Heliyon

Received:
7 November 2018
Revised:
30 January 2019
Accepted:
20 March 2019

Cite as: Haresh A. Suthar, Jagrut J. Gadit. Multiobjective optimization of 2DOF controller using Evolutionary and Swarm intelligence enhanced with TOPSIS. Heliyon 5 (2019) e01410. doi: 10.1016/j.heliyon.2019.e01410

Multiobjective optimization of 2DOF controller using Evolutionary and Swarm intelligence enhanced with TOPSIS

Haresh A. Suthar [a,*], **Jagrut J. Gadit** [b]

[a] *Electronics & Communication Engineering Department of Parul Institute of Technology, Parul University, Po. Limda, Vadodara, Gujarat, India*

[b] *Electrical Engineering Department of Faculty of Technology & Engineering, The M.S.U of Baroda, Vadodara, Gujarat, India*

[*] Corresponding author.

E-mail address: hareshsutharec@gmail.com (H.A. Suthar).

Abstract

In this paper, Evolutionary (NSGA-II and NSGA-III) and Swarm Intelligence (MOPSO) based algorithms enhanced with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed to optimize five parameters of Two Degree Of Freedom (2DOF) controller. Three objective functions, one for set point tracking and two for disturbance rejections (flow variation of input fluid and temperature variation of input fluid both are in conflict) are deployed for the problem of shell and tube heat exchanger. Three test criteria IAE, ISE and ITAE function of error (set point tracking and disturbance rejection) and time are used for evaluation of objective functions. The Pareto set of solutions are obtained after optimizing all the five parameters of 2DOF controller. In order to obtain the comparative analysis of optimization algorithms (NSGA-II, NSGA-III, and MOPSO) all the Pareto optimal solutions are combined under three separate evaluation criteria IAE, ISE, and ITAE. TOPSIS a multiple criteria decision making method is used to rank the set of Pareto optimal solutions for reducing number of Pareto optimal solutions to a single solution. The best rank solution

https://doi.org/10.1016/j.heliyon.2019.e01410

obtain for 2DOF controller parameters after applying TOPSIS on set of Pareto optimal solutions using Evolutionary (NSGA-II and NSGA-III) algorithms are compared with Swarm Intelligence (MOPSO) algorithm. To evaluate the performance optimization of 2DOF controller tuning, we compared the values of peak overshoot of step response, set point tracking error, disturbance rejection (both flow and temperature), settling time, and the percentage of solutions obtained from optimization algorithms under all three evaluation criteria IAE, ISE, and ITAE. MATLAB software tool is used to implement the above algorithms.

Keyword: Electrical engineering

1. Introduction

The design of control systems is a multiobjective problem because; it involves the optimization of more than one objective functions like set point tracking, rejection of disturbances, and robustness to model uncertainty. Two degree of freedom controller is applied for set point tracking and disturbance rejections. Two objectives set point tracking and disturbance rejections are clashing and hence trade-off exists, this result in control problem of multiobjective optimization [1]. There are two major disturbances in the process of heat exchanger, flow variation of input fluid and temperature variation of input fluid. Increase in flow variation of process fluid result in increase in mass flow rate of the fluid causes reduction in mean exit temperature of process fluid. On the contrary, increase in temperature variation of process fluid causes increase in mean exit temperature of process fluid. The step increase is applied to both the disturbances which are in conflict [2]. The prime goal in the process of heat exchanger is to keep outlet temperature of the process fluid flowing through it at desire value in the presence of two major conflicting disturbances. Hence, the problem of shell and tube heat exchanger is taken as test bench due to conflicting objectives [3].

Controller tuning is a broad research area in which tuning rules are derived from the mathematical model of the system [4]. Classical computational methods fail in tuning controller for the multiobjective optimization problems due to following reasons: (1) These methods can generate single solution from single run hence; several runs are required in order to generate Pareto set of solutions. (2) Convergence to optimal solution depends on chosen initial condition. (3) It requires differentiability of both objective function and constraints. (4) These methods fail when Pareto front is concave or discontinuous [5]. Evolutionary and Swarm based controller tuning is appealing investigators due to its efficiency to optimize parameters based on cost function, without any know-how about the process [6]. Also, these algorithms work based on population of search instead of single search hence, it provides parallelism [7]. Here, tuning of 2DOF controller is a five dimensional search space or a

https://doi.org/10.1016/j.heliyon.2019.e01410

three dimensional objective space multiobjective optimization problem for the shell and tube heat exchanger system. Hence, outperformed evolutionary (NSGA-II and NSGA-III) and swarm intelligence (MOPSO) algorithms are used for tuning five parameters of 2DOF controller.

Multiobjective evolutionary optimization algorithms are classified into two categories: elitist MOEAs [8] and non-elitist MOEAs [9, 10, 11, 12, 13]. Nondominated Sorting Genetic Algorithm II (NSGA-II), is the known elitist multiobjective evolutionary algorithm. It is proved that elitism helps in achieving better convergence in MOEAs [14]. NSGA-III is an extension of NSGA-II though; it has significant changes in selection process [15]. NSGA-II and NSGA-III outperforms other MOEAs in terms of finding diverse set of solutions and converging towards true Pareto front [14, 15].

Particle Swarm Optimization (PSO) algorithm falls under the category of swarm intelligence [16]. The different multiobjective swarm intelligence based optimization algorithms proposed by researchers are [6, 13, 17, 18, 19, 20, 21, 22, 23]. In this paper, MOPSO algorithm proposed by Carlos, Gregorio and Maximino [23] is used for optimization of 2DOF controller parameters as it is relatively easy to implement and it improves the exploratory capabilities of PSO by introducing a mutation operator. This algorithm also uses an external repository of particles to guide their own flight.

The multiobjective optimization algorithms give number of nondominated set of solutions called Pareto optimal solutions. Practically, user needs only one solution from the set of Pareto optimal solutions for particular problem. Generally, user is not aware of exact trade-off among objective functions. Hence, it is desirable to first obtain maximum possible Pareto optimal solutions and select best one using multi-criteria decision making technique. The various multi-criteria decision making techniques are MAXMIN, MAXMAX, SAW (Simple Additive Weighting), AHP (Analytical Hierarchy Process), TOPSIS, SMART (Simple Multi Attribute Rating Technique), ELECTRE (Elimination and Choice Expressing Reality) and many more [24, 25]. The major advantage of TOPSIS method is it’s rational, easy to implement, and good computational efficiency. Hence, TOPSIS is proposed as a decision support tool to rank the optimal solutions and select the best rank optimal solution [26].

The best rank solution obtain for 2DOF controller parameters after applying TOPSIS on set of Pareto optimal solutions using Evolutionary (NSGA-II and NSGA-III) algorithms are compared with Swarm Intelligence (MOPSO) algorithm. To evaluate the performance optimization of 2DOF controller tuning, we compared the values of peak overshoot of step response, set point tracking error, disturbance rejection (both flow and temperature), settling time, and the percentage of solutions obtained from optimization algorithms under all three evaluation criteria IAE, ISE, and ITAE.

https://doi.org/10.1016/j.heliyon.2019.e01410

The present paper is formulated as under: In Section 2, heat exchanger system's explanation is provided. 2DOF controller optimization methods are proposed in Section 3. In Section 4, Implementation steps of TOPSIS algorithm is discussed. 2DOF controller parameter optimization and comparison of results are discussed in Section 5. Conclusion is in Section 6.

2. Theory

Shell and tube type of heat exchanger system is widely used in industries [27, 28, 29]. The diagram shown in Fig. 1 consists of shell and tube heat exchanger system with boiler, storage tank, and controller. The fluid in heat exchanger system heats up to a set temperature using steam supplied from the boiler. Here, a process of heat exchanger system is derived as FOPDT system [30].

The outlet fluid temperature of heat exchanger system is measured by temperature sensor. Controller generates electrical control output signal (4−20 mA) based on input error signal. The control output signal (4−20 mA) is transformed to pressure signal (3−15 psig) using electronumetic means. The pressure output signal is attached with valve actuator, whose function is to position valve proportional to control signal. Flow variation of input fluid and temperature variation of input fluid are the prominent disturbances in this process. Flow variation of input fluid is more prominent disturbance compared to temperature variation in input fluid [3]. Underlying two assumptions are considered in the heat exchanger system description [31].

