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ADAPTATION OF THE HARMONY SEARCH ALGORITHM TO SOLVE THE TRAVELLING SALESMAN PROBLEM

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ABSTRACT

The travelling salesman problem (TSP) is a discrete combinatorial optimization problem; it allows us to solve a set of problems in the real world in various fields. This article presents a new meta-heuristic adaptation to solving this problem. The numerical results are applied to a set of instances of TSPLIB we showing us the effectiveness of the adaptation of the harmony search algorithm band compared to other approaches in terms of quality of the solution, the search time, and the improvement of the results in terms of the reduction in the percentage of errors.

Keywords*:* *Combinatorial Optimization, Meta-Heuristic, Travelling Salesman Problem, Harmony Search Algorithm, Local Search.*

1. INTRODUCTION

The travelling salesman problem is a famous problem of operational research. Indeed, this problem consist of finding the shortest path to travel from one seller, which begins by a departure city, passing only once through each city and coming back, to the city of departure. The objective is to find the Hamiltonian cycle in both minimal time and cost.

There are several application fields, such as logistics [1], scheduling [2], transportation [3]. For example; finding the shortest path for school buses, factories personal transportation, or for trucks used to transport goods. The travelling salesman problem (TSP) belongs to the class of NP-complete problems [4], non-polynomial complexity.

Many methods have been developed to solve the TSP problem as the descent [5], simulated annealing [6], tabu [7], and meta-heuristics methods that are generally high levelled strategies that are based on probabilistic decisions made during the research, such genetic algorithm [8] and ant algorithm [9].

This paper presents an adaptation of the harmony search algorithm to solve this problem. This article is organized as follows. In section 2, a formulation of the travelling salesman problem, in Section 3 a definition of the harmony search algorithm, in Section 4 the strategy of adapting the algorithm for TSP problem, Section 5 presents the results and debate about the algorithm, and finally, conclusions.

2. TRAVELLING SALESMAN PROBLEM

The travelling salesman problem was mentioned for the first time in 1930 by the mathematician Karl Menger [10]. Solving this problem consists of establishing the minimal length of the Hamiltonian cycle in a complete and undirected graph in which each vertex represents a city and each edge represents a path. Each path has a cost that represents the distance to get from one vertex to another.

The travelling salesman problem is composed of a set of variables:

$d_{ij} = Distance\ between\ city\ i\ and\ city\ j$

$n = |V|\ , the\ amount\ of\ cities$

$X = (x_{ij})_{\substack{1\le i\le n\\1\le j\le n}}$, the matrix to trace the path as:

$$x_{ij} = \begin{cases} 1, & if\ city\ j\ is\ visited\ immediately\ after\ city\ i \\ 0, & else \end{cases}$$

The problem consists of minimizing the length of Hamiltonian cycle:

$$\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} \quad (1)$$

With the following constraints:

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$$\sum_{i=1}^{n} x_{ij} = 1\,, for\ all\ j \in \{1, \dots, n\} \quad (2)$$

$$\sum_{j=1}^{n} x_{ij} = 1\,, for\ all\ i \in \{1, \dots, n\} \quad (3)$$

And

$$\sum_{i \in S} \sum_{j \in S} x_{ij} \in S, for\ all\ S \in N \quad (4)$$

Search the constraint equation 2 (or 3) has been proposed to ensure that every city has a single successor (pre-successor), the constraint equation 4 in order to prohibit the solutions that are sub-cycle (which passes only a subset of n city).

3. HARMONY SEARCH ALGORITHM

The harmony search algorithm (HS) is a meta-heuristic approach inspired by natural processes of musical performances. It was developed by Geem and al. [11] in 2001, and has been studied by many researchers as Lee and al. [12] Geem. [13] Saka [14, 15], and Erdal Saka [16] and Degertekin [17, 18]. The algorithm consists of finding a perfect state of harmony in a musical orchestra in which each musician plays a note, to find a better harmony. In a similar manner, each musician plays a note in the broadest possible to form a band with other musicians. If all the notes played by all the musicians are seen as harmonious, then it is stored in the memory of each of the musicians in order to get the same optimal result for the next time.

