# An Evolutionary Framework for Bi-objective Dynamic Economic and Environmental Dispatch Problems

**Forhad Zaman, Saber M. Elsayed, Tapabrata Ray and Ruhul A. Sarker**

**Abstract** A dynamic economic and environmental dispatch (DEED) problem is a challenging bi-objective optimization problem that simultaneously minimizes both operating costs and gas emissions. To solve it, several evolutionary algorithms (EAs) have been used, each of which has pros and cons, with one performing better in an early stage of evolution and another later. In this paper, to solve such problems, an evolutionary framework is designed based on two EAs, a genetic algorithm (GA) and differential evolution (DE), dynamically configures the better of the two during the evolution. In it, two sub-populations are performed, one for each of GA and DE, and their sizes updated in each generation according to the respective algorithm's performance in previous generations. Moreover, a heuristic is employed to improve the performance of the proposed algorithm by repairing infeasible individuals towards feasible directions. To demonstrate its performance, two renewable-based DEED problems are solved using the proposed and state-of-the-art algorithms. An analysis of the simulation results reveals that the proposed algorithm is the best of those considered, with the heuristic enhancing its performances.

**Keywords** Renewable energy · Economic and emission dispatch · Multiobjective optimization · Differential evolution · Genetic algorithm

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F. Zaman (✉) · S.M. Elsayed · T. Ray · R.A. Sarker
School of Engineering and Information Technology,
University of New South Wales Canberra, Canberra, Australia
e-mail: md.zaman@student.adfa.edu.au

S.M. Elsayed
e-mail: s.elsayed@unsw.edu.au

T. Ray
e-mail: t.ray@unsw.edu.au

R.A. Sarker
e-mail: r.sarker@unsw.edu.au



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# 1 Introduction

Over the last decade, economic dispatch (ED) problems have been used to determine the allocation of electricity demand among fossil fuel-based thermal generating units to minimize operating costs subject to physical and technological constraints [13]. However, the excessive use of fossil fuels produces large amounts of atmospheric pollutants that are continuously released into the environment. Therefore, alternatives to thermal energy power generation have emerged, such as solar, wind and hydro energy, which are now widely used because of their lower production costs and environmentally friendly characteristics [14, 17]. Consequently, the economic and environmental dispatch (EED), a new bi-objective optimization problem, has been introduced to simultaneously minimize operating costs and air pollution [12].

A DEED problem is an extension of the conventional EED one that schedules generators for an operational cycle in a time horizon divided into multiple periods while taking into account the intrinsic links between two hours of the ramp limit of a thermal generator [15]. Although the DEED is a more realistic problem than the EED, its computational process is also more complex because of its large number of decision variables and chain of equality constraints [13]. Moreover, considering the valve point effect (VPE) of a thermal generator's cost function, it becomes a non-linear, non-smooth, non-convex and multi-modal bi-objective optimization problem which is difficult to solve using a classical optimization approach [13, 16]. Therefore, an efficient algorithm, such as an EA, is required because of its flexible, efficient and stochastic searching feature [13].

During the last decade, several meta-heuristic methods, such as GA [13], simulated annealing (SA) [8], particle swarm optimization (PSO) [18] and DE [13], PSO—sequential quadratic programming (PSO-SQP) [11] and modified hybrid evolutionary programming (EP)–SQP (MHEP-SQP) [11] have been effectively used to solve various single-objective DED problems. Also, several algorithms, such as a binary PSO [6], hybrid PSO, non-dominated sorting GA-II (NSGA-II) with a heuristic (H-NSGA-II) [12], infeasibility-driven EA (IDEA) with a heuristic (H-IDEA) [12] and gravitational search algorithm (GSA) with GA [5], have been used to solve bi-objective DEED problems. However, most solve the problems as single-objective optimization ones by aggregating two objectives to produce a single solution, not a Pareto frontier, with many runs required to generate a set of trade-off solutions [12].

