

Research Article

Optimization of Residential Landscape Design and Supply Chain System Using Intelligent Fuzzy Cognitive Map and Genetic Algorithm

Tingyin Deng 

Sichuan University of Science & Engineering, Zigong, Sichuan 643000, China

Correspondence should be addressed to Tingyin Deng; tingyind@suse.edu.cn

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This work intends to optimize residential landscape design and Supply Chain (SC) network systems. First, Fuzzy Cognitive Map (FCM) intelligent assistance and genetic algorithm (GA) are used to study residential landscape design and its integration with SC deeply. Weight matrix interactions are employed to implement iterative inference for FCM. The functions are transformed to unify variables of different scopes. Subsequently, a weighting method is proposed to deal with the disadvantage of the simple average method being too general. In addition, the Hebbian learning algorithm is used to adjust the state nodes and the connection weights. Finally, according to the fitness function of the GA and logistic regression (LR) model, residential landscape design and SC are combined. The simulation experiment results show that the causal relationship analysis between SC networks under fuzzy cognition shows that the state errors of each specific situation are 0.21, 0.16, and 0.24, respectively. The total average error is 0.21 in the case of multiple iterations. The average error of the result vector under fuzzy cognition and the operation of the actual result is 0.20, 0.15, and 0.24, respectively, and the error value is much reduced. The simulation accuracy of the GA-LR method for residential landscape design is improved from 77% to 84.7%. The “kappa coefficient” is also improved to 82.3%. The conclusion shows that the weight matrix is used to analyze the high-quality performance of landscape design according to the specific situation of SC. For each specific case, FCM is effective in reducing errors over multiple iterations. Under the GA-LR method, fewer geographic location types and larger accuracy deviations can improve the simulation accuracy.

1. Introduction

As human needs evolve, techniques and styles change, and so do landscape design trends. Landscape architecture in the future will not only be limited to landscape design, but will also provide a series of solutions around social, economic, environmental, and other issues. Technological innovation and sustainable development means can improve people’s quality of life. The technology used in the smart landscape is mainly modern information technology, but also digital technology. The digital landscape is the main body of the smart landscape. The application of digital technology and methods can break through the limitations of traditional design techniques and construction materials and greatly release the creativity of landscape planners. Many scholars

believe that Supply Chain (SC) [1–3] is a process often used by enterprises. The actual process is that the raw materials are processed by the enterprise and finally transferred to the customers through various channels such as sales and various forms of business activities. However, with the rapid development of science and technology and the rapid progress of society, SC has long been not only used in business. At present, the SC functional network structure model is very helpful for residential landscape design [4–6]. Compared with developed countries in Europe and America, the development of residential landscape design in China is still at a low level [7–9]. For further development, China needs to make up the gap with foreign residential landscape design standards [10–12] and optimize the practical application of SC systems in related industries.

International scholars have important research theories on optimizing residential landscape design and SC systems [13–15]. There are more than 10,000 articles about landscape design in the Chinese master thesis. These research directions are standardized residential landscape design. In addition, contemporary real estate enterprises are investigated on the spot, and some historical and common problems in residential landscape design are further summarized. Chinese residential landscape design is too simple and lacks humanistic considerations. It is more inclined to residential attributes and pays less attention to the spatial, humanistic, and temporal value of landscape facilities. Foreign scholars have conducted special studies on the quality of living space [16–18] and European standards. They studied landscape design, planted seedlings, and developed norms and standards for ornamental plants. In addition, related scholars have also specialized in research strategies for 3D landscape representation. They perform 3D modeling [19–21] to seek a standardized study of landscape design. In water-constrained countries, waterwise landscaping is considered an important landscaping method to conserve water. However, there is still a concern and a lack of knowledge about people’s preferences and the factors that influence them.

Nazemi Rafi et al. [22] examined the effect of landscape factors of plant combination (level 6) and cover type (level 3) on the preferences of 207 respondents. After obtaining the preferences that participants assigned to each plot, they used regression analysis to determine the effect of landscape attributes on overall preferences. Results showed that flowering plants were more popular ($p \leq 0.01$) and less expensive ($p \leq 0.01$) in water landscapes containing only herbaceous plants compared to other designed landscapes. The Visible Green Index (VGI) reflects the degree of greening from human vision to affect health and well-being and has gradually become a new type of urban green space index. Zhu et al. [23] designed and conducted an experiment to evaluate human responses to scenes from panoramic pictures of residential green spaces projected by virtual reality. This study provides a certain theoretical basis for the landscape planning of residential areas, which is helpful to improve the VGI theory and promote its establishment as a new type of urban green space index. O’Neill and Maravelias [24] mentioned in *Towards Integrated Landscape Design and Biofuel Supply Chain Optimization* the integration of landscape design with SC networks [25–27] to determine the synergy of the systems. The research of relevant international scholars makes it possible to optimize the residential landscape design and SC system.

In the research results of relevant scholars in this field, although the theory of the combination of residential landscape standardization design and SC system network is proposed, the research direction is also standardized residential landscape design. These theories do not involve optimizing residential landscape design and SC systems. Therefore, this study innovatively uses the intelligent assistance of a Fuzzy Cognitive Map (FCM) and genetic algorithm (GA) further to optimize the residential landscape design and SC system. The innovation lies in the optimization of the SC system, a new design for the residential landscape.

2. Methods

2.1. FCM. The function of FCM is to solve complex problems. Uncertain decision-making can impact decision-makers, and FCM constructs an important process of people’s decision-making and analyzes its construction patterns to explain the external world. Cognitive maps have a variety of ways to build high-quality and often accurate results. The general principle of FCM is that the path of adjacent connection points in the cognitive graph is a vector arc segment, which expresses the causal relationship between nodes [28–30]. If any two connection points in the cognitive graph extend through a directed path, and the sign between the connection points is positive, it means that the relationship between them is positive. Otherwise, their relationship is an inverse relationship. Figure 1 shows a simple FCM.

