Evaluation of the exIWO Algorithm Based On the Traveling Salesman Problem

Daniel Kostrzewa, Henryk Josiński

Abstract—The expanded Invasive Weed Optimization algorithm (exIWO) is an optimization metaheuristic modelled on the original IWO version created by the researchers from the University of Tehran. The authors of the present paper have extended the exIWO algorithm introducing a set of both deterministic and non-deterministic strategies of individuals' selection. The goal of the project was to evaluate the exIWO by testing its usefulness for solving some test instances of the traveling salesman problem (TSP) taken from the TSPLIB collection which allows comparing the experimental results with optimal values.

Keywords—Expanded Invasive Weed Optimization algorithm (exIWO), Traveling Salesman Problem (TSP), heuristic approach, inversion operator.

I. INTRODUCTION

THE Invasive Weed Optimization (IWO) algorithm is an optimization metaheuristic, in which the exploration strategy of the search space is based on the transformation of a complete solution into another one. The authors of the original version of the algorithm from the University of Tehran were inspired by observation of dynamic spreading of weeds and their quick adaptation to environmental conditions [1].

Usefulness of the IWO was confirmed for both continuous and discrete optimization tasks. The research was focused *inter alia* on minimization of the multimodal functions and tuning of a second order compensator [1], antenna configurations [2], electricity market dynamics [3], a recommender system [4], and the join ordering problem for database queries [5].

The goal of the present paper is to evaluate both deterministic and non-deterministic selection methods implemented in the expanded version of the IWO (exIWO) which is also distinguished by the hybrid strategy of the search space exploration proposed by the authors [6]. Evaluation of the suggested modification is based on the solution of some test instances of the traveling salesman problem (TSP) taken from the TSPLIB collection [7] of the Research Group Discrete and Combinatorial Optimization at the Ruprecht-Karls-Universität Heidelberg [11].

The overview of bibliography describing the methods for

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solving the TSP would be unusually spacious. Numerous studies related to the usage of exhaustive, greedy, and evolutionary methods were mentioned in [8], whereas the IWO algorithm, according to the authors' knowledge, has never been used to this purpose by other researchers.

The organization of the paper is as follows – Section II contains a brief description of the exIWO algorithm taking into serious consideration the proposed selection methods. Results of the conducted experiments are presented and analyzed in Section III. The conclusions are formulated in Section IV.

II. THE exIWO ALGORITHM

The simplified pseudocode mentioned below describes the exIWO algorithm by means of terminological convention consistent with the "natural" inspiration of its idea. Consequently, the words "individual", "plant", and "weed" are treated as synonyms and represent a single solution of the considered optimization problem. From among significant concepts related to the form of a single solution of the TSP it is worthwhile to mention three vector representations proposed in the literature: *path*, *ordinal*, and *adjacency* as well as a matrix representation [8]. A plant used by the exIWO was designed according to the simple and natural rule of the path representation: a tour is an ordered list of cities (i.e. expressed as a vector [2 3 9 4 1 5 8 6 7]) and the order of visitation is determined by the order of vector elements (2–3–9–4–1–5–8–6–7–2).

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Create the initial population.
For each individual:
  Compute the value of the fitness
  function.
While the stop criterion is not satisfied:
  For each individual from the
  population:
    Compute the number of seeds.
    For each seed:
      Draw the dissemination method.
      Create a new individual.
      Compute the value of its
      fitness function.
  Create a new population.
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In case of the TSP the individuals from the initial population are greedily generated over the search space – the nearest city will be visited as the next one.

In the minimization problems the degree of individuals' adaptation to environmental conditions is estimated not by the value of their fitness function, but is rather interpreted by

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means of cost C which (in case of the TSP) is equivalent to the total length of tour and determines the number of seeds S_{ind} produced by a plant according to the following formula:

$$S_{ind} = S_{min} + \left\lfloor \left(C_{max} - C_{ind} \right) \frac{S_{max} - S_{min}}{C_{max} - C_{min}} \right\rfloor, \qquad (1)$$

where S_{max}, S_{min} denote maximum and minimum admissible number of seeds generated, respectively, by the best population member (characterized by cost C_{min}) and by the worst one (cost C_{max}).

