Multi-Objective Optimization of Real-Time Parameters for Thermal Management System of Hypersonic Vehicle Actuating System

Qiyuan Zhang, Zhaoxiong Wang, Yu Yao, Yunhua Li*, Senior Member, IEEE, Jinyu Sun and Yongwei Zhang

Abstract—Hypersonic vehicle actuating system will endurance great thermal load when it re-enters the atmosphere. Pump-controlled loop pipe (PCLP) is widely used to dissipate its thermal load. PCLP is a kind of organic Rankine cycle (ORC). ORC is also commonly used in residual energy recovery. To address challenges to optimize multiple conflicting objectives at the same time in ORC, a multi-objective optimization (MOO) method for ORC is proposed, using energy consumption, total exergy loss, and compression ratio as objective functions. The unconstrained multi-objective evolutionary algorithm based on decomposition and fitness rate rank based multi-armed bandit (MOEA/D-FRRMAB) is enhanced to handle constrained MOO problem. An improved entropy weight-technique for order preference by similarity to an ideal solution (entropy weight-TOPSIS) approach is proposed for selecting the best solution from Pareto optimal solutions, which can obtain a set of real-time optimized parameters of system to achieve a comprehensive optimization effect, considering the system's thermal load.

Index Terms—Mechatronic system, organic Rankine cycle, thermal management, multi-objective optimization.

I. INTRODUCTION

The mechatronic system of hypersonic vehicle usually generates a lot of heat during work, including the heat generated by electronic equipment and hydraulic actuators, mainly because the high-power electric actuator system needs strong current and high-frequency switching in the work. The heat generated is highly concentrated on the actuating system and electronic system, increasing the temperature of the actuating system, which makes the actuating system bear a large thermal load when the aircraft re-enters the atmosphere, thus affecting the flight reliability [1]. Due to the wide application of composite materials and the requirements of stealth performance, it is more and more difficult to disperse the heat inside the aircraft through the skin, and the space of the actuating system is relatively closed and narrow, which results in the heat dissipation of power teletype actuators face great challenges. PCLP is commonly used for the dispersion of thermal loads, which is an ORC system. ORC technology is an emerging thermal management solution that employs the phase change process of organic working fluids for energy conversion [2], and it finds wide application in various medium and low-temperature power generation fields [3]. ORC technology has been widely studied for its potential applications in the aerospace industry since the 1960s [4].

Despite the wide range of potential applications for ORC technology in the aerospace industry, several issues remain unresolved. The parameters of ORC system can significantly influence the effectiveness of thermal management and energy utilization efficiency [5]. Therefore, it is necessary to engage in MOO to achieve optimal system performance. Additionally, relevant algorithms are utilized to evaluate a series of Pareto solutions' quality [6]. Various complex engineering problems have been solved by numerous multi-objective evolutionary algorithms (MOEAs) [7], [8].

In MOO design for enhancing system performance, various algorithms are commonly used, including simulated annealing algorithm, non-dominated sorting genetic algorithm and particle swarm optimization [9]. Muhammad proposed an ORC system and optimized it using a genetic algorithm to solve MOO problem, with the goal of reaching the optimal points for both system entropy generation and heat exchanger thermal capacity [10]. Wang utilized an evolutionary algorithm to perform MOO of ORC system, aiming to achieve the optimal performance in waste heat recovery [11]. Pili proposed a MOO method that considers the performance of ORC under different conditions. Moreover, a method which evaluates the system uncertainty and provides a set of optimized parameters that ensure optimal performance under different load conditions was studied in [12]. Salim proposed a combined system that utilizes the cooling energy of liquefied natural gas and waste heat from dual-fuel marine engines. MOO was used to study the effects of evaporating and condensing pressures [13].

This paper studies the utilization of ORC for heat removal in aircraft and to optimize the operating parameters and to improve the efficiency of heat management in aircraft. The paper proposes an enhancement to MOEA/D-FRRMAB, named C-MOEA/D-FRRMAB, which can deal with the constrained optimization problems, and it can handle constrained MOO problems better. Next, an improved entropy weight-TOPSIS approach is proposed to objectively select the optimal flight parameters from Pareto solution set for achieving the optimal values of MOO problem in the system. Compared with the traditional TOPSIS method, the proposed method can mitigate the impact of subjective perception on the selection of optimal parameters [14].

