Unit Commitment by Considering the Uncertainty of Renewable Energy Sources

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ABSTRACT

The main idea of Unit Commitment (UC) is to decide the optimum start-up / shut-down cycle of all units throughout the operating period with a view to minimize the overall costs with respect to various generator and system constraints.

A steady rise in fuel charges and a rapid fossil fuels depletion have opened the way for the use of renewable sources for power generation. Renewable energy sources are therefore being used and installed with greater eagerness in power systems today. With the deployment of renewable sources, the UC issue becomes more complicated ,provided obvious differences in behavioral and technical restrictions on traditional thermal generation systems that need to be resolved as renewable generation will be integrated part of the electrical network.

This thesis aims to solve the problem of UC with the consolidation of wind power sources into the network. This study covered the renewable energy uncertainty by forecasting day ahead wind power and studying more than one scenario for the wind behavior. Artificial Neural Network (ANN) method is used for forecasting short-term wind and then generating extra possible scenarios for the wind power values. Two optimizations method are used for UC problem: Genetic Algorithm (GA) and Dynamic Programing (DP). The suggested approach is tested by applying it to the standard IEEE 6 and 30 bus test systems. The results show that DP method outperforms GA method in term of minimizing the total production costs. This study may help the decision-makers particularly in small power generation firms in planning day-ahead performance of the electrical networks.

Keywords: Artificial Neural Network, Dynamic Programing, Economic Dispatch, Genetic Algorithm, Unit Commitment and Wind Uncertainty.

ÖZ

Birim Taahhüdünün (UC) ana fikri, çeşitli jeneratör ve sistem kısıtlamalarına tabi olan genel maliyetleri en aza indirmek için çalışma birimleri boyunca tüm birimlerin optimum başlatma / kapatma döngüsüne karar vermektir. Yakıt maliyetlerinde istikrarlı bir artış ve fosil yakıtların hızlı bir şekilde bozulması enerji üretimi için yenilenebilir kaynakların kullanılmasına yol açmıştır. Bu nedenle, yenilenebilir enerji kaynakları günümüzde güç sistemlerinde daha fazla hevesle kullanılıyor ve kuruluyor. Bununla birlikte, aralıklı doğanın mevcudiyeti nedeniyle sistem üzerinde önemli bir etkisi zorlarlar. Yenilenebilir kaynakların konuşlandırılmasıyla, yenilenebilir enerji üretiminin entegre bir parçası olarak çözülmesi gereken geleneksel termal üretim sistemlerindeki davranışsal ve teknik kısıtlamalarda bariz farklılıklar sağlanarak UC sorunu daha karmaşık hale geliyor. Bu tez, rüzgar enerjisi kaynaklarının şebekeye entegrasyonu ile UC problemini çözmeyi amaçlamaktadır. Bu çalışma, gün öncesi rüzgar gücünü tahmin ederek ve rüzgar davranışı için birden fazla senaryo çalıştırarak yenilenebilir enerji belirsizliğini kapsamıştır. Yapay Sinir Ağı (YSA) yöntemi, kısa vadeli rüzgar tahmini ve daha sonra rüzgar enerjisi değerleri için ekstra olası senaryolar oluşturmak için kullanılır. UC problemi için iki optimizasyon yöntemi kullanılmıştır: Genetik Algoritma (GA) ve Dinamik Programlama (DP). Önerilen yöntem, standart IEEE 6 ve 30 veri yolu test sistemlerinde uygulanarak doğrulanır. Her sisteme bir rüzgar çiftliği eklenir. UC sonuçları, hem rüzgar gücünün varlığında hem de yokluğunda gösterilmiştir.

Anahtar Kelimeler: Yapay Sinir Ağı, Dinamik Programlama, Ekonomik Sevkıyat, Genetik Algoritma, Birim Bağlılığı ve Rüzgar Belirsizliği.

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α_i, β_i and γ_i	Generator i cost coefficients.
B_{ij}	ijth element of the loss coefficient square matrix.
B_{0i}	ith element of the loss coefficient vector.
B_{00}	loss coefficient constant.
DR_i	Ramp-down rate of unit i.
I_{it}	Commitment state of unit i at time t.
P_{it}	Power generation of unit i at time t.
$P_{W,it}$	Generation of wind power of unit i at time t.
$P_{D,t}$	System demand at time t.
$P_{L,t}$	System losses at time t.
$P_{i,min}$	Minimum power generation of unit i.
$P_{i,max}$	Maximum power generation of unit i.
SU_{it}	Startup cost of unit i at time t.
SD_{it}	Shutdown cost of unit i at time t.
T_i^{on}	Minimum ON time of unit i.
T_i^{off}	Minimum OFF time of unit i.
UR_i	Ramp-up rate of unit i.
w	The weight in neural network
X_i^{on}	The ON time of unit i.
X_i^{off}	The OFF time of unit i.
ANN	Artificial Neural Network.
DP	Dynamic Programming.

ED	Economic Dispatch.
UC	Unit Commitment.

Chapter 1

INTRODUCTION

1.1 Background of the Study

Over several years, power systems have seen an enormous shift from being separated systems to being an immense interconnected system. This coordinated power system is more reliable and, in parallel, has brought up several operational challenges from the system security and economics perspective. Power systems are categorized into three components: the generation, transmission and distribution systems (away from the consumption part at the end) [1]. The performances of the subsystems are interconnected. Over many years, the power system's range has extended to many locations to meet the ever-growing load demand. With this vast prevalence, due to continuously increasing power requirements, each utility in the system is facing many problems in reliable system operation. The need to supply electricity to consumers with extreme importance concerning the reliability leans utilities to plan at all levels. Moreover, an aspect that calls for attention during planning for utilities is the economics associated with the system's operation. There are several economic factors, from the level of power generation to the level of supply at the demand stage. Thus, the steps of the plan followed should provide a reliable system operation while optimizing the associated economics [2].

The power system is exposed to diverse electric load demands, with valleys and peaks at different time periods completely based on consumer requirements.

Consumers have to be supplied with electricity whenever they require it. This forces the utility to commit to (turn ON) an adequate generating unit numbers to satisfy these varying load demands during all the time periods. The option of committing all of the units and keeping them active all the time to register varying natures of the load is economically prejudicial [3] for the companies. The generating units require specific amounts of heat as input per megawatt (MW) to be generated, which demands a cost in the form of fuel needs. Heat demand per MW (heat rate), which is also known as input characteristics, differs for each generator, consequently differing for the fuel cost per MW (incremental costs) as well. This makes the commitment problem considerable. Therefore, a previous decision as to which generating units should be ON leads the company to earn a significant saving in generation costs. The operation of this decision is commonly known as unit commitment (UC), and it is considered to be one of the main optimization issues of the power systems which draws attention to daily basis operation [4].

1.1.1 Unit Commitment

UC is considered to be one of the greatest remarkable problems in power systems, as UC aims to decide the best schedule and the rate of the generating units production in the power system for a specific time interval by facing given data for the load forecast [5]. The only optimizing pattern in deciding the UC schedule is the generation costs, that must be minimized over a planning cycle while satisfying all system constraints resulting from the physical capacities of the generating unit and the network design of the transmission system. Each generator has different limitations – such as maximum and minimum generation limits, minimum down-up time, the ramp rates limit, and so forth.

The UC problem is an integration of two sub problems. The first one is deciding which generating units to be committed, and the second one actually deals with the amount generated from each committed unit. Generating units display different performance characteristics and operating efficiencies, which reflect the needed inputs. Thus, the generation costs also depend on the output amount from each committed unit separate from the option of generating units. Thus, UC problems are solved in two steps. The combination of generators yielding the minimum production cost is then chosen as a schedule for the UC in an hour [1].

1.1.2 Economic Dispatch

The operation of calculating the demanded power from each committed unit for each specific hour predetermined by the schedule for the least possible cost is called economic dispatch (ED). It is a nonlinear optimization issue, in which the control variable is the output power of each committed unit, and the determined value must be connected to the power limitation of each unit [1].

1.1.3 Renewable Energy Role

Renewable energy is underlined world widely because of its tremendous environmental advantages: free from fossil fuels and the improving of social benevolence. From the side of the planners of the power system, an sporadic kind of renewable energy technology is the concern area these days. If the output power of renewable energy is forecast accurately, technical challenges can be addressed [6]. Solar and wind energy are the most profitable, environment-friendly, and low-cost renewable energy resources which are henceforward well-promoted by policy makers and researchers [7]. At the same time, dealing with the uncertainty of renewable energy is a big challenge in which these renewable energy sources demonstrate intermittencies in the power system generation [8]. Forecasting the output of renewable energy is considered to be one of the most important area of research in the UC problem, where the accuracy of forecasting plays a major role in terms of the reliability and economy of a renewable power network [9]. Power forecasting of renewable energy is divided into four general categories: long-term, medium-term, short-term, and ultra-short-term prediction [10]. There are many approaches to forecasting the output of renewable energy – such as the use of physical methods, statistical techniques, spatial correlation models and probabilistic methods [10].

With rising attention to the need for more sustainable grids and climate change. recently power system planners have noticed a rapid amplification of renewable energy sources. The environmental and economic advantages that grow from the integration of renewable energy sources into the power system lead to an increase in the level of uncertainty and variability because of the intermittent nature [11]. The complexity of balancing generation with maintaining the reliability of the system while interacting with the system constraints with the least production cost is significant [12].

Solar and wind power units are characterized by sturdy temporal fluctuations, which can create variability in the generating power system [13]. The variability can be separated into many time scales (e.g., seconds, minutes, hours, and others); each scale is associated with management strategies, many costs, and different impacts [14].

Wind power’s impact on the power system can be divided into two types: long- and short-term impact. Long-term impact involves long-term planning periods, while short-term impact deals with the operational time structure involving power balance system related problems, which are symbolized by costs and requirements related to the fluctuation of wind power [15]. The integration of wind power turbines in the network because of major impacts into generation efficiency reserves, reliability, distribution and transmission losses, and voltage and reactive power [15].

The photovoltaic system has a lower impact on the power system than wind power. High solar system penetration may cause operational challenges, particularly during high solar and low load period [16].

The uncertainty of forecasting the output of renewable energy will affect the solution of the UC problem and may cause serious risks to the operation and control of the power system [17]. Renewable energy expectation techniques are proposed to simulate the uncertainty of renewable energy [18] while a huge amount of data has to be generated to be sure that the results are reliable, so the calculation efficiency will be restricted [19].

Recently, some new approaches to forecasting have been gripping the attention of researchers whose methods depend on artificial intelligence, such as artificial neural networks (ANNs) [20]. However, there are some approximate results, and comparisons proved that artificial methods outperform other methods in short-term prediction [21].

ANNs are among the many information mining methods used to predict the power output of a wind farm utilizing meteorological knowledge generated by NWP systems. ANNs are attempting to mimic the behavior of physiological neural networks. Analogously to the brain structure, ANNs contain single processing units identified as neurons. The neurons are grouped into layers in the group structure. -- neuron within the input layer is given one of the parameters (e.g. wind velocity and direction, temperature, humidity and atmospheric pressure) that the parameters to be expected depend. The output layer neurons reflect the quantities of the parameters to be expected (e.g. the power output of the wind farm at corresponding moments). There could also be a sequence of intermediary layers known as hidden layers. The reason the neurons connect directly is known as the pattern of communication or the network topology. [22].

ANN is a simple but flexible and powerful tool for forecasting if there are enough training data, enough computation resources, sufficient selection of input-output sample and an adequate number of hidden units. Moreover, ANN has the well-known feature of being able to deal with a problem where the relation between the input and output is neither strong nor easily computable [23].

1.1.4 Optimization

UC is considered to be an optimization problem. The main objective is to minimize running costs, with respect to many constraints such as power balance in the network, system operating and spinning reserve, unit ramp up and ramp down limits, unit minimum ON and OFF time limits and unit generation limits [24].

Different optimization methods have been designed to solve UC problems. Previously, traditional methods – such as lagrangian relaxation (LR), mixed-integer linear programming (MILP), dynamic programming (DP), and so forth – were commonly used[25]. These methods transact with UC problems by applying different calculation approaches; but they still have some deficiencies – such as the dimensional course, memory consumption, numerical problem in convergence and the quality of results still being poor [26]. Nowadays, heuristic algorithms – such as particle swarm optimization (PSO), genetic algorithm (GA) , and so forth – are commonly used, where these algorithms have better computational performance [26].

1.2 Problem Statement

UC is considered to be an important task in power system operations. Searches for the maximum cost-effective generators commitment decision of the power system to satisfy the load demand while meeting all the operational constraints on the generation resources and transmission system. This is considered a challenging problem on account of a high level of uncertainty in the load which results from the uncertainty of renewable generation.

The high penetration of renewable energy increases the instability of the network since the renewable energy system depends on the state of nature. The uncertainties of the operation of a power system integrated with renewable energy mainly include the uncertainty of renewable energy generation related to forecasting error. To reduce the danger of the uncertainty of renewable energy, many possible scenarios have to be studied for short-term and long-term planning. This can be done by generating more than one scenario for wind performance by using reliable forecasting approaches to reduce the level of error in planning systems such as the ANN system. Then by UC, the best operation schedule can be determined.

1.3 The Objectives of the Study

There are five objectives that have to be achieved by the end of this study:

- To plan the day-ahead performance of generating units in an electrical network by using the UC method.

- To forecast the day-ahead performance of a wind farm by using an ANN.
- To generate more than one wind power scenario for a day ahead by using an ANN and the Weka program.
- To study the effects of wind uncertainty on the performance of generating units and on the power production costs.
- To make comparisons between GA and DP methods in solving the UC problem.

1.4 Thesis Organization

This thesis has five chapters organized as follows:

Chapter I: In this chapter, a background of the study is proposed, followed by the problem statement and the objectives of the study.

Chapter II: Several works of literature and articles on previous related studies are explored in this section, hence giving a principle for comparison with this study.

Chapter III: In this chapter, the methodology of this study is explained in detail.

Chapter IV: In this chapter, the results and discussions of the methodology which applies to the case study, as well as explanations and comparisons, are reported.

Chapter V: In this chapter, the conclusion of the study and some recommendations are mentioned.

Chapter 2

LITERATURE REVIEW

2.1 Background

UC is one of the most important problems in electrical power system which aims to minimize the power generation costs by finding the optimal working schedule for the power generating units under several constraints. Previously, thermal power stations were dominated and the main target of UC is to minimize the operating costs and finding the best method was the main real problem. Generally, the overall cost of power generation includes the cost of oil connected to thermal power plant systems, start-up and shut-down costs. [27].

These days, with high penetration of renewable energy, unit commitment problem has become more complicated, due to the uncertainty of renewable energy sources imposed on us to study whole possible scenarios that might happen in each hour during the daytime.

There are different classifications for UC problem related to security. Three categories are considered: Price Based UC (PBUC), Security Constrained UC (SCUC) and traditional unit commitment [28].

UC started to be treated by researchers since 1940s [29]. Many papers have discussed this field and many methods have been applied to solve UC problem.

Quan et al. [30] studied a computational scope for uncertainty with renewable energy sources intermitted in stochastic UC, different reserves approaches as well as generation costs are examined from the side of model reliability and economics, the comparatives outcome show that the reserve and the generation costs are various from the recognized ones. The researcher found that the stochastic method display better robustness comparing with deterministic model and through the peak load period a higher risk level of runs in the system.

Hytowitz et al.[31] studied managing stochastic UC with uncertainty of solar energy in micro grid system, The commitment schedule is validated with solar scenario analysis, since Monte-Carlo simulations are conducted to test the proposed dispatch solution.

Osório et al.[32] studied solving UC problem under high penetration of renewable energy sources by a new generation based scenario method, a scenario of generation/reduction method combined with the method of Priority List(PL) is used to produce a new method of the generating units scheduling with renewable power units of the power system.

Pinto et al.[33] studied consolidating stochastic UC to include the uncertainty of nodal wind power system. A stochastic formulation is considered and the technical thermal generating unit limits as constraints are included, the main objective is to evaluate the capability of the approach of stochastic UC to decrease the wind power losses and load shedding compared with deterministic approach of UC problem.

Zhang et al.[34] studied the scenario reduction techniques impact of wind power system on stochastic UC. Two matrices are studied for quantifying the stochastic quality distortion of wind power through the reduction scenario process: ramp diversity and output uncertainty. The reduced economic scenario value is estimated by finding the difference between the optimal stochastic UC costs and the expected operating costs by considering all available scenarios. Several techniques of wind power scenario are reviewed and then they are categorized by both scenario reduction and scenario clustering approaches. The results display that the ramp diversity approximation is less sensitive than stochastic UC performance.

Wang et al.[35] used goal programming chance constrained to adjust the risk of Day-Ahead UC with wind power. A novel model based on goal programming chance constrained is used to optimize the adjustable risk of UC problem to expedite an efficient solution, the model is moved into a tractable MILP problem by pricewise linearization and deterministic equivalent.

Marneris et al.[36] studied the deterministic and stochastic UC by considering variability and uncertainty of renewable energy. Different deterministic and stochastic formulations for UC Day-Ahead are proposed, the concept of multi timing is proposed and explicit distinction between the fluctuation reserve and uncertainty is proposed. The Day-Ahead results are compared with different real time dispatch regime, the results of multi timing are demonstrated.

Wang et al.[37] studied UC by considering renewable energy and pumped storage by using Binary Artificial Sheep Algorithm (BASA). BASA is used to improve the performance of UC problem, that is used to evaluate the uncertainty of renewable energy effects. The method for the evaluation of scenarios is established to estimate quantitatively economy and the stabilization of the UC yields with regards to different forecasting error levels of renewable energy. Moreover, the effect of pumped hydro-energy storage on UC performance is studied. The results demonstrate that the BASA acts in better performance than traditional metaheuristic in solving UC problem. In addition, the results show that with increasing forecasting error, the operating costs of thermal power units increase.

Furukakoi et al.[38] studied UC problem as multi-objective function by considering photovoltaic uncertainty and voltage stability. The prediction of photovoltaic output error is minimized by using multipurpose operation planning approach to decrease the operation cost and to maintain the stability of the power system.

Jo et al.[39] used improved GA to solve UC problem by considering uncertainty of renewable energy sources. The methodology for dealing with UC problem is prepared by considering various uncertainties by using Monte Carlo simulation method. The improved GA shows better performance comparing with other optimization methods by applying approximation process and reserve repairing.

Ackooij et al.[40] studied the method of exact solution to solve hydrothermal UC under uncertainty of renewable energy with a combination of some constraints. The study suggests to handle the exact probability constraints of a novel mixed integer optimization model with continuous distribution and joint probability constraints. The competence of the algorithm is examined by mathematical experiments when contrasted to two common limited probability methods: the sample-based approach and the individual approach.

Yun et al.[41] studied prediction ability of wind energy optimizing and forecasting of day-to-day UC. A solid pattern of optimization for the uncertainty of the prediction of wind energy with a defined level of confidence is developed. On the basis of the predicted value of wind power and the variance function of the forecast error, a robust estimation approach for the efficiency of wind power prediction throughout the given demand peaks is developed.

Yang et al.[42] studied the analytical solution for dealing with UC problem by considering uncertainty of renewable energy and the model of Gaussian mixture. Gaussian mixture model is used for characterizing the liaison between the wind farms and the probability distribution of wind forecasting error. The research used the Newton technique to convert the constraints of chance into deterministic constraints.

Ouassima et al.[43] used a Hybrid Particle Swarm Optimization (HPSO) with Sine Cosine Acceleration Coefficients(SCAC) to solve UC problem of micro grid, which consist of wind turbine units, photovoltaic units and diesel generator units. The proposed method is used to reduce fuel costs and transaction fees with regards to certain constraints, such as demand balance and network constraints. The hybrid algorithm performance is compared with PSO and GA, and the results demonstrate the robustness of the proposed method and approve that there is a probability to get slightly closer to the optimal sustainable solution.

Bin et al .[44] made a comparison between GA and DP for solving UC problem to compare the performance of GA and DP. The comparison takes into consideration the reliability of the solution and time of operation. The study found that in the case of high dimension, DP is sturdy in obtaining high quality and stable solution, and it is possible to maintain its performance even in the case of searching over a large solution space.