In our previous research [13], it was found that, for solving different types of DED problems, one EA may perform well in an early stage of the optimization process but less well in later generations and vice versa. To efficiently solve a DED problem, multi-method EAs that integrate two or more optimization techniques in order to utilize their strengths and overcome their own and each other's weaknesses, have been developed. Similar ones, such as multiple operators of a GA in [10], a multi-operator evolutionary framework with various EAs in [4] and a general framework of two EAs (GA and DE) in [13] have been developed to solve various single-objective optimization problems. However, to the best of our knowledge, solving bi-objective DEED problems using a multi-EAs framework has not yet been explored.

In this paper, an evolutionary framework called GA-DE, in which two EAs (GA and DE) are run in parallel under two sub-populations, is designed to solve bi-objective DEED problems. Although the initial sub-population sizes are the same, they are dynamically varied in each generation based on the performance of each EA in previous generations. After a predefined number of generations (also called a cycle), only the better algorithm is allowed to run alone for a subsequent cycle. After that cycle is finished, both algorithms are run again for another cycle, with both using the same sub-population size. The process is continually repeated until a stopping criterion met. Moreover, rather than setting the control parameters of DE, self-adaptive mutation and crossover techniques that automatically configure the best ones in each generation are used. Also, a heuristic technique is employed to improve the convergence rate of each algorithm by rectifying infeasible individuals towards feasible directions. The results obtained by the proposed approach for solving two renewable-based bi-objective DEED problems, (i) hydro-thermal [1] and (ii) solar-thermal [16], are compared with those from recent state-of-the-art algorithms, with GA-DE shown to perform best.

The rest of this paper is organized as follows: Sect. 2 presents the problem formulation, Sect. 3 the proposed methodology, Sect. 4 the experimental results and analysis and Sect. 5 conclusion and future works.

## 2 Mathematical Formulations

The bi-objective hydro-thermal and solar-thermal DEED problems are formulated to determine the optimal level of power generation in each participating plant by minimizing both the fuel costs and greenhouse gas emissions while satisfying a number of constraints, as presented in this section.

### *2.1 Hydro-Thermal*

In the hydro-thermal DEED problem, the objectives are to minimize both the operating costs and gas emissions subject to a number of equality and inequality constraints.

#### 2.1.1 Objective Functions

Considering the VPE, the cost and emission functions of thermal generators are, respectively:

$$F_c\left(P_{T_{i,t}}\right)=\sum_{t=1}^{T}\sum_{i=1}^{N_T}\left(a_i+b_iP_{T_{i,t}}+c_iP_{T_{i,t}}^2+\left|d_i\sin\left\{e_i\left(P_{T_{i,t}}^{\min}-P_{T_{i,t}}\right)\right\}\right|\right)\forall i,t \quad (1)$$

$$F_E(P_{T_{i,t}})=\sum_{t=1}^{T}\sum_{i=1}^{N_T}\left(10^{-2}\left(\alpha_i+\beta_iP_{T_{i,t}}+\gamma_iP_{T_{i,t}}^2\right)+\eta_ie^{\lambda_iP_{T_{i,t}}}\right)\forall i,t \quad (2)$$

The first objective of Eq. (1) is to minimize the sum of all the fuel costs of the thermal power plants ($P_{T_{i,t}}$) under consideration ($N_T$) during an operational cycle ($T$), where, $a_i, b_i, c_i, d_i$ and $e_i$ are the cost coefficients. The second Eq. (2) is to minimize the gas emissions from the thermal plants, where, $\alpha_i$, $\beta_i$, $\gamma_i$, $\lambda_i$ and $\eta_i$ are their emission coefficients.

