Journal of Network Intelligence
Taiwan Ubiquitous Information

Volume **9**, Number **3**, August **2024**

Personalised Multi-Objective Travel Route Recommendation Based on Super Multi-Objective Optimization Algorithm

Xiang-Rong Zhang*

Henan Vocational College of Agriculture, Zhengzhou 451450, P. R. China
zjsszjss@126.com

Xue-Ying Wang

West Yunnan University of Applied Science, Dali 671000, P. R. China
wangxueying0925@163.com

Takeshi Ebara

College of Management Science
University of Cyberjaya, Persiaran Multimedia 63000, Selangor, Malaysia
xv9098@163.com

*Corresponding author: Xiang-Rong Zhang
Received November 28, 2023, revised February 6, 2024, accepted April 14, 2024.

Abstract. *Most tourists are constrained by several factors such as transportation, cost, time, attractions, hotels, etc. when making travel plans, yet existing studies have not sufficiently considered tourists' preferences and constraints, which makes it difficult to truly satisfy tourists' individual needs. Therefore, a more effective intelligent planning system for tourist routes is needed to solve this problem. In this work, a personalised multi-objective travel route recommendation method based on the super multiobjective optimisation algorithm is proposed. Firstly, to address the problem that the commonly used multi-objective optimization algorithms cannot effectively balance the global convergence characteristics and quantum behavioural characteristics, this work proposes a super-multi-objective optimization algorithm based on vector evaluation. Then, a multi-objective tourism route planning model is constructed using the hotels and attractions recommended by the tourism software and solved using the proposed hyper-multi-objective optimisation algorithm. The hotels selected by tourists are used as the starting and ending points of the tourism routes, and the personalised tourism routes are planned for tourists under the condition of satisfying the constraints. Finally, the model is validated using Chongqing city as the target city and the user's travel assistance as an example, taking the diversity of attraction types into account. The results show that compared with the dynamic programming algorithm, the non-inferior solution set of the proposed super multiobjective optimisation algorithm contains the optimal solution and the time used is shorter, which verifies that the proposed method has certain feasibility and effectiveness.*
Keywords: Tourist route recommendation; Multi-objective optimisation; Particle swarm algorithm; Quantum behaviour; Conditional constraints

---

1. **Introduction.** Tourism has become an important organisational activity for people, and with the maturity of GPS positioning technology and the improvement of transport facilities, the forms of tourism have become more diversified [1, 2]. The rapid development of mobile phones and other intelligent devices allows people to share their travelling

experience on major travel websites or make comments on some tourist attractions they have visited, which makes the travel information on the Internet become richer.

Such a large amount of tourist information brings a problem of severe information overload in the field of tourism [3, 4]. When a tourist makes a travel plan, he/she is faced with a large amount of redundant data on the Internet, and if he/she wants to find useful information for himself/herself, he/she needs to spend a lot of time, and different tourists feel differently about the subjective feelings of the same tourist attraction, and release different tourist evaluation information, which increases the difficulty of decision-making, and tourists need to inquire about attraction information, hotel information, and traffic conditions every time they travel, which greatly consumes time and energy [5, 6]. How to help tourists obtain the information they need in a large amount of redundant and useless tourism information environment, and help tourists plan a travel route that meets their own requirements is an urgent problem facing the current tourism industry.

How to determine the sequence of attractions in order to obtain the maximum tourism benefits at the minimum cost is the problem of tourism route planning. Existing tourism websites can only recommend some popular attractions to tourists, which can't satisfy the personalised needs of tourists [7]. Therefore, the intelligent recommendation of tourism routes has become the primary choice for tourists to travel, and the first problem to be solved by the intelligent recommendation of tourism routes is the planning of tourism routes [8], and a reasonable tourism route should not only satisfy the user's personalised preferences, but also enable tourists to obtain the maximum tourism benefits at the smallest cost. Although the current major tourism websites provide a large amount of tourism information, and all recommend some tourism products, popular attractions, as well as travel tips for tourists [9]. In the face of such a wealth of tourism information, tourists must spend a lot of time and energy to read, from which to find out the information they need, and then refer to other people's travel experience, and then with their own practical combination to make travel plans, meeting all of the demands of tourists is challenging. Therefore, the information provided by tourism websites will not be able to bring tourists a good experience. In addition, people are more willing to accept the recommendation of route information that meets their preferences rather than searching for travel information in a redundant environment [10].

When planning travel arrangements, most visitors are limited by a number of issues, including hotels, transportation, cost, and time. However, the studies that have already been done do not adequately take into account the preferences and limits of tourists, which makes it challenging to properly meet each visitor's unique demands [11]. To address this issue, a more sophisticated intelligent scheduling system for tourism routes is required. In this work, a personalised multi-objective tourism route recommendation method based on the super multiobjective optimisation algorithm is proposed.

1.1. **Related Work.** The tourism route recommendation problem is an important field of path planning, the research on tourism route recommendation first originated from path planning, and the most classic of the path planning problems is the traveller's problem which is often referred to as the traveller's problem [12]. When tourists plan their travel routes, they first need to collect information about hotels and attractions, and they also need to consider factors such as traffic, cost, and time constraints, which is cumbersome to achieve. For the multi-objective tourism route planning problem, the existing research theories are also relatively comprehensive, mainly divided into two categories: exact algorithms and heuristic algorithms.

Exact algorithms use mathematical methods to solve the problem directly to obtain an optimal solution. For example, an exact travel route can be obtained by solving a minimum weight Hamiltonian loop based on the Traveller's Problem (TSP) [13] or its variants. However, this approach is usually difficult to handle large-scale problems. Based on users' historical data, Abbaspour and Samadzadegan [14] proposed a time-dependent model of the route planning problem, and then solved the proposed corresponding model to obtain time-inclusive travel route planning results, which are recommended to the users. Yang et al. [15] proposed a pattern- and preference-aware travel route recommender scheme. Firstly, a system architecture is constructed based on the proposed travel route recommendation, and then the movement pattern of each user is modelled. Finally, a travel route recommendation scheme is proposed to develop travel routes and recommend personalised services for the target users. Wörndl et al. [16] proposed a path recommendation mechanism for the prediction of the next tourist attraction and the optimal path recommendation for the predicted tourist attraction. An objective function based on multiple route parameters such as distance, road congestion, weather conditions, route popularity and user preferences are designed to obtain better optimisation results for tourist routes. Majid et al. [17] extracted attraction information from tourist photographs to mine user preferences in the photographs, including weather information, social relationships and time information, in order to recommend tourists a route that meets their personalised preferences. Route.

