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GENETIC ALGORITHM BASED OPTIMIZATION OF RENEWABLE POWER PRODUCTION PROCESS

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ÖMER FARUK KURT

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Genetic Algorithm Based Optimization of A Renewable Power Production Process

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Supervisor

Asst. Prof. Dr. Ayşegül Abuşoğlu

by

Ömer Faruk Kurt

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This is to certify that we have read this thesis and that in our consensus opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master Science.

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I declare that the corresponding thesis is written according to academic and ethical rules, and that all literature information used is included in the corresponding thesis.

Ömer Faruk KURT

ABSTRACT

GENETIC ALGORITHM BASED OPTIMIZATION OF A RENEWABLE POWER PRODUCTION PROCESS

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In this thesis, a genetic algorithm based thermodynamic optimization of biogas-powered cogeneration system which is active in GASKİ WWTP is presented. In this aim, our self-adaptive codes will be developed by using Matlab software. Cogeneration system produces 1000 kW electricity and supplies heat for anaerobic digestion. The objective of optimization is selected as exergy efficiency of the overall system and also exergy efficiencies of other components are optimized. Optimization variables are selected as air-fuel mixture ratio, the pressure of air-fuel mixture at the inlet of the gas engine and temperature of jacket cooling water at the outlet of the gas engine. Optimization is applied by using elitism and roulette wheel, separately. Gas engine exergy efficiency is determined by taking into account only the fuel input and power generation for the first approach, and by taking into account the addition of thermal effects to the first approach for the second approach. Exergy efficiency of the gas engine for 1st and 2nd approaches are found as 23.5% and 45.1% in elitism method and 26.7% and 46.7% in the roulette wheel method. Exergy efficiency of exhaust gas heat exchanger is determined 46.5% in elitism and 43% in roulette wheel. Exergy efficiencies of heat exchanger-1 and heat exchanger-2 are found to be 59% and 56% in elitism and 58.2% and 56.5% in roulette wheel, respectively. Overall exergy efficiency of the system is determined 33.2% in elitism and 33.5% in roulette wheel.

Key words: Thermodynamic optimization, Biogas Engine Powered Cogeneration System, Genetic Algorithm.

ÖZET

BİR YENİLENEBİLİR GÜÇ ÜRETİM SİSTEMİNİN GENETİK ALGORİTMA YÖNTEMİ İLE OPTİMİZASYONU

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Bu tezde Gaziantep Atık Su Arıtma Tesisinde çalışmakta olan biyogaz motorlu bir kojenerasyon sisteminin genetik algoritma temelli termodinamik optimizasyonu sunulmaktadır. Bu amaçla, Matlab programı kullanılarak kendi sistem kodlarımız geliştirilecektir. Kojenerasyon sistemi 1000 kW elektrik üretmekte ve havasız çürütme tankına ısı sağlamaktadır. Optimizasyon amacı olarak sistemin ekserji verimliliği seçilmiş ve sistem bileşenlerinin ekserji verimi optimize edilmiştir. Optimizasyon değişkenleri hava-yakıt karışım oranı, motor girişindeki hava-yakıt karışım basıncı ve motor soğutma suyunun motor çıkış sıcaklığı olarak seçilmiştir. Optimizasyonda elitlik ve rulet çarkı seçilim yöntemleri ayrı ayrı uygulanmıştır. Gaz motoru ekserji verimi, birinci yaklaşım için sadece yakıt girişi ve güç üretimi göz önüne alınarak, ikinci yaklaşım için ise birinci yaklaşıma ısıl etkilerin eklenmesi göz önüne alınarak belirlenmiştir. Gaz motorunun 1. ve 2. yaklaşıma göre ekserji verimleri elitlik yöntemiyle sırasıyla %23.5 ve %45.1 ve rulet çarkı yöntemiyle %26.7 ve %46.7 olarak bulunmuştur. Egzoz gazı ısı değiştiricisi ekserji verimi elitlik yöntemiyle %46.5 ve rulet çarkı yöntemiyle %43 olarak belirlenmiştir. Elitlik yöntemi ile 1 ve 2 numaralı ısı değiştiricilerinin ekserji verimleri sırasıyla %59 ve %56, rulet çarkı yönteminde %58.2 ve %56.5 olarak belirlenmiştir. Sistemin toplam ekserji verimi ise elitlik yöntemi ile %33.2 ve rulet çarkı yöntemiyle %33.5 olarak bulunmuştur.

Anahtar kelimeler: Termodinamik optimizasyon, Biyogaz Motorlu Kojenerasyon Sistemi, Genetik algoritma.

The selection between the man who observed the water level and predicted that it would be drought when he was thrown into the pit, and people who throw off him into the pit, is an important story of human change.

Ömer Faruk Kurt

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LIST OF SYMBOLS / ABBREVIATION

S_i	suitability factor
O	objective value of chromosome
a	crank offset value (m)
S	stroke dimension (m)
B	bore of the cylinder (m)
U_p	average piston speed (m/sec)
N	piston speed (RPM)
N_c	number of cylinder
V_d	distance volume of cylinder (m^3)
V_{BDC}	bottom dead center (m^3)
V_c	minimum cylinder volume (m^3)
r_c	compression ratio
A_p	piston are (m^2)
$\dot{m}$	mass flow rate (kg/sec)
k	rate of specific heats
$\dot{E}x$	exergy rate (kW)
c	specific heat (kj/kg.K)
Q_{HV}	heating value (kj/kg)
R	gas constant ((kj/kg.K))
h	enthalpy (kj/kg)
$\dot{Q}$	rate of heat transfer (kW)
$\dot{W}$	power (kW)

Abbreviations

GA	Genetic Algorithms
ACO	Ant Colony Optimization
NSGA	Non-dominating Sorting Genetic Algorithm
TS	Tabu Search
MOGA	Multi Objective Genetic Algorithm
MOEA	Multi Objective Evolutionary Algorithm
ANN	Artificial Neural Network
ML-MOC	Multi Loops Multi Objectives Controller
WWTP	Waste Water Treatment Plant
BSM	Benchmark Simulation Model
COD	Chemical Oxygen Demand
ORC	Organic Rankine Cycle
AnD	Anaerobic Digestion
CHP	Combined Heat and Power
MBT	Maximum Break Torque
FMEA	Failure Mode and Effect Analysis
HPSO	Hybrid Particle Swarm Optimization
HRSG	Heat Recovery Steam Generator
CCP	Combined cooling and Power
FGA	Fluid Genetic Algorithm
BEPC	Biogas Engine Powered Cogeneration
EGHE	Exhaust Gases Heat Exchanger
HE	Heat Exchanger
LT	Lubricating Tank
LOHE	Lubricating Oil Heat Exchanger
AFMT	Air Fuel Mixing Tank
RPM	Revolution Per Minute

Subscripts

a	air
f	fuel
ge	gas engine
is	isentropic
$comp$	compressor
tur	turbin
opt	optimum
F	fuel
D	destruction
P	product
$rl.whl.$	roulette wheel

Greek Letters

η_m	mechanical efficiency
τ	torque
η_c	combustion efficiency
η_v	volumetric efficiency
α	pressure ratio
β	cutoff ratio
η_v	thermal efficiency
$\mathcal{E}$	exergetic efficiency

CHAPTER 1

INTRODUCTION

Human history is full of desire to be perfect in all behaviors. This fact is always controlled and determined by conscious. There is the same phenomenon in engineering which is important in engineering applications and named optimization. Increasing in the population of people in the early 19 century, inflation of requirement of people and investments of states to the war technology created a huge problem, energy. New energy production methodologies are developed and especially there are huge improvements in renewable energy. Solar energy, hydro energy and also biogas energy is used for production. However, the efficiency of these systems was small and producing of energy is required a huge amount of money and a huge amount of fuel. Because there was an entropy and scientist started to fight with this problem. Also development in physics and thermodynamic created an extra requirement of energy. Eliminating these problems was studied as optimization, and several optimization methods were used such calculus-based optimizations, numerical optimizations, and line optimizations. These developed optimization methodologies were deficient and they had a high probability of finding local optimum point.

Lack of old optimization method caused the discovery of a new optimization method which named Genetic Algorithm, in 1970. John Holand discovered the analogy between numbers and biological elements. This new method changed the development of optimization phenomena and the face of optimization studies focused on genetic algorithm, due to its usefulness for complex systems such, energy, transformation, computer science, physics etc.

Purpose of this study is that develop self-adaptive codes in Matlab software for optimization of biogas engine powered cogeneration system which operated in GASKİ WWTP in Gaziantep city. The reliability of the genetic algorithm is analyzed in this study and also requirements of optimization for energy systems are analyzed. We developed all codes in Matlab by using matrix properties of Matlab.

This study starts with a literature survey about the optimization of energy systems and the development of optimization in genetic algorithm searches in Chapter 2. Description of the genetic algorithm and steps of the algorithm are explained in Chapter 3. Thermodynamic equations and parameters of the system are written in Chapter 4. The conclusion of this thesis is in Chapter 5.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Cost and efficiency of engineering applications, especially energy applications, lead to developing systems according to cost-effective cases or optimum production cases [1]. Because of that, optimization of systems and components, scheduling of systems or distribution of production became a significant point of development.

Instead of classical optimization methods such analytical and numerical optimization, genetic algorithm (GA) optimization method is developed and its ability of usefulness and its property of easy in solving the optimization problems GA is shining at the top of optimization methods. The first idea about GA was mentioned by Holland in 1970. New approaches and different views are produced after decade such ant colony optimization ACO and particle swarm optimization [2]. Recently, non-dominate sorting genetic algorithm (NSGA-I and NSGA-II), tabu search (TS), multi-objective genetic algorithm (MOGA-I and MOGA-II), the multi-objective evolutionary algorithm based on decomposition (MOEA/D) are implemented for most of systems optimization.

Literature survey of this study consists that, optimization of biogas plants and cogeneration systems, or integrate both of them, which based on genetic algorithm and also a different type of GA methods. This chapter occurs from three sub-titles; the genetic algorithm for biogas generation and optimization of biogas power plants, genetic algorithm for cogeneration and other integrated systems' optimization, and self- adaptive software and using MATLAB.

2.2 Genetic Algorithm for Biogas Generation and Optimization of Biogas Power Plants

Life always needs energy for mankind and after nineteenth century this demand inflated significantly. After the energy crisis, saving energy and CO_2 emission had been important [3]. Mankind progressed to use environment materials for eliminating this problem such as wood, water etc. which are able to produce motion for making life easier. Also, biogas production has more reliability to produce electricity [4]. Due to the importance of biogas production, several methods of optimization were implemented and more of them found useful.

Computational solutions have a lot of constraints, for instance, the probability of finding a local optimum point and consuming much more time are two important constraints [2]. However, there is a different approach to optimize systems by using a genetic algorithm, and this section describes the optimization of biogas production systems with/without combined other systems' by using a genetic algorithm approach.

Qdais et al., [5] presented simulation of a biogas plant in Jordan, with Artificial Neural Networks (ANN), that used the connection between information which consist variables of optimization for genetic algorithm (GA). Requirements of ANN utilized from 177 days collected data of plant which included temperature, total solid, total volatile solid and pH of the system. Production of ANN used for implementation of GA due to variables of an objective function. Biogas production increased 6,9% and indicated that using ANN and GA together was useful for optimization of biogas power plants.

Martinez et al., [6] aimed to design a laboratory-scale plant for bio-digestion by using genetic algorithm methodology as a first step and gradient descend algorithm as the second step. Error values and percentages of differences between computational analyzes were discussed.

Kim and Yoo [7] proposed a multi-loops multi-objectives controller (ML-MOC) to decrease the operational cost of the WWTPs, increase the biogas production and improve nitrogen removal efficiency. Single-loop controllers were employed in benchmark model no.2 (BSM2) simulation, then single-loop controllers integratedinto one by MOGA, due to solved multi-objective optimization problems such biogas production and nitrogen removal efficiency. The result showed that using (ML-MOC) increased the nitrogen removal efficiency and biogas production by 3,6% and 3,9%, respectively.

Barik and Murrugan [8] aimed to determine the biogas production from Kajarna or mixed with cattle dung under different anaerobic conditions. Finding the biogas production under different conditions also searched and compared with experimental results. For optimization of the system used integrated ANN and GA method by using MATLAB toolbox and SIMULING 8.0. ANN results mapped the system for optimization selection for GA because of solving multi-objective optimization.

Lee et al., [9] analyzed the combustion of biogas/syngas mixtures with using GA and compared old methods which predicted species and reactions of biogas combustion such Aramco1.3 and 290Rxn mechanisms, versus GA. Simulation of the system implemented with CANTERA that used numerical simulation. Optimal extraction of biogas mixture searched with different methods that used a computational solution of a problem, however, any solutions of them wasn't able to use parallel search except GA. Comparison of these different approaches showed that GA found the optimal mechanism at the 1349th generation and contains 277 reactions and 71 species instead of 2067 reactions and 325 species which found by Aramco1.3.

Kana et al., [10] proposed to design and optimization of biogas plant by using an artificial neural network (ANN) and genetic algorithm (GA) methods. Twenty-five biogas fermentations' data was used to train of ANN that produced an objective function for applying of GA. An ANN adapted by using Neuro-solution software with a topology of 5-2-1 and for adaptation of GA, Pro-optimizer software was used. The technique of that study was that author used twenty-five data for learning of ANN and produced an objective function then used it with GA for a solution the optimization problem.

Huang et al., [11] aimed to design and optimize anaerobic digestion which, produce biogas. He used hybrid algorithm approach ANN-GA and also NSGA-II for comparing these two algorithm methods. Objective functions of the optimization were chemical oxygen demand (COD) and biogas flow rate. ANN-GA procedure was applied in MATLAB 7.0. The learning rate of the neural network was selected as 0,01 and the error goal was 0,05 and for GA probabilities of cross-over was 0,3 and mutation rate was 0,09. The results of the comparison between ANN-GA and NSGA-II showed that ANN-GA was more useful and forced method.

Li et al., [12] analyzed the optimization of landfill gas production by using ensemble-based optimization (EnOpt), however, EnOpt cannot solve non-linear constraint optimization problems. A genetic algorithm was used to solve the problem due to do not include any constraints. Results showed that the conjugate gradient method (CGEnOpt) and GA approach for simulation and optimization were more powerful and useful for landfill systems.

Vertaguer et al., [13] presented a new methodology for optimizing AnD co-digestion system by using Ant Colony Optimization that developed from an idea of ants behavior. He aimed to optimize the system with the objective of maximizing biogas generation and ACO algorithm was programmed on Java software and the initial input and constant were given in the article. Two scenarios were tried and scenario 1 found better to implement for biogas production.

Dumont et al., [14] investigated the effects of using waste heat from the biogas power plant by using Organic Rankine Cycle (ORC). Improving different cycles and different type of expanders are the main aim of this work. Thermo-economic optimization of ORC is applied by using GA with respecting technical and thermodynamic constraints.

Yağlı et al., [15] presented to optimize and compare subcritical and supercritical ORC that use exhaust gases of two biogas fueled CHP engines. Influence of turbine inlet temperature and turbine inlet pressure on performance parameters as net power production, mass flow rate, pumps total power consumption, total exergy inlet rate of the evaporator, thermal efficiency, and exergy efficiency are analyzed and performance comparison of the subcritical and supercritical ORC is evaluated. Differences of turbine inlet temperature and pressure in subcritical and supercritical cases are analyzed and compared.

Park et al., [16] analyzed the performance of biogas-fueled spark ignition engine and emission characteristics by using different methods. Analysis of system continued according to optimization of maximum brake torque (MBT) and variables are selected boost pressures, relative air-fuel ratio, spark timing, and biogas composition. After several experiments, under low boost pressure, extra H_2 is transferred into the system for analyzing the emission effect with performance optimization.

2.3 Genetic Algorithm for Cogeneration and Other Integrated Systems' Optimization

Energy generation systems contain more complex components, because of having a lot of variable for optimization systems. Computational analysis of these systems comes more difficult for engineers.

Analysis of more component and also multi-objective optimization function have been easy and useful thank to a genetic algorithm which applied by Holand in 1960 [2]. Efficiency, effectiveness, economic and reduced emission optimization of cogeneration systems could be made by using parallel search technique, also scheduling of systems is possible with using GA.

Lira-Barragan et al., [17] presented to design cogeneration system which contains steam power plant and production of biodiesel with reducing CO_2 emission, in Mexico. Heat and electricity demand of microalgae utilized from a steam power plant. Multi-objective optimization method used to increase the efficiency of a cogeneration system with decreasing of CO_2 emission. Genetic algorithm (GA) optimization used for this system because of the non-linear cogeneration model. MATLAB code was developed for GA optimization. The formulation of the system included IAPWS-IF97 formulation and objective function applied for optimal value. A Pareto front was generated for the entire system. This approach indicated a significantly decreasing of CO_2 emission for two scenarios.

Lee at al., [18] aimed to analyze combined wastewater treatment plant (WWTP) and CHP system based on a thermos-economic and thermos-environmental view with used a type of multi-objective genetic algorithm, named NSGA-II. GA optimization compared with initial optimization method which used the analytical solution, the result showed that economical cost rate improved by 16,9% and environmental cost rate reduced 5,3%.

