IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 2, 2020, accepted March 16, 2020, date of publication March 27, 2020, date of current version April 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2983744

Method for Spatial Crowdsourcing Task Assignment Based on Integrating of Genetic Algorithm and Ant Colony Optimization

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This work was supported in part by the National Nature Science Foundation of China under Grant 61972438, in part by the Major Teaching and Research Projects in Anhui Province under Grant 2018JYXM0342, and in part by the Social Science Planning Project of Anhui Province under Grant AHSKY2017D42.

ABSTRACT With the rapid development of mobile networks and the proliferation of mobile devices, Spatial Crowdsourcing (SC) has attracted the interest of industry and research groups. In addition to considering the specific spatial constraints in the existing research spatial crowdsourcing, each task has an effective duration, operational complexity, number of workers required, and incentive budget constraints. In this scenario, we studied the MQC-TA (Maximum Quality and Minimum Cost Task Assignment) problem. Firstly, the worker incentive model is established. The MQC-GAC algorithm is designed according to the MQC-TA problem to maximize the task completion quality and minimize the incentive budget. The algorithm combined the fast convergence of Genetic Algorithm and the positive feedback mechanism of Ant Colony Optimization Algorithm. Finally, the effectiveness and efficiency of the proposed method are verified by a comprehensive experiment on the data set.

INDEX TERMS Spatial crowdsourcing, task assignment, MQC-TA problem, MQC-GAC algorithm.

I. INTRODUCTION

In recent years, crowdsourcing has been widely used in business, such as the establishment and application of Amazon Mechanical Turk, crowdflower, crowdcloud and microworkers platforms. At the same time, crowdsourcing is also popular in image processing [1], database [2], NLP [3] and other research fields. With the popularity of smart phones and other mobile devices, task workers carry mobile devices with perception ability to complete tasks at task sites, and then form a new crowdsourcing mode, namely spatial crowdsourcing [4] (SC). In the spatial crowdsourcing environment, workers need to arrive at a specific work place to perform tasks. Such spatiotemporal data are closely related, such as real-time special vehicle service platform: Didi travel, where Didi users are task requesters, Didi special vehicle is workers, workers need to move to the location of Didi users to pick up passengers to the destination.

In view of the task assignment problem in the spatial crowdsourcing environment, most of the existing researches refer to the comparability between the number of tasks and the number of workers, and consider the reliability and spatial-time constraints of the task assignment, such as the distance from the worker to the task and the validity period of the task, and design effective methods to maximize the number of task assignment [6]–[9]. In [10], Zhang *et al.* researched the issue of reliability-based task assignment for spatial crowdsourcing in large labor markets, using worker credibility to indicate the reliability of successfully completed assigned spatial tasks, maximizing the maximum reliability assignment (MRA) and minimize cost assignment (MCA). Heterogeneous spatial crowdsourcing is a new type of crowdsourcing system. Heterogeneous spatial crowdsourcing task assignment (HSC-TA) aims to search a set of representative optimal assignment schemes for multi-objective optimization to maximize the coverage of assignment tasks and minimize the incentive cost [11]. Tang and Zhang [12] analyzed and solved the task assignment problem of workers mobility. Firstly, they proposed the maximum task assignment problem based on information gain (IG-MTM). Secondly, in order to solve complex spatial tasks, they proposed a feedback cooperation mechanism and

The associate editor coordinating the review of this manuscript and approving it for publication was Tossapon Boongoen.

designed a task assignment algorithm based on feedback group cooperation. In a fog-assisted SC architecture, the fog nodes deployed in the way of privacy awareness. A task assignment scheme based on bilinear matching and encryption privacy awareness had been proposed [13]. Liu and Xu [14] researched the problem of online task assignment under perceived budget in spatial crowdsourcing, aiming to maximize the number of task assignment under budget constraints (workers appear on the platform dynamically), and designed an improved threshold-based greedy algorithm (Greedy-OT), which learns results close to the optimal threshold from historical data. Xingsheng *et al.* [15] proposed an online threshold algorithm based on assignment time to solve the problem of poor assignment effect caused by single consideration of the total effect of task assignment or task effective time in the existing research. Due to the different research objects, Tianshu *et al.* [16] put forward the influence of spatial location on research spatial crowdsourcing and the strategy of how to solve the three types of research objects that appear dynamically in practical application on the basis of research object workers and spatial tasks. Qi *et al.* [17] accorded to the different quality of services (QoS) performance of Web services sharing community, and service QoS is usually context-aware and heavily dependent on spatial and temporal information, the temporal and spatial information of QoS data and the locality-sensitive Hashing (LSH) technology is integrated into the recommendation domain, and a location-aware and time-aware recommendation algorithm considering privacy is proposed. All of the above studies have not considered the global optimal assignment of task. The MQC-TA problem studied in this paper aims to solve the optimal matching problem between effective spatial tasks and online workers in a task assignment cycle by using MQC-GAC algorithm, so as to maximize task completion quality and minimize incentive expectations.

