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A Particle Swarm Optimization for Multiobjective Combined Heat and Power Economic Dispatch Problem Considering the Cost, Emission and Losses

B.Venkatesh, V.Subbu Chithira Kala

Abstract— Combined heat and power units are playing an ever increasing role in conventional power stations due to advantages such as reduced emissions and operational cost savings. This paper investigates a more practical formulation of the complex non convex, non-smooth and non-linear multi-objective economic emission dispatch that incorporates combined heat and power units. The effect of valve-point in cost function considered with adding an absolute sinusoidal term to conventional polynomial cost function. A multi-objective particle swarm optimization (MOPSO) method is applied to test case. The obtained results demonstrate the superiority of the proposed method in solving non-convex and constrained CHPED problem.

Keywords: Combined heat and power unit, valve-point effect, MOPSO, Economic Dispatch problem

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1 Introduction

THE energy efficiency of the most efficient conventional power production unit is less than 60%, but the fuel efficiency of combined heat and power (CHP) production unit can be as much as 90% [1,2]. Beside its high efficiency, CHP results in the reduction of environmental pollutants (CO_2, SO_2, SO_x, and, NO_x emissions) by about 13–18% [1]. In order to utilize CHP units more efficiently, economic dispatch problem is applied to determine the optimal combination of the power and heat sources' outputs to satisfy heat and power demand of system and operational constraints. This problem is known as CHP economic dispatch (CHPED) problem and has attracted a lot of interests in recent years. Dual dependency of heat and power production in CHP units makes the CHPED problem a complicated optimization problem, which needs powerful optimization techniques to solve it. The CHPED problem will be more complex if the effects of the valve-point in cost function and system losses are taken into account. Considering valve-point effects make the CHPED problem non-convex. Hence, using gradient based classic optimization methods does not guarantee obtaining the optimal solution. Because non-convex CHPED problem has a lot of local optima and in most cases, classical methods find a relative optimum (or local optimum) that is closest to the starting point.

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Stochastic search methods which are not based on the gradient of the objective function are used to solve constrained CHPED problem. These methods can give a good solution with reasonable computation time where the exact methods fail to produce a solution or they are too slow. Improved genetic algorithm with multiplier updating (IGA-MU) is used to solve CHPED problem in [3]. In this work, it is assumed that the cost functions of power-only and heat-only unit are linear. Optimal solution of CHPED problem using harmony search (HS) algorithm is presented in [2,4]. They used cubic cost function for power-only units and valve-point effects are not considered. In [5], multi objective CHPED problem is solved considering wind power generation using PSO algorithm. In this paper quadratic cost functions are used for CHP units and minimizing cost and emissions are considered as objectives. CHPED problem is solved using ant colony search algorithm (ACSA) in [6], In [7] mesh adaptive direct search (MADS) has been implemented to solve CHPED problem. In order to improve MADS effectiveness, the authors have used three algorithms as search strategies namely, Latin hypercube sampling (LHS), particle swarm optimization (PSO) and design and analysis of computer experiments (DACE) surrogate algorithm. Self-adaptive real-coded genetic algorithm (SARGA) has been implemented to solve the CHPED problem in [8], where penalty constraint handling strategy is used for handling equality and inequality constraints. A novel selective particle swarm optimization (SPSO) is presented in [9] to improve the efficiency of PSO algorithm in solution of CHPED problem. The convergence of PSO is improved in SPSO by refining the search by eliminating the particles exhibiting poor fitness and focusing on the more promising ones. The system loss and valve-point effect are not taken into account in the above-mentioned works. Differential evolution (DE) and bee colony optimization algorithm are proposed to solve non con-

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vex CHPED problem considering valve-point effect and network losses in [10,11], respectively. A review of research works related to short term scheduling of CHP units can be found in [12].

