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Scheduling Problem of Movie Scenes Based on Three Meta-Heuristic Algorithms

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ABSTRACT Movie scenes scheduling problem (MSSP) is the NP-hard. It refers to the process of film shooting through the reasonable sequence of film scenes to minimize the total cost of film shooting. Studying scheduling problem of this kind is based on the location of the scene shooting, the cost of the scene transfer, the different remuneration of actors, and the different duration of the film scene shooting. The actors' waiting time and transfer cost during the shooting process are reduced as much as possible to make the total film shooting cost smaller. In this paper, an ILP(integer linear programming) model is established and a TABU search based method (TSBM), a particle swarm optimization based method (PSOBM) and an ant colony based method (ACOBM) are used to study the movie scenes scheduling problem. The objective is to compare and analyze relation performances of the three methods in the problem. By compared the experiment, the results show that TSBM, PSOBM and ACOBM can effectively reduce the total cost of film shooting. Comparison with the experiments show that the optimization result of ACOBM is better, the running time of TSBM is shorter, and the optimization result of TSBM is better than that of PSOBM. In addition, the running time of ACOBM is faster than that of PSOBM by setting the number of ants and the number of particles. The potential application of this study has great relevance for the optimization and ILP.

INDEX TERMS Scene transfer, TSBM, PSOBM, ACOBM, ILP, numerical experiments.

I. INTRODUCTION

In real life, due to the influence of various factors, the sequence of film scenes shooting can't make the total cost of film optimal. Therefore, in order to optimize the sequence of film shooting to reduce the film shooting cost as much as possible, we will do the following film scenes scheduling problem. The movie scenes scheduling problem is described as follows. Let $P = \{p_1, p_2, \ldots, p_k\}$ be a set of k actors and $S = \{s_1, s_2, \ldots, s_n\}$ denote a set of n scenes, also we denote $L = \{l_1, l_2, \ldots, l_m\}$ represent a set of m different locations for shooting. The $T = \{t_1, t_2, \ldots, t_n\}$ shows the duration of n different scene shots and $W = \{w_1, w_2, \ldots, w_k\}$ means the cost of different actors for one day. The sequence of scenes taken by each actor is a subset of the sequence of filming scenes. In addition, the total time for all actors to shoot scene n is equivalent to the duration of scene n. All actors are in the crew from the beginning to the end of the film shooting. During this time, each actor will get their daily salary, no matter how long or short they are shooting on the day or they don't have a shooting task on the day.

Moreover, shooting scenes in different locations will result in transfer time among scenes, which will increase the time for actors to act in the next scene. And it is also a factor affecting the total cost of film shooting. The MSSP is how to reduce actors' waiting time in consideration of the scene transfer cost and the actors' different salaries, so as to reduce the total cost of the film in the limited shooting hours.

Up to now, there are a lot of literature on film scenes scheduling problem, but most of them don't consider the impact of different shooting locations on the total cost of film shooting. For this reason, this paper studies the movie scenes scheduling problem by considering the location of the scene shooting, the cost of the scene transfer, the different remuneration of actors, and the different duration of the film scene shooting. In this paper, the optimal solution to the problem is obtained by using operational research methods to solve the mathematical model. Operational research methods

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are widely used in personnel management, project selection and evaluation and other aspects. This paper abstracts the MSSP which is the reasonable allocation and transfer of talents in the process of film shooting into an integer linear programming model (ILP). Meta-heuristic algorithms such as tabu search based method (TSBM), particle swarm optimization based method (PSOBM), ant colony optimization based method(ACOBM), genetic based method (GBM), simulated annealing based method (SABM), artificial neural network based method (ANNBM), and evolutionary programming based method (EPBM) are effective to solve this problem. TSBM is a successful application of combinatorial optimization algorithm. It adopts a flexible memory technique in the search process, which is the tabu list. PSOBM has a simple structure and fewer parameters to control. ACOBM has strong robustness in solving performance. We adopt TSBM, PSOBM, and ACOBM to study the MSSP. And we compare and analyze their relation performances by numerical experiments in the progress.

The main content is organized as follows: In section 2, some related research on film scenes scheduling problem is summarized. In section 3, it is going to establish an integer programming (IP) model to restrict the film scenes scheduling problem. In section 4, 5, and 6, it's going to make a brief introduction of TSBM, PSOBM, and ACOBM. In section 7, the numerical experiments verify the applicability of TSBM, PSOBM, and ACOBM applied to the scheduling problem of movie scenes, and these three methods are compared. In the last part, we conclude the whole paper.

II. RELATED RESEARCH

The film shooting problem is a multi-factor optimization problem, which includes the actor's salary, the actor's shooting time in each scene, the scene shooting location and the scene transfer cost. The film scenes scheduling problem is to study these factors, make the scenes in the same place be shot continuously as possible, which purpose is to reduce the waiting time of actors and optimize the sequence of film shooting to achieve the purpose of reducing the total cost of the whole film.

The film scenes scheduling problem was originated form a restricted talent scheduling problem proposed by Adelson, Norman *et al.* [1], in which the wage of each actor is same. Cheng *et al.* [2] first classified the film scenes scheduling problem as the NP-hard, in which all actors received the same salary every day and each scene had the same shooting duration. They proposed a combined model to reduce the waiting days of actors and studied it by using a branch and bound algorithm and a heuristic algorithm. Smith [3] proposed a constraint planning model for studying the film scenes scheduling problem which are proposed by Cheng. She accelerated the constraint programming method by capturing the search states. In [4], the conceptual model was proposed a conceptual model for the movie scenes scheduling problem, and introduced the operation of each module of the model in detail. Besides, they distinguished between the movie scene scheduling problems and the resource constraint(project) scheduling problems and proved that the conceptual model can get a better solution faster than temporary rescheduling by experimenting in a decision support system.