### 2.1.2 Constraints

The hydro-thermal DEED problem includes the following constraints.

$$\sum_{i=1}^{N_T}P_{T_{i,t}}+\sum_{j=1}^{N_T}P_{H_{j,t}}=P_{D_t}\ t\in T \quad (3)$$

$$\begin{aligned}P_{H_{j,t}}&=C_{1,j}V_{j,t}^2+C_{2,j}X_{j,t}^2+C_{3,j}V_{j,t}X_{j,t}\\&+C_{4,j}V_{j,t}+C_{5,j}X_{j,t}+C_{6,i}\ j\in N_H,\ \ t\in T\end{aligned} \quad (4)$$

$$V_{j,t+1}=V_{j,t}-X_{j,t}+I_{j,t}-S_{j,t}+\sum_{r=1}^{N_{up}}\left(X_{r,(t-t_{drj})}+S_{r,(t-t_{dr,j})}\right),\ j\in N_H \quad (5)$$

$$P_{H_j}^{\min}\le P_{H_{j,t}}\le P_{H_j}^{\max}\ j\in N_H,\ t\in T \quad (6)$$

$$P_{T_i}^{\min}\le P_{T_{i,t}}\le P_{T_i}^{\max}\ \ i\in N_T,\ t\in T \quad (7)$$

$$V_{H_j}^{\min}\le V_{H_{j,t}}\le V_{H_j}^{\max}\ j\in N_H,\ t\in T \quad (8)$$

$$X_{H_j}^{\min}\le X_{H_{j,t}}\le X_{H_j}^{\max}\ j\in N_H,\ t\in T \quad (9)$$

$$\left|V_{j,t}\right|^{t=0}=V_j^{ini},\ \text{and}\ \left|V_{j,t}\right|^{t=T}=V_j^{end}\ j\in N_H \quad (10)$$

Equation (3) is the power balance constraint, where $P_{H_j}$, $X_j$, and $V_j$ are the hydro power generation, water storage rate and volume of $j$th hydro plant, respectively. $N_H$, $C_{k,j} \forall k$, $I_j$, $S_j$, $N_{up}$, and $t_{d_{r,j}}$ are the number of hydro power plants, the generation coefficient, natural water inflow rate, spillage water (assume zero, as in [1]), number of upstream plants and water transport delay from the $r$th to $j$th reservoir, respectively. The constraints in Eqs. (6)–(9) are the capacity limits of the hydro and thermal plants, water storage volume and water discharge rate, respectively, where, $P_{H_j}{}^{min}$ and $P_{H_j}{}^{max}$, $V_j{}^{min}$ and $V_j{}^{max}$, and $X_j{}^{min}$ and $X_j{}^{max}$ are the minimum and maximum output power of the hydro power plant, water storage volumes and water discharge rates, respectively. The initial and final reservoir storage volumes, which must meet the requirements of all the reservoirs, are expressed in Eq. (10), where, $V_j^{ini}$ and $V_j^{end}$ are the initial and final water volumes of the $j$th reservoir, respectively.

## 2.2 Solar-Thermal

The solar-thermal DEED problem is considered a mixed-integer non-linear bi-objective optimization problem (MINP) [6] in which the solar and thermal units are represented as binary and continuous variables, respectively. Its objective functions and constraints are described below.

### 2.2.1 Objective functions

The objective functions of the solar-thermal DEED problem are to minimize both the operating costs and gas emissions, respectively, as:

$$\text{Min} : F_C\left(P_{T_{i,t}}, U_{s_{s,t}}\right) = \sum_{t=1}^{T}\left(\sum_{i=1}^{N_T}\left(F_{c_i}(P_{T_{i,t}})\right) + \sum_{s=1}^{N_S}\left(F_{Ss}(U_{S_{s,t}})\right)\right) \tag{11}$$

$$\text{where, } F_{c_i}(P_{T_{i,t}}) = a_i + b_i P_{T_{i,t}} + c_i P_{T_{i,t}}^2 + \left| d_i \sin\left\{ e_i \left( P_{T_{i,t}}^{\min} - P_{T_{i,t}} \right) \right\} \right| \tag{12}$$

$$F_{S_s}(U_{s_{s,t}}) = PU_{\cos t_s} P_{S_{s,t}} U_{s_{s,t}}, \quad U_{S_{s,t}} \in \{0, 1\} \;\; s \in N_S \;\; t \in T \tag{13}$$

$$P_{S_{s,t}} = P_{r_s}\left\{1 + \Omega\left(T_{amb_{s,t}} - T_{ref_s}\right)\right\} \frac{Si_{s,t}}{1000} \tag{14}$$