Jorge et al. [45] studied UC by using Memetic Algorithm which is GA combined with Local Search Algorithm and then the study compared the results with traditional method such as DP and Lagrange Relaxation method. The study concluded after solving eight UC problems that for the size of units less or equal to ten units the DP choice is the best method since the optimal solution can be discovered in the time of less than four minutes.

Hao et al. [46] worked on the short-term wind output power and load forecasting by using ANN. The study used a neural network based method to handle the uncertainty of the power system operations which associate with forecasting.

Dipti et al.[47] used neural network-based prediction interval to integrate the uncertainty of wind power predictions into the stochastic UC. In this study neural network is implemented for forecasting uncertainty quantifications.

Alberto et al. [48] worked on wind power forecasting by using ANN technique.in this study, a model for the forecasting of wind power is identified which combines artificial neural network and dynamic Bayesian net. The method was applied for the unit 1 of the Villonaco wind farm in Ecuador.

You et al. [49] studied interval UC with the Integration of Wind energy by using interval optimization. A new UC interval methodology, based on the optimization of periods, is addressed in which the uncertainty of wind energy is characterized as fluctuating periods. The period of the UC with uncertainty is then transformed into a deterministic form by means of an order relationship between the amount of intervals and the level of fulfilment.

2.2 Optimization Methods for Solving UC Problem

Several techniques are used to solve the UC problem, which varied from simple methods to hybrid metaheuristic methods [50]. Many mathematical mechanisms have been used for this time dependent problem. In the past, Lagrangian relaxation was the most popular optimization method for solving UC problem [51]. There are four categories for classifying UC problem: dynamic programming, decomposition approaches, MILP approaches and metaheuristics approaches. Recently, metaheuristic process has been commonly used to solve the UC issue due to its ability to deal with huge-scale problems. [52]. Choosing the best method depends on the power plant units presented in the network and the type of the constraints. Table 2.1 represents a comparison between some optimization techniques used for solving UC problem.

Table 2.1: Comparison Between Optimization Techniques Which Used For Solving UC problem[52].

Method	Advantages	Disadvantages
Dynamic programming	Sub-problems can be managed in decomposition programs and solution feasibility can be maintained.	Commitments must be limited at any time considered. It's suffering from imprecision .
Lagrangian Relaxation	Ramp rate can be processed with Lagrangian Relaxation method. It can solve further sub-problems.	It is suffering from the existence of a duality gap.
Benders Decomposition	The problem can be separated into independent easy problems.	It takes long time for convergence.
Interior Point	It interacts smoothly with	It takes long time in

Optimization	setting the variables.	searching for the optimal target.
Stochastic Programming	The minimum operational cost is secured as a predicted value.	In deterministic formulation the computational costs will increase.
Quadratic Programming	It can solve ED together and UC problem.	It needs a long processing time. It can't fix a huge-scale problem quickly.
Mixed Integer Linear Programming	Robust modeling tool. It can deliver the optimal global solution.	It needs long time comparing with heuristics method. In large-scale problems the efficiency becomes low.
Branch and bound	If the problem in a limit size, it can find an optimal solution.	For large systems the processing time rise exponentially.
Non-linear Programming	It provides accurate medialization for the power system units.	It enhances the complexity of the problem.
Artificial Neural Network	It has the capacity to deal with incomplete data and can interact with stochastic variations in the plan of procedures.	With large problems the computational time increases exponentially.
Simulated Annealing	It can be programmed easily. It just requires any initial solution, so the algorithm will strengthen it.	It needs a long processing time to decide the near-optimal solution.
Genetic Algorithm	It provides multiple solutions. It can solve solution parameter solution structure and problems simultaneously.	The method does not give guarantee that it will provide the global optimum solution.
Evolutionary Programming	Higher dimensional problems can be handled and it can deal with noise evaluation function.	Most of the time, it does not provide the global of extreme points.
Tabu Search	It has more flexible search behavior. There is no limitation for the cost function.	It might lie in the trap of local optimum without exploring other solution space regions.
Ant Colony	This method can solve large-scale problems and it is a quick way to find a practical solution.	It is difficult to analysis it Theoretically. Each iteration the Probability distribution might change.
Particle Swarm Optimization	No need for a lot of parameters to tune, it can deal with large amount of variables and it can solve	In local search it converges slowly.

	non-differentiability and non-linearity problems.	
Fire Fly	It is easy to code and understand. It is used commonly in ED and environmental dispatch.	The speed of convergence is low.
Fuzzy Logic	It has the ability to handle type of characteristics data units. It can describe the behavior of a system qualitatively.	It cannot deal with large-scale system and the complexity exist.
Expert Systems	The can involve a huge percent of information, they can reduce the time needed for solving the problem and The knowledge base can be extended and updated.	It poses a problem if the model schedules different from new generating schedule, so it cannot easily find a solution for this issue.
Hybrid Meta-Heuristic	It can escape from local solutions and can treat with differentiable cost functions and constraints.	Fine-tuning is the main negative point.

2.3 Recent Trends in UC

UC problem has passed through different levels since 1940s, recent research trends have shifted to smart optimization algorithms (meta-heuristic methods) rather than traditional methods to improve the solution of multi objective UC problems [54] such as GA [26], Simulated Annealing (SA) [54], PSO [26],etc. These methods are based on population approaches which have the capability to identify an optimal solution to a major problem effectively. These days hybrid algorithms have been used by most of the researchers to solve the UC problem by mixing two or more of meta heuristic methods to take benefits from the features of them or to overcome the insufficiency of one of them [55].

Furthermore, higher integration of irregular renewable energy sources and relatively high price-responsive demand involvement have raised new issues to the UC process. It has become critical to have an efficient approach that generates stable UC decisions and maintains system stability in the face of increasing significant-time uncertainty. In recent years, growth in renewable energy technology has been remarkable [56].

Intelligent forecasting methods for the behavior of the renewable energy sources are generally favored over the conventional methods because of their ability to produce interrelationships between variables without use of complex mathematics . An ANN that imitates the actions of human brain functions is the most prevalent of artificial intelligence techniques. The most commonly used neural network technique is the back-propagation [57].

Chapter 3

METHODOLOGY

3.1 Economic Dispatch

Economic Dispatch (ED) is an operation that is used to determine the actual output power for all generating units that are needed to deliver all load demands at minimum costs, while obeying all the transmission network constraints for each single time period [58]. Therefore the main objective of ED is to minimize the generation costs for a set of given generators. The following equations illustrate the ED formulation [58]:

The objective function:

$$\sum_{i=1}^{N} C_i(P_i) \tag{3.1}$$

$$C_i(P_i) = \alpha_i + \beta_i P_i + \gamma_i P_i^2 \tag{3.2}$$

Where $C_i(P_i)$ is the cost function, P_i is the output power of generator i and α_i, β_i and γ_i are the generator i cost coefficients.

Such that:

$$P_{iMin} \leq P_i \leq P_{iMax} \tag{3.3}$$

$$\sum_{i}^{N} P_i = P_d + P_{loss} \tag{3.4}$$

Where i is the generator number, N is the number of generators, P_i is the output power of generator i, P_{iMin} is the minimum output power of generator i, P_{iMax} is the maximum output power of generator i, P_d is the demand power and P_{loss} is the losses power.

Equation (3.1) represents the objective function formula which aims to minimize the generation costs, equation (3.3) represents the output power limitation of each generator and equation (3.4) is the power balance constraint in the network which is necessary for obtaining the reliability of the network.

3.2 Unit Commitment

Unit Commitment (UC) aims to figure the optimum schedule and the level of production of the generating units for the power system in a specific time interval by facing a given data for the load.

Each generator has two general states ON/OFF. For instance, in the case of having three thermal units, the combinations of those three units should be as the following:

Table 3.1: Three Generating Units Combinations Status.

NO.	**Unit1**	**Unit2**	**Unit3**
1	ON	ON	ON
2	ON	ON	OFF
3	ON	OFF	ON
4	ON	OFF	OFF
5	OFF	ON	ON
6	OFF	ON	OFF
7	OFF	OFF	ON
8	OFF	OFF	OFF

Then the number of status might be eliminated with respect to the load requirements, then the function of ED works to decide the total operation cost of each combination, then we can decide which units group should take priority over the other. The optimization formula below illustrate the procedure of the UC problem [60].

The objective function:

$$min \sum_{i=1}^{NG} \sum_{t=1}^{NT} [F_{ci}(P_{it}) * I_{it} + SU_{it} + SD_{it}] \tag{3.5}$$

Subject to:

$$\sum_{i=1}^{NG} P_{it} * I_{it} + \sum_{i=1}^{NW} P_{W,it} = P_{D,t} + P_{L,t} \tag{3.6}$$

$$P_{i,min} * I_{it} \leq P_{it} \leq P_{i,max} * I_{it} \tag{3.7}$$

$$P_{it} - P_{i(t-1)} \leq \left[1 - I_{it}\left(1 - I_{i(t-1)}\right)\right] UR_i + I_{it}\left(1 - I_{i(t-1)}\right) P_{i,min} \tag{3.8}$$

$$P_{i(t-1)} - P_{it} \leq \left[1 - I_{i(t-1)}(1 - I_{it})\right] DR_i + I_{i(t-1)}(1 - I_{it}) P_{i,min} \tag{3.9}$$

$$\left[X_{i(t-1)}^{on} - T_i^{on}\right] * \left[I_{i(t-1)} - I_{it}\right] \geq 0 \tag{3.10}$$

$$\left[X_{i(t-1)}^{off} - T_i^{off}\right] * \left[I_{it} - I_{i(t-1)}\right] \geq 0 \tag{3.11}$$

$$\sum_{i=1}^{NG} R_{O,it} * I_{it} \geq R_{O,t} \tag{3.12}$$

$$\sum_{i=1}^{NG} R_{S,it} * I_{it} \geq R_{S,t} \tag{3.13}$$

Where i is the generating unit index, t is the time index, $F_{ci}(P_{it})$ is the function of production cost of unit i, P_{it} is power generation of unit i at time t, I_{it} is commitment state of unit i at time t, SU_{it} is the startup cost of unit i at time t, SD_{it} is the shutdown cost of unit i at time t, $P_{W,it}$ is the generation of wind power of unit i at time t, $P_{D,t}$ is the system demand at time t, $P_{L,t}$ is the system losses at time t, $P_{i,min}$ is the minimum power generation of unit i, $P_{i,max}$ is the maximum power generation of unit i, UR_i is the ramp-up rate of unit i, DR_i is the ramp-down rate of unit i, X_i^{on}

is the ON time of unit i, X_i^{off} is the OFF time of unit i, T_i^{on} is the Minimum ON time of unit i and T_i^{off} is the Minimum OFF time of unit i.

Equation (3.5) represents the objective function which contains the power production costs, startup costs and shut down costs, equation (3.6) represents the constraint of power balance, equation (3.7) represents the generation limits for each generator, equation (3.8) and (3.9) represent the limits of ramping up and down respectively, equation (3.10) and (3.11) represent the minimum ON and OFF time respectively and equation (3.12) and (13) represent the operating and spinning reserve of the power system respectively.

3.2.1 UC Constraints

- **Power Balance**

The summation of output power of the available generators must satisfy the load demand during each time period with taking into consideration the loss of power in the grid [55]. Refer to equation (3.6).

- **Power Bounds**

Each generator has minimum and maximum power, since the generator can not work below and above them [55]. Refer to equation (3.7).

- **Ramping Limits**

Any thermal unit can not increase or decrease its output power from the current time period to another instantaneously. The operation of increasing the output power is called ramp up and the operation of decreasing the output power is called ramp down [55]. Refer to equations (3.8) and (3.9).

- **Minimum ON and OFF Time**

In the activity of generating units, the manufacturer's specifications or engineering considerations usually require that the unit to operate for at least a certain duration of time until shutting down. Similarly, a minimum down time is enjoined on individual generating units between the successive operations [58]. Refer to equations (3.10) and (3.11).

- **Operating Reserve**

It is the available capacity of the power generating to the system during a short interval of time to supply the demand in case of supply distribution or when the generator efficiency goes down [59]. Refer to equation (3.12).

- **Spinning Reserve**

It is the extra generation capacity that is usable by controlling the output of the generators connected to the grid. This operation is done by increasing the applied torque on the turbine rotors [60]. Refer to equation (3.13).

- **Startup Costs**

The startup costs is a time exponential function that the generator has been not connected. However, the cost of startup in most cases can be considered as a constant [54]. Refer to equation (3.5).

- **Shutdown Costs**

Normally in practice, no costs are associated with shutting down of the units, but a precaution is made to include the shutting down costs in the calculation of the total costs. A constant cost may be identified for each generator as shutdown cost, and these costs are independent of the time the unit has been working before the shutdown [58]. Refer to equation (3.5).

3.2.2 Power Losses

The behavior of the network components leads to a lot of effects on the operation system. For example, when the transmission lines are taken into account in formulation, it shows some of effects such as increasing the total generating power demand due to the real power losses. Therefore it is necessary to take into consideration the consequences of the network elements for finding optimal solution to verify the system security specially in large scale power grid.

Two common methods in UC deal with transmission lines which are power flow-based ED and B-coefficient matrix-based ED [61]. The power flow-based ED method has convergence risk and time-consuming; therefore, for real-time applications it is unsuitable. However, for useful applications, B coefficient-based ED should formulate more than one frame of B coefficients throughout the specific load cycle as B coefficients are not constant because they vary depending on the load demand [61]. In this thesis B-coefficient method is used to obtain the losses in the network.

The B-coefficient matrix can be acquired by the traditional power losses formula as shown in equation (3.14) which is adopted by Kron and Widely [62].

$$P_L = \begin{bmatrix} P_{G_1} & \cdots & P_{G_i} & \cdots & P_{G_{NG}} \end{bmatrix} \begin{bmatrix} B_{11} & B_{1j} & B_{1NG} \\ \vdots & \vdots & \vdots \\ B_{1i} & B_{ij} & B_{iNG} \\ \vdots & \vdots & \vdots \\ B_{NG1} & B_{NGj} & B_{NGNG} \end{bmatrix} \begin{bmatrix} P_{G_1} \\ \cdots \\ P_{G_j} \\ \cdots \\ P_{G_{NG}} \end{bmatrix} + \begin{bmatrix} P_{G_1} & \cdots & P_{G_i} & \cdots & P_{G_{NG}} \end{bmatrix} \begin{bmatrix} B_{01} \\ \cdots \\ B_{0i} \\ \cdots \\ B_{0NG} \end{bmatrix} + B_{00} \tag{3.14}$$

where B_{ij} is the ijth component of the coefficient square loss matrix, B_{0i} is the ith component of the coefficient loss vector, and B_{00} is the coefficient loss constant. P_L is the total real losses.

3.3 Optimization

Solid optimization techniques foundations are needed to cover all parts of UC problem. In this thesis two common approaches are used which are GA as metaheuristic approach and DP as a conventional method. Since, DP is a methodical operation, which in a multi-step issue can methodically estimate a huge range of possible choices, and its answer is accurate and also has the optimal value[63]. The GA is also a powerful tool in searching for huge, separate spaces for solutions, as well as the space for alternatives is quite big, making GA suitable for the UC problem [63].

3.3.1 Genetic Algorithm

Genetic Algorithm(GA) is considered as one of the best methods among the metaheuristic approaches for solving Multi-objective optimization problems, which based on the theory of Darwin evolution. GA solves the optimization problems by simulating the evolution of species through the natural selection[64].

There are many parameters and operators used for dealing with GA method which are: cross over operator, mutation operator and the fitness value[64].

3.3.1.1 Cross Over Operator

Cross over is used to diverge the identification of the chromosomes from the current generation to another. Where two or maybe more strings were used as parents, new individuals are developed by exchanging a sub-sequence among strings as shown in the figure below.

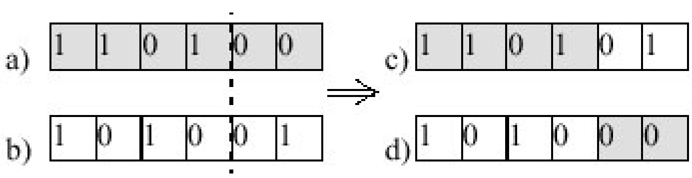

Figure 3.1: Cross Over Between Parents a and b to Create Offspring's c and d

3.3.1.2 Mutation Operator

Mutation means the modification in the genetic form of the chromosomes. The main objective of this operation is to repair the diversity through the generations, so that there would not be dead until the answer is near the optimal solution, or the optimal solution is found. Figure 3.2 illustrates the operation.

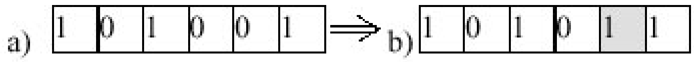

Figure 3.2: Mutation Bit-Flipping of Parent a) to create Offspring b)

3.3.1.3 Fitness Value

The fitness value is the value that whatever iterations used still the optimal value.

The following flowchart represents the procedure of GA:

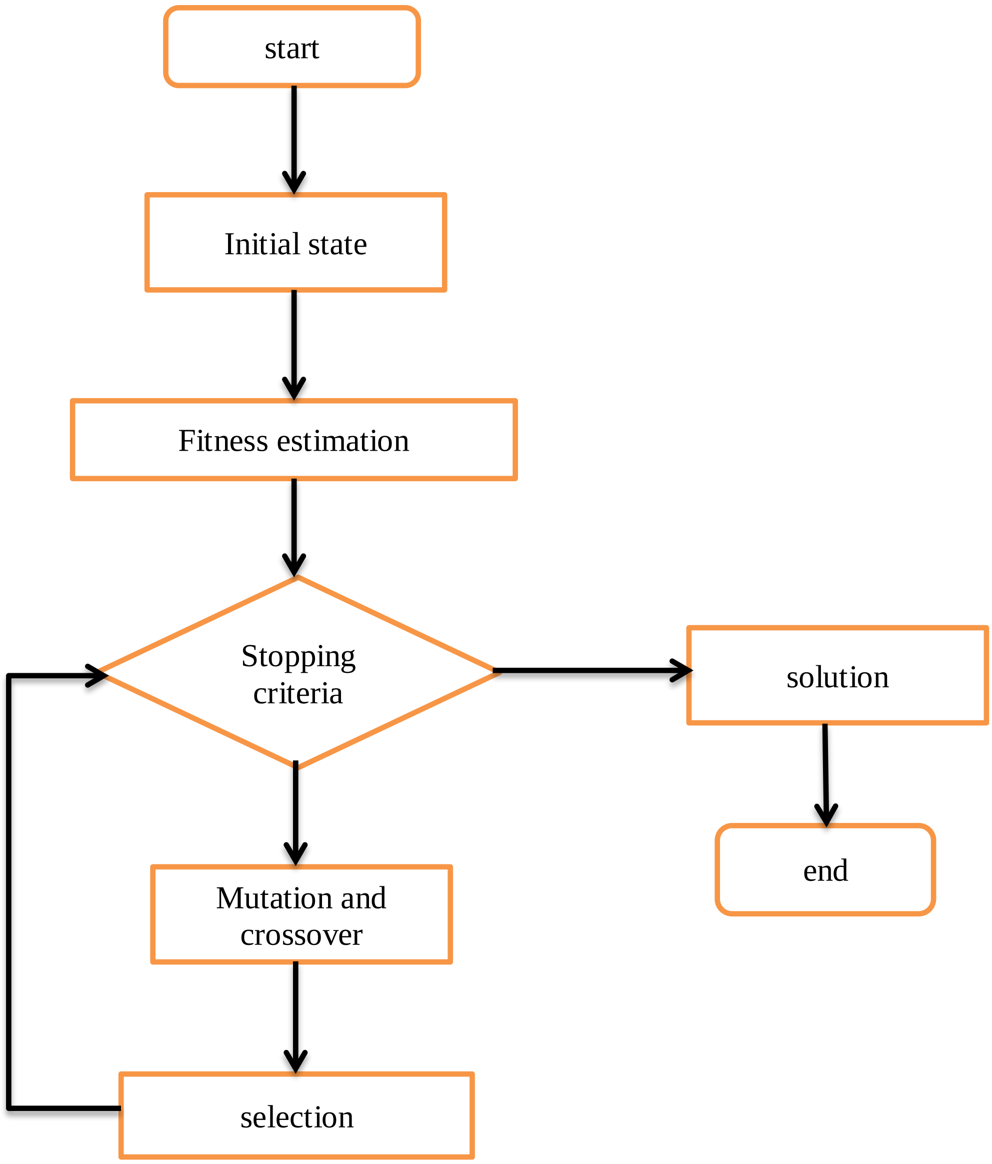

Figure 3.3: GA Procedure Flowchart [63].