Multi-objective optimisation requires simultaneous optimisation of multiple conflicting objectives, and it is difficult for an exact algorithm to find an optimal solution in a multi-dimensional objective space, while heuristic algorithms can efficiently search the complex solution space and quickly find an approximate optimal solution. Heuristic algorithms, on the other hand, are a class of approximation algorithms that obtain a suboptimal or near-optimal solution by optimising a possible solution. This approach can handle large-scale problems and can sometimes yield very good results. Many classical heuristic algorithms draw on the idea of multi-objective optimisation [18]. For example, genetic algorithms simulate the process of biological evolution to optimise multiple objectives, and particle swarm algorithms allow each particle to represent a set of multi-objective solutions and optimise all objectives through group collaboration. All these algorithms make use of the idea of population optimisation in multi-objective optimisation. Common heuristic algorithms include Genetic Algorithm (GA) [19], Simulated Annealing Algorithm (SAA) [20], Particle Swarm Algorithm (PSO) [21], etc. Chen et al. [22] used a genetic algorithm to plan personalised tourist routes. The method generates personalised routes based on tourists' budget, time, interest and other factors. Experiments show that this method can quickly find the optimal solution in complex environments, and the generated travel routes are more in line with personal preferences. Liu et al. [23] proposed to train a new meta-heuristic algorithm for dynamic planning of personalised travel routes through deep reinforcement learning. Experiments show that the method can change the route according to the real-time environment and maximise the quality of the route.

1.2. **Motivation and contribution.** Multi-objective optimisation algorithms are usually combined with heuristic algorithms for solution. An exact algorithm is used to generate a set of pareto-optimal solutions as initial solutions, and then a heuristic algorithm is used to search the solution space with the aim of finding a better set of non-inferior pareto-optimal solutions. This hybrid approach combines the advantages of both algorithms.

However, the multi-objective optimization algorithm based on heuristic algorithm still has some shortcomings, for example, when dealing with multi-constraint travel route planning, the commonly used multi-objective optimization algorithms are unable to effectively balance the global convergence characteristics and quantum behavioural characteristics of the problem, so there is an urgent need for a model that conforms to the actual scenarios, and recommends to the users travel routes that can meet their real needs.

The main innovations and contributions of this work include:

(1) Aiming at the problem that commonly used multi-objective optimization algorithms cannot effectively balance the global convergence property and the quantum behavioural property [24], this work proposes an ultra-multi-objective optimization algorithm based on vector evaluation called Vector Evaluated Quantum Particle Swarm Optimization (VE-QPSO), which is mainly composed of an objective-based vector-based individual evaluation method combined with the QPSO algorithm.

(2) Construct a multi-objective tourism route planning model using the hotels and attractions recommended by the tourism software, and solve it using the proposed super multi-objective optimisation algorithm. The hotels selected by tourists are used as the starting and ending points of the travel routes, and personalised travel routes are planned for tourists under the condition of satisfying the constraints.

2. Principles of multi-objective planning.

2.1. Multi-objective problem description. The theory of multi-objective optimisation [25] involves a number of modern mathematical disciplines, and its solution methods are often based on linear, non-linear, stochastic and numerical computational tools and techniques. At present, multi-objective planning has made important progress in both theoretical research, solution methods, and applications, making it a huge discipline.

In terms of theoretical studies, multi-objective optimisation encompasses a very wide and rich range of topics. Multi-objective optimisation problems, also known as vector extremum problems, are different from single-objective planning problems containing only one objective function, in that in general there is no optimal solution. Therefore, multi-objective optimisation is mainly concerned with making the vector objective of the problem a non-inferior efficient solution in some sense, while the theory of multi-objective optimisation is mainly concerned with investigating the nature of efficient solutions regarding various senses.

Assuming that a certain decision-making process requires the simultaneous examination of k objectives and that all objective functions are required to be as small as possible while satisfying the constraints, such an optimisation problem can be formulated as follows [26]:

$$\min_{X \subset R} F(X) = (f_1(x), f_2(x), \ldots, f_k(x))^T \tag{1}$$

$$R = \{X | g(X) \leq 0\}, g(X) = (g_1(X), g_2(X), \ldots, g_m(X))^T \tag{2}$$

$$X = (x_1, x_2, \ldots, x_n)^T, X \subset R \subset E^n \tag{3}$$

where $F(X)$ is the optimisation objective vector, $g(X)$ is the constraint vector and X is the decision variable.

In the solution process, it is difficult to find a solution vector in the constraint set R of the problem that can minimise k objective functions at the same time. For multi-objective optimisation problems, it is difficult to determine the advantages and disadvantages by simple comparisons, so the Pareto dominance principle is proposed as a basis for judging the advantages and disadvantages of multi-objective optimisation problems, based on which the concept of Pareto optimal set is defined [27].

Definition 1: For the minimisation multi-objective problem, there exist two objective vectors. If the target vector $u = (u_1, u_2, \ldots, u)_T^k$ dominates $v = (v_1, v_2, \ldots, v)_T^k$, if and only if there exists a decision variable such that Equation (4) holds.

$$u_i \leq v_i,\ i = 1, 2, \ldots, k \tag{4}$$

Definition 2: For the minimisation multi-objective problem, there are no decision variables in the feasible domain such that the target vector $v = (f_1(X_v), f_2(X_v), \ldots, f_k(X_v))^T$ dominates the target vector $u = (f_1(X_u), f_2(X_u), \ldots, f_k(X_u))^T$.

The set of all solutions satisfying Definition 2 constitutes the Pareto optimal solution set, also known as the set of non-inferior solutions, for a multi-objective optimisation problem. Each solution in the set is a Pareto optimal solution, also known as a non-inferior or efficient solution. The very nature of a multi-objective optimisation problem lies in the fact that in many cases the sub-objectives may be in conflict with each other, and an improvement in the performance of one sub-objective may cause a decrease in the performance of another sub-objective.

2.2. **Algorithms for solving multi-objective optimisation problems.** The process of obtaining the set of Pareto solutions is known as the solution process or optimisation process, which often cooperates with the decision-making process to find the final solution one needs.

For a multi-objective optimisation problem, if each sub-objective function $f_i(x)$ is assigned different fixed weights w_i $(i = 1, 2, \ldots, k)$, where w_i satisfies: $0 \leq w_i \leq 1$ and $\sum_{i=1}^{k} w_i = 1$. The magnitude of w_i represents the importance of the corresponding sub-objective function in the multi-objective optimisation problem. The linear weighted sum of each sub-objective function is:

$$F(x) = \sum_{i=1}^{k} w_i f_i(x) \tag{5}$$

where $F(x)$ is often referred to as the new utility function.

In this way, the multi-objective optimisation problem is transformed into a single-objective problem. It transforms the complex problem of solving multi-objective optimisation into a simpler single-objective optimisation problem, where running the algorithm once produces only one such Pareto-optimal solution without the involvement of a decision maker. This is the original objective-weighted method, and GA is commonly used to solve multi-objective optimisation problems. However, this method has significant drawbacks: it is closely linked to the analyst and it is a single-point iteration.