A multi-objective particle swarm optimization (MO-PSO) is used to solve non-linear and non-convex CHPED problem. More accurate modeling of CHPED problem is carried out by considering valve-point effects and losses. Appropriate penalty functions are incorporated in fitness function for handling different equality and inequality constraints. The efficiency of the proposed algorithm is evaluated by using test case

The remainder of the paper is organized as follows. Section 2 provides the mathematical formulation of the CHPED problem considering valve-point effects and losses. The proposed MOPSO algorithm is described in Section 3. Section 4 provides the step by step procedure of proposed MOPSO algorithm for solving CHPED problem. Several case studies are presented in Section 5.

2 CHP Economic Dispatch Problem Formulation

2.1 Problem Formulation

Conventional thermal units, combined heat and power units (co-generation units) and heat-only units are considered in this study. The objective function of CHPED problem is minimizing the total heat and power production Cost, Emission and Losses. The objective function can be stated as

Minimize

$$F_1(P,H) = C_1(P^{TU}) + C_2(P^{CHP}, H^{CHP}) + C_3(H^H) \quad (1)$$

$$F_2(P,H) = E_1(P^{TU}) + E_2(P^{CHP}, H^{CHP}) + E_3(H^H) \quad (2)$$

$$F_3(P) = \sum_{i=1}^{N_{TU}} \sum_{m=1}^{N_{TU}} P_i^{TU} B_{im} P_m^{TU} + \sum_{i=1}^{N_{TU}} \sum_{j=1}^{N_{CHP}} P_i^{TU} B_{ij} P_j^{CHP} + \sum_{j=1}^{N_{CHP}} \sum_{n=1}^{N_{CHP}} P_j^{CHP} B_{jm} P_n^{CHP} \quad (3)$$

2.1.1. Thermal Units (TUs) [13-17, 24-26]

$$C_1(P^{TU}) = \sum_{i=1}^{N_{TU}} (\alpha_i + \beta_i P_i^{TU} + \gamma_i (P_i^{TU})^2 \quad (4)$$

$$E_1(P^{TU}) = \sum_{i=1}^{N_{TU}} (\alpha_i + \beta_i P_i^{TU} + \gamma_i (P_i^{TU})^2 + \xi_i \exp(\lambda_i P_i^{TU})) \quad (5)$$

where $P^{TU} = [P_1^{TU}, P_2^{TU}, ...P_{N_{TU}}^{TU}]$

It is worth to note that the traditional cost function of each TU is presented in some literature as a quadratic function with smooth nature. But in reality, a sharp increase in fuel loss would be added to the fuel cost curve due to the wire drawing effects when steam admission valve starts to open. This procedure is named as Valve-point effects [9-13, 24-25] which is described as a superposition of quadratic and sinusoidal function and local optimal points of the solution space. Also, in the primal studies, the emission function of each TU was expressed s a quadratic function, but according to [26], the exponential term was added to the quadratic function for several reasons which were obtained from experiments

2.1.1. CHP Units

CHP is sometimes known as cogeneration, and is the use of a single piece of plant to simultaneously generate heat and electricity. Each CHP unit has a power-heat FOR (Feasible Operation Region), shown in Fig. 1.
The FOR is embayed by the boundary curve ABCDEF. Along the boundary curve BC, the heat capacity increases as the generation of electricity declines. The heat capacity decreases along the curve CD [15,18,19].

$$C_2(P^{CHP}, H^{CHP}) = \sum_{j=1}^{N_{CHP}} (a_j + b_j P_j^{CHP} + c_j (P_j^{CHP})^2 + d_j H_j^{CHP} + e_j (H_j^{CHP}) + f_i P_j^{CHP} H_j^{CHP}) \quad (6)$$

$$E_2(P^{CHP}, H^{CHP}) = \sum_{j=1}^{N_{CHP}} (a_j + b_j) P_j^{CHP} \quad (7)$$

Where $P^{CHP} = [P_1^{CHP}, P_2^{CHP}, ...P_{N_{CHP}}^{CHP}]$ and $H^{CHP} = [H_1^{CHP}, H_2^{CHP}, ...H_{N_{CHP}}^{CHP}]$

It should be pointed out that many researches on the operation of CHP systems, considers the curve model of fuel consumption, heat flows, thermal limits and other characteristics which is necessary to consider in the CHP operation in terms of cost function [20]. A common model for CHP cost function is the use of quadratic polynomial functions of heat and electricity power output of CHP unit plus a coupling coefficient that relates electricity power and heat [20]. Also, the emission of these units is proportional to their electricity power outputs [28].

