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# On the optimization of energy systems: Results utilization in the design process



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#### HIGHLIGHTS

- To propose a new method to show the significant of the optimization results and utilization.
- To perform the parametric study of the system.
- To apply a multi-objective optimization based on genetic algorithm.
- To demonstrated the optimum design correlations for all design parameters.

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# G R A P H I C A L A B S T R A C T



# ABSTRACT

This paper proposes a new methodology to provide a flexible optimum design tool for the multi-objective optimization of energy systems. There are many articles published on the optimization of energy systems, which use a multi-objective evolutionary algorithm for different cases. However a general method for optimization results utilization in design process is not presented to the authors' knowledge and usually equilibrium point concept is used to select the optimal solution. Here a new method is proposed to improve the optimization results utilization in the design process. This method is applied on a simple energy system to consider the correlations between the design parameter and objective functions. The proposed method is flexible and easy to implement in any design problem. Results provide a neat process of optimum design includes cost limited maximum efficiency and components parameters selection like the condenser pressure and sub cool and superheat degrees. Results also show that compressor efficiency is the most powerful parameter in the case, which has the most significance effects on the optimization results.

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### 1. Introduction

As one of the main crucial items in our daily life is the depletion of non-renewable energy, people's awareness about environmental pollution has increased. Technology policies are one of the options available for the reduction of carbon emissions and the usage of energy [1,2]. Most utility systems in current industrial plants are fossil fuel-fired systems. In fact, fossil fuel resources deplete day by day, and they will finish soon [3]. The fluctuations of the oil

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http://dx.doi.org/10.1016/j.apenergy.2016.06.095 0306-2619/© 2016 Elsevier Ltd. All rights reserved. price affect the economy of most countries. Indeed, environmental problems created by the increasing rate of fossil fuel utilization threaten the very life of humankind. Therefore, utilizing energy in an effective way and improving energy systems should be prioritized [4,5]. Since 1960s and 1970s energy resource crises and the environmental impacts of human activities have attracted strong attention. Energy resources in the market are becoming fewer and fetching higher prices as globalization progresses. This is due to several reasons, such as the growth in the global economy, the depletion of energy resources and the environmental impacts of energy production [6–8]. Besides efficiencies, the economic issue is also important in the evaluation of energy technologies, energy conversion devices and the costs of energy systems. Some



Nomenclature			
1, 2, 3, <b>Ex</b> <sub>7</sub> h T	states of working fluid exergy flow rate (J kg <sup>-1</sup> ) specific enthalpy (J kg <sup>-1</sup> ) temperature (K) encertaine under (L kg <sup>-1</sup> )	Δ ξ Subscripts	rate of change effectiveness
W P Z Q	pressure (kPa) cost (\$) heat (kW)	ex sup eV co is	exergy superheat evaporator condenser isentropic
Greek lette <b>η</b>	efficiency (%)	com	compressor

researchers [9–11] have suggested several methods to show that costs are better shared among outputs based on energy. Therefore, industries are encouraged to revise their technologies and use more green options (such as utilization of renewable and sustainable energy and alternative fuel) [12] and also highly efficient cycles with lower cost. One of the main ways to revise and improve current energy systems is the optimization of the systems and the utilization of the optimum variable in a new plan or the revision of the current variable. Optimization finds the most suitable value for a function within a given domain. On the other side, multiobjective optimization means optimizing several objectives simultaneously, with various numbers of inequality or equality constraints. Recently powerful computers are equipped with several methods which can do the optimization. To carry out an optimization, some elements of optimization formulation need to be explained. These elements include system boundaries, optimization criteria, variables, and mathematical model. Therefore, to optimize the efficiency and cost effectiveness and lessen the environmental impact of such plants, it is important to determine the locations, types and magnitudes of true inefficiencies (irreversibilities) [13–17]. To improve the application efficiency, various energy systems are studied. In this regard, there have been various studies on optimization, which have mainly been associated with cogeneration heat and power (CHP), gas turbines, steam turbines, combined cycle power plants and so on [18-21]. In most of these studies, the scientists have tried to improve the energy systems from different aspects, such as efficiency, the economy and the environmental footprint [22–25]. But a clear link between the optimization results is not proposed to the best of authors' knowledge. Hence, a new methodology to provide a scientific approach for using results in the design procedure is extremely important.

