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Research on multi-objective optimal modeling of Civics teaching content based on Boolean algebra algorithm guided by Marxist theory

Huining Guo[1,*] and Fengfen Gao[2]
[1] Weinan Normal University, Weinan, Shaanxi, 714099, China
[2] Jianghan University, Wuhan, Hubei, 430010, China
Corresponding authors: (e-mail: hnguo82@163.com).

Abstract The purpose of Civics teaching is to enhance the ideological awareness of talents and better meet the needs of society for the cultivation of talents' thoughts. Based on this, the article takes Marxist theory as a guide, introduces Boolean network algebraization and multi-objective optimization ideas, and converts the optimization of Civics teaching content into a multi-objective optimization problem. Then the BiGRU-CRF model is utilized to identify the entities of Civics teaching content, and the entity relations are extracted by convolutional neural network, and then the Civics teaching content knowledge graph is established. Based on the knowledge map of Civics teaching content, a multi-objective fuzzy dynamic optimization network model of Civics teaching content is constructed by combining the Boolean network model and the fuzzy dynamic model. The SSA algorithm is optimized by MFO algorithm, and MC-SSA algorithm is established to solve the multi-objective fuzzy dynamic optimization network model. Simulation results show that the MC-SSA algorithm has high solving accuracy and the highest degree of proximity between its Pareto solution set and the real Pareto solution set, which can effectively solve the optimal results of the MFDBN model and provide guidance for the optimization of the Civics teaching content.

Index Terms Boolean network algebraization, Marxist theory, MC-SSA algorithm, Civics teaching content

I. Introduction

Globally, major universities have attached great importance to the ideological education, especially focusing on the close integration of theory and practice path, a trend that reflects the deep understanding of higher education institutions to cultivate well-rounded talents with a sense of social responsibility, innovative spirit and practical ability [1], [2]. Marxist thinking method is a cognitive mode of thinking and methodological system for recognizing things and transforming things, specifically including dialectical thinking, systematic thinking, historical thinking, practical thinking, subjective thinking and so on [3]. As a scientific epistemology and methodology, it provides strong theoretical support and practical guidance for the ideological education in colleges and universities [4]. Through the use of Marxist thinking methods, colleges and universities can better combine the theory and practice of Civic and Political Education, so as to improve the quality of teaching and cultivate more high-quality talents who meet the needs of social development [5]-[7]. With the development of the times, colleges and universities at home and abroad are committed to optimizing teaching methods and making adjustments to teaching measures in real time according to the development of the times, so as to adapt to the social demand for talents [8], [9]. In this context, it is particularly important to explore the method of optimizing the content of Civics teaching in colleges and universities under the guidance of Marxist theory.

Multi-objective optimization evaluation is a kind of assessment and selection that involves multiple objectives, by posing problems and establishing objectives, designing and selecting evaluation contents, carrying out numerical calculations and analyses, and forming an evaluation scheme that achieves the optimal solution in the comprehensive dimension [10]. Applying it to the design of the teaching content of Civics, it can provide feedback on the effectiveness of the implementation of curriculum Civics in the evaluation object based on the degree of coupling and coordination between Marxist theory and Civics education [11], [12]. Based on the evaluation model index factor refinement analysis of the intrinsic causes affecting the effectiveness of educating people, dynamically adjust the professional teaching organization, improve the relevance of the coupling and coordination of course Civics and politics to educate people, and optimize the cultivation mode of the new technical and skilled talents [13]-[15].

This paper proposes a multi-objective optimal modeling method for Civics teaching content based on Boolean network algebraization, which is mainly guided by Marxist theory and combines the ideas of multi-objective optimization and fuzzy dynamic model. Before establishing the optimization model, this paper utilizes BiGRU-CRF model and convolutional neural network to carry out entity identification and relationship extraction of Civics teaching content, and in this way constructs the knowledge graph of Civics teaching content. In this paper, we optimize the Bottle Sea Sheath algorithm by the Moth Flame algorithm and design the MC-SSA algorithm to solve the optimal model. The effectiveness of the algorithm and model is analyzed through simulation experiments, and a specific optimization strategy for Civics teaching content is proposed.

II. Conceptualization and rationale

Civic and political teaching in the new era is constantly evolving, and under the guidance of Marxist theory, the content of civic and political education further highlights the orientation of practical teaching, and it is more conducive to the development of civic and political practical teaching by fully exploring all kinds of resources at all levels and constructing the content system of practical teaching. The construction and optimization of the content system of Civic and Political teaching should adhere to the principles of integration, systematicity and uniqueness, improve the precise, structured and informative Civic and Political practical teaching content system, and adhere to the omni-directional, dynamic and high-quality optimization of the path.

II. A. Definition of relevant concepts

II. A. 1) Marxist theory

Marxism has always regarded the problem of human beings as its core issue, and Marx pointed out that “the first premise of all human history is undoubtedly the existence of living individuals.” The concern of Marxism's anthropological theory for the “real human being” provides a more precise guiding direction for the ideological and political education of college students in the new era. To study the problem of human beings from the perspective of needs, that is, to grasp the basic attributes of “human beings”, i.e., the nature and value of human beings.

On the one hand, the needs of human beings are actually their intrinsic nature. Marx clarified that human needs are not only the determinants of the inner nature of human beings, but also the basis and driving force of all human life activities, as well as the driving force that forms the basis of human and various social relations. Human needs not only reflect the relationship between human beings and society, but also reveal the nature of human beings, and these needs drive the progress of practical activities and further promote the development of social and productive practices through the continuous fulfillment of individual needs [16].

On the other hand, the comprehensive development of man is both a historical category and a realistic goal, and it is the starting point and destination of ideological and political education. Marx's view on the comprehensive development of man provides a more precise core value for the ideological and political education of college students in the new era. The theory of comprehensive human development scientifically reveals the inherent law of comprehensive human development, and Marx believed that in order to comprehensively understand the development of human beings, we need to start from multiple perspectives, including not only the most basic needs for survival, but also, more importantly, the enjoyment of human beings as well as the need for development.

The core goal of promoting the precise content of ideological and political education for college students in the new era is to promote the free and all-round growth of college students. Therefore, when carrying out ideological and political education, colleges and universities should pay attention to exploring the inner potential of college students, improving their personal qualities, cultivating comprehensive skills, and meeting the needs of individualized development.

II. A. 2) Content of Civics Teaching

In the teaching process of ideological and political theory in colleges and universities, the teaching content plays a crucial role in the teaching effect of the ideological and political courses. In order to better promote the reform and innovation of the ideological and political theory course, it is necessary to constantly improve the ideological, theoretical and affinity and relevance of the ideological and political course. Adhere to the unity of politics and rationality, guide students with thorough doctrinal analysis, educate students with thorough ideological theories, and guide students with the powerful force of truth. Adhere to the unity of value and knowledge, and put value guidance in the teaching of knowledge. Adhere to the unity of constructive and critical, strengthen the mainstream ideology, criticize all kinds of erroneous views and trends of thought, fully embodies the rich content of ideological and political teaching on its scientific, targeted, and contemporary requirements [17].

The key to the success of the Party's ideological and political education is “unremittingly spreading Marxist theory, grasping Marxist theory education, laying a scientific ideological foundation for the growth of students throughout their lives.” When enriching and developing the teaching content of ideological and political theory courses in colleges and universities, always adhere to the theoretical achievements of Marxism and the Chineseization of

Marxism as the guide, to ensure its core role and guiding role in the content system. In teaching practice, taking Marxist theory as an important content of the teaching of ideological and political theory courses in colleges and universities, it is necessary to strengthen the role of Marxism in influencing the three views of young students.

II. B. Relevant theoretical foundations

II. B. 1) Boolean network algebraization

A Boolean network model consists mainly of a set of nodes $\{X_1, X_2, \cdots, X_n\}$ and a column of Boolean functions $\{g_1, g_2, \cdots, g_n\}$. Here, variable $X_i \in D$ is a Boolean variable whose state at the next moment depends only on its neighboring node $X_{k_1(i)}, X_{k_2(i)}, X_{k_j(i)}$, viz:

$$X_i(t+1) = g_i\left(X_{k_1(i)}(t), X_{k_2(i)}(t), \cdots, X_{k_j(i)}(t)\right) \tag{1}$$

Thus, we can rewrite the above equation as:

$$\begin{cases} X_1(t+1) = g_1\left(X_1(t), X_2(t), \cdots, x_n(t)\right) \\ X_2(t+1) = g_2\left(X_1(t), X_2(t), \cdots, x_n(t)\right) \\ \cdots \\ X_n(t+1) = g_n\left(X_1(t), X_2(t), \cdots, x_n(t)\right) \end{cases} \tag{2}$$

Suppose $f : D^n \to D$ is a Boolean function. Then, there exists a unique matrix $G_f \in \mathrm{L}_{2\times 2^n}$ such that f can be rewritten as:

$$f\left(x_1, \cdots, x_n\right) = G_f \,\text{â}_{i=1}^{n}\, x_i \tag{3}$$

Here G_f is called the structure matrix of the above equation.

