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# Hybrid Artificial Immune System Approach for Profit Based Unit Commitment Problem

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**Abstract** – This paper presents a new approach with artificial immune system algorithm to solve the profit based unit commitment problem. The objective of this work is to find the optimal generation scheduling and to maximize the profit of generation companies (Gencos) when subjected to various constraints such as power balance, spinning reserve, minimum up/down time and ramp rate limits. The proposed hybrid method is developed through adaptive search which is inspired from artificial immune system and genetic algorithm to carry out profit maximization of generation companies. The effectiveness of the proposed approach has been tested for different Gencos consists of 3, 10 and 36 generating units and the results are compared with the existing methods.

**Keywords**: Artificial immune system, Genetic algorithm, Lagrange relaxation, Profit based unit commitment and deregulation.

## 1. Introduction

In deregulated power systems, the Profit Based Unit Commitment problem is one of the important combinatorial optimization problems. In the past, the vertically integrated monopolistic power industries were dominated most of the electricity generation, transmission and distribution of the power sector. During nineties, many electric utilities and power network companies in world-wide have been changed from vertically integrated mechanism to deregulation [1]. Restructuring of the electric power industries is a very complex exercise based on energy policies and its application varies from country to country.

The trend of deregulation around the world reformed the energy sectors. Historically, the Latin America, in fact, Chile though not as well known as the UK, was the real pioneer of radical restructuring in 1982. Although many countries such as United States and most of the European countries have already restructured their power system, some of the countries like India are in the process of preparation towards deregulation [2, 3]. Therefore, a research based on this model is certainly necessary and useful for those countries.

Deregulation involves unbundling the responsibilities of vertically integrated power industries into generation companies (Gencos), transmission companies (Transcos) and distribution companies (Discos), with a central coordinator, called an Independent System Operator (ISO), to balance supply and demand in real time and to maintain system reliability and security. The restructured system allowing consumers to choose their suppliers of electric energy and provide a choice of different generation options at cheaper price. As the power industry open to competition, many of the traditional algorithms for power system operation, planning and control aspects need to be revised. Hence, the unit commitment algorithm that maximizes profit plays an essential role in such competitive environment [4].

Unit commitment is a complex optimization problem of determining the schedule of generating units within a power system subject to all prevailing constraints. In deregulated power system, the unit commitment problem (UCP) has a different objective than that of UCP in a traditional system. Previously, electric utilities had an obligation to serve their customers that all demand and spinning reserve must be completely met. But this is not necessary in the restructured system and generation companies can now consider a schedule that produces less than the predicted load demand and reserve but creates maximum profit. This problem is referred as Profit Based Unit Commitment (PBUC) problem. Under restructured environment, the individual Gencos run its unit commitment in order to maximize their own profit [5]. In this profit-based unit commitment, demand forecasts and expected market prices are important inputs to determine how much power should be offered on market for achieving maximum profit.

In the conventional power system, though the research for the unit commitment problem is developed in the last 30 years, only considerable work is carried out for research, particularly for Gencos in deregulated environment. Several researchers, therefore, have been paying attention on; efficient, near-optimal profit-based UC algorithms, which can be applied to large-scale power systems and

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have reasonable storage and computation time requirements. A review of existing literatures on the problem reveals that various numerical optimization techniques have been employed to approach the complicated profit based unit commitment problem. More specifically, these are the Dynamic Programming method (DP), the Mixed Integer Programming method (MIP), the Lagrangian relaxation method (LR) are known as local optimum methods and the Genetic Algorithm (GA), the Evolutionary Programming (EP), the Muller method, the Ant Colony Optimization (ACO), the Particle Swarm Optimization (PSO), the Immune Algorithm (IA), the Artificial Immune System (AIS), etc are known as global optimum methods. The limitations of the existing techniques are either they are not able to handle large system with non-convex generator characteristics or fails to provide accurate solution within short time under deregulated environment [6, 7].

Richter et al. [8] proposed a PBUC formulation using genetic algorithm (GA) which considers the softer demand constraints and allocates fixed and transitional costs to the scheduled hours. Madrigal et al. [9] examined the existence, determination and effects of competitive market equilibrium for unit commitment power pool auctions to avoid the conflict of interest and revenue deficiency. Valenzuela et al. [10] presented a new formulation to the unit commitment problems suitable for an electric power producer in deregulated markets. Attaviriyanupap et al. [11] explored a hybrid LR-EP method that helps Gencos to make a decision on how much power and reserve should be sold in markets, and how to schedule generators in order to receive maximum profit. Here, the authors have incorporated both power and reserve generation at the same time. Yamin et al. [12] employed an auxiliary hybrid model using LR and GA, to solve PBUC problem. Here, GA is used to update the Lagrangian multiplier. Chandram et al. [13] proposed Muller Method and Information Pre-Prepared Power Demand (IPPD) table to solve the combinatorial profit-based UC problem in deregulated environment. Delarue et al. [14] investigated the different profits for PBUC by using with and without perfect price forecast. Jacob Raglend et al. [15] demonstrated the application of particle swarm optimization technique to maximize the Gencos profit. Dimitroulas et al. [16] studied a hybrid model of Genetic Algorithm and local search algorithm called memetic algorithm to solve PBUC problem by cultural evolution. Columbus et al. [17] successfully solved the nodal ant colony optimization technique to maintain the good exploitation and exploration search capabilities, the movements of the ants are represented with binary nodes consisting of optimal combination of unit on/off status. Huang in 1999; Sun et al. in 2002; and lately, Li et al. in 2006 employed the immune algorithm (IA) to solve the traditional unit commitment problem. Here, with the embodiment of affinity computation, the possibility of stagnation in the iteration process was decreased and the computational performance was enhanced [18-20]. Liao [21] developed an improved immune algorithm for solving short term thermal generation scheduling problem. Recently, Liu et al. [22] presented Immunodomaince based Clonal Selection Clustering Algorithm for solving optimization problem.

