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## Soft Computing Techniques and Their Applications in Intelligent Industrial Control Systems: A Survey

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### Abstract

Soft computing involves a series of methods that are compatible with imprecise information and complex human cognition. In the face of industrial control problems, soft computing techniques show strong intelligence, robustness and cost-effectiveness. This study dedicates to providing a survey on soft computing techniques and their applications in industrial control systems. The methodologies of soft computing are mainly classified in terms of fuzzy logic, neural computing, and genetic algorithms. The challenges surrounding modern industrial control systems are summarized based on the difficulties in information acquisition, the difficulties in modeling control rules, the difficulties in control system optimization, and the requirements for robustness. Then, this study reviews soft-computing-related achievements that have been developed to tackle these challenges. Afterwards, we present a retrospect of practical industrial control applications in the fields including transportation, intelligent machines, process industry as well as energy engineering. Finally, future

research directions are discussed from different perspectives. This study demonstrates that soft computing methods can endow industry control processes with many merits, thus having great application potential. It is hoped that this survey can serve as a reference and provide convenience for scholars and practitioners in the fields of industrial control and computer science.

**Keywords:** soft computing, fuzzy logic, neural computing, genetic algorithm, intelligent industrial control system.

## 1 Introduction

In modern industrial processes, the automation is inseparable for an efficient and well-designed control system, which can facilitate the production planning [56], unmanned operations [17], fault identifications [61], the reduction of energy consumption [59] and so forth. The level of automation is an important embodiment of industrial intelligence [47]. Nevertheless, we should note that the industrial automation is a necessary but not a sufficient condition for industrial intelligence. The intelligence of a system should be further attributed to its flexibility, adaptability, capacity for learning, reasoning, dealing with complex dynamics, as well as managing uncertainties [39]. In other words, modern industrial control systems should not only realize automatic human-like operations, but also constantly improve the control implementation to meet the requirements of intelligence. A conventional control strategy in the industrial field is to use the proportional-integral-derivative (PID) controller [72]. It has been widely used because of its reliable transient response performance and good interpretability to engineers. However, the defects of the PID controller lie in the strong dependence on parameters tuning and the incompetence for modeling complex nonlinear systems. It cannot cater the requirements of intelligent industrial control.

Soft computing, which was first defined by Zadeh [95], is useful in developing intelligent industrial control systems. In accordance with Zadeh's definition, the keynote of soft computing is to tolerate the imprecision, uncertainty and partial truth to achieve tractability, robustness, and low solution cost [95]. Soft computing includes a collection of methods conforming to its keynote, which can be generally classified into fuzzy logic-based methods, neural computing methods, and genetic algorithm-based methods. Fuzzy logic, which was originally proposed by Zadeh [91], has a tight relation with the natural linguistic expression that often occurs in the process of human thinking, reasoning and communication [13]. It takes the truth of propositions as an imprecise linguistic variable, avoiding the black-or-white thinking paradigm. With a fuzzy inference process, the fuzzy logic has a mapping ability close to human cognition without accurate models. Neural computing is a learning process with a network structure, which can approximate any desired nonlinear function to an arbitrary degree of accuracy [24]. It is a black-box process with good adaptability and massively parallel computing ability. It does not directly use prior knowledge, but extracts knowledge from observed sample data. Genetic algorithms are optimization methods to search the global optimal solution by simulating natural evolutionary processes [8]. Each algorithm eliminates the solutions with poor performance and produces new solutions through genetic manipulations. For intractable problems, soft computing techniques allow a useful but possibly imprecise answer. They can soften the dependence on accurate mathematical models by mimicking natural biological processes, like the thinking and reasoning processes in the human brain. Such merits give rise to wide applications of soft computing techniques in many aspects of industrial control systems [1, 26, 31, 39, 55].

To clarify the development status and facilitate future research, this study aims to provide a state-of-the-art survey on soft computing techniques and their applications in industrial control. After reviewing the methodologies of soft computing, we provide a bibliometric analysis on relevant research status and trends of the discussed field. Then, the research challenges in developing intelligent industrial control systems are summarized, including the difficulties in information acquisition, the difficulties in modeling control rules, the difficulties in control system optimization, and the requirements for robustness. We review the soft-computing-related achievements developed to tackle the above challenges in terms of soft sensors, controllers, optimization methods and fault identification/correction methods. In accordance with the high-frequency keywords collected from the bibliometric analysis, we present a retrospect of practical industrial control applications in the fields of transportation, intelligent machines, process industry, and energy engineering. Finally, future research directions are

discussed in terms of four aspects, namely, the processing of massive input items when using the fuzzy controller, flexible adjustments of neural network structures and algorithms, soft sensor maintenance, and multi-controller strategy.

Through the bibliometric analysis, it is observed that the applications of soft computing methods in industrial control systems have attracted increasingly attention, among which the applications about neural computing methods have relatively high popularity. Some high-frequency keywords obtained from the bibliometric analysis help summarize research challenges. As shown from this survey, on the basis of soft computing methods, the soft sensors contribute to control information acquisition; a variety of controllers perform well in modeling nonlinear and uncertain control rules; the global optimization methods facilitate the optimization of industrial control systems; the fault identification and correction methods ensure the security and robustness of control systems. Due to the above advantages, soft computing methods can be found in many practical industrial cases that require a control design, whether about specific industrial devices like electric motors and robots, or some integrated industrial systems used for dispatching, energy management, and factory management. Future research directions are discussed to provide inspirations. It is hoped that this survey can serve as a reference and provide convenience for scholars and practitioners in the fields of industrial control and computer science.

The outline of this paper is as follows: Section 2 introduces the methodologies of soft computing. Section 3 conducts a bibliometric analysis. The research challenges on intelligent industrial control are summarized in Section 4. Section 5 reviews the soft-computing-related achievements conducive to intelligent industrial control. Section 6 focuses on practical industrial control applications. Remaining challenges and future directions are available in Section 7. The paper ends with conclusions in Section 8.

## 2 The main techniques of soft computing

The concept of soft computing was first clarified by Zadeh [95] as a collection of methodologies that aim to exploit tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost. Many methods that follow this keynote can be referred to as soft computing in a broad or narrow sense. Generally, soft computing can be mainly classified into fuzzy logic-based methods, neural computing methods, and genetic algorithm-based methods [28]. Soft computing can soften the dependence on accurate mathematical models by mimicking natural biological processes, like the thinking and reasoning processes in human brain. An example can help figure out the idea of soft computing. Imagine a face-recognition scene where a computer needs to scan a photo to see if it matches a target portrait. A traditional hard computing way should compare each pixel to find the precise similarity ratio, while the soft computing is similar to a human thinking process which can directly acquire intuitive judgments. Nowadays, soft computing is the most productive area in computational intelligence. This section reviews the main techniques of soft computing to make preliminaries for further discussions.

### 2.1 Fuzzy logic

Classical two-valued logic clearly describes the target state of an event as true or false. By virtue of the Boolean algebra [52], the two-valued logic equips computers with the ability of calculation and judgment, and lays a foundation for computer science. As per the Moravec's paradox [58], operations that are tough for humans, such as massive computation and multi-layer reasoning, can be easily solved by computers. However, it is difficult for computers to mimic natural and intuitive human mind, which is a research challenge in many fields such as artificial intelligence, pattern recognition, and control systems. This is because imprecise linguistic information is employed in the process of human thinking, reasoning, and communication, but it is hard to be modeled by classical two-valued logic. In addition to people's cognitive uncertainties, there also exist objective uncertainties caused by the changes of environment or the errors of information acquisition. To cope with these uncertainties, Zadeh [91] proposed the fuzzy sets theory in which each element can simultaneously belong to several sets with different membership degrees. Compared with the classical set theory, Zadeh's work is

seminal and subversive. Suppose that  $U$  is a domain of the base variable  $x$ . A fuzzy set  $A$  on  $U$  is defined as  $A = \{(x, \mu_A(x)) \mid x \in U\}$ , with  $\mu_A : U \rightarrow [0, 1]$  being a membership function [91]. For each  $x \in U$ ,  $\mu_A(x)$  indicates the degree to which  $x$  belongs to  $A$ . Fuzzy sets avoid the black-or-white thinking paradigm to tolerate uncertainties, which does not reduce the rigor of study. On the contrary, the fuzzy set theory quantifies uncertainty in the form of membership degrees. Such a quantification is of great significance to the development of artificial intelligence methods [97]. It allows us to study the degree of uncertainty in a mathematical way [12]. Currently, Zadeh’s pioneering paper, “Fuzzy Sets” [91], has been cited more than 4,0000 times. The classical fuzzy set is called the type-1 fuzzy set, where membership degrees are supposed to be figured out precisely. To further consider possible uncertainties about membership degrees, Zadeh [93] defined the type-2 fuzzy set with fuzzy instead of precise membership functions. In a type-2 fuzzy set, the primary membership degree is not a single value but a subset in  $[0,1]$ , with the secondary membership degree in  $[0,1]$  denoting the possibility of each primary membership degree [51].

