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SFLA approach to solve PBUC problem with emission limitation

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ABSTRACT

In this paper, the Shuffled Frog Leaping Algorithm is proposed to solve the Profit Based Unit Commitment problem under deregulated environment with emission limitation. The bi-objective function optimization problem is formulated as a maximization of the Generation Companies profit and a minimization of the emission output of the thermal units, while all of the constrains should be satisfied. This work, considers the new softer demand constraint to allocate fixed and transitional cost to the scheduled hours. The IEEE 10 unit 39 bus test system with 24 h data is taken as the input for simulation using MATLAB 7.10 version. From the results obtained, it is observed the proposed algorithm achieves maximum profit and minimum emission level with less computational time compared to traditional unit commitment.

1. Introduction

Unit Commitment (UC) is a nonlinear mixed integer optimization problem to schedule the operation of the generating units at minimum operating cost while satisfying the demand and reserve requirements. In earlier days the UC problem has to determine based on the on/off state of the generating units at each hour of the planning period and optimally dispatch the load and reserve among the committed units. UC is the most significant optimization task in the operation of the power systems. The global optimal solution to the UC problem can be obtained by complete enumeration, which is restricted to large power systems due to its excessive computational time requirements [1]. Numerous solutions have been proposed to solve the unit commitment problem [2], such as Priority List (PL), Dynamic Programming (DP), Lagrangian Relaxation (LR), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The PL method is fast but highly heuristic and gives schedule with relatively higher operating costs [2]. The DP method has the advantage of being able to solve problems of variety of sizes [3]. But it may lead to more mathematical complexity with increased in computation time, if the constraints are taken in to consideration [4]. Even though the LR is considered the best to deal with large-scale unit commitment, it cannot guarantee the optimal solution [5].

The process of deregulation and creating the market conditions in electricity sector was pioneered by Chile in 1978. It was later succeeded by England and Wales that started trading through the pool from 31st of March 1990. In power sector, the foremost process is deregulation that was taken over by the state reformation act of 1989. Most of the companies started the deregulation laws, that includes Argentinean and Chile, who were initiatives followed by South America, Peru in 1993, Bolivia and Columbia in 1994. According to Electricity Act of June 1990, deregulation and market competition was introduced in Norway. The current deregulation process in Brazil is the gradual outcome of these laws on February 1995. Many more countries like India also adopt the similar process of developing deregulation in power sector [6].

In the past decade, the power industry has moved from vertically integrated electric utilities to one that has been horizontally integrated electric utilities, in which the generation, transmission and distribution are unbundled. Consequently, the traditional method needs some changes in power generation, operation and control methods [7,8]. In deregulated power industry, unit commitment refers to optimizing generation property in order to maximize the GENeration COmpanies (GENCOs) profit called as Profit Based Unit Commitment (PBUC). Deregulation in power sector increases the efficiency and reliability of electricity production and distribution, at lower prices, higher quality, a secure and a more reliable product to consumers.

The deregulation of electric power systems has resulted in market-based competition by creating an open market environment [9]. Also, it has the advantage that customers are allowed to choose their suppliers and provide choice of different generation options at cheaper price to consumers [10].

The determination of thermal units which is to be committed and available for generation at each period and the associated generation or dispatch, during the time horizon of 1 day to 1 week can be done by the short term thermal scheduling. The economic

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Nomenclature

N	number of units
T	scheduling horizon
PD_t	system power demand at hour t
R_{it}	system spinning reserve of unit i at hour t
C	number of operating cycles for each unit i
P_{it}	output power of ith unit at hour t
$P_{i\max}$	maximum output power of ith unit
$P_{i\min}$	minimum output power of ith unit
$P_{it\max}$	maximum output power of ith unit at hour t
$P_{it\min}$	minimum output power of ith unit at hour t
$T_i(c)$	duration of operating cycle c for unit i
MU_i	maximum up-time limits of unit i
MD_i	minimum down-time limits of unit i
$H_{\text{cost}(i)}$	hot start cost of unit i
$C_{\text{cost}(i)}$	cold start cost of unit i
$C_{\text{hour}(i)}$	cold start hour of unit i
SU	start-up cost for unit i
SU_T	start-up cost
FC	fuel cost
RV	revenue
TC	total cost
PF	profit
X_{it}	operation status of unit i at hour t (1 = ON and 0 = OFF)
RU_i	ramp-up rate of unit i
RD_i	ramp-down rate of unit i
SP_i	spot price of ith unit
T_i^{ON}	minimum time that the ith unit has been continuously on line
T_i^{OFF}	minimum time that the ith unit has been continuously off line
r	random number generator with uniform distribution between 0 and 1
Round (x)	rounds of x to the nearest integer
EC_i	emission cost function of unit i

consequences of short term thermal scheduling plays a very important role, the saving of small percent helps in the reduction of fuel consumption. The reason for scheduling is now changed from cost-minimization to profit maximization of GENCO. The term of obligation to serve, is removed in this competitive environment. Now days, the generating companies consider the scheduling as the process that produces demand less than the forecasted level, if this scheduling is more profitable.

The implementation of GA (Genetic Algorithm) on Profit Based Unit Commitment problem is based on binary coding. So, the implementation and formulation of PBUC problem is difficult to get a optimal solution [11]. Particle Swarm Optimization (PSO) is a stochastic, population based evolutionary algorithm for problem solving. But PSO has some disadvantages like premature convergence and more computational time consumption to solve PBUC [12]. In [13], Muller Method was introduced to solve Economic Dispatch (ED) problem and Information Pre-Prepared Power Demand (IPPD) table was introduced to solve combinatorial sub problem for deregulated environment. In nodal ant colony optimization [14], to maintain the good exploitation and exploration search capabilities, the movements of the ants are represented with a search space consisting of optimal combination of binary nodes for unit on/off status. A hybrid computational model which is the combination of Genetic Algorithm and local search algorithm called memetic algorithm helps to cultural evolution [15]. In [16], Delarue et al. achieves the difference between the profit obtained when using perfect price forecast and without using perfect price forecast. In [17], Catalao et al. proposed a practical approach for PBUC with emission limitation, trade off curve can be found by parametrically varying the weighting factor between 0 and 1. From the literature survey, it is observed that most of the existing algorithms have some limitations to provide the qualitative solution. In this paper, Shuffled Frog Leaping Algorithm has been introduced to solve the PBUC.

