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Modified Harmony Search Algorithm Based Unit Commitment with Plug-in Hybrid Electric Vehicles

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ABSTRACT

Plug-in Hybrid Electric Vehicles (PHEV) technology shows great interest in the recent scientific literatures. Vehicle-to-grid (V2G) is a interconnection of energy storage of PHEVs and grid. By implementation of V2G dependencies of the power system on small expensive conventional units can be reduced, resulting in reduced operational cost. This paper represents an intelligent unit commitment (UC) with V2G optimization based on Modified Harmony Search Algorithm (MHSA). MHSA was conceptualized using the musical process of searching for a perfect state of harmony, just as the optimization process seeks to find a global solution that is determined by an objective function. Intelligent UC with V2G optimization in power system is presented in this paper. Since the number of PHEV in V2G is relatively high, UC with V2G optimization problem is more complex than the basic UC.

A case study based on conventional 10-unit test system is conducted to facilitate the effectiveness of the proposed method. Results show a significant amount of cost reduction with integration of V2G in UC problem. Comparison of the results with those obtained by Particle Swarm Optimization shows the effectiveness of the proposed method.

KEYWORDS: Unit Commitment (UC), Vehicle-to-Grid (V2G), Improved Harmony Search Algorithm, Plug-in Hybrid Electric Vehicle (PHEV).

1. INTRODUCTION

The power and energy industry in terms of economic importance is one of the most important sectors in the world since nearly every aspect of industrial productivity and daily life are dependent on electricity [1].

Unit commitment (UC) and generation scheduling problem involves on/off status as an integer programming and generators production levels as a nonlinear programming for use in meeting the forecasted demand for a given time horizon [2] -[3]. The optimal schedule should minimize the system production costs during the study time horizon while satisfying power system constraints including load demand, spinning reserve requirements, and the physical as well as operational constraints of each individual unit [2], [4].

Being a large scale, non-convex and mixed-integer non-linear combinatorial optimization problem, several solutions techniques have been proposed in literature to Solve UC optimization problem. Exactly optimal solution can be achieved by exhaustive enumeration but it is very time consuming, while priority list which results fast solution that sometimes lead to a non-optimal outcome [5]. Dynamic programming (DP) and Mixed Integer Programming (MIP) are other techniques for unit commitment problem that needs more computational costs [6] -[7]. Lagrangian relaxation (LR) methods [8] -[9] focus on finding an appropriate co-ordination technique for generating feasible primal solutions, while minimizing the duality gap. The main drawback of the LR method is the difficulty encountered in obtaining feasible solutions.

Being a very complicated optimization problem, different heuristic optimization algorithms have been applied to solve UC problem. Different heuristic techniques have been addressed in the literature, like Genetic Algorithm (GA) [10] -[11], Ant Colony (AC) [12], Tabu Search (TS) [13], Particle Swarm Optimization (PSO) [14] as well as Simulated Annealing (SA) [15]. To achieve more improvement to the existing unit commitment solution techniques the hybrid models such as fuzzy dynamic programming [16], genetic-based artificial neural network [17], hybridization of Lagrangian relaxation and genetic algorithm (LRGA) [18], and simulated annealing genetic algorithm (SAGA) [2] are proposed.

The main focuses of Vehicle-to-Grid (V2G) researchers have been on interconnection of energy storage of vehicles and grid [19]-[21]. The economic benefits of V2G integration into the market has been considered in these studies. However, success of V2G technology greatly depends on the efficient scheduling of PHEVs in the restricted parking lots [1].

An intelligent scheduling of V2Gs and conventional generating units can reduce operation cost of the power system and increase the reliability as well as security.

Geem et al. in [22] developed a harmony search algorithm (HSA) as a meta-heuristic approach that was conceptualized using the musical process of searching for a perfect state of harmony. Compared to the earlier meta-heuristic optimization algorithms, HSA imposes fewer mathematical requirements that can be easily adopted for various types of engineering optimization problems [23]. Recently different application of HSA has been addressed in the literature that demonstrate the potential of HSA in solving complex power system problems [24-26]. An improved harmony search algorithm (IHSA) was proposed in [27] to improve the performance and accuracy of the traditional HSA.

In this paper, unit commitment with vehicle-to-grid (UC–V2G) that was addressed in [1] is optimized with IHSA where UC–V2G involves intelligently scheduling conventional units and large number of PHEVs. It reduces operation cost of the power system effectively. In addition to fulfilling a large number of practical constraints, the optimal UC–V2G should meet the forecast load demand calculated in advance, parking lot limitations, state of charge of gridable vehicles, charging–discharging efficiency, spinning reserve requirements, etc. at every time interval such that the total operation cost and emission are minimal [1].