$$\text{Min: } F_E\left(P_{T_{i,t}}\right) = \sum_{t=1}^{T}\sum_{i=1}^{N_T} h_i\left(F_{e_i}(P_{T_{i,t}})\right) = \sum_{t=1}^{T}\sum_{i=1}^{N_T}\left(\frac{F_{ci}\left(P_i^{\max}\right)}{F_{E_i}\left(P_i^{\max}\right)}\right)\left(F_{e_i}(P_{T_{i,t}})\right) \tag{15}$$

$$\text{where },F_{E_i}(P_{T_{i,t}}) = \alpha_i + \beta_i P_{T_{i,t}} + \gamma_i P^2_{T_{i,t}} + \eta_i e^{\lambda_i P_{T_{i,t}}}\ \ i \in N_T\ t \in T \tag{16}$$

The first objective function in Eq. (11) involves the operational costs of the solar and thermal generators, and the second in Eq. (15) the gas emissions from the thermal plants normalized to the cost function. Equation (13) indicates the operational costs of solar power generation ($P_{S_{s,t}}$), where, $U_{S_{s,t}}$ is a binary decision variable that determines whether a unit is turned on or off, and $PU_{cost}$ the per unit cost of $P_{S_{s,t}}$, which expressed in Eq. (14), where $P_{r_s}$ is the rated power, $T_{ref_s}$ and $T_{amb_{s,t}}$ the reference and temperature, respectively, $\Omega$ the temperature coefficient and $Si_{s,t}$ the incident solar radiation of the $s$th plant at the $t$th time.

### 2.2.2 Constraints

The solar-thermal DEED problem has the following equality and inequality constraints.

$$\sum_{i=1}^{N_T} P_{T_{i,t}} + \sum_{s=1}^{N_S} P_{S_{s,t}} U_{S_{s,t}} = P_{D_t} + P_{loss_t}\ \ t \in T \tag{17}$$

$$P_{T_i}^{\min} \le P_{T_{i,t}} \le P_{T_i}^{\max}\ \ i \in N_T,\ t \in T \tag{18}$$

$$-DR_i \le P_{T_{i,t}} - P_{T_{i,t-1}} \le UR_i\ \ i \in N_T\ t \in T \tag{19}$$

$$\sum_{t=1}^{T}\sum_{s=1}^{N_S} P_{S_{s,t}} U_{S_{s,t}} \le 0.3 P_{D_t} \tag{20}$$

Equation (17) defines the power balance constraints, and Eqs. (18) and (19) the capacity and ramp constraints of the thermal generators, respectively, with $UR$ and $DR$ the upward and downward transition limits, respectively. The constraint in Eq. (20) is used to limit the solar share at any time based on a 30 % upper limit to avoid any uncertainty in terms of solar irradiance [6].

## 3 Proposed Bi-objective GA-DE Algorithm

In this research, an evolutionary framework is designed by configuring two optimization algorithms, namely GA and DE for solving the bi-objectives DEED problems. In the design, an initial population of size $N_P$ is generated and then randomly divided into two subpopulations of equal size of $N_{P1}$ and $N_{P2}$ for GA and DE, respectively. In subsequent generations, the new individuals in GA and DE are generated from random individuals from either subpopulation ($N_{P1}$ and $N_{P2}$) rather than only their own which results in information being exchanged between the two algorithms in each generation. Once the fitness functions of both the parents and children are evaluated, a non-dominated sorting approach [2] is applied to rank each individual, with the best $N_P$ individuals selected for the next generation.