The Kyoto Protocol is an international agreement linked to the United Nations Framework Convention on Climate Change [18]. The advantage of this agreement is that the sets binding targets for 37 industrialized countries and the European Community for reducing GHG emission. These amounts to an average of five percent against 1990 levels over the five years period 2008–2012. There are six main green house gases; they are carbon dioxide, methane, nitrous oxide, hydro fluorocarbons, per fluorocarbons, and sulfur hexafluoride. The monitor's emission from plants in the oil refining, smelting, steel, cement, ceramics, glass, and paper sectors and trading of emission allowances are done by emission trading scheme which is entered into force on Jan 2005. The Kyoto

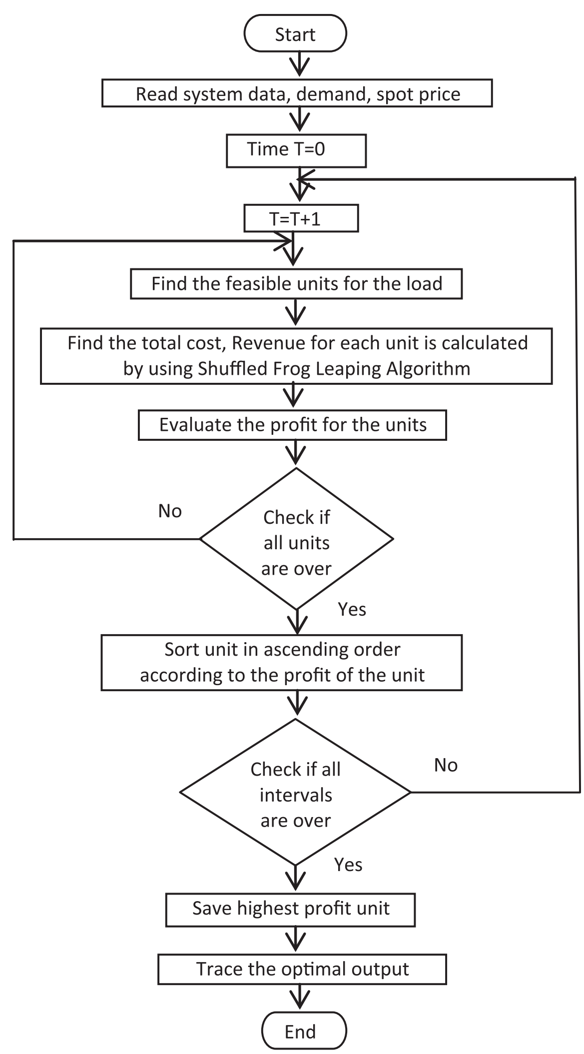

Fig. 1. Flowchart of proposed method.

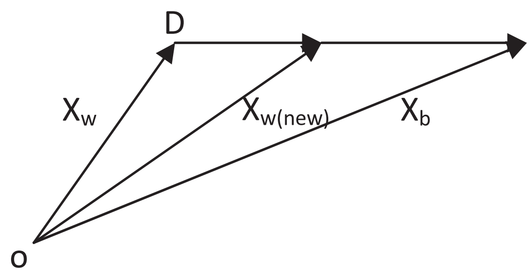

Fig. 2. Frog leaping rule.

Table 1
Forecasted demand and prices (10 generator case).

Hour (h)	Load (MW)	Price (Rs/MW h)	Hour (h)	Load (MW)	Price (Rs/MW h)
1	700	996.75	13	1400	1107
2	750	990	14	1300	1102.5
3	850	1039.5	15	1200	1012.5
4	950	1019.25	16	1050	1003.5
5	1000	1046.25	17	1000	1001.25
6	1100	1032.75	18	1100	992.25
7	1150	1012.5	19	1200	999
8	1200	996.75	20	1400	1019.25
9	1300	1026	21	1300	1039.5
10	1400	1320.75	22	1100	1032.75
11	1450	1356.75	23	900	1023.75
12	1500	1424.25	24	800	1014.75

Protocol implies new emission constraints regarding production decisions in the thermal units burning fossil fuels [19].

The first work in the minimization of emission dispatch has been done by Gent and Lamont [20]. Nanda et al. took the same problem in addition with the line flow constraints to minimize the emission [21]. They solved the problem with the classical technique which is based on co-ordination equations. Fletcher's quadratic programming method solves the optimal power dispatch problem with practical constraints [22]. The Common Economic Emission Dispatch Problem can be solved by sequential quadratic programming technique by assigning weighting factor for generation and emission cost functions, the above method was proposed by Hota et al. [23].

The fossil fueled power plants are classified as stationary sources of emission pollution. The fossil fuels are burnt to convert into electrical energy, as the result of this process, the emission occurs. The amount of emission depends on the fuel used, the level power and efficient of the technology used in the operation. The natural gas-fired power plant in combined cycle configuration generates emission two and half times higher than the pulverized coal fired power plants. In the vicinity of urban or rural zones, the coal fired power plants are polluting less and due to the weather condition or the usual high temperature inversion effect, the concentrations of pollution originate environmental impact [24].

Coal and petroleum are the primary sources of energy. High ash content in Indian coal and inefficient combustion technologies contribute to India's emission of air particulate matter and other trace gases, including gases that are responsible for the greenhouse effect. Coal is the primary fuel in thermal power plants; gasoline and diesel are the primary fuels for automobiles. There is also limited use of natural gas in these energy activities. According to the National Thermal Power Corporation, coal is used for approximately 62.3% of India's electric power generation; oil and gas account for 10.2%; water's share is 24.1%; nuclear, wind, and other power generation methods contribute to the remaining 3.4% usage. Public utilities primarily use steam in the generation of power. India is the third-largest producer of coal, but Indian coal is of poor quality with high ash content (35–50%) and low calorific value (gross heat of combustion). Electric power generation from coal-fired power plants in India is continuously increasing. The emission estimates are made for each power plant based on power generation per day and the coal used per unit generation of power.