The optimization of UC–V2G is a combinatorial optimization problem with both binary and continuous variables. The number of combinations of generating units and gridable vehicles grows exponentially in UC–V2G problems. UC–V2G optimization problem is more complex than typical UC of conventional generating units, as number of variables in UC–V2G is much higher than typical UC problems, and both cost and emission are minimized in the objective function of UC–V2G [1].

The proposed IHSA based solution approach minimizes the operation cost of the power system for UC-V2G. Moreover, spinning reserve and reliability of power systems are enhanced. The IHSA is applied to a widely used 10-unit test system. Comparing the simulation results from this study with those obtained by PSO reported in [1] reveals that the HSA is a more effective technique from the operation costs aspects.

This paper is organized as follows: Section II provides the mathematical formulation of the UC-V2G problem. Section III presents the proposed optimization technique and its application to solve UC problem. Section IV conducts the numerical simulations and presents a comparison with PSO. Finally, concluding remarks are discussed in section V.

2. PROBLEM FORMULATION

Unit commitment involves determining generating outputs of all units from an initial hour to satisfy load demands associated with a start-up and shut-down schedule over a time horizon. The objective function is to find the optimal schedule such that the total operating costs can be minimized while satisfying the load demand, spinning reserve requirements as well as other operational constraint [25].

Objective Function

Usually large cheap conventional units are used to satisfy base load demand of a power system. Most of the time, large units are therefore on however they have slower ramp rates. On the other hand, small units have relatively faster ramp rates. Besides, each unit has different cost characteristics that depend on the amount of power generation, fuel type, generator unit size, technology and so on. In UC-V2G problems, the main challenge is to schedule small expensive units to minimize cost, and to improve system reserve and reliability. PHEVs of V2G technology will reduce dependence on small/micro expensive units. But the number of PHEVs in V2G are much higher than small/micro units. Therefore profit, spinning reserve, reliability of power systems varies on scheduling optimization quality [1].

UC-V2G is a complex, large-scale optimization problem. The objective of the UC-V2G optimization problem is to minimize total operation cost, where the cost includes mainly fuel cost, start-up cost and shutdown cost.

Fuel Cost

The objective function of the conventional UC problem is a function that comprises the fuel costs of generating units, the start-up costs and shut-down costs of the committed units. The objective function in common form is formulated as:

$$Min\sum_{i-1}^{N}\sum_{t-1}^{T}[F_i(P_i^t)u_i^t + SUC_i u_i^t(1-u_i^{t-1})] \tag{1}$$

Where $F_i(P_i^t)$ is the cost function of the ith unit with generation output, P_i^t, at the tth hour. Usually it is a quadratic polynomial as follows:

$$F_i(P_i^t) = a_i + b_i \times P_i^t + c_i \times (P_i^t)^2 \tag{2}$$

Where: ai, bi and ci are fuel cost coefficients. u_i^t is the on/off status of unit i at tth time interval, $u_i^t = 0$ if unit i is off, $u_i^t = 1$ if it is on at t, N is the total number of power generating units to be committed and

T is the time period (usually the number of hours ranging from 24 to 168 hours).

Start-up Cost

The start-up cost for restarting a decommitted thermal unit, which is related to the temperature of the boiler, is considered in the optimization model. The start-up cost is defined as follows:

$$SUC_{i,t} = \begin{cases} HSC_i, & if\ T_i^D \le MD_i^{ON} \le T_i^D + CST_i \\ CSC_i, & if\ MD_i^{ON} > T_i^D + CST_i \end{cases}$$
$$1 \le t \le T \qquad i \in N \tag{3}$$

Where HSC_i and CSC_i are hot and cold start-up cost of ith unit respectively. T_i^D is the minimum down time of unit i, CST_i is a cold start time of the unit i and MD_i^{ON} is the number of hours that ith unit has been on-line since it was turned on earlier.

Shut-down cost.

Shut-down cost is constant and the typical value is zero in standard systems.

Constraints of UC-V2G

The optimization problem is subjected to a number of system and unit constraints such as: power balance, spinning reserve capacity of generating units, unit ramp-up rate and unit ramp-down rate constraints, minimum up/down time limit as well as spinning reserve requirement. Initial condition also needed to be considered in scheduling problem.

V2G Constraints

PHEVs balance in UC-V2G.

