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Research Article

Social Public Opinion Communication and Network Legal Management Based on Artificial Intelligence Cognitive Wireless Network

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Public opinion supervision is an important part of the national security supervision system. In the Internet era, especially with the rapid development of mobile social media, the position of online public opinion supervision in public opinion supervision is becoming more and more prominent. Internet public opinion supervision has a wide range of subjects, diverse objects, multiple channels, instant and efficient communication speed, and two-way interaction and has its distinctive features, but at the same time there are phenomena such as online rumors, invasion of others' privacy, and venting private anger. The existence of these problems requires strengthening the legal system of public opinion supervision, enhancing the network literacy of Internet users, government management departments, website operators, and other subjects of online public opinion supervision, continuously improving the technical level of online public opinion monitoring, and public opinion guidance ability of network supervision departments, and strengthening the regulation of online public opinion supervision through the improvement and improvement of legal system and coordinated promotion of cyberspace governance. Meanwhile, mobile Internet is the soil for social opinion dissemination. With the development of technology, cognitive wireless network is becoming an important infrastructure in the mobile Internet. Therefore, this paper studies social opinion dissemination and cyber law management in cognitive wireless networks and proposes a cognitive engine model based on artificial intelligence algorithms for cognitive wireless networks for enhancing opinion dissemination and law management. The extended experiments demonstrate the advanced performance and effectiveness of the proposed method in this paper and provide a new technical approach for enhancing public opinion dissemination and legal management.

1. Introduction

The development of the mobile Internet has promoted the rise of mobile terminals, and the widespread popularity of smart phones has caused a double change in the state of information carrying and the means of circulation. The popularity of mobile social platforms demonstrates the charm of users' strong social relationships and diversified social media topics [1]. The contact attributes, real-name attributes, and location attributes of mobile social platforms reduce trust costs and enhance communication convenience and the number of mobile social users. Communication power continues to show a blowout development [2]. With the diversified changes of online public opinion carriers and the continuous integration of the media, Chinese society has entered an era of "reading with your head down.". Figure 1 shows the growth trend of Chinese social network users [3]. As of March 2020, the number of Chinese Internet users is 904 million, and the Internet penetration rate reaches 64.5%. The increasing popularity of the Internet and the growing scale of netizens have brought about the emergence of a new media era where "everyone has a microphone." The "zero threshold" of Internet access allows people to express their different emotions and opinions freely on the social network platform, while also reducing the cost of various information interactions from all walks of life and increasing the possibility of all types of information being integrated and open to enter public life, thus forming a network of public opinion

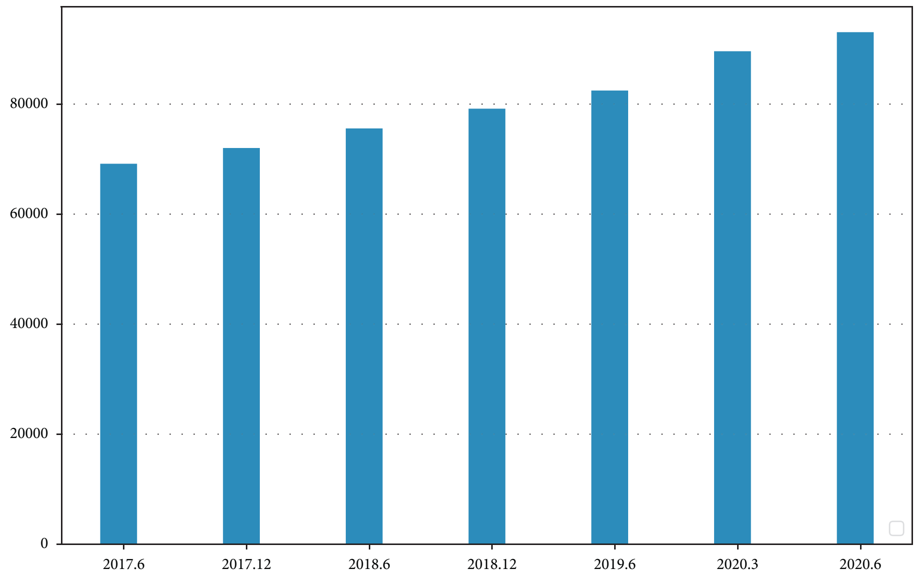

Figure 1: China's social network user growth trend chart.

that uses the Internet as a dissemination intermediary [3]. In short, online public opinion is based on the network as the carrier, with events as the core, the expression, dissemination, and interaction of the majority of netizens' emotions, attitudes, opinions, opinions, and subsequent influence. Internet public opinion, from another perspective, is the real-time dynamic reflection of various thoughts and behaviors of the public, and it is the gathering place of social sentiment and public opinion.

A large number of mobile applications have created the current era of personal media, and the research of online public opinion based on personal media is an important and brand-new field of online public opinion research. Public opinion on mobile social networks has broken the traditional media's strong control over agenda setting [4]. To a certain extent, the right to agenda setting has been handed over to ordinary citizens by the media. At the same time, the traditional communication theory believes that, in the process of opinion dissemination, "opinion leaders" actively select and interpret public opinion data in the media, which is an important "bridge" for communication between the media and ordinary social individuals, and, in mobile social platforms, the influence of opinion leaders is not limited to a small circle. Becoming an opinion leader is not only by the transmission and interpretation of information, but also more by expressing one's own attitude and position towards and handling public opinion. It can be said that public opinion on mobile social networks has given new characteristics to traditional communication theories [5].

