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Review

Overview on artificial intelligence in design of Organic Rankine Cycle

Dongpeng Zhao, Shuai Deng, Li Zhao*, Weicong Xu, Wei Wang, Xianhua Nie, Mengchao Chen

Key Laboratory of Efficient Utilization of Low and Medium Grade Energy (Tianjin University), Ministry of Education, Tianjin, China

HIGHLIGHTS

- Organic Rankine cycle design mainly involves decision making, parameter optimization and prediction.
- Detailed literature review of artificial intelligence in each step of organic Rankine cycle design process is presented.
- Intelligent optimization algorithm based on data-driven model will be an effective method to solve parameter optimization.

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ABSTRACT

Converting thermal energy into mechanical work by means of Organic Rankine Cycle is a validated technology to exploit low-grade waste heat. The typical design process of Organic Rankine Cycle system, which commonly involves working fluid selection, cycle configuration selection, operating parameters optimization, and component selection and sizing, is time-consuming and highly dependent on engineer's experience. Thus, it is difficult to achieve the optimal design in most cases. In recent decades, artificial intelligence has been gradually introduced into the design of energy system to overcome above shortcomings. In order to clarify the research field of artificial intelligence technique in Organic Rankine Cycle design and guide artificial intelligence technique to assist Organic Rankine Cycle design better, this study presents a preliminary literature summary on recent progresses of artificial intelligence technique in organic Rankine cycle systems design. First, this study analyzes four main procedures which constitute a typical design process of Organic Rankine Cycle systems and finds that design problems encountered during design process can be divided into three categories: decision making, parameter optimization and parameter prediction. In the second section, a detailed literature review on each design procedures using artificial intelligence algorithms is presented. At last, the state of art in this field and the prospects for the future work are provided.

1. Introduction

According to the BP Statistical Review of World Energy 2019 [1], global energy consumption increased by 2.9% in 2018 and will continue to increase, which will lead to increasing in energy prices and environmental challenges. Therefore, there is a growing interest in effectively exploiting low and medium grade thermal energy. Solar energy, geothermal energy, industrial waste heat, biomass, and ocean thermal energy are common low and medium grade thermal energy, which have attracted the researchers around the world. Among the currently available technologies, the Organic Rankine Cycle (ORC) has been considered as a promising solution to effectively convert low and medium grade thermal energy into electricity.

For a given heat source, an appropriate ORC system is the key to efficient utilization of energy of heat source. Therefore, design of ORC systems has become the focus of researchers. The design of ORC systems usually includes the following aspects: working fluid selection, cycle configuration selection, operating parameters optimization, and component selection and sizing [2]. There are a variety of design variables and constraints in the design process, which makes it become a highly complex problem. Meanwhile, the selection of working fluids, cycle configuration and component mainly depend on the experience and knowledge of the engineers, which make the design to become a knowledge-intensive job and usually needs large-scale expert interventions. Moreover, since the system is highly dependent on heat source and sink, a redesign is required for almost every system. Therefore, the design of ORC system is a complex and tedious work, and only a few professional and experienced engineers or researchers can complete it.

In recent years, with the development of artificial intelligence (AI), a growing number of countries have launched programs to integrate machine learning and other AI technique into energy system design processes, such as the "DIFFERENTIATE" program launched by the U.S. Department of Energy's (DOE's) Advanced Research Projects Agency-Energy (ARPA-E) [3]. This trend also appears in the ORC systems design. In the past few years, AI has made significant progress in promoting the development of ORC systems design such as computer-aided working fluids design [4], automatic cycle configuration generation or optimization [5,6], and multi-objective intelligent optimization of operating parameters [7–9]. Compared with the empirical and subjective

* Corresponding author.
E-mail address: jons@tju.edu.cn (L. Zhao).

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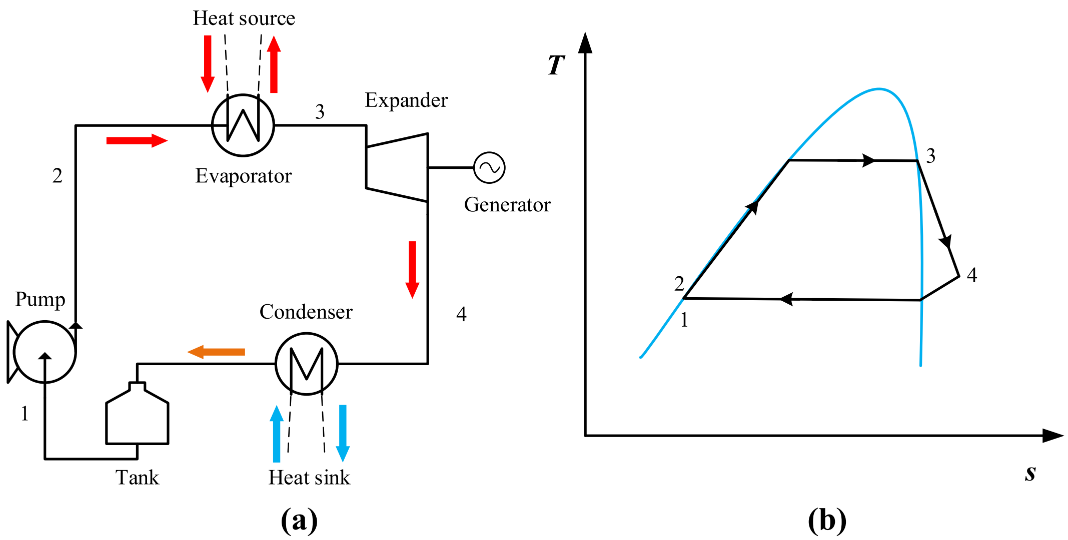

Fig. 1. Simple ORC: (a) schematic diagram; (b) T-s diagram.

design work of humans, AI is more efficient and productive in the ORC systems design. Intelligent methods such as evolutionary algorithms and expert system are showing great potential in improving ORC systems design efficiency and quality. Therefore, more and more researchers are trying to apply the AI in the design of ORC systems.

However, the relevant studies are still fragmentary and lack of systematic sorting. As a result, researchers are unable to transform specific design problems into appropriate general problems, and thus cannot choose appropriate intelligent algorithms to solve these problems. Therefore, this study aims to review the existing application of AI algorithms in ORC systems design, provide some practical advice on how to conduct AI methods to improve ORC systems performance, and clarify the future development direction of ORC systems design aided with AI. This study is organized as following. Section 2 briefly introduces ORC systems design problem and categorizes them into three types of problems. In Section 3, explanation of each design problem and literature review of corresponding application examples of intelligent algorithms are presented. Section 4 summarizes the state of art of this research field and then discusses a new trend in design of ORC systems. In the last section, main conclusions and contributions of this study are given.

2. Design problems of ORC system

ORC refers to the Rankine cycle which uses organic substances with low boiling points as working fluid. As a promising technology for the utilization of low and medium temperature heat source, ORC is widely used in the utilization of solar energy, geothermal, waste heat and ocean thermal energy, etc. There are hundreds of common organic working fluids, including hydrocarbons, hydrofluoroolefins, hydrochloroflurocarbons, siloxanes, alcohols, fluorinated ethers, ethers and so on [10]. Due to the variety of organic fluids, the design of ORC system often needs to choose a suitable working fluid. The simple ORC includes four processes: evaporation, expansion, condensation and compression, as shown in Fig. 1. With the further research on ORC, many new configurations of the ORC have been proposed. Representative configurations include regenerative ORC (Fig. 2), transcritical ORC (Fig. 3) and auto-cascade ORC (Fig. 4) [11,12]. For a given heat source, different cycle configurations can be used to achieve the purpose of thermal energy utilization. Therefore, cycle configuration selection is another important part in design of ORC system. Similarly, there are many types of devices that implement a particular process. For example, the expansion process can choose turbine, screw expanders, scroll expanders, reciprocal piston expanders and so on. Since the type of components significantly affects the investment cost of ORC system, component selection is also an important part of ORC design. In addition, the operating parameters also affect the performance of ORC system. Therefore, the operating parameters also need to be optimized after the suitable working fluids, cycle configuration and components are selected. In general, the design variables to be considered in ORC design include working fluid, cycle configuration, component and operating parameters. Moreover, different performance indicators are adopted to evaluate the system, such as safety, economy, efficiency and environmental effect. For the design of ORC systems, key factors which should be considered mainly includes performance indicator, system parameters and different heat sources and sinks, as shown in Fig. 5.

To obtain a system with best performance, it is necessary to carry out a global optimization. Unfortunately, with so many design variables and objectives, the design problem of ORC system is a highly complex and non-linear problem, and cannot be solved by using mathematical method. Generally speaking, only the optimization of operating parameters could be solved theoretically by strict mathematical methods, and the selection of working fluids, cycle configuration and components can only be evaluated one by one. Therefore, the traditional design flow of ORC systems mainly includes four steps, as showed in Fig. 6. Firstly, available cycle configurations, working fluids and component types are screened out from some predefined options based on knowledge, experience and rules. Secondly, amounts of available design options are generated by using stochastic combination method. Then, for each option, some design parameters, such as cycle state points, are optimized by using single or multiple objectives optimization algorithms. Finally, all available options with optimal parameters are compared and screened according to predefined objective. After that, the optimal design is obtained. In fact, due to the large number of operating parameters, the optimization problem of operating parameters is also a complex nonlinear problem, so it is almost impossible to use strict mathematical methods to solve it. Therefore, heuristic optimization algorithm is the only way to solve the optimization problem of operating parameters. In addition, it is impossible to evaluate all working fluids, cycle configurations and components in the actual design because of the large number of options. It is common practice to select a small number of options for evaluation based on experience, knowledge and rule. This method is very subjective and can hardly obtain the optimal design. Therefore, some emerging methods, such as AI, must be used to overcome the shortcomings of traditional methods.

