A MULTI-HEURISTIC SYSTEM FOR OPTIMIZING THE AMMONIA-WATER POWER/COOLING CYCLE COUPLED WITH AN HCCI ENGINE

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ABSTRACT

Multi-objective optimization (MOO) is of immense importance in majority of engineering applications. In previous study a MOO strategy was performed for optimizing the performance and total cost of a trigeneration system with an HCCI engine as prime mover based on NSGA-II method. The current study presents a novel multi-heuristic system (MHS) to provide a metaheuristics collaboration framework for determining the best design parameters. The offered MHS works on a proposed strategy and prefers short runs of different metaheuristics instead of one single long run of a single metaheuristic. The introduced system optimizes two objective functions of the problem in which it maximizes the exergy efficiency and minimizes the system cost. The obtained results demonstrated that by employing the proposed MHS method a further increase and reduction in exergy efficiency and the sum of the unit costs of the system products are achieved respectively compared to the previous study.

1. INTRODUCTION

Every day large amounts of energy are wasted from industrial plants and exhaust gases are released to the atmosphere. These energy losses reduce the efficiency of the plants and also increase the costs of production. Therefore, waste heat recovery through the utilization of cogeneration systems (heat and power) or trigeneration systems (power, heat and cooling) are getting more attraction. Numerous studies have been published in the literature to improve the design of energy conversion systems to get higher energy and exergy efficiencies [1, 2, 3]. Optimization of energy systems only from the thermodynamics point of view or the economic point of view, such as optimizing the system based on a single objective function like exergy or economic concepts may result in an increase in the overall costs of the system or a reduction in exergy efficiency of the system, respectively. In this regard, multi-objective optimization is considered as a power full tool to improve both exergy efficiency and cost criteria of the energy systems simultaneously. Multi-objective optimization algorithms are designed, created and applied to extract a set of solutions which demonstrate a set of feasible and good solutions to satisfy the problem objectives. Examples for the multiobjective optimization of energy systems are as follows.

Khaljani et al. [4] proposed a combined cycle based on an HCCI (Homogenous Charge Compression Ignition) engine heat recovery employing two organic Rankine cycles. Authors performed a multi objective optimization based on Non-dominated sorting genetic algorithm-II to achieve the best system design parameters from both thermodynamic and economic aspects. Optimization results indicate that the exergy efficiency of the cycle increases from 44.96% for the base case to 46.02%. Also, approximately1.3% reduction in the cost criteria is achieved. Results of the multi-objective optimization justify the results obtained through the parametric study and demonstrate that the design parameters of both ORCs have conflict effect on the objective functions.

Hajabdollahi et al. [5], modeled and optimized an organic Rankine cycle for diesel engine waste heat recovery by NSGA-II. In this work, four refrigerants including R123, R134a, R245fa and R22 were considered as working fluids. The optimization results showed that R123 is the best working fluid in both economic and thermodynamic aspects and R245fa, R134a and R22 have the next ranks, respectively.

Wang et al. [6], optimized an organic Rankine cycle through a multi-objective optimization process based on NSGA-II. The work considered exergy efficiency and capital cost as objective functions. The optimization results showed that the optimum value of the turbine pressure was between 1.8 and 2.3 MPa and the optimum value of the turbine inlet temperature was 90_C.

In another study done by Feng et al. [7], a RORC (regenerative organic Rankine cycle) and a BORC (basic organic Rankine cycle) were optimized by using the NSGA. Results showed that improvement of the exergy efficiency increases the LEC (levelized energy cost). In addition, it was found that the optimum exergy efficiency and LEC for the Pareto optimal solution of the RORC were approximately 8.1% and 21.1% higher than those of the BORC, respectively.

Jamali et al [8] proposed a combined cycle based on the Brayton power cycle and the ejector expansion refrigeration cycle and carried out a complete optimization study is carried out using a multi-objective evolutionary based genetic algorithm considering two different objective functions, heat exchangers size (to be minimized) and exergy efficiency (to be maximized).
Ahmadi et al used a multi-objective optimization method based on a fast and elitist NSGA-II (nondominated sorting genetic algorithm) to determine the best design parameters for a novel biomass-based integrated energy system.