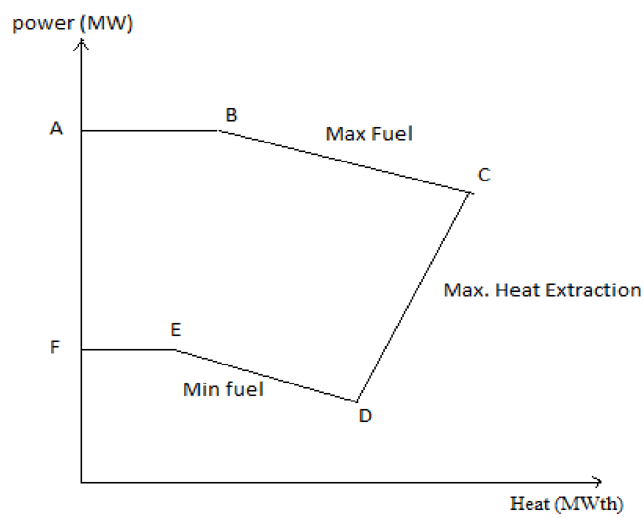


Fig.1. power-heat feasible operating region (FOR) for a CHP unit

2.1.1. Heat Units

The heat-only units are used to add flexibility to CHP units in Meeting high heat load demands. The cost and emission functions of heat-only units can be described as [15, 27, 29].

$$C_3(H^H) = \sum_{h=1}^{N_H} (a_h + b_h P_h^{CHP} + c_h (P_h^{CHP})^2) \quad (8)$$

$$E_3(H^H) = \sum_{h=1}^{N_H} (a_h + b_h) P_h^H \quad (9)$$

where $H^H = [H_1^H, H_2^H, ...H_{N_H}^H]$ It should be noted that using the experiments for characterizing the heat of heat-only units lead to a quadratic cost function according to (8). In addition the emission of these units is proportional to their heat outputs [29].

The optimization problem in eq (1), (2) and (3) should be minimized subject to the following constraints:

- Power generation and demand balance equation

$$\sum_{i=1}^{N_{TU}} P_i^{TU} + \sum_{j=1}^{N_{CHP}} P_j^{CHP} = P_d \quad (10)$$

Where Pd is the electrical power demand of system

- Heat production and demand balance equation

$$\sum_{j=1}^{N_{CHP}} H_j^{CHP} + \sum_{k=1}^{N_H} H_k^H = H_d \quad (11)$$

Where Hd is the thermal demand of system

- Capacity limits of Thermal units

$$P_i^{TU\min} \le P_i^{TU} \le P_i^{TU\max} \quad (12)$$

Where i = 1, 2,…….,N_{TU} , $P_i^{TU\min}$ and $P_i^{TU\max}$ the minimum and maximum power outputs of the ith unit in MW

- Capacity limits of Heat units

$$H_k^{H\min} \le H_k^H \le H_k^{H\max} \quad (13)$$

Where i = 1,2,…….N_H , $H_k^{H\min}$ and $H_k^{H\max}$ are the minimum and maximum thermal outputs of the kth unit in MWth

- Capacity limits of CHP units

$$P_j^{CHP\min}(H_j^{CHP}) \le P_j^{CHP} \le P_j^{CHP\max}(H_j^{CHP}) \quad (14)$$