From the literature, it has been observed that the major limitations are problem dimensions, large computational time and complexity in programming. Therefore, there exists a need for up-gradation of the existing methods or development of new hybrid models for obtaining an optimal solution for the profit-based UC problem. Hence, in this paper, an attempt has been made to couple AIS with GA for meeting the requirements of the PBUC problem over the specified time horizon. The hybrid methods are more efficient than single methods due to less production cost and better convergence performance. In this paper hybrid Artificial Immune System adopted the Clonal Selection algorithm to determine the optimal schedule of generating units in a power generation system. The objective function is viewed as an antigen and the feasible solutions as antibodies, the antibody that most fits the antigen is considered as the optimal solution to this problem.

The focus of this paper is to develop an accurate and comprehensive model for the profit-based thermal unit commitment that should yield feasible unit ON/OFF status for power generation companies. The main contributions of this paper are: an efficient and complex combinatorial PBUC problem formulation that allows to achieve the optimal solution for the case studies in moderate computational time; reducing the number of binary string variables for modeling the start-up/shut-down status and ramp rate limits of thermal units; Hybrid model that combines AIS and GA for Genco's profit maximization.

The paper is structured as follows: Section 2 provides the mathematical formulation of PBUC problem along with the notation used throughout the paper. Section 3 develops the proposed hybrid approach for solving the PBUC problem. Section 4 presents the three case studies, illustrating the numerical simulation results. Section 5 provides the conclusions.

***Nomenclature:***

| | |
|---|---|
| $PF$ | profit of Genco |
| $RV$ | revenue of Genco |
| $TC$ | total operating cost over the schedule time period of Gencos |
| $C_{it}(P_{it})$ | production cost of unit 'i' at hour $t$ |
| $SP_t$ | forecasted power price at hour $t$ |
| $S_{it}$ | startup cost of unit 'i' at hour $t$ |
| $U_{it}$ | ON/OFF status of unit 'i' at hour $t$ |
| $N$ | number of generating units |
| $n$ | Total number of antibodies |
| $T$ | scheduled time period |
| $PD_t$ | load demand at hour $t$ |

| | |
|---|---|
| $R_{it}$ | reserve generation of unit 'i' at hour $t$ |
| $SR_t$ | forecasted reserve at hour $t$ |
| $P_i^{min}$ | lower bound on the output power of unit 'i' |
| $P_i^{max}$ | upper bound on the output power of unit 'i' |
| $T_i^{on}$ | duration for which unit 'i' is continuously ON |
| $T_i^{off}$ | duration for which unit 'i' is continuously OFF |
| $MU_i$ | unit 'i' minimum up time |
| $MD_i$ | unit 'i' minimum down time |
| $P_{i(t)}$ | generation output for unit 'i' at hour t |
| $P_{i(t-1)}$ | generation output for unit 'i' at hour (t-1) |
| $RU_i$ | Ramp-up rate limit for the unit 'i' |
| $RD_i$ | Ramp-down rate limit for the unit 'i' |

## 2. PBUC Problem Formulation

Profit Based Unit Commitment problem in deregulated power systems determines the generating unit schedules for maximizing the profit of generation companies subject to all prevailing constraints such as load demand, spinning reserve and ramp rate limits. The term profit is defined as the revenue obtained from sale of energy with market price minus total operating cost of the generating company. The PBUC problem can be mathematically formulated by the following equations [23].

### 2.1 Objective function

The objective function comprises of two terms as revenue of sold power is the first term and the total operating cost of generation companies is the second term.

$$\max PF = RV - TC \tag{1}$$

$$RV = \sum_{i=1}^{N}\sum_{t=1}^{T}\left\{ (P_{it} \cdot SP_t) U_{it} \right\} \tag{2}$$

$$TC = \sum_{i=1}^{N}\sum_{t=1}^{T}\left\{ (C_{it}(P_{it}) + S_{it}) P_{it} \right\} \tag{3}$$

The total operating cost over the entire scheduling time period is the sum of production cost and startup/shutdown costs of all the generating units.

### 2.2 Constraints

The above said objective function is subjected to the following constraints.