Only predefined registered/forecasted PHEVs are considered for the optimum scheduling in UC-V2G. Total number of registered PHEVs is assumed fixed and it is considered that they are charged from renewable sources. All the vehicles discharge to the grid during a predefined scheduling period (24 h) [1].

$$\sum_{t=1}^{T} N_{V2G}(t) = N_{V2G}^{Max} \tag{4}$$

Charging-Discharging Frequency

PHEVs are charged from renewable sources and discharge to the grid. Multiple charging–discharging facilities of gridable vehicles may be considered. It should vary depending on life time and type of batteries. For simplicity, charging–discharging frequency is one per day in this study [1].

State of Charge

Each vehicle should have a desired departure state of charge level [1].

Number of discharging vehicles limit

All the vehicles cannot discharge at the same time. For reliable operation and control, limited number of vehicles will discharge at a time. This constraint also applies for power transfer, current limit.

$$N_{V2G}(t) \le N_{V2G}^{Max}(t) \tag{5}$$

Efficiency

Charging and inverter efficiencies (ξ) should be considered.

System constraints

Initial Conditions

The initial conditions of generating units include the number of hours that a unit sequence has been on-line or off-line at an hour before the scheduling will be started.

Power balance constraints

Power supplied from committed units and selected PHEVs (some percentage of total vehicles) must satisfy the load demand and the system losses, which is defined by Eq. (6):

$$\sum_{i=1}^{N} P_i(t) u_i(t) + P_v N_{V2G}(t) = D(t) + Losses$$
$$1 \le t \le T \qquad i \in N \tag{6}$$

Where, $D(t)$ is the MW load demand at time t and P_v is capacity of each vehicle.

Spinning reserve requirement

Spinning reserve requirement (SRR) is usually a pre-specified amount or equal to the largest unit or a given percentage of the forecasted load demand. Spinning reserve of committed units is the total amount of real power generation available from all synchronized units minus the present load plus the losses. It must be sufficient enough to maintain the desired reliability of a power system. Spinning reserve constraint is given by Eq. (7) [25].

$$\sum_{i=1}^{N} P_i^{Max}(t)u_i(t) + P_v^{Max} N_{V2G}(t) = D(t) + SRR(t)$$
$$1 \le t \le T \qquad i \in N \qquad (7)$$

Where: $SRR(t)$ is the SRR at time t (MW).

Unit constraints

Unit output limits

$$P_i^{\min} u_i^t \le P_i^t u_i^t \le P_i^{\max} u_i^t$$
$$1 \le t \le T \qquad i \in N \qquad (8)$$

Minimum up time limit

Minimum number of hours that a unit must be on-line since it has been turned on beforehand.

$$MD_i^{ON} \ge T_i^U \quad i \in N \qquad (9)$$

Where T_i^U is the minimum up time of unit i.

Minimum down time limit

Minimum number of hours that a unit must be off-line since it has been turned on.

$$MD_i^{OFF} \ge T_i^D \quad i \in N \qquad (10)$$

Where: and MD_i^{OFF} is the number of hours that ith unit is off-line since it has been turned off.

Ramp rate limits

Minimum and maximum generating limits that bound the generating output of each unit in a particular hour can be varied within the range of unit power outputs due to unit ramp rate constraint.

$$P_i^t - P_i^{t-1} \le RUR_i \qquad 1 \le t \le T \qquad i \in N \qquad (11)$$

$$P_i^{t-1} - P_i^t \le RDR_i \qquad 1 \le t \le T \qquad i \in N \qquad (12)$$

Where: RUR_i and RDR_i are ramp-up rate limit and ramp-down rate limit of unit i, respectively.

Prohibited operating zones

Each generator has its generation limit which cannot be exceeded at any time. Moreover, a typical thermal unit may have a certain limitation of steam valve operation, or a vibration in a shaft bearing, which may result in interference and discrete input–output performance-curve sections, called prohibited zones.

Therefore, in practical operation, adjusting the generation output of a unit must avoid all capacity limits and unit operations in prohibited zones. The feasible operating zones of a unit can be described as follows:

$$\begin{cases} \underline{P}_i \le P_i \le P_{i,1}^{Lower} \\ P_{i,j-1}^{Upper} \le P_i \le P_{i,j}^{Lower} \\ P_{i,PZ_i}^{Upper} \le P_i \le \overline{P}_i \end{cases} \quad , \ j = 2,\ldots,PZ_z \qquad (13)$$

3. MODIFIED HARMONY SEARCH ALGORITHM

A. Harmony Search Algorithm

The harmony search algorithm was derived by adopting the idea that the existing meta-heuristic algorithms are found in the paradigm of natural phenomena. The algorithm was recently developed in an analogy with music improvisation process where music players improvise the pitches of their instruments to obtain better harmony [22]. The pitch of each musical instrument determines the aesthetic quality, just as the objective function value is determined by the set of values assigned to each decision variable [23].