In addition, the selection of target weight vectors can be improved, e.g., by using pairwise restrictions to speed up the convergence of the algorithm and maintain stability.

$$w_i = \frac{\mathrm{rand}_i}{\mathrm{rand}_1 + \mathrm{rand}_i}, \quad i = 1, 2, \ldots, k \tag{6}$$

where rand_i is a non-negative random real number or a non-negative random integer.

When an individual is to be selected, a vector of target weights is first selected according to Equation (6), and then its fitness value is calculated according to Equation (5) for selection. This method is simple to operate and many Pareto optimal solutions can be obtained.

3. **Vector-based super-multi-objective optimisation algorithms.**

3.1. **PSO algorithm with quantum behaviour.** The basic idea of the PSO algorithm originated from the results of early studies on the behaviour of bird populations and exploits the principles of the biological population model. The PSO algorithm, similar to the GA algorithm, is a population-based optimization tool. The system is initialised with a set of random solutions and the optimal solution is searched for through iterations. But instead of crossover as well as mutation operations used in the GA algorithm, the particles follow the optimal particle in the solution space to search.

The particle swarm algorithm uses the concepts of "population" and "evolution" and operates on the basis of the size of the fitness values of the individuals (particles). The algorithm considers each individual as a particle without weight and volume in an n-dimensional search space, and flies at a certain speed in the search space. This flight speed is dynamically adjusted by the flight experience of the individual and the flight experience of the population. The current best position p_{best} of each particle is calculated as shown below:

$$P_i(t+1) = \begin{cases} P_i(t) & \text{if } f(x_i(t+1)) \geq f(P_i(t)) \\ x_i(t+1) & \text{if } f(x_i(t+1)) < f(P_i(t)) \end{cases} \tag{7}$$

The dynamic adjustment of each particle position is shown below:

$$V_{id}(t+1) = V_{id}(t) + c_1 r_{1d}(t)(P_{id}(t) - x_{id}(t)) + c_2 r_{2d}(t)(P_g(t) - x_{id}(t)) \tag{8}$$

$$x_{id}(t+1) = x_{id}(t) + V_{id}(t+1) \tag{9}$$

where $P_{id}(t)$ is the local optimal position of the particle, $P_g(t)$ is the "social cognitive" part, i.e. the global best position.

QPSO algorithm is a stochastic optimization algorithm, which is mainly based on the combination of PSO and universal quantum mechanics principle in quantum mechanics [28]. Compared with traditional PSO, QPSO algorithm has larger search space and better performance, so it is widely used in various optimization problems. The advantage of QPSO algorithm is that the search range of particles is increased by controlling factors, which avoids the premature convergence of traditional PSO. At the same time, because the control factors in quantum mechanics can ensure that particles have better dispersion in the search space, better global search ability can be obtained. Therefore, QPSO is often used to solve the optimization requirements of complex problems and high-dimensional problems.

In QPSO, the particle swarm moves its position according to the following three ways [29, 30].

$$\text{mbest}(t+1) = \frac{1}{M}\sum_{i=1}^{M} P_i(t) = \left(\frac{1}{M}\sum_{i=1}^{M} P_{i1}(t), \frac{1}{M}\sum_{i=1}^{M} P_{i2}(t), \ldots, \frac{1}{M}\sum_{i=1}^{M} P_{id}(t)\right) \tag{10}$$

$$PP_{ij}(t+1) = \text{radf}() \times P_{ij}(t) + (1 - \text{radf}()) \times P_{gj}(t) \tag{11}$$

$$X_{ij}(t+1) = PP_{ij}(t+1) + \text{Rand}(t+1) \times a(t+1) \times |\text{mbest}_j(t+1) - X_{ij}(t)| \times \ln\left(\frac{1}{\text{radf}(t+1)}\right) \tag{12}$$

where $\text{mbest}(t+1)$ denotes the middle position of the current best position $p_{\text{best}}(t)$ at the t-th iteration of all particles in the particle swarm, $PP_{ij}(t+1)$ is a random point between $P_{ij}(t)$ and $P_g(t)$, $a(t)$ is the contraction dilation coefficient of the QPSO, and radf() denotes a random number obeying a uniform distribution between $[0, 1]$.

The value of $a(t)$ depends on the situation and can be fixed or can vary dynamically in a certain way. $a(t)$ decreases linearly from m to n with iterations, usually $m = 1$ and

$n = 0.5$.

$$a(t) = m - (m-n)a(t) = m - (m-n) \times \frac{t}{\text{MaxTimes}} \tag{13}$$

where MaxTimes is the maximum number of iterations.

Compared with the PSO algorithm, QPSO algorithm, when dealing with multi-objective optimisation problems, can maintain the population diversity more effectively and avoid falling into the local optimal solution by introducing the quantum computing theory, and adopts the non-dominated ordering and the congestion distance index, so that it can obtain the global optimal solution while guaranteeing a more uniform distribution of the solution.

3.2. **VEQPSO.** Commonly used multi-objective optimization algorithms are unable to effectively balance the problems of global convergence properties and quantum behavioural properties, as is the case with the QPSO algorithm. Therefore, a super multiobjective optimisation algorithm based on vector evaluation is proposed.

The evolutionary approach of multiple populations is used and the selection method of typical QPSO algorithms is adapted. In each evolutionary iteration performed by the algorithm, all objective functions are treated as single-objective optimisation problems, all individuals are evaluated separately, the fitness of individuals is calculated independently, and then a certain number of individuals are selected for each objective function to form a sub-population. Assuming that the problem contains k objective functions, k subpopulations need to be formed. Each sub-population of individuals represents a set of better solutions for a certain objective function.

The proposed super multiobjective optimisation algorithm (VEQPSO) combines the individual evaluation method based on objective vectors with the QPSO algorithm, and its basic framework is shown in Figure 1.

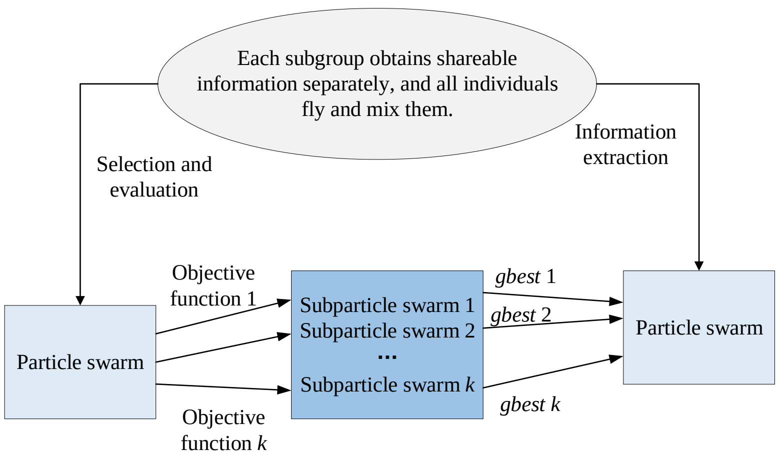


Figure 1. Framework of VEQPSO

The implementation steps of the VEQPSO algorithm are described in detail below, using the solution of a two-objective optimisation problem as a concrete example.

