An Evolutionary Programming Algorithm for Solving Unit Commitment Problem in Smart Grid Environment

Charles Christober Asir Rajan

Department of EEE, Puducherry Technological University, Puducherry 605014, India
Corresponding author's email: asir_70@pec.edu
Received: 12/12/2020, Accepted: 11/06/2021

Abstract

This paper presents a new approach to solving the unit commitment problem using Evolutionary Programming Algorithm (EPA) in smart grid environment. The objective of this paper is to find the generation scheduling such that the total operating cost can be minimized, when subjected to a variety of constraints. This also means that it is desirable to find the optimal generating unit commitment in the power system for the next H hours. This paper proposes distributed sources which includes electric vehicles and distributed generation. EPA, which happens to be a Global Optimisation technique for solving Unit Commitment Problem, operates on a system, which is designed to encode each unit's operating schedule with regard to its minimum up/down time. In this, the unit commitment schedule is coded as a string of symbols. An initial population of parent solutions is generated at random. Here, each schedule is formed by committing all the units according to their initial status ("flat start"). Here the parents are obtained from a pre-defined set of solution's i.e. each and every solution is adjusted to meet the requirements. Then, a random recommitment is carried out with respect to the unit's minimum down times. The Neyveli Thermal Power Station (NTPS) Unit - II in India demonstrates the effectiveness of the proposed approach; extensive studies have also been performed for different power systems consists of IEEE 10, 26, 34 generating units. Numerical results are shown comparing the cost solutions and computation time obtained by using the EPA and other conventional methods like Dynamic Programming, Legrangian Relaxation and Simulated Annealing and Tabu Search in reaching proper unit commitment.

Keywords:

Unit Commitment, Evolutionary Programming, Simulated Annealing, Legrangian Relaxation, Dynamic Programming

1. Introduction

Power Stations and electricity generating companies and power systems has the problem of deciding how best to meet the varying demand for electricity, which has a daily and weekly cycle. The short-term optimisation problem is how to schedule generation to minimize the total fuel cost or to maximize the total profit over a study period of typically a day, subject to a large number of constraints that must be satisfied. The daily load pattern for a given system may exhibit large differences between minimum and maximum demand. Therefore, enough reliable power generation to meet the peak load demand must therefore be synchronized prior to the actual occurrence of the load. Thus it is clear that it is not proper and economical to run all the units available all the time. Since the load varies continuously with time, the optimum condition of units may alter during any period. Therefore, the problem of determining the units of a plant that should operate for a given load is the problem of unit commitment. For total number of units of higher order, the problems associated with unit commitment have generally been difficult to solve because of uncertainty of particular aspects of the problem. For instance, the availability of fuel in precise, load forecast variable costs affected by the loading of generator units and the losses caused by reactive flows are some of the unpredictable issues. There are other problems of inconsistency that affect the overall economic operation of the electric power station. In order to reach a feasible solution for Unit Commitment Problem (UCP), different considerations must be considered.

Research endeavours, therefore, have been focused on; efficient, near-optimal UC algorithms, which can be applied to large-scale, power systems and have reasonable storage and computation time requirements. A survey of existing literature [1-33] on the problem reveals that various numerical optimisation techniques have been employed to approach the complicated unit commitment problem. More specifically, these are the Dynamic Programming method (DP), the Mixed Integer Programming method (MIP), the Lagrangian relaxation method (LR), the Branch and Bound method (BB), the Expert system (ES), the Fuzzy Theorem method (FT), the Hop Field method (H), the Simulated Annealing method (SA), the Tabu Search (TS), the Genetic Algorithm (GA), the Artificial Neural Network (ANN), the Cuckoo Optimization Algorithm (COA) and so on. The major limitations of the numerical techniques are the problem dimensions, large computational time and complexity in programming.

The DP method [1-2,13] is flexible but the disadvantage is the "curse of dimensionality", which results it may leads to more mathematical complexity and increase in computation time if the constraints are taken in to consideration. The MIP methods [3-4] for solving the unit commitment problems fail when the number of units increases because they require a large memory and suffer from great computational delay. The LR approach [5-8] to solve the short-term UC Problems was found that it provides faster solution but it will fail to obtain solution feasibility and solution quality problems and becomes complex if the number of units increased. The BB method [9] employs a linear function to represent fuel cost and start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a practical size. An ES algorithm [10,13] rectifies the complexity in calculations and saving in computation time. But it will face the problem if the new schedule is differing from schedule in database. In the FT method [11, 13, 24] using fuzzy set solves the forecasted load schedules error but it will also suffer from complexity. The H neural network technique [12] considers more constraints but it may suffer from numerical convergence due to its training process. SA [14-17,23-24] is a powerful, general-purpose stochastic optimisation technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it will take much time to reach the near-global minimum. The TS [18-20, 23] is an iterative improvement procedure that starts from some initial feasible solution and attempts to determine a better solution in the manner of a greatest – decent algorithm. However, TS is characterized by an ability to escape local optima by using a short-term memory of recent solutions.

GA [13,21-24] is a general-purpose stochastic and parallel search method based on the mechanics of natural selection and natural genetics. It is a search method to have potential of obtaining near-global minimum. And it has the capability to obtain the accurate results within short time and the constraints are included easily. The ANN [12] has the advantages of giving good solution quality and rapid convergence. And this method can accommodate more complicated unit-wise constraints and are claimed for numerical convergence and solution quality problems. The solution processing in each method is very unique. The EP [25-26] has the advantages of good convergent property and a significant speedup over traditional GA's and can obtain high quality solutions. The "Curse of dimensionality" is surmounted, and the computational burden is almost linear with the problem scale. Electric Vehicle (EV) and its impact on the cost and emission of power system are studied on basis of UC model in [28–30]. The significance and feasibility of DR and its role in supply-demand schedule are examined in [31–32]. Economical operation of distributed generation (DG) and chance-constrained schedule of active network with DG are researched [33].