Mariajayaprakash et al., [19] analyzed a cogeneration system which was integrated to sugar mills, in India, Tamil Nadu. Sugar production systems occurred failures which increase the cost of a component such screw conveyor and drum feeder, so for a solution of these failures, Fuzzy Failure Mode and Effect Analysis (Fuzzy FMEA) applied with genetic algorithm approach, because of constraints of other methods such as FMEA and Taguchi method. Integrated three methods of optimization step for that problem applied; firstly selected parameter by Fuzzy FMEA secondly, for optimization of parameters Taguchi method implemented and finally, genetic algorithm optimization technique applied. A result of optimization showed that difficult and many component systems' optimization required a combined method for the approach to the ideal case.

Alhamad et al., [20] presented to develop a new approach for optimal preventive maintenance of a cogeneration system by using genetic algorithm optimization methodology in terms of maximizing available units of the system. The system contained two stage desalination and generation so optimization implemented for both two stages separately. Steps of GA explained and different mutation rates used, so maintenance of the two systems found as more as the available number of units. Results showed that the genetic algorithm was a powerful method for using complex systems or problems.

Zidan et al., [21] proposed to find optimal design and micro-grid distributed generation of combined heat and power (CHP) system by using GA methodology. The objective functions of the problem were that minimize the total cost and total gas emission.

Borji et al., [22] aimed firstly to apply thermodynamic simulation of CHP plant which contains a downdraft bed gasifier, solid oxide fuel cell, a micro gas turbine, and a heat recovery steam generator. Then implemented optimization of the plant by using Pareto based multi-objective optimization, with applying of NSGA-II method to increase the cooled gas and CHP efficiencies, and total electrical power. By that method, optimal combinations of the plant found and most applicable of ones selected.

Chang et al., [23] presented a new approach to solving the economization problem of cogeneration system by using hybrid particle swarm optimization (HPSO). Three disturbance mechanism, generating capacity adjustment mechanism and economic dispatch of the system were analyzed.

Amirante and Tamburrano [24] proposed the applicability of small combined cycle for combined heat and power generation and optimization of applying gas to gas heat exchanger. The optimization methodology included following approximations by using modeFRONTIER software and the type of multi-objective genetic algorithms which named MOGA-II.

Shang et al., [25] proposed to design and implement multi-objective optimization, named NSGA-II for improving scheduling of store-integrated combined heat and power system. Electrical energy storage and thermal energy storage were analyzed.

Gimelli et al., [26] aimed to develop the potential of cogeneration system which contained gas engines and the case study was determined Italian hospitals. Classical algorithm and genetic algorithm, MOGA-II, was applied and compared according to total primary saving and simple payback period. Pareto optimal solutions were implemented and results shared in graphs.

Gutierez-Arriaga et al., [27] proposed to use waste heat recovery system through Organic Rankine Cycle (ORC) and This study was occurred from two stages first, heating and cooling application developed by using waste heat recovery and second, optimization of the system implemented by using a genetic algorithm which developed for multi-objective optimization. Sequential modular simulation of ORC is applied by MATLAB for determined values and optimization objective function of a multi-combined system. Then genetic algorithm implemented according to simulation. The result of the study showed that the integration of a waste heat recovery system decreased the total amount of cost, and using genetic algorithm approached the edge of an ideal solution.

Khaljani et al., [28] proposed a new combined generation cycle which integrated gas turbine and ORC through a heat recovery steam generator (HRSG). In that cogeneration system exhaust gases fed the HRSG, that applied at 35 bar, and ORC cycles. Cogeneration system was optimized by considering the environmental and economic impact of the significant parameters such integrated gas turbine and ORC, also type of multi-objective optimization approach which named NSGA-II was used. Exergy efficiency and total cost rate of the process were analyzed as objective functions of NSGA-II. Exergy efficiency increased by 4,8%, total cost decreased from 5460$/h to 4751$/h.

Abdelhady et al., [29] presented to develop an optimization for a cogeneration system that contained solar energy, fossil fuel, and heat, in Jeddah, Saudi Arabia. The main idea of mentioned cogeneration system was that using the energy efficiency and satisfy electricity and heat demand of cities. The first step of optimization problem solution was hierarchical design approach for implementation of steady-state and dynamic calculations, then multi-objective genetic algorithm approach was applied to optimize heating load and was generated power of the plant, at the same time another objective function optimized input variables such temperature, pressure, and flow rate. GA application was provided in MATLAB and design parameters were found from thermodynamic analysis of the system.

Mahmoodabadi et al., [30] proposed a new modification of the CGAM system which provides 30MW electricity, by using a combination of genetic algorithm (GA) and Particle Swarm Optimization (PSO) approaches. Optimization problem based on two objective functions which increasing exergy efficiency and decreasing total cost rate. Pareto optimal fronts of optimization were analyzed and discussed.

Ferreira et al., [31] presented an optimization of micro-gas for cogeneration system by using a genetic algorithm which was coded in Java language. GA optimization based on six variables, objective function that maximization of annual profit from the system and several constraints. Comparison between GA and other types of an algorithm such a free-derivative optimization, SQP, and PS, indicated that GA optimization was a more useful and available method.

Hajabdollahi et al., [32] proposed to design a cogeneration system with air pre-heater and inlet air cooling system and to optimize the system by using a type of multi-objective genetic algorithm that named NSGA-II. Thirteen design parameters for cogeneration were selected and also include recuperated parameters. Optimization method implemented for four plants by using two objective functions, exergy efficiency, and total cost rate. Pareto optimal fronts also analyzed and discussed according to all results which showed that exergy efficiency was improved by 33% and cost rate was improved 36% for a system which just contain air pre-heater, and optimum fin parameters discussed.

Braun et al., [33] aimed to design and optimize combined heat and power (CHP) system with using combining of neural network (NN) and evolutionary computation

(EC) based on genetic algorithm approach. Several NNs were used to design the system and compared with real data for implementation of simulation of an objective function. Optimization contained all component of the system such as engines, intercoolers, steam condenser, boiler, turbine and slurry drying. A multi-objective genetic algorithm optimization methodology was used and the aim of it was that improve fuel demand, produced electricity and useful thermal energy. For NN implementation multilayer perception model was chosen. Different multi-objective methods were analyzed and the result showed that ESPEA algorithm which is a type of genetic algorithm, found useful and the most suitable for optimization of complex systems.

Gonzalez et al., [34] presented to optimize a grid-connected system that contains CHP and hybrid renewable energy system which consisted of photovoltaic, wind and biomass power systems. Multi-objective optimization system based on genetic algorithm was used and aimed to improve life-cycle cost and environmental impact of the system and developed approach tested at the sample location. Two different strategies developed that in winter and in summer days. MATLAB toolbox was used for implementation of genetic algorithm coded. The result indicated that the genetic algorithm approach improved the life-cycle cost significantly and reduced payback time at 9 years.

Khani et al., [35] proposed to optimize the best-combined conditions for cogeneration system which was integrated from a gas turbine (GT) and solid oxide fuel cell (SOFC) without direct interaction. Multi-objective genetic algorithm methodology was used to develop exergy efficiency and economical design of the SOFC-GT system. All component of the system was analyzed and these components combined into two objective functions to improve different combining operation cases. Two objective functions were produced with using EES software because of difficulties of producing an iterative function for the actual case, also MATLAB toolbox was used for multi-objective genetic algorithm approach. Final optimal design indicated that exergy efficiency raised to 55,11% and unit cost of product reduced 170,5$/Gj.

Ghaebi et al., [36] proposed to optimize combined cooling and power (CCP) cycle which integrated from Kalina cycle and ejector refrigeration cycle. He analyzed energy, exergy and exergoeconomic analysis of the system by using EES software then solved single and multi-objective optimization of the system with genetic algorithm methodology. Results showed that the thermal efficiency of the system increased by 4,6% when exergy efficiency was nearly doubled.

Hajabdollahi and Fu [37] aimed to design a cogeneration system which was integrated from SOFC, air pre-heater and inlet air cooling system by using multi-objective optimization system, NSGA-II. Design parameters were special future of all component of the system which was necessary to use in objective functions. Two objective functions were selected, exergy efficiency and total cost rate. Finally, they applied LINMAP method to normalized objective functions according to the Pareto optimal front and shared final optimal values of exergy efficiency and total cost rate 47,12% and 748,1 $/h consequently.

Eveloy et al., [38] presented optimization of multi-component cogeneration system which contained solid oxide fuel cell-gas turbine (SOFC-GT), organic Rankine cycle and seawater reversed osmosis desalination. He used to a multi-objective genetic approach which developed in MATLAB toolbox and based on optimization of exergy efficiency and minimum cost rate. He shared final result that, the net power output of the system developed 2,4 MW, overall exergy efficiency 71,3% and total cost rate 0,0256 USD/s.

2.4 Self Adaptive Software and Using MATLAB

Genetic algorithm (GA), which based on Darwin’s evolution theory, was found reliability for engineering systems. After a decade from discovered of GA, computational methodology changed faster and researches look for a new approach to the genetic algorithm. Several studies focused on natural behavior and found new methodology about GA optimization and the other part of researches aimed to develop the efficiency of optimizer with progress on the subsystem of methodology. Applying of genetic algorithm by using simulation software or Matrix Laboratory (MATLAB) and software for prepared algorithm were mentioned.

Deb et al., [39] proposed a new method that non-dominated sorting genetic algorithm II (NSGA-II) for solving of multi-objective genetic algorithm optimization problems. Nine different problems tested and NSGA-II was found better solver except one.

Comparisons between other MOEA algorithm methodologies and NSGA-II were applied and results showed that the proposed method was a better optimizer for multi-objective problems.

Wichern et al., [40] presented experimental and simulation data from anaerobic digestion which contain grass silage analysis. The system calibrated by manually and genetic algorithm separately. The genetic algorithm was implemented with self-adaptive determination by using MATLAB software and compared with manual calibrated. Results of comparison showed that objective function improved from 34,94% to 28,30% with a genetic algorithm.

Olszewski [41] presented optimization of partially loaded steam multi-turbines by using a genetic algorithm for numerical optimization of a constrained problem (GENOCOP) which is able to optimize the system with inequality constraints and own-developed code used based on C++ for applying GA. Different strategies were formulated that four thermodynamics and one economic. The best strategy selected case C; energy efficiency maximization, however, the difference between these five strategies give other ways to solve problems by multi-objective optimization.

Kazi et al., [42] presented optimization of cogeneration system for reducing the effects of flaring, which used for cancel industrial warning and reduce heat loss from flaring by using it as an energy source. Ethylene plant selected for analyzing. Optimization problem solved by combining Linear Programming, LP, and genetic algorithm, NSGA-II, and MATLAB toolbox was used for the formulation of optimization. The Pareto solution of the system presented as power utility and heat utility graphs.

Rajanna and Saini [43] presented to optimize sizing of the integrated renewable energy system with combining different renewable energy sources such micro-hydro, solar, wind, biomass, and biogas with battery system in Karnataka, India. They used GA methodology for optimization and simulation with using self-adaptive coded in MATLAB toolbox. They focused on three objective functions that optimal size, net present cost, and cost of energy.

Hammache et al., [44] presented a new approach that for solving multi-objective optimization problems, named MOSAHIC which was a self-adaptive mechanism. All steps for this methodology presented and tested it by implemented in CGAM system with three objective functions. Results showed that MOSAHIC could implement for multi-objective and complex systems.

Atia et al., [45] proposed optimization of the solar heating system and biogas plant by using genetic algorithm methodology. GA applied in MATLAB toolbox and input variables were solar irradiance, air temperature, wind speed load demand, solar thermal energy, and auxiliary energy. Two m-file functions written and combined with MATLAB genetic algorithm toolbox. The objective function of that algorithm was the optimal area, so after several generations found 63 m^2 and solar fraction raised 98%.

Katsigiannis et al., [46] presented using of MATLAB toolbox for simulation and optimization of the hybrid power system which was analyzed on a real system which located in Chania, Greece, and focused on minimization of cost of production by using of genetic algorithm and tabu research (TS). Optimization inputs were selected as available components of the system and other parameters such mutation rate, chromosome number etc. was given in the paper. The performance of toolbox was compared with seven scenarios and sensitivity analyses were implemented.

Shariatzadeh et al., [47] aimed to design solar chimney which combined with solid oxide fuel cell and to optimize the cost of electricity by using genetic algorithm approach, in El Paso City in Texas, USA. GA was implemented and coded with MATLAB software by using self-adaptive construction of an algorithm. The optimization program compared with the real case study and results were given as graphs.

Pirkandi et al., [48] improved self-adaptive codes in MATLAB software for optimization of micro-gas turbines which adapted in combined heat and power system with using GA methodology. He selected three inputs for optimization such compressor pressure ratio, turbine inlet temperature, and air mass flow rate and focused on two optimization problems that maximizing exergetic efficiency and net power output. Sensitivity analysis for this system according to genetic algorithm approximation was determined and results showed that exergetic efficiency increased by 3% with GA methodology.

Arora et al., [49] implemented MATLAB to simulate thermodynamic analysis of Brayton cycle with finite time analysis, then multi-objective genetic algorithm optimization approach applied by using NSGA-II and MOEA/D. Design and optimization input parameters such isothermal-side effectiveness, sink-side effectiveness, regenerator-side effectiveness and working medium temperature were selected and for objective functions, power output and thermal efficiency were selected. The final optimal case was selected via TOPSIS, LINMAP, and fuzzy Bellman-Zadeh, Shannon's entropy methodologies and Pareto optimal frontiers were formed. Results of that study were shared by graphs, according to them 15% rate of thermal efficiency was improved.

Manesh and Ameryan [50] presented to design a solar-hybrid cogeneration system that includes the solar tower. They proposed to solve the optimization problem by using a genetic algorithm and cuckoo search (CS) which was occurred from the idea of cuckoo bird behaviors. Objective functions of optimization were selected as exergy efficiency and product cost. Results of GA and CS were compared by using MATLAB toolbox and showed that exergy efficiency decreased by 48% and the reduction of CO_2 was observed.

Meng and Pan [51] aimed to develop a new genetic algorithm method which named Monkey King Evolutionary algorithm, which based on the idea of Monkey King Legend of Chinese culture. Several benchmark functions applied and MKE tested and application for gasoline consumption of vehicle was given. Results of that solution were given in tables and graphs.

Jafari-Marandi and Smith [52] developed a new approach fluid genetic algorithm (FGA) for a genetic algorithm with several differences and approaches. They changed FGA based on the chromosome and population diversity. Results showed that FGA was better for analyzing of wide range problems.

Pedroso et al., [53] presented to develop a multi-objective evolutionary algorithm with differential evolution approximation and that method develops final population by using the migration of some individuals. Steps of the new approach were shared and several experiments and comparisons were applied.

CHAPTER 3

GENETIC ALGORITHM

3.1 Introduction

Development in engineering applications caused several problems for engineers through the previous century, and the optimization problem was the important one. Direct calculus-based optimization methods such as Newton, Fibonacci and Greedy methods, are operated as differential and derivation of function which is the objective of the system. These methods deal with maximum and minimum points of objective, but there were disadvantages of this type of optimization, such calculation of complex systems was consumed huge time and it was easy to stop in the local optimum point for optimization. Numerical methods of optimization, such as dynamic programming, branch-bound and back-tracking, are also weak in finding global optimization [60].

Deficiencies of these methods, which mentioned above, are lead to discover another methodology for search technique. Holand and his colleagues discovered a new way to solve optimization problems, in 1970. This technique is a combination of two fundamental branches of science, mathematics, and biology, and it named Genetic Algorithm [61]. GA is stochastic search technique and it does not deal with a type of problem. So the problem could be natural, physical, psychological etc. because in this method a user only needs fitness function and variables. Objective function could be linear, exponential, trigonometric etc. Due to the parallel search of GA, all possible combinations of objective function could be found and tried [62]. Type of objective function is not important for a genetic algorithm, so it can be discrete, continuous, multimodal etc. because of GA searches in all area of solutions. The difference between GA and other methods is shown in Figure 3.1.

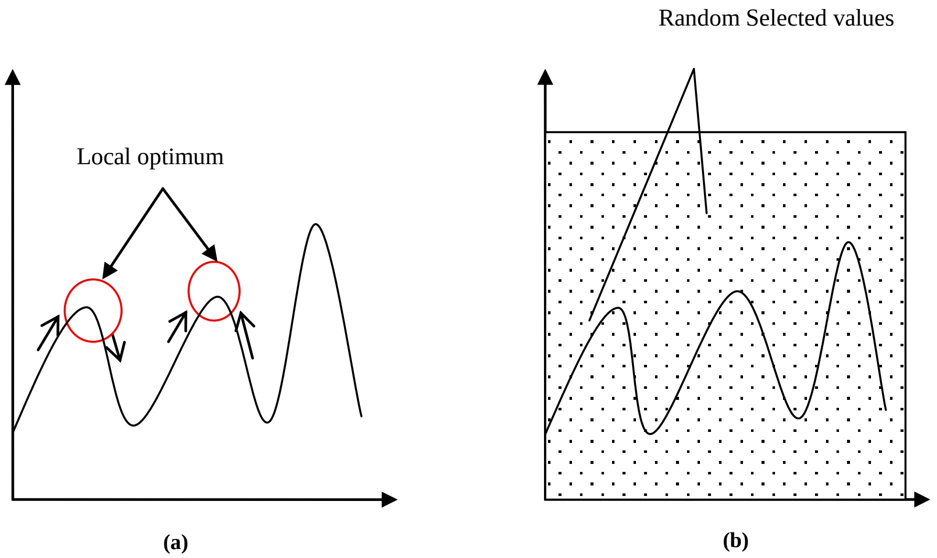


Figure 3.1 Difference between old optimization methods and GA.