The organization of the paper is organized as follows: Section 2 presents the detailed Shuffled Frog Leaping Algorithm, Section 3 presents formulation of PBUC problem, Section 4 presents the SFLA on PBUC problem and simulation results are given in Section 5 followed by a conclusion (Section 6) and references.

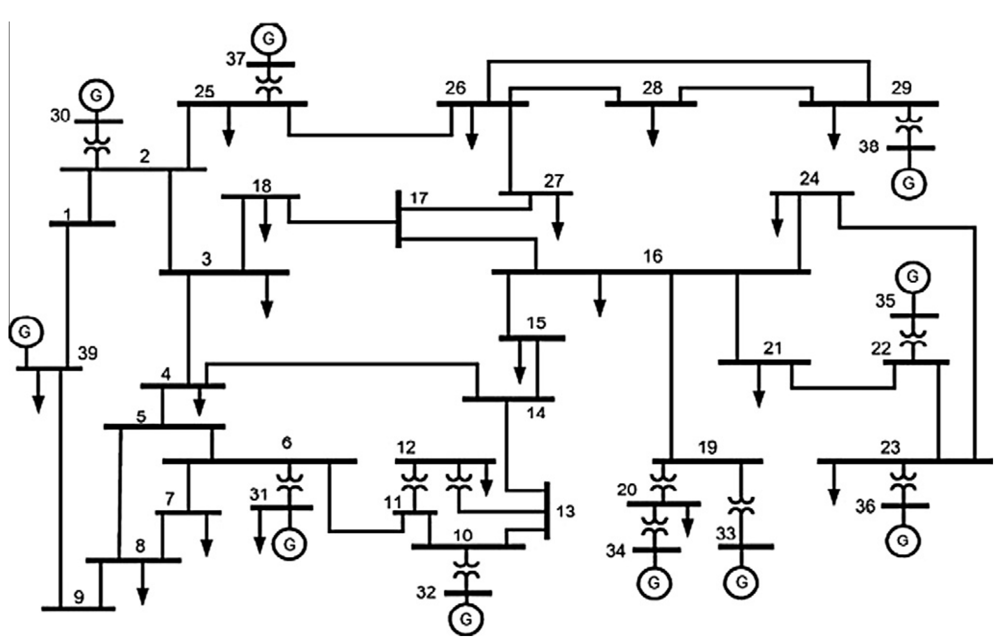

Fig. 3. Single line diagram of IEEE 39 bus systems.

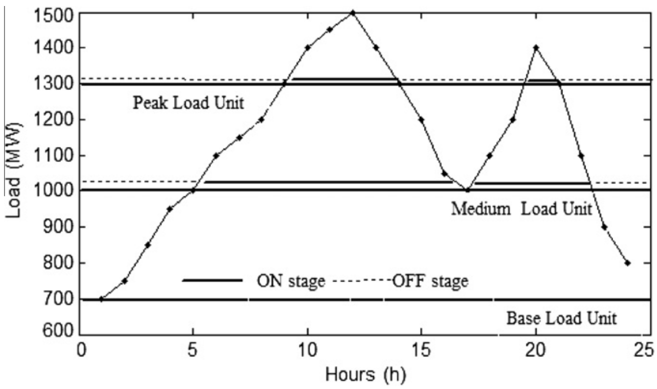

Fig. 4. Base-load, medium load and peak load unit operating cycles.

Table 2
Generator emission co-efficients.

Units	α_i (ton/h)	β_i (ton/MW h)	γ_i (ton/MW^2 h)
U – 1	10.33908	−0.24444	0.00312
U – 2	10.33908	−0.24444	0.00312
U – 3	30.03910	−0.40695	0.00509
U – 4	30.03910	−0.40695	0.00509
U – 5	32.00006	−0.38132	0.00344
U – 6	32.00006	−0.38132	0.00344
U – 7	33.00056	−0.39023	0.00465
U – 8	33.00056	−0.39023	0.00465
U – 9	35.00056	−0.39524	0.00465
U – 10	36.00012	−0.39864	0.00470

2. Shuffled Frog Leaping Algorithm (SFLA)

The SFLA is a meta-heuristic optimization method that mimics the memetic evolution of a group of frogs while seeking for the location that has the maximum amount of available food [25]. SFLA, developed by Eusuff and Lansey in 2003, can be used to solve many complex optimization problems, which are nonlinear, non-differentiable, and multi-modal [26]. SFLA has been successfully applied to several engineering optimization problems such as water resource distribution [27], bridge deck repairs [28], job-shop scheduling arrangement [29], and traveling salesman problem [30]. The most renowned benefit of SFLA is its fast convergence speed [31]. The algorithm contains elements of local search and global information exchange. The SFLA is derived from a virtual population of frogs. Each frog is distributed to a different subset of the whole population called memeplex. Within each memeplex, the individual frog holds idea that can be influenced by the ideas of other frogs, and the ideas can evolve through a process of memetic evolution. An independent local search is conducted for each

Table 4
Sfla control parameter.

#No. of units	10	System reserve	10%
#No. of hours	24	Memeplx	20
Popsize	200	New frog generation per iteration	20
Iteration	10		

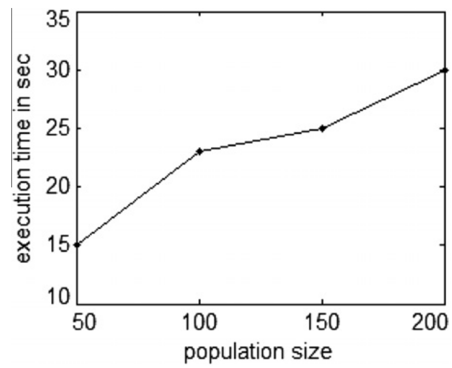

Fig. 5. Execution time.

memeplex. After a defined number of memetic evolutionary steps, frogs are shuffled among memeplexes [32,33], enabling frogs to interchange messages among different memplexes and ensure that they move to an optimal position, similar to particles in PSO. Local search and shuffling continue until defined convergence criteria are met.