In some subsequent literature, some scholars took into account the different actors' salaries and the different duration of each scene shooting when studying the problem. Banda *et al.* [5] proposed the basic dynamic programming scheme to study the film scenes scheduling problem. They improved the dynamic programs by determining upper and lower bounds, which are achieved by preprocessing and limiting searches. They showed the process of sorting scenarios from both ends, and proved that the improved dynamic programming algorithm which can deal with larger problems runs faster than the competing approaches. Hu *et al.* [6] used a branch and bound algorithm to study the movie scenes scheduling problem proposed by Da la banda *et al.* In their research, they accelerated and enhanced the branch and bound search algorithm through preprocessing, dominance rules, caching search status, etc. By numerical experiments, the branch and bound algorithm is superior to the current best exact algorithm. Wang *et al.* [7] expanded and promoted the budget issues raised by Cheng *et al.* [2]. Considering the operation costs of crew, they used the next fit algorithm and the first fit decreasing algorithm to allocate scenes to work, and adopted dynamic programming, iterated local search, and tabu search to minimize cost in film production. In 2017, Cheng *et al.* [8] studied the problem of rehearsal scheduling in music and dance performance. They provided two methods to tightening the lower bound on the minimization of talent hold cost. One is to formulate a maximum weighted matching problem, and the other is to solve a maximum weighted 3-grouping and retrieve structural information.

From the above study, we can see that most of the scholars consider the cost of actors and duration of scene shooting. They consider the wage of each actor is same and scenes have the same shooting duration.As well as the actors salaries and the duration of each scene shooting have different value. Nevertheless, different scenes may be taken in different locations to shoot in the process, which is a high potential for transfer cost. Most scholars consider shooting in one location, or do not consider the effect of locations on the shooting process. Bomsdorf and Derigs [4] studied the MSSP shot in an abandoned building. Kochetov [9] presented iterative local search methods for solving MSSP and only considered the influence of talents and scenes to the problem. Wang *et al.* [7] considered the relationship between actors and scenes and did not mention the location of the film. Therefore, it is important to study the location of scene shooting in movie scenes scheduling problem. There are also many studies similar to the movie scenes scheduling problem, such as route optimization problem, program rehearsal problem, and the problem of vehicle mobilization. In the study of movie scenes scheduling problem, we learn from the ideas and methods of these research problems. The movie scenes scheduling problem can refer to the traveling salesman problem, which is to find a shorter short-circuit line for travel, and the movie scenes scheduling problem is to find a sequence of movie shots that make the total cost of the whole movie lower. The cost between scene m and scene n can be regarded as the distance from city i to city j.

III. MODEL FORMULAS AND CONSTRAINTS

The film scenes scheduling problem is to reduce the total cost of the film by iteration to search for the best shooting sequence under the limitation of the actor shooting wage, the scene shooting duration, and the scene transfer cost. This section builds a linear programming model first. This paper applies the model to describe the MSSP and improves scheduling by improving constraints and removing useless constraints. The model consist of two parts. One is the cost of all the actors, the other is the cost of scene transfer. The time interval between the scene m and the scene n is composed of two parts. One is the time which the actors perform in the scene m, the other one is the time affected by the location of the scene shoot which the actors move from scene m to scene n.

A. SYMBOL DESCRIPTION

(1) Indicators and Sets

m, n: Index of scenes.

p: Index of actors.

a, b: Index of the location for shooting.

P: Set of all the actors.

L: Set of all shooting locations; $a, b \in L$.

R: Set of all the scenes. Set two virtual scenes 0 and T. which 0 means starting to shoot the scenes and T mean ending scenes shooting.

$$m, n \in R, R^0 = R \cup \{0\}, R^T = R \cup \{T\}, \bar{R} = R \cup \{0, T\},$$

(2) Parameters

W_p: The daily salary of actor p.

x_{mp}: Set to 1 if the actor p performs in scene m. Otherwise, set it to 0.

ω_{mnp}: Set to 1 if the actor p performs in scene m and scene n. Otherwise,set it to 0.

c_{mn}: The cost of moving from scene m to scene n.

d_m: The days for finishing scene m shooting.

(3) Decision variables

σ_{mnp}: Binary variable; if the actor p first performs in the scene m and then performs in the scene n, the value is set to 1,and zero else. It is no requirement to shoot scene m first and then follow up with scene n.

θ_{mnp}: Binary variable; if the actor p performs two adjacent scenes m and n, which the scene n is the next scene of the scene m, the value is set to 1; set it to 0 else.

μ_{mnp}: Integer variable; the time interval actor p appears between the scene m and the scene n; the actor p first performs in the scene m, and then performs in the scene n.

λ_{mn}: Binary variable; if the scene m is first shot immediately after shooting scene n, it is set to 1. Set it to 0 else.

t_m: Integer variable; the time to finish the scene m.