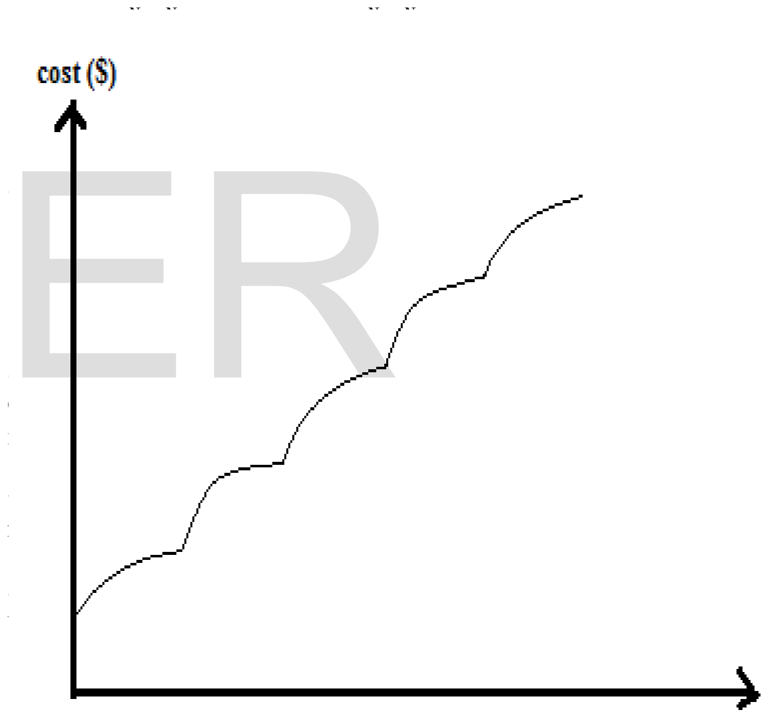
$$H_j^{CHP\min}(P_j^{CHP}) \le H_j^{CHP} \le H_j^{CHP\max}(P_j^{CHP}) \quad (15)$$

j = 1,2,…N_{CHP}

Where $P_j^{CHP\min}(H_j^{CHP})$ and $P_j^{CHP\max}(H_j^{CHP})$ are minimum and maximum power limit of jth CHP unit which are functions of Generated heat $H_j^{CHP\min}(P_j^{CHP})$ and $H_j^{CHP\max}(P_j^{CHP})$ are minimum and maximum heat limit of jth CHP unit which are functions of generated power. It should be mentioned that the power production limits of CHP units are depends on the unit heat productions and the heat production limits are depends on the unit power production

2.2 Considering Transmission Losses

Transmission losses of the system should be taken into account in order to meet the load demand exactly. System loss is a function of power production of all units. There are two approaches for calculating system transmission loss, i.e., load flow approach [21] and Kron's loss formula which is known as B-matrix method [22]. The second approach is used in this work in line with works previously published in CHPED area like as [10,11,23]. Using B-matrix coefficients, the system transmission losses can be stated as follows.



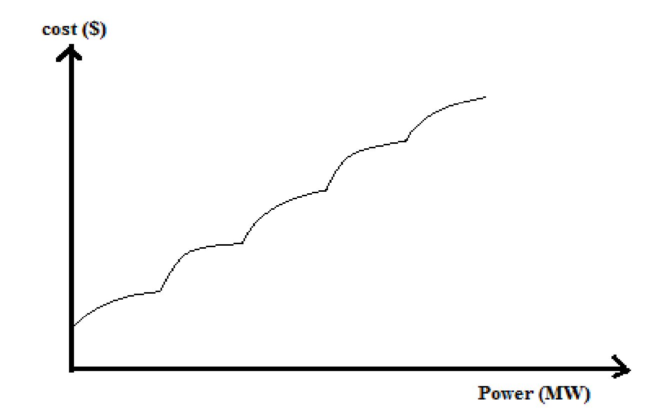


Fig 2. Illustration of fuel cost considering valve-point effects

where ς and λ are cost coefficients for modeling valve point effects. Fig. 2 shows the unit fuel cost considering valve point effects.