Thesteps in traditional design flow can be reclassified as the following four procedures: working fluid selection, cycle configuration selec-

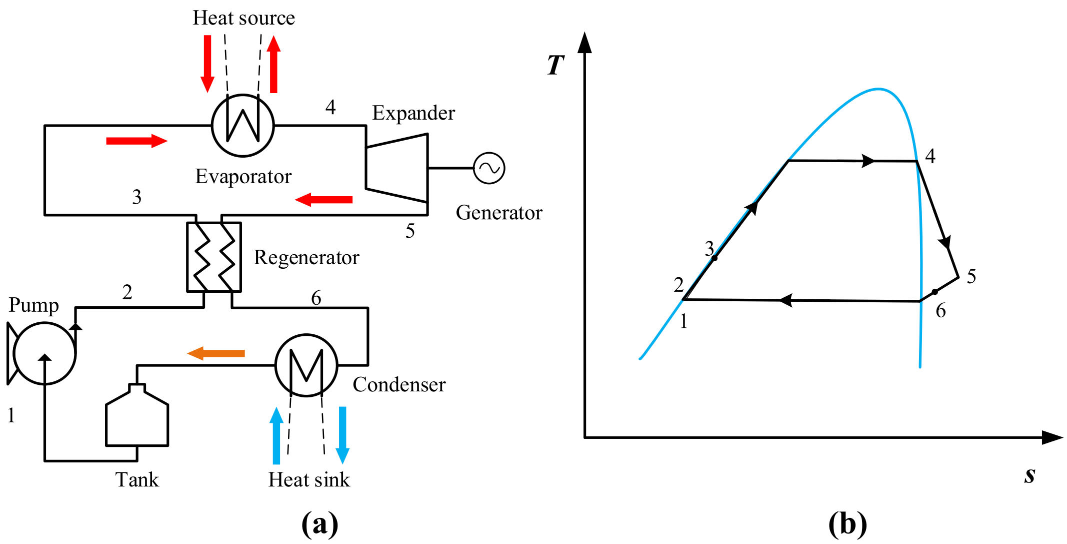

Fig. 2. Regenerative ORC: (a) schematic diagram; (b) T-s diagram.

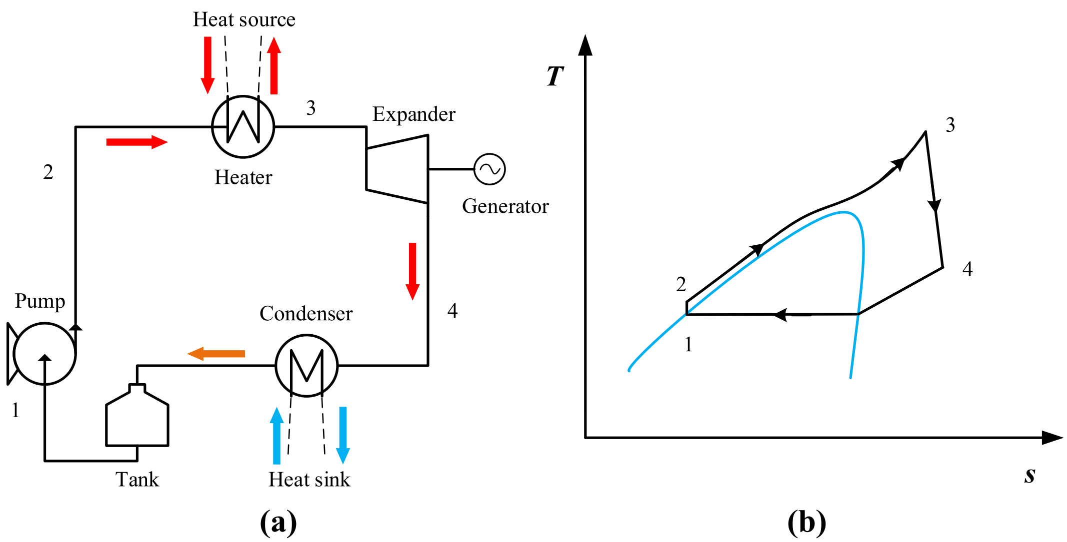

Fig. 3. Transcritical ORC: (a) schematic diagram; (b) T-s diagram.

tion, operating parameters optimization and component selection and sizing [2]. In this study, how to complete each design process is defined as a design problem. However, solving those design problems of ORC system in line with empirical practice does not guarantee an efficient system. So, more researchers are now applying AI technology to conduct ORC systems design for better system performance. According to the characteristic of those design problems, they are classified into two categories in this study: decision making, parameters optimization. Moreover, parameter prediction is often involved during the process of solving the above two problems. The relationship between four design problems and three categories problems is shown in Fig. 7. Decision making in general can be divided into two categories: one is based on heuristic guidelines, and the other is based on the value of the evaluation indicator. For example, the selection of potential working fluids for an ORC system is in the former category, while the selection of most efficient working fluids is in the latter category. In this paper, the former category was called 'Yes/NO decision problem', while the latter was called 'Max/Min decision problem'. For Yes/NO decision problem, two decision-making algorithms are usually adopted in design of ORC system, namely expert system [13] and Case-Based Reasoning method [14]. Expert system is dependent on expert experience and guidelines whereas Case-Based Reasoning is based on existing cases. For Max/Min decision problem, it can be solved by sorting method and optimization algorithms. The objective of parameters optimization is to find a set of parameters to obtain a best performance of the ORC system. According to the number of objective functions, parameter optimization problems can be divided into single-objective optimization and multi-objective optimization. Genetic algorithm (GA) and Swarm intelligence algorithm (SIO) were the most common algorithms to solve such problems. In the processes of solving decision making and parameter optimization problems, it is often necessary to calculate some parameters (i.e. performance insiders and objective functions) by building complex mathematical models based on physical principles. These models are complex and computationally intensive. Therefore, researchers tried to use data-driven models to predict the values of the required parameters. Data-driven models developed based on large amounts of data collected from simulation or experiment. Artificial Neural Network (ANN) and Support Vector Machine (SVM), which are commonly used algorithms for parameter prediction in this research field. The right column of Fig. 6 lists the intelligent algorithms that are most widely adopted in the design of ORC system. Detailed descriptions of these intelligent algorithms are readily available in the public literature and will not be covered in this study.

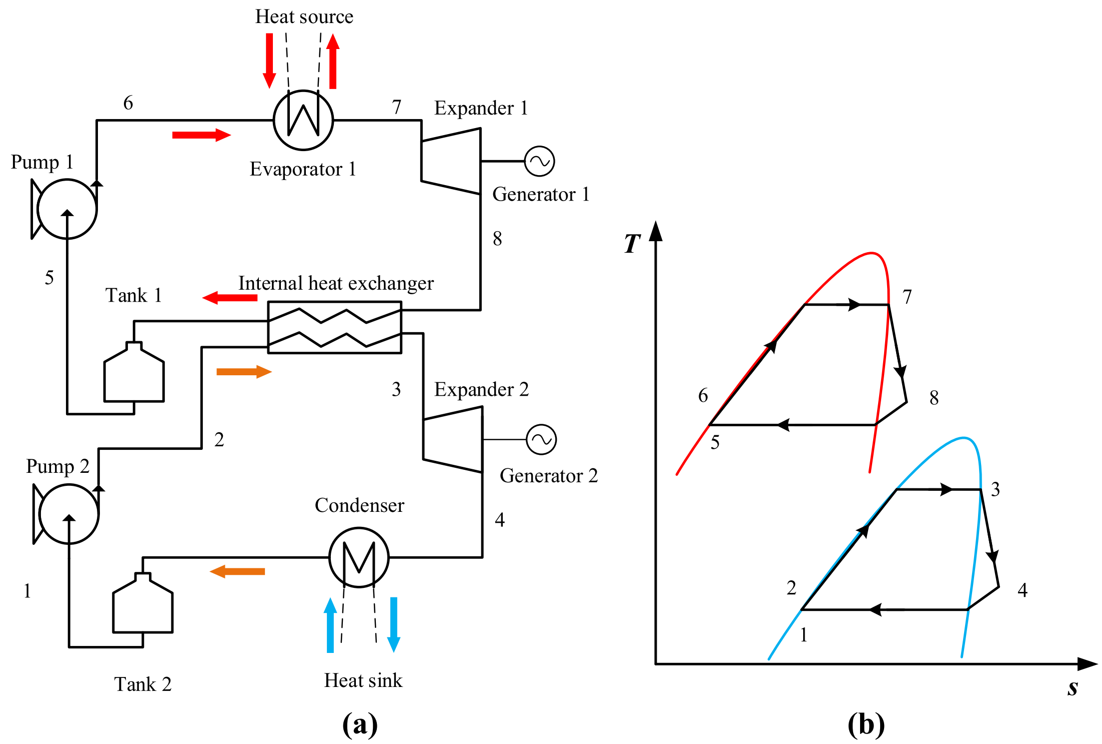

Fig. 4. Auto-cascade ORC: (a) schematic diagram; (b) T-s diagram.

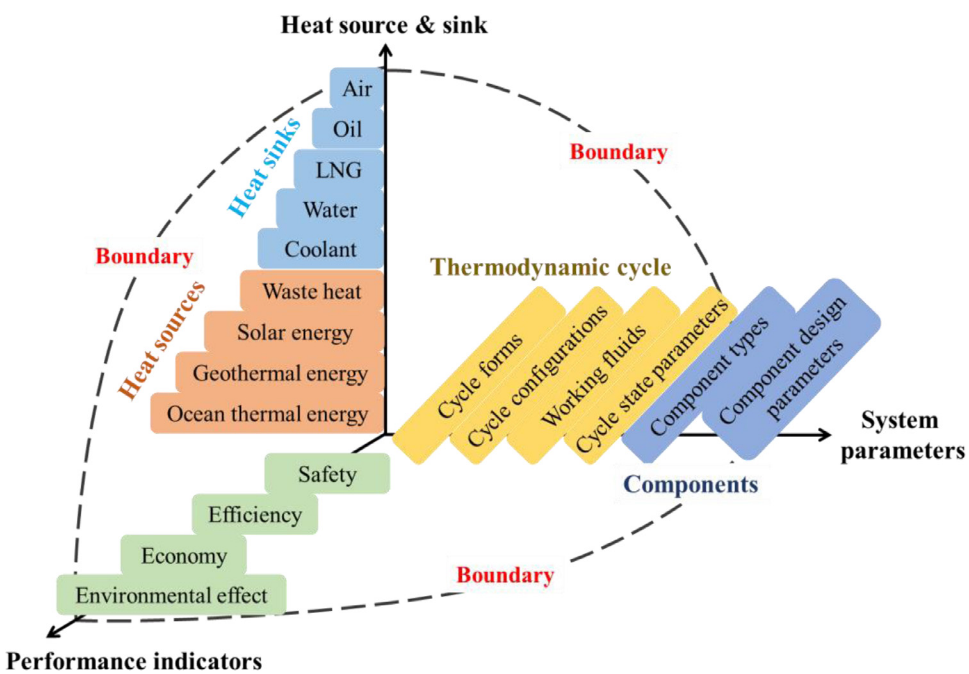

Fig 5. Key factors considered in design of ORC systems.