The flowchart of SLFA is illustrated in Fig. 1. In the first step of SFLA algorithm, an initial population of P frogs is randomly generated within the feasible search space. The location of the ith frog is represented as $X_i = (X_{i1}, X_{i2}, \ldots X_{iD})$, where D is the number of variables. The frogs are sorted in descending order according to their fitness value. Then, the entire population is divided into m memeplexes, each containing n frogs (i.e., $P = m \times n$). In this process, the 1st frog goes to the first memeplex, the 2nd frog goes to the second memeplex, mth frog goes to the mth memeplex, and frog $m + 1$ goes to the first memeplex, and so on. According to the original frog leaping rule, the position of the worst frog is updated as follows:

$$D_i = r \cdot (X_b - X_w) \tag{1}$$

$$X_w^{\text{new}} = X_w^{\text{current}} + D_{i,} \quad (D_{i\min} < D_i < D_{i\max}) \tag{2}$$

where D_i is a change of frog's position in one jump. r is a random number generator with uniform distribution between 0 and 1, $D_{i\max}$, $D_{i\min}$ is the maximum and minimum allowed change of frog's position in one jump.

Table 3
Operator data.

	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
P_i(max)	455	455	130	130	162	80	85	55	55	55
P_i(min)	150	150	20	20	25	20	25	10	10	10
A_i	1000	970	700	680	450	370	480	660	665	670
B_i	16.19	17.26	16.60	16.50	19.70	22.26	27.74	25.92	27.27	27.79
C_i	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.00079	0.00413	0.00222	0.00173
MU_i	8	8	5	5	6	3	3	1	1	1
MD_i	8	8	5	5	6	3	3	1	1	1
$H_{\text{cost}(i)}$	4500	5000	550	560	900	170	260	30	30	30
$C_{\text{cost}(i)}$	9000	10,000	1100	1120	1800	340	520	60	60	60
$C_{\text{hour}(i)}$	5	5	4	4	4	2	2	0	0	0
$I \cdot$ state	8	8	−5	−5	−6	−3	−3	−1	−1	−1

Table 5
Simulation result of the traditional UC method.

Units	Power generation of units (MW)										Generation cost (Rs)	Start up cost (Rs)	Revenue (Rs)	Profit (Rs)	Emission (ton)
(h)	1	2	3	4	5	6	7	8	9	10					
1	455	245	0	0	0	0	0	0	0	0	615740.84	0	697725.00	81984.16	682.7662
2	455	275	0	0	0	20	0	0	0	0	676071.62	7650	742500.00	58778.38	841.9329
3	455	375	0	0	0	20	0	0	0	0	754648.37	0	883575.00	128926.63	1020.89
4	455	455	0	0	0	40	0	0	0	0	838129.13	0	968287.50	130158.37	1204.403
5	455	395	130	0	0	20	0	0	0	0	900528.20	24,750	1046250.00	120971.8	1096.566
6	455	365	130	130	0	20	0	0	0	0	1005638.79	25,200	1136025.00	105,187	1065.88
7	455	415	130	130	0	20	0	0	0	0	1045017.84	0	1164375.00	119357.16	1175.338
8	455	455	130	130	0	30	0	0	0	0	1086748.50	0	1196100.00	109351.5	1272.043
9	455	455	130	130	0	80	0	0	0	50	1230342.83	2700	1333800.00	100757.17	1400.717
10	455	455	130	130	162	58	0	0	0	10	1326587.15	40,500	1849050.00	481962.85	1431.834
11	455	455	130	130	162	80	0	0	0	38	1384087.32	0	1967287.50	583200.18	1429.043
12	455	455	130	130	162	80	78	0	0	10	1468780.98	23,400	2136375.01	644194.03	1431.741
13	455	455	130	130	162	33	25	0	0	10	1353645.46	0	1549800.00	196154.54	1426.691
14	455	455	130	130	65	20	25	10	0	10	1291851.09	2700	1433250.00	138698.91	1387.083
15	405	455	130	130	25	20	25	10	0	0	1175951.74	0	1215000.00	39048.26	1200.53
16	280	455	130	130	25	20	0	10	0	0	1030203.78	0	1053675.00	23471.22	970.7845
17	230	455	130	130	25	20	0	10	0	0	993225.48	0	1001250.00	8024.52	903.446
18	330	455	130	130	25	20	0	10	0	0	1067290.08	0	1091475.00	24184.92	1053.722
19	455	440	130	130	25	20	0	0	0	0	1107257.96	0	1198800.00	91542.04	1228.534
20	455	455	130	130	162	0	68	0	0	0	1314971.23	23,400	1426950.00	88578.77	1336.859
21	455	455	130	130	105	0	25	0	0	0	1207895.94	0	1351350.00	143454.06	1304.426
22	455	455	0	130	25	0	25	10	0	0	1046364.89	2700	1136025.01	86960.12	1295.601
23	455	445	0	0	0	0	0	0	0	0	773005.94	0	921375.00	148369.06	1064.438
24	305	455	0	0	0	20	0	0	10	10	790610.52	13,050	811800.00	8139.48	1018.886
Total =											25484595.68	166,050	29312100.00	3661454.32	28244.15

If this leaping produces a better solution, it will replace the worst frog X_w. Otherwise the calculations of above (1) and (2) will be repeated with respect to the global best frog X_g. If no improvement becomes achievable in this case, the worst frog will be replaced and a new frog will be randomly generated to replace the worst frog. The calculations continue for each memeplex, and the whole population is mixed mutually in the shuffling process [28,31]. Therefore, SFLA simultaneous performs an independent local search in each memeplex using a process similar to the PSO algorithm.