As for the concept of fuzzy logic, Zadeh [95] clarified its broad and narrow senses. In a broad sense, fuzzy logic is synonymous with the fuzzy set theory. In a narrow sense, fuzzy logic is specified to a logical system where the truth of any proposition is expressed as a matter of degree and inference rules are fuzzy. Such a logical system is a key part of approximate reasoning [13] and fuzzy controller [49]. In a fuzzy logic system, the truth of a proposition is usually denoted by a linguistic variable. According to Zadeh’s definition [92, 94], a linguistic variable refers to the variable whose value is not a number but a word or phrase in a natural language. The semantics of each linguistic term yielded by a specific grammar is a fuzzy set of base variables, which makes natural linguistic information granular so that it can be processed by computers. Based on the fuzzy set theory, linguistic variables build a bridge between numerical information and linguistic information. By setting membership functions associated with linguistic variables, numerical information can be fuzzified to granulated linguistic information. Linguistic information can also be transformed into numerical information by defuzzification. Therefore, Zadeh’s theories lay a solid foundation for processing natural language and modeling human mind.

Generally, a fuzzy logic system involves fuzzification, inference and defuzzification. Figure 1 shows a schematic of a fuzzy logic system used to model a control process of water inlet valve. The system controls the opening of a valve as per the deviation between the target and current water level.

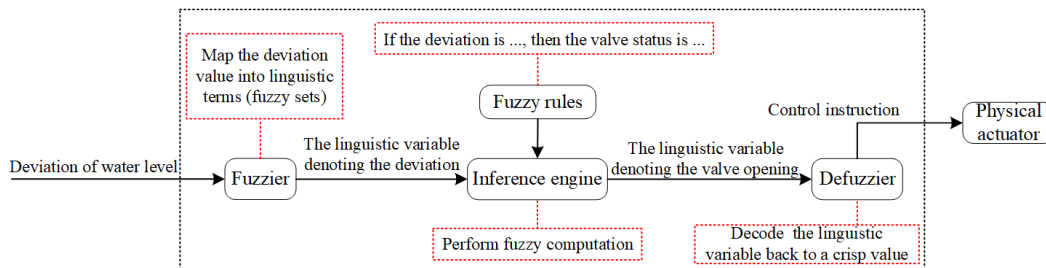


Figure 1: A schematic of a fuzzy logic system in a water inlet valve

- Fuzzification

Each crisp input is mapped into a fuzzy set by a designed membership function to tolerate the uncertainties of information acquisition. The fuzzification process can be understood as a data compression process. According to actual needs, different types of membership functions can be used in this process [3]. To facilitate the subsequent discussion, the symbolic representation of the fuzzified input information is specified as  $\text{inp} = B_I, U_I, T_{B_I}$ , where the linguistic variable  $B_I$  is mapped to the linguistic term set  $T_{B_I} = \{T_{B_I}^1, T_{B_I}^2, \dots, T_{B_I}^k\}$  with the meaning of each linguistic term  $T_{B_I}^k$  corresponding to a membership function  $\mu_{T_{B_I}^k}$ .

- Inference

Primarily, fuzzy rule base is established based on the expertise and experience of experts, avoiding complex modelling of problems. The rules are represented in a “If-Then” structure. In this way, the input and output information of a fuzzy logic system is connected. The “If” part of a rule is called its antecedent, while the “Then” part is called consequent [49]. For example, if the rainfall is heavy,

then the drain valve would be large. An inference engine decides which rule from the fuzzy rule base is fired by calculating the firing strength. We take the following fuzzy rule as an example:  $R^1$ :

$$\text{if } B_{I1} \text{ is } T_{B_{I1}}^k, \text{ and } B_{I2} \text{ is } T_{B_{I2}}^k, \text{ then } B_O \text{ is } T_{B_O}^k$$

where  $B_O$  is the consequent (output) linguistic variable of the rule. The firing strength of the rule is calculated by the “AND” operation in fuzzy logic, such that  $f^1 = \mu_{T_{B_{I1}}^k} \wedge \mu_{T_{B_{I2}}^k}$ . Then, combining the firing strength with the consequent fuzzy set, the membership degree of the output of the aforementioned rule can be obtained as  $\mu^1(x_O) = f^1 \wedge \mu_{T_{B_O}^k}(x_O)$  where  $x_O$  denotes the base variable corresponding to the linguistic variable  $B_O$ . Normally, more than one fuzzy rule is fired with different firing strength. The membership degree of the output of the whole system with  $S$  fuzzy rules is calculated using the OR operation in fuzzy logic, that is,  $\mu(x_O) = \mu^1(x_O) \vee \mu^2(x_O) \cdots \vee \mu^S(x_O)$ . Concretely, the “AND” and “OR” operations in fuzzy logic are implemented by t-conorm and t-norm functions. For example, in fuzzy control systems, the following functions were usually used [49]:  $\mu_1 \wedge \mu_2 = \min(\mu_1, \mu_2)$ ,  $\mu_1 \vee \mu_2 = \max(\mu_1, \mu_2)$ .

According to the characteristics of fuzzy rules, inference methods can be divided into Mamdani fuzzy inference [48] and Takagi–Sugeno inference [66]. In the former, the consequent of the fuzzy rule is in the form of a linguistic term, while in the latter, a polynomial function is adopted. What we introduced above is the Mamdani fuzzy inference which has been widely used to model human-like decision-making and control activities since the rule in it is in line with human thinking and expression and can be directly generated by experienced experts [81]. The Takagi-Sugeno inference method requires fuzzy modeling based on samples to obtain the consequents in the form of mathematical functions [66].

- Defuzzification

In this step, the resulted fuzzy sets of the inference engine are defuzzified into crisp outputs that can be sent out of the system for further use. There are many defuzzification methods in accordance with system characteristics and actual needs [67]. For instance, the mean of maxima method [74] selects the mean of elements with the maximum membership degree as the crisp output, while the center of gravity method [74] takes the barycenter of the area enclosed by membership function curve and abscissa as the output value. If the fuzzy logic system is based on type-2 fuzzy sets, the input crisp values are fuzzified into input type-2 fuzzy sets. Then, the inference engine is activated to yield output type-2 fuzzy sets. Particularly, a type reduction process is introduced, before defuzzification, to handle the uncertainties of membership first [36]. With the resulted type-1 fuzzy sets at hand, the output crisp values are then deduced by defuzzification.

The fuzzy logic system works on the basis of the mathematics related to fuzzy sets, including the intersection, union and complement operations of fuzzy sets and fuzzy implication [54, 91]. It is capable of completing human-like reasoning and decision-making activities in an environment of imperfect information. Moreover, many classical mathematical results have been extended to the fuzzy context [13], which facilitates the wide applications of fuzzy logic. This is why Zadeh pointed out that “fuzzy logic is not fuzzy” [96]. In fact, the fuzzy logic can make approximate reasoning and study the uncertainty in a purely mathematical way.

## 2.2 Neural computing

Neural computing based on artificial neural network is one of the most popular intelligent computing technologies. By mimicking the neuron, the fundamental cellular unit of human brain, neural computing has the capability to approximate any desired nonlinear function to an arbitrary degree of accuracy, which can be understood as a learning process [24]. In an artificial neural network, the unit similar to the brain neuron is called a processing element (see Figure 2) [27].

The input path in the processing element simulates the dendrite structure in brain neurons used to receive signals from other neurons. The connection weights represent excitatory/inhibitory relations and strength among the elements in an artificial neural network. By the weighted summation, each processing element linearizes all output data of the previous layer into an overall result. Then, activation functions (or called transfer functions) are introduced to work for nonlinear mapping to get



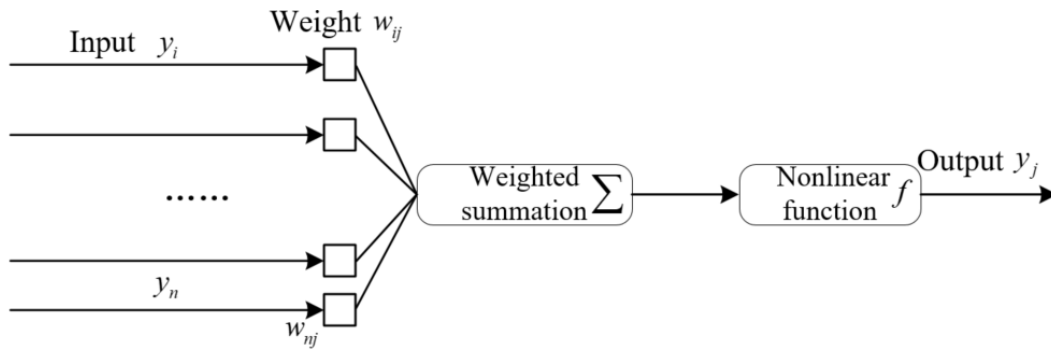


Figure 2: The structure of a processing element

the output that can be passed on. Taking the step function as an example, the nonlinear mapping process can be denoted by

$$y_j = f(\sum_{i=1}^n w_{ij}y_i) = \begin{cases} 1, & \sum_{i=1}^n w_{ij}y_i - \theta_j \geq 0 \\ 0, & \sum_{i=1}^n w_{ij}y_i - \theta_j < 0 \end{cases}, \quad i \neq j$$

where  $\theta_j$  is a threshold in the processing element.