In Figure 1, a fuzzy cognitive graph with n nodes, each node represents a concept in the system. This concept can be events, goals, trends of the system, etc. Each concept characterizes its properties using state values. Directed arcs represent the causal influence relationships between concepts. The weight w_{ij} reflects the degree of causal influence. $w_{ij} > 0$ means that the increase in C_i will lead to the increase of C_j . There is a positive causal relationship between C_i and C_j , which is indicated by “+” in Figure 1; $w_{ij} < 0$ means that the increase of C_i will increase C_j decreases. There is a negative causal relationship between C_i and C_j , that is, the part indicated by “-” in Figure 1; $w_{ij} = 0$ means that there is no causal relationship between C_i and C_j . C_i and C_j are represented by A, B, C, D, and E in Figure 1.

Based on the scenario studied in the present work, the discrete-time Markov decision process with continuous action space can be used to represent the optimal stochastic control problems of residential landscape allocation and location factor scheduling. Because of the complex transformation of the external environment, the residential landscape module cannot obtain accurate transformation information. Besides, the optimal solutions with low complexity are difficult to obtain by the general algorithm or equation through the previous methods. Therefore, the resource fuzzification of FCM under the reinforced deep learning (DL) algorithm is studied below to optimize the residential landscape design further. In the case of discrete time, the optimization aims at the conventional reinforcement learning problem composed of a residential landscape design environment and intelligent fuzzy cognitive assistance. The real-time reward is based on the timely action taken by the intelligent module after receiving the observation results in each process. The state space is the product of the resource allocation scenario of residential landscape design, that is, the current environmental state of the intelligent module. According to the DL model of the large-scale residential landscape, in equation (1), cx represents the data transmission direction and pointer; w_{ij} represents the weight; $x_i(t)$ represents the object’s value at the current moment; $x_i(t + 1)$ represents the value of the object at the next moment. The derivation process of the cognitive graph is not complicated, and its key function is

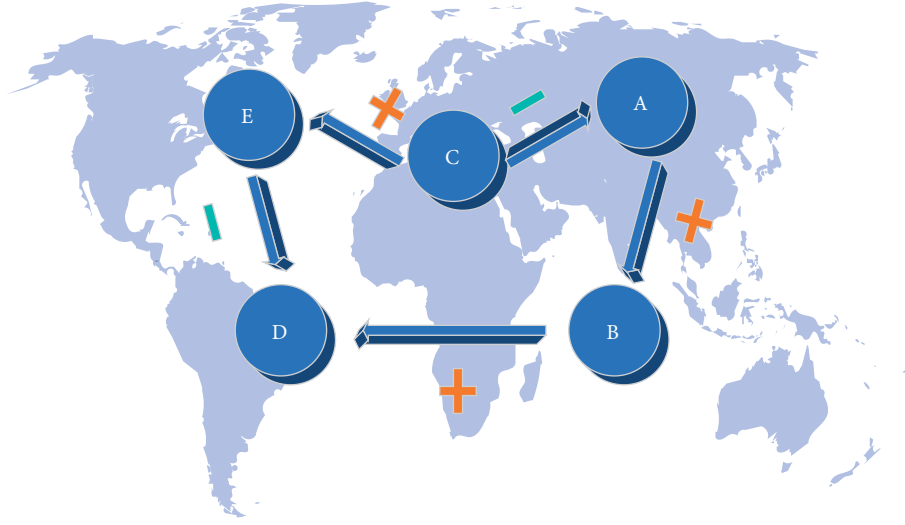


FIGURE 1: Simple FCM.

to grasp the concept nodes and weight matrix. Equation (1) represents a specific iterative function.

$$x_i(t+1) = f \left[\left(\sum_{\substack{j=1 \\ j \neq i}}^n w_{ij} x_j(t) + c x_i(t) \right) \right] \quad (1)$$

The transformation function [31] is used to change the data useless to the system. The variation range of the transformation function is $[0,1]$. Equation (2) is a threshold function; equation (3) is a hyperbolic tangent function; equation (4) is a sigmoid function [32–34]; Equation (5) is a saturation function. In equations (2)–(5), x represents a real number between 0 and 1.

$$f(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

$$f(x) = \tanh(x) \quad (3)$$

$$f(x) = \frac{1}{1 + e^{-x}} \quad (4)$$

$$f(x) = \begin{cases} 1, & x \geq \frac{1}{k} \\ kx, & -\frac{1}{k} \leq x \leq \frac{1}{k} \\ -1, & x < -\frac{1}{k} \end{cases} \quad (5)$$

Based on the general problem of simple average, the weight method is proposed, mainly used to conduct the weighted average on the simple average. Equation (6) demonstrates the principle of the method.

$$W = f \left(\sum_{k=1}^n b_k W_k \right) \quad (6)$$

In equation (6), W means the final weight; n denotes the number of experts; W_k refers to the weight matrix according to the k th expert; f stands for conversion function, which is used to change all data in the weight matrix to the range between -1 and 1 ; b_k means the accuracy of matching expert experience and knowledge.

Hebbian learning algorithm. The two most important factors in Hebbian learning of FCM are the dynamic characteristics of process and environment. The value of connection weight can be further adjusted by adjusting the state node. W_{ij} denotes the weight between node c_j and node c_i , when x_j represents the state of node c_j and x_i represents the state of c_i . Therefore, when x_j and x_i change, the adjustment function is shown in:

$$\Delta w_{ji} = \gamma w_{ji}^{k-1} + \eta A_i^{k-1} (A_j^{k-1} - \text{sgn}(w_{ji}^{k-1}) w_{ji}^{k-1} A_i^{k-1}) \quad (7)$$

In equation (7), η means learning factor; γ points to the attenuation factor.