Traditional HAS Steps of optimization procedure of traditional HSA are as follows [22], [25]:

Step 1. Initialize the optimization problem and algorithm parameters.

Step 2. Initialize the harmony memory (HM).

Step 3. Improvise a new harmony from the HM.

Step 4. Update the HM.

Step 5. Repeat steps 3 and 4 until the termination criterion is satisfied.

Initialization of the Optimization Problem and Algorithm Parameters

In this step the optimization problem is specified as follows:

Minimize $f(x)$

Subject to $x_i \in X_i$, i= 1, 2, . . . , N

where $f(x)$ is the objective function; x is a candidate solution consisting of N decision variables (x_i); X_i is the set of possible range of values for each decision variable, that is, ${}_L x_i \le X_i \le {}_U x_i$ for continuous decision variables where ${}_L x_i$ and ${}_U x_i$ are the lower and upper bounds for each decision variable, respectively; and N is the number of decision variables. In addition, HS algorithm parameters that are required to solve the desired optimization problem are specified in this step. These parameters are the harmony memory size (HMS) or the number of solution vectors, harmony memory considering rate (HMCR), pitch adjusting rate (PAR), and termination criterion (maximum number of searches). HMCR and PAR are parameters that are used to improve the solution vector; both are defined in step 3.

Initialization of the Harmony Memory

In this step, the harmony memory (HM) matrix, shown in Eq. (14), is filled with as many randomly generated solution vectors as HMS and sorted by the values of the objective function, $f(x)$.

$$\text{HM}=\begin{bmatrix} x^1 \\ x^2 \\ . \\ . \\ x^{HMS} \end{bmatrix} \tag{14}$$

Improvising New Harmony from the Harmony Memory

A new harmony vector, $x' = (x'_1, x'_2, ..., x'_N)$, is generated from the HM based on memory considerations, pitch adjustments, and randomization. For instance, the value of the first decision variable (x'_1) for the new vector can be chosen from any value in the specified HM range $(x_1^1 \square x_1^{HMS})$. Values of the other decision variables (x'_i) can be chosen in the same manner. There is a possibility that the new value can be chosen using the HMCR parameter, which varies between 0 and 1 as follows:

$$x'_i \leftarrow \begin{cases} x'_i \in \{x_i^1, x_i^2, ..., x_i^{HMS}\} & \textit{with probability HMCR} \\ x'_i \in X_i & \textit{with probability (1-HMCR)} \end{cases}$$

The HMCR sets the rate of choosing one value from the historic values stored in the HM, and (1-HMCR) sets the rate of randomly choosing one feasible value not limited to those stored in the HM. For example, a HMCR of 0.9 indicates that the HS algorithm will choose the decision variable value from historically stored values in the HM with the 90% probability or from the entire possible range with the 10% probability. Each component of the new harmony vector, $x' = (x'_1, x'_2, ..., x'_N)$, is examined to determine whether it should be pitch-adjusted. This procedure uses the PAR parameter that sets the rate of adjustment for the pitch chosen from the HM as follows:

$$\text{Pitch adjusting decision for } x_i' \leftarrow \begin{cases} \textit{Yes with probability PAR} \\ \textit{No with probability (1-PAR)} \end{cases}$$

A PAR of 0.3 indicates that the algorithm will choose a neighboring value with 30% × HMCR probability. If the pitch adjustment decision for x_i' is Yes, the pitch-adjusted value of x_i' will be $x_i'+\alpha$ where α is the value of bw × u(−1,1), bw is an arbitrary distance bandwidth for the continuous design variable, and u is a uniform distribution between −1 and 1.

Updating the Harmony Memory

In this stage, if the new harmony vector is better than the worst harmony vector in the HM in terms of the objective function value, the existing worst harmony is replaced by the new harmony. The HM is then sorted by the objective function value.

Termination Criterion

The computations are terminated when the termination criterion (maximum number of improvisations) is satisfied. Otherwise, steps 3 (improvising new harmony from the HM) and 4 (updating the HM) are repeated.

Improved Harmony Search Algorithm

The traditional HSA uses fixed values for both PAR and bw in which these values can only be adjusted at the initialization step (Step 1) and cannot be changed during new generations. The main drawback of this algorithm is that it needs much iteration to find an optimal solution. An improved Harmony Search Algorithm (IHSA) is then developed by Mahdavi et al. [28]. The IHSA has been successfully applied to various benchmarking and standard engineering optimization problems. Numerical results reveal that the IHSA can give better solutions compared to the traditional HSA and other heuristic or deterministic methods and also it is a powerful search algorithm for solving various engineering optimization problems [27].