3. Literature review of intelligent design for ORC system

3.1. Working fluid selection

Different from the traditional Rankine cycle that only uses water as working fluid, there are hundreds of organic fluids that can be used in ORC. Different working fluids have different physical properties which can affect the efficiency of ORC system, the size of the components, the system stability and safety, as well as the environmental concerns. For example, the critical temperature and the normal boiling point determine the operating temperature range of the working fluids. Thermal conductivity can affect heat transfer area of heat exchangers. The ozone depletion potential (ODP), global warming potential (GWP) and the atmospheric lifetime (ALT) can determine whether the working fluid is permitted by environmental regulations. More detailed information can be found in the Ref. [10]. Therefore, the selection of working fluids is very important in the design of ORC systems. Generally, to obtain a suitable working fluid, designer or engineer will propose some heuristic guidelines, which are based on their experience and knowledge, to identify a list of potential candidates working fluids. Subsequently, each

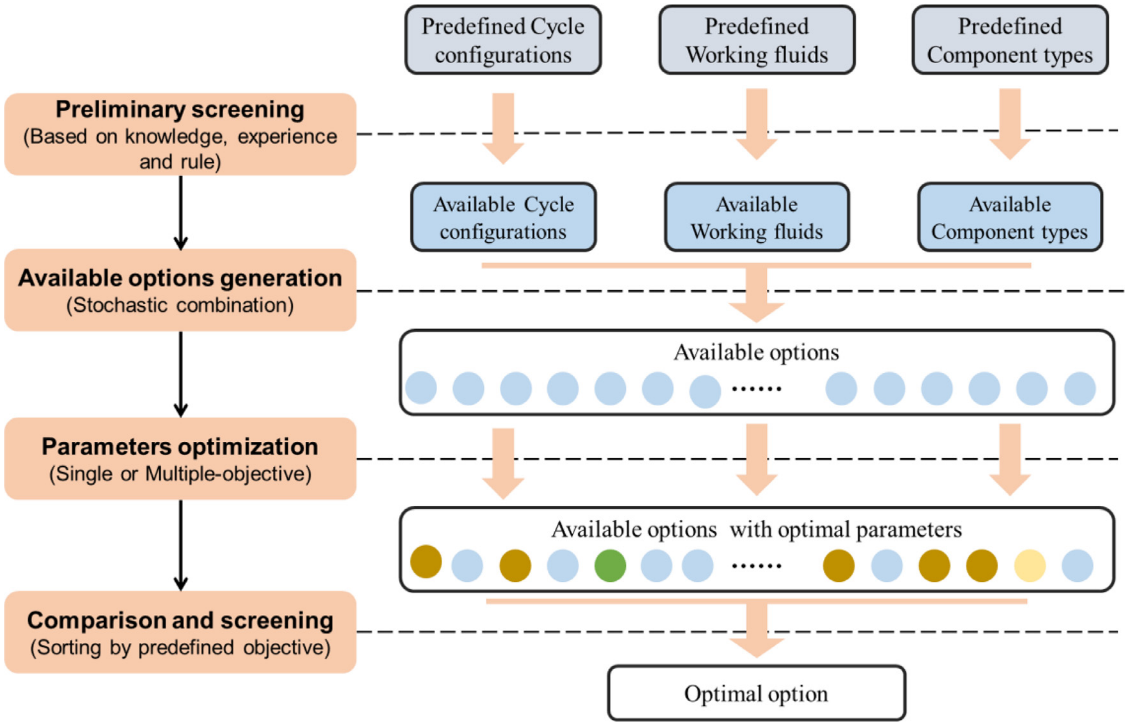

Fig. 6. The traditional design flow of ORC system.

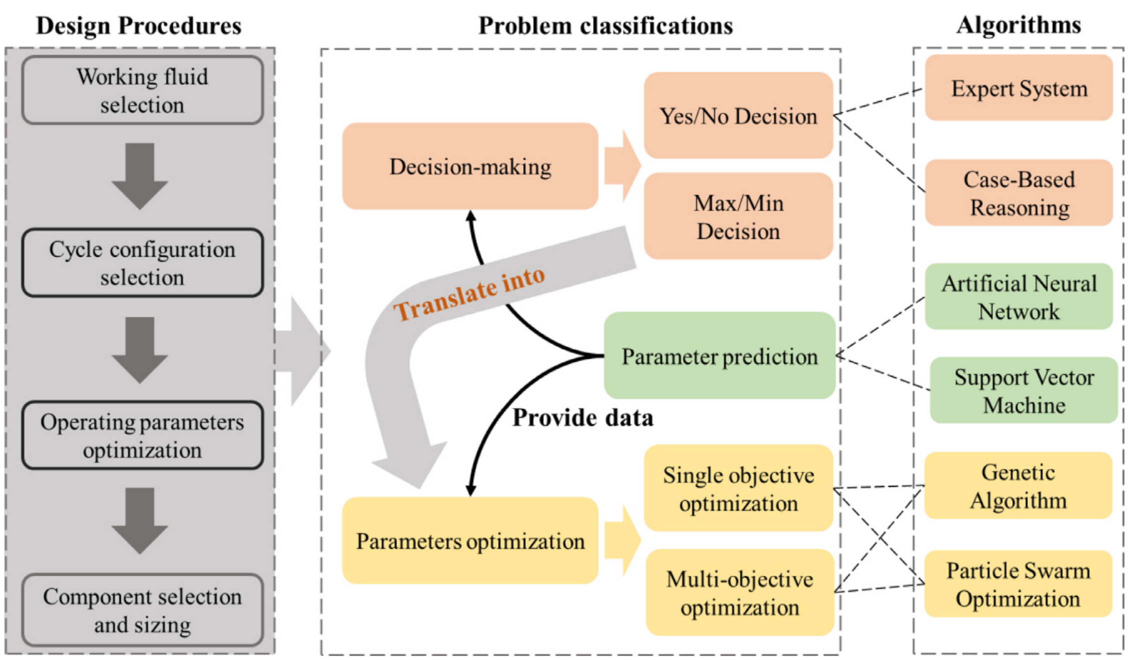

Fig. 7. ORC systems design problem classification and algorithms.

candidate working fluids will be evaluated by operating parameters optimization for the predefined cycle configuration. If necessary, component selection and sizing will be carried out to evaluate the economy of the whole system. Finally, suitable working fluids will be selected according to these evaluation results.

In this research field, most researchers conduct their own work by following the procedures mentioned above. Researchers keep coming up with new heuristic guidelines, such as Jacob number [15], near-critical region triangle [16], and so on. In addition, there are some mandatory government regulations. For example, GWP, ODP, corrosive, flammable, and toxic standards must meet the relevant requirements. Almost all researchers manually select potential candidates of working fluids from existing ones. The number of working fluids in the list of potential candidates ranges from a few to hundreds. As more new organic fluids emerge, the work will become more time-consuming. If an expert system is developed using heuristic guidelines that are wildly accepted, this will help reduce the workload of designers. To the authors' knowledge, no studies have been conducted on this topic.

The physical property is the main basis for the selection of working fluids according to heuristic guidelines. Physical properties usually can be measured by experimental methods or calculated by various equations of state. These methods are available in the existing literature and are not described in detail in this study. However, there are no available experimental data and calculation methods in some cases. So, some researches use data-driven model to predict the physical properties of working fluids. Huster et al. [17,18] used ANN method to predict the thermodynamic and transport properties of 37 working fluids. The training data is from the CoolProp. For different sates of working fluid, they trained different models with different input data (pressure for the model of saturated state, pressure and entropy for models of subcooled liquid and superheated vapor). Temperature, enthalpy, density, heat conductivity coefficient, viscosity and Prandtl number are the output variables.

A few researchers have noticed that computer-aided molecular design (CAMD) can make a difference in the selection of working fluids. In CAMD, working fluids can be described using functional groups, which can form different fluids by putting them together in different ways. Then thermodynamic properties of working fluids can be predicted based on the functional groups which it is composed by using an equation of state or data-driven models. And the structure of molecule also can be optimized. In this sense, CAMD method allows researchers to design a suitable working fluid, which may not exist currently, for a particular ORC configuration.

Papadopoulos et al. [19] used CAMD method for the first time to select the suitable pure working fluids for a simple ORC system, and later applied this method to design the working fluid mixtures for the same ORC system. Then, Palma-Flores et al. [20] used CAMD method to identify a new working fluid which could lead to a higher thermal efficiency. Su et al. [21,22] also used CAMD method to design and select the working fluids for a simple ORC system with a detail thermodynamic model. For CAMD method, how to calculate the physical properties of working fluids according to the functional groups is very important. Two common methods are empirical group-contribution methods [23] and molecular-based equations of state based on statistical associating fluid theory [24]. Similarly, some researchers developed data-driven models to calculate the physical properties. Different from the models mentioned in the previous paragraph, those models should base on the functional groups [4]. Su et al. [25] developed an ANN model based on molecular groups and a self-defined topological index to predict normal boiling point temperature of pure organic fluids. In their another study, critical temperature and pressure, liquid density and heat capacity were calculated using empirical correlations based on normal boiling point temperature.

3.2. Cycle configuration selection

Many researchers have proposed some new cycle configurations based on the simple ORC, that have been proved to be superior to the simple ORC system. Such as the multiple ORCs in series or in parallel [11], cascade ORC [26], multiple stages condensation ORC [27] and so on. Some studies have shown that cycle configuration can significantly affect the performance of the ORC system [28]. Therefore, cycle configuration selection becomes an important work in the design of ORC systems. In the traditional design procedure, this part of the work also relies on the experience and knowledge of designers. Usually, the designer selects some potential candidate configurations from existing ones, and then carries out subsequent design for each cycle configuration, and determines the final cycle configuration according to the performance of each design results. This method usually fails to screen out the optimal cycle configuration and results in a suboptimal solution, because it is difficult for the designer to include all possible cycle configurations in the candidate configurations. Moreover, screening results which rely on the experience are not guaranteed to be reliable.

To overcome the above problems, superstructure method was introduced in cycle configuration selection. Superstructure of ORC configuration is a collection of a huge number of possible cycle configurations which are constructed manually by adding and removing a process, such as regeneration, reheating, turbine bleeding and multi-stage cycles, in turn. Therefore, the superstructure consists of all possible cycle configurations and the optimum cycle configuration can be obtained through solving subsequent mixed-integer non-linear programming (MINLP) problem. Lee et al. [29] selected the optimal cycle configuration for an ORC system utilizing LNG cryogenic energy. In their study, the superstructure includes about 1024 possible cycle configuration alternatives. Yu et al. [30] proposed a method to integrate ORC into heat exchanger networks considering a superstructure with optional turbine bleeding and regeneration. Bao et al. [31] conducted a simultaneous optimization of cycle configuration and working fluid for a three-stage condensation ORC system, and considered nine cycle configurations in their superstructure.