Further, x_i is used to denote the vector form of the logic variable X_i, and so Eq. (2) can be rewritten as:

$$\begin{cases} x_1(t+1) = G_1 \,\text{â}_{i=1}^{n}\, x_i(t) \\ x_2(t+1) = G_2 \,\text{â}_{i=1}^{n}\, x_i(t) \\ \cdots \\ x_n(t+1) = G_n \,\text{â}_{i=1}^{n}\, x_i(t) \end{cases} \tag{4}$$

Here, $G_i\left(i \in [1,n]\right)$ denotes the structure matrix of the logistic function g_i.

Suppose $M \in R^{p\times n}$ and $N \in R^{q\times n}$ are two matrices with the same number of columns and the Khatri-Rao product between them is defined as:

$$M * N = \left[col_1(M)\text{â}\ col_1(N) col_2(M)\text{â}\ col_2(N) \cdots col_n(M)\text{â}\ col_n(N)\right] \tag{5}$$

Here $col_i(M)$ and $col_i(N)$ denote the i th column of matrices M and N, $i \in \left[1,n\right]$ respectively.

The algebraic expression for the system (2) can be obtained as:

$$x(t+1) = Gx(t) \tag{6}$$

Here $G = G_1 * G_2 * \cdots * G_n$, $G \in \mathrm{L}_{2^n\times 2^n}$ denote the state transfer matrix of system (2).

Since in general, the evolution result of system (2) may not meet the realistic requirements, it is usually necessary to add control inputs to system (2) to make the evolution result of the system reach the desired goal [18]. A common expression for a logic system with state inputs is:

$$\begin{cases} x_1(t+1) = \overline{g}_1\left(u_1(t), \cdots, u_m(t), x_1(t), x_2(t), \cdots, x_n(t)\right) \\ x_2(t+1) = \overline{g}_2\left(u_1(t), \cdots, u_m(t), x_1(t), x_2(t), \cdots, x_n(t)\right) \\ \cdots \\ x_n(t+1) = \overline{g}_n\left(u_1(t), \cdots, u_m(t), x_1(t), x_2(t), \cdots, x_n(t)\right) \end{cases} \tag{7}$$

Equation (7) can be rewritten as:

$$\begin{cases} x_1(t+1) = \bar{G}_1 \hat{a}_{i=1}^{m} u_i(t) \hat{a}_{i=1}^{n} x_i(t) \\ x_2(t+1) = \bar{G}_2 \hat{a}_{i=1}^{m} u_i(t) \hat{a}_{i=1}^{n} x_i(t) \\ \cdots \\ x_n(t+1) = \bar{G}_n \hat{a}_{i=1}^{m} u_i(t) \hat{a}_{i=1}^{n} x_i(t) \end{cases} \tag{8}$$

Here $\bar{G}_i \in \mathrm{L}_{2\times 2^{m+n}}$ denotes the structure matrix of the logistic function $\bar{g}_i$.

Assuming $u(t) = \hat{a}_{i=1}^{m} u_i(t)$, $x(t) = \hat{a}_{i=1}^{n} x_i(t)$, the algebraic expression for the system (7) can be obtained as:

$$x_{t+1} = \bar{G}u(t)x(t) \tag{9}$$

Here $\bar{G} = \bar{G}_1 * \bar{G}_2 * \cdots * \bar{G}_n$, $\bar{G} \in \mathrm{L}_{2^n \times 2^{m+n_o}}$.

II. B. 2) Multi-objective optimization problems

Multi-objective optimization problems (MOPs) refer to the existence of multiple objectives in a real problem, which may be in conflict or contradiction with each other, which makes it difficult to find the solution set in the space, and it is also impossible to make multiple objectives optimal at the same time, and in the process of optimizing one objective, the other objectives tend to be degraded [19].

Taking minimization of MOPs as an example, the model of the optimization problem with n-dimensional decision variables and $k(k \ge 2)$ objectives is expressed as follows:

$$\min_{x \in R^n} F(x) = \left(f_1(x), \cdots, f_k(x)\right)^T \tag{10}$$

$$s.t. \begin{cases} q_i(x) \ge 0, i = 1, \cdots, s \\ p_j(x) = 0, j = 1, \cdots, l \end{cases} \tag{11}$$

where R^n is the n-dimensional decision space, $q(x)$ and $p(x)$ denote the inequality and equation constraint functions, respectively, $F(x) = \left(f_1(x), \cdots, f_k(x)\right)^T \subseteq R^k$ is the objective function of MOPs, and R^k denotes the objective space.

Pareto domination. Suppose x_1, x_2 are two decision variables of MOPs, and x_1 is said to dominate x_2 (denoted as $x_1 \prec x_2$) if for any $i \in \{1, \cdots, k\}$ such that $f_j\left(x_1\right) \le f_i\left(x_2\right)$ and there exists some $j \in \{1, \cdots, k\}$ such that $f_j\left(x_1\right) < f_i\left(x_2\right)$, where x_1 denotes the non-dominated solution.

Pareto optimal or non-dominated solution. In the decision space R^n, a solution is said $x^* \in R^n$ to be Pareto optimal if no other solution x can be found to dominate x^*.

Pareto Optimal Solution Set. The set consisting of all Pareto-optimal solutions is called the Pareto-optimal solution set (PS), denoted as $PS = \left\{x \in R^n : \text{There exists no } y \in R^n \text{ such that } y \prec x\right\}$.

Pareto Frontier. The set of vectors obtained by mapping the decision variable x^* in the PS to the target vector space is called the Pareto frontier (PF), denoted $PF = \{F(x) : x \in PS\}$.

And one of the purposes of studying MOPs is to algorithmically solve their PFs and select results from them that measure the true PFs for presentation. Usually, each Pareto solution in the PF cannot be found out one by one, therefore, when solving the real problem, only the estimate of the true PF is found by the algorithm. If the distance between the estimate and the real PF is smaller, it indicates that the algorithm solves this MOPs better and close to the ideal state. At the same time, if the estimate of PF found by the algorithm is more dispersed and uniformly distributed, it indicates that the dispersion and uniformity of the algorithm's effect of finding the ideal is better.

III. Multi-Objective Optimization Modeling of Civics Teaching Content

Strengthening and improving ideological and political education in schools and establishing a systematic mechanism for educating people in a holistic, holistic and all-round way. This is a brand-new requirement for ideological and political education in the new era, which is reflected in the overall synergy, systematic scientificity and realistic relevance of curriculum construction. This chapter combines the knowledge map of the ideological and political teaching content with the Boolean network model, establishes a multi-objective fuzzy dynamic model of the ideological and political teaching content, and solves it by using the improved Bottle Sea Sheath Algorithm, in order to better realize the goal of the ideological and political teaching.

III. A. Knowledge Mapping of Civics Teaching Content

III. A. 1) Teaching content entity identification

In entity extraction, the labeled Civics teaching content text is divided into a training set and a validation set, which are used as inputs to the deep learning neural network. Since the text data of Civics teaching content often has more entries, this paper adopts BiGRU+CRF based on Chinese pre-trained word vectors as the deep learning model, which improves the accuracy of entity extraction of Civics teaching content through a large amount of pre-trained data.

BiGRU is a classical recurrent neural network (RNN), which consists of a gated recurrent unit (GRU) neural network with two layers of forward and backward independent of each other.GRU introduces an update gate and a reset gate on the basis of RNN, in which the update gate is responsible for determining the updating time of the hidden state, and the reset gate is responsible for determining the time when the past information affects the current hidden state.GRU can effectively solve the problem of long term memory and the gradient problem in backpropagation, and it is able to recognize long sequences of features as well as the Long Short-Term Memory (LSTM) neural network, and it has higher training efficiency compared with LSTM.

For input sequence $x = x_1, x_2, \ldots, x_T$, the forward computation of BiGRU can be expressed as:

$$\vec{h}_t = GRU\left(\vec{h}_{t-1}, x_t\right) \tag{12}$$

$$\overleftarrow{h_t} = GRU\left(\overleftarrow{h}_{t+1}, x_t\right) \tag{13}$$

where $\vec{h}_t$ and $\overleftarrow{h}_t$ denote the left-to-right and right-to-left hidden states, respectively, x_t denotes the t th element of the input sequence x , and GRU denotes the unit network model.

Splice the hidden states of the 2 directions together, the overall hidden state of the network can be obtained as:

$$h_t = \left(\overleftarrow{h}_t, \vec{h}_t\right) \tag{14}$$

Passing the hidden state to the fully connected layer yields:

$$y = soft\max\left(Wh + b\right) \tag{15}$$

where y is the output vector of the BiGRU network, W and b are the weight matrix of the fully connected layer, the bias vector, and SoftMax is the activation function, respectively.

The output of the BiGRU layer is the input of the CRF layer.CRF is essentially an undirected probability map. For input value x and output state y , the relationship between input, output of CRF model is:

$$P(y \mid x) = \frac{1}{Z(x)} \exp\left[\sum_t \sum_k \lambda_k m_k\left(y_{t-1}, y_t, x, t\right) + \sum_t \sum_l \mu_l s_l\left(y_t, x, t\right)\right] \tag{16}$$

$$Z(x) = \sum_y \exp\left[\sum_t \sum_k \lambda_k m_k\left(y_{t-1}, y_t, x, t\right) + \sum_t \sum_l \mu_l s_l\left(y_t, x, t\right)\right] \tag{17}$$

where m_k is the transfer feature function, s_l is the state feature function, λ_k and μ_l are the weights of the corresponding feature functions, and $Z(x)$ is the normalization factor.

