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Surrogate-assisted optimization for solving the multi-objective refrigeration system optimization problem for a 3-level refrigeration plant with economizer

Khongdech Kamnuk[1, 2], Natee Panagant*[3], Sujin Bureerat[3] and Nantiwat Pholdee[3]

[1]Research Machine House, Department of Engineering, Singha Beverage Co., Ltd., Nakhon Pathom 73130, Thailand
[2]Department of Mechanical Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen 40002, Thailand
[3]Sustainable Infrastructure Research and Development Centre, Department of Mechanical Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen 40002, Thailand

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Abstract

In this study, the procedure of surrogate-assisted optimization is constructed to solve the multi- objective design problem of a refrigeration system. In the refrigeration process, the required coefficient of performance (COP) can be varied to the required cooling loads. In this case, the optimum operating conditions for a specified COP range is required to reduce the power consumption of the system. In this situation, the problem turns into a multi-objective optimization problem to simultaneously maximize COP and minimize power consumption. A surrogate model of the COP and power consumption are generated using several kernel functions. The best model using a linear spline kernel function is selected and used in the optimization process. A comparative study of several recent and well-known multi-objective metaheuristics was performed to measure performance of the available algorithms. The Pareto fronts containing optimum operating conditions for the refrigeration plant over the entire range of COP values were obtained in this study.

Keywords: Surrogate model, Radial basis function, Multi-objective optimization, Metaheuristics, Refrigerant system optimization

1. Introduction

Electric power plays an important role in economic growth, transportation, technology and manufacturing. In Thailand, recent power consumption for the food industry is approximately 11000-gigawatt hours [1]. A refrigeration system is one of the most power consuming systems in the food industry. In addition, the refrigeration system pays an important role in various industries such as refrigeration systems to extend the life of food, cold rooms, cold Storage to produce coldness to keep food fresh for a long time [2, 3], etc. so reducing energy consumption in this process can save a lot of production cost.

The behavior of a real refrigeration systems is sometimes too complex to analyze with the thermofluidic theory. Recently, many mathematical model construction techniques are being employed to capture the behaviors of the refrigeration systems, such as surrogate modelling techniques [4], polynomial regression [5], the response surface method (RSM) [6], and neural networks [7]. The surrogate model is one of the most widely used techniques for predicting the characteristics of refrigeration systems such as COP [8], power consumption [9], mass flow rate [10] and exergy destruction [11]. Since metaheuristics are flexible, any metaheuristic can be easily employed to solve any black-box optimization problem. The well-known algorithms for single-objective optimization include the Genetic algorithm (GA) [12] and Particle Swarm Optimization (PSO) [13], while the Multi-object GA (MOGA) [14] and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [15] are multi-objective algorithms. There are some studies presenting the possibility of using the surrogate model with some metaheuristics for design optimization in a variety of applications such as the design of liquid cooling in batteries [16], optimizing a building's energy consumption and thermal comfort [17], and improving the energy efficiency of a vapor compression refrigeration system (VCRS) [18]. Even though there are some studies using surrogate models with metaheuristics in refrigeration problems, there are no studies on the refrigeration system with inconstant COP.

Since the required COP/cooling loads in the production are not constant and vary according to the production plans, it is necessary to obtain the optimum operating conditions of all COP ranges to minimize the power consumption in all possible scenarios. This is where multi-objective optimization come into play. In this study, we investigate a 3-level VCRS refrigeration plant with an economizer. A comparative study of surrogate-assisted optimization is conducted. The accuracies of four surrogate models with four different radial basis function (RBF) kernel functions including linear spline, thin plate spline, Gaussian and multiquadric are compared. The Mean Percentage Error (MPE) is used as an accuracy indicator in this study. The best mathematical model obtained was selected and utilized in the multi-objective optimization process. The objective functions are COP and power consumption. The operating conditions that are assigned as design variables include the opening percentage of slide valves, ambient temperature, water pump on/off status and motor fan on/off status. A comparative study of optimization algorithms including Non-dominant Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Grey Wolf Optimizer (MOGWO) [19], Multi-objective Salp Swarm Algorithm (MSSA) [20], Success History–