Although superstructure method can obtain the optimal cycle configuration, the modeling of a superstructure is a time-consuming and complex task, and it might include a huge number of cycle configurations which are infeasible or even meaningless. To overcome those weakness, Toffolo et al. [6] have developed an improved method based on the superstructure method, namely superstructure-free method or HEATSEP method [32], which have been successfully applied to the selection or design of cycle configuration of ORC system [5]. Instead of generating all possible cycle configurations in advance, this method generates new configurations from the basic configuration in the optimization process according to preset combination rule [33,34]. By encoding the cycle configuration into chromosomes in the GA, this method avoids enumerating all possible cycle configurations, thus saving computing time. The detail information about this method can be found in references [6]. Lin et al. [35] applied this method in the design of LNG energy recovery ORC system, and obtained the optimal cycle configuration for pure working fluid and mixture working fluids respectively. Although only a few researchers have focused on this method, it is more intelligent than the superstructure method and will be the future research direction.

3.3. Operating parameters optimization

Operating parameters in ORC system refer to the parameters that can be manually adjusted in the system design, including the cycle state point, the temperature and mass flow rate of heat source/sink, etc. Operating parameters are very important for the performance of ORC systems. With any given heat source, ORC system can operate with different sets of operating parameters, only a few sets of operating parameters could result in the best performance. The goal of operating parameters optimization is to find such a set of operating parameters. Therefore, operating parameters optimization is a very important work in the design of ORC systems. The usual method is to first determine the design variables, objective functions and constraints, then establish an ORC model to find the relationship between the objective function and design variables, transform it into an optimization problem, and then obtain the optimal parameters by solving the optimization problem. There are two processes where intelligent algorithms are used. Generally, the optimization problem is a nonlinear problem and difficult to solve using traditional mathematical methods. Therefore, researchers usually use intelligent algorithms to solve it, such as GA and PSO. Moreover, physical models of some ORC systems are very complex, so data-driven models are used as surrogate models to predict the value of objective functions based on design variables, which can save a lot of computation time.

For the optimization problem of operating parameters, the size of the search space depends on the number and range of design variables (depending on constraints). The former determines the dimensions of the search space, the latter determines the length of each dimension. The solution of the optimization problem is to find a position in the search space where the objective function can get the optimal value. Generally speaking, larger search space means larger computation and longer computation time. Different algorithms represent different search strategies, which can also affect the amount and time of calculation.

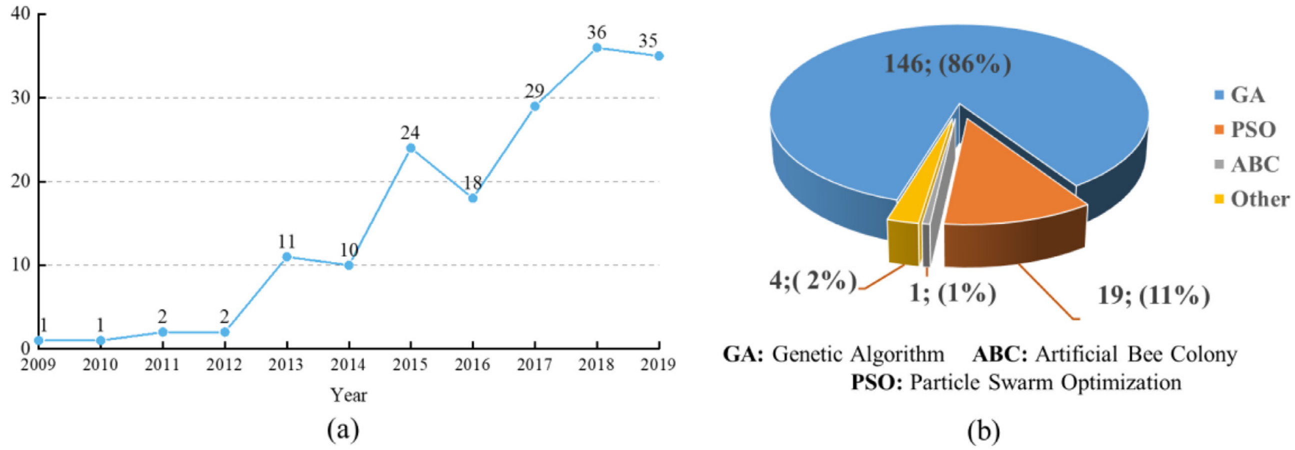

Fig. 8. Statistical information of publications about operating parameters optimization: (a) Number of publications by year; (b) Number of publications on algorithm.

According to the relationship between operating parameters and thermodynamic cycle, operating parameters can be divided into four categories: cycle parameters, interaction parameters between the cycle and heat source or sink, parameters of heat source or sink and component parameters. Cycle parameters include thermodynamic parameters of each state point of the cycle and the parameters related to the working fluids, which are the most commonly used design variables in operating parameter optimization of ORC systems. For example, evaporating pressure or temperature [36, 37], considering pressure or temperature [38, 39], superheating temperature [40]; subcooling temperature [41], mass flow rate of working fluids [42] etc. Interaction parameters between the cycle and heat source or sink, such as pinch point temperature differences in evaporator or condenser [43, 44], were also considered as design variables. Parameters of heat source or sink used as design variables include the inlet or outlet temperature of heat fluid in the evaporator [45], the inlet or outlet temperature of cold fluid in the condenser, the mass flow rate of heat or cold fluids, the specific heat capacity of hot or cold fluids and so on. Component parameters include geometric parameters and performance parameters. Some studies used geometric parameters of components as design variables, such as fin height of heat exchangers [46], while others used performance parameters as design parameters, such as the efficiency of expanders and pumps [47].

Objective functions used in operating parameters optimization usually involve several different aspects, including the product indicator, efficiency indicator, economy indicator and environmental impact. The most commonly used product indicator is net output power [48]. The commonly used efficiency indicators are thermal efficiency and exergy efficiency. There are many economic indicators used as the objective function, such as system investment cost [49], annual profit [50], the levelized cost of energy [39] and so on. Environmental impacts, such as emissions of various pollutants [51], are also used as objective functions. According to the number of objective functions to be considered, optimization problems can be divided into single-objective optimization and multi-objective optimization. The single-objective optimization problem can be solved by standard GA and PSO. For the multi-objective optimization problem, the standard GA and PSO are not applicable, so many researchers adopt the Non-dominated sorting genetic algorithm-II (NSGA-II) and Multi-objective Particle Swarm Optimization (MOPSO) to find the Pareto Front in the search space.

Fig. 8 shows the number of publications on the topic of operating parameters optimization of ORC systems using intelligent algorithms. There are about 170 literatures on this topic. Since 2013, more than 10 literatures are published each year. In those literatures, GA is the most widely used algorithm. However, many literatures are similar in methods, so this study will not describe one by one. Only some representative literatures are selected for review, as shown in Table 1. As an important part of optimization problem, the constraint conditions of operation parameters in ORC design is determined by the conditions of heat source and sink, physical properties of working fluids and experience of designers. Constraints of operation parameters are not listed in Table 1 because these constraints are subjective and do not have much guiding significance for other studies.

As shown in Table 1, an earlier literature was the study of Wang et al. [52], who designed a simple ORC system for waste heat recovery in cement industry, took evaporating pressure as the design parameter and maximum exergy efficiency as the objective function, and adopted GA to solve the optimization problem. In their work, only one design variable and one objective function were considered. Zhang et al. [41] conducted the parameters optimization of a simple ORC system for engine waste heat recovery. In their study, four parameters, evaporating pressure, superheating temperature; condensing temperature and subcooling temperature, were considered as design parameters, maximum thermal efficiency was considered as the objective function, and those parameters were optimized using GA. Wang et al. [47] optimized operating parameters of the ORC system for low grade waste heat recovery. In their study, in addition to evaporating pressure and condensing temperature, the isentropic efficiency of the expander was also used as a design parameter. Thermal efficiency was considered as the objective function and GA was adopted. Wang et al. [53] carried out an early study on multi-objective parameters optimization of an ORC for low grade waste heat recovery. In their study, exergy efficiency and overall capital cost were considered as objective functions. An improved GA, Non-dominated sorting genetic algorithm-II (NSGA-II), was used to solve the optimization problem and obtain the Pareto optimum. Moreover, pinch point temperature difference and approach temperature difference in heat exchangers were also considered as the design variables. Andreasen et al. [45] also carried out a study single objective parameters optimization of a simple ORC system utilizing geothermal energy. They took evaporating pressure, expander inlet temperature, hot fluid outlet temperature and composition of the working fluid as design variables, and net power output as the objective function. In contrast to previous studies reviewed, this study considered heat source conditions and working fluids as design variables rather than just cycle state parameters and component performance parameters. For the first time, Xi et al. [54] used PSO instead of GA to solve the parameters optimization problem in the design of ORC system. Cavazzini et al. [55] used an improved PSO method to optimize the operating parameters for a sub-critical ORC system. In their study, they realized the simultaneous optimization of pure working fluids and operating parameters by continuously and dynamically modifying the search space for different particles.

The calculation of fitness function is very important when using intelligent algorithms to solve the optimization problem. Generally speak-

Table 1
A summary of parameters optimization studies.

