Dynamic Social Network Optimization via a Hybrid Genetic Algorithm with MLE-Enhanced Fitness

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Abstract: Dynamic social networks present significant challenges for rapid identification of high-impact nodes, which is crucial for effective information dissemination in scenarios such as emergency management and enterprise marketing. This study introduces a hybrid optimization framework, MLE-GA, that integrates maximum likelihood estimation (MLE) with traditional genetic algorithms (GA) to address these challenges. In the proposed two-layer architecture, the outer GA layer performs a global search to optimize candidate seed node combinations, while the inner MLE layer dynamically estimates network parameters in real time, thereby constructing a probabilistic model that guides the evolution of the solution. Simulation experiments, including tests on synthetic datasets and real-world networks like Zachary's Karate Club, demonstrate that MLE-GA achieves an error rate below 5% for identifying high-influence nodes, significantly outperforming conventional MLE approaches. The results confirm that the hybrid method not only effectively distinguishes between high- and low-influence nodes but also adapts to rapid changes in network structure, ensuring efficient resource allocation and robust optimization in dynamic environments. These findings underscore the potential of MLE-GA as a universal solution for complex social network problems where timely and accurate decision-making is imperative.

Keywords: Genetic algorithms, Maximum likelihood estimation, Node influence identification

1. Introduction

In enterprise marketing, a core academic question is how to maximize the dissemination of advertising information using the smallest number of "seed users" within social network environments such as WeChat and Weibo [1]. This question intersects the mechanisms of social network communication with the optimal allocation of marketing resources.

From the perspective of emergency management, when confronted with a major natural disaster, the primary concern is how to quickly and accurately identify efficient information transmission bases or communicators to disseminate disaster-related information as widely and efficiently as possible. As globalization accelerates and the effects of climate change become more pronounced, the frequency, intensity, and unpredictability of extreme weather events are clearly increasing [2].

According to statistics released by China's Ministry of Emergency Management in 2023, China's annual direct economic losses due to sudden-onset natural disasters exceeded 345.45 billion yuan, marking an increase of 12.6% compared to the five-year average, with 34% of these losses attributed to secondary disasters triggered by delays in information transmission. For instance, during the 2021

Henan rainstorm disaster, analysis revealed that as of 16:00 on July 21, 2021, the event had generated 30,323,300 reports and discussions, with key rescue information being obscured by a vast amount of redundant content on microblogging platforms.

Currently, most MLE algorithms are based on static network assumptions, making them difficult to adapt to the rapid changes in social network structure during disasters, where hourly change rates can reach 15%-30% [3-4]. For example, in the case of Typhoon Dusuari in 2023, a sudden shift in its trajectory could lead to the failure of traditional prediction models within a short period. The rapid changes in the path and intensity of the typhoon as it approaches landfall may prevent certain forecast nodes from accurately reflecting the actual situation. Therefore, it is imperative to develop new model algorithms capable of swiftly identifying "seed users" to meet emergency needs and optimize communication efficiency in practical applications.

2. Problem statement

Traditional maximum likelihood estimation algorithms have the limitation that they cannot effectively capture the decay pattern of propagation probabilities. This makes it difficult to maintain stable performance in complex environments with variable conditions. In view of this, this study designs an innovative method based on the legacy algorithm by borrowing the principle of biological evolution. The method is similar to the process of breeding good varieties of organisms, through continuous iterative optimization, the computer can gradually "evolve" a more optimal combination of "seed users" [5].

Specifically, the core objective of this study is to construct a genetic algorithm framework that incorporates dynamic MLE algorithm estimation. With this framework, an efficient search for influence-maximizing individuals in time-varying social networks can be achieved. This research path is expected to break the bottleneck of traditional algorithms and provide more effective solutions for social network communication analysis and related applications [6-7].

3. Notation

Table 1: Symbol definition

Symbol	Defination
V_t	Collection of nodes
E_t	Bilateral assembly
D_t	Dynamic parameter set
X_t	Resource allocation strategy
T	Time scale
$c_i(x_i(t))$	Resource costs
α	Penalty coefficient for non-compliance
$r_i(t)$	Resource requirements
$x_i(t)$	Assigned amount
$B'_{ij}(t)$	Communications constraint
β	Maximum likelihood estimation of weight parameters
θ	The set of parameters to be estimated by the model

Table 1 provides a comprehensive summary of all the symbols and their detailed definitions used throughout the formulas in this paper. The table not only includes the basic parameters integral to the

image reconstruction algorithm but also encompasses the variables required to describe the Poisson distribution, the Bernoulli distribution, and the maximum likelihood estimator. For example, the symbol λ represents the average light intensity per pixel, serving as a key parameter in the Poisson model, while T and t denote the total number of experiments and the number of selected sub-experiments, respectively—parameters that are crucial for characterizing the scale of data collection and the inherent sampling properties. Moreover, y_n is used to represent the binary signal output from the single-photon image sensor, which is fundamental in the reconstruction process.