After a predefined number of memetic evolutionary steps within each memeplx, the solutions of evolved memeplexes ($X_1, \ldots X_p$) are replaced into new population (new population = {X_k, $k = 1, \ldots p$}); this is called the shuffling process. The shuffling process promotes a global information exchange among the frogs. Then, the population is sorted in order of decreasing performance value and updates the population best frog's position X_g, repartition the frog group into memeplexes, and progress the evolution within each memeplex until the conversion criteria are satisfied. Fig. 2 demonstrates the original frog leaping rule. The Shuffled Frog

Table 6
Simulation result of the proposed method.

Units	Power generation of units (MW)										Fuel cost (Rs)	Start up cost (Rs)	Revenue (Rs)	Profit (Rs)	Emission (ton)
(h)	1	2	3	4	5	6	7	8	9	10					
1	455	245	0	0	0	0	0	0	0	0	615740.8	0	697,725	81984.2	682.7662
2	455	295	0	0	0	0	0	0	0	0	654952.5	0	742,500	87547.5	754.7842
3	455	395	0	0	0	0	0	0	0	0	733,585	0	883,575	149,990	945.6202
4	455	455	0	0	0	0	0	0	0	0	780898.5	0	927517.5	146,619	1090.074
5	455	455	0	0	0	0	0	0	0	0	780898.5	0	952087.5	171,189	1090.074
6	455	455	0	0	162	0	0	0	0	0	949461.8	40,500	1,107,108	117146.2	1210.658
7	455	455	0	0	162	0	0	0	0	0	949461.8	0	1,085,400	135938.2	1210.658
8	455	455	0	130	160	0	0	0	0	0	1,076,303	25,200	1,196,100	94,597	1243.775
9	455	455	0	130	162	0	0	0	0	0	1,078,192	0	1,233,252	155,060	1243.775
10	455	455	130	130	162	0	0	0	0	0	1,208,323	24,750	1,759,239	526,166	1276.893
11	455	455	130	130	162	80	0	0	0	0	1,307,159	7650	1,915,731	600,922	1300.403
12	455	455	130	130	162	80	0	0	0	0	1,307,159	0	2,011,041	703,882	1300.403
13	455	455	130	130	162	68	0	0	0	0	1,294,570	0	1,549,800	255,230	1298.869
14	455	425	130	130	160	0	0	0	0	0	1,182,765	0	1,433,250	250,485	1200.405
15	455	455	0	130	160	0	0	0	0	0	1,076,303	0	1,215,000	138,697	1242.322
16	415	345	0	130	160	0	0	0	0	0	959744.9	0	1,053,675	93930.1	895.8523
17	415	295	0	130	160	0	0	0	0	0	920463.5	0	1,001,250	80786.5	808.2343
18	415	385	0	130	162	0	0	0	0	0	993108.5	0	1,083,537	90428.5	978.6314
19	455	455	0	130	160	0	0	0	0	0	1,076,303	0	1,198,800	122,497	1242.322
20	455	455	0	130	162	0	0	0	0	0	1,078,192	0	1225138.5	146946.5	1243.775
21	455	455	0	130	162	0	0	0	0	0	1,078,192	0	1,249,479	171,287	1243.775
22	455	455	0	0	162	0	0	0	0	0	949461.8	0	1,107,108	157646.2	1210.658
23	455	445	0	0	0	0	0	0	0	0	773005.9	0	921,375	148369.1	1060.438
24	455	345	0	0	0	0	0	0	0	0	694233.9	0	811,800	117566.1	842.4022
Total =											23,518,478	98,100	28,361,489	4744910.1	26617.568

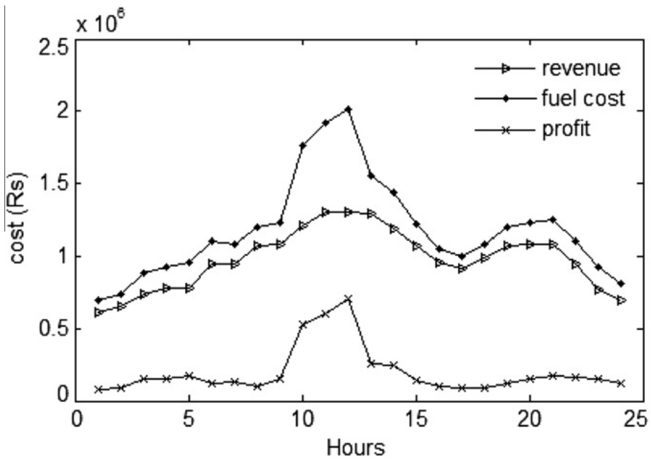

Fig. 6. Revenue, fuel cost and profit by the proposed method over 24 h for 10 units system.

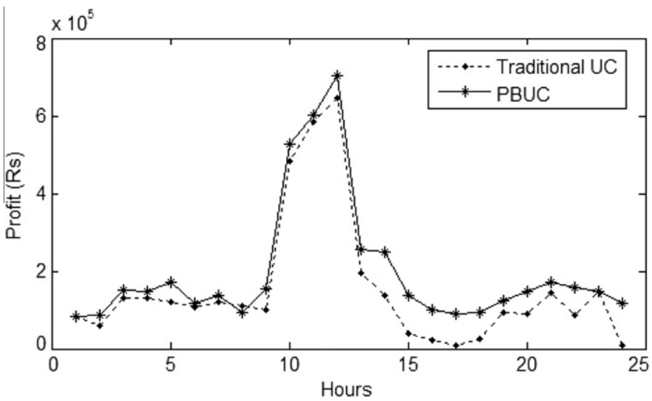

Fig. 7. Comparison of profits by traditional UC and PBUC.