*Corresponding author.
Email address: natepa@kku.ac.th
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based Adaptive Multi-Objective Differential Evolution (SHAMODE) [21], hybrid SHAMODE variant (SHAMODE-WO) [22], and Hybridization of Real-code Population-Based Incremental Learning and Differential Evolution (RPILBDE) [23] was performed to investigate the performance of available multi-objective optmizers on the refrigeration system optimization problem. The goal of this study is to find the optimum operating conditions that maximize cooling efficiency and minimize power consumption simultaneously. The problem is an unconstrained bi-objective problem. The operating conditions including the opening percentage of valves, pump on/off status, fan motor on/off status and ambient temperature are assigned as design variables. The surrogate modelling technique is employed to generate prediction models for both objective functions. Then, comparative results of well-known and recent metaheuristics are conducted to obtain optimum Pareto fronts and measure algorithm performance respectively. The hypervolume is employed as a performance indicator for the Pareto front results.

The rest of this paper are materials and methods in Section 2, results and discussions in Section 3, and conclusions in Section 4.

2. Materials and methods

2.1 Vapor compression refrigeration system

Common components of a vapor compression refrigeration system [24] are displayed in Figure 1. The heat from the low temperature side (Q_{in}) will be extracted at the evaporator. After receiving the heat, the refrigerant is turned into superheat with the compressor. After that, the refrigerant releases the energy (Q_{out}) at the condenser and condenses it into a liquid. It then flows through the expansion valve and turns into a sub-cool liquid. The cycle is continuously operated to extract the heat to reduce or maintain the temperature at the low temperature side.

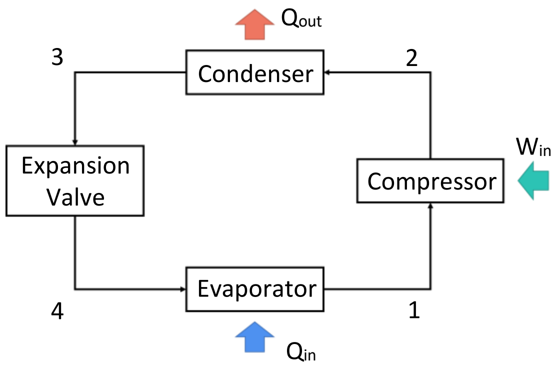

Figure 1 Diagram Vapor Compression Refrigeration System

In this study, the industrial vapor compression refrigeration system consists of two phases. Each phase consists of three levels as detailed in Figure 2. There are several equipment systems including a condenser, a compressor, a receiver, an economizer, an evaporator and a separator at each level. The VCRS investigated in this study is only approximately 90% automatic. There are still some operating conditions that are controlled by human operators. There are two types of factors that affect the COP and power consumption. Manually controlled factors are handled by the operators and automatically controlled factors are controlled by the controller of the system. The controller of the system is tuned by the designer of the system, which is not the optimum controller. In this study, the measuring instruments are installed in Phase 2. The operating conditions, COP and power consumption data used in this study are collected from the data logger of the real system. In addition, as the system is rather complex, the collected operating conditions are opening percentage of slide valves, ambient temperature, water pump on/off status and motor fan on/off status.