The HS algorithm consists of five main steps. The following algorithm (Algorithm.1) represents the optimization of the search algorithm band procedure.

Step 1. Initialize the algorithm parameters.
Step 2. Initialize the harmony memory.
Step 3. Improvise a new harmony.
Step 4. Update the Harmony Memory.
Step 5. Check the stopping criterion.

These steps are described in the next five subsections.

3.1 Initialization of the Parameters:

In this step, we initialize the algorithm parameters: the number of solutions generated (HMS), the rate of memory considered (HMCR), the adjustment rate (PAR) and the other stopping criteria like the maximal number of iterations.

3.2 Initialization of the Harmony Memory:

The initiation of the band memory HM is to generate the HMS solutions in a random way; each x solution is consisting of N elements. For each solution the objective function f is calculated, the equation (5) presents the general structure of the HM.

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{n-1}^1 & x_n^1 \\ x_1^2 & x_2^2 & \dots & x_{n-1}^2 & x_n^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & \cdots & x_{n-1}^{HMS-1} & x_n^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_{n-1}^{HMS} & x_n^{HMS} \end{bmatrix} \begin{matrix} \rightarrow \\ \rightarrow \\ \rightarrow \\ \rightarrow \\ \rightarrow \\ \rightarrow \end{matrix} \begin{matrix} f(x^1) \\ f(x^2) \\ \vdots \\ f(x^{HMS-1}) \\ f(x^{HMS}) \end{matrix} \quad (5)$$

3.3 Improvising a New Harmony:

A new solution $x = (x_1, x_2, \dots, x_n)$ using two parameters: (i) rate regardless of the harmony memory HMCR, (ii) rate setting step PAR. These parameters help the algorithm obtain solutions locally or globally improved. The solution is built for each element of the new solution as follows:

$$x_i \in \begin{cases} \{x_i^1, x_i^2, \dots, x_i^{HMS}\} \text{ with probability HMCR} \\ X_s \text{ with probability } (1 - \text{HMCR}) \end{cases}$$

Where Xs is the set of all possible elements for each variable.

Each variable obtained by the consideration of the memory is examined to determine if it should be adjusted or not. Using the second parameter the pitch adjustment rate (PAR) which controls the search for better solutions. PAR is used as follows:

$$x_i = \begin{cases} x_i + bw * u(-1{,}1) & \text{with probability PAR} \\ x_i & \text{with probability } (1 - \text{PAR}) \end{cases}$$

Where bw is a bandwidth of distance and u (-1.1) is distributed uniformly between -1 and 1.

3.4 Update the Harmony Memory:

The new generated harmony replaces the worst one stored in the memory band (HM), only if its physical condition (measured in terms of the objective function) is better than the worst harmony.

3.5 Checking the Stopping Criterion:

The execution of the algorithm terminates when the maximum number of repetitions is reached or when the algorithm finds the right harmony.

4. ADAPTATION OF THE HARMONY SEARCH ALGORITHM TO THE TRAVELLING SALESMAN PROBLEM

The search algorithm is based on the following parameters:

HM : The harmony memory that contains the entire solution.

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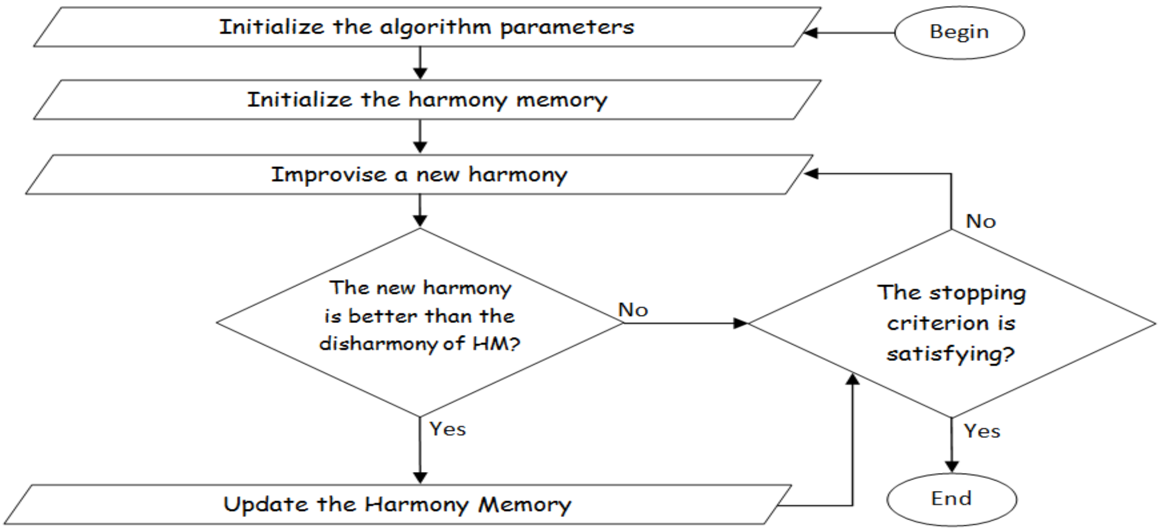
HMS : The size of the solutions memory (HM).