II. RELEVANT DEFINITIONS AND PROBLEM DESCRIPTION

A. RELEVANT DEFINITIONS

Spatial crowdsourcing (SC) is composed of a crowdsourcing platform, task publisher and workers. The task of SC platform is mainly to find the suitable workers to complete the task, with the goal of improving task coverage and commission aggregation; task publisher finds the suitable workers to complete the spatial task of its release with high quality through the platform with low time and cost; workers need to efficiently find suitable and capable tasks to obtain rewards and improve credibility [18]. At present, most task publishers publish their tasks on the spatial crowdsourcing platform, and the platform assigns tasks according to the characteristics of tasks and workers. As shown in the Figure 1 is the spatial crowdsourcing model of this research:

Firstly, the task requester sets the characteristics of effective time, geographical location, task completion time, reward for completing the task and the number of workers required to complete the task, and submits the task to SC platform; meanwhile, the workers submit their geographical location, online time and other characteristics to SC platform. SC platform assigns tasks according to the effective information provided. As shown in Figure 1, task publishers publish $t_1 \sim t_6$ different tasks on SC platform.In this paper, the operational complexity is represented by the time required to complete the task, and the reward is proportional to the operational complexity. The task defined in this paper is the tuple $t_1 : (lic_1, 8:00 \sim 9:00, 3\,\text{min}, \$3, 3)$, which requires three workers to complete the task in the physical location lic_1 between 8:00 a.m. and 9:00 a.m. the task takes about three minutes, and the workers who complete the task in the effective period of time will be rewarded accordingly.

Definition 1: Spatial crowdsourcing worker w: w is the worker of spatial crowdsourcing task, which is defined as

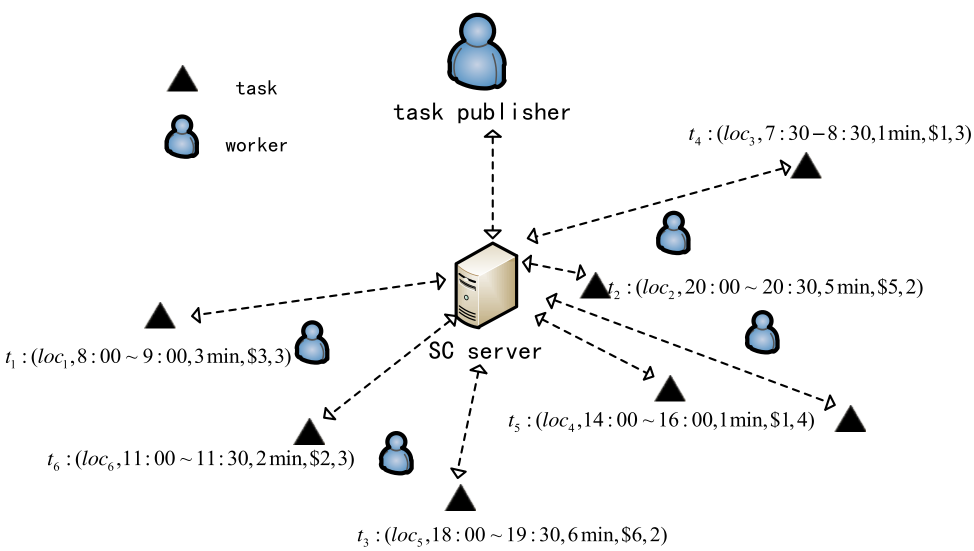

FIGURE 1. Model of spatial crowdsourcing.

$w_j = \{Q, l_w0c_j, pre_j, num_j\}$, where $Q = \{r_{ij}\}(i = 1...n)(j = 1...m)$ is the set of credibility of worker w_j to complete different tasks. When the position of worker $w_j(1 \leq j \leq m)$ at pre_j time point is l_w0c_j, $W = \{w_1, w_2, w_3, \ldots, w_m\}$ is all effective workers in the system, and num_j is the maximum number of accepted tasks.

Definition 2: Spatial crowdsourcing task t: t is a location related task published by task publishers, which requires workers to reach a specific physical location to complete. It is defined as $t_i(loc_i, vt_i, pt_i, rw_i, w_{\mathrm{j}}, num_i)$. $w_j(1 \leq j \leq n)$ workers are required to arrive at the physical location loc_i within the time interval $vt_i = [st_i, et_i]$ and complete the task. When the task is published by the publisher, t_i needs pt_i time to complete the task and the reward rw_i. num_i is the number of workers needed to complete the task t_i.

B. PROBLEM DESCRIPTION

In this section, the worker incentive model is established, and the MQC-TA (Maximum Quality and Minimum Cost Task Assignment) problem is formally defined.