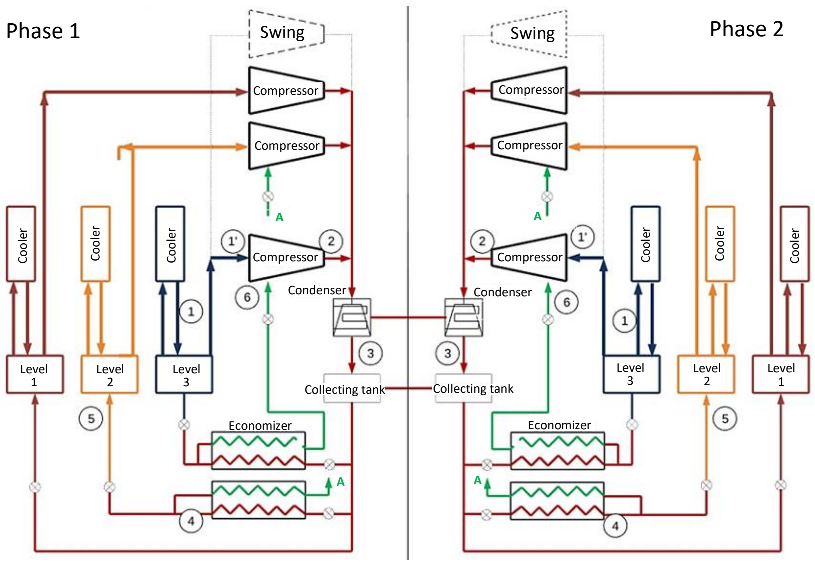

Figure 2 Diagram of Vapor Compression Refrigeration System

2.2 Vapor compression refrigeration system optimization problem

The system efficiency and COP are calculated with Equations (1) and (2) respectively.

$$Efficiency = \frac{Output}{Input} \tag{1}$$

$$COP = \frac{Heat\ power}{Electric\ power} \tag{2}$$

The aim of this study is to maximize COP and minimize power consumption simultaneously. Common optimization problems are usually described in minimization form, so the objective functions are set as the negative of COP ($f_1(\boldsymbol{x})$) *and* power consumption ($f_2(\boldsymbol{x})$) as described below:

Objective : minimize $f_1(\boldsymbol{x})$
$f_2(\boldsymbol{x})$

Design variables : $0 \leq x_{1\text{-}7} \leq 100$
$22°C \leq x_8 \leq 44\ °C$
$x_{9\text{-}24} \in [0,1]$

where, x_1, x_2, x_3, x_4, x_5, x_6, x_7 are opening percentages of the slide valves,
x_8 is the ambient temperature,
x_9, x_{11}, x_{13}, x_{15}, x_{17}, x_{19}, x_{21}, x_{23} are water pump on/off statuses,
x_{10}, x_{12}, x_{14}, x_{16}, x_{18}, x_{20}, x_{22}, x_{24} are motor fan on/off statuses.

2.3 Surrogate model

To construct a surrogate model, the coefficient vector $\boldsymbol{c}$ must be calculated by the training input and output data using (3)-(10). In this study, the design variables and objective functions from Section 2.3 are assigned as inputs and outputs in the surrogate model construction process. The mathematical or prediction models of both objective functions are constructed with the surrogate model technique in this section. The surrogate models constructed in this section will be used to perform optimization afterwards. Data used in the modeling has been stored in the Database for modeling. The operating conditions, COP and power consumption are recorded from the real refrigeration system. Since the real system is a dynamic system, it will take a while for the system to converge to a steady state after any change of operating conditions. It should be noted that 455 samples of different steady state conditions are collected for generating the surrogate model in this study. The samples are randomly separated into training and validating samples with 70% and 30% ratios, respectively.

First, the coefficient vector of the surrogate models [25, 26] is generated using (3).

$$\boldsymbol{c} = \boldsymbol{A}_t^{-1}\boldsymbol{y}_t \tag{3}$$

The interpolation matrix of the training phase, $\boldsymbol{A}_t$ is calculated with (4).

