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Profit Maximization of Generation Companies Considering Renewable Energy Integration and Unit Forced Outage Rates

[1]S. Sivasakthi, [2]S. Ganesan and [3]S. Subramanian

[1]Department of Electrical and Electronics Engineering, Krishnasamy College of Engineering and Technology, Cuddalore, Tamil Nadu, India.

[2]Department of Electrical and Electronics Engineering, Government College of Engineering, Salem, Tamil Nadu, India

[3]Department of Electrical Engineering, Annamalai University, Annamalai Nagar, Tamil Nadu, India.

E-mail: [1]sivasakthi_gayu@yahoo.co.in, [2]ganeshshriraj@gmail.com, [3]dr_smani@yahoo.co.in

ABSTRACT

Recently, the power system operational planning has been renovated because of the restructuring of the electric power sector. In competitive markets, individual generation companies (GENCOs) determine independent unit commitment (UC) schedules based on forecasted load demand and price. Here, GENCOs develop UC strategies based on the cost characteristics of their generators and revenues from spot price projection in order to maximise profit. This redefined UC is termed "profit-based unit commitment" (PBUC). Unlike convectional UC, PBUC aims to maximise profit rather than minimise costs. We are turning to renewable energy sources as a result of growing environmental concerns. Recently, wind energy has grown in popularity. Here, the traditional producing units are combined with a wind energy farm to reduce the hazardous gas emissions from the fossil generating units. Additionally, the PBUC formulation of the wind-integrated thermal power system takes reliability issues into account. The GENCOs must have a reliable tool to perform PBUC on real-world power systems. This study proposes a novel bio-inspired method called Grey Wolf Optimization (GWO) to address the profit-based scheduling problem. The realistic 10 thermal generating units confirm the GWO model's effectiveness. The simulation results demonstrate the ability of the intended method to produce cost-effective resolutions with high solution quality.

Keywords: *Generation scheduling, grey wolf optimization, profit based unit commitment, reliability analysis, wind power generation*

1. INTRODUCTION

1.1 Profit Based Unit Commitment

The Unit Commitment (UC) problem, which is used in regulated power generation, establishes the best schedule for generating units to achieve the lowest operating cost by satisfying equality and inequality criteria. Millions of dollars are annually saved when producing units are run on their optimum schedule. Conventionally, several deterministic and heuristic techniques are reported to solve UC problems. Still, the development of better models is necessary to handle the new challenges.

Recently, the power industry is moving towards horizontally integrated industry from vertically integrated industry. The usual design of the power system is centralised, and the UC problem is constructed there to save operating expenses. Now, however, as we transition to a deregulated system, generating companies seek to maximise profit by producing and reselling electricity. Here, UC has evolved from a profit-based policy known as Profit Based Unit Commitment to a minimum cost policy (PBUC).

In a competitive environment, GENeration Companies (GENCOs) may produce less real power than the anticipated demand. Here GENCOs may choose most profitable generation by considering the softer demand. This provides little flexibility in the power generation planning. The GENCOs have to maximize profit with simultaneous maintain of power quality to the consumers.

Electricity is traded as a commodity on the open electricity market under a deregulated structure. A GENCO's goal is to maximise profit on the open energy market while adhering to the generating units' inequality limits. The restrictions include the thermal units' minimum up/down times and generation constraints.

In unregulated markets, GENCOs take into account generation planning up to 24 hours in advance, depending on the availability of generating units, their individual features, and price projections. The GENCOs plan the bidding strategy for each of the following day's bidding periods.

In order to outperform their rivals, GENCOs will have additional producing units with flexible operating capability, which enables a prompt response to the ongoing changes in the conditions of the power system. As a result, the emphasis has shifted from a profit maximisation objective in the deregulated system to a cost minimization policy in the centrally planned system.

1.2 Wind Integrated Profit Based Unit Commitment

Due to wind energy's sustainability and lack of carbon emissions, its penetration in the power system has dramatically increased recently and is expected to continue to rise in the next few decades. The operation of the power system is more complicated due to the inevitability and inconsistent nature of wind power.

Abundant algorithms have been evolved for solving thermal PBUC problem. Here, the wind firm is combined with thermal generating units to dispatch the real power. The uncertainty nature of wind makes the Wind Integrated PBUC (WIPBUC) problem more complex. More exploration in the search space can increase the solution quality of WIPBUC problem. This inspires to evolve a robust technique to identify the optimum schedule for WIPBUC.

1.3 Review of Existing Methods

The PBUC problem is a large scale, non convex, non linear and mixed integer optimization problem. The determination of optimal solution for PBUC problem is complex task because of mixed integer and rapidly changing electricity markets.

In horizontal structure of power system, generation, transmission, and distribution are untied. There are several population based search approaches were reported to determine global or near global optimal solution for practical power system incorporating all the constraints. Though most of the approaches effectively tackle this problem, still improvement is required in the effective exploration and exploitation of search space. Thus, the researchers are focusing to find most profitable generation with reasonable computation time. Different methods have been devised for the optimal solution of the PBUC problem including deterministic, soft computing and hybrid methods.

1.3.1. Mathematical approaches

The practical PBUC scheduling can be determined by Lagrangian Relaxation (LR) technique. In this technique, the UC constraints are divided into number of sub problems to solve them easily. Once the Lagrangian multiplier has been suitably adjusted, it is then integrated by a main problem. The solution may oscillate and hit local optimum if the changes in the Lagrangian multiplier are slight. Li and Shahidehpour suggested the Mixed Integer Programming (MIP) approach [1] to address PBUC issues. When compared to the LR approach, the MIP method performs better. However, the computational time is increased with increase of system dimension. The non convex problems like PBUC can be solved by gradient based techniques may struck in local minima. The soft computing methods are evolved to overcome the local optima issues and excessive computation time.

1.3.2. Soft computing approaches

Various meta-heuristic methods like Genetic Algorithm (GA) [2,3], Muller method [4], Particle Swarm Optimization (PSO) [5], Memetic Algorithm (MA) [6], Parallel Artificial Bee Colony (PABC) [7], Shuffled Frog Leaping Algorithm (SFLA) [8], Memory Management Algorithm (MMA) [9], Artificial Immune System (AIS) [10], Imperialist Competitive Algorithm (ICA) [11] and Improved PSO (IPSO) [12] are developed to solve PBUC problem.

Multi-agent modelling has been used by Sharma et al. [13] to solve the PBUC problem. Decomposing the PBUC problem allows the modelling of multi-agent systems by distributing the profit maximisation among the agents. To find the most practical solution for the PBUC scheduling problem, Raglend et al. [5] have proposed a variety of particle swarm optimization strategies, including Chaotic PSO (CPSO), New PSO (NPSO), and Dispersed PSO (DPSO). Constraints related to generation, system, spinning reserve, and non-spinning reserve are taken into account. The PSO-based algorithms offer a simple implementation method that requires little parameter adjustment. However, the PSO based solutions are vulnerable to local optima with increased dimension of PBUC problems.

Nodal Ant Colony Optimization (NACO) and Parallel NACO (PNACO) have proposed by Columbus and Simon [14] to find optimum solution for PBUC problem. These ACO algorithms have variable convergence times and are subject to random decisions.

Recently, Binary Fire Works Algorithm (BFWA) [15], Improved Bacterial Foraging Algorithm (IBFA) [16], Improved Teaching Learning Based Optimization (ITLBO) technique [17], Binary Whale Optimization Algorithm (BWOA) [18] Elephant Herding Optimization (EHO) algorithm [19] and Binary fish migration optimization[20] are evolved to determine optimum schedule for PBUC problem.

The main problem related to the meta-heuristic approaches is dealing of high dimensionality PBUC problem. The large number of generating units increases the population size which in turn rise the number of fitness evaluation. The computational burden and time increase as the number of fitness evaluations increases.