***Load Demand Constraints***: In PBUC problem, power generation may be less than the demand and reserve, which allows more flexibility in unit commitment schedule.

$$\sum_{i=1}^{N} P_{it} U_{it} \le PD_t ;\ 1 \le t \le T \tag{4}$$

***Spinning Reserve Constraints***: Spinning reserve is the term used to describe the total amount of generation available from all units synchronized (i.e., spinning) on the system, minus the present load and losses being supplied.

$$\sum_{i=1}^{N} R_{it} U_{it} \le SR_t ;\ \ 1 \le t \le T \tag{5}$$

***Power Balance Constraints***:

$$P_i^{\min} \le P_i \le P_i^{\max}\ ,\ \ i = 1,.....N \tag{6}$$

*Minimum Up/Down Time Constraints:* A thermal unit can undergo only gradual temperature changes. Here Minimum up time means once the unit is running, it should not be turned off immediately. Minimum down time means once the unit is decommitted, there must be a minimum time before it can be recommitted.

$$T_i^{on} \ge MU_i\ ,\ \ i = 1,.....,N \tag{7}$$

$$T_i^{off} \ge MD_i\ ,\ \ i = 1,.....,N \tag{8}$$

***Ramp rate limits***: The ramp rate limits confine the power output movement of a generating unit between adjacent hours are given below.

$$\begin{aligned} P_i^{\max}(t) &= \min\{p_i^{\max}, P_i(t-1) + \tau . RU_i\} \\ P_i^{\min}(t) &= \max\{P_i^{\min}, P_i(t-1) - \tau . RD_i\} \end{aligned} \tag{9}$$

where $\tau$ =60 minutes is the PBUC time step.

***Crew Constraints***: The crew constraints are restricted to two or more units to be turned ON at the same time.

## 3. Proposed Approach

The natural immune system is used to protect the body against harmful organisms (called antigens) and this function is performed by lymphocyte immune cells (B and T cells mainly). When an antigen invades the body, only a few of the immune cells can recognize the invader's peptides. This recognition stimulates proliferation and differentiation of the cells produce matching clones (antibody). This process is called as clonal expansion which generates a large population of antibody-producing cells that are specific to the antigen. The clonal expansion of immune cells results in destroying or neutralizing the antigen. It also retains some of these cells in immunological memory to solve the recognition, classification and optimization tasks [24].

The major process of the natural immune system is shown in **Fig. 1,** where I-III represent the invade entering the body and activating T-Cells, which then in IV activate the B-cells, V is the antigen matching, VI is the antibody production and VII is the antigen's destruction. The

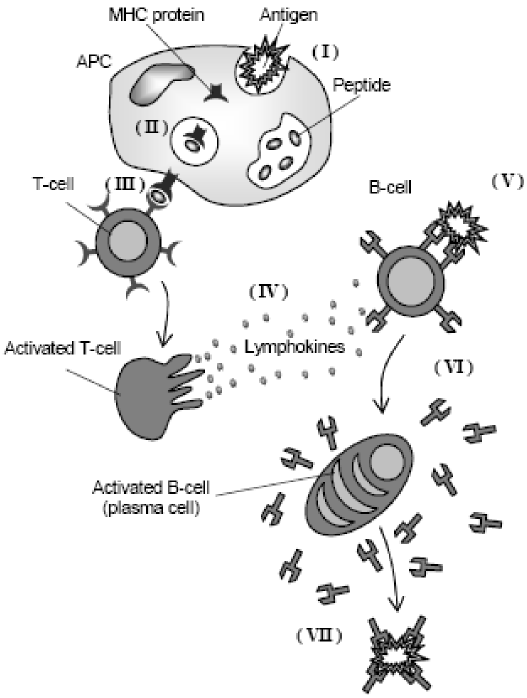


**Fig. 1.** Process of natural immune system

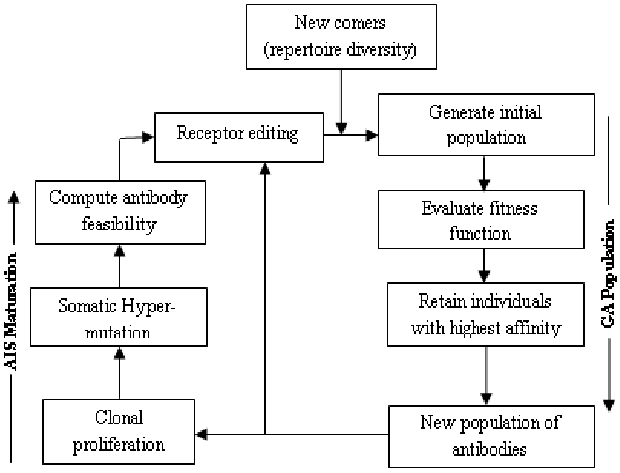


**Fig. 2.** Flow steps for hybrid AIS algorithm

biological principles of clone generation, proliferation and maturation are mimicked and incorporated into a computational algorithm invariably referred as Artificial Immune System. A few computational models have been developed based on several principles of the immune system such as immune network model, negative selection algorithm, positive selection algorithm and clonal selection algorithm. The successful applications of AIS include anomaly detection, optimization, fault diagnosis, pattern recognition, etc. Specifically, AIS provide superior performances in dealing with multi-modal, combinatorial, time dependent, and inventory optimization problems [25].