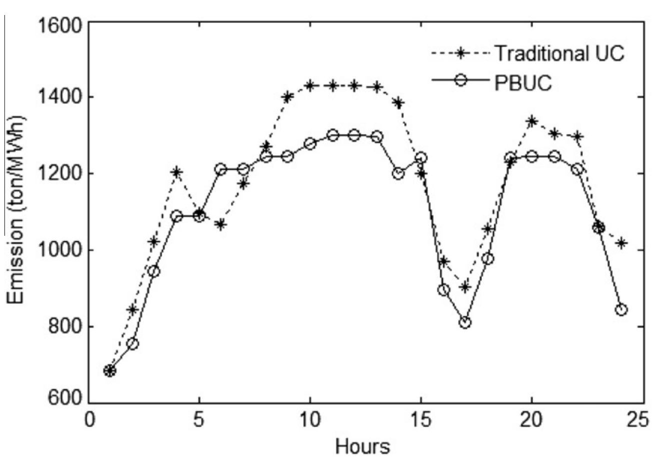

Fig. 8. Comparison of emissions by traditional UC and PBUC.

Leaping Algorithm is explained in following steps. Usually, convergence criteria can be defined as follows [33]:

i. The relative change in the fitness of the global frog within a number of successive shuffling iterations is less than a pre-specified tolerance.
ii. The maximum user specified number shuffling iterations is reached.

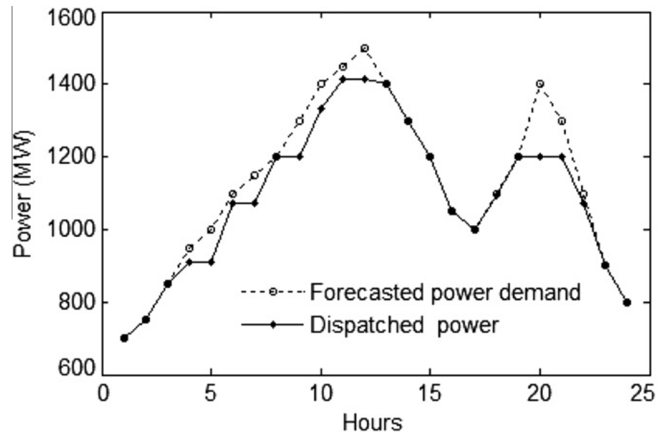

Fig. 9. Comparison between dispatched power and forecasted power demand.

2.1. Proposed method algorithm

Step 1: Generate random population of P solution and set M number of memplex.
Step 2: Set n Number of frogs and Number of local iteration in each memplex.
Step 3: Calculate fitness value using randomly produced P value.
Step 4: Arrange P value in descending order according to their fitness value.
Step 5: Determine X_b & X_w and X_g.
Step 6: Divide P solutions into M memplex.
Step 7: Calculate X_{new}.
Step 8: If X_{new} better than X_w then go to Step 12 otherwise go to next step.
Step 9: Change X_b with X_g and calculate X_{new}.
Step 10: If X_{new} better than X_w then go to Step 12 otherwise go to next step.
Step 11: Produce new P value randomly.
Step 12: Change X_w with X_{new}.
Step 13: Repeat the specific number of iterations.
Step 14: End.
Step 15: Shuffled evolved groups.
Step 16: Sort the population P in descending order of their fitness.
Step 17: If execution = true then go to next step otherwise go to Step 3.
Step 18: Find out the best solution.
Step 19: End.

3. Formulation of PBUC problem

PBUC problem in deregulated environment is one of the optimization problems. The main objective is allocation of generating units so as to maximize the profit of the generating companies. In order to increase their own profit, GENCOs undergo the Profit Based Unit Commitment based on forecasted demand, reserve, known spot prices and reserve prices in the markets. These forecasted data are very important for the GENCOs unit commitment problem because they are taking the risk of committing their own units. It can be mathematically formulated by the following equation.

The bi-objective problem:

$$\max PF = RV - TC \tag{3}$$

$$\min EC_i = \alpha_i + \beta_i \cdot P_{it} + \gamma_i \cdot (P_{it})^2 \tag{4}$$

Table 7
Comparison of the results by traditional UC and proposed method.

S. No	Method	Profit (Rs/day)	Profit (Rs/year)	Emission (ton/day)	Emission (ton/year)
1	Traditional UC	3661454.32	1336430826.8	28244.15	10309114.75
2	PBUC using SFLA	4744910.1	1731892186.5	26617.568	9715412.32

$$RV = \sum_{i=1}^{T}\sum_{i=1}^{N} P_{it}SP_iX_{it} \tag{5}$$

$$TC = \sum_{t=1}^{T}\sum_{i=1}^{N} FC_i(P_{it})X_{it} + SU_T \tag{6}$$

where α_i, β_i and γ_i are the emission co efficient of unit 'i'.

As long the unit is not off there is no need to pay the start up cost. The objective function is subjected to the following constraints.

3.1. Power demand constraint

The normal power demand constraint is modified as softer power demand constraint. Here, sum of output powers of allocated generating units is always less than or equal to forecasted power demand.

$$\sum_{i}^{N} P_{it}X_{it} \leqslant PD_t, \quad t = 1 \ldots T \tag{7}$$

3.2. Generation limit constraint

The upper and lower limits of the ith generating unit as follows

$$P_{i\min} \leqslant P_{it} \leqslant P_{i\max} \quad i = 1, \ldots N \tag{8}$$

$$0 \leqslant R_{it} \leqslant P_{i\max} - P_{i\min}, \quad i = 1, \ldots N \tag{9}$$

where $P_{i\min}$ and $P_{i\max}$ are the minimum and maximum generation of unit i.