As it can be observed from this figure, the unit production cost considering valve-point effect is higher that quadratic cost for most of the generated power. It should be mentioned that solution obtained without considering valve-point effect will not be optimal in practical operation of the system.

3 Solution Methodology

The proposed solution methodology comprises two steps. In the first step the Pareto-based Multi objective Optimization Problem (MOP) is described and then, the novel MOPSO is used to extract the POF. The optimization procedure is presented as a flowchart in Fig. 2 in order to clearly explain the different parts of the proposed algorithm.

3.1 Constrained MOPSO Framework

In single-objective optimization, the point of optimality can be objectively determined and in most situations it is also unique. In the case of multi objective decision-making, efficiency is no longer unique [30]. An efficient (non-inferior, non-dominated, or Pareto-optimal) solution is the one in which no increase can be achieved in any of the objectives without causing a simultaneous decrease in at least one of the other objectives. The full satisfaction of one objective inevitably precludes the full satisfaction of others.

A constrained multi-objective optimization problem (MOP) can be stated as follows:

$$\text{Min } F(x) = [F_1(x). F_2(x)\ldots\ldots F_n(x)] \quad (19)$$

Subject to:

$$g_i < 0\,; \quad i = 1,\ldots..n$$
$$h_j = 0\,; \quad j = 1,\ldots..m \quad (20)$$

where, i and j are the inequality and equality constraints indices, respectively. n and m are the number of inequality and equality constraints, respectively. A solution x_1 dominates a solution x_2 if the two following conditions are satisfied at the same time

$$\forall q \in \{1,2\},\ F_q(x_1) \le F_q(x_2) \quad (21)$$
$$\exists q \in \{1,2\},\ F_q(x_1) < F_q(x_2) \quad (22)$$

Eq. (21) means that x_1 is no worse than x_2 in all objective evaluations. Also, Eq. (22) means that x_1 is strictly better than x_2 in at least one objective.

The major objectives in CHP dispatch include the supply of an adequate amount of power and heat, and minimization of operating costs. Some of these objectives can be quantified using monetary measure, while others cannot. Unlike the pure monetization, in multi-objective decision-making, learning and understanding by decision-makers is emphasized, tradeoffs among fundamental concerns become more explicit, and dominated alternatives can be readily ruled out

3.2 Encoding scheme

The first step in defining a PSO algorithm is to connect the "real world" to the "PSO world", that is, to build a bridge between the practical problem and the problem solver by which the optimization is performed. Encoding is to define a mapping from the phenotypes onto a set of genotypes. In PSO, each particle flying in the search space is a potential solution. It is crucial to properly encode the individuals of the population in PSO for handling the economic CHP dispatch problem. The power or heat output of each generating unit is seen as a gene and several genes constitute an individual, which is a candidate solution for the target problem. The genes here are all real-coded and the *i*-th individual *PGi* can be represented as follows:

$$P_{Gi} = [P_{Gi1}, P_{Gi2},\ldots. P_{Gid}, \ldots, P_{GiM}], \quad i = 1, 2, \ldots, N$$

where M is the number of generators and N is the population size. P_{Gid} is the power or heat output from the *d*-th unit in the *i*-th individual. Thus, the dimension of a population is $N\times M$.

