CHAPTER 5

IMPLEMENTATION OF ARTIFICIAL IMMUNE SYSTEM ALGORITHM

5.1 INTRODUCTION

Artificial Immune System (AIS) is an adaptive system inspired from the natural theoretical immunology and observed the immune functions, principles and models, which are applied to complex problem domains. In this work, an attempt has been made through AIS approach for meeting the requirements of Gencos PBUC problem over the specified time horizon. Also, this algorithm intends to drop-out the limitations such as premature convergence and more computation time of GA method. The biological principles of clone generation, proliferation and maturation are mimicked and incorporated into a computational algorithm invariably referred as Artificial Immune System. Therefore, AIS algorithm is a bio-inspired computational paradigm (De Castro & Timmis 2002) intends to capture some of the immune system principles and processes to solve engineering optimization problems.

The clonal selection principle of AIS algorithm used to determine the optimal unit schedule of PBUC problem with an objective of Gencos profit maximization. The objective function is viewed as an antigen and the feasible solutions as antibodies, the antibody that most fits the antigen is the optimal solution to this problem. AIS algorithm works simultaneously on population of points in search space rather than just one point and this feature enables the assessment of local and global search. Further, the clonal
proliferation operator is used to produce variation in the population according to the affinity value and it enlarges the searching area of the Gencos PBUC problem.

This chapter presents clonal selection based AIS algorithm to solve the PBUC problem and analyze the performance of AIS application with three different Gencos. In addition, this chapter discusses the important principles and models of immune systems which describe the behavior and immunological process of Biological Immune System. The work flow diagram of AIS algorithm for Gencos PBUC problem is shown in Figure 5.1.
5.2 BIOLOGICAL IMMUNE SYSTEM

The Biological Immune System is a complex network of specialized tissues, organs and cells. The primary function of the immune system is to protect the body from strange elements, such as viruses and bacteria, commonly known as pathogens and to eliminate or to neutralize these foreign invaders. The efficient mechanisms of a biological immune system are memory capability, ability to classify and neutralize the effect of foreign particles. Immunity refers to the biological state which describes the defense mechanisms and techniques of an organism against foreign pathogens, known as antigens, which cause infectious diseases (Dasgupta 1999).

Figure 5.2 Process of natural immune system (Dasgupta 1999)
In natural immune system, the protection function of the body against harmful organisms (called antigens) is performed by lymphocyte immune cells (B-cells and T-cells mainly). These two types of lymphocytes play different roles in the immune response, though they may act together and control or affect each other’s function.

The major process of natural immune system is shown in Figure 5.2, where I-III represent the invaders entering the body and activating T-Cells, which then activate the B-cells in IV, V is the antigen matching, VI is the antibody production and VII is the antigen’s destruction. 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.

The understanding and investigation on natural immune system has increased significantly over the recent few years by several researchers. It leads to development of new algorithms inspired by natural immune system, under a new branch of computational intelligence known as Artificial Immune System. The AIS is an emerging, active and attractive field involving models, techniques and applications with great diversity (Wang et al 2004). It offers powerful and robust information processing capabilities for solving complex optimization problems.
5.3 ARTIFICIAL IMMUNE SYSTEM MODELS AND ALGORITHMS

Artificial Immune System is relatively young and emerging attractive field involving models, techniques and applications of great diversity. In recent years, the Artificial Immune System based modeling has drawn the attention of many researchers due to its broad applicability to different fields. Some of the significant application areas include optimization problem, Job-shop scheduling, fault detection, computer security, design of intrusion detection, data analysis and data mining applications, pattern recognition, distributed learning, sensor network, etc. This section describes a few computational models (Dasgupta & Gonzalez 2003) that have been developed based on several principles of the immune system such as immune network models, negative selection algorithm and clonal selection algorithm.

5.3.1 Immune Network Models

The main idea of immune network model is that the immune system maintains an idiotypic network of interconnected cells for antigen recognition. These cells interconnect (both stimulate and suppress) with each other in such a way that leads to stabilization of the network. The formation of such network is possible by the presence of paratope and idiotope on each of the antibody cell. The paratope present on one B-cell is recognized by another B-cell idiotopes and for the connected two B-cells, if the affinities they share exceed a certain threshold value, then the strength of the connection is directly proportional to the affinity they share.