The seeds are scattered over the search space. The hybrid strategy of the search space exploration makes use of the following component methods: dispersing, spreading and rolling down. Probability values of selection assigned to the particular methods sum to 1 and form parameters of the algorithm.

Construction of a new individual according to the *dispersing* method is based on transformations performed on the copy of the parent individual. The number of transformations equals to the conventional distance between the parent individual and the descendant in the search space. The distance is described by normal distribution with a mean equal to 0 and a standard deviation truncated to nonnegative values. The standard deviation is decreased in each algorithm iteration (i.e. for each population) and computed for the iteration *iter*, $iter \in [1, iter_{max}]$ according to the following formula:

$$\sigma_{iter} = \left(\frac{iter_{max} - iter}{iter_{max}} \right)^m \left(\sigma_{init} - \sigma_{fin} \right) + \sigma_{fin} \qquad (2)$$

The total number of iterations ($iter_{max}$) can be used with the purpose of determination of the stop criterion. The symbols σ_{init}, σ_{fin} represent, respectively, initial and final values of the standard deviation, whereas m is a nonlinear modulation factor. A tendency to gradual reduction of the distance for subsequent populations resulting from (2) accords with intention of the authors of the original IWO algorithm.

Taking into account that the distance between plants can be interpreted as the number of transformations of the parent individual resulting in construction of a new weed, value computed by the normal distribution generator is rounded to the nearest integer value. A single transformation of an individual is based on the *inversion* of a randomly chosen segment of cities. Let π be a permutation of N cities $\pi = (c_1, \ldots, c_{p1}, c_{p1+1}, \ldots, c_{p2-1}, c_{p2}, \ldots, c_N)$, $1 \le p_1 \le p_2 \le N$. The inversion of the segment between positions p_1 and p_2 leads to the permutation π' such that $\pi' = (c_1, \ldots, c_{p2}, c_{p2-1}, \ldots, c_{p1+1}, c_{p1}, \ldots, c_N)$ [10]. For the exemplary individual [2 3 9 4 1 5 8 6 7], where the cities 9 and 8 are assumed to be randomly chosen ends of the segment ($p_1 = 3$, $p_2 = 7$, hence $c_{p1} = 9$, $c_{p2} = 8$), the inversion produces a new individual [2 3 8 5 1 4 9 6 7] (the inversed fragment was underlined) [8].

The *spreading* is a random disseminating seeds over the whole of the search space. Therefore, this operation is equivalent to the random construction of new individuals.

The *rolling down* is based on the examination of the neighborhood of the parent individual. In case of discrete optimization task the neighborhood comprises individuals that differ from the parent by exactly one transformation. The best adapted individual is chosen from among the determined number of neighbors, whereupon its neighborhood is analyzed in search of the next best adapted individual. This procedure is performed k times (k is a parameter of the method) giving the opportunity to select the best adapted individual found in the last iteration as a new one.

Members of next population can be selected in both deterministic and non-deterministic manner on the basis of the following strategies: global, offspring-based and family-based which determine the set of candidates.

In case of the TSP the selection criterion is determined by the length of tour. In the non-deterministic approach the "worse" individuals get a chance to survive according to one of the following techniques: the proportionate method [8] based on the roulette-wheel concept and the algorithm modelled on the simulated annealing (SA) heuristic. In the latter case each parent plant is compared with a random candidate. If the candidate is better, he becomes a member of next population, otherwise – he survives with a certain probability which is linearly decreased similarly to one of the cooling schemes of the simulated annealing.