1) INCENTIVE MECHANISM

With the development of crowdsourcing data management technology, people-oriented incentive mechanism has become an important research hotspot of data management. How to motivate the participants and their subjective initiative to achieve a win-win situation is an important issue for all enterprises in the society. Yang *et al.* [19] introduces the reverse auction mechanism into the research work of group intelligence perception network, and designs the incentive mechanism from the perspective of perception platform and intelligent device respectively. The latter is based on the auction mechanism, and the incentive mechanism designed has achieved the excellent characteristics of computational efficiency, individual rationality, anti deception and so on. To solve the problem of time-consuming in-situ survey data collection for building wireless map based on Wi Fi indoor positioning system, Li *et al.* [20] proposed two incentive mechanisms to motivate mobile users to contribute indoor track. The first mechanism considers the fixed reward of Mu and incomplete information when the level of privacy sensitivity of CP to each mu is unknown. In order to maximize the utility of mus and CP profit, the interaction between mus and CP is attributed to two-stage Stackelberg game. The second mechanism assumes that the CP knows the data privacy sensitivity level of each mu, and considers the variable compensation of the mu. Jin *et al.* [21] an incentive mechanism based on privacy protection is designed. When designing the incentive mechanism, the characteristics of data fusion and data interference in the system are taken into account. The incentive mechanism not only satisfies the common characteristics of anti deception and individual rationality, but also provides the approximate optimal guarantee of the total payment of the auction platform. Zhang *et al.* [22], the probability of a vehicle passing a specific route is calculated according to the historical track of the vehicle in the group intelligence perception network scene. The perception task is completed in the uncertain vehicle moving scene and the incentive mechanism is designed. The execution probability of the perception task is not lower than the given threshold according to the task assignment result.

In the sptial crowdsourcing scenario of this paper, we consider designing incentive mechanism to improve the optimism of workers and the quality of completing tasks, so that task publishers can obtain the highest benefits. According to the credibility set $Q = \{r_{ij}\}$ $(i = 1...n)(j = 1...m)$ of the worker, we can see the quality of the completion of different kinds of spatial tasks in the near future. After the task is completed, the credibility set is updated according to the completion quality.

This paper designs the incentive mechanism of money reward and credibility reward and punishment. In a task assignment cycle, SC platform first selects several candidate workers with high reputation for spatial tasks, and then assigns tasks to the final workers according to the assignment mechanism designed in this paper. After a worker completes the task, the task publisher scores the worker according to the quality of the completed task. r_{ij} indicates the credibility of the worker w_j completing the task t_i. When the platform assigns task t_i to worker w_j, SC platform will update the credit score according to the task completion quality and user score of the worker after each task assignment cycle:

$$r_{ij}^n = \partial r_{ij}^{n-1} + (1-\partial)2e_{ij}r_{ij}^{n-1}$$
$$(\partial \text{ is a constant coefficient, } 0 \leq \partial \leq 1) \tag{1}$$

$e_{ij}(0 \leq e_{ij} \leq 1)$ is the evaluation of the results submitted by the SC platform. According to the above analysis, if the workers want to be assigned to the task and get high reward, they need to continue to complete the task with high quality. The ultimate goal of SC platform workers is to get remuneration. Giving money reward can motivate workers to complete assigned tasks with higher quality. If the score is greater than or equal to the historical average score of the worker, platform reward will be given, otherwise reputation and remuneration will be reduced.

2) MODEL ESTABLISHMENT

The purpose of MQC-TA problem in this paper is to select the sutiable workers to perform spatial tasks, and to maximize the quality of task completion and minimize the incentive budget. Task publishers publish different kinds of tasks, the time spent on tasks and the number of workers required constitute different complexity of tasks. In this paper, the complexity coefficient of tasks is defined to consider the impact of physical location of spatial tasks and the credibility of workers on the quality of completed tasks, and its influence coefficient is defined separately.

Definition 3: Physical location influence coefficient ℓ: because workers need to reach the spatial task position within the effective time of the task, the physical distance will have a certain impact on the quality of completing the task.

According to the historical path of workers' daily work, workers only accept tasks within their own range (within the r' range) considering their own factors. In this paper, the influence of the coefficient is defined as (6), and the distance between the current physical location of worker w_j and the physical location of spatial task t_i is $dist(w_j, t_i)$.First, according to (2):

$$rad_{\text{degree}} = \deg ree \times PI/180 \tag{2}$$

The longitude and latitude $loc_{wj}(lat_{w_j}, \text{lng}_{w_j})$ and $loc_{ti}(lat_{t_i}, \text{lng}_{t_i})$ of w_j and t_i are converted into loc_{wj} $(rlat_{w_j}, r\text{lng}_{w_j})$ and $loc_{ti}(rlat_{t_i}, r\text{lng}_{t_i})$, where $x = rlat_{w_j} - rlat_{t_i}$, $y = r\text{lng}_{w_j} - r\text{lng}_{t_i}$ and R are the earth radius. Equation (1) is calculated as follows:

$$dist(l0c_{wj}, loc_{ti}) = 2\arcsin$$
$$(\sqrt{\sin(\frac{x}{2})^2 + \cos(rlat_{w_j})\cos(rlat_{t_i})\sin(\frac{y}{2})^2 R}) \tag{3}$$
$$\ell = 1 - \max[0, \min[\log_{2r'}(dist(l0c_{wj}, loc_{ti}), 1)]] \tag{4}$$

