Harmony Search Algorithm for Load Shedding Schedule Problem

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ABSTRACT

In Libya, from time to time, the National Electricity Grid is directed by the National Electricity Company to conduct load shedding to alleviate pressure on supply at times of peak demand. This involves hours’ of power outages in the area covered by this study, namely, the Southern Electrical Grid of Libya (SEGL). The proposed approach focuses on a set of region categories to mitigate the effects of the load shedding problem by considering the demand priorities on the operation of the power system during emergencies. The classification of these region categories is solved by using a relatively new algorithm, the harmony search (HS) algorithm, which is applied to a randomly generated list of electricity deficits and region categories to identify those regions that should not experience a power outage at times of peak load. The proposed approach is applied to 50 simulated cases and compared to actual SEGL cases. The obtained results show that the proposed algorithm has a high level of classification accuracy. This proves that the HS algorithm could generate optimal solutions that simulate real cases of load shedding.

Keywords: Optimization, Decision support system, harmony search algorithm, load shedding, classification.

I Introduction

The increase in the load on the Southern Electrical Grid of Libya (SEGL) leads to shortages during the summer peak period and at times there has been a very serious deficit in power distribution across the country. In recent years, with the longitudinal power system that is in place, a large amount of power has been transmitted from the northern grid to the southern grid because of the deficiency in electricity generation in the southern region. Furthermore, system disturbances caused by the outage of large generation units or the tripping of the electric grid transmission lines can result in severe system instability. To enhance the system reliability of the power system, an effective load shedding scheme has to be designed and implemented to maintain the stability of the power generation system (Koo et al. 2013).

Load shedding (Nakawiro & Erlich 2009; Razak et al. 2012; Bhat et al. 2013) is the only demand-side management program that has been used by the utility company to reduce the peak load of the power system when it is suffering from a shortage of capacity in southern Libya. Therefore the present study aims to make two main contributions to improve the current load shedding program by (1) identifying the more important region categories in each consumer area –at the moment these are manually set and applied in load shedding, so automating this process should lead to a significant reduction in the overlapping categorization of these regions and by (2) improving the calculation of the amount of load by modeling a combined load shedding program and maintenance scheduling problem of the distribution network.

Currently, the use of region categories (Yang and Lizi 2012) cannot always produce optimal regions that can be passed through the load shedding program. Therefore the solution to this problem requires that the southern region be divided into many more categories based on the degree of importance of maintaining the electricity supply to particular areas or entities, where each region category has its own factors that consist of a list of items (airport, houses, hospital, bank, etc.). There is also a sub-problem to address in that experts have assigned categories to several regions but these overlap, which leads to misusage of load shedding for some regions and to the load being given at incorrect times to other regions. Moreover, several overlapping regions do not apply the load shedding program because it is not clear which region should perform this function.

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In this paper, we address the load shedding problem by focusing on two factors: Region and electricity deficit amount, where we assume that the time period of load shedding is fixed by two hours. The powerful capability of the heuristic optimization method is applied to the load shedding problem. In order to handle the optimization, this approach applies the harmony search (HS) algorithm.

The HS algorithm is a music-inspired meta-heuristic algorithm. Geem et al. (2001) developed this new algorithm and applied HS to many real-world problems. The basic idea of HS is that it represents the optimization problem by imitating it as a musical performance process where it is important to search for a good harmony. Based on the meta-heuristic optimization algorithm, HS imitates the natural process of how a music composer or an orchestra conductor optimizes their resources, thus managing to produce music with good harmony. Just as music improvisation seeks a best state (fantastic harmony), which is determined by aesthetic estimation, the optimization process in HS seeks a best state (global optimum), which is determined by objective function evaluation. The HS algorithm has been successfully applied to various optimization problems such as scheduling and timetabling problems, engineering optimization, design of water distribution networks, groundwater modeling, energy-saving dispatch, truss design and vehicle routing, among others (Lee and Geem 2005; Al-Betar et al. 2010; Ahmed et al. 2011).

Geem et al. (2004) applied HS to a school bus routing problem, which is a multi-objective problem, and attempted to minimize both the number of operating buses and the total travel time of all buses while satisfying bus capacity and time window constraints. The work proved that HS gives a better solution than the genetic algorithm (GA). Geem and William (2007) applied HS to an ecological conservation problem for preserving species and their habitats. The HS tries to maximize the covering species, called the Maximal Covering Species Problem (MCSP). The HS was improved to solve the problem and the experiments showed that HS gives a better solution than other meta-heuristic algorithms such as simulated annealing (SA).