GA algorithm is used to select the values with good adaptability and pass the values with high-quality characteristics to the next generation. In equation (8), M stands for the population size; F_i accords to the fitness of monomer i . Equation (8) illustrates the calculation of the probability that i is selected.

$$P_i = \frac{F_i}{\sum_{i=1}^M F_i} \quad (i = 1, 2, \dots, M). \quad (8)$$

The minimum deviation e means that the fitness of GA has been reduced to the minimum state. Then, its termination condition is expressed as:

$$|f_{\max} - f^*| < e \quad (9)$$

In equation (9), f^* represents the fitness goal and f_{\max} denotes the maximum fitness. The fitness function is set to the inverse of the prediction error to train the FCM. Equation (10) manifests its expression.

$$f = \frac{1}{e} = \frac{1}{\sqrt{(1/m) \sum_{i=1}^m (s_i - \hat{s}_i)^2}}. \quad (10)$$

In equation (10), s_i designates the actual value and \hat{s}_i stands for the predictive value of FCM.

$$\text{Probability}(gene\ j\ is\ selected) = \frac{f_j}{\sum_{k=1}^m f_k}. \quad (11)$$

In equation (11), f_j refers to the fitness value of the j th gene.

$$\min G(Q, R) = \frac{k\lambda}{Q} + h\left(\frac{Q}{2} + R - \lambda\tau\right) + \frac{Pn(R)\lambda}{Q} \quad (12)$$

In equation (12), $n(R)$ means the prediction of landscape design land; Q accords to the amount of landscape land occupation; R stands for the current land stock; and H represents the market interest rate.

$$g(s_i^t) = \begin{cases} 0, & \text{if } s_i^t < a_i \\ (s_i^t - a_i)/\{2(m_i - a_i)\}, & \text{if } a_i \leq s_i^t \leq m_i \\ 0.5 + (s_i^t - m_i)/\{2(b_i - m_i)\}, & \text{if } m_i \leq s_i^t \leq b_i \\ 1, & \text{if } s_i^t \geq b_i \end{cases}. \quad (13)$$

In equation (13), the state value of fuzzy cognition is generally set as a real number between 0 and 1. The purpose of introducing a nonlinear function approximator into the algorithm is to better deal with the problems of continuous space and multi-dimensional state space. The ordinary linear function approximators cannot properly deal with the problems of the frequency resources of the unauthorized frequency band. In the following algorithm, the residential landscape design is the core, the SC is the main structure of the algorithm, and the supply network inputs the state into S_t and outputs the result. Landscape design is triggered by the subsequent trigger action of the intelligent module under the action of the surrounding environment of the residence and feeds back to the new state. Therefore, it is necessary to standardize the numbers in this range. The standardized method is the historical minimum, maximum, and average values obtained in time t . In equation (13), s_i^t means the i th state value at time t .

$$\begin{aligned} a_i &= \min_{t \in T} \{s_i^t\} \\ b_i &= \max_{t \in T} \{s_i^t\} \\ m_i &= \text{average}_{t \in T} \{s_i^t\} \end{aligned} \quad (14)$$

The state vector can be obtained based on the operation of fuzzy cognition [35–37], which can be expressed as an equation:

$$S_t = f(S_{t-1} \times E), t = 1, 2, \dots \quad (15)$$

In equation (15), $f(S_t)$ refers to a transfer function whose specific purpose is to set the state values between 0 and 1; s_i^t represents the i th state value at time t ; \hat{s}_i^t accords to the results of the fuzzy cognitive calculation. Then, the difference between \hat{s}_i^t and s_i^t is the error in the prediction. Furthermore, equation (16) displays the square root of all state values.

$$e_t = \sqrt{\frac{1}{n} \sum_{i=1}^n (s_i^t - \hat{s}_i^t)^2}. \quad (16)$$

Equation (17) discloses the expression of the total prediction error of the GA.

$$\min \sum_{t \in T} e_t \quad (17)$$

$$\text{Probability}(gene\ j\ is\ selected) = \frac{f_j}{\sum_{k=1}^m f_k}. \quad (18)$$

In equation (18), f_j represents the fitness value of the j th weight. In the Euclidean distance, prediction results of \hat{S}_G^C are closest to the actual target vector S^T . The calculation is shown in the equation:

$$\hat{S}_G^C = \arg \min \left\{ \text{distance} \left(S^T, \hat{S}_G^T \right) \right\}. \quad (19)$$

The emergence of the definition of \hat{S}_H^C means that the analysis stops because the data collected at this time are not the category of historical data anymore.

$$\hat{S}_H^C = \arg \min \left\{ \text{distance} \left(S, \hat{S}_G^C \right) \right\} \quad (20)$$

2.2. Genetic Algorithm. GA is an optimization algorithm with a high utilization rate in the academic field, based on Darwin's *Theory of Evolution* and related elements in genetics. It can optimize the target. Its composition is generally divided into four aspects: maximum number of iterations, crossover rate, control parameters, fitness function, and chromosome coding. The foundation of GA is based on mathematical theorems. GA has great advantages for individuals with good fitness. The definition of a genetic algorithm is that genes and chromosomes are elements. Genes are the smallest elements that assemble into chromosomes. The form that exists on chromosomes is string encoding. Characters in a string represent genes. Its algorithmic meaning is the relationship between variable solution set and variable solution. Meanwhile, these solutions are combined to form the population of GA. LR method is a common learning algorithm whose advantage is that it has characteristics to describe nonlinear problems. Simultaneously, the LR model can usually solve common problems, so it has wide practicability. Equation (21) indicates the expression form of the sigmoid function of LR:

$$f(t) = \frac{1}{1 + e^{-t}}. \quad (21)$$

In equation (23), t is a variable and represents a linear function. Equation (22) refers to the expression of fitness function $Fit(f(x))$, which is implemented to find the minimum value of objective function $f(x)$:

$$Fit(f(x)) = \begin{cases} c_{\max} - f(x), & f(x) < c_{\max} \\ 0, & else \end{cases} \quad (22)$$

Equation (21) denotes the expression of fitness function $f(x)$, which is adopted to find the maximum value of objective function $f(x)$.

$$Fit(f(x)) = \begin{cases} f(x) - c_{\min}, & f(x) > c_{\min} \\ 0, & else \end{cases} \quad (23)$$

In equations (22) and (23), C_{\max} and C_{\min} mean the maximum and minimum values of the objective function, respectively. The fitness function in the present work can effectively identify all chromosomes and find unsolved and normal chromosomes. If the identification degree between them is not high, the value of the fitness function should be adjusted to ensure normal identification. This is a very important step in the design of fitness functions.