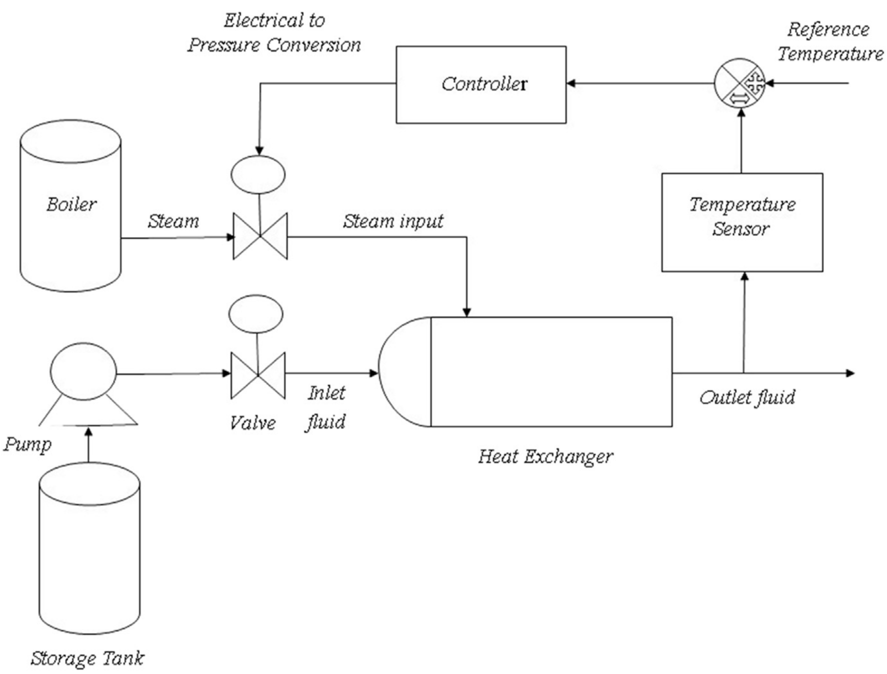

Fig. 1. Representation of heat exchanger control system.

https://doi.org/10.1016/j.heliyon.2019.e01410

(1) Similar inflow and out flow rate of fluid (kg/sec) is retained for having constant fluid level in heat exchanger system. (2)Insulating wall of heat exchanger does not accumulate any heat.

The Fig. 2 shows heat exchanger system with feed forward type 2DOF control scheme. The transfer functions of individual block in Fig. 2 is as under: system plant transfer function is defined as, $G(s) = \frac{50*e^{-2s}}{(30*S+1)}$, transfer function of flow disturbance of input fluid is $F(s) = \frac{3}{(30*S+1)}$, transfer function of temperature disturbance of input fluid is $T(s) = \frac{1}{(3*S+1)}$, control valve transfer function is $A(s) = \frac{0.1}{(3*S+1)}$, and sensor transfer function as, $H(s) = \frac{1}{(10*S+1)}$ [3, 31]. The resultant system consisting of heat exchanger with controller and disturbances are shown in following Fig. 2.

Here, feed forward type 2DOF controller comprising of serial compensator $C_s(s)$ and feed forward compensator $C_f(s)$ is used.

Where, $C_s(s)$ and $C_f(s)$ are represented as below.

$$C_s(s) = \left[K_p + \frac{K_p}{T_i S} + K_p * T_D * D(s)\right] \tag{1}$$

$$C_f(s) = -K_p \; [\alpha + \beta * T_D * D(s)] \tag{2}$$

The parameters of serial compensator $C_s(s)$ are known as proportional gain K_p , integral time T_i , and derivative time T_D , they are called as “basic parameters”. The parameters of feed forward compensator $C_f(s)$ i.e., α and β are called as “2DOF parameters”. Where, $D(s) = \frac{s}{1+\tau s}$ is approximate derivative [27]. Assume, $D_T(s)$ and $D_f(s)$ are temperature and flow disturbance step inputs respectively. Derived transfer function based on superposition principle as under which is used for optimization of 2DOF control parameters in the programming.

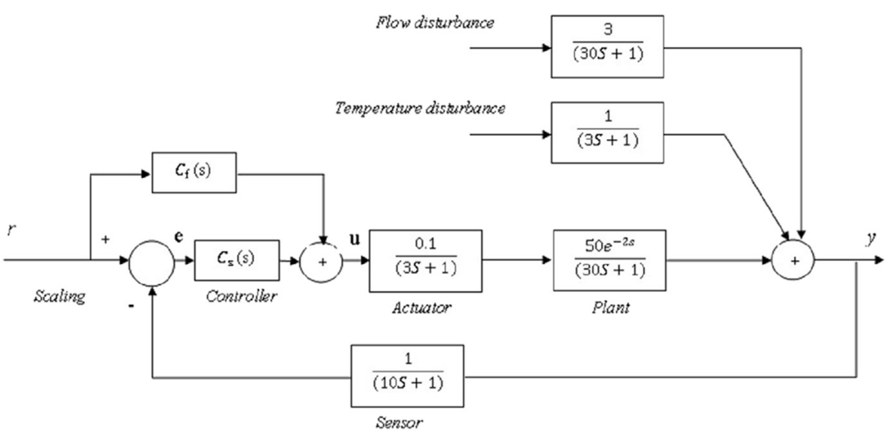

Fig. 2. Heat exchanger with controller and disturbances.

https://doi.org/10.1016/j.heliyon.2019.e01410

Case 1: Reference input r is present and both disturbances flow & temperature are zero.

$$\frac{y(s)}{r(s)} = \frac{C_f(s) + C(s)}{C(s)} * \frac{C(s)*A(s)*G(s)}{1 + C(s)*A(s)*G(s)*H(s)} \tag{3}$$

Case 2: Flow disturbance input is present and both temperature disturbance & reference input is zero.

$$\frac{y_{flow}(s)}{D_f(s)} = \frac{F(s)}{1 + C(s)*A(s)*G(s)*H(s)} \tag{4}$$

Case 3: Temperature disturbance input is present and both flow disturbance & reference input is zero.

$$\frac{y_{temp}(s)}{D_T(s)} = \frac{T(s)}{1 + C(s)*A(s)*G(s)*H(s)} \tag{5}$$

The description of heat exchanger system is provided in the previously published paper by the same authors in [32] for the optimization of 2DOF controller using GA.

3. Methodology

Three objective functions set point tracking, flow disturbance rejection, and temperature disturbance rejection are formed. An objective is to minimize set point tracking error, and both flow and temperature disturbances (which are also considered to be error). Therefore, criteria applied to evaluate the quality of system response have taken into account the variation of error over the entire range of time. The performance indices considered for evaluation of objective functions are Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-weighted Absolute Error (ITAE) described as under [4, 33].

Criterion 1: Integral of absolute value of error IAE

$$f(K_p, K_i, K_D, \alpha, \beta) = J\Big(\sum\nolimits_{k=0}^{n}[|SP - y(k)|], \sum\nolimits_{k=0}^{n}[|y_{flow}(k)|], \sum\nolimits_{k=0}^{n}[|y_{temp}(k)|]\Big) \tag{6}$$

https://doi.org/10.1016/j.heliyon.2019.e01410

Criterion 2: Integral of Squared Error ISE

$$f\left(K_p, K_i, K_D, \alpha, \beta\right) = J\left(\sum_{k=0}^{n}[SP - y(k)]^2, \sum_{k=0}^{n}\left[y_{flow}(k)^2\right], \sum_{k=0}^{n}\left[y_{temp}(k)^2\right]\right) \tag{7}$$

Criterion 3: Integral of Time-weighted Absolute Error ITAE

$$f\left(K_p, K_i, K_D, \alpha, \beta\right) = J\left(\sum_{k=0}^{n}[t*(SP - y(k))] \sum_{k=0}^{n}\left[t*y_{flow}(k)\right], \sum_{k=0}^{n}\left[t*y_{temp}(k)\right]\right) \tag{8}$$

where,

SP = Set point or reference input.

$y(k) = \frac{C_f(k)+C(k)}{C(k)} * \frac{C(k)*A(k)*G(k)}{1+C(k)*A(k)*G(k)*H(k)} * r(k)$ from Eq. (3) is process value output at k^{th} interval is a function of 2DOF controller parameters.

$y_{flow}(k) = \frac{F(k)}{1+C(k)*A(k)*G(k)*H(k)} * D_f(k)$ from Eq. (4) is flow disturbance output at k^{th} interval is a function of 2DOF controller parameters.

$y_{temp}(k) = \frac{T(k)}{1+C(k)*A(k)*G(k)*H(k)} * D_T(k)$ from Eq. (5) is temperature disturbance output at k^{th} interval is a function of 2DOF controller parameters.