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms	Heat source & sink	Cycle configuration	Working fluids
Wang et al. [52]	2009	Optimize the cycle state points for a simple ORC	Turbine inlet pressure	Exergy efficiency	GA	Waste heat	Simple ORC	R123
Rashidi et al. [56]	2011	Optimize the cycle state points for a regenerative Rankine cycle	Outlet pressures from the second and third pumps	Thermal efficiency, exergy efficiency and specific network	ABC	Waste heat & water	regenerative Rankine cycle	Water; Water-R717
Zhang et al. [41]	2011	Optimize the cycle state points for a simple ORC	Evaporating pressure, superheating temperature; condensing temperature, subcooling temperature	Thermal efficiency	GA	Waste heat of the internal combustion engine	Simple ORC	R245fa, R245ca, R236ea, R141b, R123, R114, R113 and R11
Tveitaskog et al. [67]	2012	Optimize design parameters for a heat recovery system	Exhaust outlet temperature, evaporating pressure, condensing pressure	Thermal efficiency and power output	GA	Waste heat of exhaust gas	Simple ORC	Toluene
Wang et al. [47]	2012	Select a suitable cycle configuration for waste heat recovery; Optimize the cycle state points for each configuration	Evaporation pressure, condensation temperature and the expander isentropic efficiency	Thermal efficiency	GA	Waste heat of the internal combustion engine	a simple ORC, an ORC with an internal heat exchanger (IHE), an ORC with an open feed organic fluid heater (OFOH), an ORC with a closed feed organic fluid heater (CFOH), and an ORC with a reheater	R245fa
Xi et al. [68]	2013	Select a suitable cycle configuration and working fluid	Temperature of heat source	Annual cash-flow and exergy efficiency	GA	Waste heat	Simple ORC, ORC with internal heat exchanger	30 chlorine-absent working fluids
Larsen et al. [69]	2013	Select a suitable working fluid for different ORC configurations	heat source inlet temperature	Thermal efficiency health, fire and physical hazards (A linear combination)	GA	Waste heat	Simple ORC, ORC with a recuperator	109 working fluids
Wang et al. [53]	2013	Optimize the cycle state points for a simple ORC	Turbine inlet pressure, turbine inlet temperature, pinch temperature difference, approach temperature difference and condenser temperature difference	Exergy efficiency and overall capital cost	NSGA-II (Multi-objective)	Waste heat	Simple ORC	R134a
Wang et al. [70]	2013	Select a suitable working fluid; Optimize the cycle state points for a simple ORC	Turbine inlet temperature, turbine inlet pressure, pinch temperature difference, approach temperature difference and condenser temperature difference	Exergy efficiency and investment	NSGA-II (Multi-objective)	Waste heat	Simple ORC	R123, R245fa and isobutane
Pierobon et al. [71]	2013	Select a suitable working fluid	the turbine inlet pressure, internal recuperator pinch points	Thermal efficiency	GA	Waste heat of a twin-spool gas turbine	Simple ORC	Cyclohexane
Xi et al. [72]	2013	Select a suitable working fluid for each cycle configuration	Turbine inlet pressure and temperature, fractions of the flow rate	Exergy efficiency	GA	Waste heat	Simple ORC, single-stage regenerative ORC, double-stage regenerative ORC	R123, R113, R11, R245ca, R245fa and R141b
Wang et al. [73]	2013	Select a suitable working fluid; Optimize the cycle state points for a simple ORC	Turbine inlet pressure, turbine inlet temperature, pinch temperature difference and approach temperature difference in heat recovery vapor generator	The ratio of net power output to total heat transfer area	GA	Waste heat	Simple ORC	R123, R245fa and isobutane
Hajabdollahi et al. [42]	2013	Select a suitable working fluid and optimize design parameters for a simple ORC	Nominal capacity of diesel engine, diesel operating partial load, evaporator pressure, condenser pressure and refrigerant mass flow rate	Thermal efficiency and the total annual cost	NSGA-II	Waste heat of a diesel engine	Simple ORC	R123, R134a, R245fa and R22

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Table 1 (*continued*)

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms	Heat source & sink	Cycle configuration	Working fluids
Long et al. [74]	2014	Select a suitable working fluid and optimize design parameters for a simple ORC system	Evaporation temperature, heat source inlet temperature	Overall exergy efficiency	GA	Waste heat	Simple ORC	n-Pentane, R601a, R142b, Isobutene, R600a, R141b, Butane, R123, R243ca, R245fa
Cataldo et al. [75]	2014	Select a suitable working fluid and optimize the state points for a simple ORC	Evaporation temperature and the condensation temperature	The defect of efficiency and the total heat exchange area per unit of power output	GA	Waste heat	Simple ORC	More than 10 working fluids
Bian et al. [37]	2014	Select a suitable working fluid and optimize cycle state points for a simple ORC	Evaporating temperature and degree of superheat	The ratio of heat transfer area to total net power output	GA	Waste heat	Simple ORC	R11, R113, R123 and isopentane
Imran et al. [43]	2014	Select a suitable cycle configuration and working fluid; Optimize the cycle state points	Evaporation pressure, superheat, pinch point temperature difference in evaporator and condenser	Maximum thermal efficiency and minimum specific investment cost	NSGA-II	Waste heat	Simple ORC and regenerative ORC	5 working fluids
Kalikatzarakis et al. [76]	2014	Select a suitable working fluid and optimize cycle state points for different ORC configurations	The composition of the working fluid; Mass flow rate, evaporation pressure and condensing pressure	Net Present Value	GA and SQP	Waste hear of marine propulsion engines	Simple ORC, regenerative ORC and a combination of two ORC	75 fluids
Larsen et al. [77]	2014	Optimize the cycle state points for a simple ORC	Evaporation pressure and superheating temperature	Power output	GA	Waste heat of a large marine two-stroke diesel engine	Simple ORC	R245ca
Xi et al. [78]	2014	Select a suitable working fluid and optimize cycle state points for different cycle configurations	Turbine inlet pressure, the turbine inlet temperature and the fractions of the zeotropic mixtures working fluids	Annual cash flow	GA	Waste heat	Simple ORC, ORC with internal heat exchanger	8 different zeotropic mixtures
Yang et al. [79]	2015	Select a suitable working fluid and optimize cycle state points for a simple ORC	Evaporation pressure, superheat degree, condensation temperature and exhaust temperature at the outlet of the evaporator	Net power output and total investment cost	GA	Waste heat of diesel engine	Simple orc	R600a, R601a, R245fa, R1234yf and R1234ze
Yang et al. [80]	2015	Optimize cycle state points for a simple ORC	Evaporation pressure, superheat degree and condensation temperature	Net power output per unit heat transfer area and exergy destruction rate	GA	Waste heat of a diesel engine	Simple ORC	R245fa.
Andreasen et al. [81]	2015	Select a suitable working fluid and optimize cycle state points for an ORC	Expander inlet temperature, the expander inlet pressure, the composition of the mixture, the intermediate pressure and the outlet temperature of evaporator	Net power output	GA	Waste heat	Split ORC, recuperated ORC	Binary mixtures containing propane, butane, isobutane, pentane or isopentane
Cavazzini et al. [55]	2017	Select a suitable working fluid and optimize design parameters for an ORC	Evaporating pressure, temperature difference at the pinch point in both the heat exchangers, approach point temperature difference in both the heat exchangers	Energy efficiency	ASD-PSO	Waste heat	Simple ORC	37 fluids;
Huster et al. [17]	2019	Select a suitable working fluid and optimize design parameters for an ORC	High and low pressure, WF mass flow, WF superheating at the evaporator outlet	Net power, investment cost	GA	Waste heat of internal combustion engine	Simple ORC	122 fluids
Zhao et al. [82]	2019	Optimize design parameters for a ORC	Expander inlet pressure, expander inlet temperature, exhaust temperature at the evaporator outlet	Net power output	PSO	Waste heat of internal combustion engine	Recuperative ORC	R245fa
Xi et al. [83]	2015	Select a suitable working fluid and optimize cycle state points for an ORC	Turbine inlet pressure and temperature	Annual cash flow and exergy efficiency	GA	Waste heat	Simple ORC and regenerative ORC	26 fluids

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Table 1 (*continued*)

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms	Heat source & sink	Cycle configuration	Working fluids
Hajabdollahi [84]	2015	Optimize design parameters of the CCHP-ORC system	The electric cooling ratio and nominal power ratio	Annual benefit	GA	Waste heat of diesel engine and gas turbine	Simple ORC	—
Feng et al. [85]	2015	Optimize cycle state points for each cycle configuration	Evaporator outlet temperature, condenser temperature, degree of superheat, pinch point temperature difference and degree of supercooling	Exergy efficiency and levelized energy cost	NSGA-II	Waste heat	Regenerative ORC and simple ORC	R123
Feng et al. [86]	2015	Optimize cycle state points for each cycle configuration	Evaporator outlet temperature, evaporator outlet pressure, condenser temperature, degree of superheat, pinch point temperature difference	Exergy efficiency and heat exchanger area per unit net power output	NSGA-II	Waste heat	Regenerative ORC and simple ORC	R123
Xi et al. [54]	2015	Select a suitable working fluid and optimize cycle state points for a transcritical ORC	Expander inlet temperature and the evaporate pressure	Exergy efficiency	PSO	Waste heat	Transcritical ORC	14 working fluids
Gutiérrez et al. [50]	2015	Select a suitable working fluid and optimize cycle state points for a simple ORC	Condenser pressure, boiler pressure	Gross annual profit	GA	Waste heat	Simple ORC	n-Butane, R245fa, R123
Wang et al. [36]	2015	Select a suitable working fluid and optimize cycle state points for an ORC	evaporating pressure, intermediate pressure, and degree of superheat	Net power output and exergy destruction rate	PSO	Waste heat from a diesel engine	Regenerative ORC	butane, R124, R416A, and R134a
Kalikatzarakis et al. [87]	2015	Select a suitable synthesis and optimize design and operation parameters	The composition of the working fluid; mass flow rate, evaporation pressure and condensing pressure	Net present value	GA and SQP	Waste heat of marine propulsion engines	Simple ORC	R245fa, R245ca, R365mfc, R413a
Nazari et al. [88]	2016	Select a suitable working fluid and optimize cycle state points for a combined steam-organic Rankine cycle	Steam turbine inlet pressure, Organic turbine inlet pressure, Organic preheater pinch temperature	Exergy efficiency and product cost rate	GA	Waste heat of a gas turbine	Simple ORC	R124, R152a, and R134a
Galindo et al. [38]	2016	Optimize cycle state points for a simple ORC	Evaporation pressure, condensation pressure, superheating temperature, ethanol mass flow and the temperature at the boiler outlet in the exhaust gas side	Volume Coefficient, Specific Investment Cost and Total area of heat exchangers	GA	Waste heat of gasoline engine	Simple ORC	Ethanol
Nasir et al. [49]	2016	Select a suitable working fluid and optimize cycle state points	VCC Condenser Temperature, VCC Condenser Sub cooling, ORC Condenser Pressure	Overall COP	GA	Waste heat	Simple ORC	R245fa, R123, R134a, R1234yf, R1234ze (E), Butane and Isobutane
Mahmoudi et al. [44]	2016	Optimize design parameters of a combined system	Fuel cell temperature, the current density, the carbon dioxide turbine pressure ratio and the pinch point temperature difference in the evaporator	Product unit cost and maximize the exergy efficiency	GA	Waste heat and liquefied natural gas	Simple ORC	R245fa
Ameri et al. [89]	2016	Optimize design parameters of a combined system	Inlet steam pressure to MED, pinch point temperature difference, evaporator pressure, condenser pressure, refrigerant mass flow rate and some geometrical parameters for heat recovery steam generator	Distilled water production and the total cost rate	NSGA-II	Waste heat of a gas turbine	Simple ORC	R123, R134a and R245fa