Simple genetic algorithm (SGA) has three operators: crossover operator, selection operator, and mutation operator. The selection operator refers to the operator that can simulate biological evolution, which can decide whether to retain the individual according to the value of the fitness function. Generally speaking, the probability of being selected is closely related to fitness. The higher the fitness, the greater the probability of being selected. Equation (24) signifies the specific expression of the selection operator of SGA:

$$P_i = \frac{f_i}{\sum_{i=1}^n f_i} \quad (24)$$

In equation (24), P_i accords to the probability that monomer i is selected, and f_i represents the fitness of monomer i :

$$Fit = \frac{P_1 + P_2}{P_{all}} \quad (25)$$

Equation (25) refers to the function of fitness Fit , where P_1 and P_2 represent the number of records of landscape land and non-landscape land. P_{all} stands for the total number of records in the data set of the sample. Equations (26) and (27) calculate adaptive variation rate pm and crossover rate pc , respectively.

$$P_c = pc_1 - (pc_2 - pc_1) * \frac{popsize - n}{popsize} \quad (26)$$

$$P_m = pm_1 + (pm_2 - pm_1) * \frac{popsize - n}{popsize} \quad (27)$$

In equations (26) and (27), pc_1 and pc_2 point to the maximum and minimum cross rate, respectively. Parameter n represents the number of individuals. The change of n and pc is accompanied by the iterative process of the algorithm.

The change of pm and pc is determined according to the change of n .

SGA [38–40] is the model's foundation in the present work. Its solution process is: first, the population is initialized, which is to determine the control parameters of GA and generate results. Second, the fitness value of the current monomer is calculated, the monomer is screened, and cross-operation is carried out. Third, the mutation operation is carried out and the iteration is judged immediately. Fourth, the optimal solution is output. Figure 2 displays the specific flow of GA.

The disadvantage of the rule-based method is that it is often difficult for people to formulate a good rule base in an unfamiliar scene. After the membership function is established, the corresponding processing rule base is indispensable. Finally, the proposed method is simulated, and GA is used for residential landscape design and SC system optimization. The experiment uses SYNTHIA-Dataset. This dataset is a large-scale dataset of photorealistic renderings of virtual cities with semantic segmentation information, which is proposed for scene understanding in research fields such as autonomous driving or urban scene planning and garden design. The dataset provides fine-grained pixel-level annotations for 11 categories of objects (empty, sky, buildings, roads, sidewalks, fences, vegetation, poles, cars, signal signs, pedestrians, and cyclists). Thirteen thousand four hundred seven training images were extracted from the video stream. This dataset is also known for its variability, including scenes (towns, cities, highways, etc.), objects, seasons, weather, etc. Experiments on this dataset can clearly show the improvement in the performance of the residential landscape design system after the optimization of the GA.

The software and hardware environment adopted in the experiment is Matlab. The hardware and software environment settings are on one PC. The operating system is Windows 10 version. The CPU is Intel(R) Core (TM) i9-9900K CPU @ 3.60 GHz, and the memory is 8G. The programming language adopts PyThon 3.0.

3. Results

3.1. Fuzzy Cognitive Analysis of Residential Landscape SC. Causality between SC networks under fuzzy cognition is analyzed. The storage status of landscape design land is assumed to be 1, which indicates that the actual value is much higher than that in general. In Figure 3, the interval values are the smallest when symbol values are between [0–0.1] and [0.5–0.6]. On the contrary, the interval values are the largest when symbol values are between [0.4–0.5] and [0.9–0.1]. Besides, according to the histogram, all the interval values show an increasing trend. Figure 3 shows the values of key points at the fuzzy state.

Based on simulation experiments, the weight matrix performs well in analyzing the landscape design according to the SC. Figure 4 demonstrates the specific situation of the simulation. For each specific case, the premise that the FCP can reach a fixed value is to carry out multiple iterations. Figure 4(a) depicts the state error in specific cases. The error

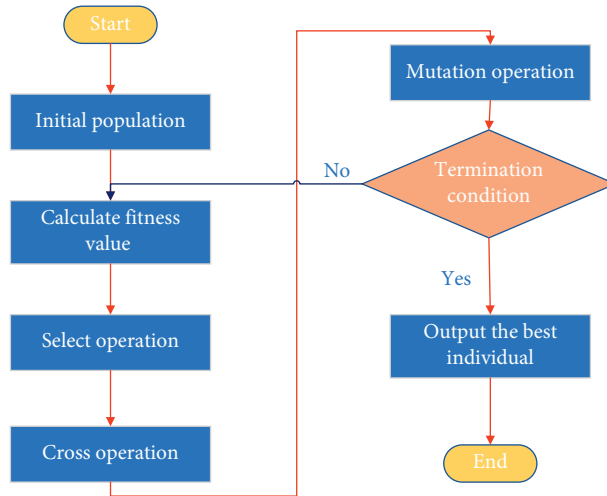


FIGURE 2: Flow of GA.

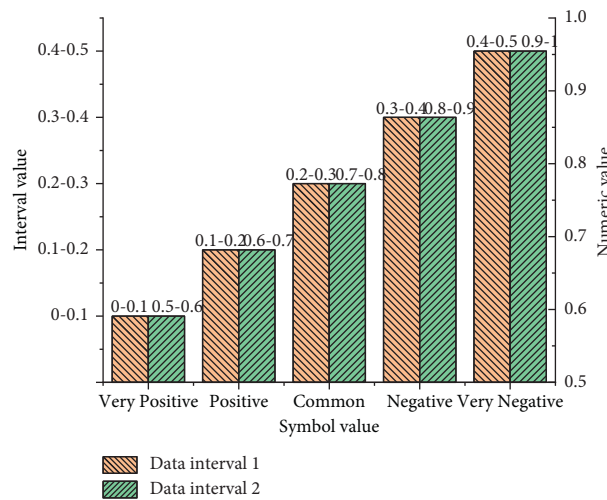


FIGURE 3: Values of key points at the fuzzy state.