The state feature of Conditional Random Field (CRF) represents the relationship between the input sequence and the current state, and the transfer feature represents the relationship between the previous output state and the current state. It can be seen that CRF not only considers the correspondence between inputs and outputs, but also the correlation between the outputs of neighboring moments. When CRF is used in combination with deep neural network, the state features can be obtained by deep neural network learning, and CRF mainly focuses on transfer features.

III. A. 2) Extraction of pedagogical content relations

Entity-relationship extraction is to obtain the entity-relationship ternary composed of head entity, tail entity, and relationship from the sentence, and input the recognized sentence entities of Civics teaching content text into the entity-relationship extraction module based on convolutional neural network. Then the feature map is obtained through the convolution operation of the convolutional layer, and then the feature map obtained by the convolutional layer is optimized through the pooling layer to obtain the corresponding feature mapping map, in which two layers of convolutional layer and pooling layer are set up respectively, and finally the entity relationship extraction results of the Civics and Political Science teaching content are obtained through the fully connected layer.

The feature map k_l output by the feature processing of convolutional layer is expressed as:

$$k_l = \tanh\left(e_v \cdot score^v\left(\theta, j_o^R\right)\right) \tag{18}$$

where e_v denotes the weights and maximum pool sampling is performed in the pooling layer to further obtain useful local feature information in the convolutional layer $A(o)$, which is expressed as Eq:

$$A(o) = \max_{l=1,2,\cdots,L}\left\{k_l(o)\right\} \tag{19}$$

The quintuple $\theta = \left(c; M; E_1; E_2; E_3\right)$ representing the relationship classification parameters is chosen as the parameters of the convolutional neural network, where c represents the input text, M represents the network structure, and E_1, E_2, and E_3 represent the weight parameters of the network. Finally, the output probability distribution result $A(o \mid c, \theta)$ is obtained, i.e., the entity relationship extraction result is:

$$A(o \mid c, \theta) = \frac{e^{p_k}}{\sum_{l=1}^{n} e^{p_l}} \tag{20}$$

where e^{pk}, e^{pl} denote the weights of the k rd and l th components containing relation p respectively, and n denotes the number of all relations classified.

The convolutional neural network is trained to optimize the relationship classification parameters θ of the neural network, and the parameters of the network are gradually adjusted to a more accurate state by optimizing the network, so that the network can better identify and extract the entity relationships in the text. The optimization of the relationship classification parameters θ can be achieved by using stochastic gradient descent method to obtain the maximum log-likelihood value of the parameters, and the log-likelihood value $K(\theta)$ of the parameters can be obtained for the entity training data pair (c, u) in a sentence:

$$K(\theta) = \sum_{c=1}^{Y} \log p(u \mid c, \theta) \tag{21}$$

Maximize the log-likelihood by stochastic gradient descent and update the network parameters θ:

$$\theta' = \theta + \mu \frac{\partial \log p\left(u \middle| c, \theta\right)}{K(\theta)} \tag{22}$$

where μ denotes the relationship index and ∂ denotes the bias rate.

Using the continuous optimization of the convolutional neural network parameter θ, the best output probability distribution results can be obtained, realizing the entity relationship extraction of the text of the Civics teaching content.

III. A. 3) Pedagogical content knowledge mapping

The construction process of Civics Teaching Content Knowledge Mapping is shown in Figure 1. The establishment of Civics Teaching Content Knowledge Mapping involves several processes, such as ontology establishment, knowledge extraction, knowledge storage, and the implementation of visualization system. However, there is no unified solution, so it is necessary to select the most suitable solution for a specific area. In this paper, based on the characteristics of the topic of Civics and the design principle of knowledge graph, a visualization system based on knowledge graph is gradually established.

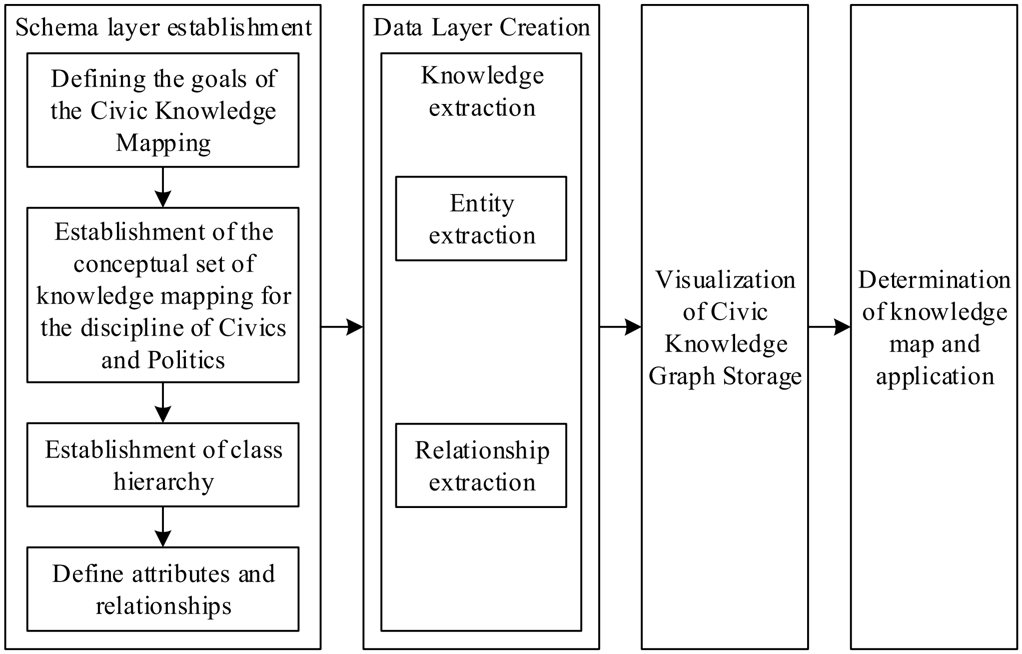


Figure 1: Knowledge graph construction process of ideological and political courses

In order to ensure the quality of Civics Teaching Content Knowledge Mapping, the data constructed in this paper are mainly from the following sources:

(1) Policy documents and cultivation programs of colleges and universities. Policy documents and cultivation programs are normative documents on politics, economy, culture and other aspects formulated by governmental agencies and schools for students in colleges and universities, which contain a certain amount of knowledge and learning requirements of Civics courses.

(2) Civic and political course materials and course syllabus. In colleges and universities, the Civic and Political Science course is a compulsory course, and the corresponding teaching materials and course syllabus contain a large amount of knowledge about the Civic and Political Science course.

(3) Social media and the Internet. With the popularization of social media and the Internet, more and more people begin to discuss and share content about politics, society, culture and other aspects on these platforms, which also include a certain amount of knowledge about the Civic and Political courses.

The original data text of the experimental corpus of the naming entity recognition task of the ideological and political teaching content is the unstructured data in the field of ideology and politics in the form of pure text crawled by using the Scrapy crawler technical framework and manual extraction, and crawling in the pure text form of the biography of famous ideological and political figures in Baidu Encyclopedia. The BIO sequence annotation paradigm is used for Chinese word segmentation, so as to ensure the effectiveness of the naming entity recognition of ideological and political teaching content and the feasibility of entity relationship extraction, and better ensure the integrity of the knowledge graph of ideological and political teaching content.

III. B. Multi-objective modeling of Civics teaching content

III. B. 1) Boolean network model

A Boolean network $G(V,F)$ is a discrete-time nonlinear dynamical system that consists of a set of Boolean nodes $V=\{x_1,x_2,\cdots,x_n,\cdots,x_N\}$ and a set of Boolean functions $F=\{f_1,f_2,\cdots,f_n,\cdots,f_N\}$. In a Boolean network, each node has only one state (0 or 1) at a point in time, where 0 means that the node's state is off (not represented) and 1 means that the node's state is on (represented). The Boolean network model can be represented as:

$$\begin{cases} x_1(t+1) = f_1\left(x_{1_1}(t), x_{1_2}(t), \cdots, x_{1_{K_1}}(t)\right) \\ \vdots \\ x_n(t+1) = f_n\left(x_{n_1}(t), x_{n_2}(t), \cdots, x_{n_{K_n}}(t)\right) \\ \vdots \\ x_N(t+1) = f_N\left(x_{N_1}(t), x_{N_2}(t), \cdots, x_{N_{K_N}}(t)\right) \end{cases} \tag{23}$$

where f_n represents the Boolean function of the n nd node x_n, and $x_n(t+1)$ is the state of node x_n at point in time $t+1$. x_{n_j} represents the j th regulating node of the target node x_n, where $j \in \{1, 2, \cdots, K_n\}$ and $n_j \in \{1, 2, \cdots, N\}$, meanwhile, K_n represents x_n the number of regulating nodes, usually called the connectivity degree of the node x_n, as a positive integer less than N. Define $K = \max\{K_n\}(n = 1, \cdots, N)$ as the maximum degree of connectivity of the Boolean network.