### 3.1 Hybrid AIS algorithm

The Artificial Immune System is a new multi-model function optimization algorithm that imitates the natural immune system. The hybrid AIS algorithm is based on clonal selection principle to solve the PBUC problem. This principle is used to describe the basic features of an immune response to an antigenic stimulus. The clonal selection algorithm reproduces those individuals with higher affinity and selects their improved matured clones. This characteristic makes the clonal selection algorithm suitable for solving complex optimization problems [26].

When the clonal selection algorithm is implemented for solving the PBUC problem, the following few adaptations have to be made [27]:

- The affinity of an antibody refers to the evaluation of the objective function.
- All antibodies are to be selected for cloning.
- The number of clones generated by the antibodies is equal.

The maximum profit is taken to be the affinity measure for the hybrid AIS-based PBUC problem. Individual with higher profit and lower total generation cost is considered to have higher affinity. The need of clonal operator is to produce a variation in the population according the affinity value. Hence, the searching area is enlarged and therefore the PBUC problem can be solved accurately.

The scheduling of profit based unit commitment problem using hybrid AIS algorithm is developed in such a way that the search engine of the genetic algorithm makes a quick decision to direct the search towards the global optimum. The probabilistic search engine of GA iteratively transforms a set of individuals in the initial population into a new population of offspring individuals. The flow steps for proposed hybrid AIS algorithm is shown in Fig. 2. Here, the genetic algorithm is hybridized with a scheme inspired on an artificial immune model, which helps to reach the optimal solution in a more efficient way [28].

### 3.2 Implementation of hybrid AIS on PBUC problem

The proposed hybrid AIS based GA algorithm can be described as follows:

***Step 1: Initialization***

Initialize the input parameters of the GA and AIS, such as the population size, the maximum number of generations, the threshold value, probability of mutation rate, the total number of antibodies.

***Step 2: Generation of initial population***

The operating time period of the first cycle of unit 'i' is initialized. So that the unit 'i' maintains the operating status (ON/OFF) of the last cycle of the previous scheduling day for at least as many hours as required to satisfy the minimum up/down time constraints [29].

$$T_i^1 = \begin{cases} +rand(\max(0, MU_i - T_i^0), T), & if \ T_i^0 > 0 \\ +rand(\max(0, MD_i + T_i^0), T), & if \ T_i^c < 0 \end{cases} \quad (10)$$

where $T_i^0$ is the time period of last cycle of the previous scheduling day.

For c < $C_i$, the operating time period of the $c^{th}$ cycle of unit 'i', $T_i^c$ is calculated through the minimum uptime and downtime constraints, the PBUC horizon and the time period of the (c-1) prior cycles of operation of the generating units.

For, $T_i^{c-1} < 0$ cycle c is in ON status with time period,

$$T_i^c = \begin{cases} +rand(MU_i, RT_i^{c-1}), & if (RT_i^{c-1} > MU_i) \\ +RT_i^{c-1}, & otherwise \end{cases} \quad (11)$$

For, $T_i^{c-1} > 0$ cycle c is in OFF status with time period,

$$T_i^c = \begin{cases} -rand(MD_i, RT_i^{c-1}), & if (RT_i^{c-1} > MD_i) \\ -RT_i^{c-1}, & otherwise \end{cases} \quad (12)$$

where $RT_i^{c-1}$ is the remaining scheduling time after allocation of the first (c-1) cycles.

$$RT_i^{c-1} = T - \sum_{p=1}^{c-1} \left| T_i^p \right| \quad (13)$$

In the random generation of initial population, the entire scheduling time period is covered with the first c < $C_i$ operating cycles and the remaining (c+1,….$C_i$) cycles are assigned with zero such that the unit's minimum uptime and downtime constraints are automatically satisfied.

***Step 3: Fitness function evaluation***

The cost function used in this hybrid AIS, has two terms. The first term is the revenue obtained from sale of energy with market price and second term is the total operating cost over the scheduling time period. The fitness function is calculated as follows.

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

$$C_{it}(P_{it}) = a_i + b_i P_{it} + c_i P_{it}^2 \quad (14)$$

Where $P_{it}$ is the output power from unit 'i' at hour *t*; $a_i$, $b_i$ *and* $c_i$ are the fuel cost function coefficients of unit 'i'.

The start-up/shut-down costs are calculated as follows:

$$SU_T = \sum_{i=1}^{N} \sum_{c=2}^{C_i} H(T_i^c) \cdot SU_i(-T_i^{c-1}) \quad (15)$$

$$SD_T = \sum_{i=1}^{N} \sum_{c=2}^{C_i} [1 - H(T_i^{c-1})] \cdot SD_i \quad (16)$$

Where

$$SU_i(-T_i^{c-1}) = \begin{cases} H_{\cos t_i} if (-T_i^{c-1}) \le C_{hour_i} \\ C_{\cos t_i} if (-T_i^{c-1}) > C_{hour_i} \end{cases} \quad (17)$$

$H(T_i^c)$ is the unit step function.