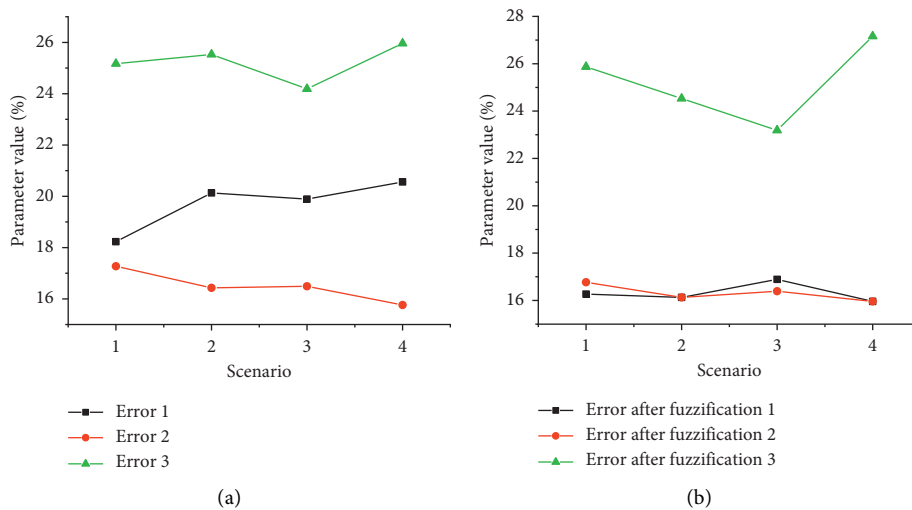


FIGURE 4: Simulation analysis of fuzzy cognition. (a) Error diagram; (b) error diagram after fuzzification.

is 0.21, 0.16, and 0.24 in turn, and the total average error is 0.21. According to the result vector under FCP and the operation of actual results, the error, in this case, is reduced a lot. According to the blurred result, the average error is 0.20, 0.15, and 0.24, in turn, according to Figure 4(b). Meanwhile, compared with the initial average error, the error value is reduced to 0.19. Figure 4 shows the fuzzy cognitive simulation analysis based on landscape design.

3.2. SC and GA Analysis. GA can achieve convergence based on multiple iterations, and the mean value of the objective function can be infinitely close to zero. Therefore, samples with prediction errors close to zero can be obtained through the optimal weight combination, which is the best regression coefficient of LR. Figure 5 shows the convergence curve of GA.

LR coefficients are obtained by genetic algorithm training. LR training can obtain specific regression coefficients. Figure 6(a) and 6(b) depicts the curves of the regression coefficients under different factors, respectively. The value of the elevation factor changes from -0.33 to -0.71 to -0.79 . In Figure 6(b), the value of the factor between the landscape design and the river changes from -0.43 to -0.45 , and the other two groups of data have an upward trend. Only the elevation factor plays a positive role in landscape design.

Figures 7 and 8 depict the simulation results of the confusion matrix for the GA-based logistic regression (LR) and the traditional LR method, respectively. The matrix is used to calculate the simulation accuracy and Kappa coefficient.

In Figure 7, the actual values of landscape and non-landscape land are 5768 and 1621, respectively, and 9845 and 5169 under simulation conditions. In Figure 8, the actual values of landscape and non-landscape land are 5208 and 2691, respectively, and they are 1675 and 5163 under simulated conditions. In the research of residential landscape design, problems such as many geographical locations and insufficient sample richness should be considered to eliminate precision bias. In Figure 9, the comparison between the GA-optimized LR and the traditional LR method shows that the simulation accuracy of the proposed GA-based LR method in residential landscape design is significantly improved from 77% to 84.7%. The “Kappa coefficient” also increases to 82.3%. The proposed algorithm has better performance.

4. Discussion on the Application of Fuzzy Cognition and GA in Landscape Design

In Sections 3.1 and 3.2, the FCM and GA analysis results of residential landscape SC show that, through simulation experiments, the weight matrix performs well in analyzing the landscape design in the SC case. Bakhtavar et al. [41] pointed out that fuzzy cognitive graphs are widely used to analyze complex, causal-based systems in modeling,

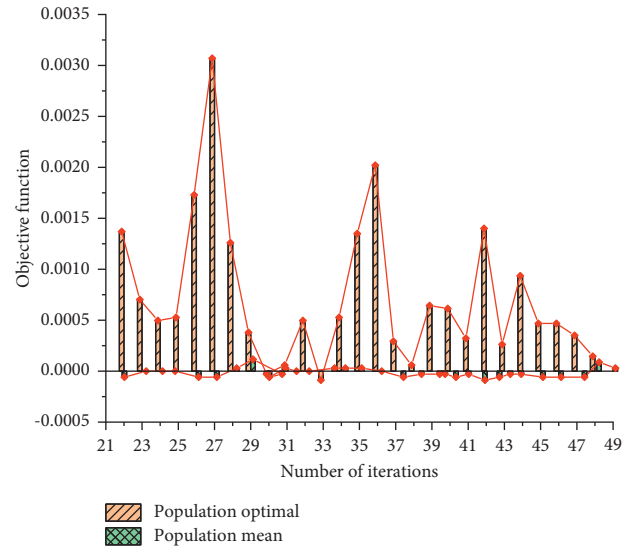


FIGURE 5: Convergence curve of GA.

decision-making, analysis, prediction, classification, etc. Managers cannot decide to implement and allocate resources to improvement projects based on the outputs of the risk management process. Rezaee et al. [42] attempted to accurately identify and prioritize potential failures in a production process with the help of crossover using an approach based on a multi-stage fuzzy cognitive graph approach and process failure mode and impact analysis techniques. Ladeira et al. [43] aimed to develop an FCM to identify and analyze the determinants of digital entrepreneurship. Iqbal et al. [44] proposed a new GA-based feature reduction technique. This hybrid approach reduced the feature set size to 42% without compromising accuracy.

The premise of a fuzzy graph reaching a fixed value is multiple iterations. In addition, the state error of the specific case is given. This error is relatively large, and the total average error is also relatively large. The operation error between the result vector under FCM and the actual result is much reduced. Furthermore, the error after blurring is reduced compared to the initial average error. GA plays a role in improving the accuracy of optimizing the eigenvalues.