5.3.2 Negative Selection Algorithm

The negative selection is a mechanism to protect the body against self-reactive lymphocytes and provide a tolerance for self-cells. It utilizes the
immune system’s ability to detect unknown antigens while not reacting to the self cells. During the generation of T-cells, receptors are made through a pseudo-random genetic rearrangement process. Then, they undergo a censoring process in the thymus (organ responsible for the maturation of T-cells in the immune system.), called the negative selection. In this process, T-cells that react against self-proteins are destroyed; thus, only those that do not bind to self-proteins are allowed to leave the thymus. These matured T-cells then circulate throughout the body to perform immunological functions and protect the body against foreign antigens (Hao & Cai-xin 2007).

5.3.3 Clonal Selection Algorithm

The clonal selection principle of AIS algorithm describes the basic features of an immune response to an antigenic stimulus and how the immune cells eliminate a foreign antigen. It establishes the idea that only those immune cells capable of recognizing an antigen, are selected to proliferate as shown in Figure 5.3. The selected cells are subjected to an affinity maturation process which improves the affinity of the selected antigens.

Clonal selection operates on both B-cells and T-cells; when the body is exposed to an antigen, B-cells would respond to produce specific antibodies to the particular antigen. Then T-cell would stimulate the B-cell to proliferate and mature into non-dividing antibody producing cells called plasma cells. In proliferation, clones are generated in order to achieve the state of plasma cells as they are the most active producers of the antibodies at a larger rate than the rate of antibody production by the B-cells. The proliferation rate is directly proportional to the affinity level i.e. higher the affinity level of B-cells more clones are generated. Clones are mutated at a rate inversely proportional to the antigen affinity i.e. clones of higher affinity are subjected to less mutation compared to those which exhibit lower affinity.
This process of selection and mutation of B cells is known as affinity maturation.

The T-cells do not produce antibodies but play an essential role in the regulation of the B-cell response and are the most excellent in cell mediated immune responses. Therefore B-cells, in addition to proliferating into plasma cells, can differentiate into long-lasting memory cells. These memory cells circulate through the blood, lymph and tissues, with the intention that when exposed to a second antigenic stimulus, they commence to differentiate into plasma cells capable of producing high affinity antibody, preselected for the specific antigen that had stimulated the primary response (De Castro & Von Zuben 2000).

Though the clonal selection algorithm is simple but is an efficient approximation algorithm for achieving the optimum solution to complex
problems. Moreover, the clonal selection algorithm reproduces those individuals with higher affinity and selects their improved matured clones and this feature makes the algorithm suitable for solving combinatorial optimization problems. This research work employs the clonal selection based AIS algorithm inspired by mechanism found in natural immune systems to effectively solve the Gencos profit based unit commitment problem of considering both thermal and wind energy resources.

5.4 CLONAL SELECTION BASED AIS ALGORITHM TO SOLVE GENCOS PBUC PROBLEM

The AIS is one of the optimization algorithms that imitate the natural immune system to solve the multi-model function optimization problem. With the aim of mimic the clonal selection AIS algorithm in PBUC problem, the antibodies and affinity are taken as the feasible solutions and the objective function respectively. The maximum profit of Gencos is taken to be the affinity measure for the AIS method and the individual with maximum profit and minimum thermal fuel cost is considered to have higher affinity. The main steps of clonal selection based AIS algorithm (Li 2009 & Liao 2006) are generation of initial population of antibodies, affinity evaluation, clonal proliferation and differentiation on the encounter of cells with antigens, maturation by carrying out somatic-hyper mutation process, eliminating old antibodies to maintain the diversity of antibodies and to avoid premature convergence, selection of antibodies whose affinities with the antigen are greater.

When the clonal selection algorithm is implemented for solving the Gencos PBUC problem, the following assumptions (Rahman et al 2006) have to be made:
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 flowchart of AIS algorithm for Gencos PBUC problem is shown in Figure 5.4, where all the input parameters of thermal, wind power generating units and AIS parameters, such as the population size, the maximum number of generations (iterations), threshold value, probability of mutation rate and the total number of antibodies are initialized.

