Combinational Models for Enhancing the PTPM Efficiency

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***Abstract*—This paper compared two combinational approaches designed to enhance the Phuket Tourism Planning Model (PTPM) efficiency, which is a tourism package searching model for tourists based on duration and tourism types. PTPM simulated the path to all destinations concerning the type of tourist attractions. A combination of fuzzy set and two well-respected theories, including genetic algorithm (GA) and particle swarm optimization (PSO) was conducted using the same data set. The criteria for travelling routing consist of the tourist attraction type which travellers want most and travel time. The experimental results show that the travelling routing using a combination of PSO and fuzzy set is more efficient than that of GA and fuzzy set under limited time and distance conditions. PTPM based on a combination of PSO and fuzzy set provided a shorter distance than the latter at 9.07 percent.**

***Keywords*—Genetic Algorithm (GA), Fuzzy set, Particle Swarm Optimization (PSO), Phuket Tourism Planning Model (PTPM), Tourism.**

I. Introduction

Phuket is a city in the southern part of Thailand and widely recognised as a world tourist destination. However, there are many tourism types classified into several categories. These complicated relationships can be troublesome for tourists who prefer to visit different tourist places that mostly suit their needs, but may be required to plan their trips. In this case, a path searching model for helping tourists obtain an appropriate path to different tourist attractions under limited time constraints is required. In Jarupunphol et al. [1], Phuket Tourism Planning Model (PTPM) was introduced as path finding model to achieve an organised schedule of tourist attractions under time and distance constraints. Initially, PTPM was based on two well-respected theories, including genetic algorithm (GA) and fuzzy sets, designed to address problems associated with travelling salesman algorithm. The authors [1], nevertheless, summarised that experimenting on Particle Swarm Optimization (PSO) should be considered as a future work due to some similarities between PSO and GA. For example, GA and PSO are determined by information shared among population members. Besides, these algorithms employ a combination of rules for determination and probability to optimise their searching processes [2]. Since there are similarities between PSO and GA, a comparison of their strengths can be worthwhile in this research. Thus, a combination of PSO and Fuzzy Set was experimented on PTPM and compared with that of GA and Fuzzy Set in this article. To ensure the experimental validity, the experiments were based on the same data and approaches conducted in the previous experiments on GA.

II. Literature Reviews

Artificial intelligence (AI) has long been applied in computer science related disciplines due to its capability in dealing with the simulation of intelligent systems. For instance, the NP-Hard solution or the problem associated with finding the most optimal solution. In many cases, evolutionary computation (EC) appears to be the best solution for the vehicle routing problem with time windows, which is an extension of the vehicle routing problem with limited timescales. There are a number of approaches introduced to solve these complicated issues which cannot be addressed by simple logics [3], [4], [5], [6]. For example, PSO, GA, and fuzzy set are two approaches for approximate reasoning that have been widely referred among research scholars.

A. Fuzzy Set

Set theory has long been applied in many disciplines [7], [8]. A crisp set, for instance, is a traditional set, which determines if an element is the set member. An estimation of either 0 or 1 is doled out to every component of the universe. Members and non-members from the set are isolated under specific tenets. Conversely, a fuzzy set is where every member in the set has an estimation of membership value representing the level of set membership [7], [9]. While a crisp set membership value is limited to 0 or 1, a membership degree of fuzzy set ranges from 0 to 1 ($\mu : X \rightarrow [0,1]$). A fuzzy set A can be represented in an equation as as $M : \mathbb{PR} \mid \forall m : M \bullet 0 \leq m \leq 1$. In the meantime, X is the fuzzy set universe, which is either discrete or continuous. For example, B is a set of Phuket tourist attractions ($X == \{PatongBeach, WatChalong, ThalangRoad\}$), which can be further explained as $B == \{(PatongBeach, 0.9), (WatChalong, 0.5), (ThalangRoad, 0.7)\}$. The number behind the attraction is the province membership value in B. If the relative universe is continuous, the membership value will be considered based on the membership function. On the other hand, the membership value will be determined by the individual if the relative universe is discontinuous.