In the multiobjective optimization problem vector of objective functions is required to be supplied for optimization. Here, vector of three objective functions are supplied for optimization of 2DOF controller parameters as under.

$$f\left(K_p, K_i, K_D, \alpha, \beta\right) = \left(\left[J_{setpoint}\ J_{flow}\ J_{temp}\right]\right) \tag{9}$$

where,

$J_{setpoint}$ = Function of set point tracking considering any of the above three criteria for evaluation one at a time.

J_{flow} = Function of flow disturbance rejection considering any of the above three criteria for evaluation one at a time.

J_{temp} = Function of temperature disturbance rejection considering any of the above three criteria for evaluation one at a time.

Implementation of algorithms and comparison of results are discussed in the following section.

https://doi.org/10.1016/j.heliyon.2019.e01410

4. Calculation

The Multi-criteria decision making tool is used to select best solution among a finite set of solutions available for multiobjective optimization problems. TOPSIS was implemented by Hwang and Yoon [24]. TOPSIS works based on calculating the Euclidian distance from each alternative to a best performing attribute called Positive Ideal Solution (PIS) and a poorest performing attribute called Negative Ideal Solution (NIS) that are defined in n-dimensional space [26]. It consists of two criteria positive and negative. Positive criteria need to be increased and negative criteria need to be decreased. This process is implemented by taking the below steps:

Step 1: Specify alternative and criteria for non-dominated set of solutions of the 2DOF controller parameters. Assume that there are m possible alternatives called $A = [A_1,\ A_2, \ldots., A_m]$ which are evaluated against criteria $C = [\ C_1,\ C_2, \ldots., C_c]$.

Step 2: Assign ratings to criteria and alternatives using matrix X shown below where, x_{ij} indicates the value of alternative A_i for criterion C_g.

$$X_{m\times c} = \begin{array}{c} \\ A_1 \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_g & C_c \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & x_{1g} & x_{1c} \\ x_{i1} & x_{i2} & x_{ig} & x_{ic} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mg} & x_{mc} \end{bmatrix} \end{array} \tag{10}$$

Step 3: Calculate weight of criteria by entropy technique to normalize decision matrix $X_{m\times c}$ using following formula.

$$q_{ig} = \frac{x_{ig}}{\left(x_{1g} + x_{2g} + \ldots x_{mg}\right)};\ \forall g \in \{1, 2, \ldots c\} \tag{11}$$

The information entropy of criterion g is represented as under.

$$\Delta_g = -k\sum_{i=1}^{m} q_{ig}.lnq_{ig};\ \forall g \in \{1, 2, \ldots c\} \tag{12}$$

where, $0 \le \Delta_g \le 1$ is assured with $k\ = 1/ln(m)$.

The entropy method for measuring weights of criteria is an objective weight technique determined by data statistical properties. Here, the index with higher information entropy Δ_g has greater variation hence, weight is calculated based on deviation degree

$$d_g = 1 - \Delta_g.\ (g = 1, \ldots, c). \tag{13}$$

The weight for criteria by the entropy method is calculated as under (14):

https://doi.org/10.1016/j.heliyon.2019.e01410

$$w_g = \frac{d_g}{(d_1 + d_2 + \ldots + d_c)} \tag{14}$$

Let λ_g be weight vector used to obtain the aggregated weight $w_g^{'}$ shown in (15).

$$w_g^{'} = \frac{\lambda_g . w_g}{(\lambda_1 . w_1 + \lambda_2 . w_2 + \ldots + \lambda_c . w_c)} \tag{15}$$

$$w^{'} = \{w_1^{'}, w_2^{'}, \ldots.., w_c^{'}\} \tag{16}$$

Step 4: Construct a normalized decision matrix using the vector normalization method, calculate normalized value r_{ig} by (17) and construct matrix $N_{m\times c}$ given by (18).

$$r_{ig} = \frac{x_{ig}}{\sqrt{\left(x_{1g}^2 + x_{2g}^2 + .. + x_{mg}^2\right)}} \tag{17}$$

$$N_{m\times c} = [r_{ig}]_{m\times c} (i = 1, \ldots, m ; g = 1, \ldots, c). \tag{18}$$

Step 5: Construct the weighted normalized decision matrix by building the diagonal matrix $w_{c\times c}^{'}$ with element $w_g^{'}$ in (15) to reach the V matrix:

$$V = N_{m\times c} . w_{c\times c}^{'} = (v_{ig})_{m\times c} (i = 1, \ldots, m ; g = 1, \ldots, c). \tag{19}$$

Step 6: Compute the positive ideal solution (PIS) A^+ and the negative ideal solution (NIS) $A^-$of the alternatives:

$$A^+ = \{(max\, v_{ig} | g \in G); (minv_{ig} | g \in G^{'})\} = (v_1^+, v_2^+, \ldots, v_c^+) \tag{20}$$

$$A^- = \{(min\, v_{ig} | g \in G); (maxv_{ig} | g \in G^{'})\} = (v_1^-, v_2^-, \ldots, v_c^-) \tag{21}$$

where, G and $G^{'}$ are the subsets of positive and negative criteria.

Step 7: Compute the distance of each alternative from PIS (d_i^+) and NIS (d_i^-):

$$d_i^+ = \sqrt{\sum_{g=1}^{c} \left(v_{ig} - v_g^+\right)^2} \tag{22}$$

$$d_i^- = \sqrt{\sum_{g=1}^{c} \left(v_{ig} - v_g^-\right)^2} \tag{23}$$

https://doi.org/10.1016/j.heliyon.2019.e01410

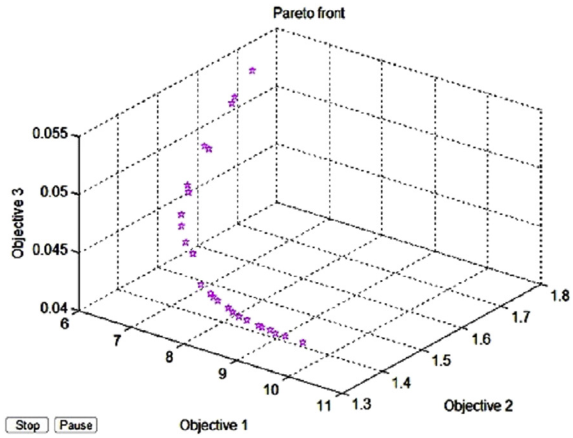

Fig. 3. Pareto plot of NSGA-II under IAE criterion.

Step 8: Compute the closeness coefficient of each alternative:

$$CC_i^+ = \frac{d_i^-}{\left(d_i^- + d_i^+\right)}; \; i = 1, 2, ..m \tag{24}$$

Step 9: Rank the alternatives.

$$v = \left\{ v_i \,\middle|\, \max_{1 \le i \le m} \left(CC_i^+ \right) \right\} \tag{25}$$

MATLAB software tool is used to implement above steps.

5. Results & discussion

The proposed steps for 2DOF controller parameters optimization using MOPSO, NSGA-II, and NSGA-III algorithms enhanced with TOPSIS are as under.

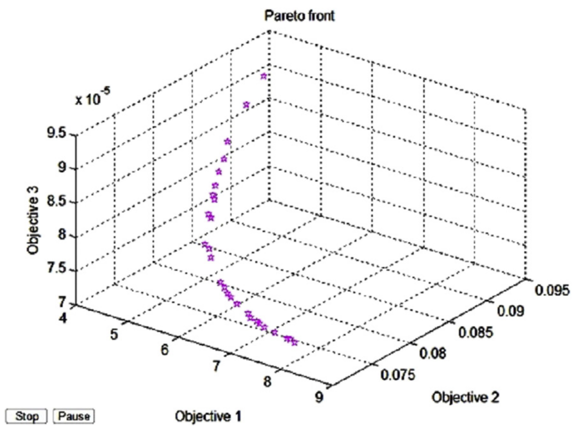

Fig. 4. Pareto plot of NSGA-II under ISE criterion.

 https://doi.org/10.1016/j.heliyon.2019.e01410

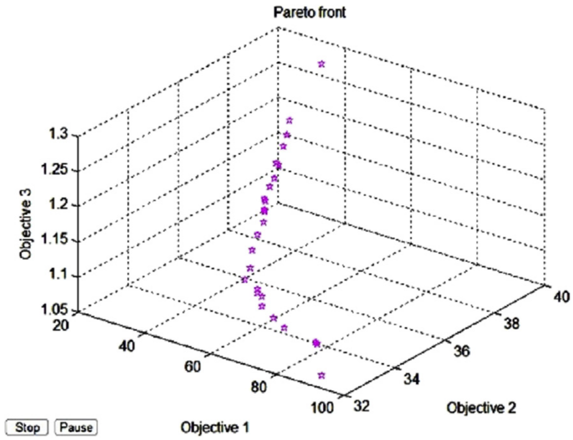

Fig. 5. Pareto plot of NSGA-II under ITAE criterion.