The artificial neural network is a topological structure formed by connecting the processing elements. The most common structure is the multilayer feedforward network (see Figure 3) which uses the backpropagation algorithm for learning [24].

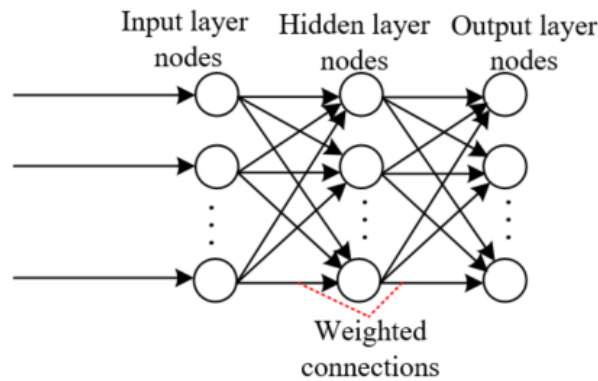


Figure 3: Multilayer feedforward neural networks

After the construction of network, sample data containing input and expected output is employed for learning. The errors between the actual output and the expected output are calculated. Then, the backpropagation algorithm returns the error signal following the original network path, and adjusts the connection weights by a gradient descent method to minimize errors. The setting of the expected output gives rise to a supervised learning process. Concretely, initial connection weights among nodes in the network are set to small random non-zero values. Suppose that when the  $p$  th pair of input and expected output are used for learning, the result obtained by the output layer node  $i$  is  $y_i^p = f(\sum_j w_{ji}y_j^p)$ , and the expected output is given as  $O_i^p$ . In the backpropagation algorithm, the sigmoid function [16], i.e.,  $f(x) = 1/(1 + e^{-x})$ , is usually taken as the activation function. Then, the total errors with a total of  $P$  pairs of input and expected output are calculated by  $E = \frac{1}{P} \sum_{p=1}^P E_p = \frac{1}{P} \sum_{p=1}^P \sum_i (o_i^p - y_i^p)^2$ . If the errors do not meet the requirements, the connection weights are adjusted to reduce errors in the learning process. The weight adjustment is proportional to the gradient  $\partial E/\partial w$ , such that  $\Delta w_{ij} = -\eta \sum_{p=1}^P \frac{\partial E_p}{\partial w_{ij}}$ , where  $\eta$  is a learning rate. For more details on the gradient descent method, please refer to [16].

## 2.3 Genetic algorithm

Genetic algorithm is an optimization method based on the biological evolutionary principle to search the optimal solution [8]. Its idea is to use simulated evolution to solve complex problems when traditional methods cannot be applied effectively or produce unsatisfactory solutions [28]. Without rigid restrictions on the properties of objective function, such as the smoothness and the concavity [46], the genetic algorithm has adaptive global optimization abilities by eliminating solutions with poor performance. Coding rules are given to associate potential solutions with their identifiers: chromosomes, so that the algorithm can work in a way similar to a natural evolutionary process, and deal with a number of candidate solutions rather than just one candidate solution [46]. A chromosome is made up of genes that represent decision variables.

Generally, an initial population of individuals (solutions) are randomly generated. Then, the fitness values of individuals are calculated by a fitting function with the codes of chromosomes being base variables defined as per desired performance indices. If the algorithm cannot find the optimal solution with a required fitness, it needs to select the individuals with relatively high fitness (strong ability to survive) as a parent population to create an offspring population by a series of genetic manipulations, including crossovers and mutations. The selections and genetic manipulations form a heuristic search process different from blind enumerations.

After the offspring population have been created, each individual in it receives a fitness value and replaces the individuals with relatively low fitness in the original population. Such a process with procreation and replacement can be understood as natural selection [28]. The genetic algorithm does not focus on the derivation and the modeling of complex problems, but on the performance of solutions, which is realized by fitting functions. There are no rigid restrictions on the continuity and differentiability of fitting functions. Starting from multiple points, the genetic algorithm can quickly approach the global optimal solution of complex problems.

## 3 A bibliometric analysis of publications on industrial control systems involving soft computing techniques

Since the Industry 4.0 strategy was proposed in 2013 [47], the intelligent automation of industrial systems has been emphasized. This raises many new requirements on modern industrial control systems, like the requirements for flexibility, adaptability, capacity of learning, reasoning, dealing with complex dynamics, as well as managing uncertainties [39]. It is observed that the merits of soft computing methods are of great significance to the intelligent industrial control systems, which gave rise to the wide applications of soft computing techniques in modern intelligent industrial control systems. This section aims to provide a bird's eye on the research status about industrial control systems involving soft computing techniques by a bibliometric analysis.

The starting point of the time range for the literature retrieval is set as 2013, with the aim to mainly show the vigorous developments of the discussed field after the Industry 4.0 strategy was proposed. We use the basic search keyword “*industrial control*”, and add “*fuzzy logic*”, “*neural network*”, “*genetic algorithm*” to form three groups of keywords. A total of 2090 literatures were obtained on December 10, 2020. Figure 4 shows the annual publication volume and annual citations of these literatures, which are presented in three groups according to the search keywords.

As can be seen from the significant growth trends of the publication volume and citations since 2013, the applications of soft computing techniques in the field of industrial control has attracted increasingly attention. More specifically, the literature on the applications of neural networks accounts for the majority in both the number of total publications and citations, showing the vitality and popularity of the neural computing technique. This is because modern industrial control systems do require the excellent merits of neural networks, such as the learning ability and massively parallel computing ability. The generalization ability of neural network and the development of hardware such as the field programmable gate array also contribute to the wide applications of neural networks. By comparison, the literature on the applications of fuzzy logic and genetic algorithms in industrial control systems is not as much as that on the applications of neural networks. Neural networks with

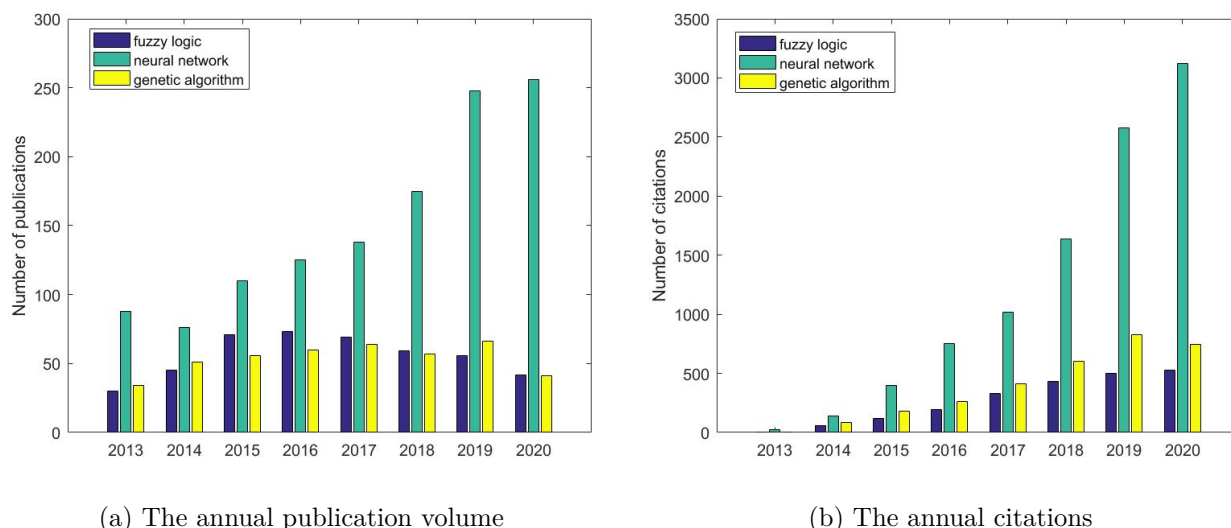


Figure 4: The annual statistics of literatures (from 2013 to December 10, 2020)

various types and structures can be combined with various learning algorithms to form innovations, while the theories of fuzzy logic and genetic algorithms are relatively mature. In many publications [1, 69, 71], the fuzzy logic and genetic algorithms were integrated with other approaches, which also integrated the neural computing technique to solve control problems.

By virtue of the VOSviewer software package [14], the co-occurrence relations of keywords in all retrieved literature are shown in Figure 5. Each node represents a keyword, and the node size represents the frequency of occurrence. A line indicates that both the two linked keywords have appeared simultaneously. Colors are mapped according to the published time of keywords. The warmer the color is, the closer the time is to the present, while the colder the color is, the farther away the time is from the present. The lines between some high-frequency keywords, namely, “neural network”, “fuzzy logic” and “genetic algorithm”, demonstrate that these approaches are not always applied separately. The keywords “soft sensors”, “nonlinear-systems”, “adaptive control”, “optimal control”, “robust control” and “fault diagnosis” imply research hotspots, from which we can summarize major research challenges pertaining to intelligent industrial control systems. Some keywords also show the hot fields of practical industrial applications since 2013. For example, in light of “speed control”, “motor”, “industrial robot”, “fermentation”, “process control”, “power”, “water” and “temperature control” with different colors, we can conclude that the hot application fields may include transportation and intelligent machines in the first few years, while chemical or bioprocess process and energy engineering in recent years. This provides inspirations for us to determine the review angles about the practical applications of soft computing techniques in modern industrial control systems.