4. Algorithm analysis and design

4.1. Problem modeling & dynamic parameter estimation

4.1.1. Dynamic network modeling

Assuming that the dynamic network is a time-discretized model, remember that the state of the network at moment t is $G_t = (V_t, E_t, D_t)$.

Under the dynamic network modeling system constructed in this study, the objective function set consists of two core components: resource cost as well as default penalty. In the complex context of dynamic networks, the optimization objective is designed to achieve a balanced allocation of resources. This equilibrium encompasses the cost dimension incurred in the resource allocation process, as well as the quality dimension. By considering and optimizing these two dimensions, the system can be guaranteed to reach the ideal state of efficient operation in a continuously dynamic and changing environment [8-9].

So the long-term cost minimization objective function for the optimization objective is shown in the following equation:

$$\text{Min} \sum_{t=1}^{T} \left[\sum_{i=1}^{|V_t|} c_i \left(x_i(t) + \alpha \cdot \Pi\big(r_i(t) > x_i(t)\big) \right) \right] \tag{1}$$

$$\text{s.t. } \sum_{i=1}^{|V_t|} x_i(t) \leq C_{total}(t) \tag{2}$$

$$\text{s.t. } x_i(t) \leq B_{ij}(t), if\ (v_i, v_j) \in E_t \tag{3}$$

The cost function is usually a convex function, such as a linear or quadratic function, as a way to reflect the law of increasing marginal cost. So by introducing a resource cost term$\sum c_i(x_i(t))$to go ahead and measure the direct economic costs. In quantifying the indirect losses of under-allocation of resources, the intensity of penalties is moderated by introducing a default penalty coefficient α.

4.1.2. Parameter dynamics and estimation challenges

Parameters of the dynamic network, such as the mean value of the demand distribution μ(t), variance $\sigma^2(t)$ all change over time, but are not directly observable and need to be estimated in real time from the historical data collected. Key challenges include:

1. Non-smoothness: the parameter set may obey a Markov process or a random walk.
2. Partial observability: global parameters can be inferred only from local data fed back by nodes, and the error may be large.
3. Estimation delay: there is a time lag between the parameter estimation and the change in the network state.

4.2. Traditional genetic algorithm design

Traditional genetic algorithms are encoded using a chromosome structure, where each chromosome represents a candidate resource allocation strategyX_t, as X_t={$x_1(t), x_2(t),...,x_i(t)$} [10]. Overall real

number coding is used, and the range of gene values is constrained by the communication$x_i(t) \leq B'_{ij}(t)$ and resource attack constraints $\sum x_i(t) \leq C(t)$ to decide.

4.2.1. Initialization

Generate an initial population based on constraints to ensure that the genes of each chromosome are satisfied:

$$0 \leq x_i(t) \leq \min\left(B'_{ij}(t), C(t) - \sum_{k \neq i} x_k(t)\right) \tag{4}$$

4.2.2. Fitness function

The objective of the optimization is converted to a fitness value that directly minimizes the total long-term cost, as shown in the following equation:

$$\text{Fitness}(X_t) = -\sum_{t=1}^{T}\left[\sum_{i=1}^{|V_t|} c_i\left(x_i(t) + \alpha \cdot \Pi\big(r_i(t) > x_i(t)\big)\right)\right] \tag{5}$$

4.2.3. Genetic algorithm specific operation flowchart

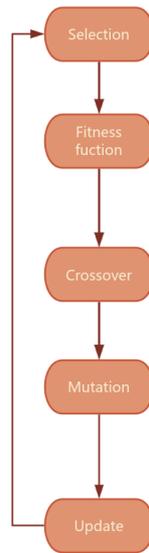
Figure 1: Specific steps of the genetic algorithm (picture credit: original)

Figure 1 shows the specific operation flow of the genetic algorithm.