Hua and Cho [26] proposed a large number of deterministic and stochastic optimization models to study a combined cooling, heating and power (CCHP) system. They optimize a CCHP with multiple objectives, such as primary energy consumption and minimizing the operational cost and carbon dioxide emissions, considering the reliability of the CCHP operation strategy for different climate conditions based on operational cost. Results show how the incentive values for primary energy consumption and carbon dioxide emissions reduction can be effectively determined using the proposed model for different climate locations. Mohamed et al. [27] investigate the economic viability of small-scale, multigeneration systems including combined cooling, heating and power and combined heat and power along with conventional heating and cooling systems. Results determined the cost optimal solutions for a net zero-energy office building with minimum life-cycle costs by using photovoltaic panel system yields. Ganjeh Kaviri et al. [23] optimized a combined cycle power plant with three main objective functions. To assess the effect of each design parameter on the objective functions, a parametric study and a sensitivity analysis were conducted and discussed in detail. The output optimum results were compared to the basic operation data. The results show that the optimum emission-cost frontier trend matches with the emission-efficiency trend. Comparing the plant operating data and the optimized data shows that the heat recovery steam generator and the duct burner are more sensitive to the optimization and that this is mainly due to the lower cost per improvement. In addition, by using the optimum values, exergy efficiency was increased to around 6% while CO<sub>2</sub> emission was reduced by 5.63%. The variation in the cost was less than a percent due the fact that a cost constraint was implemented. Suresh et al. [28] performed an analysis of advanced power plants on the basis of high ash coal. They suggested the best power plant configuration based energy, exergy and environmental analysis for a coal based thermal power plant in India. They also estimated the environmental impact of the power plant in terms of  $CO_2$ ,  $SO_x$ and NO<sub>x</sub> emissions. Results showed that, by using high ash Indian coal under Indian climatic conditions, the maximum possible plant energy efficiency is about 42.3%. Braslavsky et al. [29] investigated the optimal options for distributed energy resource technologies to reduce greenhouse gas emissions in a shopping center. They indicated the carbon reduction of the shopping center by applying a multi-optimization method using the distributed energy resources customer adoption model (DER-CAM) tool. They showed, by investigating a combined cooling, heat and power technology, the annual energy costs and carbon dioxide-equivalent emissions reduced by 8.5% and 29.6% respectively. Ehyaei and Mozafari [30] analyzed the optimization of a micro gas turbine by exergy and economic and environmental analysis employed for combined heat and power production. They optimized a system by using energy, economics and environmental analysis to meet the electrical, heating and cooling loads of a building. They indicated that the initial investment is a considerable portion of the electricity cost. Results also showed that, for an annual interest rate of 10%, the portion ranges between 31% and 40% depending on system design configurations and that lower interest rates resulted in the smaller portions. Sanaye and Hajabdollah [31] presented the thermal modeling and optimal design of compact heat exchangers. They selected six design parameters and applied multi-objective optimization to obtain the maximum effectiveness and the minimum total annual cost.

In the mentioned previous studies, multi objective optimization is used to find the optimum point. Not a general method for obtaining optimum point has been presented up to now. In addition there is no a flexible approach in which design point variations due to cost and other limitations easily implemented without further optimization run to obtain the desired single optimum point. Another issue is when components with calculated parameters for optimum point are not available. So, the provided optimization approaches are not general, flexible or suitable for real design problems. This issue is addressed in this article and a flexible optimization approach is proposed. In this approach, all data in Pareto frontier are considered optimum solutions and used to correlate the design parameters to an optimum objective function.

