Parallel Harmony Search Based Distributed Energy Resource Optimization

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***Abstract*—This paper presents a harmony search based parallel optimization algorithm to minimize voltage deviations in three phase unbalanced electrical distribution systems and to maximize active power outputs of distributed energy resources (DR). The main contribution is to reduce the adverse impacts on voltage profile during a day as photovoltaics (PVs) output or electrical vehicles (EVs) charging changes throughout a day. The IEEE 123-bus distribution test system is modified by adding DRs and EVs under different load profiles. The simulation results show that by using parallel computing techniques, heuristic methods may be used as an alternative optimization tool in electrical power distribution systems operation.**

I. Introduction

With the rapid introduction of several new technologies, such as, plug-in hybrid vehicles and solar panels, power distribution system operation is becoming more complex, and efficient operation is becoming more critical. Distribution systems need to be operated within tight voltage limits. Traditionally, this is achieved the help of tap changing transformers and capacitors banks. However, the capacitor banks provide less voltage regulation capability at lower voltages [1], and providing capacitor banks that can vary with load is difficult and expensive. The number of switching operations of capacitors is generally limited to 2-3 times a day. The number of operations of traditional tap changing transformers is also a constraint, since frequent tap changes reduce the lifetime of the mechanical taps. The development of recent power electronic assisted on load tap changers does allow extended lifetimes [2].

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Loads in power distribution systems vary in a fairly predictable daily cycle. Daily peak values are generally faced at night times after people return from work and start to use household appliances. It has been observed that mean distance range of driving, today's EV technology presents is around 100 miles [3], hence EV's will need to be charged nearly everyday. Generally, the most suitable time for charging is either nighttime at home or early morning at work. If most of the EVs in the system will be charged at around the same time of day, this will adversely affect the system voltage profile. It has been observed that power losses and voltage deviations are very high when charging is performed during the evening peak 18h00, and 21h00 [4].

Similar to our previous studies [5], [6], this paper uses inverter based DRs, and tap changing transformers for voltage control in power distribution system. To simulate high loading conditions, a sample system composed of randomly varying electrical vehicles were added to all of the single phase buses of the IEEE 123-bus distribution test system. Also, a total of 13 DRs were added and their reactive power capabilities used for voltage control.

Since the loads or DR outputs in a power distribution system can now change rapidly, optimization of the voltage control problem should be solved as fast as possible. Numerical methods must be used for solving these kind of problems, however, these problems are non-convex and using derivative information may lead to convergence problems. One approach to finding solutions is to use population based derivative free methods. By mimicking the behaviours from processes in real life, such as, from genetics, these methods create an initial random solution vector in the feasible solution space, and by the help of operators, like mutation and crossover, candidate solutions to the problem get closer to optimal solutions as the number of iterations increase. Population based methods are amenable to parallel processing to speed up computations. With the introduction of multicore personal computers, accessing parallel programming sources is much easier compared to a decade ago. This study uses Matlab's parallel computing toolbox, and uses message passing functions to provide in solving a harmony search based method. The nature of harmony search [7] optimization algorithms are particularly suitable to parallel computing, since they are based on the perturbations to solution candidates in a population. Genetic algorithms have been successfully parallelized [8] as well and have been applied to several power systems problem such as optimal facts location detection problem [9], generation expansion planning [10], reliability evaluation of composite power systems problem [11]. Still, there are relatively few parallel harmony search applications in the literature (see [12] for a scheduling application).

The paper is organized as follows. The next section briefly discusses the model of the optimization problem. Section III explains the solution algorithm and details the parallel programming approach. The approach is then illustrated one the modified IEEE 123-bus distribution test system and reports on speedups by running the program using a different number of processors.

II. Optimization Problem and Modeling

Electrical power distribution systems operation generally requires all the bus voltage magnitudes to be between 0.95 pu and 1.05 pu. This paper takes advantage of DR's reactive power capabilities and changes the tap positions of the voltage regulators and on load tap changers. The objective function aims to maximize active power output of the DRs and minimize the voltage deviations from 1.0 pu. Constraints in the objective function are the reactive power injection/absorption, and tap positions of the regulators. Loads are assumed to be constant for a given hour, and the optimization problem is solved for that specific hour of the day. Note that the current state of charge of EVs are not considered in this model. A detailed mathematical representation of the optimization problem for voltage control problem is given below:

$$\begin{aligned} \underset{X}{\text{minimize}} \quad & \sum_{i=1}^{N_{P_{DR_i}}} -P_{DR_i} + \sum_{i=1}^{N} ||V_i - 1|| \\ \text{subject to} \quad & 0.95 \leq V_i \leq 1.05 \\ & {P_{DR_i}}^2 + {Q_{DR_i}}^2 \leq {S_{DR_i}}^2 \\ & T_{min} \leq T_i \leq T_{max} \end{aligned}$$