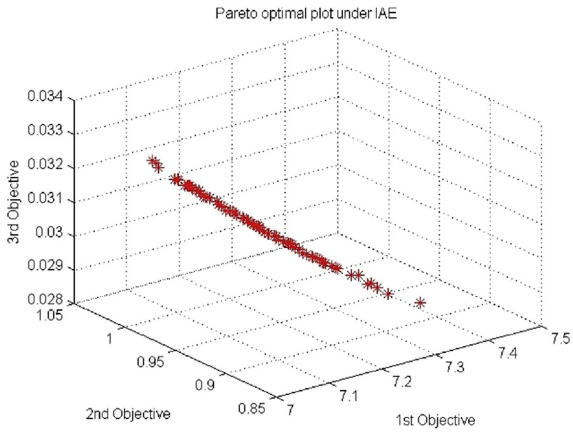

Fig. 6. Pareto plot of NSGA-III under IAE criterion.

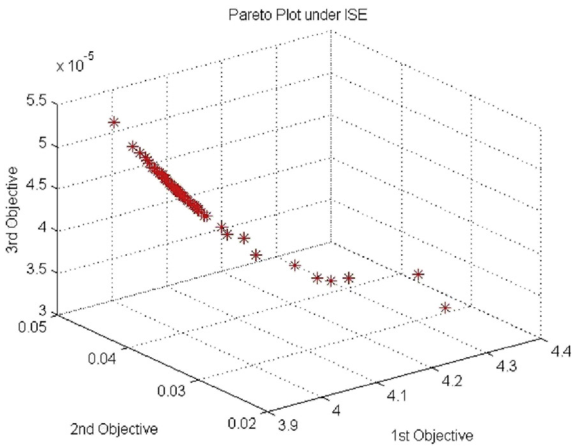

Fig. 7. Pareto plot of NSGA-III under ISE criterion.

https://doi.org/10.1016/j.heliyon.2019.e01410

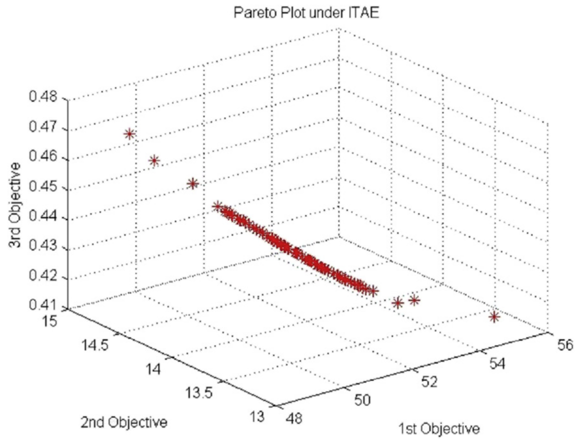

Fig. 8. Pareto plot of NSGA-III under ITAE criterion.

Step 1: Derive transfer function of plant, actuator, sensor, temperature disturbance, flow disturbance, serial controller, and feed forward controller considering the values as shown in Fig. 2.

Step 2: Set the upper & lower bound values of 2DOF controller parameters.

Step 3: Define the magnitude of input, flow disturbance and temperature disturbance as step input of magnitude 1, 0.1 and 0.01 respectively [1].

Step 4: Form the objective function, and define fitness same as objective function.

Step 5: Select the evaluation of objective function criteria IAE, ISE and ITAE one at a time.

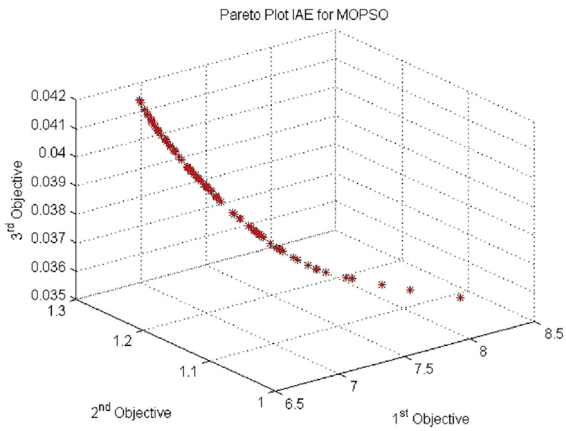

Fig. 9. Pareto plot of MOPSO under IAE criterion.

https://doi.org/10.1016/j.heliyon.2019.e01410

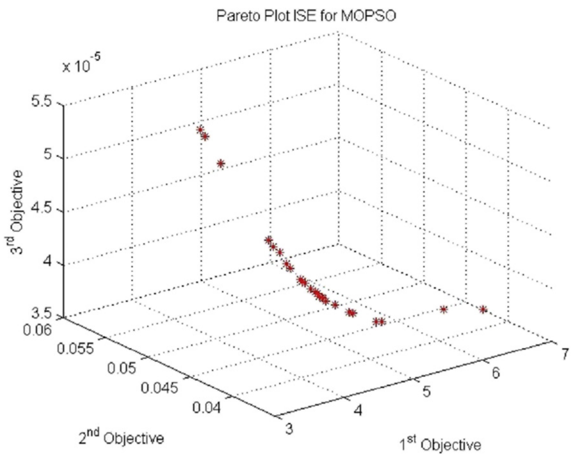

Fig. 10. Pareto plot of MOSPO under ISE criterion.

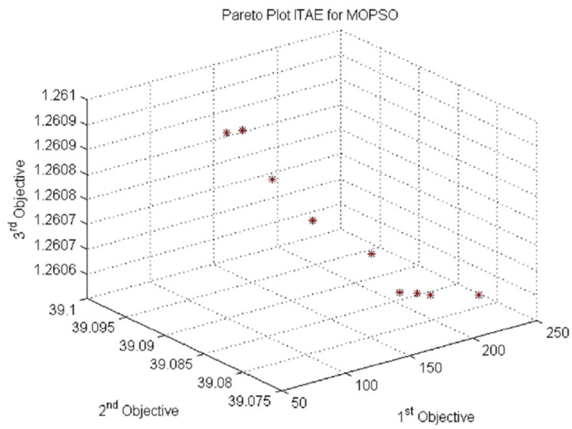

Fig. 11. Pareto plot of MOPSO under ITAE criterion.

Table 1. Pareto set of solutions using NSGA-II, NSGA-III, and MOPSO.

Type of algorithm	Number of non-dominated set of solutions under three test criteria		
	IAE	ISE	ITAE
NSGA-II	27	27	27
NSGA-III	80	80	80
MOPSO	95	26	9
Combined non-dominated solutions under each criteria.	202	133	116

https://doi.org/10.1016/j.heliyon.2019.e01410

Step 6: Initialize MOPSO parameters: Maximum Number of Iterations ‘100’, Number of populations ‘100’, Repository Size ‘100’, Inertia Weight ‘0.5’, Inertia Weight Damping Rate ‘0.99’, Personal Learning Coefficient c1 ‘1’ and Global Learning Coefficient c2 ‘2’, Number of Grids per Dimension ‘7’, Mutation Rate (varied from 0.1 to 0.9) [23].

OR

Step 6: Initialize NSGA-II parameters: Cross over percentage ‘0.8’, Mutation rate ‘0.09’, the maximum number of iterations ‘100’, Population size ‘100’ [14, 34].

Table 2. Rank of 2DOF controller parameters using TOPSIS for NSGA-II under IAE, ISE, and ITAE.