3.3 Guides Selection

A challenging task in applying PSO to handle multiobjective problems is to design a scheme for choosing both local and global guides for each particle in the swarm. Unlike single objective (SO) problems, there are no explicit concepts on how personal and global best positions can be identified in MO problems. In the single-objective PSO, the global best particle can be readily found by choosing the particle with the best position. In MO optimization problems, the optimum solutions are Pareto-optimal. Thus, each particle should select the globally best particle based on the Pareto-optimal concept. Oftentimes, the key task in MOPSO is to determine the best global search guide for each particle in the population. original *gbest* is selected from the archive, which is however not used directly to update the particle speed and position. Instead, an area around it is randomly generated based on the normal distribution. Then, tournament selection is applied to choose the *gbest* from this area, which will be used to update the particle speed and position.. Furthermore, in tournament selection, local competition is used to determine survivors. In this scheme, binary tournament selection is used where the individual with the higher fitness in the group of two individuals is selected, and the other is removed. This selection scheme can be deemed as an effective measure to increase the population diversity during the optimization process.

3.4 External Repository

The MOPSO uses an external repository which acts as an elite archive to store the non-dominated solutions. At the end of each iteration, after calculating two objective functions for each individual along the optimisation process, the non-dominated procedure for each of the individuals was checked with the other individuals using (21), (22). The non-dominated solutions selected were stored in the repository and the dominated members of the repository were deleted. It should be noted that the repository was initialized with the non-dominated solutions found in the initial population.

3.5 Constraints Handling

The satisfaction of constraints determines the feasibility of solutions. For most stochastic search based approaches, the way to deal with the constraints always has a deep impact on the quality of solutions obtained. The major strategies for constraints handling include rejecting strategy, repair strategy, penalty function, and so forth. Since PSO is essentially an unconstrained optimization algorithm, the constraints handling scheme needs to be incorporated into it in order to deal with the constrained power dispatch problem. In the selection of Pareto-optimal solutions, when any two individuals are compared, their constraints are examined first. If both satisfy the constraints, the concept of Pareto-dominance is then applied to determine which potential solution should be chosen. If both are infeasible solutions, then they are not qualified to be stored in the archive. If one is feasible and the other is not, the feasible dominates. Though this scheme is simple, it turns out to be quite effective in guaranteeing the feasibility of the non-dominated solutions throughout the optimization run.

4 Algorithm For MOPSO For CHPED Problem

The data flow of the proposed algorithm is illustrated in Fig.3 is described as follows:

• **Step 1**: Confine the search space, i.e., specify the lower and upper limits of each decision variable.
• **Step 2**: Initialize the individuals of the population. The speed and position of each particle should be initialized such that each candidate solution is within the feasible decision-variable space.
• **Step 3:** For each individual P_{Gi} of the population, the transmission loss P_{Li} is calculated using **B**-coefficient loss formula.
• **Step 4:** Evaluate the fitness of each individual P_{Gi} in terms of Pareto-dominance.
• **Step 5:** Record the non-dominated solutions found thus far and save them in the archive.
• **Step 6:** Initialize the memory of each individual where the personal best position *pbest* is stored.
• **Step 7:** Increase the generation number.
• **Step 8:** Select the personal best position *pbest* for each particle based on the memory record; Choose the global best position *gbest* from the fuzzified region using binary tournament. The niching and fitness sharing mechanism is also used throughout this process for selection of both local and global search guides.
• **Step 9:** Update the member velocity *v* of each individual *PGi* as follows:

$$v_{id}^{iter+1} = w * v_{id}^{iter} + C_1 * rand * (p_{best_{id}}^{iter} - P_{Gid}^{iter}) + C_2 * rand * (g_{best}^{iter} - P_{Gid}^{iter})$$

$$i = 1, \cdots, N; \quad d = 1, \ldots, M \quad (23)$$

where N is the population size, M is the number of generating units, and w is the inertia weight factor.
• **Step 10:** Update the gene values of each individual P_{Gi} as follows:

$$x_{id}^{iter+1} = x_{id}^{iter} + v_{id}^{iter+1} \quad (24)$$

•**Step 11:** Check all the imposed constraints to ensure the feasibility of all potential solutions using the rejecting strategy.
•**Step 12:** Update the archive which stores non dominated solutions according to the four aforementioned selection criteria.