The rest of the paper is arranged as follows. Section II describes the mathematic model of ORC. Section III presents the C-MOEA/D-FRRMAB to solve MOO problem. Section IV presents the selection of optimal solution by entropy weight-TOPSIS. Finally, the conclusions are summarized.

^{*} This work is supported by Major National Science and Technology Projects under the grant 2017-V-0015-0067. (*Corresponding author: Yunhua Li, e-mail: <u>yhli@buaa.edu.cn</u>).*

Qiyuan Zhang, Zhaoxiong Wang, Yu Yao, Yunhua Li, Jinyu Sun and Yongwei Zhang are with the School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China.

II. METHODOLOGY

A. System description

The ORC system is used to collect and dissipate the heat generated by the electromechanical systems, and its structural composition is shown in Fig. 1. The refrigerant is first pressurized by a liquid pump before entering the evaporator. This way, it absorbs the heat generated by the electronic equipment. The high-temperature and high-pressure steam generated in the evaporator is then directed to the expander. The exhaust from the expander is condensed into a liquid state by the fuel in the condenser. In this way, heat is transferred through space and ultimately released to the fuel heat sink, which ensures that the operating temperature of electronic equipment remains within the allowed range.



Fig. 1 ORC system

The T-S diagram in Fig. 2 illustrates the thermodynamic cycle process.



The ORC model established in this paper is based on the following assumptions while disregarding secondary factors:

- (1) It is assumed that there is no heat exchange between the system components and the external environment.
- (2) The model assumes that pressure losses in pipes and heat exchangers are negligible.
- (3) The refrigerant at the outlet of the condenser is in a saturated state, and the thermophysical parameters of the saturated state can be calculated using the **REFPROP 9.0 software from National Institute of** Standards and Technology (NIST).
- The efficiency of the expander and pump are (4) invariant.

B. Thermodynamic model of ORC system

The power consumption in the process 1-2 is

$$W_{\rm p} = \dot{m}(h_2 - h_1) = \dot{m}(h_{2s} - h_1) / \eta_{\rm p} \tag{1}$$

The heat absorbed by the electronic device heat sink in process 2-3 is

$$Q_{\rm ev} = \dot{m}(h_3 - h_2) \tag{2}$$

The work done by the expansion machine in process 3-4 is

$$W_{\rm t} = \dot{m}(h_4 - h_3) = \dot{m}(h_{4\rm s} - h_3) / \eta_{\rm s}$$
(3)
The heat absorbed by the condenser in the process 4-5 is

$$Q_{\rm cd} = \dot{m}(h_4 - h_5) \tag{4}$$

 $Q_{\rm cd} = \dot{m}(h_4 - h_5)$ The irreversible exergy loss is

Pump:

$$I_{\rm p} = T_{\rm amb} \dot{m} (s_2 - s_1) \tag{5}$$

Evaporator:

$$I_{\rm ev} = T_{\rm amb} \dot{m} (s_3 - s_2 - (h_3 - h_2) / T_h)$$
(6)

Expansion:

$$I_{\rm ex} = T_{\rm amb} \dot{m} (s_4 - s_3) \tag{7}$$

Condenser:

$$I_{\rm cd} = T_{\rm amb} \dot{m} (s_5 - s_4 - (h_5 - h_4) / T_{\rm amb})$$
(8)

where \dot{m} is the mass flow rate of refrigerant in g/s; while s_k , h_k denote the entropy and enthalpy values of the organic refrigerant at the different position in kJ/kg and kJ/(kg•K), k = 1,2,2s,3,4,4s,5; T_h and T_{amb} are the temperatures of the electronic equipment and equipment cabin environment, in K; $\eta_{\rm p}$ and $\eta_{\rm s}$ are the efficiency of the pump and expander.