In the above optimization expression P_{DR} and Q_{DR} represent the active power and reactive power output of the inverter based DR respectively and S_{DR} is the apparent power. V_i is the voltage magnitude of the i^{th} bus in the system. T_{min}, T_i and T_{max} represent the minimum possible tap position, actual tap position and maximum possible tap position of the regulator, respectively.

A. Daily Load Profiles

An artificially created, 24 hour daily load profile for all the buses in the system is given in Figure 1. In the simulations, it is assumed that single phase buses in the power distribution system includes EVs and charging occurs in residential areas, hence most of the EVs will be charged afterwork hours. There will be some amount of unused EVs, remaining time of days. By taking these points into consideration, a hourly percentage of EVs on a single phase bus is given in Figure 2. On each single phase bus, this curve varies by a random perturbations (a deviation of 0.05 is used). For simulating purposes, it is assumed none of the available cars are fully charged at a specific hour and all available EVs at a specific hour are charging.

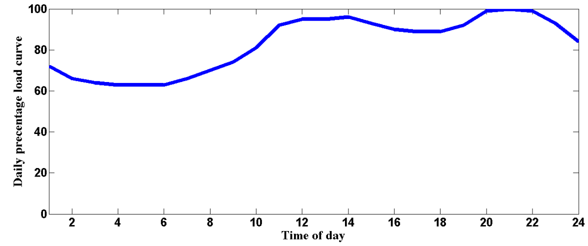

Fig. 1. Daily load curve percentage for all buses in the system

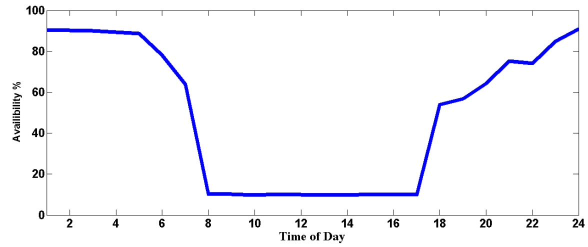

Fig. 2. Daily EV availibility curve

III. Harmony Search Algorithm for Voltage Control

The harmony search algorithm for the optimization above can be summarized as follows:

Choose a harmony memory size (HMS), harmony memory consideration rate (HMCR), and a pitch adjusting rate (PAR). Then create initial solution candidates, form a matrix HM and compute the objective function values as shown in Figure (3). Note that to obtain the objective function values, the open source simulation software OpenDSS [13], [14] is used.

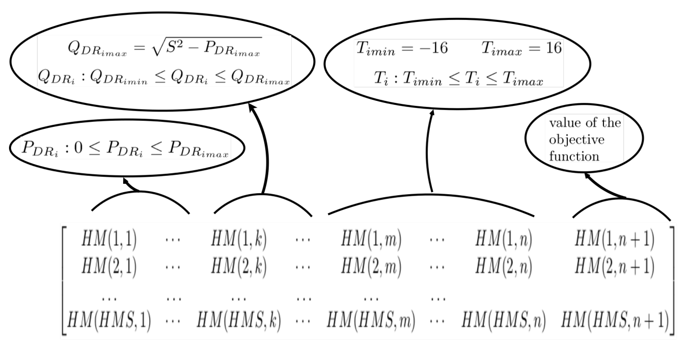

Fig. 3. Initialization process of the harmony memory

Next a new solution candidate vector is created by performing these algorithmic operations: Algorithm 1.

The value of objective function of the new solution candidate vector is computed. To determine whether this new candidate solution vector will be in the solution candidate matrix, the value of the objective function of the new solution candidate vector is compared with the worst objective function of the solution candidate matrix. If it is smaller, then the corresponding row of the solution candidate matrix is replaced with the new solution candidate vector. If it is larger, then the candidate is discarded. This process continues until a predefined stopping criterion is met.

