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Application of Multi-Objective Method in E-Sports Tourism Industry

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Abstract:

In the development of e-sports tourism, one of the problems to be solved is the scheduling of e-sports competitions. Global e-sports has attracted the attention of game fans all over the world. Due to the existence of time difference, how to achieve the ideal order of the competition scheduling is particularly important. On account of the time zone difference of fans, arranging the championship optimally is of vital importance. E-sports championship timetabling problem (ECTP) is a kind of timetabling problem. Usually, championships are arranged by experienced competition managers, which is not optimal. Intelligent algorithms are advanced heuristic methods that are very effective in many fields. But up till now, there hasn't someone who researches its application in this area. So in this paper, we first need to put forward a new mathematical model to this problem, and then we propose two evaluation function in this model. After taking the characteristic of this problem into account, we consider Multi-objective evolutionary Algorithm Based on Decomposition a great algorithm to solve this problem. But it is not suitable at first, so we made plenty of improvements, such as changing the coding method, population initialization, and genetic operation. The comparison with other algorithms shows that it has better performance in nearly all cases.

***Keywords**: Multi-objective, E-sports tourism, timetabling problem, Real world application.*

I. INTRODUCTION

In 2020, the overall market size of China's e-sports reached 147.4 billion Yuan, up 29.8% year on year, mainly from the rapid expansion of the mobile e-sports game market and the e-sports ecological market. Affected by COVID-19, users spent more time on online entertainment, driving the growth of the mobile e-sports game market to 36.8% and the e-sports ecological market to 45.2% in 2020 The integration of tourism industry is the product of tourism development to a certain stage. The integration of tourism and other industries brings new impetus to its own development. The integration of e-sports industry and tourism industry is driven by market demand and driven by interests.

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E-sports tourism is a themed tourism activity with e-sports events and activities as the main attraction. E-sports fans leave their usual home and follow e-sports to the event venue to watch or participate in e-sports events. E-sports tourism is an emerging event tourism, which is essentially no different from traditional event sports tourism (such as NBA, Football World Cup, F1 racing, etc.). E-sports tourism is mainly formed based on the interaction and integration of e-sports and tourism industry, which is a product of the integration of "sports + tourism" mode.

The traditional tourism industry is affected by seasonal factors and causes the operation of the off-peak season. During the off-season of each year, the number of tourists decreases dramatically, and the major scenic spots can only maintain the balance of income and expenditure, and some scenic spots even lose money and close down due to the lack of tourists. In order to solve the seasonal constraints of tourism, the development of e-sports tourism is a constructive measure. In the development of e-sports tourism, one of the problems to be solved is the scheduling of e-sports competitions. Global e-sports has attracted the attention of game fans all over the world. Due to the existence of time difference, how to achieve the ideal order of the competition scheduling is particularly important.

E-sports championship is one of the most famous sports events all over the world. According to the report of Newzoo [1], global e-sports revenues would grow to $1.1 billion in 2020, the global e-sports audience would reach 495.0 million in 2020, and by 2023 would reach 646 million. League of Legends (LOL) is one of the most popular e-sports worldwide. The 2019 LOL World Championship final reached a record-breaking 21.8 million Average Minute Audience (AMA), 44 million Peak Concurrent Viewers [2]. The whole championship consisted of 120 games across Berlin, Madrid, and Paris, and fans across the world watched more than 1 billion hours of content during the five weeks of the championship [3].

But fans are from different time zones, and it might be midnight for some fans to watch this game, which may only contribute little audience rating. So it's essential to arrange the schedule optimally to make this championship hit a higher commercial value.

Usually, the matches are arranged by experienced competition managers. Intelligent algorithms are not widely used in this area. Intelligent algorithms are developing rapidly and are applied to plenty of fields, such as Multi-Criteria Decision Model, job-shop scheduling [4-6], and electricity price forecasting. These problems can be well solved by intelligent algorithms.

S. Even had proved that all common timetabling problems are NP-complete, so the E-sports championship timetabling problem is also an NP-complete problem [7-10]. Although many scholars do research on job-shop problems and timetabling problems, their optimization objective functions are different from the E-sports championship timetabling problem, and their model cannot fit the E-sports championship timetabling problem well [11-12]. Till now, no one has researched in this specific area, which means we need to start from scratch. Firstly, a suitable mathematical model is needed to be founded. On the basis of extensive analyses, a new mathematical model with two evaluation functions is put forward. This model can help measure the quality of a solution with provision for the characteristic of this problem.