The main difference between the IHSA and traditional HSA is in the way the PAR and bw values are adjusted. To improve the performance of the HSA and eliminate the drawbacks of fixed values of PAR and bw, the IHSA uses variable PAR and bw values in the improvisation step (Step 3). The PAR value changes dynamically with generation number and is expressed as follows [27]:

$$PAR(gn) = PAR_{Min} + \frac{(PAR_{Max} - PAR_{Min})}{NI} \times gn \quad (15)$$

Where, PAR(gn) is pitch adjusting rate for each generation; PARMin is minimum pitch adjusting rate; PARMax is maximum pitch adjusting rate; NI is number of solution vector generations and gn is generation number

bw changes dynamically with generation number and is defined as (16):

$$bw(gn) = bw_{Max}\exp(c \times gn) \quad (16)$$

$$c = \frac{Ln(\frac{bw_{Max}}{bw_{Min}})}{NI} \quad (17)$$

Where, bw(gn) is bandwidth for each generation; bwMin is minimum bandwidth and bwMax is maximum bandwidth

B. Modified Harmony Search Algorithm

To achieved a good choice for simulating complex phenomena, sampling, numerical analysis in heuristic method needs random sequences with a long period and good uniformity. Chaos is a deterministic, random like process found in dynamical system, non-linear, which is non-converging, non-period and limited. The standard HSA algorithm has gained much attention and widespread applications in different optimization fields. But, after becoming converged, the HSA algorithm loses its efficiency to search and then becomes stopped. Thus, new operators should be added to algorithm in order to increase its ability and flexibility for solving more complicated optimization problems. To cover this problem, we introduce MHSA that develop searching process by employed CLS into HSA. Assume that our array of sensors controls the current Cji+1 that is formulated based forcing of the pendulum, by rewritten it from cos(t) to something like:

$$c_{i+1}^{j}=\begin{cases}2c_i^j\times(1+\frac{g_{best}^{k-1}}{g_{best}^{k}})\times\cos(2\pi\frac{g_{best}^{k-1}}{g_{best}^{k}}),0.5<c_i^j\le 1\\ 0.1c_i^j\times(1-\cos((1+\frac{g_{best}^{k-1}}{g_{best}^{k}}))),0<c_i^j\le 0.5\end{cases} \quad (18)$$

Where, gkbest denotes best optimal value for kit iteration and $g_{best}^{k-1}/g_{best}^{k}$ represents the fine tuning necessary to achieve the desired sequence of gyrations. The CLS operator on the GSA algorithm can be summarized as follows:

Step 1: generate an initial chaos population randomly for CLS.

$$X_{cls}^{0}=[X_{cls,0}^{1},X_{cls,0}^{2},...,X_{cls,0}^{Ng}]_{1\times N_g}$$
$$cx_0=[cx_0^1,cx_0^2,...,cx_0^{Ng}]$$
$$cx_0^j=\frac{X_{cls,0}^{j}-P_{j,\min}}{P_{j,\max}-P_{j,\min}},j=1,2,...,Ng \quad (19)$$

Where, the chaos variable can be generating as follows:

$$X_{cls}^{i}=[X_{cls,i}^{1},X_{cls,i}^{2},...,X_{cls,i}^{Ng}]_{1\times N_g},i=1,2,...,N_{chaos}$$
$$x_{cls,i}^{j}=cx_{i-1}^{j}\times(P_{j,\max}-P_{j,\min})+P_{j,\min},j=1,2,...,N_g \quad (20)$$

Step 2: determine the chaotic variables

$$cx_i=[cx_i^1,cx_i^2,...,cx_i^{Ng}],i=0,1,2,...,N_{choas}$$
$$cx_{i+1}^{j}=base\ CLS \quad j=1,2,...,Ng$$
$$cx_0^j=rand(0) \quad (21)$$

Where, Nchaos is the number of individuals for CLS. CxiNg is the ith chaotic variable. Rand() generate a random value in (0,1).

Step 3: mapping the decision variables

Step 4: convert the chaotic variables to the decision variables

Step 5: evaluate the new solution with decision variables.

4. PROPOSED ALGORITHM

UC-V2G is a mixed integer, non-linear optimization problem consisting of discrete and continuous variables.