In addition, the analysis of residential landscape SC in the GA direction can achieve convergence based on multiple iterations. The mean of the objective function can be infinitely close to zero. Therefore, the optimal weight combination obtains a sample with a prediction error close to zero, that is, the optimal regression coefficient of LR. The LR coefficients obtained by GA training and the conventional LR training obtained by the maximum likelihood estimation algorithm are used to obtain specific regression coefficients. The analysis shows that the regression coefficient values obtained by the two different methods are quite different. The regression coefficient values obtained by the two methods are quite different. The results show that only the elevation factor plays a positive role in residential landscape design. Comparing GA and conventional LR methods, the

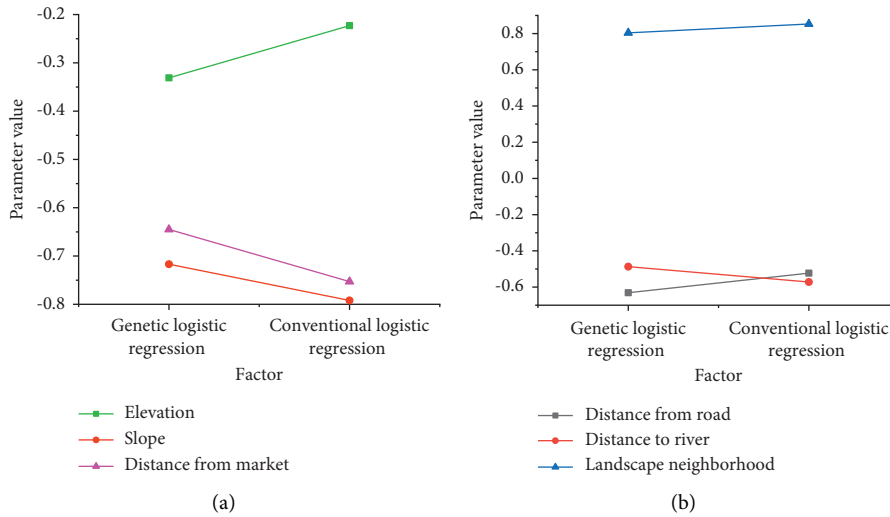


FIGURE 6: Changes of LR coefficient. (a) Genetic logistic regression coefficient. (b) Conventional logistic regression coefficient.

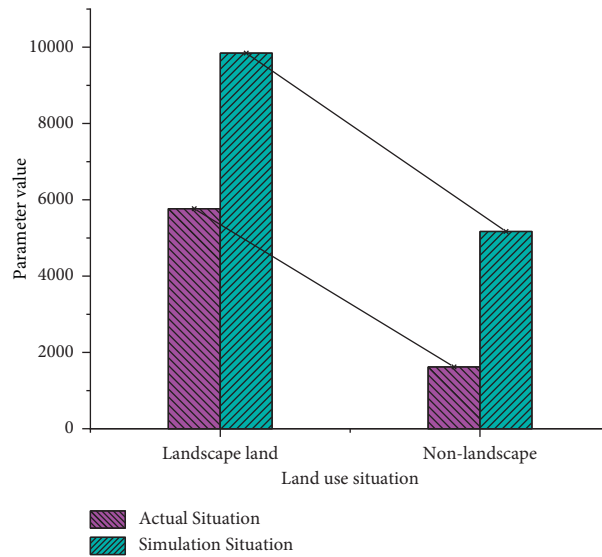


FIGURE 7: Confusion matrix for genetic LR.

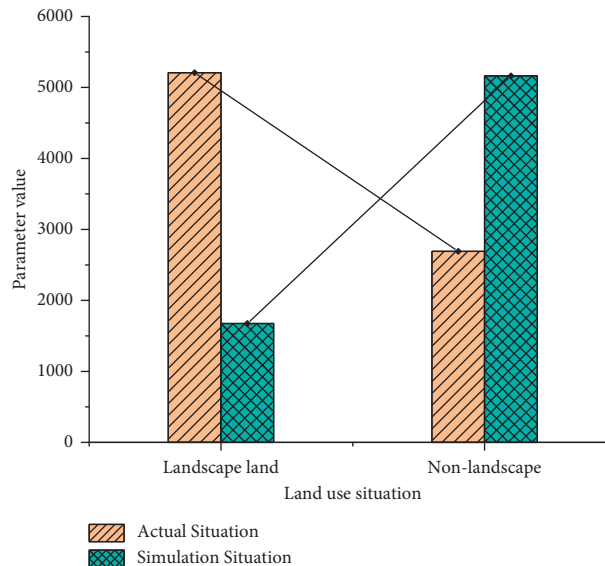


FIGURE 8: Confusion matrix for conventional LR.

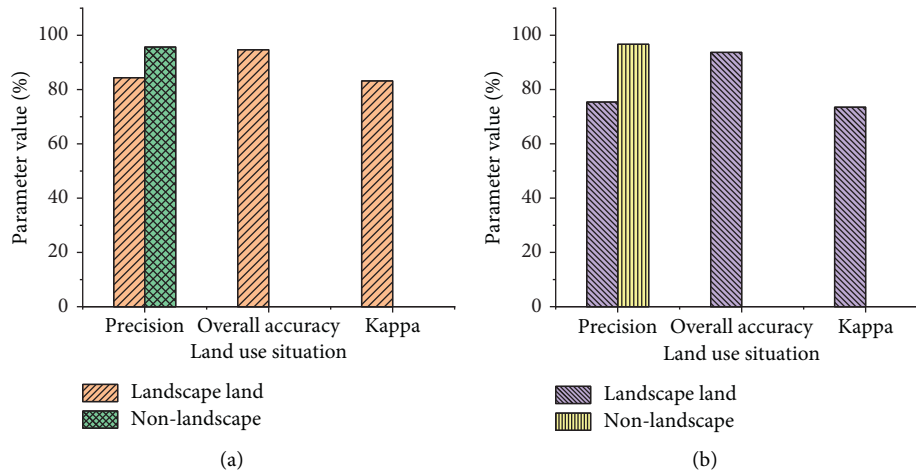


FIGURE 9: Comparison of simulation accuracy. (a) Genetic LR method; (b) conventional LR method.

simulation accuracy of the GA-LR method in residential landscape design is significantly improved. Therefore, simulated cognitive maps and GA play an irreplaceable role in residential landscape design and SC optimization.