3.3.2 Dynamic Programming

Dynamic Programming(DP) is a systematic procedure that methodically evaluates a huge number of available solutions in multistep problem. The main idea of DP is to divide the large problem into partial steps which means the optimal solutions are known in any stage to sub-problem after the technique become applicable, this condition could be expanded gradually without having to change the previous computed optimal solution to the sub-problem. Eventually, the technique applies to all of the data[65].

What type of problems can be solved by DP?

The problems which DP can solve should have two properties, the first one is if the optimal solution enfolds dealing with sub-problem then it can use optimal solution to that sub-problem. The other property key there must be polynomial different sub-problem numbers [65].

DP has a lot of advantages over the listing scheme, the main advantages being decreasing the dimensionality of any problem[67]. For example, if we have four units in a power system, any combinations of these units could serve the load, there should be maximum 15 combinations $(2^4 - 1)$ we have to test. However, if a firm priority sequence is imposed, there are just four combination to test as the following[66]:

Priority Unit 1.

Priority Unit 1 + Priority Unit 2.

Priority Unit 1 + Priority Unit 2 + Priority Unit 3.

Priority Unit 1 + Priority Unit 2 + Priority Unit 3 + Priority Unit 4.

The following algorithm represents the DP algorithm for computing the minimum costs:

$$F_{cost}(J,K) = \min[P_{cost}(J,K) + S_{cost}(J-1,L{:}J,K) + F_{cost}(J-1,L)] \qquad (3.15)$$

Where,

$F_{cost}(J,K)$ is the final total cost to be arrived at state (J,K).

$P_{cost}(J,K)$ is the production cost at state (J,K).

$S_{cost}(J-1,L{:}J,K)$ is the transition cost from the state $(J-1,L)$ to the state (J,K).

State (J,K) is the K^{th} combination in the J^{th} hour.

Figure 3.4 represents the DP flowchart with respect to the UC problem.

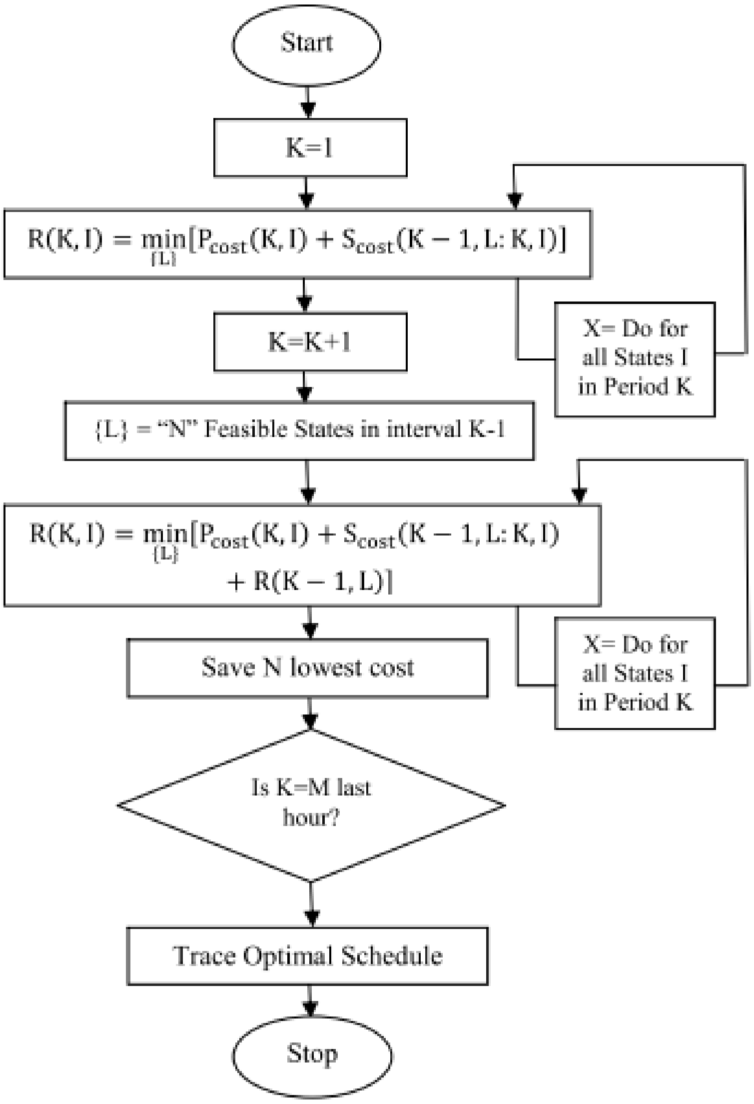

Figure 3.4: UC via DP[66].

3.4 Day-Ahead Wind Power Forecasting

During the operation of day to day, the forecasting of the short-term load is a vital and fundamental factor for scheduling and controlling the reliability of power systems. Forecasting short-term wind energy is a very essential area of study for the power sector, because the model has to manage a significant amount of varying power from the installed wind capacity [68]. Several approaches are used to predict day-ahead wind power. In this thesis neural network method is applied due to its advantages of self-learning, self-correction, and parallel processing[69].

3.4.1 Neural Network

Neural Network (NN) is a sort of machine learning that shapes itself after human brain and creates an artificial NN that enables the machine to discover through an algorithm integrating new data. While a number of artificial intelligence structures exist these days, NN's are able to perform what is considered to be deep learning. While the basic element of the brain is the neuron, the central building wall of an artificial NN is a perceptron that performs simple signal processing, and these are then linked to a large mesh network [69].

The operation of simple perceptron is shown in figure 3.5, in order to predict the output value, as shown there are two inputs X_1 and X_2, in addition there are two weights W_1 an $W_2$for the node connection. In NN, the node is the processing unit which is simply multiply the two values (X and W's) then sum all X*W values and apply them to the activation function, finally the output is the perceptron answer[65].

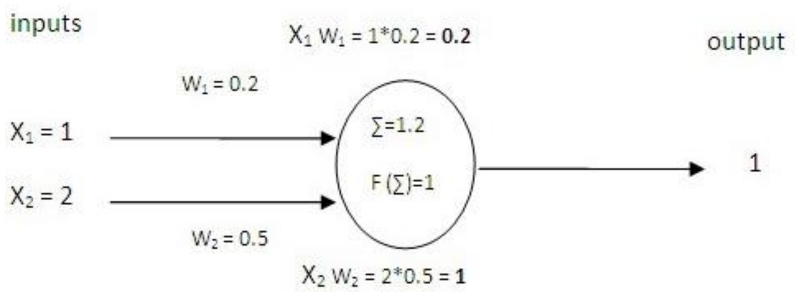

Figure 3.5: The Operation of Simple Perceptron[67].

The previous explanation represents forward propagation in NN, but in our problem we have to apply more nodes and multiple layers for NN and the estimation of each node can be computed as a simple perceptron. Figure 3.6 shows multilayer NN [70].

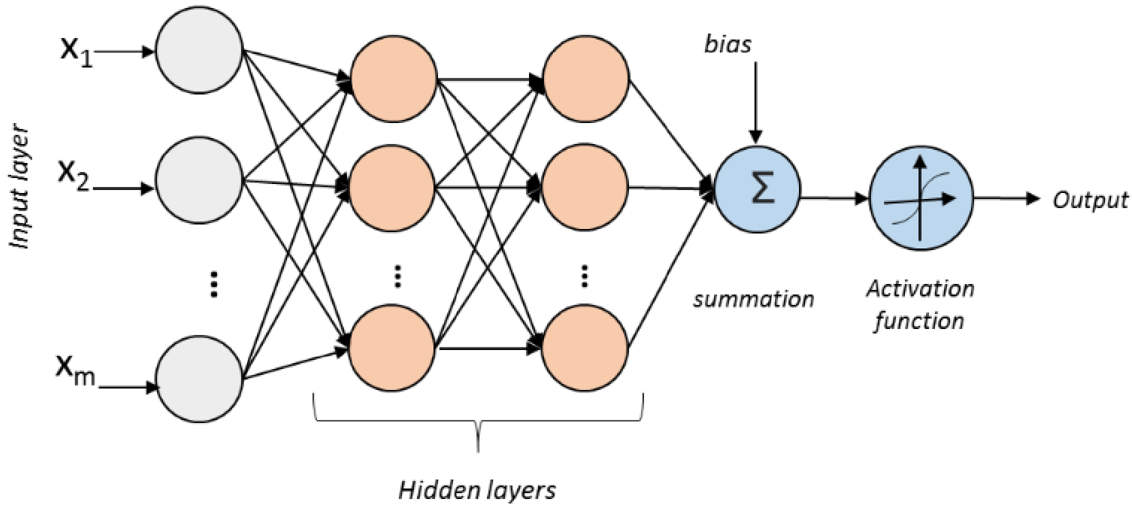

Figure 3.6: Multilayer NN [70].

3.4.2 The Weight in Neural Network

Everything in NN structure inspired by human brain. The weight in NN refers to the level of strength of the connection between the nodes, the unsigned values of weight shows much the node have the power to connect to each other's. However, it can be negative or positive. Positive sign means it is most probably to have strong connection between neurons and it is possible to transmit the data while the negative sign is vice versa [69].

Normalizing the input data is very important for having reasonable results. The following formulas are used for normalizing the input data [69]:

$$Z = \frac{X-\mu}{\sigma} \tag{3.15}$$

$$\sigma = \sqrt{\frac{\sum(X-\mu)^2}{(n-1)}} \tag{3.16}$$

Where Z is the standard score, X is the input data, μ is the mean of the input data, σ is the standard deviation and n is the number of the inputs.

For the first time the weight can be selected randomly but to determine the range of weights value equation (3.17) is used which depends on the uniform distribution [67].

$$w = 4\sqrt{\frac{6}{number_{input}+number_{output}}}\; n\epsilon\, number\ of\ inputs \tag{3.17}$$

In the first step of optimizing the predicted results in the next prediction a forward propagation have to be applied to improve the weight which is the most effective element which produce this connectivity so as a result a comparison has to be made between the output predicted and the real values. After that, apply backward propagation computations. So weight is the main tool to make connection between nodes and a factor for having less percent of error.

3.5 The Work Structure

In this thesis, UC is applied into two case studies: IEEE 6-buses which includes three thermal units in addition to one wind farm and IEEE 30-buses which includes six thermal units plus one wind farm. In the beginning a neural network approach is used to predict day ahead of the wind power performance then by using Weka program and the forecasted results of the neural network, many scenarios of wind power can be generated , two different scenarios are chosen randomly to study the uncertainty of the renewable energy. In the first case study two optimization methods are used to plan day ahead performance of the generators which are GA and DP. In the second case study DP approach is applied. Figure 3.7 represents procedure of working step by step.

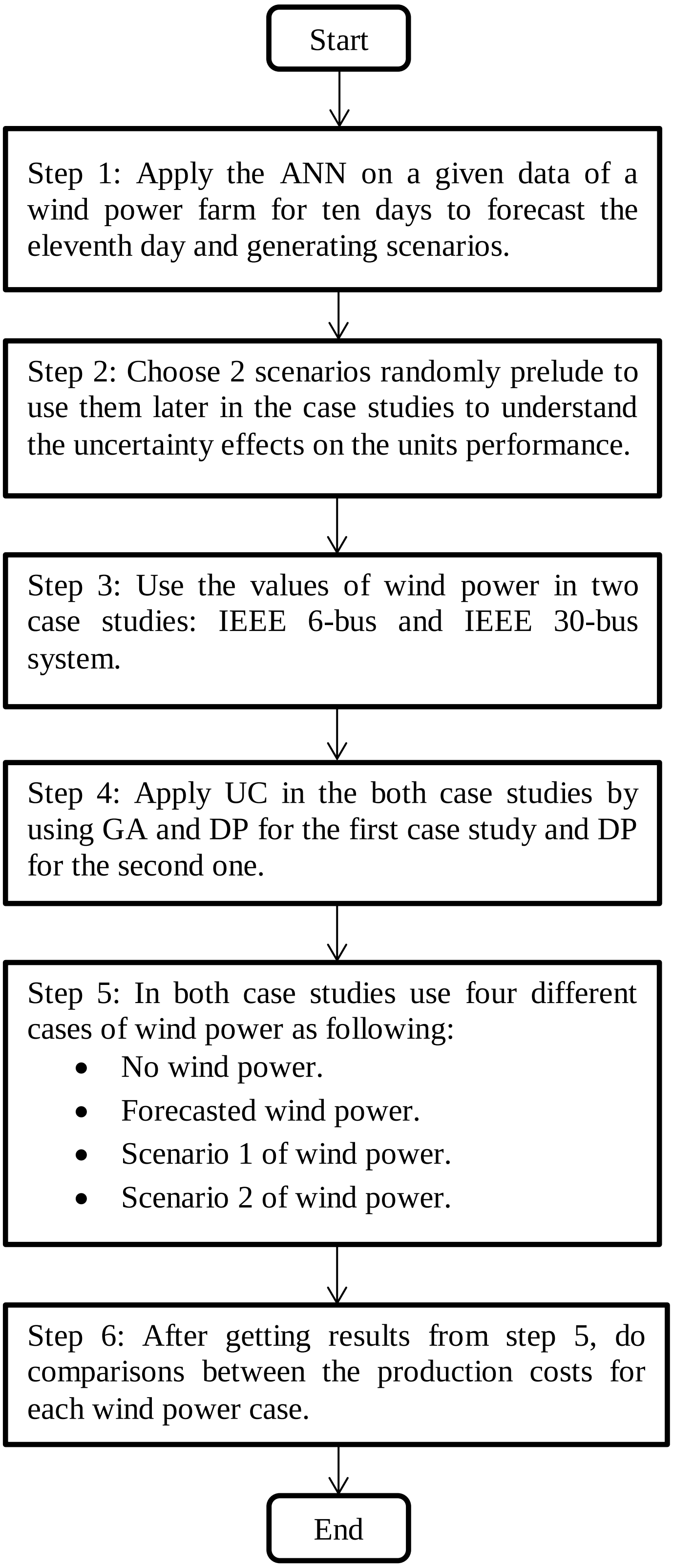

Figure 3.7: The Procedure of Working.

Chapter 4

RESULTS AND DISCUSSIONS

4.1 Case Study One (IEEE 6- Bus Test System)

A six-bus system is used for studying the impacts of fluctuating wind energy on the phase of power system. The six-bus case in figure 4.1 is used to explain the approached methodology. The system has three thermal generating units connected to a wind farm. The wind farm lies at bus 4. Table 4.1 represents the generators data, table 4.2 represents the generators operating costs and table 4.3 provides data about the load distribution for 24 hours. The used data of this case study is taken from [24].

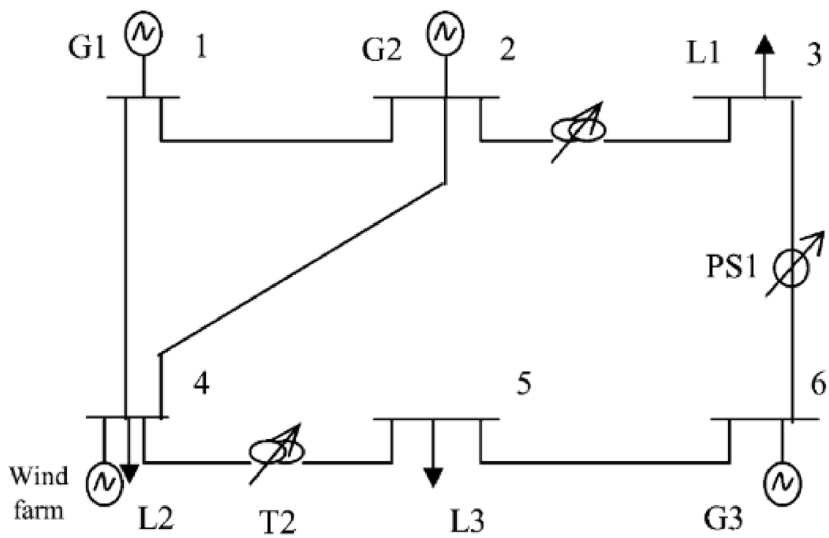

Figure 4.1: IEEE 6- Bus Test System.

Table 4.1: Generators Data.

unit	Bus number	Pmin (MW)	Pmax (MW)	Min off	Min On	Ramp (MW/h)
Gen1	1	90	200	4	4	50
Gen2	2	10	70	3	1	40
Gen3	6	10	50	1	1	15

Table 4.2: Generators Operating Costs.

Unit	Fuel Cost Coefficients			Start Up Fuel(MBtu)	Fuel Price($/MBtu)
	a	***b***	***c***		
Gen1	176.9	13.5	0.0004	100	1.2469
Gen2	129.9	32.6	0.001	300	1.2461
Gen3	137.4	17.6	0.005	0	1.2462

Table 4.3: Load demand for 24 Hours.

Hour	Pload	Hour	Pload
1	219.19	**13**	326.18
2	235.35	**14**	323.6
3	234.67	**15**	326.86
4	236.73	**16**	287.76
5	239.06	**17**	260
6	244.48	**18**	246.74
7	273.39	**19**	255.97
8	290.4	**20**	237.35
9	283.56	**21**	243.31
10	281.2	**22**	283.14
11	328.61	**23**	283.05
12	328.1	**24**	248.75

In this case study two optimization approaches are applied to decide the UC performance in the case of absence and existence of the wind farm under different scenarios. Tables 4.7- 4.10 represent the unit commitment results after applying GA method. Tables 4.11- 4.14 represent the unit commitment results after applying DP method. In each table the binary commitment and the real power values are given in addition to the production costs for each hour.

4.1.1 Forecasting Day-Ahead Wind Power and Generating Scenarios

For forecasting day-Ahead wind power, ANN method is applied by using Weka program. Ten consecutive days are used to forecast the eleventh day then to generate different possible scenarios for the same day. Table 4.4 shows the wind power data for ten consecutive days, table 4.5 shows the parameters that used in the Weka program which gives the results in table 4.6. Table 4.6 shows the forecasted wind power values and two different possible scenarios prelude to use them in the UC problem as samples to show the effect of the uncertainty on the electrical network performance.

Table 4.4: Wind Power Data for Ten Days [24].

Hour	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10
1	44.3	47.9	50.3	47.6	39	42	48.3	41.6	46.6	44.7
2	71.6	73.1	66.7	71	63.9	73.1	74	73.6	67.1	71.2
3	75.5	73.8	77.1	75.5	67.7	73.6	79.7	73.5	79.7	74.5
4	85	73	87	83.8	82	87.3	76.3	82.9	77.5	81.7
5	82.8	81.2	81.6	91	86	87.2	85.4	79	86.4	75.9
6	85.5	81	85.1	74.1	85.2	87.3	86	79.8	83.7	83.5
7	101.4	105.7	97.8	96.7	92.1	101.9	98.1	105.5	101.3	105.3
8	105.7	99.4	90.5	100.3	99.9	89.8	92.1	98.7	105.8	107.4
9	80.1	85.1	82.9	77.7	74	78.5	73.3	73.2	77	85
10	57.2	62.1	63	68	66.3	66.7	59.3	61.5	63.3	65.1
11	98.8	101.2	102.7	107.4	95.5	99.3	102.7	96.3	87.9	105.4
12	87.5	92.2	87.5	86.7	89.1	96.6	87	97.8	102.3	91.2
13	90.3	85.8	90.5	85.3	85.1	79.2	78	85	78.3	79.1
14	79	78.5	86.5	80	74.2	84.6	74.2	74.8	85.8	82.4
15	73.5	81.8	80.3	75.7	84.1	80.2	78	72.8	79.1	79.8
16	29.6	31	31.7	29.2	31.9	33.1	27.6	31.2	37.1	29.7

17	3.7	4.3	4.5	3.7	4.1	4.3	4.3	4	3.7	4.1
18	9.5	8	8.3	7.3	7.5	6.8	8.7	7.7	7.9	7.6
19	11.4	9.8	11.3	10	9.5	9.7	8.8	11.8	10.1	9.3
20	5.3	4.6	5.3	5.6	5.6	4.3	4.5	5.6	5.6	5
21	6.4	5.6	5.7	5.7	7	6.3	6.8	5.6	6.3	6.1
22	58.5	50.7	52	52.1	58.6	57.6	57.2	54.7	57.9	55.7
23	79.6	74.7	87.8	81.8	80.3	78.3	83.4	88.4	83.3	90.3
24	55.1	49.7	48.1	52.9	51.9	49.7	54.5	56.7	56	53.3

Table 4.5: Weka Parameters which Used for Building the ANN.