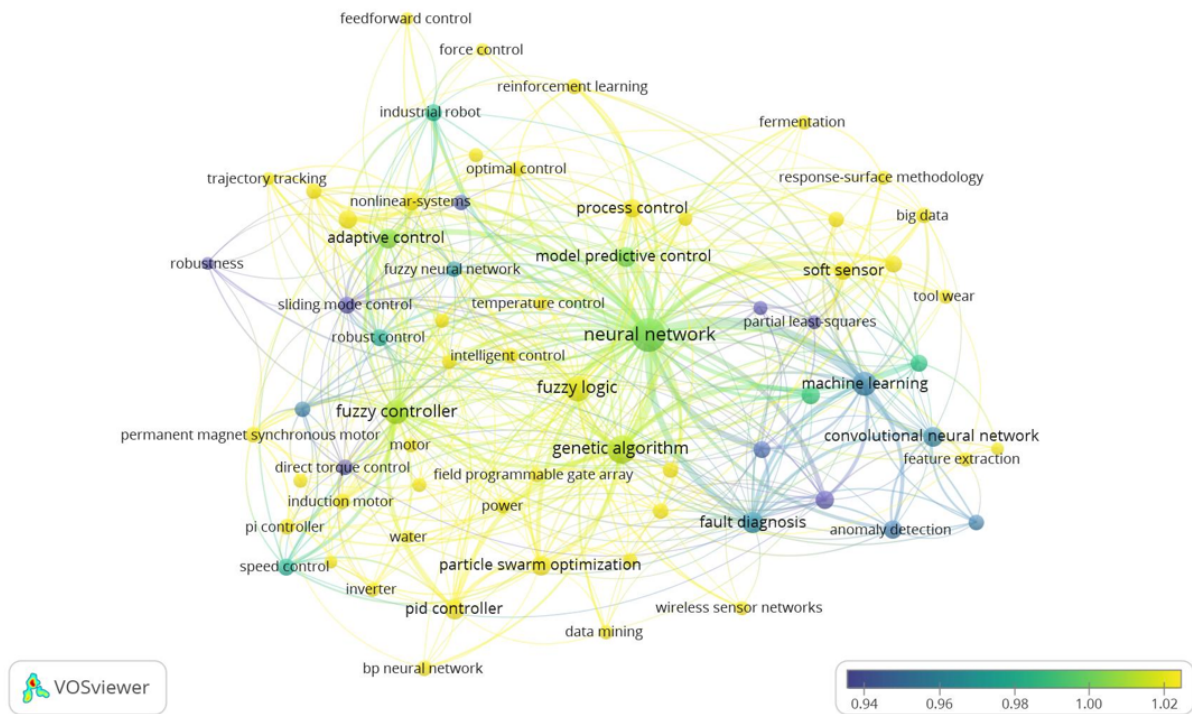


Figure 5: Keywords co-occurrence of the reviewed publications

## 4 Research challenges on intelligent industrial control systems

Modern industrial control systems should not only realize automatic human-like operations, but also constantly improve the control implementation to meet the requirements of intelligence. In light of some keywords collected in the bibliometric analysis, we summarize the research challenges on intelligent industrial control systems in this section. In the next section, we shall review the applications of soft computing techniques in modern industrial control systems in details.

### 4.1 Difficulties in information acquisition

Generally, besides the direct information from human instructions, industrial control systems need to use sensors to gather internal feedback or external information. However, not all key variables can be measured easily due to technical or economic limitations [60]. For example, to regulate biomass in a continuous stirred fermenter, it would be obligatory but difficult to have a sampling interval of one hour for analysis [70]. In this case, it is necessary to make predictions based on available data from industrial processes. One approach to do this is model-driven and based on a lot of prior process knowledge, such as the mass-conservation principle and the energy balance principle. Just like in the example above, frequent estimates of biomass can be achieved indirectly using  $\text{CO}_2$  evolution rate and dilution rate. However, the expertise may be hard-won for complex industrial processes. The other method, which is an empirical prediction based on the historical data collected in industrial processes, is worth studying. This data-driven method is free of the prior knowledge but requires frontier technologies in statistical reasoning and machine learning [34].

### 4.2 Difficulties in modeling control rules

The core work of control systems is to model control rules which involve the mapping relations between input and output. The PID controller is a mainstream choice in the industrial field because of its reliable transient response performance and good interpretability of its control strategy to engineers [20]. It maps the output of an industrial control system according to the instantaneous and accumulative errors between actual values and target values, as well as the rate of error change. However, the

performance of the PID controller largely depends on the parameter tuning [72]. The PID controller needs to deal with a large number of parameters, and has weak mathematical modeling ability and poor control effect in the face of complex nonlinear systems commonly existed in industrial fields. For example, a thermal system is inherently nonlinear due to leakage, friction, temperature-dependent flow properties, and contact resistance [75]. To model complex nonlinear control rules, it is necessary to make use of objective learning process or subjective control experience.

Moreover, subjective and objective uncertainties from multiple sources may pervade the whole industrial control system [49], which also brings difficulties in modeling control rules. When collecting information in the input path, measurements may be affected by noise or environmental changes. The feedback information as input in a closed-loop control system may be distorted. Besides, the estimates of an engineer as input may have subjective uncertainties. The implementation of control may encounter changes in operating conditions. For instance, a flexible manufacturing system usually requires changes in plant's parameters. The unmeasurable disturbance acting on control systems, such as the changes in fuel consistency acting on the engine's intake system, is also a source of uncertainties. As for the output path, physical actuators that execute control instructions are not always stable due to the depreciation or wear and tear on the machine. The above uncertainties should be handled well in the process of modeling control rules, which are significant challenges in modern intelligent industrial control systems.

### 4.3 Difficulties in control system optimization

There exist two categories of optimization problems in control systems: the optimal tuning of controllers and the optimal selection of control actions. The former mainly involves parameter optimization problems. As mentioned earlier, the PID controller is inseparable from a parameter tuning process. How to balance the requirements of a control system for response time, steady-state errors, and stability to set optimal proportional, integral and derivative gains (parameters) is worth studying. Especially for industrial control systems, unstable preconditions and nonanalytic system characteristics make the conventional tuning method [105] unable to meet the requirements for adaptability and tuning speed. The tuning of other controllers also faces a similar dilemma. When a controller is developed using fuzzy logic, it is necessary to optimize the parameters of membership functions for an excellent control effect. Even the setting of fuzzy rules can be regarded as an optimization process [100]. In a controller based on neural networks, the learning algorithm is essentially an algorithm to optimize connection weights. However, the complex characteristics of industrial control systems make it difficult to formulate appropriate programming models for the above optimizations. The programming models need to avoid a local optimum and unrealistic assumptions.

Regarding the optimal selection of control actions, with the goal of optimal control effect, optimization characteristics are reflected in the selection of control instructions rather than the operating parameters of controllers. In such optimizations, the direction of searching the optimum cannot be arbitrary for high optimization efficiency [78], which also shows the difficulties of optimization.

### 4.4 Requirements for robustness

The requirements for robustness of industrial control systems can be summarized in two aspects. On the one hand, an industrial control system should be insensitive to external disturbances. The toleration of information uncertainties is exactly helpful to improve the anti-disturbance ability. It is observed that the sliding mode controller [31] exhibits strong anti-disturbance ability. However, the sliding mode controller should be further designed for actual industrial applications due to the chattering phenomenon that may affect the control effect [55]. On the other hand, an industrial control system needs to be capable of active fault identification and correction. For example, in an electro hydraulic servo control system in aero engines, the servo valve often suffers from wear failure or leakage due to tough operating conditions [44]. The resulted performance degradation directly affects the control effect. For the fault identification, the system should mine fault features from the measured signals or compare the deviations between the practical output and the expected standard output. The fault correction can be executed through a fault compensate function [83] or adaptive

reconfiguration of failed systems [17, 33].

Soft computing techniques have been widely used to meet the above challenges. The fuzzy logic-based methods can model uncertain and experience-based control rules, and map outputs by fuzzy inference [49, 62]. The neural computing methods can develop soft sensors to collect information [37], model nonlinear control rules [75], and help construct a standard model that can serve as a benchmark to detect faults [44]. The genetic algorithm-based methods can realize the optimal tuning of controllers [72] and obtain optimal control actions [78] through a heuristic search process. These three types of techniques with their own advantages and limitations are complementary rather than competitive. They work alone or together in many aspects of industrial control systems to tackle the challenges of intelligent industrial control systems. Next, we shall review specific soft-computing-related achievements.

## 5 The soft-computing-related achievements conducive to intelligent industrial control systems

In this section, we review research achievements developed based on fuzzy logic, neural computing, and genetic algorithms in intelligent industrial control systems in terms of soft sensors, controllers, optimization methods, and fault identification/correction methods.