(1) Individual expression.

Represent each individual as a target vector, e.g., for M targets, individual X_i can be expressed as: $X_i = \{f_1(X_i), f_2(X_i), \ldots, f_M(X_i)\}$.

(2) Vector evaluation function.

Define the evaluation function for the distance to the ideal point as follows:

$$D(X_i) = \sqrt{w_1(f_1(X_i) - z_1^*)^2 + \cdots + w_M(f_M(X_i) - z_M^*)^2} \tag{14}$$

where z^* is the ideal target vector and w is the target weight vector.

(3) Quantum position update.

Quantum position update equations using QPSO:

$$X_{ij}(t+1) = X_{ij}(t) \pm \beta|\text{mbest}_j(t) - X_{ij}(t)|\ln(1/u) \tag{15}$$

where u is a random number, β is a convergence factor.

Calculate the *mbest* value for each sub-particle population.

$$\text{mbest}_1 = \frac{\text{sum}(pbest_1)}{N} \tag{16}$$

$$\text{mbest}_2 = \frac{\text{sum}(pbest_2)}{N} \tag{17}$$

(4) Vector selection.

The selection is made based on the vector evaluation function value $D(X_i)$ and the non-dominated solution vectors with smaller values are retained.

(5) Termination conditions.

Terminate the operation when the maximum number of iterations or the vector evaluation value requirement is met.

Through this integration, the target vector can be used to express the individual, give the evaluation based on the distance to the ideal point, and combine with QPSO to search the optimal solution set quickly and efficiently, so that the improved algorithm can be adapted to the multi-objective environment. The pseudo-code of VEQPSO is shown in Algorithm 1.

Algorithm 1 VEQPSO

Input: Population size N, maximum number of iterations T, convergence factor β

Output: Pareto optimal solution set

Randomly initialize the population individuals X_i $(i = 1, 2, \dots, N)$
for $t = 1$ to T **do**
  Calculate M objective function values for each X_i and construct an objective vector.
  Determine the ideal target vector Z^*.
  for each X_i **do**
    Calculate the distance $D(X_i)$ between X_i and Z^*.
  end for
  for each dimension j **do**
    Update the X_{ij} value of each X_i to the new population according to the QPSO formula.
  end for
  Calculate target vector $D(X_i)$ values for each X_i of the new population.
  Perform non-dominated sorting and congestion sorting based on $D(X_i)$ and select the better individuals to be retained in the next generation.
end for
Output the set of Pareto-optimal solutions for the final population.

4. Personalised multi-objective travel route recommendation model based on VEQPSO.

4.1. **Basic assumptions and related definitions.** It is assumed that the relationship between hotels and attractions recommended to tourists based on the personalised preferences of a particular tourist is shown in Figure 1, where A denotes the hotel, B-E denote the attractions, the connecting line between the attractions denotes whether the attractions are passable or not, the number denotes the driving time between the attractions (unit: hour), HP denotes the hotel price (unit: yuan), SP denotes the ticket price of the attraction (unit: yuan), and ST denotes the time to visit the attraction (unit: hour).

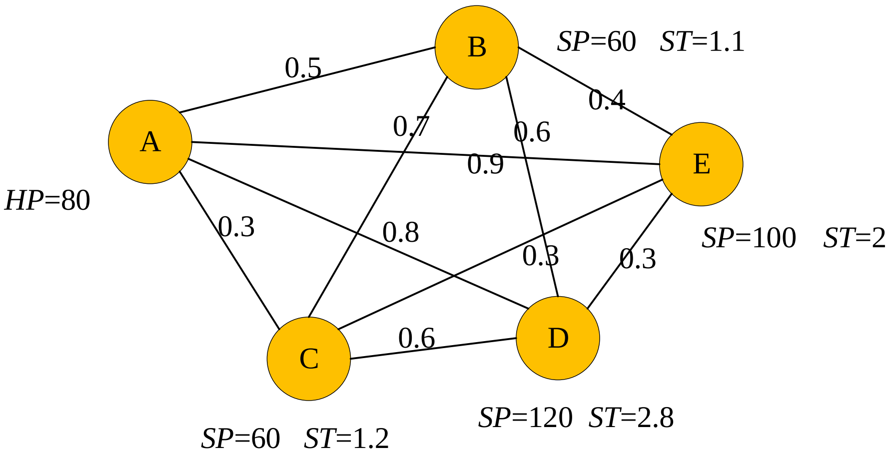


Figure 2. Rating of the relationship between the hotel and the attraction

Based on the hotel attraction scoring model, it helps tourists to plan travel routes that satisfy their preferences, taking the maximum total path score with the maximum number of attraction types as the goal of route planning, and time and cost as the constraints of the model.

Based on the above assumptions, this paper defines some relevant concepts as follows:

(1) Tourist information: each tourist has its own preference constraints, including time constraint UT, cost constraint UC, and other information.

(2) Attraction information: each attraction within the set of recommended attractions $S = \{s_1, s_2, ..., s_n\}$ should contain information such as suggested playing time ST, attraction rating SS, attraction ticket price SP, attraction type SG, suitable playing season SD, suitable playing crowd SC, longitude SL, and latitude SA.

(3) Tour route: the set of edges of a path is denoted by R, $R = \{r_1, r_2, ..., r_t\}$. The weight for any edge is the traveling time BT between two attractions.

(4) Roadmap: the roadmap, i.e., the information about the network of attractions where tourists travel, is denoted by M. Then $M = (S, R)$, S denotes the set of tourist attractions and hotels, and R denotes the set of edges between attractions.

(5) Total Tour Path: Use TR to denote the total path of tourists' tour, $TR = \{h_0, s_k, sk+1, ..., sk+n\}$. s_k denotes the attractions that tourists pass through. For a tour route, the time to reach the attraction s_k is $TRT(s_k)$.

$$TRT(s_{k+1}) = TRT(s_k) + BT(s_k, s_{k+1}) + ST(s_k) \tag{18}$$

(6) The total cost of the tour: for a total path of tourists $TR = \{h_0, s_k, sk+1, ..., sk+n\}$ the total cost TRF is the price of admission to all attractions plus the price of the tourists' hotel stay.

$$TRF = \sum_{i=1}^{n} SP(s_i) + HP \tag{19}$$

(7) Total Route Score: After a tourist chooses a tourist route $TR = \{h_0, s_k, sk + 1, ..., sk + n\}$, there will be a total route score TRS. This total route score is calculated as the sum of the scores of the various attractions that the tourist has passed.

$$TRS = \sum_{i=1}^{n} SS(s_i) \tag{20}$$

In route planning, we ultimately want to recommend to tourists the route that satisfies their constraints and has the highest total score. For example, suppose a tourist's traveling route is $A \to C \to D \to B \to A$, then its total route score is the sum of the constraint scores of the attraction C, point D, and point B.