To summarize and highlight the main points in this article, the following sub-objectives are undertaken.

- A new method of optimization results utilization is provided.
- A set of correlations between design parameters and objective functions is provided.
- A methodology of obtaining the right correlations is discussed thoroughly. The relationship between a parametric study and its application to investigate the optimization data is presented. How to judge a proper relationship is also presented.
- Finally, an algorithm for the optimum design of the cycle for any cost limit is presented.

This paper tries to fill the gap between the applied design process and theoretical methods. The flexibility of an optimization method is very important in a real design process, and not such a general process has not been proposed before.

#### 2. System configuration and description

To present the methodology, we proposed a simple cycle of a cooling system consisting of a condenser, throttle valve, evaporator and compressor. This system is a vapor compression cycle used for small to medium refrigerators and coolers. The outline of this system is represented in Fig. 1, where the condenser outlet subcool degree and the evaporator degree of the superheat are very important parameters. The outlet temperature is designed to be always lower than the saturation temperature and to provide higher cooling capacity. The superheat degree at the evaporator inlet prevents liquid from entering the gas compressor.

The most important parameters, which govern the thermodynamics of the cycles, are the effectiveness of the evaporator and condenser, the compressor's efficiency, the cycle's pressure ratio, the cycle's cold temperature and the cycle's hot temperature. Evaporator and condenser effectiveness mostly affect the size and cost of heat exchangers. It is always ensured that the evaporator inlet condition is in the two phase region. In this case, the hot temper-



Fig. 1. Simple cycle schematic.

ature is the ambient temperature, and the cold temperature is the temperature of the cold air outflow. In each design process, the cycle's basic design data and parameters are available. The design's basic data are information like ambient temperature, which is fixed during the design process. Design parameters, like cycle pressures and component sizes, are variable controllable values, which the designer can change to achieve design goals. Design goals are very different from cycle to cycle and even in a cycle. In this work, the design goal set was to achieve the lowest possible cost for the highest possible efficiency. To achieve this goal, it is required to have a very flexible optimum design tool, which will be presented in the rest of this paper.

The problem structure of this case is listed in Table 1 where the problem, design goal, design tool, basic design data and design parameters are defined.

The goal of this work is to focus on the approach, so the design problem is simplified. A complete process must include the cycle selection and the working fluid selection as well as other detailed parameters of the cycle, which results in highly complicated example and is not our intent in this work.

The result of this work is useful for those engineers who are dealing with developing and designing energy systems. In a process design, usually cost is the dominant issue. Therefore in many cases, finding the best efficiency at a specified cost limit is the real problem of design.

Design problem is not as straight forward as mentioned. This is usually an iterative process and if common methods of optimization are chosen for any iteration an optimization code should be run which is very time consuming method. This issue is going to be solved here.

# 3. Method general description

As mentioned design process is an iterative approach. If one is looking for an optimized design, with common optimum point selection method, optimization should run for any iteration. Fig. 2 shows the common design and optimization process which includes prototyping. In this algorithm if any change is required, the optimization process should be run again because a single point is selected. This will lead to a time consuming process.

In a general optimization, especially in multi objective optimization, a set of solutions are obtained. In the current approach, it is assumed that this set of solutions as the general optimum solutions. Hence, if optimum solutions are desirable in the change of constraints' variation (like cost limit), we would be able to evaluate the results from this set of solutions and there would be no further requirements for new runs. The proposed algorithm is shown in Fig. 3.

In this approach, optimization results in the first run is used to develop an optimal design model in which all optimum data are correlated to objective functions. Using these correlations, if any change is required during the process, an optimum point can be evaluated with corresponding objective functions. This method is implied on a simple model to show how to construct an optimal design model.

<b>Table 1</b> Problem structure.	
Problem	Design a vapor compression cooling cycle
Design goal	Lowest cost per highest efficiency
Design tool	Flexible design optimizer approach
Basic design data	Hot and cold streams conditions plus ambient condition as well
Design parameters	Components characteristics, degrees of subcool and superheat, cycle pressure ratio



Fig. 2. Common design and optimization progress.