NO.	**Parameter**	**Value**
1	Seed	10
2	Momentum	0.2
3	Nominal To Binary Filter	True
4	Hidden Layers	a
5	Validation Threshold	20
6	GUI	False
7	Normalize Attributes	True
8	Batch Size	100
9	Number of Decimal Places	2
10	Training Time	500
11	Resume	False
12	Learning Rate	0.3
13	Reset	True

The meaning of each parameter is explained as the following:

- Seed: used to initialize a set of numbers of the generator. Random numbers are used, in addition to mixing the training data, to tune the initial weights of the links between nodes.
- Momentum: momentum is used for updating the weight.
- Nominal To Binary Filter: this variable preprocesses the binary filter model with a nominal. This will help to increase the quality of the answer if any marginal attributes exist among the data.

- Hidden Layers: this parameter identifies the hidden layers of NN. 'a' = (attribs + classes) / 2.
- Validation Threshold: used to sever validation screening. The value here indicates how often times throughout the line the errors in the verification set can get worse until the training is over.
- GUI: this will allow the altering and pausing of the NN during training.
- Normalize Attributes: this parameter can standardize the attributes. That can greatly enhance the NN's quality. This variable also normalizes the nominal attributes (if used, after running through the nominal to binary filter) so that the binary values are between -1 and 1.
- Batch Size: this variable describes the chosen number of cases to process when performing the batch forecasting. More or less cases may be supplied but this offers an opportunity to recognize a favoured batch size.
- Number of Decimal Places: this variable specifies the amount of the decimals to be used in the design output numbers.
- Training Time: the number of periods to train through. If the validation set is non-zero, then the network can be terminated early.
- Resume: set whether classifier can keep training after performing the required number of iterations.
- learning Rate: the learning rate for updating the weight.
- Reset: this parameter allows resetting with a smaller teaching rate for the system. If the network diverges from the answer, this will reset the network with a smaller teaching rate immediately, and start training once more. This option is available only where the GUI is not set. After applying the real data for ten days into the ANN, the following table represents the forecasted wind power data for the

eleventh day and two different scenarios that are chosen randomly from 100 generated scenarios. This scenarios were generated by using Weka program.

Table 4.6: Forecasted Wind Power and Two Possible Scenarios.

Hour	Forecasted values	Scenario1	Scenario2
1	45.41	47.0564	50.15
2	70.9095	68.1466	64.119
3	76.6086	78.7354	77.807
4	77.5866	73.7246	66.294
5	76.3817	68.9752	68.806
6	81.7648	78.7344	74.653
7	104.411	110.552	109.72
8	107.494	119.56	103.58
9	79.279	84.1261	79.489
10	61.7352	69.2216	84.281
11	99.827	98.3374	101.19
12	93.5746	104.325	113.84
13	79.3324	70.9839	61.015
14	78.2397	85.0396	89.641
15	76.9768	81.659	94.822
16	30.3111	34.8125	39.573
17	3.9427	3.9302	5.1169
18	8.0945	6.7375	3.5581
19	9.769	8.8758	6.1553
20	5.4247	6.1415	5.8387
21	6.0962	5.714	5.1034
22	55.8455	54.5047	46.37
23	91.3234	104.305	106.29
24	56.475	59.7659	53.587

4.1.2 UC by Using GA Method Results

In this case the algorithm is used four times, table 4.7 shows the UC attitude in the absence of wind farm, table 4.8 represents the UC attitude in the case of forecasted wind power and tables 4.9 and 4.10 represent the two different scenarios of wind power.

4.1.2.1 UC by Using GA Case 1

UC problem is resolved to decide the dispatch units in the case of absence of the wind farm which are shown in table 4.7. As shown, generator 1 is committed for the whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 5 and 24 hours. Finally, generator 3 is committed almost during 24 hours. The total operating costs for the 24 hours in this case is $118833.4 with considering the startup costs for each generating unit. In addition, between hours 7 and 24 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.2 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.3 shows the UC results and power dispatch within thermal units.

Table 4.7: UC by using GA for IEEE 6-Bus System (Case 1).

hour	Pload	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	1	0	1	212.6805	0	10.00935	3480.245
2	235.35	1	0	1	219.7829	0	18.86697	3434.529
3	234.67	1	0	1	219.9873	0	17.85255	3419.285
4	236.73	1	0	1	219.9871	0	19.84271	3454.684
5	239.06	1	1	1	219.9988	10.00033	12.16051	4074.419
6	244.48	1	1	0	219.9089	27.78086	0	4201.342
7	273.39	1	1	1	219.9989	36.864	19.9964	4990.606
8	290.4	1	1	1	220	54.25111	19.9586	5558.352
9	283.56	1	1	1	220	47.87753	19.79247	5346.966
10	281.2	1	1	1	220	45.53967	20	5274.227
11	328.61	1	1	1	220	93.17977	19.99998	6833.903
12	328.1	1	1	1	220	92.81973	19.99999	6822.099

13	326.18	1	1	1	220	91.02993	19.9999	6763.42
14	323.6	1	1	1	220	88.47035	19.9995	6679.511
15	326.86	1	1	1	219.9831	91.84953	19.99695	6790.005
16	287.76	1	1	1	220	52.89986	19.99998	5514.893
17	260	1	1	1	220	25.11993	19.99989	4607.099
18	246.74	1	1	1	220	11.67966	20	4168.453
19	255.97	1	1	1	220	20.89025	19.99941	4469.008
20	237.35	1	1	1	215.9973	10.00012	16.10251	3989.63
21	243.31	1	1	1	219.99	10.0001	18.05972	4079.008
22	283.14	1	1	1	220	47.6803	19.99951	5344.203
23	283.05	1	1	1	219.9433	47.85186	19.27489	5336.14
24	248.75	1	1	1	220	12.68995	19.99987	4201.411
							TOTAL	118833.4

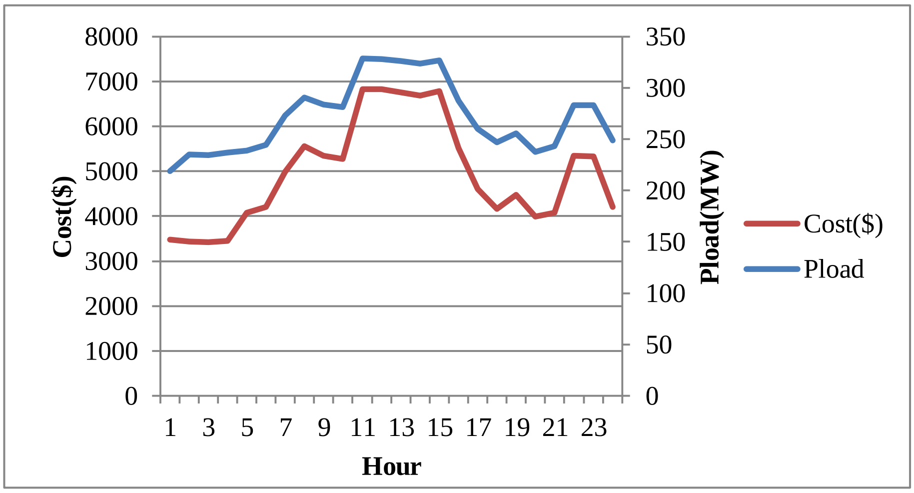

Figure 4.2: The Relation Between Production Costs Performance and the Changes of the Demand During 24 Hours (Case 1).

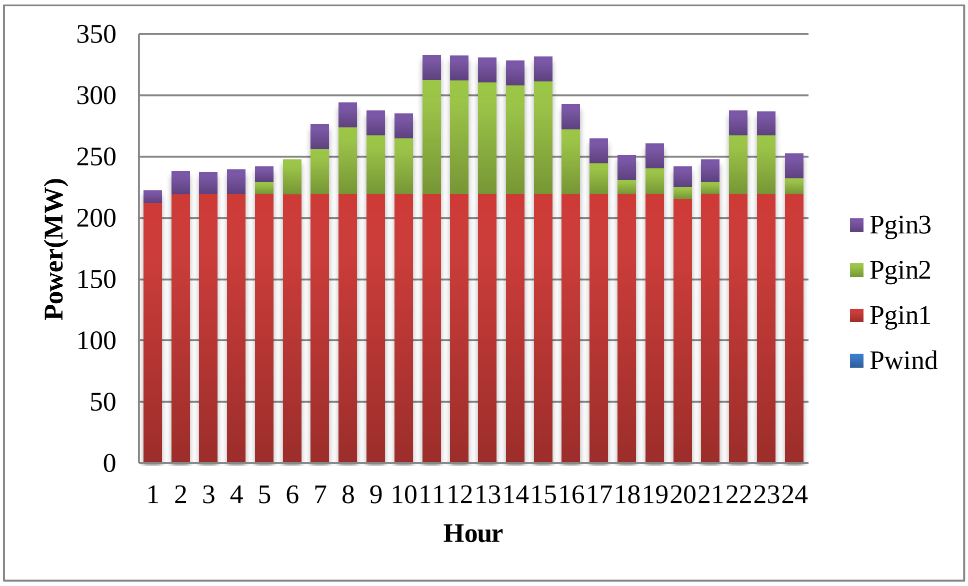

Figure 4.3: The UC and Power Dispatch in the IEEE 6-bus Test System (Case1).

4.1.2.2 UC by Using GA Case 2

Forecasted wind power with dispatch: With the forecasted wind power given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.8. As shown, generator 1 is committed for the whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 12 and 21 hours. Finally, generator 3 is committed in the period of 10 and 22 hours. The total operating costs for the 24 hours in the forecasted case is $100110.6 with considering the startup costs for each generating unit. In addition, between hours 12 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.4 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.5 shows the UC results and power dispatch within thermal units.

Table 4.8: UC by using GA for IEEE 6-Bus System (Case 2).

hour	Pload	pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	45.41	1	0	0	178.2798	0	0	3362.129
2	235.35	70.9095	1	0	0	168.4498	0	0	2894.96
3	234.67	76.6086	1	0	0	161.2313	0	0	2772.262
4	236.73	77.5866	1	0	0	162.2432	0	0	2789.459
5	239.06	76.3817	1	0	0	165.7781	0	0	2849.542
6	244.48	81.7648	1	0	0	165.925	0	0	2852.039
7	273.39	104.411	1	0	0	172.4488	0	0	2962.955
8	290.4	107.494	1	0	0	186.7158	0	0	3205.669
9	283.56	79.279	1	0	0	208.3908	0	0	3574.799
10	281.2	61.7352	1	0	1	212.9461	0	10.85839	4062.559
11	328.61	99.827	1	0	1	219.9997	0	13.35311	4237.908
12	328.1	93.5746	1	1	1	216.1969	10	11.25821	5068.851
13	326.18	79.3324	1	1	1	217.267	13.73201	19.23195	5315.215
14	323.6	78.2397	1	1	1	219.9895	14.86485	19.99886	5424.704
15	326.86	76.9768	1	1	1	214.489	28.64913	19.45034	5879.461
16	287.76	30.3111	1	1	1	217.9653	23.21944	19.99256	5729.832
17	260	3.9427	1	1	1	219.9992	21.17901	19.99861	5681.647
18	246.74	8.0945	1	1	1	210.7845	12.92544	19.87464	5186.17
19	255.97	9.769	1	1	1	219.9987	11.12575	19.99611	5272.785
20	237.35	5.4247	1	1	1	208.3902	10.00008	18.28472	4991.197
21	243.31	6.0962	1	1	1	216.7884	10	15.16531	5065.273
22	283.14	55.8455	1	0	1	219.9997	0	11.83463	4204.365
23	283.05	91.3234	1	0	0	195.7465	0	0	3359.407
24	248.75	56.475	1	0	0	196.2148	0	0	3367.383
								TOTAL	100110.6

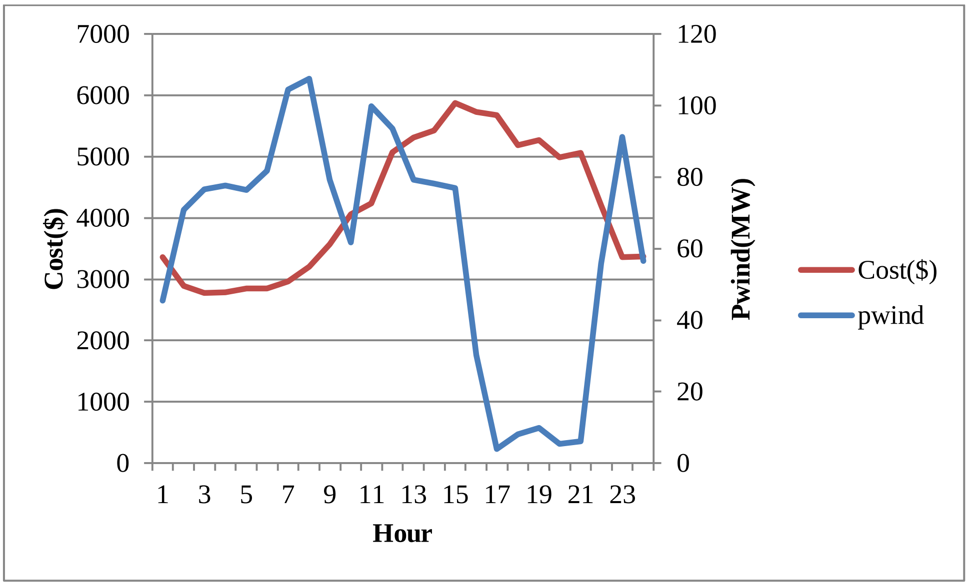

Figure 4.4: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 2).

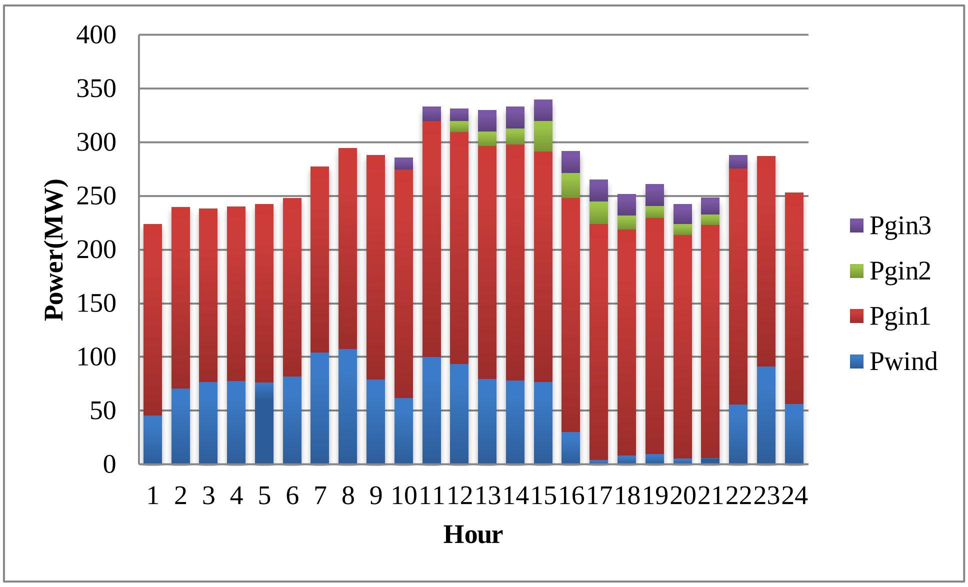

Figure 4.5: The UC and Power Dispatch in the IEEE 6-bus Test System (Case2).

4.1.2.3 UC by Using GA Case 3

First scenario of wind power with dispatch: With the first scenario of wind power given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.9. As shown, generator 1 is committed for the whole 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 12 and 21hours. Finally, generator 3 is committed during the period of 10 and 22 hours. The total operating costs for the 24 hours in the second scenario case is $98662.61with considering the startup costs for each generating unit. In addition, between hours 12 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.6 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.7 shows the UC results and power dispatch within thermal units.

Table 4.9: UC by using GA for IEEE 6-Bus System (Case 3).

hour	Pload	pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	47.0564	1	0	0	175.6334	0	0	3317.116
2	235.35	68.1466	1	0	0	170.5032	0	0	2929.873
3	234.67	78.7354	1	0	0	159.1045	0	0	2736.122
4	236.73	73.7246	1	0	0	166.1053	0	0	2855.103
5	239.06	68.9752	1	0	0	173.1847	0	0	2978.346
6	244.48	78.7344	1	0	0	168.9554	0	0	2903.556
7	273.39	110.552	1	0	0	166.3077	0	0	2858.544
8	290.4	119.56	1	0	0	174.6498	0	0	3000.387
9	283.56	84.1261	1	0	0	203.5437	0	0	3492.211
10	281.2	69.2216	1	0	1	205.6423	0	10.67587	3934.06
11	328.61	98.3374	1	0	1	219.9693	0	14.87301	4270.995
12	328.1	104.325	1	1	1	204.1065	10.00009	12.59793	4892.384
13	326.18	70.9839	1	1	1	220	10.0022	13.42767	5081.703
14	323.6	85.0396	1	1	1	219.9997	10.17112	19.99982	5234.081
15	326.86	81.659	1	1	1	220	18.08763	19.99966	5555.952
16	287.76	34.8125	1	1	1	220	21.19066	19.99869	5682.136
17	260	3.9302	1	1	1	220	21.18936	20	5682.113
18	246.74	6.7375	1	1	1	219.9936	10.00006	14.9487	5115.136
19	255.97	8.8758	1	1	1	220	12.08119	19.93284	5310.245
20	237.35	6.1415	1	1	1	201.9157	14.04323	19.9996	5083.272
21	243.31	5.714	1	1	1	218.4155	10.00002	13.9201	5065.479

22	283.14	54.5047	1	0	1	219.991	0	13.18414	4234.026
23	283.05	104.305	1	0	0	182.7644	0	0	3138.427
24	248.75	59.7659	1	0	0	192.924	0	0	3311.349
								TOTAL	98662.6

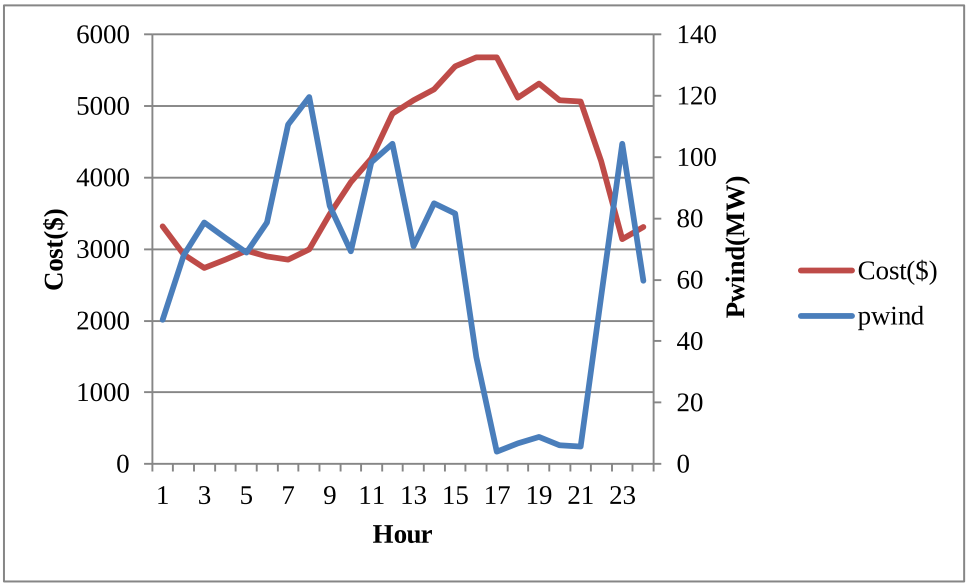

Figure 4.6: The Relation Between Production Costs and the Wind Performance During 24 Hours (Case 3).