Definition 4: Credibility influence coefficient γ: due to the uncertainty of workers, there are some adverse factors such as maximizing the benefits of workers, malicious answers and so on, which can submit low-quality tasks and cause waste of human resources. The credibility of workers directly affects the quality of task completion, so this paper calculates the credibility of workers according to the quality and quantity of tasks submitted by workers.

$$\gamma(w_{ij}) = \frac{1}{n}\sum_{i=1}^{n}(R_i + r_{ij}^n) \tag{5}$$

The worker w_j gets the score $R_i + r_{ij}^n$ after completing the task t_i;

Investigation and research show that the total incentive cost of multiple spatial tasks increases exponentially [23], which means that the more tasks assigned by workers, the lower the average bid of each task will have. In order to reduce the total budget cost, an effective strategy is to assign more tasks to each worker under the mobile sensing assignment scheme, and the incentive cost is determined by the task set

$T_j = \{t_1, t_2, \ldots, t_n\}$ to which workers are assigned as follows:

$$\text{Cos}(T_j) = \frac{1}{e^{a*(n'-1)}} * \sum_{i=1}^{n'} rw_i \tag{6}$$

In this paper, the published reward rw_i of task t_i is proportional to its processing time pt_i:

$$rw_i = \partial * tp_i \tag{7}$$

$$\text{Cos}(T_j) = \frac{1}{e^{a*(n'-1)}} * \sum_{i=1}^{n'} \partial * tp_i \tag{8}$$

The $1/e^{a*(n'-1)}$ attenuation coefficient decreases with the increase of tasks. When only one worker is assigned one task, the incentive cost announces the reward rw_i for the task.

Considering the actual situation, if more tasks are assigned to a worker, the total incentive cost will decrease exponentially. However, in order to balance the workload and avoid monopoly among workers, each worker should have the maximum ability to perform spatial tasks. In this paper, we will limit the maximum number of tasks assigned to each worker, and the number of tasks assigned to each worker will meet the maximum score. With the number of tasks, the platform will no longer be assigned to the worker. The corresponding incentive cost can be expressed as follows:

$$\text{Cos}(T_j) = \frac{1}{e^{0.2*(|T_j|-1)}} * \sum_{i=1}^{|T_j|} \partial * tp_i$$
$$T_j = \sum\nolimits_{i=1}^{n} s_{ij} \tag{9}$$

T_j indicates the number of tasks assigned by the worker w_j, $T_j \leq num_j$.

To sum up, the following global objective functions are established:

$$\begin{aligned} &\max \sum_{j=1}^{m}\sum_{i=1}^{n} \ell\gamma \bullet s_{ij} \\ &\min \sum_{j=1}^{m}\sum_{i=1}^{n} \text{Cos}(T_j) \bullet s_{ij} \\ &s.t. \\ &\quad \forall \text{t}_i \in T, \forall w_j \in W \\ &\quad \sum_{j=1}^{m} s_{ij} \leq 1, \text{s}_{ij} \in \{0, 1\} \end{aligned} \tag{10}$$

III. RELEVANT THEORY AND MODEL SOLUTION

A. GENETIC ALGORITHM AND ANT COLONY ALGORITHM

Genetic algorithm (GA) is a computational model of biological evolution process which simulates the natural selection and genetic mechanism of Darwinian biological evolution by Holland, an American scholar. It is a method to search the optimal solution by simulating the natural evolution process [24]. Each population of genetic algorithm is composed of N encoded individuals (individuals are chromosome entities with certain characteristics). Each time, individuals with larger adaptability are screened out, and after multiple operations such as combination, crossover, mutation, etc., new populations are evolved, and approximate optimal solutions are obtained. The algorithm flow is as Figure 2:

Ant colony algorithm (ACO) is a kind of simulation optimization algorithm to simulate ant's foraging behavior. It was first proposed by Italian scholar Dorigo m and others in 1991 and first used to solve TSP (traveling salesman problem) [25]. After that, the basic principle and mathematical model of ant colony algorithm are studied systematically [26]. References [27] and [28] solve the task scheduling in mobile edge computing (MEC), propose an efficient job caching method, which can better schedule jobs according to the collected information of adjacent vehicles including GPS information, and design a scheduling algorithm based on

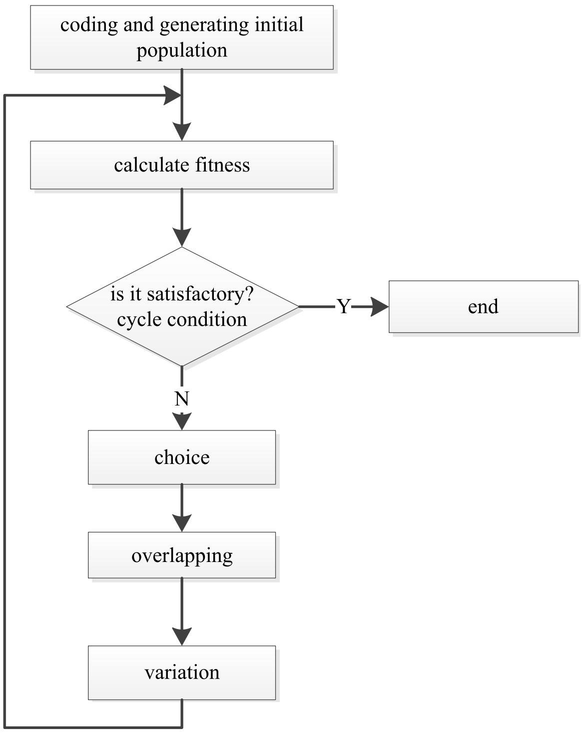

FIGURE 2. GA algorithm flow chart.