Algorithm.1 : Search Harmony Algorithm.

HMCR : Probability to choose a city in the memory.

PAR : Probability of adjustment to choose a neighbours city.

The first phase of adaptation shown in Algorithm.2 is to initialize the HMCR, PAR, and HMS settings. The second phase consists of initializing the HM harmony memory of

the HM solutions in a random way so that each solution represents an Hamiltonian cycle of cities. The third phase consists of starting to look for a solution that depends on values of parameters until the stop condition is satisfied.

In this adaptation, the algorithm stops looking for new solutions when the number of iterations of searches exceeds the maximal number, or when the algorithm manages to find the optimum of the problem's instance.

The next step is to generate a new cycle. For each index from 1 to n (number of cities) of the new solution randomly selects a number between 0 and 1 (PHMCR). If the number is strictly less than HMCR, then memory is considered, otherwise the algorithm choses a city in a random way. If the memory is considered then the algorithm selects a city from the memory. Once the city is obtained, we generate another random number between 0 and 1 (PPAR), if the latter is less than the value of the adjustment's parameter PAR, then the algorithm replaces the city obtained by one of his neighbours. Once the city is recovered, the algorithm inserts it into the current index of the new solution. Before each insertion into the new solution, the algorithm checks for the selected city, to avoid closing the cycle.

Algorithm.2 : Adaptation of the Algorithm

Begin
Initialization of the parameters: HMS, HMCR and PAR.
Initialization of the HM memory by HMS solutions.
While ((iteration <maximum number of iterations) **and** (the algorithm has not reached the best problem)) **do**
  For each i ∈ cities **do**
    If (P_{HMCR} <HMCR) **then**
      Choose a city from the HM column i.
      If (P_{PAR}<PAR) **then**
        Replace the selected city with one of its neighbours.
      end If
    else
      Select a city randomly.
    end If
    Place the chosen city in the current location of the new cycle.
  end for
  Improve the new solution by the local search method.
  Update HM memory.
end while
Return the best solution of the HM.
End.

After having generated the new solution, the algorithm applies the descent local search method on this solution to obtain a solution for the problem S, if the S solution is better than the wrong solution of the HM memory, then it releases the wrong solution of the memory and integrates the new one. Once the memory updates itself, the algorithm

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determines the position of the poor solution of the memory, increases the number of iterations, then restarts the process.

The approach of this article is applied to solve the TSP problem using the local search method as the descent method.

5. RESULTS AND DEBATE

The adaptation of the proposed algorithm is coded into a program language C+ + on visual studio 2010, the results are executed on a computer Intel (R) Core (TM) 2 Duo CPU T6570@2.10GHZ 2.10GHz and 2.00 GB of RAM. Instances used belong to TSPLib library (G. Reinelt, 1995) [19]. The distances between the cities are registered in a matrix, the initial solutions are randomly generated for each cycle, and the time of creation of the distances' matrix are not included in the execution time of the algorithm. In the algorithm, there are three key parameters that influence the performance results: the size of the memory band (HMS), the rate of the memory consideration (HMCR) and the rate of the pitch adjustment (PAR). The values of the HMS and HMCR parameters used are 0.95 and 10 [20]. for the value of the rate adjustment we applied a combination of values in the interval]0,6[with steps of 0.05 , which is shown on the figure 1 (Figure 1). it shows the variation of the average execution time of each PAR value for 8 TSPLib bodies , and from the results (Figure 2) we find that the 0.45 value minimizes the execution time. So the values of the chosen used parameters are:

Table 1: Values of the Adaptation Parameters

Parameters	Value
HMCR	0,95
PAR	0,45
HMS	10

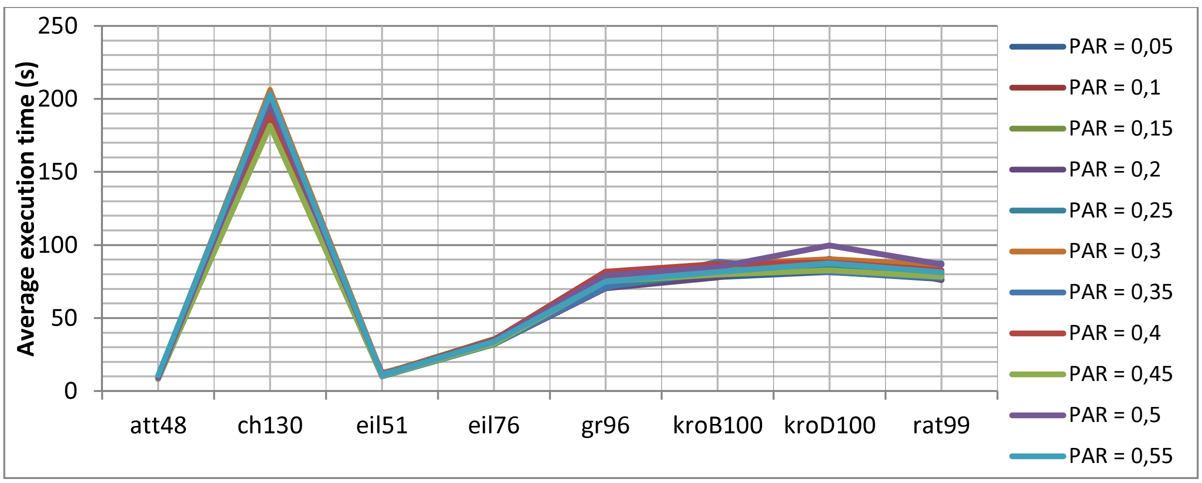

Figure 1: The Variation Of The Average Execution Time Of Each PAR Value.

Table 2 shows the effect of adaptation and the local search. Before showing the results, we will compare the best solutions obtained by the different methods used in the adaptation for 10 iterations on instances of the represented problem, which shows the obtained result by the local search method and the adaptation of the algorithm. The results of the adaptation are presented in table 3. The first column represents the best length obtained, the second indicates the number of times the algorithm reaches the optimum problem, the third shows the worst length obtained, while the fourth represents the average length of the iterations, the fifth is about the relative error, and the last column is the average execution time. The relative error is calculated as follows:

$$\textbf{Error} = \frac{(\textbf{average length} - \textbf{problem's optimum})}{\textbf{problem's optimum}} \times \textbf{100}\,\%$$

Table 2: Results of the Descent Method and the Adaptation of the Harmony Search Algorithm

Instance	Optimal	Local search	Harmony search
att48	10628	10824	10628
ch150	6528	6969	6549
gr96	55209	56558	55209
hk48	11461	11470	11461
kroA100	21282	21827	21282

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kroB100	22141	22979	22141
kroD100	21294	21488	21294
kroE100	22068	22437	22073
st70	675	691	675