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Secondly, a multi-objective optimization algorithm is needed to be chosen to solve this problem. After taking the characteristic of plenty of multi-objective optimization algorithms into account, a multi-objective evolutionary Algorithm Based on Decomposition is chosen. However, the standard version is only suitable for continuous variables, so it needs to be modified. After referring to the application of MOEA/D in other fields, the coding method, population initialization, and genetic operation are significantly modified. To Sum up, the main contributions presented in this paper are listed as follows:

- A new kind of problem (E-sports championship timetabling problem) is presented, and a mathematical model is defined according to the characteristic of this problem.

- An improved MOEA/D algorithm based on Simulated Annealing Optimization, which has better performance in the crowding of schedule and the watching rate than other intelligent optimization algorithms, is introduced.

The remainder of the paper is organized as follows. A detailed problem description will be presented in Section II. Some intelligent algorithms that can solve this problem will be introduced in Section III. The detail about using MOEA/D to solve this problem will be offered in Section IV. Section V contains experimental results and discussion. Finally, the conclusion will be presented in Section VI.

II. MATHEMATICAL MODELING

E-sports championship timetabling problem is to arrange the order of matches to get an excellent schedule. This part introduces the detail of the E-sports championship timetabling problem and defines the terms used in ECTP.

2.1. Problem Description

There are lots of global e-sports championships held every year. Since the teams come from different time zones, and the viewing rate varies from time to time each day, it is essential to make a reasonable schedule to get more viewers to watch the championship. This kind of problem is called the E-sports championship timetabling problem. ECTP is to arrange the match order of the championship reasonably to make the objective function as optimal as possible under the premise of satisfying various constraints.

2.2. Data Structures and Variables

ECTP consists of a set of n team $T = \{t_1, t_2, \dots, t_n\}$ to be divided into m group $\mathrm{G} = \{\mathrm{g}_1, \mathrm{g}_2, \dots, \mathrm{g}_\mathrm{m}\}$ averagely, a set of the number of fans of n teams $FA = \{fa_1, fa_2, \dots, fa_n\}$ and a set of the time difference between team location and host location of n teams $D = \{d_1, d_2, \dots, d_n\}$. Team id in the same group is continuous, and team id increases as the group index grows. Two teams in the same group play against each other twice, so each team ti plays $\frac{2n}{m} - 2$ matches, a set of matches of team t_i is

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$TM_i = \{tm_{i1}, tm_{i2}, \dots, tm_{i(\frac{2n}{m}-2)}$the set of all the matches^t is $TM_i = \{tm_{i1}, tm_{i2}, \dots, tm_{i(\frac{2n}{m}-2)}$.Willingness to watch games every hour on weekdays$WD = \{wd_1, wd_2, \dots, wd_{24}\}$, and willingness to watch games every hour on weekends $WE = \{we_1, we_2, \dots, we_{24}\}$. These terms are defined in TABLE I.

2.3. Hard Constraint

Hard constraints must be satisfied to produce a feasible timetable [16].

Two hard constraints are considered in this paper:

1. Two teams in the same group play against each other twice.

2. Teams that are not in the same group do not play against each other.

2.4. Soft Constraint

Soft constraints are desirable but not absolutely essential [17]. Such constraints are used to measure the quality of a timetable. In real-world situations, it is usually unrealistic to satisfy all soft constraints. Indeed, the quality of a solution depends on these constraints.

1. The match interval of each team should be near $\frac{n}{2}$ to give teams plenty of time to prepare for their matches $n \cdot \left(\frac{n-m}{m}\right)$ because there are matches, and each team will play $2 \cdot \frac{n-m}{m}$ matches.

2. Each pair of teams will fight twice, so the interval of the matches of each pair of teams should be close to $\frac{n \cdot \left(\frac{n-m}{m}\right)}{2}$ because there are $n \cdot \left(\frac{n-m}{m}\right)$ matches, and each pair of teams will play against each other twice.

3. To maximize the watching rate, taking the time zone and fans' num of each team into account is also of vital importance.

2.5. Objective Functions

The satisfaction of soft constraints determines the quality of the objective function. The better the soft constraints are satisfied, the better the objective function is [13]. The objective functions of this paper are the comprehensive evaluation of each soft constraint condition.