The hybrid methods are produced by merging artificial intelligence with deterministic techniques or other artificial intelligence techniques in order to achieve the best solution with the lowest computational burden.

1.3.3. Hybrid approaches

The LR - Evolutionary Programming (LR-EP) method [21] has developed to solve PBUC problem. The EP has used to overcome the issues related with LR. In order to develop the best schedule for the thermal units, real power and reserve generation are taken into account simultaneously. The rate of crossover, mutation, parent selection strategy, and other factors play a major role in how evolutionary processes converge. To determine optimal parameters, a sufficient number of trails has to be carried out to avoid premature convergence.

The hybrid techniques such as LR - ant colony search algorithm [22], hybrid PSO [23,24], hybrid priority list approach [25], hybrid AIS approach [26], gravitational search - logistic regression based artificial neural network [27], EP - PSO [28,29], Modified Pre–prepared Power Demand (MPPD)

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Table with ABC algorithm [30], PSO - modified dynamic programming [31], LR - Differential Evolution (DE) [32], Tabu Search (TS) - enhanced ABC [33], Binary Successive Approach (BSA) and Civilized Swarm Optimization (CSO) [34], evolutionary PSO [35] and memetic binary differential evolution algorithm [36] also have proposed for determination of optimal scheduling for PBUC problem.

1.4 Optimization Tool

The local solution trapping and small-scale applications are shortcomings of the deterministic methods. The use of initial algorithmic parameter selection, premature phenomena, solution entrapment, and processing cost are further downsides of soft computing systems. Thus, in order to tackle the PBUC problem, it is required to investigate fresh optimization strategies.

To overcome optimization issues, Mirjalili et al. suggested Grey Wolf Optimization (GWO) [37]. The unique behaviour of GWO is to imitate the grey wolf pack hierarchy, which is widely recognised for its pack hunts. The researchers are motivated by this to use grey wolf optimization to address PBUC issues. Few parameters tuning, easy to handling and simple are the advantages of the intended algorithm.

1.5 Research Gap and Contribution

Several studies have announced the discovery of the best solution for the thermal PBUC problem. Few academics have investigated PBUC scheduling with wind integration. The addition of wind energy complicates the non-linear solution space even more, making it more difficult to determine optimal scheduling, which is a challenging task. A fascinating study project is the abundance of meta-heuristic strategies published for the PBUC solution that are still improving the quality of their solution. We choose to use the grey wolf optimization method as our primary tool for finding the best solution to the WIPBUC problem because it outperforms other population-based strategies.

1.6 Paper Organization

The remainder of the article is organised as follows: The mathematical solution to the PBUC problem is described in Section 2. Section 3 has provided an explanation of how the planned method is applied. The results and debates from the numerical simulation are illustrated in Section 4. Section 5 presents the performance study of the GWO algorithm. The conclusion is described in Section 6.

2. PROBLEM FORMULATION

The main objective of the WIPBUC problem is to optimise GENCOs' overall profit over a planning horizon while also satisfying generator restrictions like generation constraints and minimum thermal unit up/down times. The time period that is scheduled in this case is 24 hours, uniformly divided into hourly parts. The decision variables in the WIPBUC issue can only be either 1 or 0, which renders the problem non-convex

2.1. Wind Generator Model

Due to the erratic nature of wind speed, wind turbine output power is inconsistent. It has zero. Since the wind turbine will stop operating when the wind speed is below the cut-in speed or exceeds the cut-out speed [38,39,40].

The wind turbine output can be expressed as follows

$$\begin{cases} P_w^{WU} = 0 \quad (V_{in} \geq V)\, or\, (V_{out} \leq V) \\ P_w^{WU} = P_{wr}\ X\ \dfrac{V - V_{in}}{V_r - V_{in}} (V_{in} \leq V \leq V_r) \\ P_w^{WU} = P_{wr} \quad (V_r \leq V \leq V_{out}) \end{cases} \tag{1}$$

The total output power of wind farm for time interval can be expressed as,

$$P_{WG} = \sum_{t=1}^{T} \sum_{w=1}^{N_{WG}} P_w^{WU} \qquad t = 1,.......T \tag{2}$$

2.2. Objective Function

Based on anticipated demand and market prices, GENCOs commit the generating units in the deregulated market to maximise profit. Given that GENCOs incur the risk of committing their generating units, these forecasted data are essential for addressing the unit commitment problem. The objective function has two parts; the first and second parts give the total revenue of sold power and the total running cost of GENCOs system, respectively. In the scheduling horizon, the profit from each dedicated generating units is given as

$$\text{maximize } PF = TR - TC \tag{3}$$

where

$$TR = \sum_{t=1}^{T} \sum_{i=1}^{N_{TG}} \left[P_{TG}(i,t) . SP(t)\right] U(i,t) + \sum_{t=1}^{T} \left[P_{WG}(t) . SP(t)\right] \tag{4}$$

$$TC = \sum_{t=1}^{T} \sum_{i=1}^{N_{TG}} \{F(P_{TG}(i,t) + SU_{TG}(i,t) + SD_{TG}(i,t)\} U(i,t) \tag{5}$$

The fuel cost of i^{th} thermal unit at t^{th} hour is estimated using second order function:

$$F(P_{TG}(i,t)) = a_i + b_i . P_{TG}(i,t) + c_i . P_{TG}(i,t)^2 \tag{6}$$

where a_i, b_i and c_i are the fuel cost function coefficients of thermal unit i.

The start-up cost is calculated as follows:

$$SU_{TG}(i,t) = \begin{cases} h - \cos t_i \ ;\ MD(i) \leq t_{OFF}(i,t) \leq MD(i) + c - s - hour_i \\ c - \cos t_i \ ;\ t_{OFF}(i,t) > MD(i) + c - s - hour_i \end{cases}$$

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(7)

For each unit, the SD_{TG} is typically given a fixed value. The SD_{TG} cost has been set at zero for each unit in this instance.

2.3. System Constraints

2.3.1. Load constraints

In PBUC, the total real power generation may or may not be sufficient to meet the network's entire load demand. The GENCOs can produce less power than or as much as the anticipated load as stated by,

$$\sum_{i=1}^{N_{TG}} P_{TG}(i,t).U(i,t) + P_{WG}(t) \le P_D(t); \quad 1 \le t \le T \tag{8}$$

2.4. Thermal Generator Constraints

2.4.1. Thermal unit generation limits

$$P_{TG}^{\min}(i,t).U(i,t) \le P_{TG}(i,t) \le P_{TG}^{\max}(i,t).U(i,t) \tag{9}$$

2.4.2. Thermal unit minimum up/down time constraints

$$[t_{ON}(i,(t-1)) - MU(i)]\ X\ [U(i,(t-1)) - U(i,t)] \ge 0 \tag{10}$$

$$[t_{OFF}(i,(t-1)) - MD(i)]\ X\ [U(i,t) - U(i,(t-1))] \ge 0 \tag{11}$$

2.4.3. Generator forced outage rate

The generator forced outage rate is taken into account when calculating the proportion of the load that is regarded as malfunctioning equipment in each period [41], and the PBUC solution must meet the following criteria:

$$\sum_{t=1}^{T} \sum_{i=1}^{N_{TG}} P_{TG}^{\min}(i,t).U(i,t).P(i) \ge P_D(t) \tag{12}$$

where $$P(i) = 1 - \zeta \tag{13}$$

2.4.4. Unit initial status

The initial state of each thermal unit must be taken into account at the beginning of the planning period.

3. PROFIT BASED UNIT COMMITMENT BASED ON GWO

The key components of the GWO algorithm include social hierarchy, encirclement, hunting, attacking, and searching for prey. This section presents the GWO algorithm's implementation for resolving the PBUC problem.