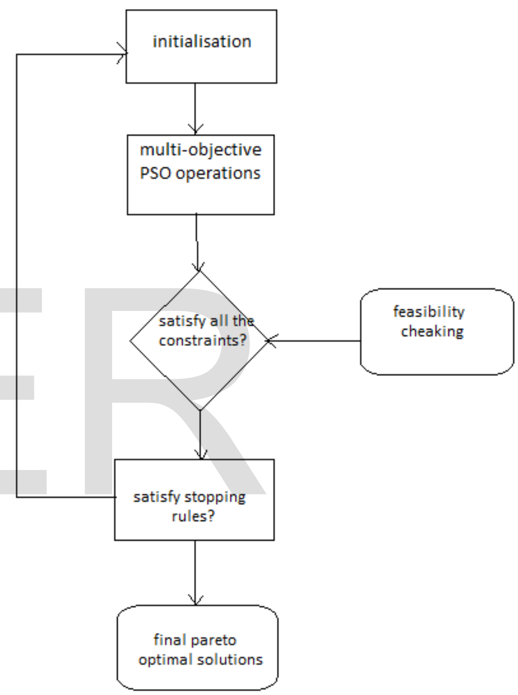


Fig.3. flow chart for the optimization process

• **Step 13:** If the current individual is dominated by the *pbest* stored in the memory, then keep the *pbest* in the memory; otherwise, replace the *pbest* in the memory with the current particle position. Provided that neither of them is dominated by the other, randomly choose one as the *pbest*.
• **Step 14:** If the stopping criteria are satisfied, then go to Step 15. Otherwise, go to Step 7.
• **Step 15:** Output a set of Pareto-optimal solutions from the archive as the final solutions. If necessary, the preferred solution is chosen based on certain measures

5 Results And Discissions

In this section the proposed method was applied to a case study to comprehensively investigate its performance on the CHPED problem.

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5.1 Description of Test System and Case Study

The case study was examined on a test system, system considering valve-point effects and transmission losses is considered to show the performance of proposed algorithm. Dataof this system are adopted from [10]. This test system consists of 7 units, where units 1–4 are power-only units, units 5 and 6 are CHP units and unit 7 is a heat only unit. The cost function parameters of this case along with the feasible region coordinates of CHP units are presented in Table 1 [10]. The coefficients of the network loss matrix are provided in the following. The unit of the B-matrix elements are 1/MW. The power units are in MW and the heat units are in MWth. The coefficients of the network loss matrix are produced in the following

$$B = 10^{-7} \times \begin{bmatrix} 25 & 20 & 15 & 15 & 14 & 49 \\ 19 & 18 & 20 & 16 & 45 & 14 \\ 15 & 12 & 10 & 39 & 16 & 15 \\ 11 & 14 & 40 & 10 & 20 & 15 \\ 17 & 35 & 14 & 12 & 18 & 20 \\ 39 & 17 & 11 & 15 & 19 & 25 \end{bmatrix}$$

5.2 Parameter Setting

The settings for the proposed algorithm as follows: the number of populations was set to 150 for the case 1 and 100 for case 2. Maximum number of iterations were 100. C_1 and C_2 were set to 2.05. ω_{max} and ω_{min} were set to 0.9 and 0.4 respectively.

TABLE 1
COST AND EMISSION PARAMETER DATA FOR TEST SYSTEM

Unit	α_i	β_i	γ_i	ς_i	λ_i	pmin	pmax
Power only units							
1	0.008	2	25	100	0.042	10	75
2	0.003	1.8	60	140	0.04	20	125
3	0.0012	2.1	100	160	0.038	30	175
4	0.001	2	120	180	0.037	40	250

Unit	a_j	b_j	c_j	d_j	e_j	fj	feasible region
CHP units							
5	0.0345	14.5	2650	0.03	4.2	0.031	[98.8, 0], [81, 104.8], [215, 180], [247, 0]
6	0.0435	36	1250	0.027	0.6	0.011	[44, 0], [44, 15.9], [40, 75], [110.2, 135.6], [125.8, 32.4], [125.8, 0]