B. MATHEMATICAL MODEL

Objective function:

Minimize

$$\sum_{m\in R}\sum_{n\in R}\sum_{p\in P}\mu_{mnp}W_p + \sum_{n\in R}\sum_{m\in R}\lambda_{mn}c_{mn}. \tag{1}$$

Constraints:

$$\sum_{n\in R^T}\lambda_{0n} = 1. \tag{2}$$

$$\sum_{m\in R^0}\lambda_{mT} = 1. \tag{3}$$

$$\sum_{n\in R^T}\lambda_{mn} = 1, \quad \forall m \in R, m \neq n. \tag{4}$$

$$\sum_{n\in R^0}\lambda_{mn} = 1, \quad \forall m \in R, m \neq n. \tag{5}$$

$$\lambda_{mn} + \lambda_{nm} \leq 1, \quad \forall m, n \in \bar{R}. \tag{6}$$

$$t_n - t_m - d_n \leq M(1 - \lambda_{mn}), \quad \forall m \in R^0, n \in R^T. \tag{7}$$

$$\sum_{n\in R}\theta_{0np} = 1, \quad \forall p \in P. \tag{8}$$

$$\sum_{n\in R}\theta_{nTp} = 1, \quad \forall p \in P. \tag{9}$$

$$\sigma_{mnp} + \sigma_{mnp} = \omega_{mnp}, \quad \forall m, n \in \bar{R}, m \neq n, \forall p \in P. \tag{10}$$

$$\theta_{mnp} \leq \theta_{mnp}, \quad \forall m, n \in \bar{R}, \forall p \in P. \tag{11}$$

$$x_{mp} \leq \sum_{n\in R^T}\theta_{mnp}, \quad \forall m \in R^0, \forall p \in P. \tag{12}$$

$$x_{mp} \leq \sum_{n\in R^0}\theta_{nmp}, \quad \forall m \in R^T, \forall p \in P. \tag{13}$$

$$t_n - t_m + M(\theta_{mnp} - 1) \leq \mu_{mnp}, \quad \forall m, n \in S, m \neq n, \forall p \in P. \tag{14}$$

$$d_n + M(\theta_{0np} - 1) \leq \mu_{0np}, \quad \forall n \in R, \forall p \in P. \tag{15}$$

$$M(\theta_{nTp} - 1) \leq \mu_{nTp}, \quad \forall n \in R, \forall p \in P. \tag{16}$$

$$M(\sigma_{mnp} - 1) \leq t_n - t_m, \quad \forall m \in R^0, \forall n \in R^T, m \neq n, \forall p \in P. \tag{17}$$

$$x_{np} - 0.5 \leq 0.5(\sum_{m\in\bar{R}}\theta_{mnp} + \sum_{m\in\bar{R}}\theta_{mnp}) \leq x_{np}, \quad \forall n \in \bar{R}, m \neq n, \forall p \in P. \tag{18}$$

$$t_n - d_n \leq M(2 - \theta_{0np} - \lambda_{mn}) + t_m, \quad \forall m \in R^0, \forall n \in R^T, \forall p \in P. \tag{19}$$

$$t_n - d_n \leq M(2 - \theta_{nTp} - \lambda_{mn}) + t_m, \quad \forall m \in R^0, \forall n \in R^T, \forall p \in P. \tag{20}$$

$$0 \leq t_n - t_m - d_n + M(1 - \theta_{mnp}), \quad \forall m \in R^0, \forall n \in R^T, \forall p \in P. \tag{21}$$

$$0 \leq t_m \leq 8d_m, \quad \forall m \in \bar{R}, \forall p \in P. \tag{22}$$

$$0 \leq \mu_{mnp}, \quad \forall m, n \in \bar{S}, \forall p \in P. \tag{23}$$

$$\sigma_{mnp}, \theta_{mnp}, \lambda_{mn} \in \{0, 1\}, \quad \forall m, n \in \bar{R}, \forall p \in P. \tag{24}$$

Under the above restrictive conditions, (1) minimize the total cost of scene transfer problem. One is the shooting cost of actors, the other is the transfer cost among scenes. It is to find the minimum value under the specified constraints according to the transformation of the scenes and the different parameters. Constraints (2) and (3) ensure that each scene has undergone complete shooting. They indicate that the sum of the transitions on the first and last scenes is one. Constraints (4) and (5) ensure that there is only one scene before and after shooting each scene, and there is no situation that multiple scenes are shot at the same time. They describe that the sum of conversion factors is one when two scenes are different and one of them is fixed. Constraint (6) limits the order about scene m and scene n. It requires that the sum of conversion factors be no more than one. Constraint (7) describes the relationship between the two variables λ_{mn} and t_m. It describes the bound constraints on the difference value of the conversion parameters, which make the actual problem meaningful. Constraints (8) and (9) ensure that each actor has shot the scene that he/she is supposed to shoot, and there is no missing or overshooting. They indicate that the sum of the parameters is one at the starting points of 0 and T. Constraints (10) and (11) limit the relationship between the three variables θ_{mnp}, ω_{mnp}, and σ_{mnp}. Constraints (12) and (13) ensure that there is only one scene before and after actor p performs in each scene, and there is no situation that actor p performs in multiple scenes at the same time. All four of them represent the limiting conditions for the transformation of two connection scenes.