With the emergence of a large number of mobile Internet devices, services that can support mobile applications will have different demands on the network itself. These new requirements prompt the network to redesign the network structure according to the variable needs of users and lead to the emergence of active or programmable networks. At present, the automated management and maintenance of the network are at a relatively low level because the network manager is a human being [6]. The network cannot be aware of its own state and application requirements, does not have its own goal and the knowledge of how to achieve this goal, and cannot reason about its own behavior. This means that the development of applications urgently requires the network itself to have "cognitive" attributes. Cognitive wireless networks can perceive the current network conditions, plan, determine, and take corresponding adaptive actions on the wireless network based on the end-to-end configuration goals of the data stream. At the same time, the wireless network can learn from these adaptive actions and apply the learned knowledge to future decisions of the network [7]. Cognitive wireless network is a complex technology. Its research content includes network architecture research, environment perception technology, knowledge representation and acquisition technology, machine reasoning technology, machine learning technology, and network reconfigurable technology.

Mobile social networks show new features in the process of people's information transmission and daily communication. They can provide users with services anytime and anywhere. They are mobile. At the same time, they are more portable and timelier than the traditional Internet. Fragmented time can be available at any time. Using the Internet, it enables people to conveniently conduct various activities on the Internet in a variety of ways, but at the same time the Internet is also a double-edged sword, which creates more convenient conditions for the breeding and dissemination of bad information [8]. With the environment, all kinds of negative information or rumors can be quickly spread through this hotbed, which seriously damages the stability and harmony of the social network environment. Therefore, it is necessary to clearly understand the transmission path and internal mechanism of public opinion information in the social network system. For speech that is harmful to society, social supervision departments can take effective measures in a timely manner to prevent the spread of speech that endangers social harmony and stability [9–13]. This article uses artificial intelligence technology to explore the problem of social public opinion communication in cognitive wireless networks through optimization methods. It focuses on the network architecture, knowledge acquisition technology, and artificial intelligence technology for more in-depth research and proposes a radial basis function (RBF), the cognitive engine model in the cognitive wireless network of the neural network. This method reconfigures communication parameters through the learning of empirical knowledge and environment to achieve a reasonable allocation of resources and improve the performance of the network system and the supervision ability in the process of public opinion dissemination. The extended experiment proves the effectiveness and accuracy of the proposed method. Furthermore, this article explores ways to improve the legal system of online public opinion management and control, management control, and guidance norms and to improve the legalization and institutionalization of China's cyberspace [10–12].

2. Social Public Opinion Technology and Management

2.1. Cognitive Wireless Network. The constantly developing wireless communication technology has brought more and more wireless electronic products, applications, and services [13]. These newborn technology products, on the one hand, bring people entertainment and convenient life, such as personal mobile communication, intelligent car communication, smart home products, and telemedicine. This series of products make the present and future life gradually become intelligent; on the other hand, the constant data communication brings the continuous data communication with many pressures and challenges to the existing communication networks and communication resources, such as the shortage of wireless spectrum resources and its unreasonable management mechanism and the exponentially increasing data in the network [14]. Therefore, how to improve the data efficiency under the existing communication conditions and ensure that users can communicate effectively at all times has gradually become one of the research hotspots of wireless network intelligence. The future trend of social development is gradually intelligent, and the development of economic and social diversity is increasingly dependent on the Internet, driven by the innovation of the knowledge society [11]. The rise of the "Internet+" model is another change in modern socioeconomic development, bringing unlimited possibilities for people in production and life. However, all these activities and ideas are predicated on the network, so the need for network intelligence becomes an inevitable demand in the new economic situation. Cognitive network (CN) is proposed in this context, and the autonomous cognitive function is one of its main features. Cognition is the learning of historical information and environmental state information, and the results of the learning are fed back to the network entities to guide their future behavior. Cognitive networks give autonomous cognitive capabilities to the entities in the network, making them intelligent enough to interact intelligently with the environment in future complex and heterogeneous networks. The scope of cognitive networks involves multiple layers of the network, and network management is carried out through a combination of layer-by-layer optimization and cross-layer design to further improve the performance of the network [15].

In recent years, one of the research hotspots in cognitive networks is cognitive wireless network technology. Cognitive wireless networks are effective techniques proposed for traditional static spectrum allocation strategies. Cognitive networks have autonomous and intelligent cognitive functions to obtain useful information in the historical and current environment to achieve an effective role for future mechanisms [16]. With the continuous development of wireless communication technology, various new regionalized communication network models such as femtocell networks and wireless access points applied to indoor environments have gradually emerged, but the diversity and disorder of wireless service types and methods make the network not well suited to meet users' requirements for quality of service. Therefore, relay nodes providing data transmission and reception services in the network need to intelligently sense complex user and network environment information, effectively manage network behavior and deploy network resources, and make the entities in the network adapt to the network environment autonomously. The cognitive network model enables the sharing of multilayer information in the network, avoiding the problem of network information asymmetry brought by the traditional strict hierarchical design. Although researchers have also given the network more adaptive adjustment capabilities for the needs of the network, it is still not completely free from human adjustment and configuration. Therefore, how to further empower network entities to intelligently make strategic autonomous adjustments based on system and environment information has become one of the research hotspots in modern communication technologies.

Similar to the idea system of artificial intelligence model, cognitive network starts from the human cognitive characteristics of the environment and uses a more systematic methodology to perceive the environmental information, mine the useful information, and integrate it to form an information base. The whole process is carried out without human intervention and eventually forms intelligent decisions to achieve the goals of wireless resource management, heterogeneous networks, security, and quality of service (QoS) [16]. The key to the intelligent cognitive process is the cognitive feedback loop, which adjusts the next step by understanding the impact of the current behavior on the network. This is illustrated in Figure 2. In the observation phase, the target of attention is the external environmental information and internal state information, and the acquired information is fused and mined to organize, and the original system state and environmental state information is combined to reason about the observed target state and form an information database. In the learning phase, the optimization target of learning is set, and learning and strategy formulation are carried out based on the acquired information. After the intelligent system forms