#### 4. Modeling and energy analysis

To optimize a cycle, at first, all of the parameters must be quantitatively correlated with the design goals, which are cost and efficiency here. To provide such a relationship, the cycle modeling must be carried out. So, the design parameters are set to link to the objective functions through the cycle model. In this regard, the design parameters and methodology are explained. The basic design, the design parameters and the energy analysis of the model are summarized in Table 2 for simplicity and ease of access.

The methodology of cycle modeling is briefly explained in a flowchart presented in Fig. 4. Input data includes design data and decision variables which come from genetic algorithm. To model this cycle, one may start with evaporator modeling. Then, throttle valve is modeled and output condition of the throttle valve is evaluated. If output flow is in a single phase region, exergy efficiency and cost function are evaluated using penalty function. Here, an eliminating penalty function is used. Since output flow condition must be met, all design parameters are removed which do not meet this requirement from optimization process Genetic Algorithm (GA) by setting maximum possible value of infinity or "inf" in MATLAB language for objective functions. If outlet is in a two phase region, the cycle modeling progress toward condenser and compressor modeling and then evaluating exergy efficiency and cost functions using provided equations in Table 2.

#### 5. Parametric study

In a parametric study of a cycle, a complete study about how the system performance varies in terms of the objective functions and the effect of each design parameter is conducted. To have a reasonable result, all the design parameters are kept constant with just one design parameter varied. Parametric study is a preliminary and fundamental step before optimization. This step gives a clear vision of the behavior of objective functions (model). By analyzing the parametric study results, possible bugs and the inconsistency of the model can be detected. These data are used to evaluate the optimization results qualitatively.

### 5.1. Effects of the superheat degree on the objective functions

The effects of the superheat degree on the cost and efficiency of the cycle are presented in Fig. 5. By increasing the superheat degree, cycle efficiency and cycle cost both rise, although the effects are very small. The cooling load is fixed, which means a lower mass flow rate is applied to the cycle. Consequently, lower compressor work is needed, which results in better cycle efficiency. To increase the superheat degree, a larger evaporator is needed. Therefore, the total cost is increased due to the larger and more expensive evaporator required.

#### 5.2. Effects of the subcool degree on the objective functions

Fig. 6 shows the effects of the subcool degree on the exergy efficiency and total cost of the cycle. It is observed that, by increasing the subcool degree, the quality at the evaporator inlet increases. This phenomenon results in a higher cooling capacity per mass of working fluid and also in a smaller size evaporator, and the throttle valve cost also reduces. On the other hand, by increasing the evaporator inlet quality, the mass flow rate reduces, which results in higher exergy efficiency and a lower total cost of the system. So, by increasing the subcool degree, the cycle is more optimum due to the exergy efficiency rising while the cost decreases.

#### 5.3. Effects of condenser pressure on the objective functions

Fig. 7 illustrates the effects of condenser pressure on the exergy efficiency and the total cost of the system. It is obvious that the condenser pressure affects the cycle exactly in reverse, in comparison with the subcool degree. By increasing the condenser pressure, the cost of the components, like the condenser and compressor, increase significantly. The higher temperature in the condenser results in a bigger condenser size since the subcool degree is fixed. So, without any significance positive affect on cooling capacity per mass of working fluid in the evaporator, the compressor's work and also the total cost rise. This means that the cycle efficiency falls. So, the condenser pressure must be kept as low as possible for an optimum design.

#### 5.4. Effects of evaporator effectiveness on the objective functions

The effectiveness of the evaporator is another important parameter, which plays a key role in the objective functions. Since all other parameters are fixed and the equations of evaporator and throttle are coupled, the cycle lower pressure is affected by the evaporator effectiveness. The reason is that, when the outlet temperature is fixed, the effectiveness determines the temperature of the evaporator inlet. So, when the effectiveness rises, the inlet temperature rises and the evaporator pressure rises as well. Thus, the compressor's work and the total cost fall. This phenomena causes a lower total cost and higher exergy efficiency. However, due to high effectiveness values, the cost of the evaporator rises sharply, which pushes the total cost upward. The trends of these effects are illustrated in Fig. 8.