C. Multi-objective parameter optimization model

During the flight phase, it may be necessary to consider multiple objectives simultaneously. This paper focuses on three primary objectives to align with engineering practice. The first objective is to minimize the power consumption of the pump. In ORC systems, the power consumed by the pump, in relation to the power generated by the turbine, is relatively high (when compared to classical steam Rankine cycles) and may account for about 5-15% of the turbine power. Another crucial objective is to reduce the overall irreversibility exergy loss. This objective seeks to minimize the loss of functional power resulting from irreversibility factors present in each component of the device. Moreover, it is imperative to minimize the pressure ratio coefficient due to the constraints posed by material hardness. Therefore, the optimization problem of the cycle is a multi-objective optimization problem. The objective functions are to minimize the energy consumption W_{p} , total exergy loss $I = I_{p} + I_{ev} + I_{ex} + I_{cd}$ and system pressure ratio coefficient $Z = P_{ev}/P_{cd}$, where P_{ev} and $P_{\rm cd}$ is the pressure of evaporator and condenser.

Based on the analysis above, 3 objectives are as follows:

$$\begin{cases} \min J_1 = W_p \\ \min J_2 = I \\ \min J_3 = Z \end{cases}$$
(9)

where J_1 , J_2 and J_3 correspond to the power consumption, total exergy loss, and pressure ratio coefficient, respectively. As a result, the objective vector can be defined as follows:

minimize
$$J = \{J_1, J_2, J_3\}$$
 (10)

The performance parameters of heat transfer can be classified into three types, namely material parameters, structural parameters, and control parameters. Structural parameters are achieved during the design phase, and material parameters are typically excluded from the optimization scope. Therefore, the control parameters become the decision variables or decision vector for the MOO of the ORC system. The decision vector is selected as

$$\boldsymbol{x} = [T_{\rm ev}, T_{\rm cd}, \dot{\boldsymbol{m}}]^{\rm T}$$
(11)

where T_{ev} is the refrigeration capacity, T_{cd} is the condenser temperature, and \dot{m} is mass flow rate of the evaporator. The objective function $\{J_1, J_2, J_3\}$ can be expressed in terms of \boldsymbol{x} .

The constraints can be described as follows:

- (1) According to the 2nd law of thermodynamics, the exergy loss should meet the constraint I > 0J.
- (2) The pump's power consumption should be limited to ensure economic efficiency and provide the minimum required power for proper operation. Thus, the pump constraint is $1W < W_p < 20W$.
- (3) The pressure ratio in the system must be kept within material limitations to avoid leakage. As a result, 1 < Z < 10.
- (4) Positive temperature difference $T_{ev} T_{cd}$ to exclude infeasible cycle configurations, i.e. $T_{ev} T_{cd} > 10$ K.

Based on the analysis above, the constraints can be expressed as

The set of the set of the function
$$f_1 = 0 - I < 0$$

 $f_2 = 1 - W_p < 0$
 $f_3 = W_p - 20 < 0$
 $f_4 = 1 - Z < 0$
 $f_5 = Z - 10 < 0$
 $f_6 = 10 + T_{cd} - T_{ev} < 0$
(12)

III. HYBRID CONSTRAINT-HANDLING TECHNIQUE BASED ON MOEA/D-FRRMAB ALGORITHM

A commonly used heuristic method for solving multi-objective optimization problems is the MOEA/D-FRRMAB algorithm. Jin proposed this algorithm with the fundamental concept of iteratively exploring the Pareto front to identify the best solution for the problem [15]. However, the traditional MOEA/D-FRRMAB algorithm encounters difficulties in solving multi-objective optimization problems. Particularly in cases with intricate constraints where the algorithm may struggle to manage the constraints, ultimately leading to decreased convergence performance. To effectively utilize the available information carried by infeasible solutions, the present study proposes an integration of the hybrid constraint handling techniques with the adaptive penalty function method into MOEA/D-FRRMAB, named C-MOEA/D-FRRMAB, which aims to balance population diversity and convergence, improving the algorithm's capacity to handle multi-objective optimization problems.