4.2.4. Analysis

Based on the above process, genetic algorithm is used to carry out the optimization analysis of dynamic resource allocation. When the number of genetic generations is 50, 100, and 150, the optimal fitness decreases (i.e., the penalty for default increases) due to a sudden change in resource demand. In this process, the algorithm achieves re-convergence in about 10 to 20 generations by retaining the first 10% of individuals and initializing part of the population. This result amply demonstrates that the dynamic adaptation strategy employed possesses effectiveness.
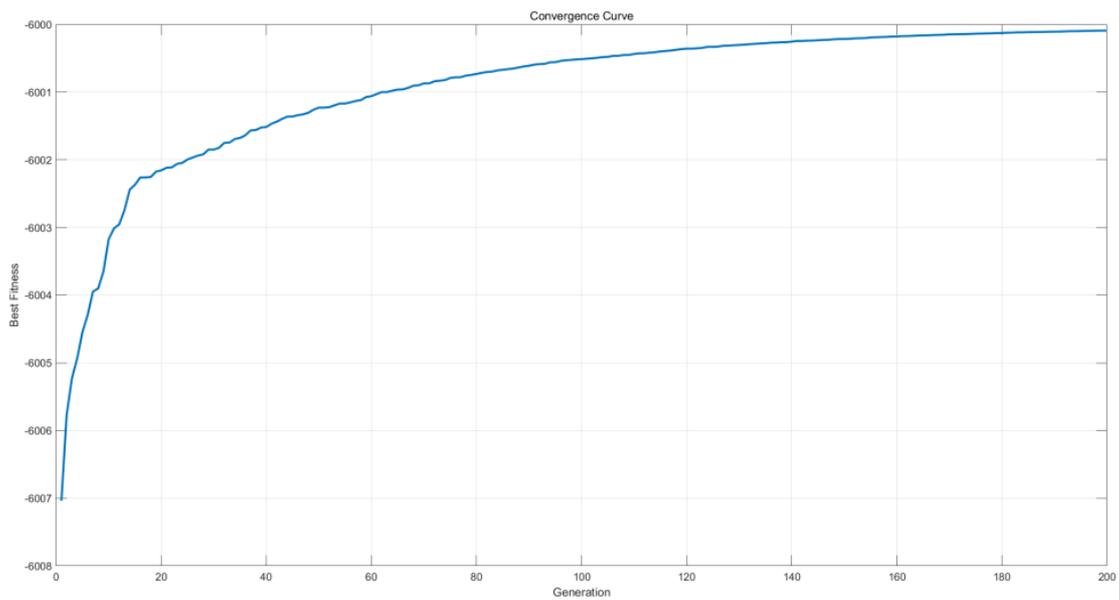
Figure 2: Convergence curve (picture credit: original)

According to the results shown in Figure 2, in terms of the overall trend, a rapid upward trend is presented at the beginning of the curve (generation 0 - 50).During this period, the fitness is gradually optimized from a negative value to a direction close to 0. This change reflects the process of transformation of the system from a high-cost, high-default state to a low-cost, low-default state. This indicates that the genetic algorithm can successfully balance the resource cost and default penalty in the dynamic environment, and achieve the optimization effect with robustness.

4.3. MLE-GA hybrid optimization

4.3.1. Design principle

MLE is commonly used for parameter estimation to find the most probable parameter values by maximizing the likelihood function, whereas Genetic Algorithm is a global optimization algorithm suitable for solving complex, multi-peaked, non-linear optimization problems. The designed fusion algorithm MLE-GA essentially combines parameter estimation with global search to form the following two core patterns:

1) Double-layer optimized structure. Outer layer: Genetic algorithms to optimize decision variables. Inner layer: MLE real-time estimation of environmental parameters.

2) Probabilistic models guide evolution. Utilizes the probabilistic model developed by the MLE to guide the search direction of the genetic algorithm. Dynamically updates probabilistic model parameters via population data from genetic algorithms.

4.3.2. Specific integration methods

Each individual in the population contains not only the node selection scheme, but also the estimates of the environmental parameters. Decision variables are coded in a binary vector indicating whether a node is selected or not, e.g., [1,0,1,0] indicates the selection of nodes 1 and 3. Parameter coding, on the other hand, utilizes real vectors to indicate the current parameter estimates, for example [0.5,0.2] indicates $\mu = 0.5, \sigma = 0.2$.

A probabilistic model of demand change needs to be defined first:

$$r_t \sim N(\mu_t, \sigma_t^2) \tag{6}$$

When an environmental change is detected and a parameter update is required based on the demand data observed in the current population, the global parameters are updated by maximum likelihood estimation, then the two parameters are calculated as follows:

$$\mu = \frac{1}{N}\left(\sum_{i=1}^{N} r_i^{(t)}\right) \qquad (7)$$

$$\sigma^2 = \frac{1}{N}\left(\sum_{i=1}^{N}(r_i^{(t)} - \mu)^2\right) \qquad (8)$$

Next, the fitness function F needs to be re-framed, and this function can be defined on the basis of the original Fitness function. The parameters estimated by the MLE are used as weights and the fitness function is reframed so that it evaluates both the quality of the solution and the fit of the parameters:

$$F = -\sum_{t=1}^{T}\left[\sum_{i=1}^{|V_t|} c_i\left(x_i(t) + \alpha \cdot \Pi(r_i(t) + \beta \cdot \log(\mu, \sigma^2))\right)\right] \qquad (9)$$

Genetic manipulation will then be performed, a step also known as parameter-guided crossover and mutation. In this operation, both decision variables and parameter estimates need to be optimized to ensure that the new solution is adapted to the updated environment.