4.2. **Objective function.** For the multi-constraint multi-objective tourism route recommendation problem, if only through the way of weighting the objective function calculation is likely to be unable to get the global optimal solution, so this paper uses the VEQPSO algorithm to solve the optimal tourism route. In the actual tourism scenario, tourists are more likely to think about which attraction is appropriate to go to next when the current attraction is finished. Using the VEQPSO algorithm, the top m routes with the highest ratings are recommended to tourists for them to choose.

Beginning with the hotel that is suggested, the travelers pick just those sites on the itinerary that they have not yet visited, and only the first n attractions with the greatest constraint ratings depending on their present location. Since the tourist must return to the hotel, when the tourist finishes touring all the attractions and finally returns to the hotel where he/she stays, we can create M tourism routes without taking the hotel limitation score into account. Only the top m routes with the highest score are available for travelers to select once the overall score for each route is determined. Our objective is to satisfy the user's requirements while optimizing the route's overall score and the quantity of picturesque locations. The objective function is set to maximise the total route score and maximise the number of attraction types under the condition of satisfying user constraints. The objective function of the model is shown below:

$$\begin{aligned} &\mathrm{Max}TRS(TR), \mathrm{Max}SG(TR) \\ &s.t.\ TRS(TR) \le UT,\ \ SG(TR) \le UC \end{aligned} \tag{21}$$

5. Experimental results and analyses.

5.1. **Experimental setting.** Firstly, the performance of the proposed VEQPSO algorithm was tested for single-objective optimisation. However, the effectiveness of the VEQPSO algorithm was tested by 2 multi-objective optimisation test functions. Finally, the model is validated by taking Chongqing city as the target city and the user's travelling help as an example under the condition of considering the diversity of attraction types.

All the above experiments were carried out in MATLAB software. The parameter specifications of the experimental computer are shown in Table 1.

5.2. **Test results for single-objective optimisation.** In order to verify the performance of the proposed VEQPSO algorithm for single-objective optimisation, four standard single-objective optimisation test functions were selected for optimisation experiments and compared with PSO, EPSO [30] and QPSO. The population size N is 100, the maximum number of iterations T is 500, the convergence factor β is 0.5, the decision variable takes the value range of [-100,100], and the distance function weight w is 1 at this time.

Table 1. Parametric specifications of the laboratory computer

Parametric	Numerical value
operating system	Windows 10
Processor Model	Intel i5-13600KF
Number of cores	14
random access memory (RAM)	8 G
hard drive	80 GB
bandwidths	1.0 Gbps

(1) Sphere function.

$$f_1(x) = \sum_{i=1}^{n} x_i^2, \quad -100 \le x_i \le 100, \quad \min f_1(x) = f_1(0, 0, \ldots, 0) = 0 \tag{22}$$

(2) Rosenbrock function.

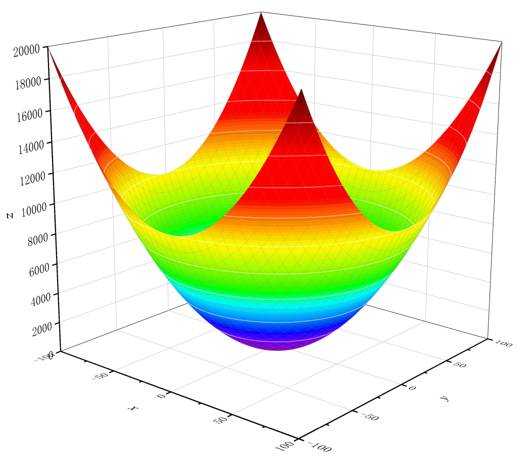
$$f_2(x) = \sum_{i=1}^{n-1} \left[100 \left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right], \quad -200 \le x_i \le 200, \quad \min f_2(x) = f_2(1, 1, \ldots, 1) = 0 \tag{23}$$

(3) Griewank function.

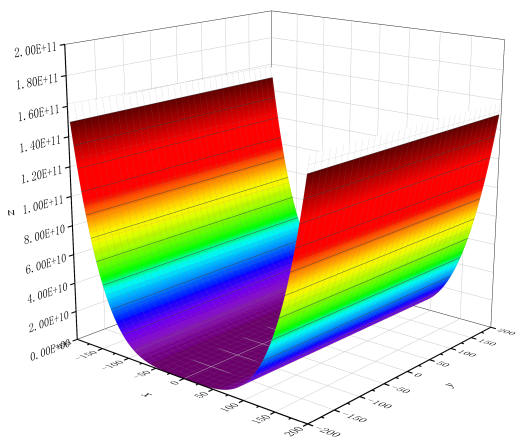
$$f_3(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, \quad -600 \le x_i \le 600, \quad \min f_3(x) = f_3(0, 0, \ldots, 0) = 0 \tag{24}$$

(4) Schaffer function.

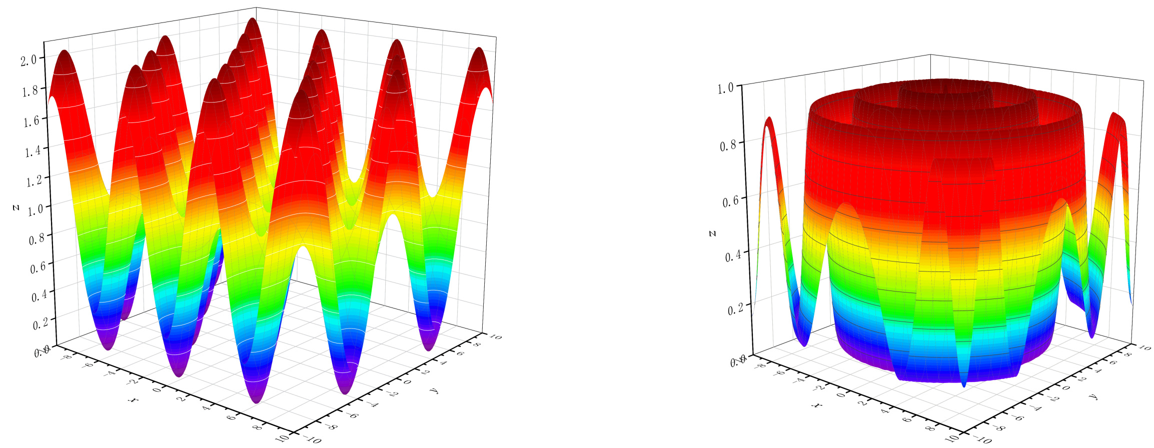
$$f_4(x, y) = 0.5 - \frac{\sin^2 \sqrt{x^2 + y^2} - 0.5}{\left(1 + 0.001 \left(x^2 + y^2\right)\right)^2}, \quad -10 \le x, y \le 10, \quad \min f_4(x, y) = f_4(0, 0) = 1 \tag{25}$$



(a) Sphere function



(b) Rosenbrock function



(c) Griewank function (d) Schaffer function

Figure 3. Shape of the curve for the 4 single-objective optimisation test functions

Each optimisation algorithm was repeated five times and averaged as the final optimisation result, as shown in Table 2.

