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Genetic algorithm for optimization of energy systems: Solution uniqueness, accuracy, Pareto convergence and dimension reduction

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ABSTRACT

Genetic algorithm (GA) is widely accepted in energy systems optimization especially multi objective method. In multi objective method, a set of solutions called Pareto front is obtained. Due to random nature of GA, finding a unique and reproducible result is not an easy task for multi objective problems. Here we discuss the solution uniqueness, accuracy, Pareto convergence, dimension reduction topics and provide quantitative methodologies for the mentioned parameters. Firstly, Pareto frontier goodness and solution accuracy is introduced. Then the convergence of Pareto front is discussed and the related methodology is developed. By comparing two different best points (optimum points) selection method, it is shown that multi objective methods can be reduced to single objective or lower dimensions in objective functions by using ratio method. Our results establish that our proposed method can indeed provide unique solution of satisfactory accuracy and convergence for a multi-objective optimization problem in energy systems.

1. Introduction

Optimization of energy systems attracts many researchers especially in recent years. Optimizing a cycle performance or design to achieve higher energy efficiencies is the basic common concept of all research studies in energy systems [1,2]. On the other hand, there are usually other criteria like economic, exergetic and environmental performances which may be considered as objectives for optimization [3–5]. Many utility systems in current industrial plants are fossil fuel-fired systems in the worldwide. Fossil fuels are not depleted, rather they are depletable due to their rate of use being out of phase with both their finite amount and their comparatively excessively high rate of use vis-à-vis their relatively very slow rate of formation in the earth's bowel. On the other hand the high price of energy in today's marketplace makes the optimum design of energy consumption management methods important [6,7]. Indeed, environmental problems created by the increasing rate of fossil fuel consumption threaten the very life of humankind. Therefore, utilizing energy in an effective way and improving energy systems should be prioritized [8–10]. In the last decade, multi-objective analysis and optimization of energy systems have become a key solution in providing a better system in optimal system configuration and optimal energy consumption [11–14]. In the last few decades, increasing global energetic and environmental issues have motivated many researchers, scientists, engineers, technologists. Energy resources in the market are becoming fewer and fetching higher prices as globalization progresses. This is due to several reasons, such as the growth in the global economy, the depletion of energy resources and the environmental impacts of energy production [15–17]. Besides efficiencies, important economic issues (increasing fuels price, environmental cost and etc.) are also highlighted in the evaluation of energy technologies, energy conversion devices and the costs of energy systems. Several methods have been suggested by various researchers. Some of the researchers have suggested methods to show that costs are better shared among outputs based on energy considerations [18–20]. Therefore, Industrial sectors are encouraged to modify their technologies and use more green options (such as utilization of renewable and sustainable energy) [21–24] as well as highly efficient cycles with lower cost. To improve current energy systems, the optimization of the systems and the utilization of the optimum variable in a new plan or the revision of the current variable is taken into consideration [25]. The most suitable value of a function within a given domain could be found by optimization. Multi-

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Nomenclature

List of acronyms

1, 2, 3, …	States of working fluid
Real	Real
Inf	Infinite
SOGA	Single objective genetic algorithm
MOGA	Molti-objective genetic algorithm
H	Specific enthalpy (J kg^{-1})
T	Temperature (K)
$\dot{W}$	Specific work (J kg^{-1})
P	Pressure (kPa)
Z	Cost ($)
Q	Heat (kW)
E	Equilibrium
D	Distance
R	ratio
G	Group

Greek letters

η	Exergy Efficiency (%)
Δ	Rate of change
ξ	Effectiveness

Subscripts

Ex	exergy
Sup	Superheat
Ev	Evaporator
Co	Condenser
Is	Isentropic
Com	Compressor

objective optimization means optimizing several objectives simultaneously, with various number of inequality or equality constraints. Among the optimization methods, evolutionary types and especially Genetic Algorithm (GA) common options in multi-objective Genetic Algorithm (MOGA) optimization due to energy systems complexity and GA capabilities [26,27].