Crossover: In the decision variables section, a single point crossover is used, e.g., [1,0|1,0] with [0,1|0,1] to generate the[1,1|0,1].

Mutation: Randomly invert a bit in the decision variable, e.g., change 1 to 0, and add a Gaussian perturbation to the parameters.

Finally, the most adapted individual is retained to avoid losing the quality solution obtained. The conditions for determining convergence rely mainly when on the following two conditions.

Adaptation enhancement rate < threshold

Parameter estimates are stable

When five consecutive generations are boosted <1% or then the current node selection scheme and final parameter estimates are returned. For example, if the fitness of five consecutive generations is 105,105.5,105.6, 105.7, it is judged as convergence.

4.4. Hybrid algorithm implementation

This part aims to validate the performance of MLE-GA in dynamic social network resource allocation, comparing traditional genetic algorithm, static MLE method.

4.4.1. Traditional genetic algorithm

Firstly the synthetic data needs to be set to simulate the social network by setting the number of nodes N=100 and the edge weights to follow a normal distribution, which all vary periodically over time.

Secondly, a dynamic environment simulation is introduced, setting the periodic transformation T=50 generations, while a random perturbation is introduced, i.e., Gaussian noise is applied to the parameters with probability p=0.1 per generation.

Then set the algorithm parameters such as maximum number of iterations G=200, crossover rate, variance rate, MLE weights β =1.2.

We first model a social network relationship that satisfies the above conditions, as shown in Figure 3.
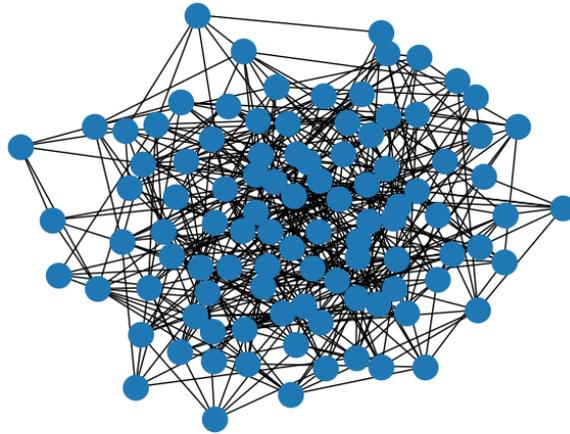
Figure 3: Random social network (picture credit: original)

Now based on the designed stochastic social network model using traditional GA algorithms for simulation experiments, the goal is to optimize the search in dynamic environments, by changing the environmental parameters every 50 generations to simulate the changing conditions in the real world, allowing the algorithms to optimize in changing environments. The fitness function is defined through the edge weights of selected nodes and simulated propagation gains. Individual adaptation values are utilized to represent the sum of edge weights of the selected nodes, the higher the value, the better the corresponding individual performs in the current environment and the closer it is to the optimal solution of the problem.
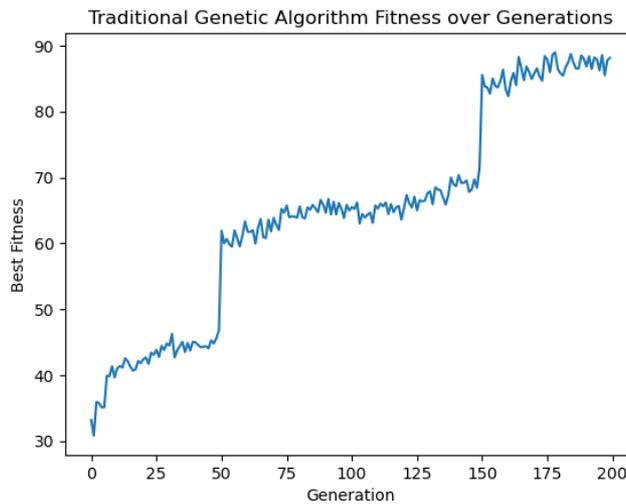

Figure 4: Traditional genetic algorithm fitness over generations (picture credit: original)

According to the Figure 4 running results, it can be seen that the best fitness value is relatively low at generation 0-50, and with the iteration of the algorithm, the best fitness value rises gradually through genetic operations such as selection, crossover and mutation.