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TABLE I. Terms Definition

Symbols	Description
n	the total number of teams
m	the total number of groups
T	the set of all teams $\lvert T\rvert = n$
G	the set of all groups $\lvert G\rvert = m$
FA	the set of the number of fans of all teams $\lvert FA\rvert = n$
D	the set of the time difference between the team zone and the host zone of all teams $\lvert D\rvert = n$
AM	the set of all the matches listed in time order $\lvert \mathrm{AM}\rvert = n \cdot \left(\frac{n-m}{m}\right)$
WD	the set of willingness to watch games every hour on weekdays $\lvert WD\rvert = 24, 0 \leq wd_i \leq 1$
WE	the set of willingness to watch games every hour on weekends $\lvert WE\rvert = 24, 0 \leq we_i \leq 1$
TMi	the set of matches of ti listed in time order. $\lvert TM_i\rvert = 2\frac{n}{m} - 2$

2.5.1. The crowding of schedule

The crowding of the schedule is expressed as

$$f1 = \frac{cost(A)}{cost(WST)} \tag{1}$$

where A is the awaiting assessment solution that contains a set of matches listed in time order, WST is a bad enough solution generated with Algorithm 1, which is used to make f1 a small value. In this algorithm, i means the index of the group, index means the index of the match, start means the smallest team id in this group, end means the largest team id in this group, note that team id in the same group is continuous, and the team id increases as the group index grows. j and k mean two teams in the same group, WST arrangement means the set of all the matches listed in time order. So it's obvious that cost (WST) is a constant value.

The function cost in equation (1) is used to compute the total crowding of the schedule of all the teams. It's calculated by two parts. One is the interval of the matches n played by a pair of teams. This ideal interval is $\frac{\mathrm{n}\cdot\left(\frac{\mathrm{n}-\mathrm{m}}{\mathrm{m}}\right)}{2}$ .The other is the match interval for each team, whose ideal interval is $\frac{\mathrm{n}}{2}$. The function cost can be calculated as

$$cost(x) = \sum_{k=1}^{m} \sum_{i=(k-1)\cdot\frac{n}{m}+1}^{k\cdot\frac{n}{m}} \sum_{j=i+1}^{k\cdot\frac{n}{m}} cal\left(fight(i,j), \frac{n\cdot\left(\frac{n-m}{n}\right)}{2}\right)\cdot\beta$$

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$$+\sum_{i=1}^{n}\sum_{l=2}^{2\frac{n}{m}-2} cal\,(pos(tm_{il}) - pos\left(tm_{i(l-1)}, \frac{n}{2}\right) \quad (2)$$

where $\sum_{k=1}^{m}\sum_{i=(k-1)\cdot\frac{n}{m}+1}^{k\cdot\frac{n}{m}}\sum_{j=i+1}^{k\cdot\frac{n}{m}} \mathrm{cal}\left(\mathrm{fight}(i,j), \frac{n\cdot\left(\frac{n-m}{n}\right)}{2}\right)$ fight is to calculate the crowding of the matches of each pair of teams, k is the index of the group, i and j are teams in the same group, $\mathrm{fight}(i,j)$ is the index interval of the two matches of the pair of teams i and j in AM. And $\sum_{i=1}^{n}\sum_{l=2}^{2\frac{n}{m}-2} \mathrm{cal}\,(\mathrm{pos}(\mathrm{tm}_{il}) - \mathrm{pos}\left(\mathrm{tm}_{i(l-1)}, \frac{n}{2}\right)$ is to calculate the crowding of each team's match interval. $\mathrm{pos}(\mathrm{tm}_{il})$ is the index of the match tmil in AM, β is to weight the crowding of the matches of each pair of teams. And cal is used to measure the relative difference between two intervals. In order to reduce the probability of small interval cases, cal uses exponent to increase the cost of small interval cases. Function cal is shown as

$$cal(a,b) = e^{\frac{b-min(a,b)}{b}+4} - e^{4} \quad (3)$$

where b is the ideal interval, a is the actual interval.

The smaller the value of f1 is, the lower the crowding of schedule is.

Algorithm 1: The way to generate WST

$i \leftarrow 1$
$index \leftarrow 0$
while $i < m + 1$ do
$start \leftarrow (i-1)\cdot(\frac{n}{m}) + 1$
end $\leftarrow i\cdot(\frac{n}{m}) + 1$
$j \leftarrow start$
while $j < end$ do
$k \leftarrow j + 1$
while $k < end$ do
$index \leftarrow index + 1$
$WSTarrangement\,[index] \leftarrow (j, k)$
$index \leftarrow index + 1$
$WSTarrangement\,[index] \leftarrow (k, j)$
end while
end while
end while

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2.5.2. Championship viewing index