"Constraint violation degree": suppose x^i is *i*-th decision vector in the solution space, $\varphi(x^i)$ is the degree of which the *i*-th individual violates the constraints, and $\varphi(x^i)$ is as

$$\varphi(\mathbf{x}^i) = \sum_{j=1}^{6} \left\{ \max f_j(\mathbf{x}^i), \mathbf{0} \right\}$$
(13)

To account for the differences in magnitudes of constraint conditions, it is necessary to standardize the constraint violation degree. The resulting standardized constraint violation degree $\varphi_{nor}(\mathbf{x}^i)$ can be expressed as

$$\varphi_{\text{nor}}(\boldsymbol{x}^{i}) = \sum_{j=1}^{6} \max\left\{ f_{j}(\boldsymbol{x}^{i}) \middle/ f_{j}^{\max}, 0 \right\}$$
(14)

where f_j^{max} represents the highest value that violates the *j*th constraint conditions, which can be expressed as

$$f_{j}^{\max} = \max_{i=1}^{N_{\max}} \left\{ 0, f_{j}(\boldsymbol{x}^{i}) \right\}$$
(15)

If all solutions are feasible, which means $f_j^{\text{max}} = 0$, then (14) mentioned above will not have any solution. It is important to consider this scenario in the optimization process. In such a scenario, the set should be defined as $f_i^{\text{max}} = 1$.

The ε -constraint method, proposed by Takahama, aims to identify feasible solutions by setting a threshold value of such that any individual with a constraint violation degree less than this threshold is considered feasible [16]. The approach adopted in this paper fully leverages the information provided by infeasible solutions located at the boundary of the feasible solution range, resulting in improved convergence performance. In this paper, the quality of individuals is compared based on the following criteria: for x^1 and x^2 , with their degree of constraint violation φ^1 and φ^2 respectively, the comparison between ε and \prec_{ε} can be defined as

$$(\boldsymbol{x}^{1}, \boldsymbol{\varphi}^{1}) \prec_{\varepsilon} (\boldsymbol{x}^{2}, \boldsymbol{\varphi}^{2}) \Leftrightarrow \begin{cases} \boldsymbol{x}^{1} \prec_{\varepsilon} \boldsymbol{x}^{2}, \text{ if } \boldsymbol{\varphi}^{1}, \boldsymbol{\varphi}^{2} \leq \varepsilon \\ \boldsymbol{x}^{1} \prec_{\varepsilon} \boldsymbol{x}^{2}, \text{ if } \boldsymbol{\varphi}^{1} = \boldsymbol{\varphi}^{2} \\ \boldsymbol{\varphi}^{1} \prec_{\varepsilon} \boldsymbol{\varphi}^{2}, \text{ otherwise} \end{cases}$$
(16)

In comparison to the feasibility rule, the ε -constraint method relaxes the constraints to some extent, which allows some non-feasible solutions with better objective values to be considered as feasible solutions. The effectiveness of this constraint handling approach heavily depends on the value selected for the parameter ε . When $\varepsilon = 0$, the constraint method can be regarded as the feasibility rule. Conversely, the constraint method becomes equivalent to the Pareto dominance-based constraint method.

For multi-constraint parameter optimization problems, the population in the early generations of evolution may predominantly comprise infeasible solutions or have a low proportion of feasible solutions. In such cases, it is imperative to swiftly identify the feasible region to accelerate the convergence of the algorithm. To achieve this, utilizing an enhanced ε -constraint method improves convergence, while in the later stages of evolution, an adaptive penalty function is employed to sustain population diversity. The specific mixed constraint handling strategy can be described as follows:

$$\begin{cases} \varepsilon(gen) = \varphi_{nor}(\mathbf{x}^{\zeta}), & \text{if } gen = 0\\ \varepsilon(gen) = (1 - \frac{gen}{g_{max}})\varepsilon(gen - 1), \text{ if } r_{gen} < \varepsilon_a \text{ and } gen < N_{\varepsilon} \\ \text{adaptive punalty function,} & \text{if } r_{gen} \ge \varepsilon_a \text{ and } gen < N_{\varepsilon} \\ \varepsilon(gen) = 0, & \text{if } gen \ge N_{\varepsilon} \end{cases}$$
(17)

where $\varepsilon(gen)$ denotes the value of ε during differing iteration processes, $\varphi_{nor}(\mathbf{x}^{\zeta})$ represents the degree to which the ζ th individual in the initial population violates the constraint conditions, and the list is sorted by degree of violated constraints in descending order, and g_{max} is the maximum number of allowed iterations; r_{gen} is a proportion of feasible solutions in the population, ε_a is a parameter that influences the search preference in all regions, and $\varepsilon_a \in [0,1]$, and N_{ε} is the optimized control parameters.