Table 2. Performance comparison of single objective optimisation

Arithmetic	**Assessment of indicators**	**Sphere**	**Rosenbrock**	**Griewank**	**Schaffer**
PSO	Average value	3.0×10^{-15}	1.1×10^{-6}	0.9×10^{-7}	1.6×10^{-16}
	Standard deviation	0.5×10^{-15}	0.3×10^{-6}	0.2×10^{-7}	0.3×10^{-16}
	Time/s	0.93	0.23	0.57	0.21
EPSO	Average value	7.6×10^{-8}	2.3×10^{-1}	2.8×10^{-8}	1.1×10^{-2}
	Standard deviation	0.7×10^{-7}	0.3×10^{-1}	0.6×10^{-8}	0.3×10^{-2}
	Time/s	12.31	12.09	12.34	6.32
QPSO	Average value	2.7×10^{-35}	2.37×10^{-5}	2.41×10^{-28}	1.33×10^{-3}
	Standard deviation	0.3×10^{-35}	0.8×10^{-5}	0.5×10^{-28}	0.2×10^{-3}
	Time/s	11.68	10.54	12.06	1.03
VEQPSO	Average value	0	0	0	0
	Standard deviation	0	0	0.6×10^{-30}	0
	Time/s	12.92	12.85	12.32	1.84

From the results of the single objective optimisation test function, it is clear that the VEQPSO algorithm has the highest overall optimisation search accuracy. From the standard deviation, the VEQPSO algorithm is less volatile. From the running time, PSO algorithm has the shortest time, and the time of VEQPSO algorithm is slightly larger than that of QPSO algorithm, which is because this paper adds the vector value calculation on the basis of QPSO algorithm, which leads to a certain increase in the time consumption. In the comprehensive analysis of the algorithm's optimisation accuracy and robustness, the VEQPSO algorithm is better than the other three algorithms, and therefore, the VEQPSO algorithm is more practical in solving single-objective optimisation problems.

5.3. **Test results of multi-objective optimisation.** In order to verify the multi-objective optimisation performance of the proposed VEQPSO algorithm, two multi-objective optimisation test functions were selected for optimisation experiments and compared with QPSO. The population size N is 100, the maximum number of iterations T is 200, the convergence factor β is 0.5, and the decision variables take values in the range of $[-100, 100]$. Note that at this point the distance function weights w_1 are 0.7 and w_2 are 0.3.

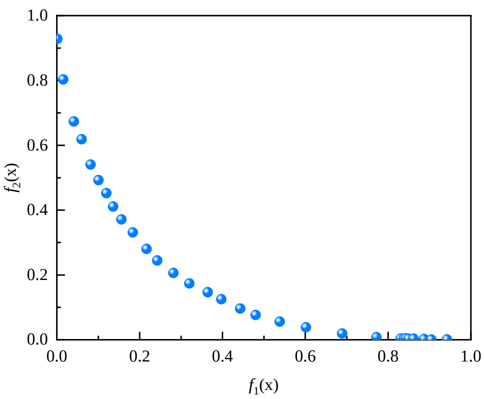
Test function 1:

$$\min f_1 = x^2,\ \min f_2 = (x-2)^2,\ x \in [0,1] \tag{26}$$

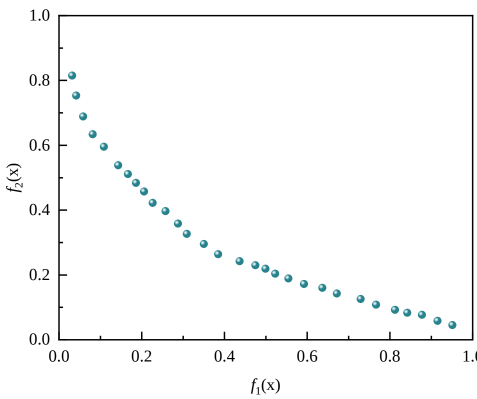
Test function 2:

$$\min f_1 = x_1,\ \min f_2 = 1 - \sqrt[4]{\frac{f_1}{g} - (f_1/g)^4},\ g = 1 + \frac{9}{n-1}\sum_{i=2}^{n} x_i,\ x_i \in [0,1] \tag{27}$$

The positions of the particles in each subpopulation are updated according to the running steps of VEQPSO. Finally, the local optimum of the particles $(pbest_1, pbest_2)$ and the global optimum of each subpopulation $(gbest_1, gbest_2)$ are calculated according to the method of single objective function, and the new particle swarm is recombined until the maximum number of iterations is satisfied. In the experimental results, 30 out of 30 particles are satisfying solutions, and the particles converge to the Pareto edge of this multi-objective optimisation problem. This shows that VEQPSO can be effectively applied to this problem. The Pareto curve of test function 1 is shown in Figure 4. The Pareto curve for test function 2 is shown in Figure 5.

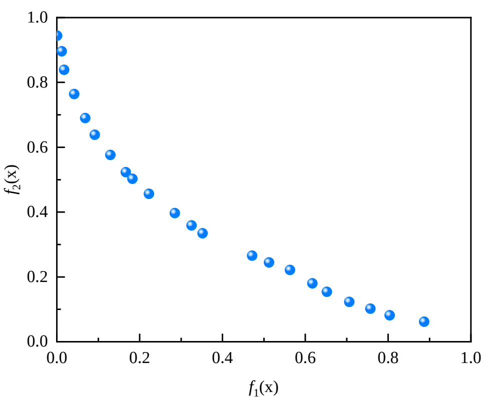


(a) VEQPSO

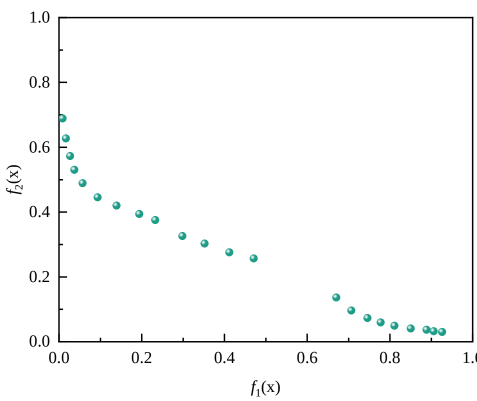


(b) QPSO

Figure 4. Pareto curve for test function 1



(a) VEQPSO



(b) QPSO

Figure 5. Pareto curve for test function 2

In the objective function space, the interface of the effective solution region is the boundary of the region of the fitness value. The test functions used in the test are all for their minimisation cases, and the effective solution region should be the lower left region of the fitness value. From the test results, it can be seen that each test function can give its effective solution region interface. The VEQPSO algorithm is able to give a more complete Pareto curve for test function 1 and test function 2.