Hence $\quad S_{it} = SU_T + SD_T; \ i = 1,....N; \ 1 \le t \le T \quad (18)$

The maximum profit over the scheduling time period is

$$\max PF = \sum_{i=1}^{N} \sum_{t=1}^{T} \left\{ (P_{it} \cdot SP_t) U_{it} - (C_{it}(P_{it}) + S_{it}) U_{it} \right\} \quad (19)$$

Based on the objective of the PBUC problem, the fitness function is formed as follows:

$$fitness \ f_i = \begin{cases} Max \ \ profit \\ Min \ \ fuel \cos t \end{cases} \quad (20)$$

***Step 4: New population of antibodies***

The individuals of highest fitness value are retained and the feasible individuals in GA are considered as initial antibodies in AIS. An antibody pool is composed of 'n' antibodies, each of which has 'm' genes. The entropy $H_j(n)$ of the *j*th gene can be expressed as in [30].

$$H_j(n) = -\sum_{k=1}^{n} P(kj) \log P(kj), \ j = 1, 2..., m \quad (21)$$

where *p(kj)* is the probability that the $k^{th}$ allele (alternative form of a gene) comes out of the $j^{th}$ gene.

The average information entropy can be expressed as

$$H(n) = \frac{1}{m} \sum_{j=1}^{m} H_j(n) \quad (22)$$

The affinity between antibodies can evaluate the mutual diversity of antibodies. If antibodies are more similar, then the affinity between antibodies is higher. The computing formulation can be represented as

$$\alpha(v, w) = \frac{1}{(1 + H(2))} \quad (23)$$

where $H(2)$ is the information entropy between antibody '*v*' and antibody '*w*'.

The entropy value $H_j(n)$ of each antibody is obtained by the Eq. (21) and then average entropy $H$(n) is determined by (22). The value of $H(2)$ is calculated in such a way that the summation of entropy of two antibodies (*v,w*) is divided by the genes of that two antibodies.

***Step 5: Clonal proliferation***

This step is processed according to the fitness values and the clones generated for all the 'n' selected antibodies are given by the following equation.

$$L_c = \left( 1 - \frac{f_i}{\sum_{i=1}^{n} f_i} \right) \times 200 \tag{24}$$

Where $L_c$ is the total number of clones generated; $f_i$ is the fitness value.

For standard cloning, 20 members of a population pool proliferate10 numbers of clones. This work considered the adaptive cloning process as given in (24), where the fittest antibody will produce more clones compared to weaker ones.

By this cloning process, the concentration of antibodies with higher affinity has been increased in the antibody repertoire (population). Antibody concentration is the proportion of some similar antibodies in the whole population. It can be expressed as

$$C_v = \frac{1}{n} \sum_{w=1}^{n} S(v, w) \tag{25}$$

$$S(v, w) = \begin{cases} 1, \alpha(v, w) \geq \varepsilon_1 \\ 0, \alpha(v, w) < \varepsilon_1 \end{cases} \tag{26}$$

Where C*v* is the concentration of antibody '*v*', and $\varepsilon_1$ is the threshold value of concentration.

***Step 6: Somatic hyper-mutation***

The cloned antibodies are then mutated with a rate that inversely proportional to the affinity; If higher the affinity, then smaller the mutation rate. The affinity value of the mutated clones is then calculated, and the 'n' highest affinity mutated clones are selected and inserted in the new repertoire instead of lowest affinity antibodies.

***Step 7: Receptor editing***

In this step, the antibody feasibility is computed and it can be expressed as

$$e(v) = A(v) \prod_{s=1}^{s} \left[ (1 - L_{v,s}^{k}) / Cv \sum_{j=1}^{n} A(j) \right] \tag{27}$$

$$L_{v,s} = \begin{cases} \alpha(v, s), \alpha(v, s) \geq \varepsilon_2 \\ 0, \alpha(v, s) < \varepsilon_2 \end{cases} \tag{28}$$

where *e(v)* is the feasibility of antibody *v*, *A(v)* is the sufficiency of antibody *v*, *S* is the total number of the suppressor cells, *k* is the suppressor index, and $\varepsilon_2$ is the feasibility threshold value.

By receptor editing process, a pool of dissimilar antibodies has been generated and then entirely newcomers are added to this pool in place of low affinity antibodies. Hence this hybrid algorithm has the ability to escape from unsatisfactory local optima and it allows the diversity of population to carry out the search towards the global optimum.

***Step 8: Stopping criteria***

The computation process will stop if the maximum number of generations has been reached. Otherwise, the computation will iterate from Step 3 to Step 7. At last, the best optimal solution is achieved based on the antibody with the highest affinity with the antigen.