### 5.1 Soft sensors for control information acquisition

In an industrial control process, empirical predictions based on historical data are valuable for the measurement of some variables used as the control input, which are often not accessible by conventional sensors due to technical or economic limitations. Such empirical predictions can be understood as data-driven soft sensors. Since some statistical reasoning methods such as the principal component regression, have the requirement for data volume and are inconvenient to handle the nonlinearity, the learning technology based on artificial neural networks has been widely used to develop soft sensors [37, 60, 85]. Shang et al. [60] pointed out that deep neural networks can contain rich information, describe highly correlated process variables and mine the process data by a semi-supervised learning process, and thus is useful for soft sensor modelling. The deep learning technique is comprised of an unsupervised pre-training phase and a supervised backpropagation phase. In the former, a deep belief network is pre-trained to obtain the initial weights of the supervised phase, and in the latter, the whole neural network is fine-tuned with the expected output playing a supervisory role. The deep belief network is established by stacking individual restricted Boltzmann machine, which has a visible layer to denote the input and a hidden layer to denote latent variables. The latent variables act as the inputs of the next Boltzmann machine and facilitate the processing of highly correlated process variables. The main steps of soft sensor modeling with the deep neural network [60] can be visualized in Figure 6.

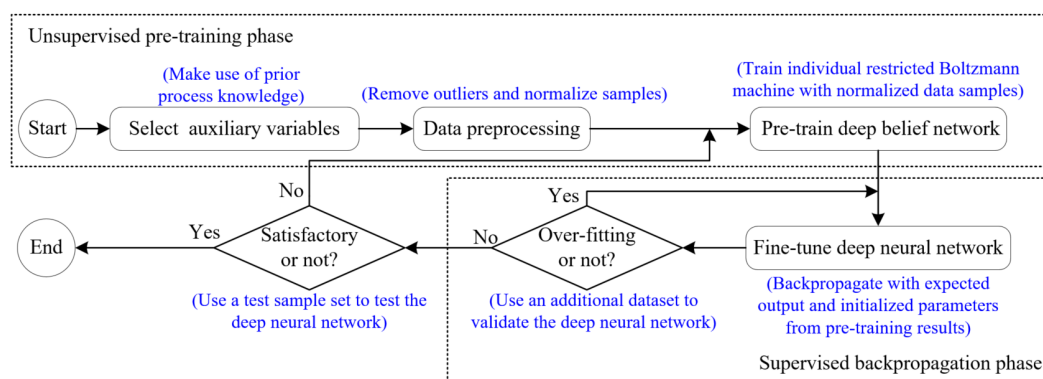


Figure 6: The main steps of soft sensor modeling with the deep neural network

To improve the adaptability of the soft sensor and avoid the deterioration of accuracy, Xie et al. [85] proposed a soft sensor based on the adaptive weight radial basis function neural network to

estimate the oxygen reaction efficiency online. Kataria and Singh [37] designed a soft sensor based on the recurrent neural network, which is structurally similar with common feedforward networks but characterized by a recurrent connection. In this way, the soft sensor is capable of extracting and learning temporal sequences from the process industry data.

In the development of soft sensors, the pre-processing of sample data and the final verification usually take a lot of efforts from operators. How to reduce manual development burden to the model is worth studying. Moreover, in most cases, a gradual deterioration of the performance of soft sensors can be observed after these sensors are put into use due to the data drifts or other common changes in the industrial process [34]. Adaptive soft sensors can address the performance degradation to some extent [85]. However, there is often no objective measure to evaluate the quality level of soft sensors. The above discussions illustrate the difficulty of soft sensor maintenance and can be taken as a motivation for future research.

## 5.2 Various controllers involving fuzzy logic and neural computing

The control system based on fuzzy logic, referred as a fuzzy controller, has been widely used in the industrial field. This is principally because it can tolerate the uncertainties of information, model nonlinear or even nonanalytic systems, and make full use of the experience of a human operator in a linguistic manner [55]. In Section 2, we have enumerated a fuzzy logic system for control (fuzzy controller) in Figure 1. Since the consequent of fuzzy rules in the controller is a linguistic term, the inference method is the Mamdani inference and the controller belongs to the Mamdani fuzzy controller [48]. By contrast, the consequent of fuzzy rules in the Takagi-Sugeno fuzzy controller [66] is a polynomial function. Suppose that the  $s$  th fuzzy rule  $R^s$  has the form:

$$\text{if } B_{I1} \text{ is } T_{B_{I1}}^k, \text{ and } B_{I2} \text{ is } T_{B_{I2}}^k, \text{ then } B_O^s = g^s(x_{I1}, x_{I2})$$

where  $x_{I1}$  and  $x_{I2}$  are crisp inputs corresponding to the linguistic variable  $B_{I1}$  and  $B_{I2}$ , respectively. Generally, the function  $g^s$  is a linear function. The inference results of different rules are aggregated by  $B_O = \left( \sum_{s=1}^S f^s B_O^s \right) / \sum_{s=1}^S f^s$ , where  $f^s$  is the firing strength of the  $s$  th rule. Unlike in the Mamdani fuzzy controller, here,  $B_O$  is no longer a linguistic variable but a numerical variable, which means that the Takagi-Sugeno fuzzy controller can yield a crisp output without defuzzification. The fuzzy rules in the Mamdani fuzzy controller can be obtained entirely based on subjective experience. However, for the Takagi-Sugeno fuzzy controller, in addition to the experience, the fuzzy modeling based on samples is necessary to get the fuzzy rules whose consequent is a polynomial function. The parameters in the polynomial function can be estimated by optimizing a least-square performance index via a weighted linear regression method.

Moreover, precise membership degrees are sometimes not enough for tolerating the uncertainties in a control system, which gives birth to the type-2 fuzzy controller [49]. For example, when a group of experts are enquired to propose fuzzy rules, they may have different opinions regarding the consequent fuzzy sets of the rules. Also, the same linguistic term may have different semantics for different controller designers. The type-2 fuzzy set that allows several membership degrees can model the above uncertainties. Compared with the type-1 fuzzy controller, the type-2 counterpart is characterized by a type-reduction process before the defuzzification, which can be executed by the centroid method, the center-of-sets method, the height method, or the center-of-sums method [35].

Fuzzy controllers define fuzzy rules with respect to prior control knowledge or experience, leading to good interpretability. However, sometimes a large number of objective sample data from control instances rather than generalizable control experience are available. In light of this, scholars have developed neural controllers based on neural computing methods [2, 5, 27, 32, 53, 63]. A neural controller uses the artificial neural network as a universal approximator to get the mapping relation between the control input and output. Compared with the fuzzy controller, the neural controller acquires the learning ability, adaptability, and objectivity at the expense of interpretability and easy-operability. The neural controller usually works in conjunction with a neural emulator to form a neural control system [7, 53]. Here, the neural emulator is used for the system identification to learn and match the dynamics of the controlled object. Figure 7 illustrates an application of feedforward neural networks to control the reversing of a truck [53]. In Figure 7, based on the current location  $(x, y)$  and

the positional angle  $\Phi$  as input, the neural controller outputs the reversing angle  $\theta$  for cab operations. The next position and positional angle are then calculated by the neural emulator which also has a neural network structure. This truck emulator has already been trained to be able to emulate the real truck. After a specified number of iterations, the errors between the actual position and the target position are calculated. Such errors can be transformed into the errors about the controller output by backpropagating through the network of the neural emulator. Then, a learning algorithm converges to a set of controller weights that minimize the errors about the controller output. In this way, the neural controller is trained to be able to control the truck from a random initial location to the target one.

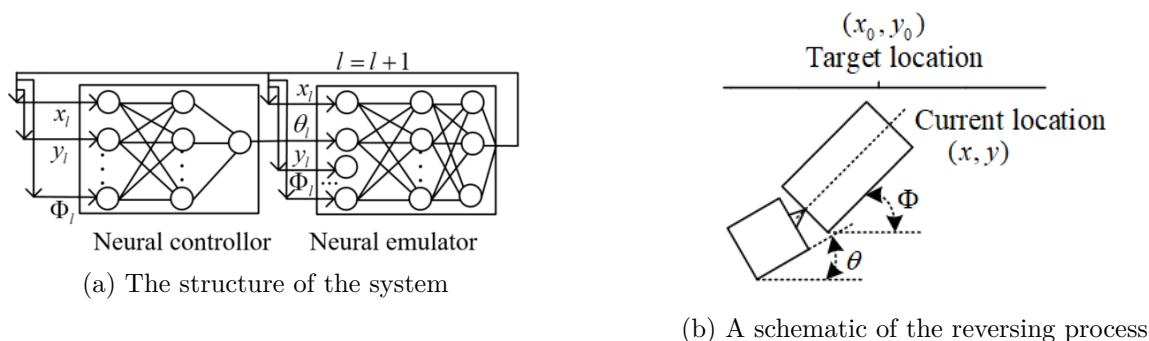


Figure 7: An application of the feedforward neural network for reversing truck

There are various structures of neural control systems according to different control strategies. The example above with two neural networks for identification and control respectively belongs to the indirect adaptive control [32]. Besides, the neural network can be connected with the controlled object directly after learning its inverse dynamics, forming a direct inverse control [5]. As for a so-called supervisory control [87], the neural network is used to learn the traditional controller that is useful in the initial stage and gradually replace it. Not only the feedforward neural network, but also other types of neural networks such as the radial basis function network [2] and the Elman network [63] can be used to design neural controllers.