Through (14), (15), and (16), it comes up with μ_{mnp}. Constraint (17) describes the relationship between the two variables σ_{mnp} and t_m. All four of them express the limiting conditions of the shooting time and the total time of the end of the first and last scenes. Constraint (18) explain p make sort according to θ_{mnp}. Constraints (19), (20), and (21) describe the relationship between the two variables θ_{mnp} and t_m. All four of them represent the constraint relations between the total shooting time and the number of shooting days. They require that the values that actor p is in the process of scene transition don't exceed the sum of the start point to the end point, and the time difference between the end of the scenes m and n shooting is not less than the linear sum of the time in the shooting process. Constraints (22), (23), and (24) define decision variables. Among them, (22) describes the constraint of the time of shooting a scene and the cut-off time of scene m, and (23) represents the non-negative constraint of the parameter. We use this model and use TSBM, PSOBM, and ACOBM to solve the film scenes scheduling problem based on medium scale environment, and analyze and compare these three methods.

IV. TABU SEARCH BASED METHOD

A. INTRODUCTION

Tabu search method is developed from the local search algorithm. It was put forward by Glove in 1986 to solve an integer programming problem. So far, it has been applied in many fields, such as combinatorial optimization, machine learning, communication system, neural network, etc. Malek *et al.* [10] studied the traveling salesman problem in the parallel environment with the tabu search algorithm, which listed the city size under various conditions, and compared tabu search algorithm with simulated annealing algorithm. When a feasible solution was obtained, the time of TSBM was better than that of simulated annealing algorithm. Brandão and Mercer [11] proposed a new tabu search algorithm to solve the multi-vehicle route scheduling problem by considering the vehicle with different capacity, the restriction of customer choice, the driver's vacation time, and the unloading time of the vehicle. Konishi and Shimba *et al.* [12] artificially found a solution to the local optimal solution of a Hopfield-type neural network by using TSBM. Through computer simulation experiments, they found that this method was superior to Tanaka *et al.* 's method of controlling the coefficient of the energy function, and could obtain a better solution in a relatively short time. In this paper, we use a tabu search method to explore the film scenes scheduling problem to reduce the total cost of film shooting.

The tabu search algorithm is a kind of generalization to the local domain. It guides the algorithm to search through the tabu table to store search process, and it is a stepwise optimization algorithm. The performance of the tabu search algorithm is affected by parameters such as initial solution, neighborhood structure, tabu table, selection strategy and break forbidden level. The TSBM is based on a local search algorithm. In this paper, we specify that the initial solution is randomly generated, and the initial solution is the initial movie shooting sequence. Based on the initial solution, the solution space is generated by the domain structure. And the domain structure searches for the direction of the solution by solving the movement. The function of tabu list is to record the search direction. The tabu length plays a non-negligible role in TSBM. If the tabu length is too short, the algorithm will easily fall into the local optimal state and can't find the global optimal solution better. If the tabu length is too long, the search time will be increased. For the break forbidden level, its selection is based on the fitness value, which is specified as the total cost of film shooting. The selection strategy is to select the solution that makes the objective function value smaller. In the candidate solution set, the break forbidden level is the optimal fitness value. If it is not in tabu list and improves the fitness, the solution is chosen due to breaking the taboo rule. The next step is to update the break level to achieve the global optimal solution.

B. THE STRUCTURE OF TABU SEARCH

1) DOMAIN STRUCTURE AND TABU LIST

The domain structure is generated by the domain movement of the 2-opt and 2-swap modes, which determines the number of solutions, the structure of solutions and the relationship among solutions. Tabu list records the moving position, which is the selection and swap position of 2-opt and 2-swap. With the progress of iteration, the tabu list will be full, then the first movement came into the tabu list will exit from the tabu list and the latest movement came into it will be stored in the tabu list to prevent the algorithm from falling into a local optimal state.

2) TABU STRATEGY AND BREAK FORBIDDEN LEVEL

The tabu strategy is to record the searched solutions with tabu list through domain structure to prevent iterative solutions from repeating and falling into a loop. As tabu strategy is to lead the solution to a new region through movement so as to get the solution better than the historical optimal solution as far as possible. Some solution regions may be missed. So there is a need for the break forbidden level to coordinate the tabu strategy.

3) SELECTION STRATEGY

The selection strategy is to choose a better solution from the domain as the initial solution for the next iteration. Described as follows:

$$y = sel_{z(x)\in U} z(x) = arg[min_{z(x)\in U} V(z(x))]$$

where y represents the best solution for the domain and x represents the current solution. We describe $z(x) \in U$ as a temporary solution and $U \subset Z(x)$ as a candidate solution set. $V(z(x))$ represents the fitness function of the candidate solution $z(x)$.

4) BASIC PROCEDURE ABOUT THE TSBM

After combing the procedures, we know:

Step 1. First we assume a value of x, then use the formula to calculate the fitness value of x. It starts with an empty set. Then specify the length of the tabu list. Besides, set step L(i.e., the number of iterations). Let $p = 1$.

Step 2. Judge if the current solution satisfies the termination condition (i.e., reaching the maximum number of iterations). If so, output the current solution and terminate the algorithm. Otherwise, turn to step 3.

Step 3. For the best solution in the candidate set, judge whether it meets the break forbidden level. If it does, update the break forbidden level and update the optimal solution x, then, go to step 6. Otherwise, turn to step 4.

Step 4. If the solution does not meet the break forbidden level, the best solution in the candidate solution set that is not in tabu list is chosen as the current solution x.

Step 5. If the optimal solution does not change after multiple iterations, a new current solution x is generated for iteration to prevent the algorithm from falling into a local optimal state.

Step 6. Update the global optimal solution $xbest$, and update the tabu list. Set $p = p + 1$, and turn to step 2.