The function $f2$ is used to measure the championship viewing index over the whole championship, which can be calculated as

$$f2 = 1 - \frac{\sum_{i=1}^{n}\sum_{j=1}^{\frac{2n}{m}-2} watching(fa_i, pos(tm_{il}), d_i)}{2\cdot\frac{n-m}{m}\cdot\sum_{k=1}^{n} fa_k} * \frac{1}{\gamma}$$

where $\sum_{i=1}^{n}\sum_{j=1}^{\frac{2n}{m}-2} \mathrm{watching}(\mathrm{fa_i}, \mathrm{pos}(\mathrm{tm_{il}}), \mathrm{d_i})$ is to calculate the estimated number of viewers during the whole championship. $\mathrm{watching}(\mathrm{fa_i}, \mathrm{pos}(\mathrm{tm_{il}}), \mathrm{d_i})$ means the prediction about the actual number of fans of $\mathrm{t_i}$ who will watch the match $\mathrm{tm_{il}}$ while the total number of fans of $\mathrm{t_i}$ is $\mathrm{fa_i}$ and the time difference to the host is $\mathrm{d_i}$. So watching is equal to the product of the fans' location time watching rate and the total number of fans. $2\cdot\frac{\mathrm{n-m}}{\mathrm{m}}\cdot\sum_{k=1}^{n}\mathrm{fa_k}$ is to calculate the sum number of viewers if all the fans watch all the matches their fond team plays, and it's a constant value. γ is the max matching rate during all the periods. The smaller the value of $f2$ is, the higher the championship viewing index is.

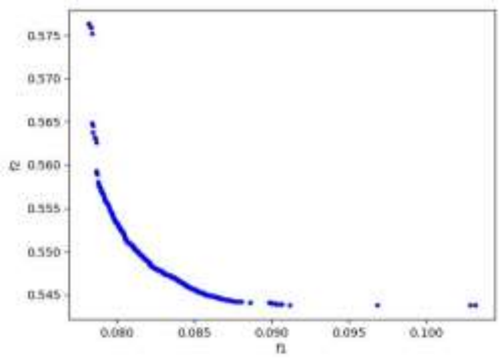

Fig 1: Pareto Front about f1 and f2

2.5.3. Necessity to set f1 and f2

$f1$ and $f2$ are used to get great solutions with different goals. $f1$ aims to get a reasonable schedule in view of the crowding. $f2$ aims to hit a higher watching rate. After the experiment, the pareto front in Figure 1 shows that the higher the watching rate is, the worse the crowding of the schedule is. In this sense, they are often inconsistent. So they can't be merged into a single objective function.

III. METHODS TO SOLVE ECTP

Methods for solving ECTP can be divided into two categories. One is deterministic algorithms, whose purpose is to find the theoretical optimal solution; the other is non-deterministic algorithms, which do not

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force on the most excellent solution, just find a "good enough" satisfactory solution.

3.1. Deterministic Algorithms

3.1.1. Backtracking pruning

Backtracking is a systematic search algorithm [14]. It searches the solution space tree, which contains all solutions to the problem from the root node with the depth-first strategy. It can always find the theoretical optimal solution, but the time complexity of this algorithm grows exponentially with the scale, even with many pruning operations. So this algorithm is only suitable when the size of the problem is small enough.

3.1.2. Greedy algorithm

Greedy algorithms make the locally optimal choice at each stage instead of considering a global optimum [15]. So greedy algorithms can't always get the optimum global result; it depends on whether the greedy strategy has after-effects. In this problem, using a greedy algorithm cannot get an optimum global solution but might get an acceptable solution with just a little cost of time.

3.2. Randomized Algorithms

3.2.1. Simulated annealing

Simulated annealing (SA) algorithm is a probabilistic algorithm based on the principle of solid annealing [18]. This algorithm works similarly to a solid complex system, which is heated first to a high temperature at which material particles can move freely. And as it cools down, its energy diminishes. If the "cooling" process is slow enough, the system will ignore the Local optimum and reach its lowest energy state, the ground state. In each step of the simulation, new solutions are generated according to the Metropolis transition rule. This rule makes a new state with a certain probability of an increase in energy (in short, a bad solution) acceptable. The rule is as follows:

$$p = \begin{cases} 1, & f(y) < f(x) \\ exp\left(-\frac{f(y)-f(x)}{T}\right), & otherwise \end{cases} \tag{5}$$

where x is a previous solution, y is a new solution, p is the probability of accepting the new solution y, function $f(x)$ is used to calculate the energy of solution x.

3.2.2. Particle swarm optimization

Particle swarm optimization (PSO) is an evolutionary computation proposed by Dr. Eberhart and Dr. Kennedy in 1995 [19]. Similar to SA, it also starts from a random solution and finds the optimal solution through iteration. But it approaches the global optimum by following the currently searched optimal value.

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PSO is well-known for its high accuracy and fast convergence. But while dealing with Complex multi-peak search problems, it might be trapped into local minima.