The adaptive penalty function can be formulated as

 $PF'(\mathbf{x}^{i}) = PF(\mathbf{x}^{i}) + (\varphi_{nor}(\mathbf{x}^{i}))^{P}(PF_{max} - PF(\mathbf{x}^{i})) \quad (18)$

where $P = 10^{\alpha(1-r_{gen})} - 1$ has the ability to adjust the punishment level for infeasible solutions, $PF'(x^i)$ is the target value after punishment, and PF_{max} denotes the maximum value of each objective vector.

IV. MULTI-OBJECTIVE OPTIMIZATION OF WORKING PARAMETERS IN FLIGHT MISSIONS

A. Working condition parameter settings

This paper demonstrates application of multi-objective optimization using a fighter jet flight mission as an example. The flight process generates a time-varying thermal load that is fixed at 40 kW.

TABLE I. presents the simulation parameters of the ORC system used in the optimization process.

| TABLE I. | MULTI-OBJECTIVE SIMULATION PARAMETERS |
|----------|---------------------------------------|
|----------|---------------------------------------|

| Parameter | Value |
|-------------------------------|-------------|
| Electronic device temperature | 420 K |
| Fuel temperature | 300 K |
| Ambient temperature | 290 K |
| Evaporation temperature | (350-390) K |
| Condensation temperature | (310-350) K |
| mass flow | (0-50) g/s |
| Environmental pressure | 0.1013 MPa |
| Pump isentropic efficiency | 0.95 |
| Valve isentropic efficiency | 0.85 |

TABLE II. shows the control parameters of the multi-objective algorithm.

| TABLE II. CONTROL PARAMETERS OF MOEA/D-FRRMA | TABLE II. | CONTROL PARAMETERS OF MOEA/D-FRRMAB |
|--|-----------|-------------------------------------|
|--|-----------|-------------------------------------|

| Control Parameter | Value |
|---|-------|
| Maximum number of generations g_{max} | 1000 |
| Population size N_{max} | 190 |
| Crossover probability p_c | 0.85 |
| Mutation probability p_m | 0.125 |
| Distribution index for crossover η_c | 30 |
| Distribution index for mutation η_m | 20 |

B. Dual objective optimal result

This section aims to optimize the flight parameters based on two out of three objectives, with all simulations assuming a thermal load of 40kW. The section will explore bi-objective optimization examples, which is minimize J_1 and J_2 .

Fig. 3 depicts the Pareto front for bi-objective. When minimize J_1 and J_2 , the overall irreversibility exergy loss and the pump power are conflicting indicators. Therefore, decreasing the pump power under the same heat load conditions may result in an increase in the overall irreversibility exergy loss. It is influenced by entropy, mass flow rate, and ambient temperature, and indirectly affected by heat transfer efficiency and expansion efficiency. Thus, it is a multi-factor indicator.



Fig. 3 Pareto front for bi-objective

During real flight missions, the thermal load is subject to variation depending on the specific flight tasks. In this paper, the algorithm is evaluated based on the uncertainty of the thermal load. When minizine two objectives, the thermal load's uncertainty value is set to Q = 30, 40 and 50 kW. The resulting updated Pareto front is presented in Fig. 4. As shown, both the overall irreversibility exergy loss and the pump power increase with increasing thermal load. Consequently, considering thermal load uncertainty is a critical factor in optimizing the parameters.