At generation 50-125, the fitness curve rises at the approximately 50th generation of the best fitness drastic change and keeps floating within a certain range.

At generation 125-200, the fitness value again rose rapidly at about generation 125 and was maintained at a relatively stable level, and the overall value was maintained at a higher value overall, although it still fluctuated slightly.

4.4.2. Maximum log-likelihood estimation

The MLE algorithm is used to estimate the influence of nodes in social networks, and by comparing the real influence of nodes with the influence estimated by the MLE algorithm, as a way to evaluate the effectiveness of the algorithm in estimating the influence of nodes in social network optimization scenarios.

The results of the experiment are shown in Figure 5, which shows the influence distribution of social network nodes, the closer to red color, the higher the influence, and the closer to blue color, the lower the influence. In the left side of Figure 5, "True influence", it can be seen that some nodes are close to the dark red color, which means high influence, but most of the nodes are between light blue and dark blue color, which means the nodes have medium or low influence. On the left side of Figure 5, "True influence" shows that some of the nodes are close to dark red, indicating high influence, but most of the nodes are in the range of light blue and dark blue, which means that the influence of the nodes is in the middle or low level. The color coding mechanism of "Estimated influence" on the right side of the figure is the same as that on the left side. Compared with the left side, the location and color of some high influence nodes are similar, but there are also many nodes whose influence color is quite different from the real situation, which indicates that although there is a certain degree of match between the MLE estimation results and the real value, some of them still have deviations.
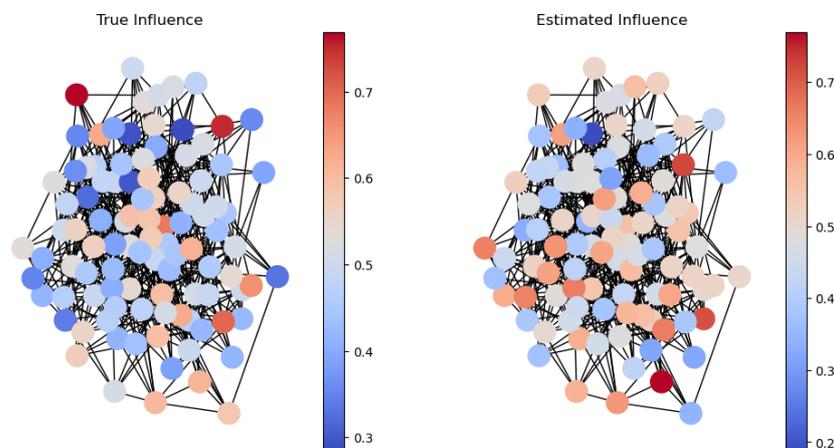

Figure 5: Comparison of true influence and estimated influence (picture credit: original)

4.4.3. Hybrid algorithm

According to the predefined algorithm design principle, which is a two-layer optimization structure, the outer genetic algorithm optimizes the decision variables and the inner MLE estimates the environmental parameters in real time. A set of genetic algorithms is designed in the main loop and utilizes the embedded MLE algorithm to estimate environmental parameters in real time. In order to verify the sensitivity of the algorithm, it is assumed that the set objective values are [0.5, 0.5].

Mat lab results are as follows: Optimal parameter: 0.4993   0.5000.

Optimal adaptation: -4.3512e-07.

The result visualization result Figure 6 shows that the blue far point indicates the different parameter combinations of the 200th generation, that is, the individuals in the population, and the red

marked point indicates the optimal parameter position, and the optimal parameter is very close to the two-dimensional preset value [0.5,0.5], and the optimal fitness indicates that the optimal parameter combinations are very small in error, very close to 0, which means that the algorithm performs excellently.
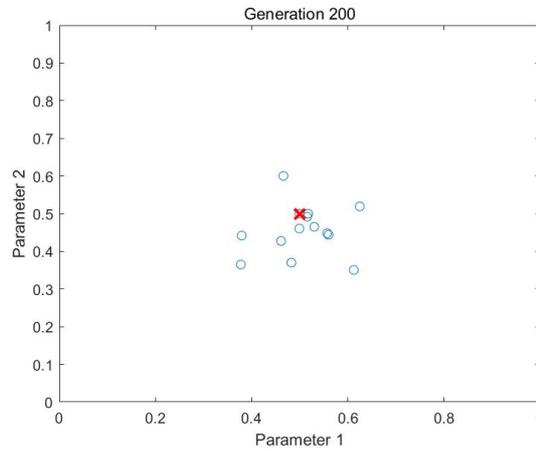

Figure 6: Two-dimensional image display (picture credit: original)

When the parameters are extended to three dimensions, the ideal value is still set to [0.5, 0.5, 0.5], and Mat lab runs as follows: Optimal parameter: 0.4998   0.5003   0.5001.