3.2.3. Genetic algorithm

Genetic algorithm (GA) is an algorithm to search for the optimum solution by simulating the natural evolution process [20]. It finds the optimal solution through iteration and approaches the global optimum by using selection, crossover, and mutation operations. Not only is it easy to implement, but it has great global search capability as well. However, it is prone to premature convergence and poor convergence.

3.2.4. Non-dominated sorting genetic algorithm II

Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a multi-objective optimization algorithm based on Pareto optimum [21]. Traditional multi-objective optimization methods transform multi-objective optimization problems into single-objective optimization problems in a specific way, which does not work well in practice. NSGA-II can provide as many representative non-inferior solutions as possible for decision makers to avoid falling into the optimal local solution, which has been widely used at present. However, the complexity of the calculation is on the high side [22].

3.2.5. Multi-objective evolutionary algorithm based on decomposition

Multi-objective evolutionary Algorithm Based on Decomposition (MOEA/D) transforms the multi-objective optimization problem into a series of single-objective sub-problems and utilizes the information of a certain number of adjacent problems to optimize these sub-problems simultaneously by using the evolutionary algorithm [16]. Because each solution on the pareto front corresponds to the optimal solution of each single-objective sub-problem, a group of pareto optimal solutions can be obtained eventually. Due to the decomposition operation, this method has great advantages in maintaining the distribution of solutions, and it can avoid falling into the local optimum by analyzing the information of adjacent problems [23-24].

IV. PROPOSED APPROACH

MOEA/D is one of the most outstanding multi-objective algorithms which has been widely used in many fields [11]. According to the characteristics of ECTP, the coding method, population initialization, and genetic operation have been modified. And to speed up the convergence rate, we compare several algorithms. From the results shown in TABLE II and TABLE III, we can figure out that SA has a much lower value than PSO and GA in nearly all cases, which means that SA has better performance (Parameter settings and data are introduced in the next section). So we choose one individual to be generated by SA.

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TABLE II. Results of different algorithms

Data	Algorithm	Average optimal value	Optimal value	Iteration times		Population size
	SA	0.3821362	0.379051			
	PSO	0.478088	0.459657	1000		500
data 1	GA	0.459181137	0.443406084	1000		500
	SA	0.3977768	0.394981			
	PSO	0.5866226	0.581836	1000		500
data 2	GA	0.571914098	0.560985987	1000		500
	SA	0.4092238	0.408283			
	PSO	0.6015977	0.592051	1000		500
data 3	GA	0.596016862	0.591899889	1000		500

TABLE III. Friedman nonparametric test results of the Average optimal value

Algorithm	Mean Rank	Final Rank
SA	1.0	1
PSO	3.0	3
GA	2.0	2

4.1. Coding Method

ECTP is to arrange matches in reasonable order. The chromosome is encoded by $n \cdot \left(\frac{n-m}{m}\right)$ matches, which are numbered from 1 to $n \cdot \left(\frac{n-m}{m}\right)$. That is to say that each gene presents a specified match. In this way can the two hard constraints above be satisfied directly. Fig 2 shows an example of the coding method, there are 6 teams and 3 groups, so there are 2 teams in each group, each team plays 2 matches. The total number of matches for the entire schedule is 6.

4.2. Population Initialization

Generate Popsize−1 individuals randomly. To speed up the convergence rate quicker, generate the other one individual by SA. Note that Tem is the current system temperature, λ is the annealing rate, Tmin

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is the end temperature. $Z = \delta \times f_1 + (1 - \delta) \times f_2$,the optimal individual is i. Fig 3 shows the process of SA.

4.3. Genetic Operation

4.3.1. Crossover operation

The standard MOEA/D algorithm uses a simulated binary crossover (SBX) crossover operator, which is only suitable for continuous variables. So Order Crossover (OX) has been used instead. Let the two Parents be Pa1 and Pa2. Concrete steps are as follows:

(1). Randomly choose two positions $i, j(1 \leq i \leq j \leq n \cdot \frac{n-m}{m})$ in Pa1, select the genes located between i andj.

(2). Generate a progeny and copy the selected genes in Pa1 to the same position in the progeny.

(3). Put the genes that are not selected by Pa1 in Pa2 into the vacant positions of the progeny in order.

Fig 4 shows an example of a crossover operation.