# 5.5. Effects of condenser effectiveness on the objective functions

The outlet condition of the condenser is fixed in pressure and temperature, so the cycle's exergy efficiency is not changed with condenser effectiveness variations as presented in Fig. 9. However, the cost of the cycle rises, which is a clear result of an increase in



Fig. 3. Proposed design and optimization approach.

#### Table 2

Design data, parameters and components models.

Basic design data	$T_5 = 30, T_7 = 15, T_8 = 10, Q_c = 3 \text{ kW}$		
Design parameters	P4, $\Delta T_{\text{subschool}}$ , $\Delta T_{\text{superheat}}$ , $\xi_{\text{ev}}$ , $\xi_{\text{co}}$ , $\eta_{\text{com}}$		
Condenser model	$\xi_{co} = \frac{T_4 - T_1}{T_1 - T_5}$	Eq. (1)	
Compressor model	$\eta_{\rm com} = \frac{(h_4 - h_3)_{\rm is}}{(h_4 - h_3)_{\rm real}}$	Eq. (2)	
Evaporator model	$\xi_{eV} = \frac{T_8 - T_7}{T_8 - T_2}$	Eq. (3)	
Throttle valve model	$h_2 = h_1$	Eq. (4)	
Working fluids	Hot stream standard air, cold	stream	
-	air, R113 as working fluid		
Exergy efficiency	$\eta_{\mathrm{ex}} = rac{\mathrm{Ex}_{\mathrm{g}} - \mathrm{Ex}_{\mathrm{7}}}{W_{\mathrm{comp}}}$	Eq. (5)	

effectiveness. Although the effectiveness does not have any direct impacts on efficiency, it has an important indirect role in the cycle. As the outlet temperature of compressor reduces, the condenser effectiveness controls the air outlet temperature. The outlet temperature of the compressor is one of the internal constraints, which prevents physically impossible design outcomes according to the second law of thermodynamics. This parameter also must be considered along with the other constraints in the optimization procedure.

#### 5.6. Effects of compressor efficiency on the objective functions

The most important parameter of the cycle design is the efficiency of the compressor. As shown in Fig. 10, the higher efficiency of the compressor definitely resulted in the higher efficiency of the cycle and an increase in total cost. By increasing the compressor efficiency, less compressor work is needed. Therefore, less fuel must be burnt to produce the same value of net work. This reduction causes less emissions, lower costs and also higher cycle exergy efficiency. The total cost increases due to the higher investment cost of the compressor. Fig. 10 also shows the significance of this parameter in comparison with the other parameters.

#### 5.7. Parametric study remarks

The following significance conclusions from the comprehensive parametric study are drawn.



Fig. 5. Effects of superheat degree on objective functions.

- 1. The superheat degree increases both the cost and efficiency of the plant.
- 2. The subcool degree increases the efficiency and decreases the cost. This effect is positive-positive in the optimization process; thus, the optimum results have the highest possible subcool degree.
- Condenser pressure has negative-negative effects, which means lower efficiency and higher cost. Hence, it is predicted that the optimum results have the lowest possible condenser pressure.
- 4. Evaporator effectiveness has positive-positive effects for almost all cases but at significantly higher value cost. This suggests that the optimum results have high evaporator effectiveness values.



Fig. 6. Effects of subcool degree on the exergy efficiency and total cost.



Fig. 7. Condenser pressure effects on total cost and exergy efficiency.



Fig. 8. Evaporator effectiveness on the total cost and exergy efficiency.

- 5. Condenser effectiveness has negative-negative effects, but, since it is related to constraints, it is not clear how the optimization results behave according to this parameter.
- 6. Compressor efficiency is the most powerful parameter, it is supposed to have a strong effect on the optimization results and it has positive-negative effects.