## 4. Results and Discussion

The proposed hybrid method (AIS-GA) coding were developed using MATLAB 7.10 software package and the system configuration is Intel Core 3 processor with 2.67 GHz speed and 4 GB RAM. In this work, three Gencos such as 3 units, 10 units and 36 units test system were considered as case study, over a specified time horizon. The computational results of PBUC problem attained by the proposed hybrid method for the three Gencos are analyzed and compared with other optimization methods like LR method, Hybrid LR-GA, LR-AIS, GA-LR and AIS-LR methods. The required system data and load demand data are taken from [11] and [12] for 3, 10 units and 36 units respectively, which are given in the following sections.

The simulation parameter settings considered in this paper are:

Population size = 30; No. of antibodies = 50;
Probability rate of mutation= 0.05;
Concentration threshold value (ε1) = 0.9;
Feasibility threshold value (ε2) = 0.85;
Maximum No. of generations = 200.

The population size and the number of antibodies are selected based on the total generating units along with scheduled time period. Owing to the stochastic nature of Genetic algorithm, 20 independent test trials are considered for each population set, with each run starting with different initial population.

### 4.1 Case study – Genco I: 3 unit test system

The system data for Genco-I is given in Table 1, where the initial status of unit 1 is '-3', it means that the number of hours the generating unit 1 has been de-committed. The load demand is varying at every instant of time period as given in Table 2. Hence, the generating units are committed at the intervals based on the forecasted load demand and corresponding power prices.

**Table 1.** System operating data for Genco-I

| Parameters | Unit 1 | Unit 2 | Unit 3 |
|---|---|---|---|
| $P_{max}$ (MW) | 600 | 400 | 200 |
| $P_{min}$ (MW) | 100 | 100 | 50 |
| a($/hr) | 500 | 300 | 100 |
| b($/MWhr) | 10 | 8 | 6 |
| c($/MW$^2$hr) | 0.002 | 0.0025 | 0.005 |
| Min up time(hr) | 3 | 3 | 3 |
| Min down time(hr) | 3 | 3 | 3 |
| Startup Cost($) | 450 | 400 | 300 |
| Initial status(hr) | -3 | 3 | 3 |

**Table 2.** Load demand data for Genco-I

| Hour | *Forecasted Demand (MW)* | *Forecasted Power Price ($/MW-hr)* |
|---|---|---|
| 1 | 170 | 10.55 |
| 2 | 250 | 10.35 |
| 3 | 400 | 09.00 |
| 4 | 520 | 09.45 |
| 5 | 700 | 10.00 |
| 6 | 1050 | 11.25 |
| 7 | 1100 | 11.30 |
| 8 | 800 | 10.65 |
| 9 | 650 | 10.35 |
| 10 | 330 | 11.20 |
| 11 | 400 | 10.75 |
| 12 | 550 | 10.60 |

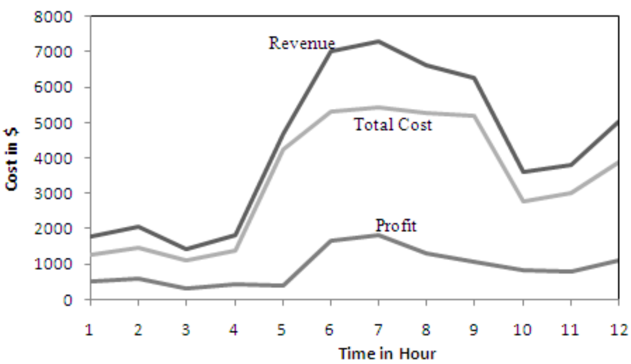


**Fig. 3.** Performance of hybrid AIS method for Genco-I

In this work, the violation of minimum up/down-time constraints is avoided by encoding the continuous operating time period of generating units. Thus, the proposed approach computes the PBUC schedule and resultant costs at the end of each generation. The Fig. 3 shows the total operating cost, revenue and profit for the feasible PBUC schedule of Genco-1 over the time period of 24 hours.

### 4.2 Case study- Genco II: 10 unit test system

The operating data and demand data for 10 units system are considered as given in [11]; only the ramp rate limits for Genco-II is in given in Table 3. This paper implemented the load distribution strategy for satisfying the limits of ramp rate constraints by the Eq. (9). From the statement of

**Table 3.** Ramp rate limits for Genco-II

| Unit i | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| $R_{uri}$(MW/hr) | 35 | 66 | 80 | 55 | 143 | 128 | 271 | 55 | 161 | 143 |
| $R_{dri}$(MW/hr) | 55 | 70 | 93 | 118 | 139 | 261 | 276 | 83 | 150 | 87 |