From the literature review, it has been observed that there exists a need for evolving simple and effective methods, for obtaining an optimal solution for the UCP. Hence, in this paper, an attempt has been made to EPA for meeting these requirements of the UCP, which eliminates the above-mentioned drawbacks. EPA seems to be promising and is still evolving. EPA has the great advantage of good convergent property and, hence, the computation time is considerably reduced. EPA is capable of determining the global or near global solution. It is based on the basic genetic operation of human chromosomes. It operates with the stochastic mechanics, which combine offspring creation based on the performance of current trail solutions and competition and selection based on the successive generations, form a considerably robust scheme for large-scale real-valued combinational optimisation. In this proposed work, the parents are obtained from a pre-defined set of solution's i.e. each and every solution is adjusted to meet the requirements. And the selection process is done using Evolutionary Strategy [25-26]. The application on the NTPS and IEEE systems consists of 10, 26, 34 generating units' shows that we can find the optimal solution effectively and these results are compared with the conventional methods.

2. Problem Formulation

2.1. Smart Grid Environment

With the progress of smart grid, DR become more active. They may play an increasingly essential part in power system operation. In this paper, EV and DG are considered in the UC model.

1) EV: Smart grid is a perfect platform for the collaborations between the system operators and EVs. With the associated techniques getting settled, it is feasible for EV to sold electricity back to the grid. There is fictional to be an aggregator to link between the system operator and a great number of EV owners [28-30]. If an EV is indolent for a certain period, its owner can sign a contract with the system operator for commitment via the load aggregator. The sum of EV can be preserved as a special unit. Considering there is an increasing peripheral cost to involve more EV proprietors, the cost function of EV is expected to be a quadratic function

$$EVeTC(EVe_k) = a_1 + b_1 EVe_k + c_1 EVe_k^2 \tag{1}$$

where:

$EVeTC$	=	EV export total cost
EVe_k	=	EV export at time k
a_1, b_1EVe_k, c_1EVe_k	=	cost coefficients of EV export at time k

Firstly, in case of emergent use of EV's owners, a lower limit of *SoC* is considered (2). Secondly, for the sake of safe operation of the gird, an upper limit on total output of EVs at each hour should be stipulated (4). Thirdly, now that EV may not be connected to the grid all the 24 h, it is sensible to set a time range limit when EV is available for the system operator (5). Fourthly, the available capacity of EVe at each hour has an upper limit, respectively.

$$SoC_{k,t} \geq SoC_{min} \tag{2}$$

$$SoC_{k,t} = \frac{C_{o,k} + \sum_{x=1}^{k} EVi_{x,t} - \sum_{x=1}^{k} EVe_{x,t}}{C_k} \tag{3}$$

$$EVe_k = \sum_{t=1}^{m} EVe_{k,t} \leq EVe_{max} \tag{4}$$

$$EVe_{k,t} = 0, k \notin [k_1, k_2] \tag{5}$$

$$EVe_k \leq EVe_{k,max} \tag{6}$$

where:

SoC	=	state of charge of EV
$SoC_{k,t}$	=	state of charge of EV t at time k
SoC_{min}	=	minimum limit of SoC at each hour
$C_{o,k}$	=	initial charging state of EV at time k
$EVe_{k,t}$	=	EV export t at time k
EVe_{max}	=	maximum limit of EV export capacity
$EVe_{k,max}$	=	maximum available EV export capacity at time k

2) DG: When more DG's are connected to the grid, then both importing and exporting power from and to the DG's should be taken into consideration in the UC model. Here the power can be sold to grid is *DGe* and the power purchased from the grid is *DGi*. The cost function of the DG is expected to be a quadratic equation

$$DG(DGe_k) = a_1 + b_1 DGe_k + c_1 DGe_k^{\ 2} \tag{7}$$

where:

DGe_k	=	DG export at time k
a_1, b_1DGe_k, c_1DGe_k	=	cost coefficients of DG

Firstly, DG's output is subject to natural resource and weather condition, so an upper limit on available DG at each hour is considered. Secondly, DG tends to be intermittent and volatile, an upper limit on its penetration rate should be set to ensure a reliable operation of the power system

$$DGe_k \leq DGe_{k,max} \tag{8}$$

$$\eta_k = \frac{DGe_k}{\sum_{i=1}^{N} (P_{i,k} I_{i,k}) + EVe_k + DGe_k} \leq \eta_{max} \tag{9}$$

where:

$DGe_{k,max}$	=	maximum available DG export capacity at time k
η_k	=	penetration rate of DG at time t
η_{max}	=	max penetration rate of DG at time t
$P_{i,k}$	=	output of unit i at time k
$I_{i,k}$	=	on/off status of unit I at time k

2.2. UC Model

The objective is to find the generation scheduling such that the total operating cost can be minimized, when subjected to a variety of constraints [27]. In the UCP under consideration, an interesting solution would be minimizing the total operating cost of the generating units with several constraints being satisfied. The major component of the operating cost, for thermal and nuclear units, is the power production cost of the committed units and this is given in a quadratic form in (10).

$$F_{it}(P_{it}) = A_i P^2{}_{it} + B_i P_{it} + C_i \quad Rs/hr \tag{10}$$

where:

A_i, B_i, C_i	=	the cost function parameters of unit i (Rs./MW^{2}hr, Rs./MWhr, Rs/hr)
$F_{it}(P_{it})$	=	production cost of unit i at a time t (Rs/hr)
P_{it}	=	output power from unit i at time t (MW)