Based on the percentage of offspring surviving to the next generation, the success rate (*SR*) of each algorithm is calculated, and their subpopulation sizes subsequently updated considering their lower ($N_{P1}^{min}$) and upper ($N_{P1}^{max}$) bounds as in Eq. (24). This process is continued until a predefined number of generations ($N_{gc}$) is performed. Then, the best algorithm is determined, based on its average *SR* (*ASR*) during the last $N_{gc}$, and used to evolve all the $N_P$ individuals from both subpopulations for the next $N_{gc}$ generations. Once subsequent $N_{gc}$ are completed, the final individuals are again equally and randomly assigned to both algorithms with two subpopulations ($N_{P1}$ and $N_{P2}$) to evaluate next $N_{gc}$ with the GA-DE algorithm terminating once the maximum number of generations, $N_G$ is over. The pseudo code of the proposed GA-DE algorithm is shown in Algorithm 1.

### 3.1 Initial Population

The chromosomes or representations of the decision variables for both GA and DE are expressed as:

$$\vec{x}_p = \begin{cases} [P_{T_{i,t}}, X_{j,t}]_{1:N_x} & \text{for hydrothermal system} \\ [P_{T_{i,t}}, U_{S_{s,t}}]_{1:N_X} & \text{for solar-thermal system} \end{cases} \tag{21}$$

where, $i = 1, 2, \dots, N_T, j = 1, 2, \dots, N_H,\ s = 1, 2, \dots, N_S,\ t = 1, 2, \dots, T, U_{S_{s,t}} \in [0, 1]$, $p \in N_P$, with $N_P$ the population size and $N_x$ the number of decision variables as $T \times (N_T + N_H)$ for the hydrothermal system, and $T \times (N_T + N_S)$ for the solar-thermal one. Each individual is generated as:

$$\vec{x}_p = \vec{x}^{\min} + \left(\vec{x}^{\max} - \vec{x}^{\min}\right)\ lhs(N_x),\ \forall p = 1, 2, \dots, N_P \tag{22}$$

where $\vec{x}^{\min}$ and $\vec{x}^{max}$ are the vectors of the lower and upper bound, respectively, and $\vec{x}_p$ the $p$th individual in the $N_P$ population, with $lhs\left(N_x\right)$ random individuals generated using Latin hypercube sampling (LHS) rules [15].

**Algorithm 1** GA-DE algorithm

**Require:** $N_G, N_P, N_{P1}^{min}$ and $N_{P1}^{max}$
1: Set, $count_1 = count_2 = 0$
2: Randomly generate initial individuals using Eq. (21)
3: Evaluate the individuals after repairing the infeasible individuals using heuristic described in Sect. 3.3
4: Randomly distribute $N_P$ individuals over two subpopulations with sizes of $N_{P1}$ and $N_{P2}$, such that $N_{P1} = N_{P2}$
5: **for** $g = 1 : N_G$ **do**
6: Set, $count_1 = count_1 + 1$
7: **if** $count_1 \leq N_{gc}$ **then**
8: Generate $N_{P1}$ and $N_{P2}$ offspring from the all $N_P$ parents using GA and DE operators, respectively
9: Repeat step 3 for both $N_{P1}$ and $N_{P2}$
10: Determine best individuals from parents and offspring based on non-dominated selection approach described in Sect. 3.4
11: Calculate $SR_{1,g}$ and $SR_{2,g}$ based on numbers of offspring of GA and DE surviving to next generation, respectively,
12: Group selected individuals, $N_P \leftarrow N_{P1} + N_{P2}$
13: Update $N_{P1}$ and $N_{P2}$ according to Eqs. (24) and (25), respectively
14: **else**
15: set, $count_2 = count_2 + 1$
16: **if** $count_2 \leq N_{gc}$ **then**
17: Calculate average success rates of GA ($ASR_1$) and DE ($ASR_2$)
18: **if** $ASR_1 > ASR_2$ **then**
19: Perform GA, considering $N_{P1} \leftarrow N_{P1} + N_{P2}$
20: **else**
21: Perform DE, considering $N_{P2} \leftarrow N_{P1} + N_{P2}$
22: **end if**
23: **end if**
24: **if** $count_2 = N_{gc}$ **then**
25: Repeat step 4 and set again, $count_1 = count_2 = 0$
26: **end if**
27: **end if**
28: **end for**

## 3.2 GA-DE Search Operators

To update the individuals in GA-DE, we use either GA or DE search operators in various stages of an evolution, as previously discussed. Of the different operators available, simulated binary crossover (SBX) and non-uniform mutation (NUM) are used in GA and two self-adaptive mutation operators and one binomial crossover in DE because they showed superior performances for solving various DED problems in [3, 12, 13, 15]. Due to the limitation of this paper's number of pages, details of these operators are not provided but can be found in [15].