3.3. Minimum up and down-time constraint

It indicates that a unit must be ON/OFF for a minimum time before it can be shutdown or restarted, respectively.

$$T_i^{\mathrm{ON}} \geqslant MU_i \tag{10}$$

$$T_i^{\mathrm{OFF}} \geqslant MD_i \tag{11}$$

3.4. System power balance and reserve constraints

Sum of the power and reserve of unit 'i' is within the limit of $P_{i\min}$ and $P_{i\max}$.

$$P_{i\min} \leqslant P_{it}X_{it} + R_{it}X_{it} \leqslant P_{i\max} \tag{12}$$

$$\sum R_{it}X_{it} \leqslant R_{it\max} \tag{13}$$

Here, reserve constraints are different from traditional UC problem because GENGOs can now select to produce reserve less than forecasted level if it creates more profit.

3.5. Ramp up and down rates

Maximum ramp-up and down rate limits the maximum increase or decrease of generated power from one time period to the next time period.

$$P_{it\max} = \min\{P_{i\max}, P_i(t-1) + \tau \cdot RU_i\} \tag{14}$$

$$P_{it\min} = \max\{P_{i\min}, P_i(t-1) - \tau \cdot RD_i\} \tag{15}$$

where τ = 60 min is the PBUC time step.

Here, expected spot price and reserve price are important parameters to the profit based UC. They are used to determine the expected revenue, which directly affects the expected profit.

4. SFLA on PBUC problem

4.1. Frog location (x) definition

In the integer coded SFLA, the frog position (x) consists of a sequence of integer numbers, representing the sequence of the ON/OFF cycle durations of each unit during the UC horizon [32]. A positive integer in the x represents the duration of continuous unit operation ON status, while a negative integer represents the duration of continuous reservation OFF status of units. The number of a unit ON/OFF cycles during the UC horizon depends on the number of load peaks during the unit commitment horizon and the sum of minimum up and down times of unit.

The power dispatchers know the number of the daily ON/OFF cycles of the thermal generating units from their operating history [34]. As shown in Fig. 3, the daily load curve (exhibiting two peaks) is used to determine the ON/OFF cycles of units. The numbers of ON/OFF cycles for the base, medium, and peak load units are equal to 2, 3, and 5, respectively. Since the number of ON/OFF cycles of thermal generating units is small in practice typically 1–5 ON/OFF cycles per day.

4.2. Initial population

The duration of the unit 'i' operation in first cycle $T_i(1)$ is initialized. So, the unit continues the operating mode (ON/OFF) of the last cycle of the previous scheduling day for at least as many hours as required to satisfy the minimum up and down time constraints.

$$T_i(1) = \begin{cases} +\mathrm{Rand}(\max(0, MU_i - T_i(0)), T), & \text{if } T_i(0) > 0 \\ -\mathrm{Rand}(\max(0, MD_i + T_i(0)), T), & \text{if } T_i(0) < 0 \end{cases} \tag{16}$$

where $T_i(0)$ is the duration of last cycle of the previous scheduling day.

For $c < C$, the operation duration of the cth cycle of unit i, $T_i(c)$,is calculated considering the minimum up, down-time constraints of the unit, the UC horizon and the duration of the $(c-1)$ prior cycles of the unit operation.

If $T_i(c-1) < 0$, cycle 'c' represents ON status with duration.

$$T_i(c) = \begin{cases} +\mathrm{Rand}(MU_i, RT_i(c-1)), & \text{if } (RT_i(c-1) > MU_i) \\ +RT_i(c-1), & \text{otherwise} \end{cases} \tag{17}$$

If $T_i(c-1) > 0$, cycle 'c' represents OFF status with duration.

$$T_i(c) = \begin{cases} -\text{Rand}(MDi, RT_i(c-1)), & \text{if } (RT_i(c-1) > MD_i) \\ -RT_i, (c-1), & \text{otherwise} \end{cases} \tag{18}$$

where $RT(c-1)$ is the scheduling time after allocation of first $(c-1)$ cycles.

$$RT_i(c-1) = T - \sum_{P=1}^{c-1} \left| T_i^P \right| \tag{19}$$

In the randomly generated cycle durations, the entire scheduling period is covered with $c < C$ operating cycles in some cases. The remaining cycles are assigned zero.

After the initialization of minimum up and down-time constraints are automatically satisfied, there is no need for the penalty function.

4.3. Leaping of worst solution

The worst fitness value X_w in each memplex is adjusted by adding vector ($D_i = r \cdot (X_b - X_W)$) to it. In this approach leads to the sum of values of $T_i(c_i)$ for each unit, which is not equal to the scheduling horizon. Therefore, the operating cycles of each unit of new X_w must be corrected, as follows:

$$T_i(c_i) = \frac{T}{\sum_{k=1}^{C} \left| T_i^k \right|} \quad i = 1, 2, \ldots N \tag{20}$$

The function r generates random number between 0 and 1. As a result, the parameters of new X_w are not integer values. So, the parameters of new X_w must be converted to integer values, as follows:

$$X'(w) = \text{Round}(\text{new } X_W) \tag{21}$$

while $X'(w)$ is new solution with integer parameters. The duration of the last nonzero cycle ($T_i(1)$) of each unit should be changed by;

$$T_i(1) = T - \sum_{k}^{l-1} |T_i^k| \quad i = 1, 2, \ldots N, \tag{22}$$

4.4. Satisfying minimum up and down-time constraints

The duration of cycles $c = 1 \ldots C - 1$ of unit 'i' are checked considering the minimum up and down-time constraint of unit 'i'.

For $T_i(0) > 0$, if $T_i(1) < MU_i$, then the duration of cycles c and $c + 1$ of unit are changed, as follows:

$$\begin{cases} T_i(c+1) = T_i(c+1) - T_i(c) + MU_i \\ T_i(c) = MU_i \end{cases} \tag{23}$$

For $T_i(1) < 0$, if $T_i(1) < MU_i$, then the duration of the cycles c and $c + 1$ of unit are changed, as follows:

$$\begin{cases} T_i(c+1) = T_i(c+1) - T_i(c) + MU_i \\ T_i(c) = MD_i \end{cases} \tag{24}$$

After leaping satisfying the time constraints, an Economic Dispatch should be calculated in scheduling horizon.