In this chapter we will describe genetic algorithm principle, natural selection, and crossover and mutation steps of algorithm.

3.2 Fundamental Elements of Genetic Algorithms

Falling of the rock from hill may be caused the first idea of moving easily when it had seen by mankind. By the way, improving the shape of the rock as a circular is optimization of a wheel, even all vehicles use wheel according to that idea. Transfer of information from one generation to another caused the new development of wheel technology. On the other hand, populations which did not see the moving of rock, may not move fast and they may not reach the water or comfortable places. So, it could be caused disadvantages even being destroyed all population. Similarly, a human cell contains chromosomes and genes which determine the physical and sentimental properties of a person, so unused gene will disappear or it will be passive in a body.

Fundamental of GA comes from the evolution theory of Charles Darwin (1859), which presents the natural selection phenomenon of nature. GA methodology is similar to the evolution theory of nature, so GA used population, mutation and crossover steps of evaluation [60]. Basic flow diagram of GA is shown in Figure 3.2.

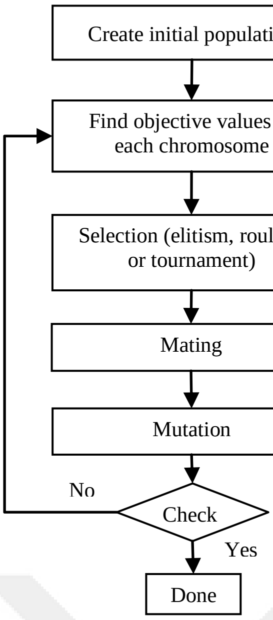


Figure 3.2 Flow diagram of the genetic algorithm.

GA designs objective's results and tries to improve results according to maximum or minimum. According to Figure 3.1, the creation of a new population is a random process and this step is applied for a variation of each chromosome. There are two types of the algorithm in GA, the first one is binary coded and second one is continuous coded GA. Fundamental elements of GA will be explained below in continuous one.

3.2.1 Genes

The smallest unit of GA is the gene, and each gene represents the variables in an objective function similar to the human body. Changing in genes caused all changing in results, so all variations in optimization are operated on genes. Schematic view of the gene is shown in Figure 3.3.

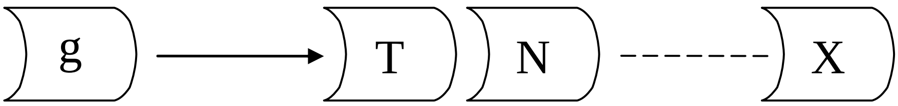


Figure 3.3 Schematic explanation of genes.

Genes could be any variable in the objective function, such as temperature, pressure, distance, and mass etc. and each individual gene is created as randomly according to constraints [2].

3.2.2 Chromosome

Combination of genes in the objective function creates a chromosome, that each result is produced by chromosome as shown in Figure 3.4. By the way, in the first generation, all chromosomes are created randomly. Evaluation of objective functions is applied by using chromosomes. In GA, chromosomes are commonly named parents of new generations [2].

Using a chromosome as a component of GA is the result of the idea of using programming easily. Because user could move some part of a chromosome or part of the population in another step, it is a useful effect for an algorithm, due to the decreasing number of indices.

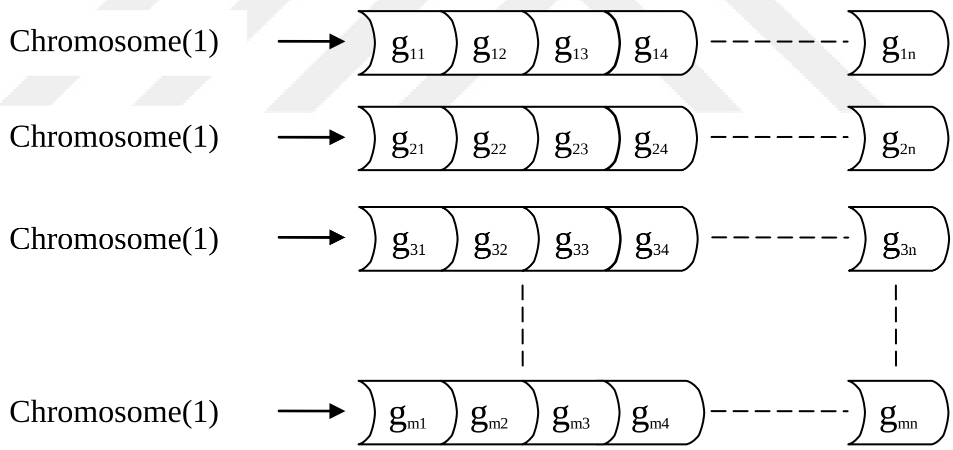


Figure 3.4 Schematic view of chromosomes in population.

3.2.3 Population

Population phenomenon of the GA determines the variety of objective function according to randomly created genes, as shown in Figure 3.5. Chromosomes produce the population or chromosome pool for selecting operation and also mutation step.

Control of population size lead the idea of natural selection, and at the end of all iterations, the size of the population must be conserved [2].

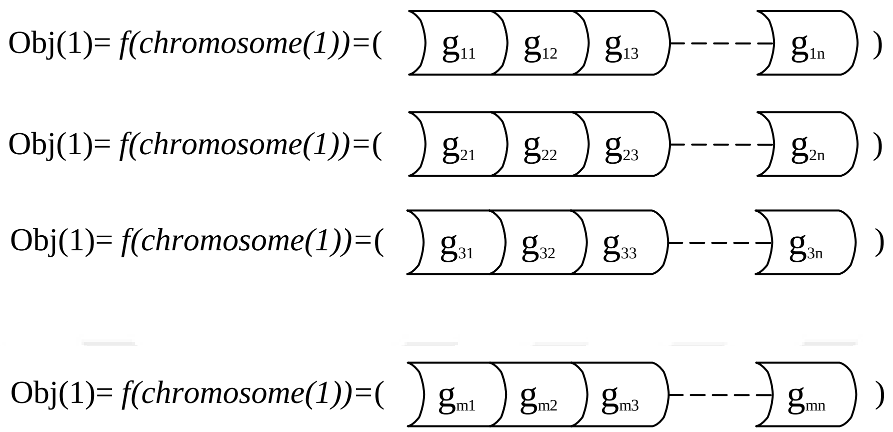


Figure 3.5 Representation of population in GA.

3.3 Selection

Next step after the creation of population is finding objective values of each chromosome according to Figure 3.1, but it is common in all optimization systems that inserting numerical values into the objective function, so it is not required to mention in a new section. In addition, explanation of finding objective values of each chromosome is shown in Figure 3.5.

Selection step is followed the finding objective values of each chromosome and in this step separation of objective values is operated to the chromosomes. We know that the age of population or age of any living changes with the adaptation of nature. For instance, when a ship is sinking the people which do not know to swim or fly will die, due to selection law of nature. Natural events always set parameters according to selection's law, such birds had changed their altitude according to finding the probability of food in the surface of the earth, and some birds changed their speed for escaping from other hunter birds [62].

Selection is the main step in GA and the most important variation is produced in here. In GA, there are several selection methods, but in this section, we will explain four types of selection.

3.3.1 Elitism Selection

Elitism is the simplest method of selection that the best chromosomes selects and transfers to the new population before crossover. In this step, finding the best objectives is applied by using the suitability factor of each chromosome, as:

$$S_i = \frac{O_i}{\sum_1^n O_i} \tag{3.1}$$

Objective value of the ith chromosome is notated O_i and S_i is the suitability factor of the ith chromosome. Suitability factor is also the density of chromosome in objective pool and probability of selection of chromosome. In elitism method, half of population is selected according to suitability factor and remains chromosomes are destroyed [2].

Table 3.1 Basic elitism selection method for GA.

Chromosomes	Objective results, O_i	Suitability/Probability, S_i
Chromosome-1	2,5	0.125
Chromosome-2	7	0.35
Chromosome-3	4	0.2
Chromosome-4	6.5	0.325
$\sum_1^n O_i$	20	1

Objective function sometimes could be as finding the minimum point of the state, for instance, cost, pollution etc. In the case of this kind of objective functions probability values must be reversed, because the probability of selection of small chromosomes must be bigger, however in Table 3.1 maximum point is searched. Last column of Table 3.1 we can observe that chromosome-2 and chromosome-4 must be selected because in this population these two chromosomes are more suitable according to an objective function. The number of members in population is decreased as half of the initial population, due to the law of conservation of population density, in crossover step, the number of members is raised as the original population's density.

3.3.2 Roulette Wheel Selection

Natural selection also uses the information of missing members of the population, because experiences are commonly transferred to the new generation and it improves the different ways of being in life. Similarly, in GA poor chromosomes could be selected for using experiences of it. The roulette wheel is a selection type which using the method of random selection [2]. Explanation of the roulette wheel is shown in Table 3.2.

Table 3.2 Basic roulette wheel selection method.

Chromosomes	Objective results, O_i	Suitability/Probability, S_i	Cumulative Probability
Chromosome-1	2,5	0.125	0.125
Chromosome-2	7	0.35	0.475
Chromosome-3	4	0.2	0.675
Chromosome-4	6.5	0.325	1
$\sum_1^n O_i$	20	1	

Cumulative probability indicates the portion of cake and cake is simulated as a population. Value of randomly selected number is located on the cake, and by following from start to finish at the angular path, the first number which is bigger than random number is selected as a new population member. A random number is selected between 0 and 1, due to probability values are in the same range.

According to Table 3.2, when a random number is between 0-0,125 chromosome-1 will be selected or between 0.675-1 chromosome-4 will be selected. Easily we can say that the bigger range is selected as a new population member.

3.3.3 Random Selection

Random selection is a selection by using a random process. The algorithm creates random integer numbers and these created numbers explain the number of chromosome in population. This method provides diversity but this method is not correct in GA due to finding a global optimum point. Because randomly selected numbers could be caused selection of low probable chromosomes [60].

3.3.4 Rank Selection

Rank selection is a different method of random selection. It is a tournament of two randomly selected chromosomes. In this selection method, there is a selection of constant P. According to Table 3.1, consider randomly selected chromosomes are chromosome-2 and chromosome-4, and randomly selected number, W, is selected as 0.4 [60].

- If W< P, the first chromosome is selected.
- If W>P, the second individual chromosome is selected.

There are many ways for rank selection and the most useful one is explained above. This type of selection is the mixing of elitism and roulette wheel and in a big difference of objective results rank selection could be used.

3.4 Crossover

Reproduction is a critical activity for every living because a transfer of physical and sentimental properties of parents is transferred to the next generation by using crossover chromosomes. First reproduction experiment is applied by Mendel in 1866. He crossed two different peas and produced a new different member. Using this basic reproduction mechanism in algorithm increases the variety of population [60]. Crossover is a big advantage for GA because a user could preview the important parameters and direct the changes by using crossover points.

Selection step is weak in diversity, but the most important objective of GA is producing results in more variety. Crossover is basically the production of new members of the population by using changing genes between two selected chromosomes, which named parent, and each parent produces two new chromosomes [60]. The basic idea of crossover is shown in Figure 3.6. Two types of crossover are used commonly, single point and double point crossover. In single point crossover, a random integer number is selected and genes of the chromosome after that point are cut off and transferred to a new chromosome [11]. In the double point chromosome, two random numbers are selected and genes between these points are transferred to the new chromosome as shown in Figure 3.6 and Figure 3.7.

Crossover rate is used in this process, that shows the rate of crossover of a population, and it is selected between 0.85 and 0.95 [2].

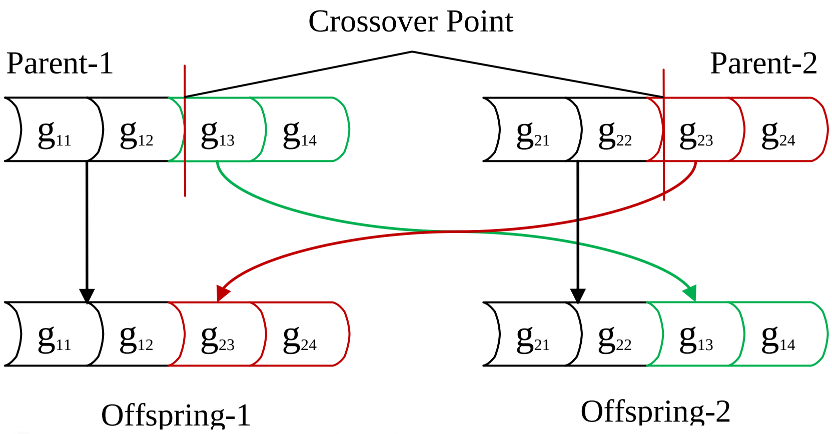


Figure 3.6 Single point crossover in GA.

Parent-1 and Parent-2 are two chromosomes from the population after natural selection. When random numerator selects crossover point as 2, first two genes of parent-1 (g11 and g12) are selected as first two genes of offspring-1 and last two genes of parent-2 (g23 and g24) are selected as last two genes of offspring-1. Also, the same method is applied for offspring-2 that first two genes of parent-2 (g21 and g22) are selected as first two genes of offspring-2 and last two genes of parent-1 (g13 and g14) are selected as last two genes of offspring-2 [62].

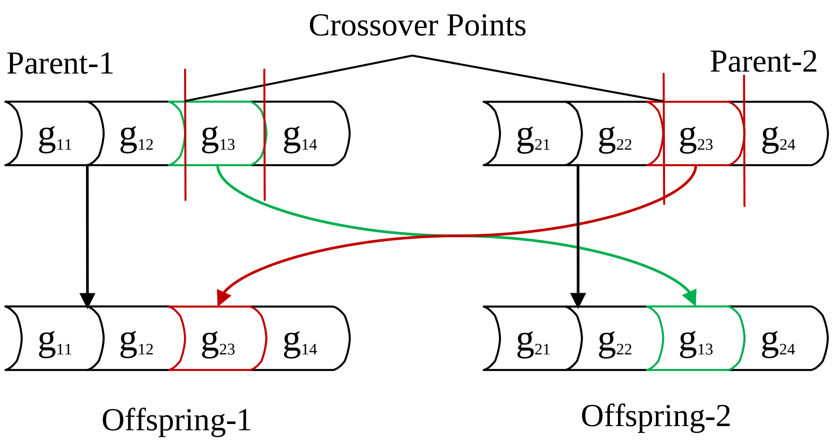


Figure 3.7 Crossover in double point method in GA.

Double point crossover contains two crossover points, and genes between these two points are exchanged for the creation of new members. This method is good for focusing on determined variables in an algorithm. One can control these points and create diversities for important variables.

3.5 Mutation

The final step in providing diversity in genetic algorithms is the process of mutation. The sudden and big change of environmental conditions in nature can lead to mutation and even destruction of species. However, this destruction and mutation could create a new species with different life in nature. Mutation can affect much of a chromosome or it can only affect a shy gene [63].

Mutation process is applied by using random generator in GA, that random matrix, with the size of population matrix, is produced between the range of 0 and 1, and each element of mutation matrix compared with the mutation rate, the element, which smaller than mutation rate, is selected as changeable gene in the population matrix, as shown in Figure 3.8.

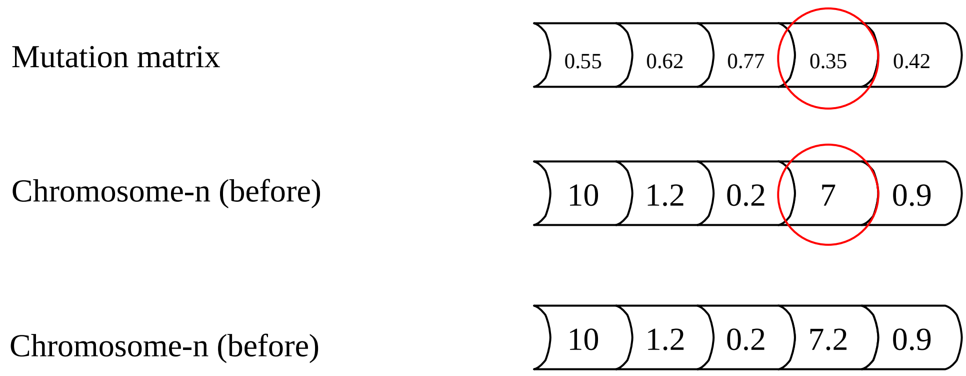


Figure 3.8 Mutation process in the chromosome.

According to Figure 3.8, red circle in mutation matrix shows the value of an element which small than mutation rate, as selected 0.4, and red circle in the chromosome matrix indicates the element which will be changed.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

Optimization of BEPC requires equations that connect each part of system and learning behavior of a system for making true approximations and defining constraints, so by using thermodynamic analysis connection between all parts of the system is achieved. By the way, exergy basis analysis is a more effective methodology to measure useful energy, and efficiencies of all parts of the system could be meaning by using it.

In this section, the analysis which required for optimization will apply and equations will be determined for transfer into the Matlab software. As we know, the most important part of optimization is the selection of variables. By the way, exergy analysis often used in engineering applications due to the simplicity in the selection of variables and clear view in available part of energy [54]. In this part description of the system will be mentioned and exergy relations of all component of BEPC will be explained separately for understanding the importance of each variable. Genetic algorithm of BEPC system, which is the fundamental aim of this study, will be applied by using our self-adaptive codes in Matlab Software and methodology of using genetic algorithm and content of it will be explained. Results of optimization will be shared by using diagrams and for each diagram there will be an analysis of component and variable.

