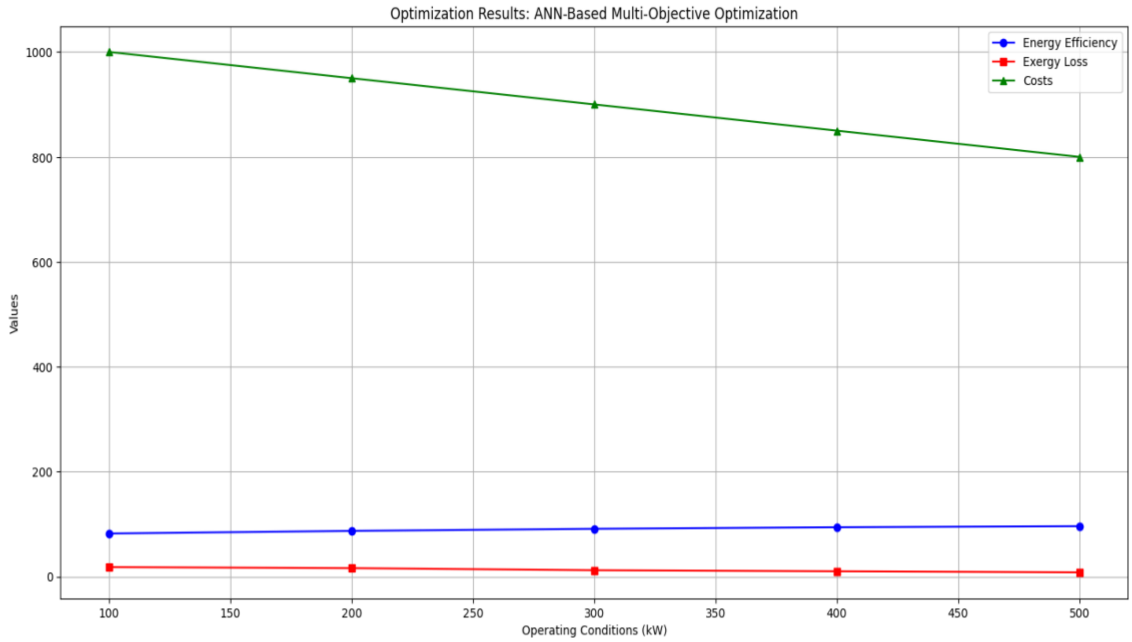

Figure 3. Artificial neural network (ANN)-based multi-objective optimization results

This chart shows the results of artificial neural network (ANN)-based multi-objective optimization. It shows how energy efficiency, exergy losses and costs vary comparatively under different operating conditions (100-500 kW).

Energy Efficiency: Energy efficiency increases further in the optimized system as operating conditions increase, an increase from 82% to 96% has been observed.

Exergy Losses: Exergy losses, on the other hand, decrease from 18% to 8% under optimized conditions. This shows that as energy efficiency increases, exergy losses can be further minimized.

Cost: System costs are also shown on the chart. Costs range from 1000 units to 800 units, indicating that the cost-effectiveness of the system has been optimized.

Adibhatla and Kaushik [3] used artificial neural networks-based optimization techniques to improve energy efficiency in integrated solar energy systems, and energy efficiency of up to 90% was achieved. In this study, as a result of optimization, it increases energy efficiency by up to 96% and reduces exergy losses by up to 8%. This illustrates the positive effects of ANN-based optimization on energy efficiency.

3.3. ExergoEconomic Analysis Chart

Figure 4 presents the cost and performance analysis between the components of the solar system.