# 6. Optimization method, objective functions and constraints

The next step is finding the optimization method, which covers two objective functions. A multi objective genetic algorithm is selected to optimize this cycle. A multi-objective problem consists of optimizing (i.e. minimizing or maximizing) several objectives



Fig. 9. Condenser effectiveness on the total cost and exergy efficiency.



Fig. 10. Effects of compressor efficiency on the objective functions.

simultaneously, with a number of inequality or equality constraints. Genetic algorithms are semi-stochastic methods, which are based on an analogy with Darwin's laws of natural selection [32]. In the last three decades, a multi-objective genetic algorithm, called a vector evaluated genetic algorithm (VEGA), was proposed by Schaffer [33]. Srinivas and Deb [34] proposed an algorithm based on non-dominated sorting and called it a non-dominated sorting genetic algorithm (NSGA). Moreover Deb [35-37] proposed the crowding distance metric, which is used when the crowding distance of an individual is the perimeter of the rectangle with its nearest neighbors at diagonally opposite corners. The type of optimizer does not affect the method concept, but, without any doubt, it is a very important step, which depends on the nature of the problem. Therefore, in this work, for model developing and optimization, MATLAB software is used. Objective functions are the overall cost of the cycle, including only the cost  $(Z_{tot})$  and the cycle exergy efficiency ( $\eta_{ex}$ ) components. Limits and upper and lower bonds are selected according to common values. A very important constraint is the throttle valve outflow condition, which must be in the two phase region.

Optimization is carried out using MATLAB build in functions. All the genetic solver parameters except for population size are MATLAB default values. Initial population is set to 250. Lower and upper bounds of variables are shown in Table 4. Decision variable are as mentioned in this table. Parameters from all components are considered in optimization.

#### 7. Results and discussion

In this paper, a multi-objective genetic algorithm is selected for the optimization process. By applying a multi-objective genetic algorithm, a Pareto frontier in two dimensions is obtained. A Pareto frontier is a set of optimum results with various cost-efficiency values. Points with low cost low efficiency and high cost high efficiency are two marginal regions, which are connected with moderated cost-efficiency points. For this reason, in many studies, these points are usually chosen as the optimum points [7,23,37,38]. However, this article tries to obtain a set of optimum design equations, which correlate the parameters of the optimum cycle to the corresponding cost and efficiency and to show how these results may be used for the design process. In the design process, there are many considerations and limitations, like cost or component availability, and one point optimization is not a flexible tool. The real optimum point depends on the procedure of decision making and the changing of parameters.

Fig. 11 shows the Pareto frontier for this optimization problem. In this figure, the optimum results are divided into two data groups: group A and group B. Definitions of these groups are shown in Fig. 12. In this figure the total cost of the optimum designs is plotted versus their respective exergy efficiency. If the main goal is looking for a specific cost, the best efficiency can be found and vice versa. Hence, the optimum results must be divided into two groups to determine a correlation for each group. Plots



Fig. 11. Pareto frontier for the optimization problem (Group A and B).



Fig. 12. Optimization results of superheat degree (group A and group B).

present useful data to understand but are hard to evaluate, therefore a function is fitted to the data and presented in Table 3. This function correlates the total cost to the exergy efficiency of the optimum cycle.

To understand the dependency and extract the optimum design correlations for all design parameters, it is necessary to plot the optimum total cost and exergy efficiency as functions of each parameter. Fig. 12 shows how the optimum results are correlated with the superheat degree. This parameter divided the data or Pareto frontier into two data groups. Group A is the high cost-high efficiency region and group B is low cost-low efficiency region. The difference is that, for group B, the superheat degree tends to be the minimum possible value, which we set as the lower bond in the optimization process, but, in group A, the superheat degree is not the maximum possible value but the highest reasonable value. As the parametric study showed, the increase in the superheat degree resulted in higher efficiency and higher cost. Therefore, the optimization procedure looks for the lowest possible value of the low efficiency points on the Pareto frontier. When optimization looks for higher efficiency points, the optimum results switch to higher superheat degrees but do not switch to the upper bond. The optimization results of the superheat degree in group A show an exact value of 7.5. The resign of this trend is not clear but its dependency on the other parameters and limitations, like the two phase flow constrain at the evaporator inlet and the second law for heat exchangers, are the reason for this behavior.