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Table 1 (*continued*)

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms	Heat source & sink	Cycle configuration	Working fluids
Bahari et al. [90]	2016	Optimize state points of the combined cycle	Temperature of the cold tank of the Stirling cycle, the pressure ratio and the temperature of the ORC condenser	Efficiency of the overall combined cycle	GA	Waste heat of a Stirling cycle	Simple ORC	—
Javan et al. [91]	2016	Optimize design parameters of a combined system	Diesel engine capacity, diesel engine part load, expander inlet pressure, expander extraction pressure, extraction ratio, condenser pressure, and evaporator pressure	Exergy efficiency, total cost rate of the system	GA	Waste heat of internal combustion engine	Simple ORC	R134a, R600, R123, and R11
Agromayor et al. [40]	2017	Optimize design parameters for different cycle configurations	The expander inlet pressure, the superheating temperature approach, and the cold temperature of the cold source	Second law efficiency	GA	Waste heat	Simple ORC, recuperated ORC and the saturated, superheated, and transcritical ORCs	29 fluids
Zhang et al. [39]	2018	Optimize design parameters for a ORC	Evaporation temperature, overheat degree, condensation temperature, undercooling degree, and working fluid flow rate	Exergy efficiency, levelised energy cost	NSGA-II	Waste heat source in industry	Simple ORC	R141b, R142b, R245ca, R245fa, R600a, and R601a
Han et al. [92]	2013	Select a suitable working fluid for a simple ORC	Turbine inlet pressure and temperature	The total irreversible loss of the system	GA	Solar energy	Simple ORC	R600, R600a, R245fa, R236fa, R236ea, R601, R601a
Scardigno et al. [93]	2015	Select a suitable working fluid and optimize cycle state points for a simple ORC	Evaporating and condensing pressure, the maximum temperature of the collector thermal fluid and a parameter representative of the temperature profiles in the heat exchangers.	Energy and exergy efficiencies and the lowest LEC (levelized energy cost)	NSGAII	Solar energy	Simple ORC	R32, R41, R125, R134a, R143a, R152a, R218, R227ea
Hajabdollahi et al. [94]	2015	Select a suitable working fluid and optimize cycle state points for an ORC	Evaporator pressure, condenser pressure, refrigerant mass flow rate, number of solar panel (solar collector), storage capacity and regenerator effectiveness	Relative annual benefit	GA	Solar energy	Regenerative ORC	R123, R245fa and isobutane
Noorpoor et al. [95]	2016	Optimize design parameters of a combined system	Turb1 inlet temperature, Turb2 inlet temperature, Cond1 outlet temperature, ORC Ex outlet temperature and Gen pressure	Energy and exergy efficiencies	GA	Solar energy	Cascade ORC	R600a
Boyaghchi et al. [96]	2015	Select a suitable working fluid and optimize the design parameters for a combined energy system	Nanoparticles volume fraction, turbine inlet mass flow rate, pressure drop of ejector, area ratio of ejector, turbine inlet pressure, turbine outlet pressure, turbine outlet temperature, pinch temperature difference of geothermal heater and collector's area	Daily thermal efficiency, total product cost, total heat exchangers area, daily exergy efficiency	NSGA-II	Solar and geothermal energies	Simple ORC	R134a, R423A, R1234ze and R134yf
Andreasen et al. [45]	2014	Select a suitable mixture working fluid and optimize design parameters for a simple ORC system	The composition of the working fluid, Expander inlet temperature, Expander inlet pressure, Hot fluid outlet temperature	Net power	GA	Geothermal	Simple ORC	30 zeotropic mixtures fluids
Fiaschi et al. [97]	2014	Select a suitable working fluid and optimize cycle state points for a simple ORC	Temperatures and mass flow rates of the thermal utility	Power output	GA	Geothermal	Simple ORC	R227ea, R134a, R1234ze, R245fa, n-butane, n-pentane, n-hexane, siloxane and benzene
Kai et al. [48]	2015	Select a suitable working fluid and optimize cycle state points for a simple ORC	Evaporation pressure, superheating of the steam, the minimum temperature in the evaporator	Net power output	GA	Geothermal	Simple ORC	Butane, R236fa, R227ea, R236ea, R245fa, R245ca

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Table 1 (*continued*)

Ref.	Year	Problem Description	Design Variables	Objective	Algorithms	Heat source & sink	Cycle configuration	Working fluids
Cao et al. [98]	2016	Optimize cycle state points for a flash ORC	Flash pressure, second flash pressure, organic turbine inlet pressure	Net power output, energy efficiency and exergy efficiency	GA	Geothermal	Flash-ORC	R245fa
Cao et al. [99]	2015	Optimize state points for a flash ORC	Flash pressure, second flash pressure, organic turbine inlet pressure	Net power output, thermal efficiency and exergy efficiency	GA	Geothermal	Flash-ORC	R245fa
Li et al. [100]	2016	Optimize cycle state points	Number of stages, evaporation temperature of different stage	output power	GA	Geothermal	Multi-stage ORC	R123
Imran et al. [101]	2016	Optimize cycle state points for different cycle configurations	Evaporation temperature, pinch point temperature difference and superheat	Specific investment cost and exergy efficiency	NSGA-II	Geothermal	Simple ORC, recuperated ORC, and regenerative ORC	R245fa
Pierobon et al. [102]	2013	Select a suitable working fluid; Optimize evaporating pressure for each cycle configuration	Maximum pressure for the bottoming cycle	Thermal efficiency	GA	Biomass	Simple ORC, double stage ORC	A hundred fluids
Donateo et al. [103]	2014	Select a suitable working fluid and optimize cycle state points	Evaporator pressure, overheating, thermal recovering, mass flow rate	Net power, working fluids flow rate and overall expander efficiency	GA	Lower temperature heat sources	ORC with internal heat exchanger	R123, R245fa and R134a
Wang et al. [104]	2016	Select a suitable working fluid and optimize cycle state points	Evaporating temperature and the condensing temperature	Energy efficiency, exergy efficiency, payback period and annual emission reduction	GA	Low grade heat energy	Simple ORC	R600a, R114, R245fa and R245ca
Khaljani et al. [105]	2015	Optimize the design parameters for a cogeneration system	Air compressor pressure ratio, isentropic efficiencies of air compressor and gas turbine, air preheater outlet temperature, turbine inlet temperature, Pinch point temperatures of HRSG and evaporator, condenser and evaporator temperatures	Exergy efficiency and total cost rate of the system	NSGA-II	Fuel	Simple ORC	R113, R123, R245fa and R600
Ebrahimi et al. [106]	2016	Optimize design parameters of a combined system	Mass flow and pressure at the inlet of ejector, evaporating temperature, compression ratio, minimum temperature of exhaust gas	Energy nominee, exergy nominee, integrated energy-exergy function	GA	Fuel	Simple ORC	
Wang et al. [107]	2018	Optimize design parameters for a ORC	Evaporating temperature, condensing temperature, warm seawater temperature at the outlet of evaporator, cool seawater temperature at the outlet of condenser, degree of superheat, and depth of cool seawater	Levelized cost of energy (LCOE) and exergy efficiency	Multi-objective PSO	Ocean Thermal Energy	Simple ORC	R717, R152a, R134a, R227ea, R600a and R601
Bao et al.[108].	2018	Optimize design parameters an ORC	Condensation temperature and the inlet pressure of the LNG turbine	Net power output, electricity production cost (EPC) and annual net income	GA	Sea water and LNG	Multi-stage condensation ORC	R134a
Sun et al. [109]	2017	Optimize the cycle state points	Turbine inlet pressure and condensing temperature	Exergy efficiency	PSO	LNG	two-stage ORC	20 fluids

ing, fitness function is the objective function or its deformation. The usual method is to establish mathematical models based on physical laws or empirical correlations to calculate fitness functions. However, those models are usually complex and time-consuming because there are a lot of equations and input parameters are required during the calculation procedure. Therefore, some researchers tried to use data-driven models instead of mathematical models. Data-driven models ignore the physical principles and figure out the underlying relationship between design variables and objective functions based on a large amount of data that already exists. ANN is most widely used to build data-driven models. Meanwhile, SVM is also gradually adopted. ANN is especially suitable for complex nonlinear problems. The data, which are used to build data-driven models, are usually from experiments or mathematical models based on physical principles or empirical correlations. And these data are split into a training set which is used to build the model and a testing set which is used to measure the accuracy. Data-driven models can greatly improve the computing speed of fitness function and reduce the time spent on optimization calculation.

Rashidi et al. [56] carried out a parameters optimization of an ORC system based on ANN and Artificial Bees Colony (ABC). In their study, they used ANN to predict the thermal efficiency, exergy efficiency and specific network, which are objective functions of optimization problem. Massimiani et al. [57] used ANN to obtain analytic expressions for all objective functions and constrains of the defined optimization problem for an ORC system, thus transforming the original complex optimization problem into a derivative-free optimization problem. Then they solved the derivative-free optimization problem using the active set algorithm. Emadi and Mahmoudimehr [58] also used ANN to estimate the objective functions when they used GA to solve the multi-objective optimization problem of a cascade ORC system. Compared to using a mathematical model, using ANN can reduce optimization run time from 16 h to 10 min for each optimization execution.

However, the accuracy and generalization of the data-driven model depend on the training data. Most data-driven models perform poorly when the input data are beyond the range of training data. Therefore, some researchers only use data-driven models to calculate complex intermediate parameters and mathematical models to calculate objective functions, which was called the hybrid model. This can reduce part of the calculation time without affecting the accuracy of models.

3.4. Component selection and sizing

After working fluids, cycle configuration and operating parameters of the ORC system are determined, the next step is to select and design the components used in the ORC system. For most ORC systems, the main components include heat exchangers, pump, and expander. With the development of technology, there are more and more types of equipment. Although different types of equipment have similar functions, they differ greatly in cost and efficiency. Therefore, the types of component will affect the overall performance and investment cost of the system. The goal of components selection is to obtain suitable components which can result in the high overall system performance. Component selection is usually done by engineers according to some heuristic guidelines, which is often limited by the engineer's experience, capabilities, and time constraints and will result in suboptimum selection results. Expert system is a potential solution to solve this question. However, as far as the authors know, there are few expert systems designed specifically for ORC system component selection. Only Richard Law et al. [13] developed a knowledge-based system for the selection and preliminary design of equipment for waste heat recovery. This system can select the appropriate technique according to the heat source and sink conditions and product requirements, and carry out the preliminary design of the selected technique.