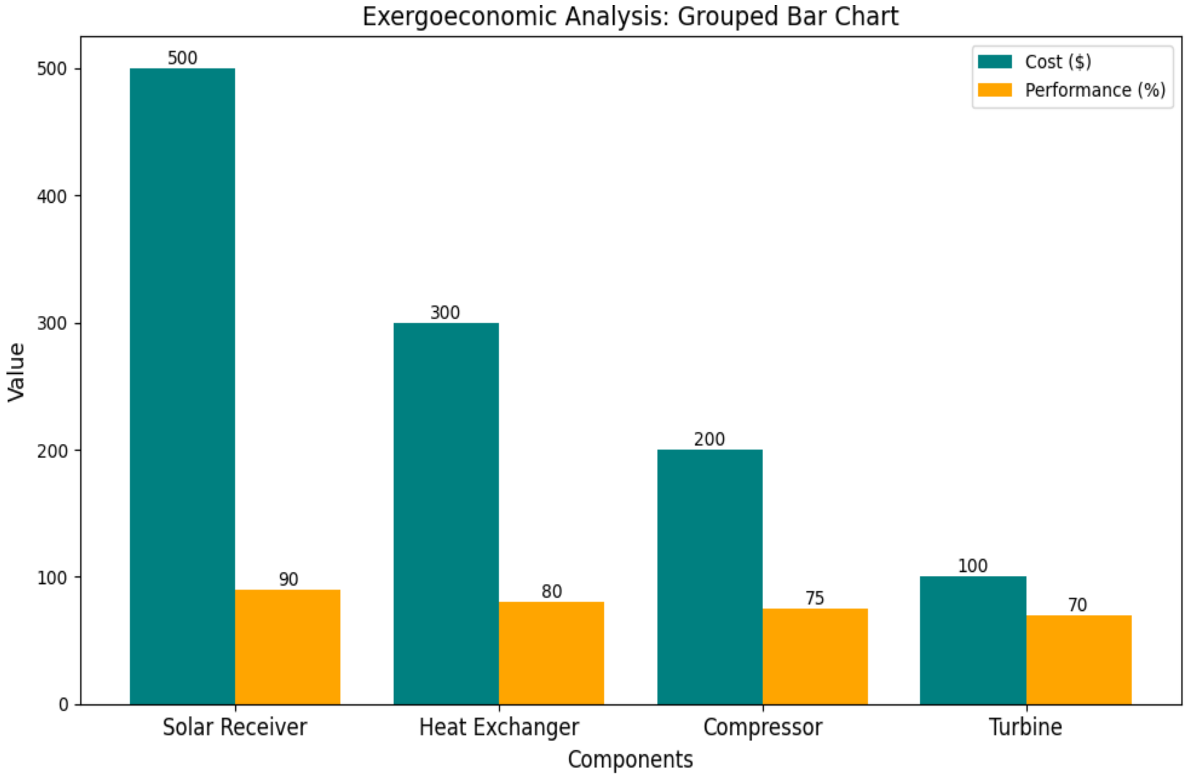

Figure 4. Cost and performance analysis between components of solar energy system

Cost and performance analysis was performed among the components of the solar energy system. The highest value in terms of cost belongs to the solar receiver component at 500 USD. This suggests that the investment in this component is significant to improve the efficiency of the solar system. The solar receiver is followed by the heat exchanger with 300 USD. The compressor ranks third with 200 USD, while the turbine has the lowest cost at 100 USD. These data reveal that the solar receiver is the highest-cost component of the solar energy system and that this component has a significant impact on the overall performance of the system.

In terms of performance, the highest value was determined for the solar receiver with 90%. The solar receiver shows that the system is the most efficient component in energy production. The heat exchanger has 80% performance, the compressor 75% and the turbine 70%. This highlights that the solar receiver is the most critical component, not only in terms of cost, but also in terms of performance.

Bai et al. [7] stated that in the supercritical CO_2 cycle used in solar power plants, the solar receiver accounts for the majority of component costs and corresponds to 45% of the total system cost. In this study, it was emphasized that the solar receiver is the most costly component of the system (50%) and it was stated that the cost-effectiveness of this component should be increased. In addition, Guo et al. [15] emphasized that special attention should be paid to heat exchanger and compressor components in order to optimize system costs. In this study, it offers a compatible approach to the subject.