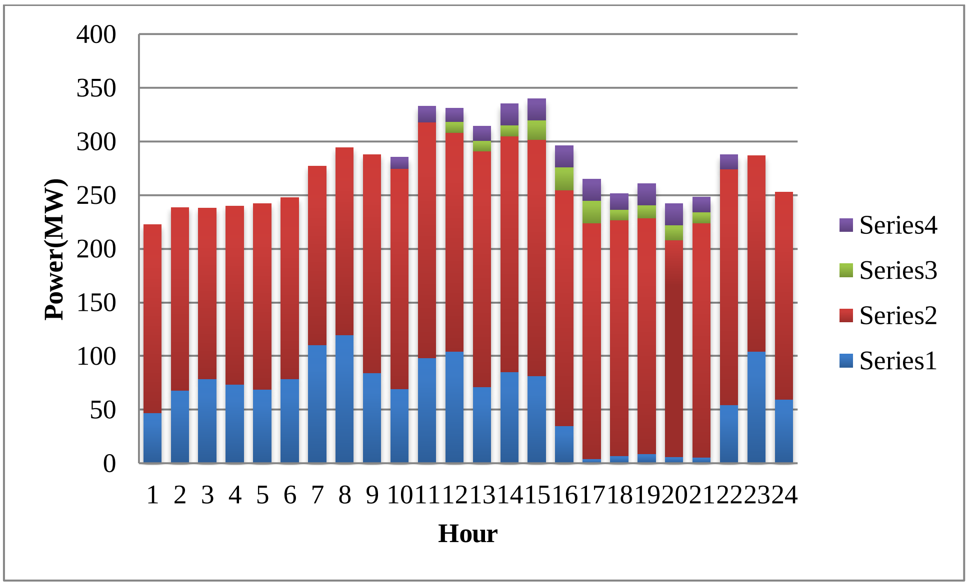

Figure 4.7: The UC and Power Dispatch in the IEEE 6-bus Test System (Case3).

4.1.2.4 UC by Using GA Case 4

Second scenario of wind power with dispatch: With the second scenario of wind power given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.10. As shown, generator 1 is committed for whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 12 and 21hours. Finally, generator 3 is committed during the period of 10 and 22 hours. The total operating costs for the 24 hours in the second scenario case is $98509.15 with considering the startup costs for each generating unit. In addition, between hours 12 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.8 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.9 shows the UC results and power dispatch within thermal units.

Table 4.10: UC by using GA for IEEE 6-Bus System (Case 4).

hour	Pload	Pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	50.15	1	0	0	172.5399	0	0	3264.504
2	235.35	64.119	1	0	0	174.5309	0	0	2998.363
3	234.67	77.807	1	0	0	160.0328	0	0	2751.897
4	236.73	66.294	1	0	0	173.5359	0	0	2981.442
5	239.06	68.806	1	0	0	173.3538	0	0	2975.469
6	244.48	74.653	1	0	0	173.0368	0	0	2972.954
7	273.39	109.72	1	0	0	167.1398	0	0	2872.69
8	290.4	103.58	1	0	0	190.6298	0	0	3272.292
9	283.56	79.489	1	0	0	208.1809	0	0	3571.222
10	281.2	84.281	1	0	1	191.1957	0	10.06305	3674.499
11	328.61	101.19	1	0	1	219.9993	0	11.99041	4207.798
12	328.1	113.84	1	1	1	194.4611	10.00023	12.72854	4730.995
13	326.18	61.015	1	1	1	215.7678	10.00004	13.06101	5001.35
14	323.6	89.641	1	1	1	204.7271	12.29477	19.98567	5059.773
15	326.86	94.822	1	1	1	220	13.32659	20	5362.366
16	287.76	39.573	1	1	1	220	20.0027	20	5633.846
17	260	5.1169	1	1	1	220	20.00345	19.99943	5633.864
18	246.74	3.5581	1	1	1	219.3981	10.00037	18.72297	5188.569
19	255.97	6.1553	1	1	1	220	14.7343	20	5419.601
20	237.35	5.8387	1	1	1	216.2587	10.00054	10.00168	4942.2

21	243.31	5.1034	1	1	1	216.8074	10.00017	16.13879	5087.145
22	283.14	46.37	1	0	1	220	0	20	4385.082
23	283.05	106.29	1	0	0	180.7799	0	0	3104.661
24	248.75	53.587	1	0	0	199.1028	0	0	3416.566
								TOTAL	98509.15

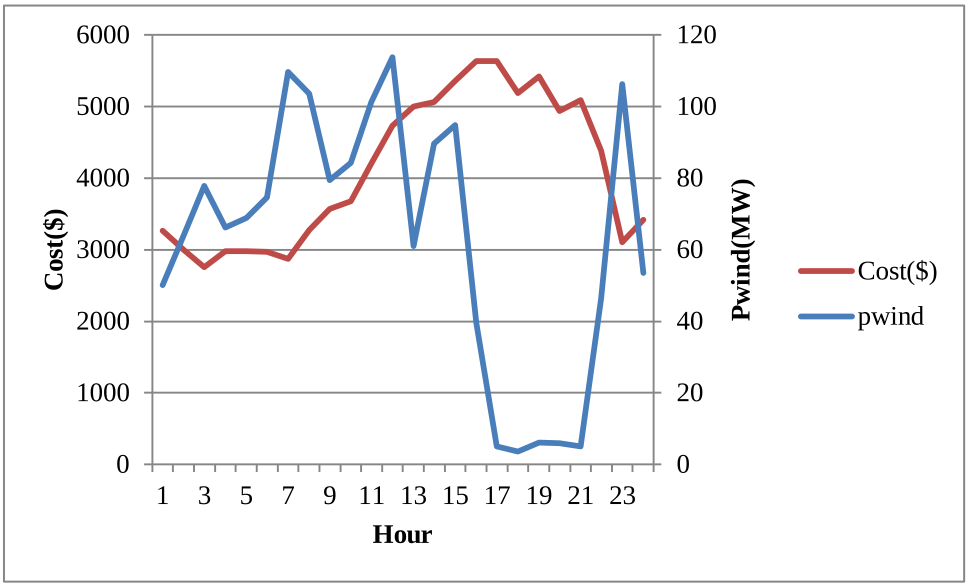

Figure 4.8: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 4).

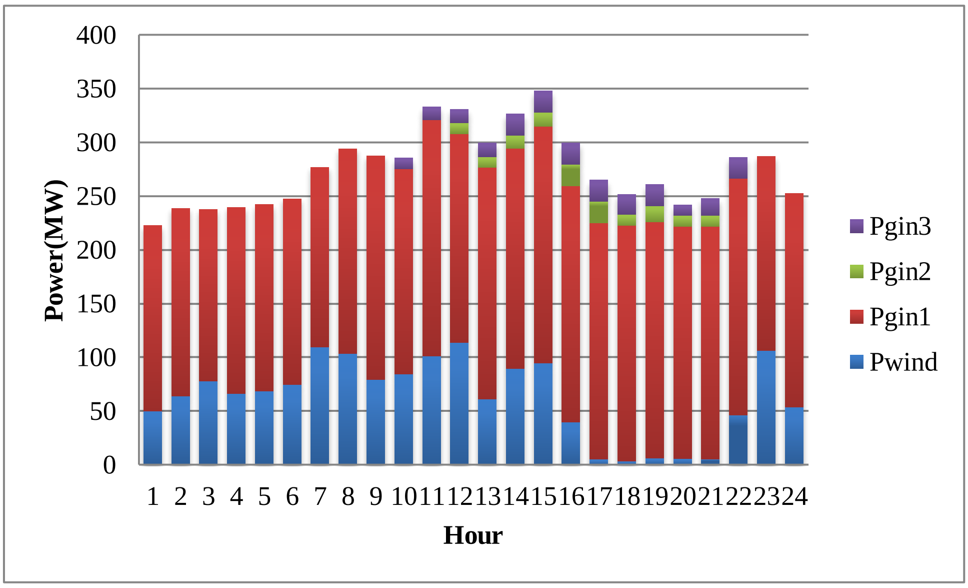

Figure 4.9: The UC and Power Dispatch in the IEEE 6-bus Test System (Case4).

4.1.2.5 Analyzing the Uncertainty of Wind Energy by Using GA Method in the Case of (IEEE 6-Bus System)

After applying UC over four different cases by using GA method in the case of IEEE 6-buses system, the changing of wind power values causes changing in the production cost as a result of changing in generators commitment to satisfy the load demand. Figure 4.10 shows the production costs performance for the four cases during the 24 hours. Figure 4.11 compares the total production cost between the four cases.

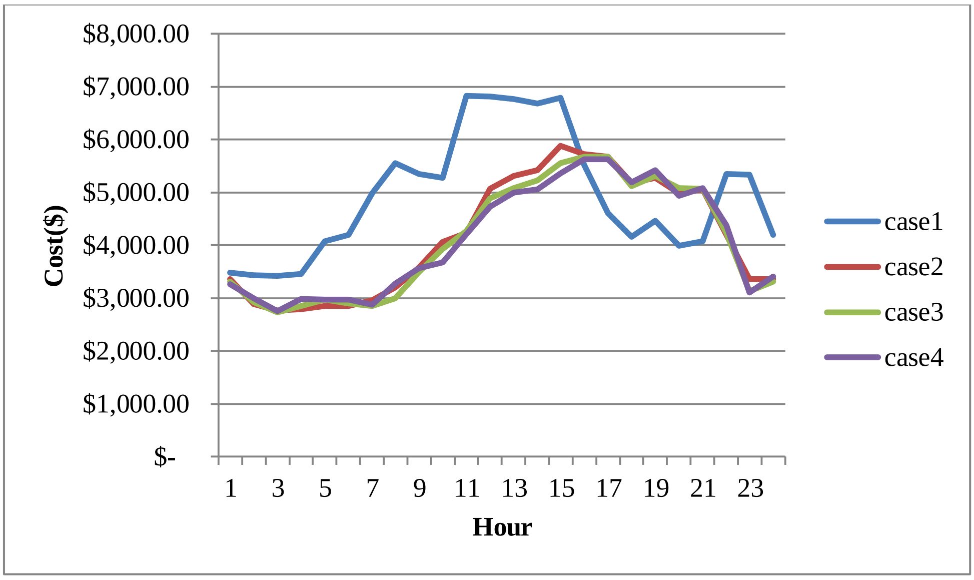

Figure 4.10: Production Costs Performance for the Four Cases During 24 Hours by GA.

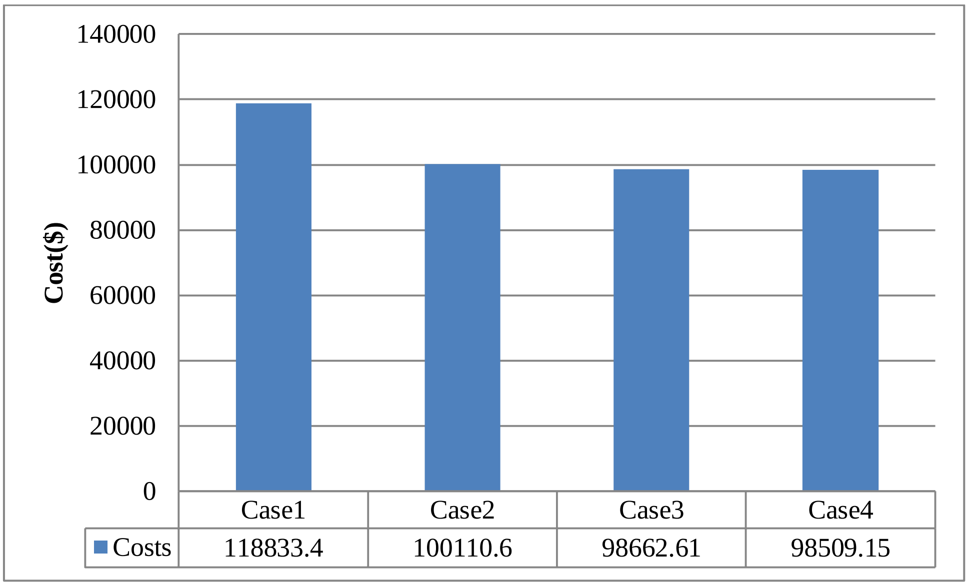

Figure 4.11: Comparison Between the Total Production Costs for the Four Cases by GA.

4.1.3 UC by Using DP Method Results

In this case the algorithm is used four times, table 4.11 represents the UC performance in the absence of wind farm, table 4.12 represents the UC performance in the case of forecasted wind power and table 4.13 and 4.14 represent the two different scenarios of wind power.

4.1.3.1 UC by Using DP Case 1

UC problem is resolved to decide the dispatch units in the case of absence of the wind farm which are shown in table 4.11. As shown, generator 1 is committed for whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed for 21 hours in the first hour in addition to the period of 5 and 24 hours. Finally, generator 3 is committed almost during 24 hours. The total operating costs for the 24 hours in this case is $118728 with considering the startup costs for each generating unit. In addition, between hours 5 and 24 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.12 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.13 shows the UC results and power dispatch within thermal units.

Table 4.11: UC by using DP for IEEE 6-Bus System (Case 1).

hour	Pload	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	1	1	1	202.7	10	10	3699.5
2	235.35	1	0	1	220	0	18.7	3633.6
3	234.67	1	0	1	220	0	17.8	3619.2
4	236.73	1	0	1	220	0	19.8	3654.6
5	239.06	1	1	1	220	10	12.2	3974.4
6	244.48	1	1	1	220	10	17.7	4072.6
7	273.39	1	1	1	220	36.9	20	4990.6
8	290.4	1	1	1	220	54.2	20	5557.7
9	283.56	1	1	1	220	47.7	20	5343.9
10	281.2	1	1	0	220	65.5	0	5437.1
11	328.61	1	1	1	220	98.2	15	6909
12	328.1	1	1	1	220	92.8	20	6822.1
13	326.18	1	1	1	220	91	20	6763.4
14	323.6	1	1	1	220	88.5	20	6679.5
15	326.86	1	1	1	220	91.8	20	6789.7
16	287.76	1	1	1	220	52.9	20	5513.9
17	260	1	1	1	220	25.1	20	4607.1
18	246.74	1	1	1	220	11.7	20	4168.5
19	255.97	1	1	1	220	20.9	20	4469
20	237.35	1	1	1	220	10	12.1	3973.4
21	243.31	1	1	1	220	10	18.1	4079
22	283.14	1	1	1	220	47.7	20	5344.2
23	283.05	1	1	1	220	47.1	20	5324.3
24	248.75	1	1	1	220	12.7	20	4201.4
							TOTAL	118728

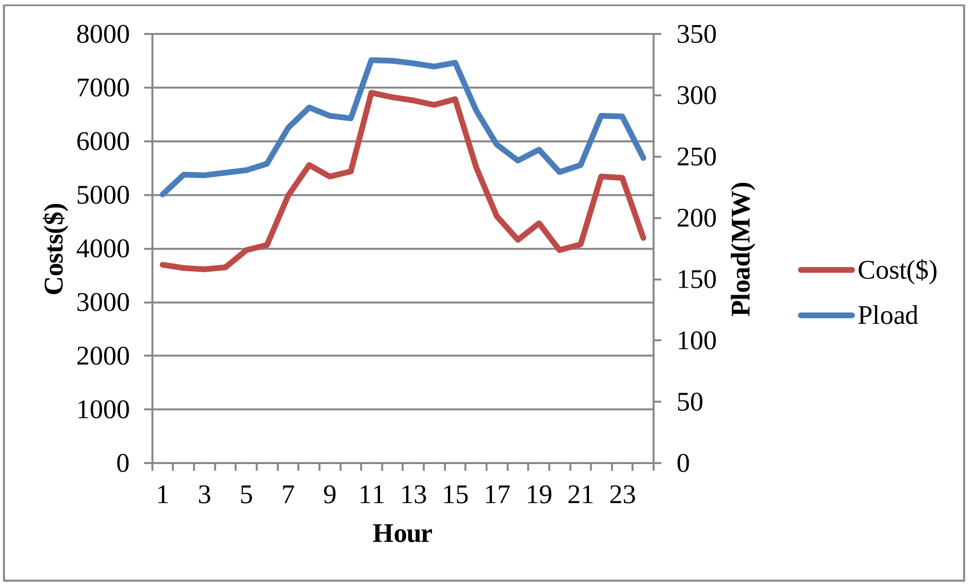

Figure 4.12: The Relation Between Production Costs Performance and the Changes of the Demand During 24 Hours (Case 1).

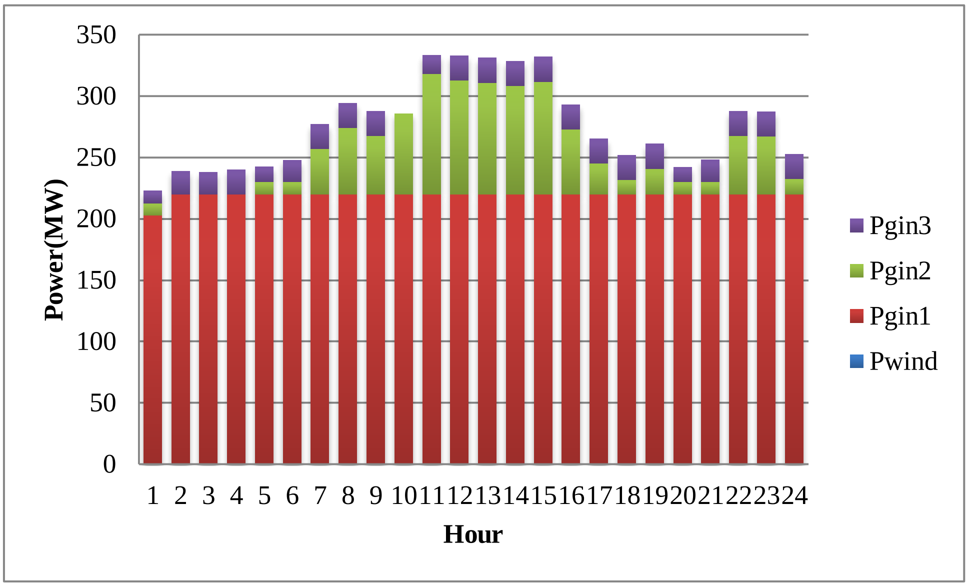

Figure 4.13: The UC and Power Dispatch in the IEEE 6-bus Test System (Case1).

4.1.3.2 UC by Using DP Case 2

Forecasted wind power with dispatch: With the forecasted wind power given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.12. As shown, generator 1 is committed for whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 13 and 22 hours. Finally, generator 3 is committed in the period of 10 and 21 hours. The total operating costs for the 24 hours in the forecasted case is $80927 with considering the startup costs for each generating unit. In addition, between hours 13 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.14 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.15 shows the UC results and power dispatch within thermal units.