Other examples for multi-objective optimization of integrated energy systems are particle swarm optimization algorithm [9,10], linear programming optimization [11,12,13] and mixed integer non-linear programming algorithm [14].
In a previous study by authors [16] a parametric study and multi-objective optimization strategy using NSGA-II carried out for a tri-generation system. The system is based on the utilization of waste heat from the HCCI engine, to generate power and cooling via an ammonia-water mixture (AWM) cycle. By considering exergy efficiency and sum of the unit costs of the system products as the objective functions, a 16.34% increase in exergy efficiency and about 10% reduction in cost criteria were achieved, respectively. In order to further improve the overall performance of the system, this study uses a novel metaheuristic collaboration framework containing the implementations of a number multi-objective metaheuristics cooperatively work on shared solution population. It maximizes the exergy efficiency and minimizes the system cost. In the proposed multi-heuristic system, some of metaheuristics which are well-known by their success are selected to be applied. The selected metaheuristics are Non-dominated Sorting Genetic Algorithm (NSGA II) [17], Multi-objective Differential Evolution (MODE) [18], Strength Pareto Evolutionary Algorithm (SPEA 2) [19] and Multi-objective Particle Swarm Optimization (MOPSO) [20]. Comparative analysis of the obtained results illustrated that the proposed MHS achieves better performance than the previous work.
The rest of this paper is organized as follows: Principles of multi-objective metaheuristic algorithms within the proposed system are briefly expressed in Section 2. Section 3 expresses the problem definition in details. Fully description of the proposed MHS for multi-objective optimization is presented in Section 4. Section 5 includes description of algorithm parameters, results and comparative analysis. Section 6 presents conclusions and some future research directions.

2. BRIEF DESCRIPTIONS OF METAHEURISTICS USED WITHIN THE PROPOSED MHS

2.1 Non-dominated Sorting Genetic Algorithm (NSGA II)

Non-dominated sorting genetic algorithm (NSGAII) is a well-known evolutionary multi-objective optimization algorithm developed in 2002 by K. Deb et al. [17]. NSGAII applies elitism and crowding operators to preserve high-quality solutions and increase spread along the Pareto front. NSGAII starts with a randomly initialized population and computes the ranks of solutions such that the rank of a solution is the number of other population elements dominating this particular individual. In fact, each rank represents a particular Pareto front in objective space. Accordingly, all solutions are sorted in increasing order of their ranks and they are assigned a rank-fitness proportional to their levels or fronts. Then, the algorithm uses the computed fitness-ranks and applies selection, crossover and mutation operators to create the offspring population. At the end of each generational step, parent and offspring populations are combined, ranks of solutions are computed and the new population is filled from ranked-sets in increasing order of rank values. If the number of elements of the latest rank exceeds the remaining space to be filled, the some of its elements are eliminated based on crowding distance criterion. The above described procedural steps are repeated until predefined termination criteria are satisfied. For the problems having strong parameter interactions, NSGAII is effective in extracting Pareto fronts closer to the optimal one. A detailed description of the NSGAII algorithm can be found in [17].

2.2 Multiobjective Differential Evolution (MODE)

In general, multi-objective implementations of differential evolution are based on extension of the single-objective differential evolution (DE) algorithm. MODE, proposed by Xue et al. [18], has similarities with the DE variant DE/best/1/bin. The proposed method implements a Pareto based approach for the selection of the best individual as follows: if the trial solution is dominated, then the best is randomly chosen from subset of non-dominated solutions. If the trial solution is non-dominated, then it is chosen as the best individual. For the purpose of population management, the authors used a (μ+λ)-selection strategy, Pareto ranking and crowding distance mechanisms are used to get solutions that have a well spread along the computed Pareto Front. MODE is used to solve unconstrained problems of high dimensionality and it is shown to generate improved solutions compared to SPEA algorithm.

2.3 Multi-objective Particle Swarm Optimization (MOPSO)

Coello et al. proposed the multi-objective particle swarm optimization (MOPSO) method that extends the standard PSO algorithm to deal with multi-objective optimization problems [20]. This method maintains an external global repository to store the non-dominated solutions extracted within the algorithm. MOPSO also uses the concept of Pareto dominance to determine the flight direction. An important issue in MOPSO algorithm is the generation of hypercubes in which coordinates of a particle is defined with respect to its objective function values. These hypercubes are then used to determine a repository element that acts as the global best solution in velocity computation of the particle under consideration. For this purpose, fitness values of hypercubes are first scaled inversely proportional to their cardinality and the one from which the global best will be taken is determined through roulette wheel selection. Detailed description of the MOPSO is presented in [20].