4.5. Fitness function calculation

The objective function of SFLA is to minimize the total generation cost of a power system for each hour while satisfying constraints. The penalty functions of reserve and generation constraints are used to solve ED for the scheduling horizon. The fuel cost function of the generation of 'P_i' in the 'i'th unit at 't'th hour

$$FC_i(P_{it}) = A_i + B_i \cdot P_{it} + C_i \cdot (P_{it})^2 \tag{25}$$

where P_{it} is the output power of ith unit at hour t, A_i, B_i and C_i are fuel cost function coefficients.

The start-up cost depends on the instant that the unit has been switched off prior to start-up.

The start-up costs are calculated as follows

$$SU_T = \sum_{i=1}^{N} \sum_{c=2}^{C} H(T_i(c)) \cdot SU_i(-T_i(c-1)) \tag{26}$$

where

$$SU_i(-T_i(c-1)) = \begin{cases} H_{\text{cost}(i)}, & \text{if } (MD_i - T_i(c-1)) \leqslant C_{\text{hour}(i)} \\ C_{\text{cost}(i)}, & \text{if } (MD_i - T_i(c-1)) > C_{\text{hour}(i)} \end{cases} \tag{27}$$

The total operation cost over the scheduling horizon is expressed by the following equation

$$TC = \sum_{t=1}^{T} \sum_{i=1}^{N} FC_i(P_{it}) X_{it} + SU_T \tag{28}$$

The overall objective of SFLA is to maximize the following fitness function subjected to a number of system and unit constraints:

$$\text{Fitness} = \begin{cases} \max \ \text{Profit} \\ \min \ \text{Emission} \end{cases} \tag{29}$$

5. Simulation result

The PBUC–SFLA formulation and solution methodology has been implemented using MATLAB 7.10 and executed on a corei3 (2.10 GHz) personal computer with 4 GB RAM. The proposed method has been tested on 10 generating units to solve the Profit Based Unit Commitment problem.

The PBUC–SFLA was run on a small system so that its solution could be easily obtained. GENCO might select to sell an allocated power rather than to sell it, in order to maximize their own profit. In the individual GENCO, the optimum schedule is obtained even if some of the units are in OFF for few hours. If there is N number of units in the system, some of them are higher fuel cost and other generating units are lower fuel cost. Therefore the GENCO decided to save production cost by OFF line some of the higher fuel cost value units and to run the other units (lower fuel cost value units) over a scheduling period. Before running the PBUC–SFLA, the GENCO wants to get an accurate hourly demand and price forecast for the period of scheduling horizon. Developing the forecasted data is an important matter, but beyond the scope of this paper.

For the results existing in this section the forecasts load and prices are taken as shown in Table 1. In addition to loading the forecasted hourly price and demand, PBUC–SFLA program needs to load the parameters of each generating unit to be considered. The single line diagram of IEEE 39 bus system is shown in Fig. 4. Emissions from coal-fired, petroleum and natural gas power plants are quite different. It is assumed that conventional thermal units are coal-fired because of low operational cost and their estimated emission co-efficient are given in Table 2 are taken from [35]. We are modeling the generators with a quadratic cost curve [e.g. $A_i + B_i \cdot P_i^t + C_i \cdot (P_i^t)^2, \alpha_i + \beta_i \cdot P_i^t + \gamma_i \cdot (P_i^t)^2$]. The data for 10 unit case is shown in Table 3. The data was selected so that the optimal solution was known a priori.

Before running the SFLA, the user needs to specify the control parameters shown in Table 4, including the number of generating units and number of hours to be measured in the study. The 'popsize' is the size of the SLFA population. The parameters listed in Table 4 were adjusted accordingly. To ensure that the PBUC–SFLA is finding optimal solutions, an exhaustive search was performed on some of the smaller cases. The execution time varies approximately linearly with popsize as shown in Fig. 5 and it shows the time in seconds to population size in numbers for the PBUC–SFLA. Number of iterations indicates how many times the SFLA will go through shuffling phase. System reserve is the percentage of reserves that the buyer must maintain for each contract. The number of iteration within the memeplex conveys how many times the new frog is generated in the SFLA.

Table 5 shows the traditional UC profit found by SFLA for selected cases. In the traditional unit commitment generating units 7, 8, 9 and 10 satisfies the minimum up/down and power balance constraints. But it gives the negative profit over the scheduling period. In our proposed methods over a scheduling period, GENCO decides turn off the higher fuel cost units such as 7, 8, 9 and 10 and it turns on lower fuel cost units namely 1, 2, 3, 4, 5 and 6. Therefore the proposed method obtains a positive profit of GENCO. Table 6 shows the proposed method scheduling and profit found by SFLA for selected cases, as through minimum up and down times are not violated. When calculating the cost of such a schedule, the algorithm ensures that the profit is based on a valid schedule by considering a banked unit, and so forth, in addition, show the best solution of the population for each of the cases.

Fig. 6 shows the fuel cost, revenue and profit during each generation of the PBUC- SFLA on the 10 unit system, 24 h/period case. Figs. 7 and 8 show the profit and emission comparison of traditional unit commitment and PBUC for 10 unit system. Fig. 9 shows that comparison between Dispatched power and Forecasted power for 10 unit test system. From Table 7, it is clear that the proposed method provides maximum profit and minimum emission output compared to Traditional UC method. Also computational time of the proposed method is 30 s.

6. Conclusion

This paper has proposed a bi objective problem for Profit Based Unit Commitment based on Shuffled Frog Leaping Algorithm under deregulated environment with emission limitation. This method increases the Profit by 22.834% and decreases the Emission 5.76% per day when compared to the traditional Unit Commitment method. Further, it provides better solutions particularly for systems containing larger number of generating units. Shuffled Frog Leaping Algorithm can provide a fast solution and the GENCOs can maximize their profit, minimizing their emission and schedule the generating units accordingly. The results achieved are quite encouraging and indicate the feasibility of the proposed technique to deal with large scale unit commitment problems in a deregulated environment.

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