Suppose that there is a set of time series data $D = [x(1), \cdots, x(\rho)] \in \square^{n \times \rho}$ containing ρ time points (moments) that contain information about the state transfer from moment $t = 1$ to $t = \rho$ that Boolean network. In particular, certain state transfers are characterized by periodicity, and when the Boolean network enters these states from any state it will fall into the corresponding cycle, so it is called attractor. An attractor can be regarded as a steady state or an oscillatory state of a Boolean network, and its concept is defined as follows: for a Boolean network (23), a state $x(t), x(t+1), \cdots, x(t+T-1)$ is an attractor if it satisfies $x(t+T) = x(t)$, $x(t+i) \neq x(t)$, and $i \in [1, T-1]$, and the attractor cycle is T.

A related study states that the probability distribution $P_\gamma(k)$ of the connectivity k of any node in a Boolean network containing N nodes satisfies the following law:

$$P_\gamma(k) = \frac{k^{-\gamma}}{\zeta(\gamma, N)}, k = 1, 2, \cdots, N \tag{24}$$

where γ is a scale-free index, and typically $\gamma \in (2,3)$, $\zeta(\gamma, N)$ is an incomplete Riemann zeta function and satisfies $\zeta(\gamma, N) = \sum_{k=1}^{N} k^{-\gamma}$.

For a Boolean network containing N nodes, one has a total of 2^N network states. These states and the allowed transfers between them form the state transfer graph of the system. The larger the number of nodes, the more complex its state transfer. Compared with the content of Civics teaching, it can be converted into a Boolean network model, that is, the goal of Civics teaching also follows the students' learning progress dynamically, and the more diversified the content of Civics teaching is, the more complex the students' learning state is.

III. B. 2) Optimized network system

Supported by the knowledge map of Civics teaching content and combined with the basic form of Boolean network model, this paper proposes a multi-objective fuzzy dynamic network model (MFDBN) of Civics teaching content by using the mathematical tool of matrix semi-tensor product as well as the fuzzy dynamic model. The objectives of the Civics teaching content are diversified and its inputs are relatively many, thus, a nonlinear MFDBN with multiple inputs and multiple outputs can be expressed as:

$$\begin{gathered} R^k : if\ z_1\ is\ F_1^k and \cdots z_i\ is\ F_i^k \cdots z_n\ is\ F_n^k \\ then \begin{cases} x(t+1) = L_k u(t) x(t) \\ y(t) = H_k x(t) \end{cases} \\ i = 1, \cdots, n; k = 1, \cdots, N \end{gathered} \tag{25}$$

The short version is:

$$\begin{aligned} & R^k : if\ z_1\ is\ F_1^k and \cdots z_i\ is\ F_i^k \cdots z_n\ is F_n^k \\ & then\ LM_k = \left[\mu_k(z), \left(L_k, H_k\right)\right] \\ & i = 1, \cdots, n; k = 1, \cdots, N \end{aligned} \tag{26}$$

Here, R^k, $k=1,\cdots,N$ are the k rd fuzzy rules of the system, also known as the k th fuzzy subsystem, N is the total number of fuzzy rules, $z_1,\cdots z_n$ is the linguistic variables of the rule antecedents, F_i^k is the i th fuzzy set of the k th fuzzy rule, F_i denotes the i th fuzzy set of the whole system, $y(t)$ is the output variables of the system, $u(t)$ is the control variables of the system, and (L_k,H_k) is the structure matrix of the fuzzy antecedent portion of the system of the k th rule where L_k is the structure matrix of the state variables and H_k is the structure matrix of the output variables.

Let $\mu_{F_1^k}$ denote the affiliation function of z_i on the fuzzy subset F_i^k. For a given input signal $z_1=z_1^*,z_2=z_2^*,\cdots,z_n=z_n^*$, the corresponding affiliation function is selected to fuzzify it according to the actual situation, and the max-min method is used for the activation of each rule $\mu_k(z)$, then:

$$\begin{cases}\mu_1(z)=\mu_{F_1^1}\left(z_1^*\right)\wedge\mu_{F_2^1}\left(z_2^*\right)\cdots\wedge\mu_{F_n^1}\left(z_n^*\right)\\ \vdots\\ \mu_k(z)=\mu_{F_1^k}\left(z_1^*\right)\wedge\mu_{F_2^k}\left(z_2^*\right)\cdots\wedge\mu_{F_n^k}\left(z_n^*\right)\\ \vdots\\ \mu_N(z)=\mu_{F_1^N}\left(z_1^*\right)\wedge\mu_{F_2^N}\left(z_2^*\right)\cdots\wedge\mu_{F_n^N}\left(z_n^*\right)\end{cases} \tag{27}$$

That is, the affiliation function of the k st fuzzy rule of MFDBN is:

$$\mu_k(z)=\mu_{F_1^k}\left(z_1^*\right)\wedge\cdots\mu_{F_i^k}\left(z_i^*\right)\cdots\wedge\mu_{F_n^k}\left(z_n^*\right) \tag{28}$$

And there is:

$$0\le\mu_k(z)\le 1,\sum_{k=1}^{N}\mu_k(z)=1 \tag{29}$$

(1) Define the posterior expression of each fuzzy rule of MFDBN as the k st local model of MFDBN, then:

$$FDBNMLM_k=\left[\mu_k(z),\left(L_k,H_k\right)\right] \tag{30}$$

(2) After defuzzification, fuzzy inference by taking large and small method, and defuzzification by weighted average method, the global model of MFDBN can be obtained as:

$$\begin{cases}x(t+1)=Lu(t)x(t)\\ y(t)=Hx(t)\end{cases} \tag{31}$$

The MFDBN fully localized model is abbreviated as:

$$MFDBN=\left[\mu(z),(L,H)\right] \tag{32}$$

where (L_k,H_k) is the structure matrix of the k nd local model of the MFDBN, (L_k,H_k) is also referred to as the k th subsystem of the MFDBN, $\mu_k(z)$ is the activation degree of the sub-model $MFDBN_k$ corresponding to each rule, and $L=\sum_{k=1}^{N}\mu(z)L_k$, $H=\sum_{k=1}^{N}\mu(z)H_k$, $\mu(z)=\mu_1(z)\vee\cdots\mu_k(z)\cdots\vee\mu_N(z)$, (L,H) are the structure matrices of the MFDBN in a global sense.

III. C. MC-SSA multi-objective optimization algorithm

III. C. 1) Bottle Sheath Optimization Algorithm

The Taruhya is a transparent barrel-shaped marine animal similar to a jellyfish, and populations of Taruhya are usually connected in chains and follow a leader. The leader of the chain has the best environmental sensing ability and is called the leader, while the rest are regarded as followers. The Bottlenose Sea Sheath Swarm Algorithm (SSA) exhibits a more rigorous and orderly hierarchical structure, which significantly enhances the global search ability of the group, and can effectively prevent local optimal traps due to the leader's insufficiency in the initial search [20]. The specific realization process is as follows:

Step1 Initialize the Bottlenose Sea Sheath population. To simulate the feeding behavior of the bottlenose sea squirt population, a $V \times B$ -dimensional Euclidean space is set as the feeding space, where V is the population size of the bottlenose sea squirt and B is the number of dimensions of the space. The food location is denoted as $P = [P_1, P_2, \ldots, P_B]$, and the bottlenose sea squirts are located at $D_n = [D_{n1}, D_{n2}, \ldots, D_{nB}]^T$ and $n = 1, 2, \ldots, V$. In order to limit the search range, the upper bound of the search is set at $Ub = [Ub_1, Ub_2, \ldots, Ub_b]^T$, and the lower bound of the search is set at $Lb = [Lb_1, Lb_2, \ldots, Lb_B]^T$. The initial population of bottlenose sea squirts is randomly generated at the beginning of the simulation. The initial population of Taru Ascidia was randomly generated at the beginning of the simulation:

$$D_{V \times B} = rand(V \times B) \times (Ub - Lb) \tag{33}$$

Step2 Update the leader space location. I.e:

$$D_e^1 = \begin{Bmatrix} P_e + c_1\left((Ub_e - Lb_c)c_2 + Lb_e\right), c_3 \geq 0.5 \\ P_e - c_1\left((Ub_e - Lb_c)c_2 + Lb_e\right), c_3 < 0.5 \end{Bmatrix} \tag{34}$$

where the leader is D^{1e}, the follower is D^{ie} ($e = 1, 2, \ldots$, the spatial position of the individual Taruheus is B, $i = 1, 2, 3, \ldots$, and the follower within the population is V), and c_2 and c_3 together determine the direction of the Taruheus' movement in the search space and the step size. In order to improve the randomness of the leader in the moving process and avoid premature convergence of the algorithm, random numbers c_2 and c_3 are selected on $[0,1]$, and the convergence factor c_1 is expressed as:

$$c_1 = 2e^{-(4l/l_{\max})^2} \tag{35}$$

In the formula, the convergence factor c_1 is a function decreasing from 2 to 0. The current iteration number is denoted by l and the maximum iteration number is denoted by $l_{\max}$, which is used to balance the algorithm's global exploration and local search capability.