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	**Closeness coefficient CC**	**Rank**	**Solution number**	**Closeness coefficient CC**	**Rank**	**Solution number**	**Closeness coefficient CC**	**Rank**
1	0.139499983	25	1	0.916156397	2	1	0.736904849	4
2	0.999790511	1	2	0.969106095	1	2	0.568957309	14
3	0.450991856	21	3	0.111113239	27	3	0.599328282	11
4	0.612548684	15	4	0.124500851	26	4	0.398997174	24
5	0.000873994	26	5	0.874856154	5	5	0.568651174	16
6	0.500815242	18	6	0.28202096	23	6	0.743282348	3
7	0.245774548	23	7	0.245031117	24	7	0.63607864	7
8	0.716252347	8	8	0.206231281	25	8	0.444637078	21
9	0.834714135	4	9	0.89583837	3	9	0.637014324	5
10	0.713062952	9	10	0.780720049	11	10	0.521594285	19
11	0.176315852	24	11	0.564060093	17	11	0.615701589	9
12	0.523272748	17	12	0.414971725	18	12	0.636593288	6
13	0.838580319	3	13	0.386584924	20	13	0.576239573	13
14	0.619401354	14	14	0.570190088	16	14	0.487027384	20
15	0.999670866	2	15	0.323650959	22	15	0.96421824	1
16	0.602867228	16	16	0.407643506	19	16	0.385520134	26
17	0.707633622	10	17	0.77134111	12	17	0.416764044	22
18	0.620119539	13	18	0.799426983	10	18	0.52914569	17
19	0.470478286	20	19	0.848795482	8	19	0.170838835	27
20	0.717695573	7	20	0.865987774	6	20	0.407484677	23
21	0.730277754	6	21	0.839758921	9	21	0.578041421	12
22	0.65026265	12	22	0.601596904	15	22	0.947696444	2
23	0.76601709	5	23	0.86343887	7	23	0.605737	10
24	0.000873994	26	24	0.732148897	14	24	0.619770205	8
25	0.660481014	11	25	0.335439278	21	25	0.396063663	25
26	0.476964994	19	26	0.884289536	4	26	0.525753039	18
27	0.346500567	22	27	0.751702822	13	27	0.568957309	14

https://doi.org/10.1016/j.heliyon.2019.e01410

Table 3. Rank of 2DOF controller parameters using TOPSIS for NSGA-III under IAE, ISE, and ITAE.

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	**Closeness coefficient CC**	**Rank**	**Solution number**	**Closeness coefficient CC**	**Rank**	**Solution number**	**Closeness coefficient CC**	**Rank**
1	0.439553488	41	1	0.317155401	33	1	0.659965912	9
2	0.210662124	64	2	0.28830177	58	2	0.359385135	62
3	0.348456745	49	3	0.405056451	12	3	0.447136428	46
4	0.971350992	1	4	0.251428197	67	4	0.661714626	8
5	0.28768881	57	5	0.267608639	61	5	0.415263455	55
6	0.545861924	28	6	0.360409747	20	6	0.407534457	56
7	0.322304835	52	7	0.302603379	48	7	0.669751308	6
8	0.677678826	14	8	0.301588821	49	8	0.545724189	25
9	0.128213252	70	9	0.252740132	64	9	0.346273572	64
10	0.279717395	59	10	0.330748807	26	10	0.257145617	76
11	0.617646691	19	11	0.231743511	72	11	0.54913437	24
12	0.682728137	10	12	0.762647655	2	12	0.416525188	54
13	0.679302693	13	13	0.302847732	47	13	0.556628155	21
14	0.774979908	6	14	0.307250078	41	14	0.432646626	50
15	0.62145335	17	15	0.266339439	63	15	0.302926938	69
16	0.676856737	15	16	0.303263049	46	16	0.421798675	53
17	0.537558448	29	17	0.304146372	44	17	0.352838672	63
18	0.125314425	71	18	0.227281613	74	18	0.539847249	28
19	0.438500882	42	19	0.319061088	31	19	0.52008084	31
20	0.216546243	63	20	0.375424795	17	20	0.600674629	17
21	0.043885699	79	21	0.249535522	69	21	0.292728238	72
22	0.526132336	34	22	0.251778613	66	22	0.44545096	47
23	0.311369363	54	23	0.305825024	42	23	0.308414571	68
24	0.682728137	10	24	0.314250724	38	24	0.373881496	61
25	0.440849961	40	25	0.377903814	15	25	0.431643379	51
26	0.116707029	73	26	0.317903252	32	26	0.44350692	49
27	0.497799896	36	27	0.371390856	19	27	0.500983321	34
28	0.80613819	5	28	0.451705244	11	28	0.339246264	65
29	0.820746197	4	29	0.387367782	14	29	0.467652281	43
30	0.830172755	3	30	0.356523335	21	30	0.541719928	27
31	0.141246346	69	31	0.333724201	25	31	0.407310364	57
32	0.429036049	44	32	0.845854233	1	32	0.299969542	70
33	0.451551397	38	33	0.546454591	8	33	0.468112783	42
34	0.668844559	16	34	0.326851505	29	34	0.596182603	18
35	0.116542605	74	35	0.459874427	9	35	0.611988201	15

(*continued on next page*)

https://doi.org/10.1016/j.heliyon.2019.e01410

Table 3. (*Continued*)

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank
36	0.451943192	37	36	0.311084497	40	36	0.297375514	71
37	0.345296355	50	37	0.28994159	57	37	0.318827228	67
38	0.022754558	80	38	0.327410882	28	38	0.337132887	66
39	0.185450287	65	39	0.233241297	70	39	0.664750022	7
40	0.060141258	78	40	0.328769444	27	40	0.000953462	80
41	0.371430373	47	41	0.32490235	30	41	0.78279646	2
42	0.297161091	55	42	0.268815717	60	42	0.278149462	73
43	0.682728137	10	43	0.352404163	23	43	0.698814442	4
44	0.100956242	75	44	0.3047964	43	44	0.544724408	26
45	0.356684181	48	45	0.458483638	10	45	0.472524781	41
46	0.570876027	24	46	0.232892679	71	46	0.426289835	52
47	0.583773938	23	47	0.209475178	77	47	0.389772951	59
48	0.184572682	66	48	0.295368743	53	48	0.671815216	5
49	0.529087805	33	49	0.398952889	13	49	0.592719166	19
50	0.331470436	51	50	0.29171257	56	50	0.399685147	58
51	0.597368105	20	51	0.316013762	35	51	0.154826454	78
52	0.555316163	27	52	0.226845923	75	52	0.638828441	12
53	0.535023021	31	53	0.303662915	45	53	0.63286338	13
54	0.559730437	25	54	0.372804087	18	54	0.278083112	74
55	0.312915395	53	55	0.349561114	24	55	0.501480823	33
56	0.082540688	76	56	0.377702607	16	56	0.465948466	44
57	0.279300305	60	57	0.316151501	34	57	0.500214902	35
58	0.29060933	56	58	0.295719881	52	58	0.609017615	16
59	0.532056477	32	59	0.295243241	54	59	0.380915994	60
60	0.726377935	8	60	0.698258206	3	60	0.534416068	30
61	0.232050518	62	61	0.266474158	62	61	0.49156618	39
62	0.772625012	7	62	0.137002069	80	62	0.27260422	75
63	0.384688528	46	63	0.315243759	37	63	0.537982991	29
64	0.695940402	9	64	0.284592551	59	64	0.49740558	36
65	0.286374769	58	65	0.227692657	73	65	0.553231672	23
66	0.517743307	35	66	0.225047538	76	66	0.589466716	20
67	0.596985476	21	67	0.674972666	5	67	0.496807092	37
68	0.448623576	39	68	0.658994266	6	68	0.778863734	3
69	0.423921555	45	69	0.599598393	7	69	0.062615749	79
70	0.067369531	77	70	0.300966448	50	70	0.473048576	40

(*continued on next page*)

 https://doi.org/10.1016/j.heliyon.2019.e01410

Table 3. (*Continued*)

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank
71	0.618913651	18	71	0.205619461	78	71	0.465774347	45
72	0.555501545	26	72	0.698258206	3	72	0.510743801	32
73	0.866894865	2	73	0.354380485	22	73	0.624099411	14
74	0.536261437	30	74	0.250648242	68	74	0.24223292	77
75	0.116868948	72	75	0.197234242	79	75	0.443820198	48
76	0.432585716	43	76	0.298779771	51	76	0.651996723	11
77	0.177506132	67	77	0.313631301	39	77	0.656274124	10
78	0.270286649	61	78	0.252374139	65	78	0.493524766	38
79	0.590010232	22	79	0.315782746	36	79	0.976027897	1
80	0.158613181	68	80	0.293856154	55	80	0.556425336	22

OR

Step 6: Initialize NSGA-III parameters: Cross over percentage '0.8', Mutation rate '0.09', the maximum number of iterations '100', Population size '100', Number of reference point supplied '66' [15].

Step 7: Supply the objective function as vector of three objectives.

Step 8: Call optimization functions MOPSO OR NSGA-II OR NSGA-III as required one at a time.

Step 9: Run the algorithm till maximum number of iteration.

Step 10: Obtain Pareto optimal set of solutions from above three algorithms NSGA-II, NSGA-III, and MOPSO under three evaluation criteria IAE, ISE, and ITAE.

Step 11: Apply TOPSIS to rank the set of Pareto optimal solutions obtained in Step 10.

Step 12: Plot the results with best rank solutions.