This part contains the description of biogas engine powered cogeneration system and its schematic diagram, thermodynamic analysis of biogas engine and other components, exergy relations of all components, optimization of BEPC, results and discussions.

4.2 Description of Biogas Engine Powered Cogeneration System

Biogas consumption of the system obtains from anaerobic digestion which operating in the GASKİ WWTP and methane rate of biogas is 61% for that system. Electricity production of biogas engine is 1000 kWh and annual energy production is 8.76 GWh. The system contains five heat exchangers, air-fuel mixing tank, lubricating tank, turbocharger, desulphurization unit, generator, and biogas engine. The system includes five fluids such, lubricating oil, water in digestion loop, water in engine cooling loop, water in the air-fuel cooling loop, and air-fuel in engine and turbocharger loops. Schematic view of the system is shown in Figure 4.1.

Biogas composition's sulfur level must be at the legal rate and also it causes corrosion in the cylinder wall [55], because of these reasons biogas pass through desulphurization unit before mixing with air. Air-fuel mixing is transferred to the turbocharger for pressurized before intake in the engine. Turbocharger contains a compressor which powered by a turbine and also turbine obtains energy from engine exhaust gases. Pressurized air-fuel mixing is transferred to the engine but pressurization also raises the temperature of the fluid and high temperature in the entrance of the engine is a disadvantage because high-temperature fluid flames up before time and that problem reduces the engine efficiency. To eliminate that effect intercooler is established as cools the mixing temperature between a turbocharger and engine intake. Air-fuel mixing passes trough intercooler unit and gets into the engine as reduced temperature fuel. Exhaust gases after leaving the turbine to get into the exhaust gas heat exchanger (EGHE) to transfer heat to the water that circulates through the digestion loop.

Engine temperature must be reduced because of flaming beforetime and strength of engine's equipment. Due to that, water circulates in the closed loop through engine jacket and transfers heat to the water which circulates in the digestion cycle according to heat exchanger (HE1) and after that, engine cooling water passes through lubrication oil heat exchanger (LOHE) to reduce the temperature of oil which circulates in closed loop for cooling the engine and lubricate components. Before engine cooling water enters the engine again it enters heat exchanger (HE2) which transfers heat from intercooler fluid to the engine cooling water.

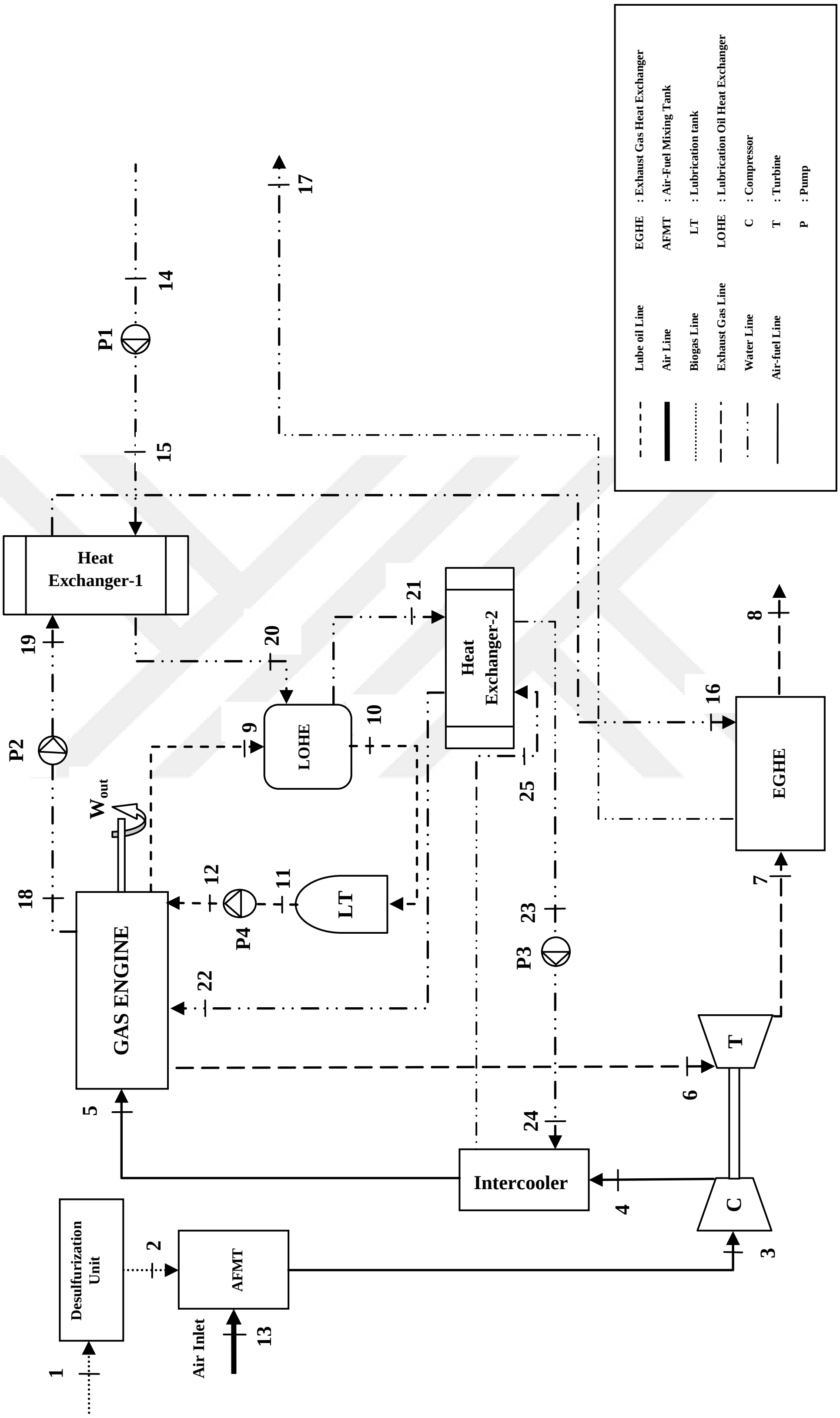


Figure 4.1 Biogas Engine Powered Cogeneration System.

4.3 Gas Engine Operating and Thermodynamic Analysis

4.3.1 Gas Engine Operating and Performance Characteristic

Biogas engine that used in BEPC system is a DEUTZ TCG2020 V12K that is a dual cycle, four stroke and 12 cylinders with V configuration. Dimensions of a gas engine are known as a design data for analysis such the cylinder bore is 170 mm, stroke is 195 mm and the engine speed is 1500 rpm. These given data could help to calculate other performance, characteristic and thermodynamic parameters.

The crank offset value is calculated as:

$$a = S/2 \tag{4.1}$$

Here S is stroke dimension. Average piston speed is also defined as:

$$U_p = 2SN \tag{4.2}$$

Piston speed is notated as N and generally given in RPM (revolutions per minute), U_p in m/sec. The maximum average piston speed for all engines will normally be in the range of 5 to 20 m/sec [56].

Displacement volume is calculated classical volume formulation for one cylinder:

$$V_d = \frac{\pi}{4} B^2 S \tag{4.3}$$

Where B is bore of the cylinder. Engine volume is calculated as multiplying V_d by a number of cylinders N_c is:

$$V_d = \frac{\pi}{4} B^2 S N_c \tag{4.4}$$

Displacement volume means the volume of piston travels from bottom dead center (BDC) to the top dead center (TDC):

$$V_d = V_{BDC} - V_{TDC} \tag{4.5}$$

Minimum cylinder volume that notated by V_c is important for thermodynamic analysis and it is related to distance volume as:

$$V_c = V_{TDC} = V_{BDC} - V_d \tag{4.6}$$

Compression ratio is expressed as:

$$r_c = \frac{V_{BDC}}{V_{TDC}} = \frac{V_c + V_d}{V_c} \tag{4.7}$$

Compression ratio leads to the improvement of engine technology because of its effect on efficiency, so bigger compression ratio causes bigger efficiency [56].

Some relation between work, pressure, and efficiencies will be given and thermodynamic analysis will be written state by state. Firstly, we have a general form of work:

$$W = \int F\,dx = \int P\,A_p dx \tag{4.8}$$

Force (*F*) is converted to work when applied through a distance (*dx*) or pressure (*P*) in the piston with piston area (A_p) will also give work.

$$A_p dx = dV \tag{4.9}$$

So work done can be written:

$$W = \int P\,dV \tag{4.10}$$

Notation of specific work and *w* specific volume *v* by using volume and work per unit mass are given:

$$w = \frac{W}{m}, \qquad v = \frac{V}{m}$$

So specific work done relation is:

$$w = \int P\,dv \tag{4.11}$$

This representation is called indicated work wi, but we know that there is irreversibility in all systems and it reduces indicated work. Work which converted as a shaft work is called break work wb [56]. The relation between indicated and break work is:

$$w_b = w_i - w_t \tag{4.12}$$

Mechanical efficiency is represented as:

$$\eta_m = \frac{w_b}{w_i} \tag{4.13}$$

The pressure in the cylinder is changing during a cycle and we need average pressure or mean effective pressure (mep) that represented as:

$$mep = w/\Delta v \tag{4.14}$$

$$\Delta v = v_{BDC} - v_{TDC} \tag{4.15}$$

Mean effective pressure is an important parameter to compare engine for design. Different type of mean effective pressure can be used by using different work terms [56]. **Break mean effective pressure (bmep)** is defined by using break work and **indicated mean effective pressure (imep)** is defined by using indicated work.

$$bmep = w_b/\Delta v \tag{4.16}$$

$$imep = w_i/\Delta v \tag{4.17}$$

Maximum values of bmep for naturally aspired spark ignition engines (SI) are between 850 to 1050 kPa, for naturally aspired compression ignition (CI) engines are between 700 to 900 kPa and for turbocharger CI engines are between 1000 to 1200 kPa [56].

There is another parameter of work that represents the ability to do work is called Torque τ and its relation with work for a four-stroke engine is represented as [56]:

$$\tau = \frac{W_b}{2\pi} = \frac{(bmep)V_d}{4\pi} \tag{4.18}$$

CI engines generally have greater torque than SI engines and large engines have very large torque values.

Power is also used for comparison and analysis of engine efficiency and both power and work are functions of engine speed.

$$\dot{W} = \frac{WN}{n} \tag{4.19}$$

$$\dot{W} = 2\pi N\tau \tag{4.20}$$

Where n is a number of revolution per cycle and N is the speed of the engine. Engine speed is a characteristic parameter that, increasing engine speed increases the power and also increases the torque or vice versa. However, engine speed must be in the specific range because of friction loses [56].

Hydrocarbon fuel required oxygen for a chemical reaction in the engine and consumption of oxygen must be determined and used in the analysis because of the importance of it. Air-fuel ratio relation (AF) describes as:

$$AF = \frac{m_a}{m_f} = \frac{\dot{m}_a}{\dot{m}_f} \tag{4.21}$$

Engine speed is related with time and engines combustion time is greatly shortened, because of that reason all of the fuel in the combustion chamber doesn't burn and some little of fuel exist with the exhaust flow. The parameter which describes that effect of fuel combustion is called combustion efficiency and notated as η_c. Typically, engines have combustion efficiency in the range of 0.95 to 0.98 [56].

According to the first law of thermodynamics all thermal conversion devices have thermal efficiency as:

$$\eta_t = \dot{W}_{net}/\dot{Q}_{in} \tag{4.22}$$

Heat addition in the system is given as:

$$\dot{Q}_{in} = \dot{m}_f Q_{HV} \eta_c \tag{4.23}$$

Another performance parameter of the engine is volumetric efficiency η_c. Amount of air intake the system means the amount of fuel addition. More oxygen means more fuel. This parameter affects the power output from the system and input energy to the system. Volumetric efficiency expressed as:

$$\eta_v = n\dot{m}_a/\rho_a V_d N \tag{4.24}$$

Where ρ_a is air density evaluated at atmospheric conditions outside the engine.

4.3.2 Thermodynamic Analysis of Gas Engine

Biogas engine that operated in GASKİ WWTP is dual cycle engine. Although the working principle of compression ignition (CI) engine is assumed as at constant pressure, there are several advantages to use this type of engine. Because ignition starts at the late of the compression stroke and big amount of energy is expended without production of pressure. Elimination of this effect in engineering systems is operated as using dual cycle engine. In a dual cycle, combustion occurs in two-step firstly, in a constant volume and secondly in constant pressure. In a dual cycle, combustion starts in the early compression stroke and intake energy is used effectively [56,59]. Typical indicator diagram for the dual cycle is shown in Figure 4.2.

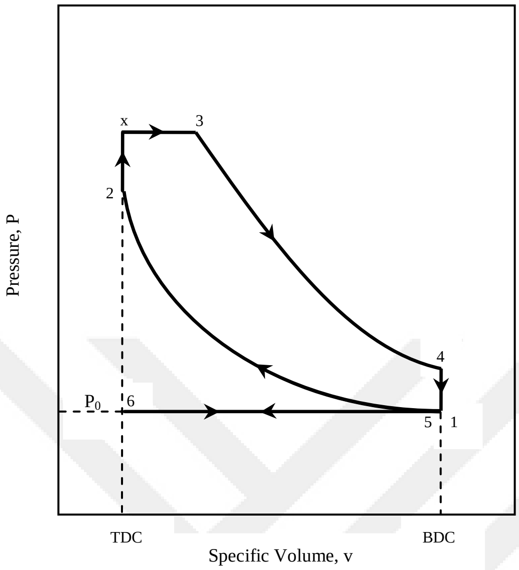


Figure 4.2 Pressure and specific volume diagram of four-stroke dual cycle engine.

All systems before start to be analyzed requires some assumptions and assumptions of this study are:

- All system operates as steady-state case.
- Fuel-air mixing is assumed as air and ideal gas.
- Combustion in gas engine assumed as the whole combustion.
- Kinetic and potential energy in all subsystems are negligible.

The thermodynamic analysis of dual cycle is the same as the diesel cycle except for heat input process. The dual cycle occurs from five processes because process 6-1 and process 5-6 are equal and cancel each othe

Process 1-2: isentropic compression stroke.

All valves closed:

$$T_2 = T_1(r_c)^{k-1} = (V_1/V_2)^{k-1} \tag{4.25}$$

$$P_2 = P_1(r_c)^k = (V_1/V_2)^k \tag{4.26}$$

$$q_{1-2} = 0 \tag{4.27}$$

$$V_2 = V_{TDC} = V_c \tag{4.28}$$

$$w_{1-2} = R(T_2 - T_1)(1 - k) = (u_1 - u_2) \tag{4.29}$$

Process 2-x constant-volume heat input (first part of combustion).

All valves closed:

$$V_x = V_2 = V_{TDC} \tag{4.30}$$

$$w_{2-x} = 0 \tag{4.31}$$

$$q_{2-x} = c_v(T_x - T_2) = (u_x - u_2) \tag{4.32}$$

$$P_x = P_{max} = P_2(\frac{T_x}{T_2}) \tag{4.33}$$

Pressure ratio is a useful parameter for optimization and efficiency of the engine could change by this parameter. We can find the pressure ratio as:

$$\alpha = \frac{P_x}{P_2} = \frac{T_x}{T_2} \tag{4.34}$$

Process x-3 constant pressure heat input (second part of combustion).

$$P_3 = P_x = P_{max} \tag{4.35}$$

$$q_{x-3} = c_p(T_3 - T_x) = (h_3 - h_x) \tag{4.36}$$

$$w_{x-3} = q_{x-3} - (u_3 - u_x) = P_3(v_3 - v_x) \tag{4.37}$$

$$T_3 = T_{max} \tag{4.38}$$

We can define the cutoff ratio for using specific volumes in an analysis:

$$\beta = \frac{v_3}{v_x} = \frac{T_3}{T_x} \tag{4.39}$$

Process 3-4 isentropic expansion stroke

All valves closed:

$$q_{3-4} = 0 \tag{4.40}$$

$$T_4 = T_3(V_3/V_4)^{k-1} = T_3(v_3/v_4)^{k-1} \tag{4.41}$$

$$P_4 = P_3(V_3/V_4)^{k} = P_3(v_3/v_4)^{k-1} \tag{4.42}$$

$$w_{3-4} = R(T_4 - T_3)(1-k) = (u_3 - u_4) \tag{4.43}$$

Process 4-5 constant volume heat rejection (exhaust blowdown)

$$v_1 = v_4 = v_5 = v_{BDC} \tag{4.44}$$

$$w_{4-5} = 0 \tag{4.45}$$

$$q_{4-5} = q_{out} = c_v(T_5 - T_4) \tag{4.46}$$

Heat input of dual cycle engine occurs in two step and generally, it is assumed equal part of the energy.

$$Q_{in} = Q_{2-x} + Q_{x-3} = m_f Q_{HV} \eta_c \tag{4.47}$$

Thermal efficiency of dual cycle:

$$(\eta_t)_{dual} = |w_{net}|/|q_{in}| = 1 - (|q_{out}|/|q_{in}|)$$

$$= 1 - c_v(T_4 - T_1)/[c_v(T_x - T_2) + c_p(T_3 - T_x)]$$

$$= 1 - (T_4 - T_1)/[(T_x - T_2) + k(T_3 - T_x)] \tag{4.48}$$

This term of efficiency can be rearranged according to compression ratio, pressure ratio and cutoff ratio as:

$$(\eta_t)_{dual} = 1 - (1/r_c)^{k-1}[(\alpha\beta^k - 1)/(k\alpha(\beta - 1) + \alpha - 1)] \tag{4.49}$$

Where k is the rate of specific heats:

$$k = c_p/c_v \tag{4.50}$$

Exergetic efficiency of biogas engine can be represented in two different approaches. The first approach deals with the rate of net work production, $\dot{W}_{net}$, and exergy of fuel. The general form of exergetic efficiency of the engine is given below:

$$\varepsilon_{ge}^{1} = \frac{\dot{E}x_{P,ge}}{\dot{E}x_{F,ge}} = \frac{\dot{W}_{net}}{\dot{E}x_{5}^{ph+ch}} \tag{4.51}$$

Where $\dot{E}x_{5}^{ph+ch}$ is the total exergy of the fuel and it is combining of physical and chemical exergy of fuel. However, that representation is not enough and it doesn't indicate all of the input and output of the engine. Due to that, the second approach can be developed as the inlet and outlet of sources to the engine. Second approach exergetic efficiency of the engine is:

$$\varepsilon_{ge}^{2} = \frac{\dot{E}x_{P,GE}}{\dot{E}x_{F,GE}} = \frac{\dot{W}_{net} + \dot{E}x_{product,auxiliary}}{\dot{E}x_{5}^{ph+ch} + \dot{E}x_{fuel,auxiliary}} \tag{4.52}$$

In that representation of efficiency $\dot{E}x_{product,auxiliary}$ is all the sources which inlet to the engine and $\dot{E}x_{fuel,auxiliary}$ is all sources that outlet from the engine. This efficiency explanation is more meaningful from the first one, because the effect of all sources, such mechanical, heat, and chemical, are included in eq.(4.52).