### 3.3 Heuristic for DEED Constraints

As previously mentioned, a DEED problem involves a number of equality and inequality constraints, all of which new solutions generated by an EA process may not satisfy, especially during the early stages of an evolution. To maintain feasibility throughout generations, in our previous research, we developed a heuristic for a single-objective DED problem [15]. In it, a DED problem with a 24-h load cycle is converted into 24 sub-problems, with the hourly infeasible individuals repaired in feasible directions based on a forward and backward slack-generation approach. In this paper, we employ this heuristic for a bi-objective DEED problem, with its detailed steps provided in [15].

### 3.4 Selection Process

To rank the chromosomes, firstly, the parents and offspring are grouped together and the best $N_P$ individuals among them selected for the next generation. To do this, we use a popular constraint-handling approach with a non-dominated sorting technique [2] in which an additional objective is considered based on the amount of relative constraint violations (CVs). Then, a crowding sorting technique and non-dominated mechanism are used to preserve diversity and elitism among the population members. The advantages of having an additional objective for constrained optimization problems are explicitly demonstrated in [9], with that of each individual of each algorithm expressed as:

$$CV_p = \sum_{k=1}^{K} \max\left(0, G_k\left(\vec{x}_p\right)\right) + \sum_{e=1}^{E} \max\left(0, H_e\left(\vec{x}_p\right) - \varepsilon_g\right) \ \forall p \in N_P \tag{23}$$

where $\vec{x}_p$ represents the $p$th individual in a sub-population, $G$ and $H$ their inequality and equality constraints, respectively, $K$ and $E$ their numbers of inequality and equality constraints, respectively, for a DEED problem.

Based on the number of individuals selected from the offspring, the $SR$ of each algorithm is calculated; for example, if 30 % of the offspring of GA survive to the next generation, $SR_1$ is 30 %. Then, the subpopulation sizes ($N_{P1}$ and $N_{P2}$) are updated for the next generation according to their normalized SRs as:

$$N_{P1} = \max\left[N_{P1}^{\min}, \min\left\{N_P \frac{SR_{1,g}}{SR_{1,g} + SR_{1,g}}, N_{P_1}^{\max}\right\}\right] \tag{24}$$
$$SR_{1,g} \cup SR_{2,g} \neq 0,\ g \in N_G$$

$$N_{P2} = N_P - N_{P1} \tag{25}$$

Equations (24) and (25) are applied when at least one SR is nonzero, whereas, if both are zero, the values of $N_{P1}$ and $N_{P2}$ remain the same as in the immediate previous generation.

## 4 Experimental Results and Analysis

For the experimental study, two standard benchmarks, (i) a 7-unit hydro thermal power system from [1, 12]; and (ii) a 19-unit solar-thermal power system from [6, 13, 14], for a 24-h planning horizon in one-hour time period are solved using our proposed and state-of-the-art algorithms with and without considering the heuristic, as follows:

1. Non-dominated sorting GA-II (NSGA-II) without heuristic,
2. Multi-objective DE (MODE) without heuristic,
3. Proposed GA-DE without heuristic,
4. NSGA-II with heuristic (H-NSGA-II),
5. MODE with heuristic (H-MODE),
6. Proposed GA-DE with heuristic (H-GA-DE),

Based on [13], $N_P, N_g$ are set to 200, 500, and 100, 1000 for the hydro-thermal and solar-thermal systems, respectively, and $NP_1^{min}$, $NP_1^{max}$, and $N_{g_c}$ to 20, 80, and 50, respectively for both. It is also noted that each algorithm evaluates an equal number of fitness functions for a fairer comparisons. Also, each one runs 30 times using a desktop personal computer which has a 3.4 GHZ Intel Core i7 processor with 16 GB of RAM using the MATLAB (R2014a) environment.