3.1. Definition of Wolf and Initial Population

The working schedule (ON/OFF) of a fossil-producing unit over the planning period is represented in the integer coded GWO by a series of integer values, that represent the Wolf Position (WP). In the wolf position, the positive and negative integers denote the lengths of continuous ON and OFF states, respectively. The load curve and the sum of the generating unit's minimum up and down times define the number of ON/OFF cycles for thermal units. For base load units, medium load units, and peak load units, there are two, three, and five ON/OFF cycles, respectively. The search space may be constrained by the reduction in base and medium unit cycles, which may result in less-than-ideal solutions. By adopting the same number of cycles for all units as the Number of Cycles (*NC*) of peak load units, this flaw can be fixed. The number of cycles for day schedule (D) is D × 5. For working scheme of N units, every solution has N × D × 5 variables.

For working period, NC-1 cycles are generated arbitrary. The initial population of the GWO is generated as follows: The running duration of the first cycle of unit i, Ti1 is initialised by taking into account the unit i operational state of the final cycle of the previous scheduling day to avoid violation of minimum up/down time limits.

$$T_i^1 = \begin{cases} +Rand\,(\max(0, T_i^{on} - T_i^0), T), & \text{if } T_i^0 > 0 \\ -Rand\,(\max(0, T_i^{off} + T_i^0), T), & \text{if } T_i^0 < 0 \end{cases} \tag{14}$$

If c is less than *NC*, considering PBUC planning horizon, operating period of previous cycle and minimum up and down time constraints of the generating units, Tic is determined.

For $T_i^{c-1} < 0$, cycle *c* is in ON mode with duration

$$T_i^c = \begin{cases} +Rand\,(T_i^{on}, BT_i^{c-1}), & \text{if } BT_i^{c-1} > T_i^{on} \\ +BT_i^{c-1}, & \text{otherwise} \end{cases} \tag{15}$$

For $T_i^{c-1} > 0$, cycle *c* is in OFF mode with duration

$$T_i^c = \begin{cases} -Rand\,(T_i^{off}, BT_i^{c-1}), & \text{if } BT_i^{c-1} > T_i^{off} \\ -BT_i^{c-1}, & \text{otherwise} \end{cases} \tag{16}$$

$$BT_i^{c-1} = T - \sum_{j=1}^{c-1} \left| T_i^j \right| \tag{17}$$

In some circumstances, the first c less than NC-1 operating cycles are sufficient to cover the whole scheduling period after accounting for the randomly generated cycle durations. Zero is used during the final cycles. The unit minimum up and down-time requirements are automatically satisfied once the starting population has been established.

3.2. GWO Execution for WIPBUC

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As a result of adopting GWO, the algorithmic process and constraint handling strategies for WIPBUC are explained as follows.

(1) The population size (PS), maximum number of epochs (iter-max), and vector values (a, A, and C) of the algorithm are initialised after reading the unit data.

(2) Initialization

The initial population (X_t) is developed as follows:

(a) The entire planning period is split into number of cycles (*NC*).

(b) All units are switched ON based on the conditions of their initial states.

(c) By taking into account the minimum up and down time constraints, the execution period is determined.

(d) This procedure is imitated for all *NC*-1 cycles and the remaining period is calculated which is the operating period of the final segment.

(e) The operational constraints are satisfied by adopting the constraint handling scheme.

(f) Within their viable bounds, the committed generating units and dependent units are chosen.

(3) Calculate each individual fitness level; the individual with the lowest fitness level is represented as the alpha, the next lowest as the beta, and the lowest as the delta..

$$Fitness = F_t + OCV \qquad (18)$$

(4) Increment *iter.*

(5) Increment search agent SAg.

(6) Change the generation of *N-1* online units based on the hunting process.

$$X^{t+1} = \frac{\left(X_\alpha - A_1.(D_\alpha)\right) + \left(X_\beta - A_2.(D_\beta)\right) + \left(X_\gamma - A_3.(D_\gamma)\right)}{3} \qquad (19)$$

Where, $D_\alpha = |C_1.X_\alpha - X|$; $D_\beta = |C_2.X_\beta - X|$; $D_\gamma = |C_3.X_\gamma - X|$; $A = 2a.rand - a$.

(7) Use strategies for handling constraints..

(8) Repeat step 5 for each SAgs. Otherwise move on subsequent step.

(9) Modify the values of the vector.

(10) Evaluate each SAgs level of fitness..

(11) Modify the values of X_α, X_β *and* X_γ.

(12) Termination criterion: Repeat steps 4 to 6, until iter-max is reached.

The flowchart for the GWO-based solution methodology is shown in Fig. 1.

4. SIMULATION RESULTS AND DISCUSSIONS

The robustness of the intended algorithm is ascertained on a conventional test system with ten thermal units and one wind farm during the course of a 24-hour planning period. The method is developed in the Matlab platform and is run on a laptop equipped with an Intel core i3 CPU running at 2.20 GHz and 4 GB of RAM.. Table 1 displays the cost and operational characteristics of thermal generating units [34]. Table 2 provides the anticipated demand and related prices. The wind farm has 20 wind turbine generators that are similar to one another and operate in parallel. Fig. 2 provides an illustration of the wind power generation data from [42].

For a typical 10-unit system with a 24-hour scheduling horizon, the simulation runs. The maximum NC for each unit is five. Fifty test trials are made for a ten thermal unit problem set. For each run, a random beginning population is created. To substantiate the vigour of the GWO in solving the PBUC problem, multiple runs have been performed

4.1. Thermal PBUC

The suggested GWO is evaluated using a standard system of ten thermal units. Here, the goal is to maximise profit while meeting the inequality constraints of the generating units. The power balance constraint is not satisfied all the period in the given planning horizon.

The derived optimal PBUC schedule is shown in Table 3, along with the actual power sharing of committed producing units. Additionally, it shows that all thermal producing units satisfy the generation restrictions, minimum up/down duration constraints, and initial status of units. P1 and P2 have higher commitment priorities than other thermal units; hence, they are committed for the entire planning horizon. The forecasted demand, total generation by all committed units and unsatisfied demand for each period are illustrated in the Fig. 3. The effectiveness of the suggested algorithm is contrasted with that of competing techniques. Table 4 displays the highest profit made using GWO and other previously disclosed techniques.

Table 4 shows that when compared to the Muller technique, ACO, Improved Pre-prepared Power Demand (IPPD), NACO, Variable Neighborhood Tabu Search - Parallel Enhanced Particle Swarm Optimization (VTS-PEPSO), PABC, PNACO, and BFWA, the GWO produces the best viable solution.

4.2. PBUC Integrated with Wind

Recently, a number of measures have been taken to boost the use of wind energy in the sector that produces electric power. Due to wind power's limited predictability and fluctuation, power system operators now face significant technological and financial hurdles. Because of this, the Wind Integrated Thermal Generating Scheduling (WITGS) issue is crucial to the creation of green power. The best choice and

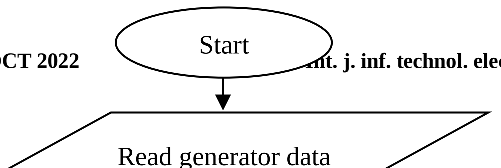

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Fig. 1. Flowchart for solution methodology using GWO

Table 1. Cost and operating characteristics of thermal generator

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Unit No.	$P_{i\,max}$ (MW)	$P_{i\,min}$ (MW)	a_i ($/h)	b_i ($/MWh)	c_i ($/MW^{2}h)	T_i^{up} (h)	T_i^{down} (h)	h_{cost} ($)	c_{cost} ($)	cshour (h)	ini state (h)
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	16.60	0.002	5	5	550	1100	4	-5
4	130	20	680	16.50	0.00211	5	5	560	1120	4	-5
5	162	25	450	19.70	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