Following Figs. 3, 4, 5, 6, 7, 8, 9, 10, and 11 are plots of Pareto optimal front of optimization of three objective functions i.e. set point tracking and disturbance rejections (Both flow and temperature) obtained for evaluation criteria IAE, ISE & ITAE using NSGA-II, NSGA-III, and MOPSO algorithms.

The number of non-dominated set of solutions obtained for 2DOF controller parameters optimization using NSGA-II, NSGA-III, and MOPSO algorithms under three test criteria IAE, ISE, and ITAE are shown in following Table 1.

https://doi.org/10.1016/j.heliyon.2019.e01410

Table 4. Rank of 2DOF controller parameters using TOPSIS for MOPSO under IAE, ISE, and ITAE.

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank
1	0.23019673	43	1	25	25	1	0.158978146	8
2	0.23019673	43	2	23	23	2	0.482927944	4
3	0.312720045	34	3	24	24	3	0.292044621	7
4	0.243222672	42	4	7	7	4	0.650128628	3
5	0.050949174	87	5	26	26	5	0.369120678	6
6	0.122341775	71	6	21	21	6	0.400733273	5
7	0.118887117	74	7	18	18	7	0.002442736	9
8	0.195762628	55	8	13	13	8	0.986438065	1
9	0.180892406	60	9	8	8	9	0.668850975	2
10	0.068071498	83	10	3	3			
11	0.368637245	23	11	6	6			
12	0.438498015	15	12	2	2			
13	0.255182165	39	13	17	17			
14	0.220514515	47	14	9	9			
15	0.21453224	52	15	5	5			
16	0.247074255	40	16	20	20			
17	0.261211809	37	17	14	14			
18	0.217878313	48	18	12	12			
19	0.007278731	94	19	15	15			
20	0.046581497	88	20	19	19			
21	0.244337626	41	21	4	4			
22	0.337775271	32	22	11	11			
23	0.003006195	95	23	10	10			
24	0.376072103	22	24	22	22			
25	0.355282527	27	25	16	16			
26	0.056130698	85	26	1	1			
27	0.163327677	65						
28	0.143472658	68						
29	0.126395308	70						
30	0.120716072	73						
31	0.107963358	75						
32	0.344657339	30						
33	0.045972154	89						
34	0.171095354	63						
35	0.538133766	11						

(*continued on next page*)

https://doi.org/10.1016/j.heliyon.2019.e01410

Table 4. (*Continued*)

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank
36	0.021098635	93						
37	0.04404276	90						
38	0.189419127	58						
39	0.13554931	69						
40	0.169115449	64						
41	0.055317839	86						
42	0.29813782	35						
43	0.354978976	28						
44	0.09546303	76						
45	0.17216143	62						
46	0.292668621	36						
47	0.364034251	25						
48	0.36039207	26						
49	0.227814308	45						
50	0.227003254	46						
51	0.353056452	29						
52	0.654700592	7						
53	0.367726791	24						
54	0.753944692	5						
55	0.99148973	1						
56	0.566617107	9						
57	0.260907806	38						
58	0.214582939	51						
59	0.183988557	59						
60	0.070307479	81						
61	0.058823445	84						
62	0.080369764	80						
63	0.091854976	77						
64	0.069951752	82						
65	0.429908931	16						
66	0.401808726	19						
67	0.481777661	13						
68	0.033793742	91						
69	0.120970091	72						
70	0.425816038	17						

(*continued on next page*)

 https://doi.org/10.1016/j.heliyon.2019.e01410

Table 4. (*Continued*)

Rank of nondominated set of solution under IAE			Rank of nondominated set of solution under ISE			Rank of nondominated set of solution under ITAE		
Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank	Solution number	Closeness coefficient CC	Rank
71	0.161906037	66						
72	0.401404308	20						
73	0.846366476	4						
74	0.752990374	6						
75	0.420206792	18						
76	0.633409989	8						
77	0.513723146	12						
78	0.191753614	56						
79	0.99148973	1						
80	0.379157043	21						
81	0.030601199	92						
82	0.540654964	10						
83	0.467590372	14						
84	0.314745086	33						
85	0.190332633	57						
86	0.343038099	31						
87	0.161042883	67						
88	0.99148973	1						
89	0.208701266	53						
90	0.089212406	78						
91	0.080776326	79						
92	0.180689375	61						
93	0.20032953	54						
94	0.216205294	49						
95	0.216103897	50						

TOPSIS algorithm is applied to prioritize the pareto set of solutions shown in Table 1. Here, minimization of peakover shoot, flow disturbance rejection, and temperature disturbance rejection are considered as three criteria C_1, C_2, and C_3 for TOPSIS. All three criteria are negative as it requires to be minimized. The weights of criteria assumed to be idential ($w = 1$). After applying TOPSIS, rank of each nondominated solution along with closeness coefficient is obtained shown in following Tables 2,3, and 4.

In order to obtain the comparative analysis of optimization algorithms (NSGA-II, NSGA-III, and MOPSO) all the Pareto optimal solutions are combined under

https://doi.org/10.1016/j.heliyon.2019.e01410

evaluation criteria IAE, ISE, and ITAE. The combined non-dominated set of solutions are 202(IAE), 133(ISE), and 116(ITAE) shown in Table 1. TOPSIS is used to obtain top 10 high rank individual solution from combined set of solution shown in Table 5.

As shown in Table 5 after merging the solutions of the algorithms, the percentage of solutions from NSGA-II is greater than NSGA-III and MOPSO under each evalution criteria. Also, the best rank solution is obtained from NSGA-II (under IAE and ISE) and MOPSO (under ITAE). Here, NSGA-II algorithm outperforms NSGA-III and MOPSO algorithms. Following Figs. 12, 13, and 14 are plots of set point tracking, flow disturbance rejection, and temperature disturbance rejection using the best rank result obtained after applying TOPSIS.

From the above figures (Figs. 12, 13, and 14), it is derived that IAE criterion of NSGA-II (Solution No-177) algorithm has minimum peak overshoot of step response (4.8%), maximum rejection of flow (33.4%), and temperature (78%) disturbances for non-dominated set of solution [1.363,0.052, 6.855,0.601,0.439]. The minimum peak overshoot of step response, maximum rejection of flow, and temperature disturbances are achieved under ISE and ITAE using NSGA-II (Solution No-82) and MOPSO(Solution No-115) algorithms respectively, values are shown in following Table 6.

The settling time for set point tracking response, flow disturbance rejection response, and temperature disturbance rejection response is derived from the above figures (Figs. 12, 13, and 14), shown in following Table 7.

Table 5. Top 10 optimal solutions obtained using TOPSIS from NSGA-II, NSGA-III, and MOPSO under IAE, ISE, and ITAE.

Top 10 solution from the combined set of solution under IAE				Top 10 solution from the combined set of solution under ISE				Top 10 solution from the combined set of solution under ITAE			
Algorithm	**Solution number**	**Closeness coefficient CC**	**Rank**	**Algorithm**	**Solution number**	**Closeness coefficient CC**	**Rank**	**Algorithm**	**Solution number**	**Closeness coefficient CC**	**Rank**
NSGA-II	177	0.999790511	1	NSGA-II	82	0.969106	1	MOPSO	115	0.986438	1
NSGA-II	190	0.999670866	2	NSGA-II	81	0.916156	2	NSGA-II	79	0.976028	2
MOPSO	55	0.99148973	3	NSGA-II	89	0.895838	3	NSGA-II	95	0.964218	3
MOPSO	79	0.99148973	4	NSGA-II	106	0.88429	4	NSGA-II	102	0.947696	4
MOPSO	88	0.99148973	5	MOPSO	133	0.881947	5	NSGA-III	41	0.782796	5
NSGA-III	99	0.971350992	6	NSGA-II	85	0.874856	6	NSGA-III	68	0.778864	6
NSGA-III	168	0.866894865	7	NSGA-II	119	0.866528	7	NSGA-II	86	0.743282	7
MOPSO	73	0.846366476	8	NSGA-II	100	0.865988	8	NSGA-II	81	0.736905	8
NSGA-II	188	0.838580319	9	NSGA-II	103	0.863439	9	NSGA-III	43	0.698814	9
NSGA-II	184	0.834714135	10	MOPSO	117	0.854689	10	NSGA-III	48	0.671815	10

 https://doi.org/10.1016/j.heliyon.2019.e01410

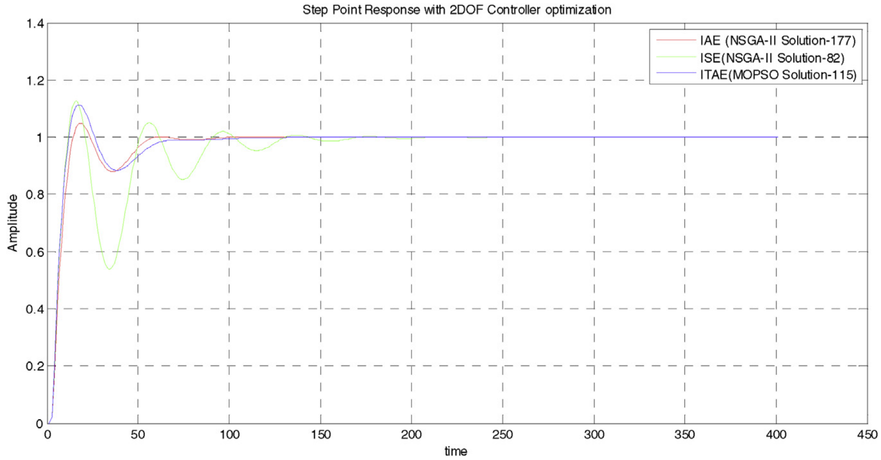

Fig. 12. Set point response with the best rank result from TOPSIS for 2DOF controller optimization.