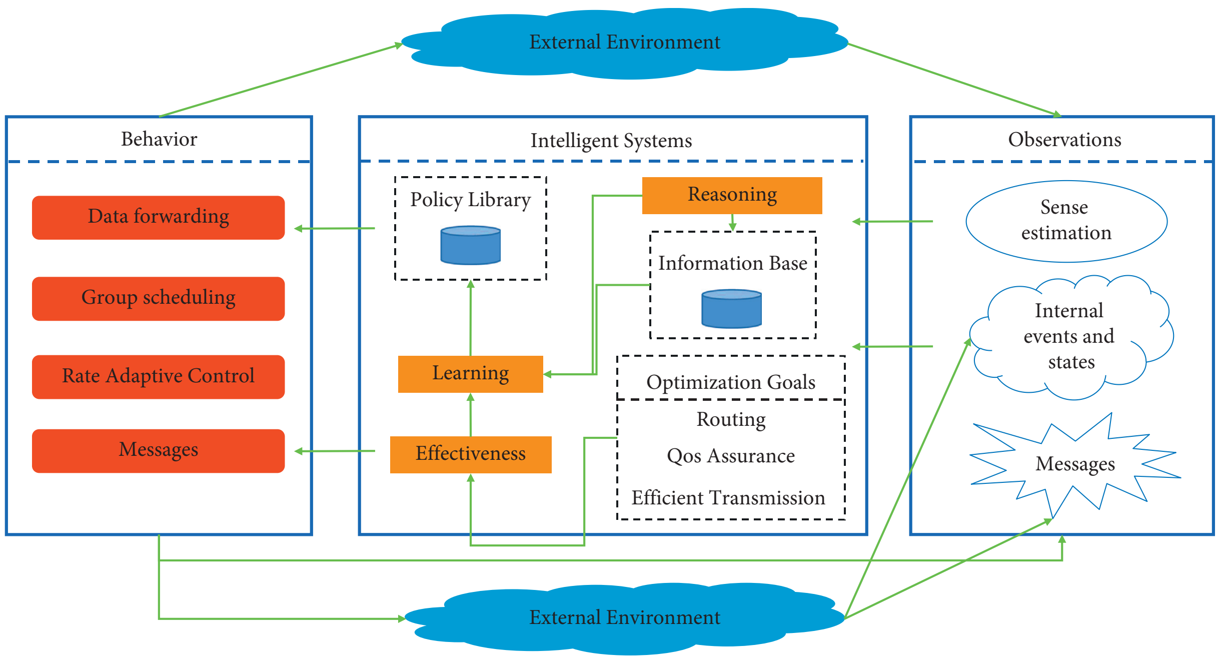

Figure 2: Intelligent cognitive loop.

the final policy, policy implementation is performed, such as adaptive data rate control, group scheduling, and routing. The implementation of behavior eventually affects the current environment again, generating new environmental state information and forming a new round of intelligent cognitive process [17].

The intelligent cognitive process based on perception, learning, reasoning, and behavior can adaptively make decisions based on changes in the environment, making the network more intelligent. The cognitive process was first used by military personnel to understand the thinking process and behavior of opponents and then gradually applied to business and artificial intelligence [18]. Cognitive networks integrate multiple networks to achieve end-to-end goals and are characterized by heterogeneity and complexity. As shown in Figure 3, users need to implement communication between different networks. Cognitive network is based on the fusion of various network pieces of information. Between the terminals of the network, the network can perceive and share information with each other, so as to improve the resource usage and information sharing under the traditional heterogeneous network. Case. The terminal node selects the appropriate way to access the network through the network information, and adjusts the communication mode in the subsequent communication process. In a large-scale network environment, artificial intelligence algorithms can make the network highly intelligent in terms of information acquisition, working parameter settings, and behavioral decision-making.

2.2. Social Opinion Dissemination. Social network public opinion is based on traditional media, through the Internet, using the Internet as a carrier to express the emotions of most netizens. Internet public opinion is a collection of attitudes, emotions, and opinions expressed by people around the occurrence, development, and changes of hot social events in a certain social space. The mapping of public opinion on the Internet: with the rapid development of mobile Internet, more netizens transmit information and express opinions through mobile Internet platforms [19]. As an expression of the public's attitudes and emotions towards hot social events, social network public opinion is also an objective social phenomenon that shows the development of the overlapping relationship between society and network society. The dissemination of some focal issues in social network public opinion has the characteristics of wider influence, stronger influence, and faster reflection than traditional media public opinion dissemination. Online media has become one of the main carriers that reflect social public opinion, and it is the "fourth media" after radio, newspapers, and television.

Summarizing the characteristics of social opinion from different perspectives of social opinion dissemination, it can be divided into two aspects: one is from the perspective of the subject, including two types; one is the information publisher and the other is the information receiver; the other is from the perspective of the object [20], also including two types, one is the published information and the other is the information dissemination medium. The network public opinion has the scale of subject, advanced media, diversity and sea of objects, convergence of rendezvous, and complexity of network structure. Based on the summary of scholars, this paper proposes the following characteristics of online public opinion: 1. There is the huge amount of disseminated information and the obvious characteristics of interactivity and immediacy. The interactivity of social network public opinion is mainly reflected in three aspects:

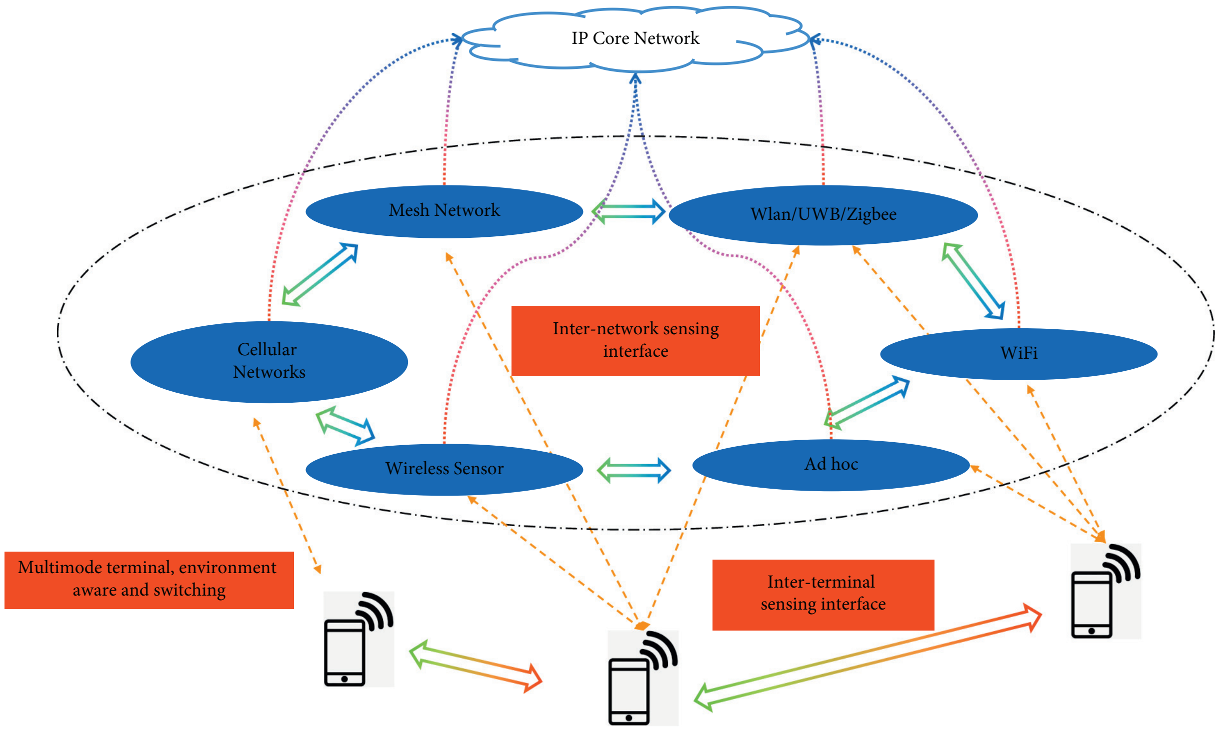

Figure 3: Heterogeneity of cognitive networks.

the interaction between netizens and the government, netizens, and the media and netizens. And the immediacy of online public opinion is reflected in the fact that netizens, as the main participants and promoters of online public opinion dissemination, are the dominant factor in the dissemination of online public opinion information. The high selectivity of online public opinion dissemination reflects not only the huge amount of information disseminated by online public opinion, but also its interactivity, immediacy, and independent dissemination. From the perspective of individual netizens, the simple acts of paying attention, clicking, posting news, and forwarding comments have little impact on the effect of spreading online public opinion, but the participation and discussion of a large number of netizens can form a complex information chain, time chain, and development chain, synchronizing with the development of the event itself, which is synchronized with the development of the event itself [21]. 3. Networked, comprehensive, dynamic, and aggregated features of social network public opinion involve the emotions, opinions, and attitudes of different individuals, and, compared with traditional public opinion, Internet users' emotions tend to be polarized, attitudes change, and opinions are more diversified. The topics of online public opinion are constantly extended in the evolution of communication, and various opinion-derived events occur frequently, which may easily lead to offline mass incidents. 4. There is highly sudden and geometric fission in information dissemination. Network public opinion involves many fields and public opinion hotspots are complex and changeable. Certain social hotspots, including "anticorruption" and "wealth gap," are the key concerns of Internet users. Due to the anonymity of social networks, the superposition and differentiation of information dissemination, and the convenience of mobile social media, Internet public opinion spreads geometrically and is fissionable.

The evolution process of public opinion on social networks is the process from the generation to the extinction of public opinion, and it runs in accordance with certain internal laws. The concept of life cycle originated in the field of biology. It refers to a series of changes stages in the function or form of an organism during the evolution of life. The online public opinion events are divided into three stages: the gestation period, the outbreak period, and the recession period, and the law of the theme evolution is revealed and analyzed; the Weibo public opinion is divided into four stages: the incubation period, the warm-up period, the hot discussion period, and the recession period, Constructed a "six-stage" model of the development life cycle of public opinion on public emergencies, which is composed of the gestation phase, the outbreak phase, the diffusion phase, the repetition phase, the fading phase, and the long tail phase. The life cycle of social network public opinion information dissemination is based on three stages, namely, the sudden period, the spreading period, and the dissipating period, as shown in Figure 4.

2.3. Public Opinion Network Legal Management. Social networks have brought people into the "micro" era of information circulation. More sources of information, more convenient delivery, and more equal access all make our world smaller and flatter. In this era, when everyone is concerned about participation, the judiciary naturally

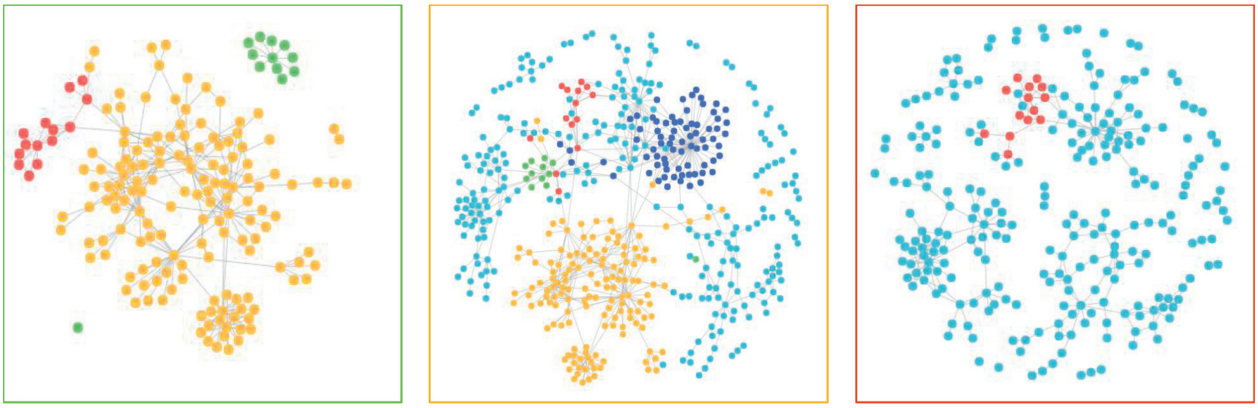

Figure 4: Social opinion dissemination process.