Step3 Update the follower space position. Namely:

$$D_e^i = 1/2\left(D_e^i + D_e^{i-1}\right) \tag{36}$$

III. C. 2) Moth Flame Optimization Algorithm

Moth Flame Optimization Algorithm (MFO) is a novel swarm intelligence optimization algorithm based on the navigation mechanism of moths during flight in simulating the spiral flight path of moths [21]. The principle is that the moth updates its position according to the flame, and when it is far away from the flame, the moth adopts a straight flight. When approaching the flame, the moth will fly in a spiral path around the light source, and the moth will search for the brightest light source by moving step by step.

The two central factors in the Moth Flame algorithm are the moth and the flame, denoted by M for the moth factor, M takes the value of the solution of the problem, extended to a multidimensional space, and M can be represented by a matrix:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,d} \\ m_{2,1} & m_{2,1} & \cdots & m_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n,1} & m_{n,1} & \cdots & m_{n,d} \end{bmatrix} \tag{37}$$

Where n represents the number of moths and d represents the dimension size, i.e. the number of control variables to be solved.

The fitness values of the moths are stored in a n-dimensional array OM, and the fitness value of the i th moth is OM_i. Array OM is represented as follows:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \tag{38}$$

The positional parameters of each moth are brought into the corresponding fitness function to solve for it, and the result obtained is the fitness of that moth, and the fitness array OM is formed by putting all the fitnesses of all the moths together.

With the above description, the flame population and the moth population have the same dimension, and the flame is represented by F. The matrix of the flame population is:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & F_{1,d} \\ F_{2,1} & F_{2,1} & \cdots & F_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ F_{n,1} & F_{n,1} & \cdots & F_{n,d} \end{bmatrix} \tag{39}$$

where n represents the number of flames and d represents the dimension size, i.e., the number of control variables to be solved.

The M and F matrices have the same number of elements. The fitness values of the flames are also stored in the associated arrays, the i th flame corresponds to a fitness value of OF_i in the array OF and is represented as follows:

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \tag{40}$$

In the MFO algorithm, the position of the moth near the flame is updated with the formula:

$$M_i = D_i \cdot e^{ct} \cdot \cos(2\pi t) + F_j \tag{41}$$

where $D_i = \left|F_j - M_i\right|$ is the distance between the moth M_i and F_j flames, c denotes a function of the spiral shape correlation, $t \in [-1,1]$, $t = -1$ denotes the closest flames, and $t = 1$ denotes the farthest flames.

The formula for the adaptive reduction of the number of flames is:

$$flame\_no = round\left(N - k \cdot \frac{N-1}{k_{\max}}\right) \tag{42}$$

where N denotes the maximum number of flames, k denotes the current number of iterations, and $k_{\max}$ denotes the maximum number of iterations.

III. C. 3) MC-SSA solving process

The SSA algorithm has some defects in that there is a large randomness in the updating of follower's positions during the iteration process, which leads to a less comprehensive search. In addition, SSA is easy to fall into local optimal solutions, leading to premature convergence. In order to solve these problems, this paper proposes the MC-SSA algorithm based on the improvement of the MFO algorithm, relying on the MC-SSA algorithm to carry out the solution to the MFDBN model established in the previous section, so as to realize the multi-objective optimization of the content of Civics teaching.

The multi-objective solution flow of the MC-SSA algorithm is shown in Fig. 2.MC-SSA improves the original SSA by introducing two different groups of followers, i.e., “follower group A” and “follower group B”. First, we embed the MFO into the original SSA and use it to update the position of “follower group A”, which enables a broader global search and improves the global exploration capability. Second, we introduce a Communication Mechanism (CM) strategy for updating the positions of “Follower Group B” to enhance the exploration capability of the local region and thus overcome the problem of falling into local optimal solutions.

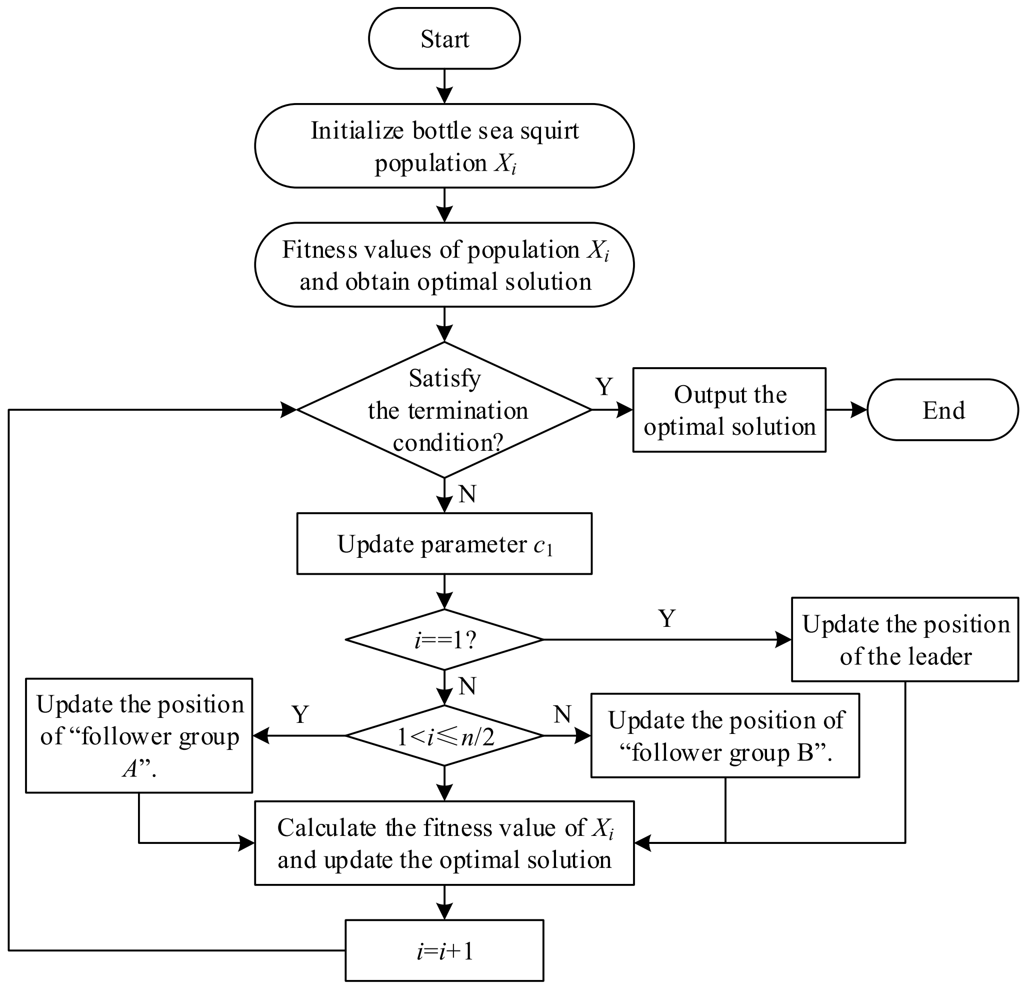


Figure 2: Multi-objective process of MC-SSA algorithm

When "$i=1$", the leader's position is updated as described in the SSA algorithm.

When "$1<i\le\frac{n}{2}$", the position update of "follower A group" will be localized MFO embedding, denoted as:

$$Afollowers_j^i = Dis\tan ce \times e^{bt} \times \cos(2\pi t) + x_j^1 \tag{43}$$

Where 1 denotes the position of the i rd follower in the j th dimension of "follower group A", $Dis\tan ce$ denotes the distance between the i th individual and the leader, and b and t have the meanings described above.

$Distance$ can be expressed as:

$$Distance = \left|x_j^i - x_j^1\right| \tag{44}$$

When "$\frac{n}{2}<i\le n$", the position update of "follower group B" adopts the CM policy, which can be expressed as follows:

$$Bfollowers_j^i = \mu \times x_j^i - (1-\mu) \times \frac{\left(x_j^1 + x_j^2\right)}{2} \tag{45}$$

where $Bfollowers_j^i$ denotes the position of the i th follower in the “follower B group” in dimension j, and $\mu \in [0,1]$, x_j^1 and x_j^2 are the two optimal individuals in dimension j.

IV. Multi-objective optimization and strategy of Civics teaching content

“Establishing morality and educating people” has always been the fundamental concept of the Communist Party of China (CPC) and the state in cultivating talents, and it is also the ultimate goal of ideological and political teaching work. Teachers in the process of carrying out the education of the Civic and Political Science Program should regard “cultivating morality and educating people” as their most crucial core teaching task, and continuously improve the personal political literacy of the students in colleges and universities and promote their physical and mental healthy growth and development. College students, as the main driving force of the current social development, are seriously lacking in social experience and have a vague self-knowledge. Therefore, it is necessary to cultivate their sense of social responsibility in time, improve the effectiveness and rationality of the work of ideological education in colleges and universities, and cultivate talents to meet the needs of the current era of development.