All these equations set in a program and there are some constants and standards. List of constants and values of working fluid at zero states are given in Table 4.1.

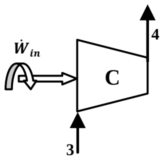
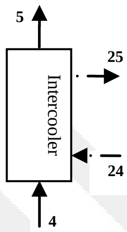
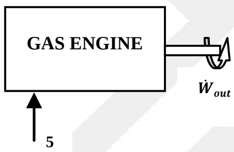
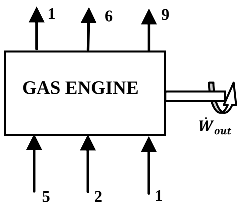
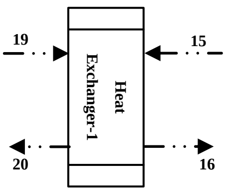
Table 4.1 Gas engine characteristic and thermodynamic data.

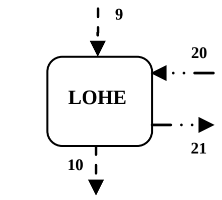
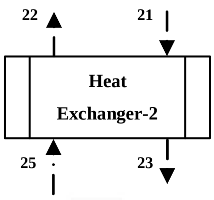
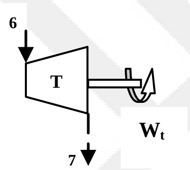
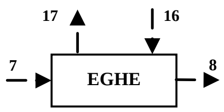
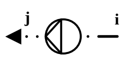
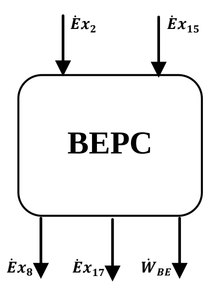
Parameter	Notation	Value	Unit
Cylinder Bore	B	170	mm
Stroke	S	195	mm
Number of Cylinders	N_c	12	-
Engine Speed	N	1500	rpm
Compression Ratio	r_c	13.5	-
Mass Flow Rate of Air	$\dot{m}_a$	1.387	kg/s
Mass Flow Rate of Fuel	$\dot{m}_f$	0.129	kg/s
Initial Temperature of Air-Fuel Mixing	T_0	25	C°
Initial Pressure of Air-Fuel Mixing	P_0	1.00	bar
Constant Pressure Specific Heat	$c_{p,air}$	1.108	kj/kg.K
Constant Temperature Specific Heat	$c_{v,air}$	0.821	kj/kg.K
Gas Constant of Air	R	0.287	kj/kg.K
Heating Value	Q_{HV}	17892	kj/kg
Combustion Efficiency	η_c	1	-
Mechanical Efficiency	η_m	0.74	-

4.4 Energy and Exergy Analysis of Other Component of BEPC

Analysis of all system requires all of energy equations of a component of the system. After thermodynamic analysis of gas engine, analysis of turbocharger and heat exchangers will be inserted. Analysis and optimization of the system will be developed according to exergetic efficiency unit by unit. All of component's kinetic and potential energy changing are negligible.

Table 4.2 Energy and exergy relations of each component of BEPC.

Component	Energy and Exergy Relation
	$\dot m_3 = \dot m_4 = \dot m_{air-fuel}$, $\eta_{is,comp.} = \frac{\dot w_s}{\dot w_a} = \frac{h_{4,s}-h_3}{h_4-h_3}$ $\dot Ex_{F,C} = \dot W_{in} = \dot W_{out,t}$, $\dot Ex_{P,C} = \dot Ex_4 - \dot Ex_3$ $\varepsilon_C = \frac{\dot Ex_{P,C}}{\dot Ex_{F,C}} = \frac{\dot m_a((h_4-h_3)-T_0(s_4-s_3))}{\dot W_{in}}$
	$\dot m_5 = \dot m_4 = \dot m_{air-fuel}$, $\dot m_{24} = \dot m_{25} = \dot m_{IC-water}$ $\dot m_4(h_4 - h_5) = \dot m_{25}(h_{25} - h_{24})$ $\dot Ex_{F,I} = \dot Ex_4 - \dot Ex_5$, $\dot Ex_{P,I} = \dot Ex_{25} - \dot Ex_{24}$ $\varepsilon_I = \frac{\dot Ex_{P,I}}{\dot Ex_{F,I}} = \frac{\dot m_{w3}((h_{25}-h_{24})-T_0(s_{25}-s_{24}))}{\dot m_a((h_4-h_5)-T_0(s_4-s_5))}$
	$\dot Ex^1{}_{F,BE} = \dot Ex_5^{ph+ch}$, $\dot Ex^1{}_{P,BE} = \dot W_{BE}$ $\varepsilon^1{}_{BE} = \frac{\dot Ex_{P,BE}}{\dot Ex_{F,BE}} = \frac{\dot W_{BE}}{\dot Ex_5^{ph+ch}}$
	$\dot Ex^2{}_{F,BE} = \dot Ex_5^{ph+ch} + \dot Ex_{12} + \dot Ex_{22}$ $\dot Ex^2{}_{P,BE} = \dot W_{BE} + \dot Ex_6 + \dot Ex_9 + \dot Ex_{18}$ $\varepsilon^2{}_{BE} = \frac{\dot Ex_{P,BE}}{\dot Ex_{F,BE}} = \frac{\dot W_{BE} + \dot Ex_6 + \dot Ex_9 + \dot Ex_{18}}{\dot Ex_5^{ph+ch} + \dot Ex_{12} + \dot Ex_{22}}$
	$\dot m_{19} = \dot m_{20} = \dot m_{JCC-water}$, $\dot m_{15} = \dot m_{16} = \dot m_{DC-water}$ $\dot m_{20}(h_{20} - h_{19}) = \dot m_{16}(h_{16} - h_{15})$ $\dot Ex_{F,HE-1} = \dot Ex_{19} - \dot Ex_{20}$, $\dot Ex_{P,HE-1} = \dot Ex_{16} - \dot Ex_{15}$ $\varepsilon_{\substack{heat \\ exchanger-1}} = \frac{\dot m_{w1}\left((h_{16} - h_{15}) - T_0(s_{16} - s_{15})\right)}{\dot m_{w2}\left((h_{19} - h_{20}) - T_0(s_{19} - s_{20})\right)}$

	$\dot{m}_9 = \dot{m}_{10} = \dot{m}_{lube-oil}$, $\dot{m}_{20} = \dot{m}_{21} = \dot{m}_{JCC-water}$ $\dot{m}_9(h_9 - h_{10}) = \dot{m}_{21}(h_{21} - h_{20})$ $\dot{E}x_{F,LOHE} = \dot{E}x_9 - \dot{E}x_{10}, \dot{E}x_{P,LOHE} = \dot{E}x_{21} - \dot{E}x_{20}$ $\varepsilon_{LOHE} = \frac{\dot{E}x_{P,LOHE}}{\dot{E}x_{F,LOHE}} = \frac{\dot{m}_{w2}((h_{21}-h_{20})-T_0(s_{21}-s_{20}))}{\dot{m}_l((h_9-h_{10})-T_0(s_9-s_{10}))}$
	$\dot{m}_{21} = \dot{m}_{22} = \dot{m}_{JCC-water}$, $\dot{m}_{23} = \dot{m}_{25} = \dot{m}_{IC-water}$ $\dot{m}_{22}(h_{22} - h_{21}) = \dot{m}_{25}(h_{25} - h_{23})$ $\dot{E}x_{F,HE-2} = \dot{E}x_{25} - \dot{E}x_{23}$, $\dot{E}x_{P,HE-2} = \dot{E}x_{22} - \dot{E}x_{21}$ $\varepsilon_{heat\ exchanger-2} = \frac{\dot{m}_{w2}((h_{22}-h_{21})-T_0(s_{22}-s_{21}))}{\dot{m}_{w3}((h_{25}-h_{23})-T_0(s_{25}-s_{23}))}$
	$\dot{m}_7 = \dot{m}_6 = \dot{m}_{air-fuel}$, $\eta_{is,tur.} = \frac{\dot{w}_a}{\dot{w}_s} = \frac{h_6-h_7}{h_6-h_{7,s}}$ $\dot{E}x_{F,T} = \dot{E}x_6 - \dot{E}x_7$, $\dot{E}x_{P,T} = \dot{E}_6 - \dot{E}_7$ $\varepsilon_T = \frac{\dot{E}x_{P,T}}{\dot{E}x_{F,T}} = \frac{\dot{m}_a(h_6 - h_7)}{\dot{m}_a((h_6 - h_7) - T_0(s_6 - s_7))}$
	$\dot{m}_7 = \dot{m}_8 = \dot{m}_{air-fuel}$, $\dot{m}_{17} = \dot{m}_{18} = \dot{m}_{DC-water}$ $\dot{m}_7(h_7 - h_8) = \dot{m}_{17}(h_{17} - h_{18})$ $\dot{E}x_{F,EGHE} = \dot{E}x_7 - \dot{E}x_8$, $\dot{E}x_{P,EGHE} = \dot{E}x_{17} - \dot{E}x_{16}$ $\varepsilon_{EGHE} = \frac{\dot{m}_{w1}((h_{17} - h_{16}) - T_0(s_{17} - s_{16}))}{\dot{m}_a((h_7 - h_8) - T_0(s_7 - s_8))}$
	$\dot{m}_i = \dot{m}_j = \dot{m}_{water}$, $\dot{E}x_{F,P} = \dot{W}_P$, $\dot{E}x_{P,P} = \dot{E}x_j - \dot{E}x_i$ $\varepsilon_P = \frac{\dot{E}x_{P,P}}{\dot{E}x_{F,P}} = \frac{\dot{m}_{w2}\left((h_j - h_i) - T_0(s_j - s_i)\right)}{\dot{W}_P}$
	$\dot{E}x_{F,BEPC} = \dot{E}x_2 + \dot{E}x_{15}$ $\dot{E}_{P,BEPC} = \dot{W}_{BE} + \dot{E}x_{17} + \dot{E}x_8$ $\varepsilon_{BEPC} = \frac{\dot{E}x_{P,BEPC}}{\dot{E}x_{F,BEPC}} = \frac{\dot{W}_{BE} + \dot{E}x_{17} + \dot{E}x_8}{\dot{E}x_2 + \dot{E}x_{15}}$

4.5 Designing a Genetic Algorithm and Results

In this study single objective genetic algorithm is used and all component of BEPC is analyzed according to the maximum point of exergetic efficiency of BEPC. The actual case of a system is used to determine of constraints. These constraints include considering maximum and minimum combustion temperature of biogas to determine the range of pressure ratio of the compressor, air-fuel ratio and pinch point analysis of heat exchangers.

4.5.1 Constraints of Objective and Input Parameters

Cogeneration systems are complex systems to understand a mechanism of variables and observe efficiency changing through optimization. The system is continuously but for understanding the behavior of a system, analysis of each component with objective and variable is shown in Table 4.3.

Table 4.3 Objectives and variables for the component of BEPC**.** State number and component names refer to schematized in Figure 4.1.

Component	Objective	Variable
Compressor	Increasing pressure of air-fuel mixture used by biogas engine.	Pressure, P_4
Intercooler	Decreasing the temperature of pressurized air-fuel mixture used by biogas engine.	Temperature, T_5
Biogas Engine	Power Production	Air-fuel ratio
HE-1	Increasing the temperature of water which used by digestion cycle.	Temperature, T_{16}
LOHE	Decreasing the temperature of oil that lubricates engine’s components and operates for cooling the engine.	Temperature, T_{10}
HE-2	Decreasing the temperature of water which absorbs heat from air-fuel mixture before entering the engine.	Temperature, T_{23}
Turbine	Producing shaft work required by compressor.	Temperature, T_7
EGHE	Increasing the temperature of water that satisfies heat to the anaerobic digestion.	Temperature, T_{17}
Pumps	Increasing the pressure of water which entering heat exchanger.	Pressure, P_j
BEPC	Power production and supply heat demand of digestion.	AF, P_4, T_{19}

Design parameters and catalog values of biogas engine are given and combustion range of biogas in air according to literature is between 900 K and 1080 K [55,58], so the pressurization range could be determined as in Table 4.3. Also, the air-fuel ratio is an important parameter for optimization of biogas engine, so according to literature air-fuel ratio is between 5 and 15 [55, 56]. The temperature of jacket cooling water leads optimization of heat exchangers. Steady case values are used and pinch point analysis of system applied, so results indicated that 9kW heating and 460kW cooling could be added to that system and pinch point of the system found 86.5 C°. According to that values, a selected range of cooling water is shown in Table 4.4 and input parameters in Table 4.5.

Table 4.4 Constraints of optimization parameters for BEPC.

Parameters	Range
Air-fuel ratio, AF	5-15[55,56]
Air fuel mixture inlet Pressure, P_5 (bar)	1.85-2.2
Jacket cooling water temperature, T_{19} (C°)	86.5-90

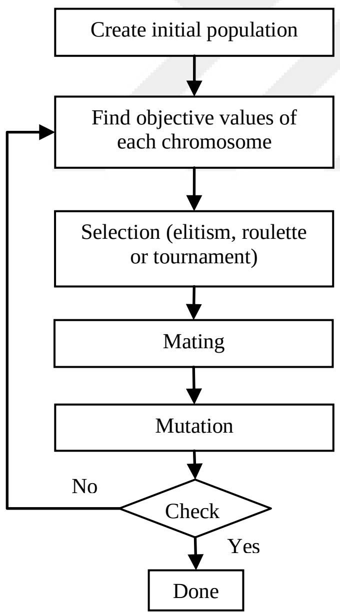
Table 4.5 Fixed parameters of BEPC.

Parameters	Value
Temperature of water inlet to the system from digestion loop (C°)	75.8
Temperature of water outlet from the system to digestion loop (C°)	88.0
Temperature of water enters to the intercooler (C°)	50.0
Temperature of air enters to engine (C°)	52.0
Mass flow rate of water through digestion loop (kg/s)	20.88
Mass flow rate of water through intercooler loop (kg/s)	15.61
Mass flow rate of water through jacket cooling loop (kg/s)	11.28
Mass flow rate of lubricating oil (kg/s)	20.0
Temperature of water enters to the engine in jacket cooling loop (C°)	78.5
Isentropic efficiency of compressor	0.6
Temperature of lube-oil enters to the LOHE (C°)	100.6
Pressure of air at inlet to turbine (kPa)	240
Temperature of air at inlet to turbine (C°)	460

These fixed parameters, in Table 4.5, are the input parameters of a genetic algorithm. In the idea of production of a useful algorithm and convert it to ready-made software, it is important to design a genetic algorithm as a changeable for a user. Conditions could be a change for each system and parameters of each system are different, due to that program must be occurred only from contact equations without any constant value. Thermodynamic properties tables of working fluids are inserted into the algorithm and selection of each value such entropy, enthalpy and temperature will be automatically applied by an algorithm.

4.5.2 Setup Genetic Algorithm in Matlab

Flow chart of the genetic algorithm could be revised as understandable to creating self-adaptive codes. The first step, input fixed parameters as expressed in the previous section.



- ***Cycle***

- ***input(fixed parameters)***
- ***create(NpxVariables)***
- *% Np is number of individual chromosome.*
- ***determine(variables in chromosome)***
- ***calculations(equations)***
- ***sort(chromosomes)***
- ***natural selection(population)***
- ***mating(chromosomes)***
- ***mutation(genes)***

- ***cycle+1***

Figure 4.3 Flow chart of the self-adaptive coded genetic algorithm.

4.5.2.1 Creation of a First Population

The fundamental of Matlab is based on matrix-based procedures. Due to that in Matlab we produced all of the genetic algorithm codes according to a matrix-based idea. The first population is the matrix that is produced from 3 columns and 50 rows because each column represents a variable. Chromosome number of population, *psize*, is selected 50.

```
population1=unifrnd(5,15,[psize,1]);
population2=unifrnd(185,220,[psize,1]);
population3=unifrnd(86.5,90,[psize,1]);
population=[population1 population2 population3];
```

Figure 4.4 Production of the first population in Matlab.