Table 4.12: UC by using DP for IEEE 6-Bus System (Case 2).

hour	Pload	pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	45.41	1	1	0	167.3	10	0	2902
2	235.35	70.9095	1	1	0	167.7	0	0	2453
3	234.67	76.6086	1	0	0	161.2	0	0	2364
4	236.73	77.5866	1	0	0	162.2	0	0	2378
5	239.06	76.3817	1	0	0	165.8	0	0	2426
6	244.48	81.7648	1	0	0	165.9	0	0	2428
7	273.39	104.411	1	0	0	172.4	0	0	2517
8	290.4	107.494	1	0	0	186.7	0	0	2712
9	283.56	79.279	1	0	0	208.4	0	0	3008
10	281.2	61.7352	1	0	0	213.8	0	10	3395
11	328.61	99.827	1	0	1	220	0	13.4	3540
12	328.1	93.5746	1	0	1	220	0	19.2	3644
13	326.18	79.3324	1	1	1	220	11.7	20	4169
14	323.6	78.2397	1	1	1	220	10.2	20	4121
15	326.86	76.9768	1	1	1	220	14.9	20	4272
16	287.76	30.3111	1	1	1	220	22.6	20	4523
17	260	3.9427	1	1	1	220	21.2	20	4478
18	246.74	8.0945	1	1	1	220	10	13.6	4000
19	255.97	9.769	1	0	1	220	11.1	20	4150
20	237.35	5.4247	1	0	1	220	0	16.7	3599
21	243.31	6.0962	1	1	1	220	10	12	3971
22	283.14	55.8455	1	1	0	220	11.8	0	3682

23	283.05	91.3234	1	1	0	185.7	10	0	3154
24	248.75	56.475	1	0	0	196.2	0	0	2841
								TOTAL	80927

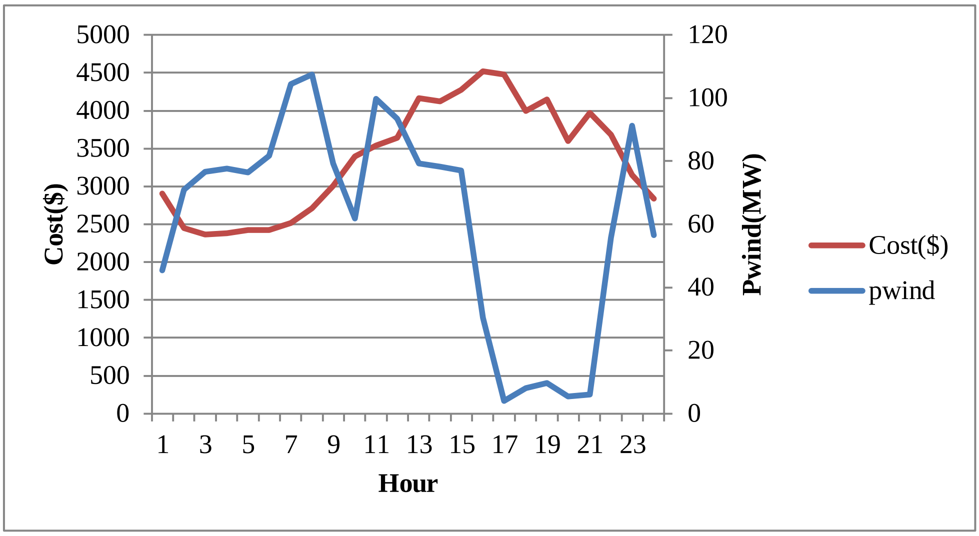

Figure 4.14: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 2).

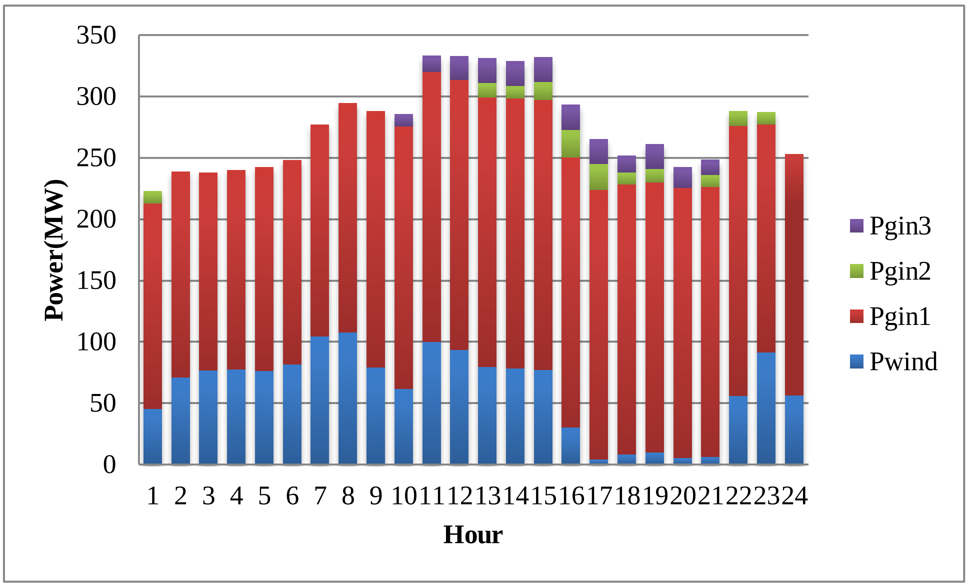

Figure 4.15: The UC and Power Dispatch in the IEEE 6-bus Test System (Case2).

4.1.3.3 UC by Using DP (Case 3)

First scenario of wind power with dispatch: With the first scenario of wind power which given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.13. As shown, generator 1 is committed for whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 13 and 23hours. Finally, generator 3 is committed during the period of 11 and 21 hours. The total operating costs for the 24 hours in the second scenario case is $80073 with considering the startup costs for each generating unit. In addition, between hours 13 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.16 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.17 shows the UC results and power dispatch within thermal units.

Table 4.13: UC by using DP for IEEE 6-Bus System (Case 3).

hour	Pload	pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	47.0564	1	1	0	165.6	10	0	2880
2	235.35	68.1466	1	0	0	170.5	0	0	2490
3	234.67	78.7354	1	0	0	159.1	0	0	2335
4	236.73	73.7246	1	0	0	166.1	0	0	2430
5	239.06	68.9752	1	0	0	173.2	0	0	2527
6	244.48	78.7344	1	0	0	169	0	0	2469
7	273.39	110.5521	1	0	0	166.3	0	0	2433
8	290.4	119.56	1	0	0	174.6	0	0	2547
9	283.56	84.1261	1	0	0	203.5	0	0	2941
10	281.2	69.2216	1	0	0	216.3	0	0	3116
11	328.61	98.3374	1	0	1	220	0	14.8	3566
12	328.1	104.3248	1	0	1	218.5	0	10	3460
13	326.18	70.9839	1	1	1	220	20	20	4441
14	323.6	85.0396	1	1	1	220	10	13.4	3997

15	326.86	81.659	1	1	1	220	10.2	20	4119
16	287.76	34.8125	1	1	1	220	18.1	20	4377
17	260	3.9302	1	1	1	220	21.2	20	4479
18	246.74	6.7375	1	1	1	220	10	14.9	4024
19	255.97	8.8758	1	1	1	220	12	20	4179
20	237.35	6.1415	1	0	1	220	0	16	3586
21	243.31	5.714	1	1	1	220	10	12.3	3978
22	283.14	54.5047	1	1	0	220	13.2	0	3726
23	283.05	104.3054	1	1	0	172.8	10	0	2977
24	248.75	59.7659	1	0	0	192.9	0	0	2796
								TOTAL	80073

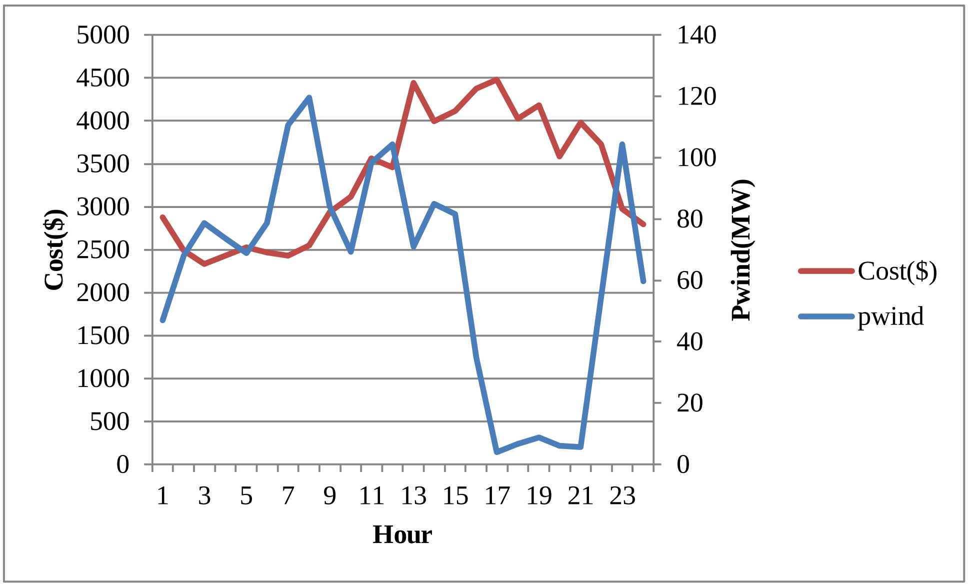

Figure 4.16: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 3).

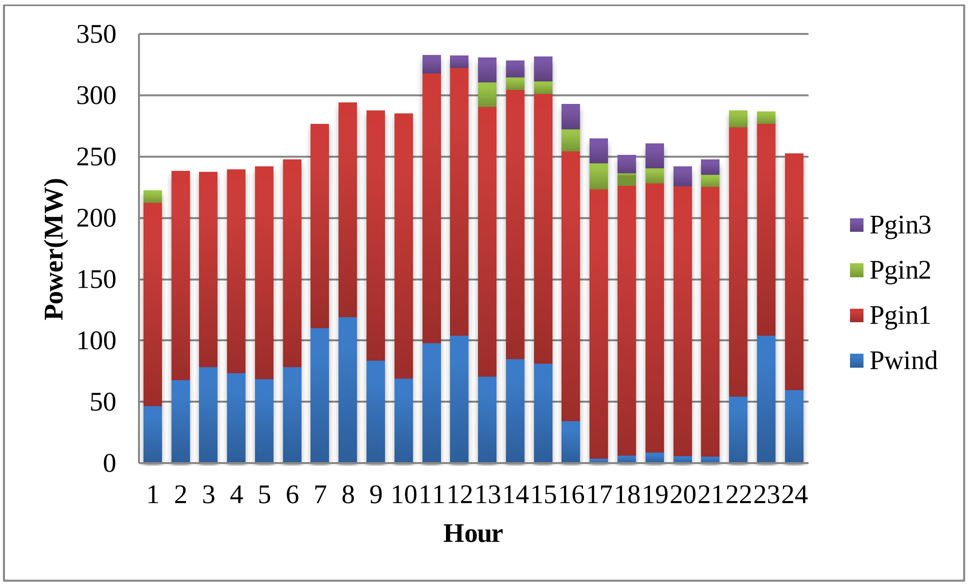

Figure 4.17: The UC and Power Dispatch in the IEEE 6-bus Test System (Case3).

4.1.3.4 UC by Using DP (Case 4)

Second scenario of wind power with dispatch: With the second scenario of wind power which given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.14 As shown, generator 1 is committed for whole the 24 hours which is the cheapest unit. Generator 2 which has the most expensive operational costs is committed in the period of 13 and 23hours. Finally, generator 3 is committed during the period of 11and 22 hours. The total operating costs for the 24 hours in the second scenario case is $80334 with considering the startup costs for each generating unit. In addition, between hours 12 and 21 all units work together to face the load demand and the system registered the maximum operating cost in this period. Figure 4.18 represents the relation between production costs performance and the wind performance during 24 hours. Figure 4.19 shows the UC results and power dispatch within thermal units.

Table 4.14: UC by using DP for IEEE 6-Bus System (Case 4).

hour	Pload	pwind	ON/OFF			Pgin1	Pgin2	Pgin3	Cost($)
1	219.19	50.15	1	1	0	162.5	10	0	2838
2	235.35	64.119	1	0	0	174.5	0	0	2545
3	234.67	77.807	1	0	0	160	0	0	2348
4	236.73	66.294	1	0	0	173.5	0	0	2532
5	239.06	68.806	1	0	0	173.4	0	0	2529
6	244.48	74.653	1	0	0	173	0	0	2525
7	273.39	109.72	1	0	0	167.1	0	0	2444
8	290.4	103.58	1	0	0	190.6	0	0	2765
9	283.56	79.489	1	0	0	208.2	0	0	3005
10	281.2	84.281	1	0	0	201.3	0	0	2910
11	328.61	101.19	1	0	1	220	0	12	3515
12	328.1	113.84	1	0	0	219	0	0	3152
13	326.18	61.015	1	1	1	220	35	15	4841
14	323.6	89.641	1	1	0	220	18.8	0	3910
15	326.86	94.822	1	1	1	217	10	10	3895
16	287.76	39.573	1	1	1	220	13.3	20	4221
17	260	5.1169	1	1	1	220	20	20	4440
18	246.74	3.5581	1	1	1	220	10	18.1	4080
19	255.97	6.1553	1	1	1	220	14.7	20	4268
20	237.35	5.8387	1	0	1	220	0	16.3	3591
21	243.31	5.1034	1	1	1	220	10	12.9	3988
22	283.14	46.37	1	1	1	220	10	11.3	3959
23	283.05	106.29	1	1	0	170.8	10	0	2950
24	248.75	53.587	1	0	0	199.1	0	0	2881
								TOTAL	80334

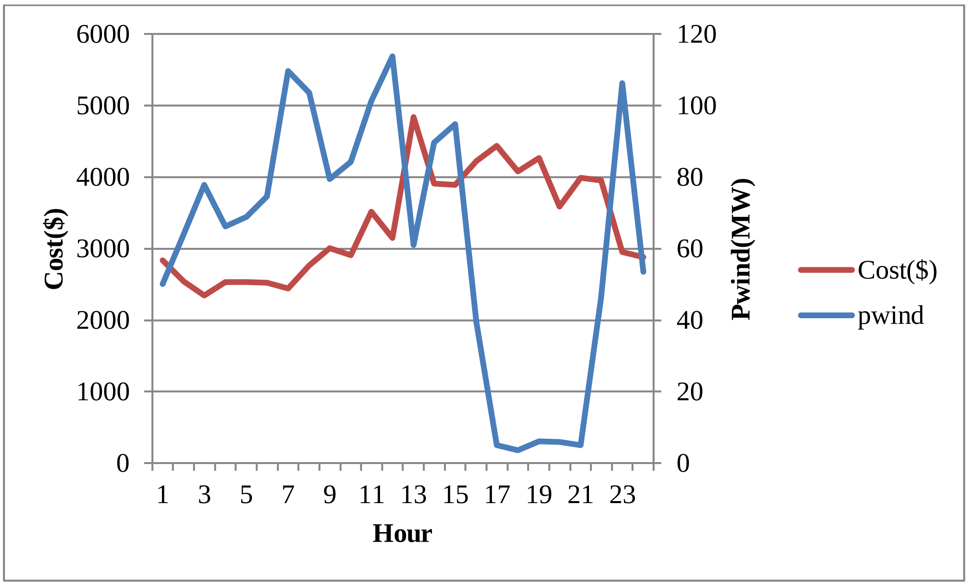

Figure 4.18: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 4).

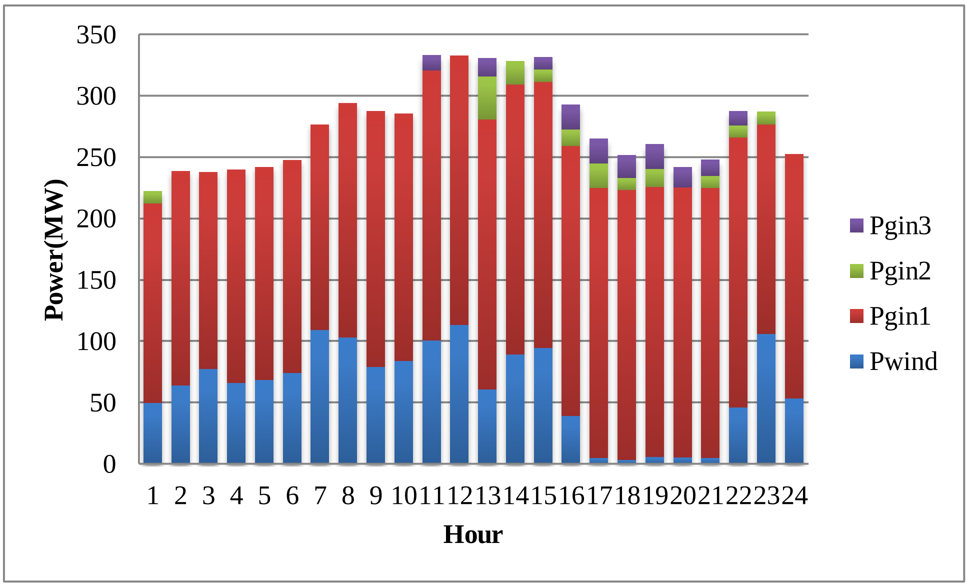

Figure 4.19: The UC and Power Dispatch in the IEEE 6-bus Test System (Case4).

4.1.3.5 Analyzing the Uncertainty of Wind Energy by Using DP Method in the Case of (IEEE 6-Bus System)

After applying UC over four different cases by using DP approach in the case of IEEE 6-buses system, the changing of wind power values causes changing in the production cost as a result of changing in generators commitment to satisfy the power demand. Figure 4.20 illustrates the performance of the production costs for the four cases during the 24 hours. Figure 4.21 compares the total production cost between the four cases.

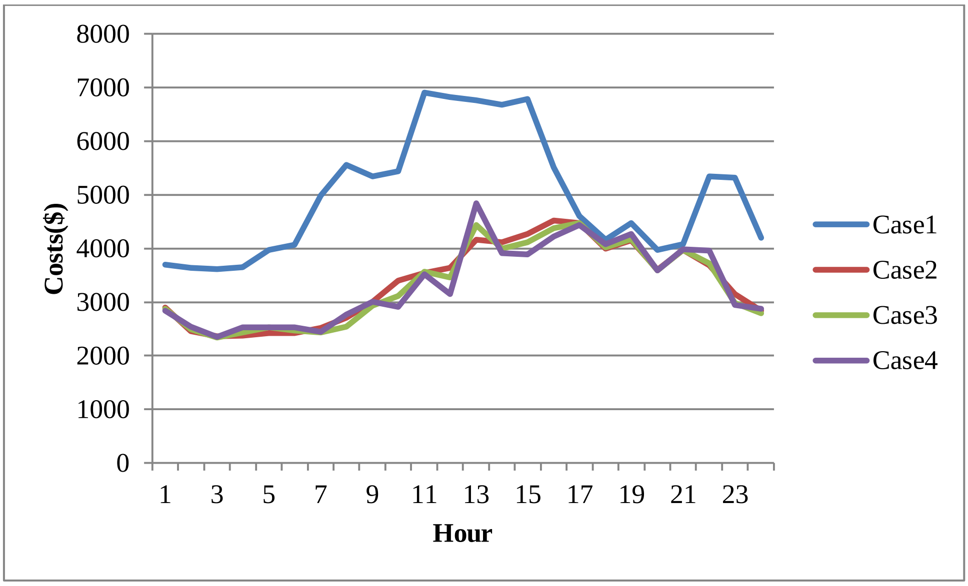

Figure 4.20: Production Costs Performance for the Four Cases During 24 Hours by DP.

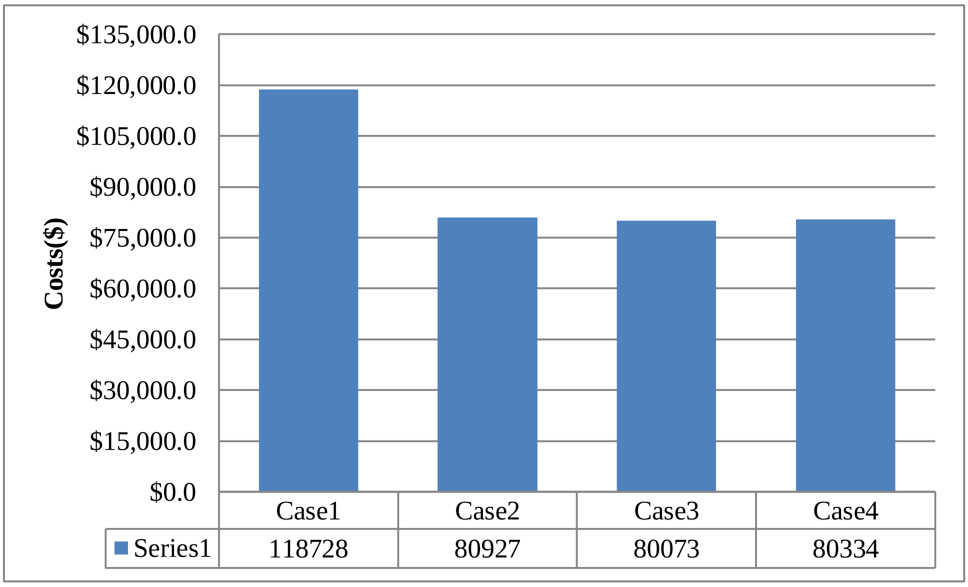

Figure 4.21: Comparison Between the Total Production Costs for the Four Cases by DP.