(3,4)	(6,5)	(5,6)	(2,1)	(4,3)	(1,2)

Fig 2: n=6 m=3

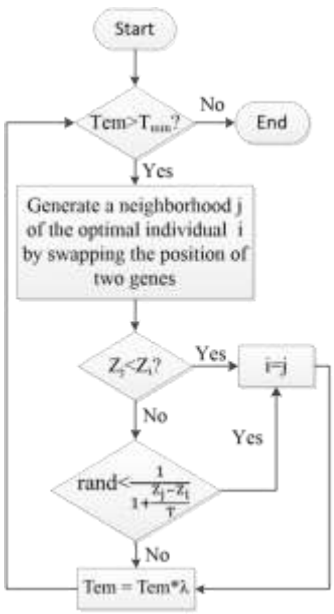

Fig 3: The process of SA

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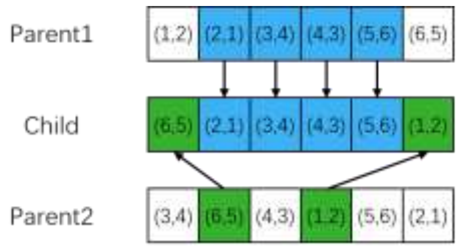

Fig 4: Cross over schematic diagram

4.3.2. Mutation operation

The polynomial mutation used in MOEA/D is not suitable for this problem. A swap mutation is used instead. Find two positions i and j ($i \neq j$) and swap the i-th gene and the j-th gene.

4.4. Calculation Flow

The implementation procedure of SA+MOEA/D is shown in Algorithm 2.

V. EXPERIMENTAL STUDY

In this section, a series of experiments are done to verify the performance and feasibility of the SA+MOEA/D. First, the parameter settings of the research are described in Section 5.1. Section 5.2 investigates the distribution and convergence of the SA+MOEA/D, and it's compared with the MOEA/D and the NSGA-II [12].

5.1. Parameter Settings

In order to simulate the real situation, a survey is carried out to find the watching rate during different times. One hundred ninety-two people took part in this survey from different areas of China. The watching rate on weekdays is shown in TABLE VI, and the watching rate on weekends is shown in TABLE VII. The championship rule is similar to the rule in the 2019 LOL World Championship. Each day will hold a match per hour from 15:00 to 20:00, and each match lasts for an hour. The first match starts on Friday. The host is in UTC.

Test cases are displayed in TABLES VIII, IX, and X. The difference between them is the group size and the number of teams. TABLE VIII lists 16 teams which are divided into 4 groups. TABLE IX consists of 32 teams of 4 Groups. There are 8 Groups made up of 64 teams in TABLE X. These 3 test data can measure the performance of algorithms in different situations.

Because the calculation methods of the single-object and the multi-object are different, a weighting function f is used to compare them, $f = \alpha * f1 + (1 - \alpha) * f2$, $\alpha = 0.3$, $\beta = 2$. According to TABLE VI and TABLE VII, $\gamma = 0.3788$.

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The Cross rate is 0.8, the mutate rate is 0.2, the population size is 500, and the probability of selection is 0.7. And in its initialization, $\delta = 0.3$, Tem = 10000, $\lambda = 0.9999$, and $T_{\min} = 10^{-14}$.

The PSO, SA were implemented in c++ and compiled with MinGW-w64, while the NSGA-II, MOEA/D and SA+MOEA/D were implemented in python and compiled with python3.7. And they are executed using a computer with 8 Inter Core Ryzen7-4800U 4.2 GHz CPUs and 16GB memory. The operating system was Microsoft Windows 10.

Algorithm 2 Procedure of SA+MOEA/D

Parameters: Elite population EP, population size s, neighborhood size ne, reference point z

Step 1: Initialization.

Step 1.1: $EP \leftarrow \phi$.

Step 1.2: For each weight λ^i, determine its ne adjacent weight vectors $\lambda^{i^1}, \dots, \lambda^{i^{ne}}$, mark its neighborhood $NS_i \leftarrow i_1, \dots, i_{ne}$.

Step 1.3: Initialize the population $x^1, \dots, x^s$, choose one individual to be generated by SA, and calculate their target vector values.

Step 1.4: Initialize the current reference point $z_j \leftarrow min_{i\in 1,\dots,s} f_j(x^i)$.

Step 2: Update. For $i \in \{1, \dots, s\}$, do the following operations.

Step 2.1: Genetic recombination: choose two individuals randomly from the neighborhood $NS_i \leftarrow \{i_1, \dots, i_{ne}\}$, generate a new individual x by using the recombination operator.

Step 2.2: Amend the solution x according to the constraints to generate the solution x'

Step 2.3: Update the current reference point z.

Step 2.4: For $j \in NS\_i$, update the individuals in the neighborhood. If $g^{te}(x'|\lambda^j) \leq g^{te}(y^j|\lambda^j)$, then$y^j \leftarrow x'$, where y^j is the individual in the subproblem of the j_{th} weight.