Table 3. The Results of the Harmony Adaptation Proposed for TSP

Instance	Optimal	HS					
		Best	N_{best}	Worst	Average	% Error	Time
att48	10628	10628	10	10628	10628	0	00:00:08:54
bayg29	1610	1610	10	1610	1610	0	00:00:02:07
bays29	2020	2020	10	2020	2020	0	00:00:02:03
bier127	118282	118498	1	119165	11843.5	0.474713	00:02:54:78
brazil58	25395	25395	10	25395	25395	0	00:00:16:28
burma14	3323	3323	10	3323	3323	0	00:00:00:29
ch130	6110	6110	1	6171	6143.1	0.541735	00:03:01:54
ch150	6528	6553	1	6609	6583.1	0.844056	00:06:30:38
dantzig42	699	699	10	699	699	0	00:00:05:82
eil51	426	426	7	427	426.3	0.070423	00:00:10:46
eil76	538	538	3	543	540.2	0.408922	00:00:32:41
eil101	629	630	1	642	636.9	1.25596	00:01:15:10
fri26	937	937	10	937	937	0	00:00:01:36
gil262	2378	2435	1	2446	2438.4	2.53995	00:26:56:00
gr17	2085	2085	10	2085	2085	0	00:00:00:55
gr21	2707	2707	10	2707	2707	0	00:00:00:88
gr24	1272	1272	10	1272	1272	0	00:00:01:45
gr48	5046	5046	10	5046	5046	0	00:00:09:18
gr96	55209	55209	1	55436	55334.3	0.226956	00:01:11:85
hk48	11461	11461	10	11461	11461	0	00:00:09:02
kroA100	21282	21282	10	21282	21282	0	00:01:22:15
kroB100	22141	22141	5	22211	22158.2	0.077684	00:01:19:68
kroC100	20749	20749	10	20749	20749	0	00:01:23:26
kroD100	21294	21294	3	21389	21338.4	0.208509	00:01:22:65
kroE100	22068	22068	3	22106	22084.6	0.075222	00:01:22:18
lin105	14379	14379	10	14379	14379	0	00:01:35:71
pr76	108159	108159	10	108159	108159	0	00:00:35:58
pr107	44303	44303	5	44347	44317.9	0.033632	00:01:35:66
rat99	1211	1215	1	1220	1217.8	0.561519	00:01:18:20
rd100	7910	7910	4	7914	7911.4	0.017699	00:01:21:62
st70	675	675	10	675	675	0	00:00:28:18
swiss42	1273	1273	10	1273	1273	0	00:00:06:93
ulysses16	6859	6859	10	6859	6859	0	00:00:00:73
ulysses22	7013	7013	10	7013	7013	0	00:00:01:45

After the evaluation of the adaptation on a set of instances of the problem, Table 4 compares its performance versus other existing algorithms such as Genetic Algorithm (GA), particle swarm optimization (PSO), Artificial Neural Network (ANN), the Ant Colony Optimization (ACO), Simulated Annealing (SA) and Chaotic Ant Swarm (CSA).

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Table 4. Calculation of the Average Results of Many Meta-Heuristiques Approches

Method	Eil51	Berlin52	St70	Eil76	KroA100
Optimal Solution	426	7542	675	538	21282
HS	**426.3**	**7542**	**675**	**540.2**	**21282**
GA (Kuo et al, 2010) [21]	438	7738	-	-	22141
GA (Soak et al, 2004) [22]	429	-	-	-	21445
PSO (Shi et al (2007) [23]	436.9	7832	697.5	560.4	-
PSO (Shi et al (2006) [24]	444.6	7960	733.2	587.4	-
ANN (Creput and Koukam, 2009) [25]	435.1	-	681.7	553.5	21524.6
ANN (Cochrane and Beasley, 2003) [26]	438	8070	-	561	21560
ANN (Somhom, 1997) [27]	440.5	8025	-	562.2	21616
ACO (Puris et al, 2007) [28]	-	7594	750	-	-
ACO (Tsai et al, 2004) [29]	430	-	-	552.6	21457
SA (Liu et al, 2009) [30]	432.5	7718.5	-	564	-
CAS (Wei, 2011) [31]	439	-	-	559	21552

6. CONCLUSION

We have implemented a matching harmony search algorithm to solve the problem of salesmen in order to find the best optimized path way. An empirical study has been done in order to determine the impact of the parameters of harmony search algorithm upon solutions' quality. The ability of the algorithm was demonstrated using multiple instances of the TSP problem, and it was concluded that the proposed adaptive algorithm is more effective in finding the best solutions, and also its performance compared to other optimization methods such as genetic algorithm and simulated annealing and ant. Thus, we believe that our adaptation will be adapted to solve other optimization because of its fast and reliable convergence.

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