B. Genetic Algorithm (GA)

GA is a calculative algorithm designed to obtain an optimal solution by simulating the living organisms evolution [3], [10], [11], [12]. Creatures that take after the correct will survive and and be chosen to inherit the right traits to their posterity influencing the later creatures suit the living environment. The theory of evolution illustrates how GA address different problems associated with the form of Chromosome and Fitness function. For instance, each chromosome fitness value is assessed using different techniques for selection, e.g., ranking, tournament, and roulette wheel. Then, a proper chromosome will be selected for modifications and transformed to a new chromosome. In this case, genetic operators will be used to modify the chromosome. The selection and modification process will be iterative until meeting the evolution termination. In [13], a hybrid algorithm between ant colony algorithm and genetic algorithm is introduced to address the traveling salesman problems. While genetic algorithm is adopted to provide information pheromone, the ant colony algorithm is used to obtain different solutions via accumulated and renewed information pheromone. GA is widely used to solve path finding problems because this algorithm is capable of addressing several complex issues [3]. For example, the tourism path finding must take hours and locations into account, but the distribution of path finding requires significant amount of time and expense resources. Figure 1 represents steps to finding a tourist destination using GA and fuzzy set.

C. Particle Swarm Optimization (PSO)

Particle swarm optimisation (PSO) is another recommended evolutionary computation (EC) technique, which was invented by Kennedy and Eberhart [14]. PSO was designed to solve problems by using repetitive attempts to enhance a representative solution based on a given quality measure shared by all the swarm members [15], [16]. PSO has been widely used to find the outcome of a complex problem (NP-Hard) using evolutionary computation. Similar to GA, the notion of PSO is based on the Charles Darwin's evolutionary theory of life in which all life is related and has descended from a common ancestor [14]. The PSO's algorithm mimics the evolution of life evolved from the social behaviour of living things, such as the movement of a flock of birds that feeds simultaneously. Each flock of birds serves to fly, search for food, and possibly move to the place at the same time. Given that swarm is a set of particles (S), each bird treated as a particle is a potential solution is required to capture two vector data, including a position vector ($X_i = (x_{i1}, x_{i2}, ..., x_{in}) \in \mathbf{R}''$) and a flying velocity vector ($V_i = (v_{i1}, v_{i2}, ..., v_{in}) \in \mathbf{R}''$). With any problem parameters, there exists a variable, which is a set of individual particles, as in equation.

PSO starts from initialising with a collection of random particles. Then, PSO will update each generation to search for an optimal solution. Each particle is updated by following two "best" values in every iteration. The best fitness or 'solution' is derived from the first one that has achieved. This value is called *pbest* in which each particle maintains individual