The startup cost depends upon the down time of the unit, which can vary from a maximum value, when the unit i is started from cold state, to a much smaller value, if the unit i has been turned off recently. The startup cost calculation depends upon the treatment method for the thermal unit during down time periods. The start-up cost S_{it}, is a function of the down time of unit i as given in (11).

$$S_{it} = So_i[1 - D_i \exp(-Toff_i / Tdown_i)] + E_i \; Rs \tag{11}$$

where:

So_i	=	unit i cold start – up cost (Rs)
D_i, E_i	=	start – up cost coefficients for unit i

The overall objective function of the UCP is given in (12).

$$F_T = \sum_{t=1}^{T}\sum_{i=1}^{N}[(F_{it}(P_{it})U_{it} + S_{it}V_{it})] + \sum_{k=1}^{24}[EVe(EVe_k) + DG(DGe_k)] \quad Rs/Hr \tag{12}$$

where:

U_{it}	=	unit i status at hour t =1(if unit is ON) =0 (if unit is OFF)
V_{it}	=	unit i start up / shut down status at hour t =1 if the unit is started at hour t and 0 otherwise
F_T	=	total operating cost over the schedule horizon (Rs/Hr)
S_{it}	=	start up cost of unit i at hour t (Rs)

2.3. Constraints

Depending on the nature of the power system under study, the UCP is subject to many constraints, the main being the load balance constraints and the spinning reserve constraints. The other constraints include the thermal constraints, fuel constraints, security constraints etc. [27]

1) *Load Balance Constraints*

The real power generated must be sufficient enough to meet the load demand and must satisfy the following factors given in (13).

$$\sum_{i=1}^{N} P_{it}U_{it} = PD_t - EVe_k - DGi_k - DGe_k + PL_k \tag{13}$$

where:

PD_t	=	system peak demand at hour t (MW)
N	=	number of available generating units
U (0,1)	=	the uniform distribution with parameters 0 and 1
UD (a,b)	=	the discrete uniform distribution with parameters a and b

2) *Spinning Reserve Constraints*

The spinning reserve is the total amount of real power generation available from all synchronized units minus the present load plus the losses. The reserve is considered to be a pre specified amount or a given percentage of the forecasted peak demand. It must be sufficient enough to meet the loss of the most heavily loaded unit in the system. This has to satisfy the equation given in (14).

$$\sum_{i=1}^{N} P\max_i U_{it} \geq (PD_t + R_t); 1 \leq t \leq T \tag{14}$$

where:

$Pmax_i$	=	Maximum generation limit of unit i
R_t	=	spinning reserve at time t (MW)
T	=	scheduled time horizon (24 hr)

3) *Thermal Constraints*

The temperature and pressure of the thermal units vary very gradually and the units must be synchronized before they are brought online. A time period of even 1 hour is considered as the minimum down time of the units. There are certain factors, which govern the thermal constraints, like minimum up time, minimum down time and crew constraints.

a) *Minimum up time:*

If the units have already been shut down, there will be a minimum time before they can be restarted and the constraint is given in (15).

$$Ton_i \geq Tup_i \tag{15}$$

where:

Ton_i	=	duration for which unit i is continuously ON (Hr)
Tup_i	=	unit i minimum up time (Hr)

b) *Minimum down time:*

If all the units are running already, they cannot be shut down simultaneously and the constraint is given in (16).

$$Toff_i \geq Tdown_i \tag{16}$$

where:

$Tdown_i$	=	unit i minimum down time (Hr)
$Toff_i$	=	duration for which unit i is continuously OFF (Hr)

4) *Must Run Units*

Generally in a power system, some of the units are given a must run status in order to provide voltage support for the network.

The entire problem formulation for solving the UC using EP in Smart Grid environment is formulated as block diagram and is shown in Fig. 1.