Table 2. Forecasted load and associated prices

Hours	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	***9***	**10**	**11**	**12**
Load (MW)	700	750	850	950	1000	1100	1150	1200	*1300*	1400	1450	1500
Energy Price ($/MWh)	22.15	22	23.1	22.65	23.25	22.95	22.5	22.15	*22.8*	29.35	30.15	31.65
Hours	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	***21***	**22**	**23**	**24**
Load (MW)	1400	1300	1200	1050	1000	1100	1200	1400	*1300*	1100	900	800
Energy Price ($/MWh)	24.6	24.5	22.5	22.3	22.25	22.05	22.2	22.65	*23.1*	22.95	22.75	22.55

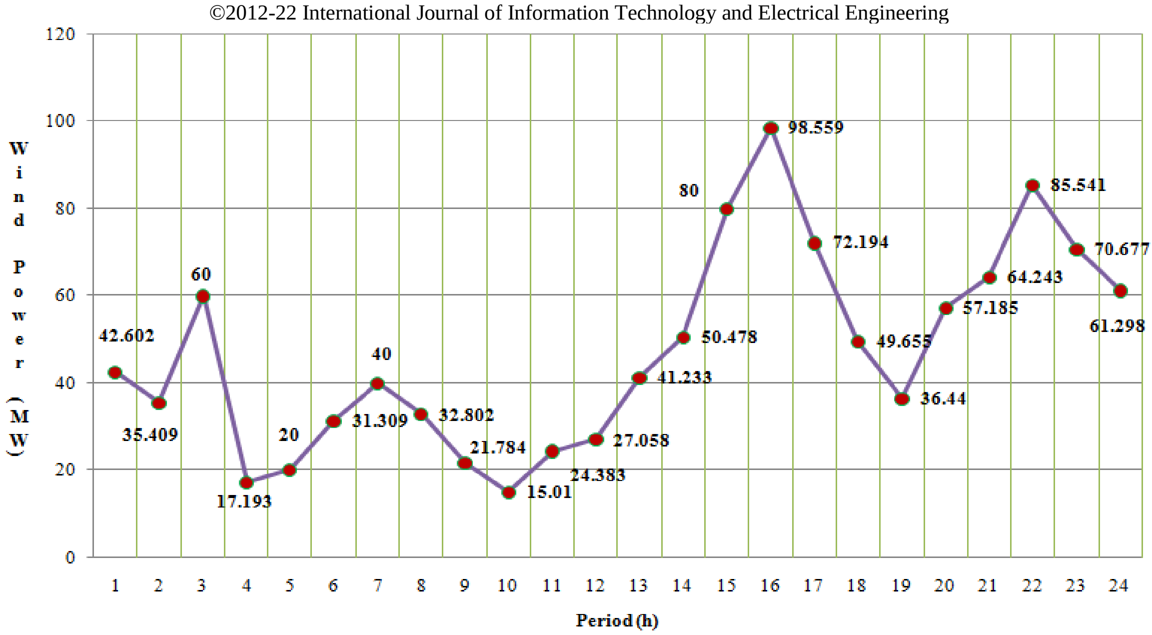

Fig. 2. Wind power generation data.

Table 3. Optimal PBUC schedule of 10-unit system

Hour	Real power output of units in MW										Cost ($)	Revenue($)	Profit($)	Demand Met (MW)
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10				
1	455	245	0	0	0	0	0	0	0	0	13683.13	15505.00	1821.87	700
2	455	295	0	0	0	0	0	0	0	0	14554.50	16500.00	1945.50	750
3	455	395	0	0	0	0	0	0	0	0	16301.89	19635.00	3333.11	850
4	455	455	0	0	0	0	0	0	0	0	17353.30	20611.50	3258.20	910
5	455	415	0	130	0	0	0	0	0	0	20072.77	23250.00	3177.23	1000
6	455	455	0	130	0	0	0	0	0	0	20213.96	23868.00	3654.04	1040
7	455	455	0	130	0	0	0	0	0	0	20213.96	23400.00	3186.04	1040
8	455	455	0	130	0	0	0	0	0	0	20213.96	23036.00	2822.04	1040
9	455	455	130	130	0	0	0	0	0	0	24205.75	26676.00	2470.25	1170
10	455	455	130	130	162	68	0	0	0	0	30908.21	41090.00	10181.79	1400
11	455	455	130	130	162	80	0	0	0	0	29047.98	42571.80	13523.82	1412
12	455	455	130	130	162	80	0	0	0	0	29047.98	44689.80	15641.82	1412
13	455	455	130	130	162	0	0	0	0	0	26851.61	32767.20	5915.59	1332
14	455	455	130	130	130	0	0	0	0	0	26184.02	31850.00	5665.98	1300
15	455	455	130	130	30	0	0	0	0	0	24150.34	27000.00	2849.66	1200
16	455	455	0	130	0	0	0	0	0	0	20213.96	23192.00	2978.04	1040
17	455	455	0	0	0	0	0	0	0	0	17353.30	20247.50	2894.20	910
18	455	455	0	0	0	0	0	0	0	0	17353.30	20065.50	2712.20	910
19	455	455	0	0	0	0	0	0	0	0	17353.30	20202.00	2848.70	910
20	455	455	0	0	0	0	0	10	0	0	17353.30	20611.50	3258.20	910
21	455	455	0	0	0	0	0	0	0	0	17353.30	21021.00	3667.70	910
22	455	455	0	0	0	0	0	0	0	0	17353.30	20884.50	3531.20	910
23	455	445	0	0	0	0	0	0	0	0	17177.91	20475.00	3297.09	900
24	455	345	0	0	0	0	0	0	0	0	15427.42	18040.00	2612.58	800
Total											**489942.44**	**597189.30**	**107246.86**	**24756**

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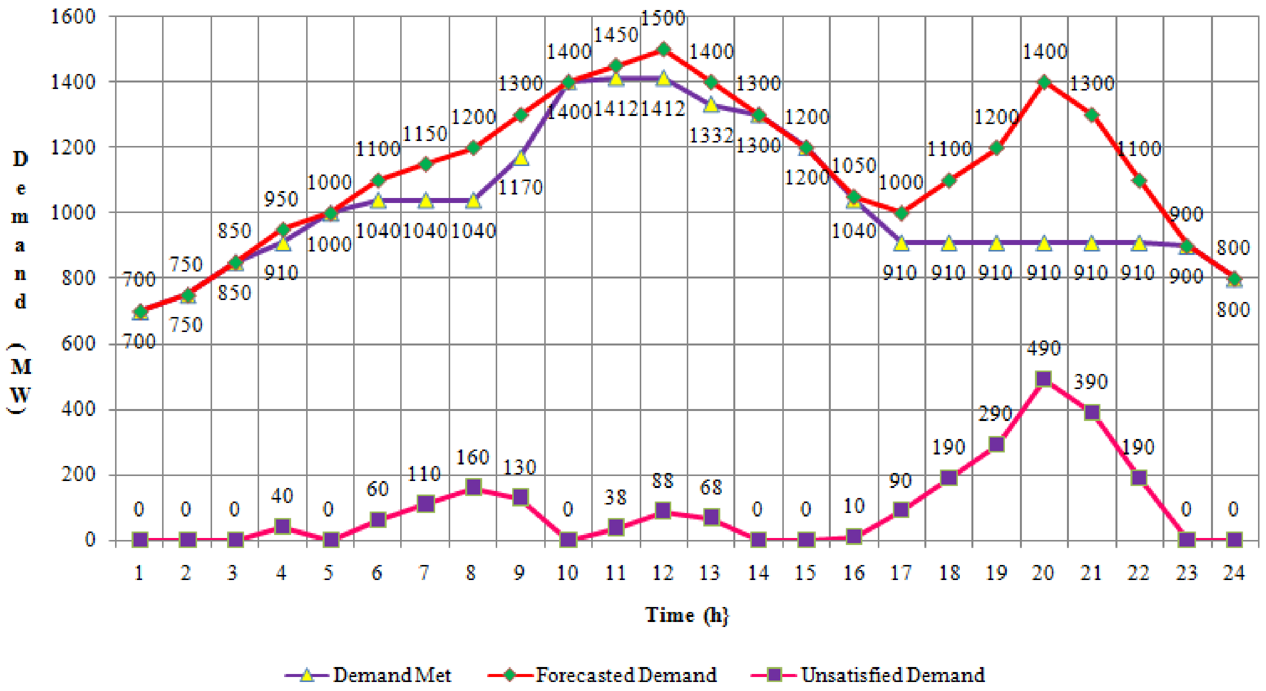

Fig. 3. Demand Vs time curve of thermal PBUC.