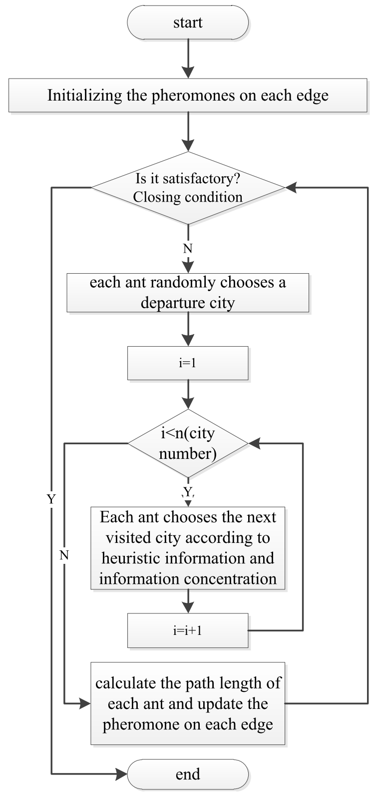

FIGURE 3. ACO algorithm flow chart.

Ant Colony Optimization (ACO) to solve the task assignment problem. Figure 3 is the flow chart of ant colony algorithm solving TSP problem.

B. GENETIC ANT COLONY ALGORITHM

Genetic algorithm (GA) and ant colony algorithm (ACO) have the advantages of global search and probabilistic random search, but they are easy to fall into local optimum. The search speed of genetic algorithm (GA) is faster. ACO is a distributed algorithm with positive feedback mechanism. The disadvantage of genetic algorithm (GA) is that it is easy to produce many unnecessary iterations in the later stage of the algorithm, resulting in low accuracy and efficiency. The pheromone of ant colony algorithm (ACO) accumulates for a long time in the early stage of research. Figure 4 is the flow chart of genetic ant colony algorithm:

C. TASK ASSIGNMENT BASED ON MQC-GAC ALGORITHM

In the initial stage of the algorithm, the MQC-GAC algorithm uses the fast and random global search characteristic of genetic algorithm (GA) to generate the optimal solution of the initial task assignment as the initial pheromone distribution of the ant colony algorithm (ACO). On the premise of a certain initial pheromone distribution, the global convergence ability and parallel positive feedback of the ACO are used to obtain the global optimal solution.

Selection, crossover and mutation are the basic genetic operators in genetic algorithm (GA). Because the selection of crossover probability and mutation probability directly affects the performance of the algorithm, the higher the individual fitness, the greater the probability of crossover and mutation. Therefore, this paper adopts adaptive crossover and mutation, and its probability expression is as follows:

$$P_{cro} = \begin{cases} P_{cro1} * \dfrac{1}{(P_{cro1} - P_{cro2}) + e^{\frac{\lambda' - \lambda_{avg}}{\lambda_{\max} - \lambda_{avg}}}}, & \lambda' \geq \lambda_{avg} \\ k_1 * P_{cro1}, \lambda' \geq \lambda_{avg} \end{cases} \tag{11}$$

$$P_{\text{var}} = \begin{cases} P_{\text{var}1} * \dfrac{1}{(P_{\text{var}1} - P_{var2}) + e^{\frac{\lambda' - \lambda_{avg}}{\lambda_{\max} - \lambda_{avg}}}}, & \lambda' \geq \lambda_{avg} \\ k_2 * P_{var1}, \lambda' \geq \lambda_{avg} \end{cases}$$

$$0.5 \leq k_1, k_2 \leq 1 \tag{12}$$

$\lambda_{\max}$ represents the maximum fitness function value in genetic algorithm (GA), λ_{avg} represents the average fitness function value; λ' represents the larger fitness function value in the two individuals to be crossed, and λ represents the fitness function value of the individuals to be mutated. The pheromone Volatilization Coefficient $\rho(n)$ of ant colony algorithm (ACO) directly affects the global search ability and convergence speed of the algorithm. In this paper, the coefficient is designed to be adaptive. The initial value is $\rho = 0.999$. when the optimal value of the objective function does not change significantly after n cycles, the ρ value is reduced to:

$$\rho' = rand()/10 * (RAND\_MAX + 1)$$

$$\rho(n+1) \begin{cases} (0.9 + \rho' * \rho(n), & \rho(n+1) \geq \rho_{\min} \\ \rho_{\min}, & other \end{cases} \tag{13}$$