cannot be separated from the "surroundings" of the masses. The reality has shown that it is difficult for judicial opinions to ignore voices from the Internet and the judicial system is also working hard to remove its mystery [22]. However, how to achieve judicial independence from multiple opinions and how to weigh the value of public opinion within the scale of the law are all questions that the judiciary under social networks cannot avoid in the process of confronting the people directly.

The new characteristics of the relationship between justice and public opinion under social networks: public opinion reflects the collection of tendencies, attitudes, and opinions of a certain number of people in society on specific public issues. Such specific public issues are often related to the well-being of people's lives and the peace of society. Until the emergence of newspapers and other traditional media, citizens' opinions finally had a centralized and standardized way of expression, and this way of expression gradually penetrated into the realm of public life in the form of public opinion. Inevitably, the issue of the relationship between justice and public opinion has finally entered people's field of vision. This relationship has the following new characteristics: first, compared with the traditional relationship between public opinion and justice, justice will face the public directly under social networks. In the traditional public opinion environment, media such as newspapers and TV broadcasts have the right to speak [23]. They have professional information acquisition channels and information exchange mechanisms. Collecting information and processing and disseminating information are their way of survival. The reason why social networks can emerge as new media and dare to challenge the status of traditional media is precisely because they can provide a relatively fair voice platform. This kind of fair discourse platform, to a certain extent, eliminates the obstacles formed by the information processing mechanism of traditional media. Second, social networks have become a tool for litigation participants to reach favorable litigation requests. Social networks have removed obstacles to the circulation of information, but, at the same time, their spreading amplification effect has also made people increasingly worried about the leakage of personal privacy. Third, judicial officials have actually entered the field of public opinion formation. The court's access to social network platforms can be said to be both passive and active. Voices from the Internet can no longer be ignored. It is better to change from passive to active, speak actively, clarify the basis for the trial, and promote the concept of the rule of law.

By analyzing the characteristics of the relationship between justice and public opinion in the social network era, it can be seen that, different from the relationship between justice and public opinion in the traditional media era [24], social networks have eliminated the information filtering mechanism constructed by traditional media, allowing justice to face online public opinion; it is also different from the former social network. With the interactive methods of the times, the court has become a participant in the creation of public opinion under social networks, which has moved the stage of public opinion formation forward. The court, like ordinary netizens, is both the initiator and the participant of the topic, and, at the same time, it is also striving to be the leader of public opinion. Finally, the spreading effect of social networks makes it a public opinion tool used by parties to fulfill their own demands, forcing the court to make prudent judgments on related cases.

3. Method

3.1. RBF Neural Network. RBF neural network has the advantages of general network but also has strong clustering analysis ability; the theory has proved that in the forward network RBF network is the optimal network to complete the mapping function and has been widely used in pattern recognition, intelligent learning, etc. [18]. The input layer of RBF neural network includes the input source node, the number of neurons in the hidden layer depends on the stated problem, and its transformation function is a radially symmetric and decaying non-negative nonlinear function. RBF neural network generalization capability: the generalization capability depends on the network topology and the training sample characteristics. In this paper, the perceptual sample data are divided into three sets: a training sample set ***T*** for training the network, a test sample set ***S*** for evaluating the generalization ability of the network, and a utility sample set ***V***. RBF neural network structure optimization: the number of nodes in the input and hidden layers is determined by the network structure; the learning accuracy of the RBF neural network is determined by the number of nodes in the input layer; the learning speed and generalization ability of the RBF neural network are determined by the number of nodes in the hidden layer.

3.2. RBF Neural Network Cognitive Engine Model. Cognitive radio network (CR) is an intelligent wireless communication system that can dynamically adjust parameters according to environmental changes and service requirements to improve system performance, and its core technology is the design of cognitive engine. The cognitive engine can introduce reasoning and learning methods from the field of artificial intelligence to realize the sensing, adaptive, and learning capabilities of CR. CR cognition consists of sensing, learning, reasoning, and decision-making, and the flow of cognitive information in these links forms a complete cognitive loop. Based on the perceived information, this paper focuses on three parts: learning, reasoning, and decision-making. The learning is to train the learning model, the reasoning is to estimate the performance of configuration parameters, and the decision is to find the best configuration based on the performance estimation and user requirements [25]. The CR cognitive engine completes the configuration of routing protocol (*RP*), data rate (*Rate*), MAC window (*CWmax*, *CWmin*), and transmit power (*P*), and its model is shown in Figure 5.

The per-processing module determines the number and form of targets based on the perceptual information and reconfiguration requirements of the cognitive engine to form the RBF neural network input. The network topology module determines the number of neurons and the weights of each connection. The model training and testing are performed by the outer layer and inner layer neural networks, with cognitive information flowing from the outer layer to the inner layer neural networks, and the network training and testing process is as follows: the network model is trained to simulate the communication environment using ***T***, and the generalization capability of the network model is evaluated based on ***S*** and ***V***. The RBF neural network model library builds the CR parameter configuration solution set based on the previous module. The configuration decision module finds the optimal configuration parameters based on the user requirements and the model library output.