IV. A. Entity Identification and Relationship Extraction Validation

IV. A. 1) Entity identification effectiveness

In this paper, we constructed the Civics Teaching Content Knowledge Graph before establishing the MFDBN model, in which the BiGRU-CRF model is utilized for Civics Teaching Content Named Entity Recognition. In order to verify the effectiveness of the method, this section carries out simulation verification of it. The experimental model in this paper is built using the deep learning TensorFlow framework, and the acquired Civics teaching content text is used as the dataset to carry out the training, and at the same time, a comparison test is made with BiLSTM, BiGRU, BiLSTM-CRF model and BERT-BiLSTM model, and the accuracy, recall and F1 value are selected as the evaluation indexes. Figure 3 shows the results of recognizing the entity of Civics teaching content with different models.

From the experimental results, it can be seen that the BiGRU-CRF model proposed in this study shows significant improvement in all indicators. The named entity recognition effect on the Civics teaching content text has achieved significant improvement in the key indexes of accuracy, recall and F1 value, whose values reach 0.924, 0.905, 0.947, respectively.Compared with the BERT-BiLSTM model, the BiGRU-CRF model proposed in this paper improves 10.13% in accuracy, 11.18% in recall, 11.18% in F1 value, and 10.13% in F1 value. , 11.18%, and 11.28%. Compared to the BiLSTM-CRF model, the model in this paper improves 7.07%, 7.48%, and 7.37% in accuracy, recall, and F1 value, respectively. This indicates that the BiGRU-CRF model is able to recognize target entities and relationships more accurately when dealing with the Civics teaching content text dataset, and has better performance performance compared to the existing models. This finding is of great significance in solving the current challenges in entity recognition and relationship extraction tasks, and provides strong support for further improving the entity recognition effect and application of Civics teaching content.

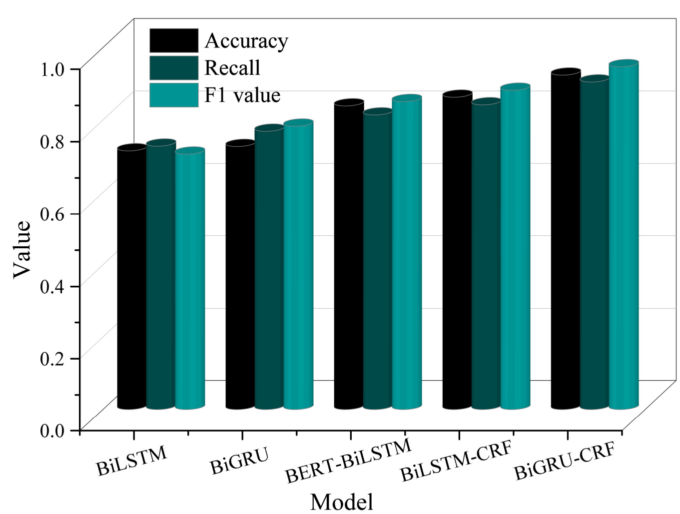


Figure 3: Thinking of political teaching content entity recognition

Fig. 4 shows the curves of accuracy and loss value of different models on the test set with the number of iterations, where Fig. 4(a)~(b) shows the accuracy and loss value, respectively. As can be seen from the figure, the accuracy rate of the BiGRU-CRF model in this paper increases more, and the loss value reduction stabilizes around 0.046.

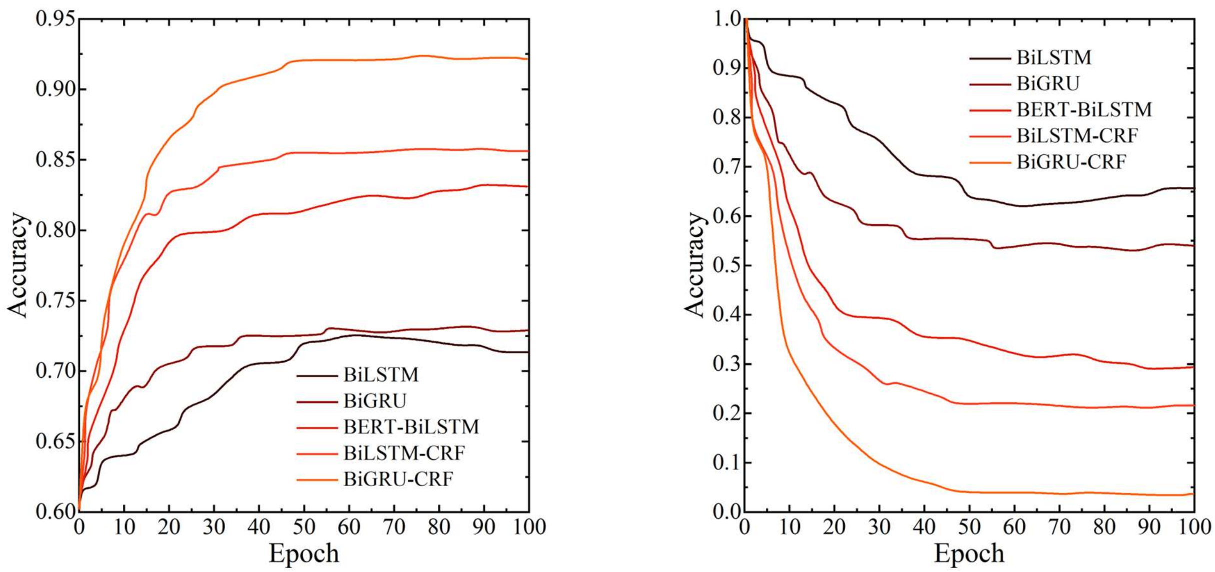
The increase in accuracy rate is mainly due to the following reasons:

(1) After the introduction of BiGRU, in the process of recognizing named entities in the text of Civics teaching content, the model pays more attention to the information related to the current task and assigns higher weights to it, which can help the model pay extra attention to certain information and thus improve the accuracy rate.

(2) For long sentences, BERT's ability to capture information is still insufficient, and the addition of BiGRU can help the recognition model deal with long-distance dependencies to better strengthen the model's ability to deal with long sentences, which is one of the main reasons for the improvement of the accuracy.

(3) For the useless information in the text, CRF can accurately identify and eliminate it, so as to reduce the interference of fuzzy information to the recognition model, and to ensure that the Civics Teaching Content Named Entity Recognition Model handles important information.

(4) CRF's ability to deal with the relationship between contexts and to understand the context in a prominent way also plays a role in the accuracy of the recognition.



(a) Accuracy (b) Loss value

Figure 4: Accuracy and loss value

IV. A. 2) Feasibility of relationship extraction

In the Civics teaching content text relationship extraction dataset, the relationship extraction model proposed in this paper is comprehensively compared with several mainstream models RNN, PCNN, BiLSTM and GRU, and the experimental results are shown in Table 1. The performance of this paper's model is better than the mainstream models in the entity-relationship extraction task of Civics teaching content text.The performance of BiLSTM and GRU is more general, and the F1 values are 16.69% and 17.82% different from this paper's model, respectively. This is due to the lack of local features in both models, simply using contextual information can not meet the entity relationship extraction task of Civics teaching content text, the overall error is larger.RNN focuses more on the text-dependent signs and local features extraction, ignoring the propagation of the model error, which reduces the extraction performance of the model, and the F1 value is 11.31% different from that of this paper's model. PCNN carries out attention pooling and maximum pooling, the extraction effect has been improved, but the use of a single attention mechanism in the Civics teaching content text entity relationship extraction task is not optimal, compared with this paper's model F1 value difference of 9.53%. The model in this paper integrates the deep residual neural network and PCNN model to extract the dependency inclusion correlation between the contextual semantics and relationship of Civics teaching content text, which can reduce the noise effect brought by the wrong annotation, and the multi-layer attention mechanism corresponds to the correlation between the entity and the context, which is better to enhance the weight for the key features, and it can improve the accuracy of the relationship extraction for the Civics teaching content text.

Table 1: Comparison of entity relationship extraction model performance (%)

Model	Accuracy	Recall	F1
RNN	84.06	81.57	82.23
PCNN	86.18	82.63	84.01
BiLSTM	82.49	76.41	76.85
GRU	80.27	75.39	75.72
Ours	93.54	91.28	92.16

IV. B. Multi-objective optimization of Civics teaching content

IV. B. 1) Algorithm performance comparison

In this paper, the MC-SSA algorithm is used to solve the MFDBN model constructed in the previous paper as a way to realize the multi-objective optimization of Civics teaching content. In order to verify the performance of the algorithm, this paper uses a total of 14 test problems, MMF1-MMF8 and MMMOP1-MMMOP6, to verify the validity and superiority of MC-SSA, which can systematically verify the performance of the proposed algorithm. For the performance of the algorithm, this paper uses two performance metrics, rHV and IGDx, to evaluate the distribution of the population in the target space and decision space, respectively. The rHV reflects the closeness of the resulting Pareto front to the actual Pareto front and the diversity of the algorithms. The smaller the value of rHV, the closer the obtained PF is to the actual PF and the better the performance of the algorithm. IGDx reflects the closeness between the resulting Pareto solution set and the true Pareto solution set, i.e., the convergence of the algorithm.The smaller the value of IGDx, the closer the resulting solution set is to the reference set of points, and the better the algorithm performs. The comparison algorithms are SGAII, CMMO, CoMMEA, HREA, MMEAWI, PSO-SCD, MOEATAR. The population size of all the algorithms is set to 300, the maximum number of iterations is set to 5000, and they are run independently for 20 times. Tables 2 and 3 show the results of the statistical comparison of the means of rHV and IGDx, respectively.