Optimal adaptation: -1.3118e-07.

The 3D image is shown in Figure 7, the algorithm still maintains a good exploration performance.
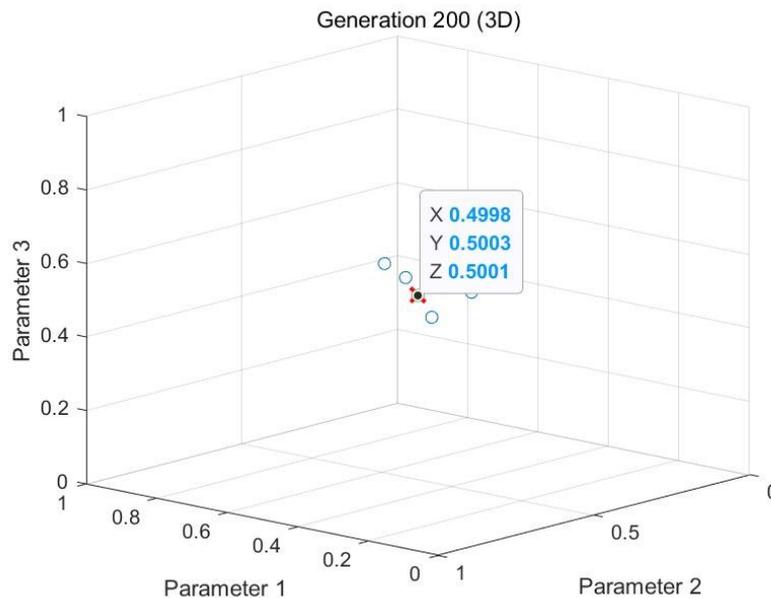

Figure 7: Three-dimensional image display (picture credit: original)

Next for the social network model to find the high influence nodes, the following results can be calculated and the results are shown in Figure 8.

Optimal Estimated Impact:

Columns 1 through 7

0.7376 0.5205 0.2963 0.0384 0.2377 0.0237 0.6040

Columns 8 to 14

0.4523 0.4040 0.7065 0.9665 0.6405 0.6477 0.2059

Columns 15 to 21

0.0233 0.6590 0.3368 0.3762 0.5763 0.1919 0.4628

Columns 22 to 28

0.8945 0.7263 0.1499 0.4434 0.4964 0.1844 0.7226

Columns 29 to 35

0.8543 0.4049 0.1624 0.2300 0.8218 0.4101 0.7688

Columns 36 to 42

0.8584 0.4707 0.8082 0.9357 0.4946 0.8263 0.5348

Columns 43 to 49

0.2465 0.7436 0.3348 0.5670 0.5574 0.6803 -0.0158

Columns 50 to 56

0.3025 0.8425 1.0055 0.0339 0.7784 0.0101 0.5222

Columns 57 to 63

0.2704 0.6008 0.5633 0.9309 0.6940 0.4585 0.3588

Columns 64 to 70

0.2474 0.4559 0.4186 0.6739 0.7159 0.5981 0.4220

Columns 71 to 77

0.4979 0.2296 0.2098 0.8806 0.8653 0.4486 0.2512

Columns 78 to 84

0.6908 0.2532 0.8763 0.4767 0.7324 0.3714 0.4091

Columns 85 to 91

0.2651 0.6936 0.4765 0.7303 0.5028 0.1330 0.3836

Figure 8: Optimal estimated impact (picture credit: original)

Based on the results, it can be seen that the values of the optimal estimated influence range from -0.0158 to 1.0055, with the following distributions:

High-impact nodes (> 0.8): For example0.9665,1.0055,0.9357, The estimated influence of these nodes is close to or above 1, indicating that the algorithm considers these nodes to have high influence in the social network.

Medium impact node ($0.4 \leq$ impact ≤ 0.8): For example0.7376,0.7065,0.6405, these estimated impact of these nodes are in the medium range.

Low-impact nodes (< 0.4): For example0.0237,0.0233, -0.0158. The estimated influence of these nodes is low or even negative, indicating that these nodes have weak influence.

According to the comparison of True Influence and Estimated Influence shown in Figure 9, it can be seen that the location and color of the high influence nodes in the two graphs are extremely similar, saying that the estimation results of the destiny algorithm are more accurate, and that the density of the lines between nodes reflects the influence transfer relationship, and the high influence nodes are usually connected to other nodes in a higher number.