Population size is the number of a row as shown in Figure 4.4, and according to constraints, the population is created randomly.

After the creation of population we must represent the name of variables to the algorithm in the correct order. By using equations that inserted in the algorithm from the thermodynamic analysis, the first objective result will be calculated. Objective results are also a matrix that occurs from one column and 50 rows. The first result will show the optimum first point of the system. However, genetic algorithm deals with enhancement of these results.

4.5.2.2 Applying of Natural Selection

Separation of the first result is the main idea of this step. In this study, we used elitism and roulette wheel methods for selection. Natural selection is the first step in starts to improve a variety of population. Figure 4.5 shows the self-adaptive codes of elitism and roulette wheel selections respectively.

```
if (pairs(i)>pairs(i+1))
arapop(i)=population(i);
```

(a)

```
for i=1:psize
    idx=find(rs(i)<cprobs, 1);
    arapop(i,:)=population(idx,:);
```

(b)

Figure 4.5 (a) A basic idea of elitism and **(b)** roulette wheel by using self-adaptive codes.

4.5.2.3 Applying of Crossover

We design algorithm as crossing chromosomes by using random mating method for creating an improved population, called intermediate population. This new population includes variety in the objective result. We select single point crossover and crossover rate is selected 0.85, so minimum 85 percent of the population is crossed.

```
if rs<pcross
    cpoint= unidrnd(d-1);
    station= parent1(cpoint+1: end);
    parent1(cpoint+1:end)=parent2(cpoint+1:end);
    parent2(cpoint+1:end)= station;
    arapop(parent1idx, :)= parent1;
    arapop(parent2idx, :)= parent2;
end
```

Figure 4.6 Design of single point crossover in Matlab.

According to Figure 4.6, the piece of chromosome that has been cut off must be kept in an empty matrix, called station. Because of exchange in matrix columns could lose the part of this piece of chromosome.

4.5.2.4 Applying of Mutation

Mutation is the last part of the algorithm and improves the variety of population by using randomly selected mutation matrix. The mutation rate of this study is selected 0.4, so the maximum 40 percent of the population will be mutated. Mutation is also applied by using increasing and decreasing the value of genes, as shown in Figure 4.7.

```
if (rs(i, 1)<pmutation)
    rs2=unifrnd(-1,1);
    population(i,1)= arapop(i,1)+ rs2*delta*(15-5);
end
```

Figure 4.7 Design of mutation operation in Matlab.

Delta is number that gives negative and positive values for subtracting and the addition of a value to the mutated genes.

4.5.3 Results

The thermodynamic analysis represents the change of efficiency by variables and efficiency of all components is determined, but the optimum range of variables or the optimum range of efficiency problem is needed to define correctly. The genetic algorithm creates a range for variable and also a measurement of variables' importance is an advantage of a genetic algorithm. In figures that results of genetic algorithm optimization if the range of the variable is tiny the importance of a variable is huge.

4.5.3.1 Optimization Results by Using Elitism

Results of changing of variables according to iteration are shown in Figure 4.8. for air-fuel ratio, in Figure 4.9 for P_5 and in Figure 4.10 for T_{15}. Observation of diversity in variables could determine the effectiveness of the method because all results change with the changing of variables.

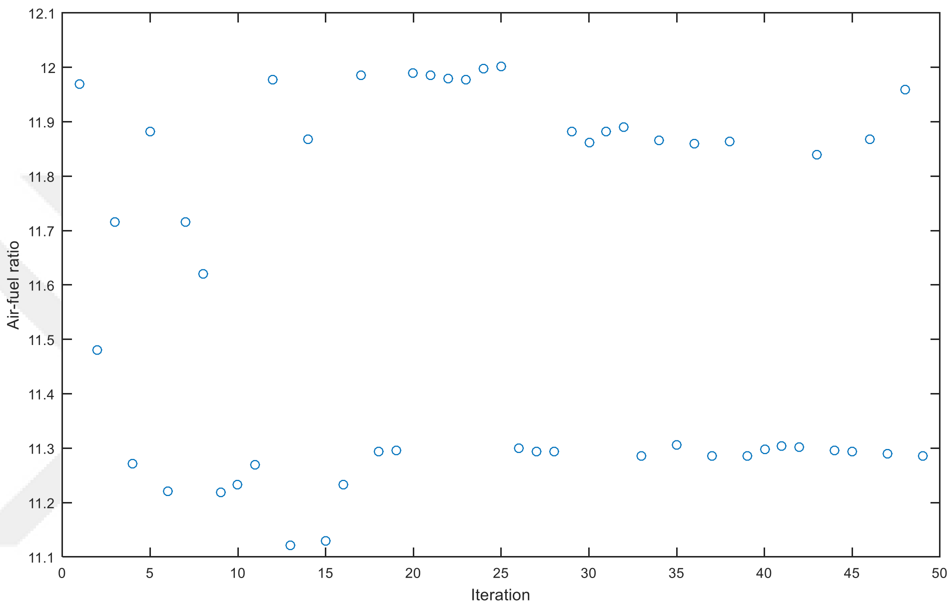


Figure 4.8 Changing of air-fuel ratio according to iteration.

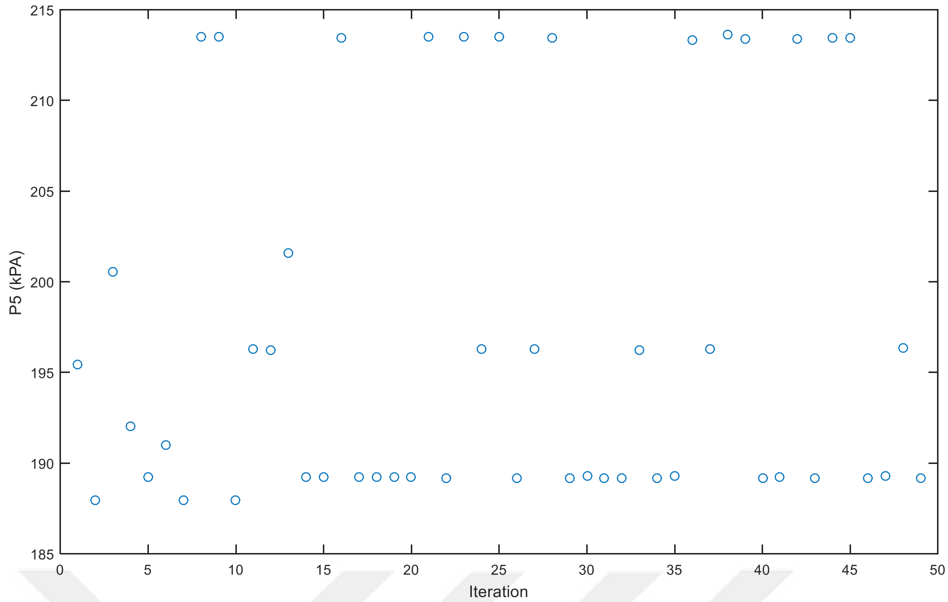


Figure 4.9 Variation of P_5 according to iteration.

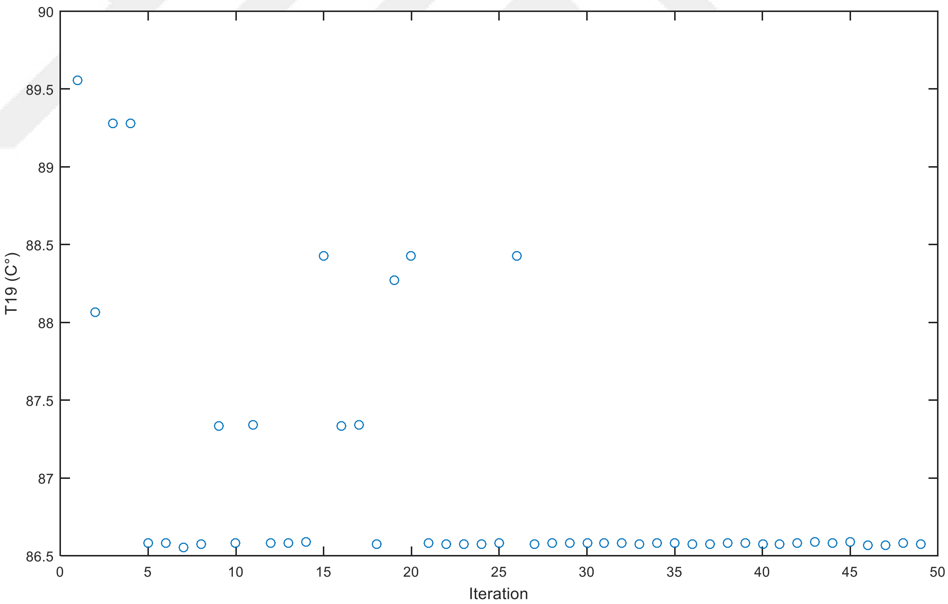


Figure 4.10 Variation of T_{19} according to iteration.

According to elitism selection method, in Figure 4.8 optimum distribution of air-fuel ratio is shown and its optimum point is found to be 11.3, in Figure 4.9 changing of inlet pressure of engine is shown and its optimum point is found 189.2 kPa and in

Figure 4.10 optimum variation of jacket cooling water temperature that inlet to the HE-1 is drawn and its optimum value is found 86.5 C°.

Small changing in AF, affects the amount of fuel and also this effect lead to the efficiency of BEPC. Pressure of inlet to engine changes between 189 and 213 kPa, but algorithm tried to search the optimum case of these three variables. Figure 4.8 and Figure 4.9 indicated that different varieties of AF and P_5 are tried, for instance at iteration 5, 10 and 20, it can be seen high and low values of all variables are tried, but the optimum point of the system shown that increasing of AF is more effective than increasing of P_5. Exergetic efficiency of BEPC is found to be in the range of 33% and 34%.

Elitism method could be considered as one direction diversity method, so diversity could be developed by using crossover and mutation steps effectively.

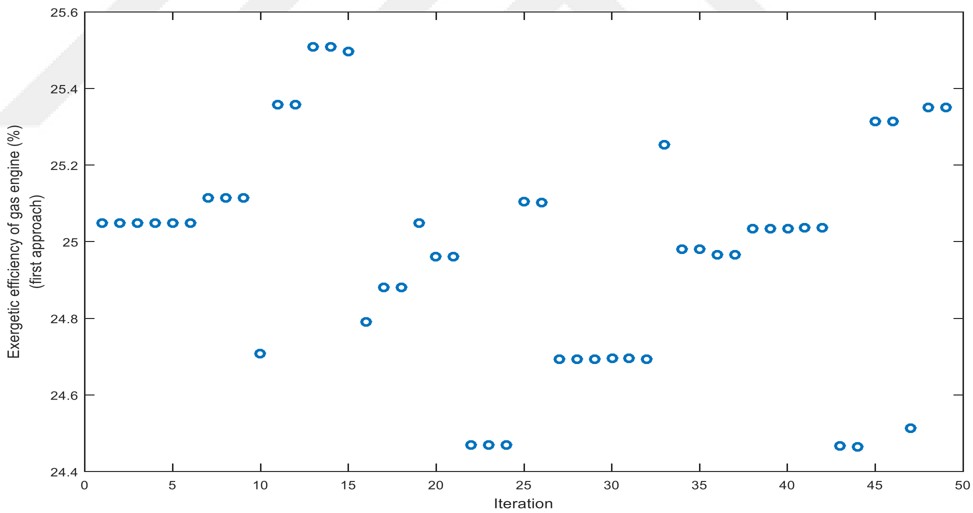


Figure 4.11 Diagram of changing 1^{st} approaching gas engine exergetic efficiency with iteration.

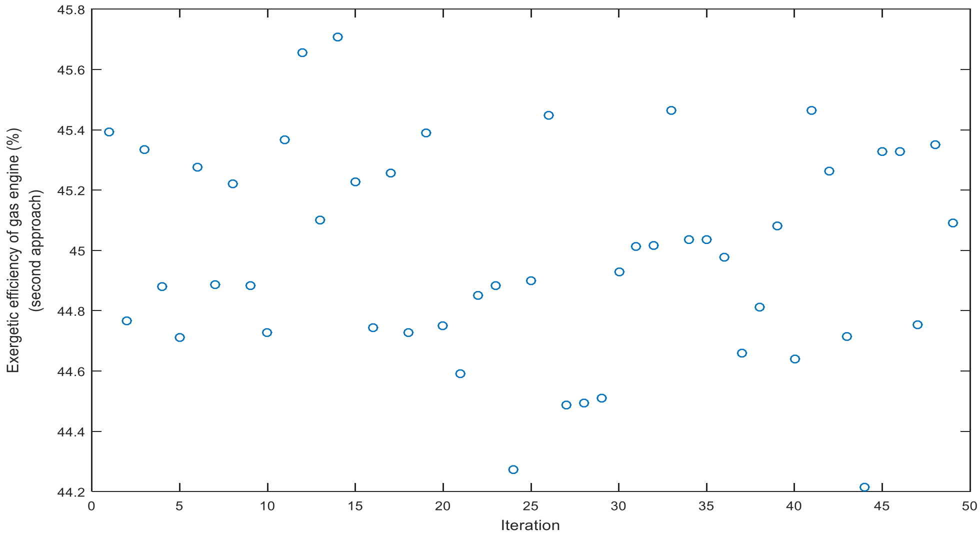


Figure 4.12 Diagram of changing 2nd approaching gas engine exergetic efficiency with iteration.

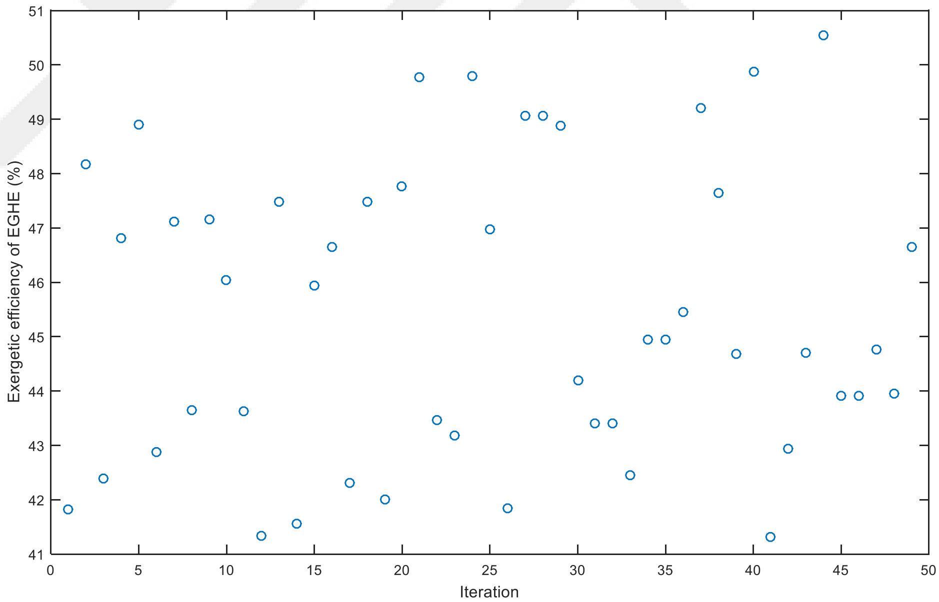


Figure 4.13 Exergetic efficiency of EGHE with iteration in elitism selection method.

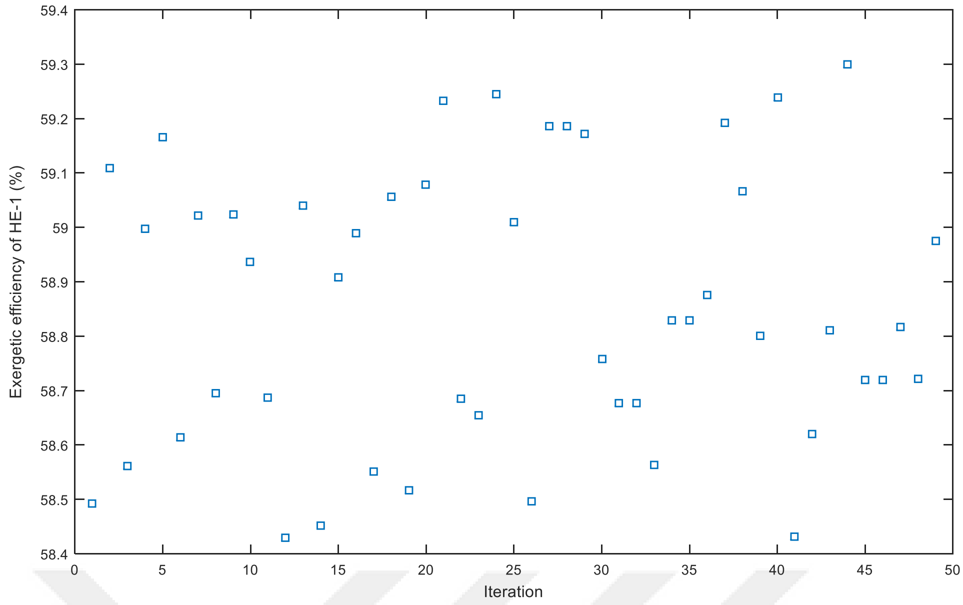


Figure 4.14 Exergetic efficiency of HE-1 according to elitism selection.

