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An intelligent hybrid algorithm for 4- dimensional TSP

Samir Maity[a,*], Arindam Roy[b], Manoranjan Maiti[c]

[a] Dept. of Computer Science, Vidyasagar University, Medinipur, 721102, WB, India
[b] Dept. of Computer Science, P.K. College, Contai, Purba Medinipur, 721401, WB, India
[c] Dept. of Applied Mathematics, Vidyasagar University, Medinipur, 721102, WB, India

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ABSTRACT

In this paper, a hybridized algorithmic approach to solve 4- dimensional Travelling Salesman Problem (4DTSP) where different paths with various number of conveyances are available to travel between two cities. The algorithm is a hybridization of rough set based ant colony optimization (rACO) with genetic algorithm (GA). The initial solutions are produced by ACO which act as a selection operation of GA and then GA is developed with a virgin extended rough set based selection (7-point scale), comparison crossover and generation dependent mutation. The said hybrid algorithm rough set based Ant Colony Optimization (rACO) with Genetic Algorithm (rACO-GA) is tested against some test functions and efficiency of the proposed algorithm is established. The 4DTSPs are formulated with crisp and bi-fuzzy costs. In each environment, some statistical significant studies due to different time constraint values and other system parameters are presented. The models are illustrated with some numerical data. The proposed algorithm or its modified form can be easily adapted for applications in real life industrial information gathering. Proposed hybrid algorithm can be apply for industrial enterprise such as airline and supply chain, etc.

1. Introduction

In optimization, the TSP is one of the most intensively studied problems. TSP is a well-known NP-hard combinatorial optimization problem by Lawler et al. [1]. Different types of TSPs have been solved by the researchers during last two decades. These are Focacci et al. [2] solved TSPs with time windows, Chang et al. [3] considered stochastic TSP, Petersen et al. [4] formulated double TSP, Majumder et al. [5] solve through GA for asymmetric TSP [5], Moon et al. [6] solved TSP with precedence constraints, etc. All these TSPs are 2-dimensional. Recently different types of classical 2D, 3D (solid) TSPs are studied by Maity et al. [7–9] in different uncertain environments. To solve TSPs, a powerful heuristics learning techniques require to find the near optimal solutions. The research on the efficient algorithm for TSPs is still a frontier subject.

In real life, for travelling from one city to another, different paths are available with a set of conveyances at each station. In that case, a salesperson has to design the tour for minimum cost maintaining the TSP conditions and using the appropriate paths with suitable conveyances at different cities. This problem is called 4- dimensional TSP (4DTSP), which involve 'paths' and 'vehicles' between two cities- from 'origin' to 'destination'. Travelling cost from one city to another city depends on the types of conveyances, condition of roads, geographical areas, weather condition at the time of the travel, etc, so there always prevail some uncertainties/vagueness. For this reason it is better to model the costs by uncertain parameters as bi-fuzzy values.

As optimization of bi-fuzzy objective is not well defined, we use fuzzy possibility and necessity based approaches [9,10] to represent and to solve the bi-fuzzy 4DTSP.

The intelligent algorithm is another resolution for TSP. The motivation behind hybridizations of different algorithmic concepts is usually to obtain better performing systems that exploit and unite advantages of the individual pure strategies, i.e. such hybrids are believed to be benefited from synergy. Recently some intelligent algorithms such as anterior artificial neural network [11], particle swarm optimization (PSO) and the combinations of ACO with simulated annealing (SA) [12] have been applied for TSP. A survey of hybrid meta-heuristics in combinatorial optimization by Blum et al. [13] is done. Also a novel imperialist competitive algorithm for generalized TSP has been proposed by Ardalan et al. [14]. Psychas et al. [15] is advised a hybrid evolutionary algorithms for the multiobjective TSP.

The genetic algorithm (GA) is one of the competitive intelligent algorithm for discrete optimization. There are many types of GA developed by the researchers such as Localized GA (LGA) [16],

* Corresponding author.
E-mail addresses: maitysamir13@gmail.com (S. Maity), royarindamroy@yahoo.com (A. Roy), mmaiti2005@yahoo.co.in (M. Maiti).