In (Degertekin 2008), a HS algorithm was applied to find the optimum design of steel frames. The benchmark examples presented in that study revealed that HS is able to obtain lighter frames when compared to GA and SA; HS yielded 1.2–5.0% lighter frames than the ones obtained by GA, ant colony optimization (ACO) and SA-based designs. In addition to obtaining lighter frames, HS required less than or approximately the same computational effort as GA, SA and ACO. The average weights of the frames in the examples were close to the optimum weights for HS. Standard deviations of the frames’ weights were also quite small in comparison with the frame weights. These findings prove that HS is able to find global optima and that it could be used as a powerful optimization technique for steel frame design using discrete and real design variables.

Despite the good results obtained for the abovementioned optimization problems, to date HS has yet to be applied to power load problems and specifically the load shedding problem. Since load shedding is critical in finding the optimal number of regions and thereby retaining the quality of load shedding distribution, HS has the potential to solve this problem. In fact, solving the load shedding problem will be of benefit to real-world electric load applications.

The rest of this paper is organized as follows: The description of the problem is discussed in section II. The proposed HS algorithm and constraint handling techniques are explained in section III. Simulation results are discussed in section IV and, finally, concluding remarks and suggestions for future work are given in section V.

II PROBLEM FORMULATION

Since the aim of this research is to handle the load shedding problem, it is important to minimize the error rate of the category classification in terms of identifying the more important loads by considering different load priorities. The problem is subject to operating constraints and the mathematical model can be expressed as follows:

Definition 1: $D=\{d_i \in D>P\}$, where $D$ is deficit in electricity and $D=$ power generation, $P$ is the power consumer and $P=$ the peak of the SEGL;

Definition 2: $R=\{r_1,r_2,r_3,\ldots, r_{m+1}, r_n\}$, where $r \in R$ is the region of the SEGL and $n$ is the number of regions;

Definition 3: $C=\{c_1,c_2,c_3,\ldots,c_{m_1},c_{m}\}$, where $c \in C$ is the region category and $m$ is the number of categories;

Definition 4: $I=\{i_1,i_2,i_3,\ldots,i_{k_1},i_x\}$, where $i \in I$ is the region items and $x$ is the number of items.
Figure 1 shows an example of the important regions with their class category. It shows the set of items indexed with regions and class labels.

Table 1 shows the list of items with their importance (points) and (time). The points are used to calculate the importance of each category by summing the number of points and sorting the categories based on the number of the points in each category, as shown in Eq. (1). The time is used to supply the load shedding time for each category in the SEGL.

$$F(x) = \sum_{i=0}^{i=10} \frac{i}{N}, i \equiv I = \{i_1, i_2, \ldots, i_N\}$$  \hspace{1cm} (1)

### III HS ALGORITHM

In this section, we explain our proposed HS algorithm. It is based on the basic HS algorithm with a multi-pitch adjusting rate as well as the following five steps: i) parameter initialization; ii) harmony memory initialization; iii) new harmony improvisation; iv) harmony memory update; and v) termination criterion check. These steps are explained below and the HS algorithm parameters are as follows: Harmony memory size (HMS) = the number of simultaneous solution vectors in the harmony memory (HM); HMCR = harmony memory consideration rate; PAR = pitch adjusting rate); and the number of improvisations means the number of fitness function evaluations.

#### Step 1: Parameter Initialization

In this first step, the optimization problem is specified using the one decision variable (D) which represents the electric deficit and $F(x)$ is the fitness function, and HMS represents the number of candidate solutions for each D as a variable value of the deficit in electricity. Figure 2 represents example of HMS.

In this study, there are 50 randomly selected candidate HMS values and each candidate represents a deficit ($d_i$) with a random region category, item and class of the region for the shedding load problem $D$, where $N$ is the number of decision variables, $k$ is the HMS and $d_i$ is the random solution. Here, HMCR=0.2 and PAR=0.9. The HM is shown in Eq. (2):

$$HM = \{d_i(1), d_i(2), d_i(3), \ldots, d_i(HMS)\}$$  \hspace{1cm} (2)

Here, HMS is the number of candidate values for the discrete decision variable and $d_i$ is the decision variables as in Eq. (2).
\[ F(X) = \{ f(x^1), f(x^2), f(x^3), \ldots, f(x^{\text{HMS}}) \}. \tag{3} \]

In Eq. 3, \( f(x^1), f(x^2), \ldots, f(x^{\text{HMS}}) \) shows each solution vector for the design variable and the corresponding fitness function value.

**Step 2: Harmony Memory Initialization**

In Step 2, the \( HM \) is crammed with as many randomly generated solution vectors as the size of the \( HM \) will allow. In HM initialization every harmony \( i \) randomly generates the solution vector \( d_i = \{ d_{i1}, d_{i2}, \ldots, d_{i\text{HMS}} \} \), where \( \{2 \leq i \leq n\} \) and \( \text{HMS} \) is the number of solutions in the \( HM \).

The random values generated range between 2MW up to 100MW for \( d_i \), while random items range between the values shown in Table 1, where the random values represent the real values of the items list, as shown in Table 1. The fitness function \( F(x) \) is calculated as described above in section II.