As can be seen from Table 2, the MC-SSA algorithm set up in this paper obtains optimal rHV values on all the test problems.SGAII achieves sub-optimal rHV values on 5 test problems, which may be due to the fact that SGAII employs the mini-habitat approach as well as the crowding approach, strategies which are able to provide better performance for the algorithm.CMMO is ranked second on the 7 test problems, while CoMMEA and CMMO perform similarly as both employ co-evolutionary strategies.HREA combines different optimization techniques and strategies aiming to improve search efficiency and global convergence, which is slightly less effective than CMMO.MMEAWI ranks third on MMF2 and performs mediocrely on the other test problems, which may be attributed to the fact that it is more sensitive to the weight settings, is limited by the simple weighted summation method and has some challenges in dealing with complex problems. While PSO-SCD performs poorly on most of the tested problems, this may be due to the fact that its diversity maintenance mechanism is ineffective, causing it to fall into a local optimum prematurely.MOEATAR ranks second on MMMOP1 and MMMOP3, and performs mediocrely on the other tested functions, a situation which may be attributed to the fact that the algorithm runs the risk of converging to a local optimal solution. Despite the fact that MOEATAR employs a trade-off factor and a ranking strategy to balance the relationship between the objective functions, there is still a potential risk of falling into a local optimum when dealing with complex multi-objective optimization problems. This may lead to difficulties for the algorithm to efficiently find the global optimal solution or generate a high-quality solution set for the Pareto frontiers. Overall, the MC-SSA algorithm has a better distribution among all algorithms.

From Table 3, it can be seen that the MC-SSA algorithm outperforms the comparison algorithms SGAII, CMMO, CoMMEA, HREA, and MMEAWI in terms of IGDx values on 10 test problems, namely MMF2, MMF3, MMF4, MMF6, MMF8, MMMOP1, MMMOP2, MMMOP3, MMMOP4, and MMMOP6, respectively, PSO-SCD and MOEATAR.The MC-SSA algorithm achieves optimal IGDx values on four test problems and performs mediocrely on five test problems, namely, MMF1, MMF5, MMF7, and MMMOP5, suggesting that it performs poorly on test problems with multiple Pareto fronts. Overall, the MC-SSA algorithm has the highest degree of closeness between the Pareto solution set and the true Pareto solution set. Therefore, solving the MFDBN model using the MC-SSA algorithm has high feasibility and can provide algorithmic support for obtaining the optimal objective of the Civics teaching content.

Table 2: The rHV value of eight algorithms

-	SGAII	CMMO	CoMMEA	HREA	MMEAWI	PSO-SCD	MOEATAR	MC-SSA
MMF1	1.382	**1.362**	1.391	1.389	1.388	1.391	1.383	**1.141**
MMF2	1.411	1.393	1.402	1.404	**1.395**	1.452	1.422	**1.152**
MMF3	1.403	**1.391**	1.398	1.398	**1.396**	1.446	1.428	**1.151**
MMF4	2.519	**2.245**	2.251	2.249	2.251	2.251	2.484	**1.852**
MMF5	**1.386**	1.383	1.392	1.387	1.389	1.390	1.389	**1.148**
MMF6	**1.387**	1.388	1.391	1.387	1.388	1.389	1.388	**1.136**
MMF7	1.389	**1.382**	1.388	1.390	1.391	1.389	1.389	**1.135**
MMF8	2.883	2.879	2.901	2.881	2.886	2.887	2.931	**2.320**
MMMOP1	1.715	**1.716**	1.715	1.721	1.725	4.552	**1.715**	**1.573**
MMMOP2	2.885	**2.875**	2.942	2.909	2.882	6.853	2.983	**2.701**
MMMOP3	2.872	**2.876**	2.921	2.895	2.879	2.951	**2.875**	**2.602**
MMMOP4	**2.876**	2.873	**2.876**	2.873	2.897	8.416	2.878	**2.693**
MMMOP5	**2.875**	2.872	2.871	2.892	2.889	9.173	2.873	**2.715**
MMMOP6	**2.879**	2.921	2.923	2.963	3.048	3.205	2.997	**2.638**

Table 3: The IGDx value of eight algorithms

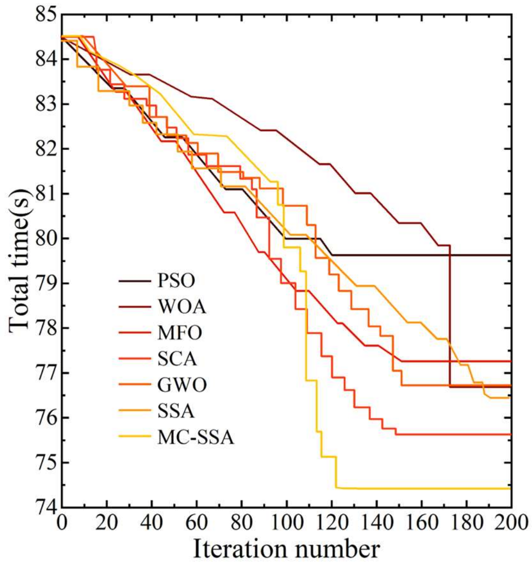
-	SGAII	CMMO	CoMMEA	HREA	MMEAWI	PSO-SCD	MOEATAR	MC-SSA
MMF1	4.365	**3.341**	3.408	3.552	4.095	6.034	5.898	4.281
MMF2	5.342	1.872	**1.859**	2.446	1.937	6.349	5.916	**1.715**
MMF3	4.183	**1.661**	**1.347**	1.837	1.854	5.652	4.796	**1.183**
MMF4	2.712	1.900	2.240	1.941	2.441	4.401	1.221	**1.762**
MMF5	8.445	5.963	5.743	5.823	6.981	1.105	9.416	7.563
MMF6	7.342	5.583	**5.452**	5.369	6.245	9.904	8.147	**5.431**
MMF7	2.324	**1.942**	2.175	1.907	2.404	4.115	3.406	2.543
MMF8	9.861	4.543	4.721	4.074	6.097	1.257	3.716	**4.171**
MMMOP1	**2.058**	**1.969**	2.378	2.561	**1.146**	2.653	**2.152**	**1.832**
MMMOP2	1.631	1.115	1.046	5.416	8.692	3.395	5.864	**5.206**
MMMOP3	1.882	1.051	2.692	1.509	1.221	4.618	**1.753**	**3.612**
MMMOP4	1.427	3.195	**2.707**	7.883	1.005	1.674	3.827	**3.016**
MMMOP5	1.604	**3.273**	**2.715**	8.278	8.127	1.682	4.341	6.418
MMMOP6	4.002	1.469	**0.714**	7.256	2.883	2.223	2.868	**6.074**

IV. B. 2) Multi-objective optimization results

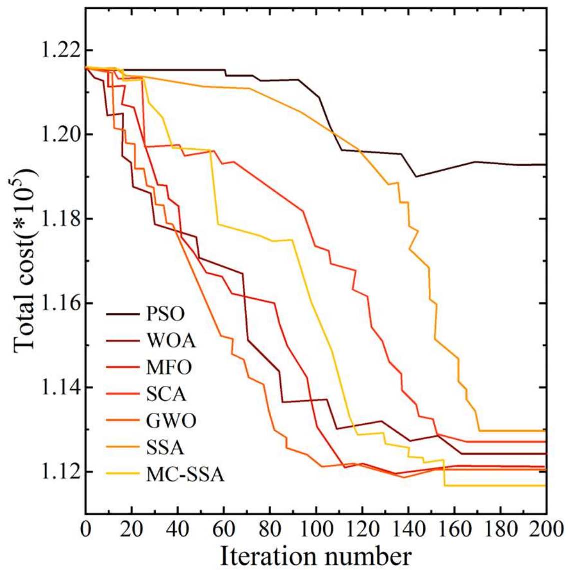
In order to verify the effectiveness of MC-SSA algorithm and MFDBN model, the Civics Teaching Content Resource Distribution Network of a university is taken as the research object. According to the actual situation of Civics teaching content resource allocation mentioned above, the Civics teaching content resource allocation network planning model is constructed and numerical examples are analyzed. Based on the MFDBN model established in the previous section, the corresponding resource allocation cost function and fairness function are set, and then the Civics Teaching Content Resource Allocation Network Planning Model is obtained. On this basis, the MC-SSA algorithm is used to solve the optimization problem of Civics teaching content resource allocation network, and the solution process is realized through MATLAB software simulation.