Set of candidates for the *global* selection consists of all μ parent plants and all λ their newly created descendants. This approach, which was a basis for the original IWO method, is commonly denoted in the literature of evolutionary algorithms as $(\mu + \lambda)$ [8]. By contrast, the *offspring-based* selection, described as (μ, λ), $\lambda \ge \mu$, is limited solely to the set of λ descendants and thus should decrease the risk of stagnation at non-optimal points in the search space [8]. If the best individual so far was grown in the current population, then despite the fact that it cannot be retained in the next population it will be stored with an eye to the final optimization result. According to the rules of the *family-based* selection, based on the idea presented in [9], each plant from the first population is a protoplast of a separate family. A family consists of a parent weed and its direct descendants. In the deterministic version only the best individual of each family survives and becomes member of the next population giving a chance for the preservation of characteristic features of the family.

For all the aforementioned selection methods cardinality of a population remains constant in all algorithm iterations.

III. EXPERIMENTAL RESULTS

101 instances of symmetric TSP and 17 instances of asymmetric TSP from the TSPLIB collection were used as test data for the purpose of evaluation of the exIWO. The number of trial runs for each TSP instance was equal to 10. Every 100 iterations the quotient K of the length of the current best

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solution and the optimal value was stored. The stop criterion was determined by the number of iterations equal to 1000, which is big enough to determine whether successive solutions converge to optimum or not. The K values averaged over all instances are presented in Figs. 1-6 (symmetric instances) and 7-12 (asymmetric instances) separately for deterministic, proportionate and SA-based selection. In the last case 4 initial values of the probability p_0 of acceptance of the worse solution were tested: 0.1, 0.25, 0.5, 1. Population cardinality depended on the number of cities in a test set – for routes with less than 150 cities a population contained 200 individuals, otherwise – 50. The best exIWO results were achieved for particular test instances using different values of other algorithm parameters (m, probabilities of dispersing, spreading and rolling down, S_{max}, S_{min}, σ_{init}, σ_{fin}). Only the number k of neighborhoods examined during the rolling down remained equal to 2.
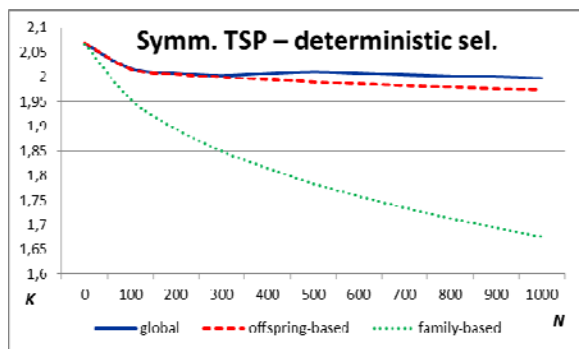
Fig. 1 Deterministic selection for symmetric TSP
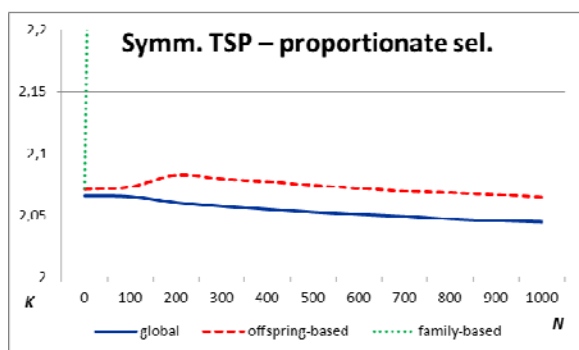
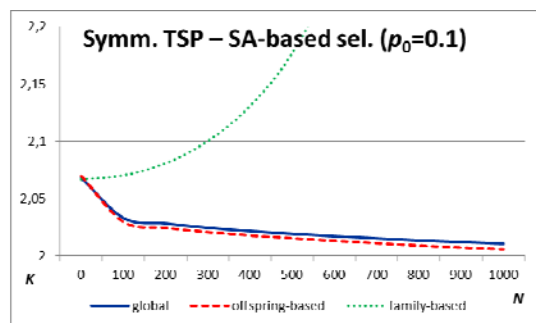Fig. 2 Proportionate selection for symmetric TSP
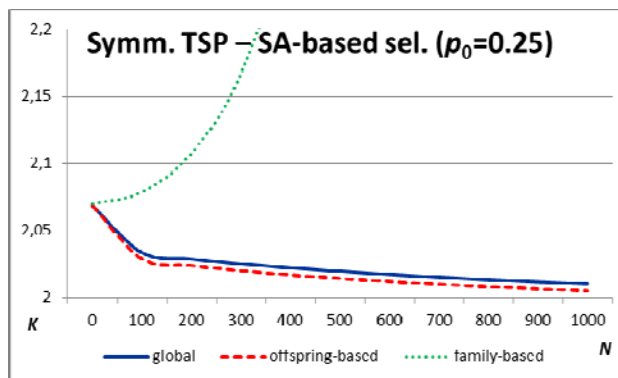