5.4.1 Generation of Initial Population of Antibodies

The initial population of antibodies is obtained by assigning a binary digit to the ON/OFF operating status of each generating unit, which is generated at random. The operating time period of the first cycle for unit ‘i’, \( T_{i}^{0} \) is initialized by the Equation (5.1), 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 (Morteza et al 2009).

\[
T_{i}^{1} = \begin{cases} 
+ rand(max(0, MU(i) - T_{i}^{0}), T), & \text{if } T_{i}^{0} > 0 \\
- rand(max(0, MD(i) + T_{i}^{0}), T), & \text{if } T_{i}^{0} < 0 
\end{cases}
\]

(5.1)

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 and the time period of \( (c-1) \) prior cycles of operation of the generating units.
For $T_i^{c-1} < 0$, cycle $c$ is in ON status with time period as given below:

$$T_i^c = \begin{cases} + \text{rand}(MU(i), RT_i^{c-1}), & \text{if } RT_i^{c-1} > MU(i) \\ + RT_i^{c-1}, & \text{otherwise} \end{cases}$$ (5.2)
For $T_{i}^{c-1} > 0$, cycle $c$ is in OFF status with time period as given below:

$$T_{i}^{c} = \begin{cases} -\text{rand}(MD(i), RT_{i}^{c-1}), & \text{if } RT_{i}^{c-1} > MD(i) \\ -RT_{i}^{c-1}, & \text{otherwise} \end{cases}$$  \hspace{1cm} (5.3)

where $RT_{i}^{c-1} = T - \sum_{j}^{c-1} |T_{j}|$;

$C_{i}$ is the number of ON/OFF cycles of thermal unit ‘$i$’ and $RT_{i}^{c-1}$ is the remaining scheduling time after allocation of the first $(c-1)$ cycles.

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 $(c+1, \ldots, C_{i})$ cycles are assigned with zero such that the unit’s minimum uptime and downtime constraints are automatically satisfied. If the status of a generating unit violated the minimal up-time or minimal down-time constraints, then it would be reversed. Also, the randomly generated binary strings are then decoded into real values to check for constraint violation in this process. If the units’ status violated the system constraints, then this step would be performed again as the string is randomly generated, decoded and checked for violation. This process is repeated until a pre-defined fixed size of population is attained.

### 5.4.2 Affinity Evaluation

An immune system generates different antibodies according to the affinity reformation between antigens and antibodies or between two antibodies. This research work considered two forms of affinity evaluation for the clonal selection based AIS approach. One of the forms describes the relationship between an antibody and the antigen, where the generation mixture of intensity between the objective function and the optimal solution is
investigated. The other form accounts for the degree of attachment between antibodies, and thus the mutual diversity of antibodies can be evaluated (Liao 2006). The affinity measure or the fitness is calculated as follows:

The fuel cost of $i^{th}$ thermal unit at $t^{th}$ hour is estimated using second order function given by the Equation (5.4).

$$F(P_{TG}(i, t)) = a_i + b_i \cdot P_{TG}(i, t) + c_i \cdot P_{TG}(i, t)^2$$  \hspace{1cm} (5.4)

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

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

$$SU_{TG}(T) = \sum_{i=1}^{N_{TG}} \sum_{t=1}^{T} H(T^c_i) \cdot SU(i, -T^c_i)$$  \hspace{1cm} (5.5)

$$SD_{TG}(T) = \sum_{i=1}^{N_{TG}} \sum_{t=1}^{T} [1 - H(T^c_i)] \cdot SD(i)$$  \hspace{1cm} (5.6)

where $H(T^c_i)$ is the unit step function an

$$SU(i, -T^c_i) = \begin{cases} H_{cost}(i), & \text{if } (-T^c_i) \leq C_{Hour}(i) \\ C_{cost}(i), & \text{if } (-T^c_i) > C_{Hour}(i) \end{cases}$$

The maximum profit over the scheduling time period for the thermal and wind-thermal PBUC problems is given in chapter 2. Based on the objective of the Gencos PBUC problem, the affinity measure is formed and is given in the Equation (5.7).

$$Affinity\ measure\ A_m = \begin{cases} \max \text{ Genco profit} \\ \min \text{ thermal fuel cost} \end{cases}$$  \hspace{1cm} (5.7)
The individuals of highest affinity value are retained and an antibody pool is created with ‘n’ number of antibodies, each of which has ‘m’ genes. The entropy $H(k,n)$ of the $l^{th}$ gene can be expressed by the Equation (5.8),

$$H(k,n) = -\sum_{i=1}^{n} P(lk) \cdot \log P(lk), \quad k = 1,2,...,m$$  \quad (5.8)

where $p(lk)$ is the probability that the $l^{th}$ allele (alternative form of a gene) comes out of the $k^{th}$ gene. The average information entropy (Li et al 2009) is given in the Equation (5.9).