5.4. **Tourism route planning model validation.** Taking Chongqing City as the target city, the model is validated with the tourism help of Weibo as an example under the condition of considering the diversity of attraction types. According to the recommended hotels and attractions, a multi-objective tourism route planning model is used to help tourists plan their routes. The objective function is set to maximise the overall path value and maximise the number of attraction types. In the model, the following behaviours are simulated, the travel time of the tourists does not exceed 20 hours and the cost budget is within 5000 RMB. For ease of calculation, assume that $n = 2$, i.e., when using the VEQPSO algorithm, each attraction is expanded downward to two attractions. There are no more than three paths remaining after the number with the greatest profit is calculated. The specific model of the problem is as follows:

$$\begin{array}{l} \mathrm{Max}\,TRS(TR), \mathrm{Max}\,SG(TR) \\ s.t.\; TRS(TR) \leq 20,\;\; SG(TR) \leq 5000 \end{array} \tag{28}$$

The larger the value of the parameter n, the more comprehensive the recommended results will be, but the running time of the algorithm will be higher. In order to verify the running efficiency of the VEQPSO algorithm, we set n to be taken from 1 to 6 variations, then the running efficiency comparison results are shown in Figure 6.

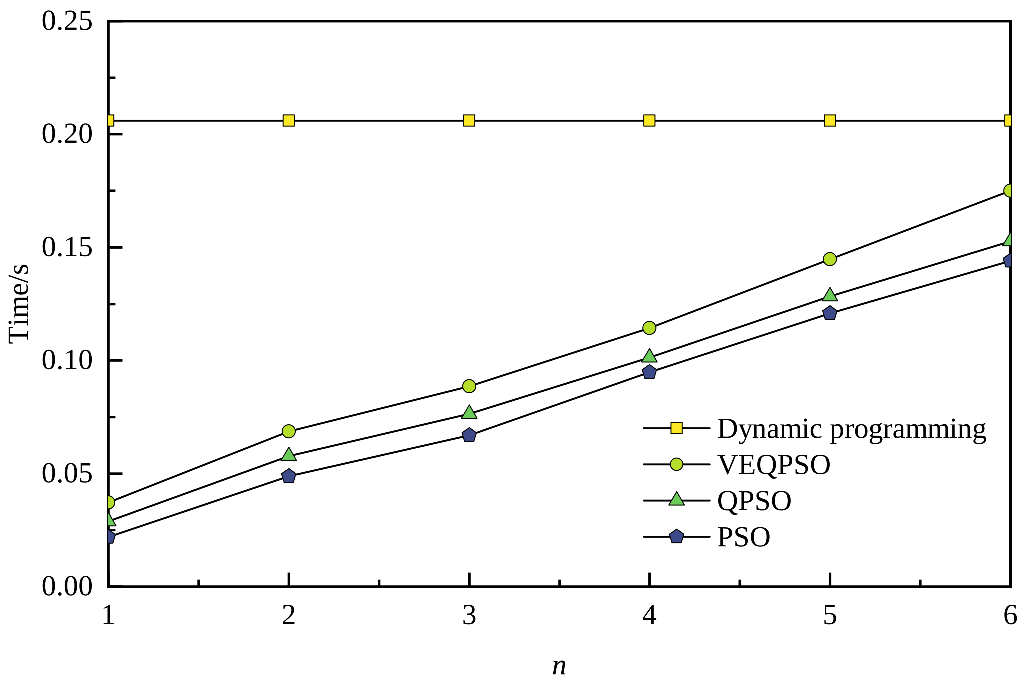


Figure 6. Operational efficiency comparison results

It can be seen that the running time of the VEQPSO algorithm, PSO algorithm and QPSO algorithm all increase with the increase of n, while the running time of the dynamic planning algorithm is constant. The running time of the VEQPSO algorithm is greater than that of the PSO algorithm and QPSO algorithm. However, when n is 6, the execution time of the VEQPSO algorithm is 0.172 s, while the running time of the dynamic programming algorithm is 0.206 s. Moreover, the dynamic programming algorithm has the property of overlapping sub-problems, which needs to consume a larger amount of space, so the model uses the VEQPSO algorithm with a shorter time and a smaller space requirement, therefore, using the VEQPSO algorithm has a higher performance, which is more suitable for solving the model.

Overall, in solving the multi-constraint multi-objective travel route planning problem, the VEQPSO algorithm is more suitable for larger scale multi-constraint multi-objective problems than the dynamic programming algorithms, PSO algorithm and QPSO algorithm.

6. **Conclusion.** In this work, an ultra-multi-objective optimisation algorithm based on vector evaluation-VEQPSO is proposed, which mainly consists of an individual evaluation method based on objective vectors combined with the QPSO algorithm. Firstly, a multi-constraint multi-objective tourism route planning model is constructed and solved using the proposed VEQPSO algorithm. Travelers' preferred hotels serve as the beginning and finish locations of customized tourism routes, which are designed for them as long as the restrictions are met. Finally, taking Chongqing as the target city, the model is validated using the user's travel assistance as an example under the condition of considering the diversity of attraction types. The simulation results show that compared with the QPSO algorithm, the VEQPSO algorithm can give more complete Pareto curves, which verifies its effectiveness in multi-objective and single-objective optimisation. In solving the multi-constraint multi-objective travel route planning problem, the VEQPSO algorithm is more suitable for larger scale multi-constraint multi-objective problems than the dynamic programming algorithm.

Acknowledgement. This work supported by the 2023 Henan provincial key R&D specially funded project (No.232400410281) and the scientific research and innovation team of rural homestay by Henan Agricultural Vocational College (No. HNACKT-2021-02).

REFERENCES

[1] F. Fusté-Forné, and L. Mundet i Cerdan, "A land of cheese: from food innovation to tourism development in rural Catalonia," *Journal of Tourism and Cultural Change*, vol. 19, no. 2, pp. 166-183, 2021.