V. PARTICLE SWARM OPTIMIZATION BASED METHOD

A. INTRODUCTION

The PSOBM is a stochastic optimization parallel element heuristic algorithm based on swarm intelligence proposed by Eberhart and Dr. Kennedy in 1995. This algorithm has a simple structure and fewer parameters to control, which has attracted the attention of domestic and foreign researchers. And it has been widely used in multi-objective optimization problems, nonlinear integer and mixed integer constrained optimization problems, neural networks, and signal processing. Salman *et al.* [13] used the particle swarm optimization algorithm to study the task assignment problem of a Np-complete problem, and compared it with the probabilistic heuristic genetic algorithm based on population on the randomly generated task interaction graph. They proved the effectiveness of the PSOBM. Jerald *et al.* [14] studied the scheduling optimization problem of flexible manufacturing system in large-scale with PSOBM by designing different scheduling mechanisms to minimize the idle time of machines and the total penalty cost that does not meet the deadline at the same time. Jmal *et al.* [15] studied k-travel-repairman problems in the field of transport of goods and services, and they proposed a quantum particle swarm optimization method involving heuristic repair operators in order to avoid violating problem constraints.

The basic concept of PSOBM is derived from the study of foraging behavior of birds. Its idea is to find the shortest path by simulating the foraging behavior of birds and the process of sharing information among bird groups. In the iterative process, each particle keeps changing its position and speed like a bird. Search direction and position of each particle are determined by its own speed. And each particle has an fitness value determined by the objective function. Each particle can record the current best particle and continue to search within the solution space. The number of particles affects the search time of the algorithm. Each iteration of the particle position is not completely randomly generated, and the individual position is updated by tracking the optimal position of the individual particle fitness value and the optimal position of the fitness value of all particle searches, which can be used as the basis of the next iteration to find the global optimal solution [16]. In this paper, we use the PSOBM to study a non-continuous integer linear programming model, and specify that the sequence of scene exchange represents the direction of particle search and the fitness value of the particle is the total cost value of the film under the shooting sequence.

B. THE BASIC FLOW OF THE PSOBM

Step 1: Set Num (i.e., the number of particle groups) and G (i.e.,the maximum number of iterations). Let $m = 1$.

Step 2: Initialize the particle swarm. Specify the initial position and speed of each particle.

Step 3: Calculate the fitness value $f(x)$ of each particle on the basis of the objective function.

Step 4: Local comparison is made for each particle to compare its fitness value $f(x)$ with the fitness value of the current optimal position *pbest*. If the fitness value is better than that of *pbest*, replace the *pbest* and update the optimal value.

Step 5: Global comparison is conducted for each particle. If the best fitness value among all particles is better than the global fitness value, the global position *gbest* is replaced with the position of the particle corresponding to the best fitness value, and the global optimal value is updated.

Step 6: Update the position and speed of each particle.

Step 7: If the number of iterations reaches G or the number of iterations does not update the global optimal value, end the iteration. Otherwise, $m = m + 1$,and turn to step 2.

VI. ANT COLONY OPTIMIZATION BASED METHOD

A. INTRODUCTION TO THE ACOBM

The ant colony algorithm, which has the characteristics of information distribution, diversity, positive feedback and strong robustness, is a heuristic global optimization algorithm proposed by Dorigo *et al.* [17]. It was first applied to the problem of travel agents. The advantages of ant colony algorithm make it widely concerned by researchers, and it is used in many fields such as job scheduling, path planning, combinatorial optimization and data mining. Wang [18] proposed a polymorphic ant strategy by defining different categories of ants and adopting various pheromone updating strategies, and combined with improved heuristic information to calculate the transfer probability of ants. She concluded the method can solve the problem of shop scheduling problem well. Xiao and Li [19] proposed an improved ant colony algorithm with modifying the pheromone update strategy by adjusting the pheromone residuals. They constructed a multi-constrained and multi-objective exam scheduling model and verified that the improved ant colony algorithm can effectively solve the problem of exam scheduling optimization. Zhang *et al.* [20] proposed a data collection strategy based on the ACO with mobile sink to study industrial wireless sensor network problems. In their research, on the one hand, they cited the selection of rendezvous nodes based on entropy weight method; on the other hand, they used ant colony algorithm to obtain the optimal access path of mobile sink, and the simulation results proved that the strategy could achieve the purpose of reducing network delay and extending network life.

Ant colony algorithm is derived from the study of foraging behavior of ants in nature. Its idea is to find the optimal path and solution by simulating the information transmission of ant colony during foraging. Each ant can release pheromones to change the surrounding environment, and timely sense changes in the surrounding environment and guide their movements. The number of ants also affects the search time of the algorithm. In the research problem, all paths of the whole ant colony constitute the solution space of the problem to be optimized. On the path with optimal objective function value, pheromones released by ants will gradually increase, and pheromones in other paths will dissipate with a certain probability. Each ant can sense the path that has the most pheromones and move toward it. That create a positive feedback mechanism to make the whole ant colony finally concentrate on the best route, which is the optimal solution of the problem to be optimized. The ACOBM is used to optimize the movie scene scheduling problems in this paper.

B. THE BASIC FLOW OF THE ACOBM

Step 1: Set M(i.e., the total number of ants) and *Num* (i.e., the maximum number of iterations). Set the pheromone evaporation coefficient, heuristic factor and pheromone factor. Let $m = 1$.

Step 2: Initialize each ant, randomly place the ants at different starting points, and plan the path each ant moves.

Step 3: Calculate the objective function value of each ant in the current path, compare and record the current iterative optimal solution, and update the pheromone on the path.