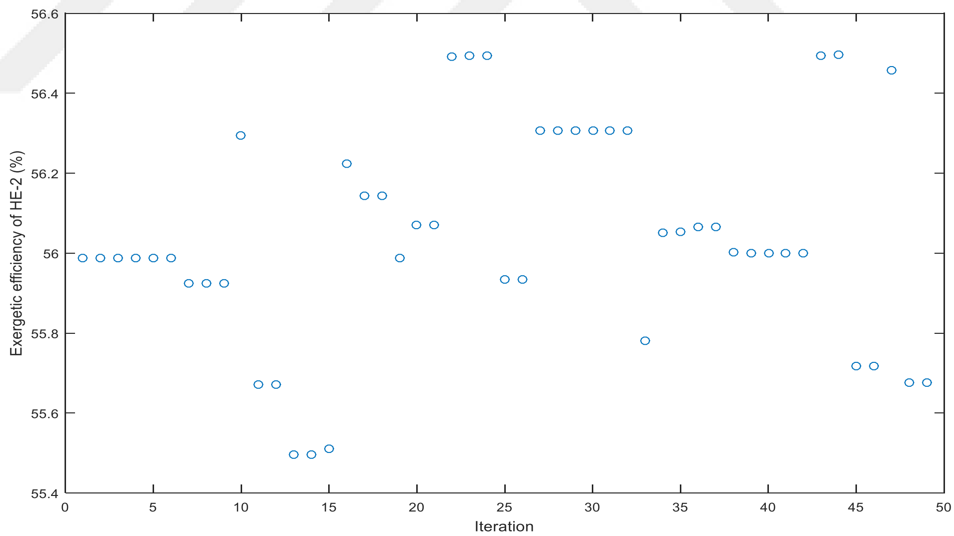


Figure 4.15 Exergetic efficiency of HE-2 in elitism selection.

According to elitism selection, exergetic efficiencies of components of BEPC are given above in figures. Exergetic efficiency of the gas engine for the 1st approach, according to eq.(4.51), is found to be 25.35% and for 2nd approach, according to eq.(4.52) is found at 45.1%. Results for EGHE indicated that optimum range is between 43% and 47%. Exergetic efficiencies for HE-1 and HE-2 are found to be 59% and 56% respectively.

Gas engine 1st approach efficiency changes between 24.5% and 25.6% and this range are produced due to the variation of AF and P_5 because of eq.(4.51) doesn't contain effects of other components of BEPC. Decreasing of AF is lead to increase in heat input and also increase the temperature of first combustion stroke, however, the second combustion occurs in constant pressure case and the effect of pressure is most important in that state. We designed the algorithm according to all these parameters and algorithm showed that the optimum balance between variables is close to the optimum point of the gas engine. Second approach efficiency of the engine indicated that the effect of lubricating and jacket cooling is significant, due to the difference between the two efficiency results.

Heat exchangers' efficiencies are changed according to pinch point that shown in the above figures. The efficiency of HE-1 affects efficiencies of EGHE and HE-2, because of increases in efficiency of HE-1 decreases the temperature of water which inlet to the HE-2. Also increasing in temperature of T_{16} is increase the efficiency of EGHE, due to consuming less energy for reaching expected temperature.

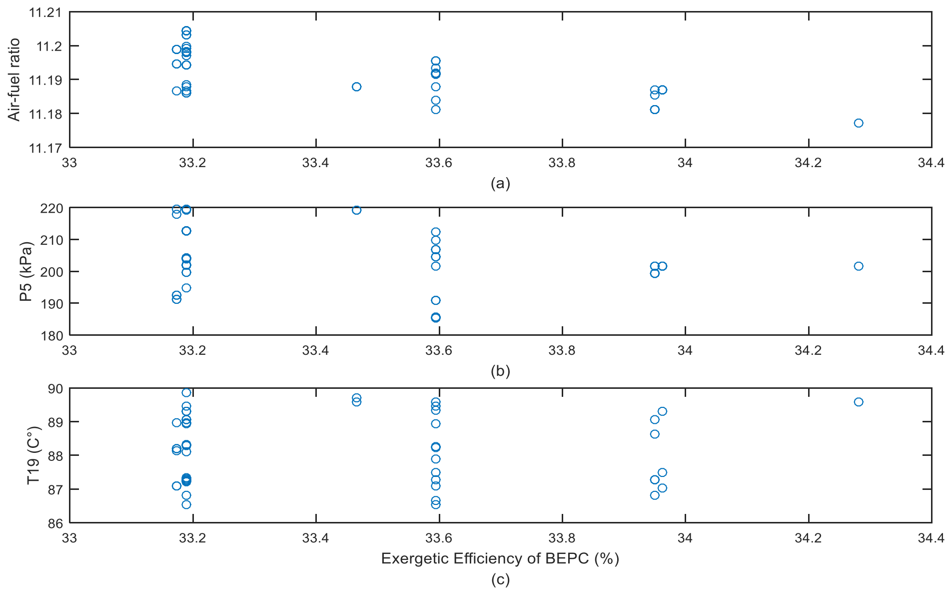


Figure 4.16 Exergetic efficiency of BEPC according to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}

Distribution of variables in the algorithm and their effects on the BEPC are indicated in Figure 4.14. The results show that the density of points through 33.2 is the global optimum point and other densities could be local optimum points. Each of these points is the result of 50 objective values. That means the magnitude of the result matrix is 50x50. Optimum efficiencies by using elitism selection are given in Table 4.6.

Table 4.6 Energy and exergy results of components of BEPC by using elitism method. State number and component names refer to schematized in Figure 4.1.

Component	States	$\dot{Q}_{opt,elitism}$ (kW)	$\dot{W}_{opt,elitism}$ (kW)	$\dot{E}x_{Fopt,elitism}$ (kW)	$\dot{E}x_{Popt,elitism}$ (kW)	$\dot{E}x_{Dopt,elitism}$ (kW)	$\varepsilon_{opt,elitism}$ (%)
Compressor	3-4	-	137.2	137.2	101.4	35.8	74.00
Intercooler	4-5	96.3	-	15.5	8.0	7.5	51.6
Turbine	6-7	-	166.5	189.74	166.5	23.24	87.75
EGHE	7-8	472.2	-	166.4	77.4	89.0	46.5
P1	14-15	-	2.1	2.1	2.08	0.02	99.04
P2	18-19	-	12.4	12.4	7.83	4.57	63.14
P3	23-24	-	3.4	3.4	2.3	1.1	67.64
P4	11-12		98.88	98.88	27.25	71.55	27.58
LOHE	9-10	512	-	94.8	53.42	41.38	56.35
HE-1	19-20	605.2	-	156.0	92.0	64.0	59.0
HE-2	23-25	97.0	-	14.4	8.0	6.4	55.5
Gas Engine	-	-	998.1	3936.5[1]	998.1[1]	2938.4[1]	25.4[1]
	-	-		4470.4[2]	2017.7[2]	2452.7[2]	45.1[2]
BEPP	-	1782.7	998.1	4204.3	1412.8	2756.8	33.2

The efficiency of a gas engine is found at 25.4%, but the efficiency of BEPC is found at 33.4%. This difference is because of using heat exchangers. The second approach of biogas engine exergetic efficiency is also about using heat recovery without HE-2 and EGHE. Addition of heat recovery into the second approach efficiency of the engine is meaning because heat distribution of the engine affects the efficiency.

4.5.3.2 Optimization Results by Using Roulette Wheel

Roulette wheel selection is used the second method in the optimization of BEPC. Optimization result for this method according to 1000 kW produced energy is shown below as diagrams.

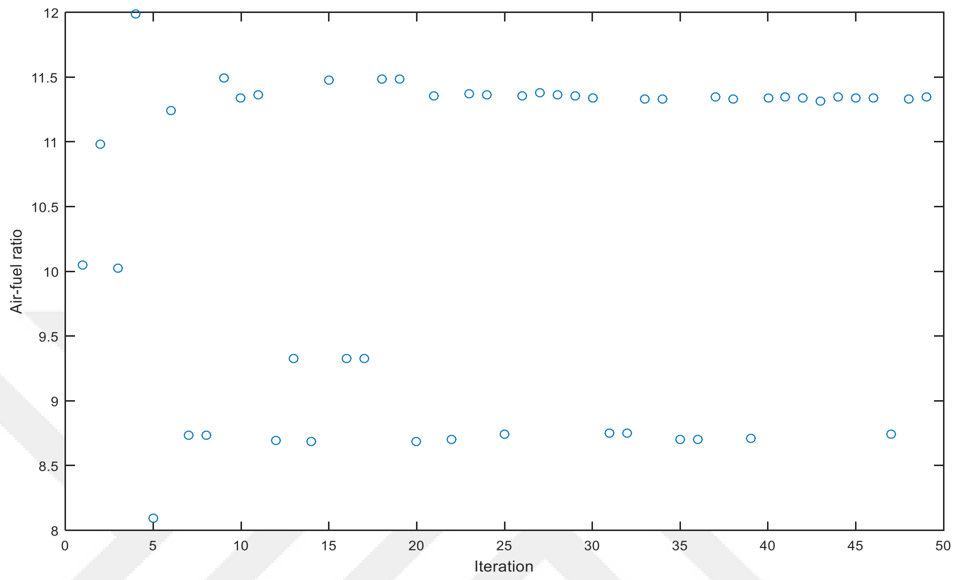


Figure 4.17 Changing of AF according to iteration in roulette wheel selection method.

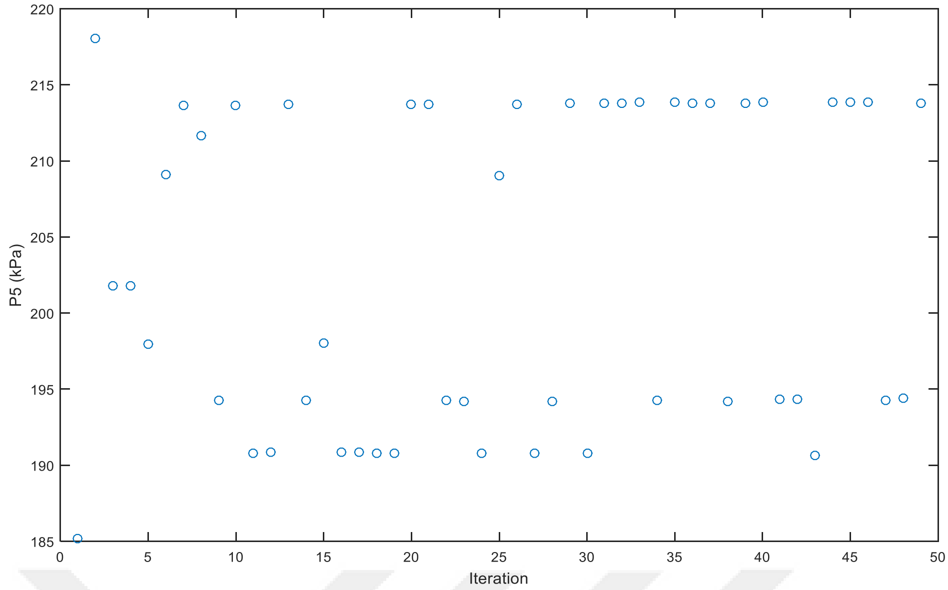


Figure 4.18 Variations of P_5 according to iteration in roulette wheel selection method.

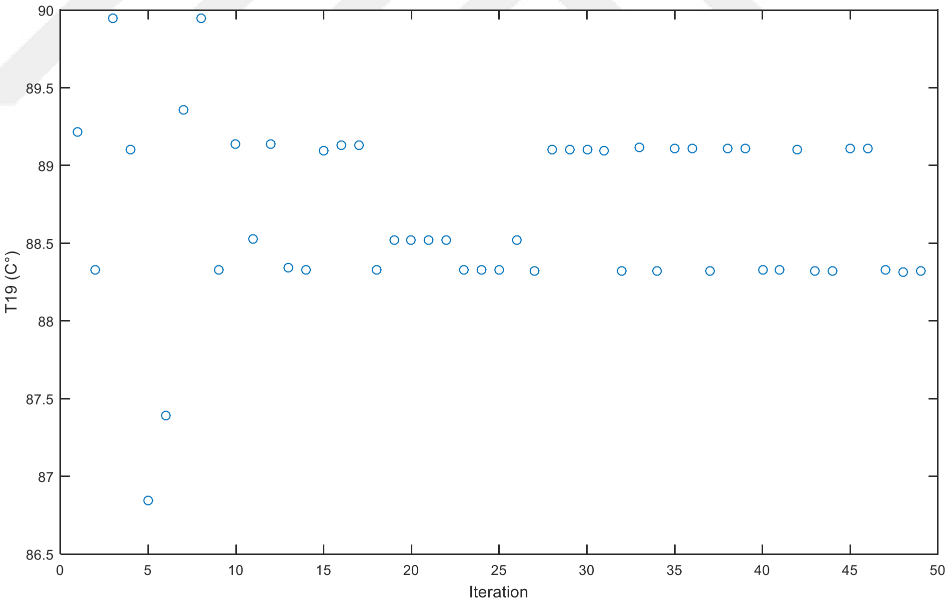


Figure 4.19 Changing of T_{19} according to iteration in roulette wheel selection method.

Results of roulette wheel selected optimization, which is shared above, indicated that this type of selection gives more variety. In Figure 4.17 air-fuel ratio range is bigger than a range in elitism because in a roulette wheel chromosomes are selected randomly and the selection of small valued chromosome is probable although it has small probability. Roulette wheel selection method affects on P_5 as a wider range of changing.

Air-fuel ratio is found to be between 11 and 11.5, a pressure of air-fuel mixture entering to the engine, P_5, is found as 214 kPa and T_{19}, cooling jacket that outlet from the engine is found to be 88.5 C°. Exergetic efficiency of BEPC is found 33.5. Each component is analyzed and the results of them are given below.

Results showed that increases in AF lead the small amount of fuel and because of that pressure is selected high for production of 1000 kW energy. However, increasing of pressure is led the increasing of irreversibilities.

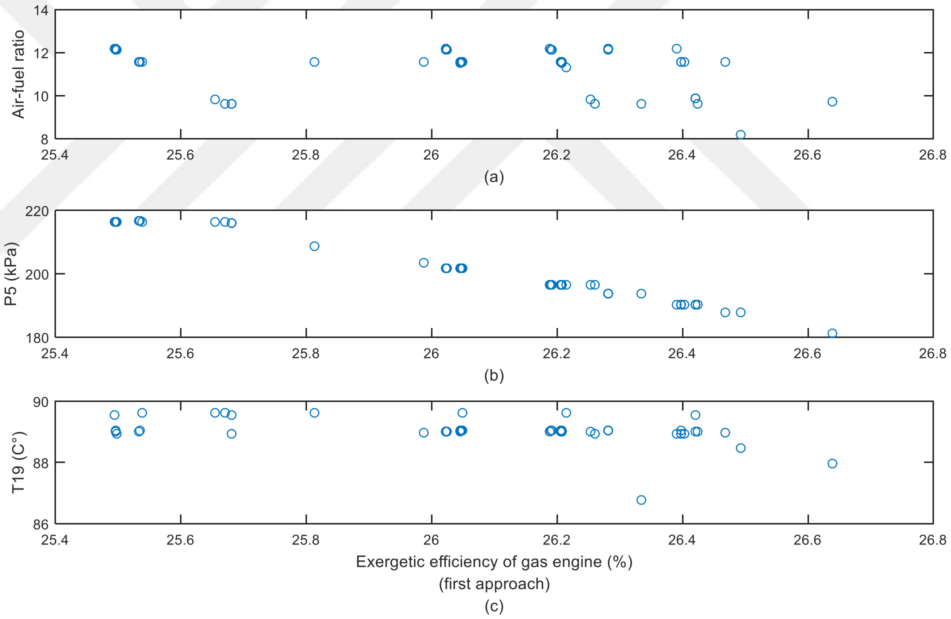


Figure 4.20 Results of roulette wheel selection used optimization for exergetic efficiency of gas engine in first approach with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

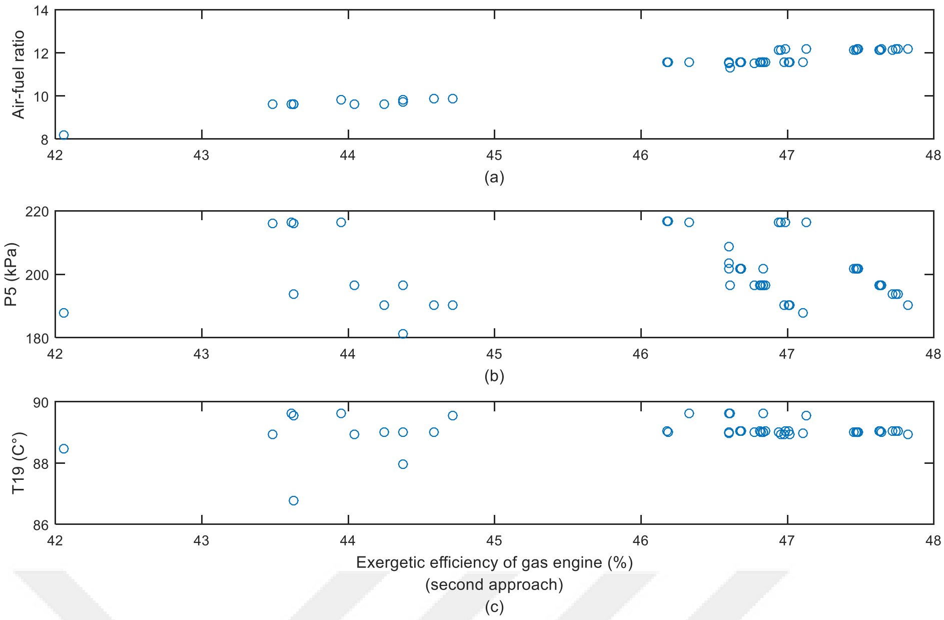


Figure 4.21 Results of roulette wheel selection used optimization for exergetic efficiency of gas engine in second approach with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