In the proposed approach, each harmony vector has two fields for the conventional generating units and V2G scheduling. Harmony vector, x' is constituted of {Generating unit: An N × T binary matrix; Vehicle: An T × 1 integer column vector}. Binary HSA can easily handle the optimization problem of an N × T binary matrix for generating units because possible state of a generating unit is either 1 or 0 only [25]. On the other hand, basic HSA has the great abilities for the optimization of an T × 1 integer column vector for PHEVs, as possible number of connected PHEVs varies from 0 to $N_{V2G}^{Max}(t)$ at hour t.

The flowchart of the proposed IHSA for UC-V2G optimization problem is shown in Fig. 1. The details of proposed algorithm are explained in the following sections.

Initialize the optimization problem and algorithm parameters

At the first step of the proposed algorithm, as discussed in the previous section, the optimization problem and HSA parameters, HMS, HMCR and PAR should be initiated.

Initialize the HM

Afterward HM, that is N+1 × T mixed integer matrix, as mentioned above, is initialized. For taking into account ramp rate of the tth hour, $P_{\min}^{i}$ and $P_{\max}^{i}$ of the conventional generating units in the tth hour are restricted using Eq. (11) and Eq. (12) as follows:

$$P_{max}^{i,t} = \min\{(P^{i,t-1} + RUR^{i}), P_{max}^{i}\} \quad 1 \le t \le T \quad i \in N \tag{18}$$

$$P_{min}^{i,t} = \max\{(P^{i,t-1} - RDR^{i}), P_{min}^{i}\} \quad 1 \le t \le T \quad i \in N \tag{19}$$

Improvise a new harmony from HM

At this step, as discussed in the previous section, new harmony vectors are improvised from the HM based upon memory considerations, pitch adjustments, and randomization. Number of new harmony vectors should be as the same as HMS. As shown in Fig. 1 three steps are considered for improvising new harmony from HM. Since the UC of conventional units problem and V2G scheduling are different, new harmony from HM is improvised for UC and V2G separately then these two are merged. Initially a new harmony is improvised from the matrix (N × T) called HMUC which represent conventional generating units, and then this process is performed for V2G using HMV2G. Finally these new matrixes are merged to build a new harmony vector that based on that scheduling is determined.

New harmony vectors are compared with harmony vectors in HM in term of objective function value. New HM is updated by replacing weaker vectors of old HM with stronger vectors of the newly generated vectors. Result of this step is an updated HM that contains strongest vectors of both harmony vectors that were stored in HM and improvised vectors.