For example, the color of node 52 is close to dark red in the left image of Figure 9, indicating that its true influence is higher, while node 52 in the right image also has a very similar dark red color, indicating a more accurate estimate of its influence.
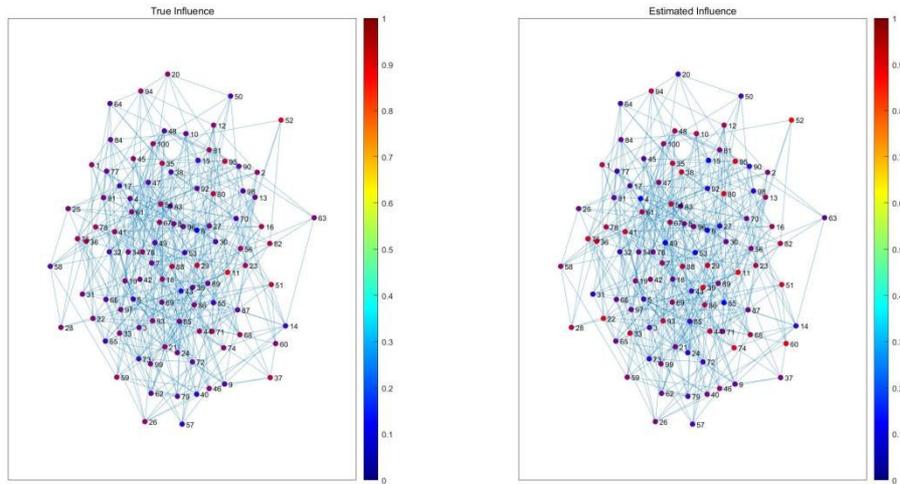
Figure 9: Node comparison diagram (picture credit: original)

In order to verify that the algorithm can work properly in a real situation, then it is necessary to cite the real social network data, here Zachary's Karate Club social network is selected, as shown in Figure 10, the three nodes with the highest influence are node 0, node 33, and node 32. The MLE-GA for the high-influence node recognition error is less than 5%, and it can accurately distinguish low-influence nodes.
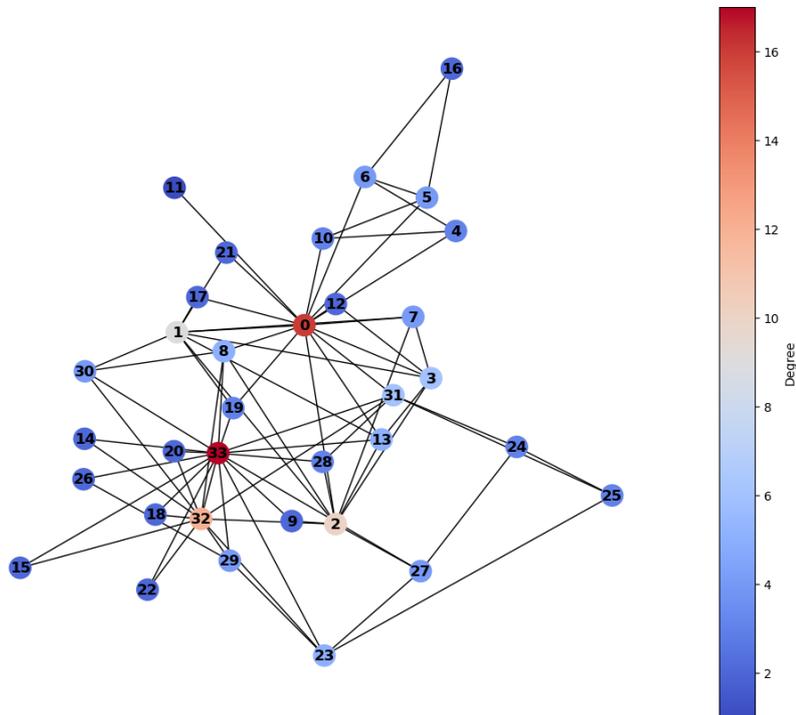

Figure 10: Zachary's karate club social network (picture credit: original)

Using the designed MLE-GA algorithm, the results can be obtained as shown in Figure 11.