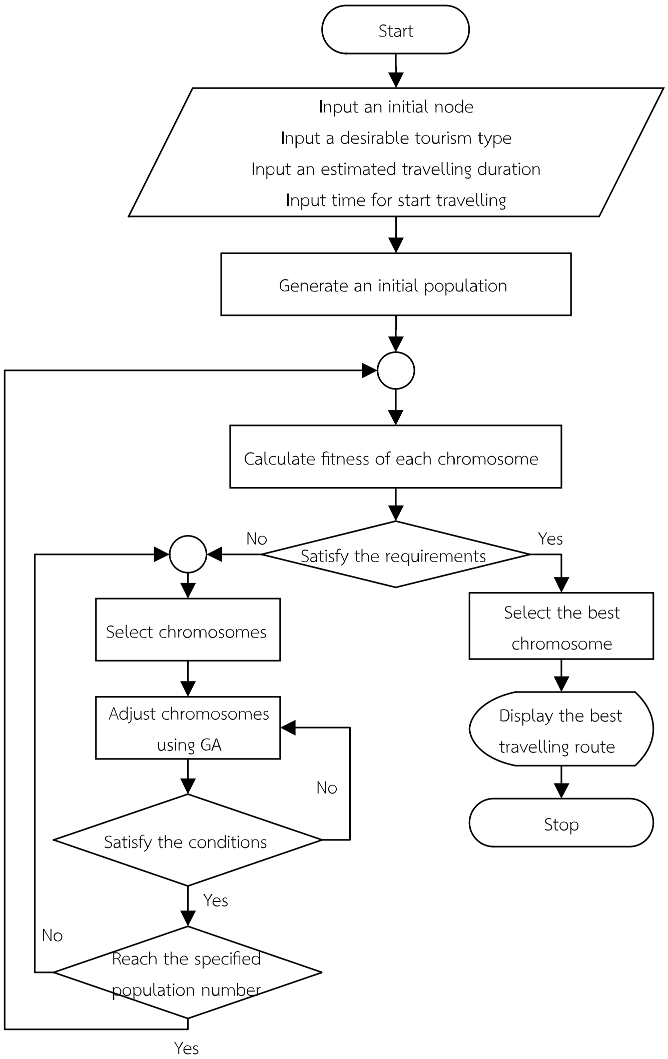

Fig. 1. A tourism route searching using GA and fuzzy set

best position ($P_i = (p_{i1}, p_{i2}, ..., p_{in}) \in \mathbf{R}'' \Rightarrow pbest_i = f(P_i)$). Another "best" value is traced by the particle swarm optimiser, which is the best value aqquired by any particle of the population. This best value is considered as a global best (*gbest*) in which swarm maintains its global best ($P_g \in \mathbf{R}'' \Rightarrow gbest = f(P_g)$). When a particle takes part of the population as its topological neighbours, the best value is a local best (*lbest*). After finding the two best values, the particle updates its velocity and positions with following equation (1) with $r_1, r_2\, U(0,1)$ and ϕ_1, ϕ_2 : $accelerationconstant$ and (2).

$$V_i^{t+1} = V_i^t + \phi_1.r_1(P_i - X_i^t) + \phi_2.r_2(P_g - X_i^t) \quad (1)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

Figure 2 shows steps to finding a tourist destination using PSO and fuzzy set.

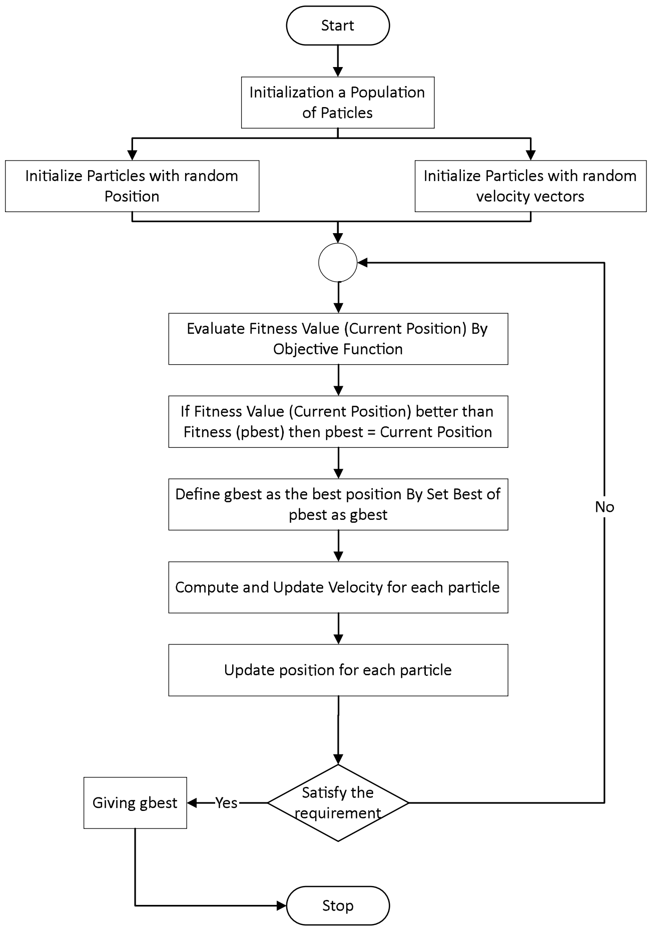

Fig. 2. A tourism route searching using PSO and fuzzy set

Node (km/m)	01	02	03	04	05
01	0.00/0	11.30/13	13.00/17	22.80/26	22.90/27
02	13.20/15	0.00/0	11.70/18	14.20/20	14.30/21
03	10.70/14	11.60/18	0.00/0	14.60/25	14.70/26
04	18.40/22	10.90/19	8.90/20	0.00/0	3.20/9
05	22.90/26	15.40/22	13.40/24	3.00/9	0.00/0

TABLE I
DISTANCE/DURATION (KILOMETRES/MINUTES)