[2] C. P. Barros, and F. P. Alves, "Productivity in the tourism industry," *International Advances in Economic Research*, vol. 10, no. 3, pp. 215-225, 2004.

[3] T. Pencarelli, "The digital revolution in the travel and tourism industry," *Information Technology & Tourism*, vol. 22, no. 3, pp. 455-476, 2020.

[4] M. I. Arshad, M. A. Iqbal, and M. Shahbaz, "Pakistan tourism industry and challenges: a review," *Asia Pacific Journal of Tourism Research*, vol. 23, no. 2, pp. 121-132, 2018.

[5] N. Gooroochurn, and G. Sugiyarto, "Competitiveness indicators in the travel and tourism industry," *Tourism Economics*, vol. 11, no. 1, pp. 25-43, 2005.

[6] G. R. Fick, and J. Brent Ritchie, "Measuring service quality in the travel and tourism industry," *Journal of Travel Research*, vol. 30, no. 2, pp. 2-9, 1991.

[7] G. W.-H. Tan, V. H. Lee, B. Lin, and K.-B. Ooi, "Mobile applications in tourism: the future of the tourism industry?," *Industrial Management & Data Systems*, vol. 117, no. 3, pp. 560-581, 2017.

[8] L. Zhang, "Intelligent tourism route recommendation method based on big data," *International Journal of Autonomous and Adaptive Communications Systems*, vol. 13, no. 4, pp. 329-341, 2020.

[9] F.-M. Hsu, Y.-T. Lin, and T.-K. Ho, "Design and implementation of an intelligent recommendation system for tourist attractions: The integration of EBM model, Bayesian network and Google Maps," *Expert Systems with Applications*, vol. 39, no. 3, pp. 3257-3264, 2012.

[10] J. Luo, and X. Duan, "Intelligent recommendation of personalised tourist routes based on improved discrete particle swarm," *International Journal of Computational Science and Engineering*, vol. 25, no. 6, pp. 598-606, 2022.

[11] W. Xiaolu, "Design of travel route recommendation system based on fast Spark artificial intelligence architecture," *International Journal of Industrial and Systems Engineering*, vol. 38, no. 3, pp. 328-345, 2021.

[12] X. Huang, "Personalized travel route recommendation model of intelligent service robot using deep learning in big data environment," *Journal of Robotics*, vol. 2022, pp. 1-8, 2022.

[13] J. Gu, and X. Huang, "Efficient local search with search space smoothing: A case study of the traveling salesman problem (TSP)," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 24, no. 5, pp. 728-735, 1994.

[14] R. A. Abbaspour, and F. Samadzadegan, "Time-dependent personal tour planning and scheduling in metropolises," *Expert Systems with Applications*, vol. 38, no. 10, pp. 12439-12452, 2011.

[15] G. Yang, Y. Han, H. Gong, and T. Zhang, "Spatial-temporal response patterns of tourist flow under real-time tourist flow diversion scheme," *Sustainability*, vol. 12, no. 8, 3478, 2020.

[16] W. Wörndl, A. Hefele, and D. Herzog, "Recommending a sequence of interesting places for tourist trips," *Information Technology & Tourism*, vol. 17, pp. 31-54, 2017.

[17] A. Majid, L. Chen, H. T. Mirza, I. Hussain, and G. Chen, "A system for mining interesting tourist locations and travel sequences from public geo-tagged photos," *Data & Knowledge Engineering*, vol. 95, pp. 66-86, 2015.

[18] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Engineering*, vol. 5, no. 1, 1502242, 2018.

[19] S. Katoch, S. S. Chauhan, and V. Kumar, "A review on genetic algorithm: past, present, and future," *Multimedia Tools and Applications*, vol. 80, pp. 8091-8126, 2021.

[20] V. Mundada, and S. K. R. Narala, "Optimization of milling operations using artificial neural networks (ANN) and simulated annealing algorithm (SAA)," *Materials Today: Proceedings*, vol. 5, no. 2, pp. 4971-4985, 2018.

[21] M. Jain, V. Saihjpal, N. Singh, and S. B. Singh, "An overview of variants and advancements of PSO algorithm," *Applied Sciences*, vol. 12, no. 17, 8392, 2022.

[22] C. Chen, S. Zhang, Q. Yu, Z. Ye, Z. Ye, and F. Hu, "Personalized travel route recommendation algorithm based on improved genetic algorithm," *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 3, pp. 4407-4423, 2021.

[23] F. Liu, C. Liu, Q. Zhao, and C. He, "A hybrid teaching-learning-based optimization algorithm for the travel route optimization problem alongside the urban railway line," *Sustainability*, vol. 13, no. 3, 1408, 2021.

[24] Y. Tokiwa, C. Stingl, M.-S. Kim, T. Takabatake, and P. Gegenwart, "Characteristic signatures of quantum criticality driven by geometrical frustration," *Science Advances*, vol. 1, no. 3, e1500001, 2015.

[25] L. Kang, R.-S. Chen, N. Xiong, Y.-C. Chen, Y.-X. Hu, and C.-M. Chen, "Selecting Hyper-Parameters of Gaussian Process Regression Based on Non-Inertial Particle Swarm Optimization in Internet of Things," *IEEE Access*, vol. 7, pp. 59504-59513, 2019.

[26] T.-Y. Wu, A. Shao, and J.-S. Pan, "CTOA: Toward a Chaotic-Based Tumbleweed Optimization Algorithm," *Mathematics*, vol. 11, no. 10, 2339, 2023.

[27] T.-Y. Wu, H. Li, and S.-C. Chu, "CPPE: An Improved Phasmatodea Population Evolution Algorithm with Chaotic Maps," *Mathematics*, vol. 11, no. 9, 1977, 2023.

[28] F. Zhang, T.-Y. Wu, Y. Wang, R. Xiong, G. Ding, P. Mei, and L. Liu, "Application of Quantum Genetic Optimization of LVQ Neural Network in Smart City Traffic Network Prediction," *IEEE Access*, vol. 8, pp. 104555-104564, 2020.

[29] N. Kumar, S. K. Mahato, and A. K. Bhunia, "A new QPSO based hybrid algorithm for constrained optimization problems via tournamenting process," *Soft Computing*, vol. 24, pp. 11365-11379, 2020.

[30] G. He, and X.-l. Lu, "Good point set and double attractors based-QPSO and application in portfolio with transaction fee and financing cost," *Expert Systems with Applications*, vol. 209, 118339, 2022.

[31] N. A. Mahmud, N. Y. Dahlan, W. N. W. M. Adnan, A. Tumian, and M. S. Onn, "Optimum energy management strategy with NEM-ETOU for campus buildings installed with solar PV using EPSO," *Energy Reports*, vol. 9, pp. 54-59, 2023.