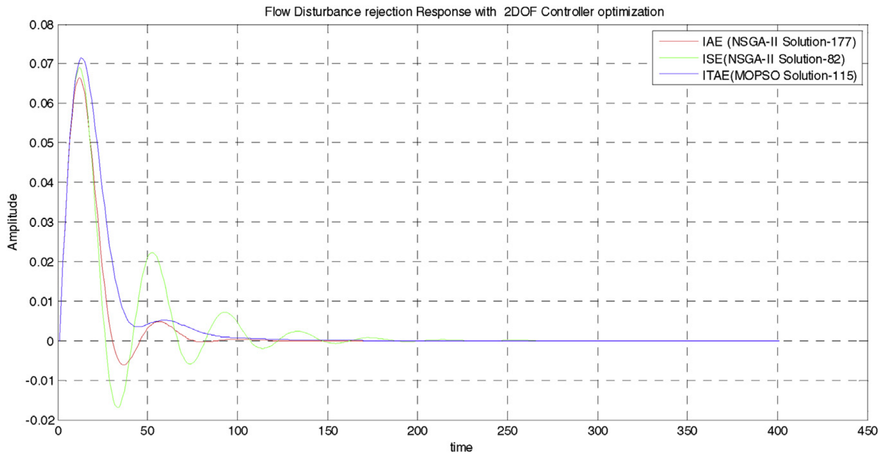

Fig. 13. Flow disturbance rejection response with the best rank result from TOPSIS for 2DOF controller optimization.

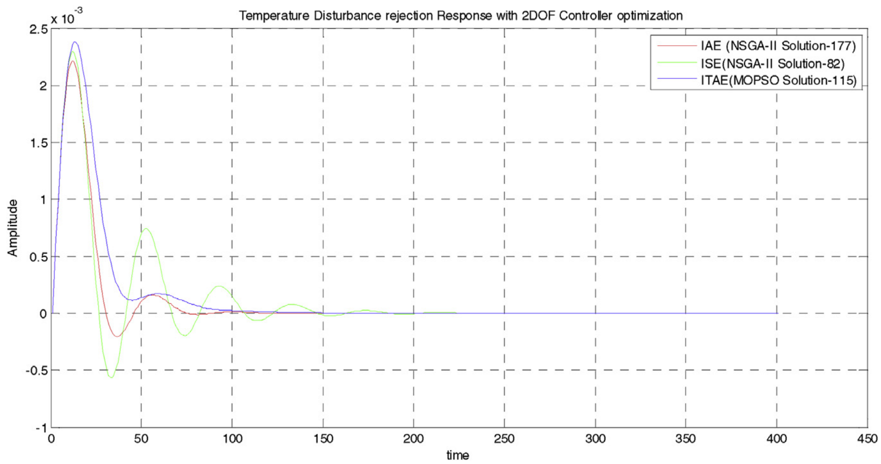

Fig. 14. Temerature disturbance rejection response with the best rank result from TOPSIS for 2DOF controller optimization.

https://doi.org/10.1016/j.heliyon.2019.e01410

Table 6. Parameters of 2DOF controller after applying TOPSIS from NSGA-II, NSGA-III, and MOPSO.

Optimization of 2DOF controller parameter [K_p, K_i, K_d, α, β]	**Peak overshoot of step response in (%)**	**Reduction of Flow disturbance in (%)**	**Reduction of temperature disturbance in (%)**
NSGA-II (Solution No-177) under IAE [*1*.363,0.*052*, *6.855*,0.601,0.439]	4.8	33.4	78
NSGA-II (Solution No-82) under ISE [*1*.677,0.*0454*, *4.886*,0.619,0.215]	12.59	31	77
MOPSO(Solution No-115) under ITAE [1.090,0.035,5.876,0.433,0.40]	11.35	28.5	76

Table 7. Settling time of the system from the best rank solution under IAE, ISE, and ITAE.

Optimization of 2DOF controller parameter [K_p, K_i, K_d, α, β]	**Set point response in (sec)**	**Flow disturbance response in (sec)**	**Temperature disturbance response in (sec)**
NSGA-II (Solution No-177) under IAE [*1*.363,0.*052*, *6.855*,0.601,0.439]	52	120	89
NSGA-II (Solution No-82) under ISE [*1*.677,0.*0454*, *4.886*,0.619,0.215]	150	186	187
MOPSO(Solution No-115) under ITAE [1.090,0.035,5.876,0.433,0.40]	62	149	100

It is derived from Table 7, that settling time of the system is minimum under IAE criterion of NSGA-II (Solution No-177) algorithm.

6. Conclusion

In this paper, Evolutionary (NSGA-II and NSGA-III) and Swarm Intelligence (MOPSO) based algorithms enhanced with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is employed to optimize five parameters of Two Degree Of Freedom (2DOF) controller for the problem of shell and tube heat exchanger system. The test problem involves maintaining outlet temperature of process fluid flowing through heat exchanger at set point in the presence of two major conflicting disturbances, (1) Flow variation of input fluid and (2) Temperature variation of input fluid. The step input is applied as disturbance for both flow and temperature disturbances. Three test criteria IAE, ISE and ITAE function of error (set point tracking and disturbance rejection) and time are used for evaluation of objective functions. The Pareto set of solutions are obtained after optimizing all the five parameters of 2DOF controller using Evolutionary (NSGA-II and NSGA-III) and Swarm Intelligence (MOPSO) algorithms, results shown in Table 1. TOPSIS

https://doi.org/10.1016/j.heliyon.2019.e01410

a multiple criteria decision making method is used to rank the set of Pareto optimal solutions for reducing number of Pareto optimal solutions to a single solution. In order to obtain the comparative analysis of optimization algorithms (NSGA-II, NSGA-III, and MOPSO) all the Pareto optimal solutions are combined under evaluation criteria IAE, ISE, and ITAE. The combined non-dominated set of solutions are 202(IAE), 133(ISE), and 116(ITAE). TOPSIS is used to obtain top 10 high rank individual solution from combined set of solution. The performance optimization of 2DOF controller tuning was evaluated by comparing the values of peak overshoot of step response, set point tracking error, disturbance rejection (both flow and temperature), settling time, and the percentage of solutions obtained from optimization algorithms under criteria IAE, ISE, and ITAE. Here, three negative criteria C_1 (peakover shoot), C_2(flow disturbance rejection), and C_3(temperature disturbance rejection) having identical weights ($w = 1$) are considered for priporitizing the solutions using TOPSIS.

From the results shown in Table 5, it is concluded that after merging the solutions of the algorithms, the percentage of solutions from NSGA-II is greater than NSGA-III and MOPSO under three evaluation criteria IAE, ISE, and ITAE. Also, the best rank of solution is obtained from NSGA-II (under IAE and ISE) and MOPSO (under ITAE). From the above figures (Figs. 12, 13, and 14), it is concluded that IAE criterion of NSGA-II (Solution No-177) algorithm has minimum peak overshoot of step response (4.8%), maximum rejection of flow (33.4%), and temperature (78%) disturbances for non-dominated set of solution [1.363,0.052, 6.855,0.601,0.439]. The minimum peak overshoot of step response, maximum rejection of flow, and temperature disturbances are achieved under ISE and ITAE criteria using NSGA-II (Solution No-82) and MOPSO(Solution No-115) algorithms respectively. It is derived from Table 7, that settling time of the system is minimum under IAE criteria of NSGA-II (Solution No-177). From this, it is concluded that, NSGA-II algorithm outperforms NSGA-III and MOPSO algorithms for this particular test problem.