Fig. 13 indicates the optimum results as a function of condenser pressure. As it is shown in this figure, condenser pressure for all optimum results is considered to be the lowest possible value. This trend can also be inferred from parametric study results, which hold that the condenser pressure has negative-negative effects. Consequently, while the optimization is searching for the optimum point, the lowest possible value of condenser pressure is chosen, which causes the highest exergy efficiency and the lowest total cost.

The parametric study predicted that the subcool degree has a positive direct correlation with both objective functions (exergy efficiency and total cost). This trend is also proved by the optimization results shown in Fig. 14. Since efficiency rises while cost decreases, the optimum point is the point with the highest value of the subcool degree. The optimization results choose the highest possible value of the subcool degree in the design procedure.

For the two previous parameters (condenser pressure and subcool degree) the constraints, which are the lowest and highest

Table 3			
Design correlations	for	various	parameters.

Parameter	Group	Design correlation (as a function of cost)
Group A & B	A B	$6.3335e + 03 + 03 < Z_t$ $5.7456e + 03 < Z_t < 6.3335e + 3$
T <sub>sup</sub>	A B	$T_{sup} = 7.5 \circ C$ $T_{sup} = 1 \circ C$
$\eta_{ m ex}$	А	$\eta_{ex} = \frac{p_1 Z^2 + p_2 Z + p_3}{Z + a_3}$
	В	$\eta_{\text{ex}} = p_1 Z^2 + p_2 Z + p_3$ $p_1 = -0.001153, \ p_2 = 0.008957, \ p_3 = 0.1975 \ Z = \frac{Z_1 - 5970}{172}$
Pc		100 kPa or minimum possible value
T <sub>sub</sub>		10 °C or maximum possible value
ζ <sub>co</sub>	А	$\begin{split} \xi_{\rm co} &= \frac{p_1 Z^2 + p_2 Z + p_3}{Z^2 + q_1 Z + q_2} \\ p_1 &= 0.6911, \ p_2 = 0.8975, \ p_3 = 0.3308, \ q_1 = 1.272, \ q_2 = 0.4684 \\ Z &= \frac{z_1}{100 - 9.301} \end{split}$
	В	$0.6 < \xi_{co} < 0.61$
ζeV	A B	$\begin{array}{l} 0.89 < \xi_{\rm ev} < 0.9 \\ \xi_{\rm ev} = \frac{p_{1}Z^{4} + p_{2}Z^{2} + p_{4}Z^{2} + p_{4}Z^{2} + q_{4}}{p_{1} = -1.03, \ p_{2} = 1657, \ p_{3} = 1230, \ p_{4} = -1035, \ p_{5} = 505.1 \\ q_{1} = 1845, \ q_{2} = 1372, \ q_{3} = -1155, \ q_{4} = 564 \ Z = \frac{Z_{1} - 5970}{172} \end{array}$
$\eta_{\rm com}$	А	$\eta_{\rm com} = \frac{p_1 Z^2 + p_2 Z + p_3}{Z + q_1}$
	В	$p_1 = -0.02543$ , $p_2 = 1.405$ , $p_3 = -10.2$ , $q_1 = -8.303.2 = 2_t$ $\eta_{com} = p_1 Z^2 + p_2 Z + p_3$ $p_1 = -0.002699$ , $p_2 = 0.02766$ , $p_3 = 0.6398$ , $Z = \frac{Z_t - 5970}{172}$ • One may chooses the most economic feasible design for condenser instead of using these correlations

#### Table 4

Lower and upper bounds of design parameters in optimization procedure.