$$H(n) = \frac{1}{m} \sum_{l=1}^{m} H(k,n)$$  \quad (5.9)

Consequently, the mutual diversity of antibodies is evaluated through the entropy of antibodies. If antibodies are more similar, then the affinity between antibodies is higher. The computing formulation can be represented in the Equation (5.10).

$$\alpha(x,y) = \frac{1}{1 + H(2)}$$  \quad (5.10)

where $H(2)$ is the information entropy between antibody ‘x’ and ‘y’. The antibody having the highest affinity value is retained and stored in the memory.

### 5.4.3 Clonal Proliferation

Clonal proliferation is processed according to the affinity values of antibodies. Each of the antibodies from the initial population pool is copied into a fixed number of clones to generate a temporary population of clones. In maximization problem, a pool member with higher objective value is
considered to have higher affinity. The proliferation rate is directly proportional to the affinity of the antibodies (Rahman et al 2006) and the clones generated for all the ‘n’ selected antibodies are given by the Equation (5.11).

\[ L_c = \left(1 - \frac{A_m}{\sum A_m}\right) \times 200 \]  

(5.11)

where \( L_c \) is the total number of clones generated; \( A_m \) is the affinity measure value.

For standard cloning, 20 individuals of a population pool proliferates 10 numbers of clones. This work considered the adaptive cloning process as in (5.11), 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 follows:

\[ C(x) = \frac{1}{n} \sum_{y=1}^{n} S(x, y) \]  

(5.12)

where \( S(x, y) = \begin{cases} 1, & \alpha(x, y) \geq \varepsilon_1 \\ 0, & \alpha(x, y) < \varepsilon_2 \end{cases} \); \( C(x) \) is the concentration of antibody ‘\( x \)’, and \( \varepsilon_1 \) is the threshold value of concentration. Also, the antibody with high affinity and low concentration will most likely be retained for the next generation.

5.4.4 Somatic Hyper-Mutation

The population of cloned antibodies is made to undergo maturation process through somatic hyper-mutation mechanism. The hyper-mutation is
carried out with a rate that is inversely proportional to the affinity; Higher the
affinity, then smaller the mutation rate and vice versa. The number of
mutations ‘M’ is determined by an inverse proportional law given by the
Equation (5.13).

\[ M = \left[ (\beta \times l) + 1 \right] \tag{5.13} \]

where \( \beta = e^{-\rho \hat{A}_m(x)} \); \( l \) is the length of any individual solution, \( \beta \) represents
the mutation rate, \( \rho \) determines the shape of the mutation rates and \( \hat{A}_m(x) \) is
the affinity value normalized in \([0, 1]\). Once the objective function is
normalized into the range \([0,1]\), the best solutions are closer to 1, while the
worst ones are closer to 0.

The cloning operator coupled with the hyper-mutation operator,
performs a local search around the cloned solutions. 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.

### 5.4.5 Receptor Editing

The receptor editing process suppresses the old antibodies, in order
to maintain the diversity of the population and to avoid the premature
convergence. Accordingly, the antibody feasibility is computed and it can be
expressed by the Equation (5.14).

\[ e(x) = A(x) \cdot \prod_{i=1}^{s} \left[ (1 - L_{x,i}) \right] / \left( \sum_{i=1}^{n} A(k) \right) \tag{5.14} \]
where \( L(x,s) = \begin{cases} \alpha(x,s), & \alpha(x,s) \geq \varepsilon_2 \\ 0, & \alpha(x,s) < \varepsilon_2 \end{cases} \), \( e(x) \) is the feasibility of antibody \( x \), \( A(x) \) is the sufficiency of antibody \( x \), \( A(k) \) is the sufficiency of antibody \( k \), \( s \) is the total number of the suppressor cells, \( q \) is the suppressor index, and \( \varepsilon_2 \) is the feasibility threshold value.