**Step 3: New Harmony Improvisation**

Basically, a new harmony vector, \( d' = (d'_1, d'_2, \ldots, d'_{\text{HMS}}) \) is improvised by following three rules: (i) random selection, (ii) \( \text{HMCR} \) consideration, and (iii) multi-pitch adjustment:

1. **Random selection**

When \( HS \) determines the value \( \hat{x}_d \) for the new harmony \( d' = (d'_1, d'_2, \ldots, d'_{\text{HMS}}) \), it randomly picks any two values from the total value range \( \{ d_1(1), \ldots, d_{\text{HMS}} \} \) with a probability of \( 1-\text{HMCR} \).

2. **HMCR consideration**

When \( HS \) determines the value \( \hat{x}_i \), it randomly picks any two values from \( HM = \{ d_1(1), \ldots, d_1(\text{HM}) \} \) with the probability \( \text{HMCR} \). The probability of \( \text{HMCR} \) can be calculated using the uniform distribution \( U(0,1) \) as follows:

\[ P_{\text{HMCR}} = \text{int}(U(0,1), \text{HMS}) + 1. \tag{4} \]

As the musician plays any pitch out of the preferred pitches in his/her memory (for example, \( k \) candidates is the number of random solutions \( d \) for decision variable \( HM = \{ k_1, k_2, k_3, \ldots, k_{\text{HMS}}, k_{\text{HMS}} \} \), the value of the decision variable \( d'_i \) is chosen from any number of pitches stored in the \( HM \) with the probability \( P_{\text{HMCR}} \) while it is randomly chosen, as shown in Eq. (4) above.

3. **Multi-pitch adjustment**

After the value of \( \hat{x}_i \) has been randomly picked from the \( HM \) in the above memory consideration process, it can be further adjusted into neighboring values by adding a certain amount to the value with the probability \( \text{PAR} \) as shown in Eq. (5):

\[ P_{\text{PAR}} = \text{int}(U(0,1), \text{HMS}) + 1. \tag{5} \]

For example, the value of \( k_i \) can be adjusted to \((k_i + m)\) with respect to \((1 < i < n)\), with a range of the items list, while the original pitch obtained in the \( HM \) consideration is maintained at the probability \( \text{PAR} \).

**Step 4: Harmony Memory Update**

If the new harmonies \( F(x_{\text{random1}}) \) and \( F(x_{\text{random2}}) \) are better than both the selected old harmonies \( F(x_1) \) and \( F(x_2) \) in the \( HM \), as judged by the fitness function value, the new harmony values are included in the \( HM \) and the existing worst old harmony values are excluded from the \( HM \).

**Step 5: Termination Criteria Check**

If the termination criterion (the number of improvisations) is reached, the computation is stopped. Otherwise, Steps 3 and 4 are repeated.
IV APPLICATION OF HS TO THE LOAD SHEDDING PROBLEM

Data from SEGL is used to test the effectiveness of the proposed algorithm. The test system used in this study has five previous categories of cases of actual load shedding in the SEGL and 50 simulated categories generated by the HS algorithm. The $k$-NN algorithm is invoked simultaneously in the HS process to classify the categorized data.

<table>
<thead>
<tr>
<th>Table 2: Simulated cases with HS algorithm.</th>
</tr>
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<tbody>
<tr>
<td>Previous cases</td>
</tr>
<tr>
<td>Load shedding case number of SEGL</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
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</tbody>
</table>

Table 2 shows the classification rate of the previous category cases and simulated cases. It can be seen that the proposed approach has a high classification rate in most cases. We can conclude from the table that the experiment generally succeeded in the production of good-quality simulated solutions. This means that the approach could be used in solving the load shedding problem and be applied to any new and unexpected peaks in the southern region. For example, the table shows that the amount of the deficit in SEGL case 3 is 70 MW and the solution produced by HS(case number 9) is close to that, with a classification accuracy of 0.93, which is a very high accuracy of classification. Another example of a high accuracy of classification by HS is that of SEGL case 1 and HS case 33, where the accuracy recorded as 0.87.

These results suggest that the proposed approach can succeed in producing good-quality random solutions and can be used to solve the load shedding problem. Moreover, the K-NN classification succeeded in improving the load shedding process significantly.

V CONCLUSION

In this paper, the HS algorithm was applied to generate 50 time-scheduling tables for the load shedding problem in the SEGL. Each table was generated with a number of categories and deficits. Then the $k$-NN classification algorithm was applied to evaluate the best random solutions in the HM. The obtained results shows that the generated cases are fit to be used in future load shedding schedule problem in the SEGL.

From our experiment, we can conclude that our proposed approach can obtain accurate solutions, and that it could be used to solve the problem of mitigating electrical loads and any unexpected load failure in the southern region of the electric grid in Libya. We can also say that the $k$-NN algorithm succeeded in significantly improving the classification process.

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