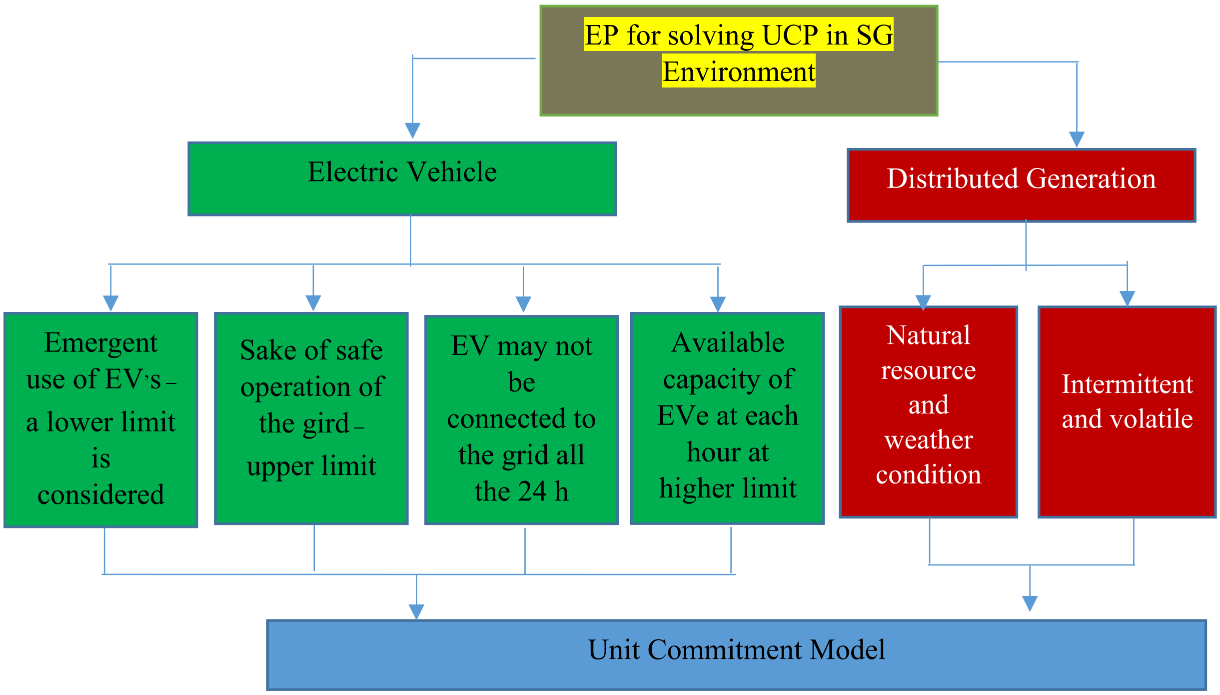

Fig. 1 Block diagram of UC using EP in smart grid environment.

3. Evolutionary Programming

3.1. Introduction

EP is a mutation-based evolutionary algorithm applied to discrete search spaces. David Fogel (Fogel 1988) extended the initial work of his father Larry Fogel (Fogel, 1962) for applications involving real-parameter optimization problems. Real-parameter EP is similar in principle to evolution strategy (ES), in that normally distributed mutations are performed in both algorithms. Both algorithms encode mutation strength (or variance of the normal distribution) for each decision variable and a self-adapting rule is used to update the mutation strengths. Several variants of EP have been suggested (Fogel, 1992).

3.2. Evolutionary Strategies

For the case of Evolutionary strategies D. B. Fogel remarks "evolution can be categorized by several levels of hierarchy: the gene, the chromosome, the individual, the species, and the ecosystem." Thus, while Genetic Algorithms stress models of genetic operators, Evolutionary Strategies emphasize mutational transformation that maintains behavioral linkage between each parent and its offspring at the level of the individual. Evolutionary Strategies are a joint development of Bienert, Rechenberg, and Schwefel. The first applications were experimental and addressed some optimization problems in hydrodynamics.

3.3. EP General Algorithm

Evolutionary programming [25-26] is conducted as a sequence of operations and is given below. The schematic diagram of the EP algorithm is shown in Fig. 2.

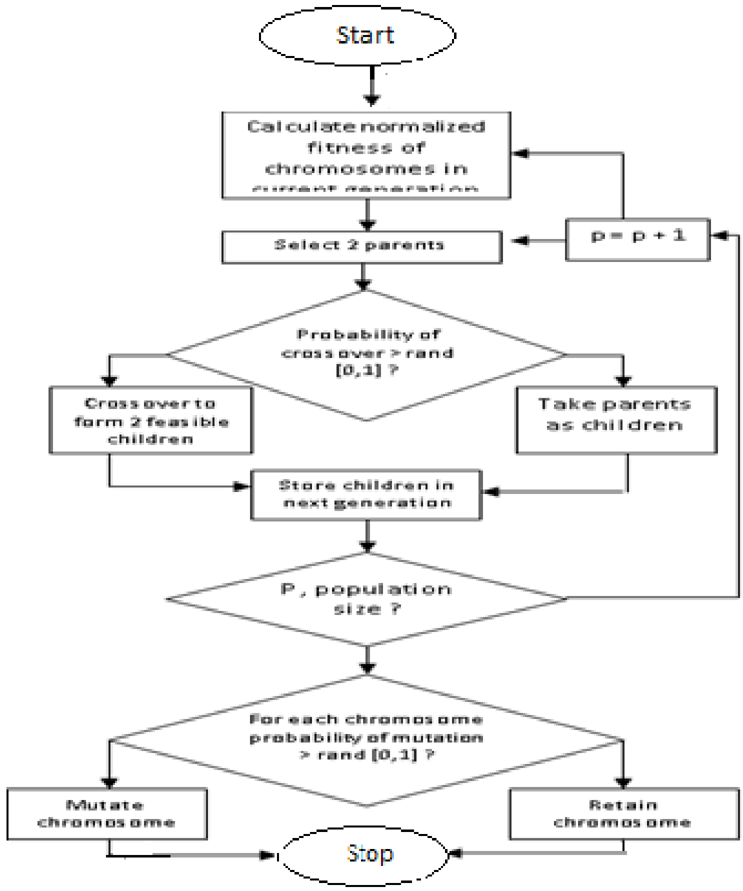

Fig. 2 Flowchart of Evolutionary Programming Algorithm

Algorithm 1 EP General Algorithm

1. The initial population is determined by setting $s_i = S_i \sim U(a_k, b_k)^k$ i =1,…,m, where S_i is a random vector, s_i is the outcome of the random vector, $U(a_k, b_k)^k$ denotes a uniform distribution ranging over $[a_k, b_k]$ in each of k dimensions, and m is the number of parents.
2. Each s_i, i=1,…,m, is assigned a fitness score $\vartheta(s_i) = G(F(s_i), v_i)$, where F maps $s_i \rightarrow R$ and denotes the true fitness of s_i, v_i, represents random alteration in the instantiation of s_i, random variation imposed on the evaluation of $F(s_i)$, or satisfies another relation s_i, and $G(F(s_i), v_i)$ describes the fitness score to be assigned. In general, the functions F and G can be as complex as required. For example, F may be a function not only of a particular s_i, but also of other members of the population, conditioned on a particular s_i.
3. Each s_i, i =1,…,m, is altered and assigned to s_{i+m} such that
   $s_{i+m} = s_{i,j} + N(0, \beta j\ \vartheta(s_i) + z_j), j = 1,\ldots,k$