Besides the idea of the fuzzy logic, to avoid the black-or-white thinking paradigm, much work in control systems was based on the combination of various controllers. When we are attracted by the popularity of the intelligent control systems based on fuzzy logic or neural computing, it is also necessary to keep in mind the characteristics of some conventional controllers. Table 1 shows a comparison of different controllers. Among them, the conventional controllers including the PID controller and sliding mode controller have vital advantages. The PID controller is a closed-loop control system where the control signal is a linear function of errors, changes of errors, and the rate of error changes. The sliding mode controller drives the state of the controlled system to move purposefully according to the trajectory of the predetermined sliding surface.



Table 1: Comparison of different controllers

Types	Basic components	Advantages	Disadvantages
<b>Fuzzy controller</b>	Membership functions; fuzzy rules; fuzzy inference	Ability to cope with nonlinearity and uncertainty; good interpretability; easy-operability	Subjectivity; lack of learning ability; low control accuracy
<b>Neural controller</b>	Artificial neuron; network structure; collection weights	Suitable for objects that cannot be describe with rules or models; ability to cope with nonlinearity; massively parallel computing ability; learning ability; objectivity	Poor interpretability; strict convergence requirement; complex network design
<b>PID controller</b>	Proportional element; integral element; derivative element	Simple structures; good transient response performance; strong stability; low design cost	Weak ability to cope with nonlinearity and uncertainty; dependence on the parameter tuning
<b>Sliding mode controller</b>	State equations; switching functions; sliding surface	Strong robustness; quick response	Chattering phenomenon

Next, we review hybrid controllers based on more than one control principle. Many neural-fuzzy systems combining the fuzzy logic and neural computing techniques have been developed to solve control problems [1, 31, 43, 76, 102]. The fuzzy logic system has been encoded to neural networks based on the generalizability of networks [30] or the functional equivalence [82]. The input and output nodes represent the input states and output control actions, and the hidden nodes work as membership functions and rules. The unsupervised learning algorithm can be used to identify data clusters implying the existence of fuzzy rules, while the supervised algorithm can train the network to extract fuzzy rules and determine membership functions [43]. As a result, the reasoning characteristic of fuzzy controllers and the generalization and learning capabilities of neural networks are combined. The fuzzy rules and membership functions are obtained objectively, and the neural network originally with a black-box structure becomes easy to understand.

The combination of the fuzzy logic and PID control strategy can be summarized in two aspects [103]. On the one hand, the fuzzy controller acts as a main body, and the control outputs are inferred based on the fuzzy logic, with the errors, changes of errors, and the rate of error changes being the control inputs [9, 15]. Namely, the conventional PID controller uses PID gains to establish a linear function, while the fuzzy inference is used to consider the nonlinearity of the system. Such a combination not only maintains the merits of the PID control, but also bypasses the limitations of nonlinearity and uncertainty. On the other hand, taking the PID controller as a main body, some fuzzy rules and a fuzzy inference engine have been used to tune the PID gains online for desired controller performance [6, 68]. The reasoning characteristic of fuzzy logic is embodied in the parameter tuning process.

In the sliding controller, the sliding surface free from parameter fluctuations and disturbances makes the controller have strong robustness, which comes at the expense of obvious chattering phenomenon of outputs. The fuzzy logic can help handle uncertainties and form a fuzzy boundary layer to eliminate the chattering phenomenon in the sliding controller [41, 45, 69]. Meanwhile, a supervisory sliding mode controller can be embedded in the fuzzy controller for an improvement of robustness and stability [10, 11, 77]. The control target changes from tracking errors to the sliding surface function. As long as the control signal makes the sliding surface function be zero, the errors will gradually reach zero.

There are still some research gaps to be improved. The fuzzy logic faces the curse of dimensionality:



the number of rules increases exponentially with the number of input items [82]. The subjective fuzzy rule based on experience may bring heavy cognitive burden to the controller designer. Even if a neural network can be used to extract fuzzy rules, a large number of nodes may slow down the learning speed and make the algorithm fall into a local optimum. The design of advanced learning algorithms for neural networks is an attractive direction. Moreover, when the neural network is combined with the type-2 fuzzy logic, the existence of an additional type reduction process may affect the learning effect.

### 5.3 Optimization of control systems based on genetic algorithms

As a heuristic search technique, the genetic algorithm can cater to the characteristics of industrial control systems well and solve many optimization problems in industrial control systems. A common application lies in the parameter tuning of PID controllers [20, 68, 72, 99], since the conventional tuning method [105] is time-consuming and needs to measure the ultimate gain and the ultimate period of the plant (controlled object). Concretely, in [20], the PID gains to be optimized were assigned with value ranges and encoded as binary strings. The fitness function used for selection was formulated as per the system's requirements for response time, steady-state errors and stability. The results of simulations and comparisons turned out that the controllers based on genetic algorithms for parameter tuning have few overshoots and rising time. Even in a parameter tuning process that has been combined with fuzzy logic [68], the genetic algorithm is useful in adjusting control parameters to meet optimality criteria. Guo et al. [20] adopted the genetic algorithm to determine the parameters involved in membership functions when using a fuzzy controller, such as the mean and standard deviation in the Gaussian membership function. Given the membership functions regarding inputs and outputs, Zhang and Li [100] employed the genetic algorithm to obtain the optimal fuzzy rules that give the best control performance, such as reaching the desired state in a short time. The fuzzy rule table was converted into a one-dimensional sequence and treated as a chromosome. The question that this approach answered was what fuzzy rules are most effective when the desirable state of the controlled subject is certain.

The parameters of deep neural networks (usually more than two layers) are difficult to optimize by conventional gradient descent. In the neural controller using the feedforward and radial basis function neural networks, the genetic algorithm can replace the gradient descent method as a learning algorithm, to strive for an adaptive global optimization ability [42, 102]. Sometimes the local search ability of genetic algorithms does not meet the requirements and the convergence speed is slow, which leaves some suspense to improve the genetic algorithm in terms of the genetic manipulations or the fitness function.

The optimization characteristic of the genetic algorithm can also be reflected in the selection of optimal control actions, which was defined as a genetic algorithm controller [31, 78]. Initially, the genetic algorithm was only used as a minor compensatory tuner because of the instability of the algorithm, until Wai et al. [78] combined the robustness of the sliding mode control and the heuristic searching characteristic of the genetic algorithm. Further by virtue of the fuzzy logic [78] and the neural-fuzzy systems [31], the evolutionary directions and steps of the algorithm were stipulated for a strong stability.

### 5.4 Fault identification and correction methods for control systems

The fault identification and correction technologies lay a foundation for the fault-tolerant control [83] and are powerful in guaranteeing the reliability and safety of control systems. Especially in industrial control systems, the sensors and actuators are likely to fail due to tough operation conditions and long working hours. There exists a strong incentive to identify possible faults and compensate for their negative impacts on the control effect.

Regarding the fault identification, the signal-based method and model-based method have been frequently-used [44]. The former extracts fault features from the measured signals in the control process. Many neural network-based approaches have been used to implement this process. Yuan et al. [90] used a branch of the recurrent neural network, namely, the long short-term memory network, to identify the faults of an aero engine. This kind of neural network is capable of handling the long-term historical data including sensor values and operation records, and providing the probability

of fault occurrence under complex operation modes and hybrid degradations. Zhong et al. [104] designed a feature mapping method to expand the ability of the convolutional neural networks in fault identification under small sample condition. They extracted the feature representations for limited fault dataset by using the internal layers of the convolutional neural network trained as per the normal dataset. However, the soft fault, which has a strong impact on the system reliability but weak signs and slow evolutions, is a common failure mode in the industrial process [44]. The signal-based method using off-line samples has poor real-time performance, and thus is not competent for the soft fault identification. In this regard, the model-based method as an alternative was developed to monitor the errors between practical outputs and the outputs of the standard model [18]. Specific to the modeling of the standard model, Liu et al. [44] proposed a reliable method with little computing burden. Besides a routine mechanism model, a feedforward neural network was introduced as a correction model to take into account the uncertain features of the system. The network compensated the output errors of the mechanism model according to the sample inputs and outputs, which greatly improved the modeling accuracy. Then, a fault observer was developed based on the residuals between the practical outputs and the outputs of the standard mechanism-neural network model. A median exponential filtering method acting on the squared residuals equipped the observer with strong robustness to eliminate the disturbance of impulsive noises in measurement.

To compensate the negative effects of faults on control performance, Gao et al. [17] employed the radial basis function network to approximate the abnormal dynamics caused by actuator faults or disturbances, forming an adaptive reconfiguration mechanism. The idea of reconfiguration can also be applied in fuzzy controllers. Jia et al. [33] invented a learning observer for the Takagi-Sugeno fuzzy system to collect the reconstructed information about system states and actuator faults in the case of unavailable measurements. With the real-time information at hand, a state-feedback-based reconfigurable fuzzy controller was designed for fault correction. Similarly, after using a fuzzy observer to estimate unmeasured states, Tong et al. [73] utilized the backstepping technique to obtain the fault-tolerant control law, which could guarantee that the tracking errors of the controller converge to a small neighborhood of zero in the face of actuator faults and unmeasured states.