In this process, an antibody \((x)\) is allowed to remain in the population pool for at most \( \varepsilon_2 \) value. If the feasibility of an antibody is lesser than this threshold value, then this antibody corresponds to local optima and must be suppressed from the current population, no matter what its affinity value may be. Hence the clonal selection AIS algorithm has the ability to escape from unsatisfactory local optima and carry out the search towards the global optimum.

In addition to receptor editing, a pool of entirely newcomers of dissimilar antibodies has been randomly generated and added in place of low affinity antibodies according to their sufficiency values. Adding a fraction of newcomer antibodies to the pool makes the repertoire diversity of population. A new population of the same size as initial population of the antibodies is selected from the mutated clones and this completes the first iteration.

5.4.6 Stopping Criterion

The stopping criterion used in this work is the maximum number of generations. In AIS algorithm, the number of iterations is termed as number of generations. If the stopping criterion is satisfied, then the iterative process is stopped. Else, in the next iteration, the new population of antibodies is made to undergo cloning proliferation and somatic hyper-mutation. The best affinity and the corresponding antibodies retained in the memory at the end of
the stopping criterion and are selected as the best optimum schedule of generating units involved in the PBUC process for that time interval. Then the profit and total cost for all the sub-intervals in that time interval are computed. Finally, the optimal solution is obtained based on the antibody of highest affinity with the antigen.

5.4.7 AIS Simulation Parameters

The simulation parameters for AIS algorithm such as population size and mutation rate are the important factors that determine the effectiveness of the algorithm that avoids the premature convergence as well as the additional computation of this algorithm. Therefore the selection of AIS parameters becomes necessary to solve the Gencos PBUC problem in deregulated markets. The AIS simulation parameters considered in this research work are given in Table 5.1. Also, the Pseudo code for AIS algorithm to solve the PBUC problem is shown in Figure 5.5.

Table 5.1 AIS simulation parameters

<table>
<thead>
<tr>
<th>Simulation Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Antibodies (n)</td>
<td>60</td>
</tr>
<tr>
<td>Probability rate of mutation ((p_m))</td>
<td>0.05</td>
</tr>
<tr>
<td>Concentration threshold value ((c_1))</td>
<td>0.9</td>
</tr>
<tr>
<td>Feasibility threshold value ((c_2))</td>
<td>0.85</td>
</tr>
<tr>
<td>Selection rate</td>
<td>0.8</td>
</tr>
<tr>
<td>Maximum no. of generations (iterations)</td>
<td>200</td>
</tr>
</tbody>
</table>
5.4.8 Pseudo code for AIS Algorithm

```
Begin
Initialize the parameter settings
  gen_no ← 0
step 1: Create an initial population of antibodies (feasible PBUC schedule)
while gen_no ≤ gen_no max do
  step 2: Evaluate the affinity value (objective function value)
    for each antibody n, i=1,2,…pAIS
      determine Affinity measure \( A_m = \begin{cases} \max \text{ Genco profit} \\ \min \text{ thermal fuel cost} \end{cases} \)
      calculate the entropy \( H_k(n) \), k=1,…m
    endfor
    if \( H_k(n) \leq H(n) \) do
      step 3: Clonal proliferation
        for each selected n, do
          if concentration \( C_x(n) \leq 0.9 \) then
            promote (clone) through \( L_r = \left(1 - \frac{A_m}{\sum A_m}\right) \times 200 \)
          endif
        endfor
    endfor
    step 4: Somatic hyper-mutation
      for each clone do
        if \( \text{rand()} \leq 0.05 \)
          Number of mutations \( M = \left[ (\beta \times l) + 1 \right] \)
        endif
      endfor
    step 5: Receptor editing
      for each cloned antibody do
        if feasibility \( e(x) \leq 0.85 \) then
          eliminate antibody with lowest affinity values
        endif
      update antibody repertoire diversity with new randomly generated antibodies
    endfor
  endwhile
end
```

Figure 5.5 AIS Pseudo code for Gencos PBUC problem
5.5 NUMERICAL RESULTS OF AIS APPROACH FOR GENCOS PBUC PROBLEM

The performance of AIS algorithm to solve the Gencos PBUC problem was tested with three different Gencos using MATLAB 7.10.