   $N(0, \beta j\ \vartheta(s_i) + z_j)$ represents a Gaussian random variable with mean μ and variance σ^2, β_j is a constant of proportionality to scale $\vartheta(s_i)$, and zj represents an offset to guarantee a minimum amount of variance,
4. Each s_{i+m}, i=1,…,m, is assigned a fitness score
   $\vartheta(s_{i+m}) = G(F(s_{i+m}), v_{i+m})$

5. For each s_i, i=1,…,*2m*, a value wi is assigned according to

$$w_i = \sum_{t=1}^{c} w_t^*$$

$$w_t^* = \begin{cases} 1, & \text{if } \vartheta(s_i) \le \vartheta(s_i); \\ 0, & \text{otherwise;} \end{cases}$$

Where ρ = [2*mu*₁ +1], ρ ≠ i, [*x*] denotes the greatest integer less than or equal to *x*, *c* is the number of competitions, and u1~*U* (0,1).
6. The solutions s_i, *I* = 1…2m, are ranked in descending order of their corresponding value W_i [with preference to their actual scores $\vartheta(s_i)$ if there are more than *m* solutions attaining a value of *c*]. The first *m* solutions are transcribed along with their corresponding values $\vartheta(s_i)$ to be the basis of the next generation.
7. The process proceeds to step 3, unless the available execution time is exhausted or an acceptable solution has been discovered.

3.4. Evolutionary Programming for UCP

Algorithm 2 EP for UCP

1. Initialize the parent vector $p = [p_1, p_2, \ldots p_n]$, $i = 1,2,\ldots N_p$ such that each element in the vector is determined by $p_j \sim$ random (p_{jmin}, p_{jmax}), $j = 1,2,\ldots N$, with one generator as dependent generator.
2. Calculate the overall objective function if the UCP is given in equation (12) using the trail vector p_i and find the minimum of F_{Ti}.
3. Create the offspring trail solution p_i' using the following steps.
   (a) Calculate the standard deviation
   $$\sigma j = \beta(F_{Tij} / \min(F_{Ti}))(P_{j\max} - P_{j\min})$$
   (b) Add a Gaussian random variable $N(0, \sigma_j^2)$ to all the state variable of p_i, to get p_i'.
4. Select the first N_p individuals from the total $2N_p$ individuals of both p_i & p_i' using the following steps for next iteration.
   (a) Evaluate $r = (2N_p$ random $(0,1) + 1)$
   (b) Evaluate each trail vector by W_{pi}=sum (W_x), Where $x = 1,2,\ldots N_p$, $i = 1,2,\ldots 2N_p$ such that $W_x = 1$ if $F_{Tij} / (F_{Tij}+F_{Tir}) <$ random (0,1), otherwise, $W_x = 0$.
5. Sort the W_{pi} in descending order and the first N_p individuals will survive and are transcribed along with their elements to form the basis of the next generation.
6. The above procedure is repeated from step (2) until a maximum number of generations N_m is reached.
7. Selection process is done using Evolutionary strategy.

4. Numerical Results

A NTPS in India with seven generating units from I to VII, each with a capacity of 210MW, has been considered as a case study. A time period of 24 hours is considered; the unit commitment problem is solved for these seven units and also compared with IEEE 10, 26, and 34 generating unit power systems**.** The required inputs for solving the UCP are briefed here**.** The total number of generating units, the maximum real power generation of each unit and the generation system operation data of each unit are tabulated for a day, respectively, as shown in Table 1 and Table 2 for NTPS**.** The cost coefficients of DR is shown in Table 3. EV and DG are set at units V and VII respectively, since the load demands at these units are quite high compared with other units.

Table 1 Daily Generation of Seven Units in MW.

Hour	*Pmax*	I	II	III	IV	V	VI	VII
1	840	60	80	100	101	149	150	200
2	757	60	0	100	100	147	150	200
3	775	60	0	100	115	150	150	200
4	773	60	0	100	113	150	150	200
5	770	60	0	100	110	150	150	200
6	778	60	0	100	118	150	150	200
7	757	60	0	100	100	147	150	200
8	778	60	0	100	118	150	150	200
9	770	60	0	100	110	150	150	200
10	764	60	0	100	104	150	150	200
11	598	60	0	99	97	142	0	200
12	595	60	0	100	96	139	0	200
13	545	0	0	100	99	146	0	200
14	538	0	0	99	97	142	0	200
15	535	0	0	100	96	139	0	200
16	466	0	0	0	116	150	0	200
17	449	0	0	0	101	148	0	200
18	439	0	0	0	97	142	0	200
19	466	0	0	0	116	150	0	200
20	463	0	0	0	113	150	0	200
21	460	0	0	0	110	150	0	200
22	434	0	0	0	95	139	0	200
23	530	60	0	0	120	150	0	200
24	840	60	80	100	101	149	150	200

Some other parameters in our model are assumed as follows. The lower limit of *SoC* is 25%. The average of *SoC* before dispatching is 75%. The average battery capacity of EVs is 34 kWh. The quantity of EVs that can conduct EVe is 8500. In order to facilitate management, this paper assumes that the system operator will only sign contract of EVe if the EVs are available in the evening. Accordingly, the available periods of all the EVs are the same in this paper, assumed 20–24 o'clock. The available capacity of EVe at these hours is 24, 23, 22, 21, and 20 MW, respectively. The maximum bearing capacity of the grid for EVe is assumed to be 24 MW at each hour. The upper limit of demand curtailment response is 7% of total load demand in this hour, and the upper limit within a day is 320 MWh. Now that solar power may be the main DG source, the available DG is set higher during the day. Specifically, it is 40 MW between 7 o'clock and 17 o'clock and 20 MW during the other time, among which two-thirds are used by consumers themselves and one-third would be sold to the grid. The upper limit of DG penetration rate is 6%. This paper considers four scenarios as shown in Table 4.