The internal mutual constraints in complex industrial control systems make the faults present new characteristics. To be specific, the faults in complex systems may be hierarchical, which complicates the information used for the fault identification. There may be propagation relations and correlations among different kinds of faults. Moreover, the fault identification process in a complex system has to deal with a large amount of operation data accumulated over a long period of time.

## 6 Applications of soft computing techniques in practical industrial control systems

This section focuses on practical applications of soft computing techniques in industrial control systems, which include but are not limited to transportation, intelligent machines, process industry, and energy engineering. The involved literatures are summarized in Table 2.

Table 2: The relevant practical applications involved in the review

References	Year	Methodologies	Achievements	Specific application	Fields
Liu et al. [45]	2017	FL; SMC	Controller	Flight control	
Liu et al. [44]	2021	NC	FI	Aero engine	
Yuan et al. [90]	2016	NC	FI	Aero engine	
Sardarmehni et al. [59]	2019	FL	Controller	Auto engine	
Yang et al. [89]	2010	FL; GA	Controller; optimization	Auto engine	Transportation
Gao et al. [17]	2015	NC	FI; FC	Train driving	
Meng et al. [50]	2014	FL; NC	Controller	Vessel driving	
Su et al. [65]	2020	FL	Controller	Air traffic control	
Jandaghian et al. [28]	2008	FL	Controller	Railway dispatching	
Wang and Hung [79]	2013	FL; NC	Controller	Missile navigation	
Teng et al. [69]	2020	FL; SMC; PIDC	Controller	Robotic operation	
Hacene and Mendil [21]	2019	FL	Controller	Robotic OA	Intelligent machines
Gu and Qiang [19]	2015	FL; NC; GA	Controller; optimization	Washing control	
Ariza-Zambrano et al. [5]	2020	NC	Controller	Vibration control	
Huang et al. [25]	2015	NC	FC	Mechanical FC	
Kataria and Singh [37]	2018	NC; PIDC	Soft sensor; controller	Distillation column	
Xie et al. [85]	2020	NC	Soft sensor	Iron removal process	Process industry
Wang et al. [80]	2018	FL	Controller	Waste fermentation	
Kondakci and Zhou [38]	2017	FL; NC; GA	Controller; optimization	Food processing	
Sun et al. [64]	2020	NC	FI	Chemical FI	
Sitharthan et al. [63]	2020	NC	Controller	Motor torque control	Energy engineering
Harzelli et al. [22]	2020	NC	FI	Motor torque control	
Arcos-Aviles et al. [4]	2018	FL	Controller	Residential microgrids	
Yang et al. [88]	2004	FL	Controller	Wind-solar system	
Lü et al. [46]	2020	GA	Optimization	Hybrid fuel cell	
Ahmed et al. [2]	2020	NC	Controller	Building heating	
Radziszewska-Zielina [57]	2011	FL	Controller	Partnership management	Other applications
Qin et al. [56]	2011	FL	Controller	Production planning	
Xing et al. [86]	2019	NC	Controller	Quality control	
Ho et al. [23]	2015	FL; GA	Controller; optimization	Inventory control	
Xibilia et al. [84]	2020	NC	Soft sensor	Environmental safety	

**Note.** FL denotes “fuzzy logic”; SMC denotes “sliding mode control”; NC denotes “neural computing”; GA denotes “genetic algorithm”; PIDC denotes “PID control”; OA denotes “obstacle avoidance”; FI denotes “fault identification”, FC denotes “fault correction”.

## 6.1 Transportation

In the field of transportation, control systems based on soft computing methods can work for specific transportation devices or an integrated dispatching system. First, we review the former in several subdivisions. The aviation industry is a typical subdivision that can be first considered here. The flight movement has nonlinear characteristics, and faces complex, uncertain and risky external environment. Liu et al. [45] embedded the fuzzy logic in a sliding mode controller to achieve the control system design about the longitudinal motion of a saucer-shaped aircraft. They used the outputs of the fuzzy controller to replace symbolic terms in the sliding mode controller. The simulation showed that the proposed method could track the attitude angle, smooth the control signal and weaken the chattering phenomenon in the original sliding mode controller. Some special working conditions faced by aviation devices involve great risks. For instance, Liu et al. [44] pointed out that the servo valve of a servo control system in aero engines may suffer from wear failure or leakage due to tough operating conditions. Thus, they used a feedforward neural network to help construct a standard model as a

benchmark for fault identifications. The learning ability of the neural network improved the modeling accuracy. A similar application can be found in [90], where a long short-term memory network was used to identify the faults of an aero engine and make preparations for the estimation of remaining useful life. The difference between the contributions in [44] and [90] is that the neural network in [90] was directly used for extracting fault features instead of establishing standard models.

There also exist related applications in the vehicle sector. Specific to devices, the control of the automotive internal combustion engine is a focus point. To strive for an excellent engine performance but little emission and fuel consumption, many key variables should be controlled, including engine speed, engine torque, spark ignition timing, fuel injection timing, air-fuel ratio, and so forth [40, 59, 89]. Sardarmehni et al. [59] proposed a fuzzy model predictive controller to reduce the pollution emission in a spark ignition internal combustion engine. The controlled variable was the amount of normalized air-fuel ratio in the engine. The engine system was identified by fuzzy modeling along with offline trainings. The final control signals were yielded by a gradient descent algorithm. In [89], to achieve proper regulation of different energy elements in a hybrid vehicle with both combustion engine and electric motor, a fuzzy controller integrated with the genetic algorithm was employed. The genetic algorithm optimized the parameters of membership functions in the fuzzy controller, with the whole cycle fuel consumption and emission being the fitness function. Since the autonomous driving is a hot research topic [98], the control about the vehicle traction and braking is also worth reviewing. In this regard, Gao et al. [17] studied the adaptive fault-tolerant control of the train driving, which might face nonlinear resistances, disturbances and actuator failures during the train movement. They employed the radial basis function neural network to approximate the above abnormal dynamics online, forming an adaptive reconfiguration mechanism. In this way, there was no need to manually adjust controller parameters as per various abnormal dynamics. The proposed feedback control laws can ensure that the train tracks a desirable speed-distance curve with errors converging to zero or small residual sets. Similar applications of driving control can be found in the vessel domain. Meng et al. [50] developed a fuzzy controller and a neural network controller respectively to construct a dynamic positioning system, which kept the vessels with active thrusters having correct positions and orientations for marine operations. The seaman's experience was used to directly construct fuzzy rules in the fuzzy controller, or indirectly train the network in the neural network controller. They [50] found the later had high positioning accuracy and good robustness.

Besides the applications in the above transportation devices, soft computing methods also facilitate the control of transportation-related dispatching systems. Su et al. [65] developed an automatic air traffic control system based on fuzzy logic, aiming at reducing the control decision time and avoiding further delays in aircraft approaching. Jandaghian et al. [28] designed two fuzzy controllers for railway transportation dispatching. One worked as an automatic driver to control individual trains, and the other acted as a dispatching role. Both controllers worked together to avoid disorderliness caused by delay or different train priorities. Wang and Hung [79] developed a missile guidance system by a fuzzy neural network controller, which can dispatch a defending missile to intercept an attacking missile in a complex air battle scenario full of uncertainties. The proposed controller is characterized by activated weights to perform path planning for the defending missile. The weights were updated by the Lyapunov stability constraints to maintain the stability of the path planning. The method obtained excellent guidance performances with easy design and little computation load.

## 6.2 Intelligent machines

This part focuses on the applications of soft computing techniques in intelligent machines. Here, the term "machines" refers to robots or mechanical devices used in daily life or industrial production. Unsurprisingly, the intelligent control of these machines is inseparable from the support of soft computing methods to acquire flexibility and adaptability. Teng et al. [69] presented a fuzzy sliding mode control strategy for an exoskeleton robot. This exoskeleton robot can assist people with neuromuscular dysfunction to carry out their daily activities. Because of the need for interactions between the exoskeleton robot and the human upper limb, the control may suffer from unmodeled dynamics, external disturbances and uncertainties. These problems could be well solved by a robust sliding controller, with the fuzzy logic eliminating the chattering. Teng et al. [69]'s control strategy

also involved a proportional-derivative control part to inherit its advantage in response speed. The control output included the trajectory planning of the automatic arm and the hand motion. Moreover, the obstacle avoidance control of robots is also a research hotspot and can be found in [21], where a fuzzy controller helped the robot track either static or dynamic target while avoiding either static or dynamic obstacles along its path.

Another impressive application of soft computing techniques is the intelligent control of the washing machine. In [19], a fuzzy controller as the main body, along with a neural network learning algorithm and a genetic algorithm, were used to control the washing time, strength, temperature and detergent amount according to the turbidity and material of clothes in the washing machine. The function of the neural network was to learn the parameters in membership functions, while the genetic algorithm was applied to optimize the weights in the network. The proposed method tolerated the uncertainties of input, and made full use of historical data.

When it comes to the control of mechanical devices, a common problem is how to keep the physical structure stable. The mechanical devices with stiffness, mass and damping are sensitive to the disturbance, and easy to present a vibration or a fault. In [5], to achieve an active vibration suppression for a cantilever plate model, a neural network was utilized to identify the inverse dynamics of the controlled device. Such an inverse identification was free of an accurate mathematical model, and could determine optimal control signals corresponding to the desired output. In [25], after the fault identification considering the friction issues in mechanical systems, a neural network was applied as a nonlinear approximator to approximate the fault function for fault correction. In this way, a fault-tolerant control strategy applied to mechanical systems was developed.