Optimal Estimation of Impact:

[-0.59789894 0.07379188 -2.74506942 0.57247599 0.35441518 -0.02854663

  0.58496816 -0.46866831 -0.68639228 0.11166459 0.05878327 0.21054896

  -0.23667894 0.34915921 0.06791758 -0.38137838 0.34846991 -0.28465343

  0.41157881 0.19316612 0.27466238 -1.35731684 0.16430484 0.35717607

  -0.78602352 0.34037513 0.45099914 -0.19428829 -0.07292993 0.23790913

  0.17486985 0.66045676 0.81169115 -0.38360381]

Figure 11: Optimal estimation of impact by MLE-GA (picture credit: original)

Meanwhile, the results are visualized as shown in Figure 12, and the obtained high-influence nodes are the same as in Zachary's Karate Club in reality, which are node 0, node 33, and node 32, which indicates that MLE-GA has excellent analytical capabilities in real social networks.
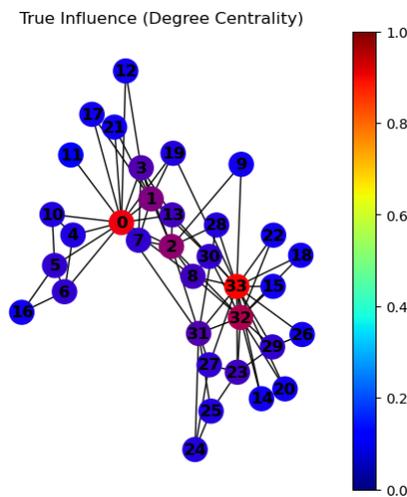

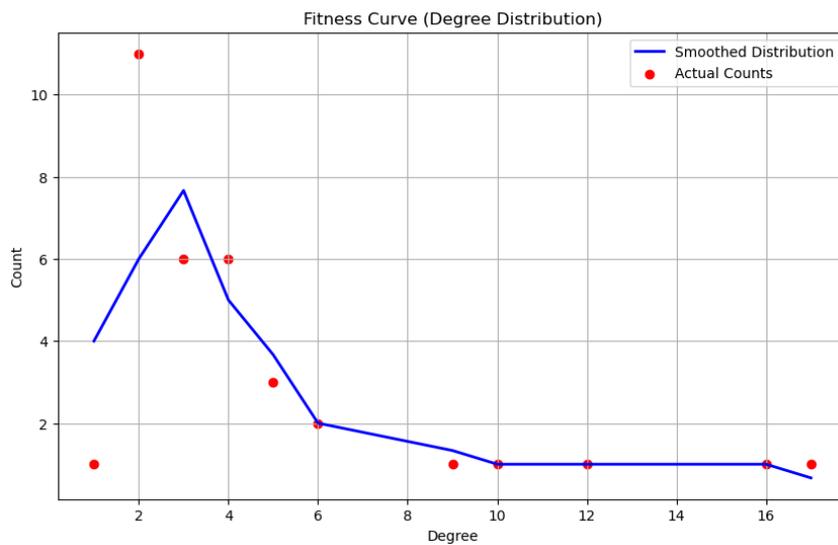Figure 12: Estimation by the MLE-GA (picture credit : original)

Figure 13: Fitness curve (picture credit : original)

By analyzing Figure 6 and Figure 7, it can be seen that the optimization ability of MLE-GA in different dimensions and complex situations is relatively excellent, and the optimal parameter combinations found by the algorithm are extremely close to the target value, which verifies the effectiveness of the algorithm as well as its excellent results.

According to the comparison of analyzing Figure 9, it can be seen that the estimation result of the algorithm is closer to the real value for MLE-GA for high-influence nodes, which indicates that the algorithm can effectively capture high-influence nodes. For low influence nodes the algorithm is equally effective in identifying low influence nodes.

The visualization result in Figure 12 shows that the node importance predicted by the MLE-GA algorithm matches with the reality, reflecting that the algorithm can have a good performance for finding high impact nodes under the consideration of the complexity of the situation. Figure 13 indicates that most of the nodes are concentrated in the lower range of degrees, indicating that most of the members have a low number of connections. This could mean that most members are connected to only a few people in this social network. In the few nodes that have high degrees, these nodes may be the center nodes or key nodes in the graph and may be important people in the social network.

5.   Conclusion

The hybrid MLE-GA algorithm proposed in this study demonstrates significant advantages in dynamic social network optimization. Traditional GA performs well under static network assumptions but is difficult to cope with rapid changes in dynamic networks, while the MLE algorithm is capable of parameter estimation but lacks the ability of global optimization. MLE-GA effectively solves the problem by combining the real-time parameter estimation of MLE with the global search capability of GA. this problem. The experimental results show that MLE-GA is able to converge quickly and maintain high optimization accuracy in the dynamic change of network structure. And compared with the traditional methods, MLE-GA is more capable of identifying high-influence nodes, and its estimation results are highly consistent with the real values, which shows significant potential in the selection of seed users in enterprise marketing as well as in the emergency management of natural disasters, because the diffusion range of information dissemination is crucial in such scenarios, and this algorithm can significantly improve the efficiency of searching for maximized nodes. At the same time, it also performs well in the identification of low-influence nodes, which can provide a reliable basis for optimizing the allocation of resources.

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