Unit	a_h	b_h	c_h	hmin	hmax
Heat only units					
7	0.038	2.0109	950	0	2695.2

5.3 Case Studies

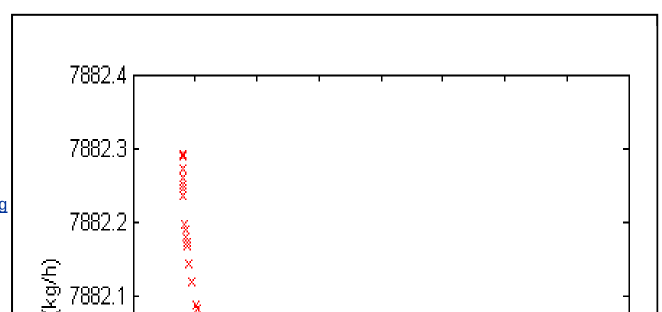
5.3.1 Case 1

The cost and emission objectives were solved using the proposed method. Test system data are presented in table 1. Total power demand is 200 MW and total Heat demand is 115 MW. The optimal obtained dispatch results are obtained using MOPSO.

TABLE 2
RESULTS FOR CASE 1

Output	MOPSO
P1(MW)	37.9183
P2(MW)	75.7139
P3(MW)	129.5753
P4(MW)	49.7975
P5(MW)	151.9587
P6(MW)	70.3243
H5(MWth)	157.2437
H6(MWth)	102.3574
H7(MWth)	24.9663
Total cost($/h)	11612.45
Total emission(kg/h)	7882.91

The results are shown in table 2. The Pareto optimal front for the non-dominated solutions are shown in fig.4.



5.3.2 Case 2

The cost, emission and power loss objectives were solved using the proposed method. Test system data are presented in table 1. Total power demand is 200 MW and total Heat demand is 115 MW. The optimal dispatch results are obtained using MOPSO.

TABLE 3
RESULTS FOR CASE 2

Output	MOPSO
P1(MW)	50.2
P2(MW)	31.1
P3(MW)	142.8
P4(MW)	228.05
P5(MW)	119.68
P6(MW)	98.2
H5(MWth)	108.57
H6(MWth)	120.5
H7(MWth)	1858.6
Total cost($/h)	11680.34
Total emission(kg/h)	7900.56
Total losses (MW)	0.08403

The results are shown in table 3. The Pareto optimal front for the non-dominated solutions are shown in fig.5.

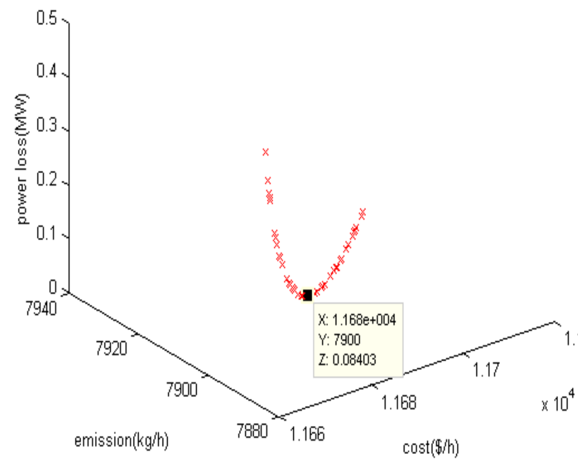


Fig. 5. Pareto optimal front for case 2 (non-dominated solutions)

6 CONCLUSION

A Multi-objective PSO approach for solving CHPED problem is proposed in this paper. A test case is used to illustrate the MOPSO. Valve-point effects, transmission losses, capacity limits and heat-power dependency constraints are considered in studied system. The obtained results using MOPSO are converged to a better and feasible solution. As future work, the CHPED problem can be extended by considering more practical constraints like as heat losses and multiperiod modelling.

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