Create a random number R_1
if $R_1 <$ *HMCR* **then**
  Generate a random solution candidate vector
else
  for *each column in HM* **do**
    Randomly pick an element
    Create a random number R_2
    if $R_2 <$ *PAR* **then**
      $HM(i,j) = HM(i,j) \mp$
      $$\begin{cases} \text{for} \quad P_{DR}, & P_{DR_i max} \times 0.01 \\ \text{for} \quad Q_{DR}, & Q_{DR_i max} \times 0.01 \\ \text{for} \quad T, & 1 \end{cases}$$
    end
  end
end
end

Algorithm 1: New solution candidate vector

A. Parallel Harmony Search Algorithm

Since genetic algorithms were among the first population based derivative free algorithms, they not surprisingly were among the firstly parallelized. Four different approaches have been used to parallelize them. These approaches are: a single population master slave, multi population, fine-grained and hierarchical hybrids [8]. These same ideas may also be applied to most of the other population based derivative free algorithms. Of these four, the multiple population based approach is typically the most efficient one and what is adopted here. A brief explanation of this approach is as follows: the harmony search optimization module is run on each available processor with the best solution candidates are sent to the neighbouring processor every N iterations. The processors also send their best results to the first processor in every M iterations. This process is depicted in Figure 4. The harmony search optimization module running on each processor consists of sub-populations whose number of elements is HMS divided by the number of processors. Note the the number of elements in the sub-population is rounded to the closest integer. Then best of these results is broadcast to all of the processors, so all of the running algorithms can modify their results every M and N iterations. The rate of N, called the migration rate, together with M, determines the speed of convergence.

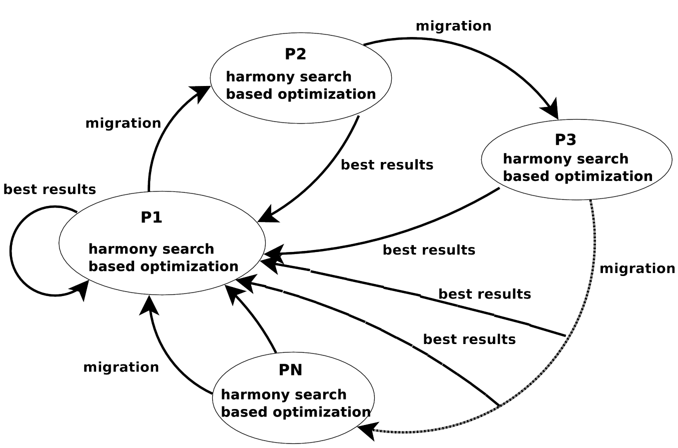

Fig. 4. Parallel Harmony Search

IV. Tests and Results

The IEEE 123-bus distribution system [15], single line diagram of which is given in Fig. 5, was used in the simulations. The following modifications were made to the original IEEE 123 Bus Distribution Test System. All together 13 DRs were added to the buses, with the given location, phase, apparent power, maximum and minimum active power, and maximum and minimum reactive power output information in Table I. The locations of the DRs are same as those of [16], however apparent power magnitudes are modified. There are totally 7 regulators in the system and they located at buses 150 (phase A), 9 (phase A), 25 (phase A,C), 160 (3 phase).