Step 4: Determine whether the iteration reaches *Num*. If the number of iterations reaches *Num*, end the entire program and output the solution, otherwise, set $m = m + 1$ and turn to step 2.

VII. NUMERICAL EXPERIMENTS

A. EXPERIMENTAL DATA SETTING

In this section, the TSBM, PSOBM and ACOBM are used to solve the MSSP. The experimental analysis methods of Zhen *et al.* [21] and Zhen [22] will be used in this paper.

The experimental data set for this paper is as follows. For the scene transfer cost c_{mn} from scene m to scene n, they are randomly generated in the range of 0 to 10000. Furthermore, here is a constraint that requires that c_{mn} equal to c_{nm}. For the daily wage W_p of actor p, they are randomly generated from a range of $CHY80$ per day to $CHY100$ per day. In addition, the locations are randomly assigned for shooting the scenes. For example, there are 5 scenes and 2 shooting locations. Firstly, we assume that the result of sequence is $3-5-2-4-1$ by sorting the five scenes randomly. Then, we randomly generate an integer a_1 with a range between 1 and 5(including 1 and 5). If a_1 is equal to 3, scenes 3, 5, and 2 are sequentially taken at the first location, and scenes 4 and 1 are sequentially shot at the second location. The time interval between the scene m and the scene n is the sum of the shooting time of all the actors in the scene m and the transition time of actors from scene m to scene n. The shooting time and the transition time are randomly generated as well. If scene m and scene n are shot at the same location, the transition time between them is set to 0. The parameters x_{mp} (i.e., set it to 1 when the actor p has a show in scene m) and ω_{mnp} (i.e., set it to 1 when the actor p performs in scene m and scene n) are generated based on the actor p.

TABLE 1. The performance of the proposed solution method.

case id	TSBM		PSOBM		ACO		Gap1	Gap2
S-A-P	OBJ_T	$T_T(s)$	OBJ_P	$T_P(s)$	OBJ_A	$T_A(s)$		
$50-20-10-1$	$3.7077E+05$	4.3125	$3.9922E+05$	51.0781	$3.6021E+05$	37.6719	2.9316%	10.8298%
$50-20-10-2$	$3.7263E+05$	4.1875	$3.7636E+05$	48.9219	$3.7238E+05$	37.2813	0.0671%	1.0688%
$50-20-10-3$	$3.8803E+05$	4.0938	$4.0395E+05$	50.3750	$3.7445E+05$	37.2031	3.6267%	7.8782%
$60-20-10-1$	$4.7308E+05$	5.8281	$4.9318E+05$	73.5938	$4.5373E+05$	60.4375	4.2647%	8.6946%
$60-20-10-2$	$4.6064E+05$	5.9688	$4.8493E+05$	71.8750	$4.5521E+05$	60.6719	1.1929%	6.5289%
$60-20-10-3$	$4.5909E+05$	5.7031	$4.8576E+05$	72.1563	$4.4184E+05$	60.8719	3.9041%	9.9402%
$60-30-10-1$	$5.8198E+05$	9.9219	$5.9425E+05$	87.6406	$5.7111E+05$	68.5625	1.9033%	4.0518%
$60-30-10-2$	$5.9531E+05$	10.0781	$6.0356E+05$	85.6719	$5.7798E+05$	67.4531	2.9984%	4.4258%
$60-30-10-3$	$5.8824E+05$	9.6719	$5.9266E+05$	86.0781	$5.7069E+05$	66.9375	3.0752%	3.8497%
$70-30-20-1$	$6.8394E+05$	14.1875	$6.9965E+05$	128.4688	$6.8140E+05$	104.1406	0.3728%	2.6783%
$70-30-20-2$	$6.9982E+05$	14.5625	$7.0377E+05$	134.0938	$6.8159E+05$	102.7188	2.6746%	3.2542%
$70-30-20-3$	$6.7796E+05$	14.7500	$6.9132E+05$	127.0625	$6.7540E+05$	102.4063	0.3790%	2.3571%
$100-30-20-1$	$9.9402E+05$	35.1875	$1.0230E+06$	330.6719	$9.8445E+05$	294.3438	0.9721%	3.9159%
$100-30-20-2$	$1.0138E+06$	36.2500	$1.0268E+06$	345.1406	$9.8029E+05$	308.2813	3.4184%	4.7445%
$100-30-20-3$	$1.0293E+06$	37.2813	$1.0378E+06$	330.7969	$9.9602E+05$	305.8750	3.3413%	4.1947%
					Avg.		2.3415%	5.2275%

TABLE 2. Comparison of TSBM and PSOBM.