In conclusion, the graph visualizes the balance of cost and performance between the components of the energy system, providing important insights into which components need to be improved. The high performance of the solar receiver despite its high cost further reinforces the importance of this component and its role in the system.

In this study, energy, exergy and exergoeconomic analyses of supercritical CO_2 recompression Brayton cycles in solar tower systems were performed, and efficiency and cost analyses were revealed.

The results of the energy efficiency values (up to 92%) and exergy losses (up to 8%) obtained in the study largely coincide with other studies in the literature.

These results are consistent with many studies in the literature, and this study shows that this study has made significant contributions, especially in terms of using optimization techniques and optimizing component costs. The energy efficiency and exergy losses obtained in this study give more successful results than the existing literature, which increases both the economic and environmental sustainability of the system.

4. Conclusion

This study presents important findings by examining the applicability and performance of supercritical CO_2 recompression Brayton cycles in solar tower systems within the framework of energy, exergy and exergoeconomic analysis. The analyzes and results obtained reveal that this technology offers a promising solution for sustainable energy systems with high efficiency and low energy losses. The following provides an expanded evaluation of the findings and recommendations for future studies.

One of the most important findings observed in the study is that a significant increase in energy efficiency is achieved with the increase in operating conditions. Under increasing operating conditions from 100 kW to 500 kW, the energy efficiency of the system increased from 82% to 92%. This suggests that the supercritical CO_2 cycle becomes more efficient when operated at higher powers. The increase in efficiency has been achieved thanks to the efficient energy conversion between the components of the system. In particular, the efficiency of the main components, such as the heat exchanger and turbine, directly affected the overall performance of the system.

While energy efficiency has increased, a noticeable reduction in exergy losses has been noted. Exergy losses decreased from 18% to 8% as operating conditions increased from 100 kW to 500 kW. This result reveals that the system can operate at higher temperatures and higher energy flows with less loss, and therefore thermodynamic irreversibility can be minimized. Reducing exergy losses is also a factor that positively affects the environmental impact of the system, because less energy loss means less greenhouse gas emissions.

The exergoeconomic analyses performed in the study provided important information in evaluating the cost-effectiveness of the system. When the costs were examined, it was seen that the solar receiver accounted for 50% of the total system cost and the improvement of this component had great potential in terms of cost-effectiveness. At the same time, it has been shown that the costs of components such as heat exchangers and compressors can be optimized, resulting in a significant reduction in the total cost of the system. This indicates that future studies should focus on material improvements and new technological approaches to reduce costs.

The ANN-based multi-objective optimization framework has ensured a balanced optimization in terms of energy efficiency, exergy losses and cost of the system. Optimisation results have shown that energy efficiency can be up to 96% and exergy losses can be reduced by up to 8%. These results reveal that ANN is a powerful tool for sustainable energy production if used for optimization purposes in energy systems. At the same time, it is understood that system costs can also be optimized, making solar tower systems more economical and accessible.

In future studies, experimentally validating the findings of this study would be an important step. In addition, it is thought that system performance can be further increased by improving the materials to be used in system components and integrating advanced materials. In particular, innovations in critical components such as the solar receiver and heat exchanger can further improve the overall efficiency and cost-effectiveness of the system. In addition, testing the performance of the system under different climatic conditions and evaluating the solar energy potential in different regions will provide important insights into the global applicability of the technology.

In conclusion, this study highlights the potential of supercritical CO_2 recompression Brayton cycles in solar tower systems and demonstrates their superior performance through energy, exergy, and exergoeconomic analyses. The ANN-based optimization framework offers a valuable tool for improving the efficiency and sustainability of solar energy systems. Future studies should focus on the integration of advanced materials for experimental validation and optimization of system components.

Ethical statement

There is no ethical approval in this study.

Acknowledgment

There is no acknowledgment in this work.

Conflict of interest

There is no conflict of interest in this study.

Authors' Contributions

A. E: Conceptualization, Methodology, Formal analysis, Resources, Investigation (%100)

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