Parameter	$P_{\rm c}~({\rm kPa})$	$T_{\rm sub}$ (°C)	$T_{\sup}$ (°C)	$\eta_{\rm com}$	ζev	$\xi_{co}$
Lower bound	100	1	1	0.6	0.6	0.6
Upper bound	300	10	10	0.9	0.9	0.9

possible values (lower and upper bonds), are chosen, and the results are not different for the group A and group B data. However, for the rest of the parameters (evaporator effectiveness, compressor efficiency and condenser effectiveness) group A and group B must be separated. Fig. 15 shows cost efficiency as a function of evaporator effectiveness. As it was discussed previously and inferred from the parametric study, for both group A and group B, the effectiveness of the evaporator is significantly high and near to the upper bond. However, for group A, the optimum values are higher than 0.89, and the optimum values for group B are from 0.85 to near 0.9. So, two different correlations for two data groups must be used as listed in Table 3. While cost of the evaporator is a function of its effectiveness, group B data has lower effectiveness values.

The parametric study results indicate that compressor efficiency is the most important parameter. Fig. 16 shows how optimum results in both exergy efficiency and total cost terms are correlated strongly in a smooth trend with compressor efficiency. So, compressor efficiency is the most important design parameter in the optimization process. In this figure, two correlations for the two data groups, A and B, are defined. The trends are significantly similar to the parametric study results. The linear characteristic of the efficiency correlation is due to the exergy efficiency definition.



Fig. 13. Optimization results of condenser pressure.



Fig. 14. Optimization results of subcool degree.



Fig. 15. Optimization results of evaporator effectiveness (group A and group B).



Fig. 16. Optimization results of compressor efficiency (group A and group B).



Fig. 17. Optimization results of condenser effectiveness (group A and group B).

The parametric study results suggest that the influence of compressor effectiveness on efficiency is negligible. This parameter does not have a clear correlation with efficiency but does have a higher degree of correlation with cost as expected and shown in Fig. 17. In this figure, two correlations for the two data groups are proposed, but one may conclude that optimum condenser effectiveness at any efficiency is that which is the most economic and makes a feasible heat transfer phenomenon in the condenser.

Table 3 provides all obtained correlations for the design parameters. This table shows that, to design a cycle with a limited cost, at first, the maximum possible efficiency should be estimated. Then, the cost limit of higher or lower values must be adjusted. Afterward, the design process starts by selecting the condenser pressure, subcool degree and superheat degree. Based on what group data we choose (based on the cost criteria), the appropriate correlation should be selected to find the compressor efficiency and evaporator effectiveness. For condenser effectiveness, the correlated function is used, or one may chose the most economic design, which makes the process feasible according to the second law of thermodynamics.

These correlations are obtained the for upper and lower bounds provided in Table 4 and are only valid within the mentioned limits.

#### 8. Conclusion

This paper defined and proposed a methodology to provide a flexible optimum design tool for all optimization processes. In this regard, first a set of optimum results is determined. Then, the optimum results are analyzed in order to show the correlations between the design parameter and objective functions. Finally, the optimum cycle with maximum allowable cost was designed according to the design limits or goals, such as project cost. This method is flexible and easy to implement for any design problems. To summarize and highlight the main points in this article, we should mention:

- An optimum design procedure is proposed.
- The importance and application of a parametric study in the optimization procedure is discussed in detail.
- A new method for analyzing the optimization data is proposed.
- A procedure for how the optimization data can be summarized in design correlations is determined.
- How optimization tools can provide a flexible optimum design tool is shown.

Without any doubt, a complete design process is not presented here, and much more detailed procedures are involved and should be considered. However, the main idea can be implemented in any design procedure with any order of complexity.

In addition in this method we assumed that optimization results are general solutions. The criteria and requirements for such assumptions can be the subject of further studies. In addition all types of constrains and changes are not discussed here. Treatment of different types and constraints needs more research and studies too.

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