From the comprehensive performance of the network, the RBF neural network with one hidden layer outperforms the RBF neural network with multiple hidden layers, so the outer and inner networks designed in this paper both contain one hidden layer. In a channel model, the number of neurons in the hidden layer is determined using the neural network performance evaluation function, and the node increment algorithm is as follows: (1) for a certain environment, the empirical data are divided into training set T, utility set V, and test set S. T, S, and V account for t, s, and v percent of the total perceptual data, respectively. (2) The network is trained using set T, and the network generalization performance is tested using sets S and V. (3) The number of neurons is gradually increased, and the network generalization performance is tested using the minimum mean square error (MMSE) [26]. The number of neurons is gradually increased and the network performance is compared using the minimum mean square error (MSE). (4) The number of neurons in a specific environment is determined by comparison.

The output of the input vector *Pv* through the RBF neural network can be calculated by the first following equation for the sample values of data perceived in an environment. In the RBF neural network, there are various feasible definitions of neuron learning functions, and, in this paper, we adopt the learning function of the second following equation:

$$\phi = f\left(\|W - Pv\|_2 \cdot b\right) = radbas\left(\|W - Pv\|_2 \cdot b\right), \quad (1)$$

$$\begin{aligned} radbas\left(x_i\right) &= e^{-\left(x_i^2/\delta_2\right)}, \\ radbas\left(x_i\right) &= x_i. \end{aligned} \quad (2)$$

In (1), φ is the neuron output result, W is the weight, b is the threshold, $radbas(x_i)$ is the radial basis function, and $\|.\|_2$ is the Euclidean distance. Equation (2) is the hidden layer Gaussian neuron learning function and the output layer linear neuron transfer function, x_i is the i-th neuron input value, δ is the expansion parameter controlling the RBF width, and $radbas(x_i)$ is the i-th neuron output network value. After determining the network input and output and topology, the network model is trained and the CR model library is established by performance testing.

The CR parameter configuration mainly includes the setting of the weights of each user requirement index and the calculation of the corresponding configuration utility value. In this paper, we consider 3 user service quality requirements with weights $W1, W2, W3$, and define the utility function E, as shown in (3).

$$Ej = w_1 \times \frac{\left|\log 10\left(TP_j\right)\right|}{\max\left|log10\left(TP_j\right)\right|} + w_2 \times \frac{\left|log10\left(\mathrm{Drop}_j\right)\right|}{max\left|log10\left(Drop_j\right)\right|} + w_3 \times \frac{\left|\log 10\left(Delay_j\right)\right|}{\max\left|log10\left(Delay_j\right)\right|}, \quad j = 1 \ldots n, \quad (3)$$

where n is the perceived n sets of samples, and TP_j, $Drop_j$, and $Delay_j$ are the throughput, packet loss rate, and network delay of the j-th sample set, respectively. The RBF neural network obtains different output configurations after learning the perception information and decides the current environment parameter configuration according to user needs, *SNR*, and utility value *E*. When there are multiple sets of configuration solutions with the same *E* value, take the set of parameter configuration with the smallest P [27].

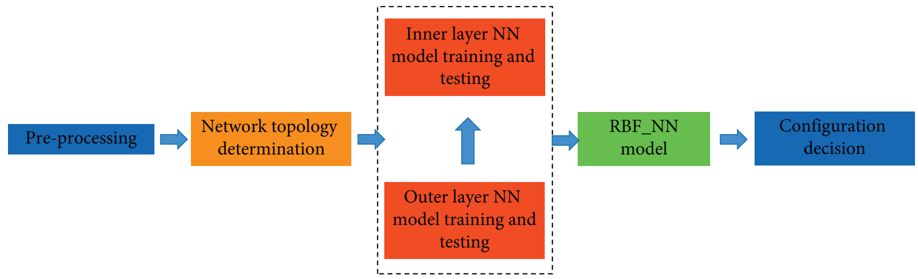

Figure 5: RBF neural network cognitive engine model.

3.3. Algorithm implementation. The implementation process of CR cognitive engine model algorithm based on RBF neural network is shown in Figure 6. The main steps are as follows: (1) preprocess the original sample data. Initialize engine parameters, such as the number of neurons and user demand weights. (2) Construct the outer layer and inner layer to learn the reasoning model, use T to train the neural network to learn the reasoning model, and use S and V to evaluate the generalization ability and performance of the network [28]. Store the trained learning model in the network model library. (3) Find the target output according to the perception information and user needs. If the output belongs to the sample target training set, the configuration decision is used to find the configuration corresponding to the maximum utility value; otherwise, the learning inference model of the environmental condition is retrained. (4) The configuration decision is to reconfigure the working parameters according to user needs and environmental conditions.

4. Experimentation and Evaluation

4.1. Evaluation Metrics. To evaluate the cognitive engine, this paper uses mean square error *MSE* and regression rate *RR* to test the performance of neural network learning models. *MSE* and *RR* measure the stability and accuracy of prediction results, respectively. MSE is defined as [29]

$$\mathrm{MSE} = \frac{1}{N}\sum_{1}^{N}\left(O_i - T_i\right)^2, \quad i = 1\ldots N. \tag{4}$$

Among them, O_i is the i-th output of the neural network, T_i is the i-th target value, and N is the total number of test samples.

Regression rate *RR*: the parameter solution adopts integer coding and the neural network output is a floating-point number. Add 0.5 to it and then round down to equal the original integer value, which is a regression. For example, the code is 4, the neural network outputs 3.854, 4.356, and 5.013, and the output is 4, 4, and, 5 after processing, and the number of regressions is 2. The quotient of the number of regressions of the N groups of samples and the total number N is the regression rate of this test; namely,

$$RR = \frac{\sum_{1}^{N} V_i}{N} \times 100\%,$$
$$V_i = \begin{cases} 1, & \mathit{when}\ \left(\mathrm{floor}\left(O_i + 0.5\right) - T_i\right) = 0, \\ 0, & \text{other}, \end{cases} \tag{5}$$

where *floor(x)* is the function of rounding down.