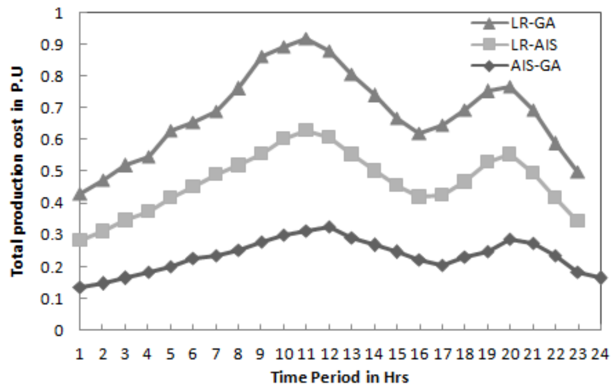


**Fig. 4.** Comparison of total production cost of Genco-II

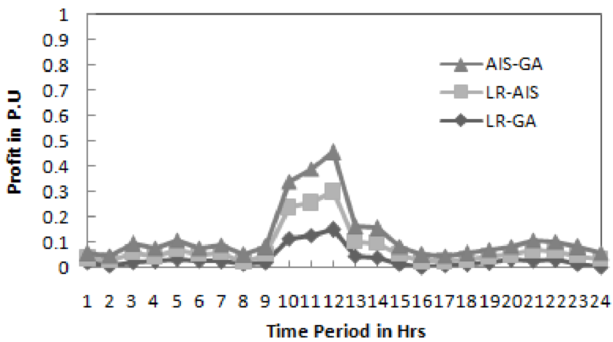


**Fig. 5.** Profit comparison of Genco-II by different methods

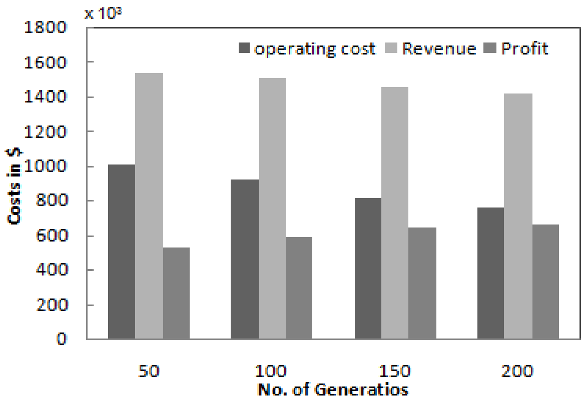


**Fig. 6.** Performance of hybrid AIS on Genco-III over 50,100,150 and 200 generations

PBUC problem, Gencos could produce the power below forecasted level in some of the operating time period to satisfy the constraint as in (4).

It can be observed from Table 4, where unit 10 is retained to turn-off in all the scheduling period of optimal

PBUC schedule and the resultant operating costs, profits of Genco-II is given in Table 5. It is found that the operating few generating units producing higher profit than operating all the units in specified time horizon. The comparisons of total production cost and profit for Genco-II obtained by LR-GA, LR-AIS and proposed methods are shown in Fig. 4 and Fig. 5 respectively.

### 4.3 Case study-Genco III : 36 unit test system

The Genco III consists of 118 buses with 36 generating units and the system operating data and load demand data taken from [12] is used for obtaining optimal profit-based unit commitment schedule over a time period of 24 hours. The performance of proposed method on Genco-III is given in Fig. 6, where the operating cost and profit in every successive generation could significantly be compared with the preceding generation.

From Table 6, it can be observed that the proposed hybrid AIS approach produces 1.13 times higher the profit and 0.93 times lesser the operating cost than the existing methods. The term per unit (p.u) value is the ratio of actual value to base value and this paper considered the base value of 100 for comparing the results of different methods. The results of global optimum methods are used as an initial point to local optimum methods for providing many possibilities to search the global optimum point. The results are compared with not only LR-GA, LR-AIS and AIS-GA but also, with GA-LR, AIS-LR and GA-AIS as given in Table 7. In this work, the PBUC problem is solved with a fixed population size and hence there may not be

**Table 5.** Revenue, profit and operating cost of Genco-II by proposed approach

| Hour | Load demand (MW) | Operating cost in $ | Revenue in $ | Profit in $ |
|---|---|---|---|---|
| 1 | 700 | 13683.13 | 15505.01 | 1822.01 |
| 2 | 750 | 14554.50 | 16500.00 | 1945.80 |
| 3 | 850 | 16302.01 | 19635.10 | 3523.31 |
| 4 | 950 | 17351.68 | 20612.11 | 3199.87 |
| 5 | 1000 | 17352.02 | 20058.16 | 3910.50 |
| 6 | 1100 | 21334.37 | 23868.00 | 2653.42 |
| 7 | 1150 | 20213.26 | 23400.00 | 3268.00 |
| 8 | 1200 | 20116.00 | 22306.00 | 2879.22 |
| 9 | 1300 | 24206.02 | 25876.39 | 2637.00 |
| 10 | 1400 | 30567.01 | 41092.04 | 10098.20 |
| 11 | 1450 | 29048.00 | 42466.21 | 13643.24 |
| 12 | 1500 | 29047.14 | 44690.13 | 15726.11 |
| 13 | 1400 | 27197.20 | 34440.03 | 5897.21 |
| 14 | 1300 | 25371.37 | 31850.04 | 5754.66 |
| 15 | 1200 | 23839.53 | 27250.01 | 3156.60 |
| 16 | 1050 | 21005.04 | 23415.13 | 2641.05 |
| 17 | 1000 | 20133.50 | 22250.00 | 2281.72 |
| 18 | 1100 | 21879.00 | 24255.00 | 2513.76 |
| 19 | 1200 | 22579.00 | 25974.02 | 2658.00 |
| 20 | 1400 | 22423.75 | 26501.01 | 3419.50 |
| 21 | 1300 | 21309.00 | 27027.40 | 3972.13 |
| 22 | 1100 | 19946.51 | 23868.23 | 3782.30 |
| 23 | 900 | 17178.02 | 19147.50 | 3309.72 |
| 24 | 800 | 15427.00 | 17394.12 | 2623.00 |
| **Total Cost ($)** | | **512063.951** | **619380.2** | **107316.11** |