### 6.3 Process industry

For the control issues in process industry fields, like the chemical industry, bioprocess industry and steel industry, a core challenge is to effectively collect the process industry data for the subsequent process control and supervision. The complex characteristics of process industry data were summarized in [34], which include the presence of missing values, data co-linearity, drifting data, and data outliers. In light of this, not all key variables can be easily measured. The data-driven soft sensor that we have reviewed before is an effective approach to acquire process industry data. The neural network learning algorithm lays a foundation for the development of various soft sensors. Starting with an example about the chemical process, Kataria and Singh [37] used a soft sensor based on the recurrent neural network to estimate the bottoms product composition in a reactive distillation column involving an esterification reaction. The product concentration was controlled by a proportional-integral controller, and supervised online by the proposed soft sensor. The neural network was trained by the tray temperatures and corresponding product concentration, obtained from an open loop model of the distillation column. Back to the closed loop control process, the trained recurrent neural network was capable of handling sequential data and estimating the composition with small mean square errors. Furthermore, in an iron removal process, the outlet ferrous ion concentration in a desired range can be obtained by controlling the oxygen flow rate and zinc oxide additive rate. The measured oxygen amount does not represent the actual amount in the reaction. Therefore, Xie et al. [85] used an adaptive soft sensor with radial basis function neural network to estimate the oxygen reaction efficiency online. Their work is also characterized by a fuzzy logic compensator to cooperate with a steady-state optimal controller for excellent control signals.

Besides soft sensors, various controllers also have their application implications in the process industry. Wang et al. [80] designed a fuzzy controller to control the temperature during a vegetable waste fermentation process. As per the environment temperature and the fermentation heat from the vegetable waste, the controller adjusted the blender's rotation rate and the power of the heating devices. A highlight lied in the use of semi-tensor product matrices to convert fuzzy inference into simple matrix operations. Kondakci and Zhou [38] made a survey about the applications of advanced control technologies involving fuzzy controllers and neural network controllers in the food processing industry. There exist baking process, drying process, brewing process as well as dairy process in the food processing industry. Various raw materials and different processing conditions give rise to the complex process dynamics and the nonlinearities in the food processing process. Kondakci and Zhou



[38] pointed out that the integration of fuzzy and neural controllers may deliver a decent solution for the food processing control, bringing high food product quality and low production costs.

Moreover, Sun et al. [64] proposed a fault identification method using a Bayesian recurrent neural network, which is applicable to the control of general chemical process. The proposed method with uncertainty estimates allowed for real-time fault identification and fault propagation analysis in chemical processes.

## 6.4 Energy engineering

The applications of soft computing-based intelligent control technologies in the energy engineering are reviewed in two aspects, namely the control of specific devices like electric motors and converters, and the control of energy management systems like smart grids. The electric motor is a main device to convert electric energy into mechanical energy. The control of its torque has a huge impact on the operation efficiency and the use ratio of electric energy. Sitharthan et al. [63] presented an Elman neural network controller to mitigate torque ripples and ill harmonics in a permanent magnet synchronous motor. The controller adjusted the pulse width modulation to control the switching of an impedance source inverter. Compared with standard proportional-integral controllers, the proposed controller is characterized by the full use of modulation in the duty cycle. For the fault identification when controlling an induction motor, Harzelli et al. [22] applied a neural network with an elaborate training data set to replace a signal-based method, which can clarify the specific type of faults.

With regard to the control in energy management system, Arcos-Aviles et al. [4] utilized a fuzzy controller to smooth the grid power profile of a grid-connected residential microgrids. The controller adjusted the power delivered/absorbed by the mains as per the microgrid energy gradient and the remaining capacity of batteries, aiming at meeting ideal quality criteria of the grid power profile. Another aspect of the use of fuzzy controllers appears in the hybrid wind-solar power system [88]. According to the power datum of wind turbine, photovoltaic array and electric load, the controller allocated the generation ratio of wind and solar. Moreover, Lü et al. [46] made a review about the use of genetic algorithms in the control strategies related to energy management of the hybrid fuel cell power system. The purpose of control was to improve the energy utilization efficiency and extend the life of the fuel cell. They exemplified that the optimization capacities of genetic algorithms can be used not only in fuzzy controllers and neural network controllers, but also in developing optimal control strategies independently for energy management.

## 6.5 Other applications

The industrial control applications of soft computing methods can also be found in other industrial fields, like the construction industry and factory management. Ahmed et al. [2] used three types of neural networks to identify and control the heating system of a construction for reducing energy consumption and keeping comfortable indoor temperature. They considered a working office with complex nonlinearity under environment and occupant constraints. Considering three cases of the wall insulation, a supervisor based on a switching logic was designed to select the appropriate controller. Radziszewska-Zielina [57] proposed a fuzzy controller to help construction enterprises manage the relationships with other transactors such as equipment suppliers and subcontractors. The controller advised preserving or changing the partnering relations as per the relation parameters that have significant impacts on the operation of construction enterprises. As for the factory management, relevant approaches were put into practice in production planning [56], quality control [86], inventory control [23] and environmental safety control [84].

In a word, soft computing techniques have considerable application potential in industrial control systems. They can be found in nearly all cases that require a control design, whether about specific industrial devices like electric motors and vehicles, or some integrated industrial systems used for dispatching, energy management and factory management.



## 7 Lesson learnt from the survey and future prospects

Based on the above review and new industrial system features, we present remaining challenges and future research directions in regard to the industrial control applications of soft computing techniques:

1) While modern industrial systems pursue intelligence constantly, the control systems acting on them need to handle massive input items. In this case, if a fuzzy controller is used, the number of fuzzy rules will increase exponentially with the number of input items, which refers to the so-called curse of dimensionality [82]. In this regard, subjective rules based on experience or expertise of experts and the fuzzy inference calculation may become intractable and require heavy workloads. Besides, conflicts may arise among numerous rules. Some fuzzy rules may be incomplete and inconsistent. The interpretability of the fuzzy inference may be weakened. There have been limited research about these issues [80, 82], and, as far as we know, there is no method considering all these issues at the same time. This direction is worthy of future attention and research efforts.

2) The structure and algorithm of neural networks need to be constantly improved to facilitate industrial control applications. Following the preceding discussions, in the case of massive fuzzy rules in the fuzzy controller, besides making subjective rules, an objective way using the neural computing can extract fuzzy rules. However, a large number of neural network nodes due to massive rules may slow down the learning speed and make the algorithm fall into a local optimum. Moreover, regarding the fault identification and correction, a complex industrial process can accumulate a large amount of operation data over a long period of time. There may exist propagation relations and correlations among hierarchical faults. In these application scenarios, the neural network should be capable of coping with a large amount of data and highly correlated variables. It is necessary to flexibly adjust the structures and algorithms of neural networks according to actual needs.

3) Specific to the development of soft sensors, it often takes a lot of efforts from operators for the pre-processing of the sample data and the final verification. It is motivated to study how to move some manual development burden to the model. Moreover, the data drifts or other common changes in the industrial process may give rise to a gradual deterioration of the soft sensors' performance. However, there is often no objective measure for evaluating the quality levels of soft sensors. The above discussions illustrate the difficulty of soft sensor maintenance and can be taken as a motivation for future research.

4) In the industrial control process, various operation environments may require the merits of multiple controllers. For instance, in a flexible manufacturing cell, different operation modes are adopted as per the ever-changing personalized needs. Single control strategy in this context cannot guarantee the desirable performance. The combination of different control strategies, like the neural-fuzzy controllers, can cater the requirement to some extent. However, the design of the combination cannot allow for a flexible switch. A promising direction is to introduce a kind of multi-controller strategy with a switching logic to determine the appropriate controlling mode at different times. In [6], a fuzzy selector used the fuzzy logic to select which controller is dominant according to the control effect, which provides inspirations for the design of switching logic. This could be a good idea for future investigation.

## 8 Conclusions

Soft computing techniques can equip modern industry control systems with intelligence, including flexibility, adaptability, capacity for learning, reasoning, dealing with complex dynamics and managing uncertainties. This study presented a survey about the soft computing techniques and their industrial control applications. Followed by the theoretical introductions of fuzzy logic, neural computing and genetic algorithms, a bibliometric analysis of publications on industrial control systems involving soft computing techniques was presented to provide a bird's eye on the research status about industrial control systems involving soft computing techniques. Then, research challenges of intelligent industrial control and corresponding soft-computing-related achievements were reviewed. All-pervasive application cases showed the considerable potential of soft computing techniques in industrial control. Future research directions in regard to the industrial control applications of soft computing techniques were

provided for the reference of researchers and practitioners.

We should note that there exists a limitation of this study that the publications on the discussed field are so massive that an exhaustive coverage in this study is impossible. Perhaps many wonderful papers have been unfortunately missed. The keywords for the bibliometric analysis are not unique. However, we hope this study did reflect meaningful results for readers.

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## Author contributions. Conflict of interest

The authors contributed equally to this work. The authors declare no conflict of interest.

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