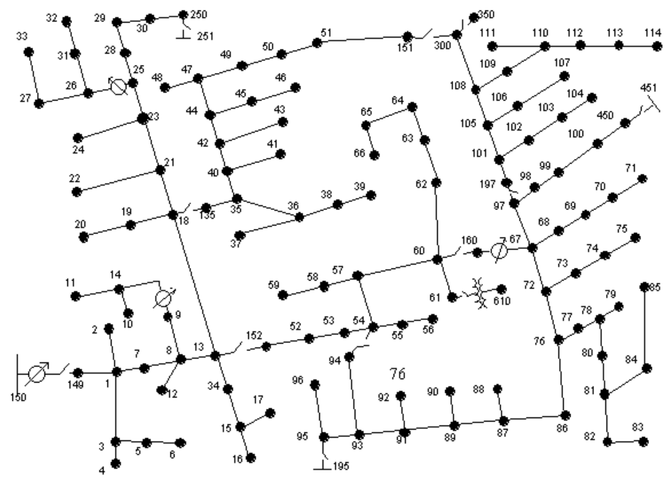

Fig. 5. IEEE 123 Test System

TABLE I. DRs added to IEEE 123 Bus Distribution Test System

Bus No	# of phases	S_{max} (MVA)	A. Power Output (max./min.) (kW)	R. Power Output (max./min.) (kVAr)
14	1	300	150/0	259.81/-259.81
27	1	300	150/0	259.81/-259.81
39	1	150	75/0	129.90/-129.90
49	3	600	300/0	519.61/-519.61
66	1	300	150/0	259.81/-259.81
75	1	120	60/0	103.92/-103.92
85	1	120	60/0	103.92/-103.92
86	3	1500	750/0	1299.00/-1299.00
107	1	120	60/0	103.92/-103.92

It is assumed in the simulations that each single phase load has EV charging capability and at each single phase bus the number available of EVs for charging are $\frac{P_{\text{load}_i}}{4}$. Also, the test system is assumed to include 4 EV charging stations, locations of which are buses 22, 42, 88, and 102, each with a capacity of maximum 500 EVs. All the EVs in the system are assumed to require 3.3 kW for charging 1 hour and the total time needed for them to be charged to reach a full state of charge (SOC) is 6 hours. Note that in the simulations, since the main aim of the paper is to show the efficiency of the parallel programming, the main consideration is the number available cars at a specific time for charging. Hence, their SOC status was not investigated.

The algorithm was run on a computer with 16 GB RAM, 2.27 GHz, 2 Intel Xeon CPU processors each composed of 6 cores. Matlab's parallel computing toolbox [17], which allows message passing type of communications, was used in the simulations. The message passing functions: labSend, labReceive and labBroadcast were used for point to point communication purposes. In the simulations, the parameters of harmony search algorithm are selected as follows: $HMCR = 0.9$, $PAR = 0.3$ and HMS was chosen as the total number of elements in all sub-populations.

Two test cases are simulated:

- Case 1 simulated the charging, and voltage regulation at 8 am, where the penetration level of EVs were not high (from daily availability curve it may be seen that the available EVs for charging are approximately 15% of all EVs.)
- Case 2 simulated the charging and voltage regulation at 10 pm, where the penetration level of EVs was high (from daily availability curve it may be seen that the available EVs for charging are approximately 85% of all EVs.)

Both in Case 1 and Case 2, initial voltage profiles of the buses were found when all DRs active and reactive power outputs, and tap positions of the regulators were set to nominal value. This is illustrated for 8 am in Figure 6, and for 10 pm in Figure 7 and all phase voltage profiles with respect to the physical locations of buses in the test system are shown. Note that in these figures and following all figures, blue represents the distribution system network, green represents bus voltage magnitudes that are in between 0.95 and 1.05 pu, and red represents the bus voltage magnitudes that are out of that range. As can be seen in the figures, the loading conditions at 10 pm are heavier compared to the conditions at 8 am and as a result more bus voltage magnitudes at 10 pm fall outside of the desired range.

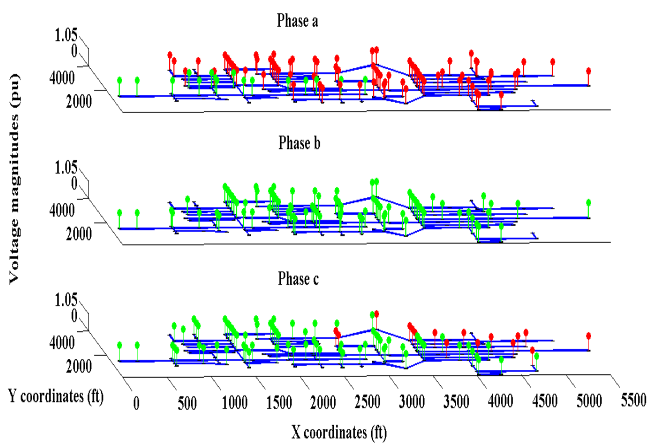

Fig. 6. Phases a, b, c, voltage profiles versus physical locations graph at 8 am (No DR output, all taps set to nominal)

After performing optimization for Case 1 and Case 2, the obtained bus voltage magnitudes are shown in Figure 8 and Figure 9, respectively. As can be seen from the figures, the post optimization bus voltage magnitudes are in the secure operation range for both Case 1 and Case 2.