$$\boldsymbol{A}_t = \begin{bmatrix} \varphi(\|\boldsymbol{x}_{1,t}-\boldsymbol{x}_{1,t}\|) & \varphi(\|\boldsymbol{x}_{2,t}-\boldsymbol{x}_{1,t}\|) & \cdots & \varphi(\|\boldsymbol{x}_{N,t}-\boldsymbol{x}_{1,t}\|) \\ \varphi(\|\boldsymbol{x}_{1,t}-\boldsymbol{x}_{2,t}\|) & \varphi(\|\boldsymbol{x}_{2,t}-\boldsymbol{x}_{2,t}\|) & \dots & \varphi(\|\boldsymbol{x}_{N,t}-\boldsymbol{x}_{2,t}\|) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(\|\boldsymbol{x}_{1,t}-\boldsymbol{x}_{N,t}\|) & \varphi(\|\boldsymbol{x}_{2,t}-\boldsymbol{x}_{N,t}\|) & \dots & \varphi(\|\boldsymbol{x}_{N,t}-\boldsymbol{x}_{N,t}\|) \end{bmatrix} \tag{4}$$

where, $\boldsymbol{y}_t$ is the output vector of the training data, $\boldsymbol{x}_{1,t}$, $\boldsymbol{x}_{2,t}$,…, $\boldsymbol{x}_{N,t}$ are the input vectors of the training data, $\|\boldsymbol{x}_i-\boldsymbol{x}_j\|$ is the Euclidian norm of $\boldsymbol{x}_i-\boldsymbol{x}_j$ and $\varphi(r)$ is the kernel function of r. The six kernel functions [27] used in this study as detailed in (5)-(10).

- linear spline: $\varphi(r) = r$ (5)
- cubic spline: $\varphi(r) = r^3$ (6)
- thin plate spline: $\varphi(r) = r^k ln(r)\ ;\ k \in \{2,4,\dots\}$ (7)
- Gaussian: $\varphi(r) = exp(-r^2/\theta)$ (8)
- multiquadric: $K = (1+\|x-x_i\|^2/\theta)^{1/2}$ (9)
- inverse multiquadric: $K = \frac{1}{(1+\|x-x_i\|^2/\theta)^{1/2}}$ (10)

For this research, four kernel functions are used: linear spline, thin plate spline, Gaussian and multiquadric. After the coefficient vector $\boldsymbol{c}$ is obtained, the output prediction using the validation data can be computed by (11)-(12).

$$\boldsymbol{y}_p = \boldsymbol{A}_v\boldsymbol{c} \tag{11}$$

$$\boldsymbol{A}_v = \begin{bmatrix} \varphi(\|\boldsymbol{x}_{1,v} - \boldsymbol{x}_{1,t}\|) & \varphi(\|\boldsymbol{x}_{2,v} - \boldsymbol{x}_{1,t}\|) & \cdots & \varphi(\|\boldsymbol{x}_{N,v} - \boldsymbol{x}_{1,t}\|) \\ \varphi(\|\boldsymbol{x}_{1,v} - \boldsymbol{x}_{2,t}\|) & \varphi(\|\boldsymbol{x}_{2,v} - \boldsymbol{x}_{2,t}\|) & \dots & \varphi(\|\boldsymbol{x}_{N,v} - \boldsymbol{x}_{2,t}\|) \\ \vdots & \vdots & \ddots & \vdots \\ \varphi(\|\boldsymbol{x}_{1,v} - \boldsymbol{x}_{N,t}\|) & \varphi(\|\boldsymbol{x}_{2,v} - \boldsymbol{x}_{N,t}\|) & \dots & \varphi(\|\boldsymbol{x}_{N,v} - \boldsymbol{x}_{N,t}\|) \end{bmatrix} \tag{12}$$

where, $\boldsymbol{y}_p$ is the predicted output vector of the validating data, and $\boldsymbol{x}_{1,v}, \boldsymbol{x}_{2,v}, \dots, \boldsymbol{x}_{N,v}$ are the input vectors of the validation data. The mean percentage error (MPE) of the predicted output vector ($\boldsymbol{y}_p$) compared to the real output of the validating data ($\boldsymbol{y}_v$) is then calculated with (13) to ensure the accuracy [28] of constructed models.

$$MPE = \frac{\sum_{i=1}^{N_v} \left|\frac{y_p - y_v}{y_v}\right|}{N_v} \times 100 \tag{13}$$

where, N_v is the number of the validating data.