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Adaptive GA (AGA) [17], Enhance GA [18], Efficient GA [19], tang et al. [36] also study the analysis of gene GA [36], etc., which are used to get the optimal solutions in different research areas. Last and Eyal [20] and Roy et al. [21] improved the performance of GAs by providing a new fuzzy based extension of the life time feature.

ACO is an important soft computing technique [28] for solving optimization problems. In ACO, the behavior of real ants to find the shortest path between their nest and food source, has been used. Several ACO algorithms are available to solve the well-known NP-Hard TSP. Dorigo et al. [22] described an artificial ant colony capable of solving the TSP. Cheng et al. [23] presented a modified ant colony system for solving the TSP with time windows. Ibanez et al. [24] proposed a Beam-ACO which is a hybrid method combining ACO with beam search to solve TSP. By Ghafurian et al. [25] proposed an ACO algorithm for solving fixed destination multi-depot multiple traveling salesmen problems. Bai, Yang, Chen, Hu and Pan et al. [26] proposed a model inducing max-min ant colony optimization for Asymmetric TSP.

In spite of the above developments, there are some lacunas in the development of real life TSPs.

- Till now, none considered the different routes with some conveyances for travel from one city to another. But, this is a practical real life phenomena. Here we have considered both paths (routes) and conveyances at each station and hence some 4DTSPs have been formulated and solved.
- A hybrid algorithm rACO-GA with rough set based pheromone dependent selection strategy is developed and applied for solution.
- In support of the new technique, some statistical and sensitivity analyses are presented.

For 4DTSPs, solutions, an intelligent hybridized algorithm which is a combination of ACO and GA is proposed. Here initial solutions are given by ACO, then pheromone of each chromosome is divided as linguistic values- Very Very Small (VVS), Very Small (VS), Small (S), Medium (M), High (H), Very High (VH) and Very Very High (VVH). According to the linguistic values, probability of crossover p_c is created of each chromosome. Here ACO is used as the selection operation of GA. Also for the first time, the trust measure of rough variable in 7-point scale is presented. Comparison crossover [7] and a new generation dependent random mutation are also implemented in the present algorithm. The proposed algorithm is tested with standard data set from TSPLIB [27] against the classical/simple GA (SGA) which is the combination of Roulette Wheel Selection (RWS), cyclic crossover and random mutation and hence the efficiency of the new algorithm is established. 4DTSPs formulated in different environments are solved by both proposed intelligent hybrid rACO-GA and SGA with some virtual data set. Some sensitivity analyses and statistical testing are presented.

The proposed algorithm or its modified form easily adopted real life industrial information gathering [30,31], decision making [32–34] and solve the industrial enterprise problem such as Information and communications technologies (ICT) [38–40], supply chain [35,37], airline [41], etc. Since the proposed hybrid algorithm is a part of soft computing techniques and it is well suited for optimization such as particularly in logistic supply chain.

This paper is organized as follows: Mathematical preliminaries are described in Section 2. In Section 3, rACO-GA is presented. In Section 3, the complexity of the rACO-GA is computed. Again in Section 4, different kinds of TSPs are given. We illustrate the above problems using some empirical data with discussion in Section 5. Finally, Conclusion of the paper with the scope of future development is illustrated in Section 6.

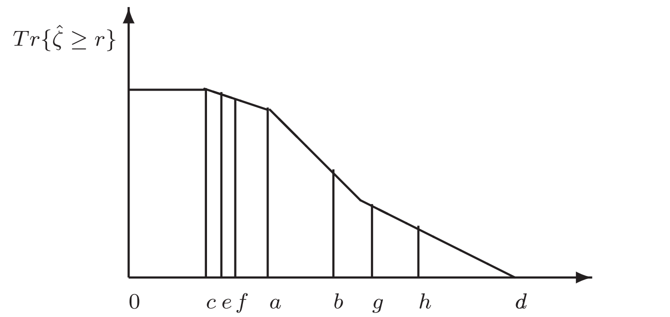

Fig. 1. $Tr\{\hat{\zeta} \geq r\}$ function curve.

2. Mathematical Preliminaries

2.1. Bi-fuzzy variable

Definition: A fuzzy fuzzy (Fu-Fu) variable ξ is a fuzzy variable with fuzzy parameters.