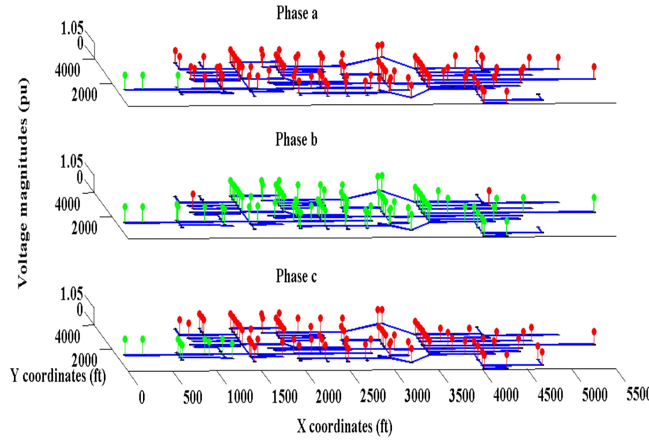

Fig. 7. Phases a, b, c, voltage profiles versus physical locations graph at 10 pm (No DR output, all taps set to nominal)

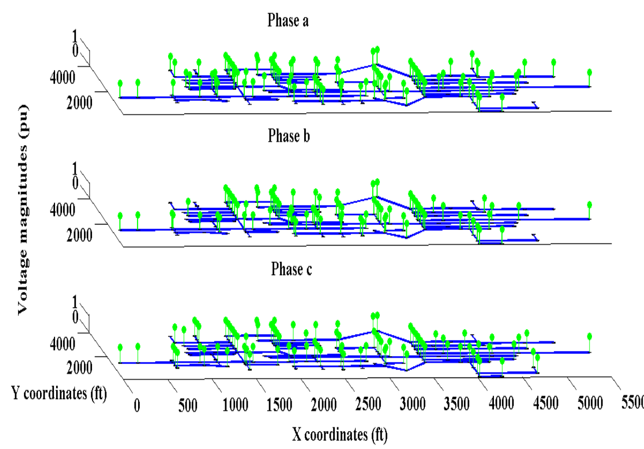

Fig. 8. Phases a, b, c, voltage profiles versus physical locations graph at 8 am (post optimization bus voltage magnitudes)

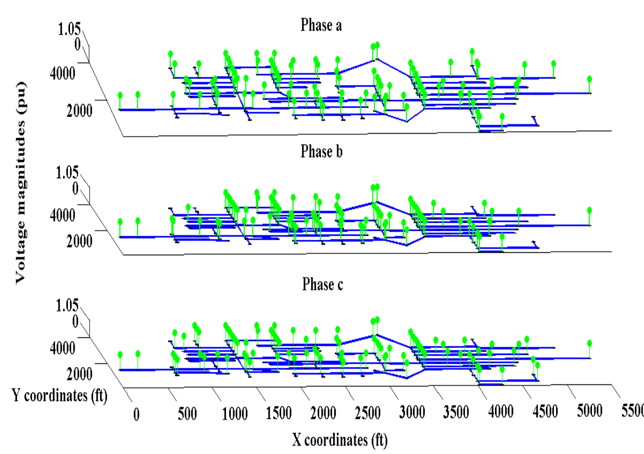

Fig. 9. Phases a, b, c, voltage profiles versus physical locations graph at 10 pm (post optimization bus voltage magnitudes)

Minimum and maximum bus voltage magnitudes of all phases, mean value of bus voltage magnitudes of all phases, and their standard deviations for post optimization values at 8 am and 10 pm are given in Table II.

TABLE II. IEEE 123 BUS DISTRIBUTION TEST SYSTEM, BUS VOLTAGE MAGNITUDES

Phase	Min	Max	Mean	Std. Dev.	Time
A	0.9636	1.0387	0.9997	0.0204	10 pm
B	0.9626	1.0375	0.9997	0.0113	10 pm
C	0.9675	1.0375	1.0016	0.0119	10 pm
A	0.9876	1.0131	1.0002	0.0070	8 am
B	0.9905	1.0125	0.9979	0.0038	8 am
C	0.9846	1.0130	0.9966	0.0072	8 am

Active power outputs of the DRs and Tap positions are given in Tables III and IV for 8 am and 10 pm, respectively.