2.4 Strength Pareto Evolutionary Algorithm (SPEA2)

Strength Pareto Evolutionary Algorithm is an evolutionary multi-objective optimization method proposed by Zitzler et al. [19]. The algorithm uses a regular population and maintains an external archive for storage of non-dominated solutions. Each archive element A(i) is assigned a strength value S(i) which is equal to the number of population elements that are dominated by or equal to A(i). For archive elements, S(i) also represents the fitness value FA(i) of A(i). For a population element P(j), its fitness FP(j) is calculated from the sum of S(i) values of archive members that dominate or equal to P(j). A one is added to this sum to avoid zero fitness values. These fitness values, FA(i) and FP(j), are called the raw fitness and they may cause ranking difficulties when most individuals do not dominate each other. To solve this problem, SPEA2 introduces density information to differentiate between individuals having identical raw fitness values and actual fitness of an individual is taken as the sum of its raw fitness and the density information. Following the actual fitness computation, external archive is updated by extracting non-dominated solutions from union of population and old archive members. Finally, a mating pool is formed using updated archive elements through binary tournament selection and offspring individuals are generated with crossover and mutation operators. Experimental evaluations over sets of well-known test problems demonstrated that SPEA2 achieved a success similar to that of NSGAII.

3. Problem definition

Figure 1 displays the schematic diagram of the considered trigeneration system. The engine intake air is first compressed to and then flows into two intercoolers. Exhaust gases leaving the engine are expanded in turbine 1 to produce the required work for the compressor. The bottoming cycle is an ammonia-water cogeneration cycle which recovers the energy content of exhaust gases at a temperature of 525.1 K. The AWCC which produces power and refrigeration simultaneously is actually a combination of the Rankine and absorption refrigeration cycles. Ammonia solution with low pressure and basic concentration (state point 11) is pumped to a high pressure. After being heated in the heat exchanger, the solution enters the generator where it is separated into weak solution (with less ammonia concentration) and ammonia-rich vapor. The vapor is then sent to the condenser 1 before being condensed to liquid in condenser 2. On the other hand the weak ammonia-water solution exiting the generator is delivered to the boiler where it is heated and becomes saturated vapor before being superheated in the super heater. The superheated vapor is then expanded in the turbine 2 to produce power. The liquid ammonia from condenser 2 goes to the evaporator through the expansion valve to cool the space to be refrigerated. The low pressure ammonia vapor exiting the evaporator passes through the absorber where it is absorbed by the ammonia-water solution coming from the condenser 1 and the turbine 2. Finally the basic ammonia-water saturated liquid is formed and thus the cycle is completed.

In order to evaluate the system from thermodynamic point of view, the conservation of mass principal along with the first and second laws of thermodynamics are applied to each component of the system which is considered as a control volume. The detailed description of the system and the energetic, exergetic, and exergoeconomic relations for the components of system were provided in the previous studies [15, 16]. The purpose of the study is achieving higher exergy efficiency ($\eta_{(II,AWCC)}$) while reducing the sum of the unit costs of the system products ($c_{(p,total)}$). In this work AWMT inlet pressure ($P_{(in,AWM\ Turbine)}$), Generator temperature (T_{Gen}), Ammonia mass fraction in basic solution (X_b), Pinch point temperature difference (ΔT_{Pinch}), Turbine isentropic efficiency (η_T) are selected as decision variables.

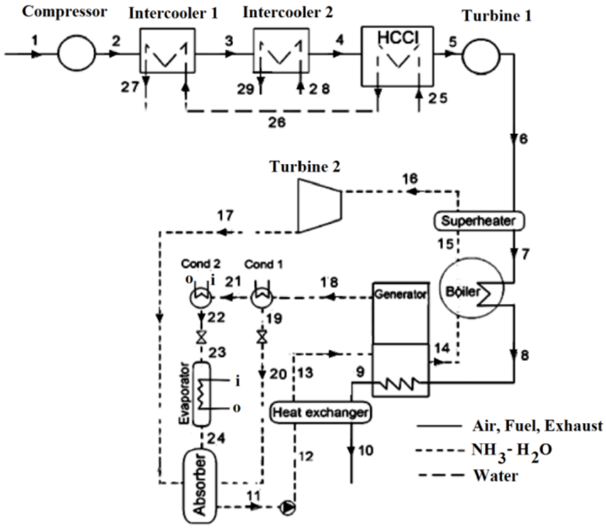


Fig1. Schematic diagram of the tri-generation system [15].