The following recommendations are proposed for future work in tuning of 2DOF controller parameters:

1. The performance of NSGA-II, NSGA-III and MOPSO algorithms may be compared with other class of algorithms like: Ant colony algorithm, Artificial Bee colony algorithm and others.
2. The criteria for evaluation of objective functions can be tried other than used one IAE, ISE and ITAE to see the results.
3. Here, results are tested by applying step inputs of magnitude 1, 0.1 and 0.01 for set point tracking, flow disturbance, and temperature disturbance. The other inputs can be applied to verify the performance of algorithms.

https://doi.org/10.1016/j.heliyon.2019.e01410

4. No modifications in the standard proposed algorithms NSGA-II, NSGA-III, and MOPSO is done except varying algorithmic parameters for better result like; number of population, crossover, mutation, supplying reference points, repository Size, inertia weight, values of random numbers, number of grids per dimension, and mutation rate. Hence, modification in existing algorithm can be thought to improve the performance of algorithms.
5. Instead of considering just three objective optimization problem, many other objectives can be added and problem can be extended to many-objective optimization instead of multi-objective optimization.

Declarations

Author contribution statement

Haresh A. Suthar: Conceived and designed the experiments; Performed the experiments; Wrote the paper.

Jagrut J. Gadit: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Acknowledgements

The authors would like to thank the anonymous reviewers and the editor for their valuable comments and suggestions.

References

[1] Mituhiko Araki, Hidefumi Taguchi, Two-Degree-of-Freedom PID controllers, Int. J. Control Autom. Syst. 1 (4) (December, 2003).

 https://doi.org/10.1016/j.heliyon.2019.e01410

[2] Manish Mishra, P.K. Das, Sunil Sarangi, Transient behaviour of crossflow Heat exchangers due to perturbations in temperature and flow, Int. J. Heat Mass Transf. (2006).

[3] M. Gopal, Control Systems: Principles and Design, Tata McGraw-Hill Education, 2002.

[4] Subhransu Padhee, Controller design for temperature control of heat exchanger system: simulation studies, WSEAS Trans. Syst. Control 9 (2014).

[5] R.S. Rosenberg, Simulation of Genetic Populations with Biochemical Properties, Ph.D. thesis, University of Michigan, Ann Harbor, Michigan, 1967.

[6] K.E. Parsopoulos, M.N. Vrahatis, Particle swarm optimization method in multiobjective problems, in: Proc. 2002 ACM Symp, Applied Computing (SAC'2002), Madrid, Spain, 2002, pp. 603−607.

[7] D. Corne, M. Dorigo, F. Glover (Eds.), New Ideas in Optimization, McGraw-Hill, London, UK, 1999.

[8] K. Deb, Multi-objective Optimization Using Evolutionary Algorithms, Wiley publication, 2003.

[9] G. Rudolph, A. Agapie, Convergence properties of some multi-objective evolutionary algorithms, in: Proceedings of the 2000 Conference on Evolutionary Computation, vol. 2, IEEE Press, Piscataway, New Jersey, July 2000, pp. 1010−1016.

[10] E. Zitzler, L. Thiele, Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach, IEEE Trans. Evol. Comput. 3 (4) (Nov. 1999) 257−271.

[11] E. Zitzler, M. Laumanns, L. Thiele, SPEA2: Improving the strength pareto evolutionary algorithm, in: EUROGEN 2001. Evolutionary Methods for Design, Optimization and Control with Applications to Industrial Problems, 2002, pp. 95−100. Athens, Greece.

[12] J.D. Knowles, D.W. Corne, Approximating the nondominated front using the pareto archived evolution strategy, Evol. Comput. 8 (2) (2000) 149−172.

[13] S. Mostaghim, J. Teich, Strategies for finding good local guides in multi-objective particle swarm optimization (MOPSO, in: Proc. 2003 IEEE Swarm Intelligence Symp., Indianapolis, IN, Apr. 2003, pp. 26−33.

[14] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA−II, IEEE Trans. Evol. Comput. 6 (2) (Apr. 2002) 182−197.

 https://doi.org/10.1016/j.heliyon.2019.e01410

[15] K. Deb, Jain, An evolutionary many-objective optimization algorithm using reference-point based non-dominated sorting approach, Part I: solving problems with box constraints, IEEE Trans. Evol. Comput. 18 (4) (August. 2014) 577−600.

[16] J. Kennedy, R.C. Eberhart, Particle swarm optimization, in: Proc. IEEE International 1st Conference on Neural Networks vol. IV, IEEE service center, Piscataway, NJ, 1995, pp. 1942−1948.

[17] J. Moore, R. Chapman, Application of Particle Swarm to Multiobjective Optimization, Department of Computer Science Software Engineering, Auburn Univ., 1999.

[18] T. Ray, K.M. Liew, A swarm metaphor for multiobjective design optimization, Eng. Optim. 34 (2) (Mar. 2002) 141−153.

[19] X. Hu, R. Eberhart, Multiobjective optimization using dynamic neighborhood particle swarm optimization, in: Proceeding of Congess Evolutionary Computation (CEC'2002), vol. 2, Honolulu, HI, May 2002, pp. 1677−1681.

[20] J.E. Fieldsend, S. Singh, A multi-objective algorithm based upon particle swarm optimization, an efficient data structure and turbulence, in: Proceeding 2002 U.K. Workshop on Computational Intelligence, Birmingham, U.K., Sept. 2002, pp. 37−44.

[21] X. Hui, R.C. Eberhart, Y. Shi, Particle swarm with extended memory for multiobjective optimization, in: Proceeding 2003 IEEE Swarm Intelligence Symp., Indianapolis, IN, Apr. 2003, pp. 193−197.

[22] X. Li, et al., A nondominated sorting particle swarm optimizer for multiobjective optimization, in: E. Cantú-Paz, et al. (Eds.), Lecture Notes in Computer Science, vol. 2723, Proc. Genetic and Evolutionary Computation—GECCO 2003—Part I, July 2003, pp. 37−48. Berlin, Germany.

[23] Coello, et al., Handling multiple objectives with Particle swarm optimization, IEEE Trans. Evol. Comput. 8 (3) (June 2004) 256−278.

[24] C.L. Hwang, K.P. Yoon, Multiple Attribute Decision Making: Methods and Applications, Springer-Verlag, 1981.

[25] Ewa Roszkowska, Multi-criteria decesion making models by applying TOPSIS method to crisp and interval data, Mult. Criteria Decis. Making 6 (2011) 200−230.

[26] Madjid Tavana, Zhaojun Li, Mohammadsadegh Mobin, Mohammad Komaki, Ehsan Teymourian, Multi-objective control chart design optimization using

https://doi.org/10.1016/j.heliyon.2019.e01410

NSGA-III and MOPSO enhanced with DEA nad TOPSIS, J. Expert Syst. Appl. (2016) 17–39.

[27] Ramesh K. Shah, Dusan P. Sekulic, Fundamentals of Heat Exchanger Design, John Willey and Sons, USA, 2003.

[28] Sadik Kakaç, Hongtan Liu, Heat Exchangers: Selection, Rating and Thermal Design, second ed., CRC Press, 2002.

[29] Duran Orlando, Nibaldo Rodriguez, Luiz Airton Consalter, Neural networks for cost estimation of shell and tube heat exchangers, Proc. Int. Multi Conf. Eng. Comp. Sci. II (2008) 1584–1589.

[30] Yuvraj Bhushan Khare, Yaduvir Singh, PID control of heat exchanger system, Int. J. Comput. Appl. 8 (6) (October 2010).

[31] B.G. Liptak, Heat Exchanger Control and Optimization Book, 2006.

[32] Haresh A. Suthar, J.J. Gadit, Two degree of freedom controller optimization using GA for shell and tube heat exchanger, in: 11th International Conference on Intelligent Systems and Control (ISCO2017), 5-6 Jan. 2017, pp. 1–7. Coimbatore.

[33] Farhan A. Salem, Albaradi A. Rashid, PID controllers and algorithms: selection and design techniques applied in mechatronics system design-part-II, Int. J. Eng. Sci. (May 2013) 91–203. ISSN 2306-6474.

[34] K. Deb, S. Agrawal, A. Pratab, T. Meyarivan, A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II,, in: Marc Schoenauer, et al. (Eds.), Proceedings of the Parallel Problem Solving from Nature VI Conference, Springer, Paris, France, 2000, pp. 849–858. Lecture Notes in Computer Science No. 1917.

 https://doi.org/10.1016/j.heliyon.2019.e01410