4.1.4 GA and DP Results Discussion

After applying two optimization methods on the UC problem to plan Day-Ahead IEEE 6-Buses system and decide which generator has to work in each hour, then by applying the ED for each case the total production costs for each scenario is explained in table 4.15 and analyzed in figure 4.22.

Table 4.15: Comparison Between GA and DP in Term of Total Production Costs.

Case	GA Production Costs ($)	DP Production Costs ($)	Difference in favor of DP($)
No Wind Farm	118833.4	118728	105.4
Forecasted Wind Power	100110.6	80927	19183.6
Scenario 1	98662.61	80073	18589
Scenario 2	98509.15	80334	18175.15

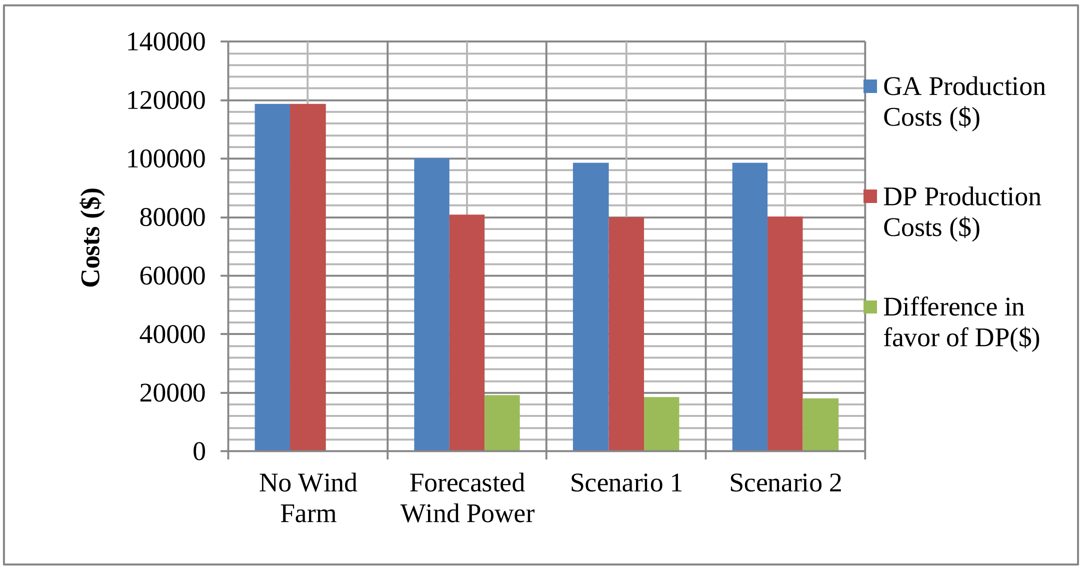

Figure 4.22: Comparison Between GA and DP in Term of Total Production Costs.

From the previous results we can conclude that DP approach outperform GA approach in this case study. This result completely agrees with the study of

Valenzuela, J. results, in which for the size of units less or equal to ten units the DP method is the best method [43].

The following four figures illustrate a comparison between GA and DP production costs through 24 hours. As shown, DP costs are less than GA costs, therefore we can claim that for this case study it is better to use DP for planning Day-Ahead commitment than GA.

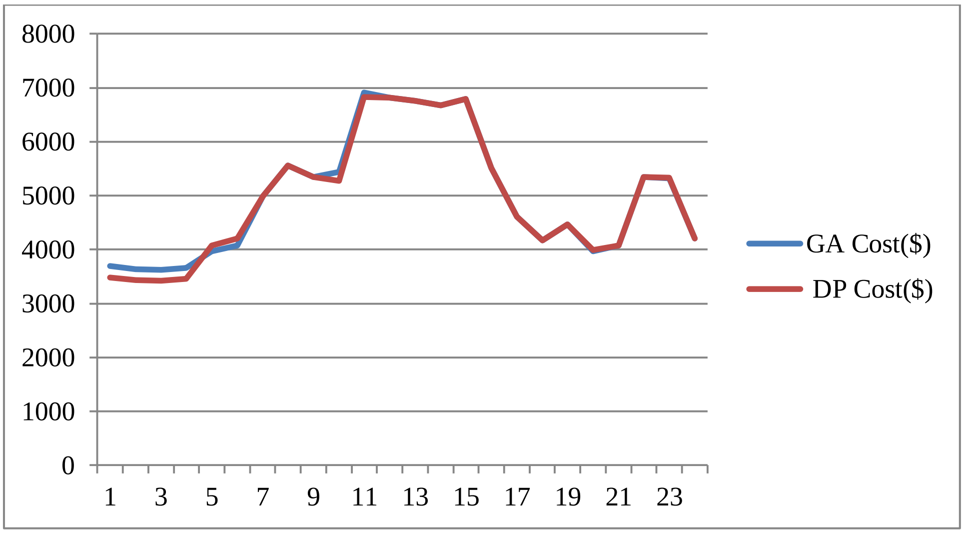

Figure 4.23: The Hourly Total Costs of the Operation in both GA and DP (Case1).

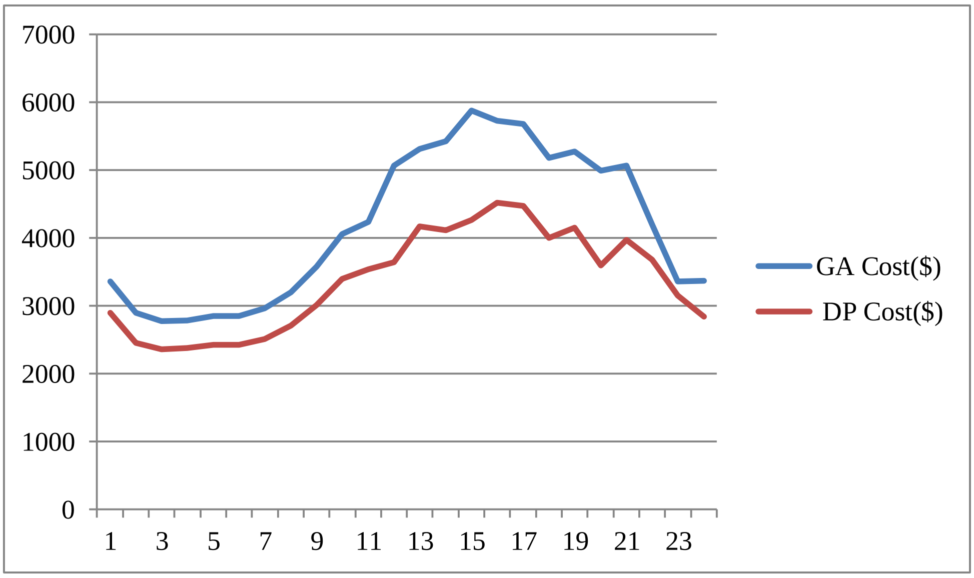

Figure 4.24: The Hourly Total Costs of the Operation in both GA and DP (Case2).

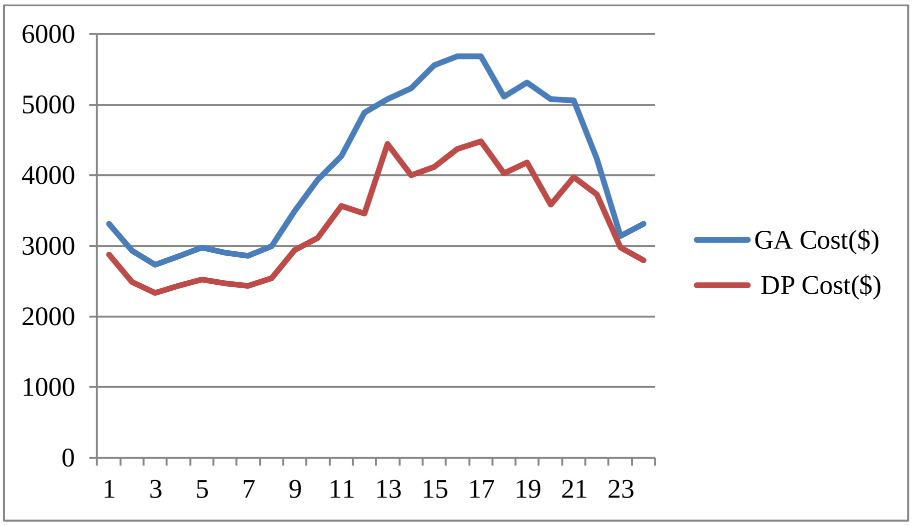

Figure 4.25: The Hourly Total Costs of the Operation in both GA and DP (Case3).

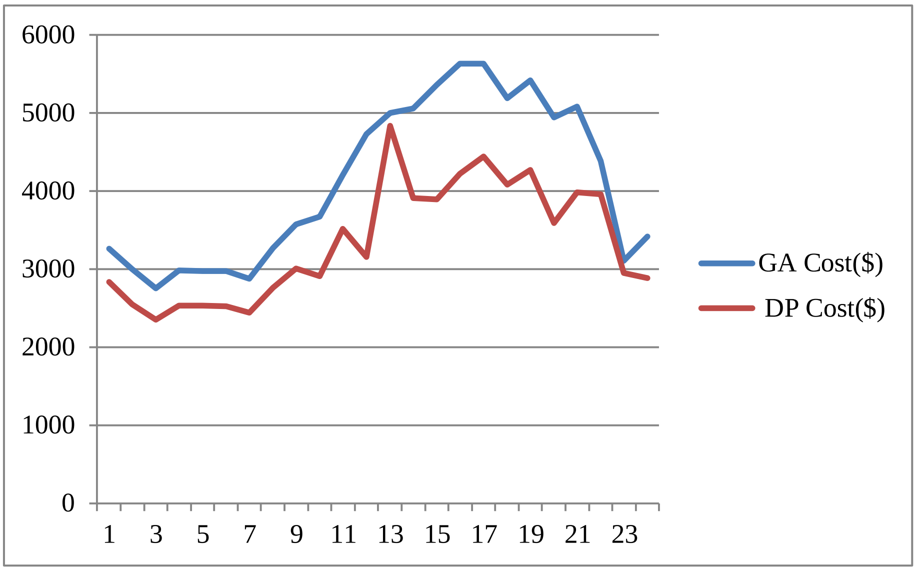

Figure 4.26: The Hourly Total Costs of the Operation in both GA and DP (Case4).

4.2 Case Study Two (IEEE 30-Bus Test System)

A 30-bus system is applied for studying the impacts of fluctuating wind energy on the state of power system. The 30-bus case in figure 4.27 is used to explain the methodology. The system includes six thermal generating units and a wind farm. Thermal units lie at buses 1,2,5,8,11 and 13 respectively. The wind farm lies at bus 16. Table 4.16 represents the generators data and generators operating costs. Table 4.17 provides data about the load demand for 24 hours. Table 4.18 represents Loss

Coefficients of the IEEE 30-bus system. The used data of this case study is taken from [1].

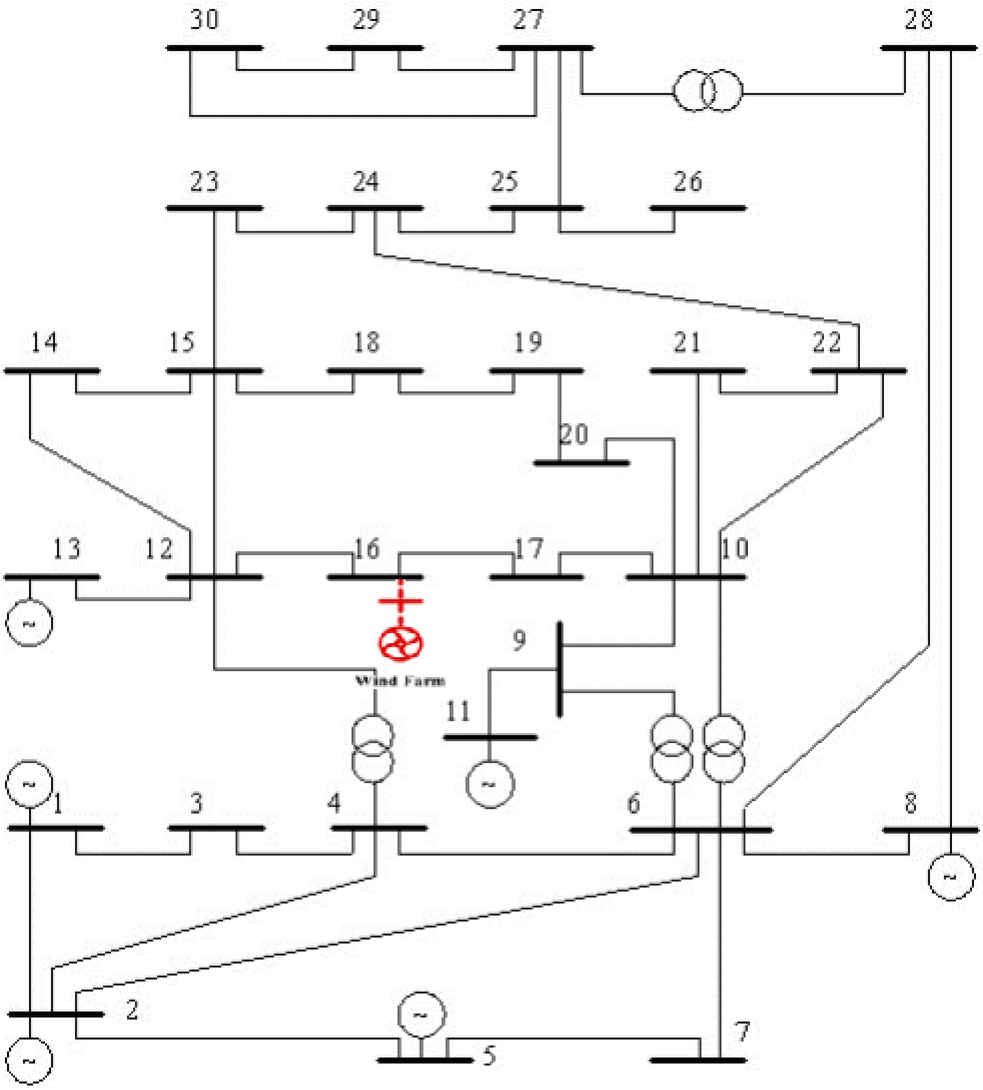

Figure 4.27: IEEE 30- Bus Test System.

Table 4.16: IEEE 30-Bus Units Data.

Unit	Bus No.	Pmax (MW)	Pmin (MW)	Cost Coefficients			Min. ON (hr)	Min. OFF (hr)	Initial Status (hr)	Cold Start Hour	Shut down cost	Start up Costs	
				a	b	c						Hot	Cold
1	1	200	50	0.00375	2	0	1	1	2	2	50	70	176
2	2	80	20	0.0175	1.75	0	2	2	3	2	60	74	187
3	13	50	15	0.0625	1	0	1	1	2	1	30	110	113
4	22	35	10	0.00834	3.25	0	1	2	3	1	85	50	267
5	23	30	10	0.025	3	0	2	1	2	1	52	72	180

6	27	40	12	0.025	3	0	1	1	2	1	30	40	113

Table 4.17: IEEE 30-Bus Hour Load Demand.

Hour	Pload	Hour	Pload
1	166	13	170
2	196	14	185
3	229	15	208
4	267	16	232
5	283.4	17	246
6	272	18	241
7	246	19	236
8	213	20	225
9	192	21	204
10	161	22	182
11	147	23	161
12	160	24	131

Table 4.18: Loss Coefficients of the IEEE 30-Bus System[65].

Coefficient B	Value	Coefficient B	Value
B1	0.015751	B24	0.036122
B2	0.004148	B25	0.021162
B3	−0.0163430	B26	0.037327
B4	−0.0041543	B33	0.035597
B5	−0.0070962	B34	0.016785
B6	0.008479	B35	0.00187
B11	0.026653	B36	0.01678
B12	0.032813	B44	0.04962
B13	0.007563	B45	0.023143
B14	0.017716	B46	0.034977
B15	0.003144	B55	0.013355
B16	0.020161	B56	0.014568
B22	0.054859	B66	0.054766
B23	0.02842		

In this case study DP method is applied to decide the UC performance in the case of absence and existence of the wind farm under different scenarios. Tables 4.19-4.22 represent the unit commitment results after applying DP method.

4.2.1 UC by Using DP (Case 1)

UC problem is solved to determine the dispatch units in the case of absence of the wind farm which are shown in table 4.19. As shown, generator 1,2 and 3 are committing for whole the 24 hours which is the cheapest units, while units 4,5 and 6 they are in off case so we can consider them as backup generators for different load demand . The total operating costs for the 24 hours in this case is $8860 with considering the startup and shut down costs for each generating unit. In addition, between hours 1 and 24 the first three units are working for the whole period to face the load demand. Figure 4.28 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.29 shows the UC results and power dispatch within thermal units.

Table 4.19: UC by using DP for IEEE 30-Bus System (Case 1).

Hr	Pload	ON/OFF						G1	G2	G3	G4	G5	G6	Prod Cost
1	166	1	1	1	0	0	0	50	70.7	50	0	0	0	274
2	196	1	1	1	0	0	0	72.2	80	50	0	0	0	334
3	229	1	1	1	0	0	0	110.5	80	50	0	0	0	411
4	267	1	1	1	0	0	0	149	80	50	0	0	0	488
5	283.4	1	1	1	0	0	0	164	80	50	0	0	0	518
6	272	1	1	1	0	0	0	150.8	80	50	0	0	0	492
7	246	1	1	1	0	0	0	125.5	80	50	0	0	0	441
8	213	1	1	1	0	0	0	89.8	80	50	0	0	0	370
9	192	1	1	1	0	0	0	68.7	80	50	0	0	0	327
10	161	1	1	1	0	0	0	50	64.7	50	0	0	0	263
11	147	1	1	1	0	0	0	50	50	50	0	0	0	238
12	160	1	1	1	0	0	0	50	64.9	50	0	0	0	264
13	170	1	1	1	0	0	0	50	73.5	50	0	0	0	279
14	185	1	1	1	0	0	0	61.1	80	50	0	0	0	312
15	208	1	1	1	0	0	0	84.5	80	50	0	0	0	359
16	232	1	1	1	0	0	0	110.4	80	50	0	0	0	411
17	246	1	1	1	0	0	0	125.4	80	50	0	0	0	441
18	241	1	1	1	0	0	0	118.1	80	50	0	0	0	426
19	236	1	1	1	0	0	0	113.6	80	50	0	0	0	417

20	225	1	1	1	0	0	0	104	80	50	0	0	0	398
21	204	1	1	1	0	0	0	81.1	80	50	0	0	0	352
22	182	1	1	1	0	0	0	56.5	80	50	0	0	0	303
23	161	1	1	1	0	0	0	50	65.2	50	0	0	0	264
24	131	1	1	1	0	0	0	50	45.2	38.1	0	0	0	217
Total														8860

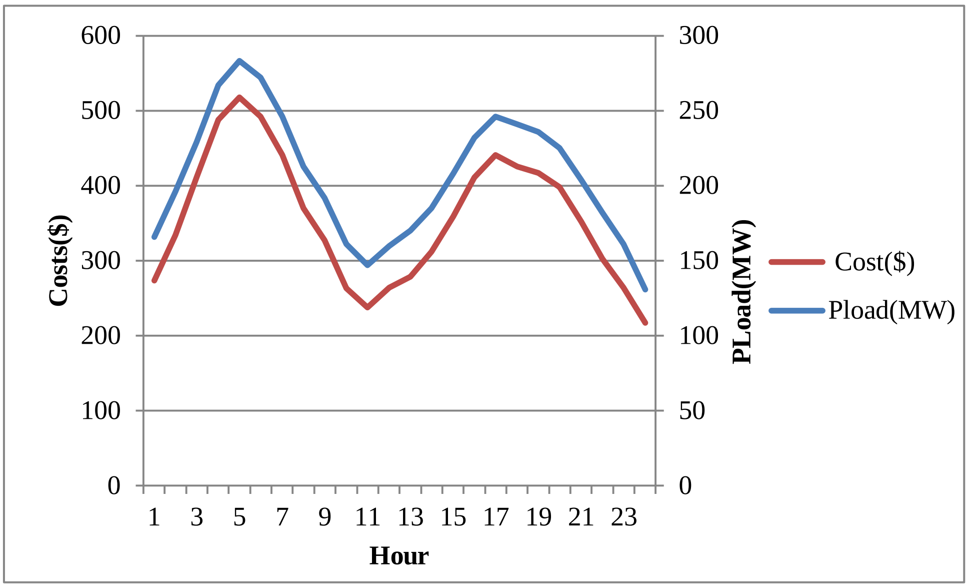

Figure 4.28: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 1).