5. Conclusion

The problem of combining residential landscape design with SC management and the current residential design in China is further optimized and improved to narrow the gap with foreign high-quality residential landscape design. The research work is to model, simulate and optimize residential landscape design. First, the previous research is the basis for the theoretical support. Classification and summarization are made according to the residential landscape design and the regional characteristics of geographical location, and LR is adopted as the model, which is combined with GA and the conventional LR method. Afterward, the fitting degree of this model is not enough, and the fitting ability is still weak due to the deviation of regional data and the influence of geographical location characteristics. Based on this situation, the GA-LR model is used to analyze residential landscape design and further study it. Finally, the model eventually has a good fitting effect, and its reliability is confirmed by verification and analysis. Besides, based on the SC management analysis of residential landscape design and the simulation research of SC network oriented to FCM, the logical relationship of SC network is very strong, which can well analyze the causal relationship between various nodes. Simultaneously, the complex state nodes can also be handled well further to ensure the accuracy and universality of each link. The following conclusions are drawn: (1) the weight matrix can analyze the high-quality performance of landscape design according to the situation of SC; (2) for each specific case, in the case of multiple iterations, the total average error of model simulation is small; (3) this method is very helpful to study residential landscape design; and (4) under the genetic LR method, the simulation accuracy can be significantly improved in the face of fewer types of geographical location and large accuracy deviation. The

simulation data can show that the FCM constructed in the present work and the combination with the SC network system can better analyze and optimize the residential landscape design. There are still some deficiencies in the simulation accuracy calculation under genetic and conventional LR methods. A few types are considered for the geographical location of residential landscape design, and the sample richness is not enough so the accuracy deviation may be large. This problem will be the focus of follow-up research.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Consent

Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

- [1] S. Min, Z. G. Zacharia, and C. D. Smith, "Defining supply chain management: in the past, present, and future," *Journal of Business Logistics*, vol. 40, no. 1, pp. 44–55, 2019.
- [2] H. Fatorachian and H. Kazemi, "Impact of Industry 4.0 on supply chain performance," *Production Planning & Control*, vol. 32, no. 1, pp. 63–81, 2021.
- [3] R. Casado-Vara, J. Prieto, F. D. Prieta, and J. M. Corchado, "How blockchain improves the supply chain: case study alimentary supply chain," *Procedia Computer Science*, vol. 134, pp. 393–398, 2018.
- [4] H. S. Cinar and N. K. Aktas, "Xeriscape analysis: a case study in a residential garden in Istanbul," *J Environ Prot Ecol*, vol. 19, no. 4, p. 1904, 2018.
- [5] K. R. Colter, A. C. Middel, and C. A. Martin, "Effects of natural and artificial shade on human thermal comfort in residential neighborhood parks of Phoenix, Arizona, USA," *Urban Forestry and Urban Greening*, vol. 44, Article ID 126429, 2019.
- [6] G. R. Roshan, R. Oji, and S. Attia, "Projecting the impact of climate change on design recommendations for residential buildings in Iran," *Building and Environment*, vol. 155, pp. 283–297, 2019.
- [7] A. Hami, F. F. Moula, and S. B. Maulan, "Public preferences toward shopping mall interior landscape design in Kuala Lumpur, Malaysia," *Urban Forestry and Urban Greening*, vol. 30, pp. 1–7, 2018.
- [8] S. M. H. Atwa, M. G. Ibrahim, A. M. Saleh, and R. Murata, "Development of sustainable landscape design guidelines for a green business park using virtual reality," *Sustainable Cities and Society*, vol. 48, Article ID 101543, 2019.
- [9] P. Motealleh, W. Moyle, C. Jones, and K. Dupre, "Creating a dementia-friendly environment through the use of outdoor natural landscape design intervention in long-term care facilities: a narrative review," *Health & Place*, vol. 58, Article ID 102148, 2019.
- [10] S. Khatibi, L. Zare, and M. H. Kaboli, "The effect of green space and landscape design on promoting the sense of space belonging to the residential complex," *Hoviatshahr*, vol. 12, no. 3, pp. 19–28, 2018.
- [11] L. A. Warner, J. M. Diaz, and A. K. Chaudhary, "Informing urban landscape water conservation extension programs using behavioral research," *Journal of Agricultural Education*, vol. 59, no. 2, pp. 32–48, 2018.
- [12] Y. Feng, "Design of landscape gardens in urban residential areas," *Journal of Landscape Research*, vol. 10, no. 3, pp. 24–34, 2018.
- [13] M. R. Saavedra, C. H. de O Fontes, and F. G. M. Freires, "Sustainable and renewable energy supply chain: a system dynamics overview," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 247–259, 2018.
- [14] S. Tiwari, C. K. Jaggi, M. Gupta, and L. E. Cárdenas-Barrón, "Optimal pricing and lot-sizing policy for supply chain system with deteriorating items under limited storage capacity," *International Journal of Production Economics*, vol. 200, pp. 278–290, 2018.
- [15] M. L. Tseng, A. S. F. Chiu, G. Liu, and T. Jantaralolica, "Circular economy enables sustainable consumption and production in multi-level supply chain system," *Resources, Conservation and Recycling*, vol. 154, Article ID 104601, 2020.
- [16] X. Feng and T. Astell-Burt, "Residential green space quantity and quality and symptoms of psychological distress: a 15-year longitudinal study of 3897 women in postpartum," *BMC Psychiatry*, vol. 18, no. 1, pp. 348–411, 2018.
- [17] L. Rui, R. Buccolieri, Z. Gao, W. Ding, and J. Shen, "The impact of green space layouts on microclimate and air quality in residential districts of Nanjing, China," *Forests*, vol. 9, no. 4, p. 224, 2018.
- [18] R. Aerts, S. Dujardin, B. Nemery et al., "Residential green space and medication sales for childhood asthma: a longitudinal ecological study in Belgium," *Environmental Research*, vol. 189, Article ID 109914, 2020.
- [19] D. Antón, B. Medjdoub, R. Shrahily, and J. Moyano, "Accuracy evaluation of the semi-automatic 3D modeling for historical building information models," *International Journal of Architectural Heritage*, vol. 12, no. 5, pp. 790–805, 2018.
- [20] V. Fantini, M. Bordoni, F. Scocozza et al., "Bioink composition and printing parameters for 3D modeling neural tissue," *Cells*, vol. 8, no. 8, p. 830, 2019.
- [21] A. I. Benzer and B. Yildiz, "The effect of computer-aided 3D modeling activities on pre-service teachers' spatial abilities and attitudes towards 3D modeling," *Journal of Baltic Science Education*, vol. 18, no. 3, pp. 335–348, 2019.
- [22] Z. Nazemi Rafi, F. Kazemi, and A. Tehranifar, "Public preferences toward water-wise landscape design in a summer season," *Urban Forestry and Urban Greening*, vol. 48, Article ID 126563, 2020.
- [23] H. Zhu, F. Yang, Z. Bao, and X. Nan, "A study on the impact of Visible Green Index and vegetation structures on brain wave change in residential landscape," *Urban Forestry and Urban Greening*, vol. 64, Article ID 127299, 2021.
- [24] E. G. O'Neill and C. T. Maravelias, "Towards integrated landscape design and biofuel supply chain optimization," *Current Opinion in Chemical Engineering*, vol. 31, Article ID 100666, 2021.
- [25] H. C. Su, T. W. D. Kao, and K. Linderman, "Where in the supply chain network does ISO 9001 improve firm productivity?" *European Journal of Operational Research*, vol. 283, no. 2, pp. 530–540, 2020.
- [26] F. Goodarzi, H. Hosseini-Nasab, J. Muñuzuri, and M. B. Fakhrazad, "A multi-objective pharmaceutical supply chain network based on a robust fuzzy model: a comparison of meta-heuristics," *Applied Soft Computing*, vol. 92, Article ID 106331, 2020.
- [27] B. Zahiri, P. Jula, and R. T. Moghaddam, "Design of a pharmaceutical supply chain network under uncertainty considering perishability and substitutability of products," *Information Sciences*, vol. 423, pp. 257–283, 2018.
- [28] P. Morone, P. M. Falcone, and A. Lopolito, "How to promote a new and sustainable food consumption model: a fuzzy cognitive map study," *Journal of Cleaner Production*, vol. 208, pp. 563–574, 2019.
- [29] K. Papageorgiou, P. K. Singh, E. Papageorgiou, H. Chudasama, D. Bochtis, and G. Stamoulis, "Fuzzy cognitive map-based sustainable socio-economic development planning for rural communities," *Sustainability*, vol. 12, no. 1, p. 305, 2019.
- [30] M. Alipour, R. Hafezi, E. Papageorgiou, M. Hafezi, and M. Alipour, "Characteristics and scenarios of solar energy development in Iran: fuzzy cognitive map-based approach," *Renewable and Sustainable Energy Reviews*, vol. 116, Article ID 109410, 2019.
- [31] F. Gu, S. Chen, Z. Zhou, and Y. Jiang, "An enhanced normalized step-size algorithm based on adjustable nonlinear transformation function for active control of impulsive noise," *Applied Acoustics*, vol. 176, Article ID 107853, 2021.