GA method is a stochastic algorithm which is based on reproduction and selection of candidate solutions, and how animal populations evolve in nature [28]. In the first step of GA optimization, initial population is chosen randomly from the domain. This means one may find non unique solution over a specific domain. The issue gets worse and more problematic when a multi objective problem is going to be solved. In multi objective problems, usually there are a set of possible answers instead of an answer. If one runs the computer simulation code with the same settings and inputs, different solutions (means different values for objective functions and decision variables) are achieved. This is due to the fact that genetic algorithm is a random search one which starts with different starting values each time [29,30]. This means that if an optimum point is found in the optimization problem (more common in MOGA problems), and the code is repeatedly executed thereafter, it may not be possible to produce exactly the same solution, making the method to be of questionable reliability. There have been various studies on optimization, which have mainly been associated with combined heat and power (CHP) generation, gas turbines (GT), steam turbines (ST), combined cycle power plants (CCPP) and so on [31–33].

Sanaye and Hajabdollah [34] proposed the optimal design of compact heat exchangers. Six design parameters were selected by the authors who applied multi-objective optimization to achieve the maximum effectiveness and the minimum total annual cost. Ganjehkaviri et al. [3] optimized a combined cycle power plant (CCPP) with three main objective functions. To assess the impact of each design parameter on the objective functions, a parametric study and a sensitivity analysis were performed and discussed in detail. The results demonstrate that the optimum emission-cost frontier trend matches with the emission-efficiency trend. The comparison between the plant operating data and the optimized data confirms that the heat recovery steam generator (HRGS) and the duct burner (DB) are more sensitive to the optimization which is mainly due to the lower cost per improvement. Furthermore, by using the optimum values, exergy efficiency increased around 6% while CO_2 emission reduced by 5.63%. The variation in the cost was less than percent due the fact that cost constraint was implemented. Suresh et al. [35] suggested the best power plant configuration based on energy, exergy and environmental analysis for a coal-fuelled thermal plant in India considering the environmental impact of the power plant in terms of CO_2, SO_x and NO_x emissions. It was found that, by using high ash Indian coal under Indian climatic conditions, the maximum possible plant energy efficiency is about 42.3%. Bracco and Siri investigated an optimal performance analysis of a CCPP with a single pressure heat recovery steam generator (HRSG) from exergy point of view [36]. Paolo Maria et al. [37] studied cost-optimality design for zero energy office buildings located in a warm climate. They applied a number of energy efficiency measures to the envelope and the systems of a virtual reference office building. They used primary energy consumption and global costs to identify the cost-optimal configuration from a financial and macroeconomic analysis. Sahin and Ali [38] optimized a combined Carnot cycle in a cascade form, including internal irreversibility for steady-state operation. Ayman Mohamed et al. [39] investigated the economic viability of small-scale, multi-generation systems including combined cooling, heating and power and combined heat and power along with conventional heating and cooling systems. They were able to determine the cost-optimal solutions for a net zero-energy office building with minimum life-cycle costs by using photovoltaic panel system yields. Hajboldahi et al. [33] optimized a regenerative solar organic Rankine cycle system. They used the real parameter Genetic Algorithm to find the maximum value of relative annual benefit. The design parameters of this system were evaporator pressure, condenser pressure, refrigerant massflow rate, number of solar panel (solar collector), storage capacity and regenerator effectiveness.

Design parameters, like cycle pressures and component sizes have variable controllable values, which the designer can change to achieve optimal design. Design goals are very different from cycle to cycle and even within a cycle.

In this work, the design goal set was to achieve the lowest possible cost for the highest possible efficiency. For this reason the ratio parameter is introduced which means how much must be paid for unit of efficiency. This means lowest cost per efficiency or better to say lowest cost per highest efficiency as we are looking at pareto optimal solutions. To achieve this goal, it is required to have a very flexible optimum design tool, which will be presented in the rest of this paper.

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