Expert Systems With Applications 46 (2016) 196–223

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

An imprecise Multi-Objective Genetic Algorithm for uncertain Constrained Multi-Objective Solid Travelling Salesman Problem

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

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

A R T I C L E I N F O

Keywords:
CMOSTSP
Fuzzy set based selection
Adaptive crossover
Generation dependent mutation
iMOGA

A B S T R A C T

In this paper, an imprecise Multi-Objective Genetic Algorithm (iMOGA) is developed to solve Constrained Multi-Objective Solid Travelling Salesman Problems (CMOSTSPs) in crisp, random, random-fuzzy, fuzzy-random and bi-random environments. In the proposed iMOGA, '3- and 5-level linguistic based age oriented selection', 'probabilistic selection' and an 'adaptive crossover' are used along with a new generation dependent mutation. In each environment, some sensitivity studies due to different risk/discomfort factors and other system parameters are presented. To test the efficiency, combining same size single objective problems from standard TSPLIB, the results of such multi-objective problems are obtained by the proposed algorithm, simple MOGA (Roulette wheel selection, cyclic crossover and random mutation), NSGA-II, MOEA-D/ACO and compared. Moreover, a statistical analysis (Analysis of Variance) is carried out to show the supremacy of the proposed algorithm.

1. Introduction

Genetic algorithms (GAs) are robust search algorithms that use the operations of natural genetics to find the optimum through a search space. Recently, GAs have been used to solve several single and multi-objective decision making problems. In multi-objective optimization techniques (MOOTs), a Pareto Front (PF) is generated and an optimum solution set should be very close to the true PF. But, the above two goals are conflicting for the fixed number of functions, evaluations as the first property requires intensive search over a particular region of the search space and the second one for the uniform search of the whole region. Thus MOOTs make a trade-off between exploration and exploitation. The first real implication of multi-objective evolutionary algorithm (vector evaluated GA or VEGA) was suggested by David Schaffer in 1984. Then Goldberg suggested to implement domination principle in evolutionary algorithm (EA). Realizing the potential of a good multi-objective evolutionary algorithm (MOEA) (Deb, 2001; Rubio, Sen, Longstaff, & Fletcher, 2013) which can be derived from Goldberg's suggestions, researchers developed different versions of MOEAs such as multi-objective GAs (MOGAs), Niched Pareto GAs (NPGAs) (Horn, Nafpliotis, & Goldberg, 1994), non-dominated sorting GAs (NSGAs) (Deb, 2002), hybrid scatter search like MOGA by Durillo, Nebro, Luma, and Alba (2009), decomposition -based MOAs like MOiA/D-DE (Li & Zhang, 2009), archive-based micro GAs like AMGA2 (Tiwari, Adel, & Deb, 2011), etc. In AMGA2, a modified definition of crowding distance for the generation of mating pool has been presented. Recently, an archived-based steady-state micro genetic algorithm (ASMiGA) has been developed with new environmental selection and mating selection strategies (Nag, Pal, & Pal, 2015).

TSP is a well-known NP-hard combinatorial optimization problem (Lawler, Lenstra, Rinnooy Kan, & Shmoys, 1985). Different types of TSPs have been solved by the researchers during last two decades. These are TSPs with time windows (Focacci, Lodi, & Milano, 2002), stochastic TSP (Chang, Wan, & Tooi, 2009), double TSP (Petersen & Madsen, 2009), asymmetric TSP (Majumder & Bhunia, 2011), TSP with precedence constraints (Moon, Ki, Choi, & Seo, 2002). Wang (2015) proposed an approximate method on sparse graph for TSP, Nagata and Soler (2012) developed a new GA for asymmetric TSP, Che and Ohiem (2012) considered genetic simulated annealing ant colony systems with PSO to solve TSP, Dong, Guo, and Tickle (2012) proposed a cooperative GA for general TSP, Albanyrak and Allahverdi (2011) developed a new mutation operator to solve TSP by GA, Xu and Tao (2012) solved multi-objective problem with power station operation, Elaoud, Teghem, and Loukil (2010) proposed multiple crossover and mutation operators with dynamic selection scheme in MOGA for multi-objective TSP (MOTSP), Lust and Teghan (2010) presented two-phase Pareto local search (2PPLS) for bi objective TSP, Filippi and Stevanato (2013) considered a Pareto ϵ approximation named as ABE

* Corresponding author. Tel.: +91 9874512894.
E-mail addresses: maitysamir13@gmail.com, samirmca13@gmail.com (S. Maity), royarindamroy@yahoo.com (A. Roy), mmaiti2005@yahoo.co.in (M. Maiti).

http://dx.doi.org/10.1016/j.eswa.2015.10.019
0957-4174/

algorithm for MOTSP, Lust and Jaszkiewicz (2010) presented Pareto memetic algorithm with path relinking and efficient local search for MOTSP, Samanlioglu, Ferrel, and Kurz (2008) proposed weakly Pareto optimal solutions for symmetric MOTSP with memetic random-key GA, Zhou, Gao, and Zhang (2011) considered multi-objective estimation of distribution algorithm based on decomposition (MEDA/D) for some particular MOTSPs. Paquete and Stutzle (2009) analyze algorithmic components of stochastic local search algorithms for the multiobjective traveling salesman problem. For generation based evolutionary algorithms, normally most of the solutions of the parent population are replaced by children in each generation. In MOGA, this diversity is created using the crowding distance and several researchers developed different MOGAs (Deb & Tiwari, 2006; Xia, Zhuang, & Yu, 2013) modifying the crowding distance. Again, the different MOGAs incorporate the various selection strategies. NSGA-II and SPEA-2 (Zitler, Laumanns, & Thiele, 2001) use the fast non-dominated sort and strength of Pareto evolutionary approach respectively. Florios and Mavrotas (2014) proposed a Multi-Objective Mathematical Programming (MOMP) method which is capable of generating the exact Pareto set in Multi-Objective Integer Programming (MOIP) problems for producing all the Pareto optimal solutions.