4.2. Network Initialization. The initial value of the number of hidden layer neurons is 5, the delay for the window network of size 5 is 5, the learning rate is 0.0001, the outer neural network contains 21 input neurons and 1 output neuron, and the inner layer contains 16 input neurons and 5 output neurons, the inner and outer layer training target is 0.02, and the maximum training algebra is 1000. The proportions of T, S, and V are 60%, 20%, and 20%. The experimental environment of this article is as follows: the hardware environment is Linux system, NVIDIA GTX 2080Ti; the software environment is Python3.5, sklearn0.20.3, and other toolkits.

4.3. Results and Analysis. In order to test the effectiveness of the RBF neural network learning model, the simulation results are compared with the BP network learning model. The number of input and output neurons in the inner and outer layers of the BP network is the same as that of the RBF neural network. There are 15 hidden neurons in the outer network, 20 hidden neurons in the inner layer, 0.02 in the inner and outer layers, and a maximum number of training algebras of 1,000. Import T into the BP and RBF learning models, respectively. Randomly select 10 sets of data, and each set of data contains 50 test samples for testing and evaluating the performance of each network. Calculate *MSE* and *RR* according to (4) and (5) and find their mean values MSEaver and RRaver. The results are shown in Tables 1–7.

Tables 1 and 2 show the *MSE* and *RR* of the outer neural network routing configuration. The *MSEaver* and *RRaver* of the BP model in Tables 1 and 2 are 0.0785 and 92.2%, while the RBF corresponds to 0.0230 and 98.8%. It is known from the shape of MSE that the RBF model is more stable than the BP model and its value is better than the BP model by 0.0555. From the RR shape, it is known that the prediction accuracy rate of the RBF model is higher than that of the BP model and is stable at 98% (about 6.6% better than BP). This shows that the outer neural network of RBF is effective for the selection of routing protocol (RP).

Tables 3-7 show the *MSE* and *RR* of the *DSDV* subnetwork parameter configuration. Tables 3–5 represent the *MSE* of *Rate*, *CW*, and *Power*, and Table 6 and 7 represent the RR of rate and CW, respectively.

In Tables 3–5, BP's rate, CW, and power's MSEaver are 1.2888, 0.2393, and 0.0537; rate and CW's RRaver are 31.2%

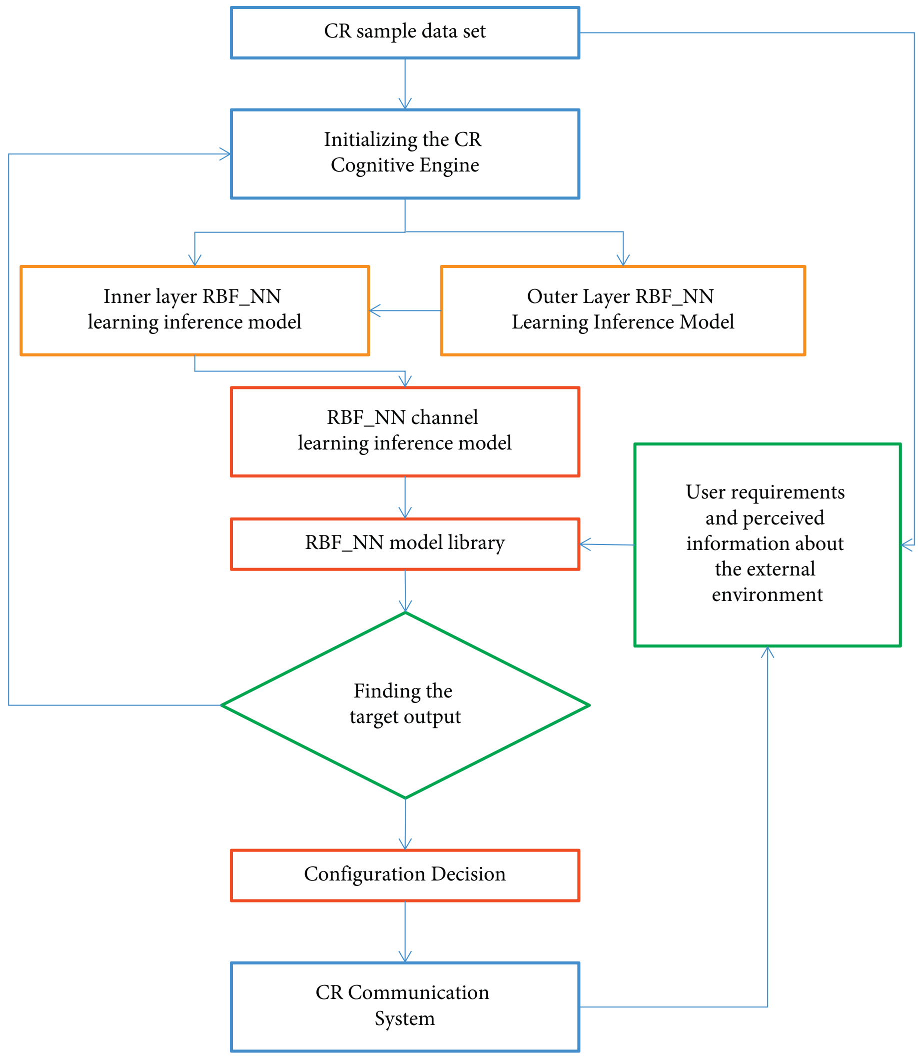

FIGURE 6: RBF neural network cognitive engine model flow chart.

TABLE 1: Outer layer neural network metrics MSE.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.06	0.07	0.03	0.10	0.06	0.07	0.04	0.20	0.13	0.05
RBF	0.02	0.05	0.02	0.01	0.03	0.02	0.03	0.02	0.05	0.02

TABLE 2: Outer layer neural network metric RR.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.87	0.96	0.97	0.95	0.92	0.94	0.93	0.86	0.78	0.94
RBF	0.98	0.97	0.98	0.99	0.98	0.99	0.97	0.99	0.99	0.99

TABLE 3: MSE of the inner layer neural network DSDV subnetwork Rate.