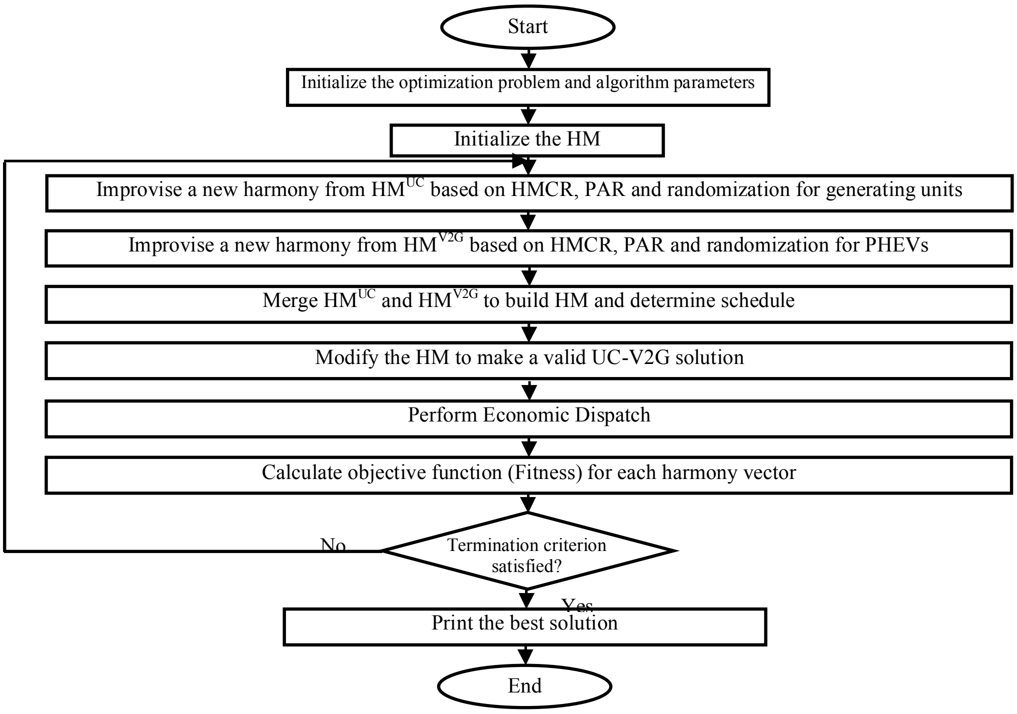

Fig. 1. Flowchart of the proposed IHSA for UC-V2G optimization Problem

Modifying the HM

In this stage, a repairing mechanism is applied to HM that will check load demand, spinning reserve, min up/down time limits at all of the hours at the desired time horizon and V2G constraints. In this process, the harmony vectors that did not satisfy load demand or min up/down limit will be modified. For checking load demand and spinning reserve Eq. (7) will be considered such that the sum of the PMax of the committed units and P_v^{Max} of scheduled PHEVs should be more than sum of the forecasted demand and spinning reserve requirement. Other constraints are handled in this stage such that all of the optimization problem constraints are satisfied.

Economic Dispatch

UC associated with economic dispatch is a useful tool to find the most economical generation schedule. The economic dispatch determines the output of all online units with the objective function of minimum total operating costs at a given hour [25]. A lambda iteration method is used in this study to determine the optimal economic dispatch of the committed units along with PHEVs.

Fitness Calculation

In this step, based upon economic dispatch results and with consideration of start-up costs, the objective function is calculated for each harmony vector of HM.

Termination criterion

The proposed IHSA will be stopped when the termination criterion is satisfied; otherwise, the algorithm will go back to steps 3. In this study termination criterion is the maximum number of improvisations.

5. RESULTS AND DISCUSSION

A widely used 10-unit test system is considered for simulation with 50,000 PHEVs, which are assumed to be charged from renewable sources, so the results will be comparable with those obtained by PSO reported in [1]. Load demand of this test system is depicted in fig. 2 while generating unit's characteristics of the 10-unit system are provided in Appendix.

Vehicles are charged from renewable sources and they discharge to the grid so that the total running costs are minimized while all of the system, unit and V2G constraints are fulfilled. Load demand and unit characteristics of the 10-unit system are collected from [25]. The spinning reserve requirement is 10% of the load demand, cold start-up cost is double of hot start-up cost, and total scheduling period is 24 h. Like other heuristic algorithms IHSA is stochastic and convergence depends on proper setting of parameter values. Table I provides the IHSA parameters.

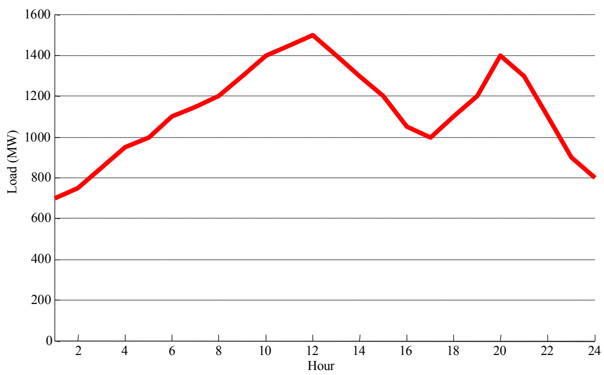

Fig. 2. Load demand of 10-unit test system

Table I

Improved harmony search algorithm parameters

HMS	HMCR	PAR_{MAX}	PAR_{MIN}	BW_{MAX}	BW_{MIN}	NI

20	0.85	0.99	0.40	1	0.00001	500

Other parameters in optimization problem as follows: total number of vehicles = 50,000; maximum battery capacity = 25 kWh; minimum battery capacity = 10 kWh; average battery capacity, PV = 15 kWh; maximum number of discharging vehicles at each hour, $N_{V2G}^{Max}(t)$ =10% of total vehicles; total number of PHEVs in the system, N_{V2G}^{Max} = 50,000; charging–discharging frequency = 1 per day; scheduling period = 24 h; departure state of charge = 50%; efficiency= 85%.

The best solutions of the proposed IHSA with and without PHEVs are shown in Tables II and III, respectively.

Generation cost (fuel cost plus startup cost) is \$563,977 when PHEVs are not considered in the 10-unit test system during 24-h (Table II). Generation cost is \$553,985 when 50,000 PHEVs are considered in the same system (Table III).

Table IV provides the comparison of results of the proposed IHSA and those obtained by PSO in [1]. As the results demonstrate the proposed IHSA is a more powerful tool than PSO. The IHSA is more capable in finding the best schedule of both of UC and UC-V2G optimization problems.