Traveling costs, times and risk factors 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, times and risk factors by uncertain parameters as random, random-fuzzy, fuzzy-random and bi-random values. Also, a salesman must maintain a maximum risk/discomfort level at each step and also ensure a maximum total risk/discomfort factor for the entire trip. Such kind of constraint is called risk/discomfort factor constraints.

The present problem is more complicated due to the uncertainty/impreciseness of the costs and times with uncertain risk/discomfort factors. For the random values of the costs and times with risk/discomfort factors, chance-constrained programming techniques, which were originally developed by Charnes and Cooper (1959) are implemented. For the random-fuzzy CMOSTSP, the approach of Katagiri, Uno, Tsuda, and Tsubaki (2013) is utilized. Again for fuzzy-random CMOSTSP, the model is transformed to crisp using the method of Liu (2004). Similarly, for the bi-random costs and times with risk/discomfort factors, equilibrium chance constraints, according to Peng and Liu (2005); 2007) are used.

Our contribution in this paper is as follows:

- New selection strategies as fuzzy set (3-level linguistic) based, fuzzy extended (5-level linguistic) age based and probabilistic selection are proposed.
- A new proposed Adaptive crossover, most suitable for TSPs is introduced.
- A virgin generation dependent random and fixed point mutations are proposed.
- CMOSTSPs are more realistic TSPs. Recently Changdar, Mahapatra, and Pal (2014) solved unconstrained MOSTSP only in fuzzy environment. Here, CMOSTSPs are developed in several uncertain environments such as random, random-fuzzy, fuzzy-random and bi-random with constraints.
- The new iMOGAs are tested with different data sets from TSPLIB (TSPLIB) and the efficiency of the proposed algorithm is established in terms of iteration/generation.
- Moreover, the supremacy of the proposed algorithm is illustrated statistically with the help of the statistical test ANOVA.

In this paper, some CMOSTSPs are formulated with different risk/discomfort factors for different conveyances and routes. A maximum total risk/discomfort is imposed for the entire tour in the form of a constraint. These models are developed with crisp, random, random-fuzzy, fuzzy-random and bi-random costs and times with risk/discomfort factors. For the solution, an imprecise multi-objective GA (iMOGA) is proposed using 3- and 5-level linguistic based selections depending on the corresponding age and linguistic values.

CMOSTSPs formulated in different environments are solved by proposed iMOGA, classical MOGA and NSGA-II for some empirical data sets. Alternative near optimum paths along with optimum path are presented for each CMOSTSP. Some sensitivity analyses are performed due to different risk/discomfort factors and other system parameters. As multi-objective standard TSPLIB is not available, combining same size single objective problems from standard TSPLIB (TSPLIB, 1995), the results of such multi-objective problems are obtained by the proposed algorithm, simple MOGA (Roulette wheel selection, cyclic crossover and random mutation) and NSGA-II and compared. Moreover, the supremacy of the proposed algorithm is illustrated statistically with the help of the statistical test ANOVA.

This paper is organized as follows: in Section 1, a brief introduction is given. In Section 2, iMOGA is presented. Section 3 gives different kinds of CMOSTSP. In Section 4 numerical experiments are performed. The statistical test is given in Section 5, some discussions are furnished in Section 6. Finally, we conclude the paper with conclusions in Section 7, the mathematical preliminaries are presented in Appendix A.

2. Proposed iMOGA

Here a new algorithm for iMOGA using the fuzzy (3-level linguistic) and fuzzy extended (5-level linguistic) age based (FEA) selection, probabilistic selection, an adaptive crossover and a virgin generation dependent mutation is developed. Initially a randomly set of potential solutions is generated and then using proposed algorithm, we find out the Pareto optimal solutions until the termination criteria are encountered. The proposed iMOGA and its procedures are presented below:

2.1. Representation

Here a complete tour on N cities represents a solution. So an N dimensional integer vector $X_i = (x_{i1}, x_{i2}, \dots, x_{iN})$ is used to represent a solution (path), where $x_{i1}, x_{i2}, \dots, x_{iN}$ represent N consecutive cities in a tour. Population size number M and ith solution $X_i = (x_{i1}, x_{i2}, \dots, x_{iN})$, where $x_{i1}, x_{i2}, \dots, x_{iN}$, are randomly generated by random number generator between 1 to N maintaining the TSP conditions such as not repeating of cities (nodes) and also satisfying the constraints. Fitness are evaluated by summing the costs and times between the consecutive cities (nodes) of each solution (chromosome). The $f(X_i)$ represents the ith solution fitness in the solution space. Since the maximum population size is M, so M numbers of solutions (chromosomes) are generated randomly.

2.2. Selection

Here three selection procedures are used for the selection of chromosomes. These are as follows:

2.2.1. Fuzzy set based age dependent selection

For the solution of an optimization problem, in our proposed iMOGA, the age of a chromosome is determined by a new mechanism based on weighted mean of their two objective values i.e. fitness values and then a **'fuzzy age based selection'** is applied. Here the age of each chromosome lies in a region of the common age represented by a fuzzy set using three linguistic expressions. These regions are termed as "young", "middle" and "old". So for the age of each chromosome, a linguistic value – young, middle or old is created. Now according to the age distributions of the members (in pair) of the mating pool, similar linguistic variables such as low, medium and high