Table 4. Performance comparison of GWO

Technique	Profit ($)	Profit improvement ($)
TS-RP	101086.00	6160.86
TS-IRP	103261.00	3985.86
Muller method	103296.00	3950.86
ACO	103890.00	3356.86
IPPD	105549.00	1697.86
NACO	105873.80	1373.06
VTS-PEPSO	105873.00	1373.86
PABC	105878.00	1368.86
PNACO	105942.00	1304.86
BFWA	106850.69	396.17
GWO	**107246.86**	--

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Table 5. Wind combined PBUC schedule of 10-unit system

Hour	Real power output of units in MW										Wind Power (MW)	Cost ($)	Revenue($)	Profit($)	Demand Met (MW)
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10					
1	455	202.4	0	0	0	0	0	0	0	0	42.602	12941.77	15505.00	2563.23	700.0
2	455	259.6	0	0	0	0	0	0	0	0	35.409	13937.24	16500.00	2562.76	750.0
3	455	335	0	0	0	0	0	0	0	0	60	15252.71	19635.00	4382.29	850.0
4	455	455	0	0	0	0	0	0	0	0	17.193	17353.30	21000.92	3647.62	927.2
5	455	395	0	130	0	0	0	0	0	0	20	19722.55	23250.00	3527.45	1000.0
6	455	455	0	130	0	0	0	0	0	0	31.309	20213.96	24586.54	4372.58	1071.3
7	455	455	0	130	0	0	0	0	0	0	40	20213.96	24300.00	4086.04	1080.0
8	455	455	0	130	0	0	0	0	0	0	32.802	20213.96	23762.56	3548.61	1072.8
9	455	455	130	130	0	0	0	0	0	0	21.784	24205.75	27172.68	2966.93	1191.8
10	455	455	130	130	162	53	0	0	0	0	15.01	30561.39	41090.29	10528.90	1400.0
11	455	455	130	130	162	80	0	0	0	0	24.383	29047.98	43306.95	14258.97	1436.4
12	455	455	130	130	162	80	0	0	0	0	27.058	29047.98	45546.19	16498.21	1439.1
13	455	455	130	130	162	0	0	0	0	0	41.233	26851.61	33781.53	6929.92	1373.2
14	455	455	130	130	79.52	0	0	0	0	0	50.478	25147.51	31850.00	6702.49	1300.0
15	455	455	55	130	25	0	0	0	0	0	80	22778.00	27000.00	4222.00	1200.0
16	455	455	0	0	0	0	0	0	0	0	98.559	17353.30	22490.87	5137.57	1008.6
17	455	455	0	0	0	0	0	0	0	0	72.194	17353.30	21853.82	4500.52	982.2
18	455	455	0	0	0	0	0	0	0	0	49.655	17353.30	21160.39	3807.09	959.7
19	455	455	0	0	0	0	0	0	0	0	36.44	17353.30	21010.97	3657.67	946.4
20	455	455	0	0	0	0	0	0	0	0	57.185	17353.30	21906.74	4553.44	967.2
21	455	455	0	0	0	0	0	0	0	0	64.243	17353.30	22505.01	5151.71	974.2
22	455	455	0	0	0	0	0	0	0	0	85.541	17353.30	22847.67	5494.37	995.5
23	455	374.3	0	0	0	0	0	0	0	0	70.677	15940.02	20474.93	4534.91	900.0
24	455	283.7	0	0	0	0	0	0	0	0	61.298	14357.47	18040.00	3682.53	800.0
Total												**479260.25**	**610578.06**	**131317.81**	**25325.6**

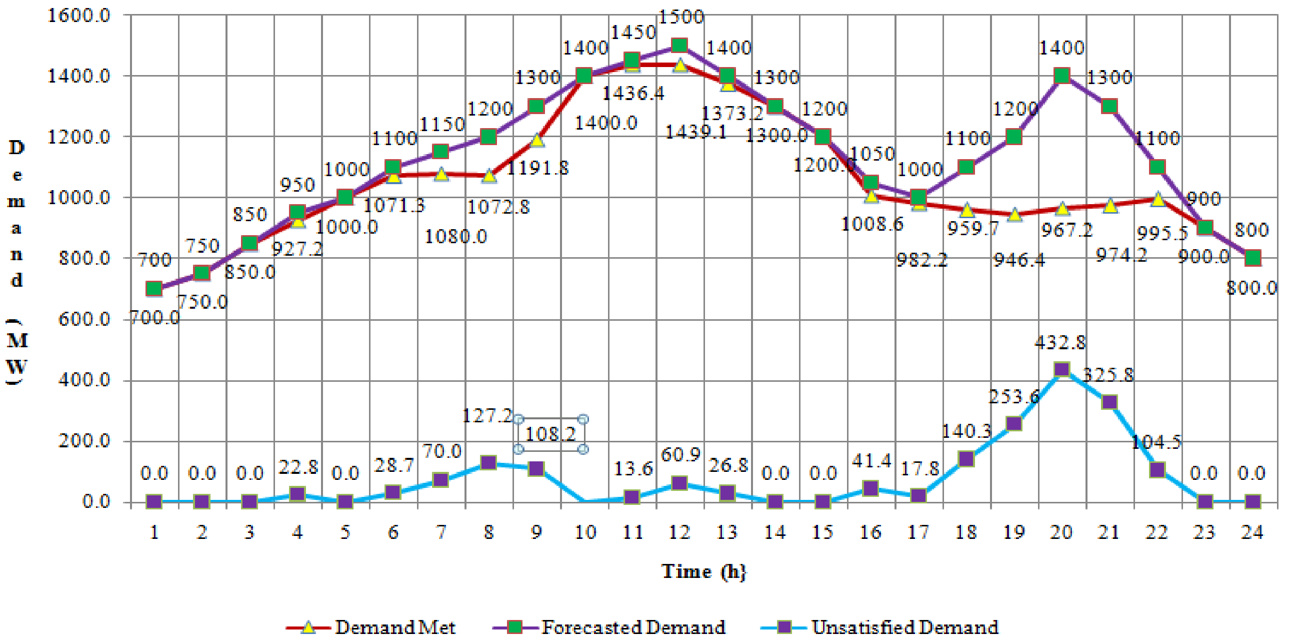

Fig. 4. Demand Vs time curve of wind integrated PBUC.