The best solution of other deterministic and heuristic algorithms along with average of the solutions and worst solution are also provided in this table. As it can be seen IHSA is the best solution that guarantees high quality solution and not only results the best solution but also has the best average among the presented methods

TABLE II

SChedule and dispatch of generating units for 10-unit test system without v2g

Units	Hours																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
2	245	295	370	455	390	360	410	455	455	455	455	455	455	455	455	310	260	360	455	455	455	455	420	345
3	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
4	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
5	0	0	25	40	25	25	25	30	85	162	162	162	162	85	30	25	25	25	30	162	85	145	25	0
6	0	0	0	0	0	0	0	0	20	33	73	80	33	20	0	0	0	0	0	33	20	20	0	0
7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
8	0	0	0	0	0	0	0	0	0	10	10	43	10	0	0	0	0	0	0	10	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0
V2G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

TABLE III

Schedule and dispatch of generating units and PHEVs for 10-unit test system with 50,000 PHEVs

Units	Hours																						
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
2	23	28	24	34	37	35	39	44	45	45	45	43	45	45	44	29	24	34	44	45	44	44	41	33

	0.6	0.8	9.1	5.6	7.8	1.6	6.5	2.9	5	5	5	2.6	5	5	2.9	3.6	3.6	3.6	2.8	5	4.5	4.5	3.3	7.8
3	0	0	0	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
4	0	0	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	130	0	0	0
5	0	0	0	0	25	25	25	25	73.4	162	162	162	139.7	74.5	25	25	25	25	25	137.7	85	145	25	0
6	0	0	0	0	0	0	0	0	20	20.7	54.1	80	33	20	0	0	0	0	0	33	20	20	0	0
7	0	0	0	0	0	0	0	0	25	25	25	25	25	25	0	0	0	0	0	25	25	25	0	0
8	0	0	0	0	0	0	0	0	0	0	10	55	10	0	0	0	0	0	0	10	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	10	10	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V2G	14.4	14.2	15.9	19.4	12.2	8.4	13.5	17.1	11.6	22.3	18.9	22.4	22.3	10.5	17.1	16.4	16.4	16.4	17.2	24.3	10.5	10.5	6.7	7.2

TABLE IV

Comparison of the total costs for different techniques

Comparison of Different Method (Total Cost $)									
	DP			LR			EP		
	Best	Averaged	Worst	Best	Averaged	Worst	Best	Averaged	Worst
UC	565,825	N/A	N/A	565,825	N/A	N/A	564,551	565,352	566,231
UC-V2G	-	-	-	-	-	-	-	-	-
	GA			PSO			IHSA		
	Best	Averaged	Worst	Best	Averaged	Worst	Best	Averaged	Worst
UC	565,825	N/A	570,032	565,325.9	N/A	N/A	563,977.1	564,257.6	565,825.2
UC-V2G	-	-	-	554,509.5	557,584.4	559,987.8	553,985.3	556,314.7	559,987.8

CONCLUSIONS

An intelligent UC-V2G optimization problem based on one of the most powerful heuristic algorithms, Improved Harmony Search Algorithm, has been proposed in this paper. Being a very complex optimization problem (since the number of PHEV in V2G is relatively high), UC-V2G optimization problem is more complex than the basic UC and needs more elaboration. Conventional 10-unit test system has been studied to show the effectiveness of the proposed method. Results show operation costs of the system can be effectively reduced with integration of V2G in UC problem. Comparing the results of IHSA with PSO demonstrates the high capability of the proposed method.

TABLE A-1

Generating unit's characteristics of the ten-unit system

Unit no.	P_i^{max}	P_i^{min}	a_i	b_i	c_i	T_i^{on}	T_i^{off}	HSC_i	CSC_i	CST_i	IS
1	455	150	1000	16.19	0.00048	8	8	4500	9000	5	8
2	455	150	970	17.26	0.00031	8	8	5000	10000	5	8
3	130	20	700	16.6	0.002	5	5	550	1100	4	-5
4	130	20	680	16.5	0.00211	5	5	560	1120	4	-5
5	162	25	450	19.7	0.00398	6	6	900	1800	4	-6

6	80	20	370	22.26	0.00712	3	3	170	340	2	-3
7	85	25	480	27.74	0.00079	3	3	260	520	2	-3
8	55	10	660	25.92	0.00413	1	1	30	60	0	-1
9	55	10	665	27.27	0.00222	1	1	30	60	0	-1
10	55	10	670	27.79	0.00173	1	1	30	60	0	-1

1. APPENDIX

The generating unit's characteristics of the ten-unit system are provided in Table A-1

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