Theorem 2.1 [9]. *Assume that $\tilde{\tilde{c}}_{ij}(\theta)$ is a LR bi-fuzzy variable, for any $\theta \in \Theta$. Then the membership function of $\tilde{\tilde{c}}_{ij}(\theta)$ is*

$$\mu_{\tilde{\tilde{c}}_{ij}(\theta)}(t) = \begin{cases} L\left(\frac{c_{ij}(\theta)-t}{\alpha^c_{ij1}}\right) \text{ if } c_{ij}(\theta) \geq t, \alpha^c_{ij1} > 0, \\ R\left(\frac{t-c_{ij}(\theta)}{\beta^c_{ij1}}\right) \text{ if } c_{ij}(\theta) \leq t, \beta^c_{ij1} > 0 \end{cases} \tag{1}$$

where the fuzzy vector $(c_{ij}(\theta))_{n\times 1} = (c_{i1}(\theta), c_{i2}(\theta), c_{i3}(\theta), \ldots c_{in}(\theta))^T$ is also LR fuzzy variable with membership function as follows,

$$\mu_{c_{ij}}(t) = \begin{cases} L\left(\frac{c_{ij}-t}{\alpha^c_{ij2}}\right) \text{ if } c_{ij} \geq t, \alpha^c_{ij2} > 0, \\ R\left(\frac{t-c_{ij}}{\beta^c_{ij2}}\right) \text{ if } c_{ij} \leq t, \beta^c_{ij2} > 0 \end{cases} \tag{2}$$

and $\alpha_{ij1}, \alpha_{ij2}, \beta_{ij1}, \alpha_{ij2}$, are the left and right spread of $\tilde{\tilde{c}}_{ij}(\theta)$ and c_{ij}, i=1,2..,m, j=1,2... ,n, the reference function L, R:[0,1]→ [0,1] satisfies that $L(1) = R(1) = 0$, $L(0) = R(0) = 1$, and it is a monotone function. Thus $Pos\{\omega|Pos\{\{\tilde{\tilde{c}}_{ij}(\theta)^T \geq f_i\} \geq \delta_i\} \geq \gamma_i$ is equivalent to $c_i^T x + R^{-1}(\delta_i)\beta^{cT}_{i1}x + R^{-1}(\gamma_{i1})\beta^{cT}_{i2}x \geq f_i, i = 1, 2, \ldots, m$, where δ_i, $\gamma_i \in [0, 1]$ are predetermined confidence levels. Here Pos *stands for possibility approach.*

2.2. Rough set

Rough Variable [29]:

Let a rough variable ζ is a measurable function from the rough space $(\Lambda, \Delta, \kappa, \Pi)$ to the set of real numbers, i.e. for every Borel set of $\Re$, $\{\lambda \in \Lambda|\eta(\lambda) \in B\} \in \kappa$. The lower ($\underline{\zeta}$) and upper ($\overline{\zeta}$) approximations of the rough variable ζ are given by $\zeta = \{\zeta(\lambda)|\lambda \in \Lambda\}$.

Trust Measure [29]:

Let $(\Lambda, \Delta, \kappa, \Pi)$ be a rough space. The trust measure of event C is denoted by Tr$\{C\}$ and defined by Tr$\{C\} = \frac{1}{2}(\underline{Tr}\{C\} + \overline{Tr}\{C\})$. Upper and lower trust measures of event B are respectively defined by $\overline{Tr}\{C\}) = \frac{\Pi\{C\}}{\Pi\{\kappa\}}$, and $\underline{Tr}\{C\} = \frac{\Pi\{C\cap\Delta\}}{\Pi\{\Delta\}}$. When enough information about the measure Π is not available, it may be treated as the Lebesgue measure. Here first time the trust measure for 7-point scale of the rough event $\hat{\zeta} \geq r$, $Tr\{\hat{\zeta} \geq r\}$ and its function curve (cf. Fig. 1) is presented, where r is a crisp number, $\hat{\zeta}$ is a rough variable given by $\hat{\zeta}$=([a,b],[c,d]), $0 \leq c \leq e \leq f \leq a \leq b \leq g \leq h \leq d$.