After component selection is completed, proper sizing of components needs to be determined, because it is very important for an efficient ORC system operation. The conventional sizing method is based on the design condition and some safety factors. In this process, a large number of geometric parameters are determined empirically. As a result, although the components can meet the demands, they are mostly uneconomical and inefficient. Therefore, research was conducted attempting to optimize the size of components to achieve higher economy and efficiency.

GA and PSO were usually used for components sizing. Cinnella et al. [59] conducted a multi-objective optimization for 11 geometric parameters of the turbine by using GA. In their work, they gave a set of optimal geometric parameters of the airfoil, which can lead the minimum mean drag coefficient and its standard deviation. Erbas et al. [60] also carried out the geometric parameters optimization of turbines using GA, taking into account 6 design variables and two objective functions (full load efficiency and off-design efficiency). Rahbar et al. [61–63] firstly optimized 9 parameters of the turbine with efficiency as the objective function, and then optimized those parameters with efficiency and overall size as the objective function. In their studies, there used standard GA and NSGA-II respectively. Later, they used other three parameters as design variables to optimize the size of the radial inflow turbine. Zhai et al. [64] also used GA to optimize size of the turbine, while they considered the entire ORC system model rather than just the component model.

Because heat exchangers and other equipment are widely used in the industrial field, only a few studies are about the size optimization of heat exchangers used in ORC systems. Imran et al. [65] carried out a multi-objective optimization of evaporator used in ORC system. They chose the chevron type plate evaporator and took length, width and plate spacing as the design variables. The objection functions are cost of evaporator and total pressure drop, and NSGA-II was used. Xu et al. [66] conducted a multi-objective optimization of evaporator and condenser for a subcritical ORC system. They considered 9 design variables and three objective functions, including thermal efficiency, specific cost and heat exchanger area per unit power output. GA was used to solve the optimization problem and fuzzy multi-criteria decision-making method was used to select suitable type of heat exchanger. Liu et al. [46] carried out a multi-objective optimization of fin-and-tube evaporator using PSO. Inlet radius of the tube side, the inlet radius of the shell side, fin height, fin thickness and fin spacing were considered as design variables, and total annual cost, volume of tube bundle, and exhaust pressure drop were considered as objective functions.

4. Discussion and further work

4.1. Summary of research status

From the existing literatures, the application of artificial intelligence in design of ORC systems mainly includes three aspects: decision making, parameters optimization and parameter prediction. Among these aspects, parameters optimization is the most concerned by researchers, while there are few researches related to decision making and parameter prediction based on data-driven model.

4.1.1. Decision-making

Although expert system is a good decision-making tool, there are few researches on the development of expert systems for design of ORC systems. In the selection of working fluids and components, there are a lot of heuristic guidelines. Therefore, it is necessary to organize these heuristic guidelines into an expert system to preselect of working fluids and components. The essence of decision making based on expert system is to use computer program to do repetitive work instead of human. In ORC design, it is only used to exclude unsuitable working fluids, cycle configuration, or component types according to simple guidelines. For example, it can be used to select working fluids which flammability, corrosivity, temperature range and other parameters meet the predefined standards, as shown in Fig. 9. Moreover, the CBR is an efficient and fast method to make initial decision based on previous data. However, this decision method cannot guarantee the optimal result. It only be used as

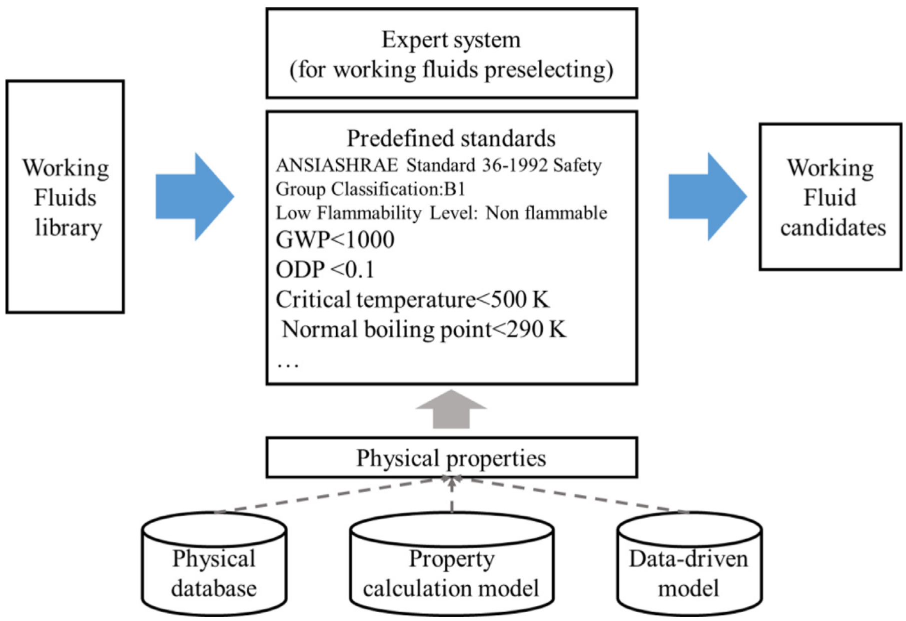

Fig. 9. An expert system for working fluids preselecting.

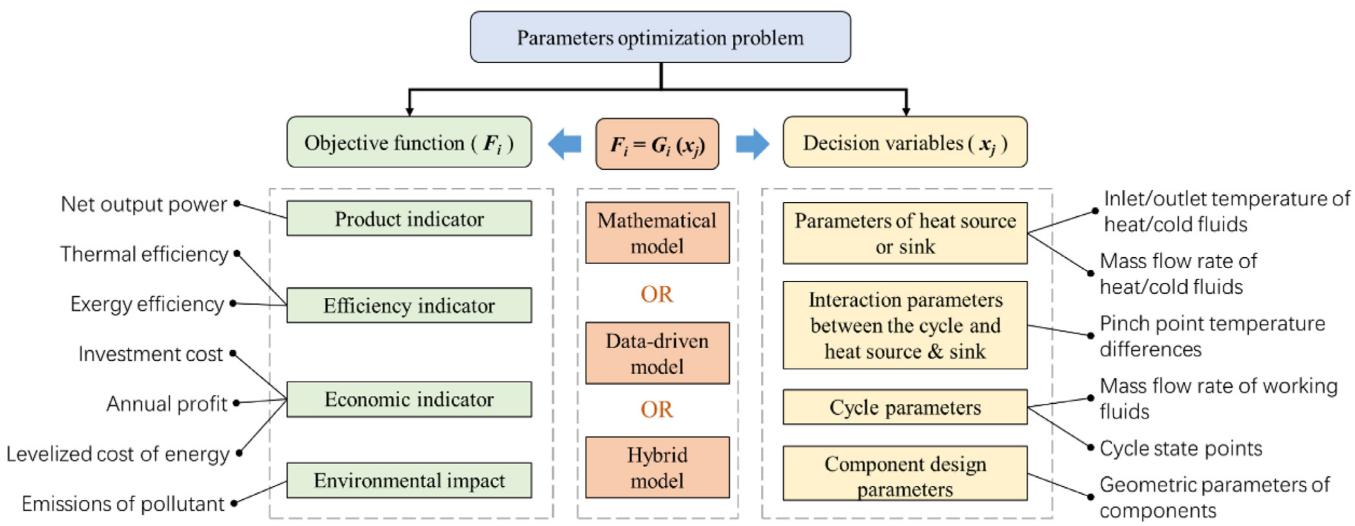

Fig. 10. Characteristics of parameters optimization in ORC systems design.

a reference in the early stage of design. However, in the design of ORC systems, decision making will play a smaller and smaller role.

4.1.2. Parameters optimization

Fig. 10 shows the characteristics of parameters optimization in design of ORC systems. The design variables which have been considered in existing literature mainly involves four aspects: cycle parameters, interaction parameters between the cycle and heat source or sink, parameters of heat source or sink and component parameters. It contains almost all the variables in the ORC design except the type of working fluids and the cycle configuration. And the most commonly considered parameters are cycle state parameters. The objective function which have been considered in existing literature mainly involves product indicator, efficiency indicator, economic indicators and environmental impact. Among them, product indicator and efficiency indicator are the most commonly adopted. In the early stage, researchers only considered one objective function. In recent years, most researchers have considered multiple objective functions. Meanwhile, economic indicator and environmental impact have been paid more and more attention. For the calculation of objective function, researchers began to use the data-driven model or hybrid model to replace the complex mathematical model. In the future, the solution of parameters optimization problem in design of ORC system would be based on intelligent algorithm and data-driven model. In addition to GA and PSO commonly used in existing researches, many new intelligent optimization algorithms have been developed in recent years, such as quantum genetic algorithm [77], flower pollination algorithm [78], shuffled frog leaping algorithm [79] and so on. This requires flexible selection of different algorithms when solving parameters optimization problems in following researches.

4.1.3. Parameters prediction

In recent years, with the rapid development of machine learning, researchers have tried to extract some valuable information from a large amount of data. One of the embodiments of this trend in ORC design is the parameter prediction method based on data-driven model that is widely concerned based on data-driven model. Table 2 presents a summary of data-driven models discussed in this paper. ANN is most widely used methods for parameter prediction, owing to their good nonlinear mapping ability and high degree of parallel processing of information capacity. As shown in Table 2, the published data-driven model mainly

Table 2
A summary of data-driven models discussed in this study.