- [32] P. Goel and S. S. Kumar, "Certain class of starlike functions associated with modified sigmoid function," *Bulletin of the Malaysian Mathematical Sciences Society*, vol. 43, no. 1, pp. 957–991, 2020.
- [33] Z. Qin, Y. Qiu, H. Sun et al., "A novel approximation methodology and its efficient vlsi implementation for the sigmoid function," *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 67, no. 12, pp. 3422–3426, 2020.
- [34] Y. C. Wu, C. W. Chow, Y. Liu et al., "Received-signal-strength (RSS) based 3D visible-light-positioning (VLP) system using kernel ridge regression machine learning algorithm with sigmoid function data preprocessing method," *IEEE Access*, vol. 8, pp. 214269–214281, 2020.
- [35] H. S. Firmansyah, S. H. Supangkat, A. A. Arman, and P. J. Giabbanelli, "Identifying the components and interrelationships of smart cities in Indonesia: supporting policy-making via fuzzy cognitive systems," *IEEE Access*, vol. 7, pp. 46136–46151, 2019.
- [36] P. P. Groumpos, "Intelligence and fuzzy cognitive maps: scientific issues, challenges and opportunities," *Studies in Informatics and Control*, vol. 27, no. 3, pp. 247–264, 2018.
- [37] I. Pluchinotta, D. Esposito, and D. Camarda, "Fuzzy cognitive mapping to support multi-agent decisions in development of urban policymaking," *Sustainable Cities and Society*, vol. 46, Article ID 101402, 2019.
- [38] H. Liu, S. Shi, P. Yang, and J. Yang, "An improved genetic algorithm approach on mechanism kinematic structure enumeration with intelligent manufacturing," *Journal of Intelligent and Robotic Systems*, vol. 89, no. 3-4, pp. 343–350, 2018.
- [39] B. Li, P. Hu, N. Zhu, F. Lei, and L. Xing, "Performance analysis and optimization of a CCHP-GSHP coupling system based on quantum genetic algorithm," *Sustainable Cities and Society*, vol. 46, Article ID 101408, 2019.
- [40] B. Rolf, T. Reggelin, A. Nahhas, S. Lang, and M. Müller, "Assigning dispatching rules using a genetic algorithm to solve a hybrid flow shop scheduling problem," *Procedia Manufacturing*, vol. 42, pp. 442–449, 2020.
- [41] E. Bakhtavar, M. Valipour, S. Yousefi, R. Sadiq, and K. Hewage, "Fuzzy cognitive maps in systems risk analysis: a comprehensive review," *Complex & Intelligent Systems*, vol. 7, no. 2, pp. 621–637, 2021.
- [42] M. J. Rezaee, S. Yousefi, M. Valipour, and M. M. Dehdar, "Risk analysis of sequential processes in food industry integrating multi-stage fuzzy cognitive map and process failure mode and effects analysis," *Computers & Industrial Engineering*, vol. 123, pp. 325–337, 2018.
- [43] M. J. M. Ladeira, F. A. F. Ferreira, J. J. M. Ferreira, W. Fang, P. F. Falcão, and A. A. Rosa, "Exploring the determinants of digital entrepreneurship using fuzzy cognitive maps," *The International Entrepreneurship and Management Journal*, vol. 15, no. 4, pp. 1077–1101, 2019.
- [44] F. Iqbal, J. M. Hashmi, B. C. M. Fung et al., "A hybrid framework for sentiment analysis using genetic algorithm based feature reduction," *IEEE Access*, vol. 7, pp. 14637–14652, 2019.