Fig. 4 Pareto fronts with uncertainty of heat load

It is worth noting that the heat transfer effectiveness is subject to variation with different temperature differences between evaporation and condensation. Hence, it is crucial to evaluate the uncertainty of the temperature difference in the heat exchanger. When minizine two objectives, assuming a certain level of variation in the temperature difference, i.e. $\Delta T = 10, 20$ and 30 K, the updated Pareto front is presented in Fig. 5. It means that the change in the heat transfer temperature difference did not have a significant impact on the obtained Pareto optimal solutions.



Fig. 5 Pareto fronts with uncertainty of temperature difference

C. Three-objective optimal result

We aim to concurrently optimize three objectives, namely: minimizing J_1 , J_2 and J_3 .

Fig. 6 indicates the Pareto front for three objectives. From Fig. 6, it is apparent that the constrained optimization algorithm produced a Pareto solution set that is more uniformly distributed. The optimized parameter values resulting from the optimization will be utilized to select flight parameters. Additionally, the optimal parameters can be used to establish a parameter database that can be promptly accessed during real flight missions.





V. BASED ON THE ENTROPY WEIGHT-TOPSIS METHOD FOR OPTIMAL SOLUTION SELECTION

The MOEA/D-FRRMAB algorithm generates numerous uniformly distributed non-dominated solutions, as demonstrated in Fig. 6. However, during actual flight missions, only a single parameter set is necessary. To assess the quality of the solutions that dominate, an improved entropy weight-TOPSIS was utilized in this research. Unlike traditional subjective analysis, the weights of each index were determined using entropy weighting, which is a more objective method.

The entropy weight-TOPSIS method is a 11-step process as described, as illustrated in Fig. 7. After extensive testing of the algorithm, improvements were made in the fifth step. As a result of these improvements, the new evaluation criteria matrix could measure the degree of dispersion in a better way. The optimized entropy weight-TOPSIS method generates proximity and ranking for points in the Pareto front. The proximity of the solutions corresponds to their ranking. Solutions with higher proximity are given a higher rank.

The current method for normalizing the standard matrix involves using (19) for the calculation.

$$P_{ij} = s_{ij} / \sum_{j=1}^{n} s_{ij}$$
(19)

However, it does not reflect the degree of dispersion and therefore cannot be used to calculate entropy. This is because entropy is a measure of the degree of dispersion, not the degree of concentration. Thus, probabilities cannot be calculated based solely on concentration. In contrast, the variable P_{ij} measures concentration.

Therefore, we use (20) to calculate the entropy of the data, which reflects its degree of dispersion. This method can avoid the problem in probability calculation. The specific steps are reflected in step 5 of Fig. 7.

$$P_{ij} = (s_{ij} - \overline{s}_i)^2 / \sum_{j=1}^{n} (s_{ij} - \overline{s}_i)^2$$
(20)

where P_{ij} and P_{ij} ' represent the old and new weight respectively, s_{ij} is element in evaluation criteria matrix, \overline{s}_i is the average of s_{ij} as j goes from 1 to 3.



Fig. 7 Enhanced entropy weight-TOPSIS method

The entropy weight-TOPSIS approach was used in this study to determine the optimal flight parameters for quality flow rate of the evaporator, condenser temperatures, and refrigeration capacity. According to Part C in Section IV, the Pareto fronts are different for different heat loads, and using the entropy weight-TOPSIS method to select the optimal solution among the Pareto fronts for Q = 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70 and 75kW, the results in Fig. 8 are obtained. Fig. 8 presents the results.



VI. CONCLUSIONS

This paper establishes a MOO mathematical model for organic Rankine cycles, which can minimize energy consumption, exergy losses, and compression ratio coefficients. Additionally, a hybrid constraint processing strategy is proposed in order to handle the MOO problem with constraints. This proposed strategy utilizes the information of excellent infeasible individuals to significantly improve the effectiveness of the MOEA/D-FRRMAB optimization algorithm.

The generation of the evaluation criteria matrix in the entropy weight-TOPSIS method is improved to make it a better measure of the degree of dispersion. Using the improved method to choose the optimal solution in the Pareto front makes the selection more objective.

These measures improve the stability of the ORC, and help to recover heat generated by electromechanical systems. In the future, more influencing factors in the operation of hypersonic vehicle will be considered and improve our work.