Table 2 Generation System Operation Data.

Unit	P_{min} (MW)	P_{max} (MW)	Running Cost			Start-up cost		
			C_i (Rs)	B_I (Rs/MWh)	A_i (Rs/MWh^2)	So_i (Rs)	D_i (Rs)	E_i (Rs)
1	15	60	750	70	0.255	4250	29.5	10
2	20	80	1250	75	0.198	5050	29.5	10
3	30	100	2000	70	0.198	5700	28.5	10
4	25	120	1600	70	0.191	4700	32.5	9
5	50	150	1450	75	0.106	5650	32	9
6	50	150	4950	65	0.0675	14100	37.5	4.5
7	75	200	4100	60	0.074	11350	32	5.5

Table 3 Cost Coefficients of DR.

DR	Running Cost		
	C_i (Rs)	B_i (Rs/ MWh)	A_i (Rs/ MWh^2)
EVe	750	70	0.255
DGb	1250	75	0.198

Table 4 Operation Settings.

	Operation Settings
Operation 1	EV Not Connected, DG Not Connected
Operation 2	EV Connected, DG Not Connected
Operation 3	EV Not Connected, DG Connected
Operation 4	EV Connected, DG Connected

Table 5 Comparisons of cost and CPU time for NTPS, 10, 26, 34 unit systems.

System	Methods	Total Cost (p.u.)	CPU Time (Sec)
7 – Unit Utility System	DP	1.00000	605
	LR	0.96481	578
	SA	0.95000	570
	TS	0.95239	575
	EP	0.94120	546

System	Methods	Total Cost (p.u.)	CPU Time (Sec)
10 – Unit IEEE System	DP [1]	1.00000	325
	LR [6]	0.94123	279
	SA [17]	0.93210	285
	TS [18]	0.93435	290
	EP	0.92336	254
26 – Unit IEEE System	DP [1]	1.00000	509
	LR [6]	0.95968	495
	SA [17]	0.94570	489
	TS [18]	0.94750	494
	EP	0.93680	478
34 – Unit IEEE System	DP [1]	1.00000	1452
	LR [6]	0.99910	1368
	SA [17]	0.98015	1370
	TS [18]	0.98291	1376
	EP	0.97210	1362

The status of unit i at time t and the start-up / shut - down status obtained are the necessary solution for SA, TS, EPA, DP, LR methods for NTPS. The comparison of the total costs and Central Processing unit (CPU) time is shown in Table 5 for NTPS, 10, 26, and 34 generating unit power systems. Fig. 3 represents the total production cost obtained by each parent for 25 iterations in EPA. Similarly, for 50 and 100 iterations are obtained. Fig. 4 gives the plot of EPA average performance from 1000 runs. The Fig. 5 gives the plot of No. of iteration versus the time taken to complete those iterations and the maximum production cost obtained under each iteration.

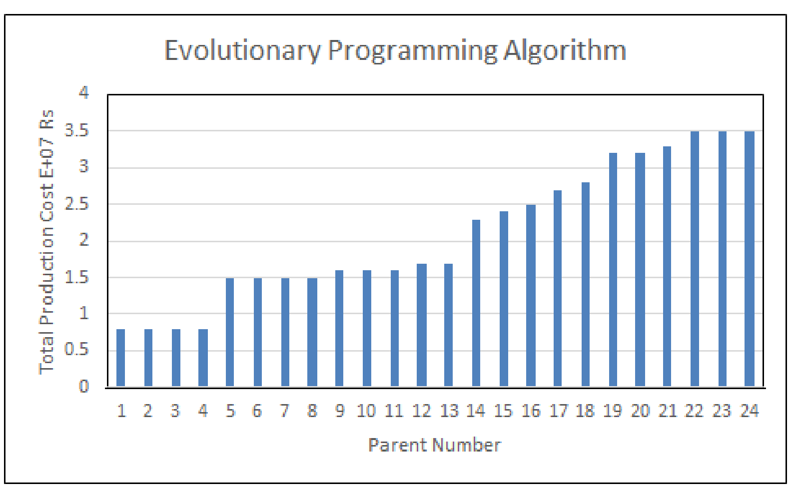

Fig. 3 Total production cost for 25 iterations.

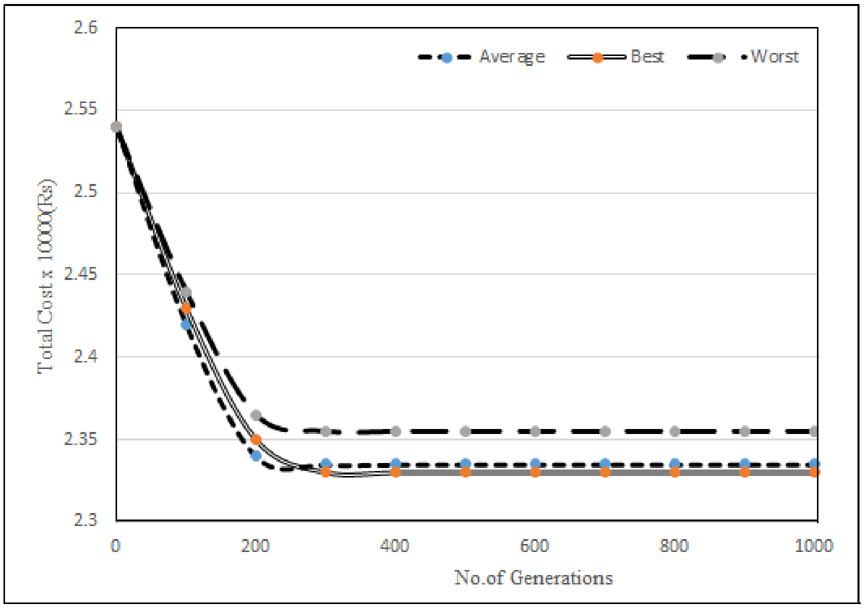

Fig. 4 EPA average performance from 1000 runs.