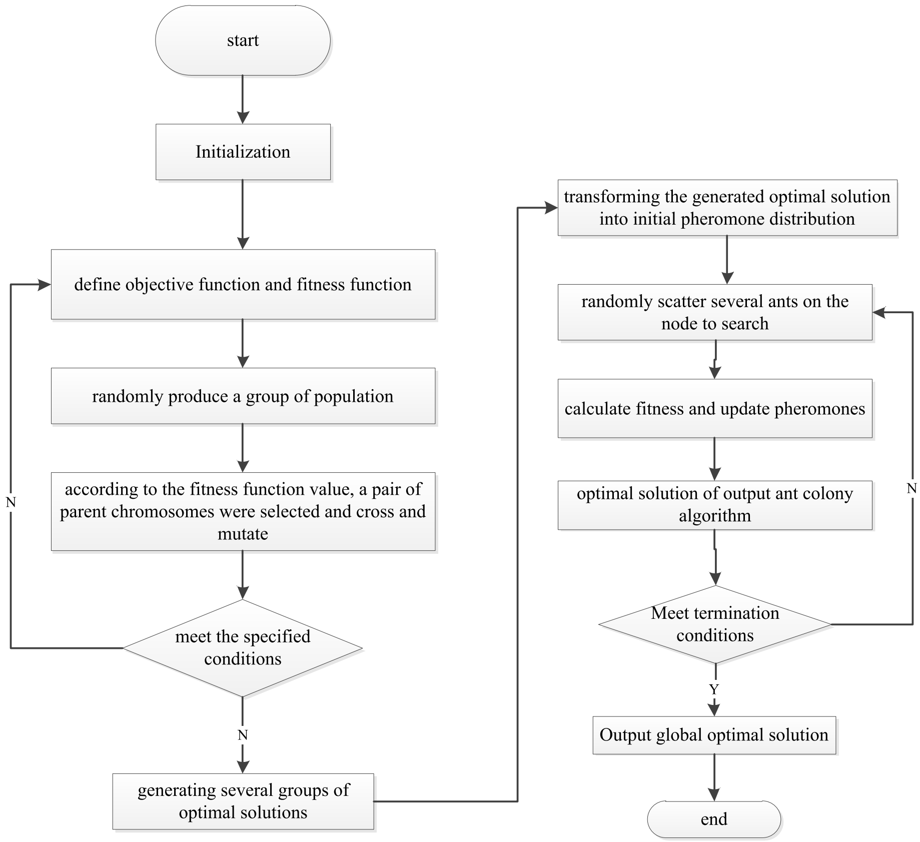

FIGURE 4. Flow chart of genetic ant colony algorithm.

TABLE 1. Parameters of MQC-GAC algorithm.

parameter name	parameter symbol
population size	N
iteration times	G
crossover probability	P_c
mutation probability	P_m
pheromone factor	α
heuristic factor	β
volatilization coefficient	ρ
pheromone quantity	P

IV. EXPERIMENTS AND ANALYSIS

The Gowalla dataset was used as experimental data for this study. Gowalla is a location-based social networking site. Users can share their location information through check-in, with a total of 196,591 user information and 6,442,890 check-in information. The following is an experimental analysis of proposed mechanism and algorithm for solveing MQC-TA problem from different perspectives. The experimental results obtained by averageing after 50 experiments in this article. This experiment runs on a machine with 2.10GHz AMD Ryzen 5 3500U processor and 8 GB memory. The operating system is windows 10, and the programming language is Java. Figure 5 to Figure 9 shows the number of workers, number of tasks, ∂ constant coefficient, number of algorithm iterations and the effect of simultaneous action of number of tasks and number of workers on the mass fraction 1γ. Under the condition of fixed incentive cost, compared with the SCTAM_PSO algorithm in [5], it can be seen that the MQC genetic ant colony algorithm proposed in this paper is more superior and improves the task completion quality of the work, as shown in Figure 5. As is shown

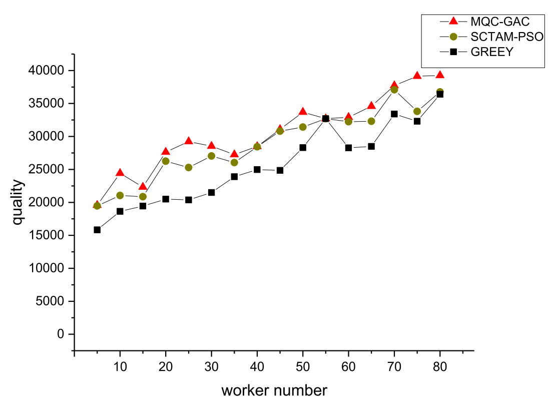

FIGURE 5. Effect of number of workers on quality score.

Algorithm 1 MQC-GAC Algorithm

Input: T task set, W worker set

Output: task completion quality score $\ell\gamma$, incentive cost cos

Step 1: initialize the relevant parameters of genetic algorithm: $N = 50$, G, $P_c = 0.9$, $P_m = 0.9$, $\rho = 0.999$,iterate the current algebra generation $= 0$.