Step 2.5: Update EP.

Step 3: Termination condition judgment: if the termination condition is not satisfied, then go to step 2 or terminate the evolutionary process.

5.2. Comparison with other Alogrithms

To evaluate the performance of the SA+MOEA/D roundly, the SA+MOEA/D is compared with NSGA-II and MOEA/D. We use HV [28] to evaluate the performance of the algorithms. GD [27] and IGD [26] need the real pareto front, which is impossible for this real-world problem. The bigger the value of HV is, the better the performance is. The results with test data 1, 2, and 3, which are calculated as the average of 10 operations, are shown in TABLE IV. From the results, it can be seen that SA+MOEA/D has a higher value in most situations, which denotes that it works better. And as the data size grows, the gap between SA+MOEAD and the other two algorithms are getting larger.

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To evaluate the algorithms in the index scientifically, the Friedman nonparametric test method is used to sort the algorithms in this paper [25]. The results are shown in TABLE V. And from TABLE V, it can be seen that SA+MOEA/D has a higher value than MOEA/D and NSGA-II in HV, which means SA+MOEA/D works better. To visually see the improvement of the initialization of SA in both distribution and convergence, the results of different generations are compared in Figs 3, 4.

From Fig 3, it can be seen that SA+MOEA/D has better distribution than MOEA/D and NSGA-II. And the convergence of SA+MOEA/D is far better than the convergence of MOEA/D and NSGA-II. As the generation increases, both the distribution and convergence of the SA+MOEA/D are getting more superior.

Fig 4(a) and Fig 4(b) show the convergence of SA+MOEA/D and MOEA/D. As can be seen, SA+MOEA/D works much better than MOEA/D while the generation is smaller than 10000. And both of them need more than 80000 generations to get complete convergence.

Above all, the SA+MOEA/D has excellent distribution and can get complete convergence much quicker than the MOEA/D and NSGA-II. So the using SA to initialize the population saves lots of time to get full convergence and helps get a better distribution and a better convergence.

TABLE IV. The average value of HV of different algorithms

Dataset	Algorithm	Average
data1	SA+MOEA/D	0.10861607
	MOEA/D	0.105596436
	NSGA-II	0.110090905
data2	SA+MOEA/D	0.044841091
	MOEA/D	0.026732158
	NSGA-II	0.003470215
data3	SA+MOEA/D	0.008733425
	MOEA/D	0
	NSGA-II	0

TABLE V. Friedman test results of HV Algorithm Mean Rank Final Rank

SA+MOEA/D	2.67	1
MOEA/D	1.50	3
NSGAII	1.83	2

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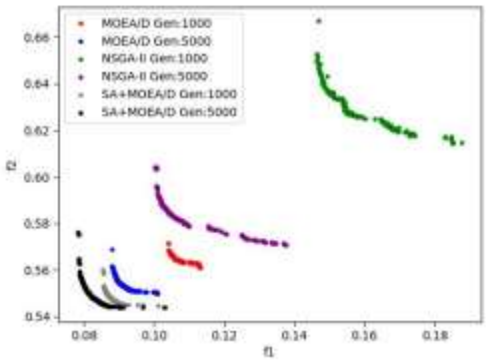
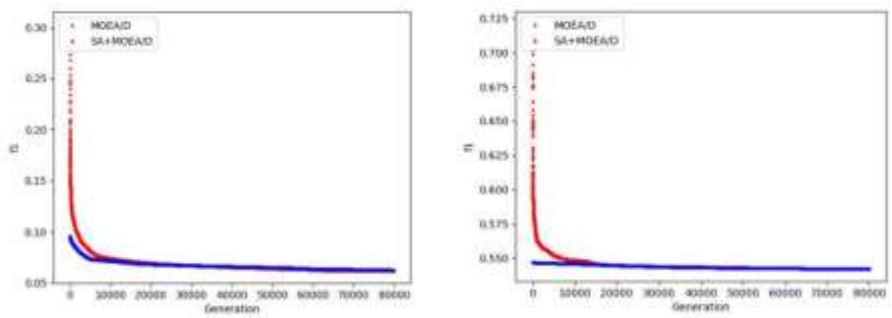


Fig5: Distribution of Pareto optimal solution set in different generations

TABLE VI. Watching rate in weekdays

Time	1-7	8-11	12-15	16-17	18-12	23-24
Watching rate	1.66%	2.65%	5.30%	5.63%	25.02%	9.28%



(a) (b)