**Table 4.** Optimal unit schedule of Genco-II by hybrid AIS

| Hour | Load Demand (MW) | Unit Status | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Traditional UC schedule | | | | | | | | | | Profit Based UC schedule | | | | | | | | | |
| | | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 |
| 1 | 700 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 750 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 850 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 950 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1000 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 1100 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1150 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 1200 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 1300 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 10 | 1400 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 11 | 1450 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 12 | 1500 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 13 | 1400 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 14 | 1300 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 15 | 1200 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 16 | 1050 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 17 | 1000 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 18 | 1100 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 1200 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 1400 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 21 | 1300 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 22 | 1100 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 23 | 900 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 24 | 800 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table 6.** Comparisons of total cost, profit and CPU time of LR-GA, LR-AIS with AIS-GA

| Test system | Method | Total Cost in p.u | Profit in p.u | CPU time in sec |
|---|---|---|---|---|
| Genco-I 3 units | LR | 0.98176 | 0.82745 | 90 |
| | LR-GA | 0.93986 | 0.92375 | 75 |
| | LR-AIS | 0.93084 | 0.93128 | 60 |
| | Hybrid AIS-GA | 0.92147 | 0.96083 | 45 |
| Genco-II 10 units | LR | 0.98234 | 0.82510 | 140 |
| | LR-GA | 0.94045 | 0.93263 | 125 |
| | LR-AIS | 0.93172 | 0.94185 | 118 |
| | Hybrid AIS-GA | 0.92810 | 0.96127 | 100 |
| Genco-III 36 units | LR | 0.97962 | 0.83621 | 850 |
| | LR-GA | 0.95861 | 0.93578 | 720 |
| | LR-AIS | 0.94979 | 0.94076 | 680 |
| | Hybrid AIS-GA | 0.92763 | 0.96582 | 600 |

**Table 7.** Comparisons of total cost, profit and CPU time of GA-LR, AIS-LR with GA-AIS

| Test system | Method | Total Cost in p.u | Profit in p.u | CPU time in sec |
|---|---|---|---|---|
| Genco-I 3 units | LR | 0.98176 | 0.82745 | 90 |
| | GA- LR | 0.940104 | 0.92587 | 74 |
| | AIS- LR | 0.93093 | 0.93586 | 61 |
| | Hybrid GA-AIS | 0.92475 | 0.96294 | 45 |
| Genco-II 10 units | LR | 0.98234 | 0.82510 | 140 |
| | GA- LR | 0.94153 | 0.93537 | 124 |
| | AIS- LR | 0.93426 | 0.94395 | 116 |
| | Hybrid GA-AIS | 0.92908 | 0.96413 | 99.5 |
| Genco-III 36 units | LR | 0.97962 | 0.83621 | 850 |
| | GA- LR | 0.95911 | 0.93759 | 720 |
| | AIS- LR | 0.95015 | 0.94482 | 679 |
| | Hybrid GA-AIS | 0.92916 | 0.96724 | 600 |

enough diversity in the initial strings to ensure that the GA searches the entire problem space. Further the results will be improved by incorporating different population and automated parameter selection methodology.

The findings of the proposed algorithm are: there is no limitation on the size of the problem that has been addressed; No relaxation of constraints is required; population of feasible solutions are produced at each generation and throughout the evolution process; the mutation rate has the most significant impact and the size of the antibodies has a slight effect on the performance of the hybrid AIS algorithm. This is because of the somatic hyper-mutation allows the proposed method to search the space around a specific antibody with higher affinity.

## 5. Conclusion

This paper presents a solution to profit based unit commitment problem using hybrid Artificial Immune System approach. In this work, the clonal selection principle inspired from AIS is coupled into a standard GA search engine in order to move the population towards the feasible region. Also, the optimal and near optimal antibodies in each generation are reserved to the next generation to achieve a higher-quality feasible solution. This paper considered three Gencos to demonstrate the effectiveness of proposed hybrid approach and the simulation results were compared with the results obtained by conventional LR method, Hybrid LR-GA and LR-AIS methods. The test results shown that the hybrid AIS approach having well global searching performance and is an efficient algorithm to solve the profit based unit commitment problem in restructured electricity markets.

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