4. The proposed multi-heuristic system for optimizing the ammonia-water power/cooling cycle coupled with an HCCI engine

This section expresses the proposed multi-heuristic system (MHS) based on a novel collaboration mechanism for the solution of multi-objective ammonia-water power/cooling cycle optimization problem. As shortly mentioned above, the proposed system includes four multi-objective metaheuristics which cooperatively work on shared solutions to maximize the exergy efficiency and minimize the system cost. Architectural description of the proposed system is presented in Fig. 2.

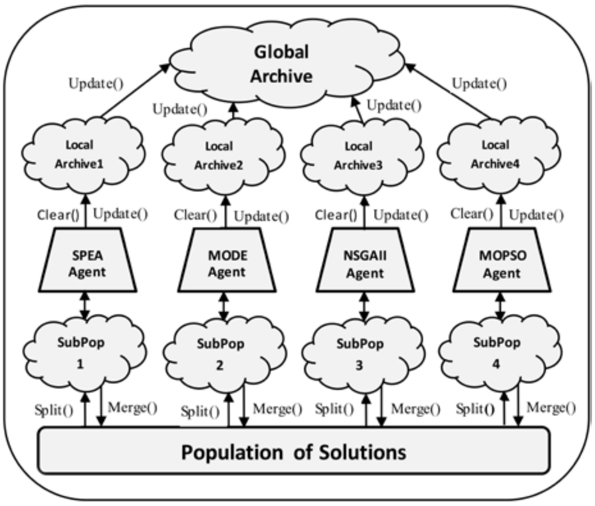


Fig. 2. Architectural description of the proposed multi-agent system.

The proposed multi-heuristic system (MHS) comprises one fixed sized population, one global archive and four metaheuristics with local archives embedded. The system works iteratively in sessions consisting of two consecutive steps: in the first step, the population of solutions is shuffled and split randomly into four equal sized subpopulations. Later on, subpopulations are supplied to the metaheuristics one for each. In the second step, each metaheuristic is applied to operate on its own subpopulation of solutions. An epoch begins with a new assignment of metaheuristics and ends up when termination criteria are satisfied. Individual metaheuristics have their own local archive which must be cleared in the beginning of each epoch. The local archives are updated during the metaheuristic ececution and used to keep all non-dominated solutions extracted in an epoch, whereas the system encompasses a global archive to keep all non-dominated solutions found by all metaheuristics in all epochs. That is to say, global archive resembles the Pareto-Front resulted by merging all local archives with the global archive at the end of each epoch. The system combines global archive current contents with the new local archives and eliminates those dominated solutions from this combination. Meanwhile, at the end of each epoch, all subpopulations are merged to construct a global population to be used in next epoch. In that fashion, all metaheuristics collaborate with each other by sharing their search experiences through aggregating the improved subpopulations and extracted local archives in a common population and in a common global archive respectively.

Currently, the proposed multi-heuristic system comprises four metaheuristics, namely NSGAII, SPEA2, MODE and MOPSO. The proposed multi-heuristic system prefers short runs of different metaheuristics instead of one single long run of a single metaheuristic. This way, metaheuristics will be able to cover the inabilities of other metaheuristics in extracting more promising parts of search space. However the proposed system is flexible enough to add a new multi-objective metaheuristic or remove an existing one. All metaheuristics in the proposed system use the same solution representation; therefore there is no need to convert solutions when they are exchanged between different metaheuristics in the system. Effectiveness of the obtained multi-heuristic system is investigated in the next section. Results presented in tables clearly demonstrate that the all goals on the design of the proposed multi-heuristic system are achieved.

5. Results and evaluations

Performance evaluation of the proposed system and its robust success against state-of-the art method is presented in this section. Algorithmic parameters of the metaheuristic methods used within the proposed multi-heuristic system are given in Table 1. All of the parameters in Table 1 are collected from well-known conventional implementations of the corresponding metaheuristic algorithms. Implementation of the proposed system is carried out using Matlab® programming language environment.

Table 1 Algorithmic parameters of the metaheuristic methods used within the proposed system.