### 4.1 Hydro-Thermal DEED

In this section, a 7-unit bi-objective hydro-thermal DEED problem comprising 3 thermal and 4 hydro units is solved using the proposed and state-of-the-art algorithms on the same platform. Once the 30 random runs of each algorithm are completed, their hyper-volume (HV) values are calculated based on their normalized fitness values as [7]:

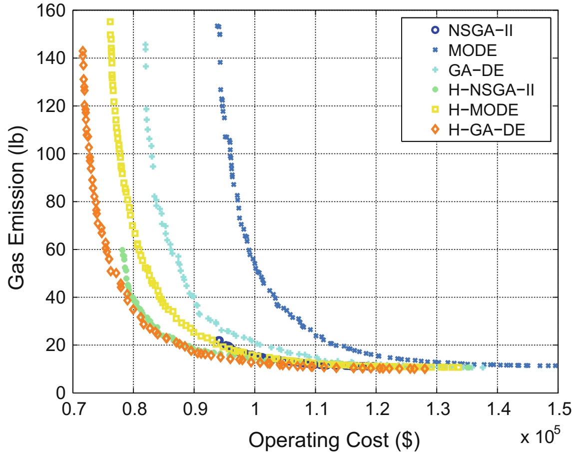
$$f_{norm} = \frac{f - f_{ideal}}{f_{Nadir} - f_{ideal}} \tag{26}$$

where, $f_{norm}$ and $f$ are the normalized and actual function values, respectively, and $f_{ideal}$, and $f_{Nadir}$ the ideal and nadir points [7] for this problem, respectively, which are found to be (7.17E+4,10.09) and (1.28E+5,142.95), respectively from all the runs of all the algorithms considered. The best, mean, median, worst, and standard deviation (STD) of the HV values obtained from algorithm with and without the heuristic

**Table 1** Comparison of performances of algorithms for hydro-thermal DEED

| Algorithm | HV (reference: [1,1]) | | | | | Time (sec) | MR |
|---|---|---|---|---|---|---|---|
| | Best | Mean | Median | Worst | STD | | |
| NSGA-II | 0.59 | 0.53 | 0.54 | 0.44 | 0.05 | 56.81 | 1.60 |
| MODE | 0.49 | 0.43 | 0.44 | 0.35 | 0.05 | **48.91** | 1.70 |
| GA-DE | 0.71 | 0.67 | 0.68 | 0.63 | 0.03 | 53.75 | 2.70 |
| H-NSGA-II | 0.84 | 0.81 | 0.81 | 0.79 | 0.01 | 237.82 | 4.90 |
| H-MODE | 0.81 | 0.77 | 0.78 | 0.71 | 0.03 | 232.55 | 4.10 |
| H-GA-DE | **0.91** | **0.89** | **0.89** | **0.87** | **0.01** | 234.41 | 6.00 |

**Fig. 1** Pareto-frontiers for hydro-thermal problem




are shown in Table 1. It is indicated that the proposed approach with the heuristic (H-GA-DE) obtains the best and most consistent results of all the algorithms in a reasonable computational time. The Pareto-frontiers of the best runs based on the HV values for all the algorithms are plotted in Fig. 1 which also shows the superiority of the proposed algorithm. In fact, the GA-DE approach obtains the best non-dominated solutions, both inclusive and exclusive of the heuristic, with H-GA-DE the best algorithm of all. Also, a Friedman test is performed considering the HV of each run of each algorithm with their mean ranks (MRs) are listed on Table 1 which proved that the H-GA-DE is the best algorithm.