Tourism Types\Node	01	02	03	04	05
Ecotourism	0.0	0.0	0.0	0.6	0.0
Cultural Tourism	0.7	0.0	0.0	0.2	0.0
Beaches	0.0	0.5	0.0	0.0	1.0
Sightseeing Spots	0.0	0.5	0.0	0.2	0.0
Arts Tourism	0.0	0.0	1.0	0.0	0.0
Historical Tourism	0.3	0.0	0.0	0.0	0.0
Time Spent (Minutes)	40	30	20	45	60
Opening Hours	8.00	10.00	6.00	9.00	6.00
Closing Hours	18.00	20.00	18.00	17.00	19.00

TABLE II
TOURISM TYPES AND NODES

III. METHODOLOGY

In [1], a path searching model development was assumed that 1) the tourists will start leaving from their hotels and get back to the hotels after sightseeing; 2) the tourists will visit several tourism types, and 3) each tourism type is different in traveling time. In this case, the research methodology was divided into three parts: 1) data preparation; 2) PTPM analysis and design; and 3) PTPM testing.

A. Data Preparation

The Google Maps API Web Service was deployed to find the shortest travelling time based on distance (kilometers) and duration (minutes) from one tourist attraction to another. Table I represents distance-based nodes and duration-based nodes.

Each tourist attraction node was categorised into a set of tourism type further grouped into different tourism types based on fuzzy set. Thus, this fuzzy set universe is an aggregation of eighty tourist attractions in Phuket in which the membership value is taken from survey participants, including experienced staff in tourism and local people. The participants are required to define the membership value and specify each tourist attraction into its tourism type. The membership value summary of each tourism type for each attraction is equal to 1. Then, the membership value average will be calculated for the further experiment. Membership values of tourist attractions, including its opening and closing hours, are represented in Table II.

Tourist attractions are grouped into what type of travel set. Each can be classified into several types of tourism using fuzzy sets, where the membership of nodes in each travel set is between 0 and 1, and the relative universe of fuzzy sets is a tourist attraction. There are 80 nodes in Phuket that are intermittent, discrete and sequential. This membership fee is based on a survey of 30 local Phuket tourism and tourism personnel, who asked respondents to determine the membership of each tourist destination. The questionnaire has measured the quality of confidence. The total membership of each tourist category in each tourist attraction must be equal to 1.

B. PTPM Testing

The PTPM with a combined PSO and fuzzy set was experimented in similar way to that of GA and fuzzy set with 100 permutations. This testing assesses the performance of PTPM for offering a tourism package based on the participants' requirements. Obtain relevant data such as beginning node, tourist attraction type, sightseeing time, and departure is the first testing step and followed by using a genetic algorithm to find the best route and design the pathfinding chromosome, which contains the nodes gene in the tourism routes. Please note that the relationship of each node is sequential. To obtain min value, the objective function calculates the proper chromosome evaluated by the most fitness value (FV) described in equation 3.

$$Objective\,function = min(FV) \tag{3}$$

Chromosome	1	5	3	2	6	4	7	8	9

TABLE III
CHROMOSOME DESIGN

Chromosome	1	5	**3**	**2**	**6**	**4**	7	8	9
Flipped Chromosome	1	5	**4**	**6**	**2**	**3**	7	8	9
Swapped Chromosome	1	**7**	3	2	6	4	**5**	8	9
Shifted Chromosome	1	7	3	2	**4**	**7**	**8**	**9**	**6**

TABLE IV
CHROMOSOME FLIPPING, SWAPPING, AND SHIFTING

The *FV* will be determined from the memberships total in the set of tourism types demanded by each chromosome node as described in equation 4. If the chromosome contains an identical node to the most required tourism type, the *FV* will be high. In addition, the *FV* will increase in accordance with the number of nodes in the chromosome. While n is the number of nodes in the chromosome, m is the number of types of the tourist interest, and μ_j (node i) represents a tourism set membership value at j of the node i. To identify the next generation chromosome, the tournament approach will be applied in which the most appropriate chromosome value will be randomly chosen from each sampling of four chromosomes.

$$FV = \sum_{i=1}^{n}\sum_{j=1}^{m} \mu_j(node) \tag{4}$$

Conversely, few nodes in the chromosome will also be randomly deleted if there is an overtime. A newly transformed chromosome will be evaluated as if it meets the conditions: 1) each chromosome node must be distinct; 2) the traveling time must be less than the time; and 3) each chromosome node must be verified if the traveling time is acceptable. Please note that the chromosome modification will repeat until the chromosome is appropriate. While n is the number of nodes in the chromosomes, t_i is the traveling time at i-node, and t_{ij} is the traveling time spent from node i to node j as represented in equation 5.