Ref.	Year	Input features	Output	Algorithms	Research Objective	Level
Arslan et al. [110]	2011	Vapor fraction of geothermal water, working fluids, outlet temperature of geothermal water from the system, outlet temperature of working fluid from evaporator and outlet temperature of working fluid from condenser, outlet pressure of working fluid from evaporator	Generated power and required circulation pump power	ANN	Predict value of objective function during operating parameters optimization for an ORC-binary system using geothermal energy	System
Rashidi et al. [56]	2011	Outlet pressures from the second and third pumps	Thermal efficiency, exergy efficiency and specific network	ANN	Predict value of objective function during operating parameters optimization for a regenerative ORC system with two feedwater heaters	System
Arslan et al. [111]	2014	Vapor fraction of geothermal water, working fluids, outlet temperature of geothermal water from the system, outlet temperature of working fluid from evaporator, and outlet temperature of working fluid from condenser	Generated power and required circulation pump power	ANN	Predict the performance of ORC-Binary power plant	System
Zhang et al. [112]	2014	Mass flow rate and the inlet temperature at evaporator of waste heat	Energy conversion efficiency	SVM	Predict value of objective function during operating parameters optimization for controlled simple ORC system	System
Agromayor et al. [40]	2017	Evaporation temperature and the condensation temperature	Thermal efficiency, exergy efficiency and the annual emission reduction, and the minimization of payback period	ANN	Predict value of objective function during multi-objective optimization for a simple ORC system and a regenerative ORC system	System
Zhang et al. [113]	2017	Vehicle speed, the traffic lights at the intersection, the automobile gear position and clutch state	Temperature and the mass flow rate of exhaust gas	SVM	Predict dynamic behavior of heat source to adjust operating parameters of a simple ORC system	System
Dong et al. [114]	2018	Hot water temperature at the evaporator inlet, hot water temperature at the evaporator outlet/pre-heater's inlet, hot water temperature at the pre-heater's outlet, cooling water temperature at the condenser inlet, cooling water temperature at the condenser outlet, working fluid temperature at the expander inlet/evaporator outlet, working fluid temperature at the expander outlet/condenser inlet, the working fluid temperature at the pre-heater outlet/the evaporator inlet and the working fluid temperature at the condenser outlet/working fluid pump inlet	power output	SVM; ANN	Predict the performance of an experimental rig of a simple ORC, and compare the differences of two algorithms	System
Kılıç et al. [115]	2019	Working fluids, steam generator temperature, condenser temperature, subcooling temperature, and superheating temperature	Efficiency	ANN	Predict the performance of a simple ORC system	System
Palagi et al. [116]	2019	Temperature and pressure of the working fluid at the inlet of the turbine, mass flow rate and temperature of the thermal oil at the inlet of the evaporator	Mass flow rate and pressure of working fluids	ANN	Predict the dynamic behavior of a simple ORC system	System
Zhi et al. [117]	2019	Heat source temperature, heat sink temperature, mass flow rate of R1234ze(E), pump efficiency, turbine efficiency, and regenerator effectiveness	Thermal efficiency, exergy efficiency, best high pressure	ANN	Predict the best operating parameters and performance of a transcritical ORC system	System
Khosravi et al. [118]	2019	Solar radiation, well temperature, working fluid mass flow rate, turbine output pressure, surface area of the solar collector and preheater inlet pressure	Net power output, energy efficiency, exergy efficiency and levelized cost of energy (LCOE)	ANN	Predict the performance of a geothermal based-ORC equipped with solar system	System
Herawan et al. [119]	2017	Throttle angle, engine speed, vehicle speed, and exhaust temperature	Power output	ANN	Predict the performance of turbine in the ORC system which were driven by waste heat of an aspirated spark ignition engine	Component
Yang et al. [120]	2018	Working fluid volume flow rate, expander torque, expander inlet pressure, expander outlet pressure, expander inlet temperature, condenser outlet temperature and pump outlet pressure	Power output of the single screw expander	ANN	Predict value of objective function during parameters optimization of a simple ORC for diesel engine waste heat recovery	Component
Huster et al. [18]	2019	Pressure, entropy and enthalpy	Physics property of working fluids	ANN	Predict the physics property of working fluids during the calculation of a simple ORC performance	Working fluids
Huster et al. [17]	2019	Pressure, temperature	Physics property of working fluids	ANN	Predict the physics property of working fluids during the calculation of a simple ORC performance	Working fluids
Luo et al. [121]	2019	Molecular groups, topological index	Normal boiling temperature, critical pressures	ANN	Predict the key properties to calculate other properties	Working fluids

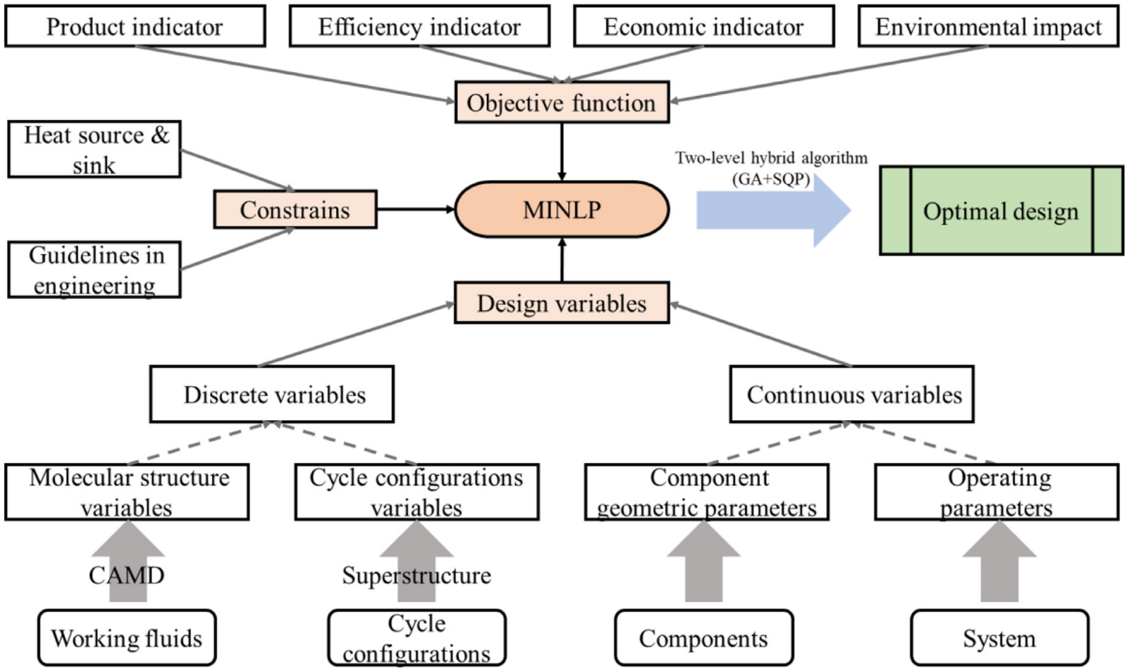

Fig. 11. MINLP optimization problem for ORC design.

involves three aspects: working fluids, components, and system. Moreover, most of the researches are aimed at establishing an alternative model for performance calculation of ORC systems, because the conventional mathematical model is very complex and time-consuming. In some studies, a data-driven model has been used to calculate the fitness function to reduce the computation time of the optimization process. This is exactly the development trend in the future mentioned in the previous paragraph. It is worth mentioning that the accuracy and generalization ability of data-driven model are very important for the application of that model. Therefore, how to train a high accuracy and strong generalization ability of data-driven is the key of parameter prediction. The performance of the data-driven model depends on the algorithm and training data. Current studies show that ANN is a good algorithm to deal with parameter prediction in ORC system. However, there are other algorithms need to be studied, such as SVM. In addition to selecting the appropriate algorithm, training data collection is very important. The training data should cover the whole range of all design variables. Compared with collecting experimental data, it is more feasible to obtain training data through mathematical model. In addition, if the training data cannot cover the whole range of design variables, the model needs to be retrained during the calculation.

4.2. A new trend in ORC systems design

Although the use of AI technique has made it easier to design ORC systems, these factors including working fluids, cycle configurations and components are not really integrated into a global optimization problem. The separation of working fluids selection, cycle configuration selection, operating parameters optimization and component selection and sizing may lead to suboptimal solutions if the preselection of the working fluids, cycle configurations or component type fails. To capture the trade-offs between the different factors, a potential approach is to integrate the various factors into an integrated optimization problem. In previous studies, only the operating parameters and geometric parameters of the components are usually the parameters that can be optimized. CAMD method [4] can generate all possible organic working fluids with different functional groups as the element. This allows the working fluids to be integrated into the optimization problem as a design variable. Similarly, superstructure method [29] includes almost all cycle configurations. Therefore, cycle configurations also can be integrated into the optimization problem as a design variable. In this way, ORC design can obtain the optimal design by solving a global optimization problem, as shown as in Fig. 11. Schilling et al. [122] have made some worthwhile attempts. In their study, they proposed a novel method base on CAMD and superstructure to solve the integrated design problem of working fluid, state points and cycle configuration for ORC systems. For such integrated optimization problem, the design variables should include the type of working fluids, cycle configuration, the type of component, component geometric parameters, and operating parameters mentioned in Section 3.3. It is worth mentioning that the first three variables are discrete variables. Therefore, such integrated optimization problem is a mixed integer nonlinear programming (MINLP) optimization problem.

The MINLP optimization problem is an important problem in mathematics [123]. However, such integrated optimization involves a variety of design variables and constraints, which make it difficult to solve the problem. The most difficult part in solving the integrated optimization is the quick search of the design space and the quick calculation of the objective function. Intelligent algorithm is a powerful tool for quick search in the design space. At present, the more effective algorithm is a two-level hybrid algorithm of GA and sequential quadratic programming algorithm (SQP) [35]. In outer level, GA is used to find the best integer solutions, then the original MINIP decomposes to a series of nonlinear programming problems which are solved by SQP. In order to calculate the objective function, a complex mathematical model containing many physical principles needs to be established, such as physical property calculation equations, cycle performance calculation equations and so on. The calculation of this mathematical model is very time-consuming. To calculate the objective function quickly, data-driven models should be used partly or completely instead of complex mathematical models.

5. Conclusion

In this study, design problems, solving methods with artificial intelligence technique and application cases in the design of Organic Rankine Cycle system are summarized for the first time. The main findings and contributions of this paper are summarized as following:

1) The design process of Organic Rankine Cycle systems contains four steps. In the process of step completion, three problems are mainly involved, i.e. decision making, parameters optimization and parameter prediction. The corresponding solving methods and application examples are also presented and these results can be used as references for subsequent studies.
2) The selection of working fluids, cycle configurations and component types belongs to the category of decision-making problem. This study introduces two solving methods which are expert system and case-based reasoning, and expert system is the most promising method. However, few studies have been done on customized expert system for design of Organic Rankine Cycle systems, which would be the direction of future research.
3) Except for decision making, other design problems could be transformed into a parameter optimization problem. Genetic algorithm is used to solve the optimization problem in most studies. Apart from the standard genetic algorithm, several improved algorithms have been adopted to obtain the better performance. The calculation of fitness function is very important for the implementation of genetic algorithm. Conventional fitness calculation methods are usually based on a complex mathematical model whose calculation often has heavy computing burden. Due to the fast computing speed and high computing accuracy of data-driven models, many studies use data-driven models to calculate fitness.
4) Working fluids, cycle configurations and operating parameters are optimized simultaneously by solving a mixed integer nonlinear programming optimization problem, that is a new trend in design of Organic Rankine Cycle systems.

Declaration of Competing Interest

None.

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