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Table 6. Maximum output of thermal units constrained by FOR

Unit	1	2	3	4	5	6	7	8	9	10
Maximum output considering FOR (MW)	441.35	441.35	126.1	126.1	157.14	77.6	82.45	53.35	53.35	53.35

Table 7. Wind combined PBUC schedule of 10-unit system with FOR

Hour	Real power output of units in MW										Wind Power (MW)	Cost ($)	Revenue($)	Profit($)	Demand Met (MW)
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10					
1	441.4	216.1	0	0	0	0	0	0	0	0	42.602	12952.45	15505.00	2552.55	700.0
2	441.4	273.2	0	0	0	0	0	0	0	0	35.409	13947.87	16500.00	2552.13	750.0
3	441.4	348.6	0	0	0	0	0	0	0	0	60	15263.46	19635.00	4371.54	850.0
4	441.4	441.4	0	0	0	0	0	0	0	0	17.193	16887.04	20382.58	3495.54	900.0
5	441.4	412.5	0	126.1	0	0	0	0	0	0	20	19735.66	23250.00	3514.34	1000.0
6	441.4	441.4	0	126.1	0	0	0	0	0	0	31.309	19681.24	23870.50	4189.26	1040.0
7	441.4	441.4	0	126.1	0	0	0	0	0	0	40	19681.24	23598.00	3916.76	1048.8
8	441.4	441.4	0	126.1	0	0	0	0	0	0	32.802	19681.24	23071.48	3390.24	1041.6
9	441.4	441.4	126.1	126.1	0	0	0	0	0	0	21.784	23606.31	26372.40	2766.09	1156.7
10	441.4	441.4	126.1	126.1	157.1	77.6	0	0	0	0	15.01	30430.49	40639.48	10208.99	1384.7
11	441.4	441.4	126.1	126.1	157.1	77.6	0	0	0	0	24.383	28290.49	42029.79	13739.30	1394.0
12	441.4	441.4	126.1	126.1	157.1	77.6	0	0	0	0	27.058	28290.49	44205.49	15915.00	1396.7
13	441.4	441.4	126.1	126.1	157.1	0	0	0	0	0	41.233	26150.24	32798.52	6648.27	1333.3
14	441.4	441.4	126.1	126.1	114.6	0	0	0	0	0	50.478	25266.61	31850.00	6583.39	1300.0
15	441.4	441.4	86.17	126.1	25	0	0	0	0	0	80	22771.50	27000.00	4228.50	1200.0
16	441.4	441.4	0	0	0	0	0	0	0	0	98.559	16887.04	21882.08	4995.03	981.3
17	441.4	441.4	0	0	0	0	0	0	0	0	72.194	16887.04	21246.39	4359.35	954.9
18	441.4	441.4	0	0	0	0	0	0	0	0	49.655	16887.04	20558.43	3671.39	932.4
19	441.4	441.4	0	0	0	0	0	0	0	0	36.44	16887.04	20404.91	3517.87	919.1
20	441.4	441.4	0	0	0	0	0	0	0	0	57.185	16887.04	21288.40	4401.35	939.9
21	441.4	441.4	0	0	0	0	0	0	0	0	64.243	16887.04	21874.38	4987.34	946.9
22	441.4	441.4	0	0	0	0	0	0	0	0	85.541	16887.04	22221.13	5334.09	968.2
23	441.4	388.0	0	0	0	0	0	0	0	0	70.677	15952.03	20474.93	4522.90	900.0
24	441.4	297.4	0	0	0	0	0	0	0	0	61.298	14369.50	18040.00	3670.50	800.0
Total												**471167.17**	**598698.88**	**127531.71**	**24838.3**

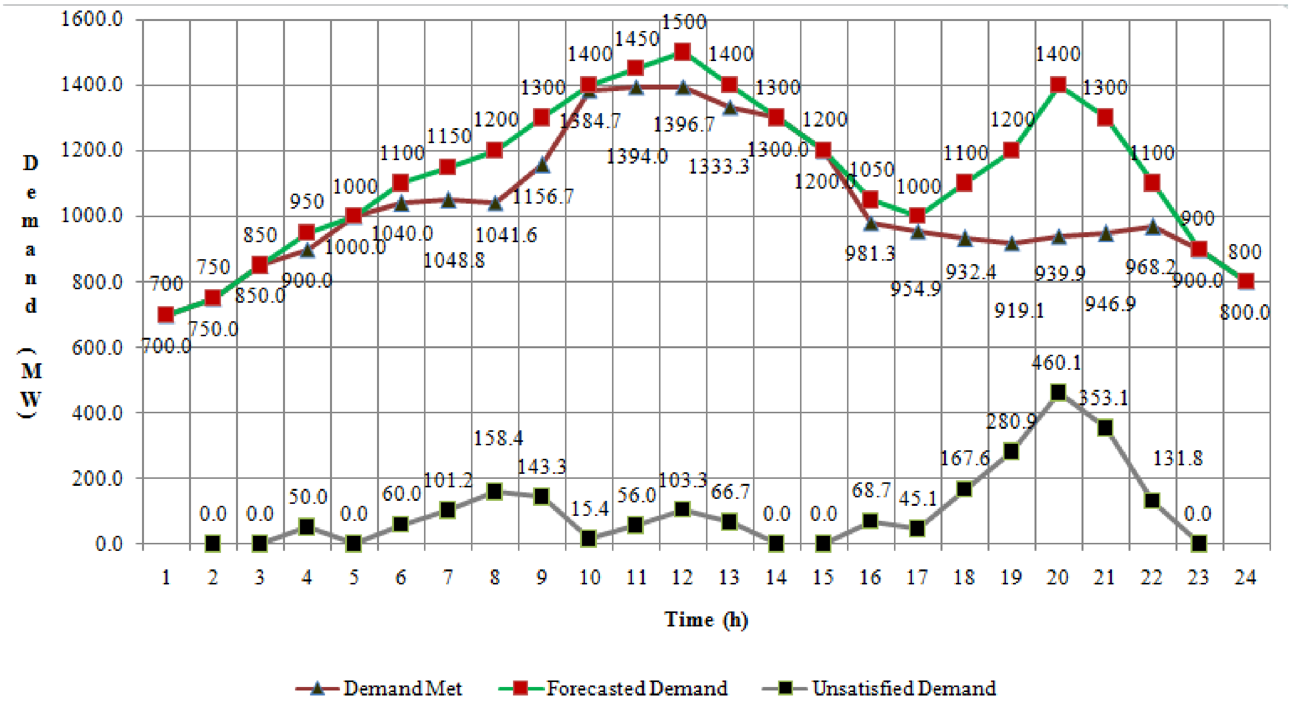

Fig. 5. Demand Vs time curve of reliability constrained WIPBUC.

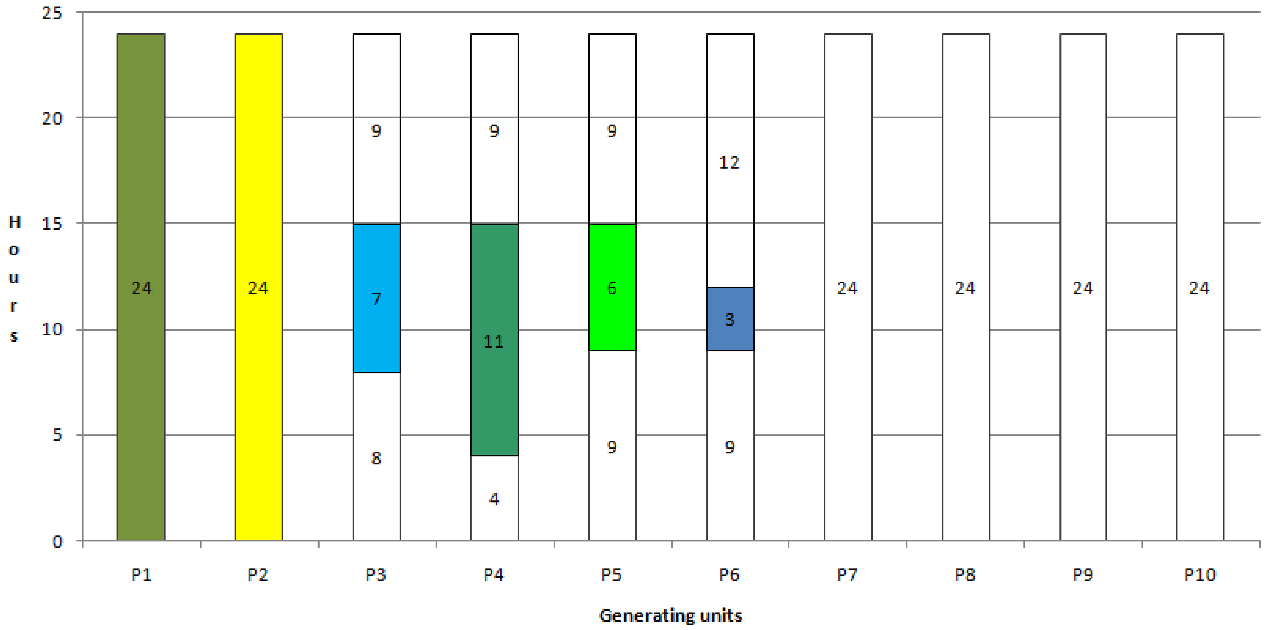

Fig. 6. Configuration for final population to WIPBUC problem.