Fig. 3 SA-based selection for symmetric TSP (p_0=0.1)

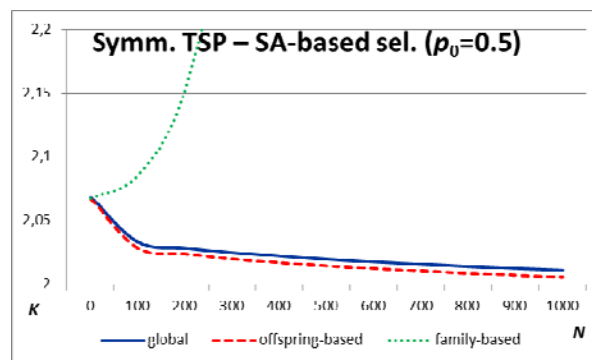Fig. 4 SA-based selection for symmetric TSP (p_0=0.25)
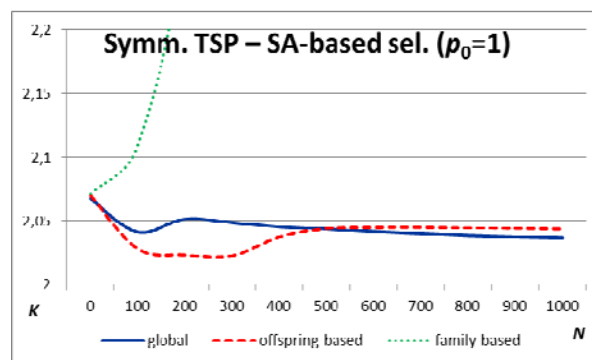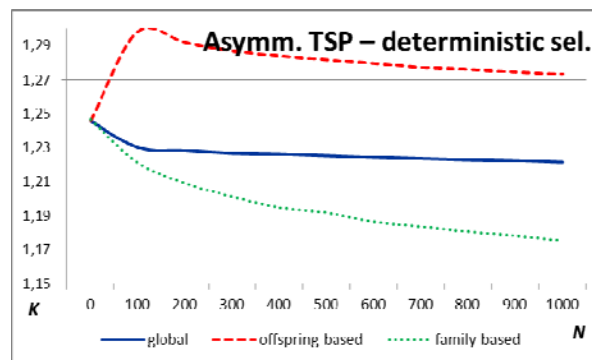

Fig. 5 SA-based selection for symmetric TSP (p_0=0.5)