Model	1	2	3	4	5	6	7	8	9	10
BP	1.40	1.50	1.60	1.10	1.10	1.10	1.20	1.30	1.40	1.50
RBF	0.02	0.03	0.02	0.02	0.04	0.04	0.03	0.01	0.02	0.01

and 59.2%. The RBF corresponds to 0.0476, 0.0162, and 0.0219 and 96.2% and 98.4%. From Tables 3–5, it is known that the prediction stability of the two models for the three parameters is successively improved and the RBF stability is better. It is known from MSEaver that the stability of the two models to rate is worse than the other two parameters; from

Table 4: MSE of the inner neural network DSDV subnetwork CW.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.23	0.20	0.21	0.22	0.23	0.21	0.23	0.22	0.21	0.20
RBF	0.02	0.03	0.02	0.01	0.01	0.02	0.01	0.03	0.04	0.02

Table 5: MSE of the inner neural network DSDV subnetwork Power.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.06	0.07	0.04	0.05	0.04	0.03	0.06	0.07	0.08	0.09
RBF	0.02	0.02	0.03	0.02	0.04	0.03	0.04	0.04	0.05	0.03

Table 6: RR of the inner neural network DSDV subnetwork Rate.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.23	0.24	0.20	0.30	0.40	0.35	0.36	0.35	0.40	0.35
RBF	0.99	0.97	0.97	0.98	0.89	0.90	0.97	0.99	0.96	0.99

Table 7: RR of the inner neural network DSDV subnetwork CW.

Model	1	2	3	4	5	6	7	8	9	10
BP	0.54	0.63	0.61	0.50	0.57	0.69	0.58	0.60	0.58	0.70
RBF	0.99	0.98	0.98	0.99	0.98	0.99	0.99	0.98	0.97	0.99

RRaver, it is known that the RR of the two models to CW is higher than the RR of rate. Tables 6 and 7 show that the regression rate of RBF is 65.0% higher than that of BP on average and 39.2%, which means that the success rate of RBF reconfiguration is higher.

5. Cognitive Engine and Legal Management of Public Opinion

The adjustment effect of laws and regulations on social life depends on the implementation of the law. Only by relying on law enforcement can the legal provisions on paper be transformed into the good legal order that legislators expect. To strengthen the accuracy and strength of law enforcement, we must first set up a special network public opinion monitoring and response agency. The cognitive engine based on artificial intelligence cognitive wireless network proposed in this paper can accurately detect public opinion risks and crises, provide a guarantee for accurate law enforcement, and is an important tool for establishing a comprehensive and efficient public opinion monitoring platform.

Through the "human-machine integration" normalized tracking and monitoring to strengthen the monitoring, analysis, and judgment of public opinion, the relevant law enforcement agencies can further or even fully grasp the dynamic trend of public opinion and detect and carry out early warning and intervention before the outbreak of public opinion crisis. The specialized network public opinion response agency can not only unify the standards of network governance, bringing the behavior of netizens and network public opinion management into the legal track, but also help integrate public opinion guidance and control with response work and actively guide the sound development of public opinion. It lawfully investigates and punishes illegal speeches and behaviors in public opinion crisis events and enhances the accuracy and strength of law enforcement. Specialized network public opinion monitoring and response agencies are not only conducive to gathering professional and technical personnel and building professional network law enforcement teams, but also convenient for uniform quality and ability training of network supervision law enforcement personnel, so as to strengthen their legal awareness and professionalism and realize their technology keeping up with the times in knowledge and ability. Relevant law enforcement personnel should take a correct attitude, positively respond to public opinion emergencies, and face and deal with public opinion outbreaks at the first time, so as to compete for public opinion management opportunities and reduce the negative impact of public opinion outbreaks. Setting up a special network public opinion monitoring and responding to law enforcement agency is an important link in improving the ability of network public opinion to rule by law.

6. Conclusion

With the rapid development of the mobile Internet, the traditional form of public opinion communication has been transformed into a social media public opinion communication form. The change in the form of public opinion information dissemination shows to a certain extent that social media, especially in the mobile Internet environment, has subtly affected the lives of social citizens and has played an important role in guiding the dissemination of public opinion information and reshaping the communication structure of cyberspace. Due to the real-time, difficult-to-track, and easy-to-disguise characteristics of mobile wireless networks, many dangerous groups or individuals wantonly spread on the network speech that affects and undermines social stability and unity, causing erroneous public opinion guidance to the broad masses and hiding the content. The risk of public opinion is unpredictable. With the wide application of technology and the use of various places in people's life and work, the scope and extent of its use has not been lower than that of wired networks. Therefore, monitoring of public opinion on wireless networks has become very necessary and urgent. Therefore, this paper proposes a cognitive engine model based on artificial intelligence to recognize wireless networks. The cognitive engine model can introduce reasoning and learning methods in the field of artificial intelligence to realize the perception, adaptation, and learning capabilities of cognitive wireless networks for the spread of public opinion. In order to adapt to the changing wireless environment and user needs of social public opinion, a cognitive engine design method based on Radial Basis Function (RBF) Neural Network is proposed. This method reconfigures communication parameters through learning of empirical knowledge and environment to achieve reasonable resource allocation and to improve the cognitive wireless network system's ability of spreading social public opinion and network legal management. Further, this article explores the method and path of cognitive wireless network applied to the legal management of public opinion dissemination network and provides new solutions for social public opinion dissemination and network legal management. In the future, we plan to develop a cognitive engine model based on long and short-term memory networks to further improve the monitoring capabilities of social network public opinion dissemination.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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