case id	TSBM		PSOBM		Gap3
S-A-P	OBJ_T	$T_T(s)$	OBJ_P	$T_P(s)$	
$50-20-10-1$	$3.7077E+05$	4.3125	$3.9922E+05$	51.0781	7.6732%
$50-20-10-2$	$3.7263E+05$	4.1875	$3.7636E+05$	48.9219	1.0010%
$50-20-10-3$	$3.8803E+05$	4.0938	$4.0395E+05$	50.3750	4.1028%
$60-20-10-1$	$4.7308E+05$	5.8281	$4.9318E+05$	73.5938	4.2488%
$60-20-10-2$	$4.6064E+05$	5.9688	$4.8493E+05$	71.8750	5.2731%
$60-20-10-3$	$4.5909E+05$	5.7031	$4.8576E+05$	72.1563	5.8093%
$60-30-10-1$	$5.8198E+05$	9.9219	$5.9425E+05$	87.6406	2.1083%
$60-30-10-2$	$5.9531E+05$	10.0781	$6.0356E+05$	85.6719	1.3858%
$60-30-10-3$	$5.8824E+05$	9.6719	$5.9266E+05$	86.0781	0.7514%
$70-30-20-1$	$6.8394E+05$	14.1875	$6.9965E+05$	128.4688	2.2970%
$70-30-20-2$	$6.9982E+05$	14.5625	$7.0377E+05$	134.0938	0.5644%
$70-30-20-3$	$6.7796E+05$	14.7500	$6.9132E+05$	127.0625	1.9706%
$100-30-20-1$	$9.9402E+05$	35.1875	$1.0230E+06$	330.6719	2.9154%
$100-30-20-2$	$1.0138E+06$	36.2500	$1.0268E+06$	345.1406	1.2823%
$100-30-20-3$	$1.0293E+06$	37.2813	$1.0378E+06$	330.7969	0.8258%
				Avg.	2.8139%

B. PERFORMANCES OF THE PROPOSED SOLUTION METHOD

This paper designs a TSBM, PSOBM and ACOBM to solve the MSSP of the NP-hard. We compare the total cost of the movie from the TSBM and PSOBM to the total cost of the movie from the ACOBM. TABLE 1 shows the result of comparing the TSBM, PSOBM, and ACOBM. In the first column of TABLE 1, the former three values of ''Case id'' describe the scale of scenes, actors, and shooting locations of the movie, respectively. The fourth value represents the index of different cases with the same parameters (i.e., the number of scenes, actors and locations remains unchanged). The main difference between the three cases is due to the difference in the salary of each actor and the cost of the scenes transfer. OBJ_T, OBJ_P, and OBJ_A in the paper respectively show the objective function values (i.e, the total cost of the movie) of the TSBM, PSOBM, and ACOBM. $T_T(s)$,$T_P(s)$ and $T_A(s)$ show the time of computer CPU for the TSBM, PSOBM, and ACO from the start of the run to the end of the run. And $Gap1 = \frac{OBT_T-OBJ_A}{OBJ_A}$, $Gap2 = \frac{OBT_P-OBJ_A}{OBJ_A}$.

As can be seen from the TABLE 1, the TSBM getting a solution is faster than that of the PSOBM and ACOBM, and the ACOBM getting a solution is faster than that of the PSOBM. The average difference rate of the TSBM and ACOBM is 2.3415%. The average difference rate of the PSOBM and ACOBM is 5.2275%. Therefore, in the medium-scale MSSP, TSBM, PSOBM and ACOBM can optimize the MSSP. Moreover, ACOBM can get better results, and TSBM that obtains the result time is shorter.

C. COMPARISON OF TSBM AND PSOBM

For the medium-sized problem of the MSSP, the TSBM, PSOBM, and ACOBM can optimize it to reduce the total cost of film scenes shooting, but the result of ACOBM are relatively good. Next, we further explore the effectiveness of the TSBM and PSOBM on the same scale. We conduct comparative experiments on the TSBM and PSOBM. The TABLE 2 lists the comparison results of TSBM and PSOBM at the same scale. And we define $Gap3 = \frac{OBT_P-OBJ_T}{OBJ_T}$.

As can be seen from the TABLE 2, the average difference rate of the TSBM and PSOBM is 2.8139%. Compared with

TABLE 3. Notation list.

symbols	note
m, n	index of scenes
p	index of actors
a, b	index of location for shooting
P	set of all the actors
L	set of all shooting locations
R	set of all the scenes
W_p	the daily salary of actor p
x_{mp}, ω_{mnp}	parameters, referring Symbol description in the article for details
c_{mn}	the cost of moving from scene m to scene n
d_m	the days for finishing scene m shooting
$\sigma_{mnp}, \theta_{mnp}, \mu_{mnp}, \lambda_{mn}$	decision variables, referring Symbol description in the article for details
t_m	the time to finish the scene m
x	the current solution
y	the best solution for the domain
Z	the candidate solution
U	a subset of Z
z	an element of U
V	the fitness function

PSOBM, TSBM can get better results in less time. For the medium-scale MSSP, the TSBM is better than PSOBM.

In the section, this result of the comparison and analysis shows that the optimization of ACOBM is the best and the running time of TSBM is the faster. Based on the purpose of minimizing the total cost in the MSSP, the ACOBM is the more appropriate for the problem in a real-world context. The shortcoming here is that a unified approach to optimization result and running time is not found, which we will improve it in a future study.

VIII. CONCLUSION

In this paper, the wage of each actor, scene transfer cost and scene shooting location are considered to study the optimal problem of the scenes scheduling mainly. The purpose of this paper is to take into account the actors' salary, shooting time, shooting location and scene transfer cost within the specified film shooting time to minimize the actors' waiting time and transfer cost during the shooting process. We use the ILP model to implement the MSSP through the TSBM, PSOBM and ACOBM, and analyze and compare the proposed methods. To solve the problem of the movie scenes scheduling, the work of this paper includes the following two aspects:

(1) Being different from other studies on the MSSP, we consider the wage of each actor, the scene transfer cost, and the scene shooting location in the research process.