In order to verify the effectiveness of MC-SSA algorithm in solving the network planning of Civics teaching content resource allocation, MC-SSA algorithm is used to solve the multi-objective model with PSO algorithm, WOA algorithm, MFO algorithm, SCA algorithm, GWO algorithm and the original SSA algorithm. Figure 5 shows the solving results of the network model of Civics Teaching Content Resource Allocation, in which Figures 5(a)~(d) show the response time, total cost, relative fairness and multi-objective iteration results, respectively, and Table 4 shows the solving results of the multi-objective model.

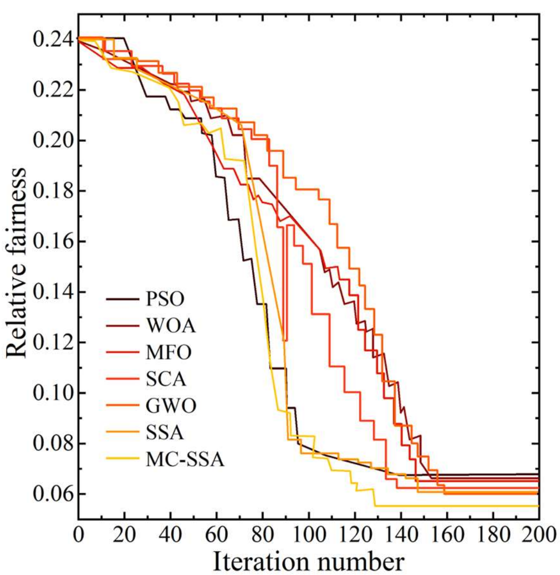
As can be seen from the figure, when solving the minimum network response time for network planning of Civics teaching content resource allocation, the MC-SSA algorithm achieves the optimal solution, the optimal solution is about 74.5s, and the MC-SSA algorithm achieves the optimal solution in about 120 iterations, which is better than other algorithms. The optimal solution for the minimum total cost of network planning is 113478, and the MC-SSA algorithm finds the optimal solution in about 160 iterations. The optimal solution for the minimum relative unfairness of network planning is 0.055, and the MC-SSA algorithm finds the optimal solution in about 130 iterations. In summary, for the multi-objective model solution of network planning of Civics teaching content resource allocation, MC-SSA algorithm can find the optimal and the fastest convergence speed, and reaches convergence in less than 90 iterations, which is significantly better than other algorithms. Therefore, the MC-SSA algorithm can effectively solve the multi-objective fuzzy dynamic optimization model of Civics teaching content, and relying on the numerical solution results can better realize the optimal allocation of resources related to Civics teaching content, and provide a guarantee for promoting the quality of Civics teaching.



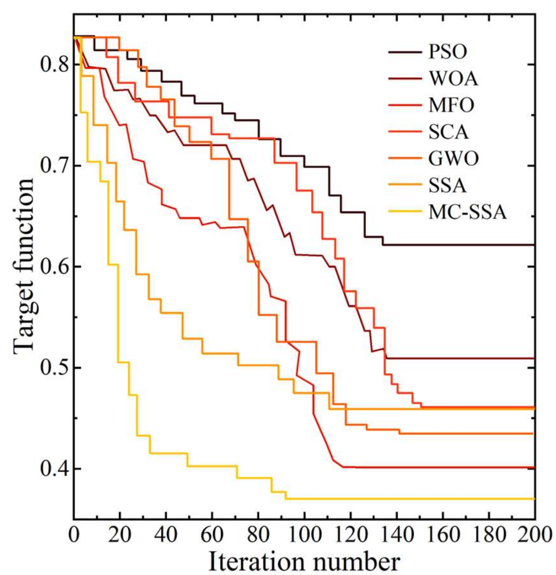
(a) Response time



(b) Total cost



(c) Relative fairness



(d) Multitarget iteration

Figure 5: The solution of the model MFDBN model

Table 4: The solution of the multi-objective optimization model

Algorithm	Response time	Total cost	Relative fairness	Multitarget
PSO	93.15s	117269.24	0.1842	0.7253
WOA	89.24s	117137.65	0.1674	0.5687
MFO	85.27s	117138.59	0.1645	0.4520
SCA	88.06s	117195.43	0.1563	0.5179
GWO	87.24s	117089.23	0.1583	0.4883
SSA	88.32s	117121.37	0.1588	0.5192
MC-SSA	81.59s	117005.18	0.1542	0.4026

IV. C. Strategies for optimizing the content of Civics teaching

IV. C. 1) Innovative teaching methods

In order to better stimulate students' learning interest and enthusiasm, and then improve the effect of Civics teaching, teachers should actively explore and adopt new teaching methods.

First of all, teachers integrate actual cases in international politics, economy, culture and other fields related to their majors into the content of Civics and Politics, guide students to use their professional knowledge to interpret and discuss, deepen their understanding of Civics and Politics theories, cultivate students' ability to analyze and solve problems, and improve their critical thinking ability. Teachers can also design simulated international conferences, business negotiations and other scenarios, so that students can communicate and express themselves in a simulated environment, exercise their expression skills, experience and understand the application of Civics and Politics knowledge in practical work in actual operation, and improve the sense of learning participation and experience.

Secondly, using the existing online teaching platforms such as MOOCs and SPOCs in colleges and universities, we provide students with video lectures, online tests, and learning communities on course Civics and Politics, so that students can learn according to their own learning progress and interests. Microclasses are short and concise teaching videos, and teachers can make microclasses related to national politics and culture for a certain Civics knowledge point, making students analyze Civics knowledge while learning. Social media and collaboration tools such as WeChat groups, QQ groups, and Zoom meetings are utilized to establish learning communities and encourage learning exchanges and discussions among students. This can break the limitations of the traditional classroom, so that students can share their learning experiences and experiences in a more relaxed and free environment, and promote the dissemination and application of knowledge.

IV. C. 2) Development of teaching resources

In recent years, the quality of Civics teaching in colleges and universities has made great progress. Teachers should accurately improve the Civics teaching programs and strategies for the problems and deficiencies in the process of Civics teaching, and promote Civics teaching to a deeper development. Teachers should actively use online and offline channels to strengthen the development and utilization of Civics teaching resources and materials, integrate the existing Civics teaching materials, and at the same time, tap the Internet resources and digital cases, collect local Civics elements and related content, and create distinctive Civics school-based teaching materials, so as to provide solid support for classroom teaching and Civics activities. Teachers can develop and organize relevant materials and resources with local cases to enrich the content of the school-based curriculum, further enrich the connotation of Civics teaching, and help students “broaden their horizons, increase their knowledge, and improve their skills” at the same time.

In addition, teachers should make full use of online platforms and tools such as Bagui Teaching Channel, Cloud Class, China Knowledge Network, etc., to collect digital resources and materials related to the Civics course, and flexibly adjust the Civics cases and teaching modules according to the teaching needs, so as to keep the freshness and attractiveness of Civics teaching and ensure the effective enhancement of the core Civic and political literacy of students.

IV. C. 3) Optimizing teaching evaluation

The design of Civics teaching in the intelligent era cannot be separated from the support of intelligent teaching systems, especially the empowerment of artificial intelligence has brought about a revolution in multimodal intelligent scenarios, such as intelligent marking, intelligent grading, intelligent generation of evaluation reports, etc., which realizes the data tracking and regulation of the whole process of Civics teaching. However, whether the support of intelligent systems for the teaching of Civics and Political Science classes is in line with the teaching law again depends on the systematic analysis of students' learning behavior and teachers' practical experience. Therefore, in the process of improving and optimizing the teaching design of Civics and Political Science classes, it is necessary to adhere to systematic thinking, strengthen the research on the theory of teaching design of Civics and Political Science classes, and establish a positive, steady, systematic and comprehensive practice strategy. Relying on the intelligent reform of teaching evaluation, improve and perfect the system related to the teaching design of Civics and Political Science courses, promote the organic integration of teaching evaluation with teaching objectives, teaching content and teaching methods, and realize the overall intelligence of the teaching design of Civics and Political Science courses.

Evaluate the structural changes brought about by the development of a new generation of artificial intelligence to the teaching of the Civic and Political Science Course, and focus on the digital evaluation of the degree of human development, development stage, and growth space on the basis of data model construction. Taking the intelligent analysis of the ideological and moral cultivation of educational objects as the core, it conducts scientific, objective and comprehensive assessments of learners' emotions and attitudes, highlighting the certification of students' individual abilities, so as to realize “one-to-one” precision evaluation.

V. Conclusion

In this paper, guided by Marxist theory, combining with Boolean network algebraization to convert the Civics teaching content into a multi-objective optimization problem, the multi-objective fuzzy dynamic optimization network model of Civics teaching content is established based on Civics teaching content knowledge map, and the optimization results are solved by MC-SSA algorithm. The simulation results show that the MC-SSA algorithm has better solving performance, and the closest degree of proximity between its Pareto solution set and the real Pareto solution set. And relying on MC-SSA algorithm can effectively solve the multi-objective fuzzy dynamic network optimization model of Civics teaching content, which provides guidance for the optimization of Civics teaching content. That is, the dimensions of innovative teaching methods, rich teaching resources and optimized teaching evaluation lay the foundation for the improvement of the quality of Civics teaching in colleges and universities.

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