REFERENCES

- D. Li, S. J. Dong, J. Wang, and Y. H. Li, "Thermal dynamics and thermal management strategy for a civil aircraft hydraulic system," *Therm. Sci.*, vol. 24, pp. 2311–2318, 2020.
- [2] O. Boydak, I. Ekmekci, M. Yilmaz, and H. Koten, "Thermodynamic investigation of organic Rankine cycle energy recovery system and recent studies," *Therm. Sci.*, vol. 22, pp. 2679–2690, 2018.
- [3] K. Rahbar, S. Mahmoud, R. K. Al-Dadah, N. Moazami, and S. A. Mirhadizadeh, "Review of organic Rankine cycle for small-scale applications," *Energy Convers. Manage.*, vol. 134, pp. 135–155, Feb. 2017.
- [4] S. Saadon, "Computational modelling of an organic Rankine cycle (ORC) waste heat recovery system for an aircraft engine," *MATEC Web Conf.*, vol. 151, Feb. 2018, Art. no. 02001.
- [5] E. Cihan, and B. Kavasogullari, "Energy and exergy analysis of a combined refrigeration and waste heat driven organic Rankine cycle system," *Therm. Sci.*, vol. 21, pp. 2621–2631, 2017.
- [6] A. Zhou, B. Y. Qu, H. Li, S. Z. Zhao, P. N. Suganthan, and Q. Zhang, "Multi-objective evolutionary algorithms: A survey of the state of the art," *Swarm Evol. Comput.*, vol. 1, pp. 32–49, Mar. 2011.
- [7] H. Abdi, N. A. Messaoudene, L. Kolsi, and M. Belazzoug, "Multi-objective optimization of operating parameters of a PEMFC under flooding conditions using the non-dominated sorting genetic algorithm," *Therm. Sci.*, vol. 23, pp. 3525–3537, 2019.
- [8] M. Jiang, and Z. Pan, "Optimization of open microchannel heat sink with pin fins by multi-objective genetic algorithm," *Therm. Sci.*, vol. 26, pp. 3653–3665, 2022.
- [9] S. Hu, Z. Yang, J. Li, and Y. Duan, "A review of multi-objective optimization in organic Rankine cycle (ORC) system design," *Energies*, vol. 14, Oct. 2021, Art. no. 6492.

- [10] M. T. Nasir, M. C. Ekwonu, J. A. Esfahani, and K. C. Kim, "Performance assessment and multi-objective optimization of an organic Rankine cycles and vapor compression cycle based combined cooling, heating, and power system," *Sustain. Energy Techn.*, vol. 47, Oct. 2021, Art. no. 101457.
- [11] J. Wang, Z. Yan, M. Wang, M. Li, and Y. Dai, "Multi-objective optimization of an organic Rankine cycle (ORC) for low grade waste heat recovery using evolutionary algorithm," *Energy Convers. Manage.*, vol. 71, pp. 146–158, Jul. 2013.
- [12] R. Pili, S. B. Jørgensen, and F. Haglind, "Multi-objective optimization of organic Rankine cycle systems considering their dynamic performance," *Energy*, vol. 246, May. 2022, Art. no. 123345.
- [13] M. S. Salim, and M. H. Kim, "Multi-objective thermo-economic optimization of a combined organic Rankine cycle and vapour compression refrigeration cycle," *Energy Convers. Manage.*, vol. 199, Nov. 2019, Art. no. 112054.
- [14] P. Zhang, H. Li, Y. Ni, F. Gong, M. Li, and F. Wang, "Security aware virtual network embedding algorithm using information entropy TOPSIS," J. Netw. Syst. Manag., vol. 28, pp. 35–57, Jan. 2020.
- [15] Y. Jin, "Surrogate-assisted evolutionary computation: Recent advances and future challenges," *Swarm Evol. Comput.*, vol. 2, pp. 61–70, Jun. 2011.
- [16] T. Takahama, and S. Sakai, "Constrained optimization by the ε constrained differential evolution with gradient-based mutation and feasible elites," in *IEEE Congr. Evol. Comput.*, Jul. 2006, pp. 1–8.