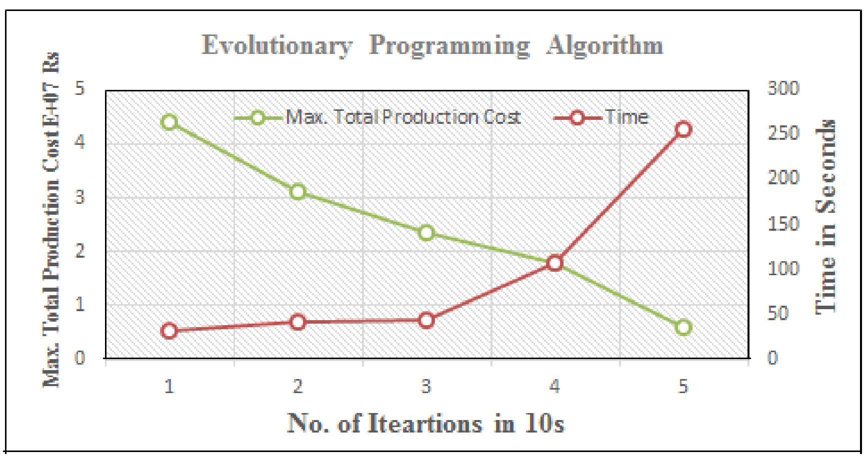

Fig. 5 No. of iterations vs time taken & max. production cost.

From these results, the EPA had lesser total cost and took lesser CPU time in all the power systems considered including NTPS. As we indicated in the paper, the EPA has also proved to be an efficient tool for solving the important economic dispatch problem for units with "non-smooth" fuel cost functions as referred in [26]. Such functions may be included in the proposed EPA search for practical problem solving. There is no obvious limitation on the size of the problem that must be addressed, for its data structure is such that the search space is reduced to a minimum; no "relaxation of constraints" is required; instead, populations of feasible solutions are produced at each generation and throughout the evolution process. The main advantages of the proposed algorithm are speed.

The proposed EPA approach was compared to the related methods in the references indented to serve this purpose, such as the DP, LR with a zoom feature, the SA, and the TS algorithms. Further EPA can start with any initial solution and improves on it to find optimal solution with a high probability. By means of stochastically searching multiple points at one time and considering trail solutions of successive generations, the EPA approach avoids entrapping in local optimum solutions. In comparison with the results produced by the referenced techniques, the EPA obviously displays a satisfactory performance with respect to the quality of its evolved solutions and to its computational requirements.

5. Conclusions

This paper presents an EPA to solve the unit commitment problem in smart grid environment. In this method, the essential processes simulated in the procedure are mutation, competition, and selection. The mutation rate is computed as a function of the ratio of the total cost by the schedule of interest to the cost of the best schedule in the current population. Competition and selection are applied to select from among the parents and the offspring, the best solutions to form the basis of the subsequent generation. In comparison with the results produced by the referenced techniques (DP, LR and SA & TS), the EPA obviously displays a satisfactory performance. There is no obvious limitation on the size of the problem that must be addressed, for its data structure is such that the search space is reduced to a minimum; No relaxation of constraints is required; instead, populations of feasible solutions are produced at each generation and throughout the evolution process; Multiple near optimal solutions to the problem involving multiple constraints and conflicting objectives can be obtained in a reasonable time with the use of heuristics.

Acknowledgement

The author is to acknowledge the support of AICTE, New Delhi for the RPS project titled as "Development of Hybrid Algorithms to Solve the Unit Commitment Problem in Smart Grid Network using Soft Computing Techniques" sanctioned during 2017-2020.

References

[1] Snyder, W. L., Powell, H. D., & Rayburn, C. (1987). Dynamic programming approach to unit commitment. *IEEE Transactions on Power Systems*, *3*(2), 339-350.

[2] Hsu, Y. Y., Liang, C. C., Lin, C. J., & Huang, C. T. (1991). Dynamic security constrained multi-area unit commitment. *IEEE Transactions on Power Systems*, *6*, 1049-1055.

[3] Samer T., & John R. B. (2000). Using integer programming to refine Lagrangian-based unit commitment solutions. *IEEE Transactions on Power Systems*, *15*(1), 151-156.

[4] Mohan, M. R., Kuppusamy, K., & Abdullah Khan, M. (1992). Optimal short-term hydro-thermal scheduling using decomposition approach and linear programming method. *International Journal of Electrical Power and Energy Systems*, *14*(1), 39-44.

[5] Ngundam, J. M., Kenfack, F., & Tatietse, T. T. (2002). Optimal scheduling of large-scale hydrothermal power systems using the Lagrangian relaxation technique. *International Journal of Electrical Power & Energy Systems, 22*(1), 237-245.

[6] Bakirtzis, A. G., & Zoumas, C. E. (2000). Lambda of Lagrangian relaxation solution to unit commitment problem. *IEE Proceedings - Generation, Transmission and Distribution, 147*(2), 131-136.