5.5.1 Case Study-Genco I: Results of 10 Thermal Units with 24 Hours System

The forecasted load demands specified in Appendix A.1 are supplied from thermal generating units of Genco-I and the optimal schedule using AIS method is given in Table 5.2. By ignoring the wind power generation, the Minimum Spinning Reserve (MSR) level of the Genco-I is assumed to be 20% of peak load demand in 24 hours scheduled time horizon (i.e., 300MW for all 24hours).

Table 5.2 Optimal schedule of AIS method for Genco-I

<table>
<thead>
<tr>
<th>Hour</th>
<th>Load Demand (MW)</th>
<th>Commitment schedule of Thermal units only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>T1</td>
</tr>
<tr>
<td>1</td>
<td>700</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>750</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>850</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>950</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>1000</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>1100</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>1150</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>1200</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>1300</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>1400</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>1450</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>1500</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>1400</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 5.2 (Continued)

<table>
<thead>
<tr>
<th>Hour</th>
<th>Load Demand (MW)</th>
<th>Commitment schedule of Thermal units only</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>T1</td>
</tr>
<tr>
<td>14</td>
<td>1300</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>1200</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>1050</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>1000</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>1100</td>
<td>1</td>
</tr>
<tr>
<td>19</td>
<td>1200</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>1400</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>1300</td>
<td>1</td>
</tr>
<tr>
<td>22</td>
<td>1100</td>
<td>1</td>
</tr>
<tr>
<td>23</td>
<td>900</td>
<td>1</td>
</tr>
<tr>
<td>24</td>
<td>800</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 5.6 Revenue, total cost and profit of Genco-I using AIS method
136

Figure 5.7 Comparison of total cost for Genco-I

The AIS algorithm produces the total operating cost over the 24 hours scheduled time period as $23084308.80 and the profit as $4764135.26, as shown in Figure 5.6. The total cost by AIS technique is compared with the total costs obtained from LR and GA methods as shown in Figure 5.7, where the total costs obtained from AIS method was reduced by about 11.54% compared to the LR method and 5.93% lesser than the GA method. Also, the profit obtained by this technique was about 1.078 times greater than that of LR algorithm.

5.5.2 Case Study-Genco II: Results of 3 Thermal Units with 12 Hours System

The performance of AIS method has been evaluated for small scale power systems of 3 thermal generating units. The Figure 5.8 shows the simulation results of small system of Genco-II, where the optimal value of total cost $2193567.25 and profit $516436.00 were achieved from AIS method with 60 seconds.
Figure 5.8 Optimal Results of Genco-II by AIS method

Moreover, the simulations were done for different number of generations as shown in Figure 5.9 and the computational results at both 150 generations and 200 generations were nearer to each other. The simulation results of AIS method were compared with the GA and LR methods; particularly the profit comparison for Genco-II is shown in Figure 5.10.

Figure 5.9 Comparison of revenue, total cost and profit for Genco-II by AIS method
While comparing the results of AIS technique with the other methods, the total operating cost has been reduced by about 0.157 times lesser and the profit has been raised by about 1.32 times more than that of LR method. Thus the performance of AIS approach greatly improved for small power systems also.

5.5.3 Case Study-Genco III: Results of 10 Thermal + 2 Wind Units with 24 Hours System

The PBUC schedule, revenue, total cost and profit of the AIS method is given in Table 5.3 and it can be observed that significant savings in thermal fuel cost and increase in profit with the installation of wind turbine generator power. For this Genco-III, the total cost is `21852855.45 and the total profit is `5983822.96. When simulating the PBUC schedule, the two wind power generating units W1 and W2 are committed to ON-line from 9th hour to 18th hour. Also, the wind unit W1 generated the rated power of 60MW at 13th hour when the wind speed is 14.17m/s, which lies between the rated speed and the cut-out speed of that wind power unit.
Table 5.3 Optimal results of AIS method for Genco-III

<table>
<thead>
<tr>
<th>Hour</th>
<th>Commitment schedule of Thermal and Wind units</th>
<th>Total Revenue (())</th>
<th>Total Cost (())</th>
<th>Profit (())</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>T2</td>
<td>T3</td>
<td>T4</td>
<td>T5</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>15</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>18</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>19</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>21</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>22</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>23</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>24</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Total: \(27836678.40\) \(21852855.45\) \(5983822.96\)

Computational time: 100 seconds
The wind power penetration will require the scheduling with additional reserve. This significantly increases the operating costs. But still the total operating costs decrease by increasing the amount of actual wind power generation. It is found that the percentage decrease of the cost saving (\(1013981.89\) for the peak demand of 1500MW) by the wind generator is greater than the increase of the added costs (\(994265.50\) for 1500MW) from the additional reserve requirement.