2.4 Optimization algorithms

There are six algorithms including NSGA-II, MOGWO, MSSA, SHAMODE, SHAMODE-WO and RPBILDE employed in this study.

The NSGA-II is one of the most well-known multi-objective metaheuristics developed by Kalyanmoy Deb [29]. The algorithm is improved from its single-objective variant, a Genetic Algorithm (GA) [30] which is inspired by Charles Darwin's theory of evolution. The GA is integrated with the non-dominated sorting technique to create NSGA-II for handling the multiple objective design problem.

The MOGWO was presented by Mirjalili et al. in the year 2014 [31], inspired by the behavior of grey wolves. It incorporates the social hierarchy of wolves into its reproductive process, where each new solution, represented by Omega (ω), is guided by three pack leaders, Alpha (α), Beta (β) and Delta (δ).

MSSA was proposed by Seyedali Mirjalili et al. in 2017 [32]. It was inspired by the behavior of salps, which have cylindrical bodies with tissue similar to jellyfish. The deep ocean swarming behavior of salps, referred to as the "salp chain," was used as a basis for creating a mathematical model to imitate the movement of salp leaders and followers for generating new solutions.

SHAMODE is a multi-objective variant of SHADE, which is an improved version of a Differential Evolution (DE) variant, JADE that utilizes an adaptive strategy [33]. SHADE was introduced in 2013 by Ryoji Tanabe and Alex Fukunaga, who added memory to the adaptive parameters [34]. SHAMODE [20], presented by Panagant, Natee, et al. in 2019, includes several improvements that make it well-suited for multi-objective problems. Additionally, SHAMODE comes with a hybrid Whale Optimization Algorithm (WOA) [35] version called SHADE-WO. The spiral movement process from WOA is integrated to improve its search performance.

RPILBDE [36] is a hybrid algorithm between Population Based Incremental Learning (PBIL) and Differential Evolution (DE). During the reproduction process, parent solutions are generated using the probability matrix of PBIL. Offspring are then created by applying mutation, crossover, and selection operators from DE. The probability matrix of PBIL is iteratively updated with the inclusion of new non-dominated solutions.

Some algorithms have some user-defined parameters. Parameters of all algorithms used in this study are listed in Table 1.

Table 1 Parameter settings of optimization algorithms

Algorithm	Detail
Non-dominant sorting genetic algorithm II (NSGA-II)	mutation rate = 0.1 crossover rate = 0.33
Multi-objective Grey Wolf Optimizer (MOGWO)	N/A
Multi-objective Salp Swarm Algorithm (MSSA)	N/A
Success History–based Adaptive Multi-objective Differential Evolution (SHAMODE) and the hybrid variant with Whale Optimization Algorithm (SHAMODE-WO)	x_{pbest} = 0.11 Achive ratio = 1.4 F_i = 4 $mean_{wa}$ = 5 $mean_{wl}$ = 1 $v_{i,G}$ = 1
Hybridization of Real-code Population-Based Incremental Learning and Differential Evolution (RPILBDE)	crossover probability = 0.7 scaling factor = 0.8 crossover rate = 0.5

2.5 Hypervolume (HV)

Hypervolume, provided by Zitzler and Thiele [37], is a very popular performance indicator. The hypervolume (HV) of bi-objective problems is displayed in Figure 3. It represents the area between the extremum or reference point and a Pareto front in bi-objective problems. A better Pareto front is indicated by a higher HV value.

From Figure 3, the hypervolume of the Pareto front is the area between P(1), P(2) and P(3), and the reference point. The area is the summation of the sub-area (each black box) of each solution. The hypervolume can indicate both advancement and the spread of the front.