[7] Chang, C. P., Liu, C. W., & Liu, C. C. (2000). Unit commitment by Legrangian relaxation and genetic algorithms. *IEEE Transactions on Power Systems*, *15*(2), 707-714.

[8] Nieva, R., Inda, A., & Guillen, I. (1987). Lagrangian reduction of search-range for large-scale unit commitment. *IEEE Transactions on Power Systems*, *2*, 465-473.

[9] Cohen, A. I., & Yoshimura, M. (1983). A branch and bound algorithm for unit commitment. *IEEE Transactions on Power Apparatus and Systems*, *102*(2), 444-451.

[10] Ouyang, Z., & Shahidehpour, S. M. (1990). Short term unit commitment expert system. *International Journal of Electrical Power System Research*, *20,* 1-13.

[11] Su, C. C., & Hsu, Y. Y. (1991). Fuzzy dynamic programming: an application to unit commitment. *IEEE Transactions on Power Systems*, *6*(3), 1231-1237.

[12] Sasaki, H., Watanabe, M., Kubokawa, J., & Yorino, N. (1992). A solution method of unit commitment by artificial neural networks. *IEEE Transactions on Power Systems*, *7*(3), 974-981.

[13] Padhy, N. P. (2000). Unit commitment using hybrid models: a comparative study for dynamic programming, expert systems, fuzzy system and genetic algorithms. *International Journal of Electrical Power & Energy Systems*, *23*(1), 827-836.

[14] Zhuang, F., & Galiana, F. D. (1990). Unit commitment by simulated annealing. *IEEE Transactions on Power Systems*, *5*(1)*,* 311-318.

[15] Kirkpatrick, S., Gelatt, C. D., & Vecehi, M. P. (1983). Optimisation by simulated annealing. *Science*, *220*, 671-680.

[16] Shokri, Z., Selim, & Alsultan, K. (1991). A simulated annealing algorithm for the clustering problem*. Pattern Recognition*, *24*(10), 1003-1008.

[17] Mantawy, A. H., Abdel-Magid, Y. L. & Selim, S. Z. (1998). A simulated annealing algorithm for unit commitment*. IEEE Transactions on Power Systems*, *13*(1), 197-204.

[18] Mantawy, A. H., Abdel-Magid, Y. L. & Selim, S. Z. (1998). A unit commitment by Tabu Search. *IEE Proceedings - Generation, Transmission and Distribution*, *145*(1), 56-64.

[19] Lin, W. M., Cheng, F. S., & Tsay, M. T. (2002). An improved tabu search for economic dispatch with multiple minima. *IEEE Transactions on Power Systems*, *17*(1), 108-112.

[20] Bai, X., & Shahidehpour, M. (1996). Hydro-thermal scheduling by tabu search and decomposition method. *IEEE Transactions on Power Systems*, *11*(2), 968-975.

[21] Wu, Y. G., Ho, C. Y., & Wang, D. Y. (2000). A diploid genetic approach to short-term Scheduling of hydro-thermal system. *IEEE Transactions on Power Systems*, *15*(4), 1268-1274.

[22] Hong, Y. Y., & Li, C. Y. (2002). Genetic algorithm based economic dispatch for cogeneration units considering multiplant multibuyer wheeling. *IEEE Transactions on Power Systems*, *17*(1), 134-140.

[23] Mantawy, A. H., Abdel-Magid, Y. L. & Selim, S. Z. *(*1999*)*. Integrating Genetic Algorithm, Tabu Search and Simulated Annealing For the Unit Commitment Problem. *IEEE Transactions on Power Systems*, *14*(3), 829-836.

[24] Wong, K. P., & Wong, Y. W. (1996). Combined genetic algorithm / simulated annealing / fuzzy set approach to short-term generation scheduling with take-or-pay fuel contract. *IEEE Transactions on Power Systems*, *11*(1), 128-135.

[25] Juste, K. A., Kita, H., Tanaka, E., & Hasegawa, J. (1999). An evolutionary programming solution to the unit commitment problem. *IEEE Transactions on Power Systems*, *14*(4), 1452-1459.

[26] Yang, H. T., Yang, P. C., & Huang, C. L. (1996). Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions. *IEEE Transactions on Power Systems*, *11*(1), 112-117.

[27] Wood, A. J. & Woolenberg, B. F. (1996). *Power Generation and control (2nd Edn)*. New York, USA: John Wiley and Sons.

[28] Lu, L., Wen, F., Xue, Y., & Xin, J. (2011). Unit commitment in power systems with plug-in electric vehicles. *Dianli Xitong Zidonghua/Automation of Electric Power Systems*, *35*, 16–20.

[29] Khodayar, M. E., Wu, L., & Shahidehpour, M. (2012). Hourly coordination of electric vehicle operation and volatile wind power generation in SCUC. *IEEE Transactions on Smart Grid, 3*(3), 1271–1279.

[30] Ikeda, Y., Ikegami, T., Kataoka, K. & Ogimoto, K. (2012, July 22-26). *A unit commitment model with demand response for the integration of renewable energies*. 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA.

[31] Du, P., & Lu, N. (2011). Appliance commitment for household load scheduling. *Appliance commitment for household load scheduling*, *2*(2), 411–419.

[32] Moghimi, H., Ahmadi, A., Aghaei, J., & Rabiee, A. (2013). Stochastic techno economic operation of power systems in the presence of distributed energy resources. *International Journal of Electrical Power & Energy Systems, 45,* 477–488.

[33] Goleijani, S., Ghanbarzadeh, T., Nikoo, F. S., &. Moghaddam, M. P. (2013). Reliability constrained unit commitment in smart grid environment. *Electric Power Systems Research, 97,* 100–108.