![Figure 5.11 Total cost comparison for Genco-I and Genco-III by AIS method](image)

This has been verified through simulation by acquiring proper value to the \(P_{WGT}(t)\) without adjusting the wind power generation, since a large wind power penetration will usually achieve maximum reduction in fuel cost. Besides, the total cost of Genco-III is reduced while operating thermal and wind generator units together, than operating the thermal units alone as shown in Figure 5.11.

The total cost for the peak load demand of 1500MW is \(1201121.30\) for Genco-III, but for the same load condition the total cost is \(1310872.50\)
for Genco-I, thus the savings in thermal fuel cost is about 8.37%. Furthermore, the profit comparison between the Genco-I and Genco-III as in Figure 5.12, shows that the combined operation of thermal and wind generator units produces the profit of 1.36 times higher than the individual operation of thermal units.

**Figure 5.12** Comparison of profit for Genco-I and Genco-III using AIS method

**Table 5.4** Performance of AIS method on Genco-III for different wind speeds

<table>
<thead>
<tr>
<th>System conditions</th>
<th>Mean speed of W1=5.46m/s</th>
<th>Mean speed of W2=3.87m/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{WGT}^*$</td>
<td>0 MW</td>
<td>60 MW</td>
</tr>
<tr>
<td>$MSR_s$</td>
<td>300 MW</td>
<td>300 MW</td>
</tr>
<tr>
<td>$AUSR$</td>
<td>--</td>
<td>6 MW</td>
</tr>
<tr>
<td>$ADSR$</td>
<td>--</td>
<td>6 MW</td>
</tr>
<tr>
<td>$WPC$</td>
<td>--</td>
<td>without</td>
</tr>
<tr>
<td>Profit (’000)</td>
<td>4764135.26</td>
<td>4940261.45</td>
</tr>
</tbody>
</table>

$WPC$- Wind Power Curtailment
To evaluate the robustness of the AIS approach, various operating conditions, system configurations and mean wind speed of two distinct wind farms corresponding to the location are considered. The multiple operation conditions are given in Table 5.4, which illustrate the impact of various system constraints on the profit of thermal and wind power Gencos. The cases 2 and 2.1 give the comparative results of Genco-III with and without considering Wind Power Curtailment (WPC). When the wind speed reaches beyond the cut-out speed of 25m/sec., the power generation of wind units is restricted to rated power. So, the profit of Genco-III with WPC has been slightly improved than that without WPC.

Moreover, the profit of Genco-III obtained by AIS algorithm was compared with the GA and LR methods as shown in Figure 5.13. The Genco-III profit using AIS method has been improved significantly, about 1.358 times higher than the LR method and the total cost of Genco-III using AIS technique was reduced by about 5% and 15.42% lesser than the GA and LR methods respectively.

Figure 5.13 Profit comparison for Genco-III
5.6 SUMMARY

The AIS approach is having well global searching performance for solving the Gencos PBUC problem considering thermal and wind energy systems. In this method, the optimal and near optimal antibodies in each generation are reserved to the next generation to achieve a higher-quality feasible solution. While comparing the scheduling of thermal units only, the scheduling of thermal generating units along with wind power units considerably saves the total thermal fuel cost by about 5.33% and produces higher profit.

Further, the findings of the AIS 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 AIS algorithm. This is because the Somatic hypermutation allows the AIS method to search the space around a specific antibody with higher affinity.

Although clonal selection based AIS algorithm has attained great achievement in power system optimization domains, there are still some theoretical issues that need to be further explored, such as the development of combined frameworks, scalability and programming complexity. The developments of the artificial immune systems would benefit not only from the inspiration of biological immune principles and mechanisms, but also hybridization with other soft computing paradigms, such as genetic algorithms, neural networks and fuzzy logic. The hybrid methods could also be further studied and applied to solve complex real-world problems. With this intention, hybrid approach of Artificial Immune System and Genetic Algorithm has been developed to solve the Gencos PBUC problem in the next chapter of this dissertation.