## *4.2 Solar-Thermal DEED*

To demonstrate the performances of the six algorithms, with and without the heuristic, on larger problems, in this section, we solve a 19-unit solar-thermal DEED problem formulated as a mixed-integer, non-linear, bi-objective optimization one that

**Table 2** Comparison of performances of algorithms for solar-thermal DEED

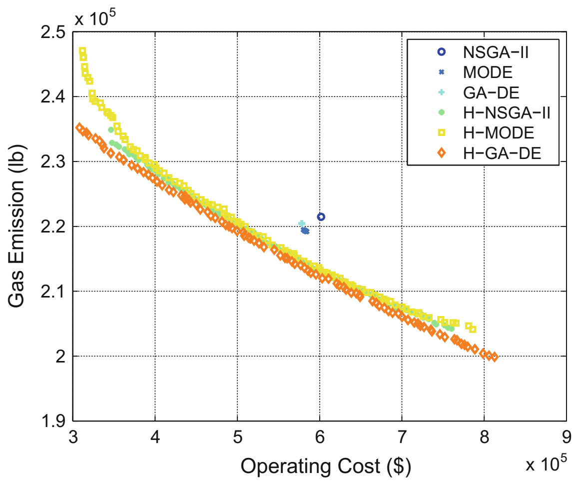
| Algorithm | HV (reference: [1,1]) | | | | | Time (sec) | MR |
|---|---|---|---|---|---|---|---|
| | Best | Mean | Median | Worst | STD | | |
| NSGA-II | 0.18 | 0.17 | 0.17 | 0.15 | 0.01 | 64.47 | 1.00 |
| MODE | 0.21 | 0.20 | 0.21 | 0.18 | 0.01 | **52.21** | 2.80 |
| GA-DE | 0.20 | 0.19 | 0.20 | 0.18 | 0.01 | 75.38 | 2.20 |
| H-NSGA-II | 0.52 | 0.51 | 0.51 | 0.51 | 0.00 | 158.21 | 5.00 |
| H-MODE | 0.50 | 0.49 | 0.49 | 0.47 | 0.01 | 148.30 | 4.00 |
| H-GA-DE | **0.56** | **0.55** | **0.55** | **0.54** | **0.00** | 212.48 | 6.00 |

minimizes both the operating costs and gas emissions. The binary decision variables of the solar units are handled as continuous ones and then rounded off in order to avoid different representations.

Once the 30 independent runs are completed, the functions' values are normalized according to Eq. (26) based on nadir and ideal points, and found to be, (8.17E+5, 2.36E+5) and (3.08E+5, 2.0E+5), respectively. Subsequently, the HV of each run is calculated and the best, mean, median, worst and STD values presented in Table 2 which indicates that the proposed H-GA-DE obtains the best solutions of all the algorithms within a reasonable computational time. Also, based on the MR of the Friedman test, H-GA-DE is the best algorithm once again.

The Pareto frontiers of the best runs based on the HV values are presented in Fig. 2 in which it is clear that including a heuristic significantly improves the performances of all the algorithms considered, with the proposed H-GA-DE the best in terms of obtaining non-dominated solutions. In fact, when the algorithms do not include the heuristic, as their numbers of feasible solutions are very limited, the range of Pareto

**Fig. 2** Pareto-frontiers for solar-thermal problem



frontiers is very narrow. Conversely, when the heuristic is applied to rectify infeasible solutions towards a feasible direction, the algorithms quickly obtain non-dominated feasible solutions while simultaneously minimizing both objectives.

## 5 Conclusion and Future Work

In this paper, an evolutionary framework based on the automatic configuration of GA and DE was designed to solve bi-objective DEED problems. In it, random individuals from the initial population were evaluated in parallel through two different sub-populations, one using GA and the other DE. The sub-population sizes were dynamically updated during the evolutionary process based on their prior performances, with the better-performing algorithm receiving more individuals to evolve and vice versa. To enhance the performance of the proposed algorithm, a heuristic was employed to rectify infeasible individuals. The proposed framework was tested by solving two renewable-based bi-objective DEED problems using the proposed and state-of-the-art algorithms. A comparison indicated that the proposed GA-DE framework consistently performed better than all the other algorithms, with the heuristic greatly enhancing all their performances.

In future, bi-objective DEED problems could be solved using this configuration but with more algorithms and the uncertainty factors of renewable sources incorporated in the model.

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