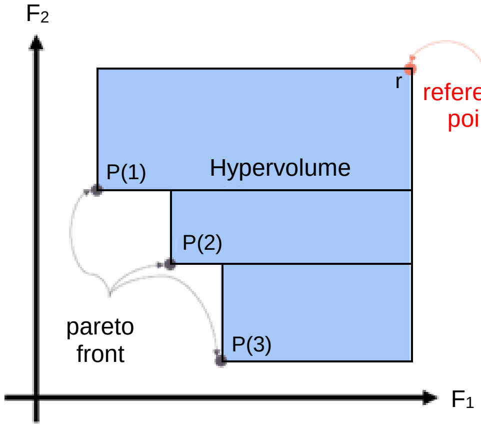

Figure 3 The hypervolume indicator

3. Results and discussion

The initial stage of the study involves building surrogate models. The accuracy of the surrogate models for the COP and power consumption objectives is shown in Table 2. The table compares the MPE of four different kernel functions, including linear spline, thin plate spline, Gaussian, and multiquadric. The prediction errors for COP and power consumption range from 1.5827 - 4.3513% and 1.9546 – 8.7142% respectively. The best kernel function for predicting COP and power consumption is the linear spline function, with an MPE of 1.5827% and 1.9546% respectively. The runner-up functions for both predictions are the thin plate spline with errors of 3.0460% and 4.6350% respectively. The results indicate that the linear function outperforms all other functions, implying that the best relation between the design variables and objectives is a linear one.

Table 2 Evaluation results of model accuracy replacement for radial basis function.

Kernel function	MPE	
	Coefficient of Performance (COP)	**Power consumption (Power, kW)**
linear spline	**1.5827**	**1.9546**
thin plate spline	3.0460	4.6350
Gaussian	3.4842	5.8080
multiquadric	4.3513	8.7142

With the results obtained, the surrogate models using the linear spline function with the best accuracy are selected to use in the optimization process in the second phase of this study. Multi-objective optimization is then evaluated in the second phase. The results of six competitors including MOGWO, MSSA, SHAMODE, SHAMODE-WO, NSGA-II and RPBILDE were evaluated in this study. For a fair comparison, all algorithms were evaluated with the same number of populations and number of generations, which were set as 100 and 150 respectively. In this study, 10 independent runs of all algorithms were evaluated. Additional statistical results including average, maximum, minimum and standard deviation of the hypervolume were calculated to measure performance of competitors in both speed and consistency aspects. The best Pareto fronts of all algorithms with highest HV are displayed in Figure 4. All algorithms can obtain acceptable Pareto fronts. All fronts advance to the bottom-right of the figure in order to maximize COP and minimize power consumption simultaneously.