Step 2: calculate the fitness function, i.e. the objective function (11).

Step 3: choose: Roulette.

Step 4: cross: two point cross, cross probability adaptive (12).

Step 5: mutation: single point mutation, adaptive mutation probability (13).

Step 6: compare the fitness value of MQC genetic ant colony algorithm to obtain the global optimal value.

Step 7: initialize the pheromone of ACO algorithm, and use step 6 to obtain the optimal solution to initialize the pheromone of ACO algorithm. Step 6 obtains the sub optimal solution $M = (m_1, m_2, m_3, \ldots, m_n)$ as the initial pheromone of ant colony algorithm, M m_j represents worker w_j. The quality fraction matrix $\ell\gamma_{n\times n}$ and the incentive cost matrix $Cos_{n\times n}$ are defined.

Step 8: calculate transfer probability.

Step 9: calculate the path length of each ant to complete a journey.

Step 10: update the pheromone concentration of the first ant in the sub group, and the pheromone volatilization coefficient $\rho(n)$ is adaptive (14).

Step11: output the optimal value, compare the obtained optimal solution, if it is the optimal solution, update the global optimal solution; otherwise, cycle **step** 8 and **step** 9 until the optimal solution or maximum iteration is obtained.

Step12: output completion quality score $\ell\gamma$ and incentive cost cos.

in Figure 6,with the increase of the number of tasks, the quality scores of MQC-GAC algorithm and SCTAM_PSO algorithm tend to be balance with the number of effective workers and fixed incentive costs.The assignment strategy is better than [5]. Figure 7 shows the effect of constant coefficient ∂ on the quality of task completion. Due to the limitation of incentive cost, with the increase of coefficient, the rewards received by workers are related to their own ability, and also related to the amount of rewards issued by tasks, so the task completion quality changes.

Figure 8 shows the impact of the number of iterations on the quality score. The MQC-GAC algorithm proposed in this paper approaches the optimal value with the increase of the number of iterations. Figure 9 shows the impact of the number of workers and tasks on the quality score. The more workers, the higher the quality of task completion.

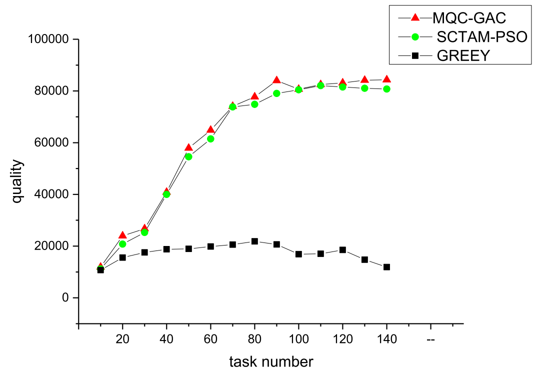

FIGURE 6. Effect of task number on quality score.

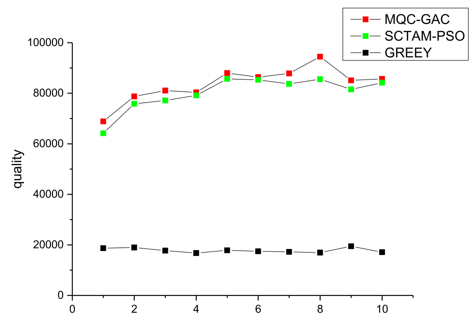

FIGURE 7. Effect of constant coefficient ∂ on mass fraction.

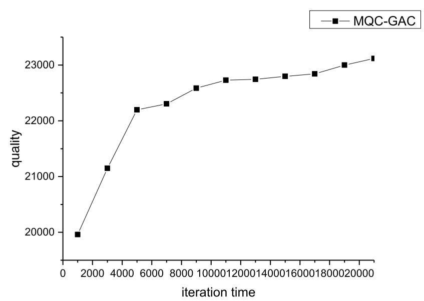

FIGURE 8. Influence of iteration times on mass fraction.

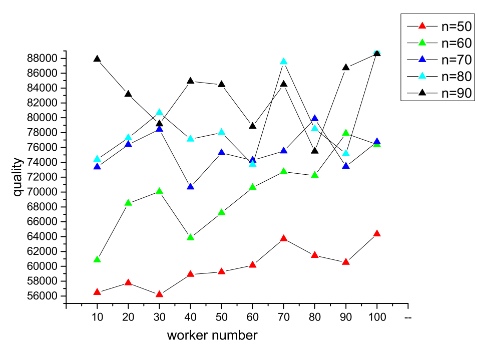

FIGURE 9. Effect of number of workers and tasks on quality score.

Figure 10 to Figure 13 show the impact of related factors on incentive cost. SC platform should consider not only the completion quality of tasks released by task publishers, but also the interests of task publishers and workers.