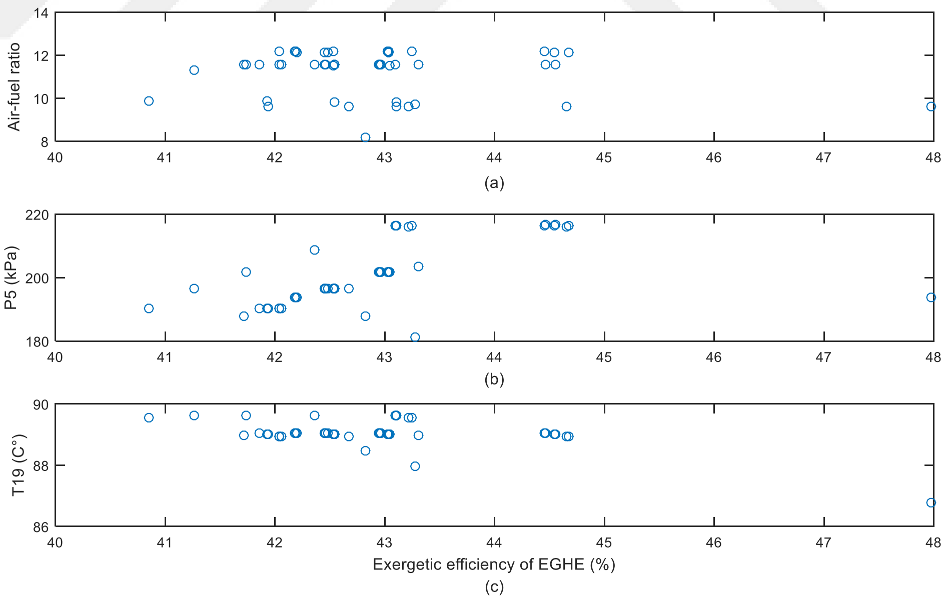


Figure 4.22 Results of roulette wheel selection used optimization for exergetic efficiency of EGHE with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

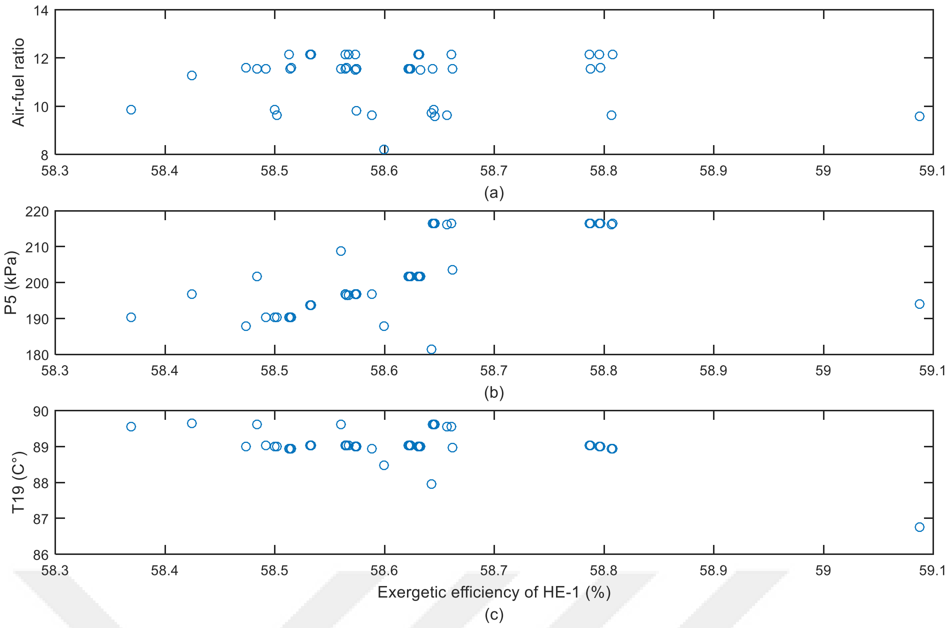


Figure 4.23 Results of roulette wheel selection used optimization for exergetic efficiency of HE-1 with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

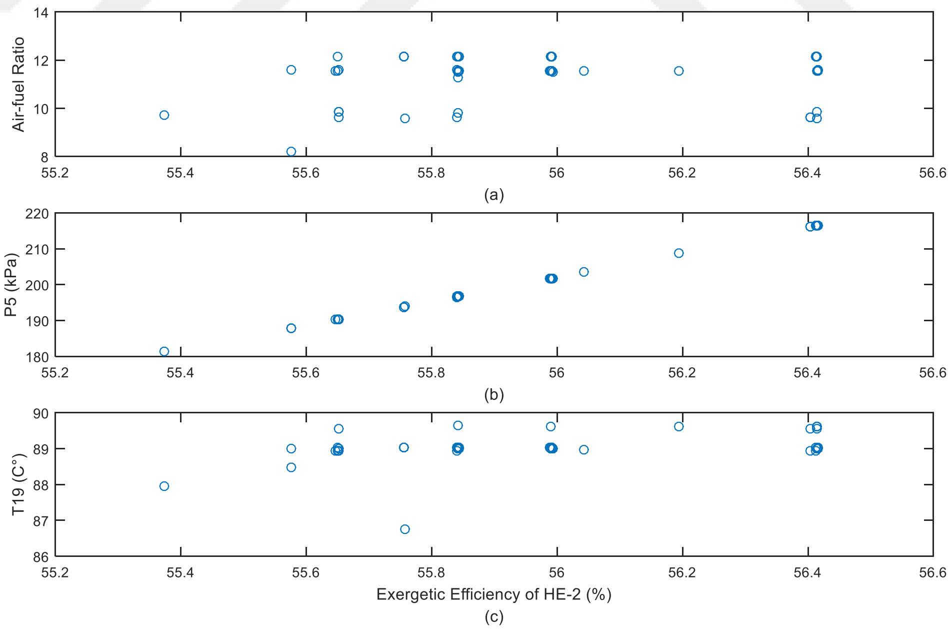


Figure 4.24 Results of roulette wheel selection used optimization for exergetic efficiency of HE-2 with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

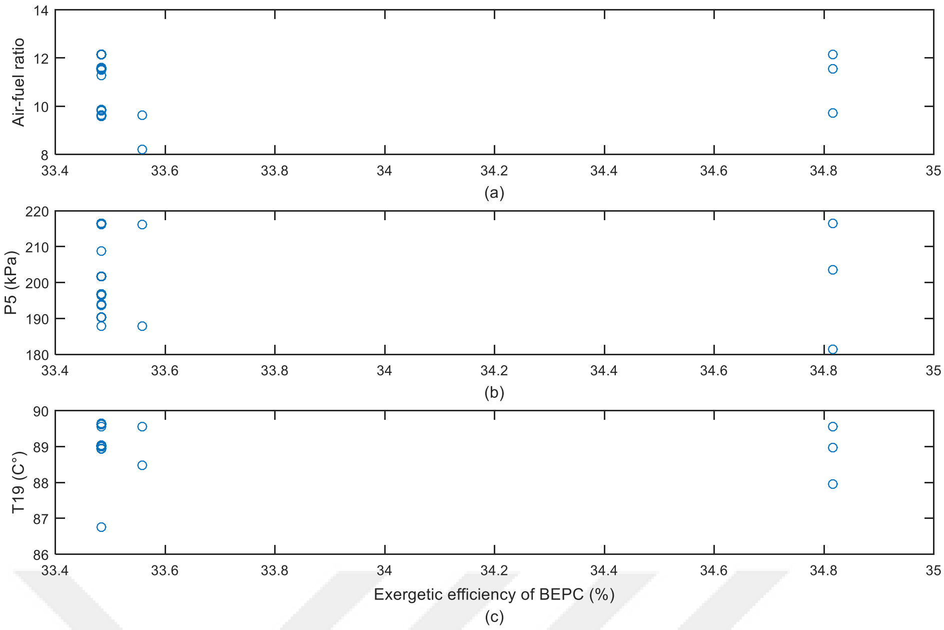


Figure 4.25 Results of roulette wheel selection used optimization for exergetic efficiency of BEPC with respect to **(a)** air-fuel ratio **(b)** P_5 and **(c)** T_{19}.

In Figure 4.20 efficiency of biogas engine for a 1st approach is found to be in the range of 26% and 26.5% according to the range of variables. It is due to increasing the pressure of entering the engine and also increasing air-fuel ratio. In Figure 4.21 2nd approach of gas engine efficiency is found to be in the range of 46% and 48%. Distribution of results indicated the effectiveness of the selection method as shown in Figure 4.20-25, there is a narrow range for variables in elitism method due to the behavior of elitism in nature. However, the roulette wheel gives a wide range of variables and results. In Figure 4.22 exergetic efficiency of EGHE is found in the range of 41% and 44%, exergetic efficiency of HE-1 is found to be 58.6% as shown in Fig. 4.23. Results for HE-2 are found as in the range of 55.6% and 56.5%, given in Fig. 4.24. All results of BEPC are given in Table 4.7.

Table 4.7 Energy and exergy results of components of BEPC by using elitism method. State number and component names refer to schematized in Figure 4.1.

Component	States	$\dot{Q}_{opt,rl.whl}$ (kW)	$\dot{W}_{opt,rl.whl.}$ (kW)	$\dot{E}x_{Fopt,rl.whl.}$ (kW)	$\dot{E}x_{Popt,rl.whl.}$ (kW)	$\dot{E}x_{Dopt,rl.whl.}$ (kW)	$\varepsilon_{opt,rl.whl.}$ (%)
Compressor	3-4	-	150	150	111.4	38.6	74.3
Intercooler	4-5	108.9	-	18.5	9.1	9.4	49.2
Turbine	6-7	-	159.9	181.7	159.9	21.8	88.0
EGHE	7-8	390.9	-	149.6	64.3	85.3	43.0
P1	14-15	-	2.1	2.1	2.08	0.02	99.04
P2	18-19	-	12.4	12.4	7.83	4.57	63.14
P3	23-24	-	3.4	3.4	2.3	1.1	67.64
P4	11-12		98.88	98.88	27.25	71.55	27.58
LOHE	9-10	512	-	94.8	53.42	41.38	56.35
HE-1	19-20	686.6	-	179.2	105.1	74.1	58.6
HE-2	23-25	109.7	-	16.3	9.1	7.2	55.8
Gas Engine	-	-	999.6	3745.2 [1]	999.6 [1]	2745.6 [1]	26.7 [1]
	-	-		4372.0 [2]	2040.8 [2]	2331.2 [2]	46.7 [2]
BEPP	-	1808.1	999.6	4092.8	1371.08	2648.6	33.5

The efficiency of BEPC is found as 33.5% and results show that the crossover rate of the algorithm is enough to change the variables values. Due to having three variables, crossover point has just two probability, point 1 and point 2. In both two cases first variable don’t change in the step of crossover, and if it is dominant in an objective, variety of objective function will be decreased.

CHAPTER 5

CONCLUSION

Optimization of biogas engine powered cogeneration (BEPC) system that operates in GASKİ WWTP in the city of Gaziantep, is operated by using a genetic algorithm. Biogas consumption of the system is supplied from anaerobic digestion which produces biogas from waste. Methane composition of biogas is 61% and electricity production is 1000 kW, so annual production is 8.76 kWh. Self-adaptive codes in Matlab software are used for genetic algorithm process and two different natural selection methods are compared.

Description of BEPC is shown in Figure 4.1 and all working fluids are explained. All equipment of BEPC and their work principles are expressed. Performance characteristic and thermodynamic analysis of gas engine, DEUTZ TCG2020 V12K, is operated and all parameters are given in Table 4.1. Obtained equations from operating and thermodynamic analysis are used in the genetic algorithm.

1. Energy and exergy relations of all subsystem of BEPC are analyzed in Table 4.2. Two different approximations for exergy efficiency of a gas engine are determined in eq. (4.51) and eq. (4.52). The objective of all equipment of BEPC with variables are given in Table 4.3, and variables of the objective function are selected as air-fuel mixture ratio, a temperature of jacket cooling water that outlet from the engine (T_{19}) and pressure of at the entrance of gas engine (P_5).

2. Constraints of variables of objective functions are given in Table 4.4, as 5-15 for air-fuel mixture ratio, 1.85-2.2 kPa for P5 and 86.5-90 C° for T_{19}. Pinch point analysis of the system is applied and results are used in determining of constraints.

Also from technical data of gas engine are used for determining constraints of P_5. Fixed parameters of the objective function are given in Table 4.5.

3. Self-adaptive coded flow chart for a genetic algorithm is given in Figure 4.3 and fundamental codes are created according to the information that given in Chapter 3 by using continuous numbers. Basic codes of a self-adaptive algorithm are given in Figure 4.4, 4.5, 4.6, 4.7 and crossover rate and mutation rate are selected 0.95 and 0.40 respectively. The density of population is selected 50 members and each member created from 3 columns.

4. Results of optimization by using elitism selection method for 3 variables are given in Figure 4.8, 4.9, 4.10. According to elitism selection method results for air-fuel ratio, T19 and P5 are determines as 11.3, 189.2 and 86.5 respectively. Importance of focusing on a selected gap of variables is presented, especially in air-fuel mixture, as shown in Figure 4.8. Effects of variables on the objective function are discussed for each variable and changing of variables in result area is also discussed.

5. Changing of exergy efficiency of biogas engine according to 1st and 2nd approach is determined 25.35% and 45.1% respectively, as shown in Figure 4.11, 4.12, and these figures show the changing of efficiencies according to iteration. Exergetic efficiency of exhaust gas heat exchanger (EGHE) is found to be in the range of 43-47% as shown in Figure 4.13. Effect of changing of T_{19} on EGHE is discussed and also the effect of efficiency of EGHE on the overall efficiency of BEPC is discussed.

6. Exergetic efficiencies of the heat exchanger 1 (HE-1) and the heat exchanger 2 (HE-2) are determined to be 59% and 56% respectively and results are shown in Figure 4.14, 4.15. The range of diversity of HE-1 and HE-2 are discussed according to the variation of variables. The overall efficiency of BEPC is determined as 33.2% and shown in Figure 4.16 according to changing of variables. Effects of all variables on the overall efficiency of BEPC are discussed and methodological effects on overall efficiency are mentioned.

7. Optimum results of all equipment are given in Table 4.6. Heat, exergy product, exergy fuel and exergy destruction of all components are given with their state numbers which are given in Figure 4.1.

8. Second selection method, roulette wheel, is applied to the BEPC according to fundamentals of selection that expressed in Chapter 3. Changing of variables are shown in Figure 4.17, 4.18, 4.19 and result for the air-fuel mixture, T_{19} and P_5 are determined as 11.5, 88.5 C° and 214 kPa respectively. The diversity of all variables is discussed and range of air-fuel mixture, in Figure 4.17 is compared with the results of the air-fuel mixture in elitism selection as shown in Figure 4.8. Advantages and disadvantages of the two methods are mentioned.

9. The optimum range of gas engine according to 1st and 2nd approaches is determined by using Eq. (4.51) and Eq. (4.52) and they found to be in the range of 26% and 26.5%. Results for a gas engine are shown in Figure 4.20, 4.21. Changing of efficiency according to all variables is shown and the effects of each variable are discussed. The density of variables, which collect in result points or in the range of result, is discussed with roulette wheel selection idea.

10. Diversity effect of T_{19} in roulette wheel is discussed and effects of T_{19} on the efficiency of exhaust gas heat exchanger (EGHE) are discussed. Exergetic efficiency range of EGHE is found to be 41% and 44%, as shown in Figure 4.22. Difference between efficiencies of EGHE according to roulette wheel and elitism is mentioned and methodological effects are discussed. Exergetic efficiencies of HE-1 and HE-2 are determined according to a roulette wheel in Figure 4.23, 4.24 and optimum points of HE-1 and HE-2 are found to be 58.6% and 56.5% respectively. Heat distribution of T_{19} for HE-1 and HE-2 is discussed and diversity of HE-1 is mentioned according to overall BEPC efficiency.

11. The overall efficiency of BEPC is determined as 33.5% according to the roulette wheel in Figure 4.25 and results analyzed on each variable. The density of variables on optimum point and their effects on overall efficiency is discussed. Advantages and disadvantages of selection methods are discussed according to energy systems optimizations. Efficiencies, exergy product, exergy fuel and exergy destruction of all components are determined in Table 4.7.

12. In this study, we see that genetic algorithm optimization is useful for energy systems, and the genetic algorithm could reach close to the actual values. The genetic algorithm is able to predict the efficiency of the system before designing. Due to this property of genetic algorithm self-adaptive coded genetic algorithm is more useful, because one can adapt the algorithm to the systems conditions easily. Two different methods in genetic algorithm could use for energy systems and they could be developed by inserting another software or solver programs. Optimization of a complex system could be easily analyzed in the genetic algorithm. Second law efficiency of the system could more effective to obtain an optimum point of the objective.

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