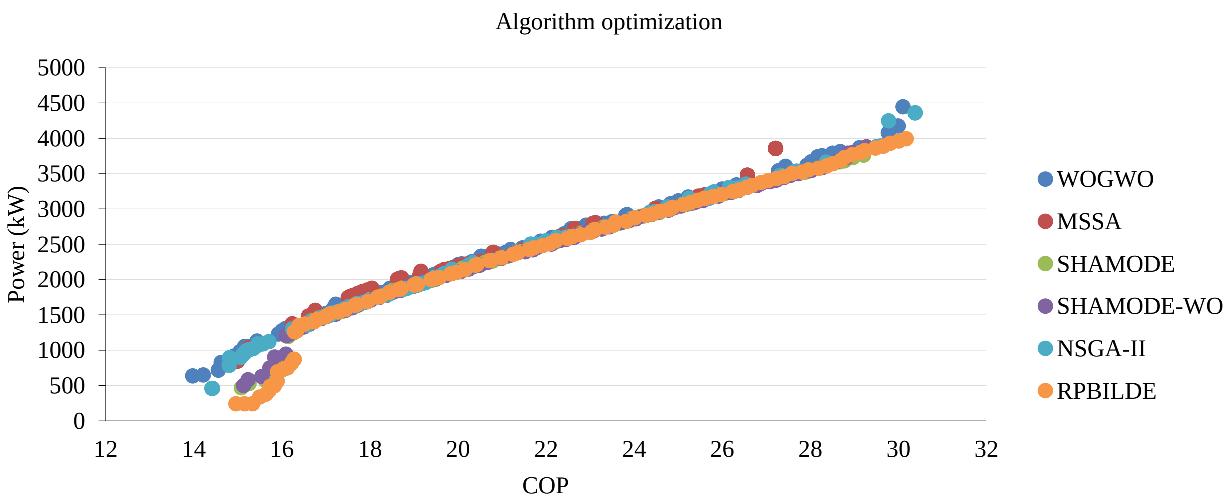

Figure 4 Pareto front of radial basis function with Algorithm optimization

The results from the figure indicate that the best solutions of several top performers are not significantly different. To further examine the results, the statistical hypervolume (HV) data from Table 3 is analyzed. From the table, RPBILDE can outperform all competitors with the best results in all statistical values including average, maximum, minimum and standard deviation of HV. In terms of speed, the best performing algorithm is selected based on the best average HV. The fastest algorithm in this case is RPBILDE with an average HV of 42942.50, followed by SHAMODE and SHAMODE-WO with average HV values of 41208.00 and 41047.50 respectively. The worst performing algorithm, which is dominated by all the other competitors, is MSSA with an average HV of 35099.50.

Table 3 Evaluation results of Hypervolume for Algorithm optimization.

HV	Algorithms					
	WOGWO	**MSSA**	**SHAMODE**	**SHAMODE-WO**	**NSGA-II**	**RPBILDE**
Average	38330.70	35099.50	41208.00	41047.50	39605.60	**42942.50**
Max	39571.00	36374.00	41805.00	41664.00	40493.00	**43282.00**
Min	37311.00	32374.00	40653.00	40384.00	38479.00	**42646.00**
STD	855.51	1353.42	375.08	378.18	650.62	**211.87**

In this study, the best Pareto front with maximum HV was obtained using the RPBILDE algorithm, with an HV of 43282.00. The second and third best algorithms are SHAMODE and SHAMODE-WO, with HVs of 41805.00 and 41664.00, respectively.

In a worst-case scenario, the best algorithm is the one with the highest minimum HV among all the competitors. In this case, the best algorithm is RPBILDE with the minimum HV of 42646.00. The second and third best algorithms in this scenario are SHAMODE and SHAMODE-WO, with the worst HVs of 40653.00 and 40384.00, respectively.

The standard deviation (STD) of the HV is used to measure the consistency of algorithms. In this study, the most consistent algorithm was RPBILDE, with a STD of 211.87. The second and third most consistent algorithms were SHAMODE and SHAMODE-WO, with STDs of 375.08 and 378.18, respectively.

Overall, the winner in this study is obviously RPBILDE. It provided the best results in all statistical indicators. It is the best algorithm in speed, consistency and worst-case scenario aspects.

4. Conclusions

This study presents the possibility of using a surrogate-assisted optimization technique to approximate the optimum operating conditions of the 3-level refrigeration plant with an economizer. Since the operating COP of the plant can be varied due to the inconstant cooling loads, the multi-objective optimization problem of the refrigeration system is formulated. The prediction models of COP and power consumption, the objective functions of the problem, are constructed using the RBF surrogate model technique. Several kernel functions are compared, and the most accurate surrogate models generated with linear spline function are selected for predicting the object functions in the optimization process. A comparative study on the multi-objective refrigeration problem was conducted. The study concludes that RPBILDE is the most efficient algorithm in terms of speed and consistency. The Pareto front results give the optimal operating conditions for the refrigeration plant over the entire range of COP values. These results can be used to improve optimization algorithms for refrigeration systems. Furthermore, the accuracy of the surrogate model should be further validated with future operating data to ensure its reliability.

5. Acknowledgements

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