TABLE III. POST-OPTIMIZATION DR OUTPUTS

Bus No/ Phase	A. Power Output (kW) 8 am	R. Power Output (kVAr) 8 am	A. Power Output (kW) 10 pm	R. Power Output (kVAr) 10 pm
14/A	147.83	-195.51	149.38	248.60
27/A	147.98	194.04	149.16	218.01
39/B	73.94	7.39	73.66	-93.80
49/A	299.44	148.27	296.12	506.31
49/B	298.75	-81.91	299.14	-373.52
49/C	298.09	-24.38	298.89	98.23
66/C	149.39	-7.26	147.85	197.11
75/C	59.59	27.75	59.81	16.40
85/C	58.25	59.27	58.48	-58.61
86/A	747.55	-52.68	749.85	1075.77
86/B	748.70	-254.19	749.80	-102.71
86/C	748.80	-141.91	748.89	858.73
107/B	59.60	-19.03	59.55	87.17

TABLE IV. POST-OPTIMIZATION TAP POSITIONS

Tap No/ Phase	Tap position 8 am	Tap position 10 pm
150/A	2	6
9/A	0	-3
25/A	1	1
25/C	4	-2
160/A	2	-8
160/B	0	0
160/C	0	3

Figure 10 shows the relative speedup of the solution times with respect to the number of processing units for Case 1 and Case 2. Note that these values are obtained when N is set 100, and M is set to 500. Speedup is found by using the following formula:

$$\text{Relative speedup (n,p)} = \frac{\text{Solution time with 1 processor}}{\text{Solution time with p processors}} \tag{1}$$

The optimization problem is solved by using a single processor in 3813 seconds for Case 1, and 4022 seconds for Case 2. The fastest solution times was obtained in 640 seconds by using 4 processors for Case 1 and 978 seconds by using 5 processors for Case 2. From the figure, it is seen that speed increase almost linearly up to 4 processors for Case 1 and up to 5 processors for Case 2, and then either they decrease or level off. This behaviour is mainly because of the communication overhead between the processors. One other point to be discussed is the super-linear behaviour of Case 1 going from 3 to 4 processors. Parallel algorithms are not expected to exceed linear speedup line shown in the figure generally due to Amdahl's Law [18]. However, due to the nature of the evolutionary algorithms super-linear speedups may at times be obtained. The reasons for this behavior can stem from implementation, numerical artefact or physical system characteristics [19]. The nature of the evolutionary algorithms are based on population based searches over a search space. Since the population is split in sub-populations, the parallel algorithm may find the solution faster while searching a larger search space, with more physical resources, and this may lead to super-linear speedups.

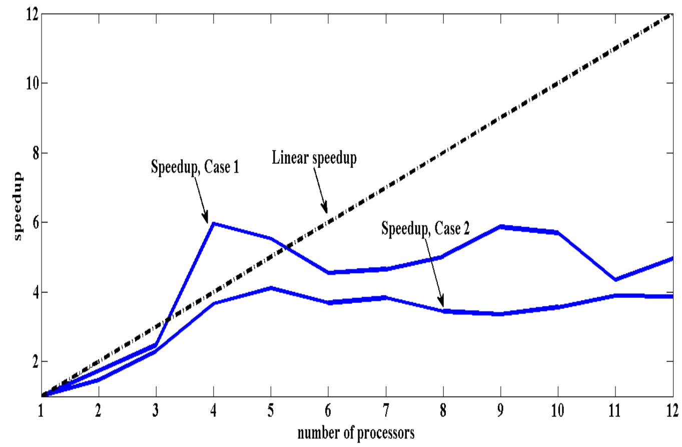

Fig. 10. Speedup graphic

V. CONCLUSION

The voltage deviation minimization problem is solved together with maximizing DR active power output by analyzing two cases in an unbalanced electrical distribution system. A Harmony search algorithm is used and faster solutions were obtained by implementing parallel computation. The IEEE 123-bus distribution test system was modified to for these two test cases: a) a lightly loaded system with a low level of EV charging at 8 am. b) a heavier loaded system with a higher level EV charging at 10 pm. Simulation results show that harmony search based parallel computing approach was successful in finding near optimal solutions, and parallelization improved computation time by a factor of 5.96 for Case 1 and 4.11 for Case 2. With the development of multicore computers, application of parallel programming techniques is becoming much easier, and the disadvantage of longer computation times of population methods may be overcome by using this type of algorithm. The authors think that with more computational sources even better speedups may be obtained and these type of parallel algorithms may be attractive in the near future.

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