Fig. 6 SA-based selection for symmetric TSP (p_0=1)
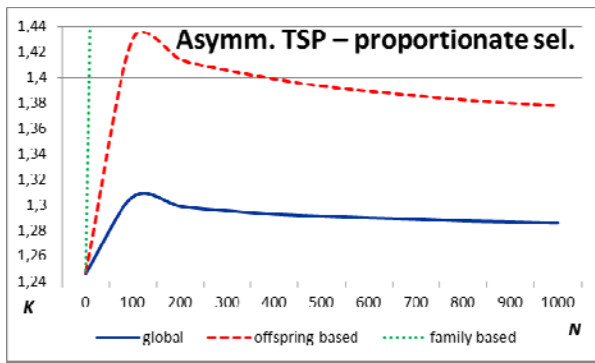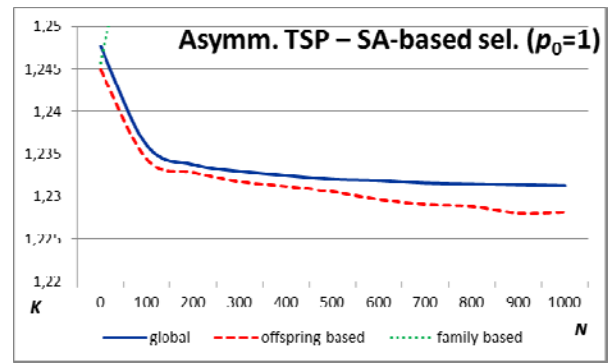

Fig. 7 Deterministic selection for asymmetric TSP

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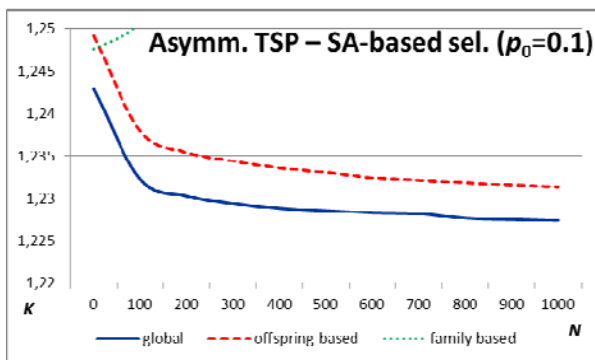
Fig. 8 Proportionate selection for asymmetric TSP

Fig. 9 SA-based selection for asymmetric TSP (p_0=0.1)

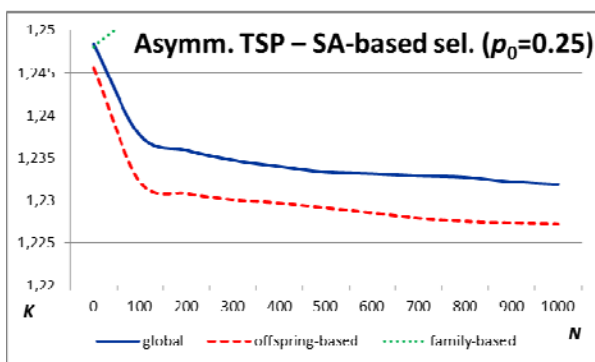Fig. 10 SA-based selection for asymmetric TSP (p_0=0.25)

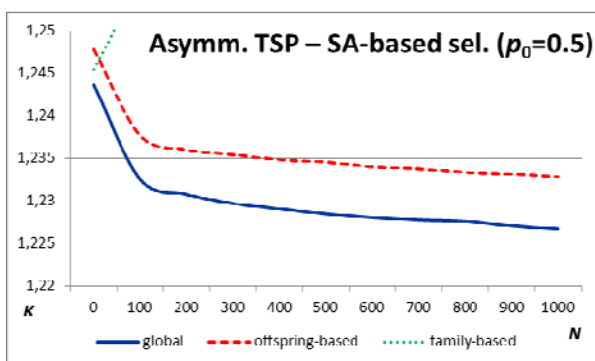
Fig. 11 SA-based selection for asymmetric TSP (p_0=0.5)

Fig. 12 SA-based selection for asymmetric TSP (p_0=1)

The best results were achieved using the deterministic variant of the family-based selection. On the other hand, it is necessary to mention that for non-deterministic methods the family-based selection does not converge to the optimum.

IV. CONCLUSION

The research confirmed the usefulness of the exIWO for solving discrete optimization problems.

Usage of the TSPLIB collection gave the opportunity to compare the achieved results with optimal values for particular TSP instances.

The deterministic variant of the family-based selection combined with greedy method of initialization of the first population turned out to be successful owing to gradual improvement of "nonaccidental" protoplasts from the initial population.

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