$$\sum_{i=1}^{n} t_i + \sum_{i=1, i\neq j}^{n} t_{ij} \leq availableTime \tag{5}$$

According to Table III, the chromosome nodes are 1 5 3 2 6 4 7 8 9. This implies that the traveling route begins at node 1. After that, the route will shift to node 5 and 9 according to the membership value sequence. The routing node will diminish from the last node to the beginning node again. The tournament approach will adjust the sequence of nodes using random position selection methods, e.g., flipping, swapping, and shifting to get a shorter distance and time as shown in Table IV. If the time still remains, additional nodes will be randomly chosen and appended in the chromosome.

IV. RESULTS AND DISCUSSION

The effectiveness combinational models, including PSO with fuzzy set and GA with fuzzy set, based on the interested tourism type for the traveling path finding was measured and compared. Although both PSO and GA can generate solutions in the neighbourhood of two parents, PTPM based on a combination of PSO and fuzzy set provided a shorter distance than that of GA and fuzzy set at 9.07 percent. While the average of the first combination is 18.45 kilometres per 100 permutations, the latter average is 20.29 kilometres per the same number of permutations. The number of populations carried out by two combinational models appear to be a factor underlying this minor difference. For example, PSO is based on two populations, including *pbests* and current node positions allowing greater diversity and exploration over a single population *pbests* of GA [17], [18]. Besides, the momentum effects on particle movement of PSO can allow faster convergence when a particle migrates in the direction of a gradient. Figure 3 represents the efficiency of two combinational approaches for tourism route searching.

V. CONCLUSIONS AND FUTURE WORK

This research compares two combinational models of AI theories, including PSO and GA with fuzzy set for tourism package searching. Both of which are the heuristic search methods, and which are both methods of evolutionary computation. The experiments were conducted using the same data set and permutations to find an optimised travel route that offered a travel package matching the traveller interests under limited time constraints. In general, the performance of both combinational models is similar depending on the problem nature and the provided data. The experimental results implied that a combination of PSO and fuzzy set were capable of yielding more satisfactory results than that of GA and fuzzy set due to its shorter distance in average calculated from 100 permutations. Given that the PSO is better than the GA for providing the tourist attraction package in Phuket, the PSO can be considered as a model to select a better tourism nodes than the GA.

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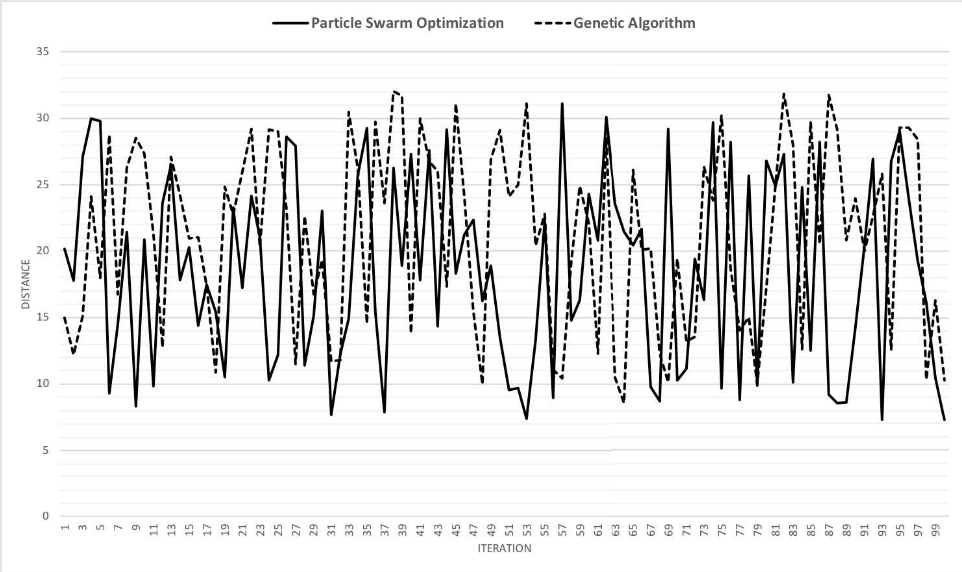

Fig. 3. A comparison of GA and PSO for tourism route searching

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