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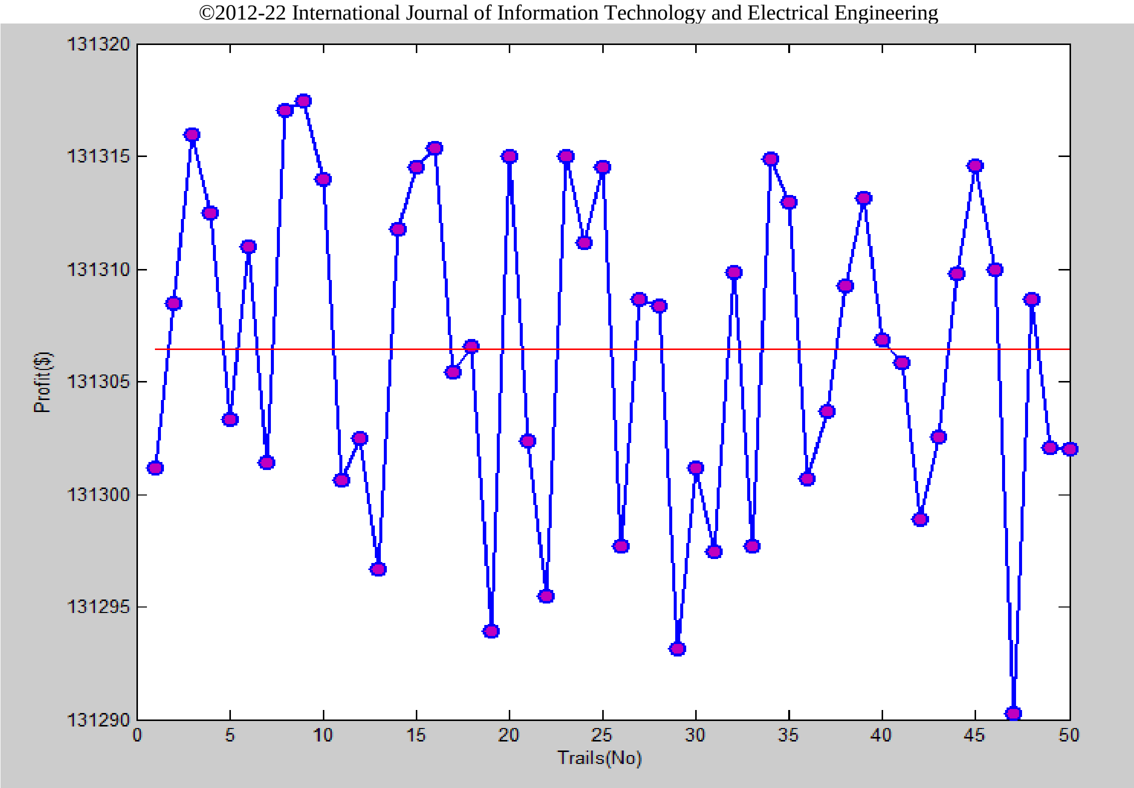

Fig. 7. Robustness characteristics of WIPBUC.

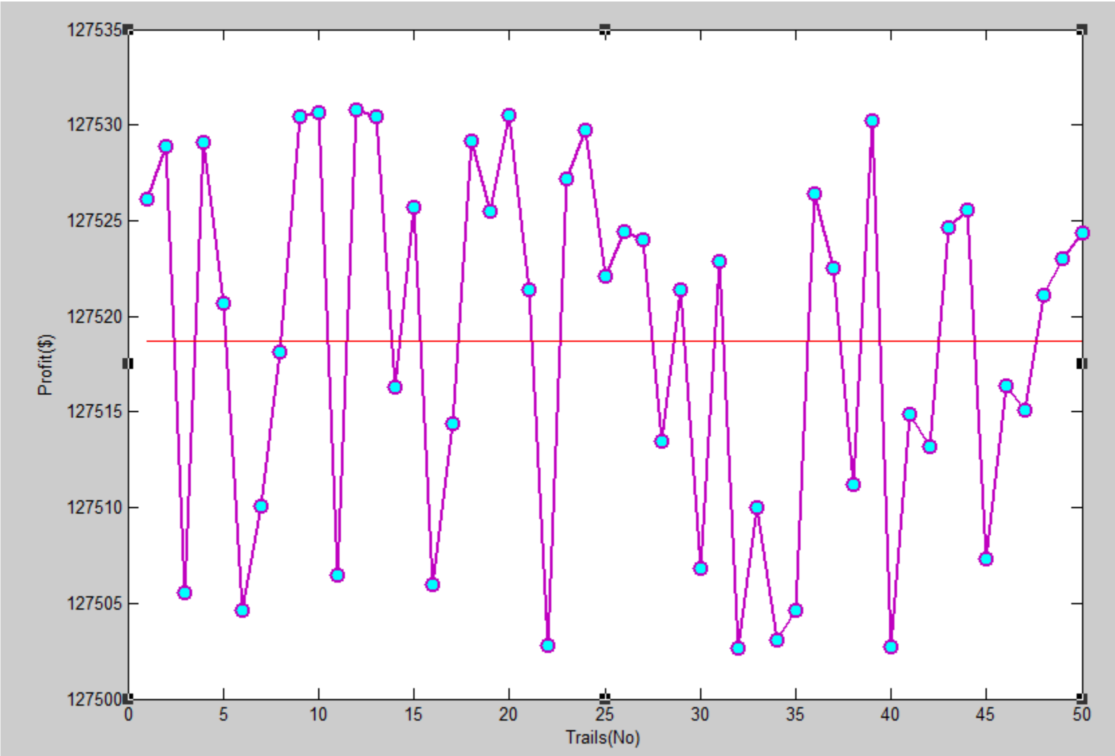

Fig. 8. Robustness characteristics of WIPBUC with FOR.

dispatch of thermal units are adjusted based on the output of the wind farm. As a result, WITGS is a challenging optimization issue where the goal is to find the best feasible schedule for generating units. Here, the GWO method is used to calculate the schedule for generating the thermal units.

Table 5 displays the real power sharing of the online generating units and the optimal PBUC plan that is obtained. All of the thermal generating units in this situation satisfy the equality and inequality constraints. When compared to Table 3, P4 is now shut off at the sixteenth interval since a wind farm with thermal producing units was added. The real power dispatch of P2 is reduced significantly at intervals 1 to 3, 5, 23 and 24. The reduced power dispatch at 15th hour in P3 and 10th hour in P6. On P5, the lower power dispatch is realisable between the 14th and 15th hour. The amount of demand that the wind integrated thermal producing system can satisfy has significantly grown, increasing overall profit. The profit is increased by $24070.95 compared with thermal PBUC Schedule. By comparing with Table 3, the total demand met for entire planning horizon is also increased by 569.6 MW. The total cost, revenue and profit obtained in this case are $479260.25, $610578.06 and $131317.81 respectively. Fig. 4 shows the demand versus time curve of wind integrated PBUC. It represents the forecasted demand, total generation by all committed units and unsatisfied demand for each interval.