Metaheuristic	Algorithm Parameters
MOPSO	|Pop| = 75, C1=2.0, C2=2.0, ω_{max}=0.9, ω_{min}=0.4
MODE	|Pop| = 75, Scaling_Factor=0.5, P_C =0.7
SPEA2	|Pop| = 75, P_C =0.9, P_m=1.0/Num_Vars, Distribution_Index=20
NSGAII	|Pop| = 75, P_C =0.9, P_m=1.0/ Num_Vars, Distribution_Index=20,

Similar to Bahlouli et al. [16], 250 generations are considered totally for all metaheuristics and the population size for each metaheuristic is totally 300 individuals as 75 each. Meanwhile, the ranges of the input parameters used in the optimization process are listed in Table 2.

Table 2 The design parameters range in optimization

Parameter	Range
$P_{in,\ AWM\ turbine}(bar)$	15-30
$T_{GE}(k)$	420-440
X_b	0.34-0.4
$\Delta T_{pp}(K)$	10-20
η_T	0.7-0.9

In the optimization problem of the cycle, two objectives are selected namely: the exergy efficiency $\eta_{II,AWCC}$ and the sum of the unit costs of the system products $C_{p,tot}$. The goal of the optimization is the maximization of the exergy efficiency and minimization of the second objective.

Figure 3 shows the plot of computed Pareto front extracted by MHS for two-objective test problem including 500 non-dominated solutions.

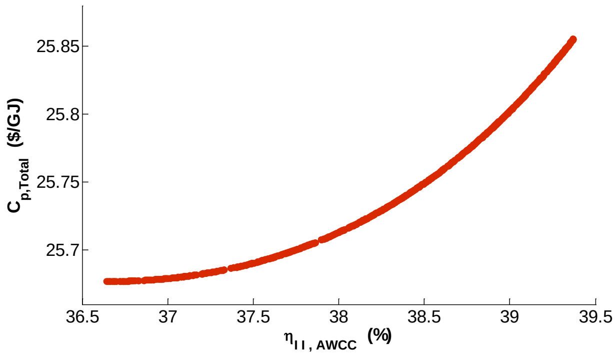


Fig. 3. The Pareto-Front extracted by MHS.

Also, Figure 4 illustrates the plots of best computed Pareto-Front obtained by MHS against the Pareto-Front extracted by Bahlouli et al. published in [16]. In ref. [16] since increasing the exergy efficiency from 36% to 39% increases the cost rate of product insignificantly, point B with the exergy efficiency of 39.16% and the sum of the unit cost of the products 25.97$/GJ had been selected as final optimize point. With the same reason, point A with the exergy efficiency of 39.37% and the sum of the unit cost of the products 25.85$/GJ is selected as final optimum point in this work.

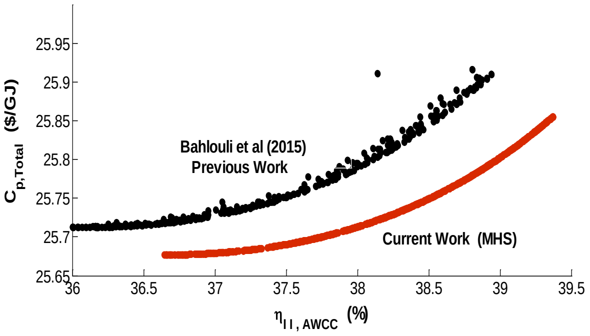


Fig. 4. The Pareto-Front extracted by MHS and previous work.

Table 3 shows all the design parameters and thermodynamic characteristics of three different points namely, base point, point B of multi-objective optimization strategy using NSGA-II and point A of multi-objective optimization strategy using the proposed multi-heuristic system (MHS) in current work. A companion between the results for point A with point B reveals that the proposed multi-heuristic system has better capability in improving both exergy efficiency and the sum of unit costs of the system products compared to the NSGA-II. The increase in exergy efficiency by employing MHS in optimization process is about 0.56 percent greater than the use of NSGA-II. Also, it is about 0.45 percent effective in the reduction in the sum of unit costs of the system products compared to NSGA-II method.