Therefore, the establishment of incentive mechanism improves the enthusiasm of workers, allowing them to complete tasks faster and with higher quality, and also has a certain impact on the cost of task publishers. Figure 10 shows the impact of the number of workers on the incentive cost. Under the same number of workers and spatial tasks, the incentive cost of MQC-GA ant colony algorithm proposed in this paper is lower than that of SCTAM-PSO algorithm. Figure 11 shows the impact of the number of tasks on the incentive cost. From the comparative experiment, it can be seen that with the increase of the number of tasks, the incentive cost is generally becoming higher, and the incentive cost generated by the assignment strategy of MQC-GA ant colony algorithm is higher. This is lower than SCTAM-PSO algorithm. Figure 12 shows the impact of the number of iterations on the incentive cost. When the number of tasks and the number of workers are fixed, the incentive cost decreases with the increase of the number of iterations. Figure 13 shows the impact of the number of tasks and workers on the incentive cost. Figure 14 shows the impact of the number of tasks and workers on the runtime at 3000 iterations.

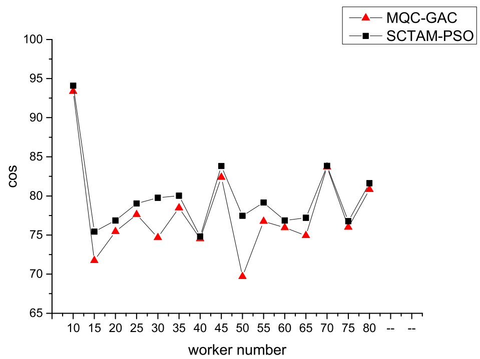

FIGURE 10. Impact of number of workers on incentive cost.

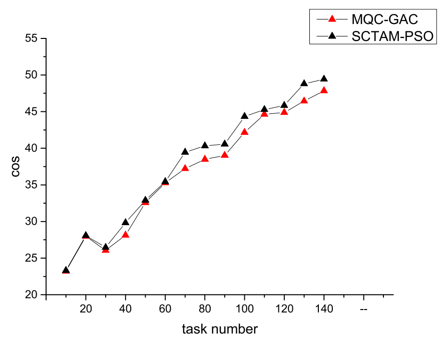

FIGURE 11. Impact of task number on incentive cost.

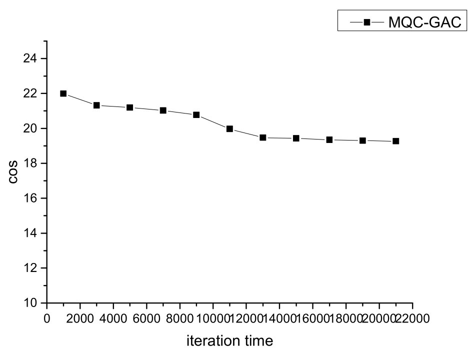

FIGURE 12. The influence of iteration on incentive cost.

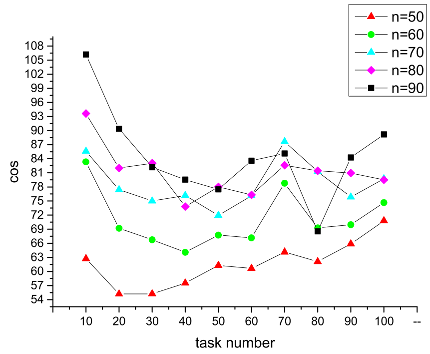

FIGURE 13. Impact of number of tasks and workers on incentive cost.

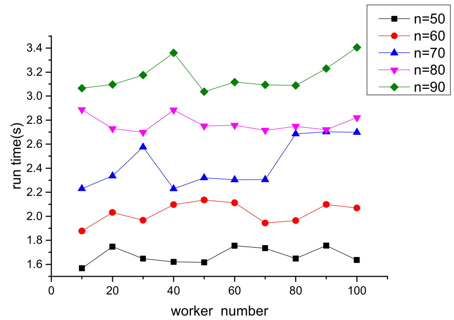

FIGURE 14. Impact of number of tasks and workers on run time.

V. CONCLUSION

In addition to considering the specific spatial constraints in the existing research spatial crowdsourcing, each task has an effective duration, operational complexity, the number of workers required and the incentive budget limit, and the task assignment problem in this scenario is described mathematically. The MQC-TA problem was proposed, and the corresponding objective function is established. MQC-GAC algorithm is used to optimize the task assignment in this paper. The genetic algorithm of the algorithm adopts adaptive crossover and mutation, and the ant colony algorithm partially designs adaptive pheromone volatility coefficient. In the experiment, the real data set is used to prove that the MQC-GAC algorithm proposed in this paper realizes the combination of the two algorithms, and improves the global optimization ability and the speed of searching the optimal solution of the algorithm. However, the research in this paper is limited to the task assignment of spatial crowdsourcing in static scenarios, where both workers and spatial tasks are assigned under known circumstances. In the future research work, the real-time factors of workers and spatial tasks will be taken into account.

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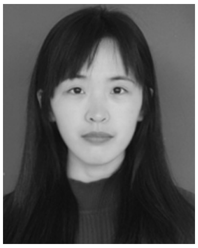

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