4.3. Reliability Constrained PBUC

In recent years, the power system reliability becomes crucial criteria in the power system operation and control. Several optimization tools have developed to improve the better operations in the power system. The performance of power system has enhanced by developing the reliability constrained optimization techniques. Planning for the electricity system takes into account the uncertainties. All possible combinations of all component states are considered when preparing the system state. The probability of components appears in the component state. By determining the generation capacity needed to meet the demand of the system load, power generation systems are evaluated. Here, we assume that the transmission and distribution facilities are completely reliable.

The reliability index is evaluated to assess the reliability of the power system. Although there are other indices, Forced Outage Rate (FOR) is the most fundamental and can be regarded as a trustworthy condition for the efficient operation of the power system. This has led to the formulation of the reliability restricted economic power system operation problem. For each thermal unit, the forced outage rate of 3% of the total generating capacity is taken into account. Table 6 displays the maximum possible output of all thermal units when the forced outage rate is taken into account.

Table 7 shows the best feasible PBUC schedule obtained and real power sharing of committed thermal generating units. Here, the maximum output of each thermal unit is restricted by their forced outage rate limit which increases the operating cost in each interval. The increased operating cost reduces the total profit for given planning period. Referring Tables 5 and 7, the total profit and demand supplied for the scheduling horizon are lowered by $3786.10 and 487.3 MW respectively. Both cases 2 and 3 have identical scheduling plans. The addition of FOR limitations only affected the dispatches of the committed producing units. The total cost, revenue and profit obtained in this case are $471167.17, $598698.88 and $127531.71 respectively This case study also satisfies operational constraints, including generation limits, minimum up/down times and initial status of units. Fig. 5 shows the demand versus time curve of reliability constrained WIPBUC. The arrangement for the integrated population to wind PBUC problem is shown in Fig. 6.

5. PERFORMANCE ANALYSIS

5.1. Solution Quality

The highest profit generated by using the GWO is marginal compared to previously reported strategies, as can be shown from Tables 4, 5, and 7. The statistical analysis for the PBUC problem is shown in Table 4 using the standard ten unit system. Table 4 indicates that the profit made by the GWO is much higher than that made by other methods currently in use. It highlights how the GWO provides the best practical answer for the selected PBUC challenges. The GWO approach performs exceptionally well when looking for a better solution.

5.2. Robustness

The initial population is created using random numbers in stochastic soft computing approaches like GWO. As a result, uncertainty is a fundamental aspect of GWO. So many trials should be run to evaluate the effectiveness of the intended algorithm. Multiple trails have led to the best option. Due to the practical nature of PBUC, it is anticipated that each run of the execution will get closer to the overall optimum solution. The robustness of GWO is tested by performing fifty trials to identify the best scheduling. Figures 7 and 8 make it abundantly evident that the GWO method is significantly more robust than previous reported techniques.

5.3. Success Rate

It shows how many trials are conducted before the total profit obtained is higher than the mean profit. The success rate of GWO is remarkably high in both situations. Additionally, it is seen that there is less of a difference between the mean and worst profit. When compared to other existing algorithms, it can be concluded that the GWO method has a fair success rate and resilience.

6. CONCLUSION

This paper describes the wind integrated PBUC problem solution using a revolutionary swarm intelligence approach called GWO. The difference between total revenue and total cost represents the total objective function. For all generating units, the generation caps and minimum up/down time restrictions are also met. On a conventional ten unit system, the suggested technique has been tested. Additionally, the integration of the forced outage rate limitation with the

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aforementioned system is illustrated. It can be concluded that the suggested strategy increases overall profit while consuming less fuel and emitting fewer thermal units. GWO is easy to deploy, and it handled the operational constraints well. GWO can consistently find the best solution to the WIPBUC puzzle. Results show how effective the GWO algorithm is at resolving the WIPBUC problem.

LIST OF ABBREVIATIONS

ζ	forced outage rate
$P_{TG}^{\max}(i,t)$	maximum generation of thermal unit *i* at hour *t*, in MW
$P_{TG}^{\min}(i,t)$	minimum generation of thermal unit i at hour *t*, in MW
BT_i^{c-1}	scheduling time remaining after the allocation of the first *c* -1 cycles
$c\text{-}cost_i$	cold start cost of unit *i* in $
$c\text{-}s\text{-}hour_i$	cold start time of unit i
$F(P_{TG}(i,t))$	operating fuel cost of thermal unit *i* at hour *t*
$h\text{-}cost_i$	hot start cost of unit *i* in $
i	index of thermal generating unit
$MD(i)$	minimum down time of thermal unit *i*
$MU(i)$	minimum up time of thermal unit *i*
N_{TG}	number of thermal generating units
N_{WG}	number of wind generating units
$P_D(t)$	system load demand at hour *t*, in MW
PF	total profit of GENCO over planning horizon
$P_{TG}(i,t)$	power generation of thermal generating unit *i* at hour *t* in MW
$P_{WG}(t)$	actual power generation of wind farm at hour *t* in MW
P_{wr}	wind turbine rated power in MW
Rand	random number generator with uniform distribution between 0 and 1
$SD_{TG}(i,t)$	shut down cost of thermal unit *i* at hour *t*
$SP(t)$	forecasted power price at hour *t*, in Rs/MW hr
$SU_{TG}(i,t)$	start up cost of thermal unit *i* at hour *t*
t	index of hour (sub interval)
T	total scheduling period
TC	total operating costs of GENCO
T_i^{off}	minimum down time of unit *i*
T_i^{on}	minimum up time of unit *i*
$t_{OFF}(i,t)$	duration for which thermal unit *i* had been continuously down till period *t*
$t_{ON}(i,t)$	duration for which thermal unit *i* had been continuously up till period *t*
TR	total revenues of GENCO
$U(i,t)$	commitment status of thermal unit *i* at hour *t* (On =1, OFF =0)
V	actual wind speed in m/s
V_{in}	wind turbine cut-in speed in m/s
V_{out}	wind turbine cut-out speed in m/s
V_r	wind turbine rated wind speed in m/s

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AUTHOR PROFILES

S.Sivasakthi was born in India, in 1978. He received the B.E. degree in Electrical and Electronics Engineering from the University of Madras, Madras, 1999. The M.E. degree in Power Systems Engineering and Ph.D. degree in Electrical and Electronics Engineering from the Annamalai University, Chidambaram, India in 2008 and 2019 respectively. He is a Professor & Head in Electrical and Electronics Engineering at the Krishnasamy College of Engineering & Technology, Cuddalore, India.

S.Ganesan (Senior Member IEEE) was born in India, in 1981. He received the B.E. degree in Electrical and Electronics Engineering, the M.E. degree in Power Systems Engineering and Ph.D. degree in Electrical and Electronics Engineering from the Annamalai University, Chidambaram, India. He is working as Assistant Professor in the Department of in Electrical and Electronics Engineering , Government College of Engineering, Salem, Tamil Nadu, India. He has authored 20 SCI research articles. His research interests include power system operation and control.

S.Subramanian (Senior Member IEEE) was born in India, in 1968. He received the B.E. degree in Electrical and Electronics Engineering, the M.E. degree in Power Systems Engineering and Ph.D. degree in Electrical and Electronics Engineering. He is working as Professor and Head in the Department of Electrical Engineering, Annamalai University, Annamalai Nagar, Tamil Nadu, India. He has authored 62 SCI research articles. His research interests include power system operation and control.