(2) For the medium-scale MSSP, we implement TSBM, PSOBM and ACOBM methods to compare and analyze their relative performances. The TSBM, PSOBM and ACOBM can work for solving the medium-scale MSSP. The optimization results of the ACOBM are better than those of the TSBM and PSOBM, and the results of the TSBM are better than those of the PSOBM. In terms of running time, the TSBM can get optimization results faster. The running time of ACOBM and PSOBM are respectively affected by the number of ants and the number of particles. By adjusting the number of ants and the number of particles, we find that the running time of the ACOBM can be faster than that of the PSOBM.

The limitation of this article is that we don't find a quantity interval in which the ACOBM is better than the PSOBM in running time. For future research, we will break through this limitation and find a better method to extend our work, which outperform the TSBM in the running time and the ACOBM in the operation result in this paper.

NOTATION LIST

The symbols used in the whole paper are explained in TABLE 3.

REFERENCES

[1] J. M. Norman, G. Laporte, and R. M. Adelson, "A dynamic programming formulation with diverse application," *Oper. Res. Quart.*, vol. 27, no. 1, pp. 119–121, 1976.

[2] T. C. E. Cheng, J. E. Diamond, and B. M. T. Lin, "Optimal scheduling in film production to minimize talent hold cost," *J. Optim. Theory Appl.*, vol. 79, no. 3, pp. 479–492, Dec. 1993.

[3] B. M. Smith, "Constraint programming in practice: Scheduling a rehearsal," Res. Rep. APES-67-2003, Sep. 2003, p. 13.

[4] F. Bomsdorf and U. Derigs, "A model, heuristic procedure and decision support system for solving the movie shoot scheduling problem," *OR Spectr.*, vol. 30, no. 4, pp. 751–772, Oct. 2008.

[5] M. G. de la Banda, P. J. Stuckey, and G. Chu, "Solving talent scheduling with dynamic programming," *INFORMS J. Comput.*, vol. 23, no. 1, pp. 120–137, Feb. 2011.

[6] H. Qin, Z. Zhang, A. Lim, and X. Liang, "An enhanced branch-and-bound algorithm for the talent scheduling problem," *Eur. J. Oper. Res.*, vol. 250, no. 2, pp. 412–426, Apr. 2016.

[7] S.-Y. Wang, Y.-T. Chuang, and B. M. T. Lin, "Minimizing talent cost and operating cost in film production," *J. Ind. Prod. Eng.*, vol. 33, no. 1, pp. 17–31, 2016.

[8] T. C. Cheng, B. M. Lin, and H. L. Huang, "Talent hold cost minimization in film production," *J. Ind. Manage. Optim.*, vol. 17, no. 1, pp. 223–235, 2017.

[9] Y. Kochetov, "Iterative local search methods for the talent scheduling problem," in *Proc. 1st Int. Symp. 10th Balkan Conf. Oper. Res.*, Jun. 2014, pp. 282–288.

[10] M. Malek, M. Guruswamy, M. Pandya, and H. Owens, "Serial and parallel simulated annealing and tabu search algorithms for the traveling salesman problem," *Ann. Oper. Res.*, vol. 21, no. 1, pp. 59–84, Dec. 1989.

[11] J. Brandão and A. Mercer, "A tabu search algorithm for the multi-trip vehicle routing and scheduling problem," *Eur. J. Oper. Res.*, vol. 100, no. 1, pp. 180–191, Jul. 1997.

[12] J. Konishi, S. Shimba, J. Toyama, M. Kudo, and M. Shimbo, "Tabu search for solving optimization problems on Hopfield neural networks," in *Proc. 3rd Int. Conf. Knowl.-Based Intell. Inf. Eng. Syst.*, 1999, pp. 518–521.
[13] A. Salman, I. Ahmad, and S. Al-Madani, "Particle swarm optimization for task assignment problem," *Microprocessors Microsyst.*, vol. 26, no. 8, pp. 363–371, Nov. 2002.
[14] J. Jerald, P. Asokan, G. Prabaharan, and R. Saravanan, "Scheduling optimisation of flexible manufacturing systems using particle swarm optimisation algorithm," *Int. J. Adv. Manuf. Technol.*, vol. 25, nos. 9–10, pp. 964–971, May 2005.
[15] S. Jmal, B. Haddar, and H. Chabchoub, "Apply the quantum particle swarm optimization for the K-traveling repairman problem," *Soft Comput.*, vol. 23, no. 23, pp. 12547–12560, Dec. 2019.
[16] N. G. Zhao and J. S. Deng, "A review of particle swarm optimization algorithm," *Sci. Technol. Innov. Herald*, vol. 12, no. 26, pp. 216–217, 2015.
[17] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 26, no. 1, pp. 29–41, Feb. 1996.
[18] L. H. Wang, "Ant colony algorithm and its application in workshop scheduling," M.S. thesis, School Manage., Hefei Univ. Technol., Hefei, China, 2009.
[19] L. Xiao and Z. Li, "An improved ant colony algorithm and It's application in exam-arrangement," in *Proc. 2nd Int. Workshop Intell. Syst. Appl.*, May 2010, p. 1.
[20] H. Zhang, Z. Li, W. Shu, and J. Chou, "Ant colony optimization algorithm based on mobile sink data collection in industrial wireless sensor networks," *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, pp. 1–10, Dec. 2019.
[21] L. Zhen, E. P. Chew, and L. H. Lee, "An integrated model for berth template and yard template planning in transshipment hubs," *Transp. Sci.*, vol. 45, no. 4, pp. 483–504, Nov. 2011.
[22] L. Zhen, "Modeling of yard congestion and optimization of yard template in container ports," *Transp. Res. B, Methodol.*, vol. 90, pp. 83–104, Aug. 2016.

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