Fig6: Convergence in different generations

TABLE VII. Watching rate in weekends

Time	1-7	8-11	12-15	16-17	18-12	23-24
Watching rate	4.36%	5.45%	16.35%	19.35%	37.88%	14.71%

TABLE VIII. Test data 1

Group	1	1	1	1	2	2	2	2
Num of fan	22447	48147	1132138	64035	68013	45183	113631	460394
Time difference from host	-9	2	1	8	-4	-9	12	-10

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Group	3	3	3	3	4	4	4	4
Num of fan	201150	94151	698927	1154908	1124522	894525	79891	99764
Time difference from host	5	-9	-11	7	-12	4	-4	2

TABLE IX. Test data 2

Group	1	1	1	1	1	1	1	1
Num of fan	1992653	782778	26839	1089	3446064	7884417	28815	420384
Time difference from host	-4	0	-3	-5	-1	-8	-2	3
Group	2	2	2	2	2	2	2	2
Num of fan	230353	459855	347915	61048	536578	38944	170802	356369
Time difference from host	-10	-10	11	4	5	2	-7	8
Group	3	3	3	3	3	3	3	3
Num of fan	57866	122741	613139	186654	423036	516927	190428	906406
Time difference from host	6	-12	1	-9	4	11	6	-9
Group	4	4	4	4	4	4	4	4
Num of fan	665770	412589	354089	434289	1468966	2594158	82945	271064
Time difference from host	2	-3	-6	-12	6	-7	6	-4

TABLE X. Test data 3

Group	1	1	1	1	1	1	1	1
Num of fan	1992653	782778	26839	1089	3446064	7884417	28815	420384
Time difference from host	-4	0	-3	-5	-1	-8	-2	3
Group	2	2	2	2	2	2	2	2
Num of fan	230353	45985 下·5	347915	61048	536578	38944	170802	356369
Time difference from host	-10	-10	11	4	5	2	-7	8
Group	3	3	3	3	3	3	3	3
Num of fan	57866	122741	613139	186654	423036	516927	190428	906406
Time difference from host	6	-12	1	-9	4	11	6	-9

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Group	4	4	4	4	4	4	4	4
Num of fan	665770	412589	354089	434289	1468966	2594158	82945	271064
Time difference from host	2	-3	-6	-12	6	-7	6	-4
Group	5	5	5	5	5	5	5	5
Num of fan	535384	3092020	385184	60082	812003	1375628	1383860	291105
Time difference from host	6	-5	1	-9	-12	-9	3	-7
Group	6	6	6	6	6	6	6	6
Num of fan	85029	250335	125018	62690	493877	585505	180936	108486
Time difference from host	-7	-6	7	8	2	5	-2	10
Group	7	7	7	7	7	7	7	7
Num of fan	204895	46405	90462	34031	51714	337942	263423	6665253
Time difference from host	-3	5	-5	-6	-6	-12	4	-10
Group	8	8	8	8	8	8	8	8
Num of fan	171078	44663	338986	347961	380870	196323	78860	51911
Time difference from host	8	-11	-5	2	6	2	0	-7

VI. CONCLUSION

E-sports tourism relies on the development of e-sports. Compared with traditional sports tourism, e-sports tourism started later, but it has developed rapidly in recent years. By using e-sports related products, the tourism resources are integrated and innovated, and new characteristic tourism products and services are developed. Compared with the traditional tourism development model, e-sports tourism cannot be restricted by tourism resources and seasons and other factors. Meanwhile, e-sports tourism has a strong fan economy, which can be watched online or at the venue of the competition, realizing the interaction between online and offline fan economy. For the countries and cities hosting e-sports, it is also one of the ways to increase popularity and drive economic development. E-sports has a long schedule. If reasonable scheduling and proper competition time can be carried out, e-sports fans can also visit the scenic spots, historical relics and historic sites of the event venue during non-competition period, realizing the integration of "culture + sports + tourism".

ECTP is a valuable problem, but up until now, matches are still usually arranged by an experienced competition manager, which takes several days, while using this method only takes a few minutes. Nobody has researched the usage of intelligent algorithms in this area. So in this paper, according to the characteristic of ECTP, a new mathematical model is built, and two evaluation functions are brought out. Then a multi-objective algorithm is presented to solve the problem after much modification with the coding method, population initialization, and genetic operation. After testing with other algorithms using the mathematical model we built, it has a better performance.

ECTP can be solved with multi-objective algorithms. But MOEA/D has a lousy performance not only in convergence but also in distribution. In order to speed up the convergence rate and optimize the distribution, SA is used to initialize the population. According to experiments down in section V, the SA+MOEA/D takes less than half of the time that the MOEA/D uses and has a greater distribution than MOEA/D.

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