Table 4. Comparison of base and optimization results of the parameters for the combined cycle

Design parameter	Base	Optimized (NSGA-II) Point B (ref. [16]	Optimized (MHS) Point A
$P_{in,AWM\ Turbine}$ (bar)	20	29.89	32.00
T_{Gen} (K)	430	420.2	420.00
X_b	0.4	0.342	0.34
ΔT_{Pinch}(K)	15	10.01	10.00
η_T	0.85	0.90	0.90
η_P	0.70	0.70	0.70
Performance of the AWCC			
Exergy efficiency (%)	22.8144	39.1596	39.3708
Unit costs of the system products ($/GJ)	28.89	25.9721	25.8553

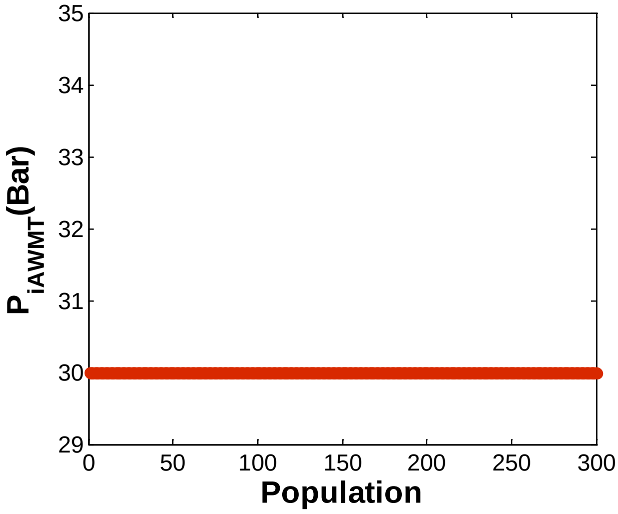
The IGD (Inverted Generational Distance) metric is used to calculate the distance between two competitive algorithms [21]. This metric measures both convergence and diversity.

Let PF1 is a set of non-dominated solutions in Pareto front found by MHS and PF2 is the set of non-dominated solutions in the Pareto-Front discovered by Bahlouli et al. [16].

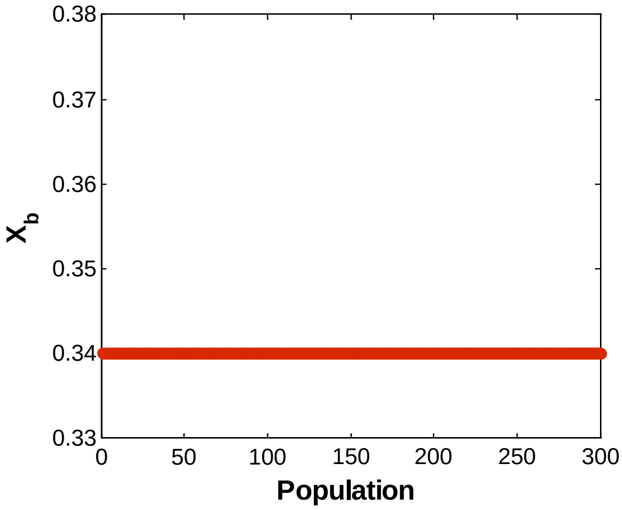
$$IGD = \frac{\sum_{v \in PF1,\ x \in PF2} d(v,x)}{|PF1|} \quad (1)$$

d(v,x) denotes the minimum Euclidean distance between the points v and x. The IGD value for figure 4 is calculated as 74.134 which shows that there is significant distance between two Pareto-Fronts and they are far from each other.

The scattered distributions of design variables are displayed in Figure 5 to get insight on these variables. The trends of results are in consistence with the reported results in ref. [16]. It can be seen from this figure that while AWMT inlet pressure and AWMT isentropic efficiency (Figures 5a and 5e) have tendency of being highest values, this trend is vice versa for ammonia mass fraction in basic solution and generator temperature (Figures 5b and 5c). These information shows that an increase and decrease in these design variables will cause to better optimization result, respectively. For instance, an increase in AWMT inlet pressure leads exergy efficiency to be increased and sum of the unit cost of the products for the system to be decreased. However, Figure 5d shows that this is not the case for pinch point temperature difference and this variable has a scattered distributions. This observation suggests that the pinch point temperature difference has a significant role for exergy efficiency and total cost rate trade-off.



(5.a)



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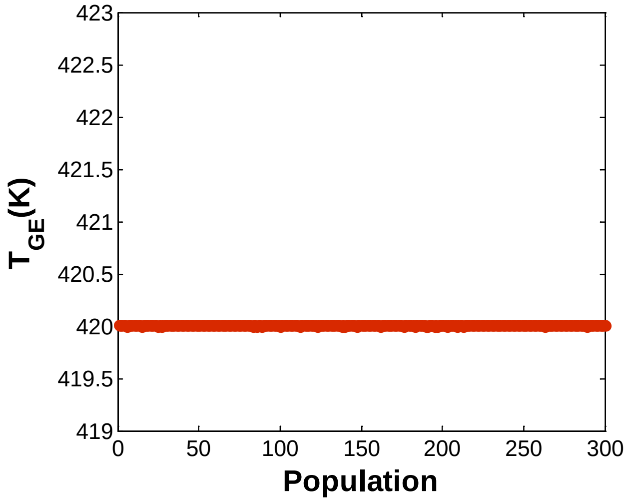
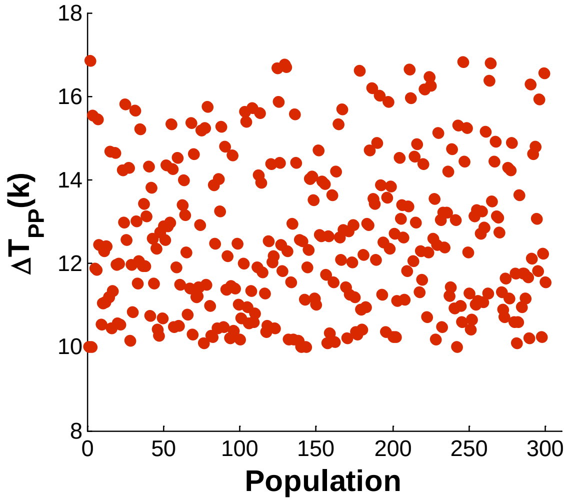
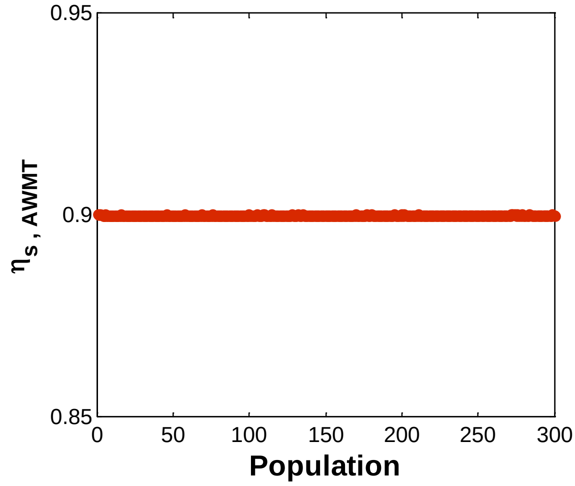


(5.c)



(5.d)



(5.e)

Fig. 5. The Pareto-Front extracted by MHS and previous work.

6. Conclusions and future works

This study presents a new approach to design a cooperative multi-heuristic system for the solution of ammonia-water power/cooling cycle coupled with an HCCI engine. In the proposed method, a number of metaheuristics are implemented as individual search technique. The global population is divided into subpopulations randomly each subpopulation is optimized by an assigned metaheuristic. The results reveal that implementing the proposed method improves both exergy efficiency and the sum of the unit costs of the system products compared to the previous study by Bahlouli et al. [16]. Further research is planned to extend the proposed MHS with additional MOO agents and consider its use for practical real-valued problems in mechanical engineering and energy systems.

Nomenclature

$C_{p,Total}$	unit costs of the system products (\$ GJ^{-1})
p	pressure (Pa)
T	temperature (K)
x_b	basic solution ammonia concentration
Greek symbols	
η_{II}	second law efficiency
Subscripts	
GE	Generator
p	Pump
pp	pinch point
sup	Superheater
turb	Turbine
tot	Total
P	Product
Abbreviations	
AWCC	ammonia water cogeneration cycle
ORC	Organic Rankine cycle
AWM	Ammonia water mixture
NSGA II	Non-dominated Sorting Genetic Algorithm
MODE	Multi-objective Differential Evolution
SPEA 2	Strength Pareto Evolutionary Algorithm
MOPSO	Multi-objective Particle Swarm Optimization
MHS	Multi-Heuristic System
HCCI	Homogeneous charge compression ignition
cond	Condenser

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