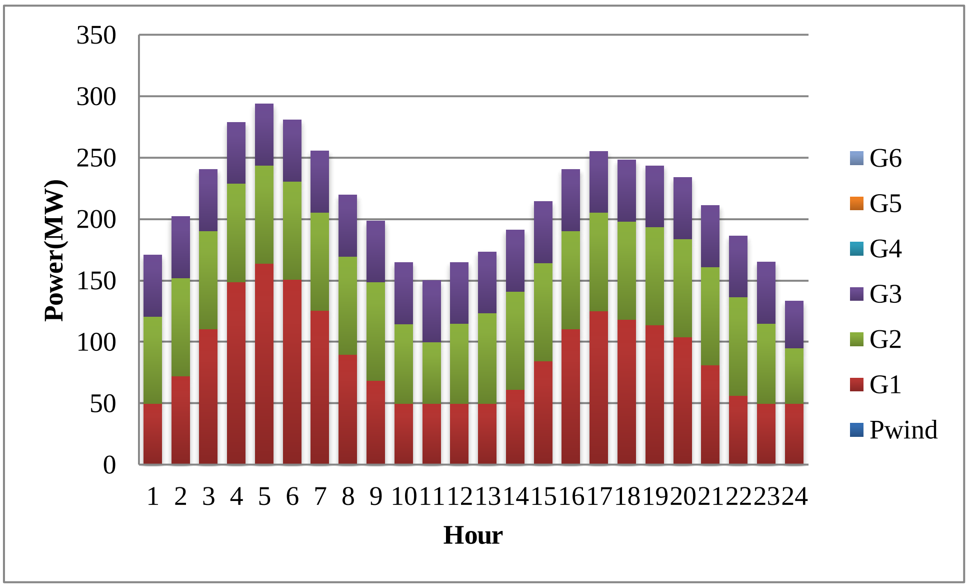

Figure 4.29: The UC and Power Dispatch in the IEEE 30-bus Test System (Case1).

4.2.2 UC by Using DP (Case 2)

Forecasted wind power with dispatch: With the forecasted wind power which given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.20. As shown, generator 1 commits in two periods(1-7)and(15-22) which are the high load intervals, generators 2 and 3 are committing for whole the 24 hours which are the cheapest units, while units 4,5 and 6 are in off case so we can consider them as backup generators for different load demand . The total operating costs for the 24 hours in this case is $6684with considering the startup and shut down costs for each generating unit. In addition, between hours 1 and 24 the second and third units are working for the whole period to face the load demand. Figure 4.30 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.31 shows the UC results and power dispatch within thermal units.

Table 4.20: UC by using DP for IEEE 30-Bus System (Case 2).

Hr	Pload	Pwind	ON/OFF						G1	G2	G3	G4	G5	G6	Prod Cost
1	166	45.41	1	1	1	0	0	0	50.0	25.3	50.0	0	0	0	194
2	196	70.9095	1	1	1	0	0	0	50.0	31.3	50.0	0	0	0	205
3	229	76.6086	1	1	1	0	0	0	62.7	51.3	50.0	0	0	0	265
4	267	77.5866	1	1	1	0	0	0	80.2	71.3	50.0	0	0	0	335
5	283.4	76.3817	1	1	1	0	0	0	87.6	80.0	50.0	0	0	0	365
6	272	81.7648	1	1	1	0	0	0	69.0	80.0	50.0	0	0	0	328
7	246	104.411	1	1	1	0	0	0	50.0	60.0	41.1	0	0	0	246
8	213	107.494	0	1	1	0	0	0	0	62.3	50.0	0	0	0	159
9	192	79.279	0	1	1	0	0	0	0	69.4	50.0	0	0	0	172
10	161	61.7352	0	1	1	0	0	0	0	52.9	50.0	0	0	0	143
11	147	99.827	0	1	0	0	0	0	0	50.7	0	0	0	0	89
12	160	93.5746	0	1	1	0	0	0	0	56.3	15.0	0	0	0	114
13	170	79.3324	0	1	1	0	0	0	0	66.1	28.0	0	0	0	144
14	185	78.2397	0	1	1	0	0	0	0	71.9	41.0	0	0	0	167
15	208	76.9768	1	1	1	0	0	0	50.0	51.9	35.6	0	0	0	226
16	232	30.3111	1	1	1	0	0	0	89.6	71.9	48.6	0	0	0	354
17	246	3.9427	1	1	1	0	0	0	121.5	80.0	50.0	0	0	0	433
18	241	8.0945	1	1	1	0	0	0	110.0	80.0	50.0	0	0	0	410

19	236	9.769	1	1	1	0	0	0	103.9	80.0	50.0	0	0	0	398
20	225	5.4247	1	1	1	0	0	0	98.5	80.0	50.0	0	0	0	387
21	204	6.0962	1	1	1	0	0	0	75.0	80.0	50.0	0	0	0	340
22	182	55.8455	1	1	0	0	0	0	50.7	80.0	0	0	0	0	241
23	161	91.3234	0	1	0	0	0	0	0	73.9	0	0	0	0	129
24	131	56.475	0	1	0	0	0	0	0	76.8	0	0	0	0	134
Total															6684

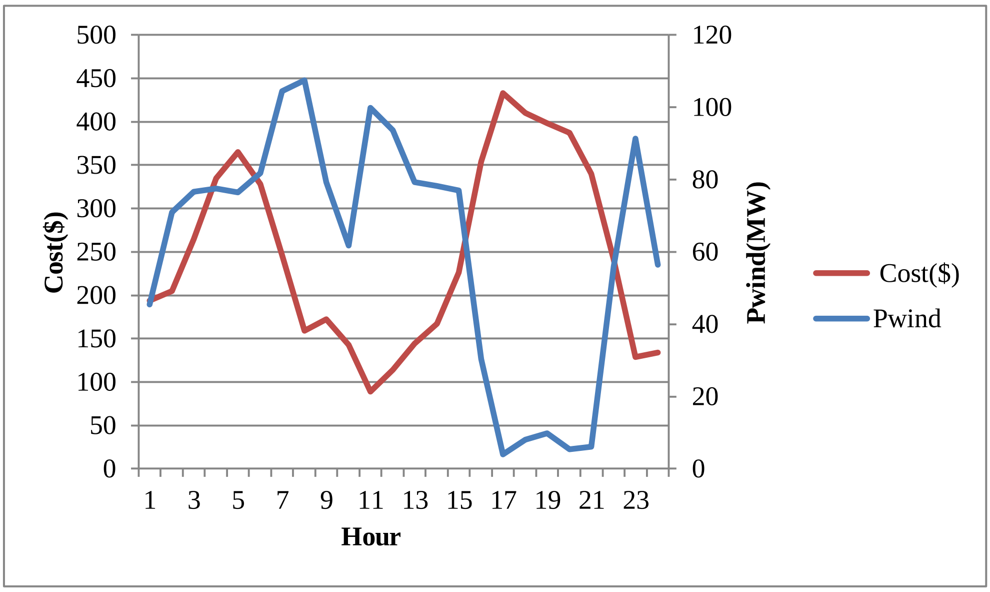

Figure 4.30: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 2).

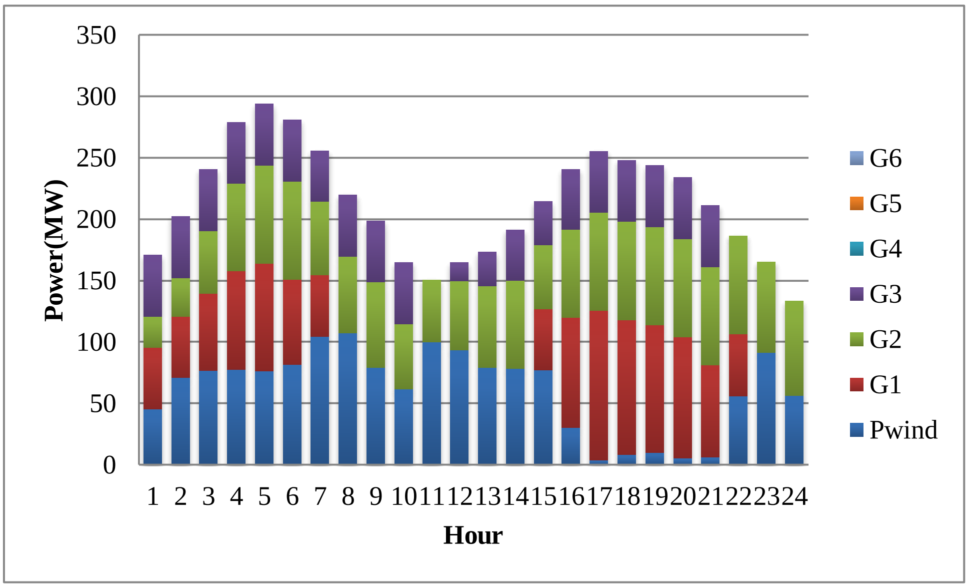

Figure 4.31: The UC and Power Dispatch in the IEEE 30-bus Test System (Case2).

4.2.3 UC by Using DP (Case 3)

First scenario of wind power with dispatch: With the first scenario of wind power which given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.21. As shown, generators 1 ,2 and 3 are committing alternately for whole the 24 hours which is the cheapest units, while units 4,5 and 6 are in off case so we can consider them as backup generators for different load demand . The total operating costs for the 24 hours in this case is $6722 with considering the startup and shut down costs for each generating unit. In addition, between hours 1 and 24 the first and third units are almost working for the whole period to face the load demand. Figure 4.31 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.32 shows the UC results and power dispatch within thermal units.

Table 4.21: UC by using DP for IEEE 30-Bus System (Case 3).

Hr	Pload	Pwind	ON/OFF						G1	G2	G3	G4	G5	G6	Prod Cost
1	166	47.0564	1	0	1	0	0	0	73.7	0	50.0	0	0	0	197
2	196	68.1466	1	0	1	0	0	0	84.0	0	50.0	0	0	0	218
3	229	78.7354	1	0	1	0	0	0	111.8	0	50.0	0	0	0	274
4	267	73.7246	1	0	1	0	0	0	155.3	0	50.0	0	0	0	361
5	283.4	68.9752	1	0	1	0	0	0	175	0	50.0	0	0	0	400
6	272	78.7344	1	0	1	0	0	0	152	0	50.0	0	0	0	354
7	246	110.5521	1	0	1	0	0	0	102.0	0	42.9	0	0	0	247
8	213	119.56	1	0	1	0	0	0	52.0	0	48.3	0	0	0	152
9	192	84.1261	1	0	1	0	0	0	64.6	0	50.0	0	0	0	179
10	161	69.2216	1	0	1	0	0	0	50.0	0	45.4	0	0	0	146
11	147	98.3374	1	0	0	0	0	0	52.2	0	0	0	0	0	104
12	160	104.3248	1	0	0	0	0	0	60.6	0	0	0	0	0	121
13	170	70.9839	1	1	1	0	0	0	67.5	20.0	15.0	0	0	0	185
14	185	85.0396	1	1	1	0	0	0	50.0	28.1	28	0	0	0	177
15	208	81.659	1	1	1	0	0	0	50.0	41.8	41.0	0	0	0	214
16	232	34.8125	1	1	1	0	0	0	93.8	61.8	50.0	0	0	0	346
17	246	3.9302	1	1	1	0	0	0	121.5	80.0	50.0	0	0	0	433
18	241	6.7375	1	1	1	0	0	0	111.4	80.0	50.0	0	0	0	413
19	236	8.8758	1	1	1	0	0	0	104.8	80.0	50.0	0	0	0	400
20	225	6.1415	1	1	1	0	0	0	97.8	80.0	50.0	0	0	0	386

21	204	5.714	1	1	1	0	0	0	75.4	80.0	50.0	0	0	0	341
22	182	54.5047	1	1	0	0	0	0	52.0	80.0	0	0	0	0	244
23	161	104.3054	0	1	0	0	0	0	0	60.9	0	0	0	0	107
24	131	59.7659	0	1	0	0	0	0	0	73.5	0	0	0	0	129
Total															6722

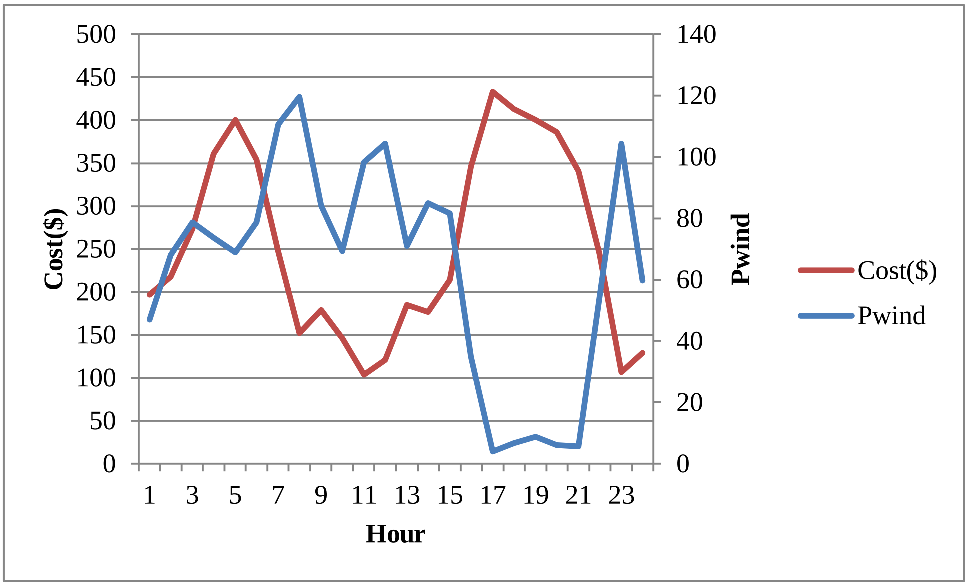

Figure 4.32: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 3).

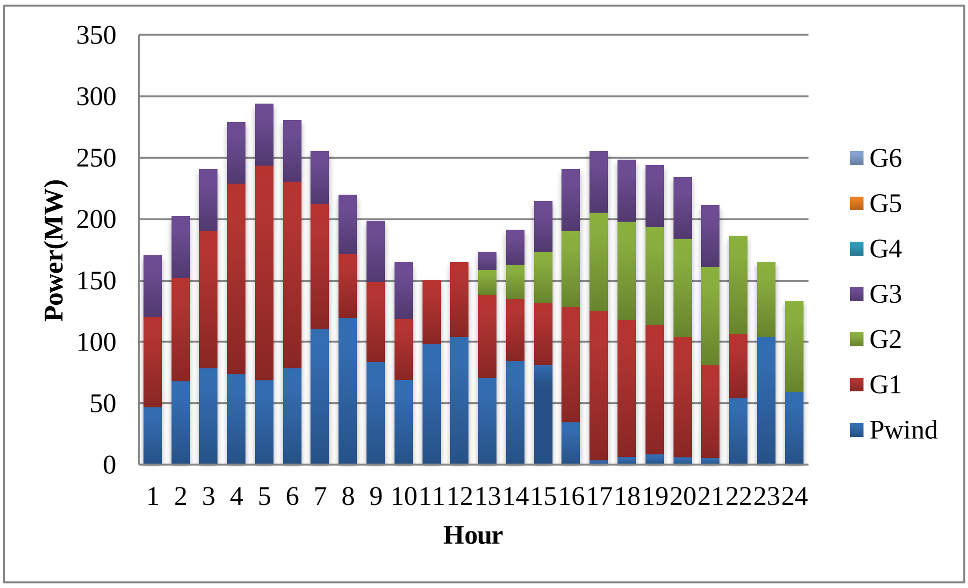

Figure 4.33: The UC and Power Dispatch in the IEEE 30-bus Test System (Case3).

4.2.4 UC by Using DP (Case 4)

The second scenario of wind power with dispatch: With the second scenario of wind power which is given in table 4.6 the UC problem is solved to determine the dispatch units which are shown in table 4.22. As shown, generators 1 , 2, 3, 4 and 6 are committing alternately for whole the 24 hours , while unit 5 is in off case so we can consider it as backup generators for different load demand . The total operating costs for the 24 hours in this case is $6912 with considering the startup and shut down costs for each generating unit. Figure 4.34 represents the relation between production costs performance and the changes of the demand during 24 hours. Figure 4.35 shows the UC results and power dispatch within thermal units.

Table 4.22: UC by using DP for IEEE 30-Bus System (Case 4).

Hour	Pload	Pwind	ON/OFF						G1	G2	G3	G4	G5	G6	Prod Cost
1	166	50.15	0	1	1	1	0	1		48.6	50	10	0	12	204
2	196	64.119	1	1	1	1	0	1	50	28.6	37.5	10	0	12	256
3	229	77.807	1	1	1	1	0	1	50	40.7	50	10	0	12	290
4	267	66.294	1	1	1	1	0	1	80	60.7	50	10	0	12	385
5	283.4	68.806	1	1	1	1	0	1	73.2	80	50	10	0	12	405
6	272	74.653	1	1	1	1	0	1	54.1	80	50	10	0	12	367
7	246	109.72	0	1	1	1	0	1	0	73.8	50	10	0	12	248
8	213	103.58	0	1	1	1	0	1	0	53.8	40.5	10	0	12	203
9	192	79.489	0	1	1	1	0	1	0	47.2	50	10	0	12	201
10	161	84.281	0	1	1	0	0	1	0	27.2	41.2	0	0	12	125
11	147	101.19	0	1	1	0	0	0	0	20	29.3	0	0	0	64
12	160	113.84	0	1	1	0	0	0	0	20	31.1	0	0	0	66
13	170	61.015	1	1	1	0	0	0	50	20	42.5	0	0	0	178
14	185	89.641	1	1	1	0	0	0	50	20	31.5	0	0	0	167
15	208	94.822	1	1	1	0	0	0	50	25.2	44.5	0	0	0	189
16	232	39.573	1	1	1	0	0	1	93.6	45.2	50	0	0	12	352
17	246	5.1169	1	1	1	0	0	0	135.2	65.2	50	0	0	0	434
18	241	3.5581	1	1	1	0	0	0	114.6	80	50	0	0	0	419
19	236	6.1553	1	1	1	0	0	0	107.5	80	50	0	0	0	405
20	225	5.8387	1	1	1	0	0	0	98.1	80	50	0	0	0	386
21	204	5.1034	1	1	1	0	0	0	76	80	50	0	0	0	342
22	182	46.37	1	0	1	0	0	0	90.1	0	50	0	0	0	230
23	161	106.29	1	0	0	0	0	0	58.9	0	0	0	0	0	118

24	131	53.587	1	0	0	0	0	0	79.7	0	0	0	0	0	159
Total															6912

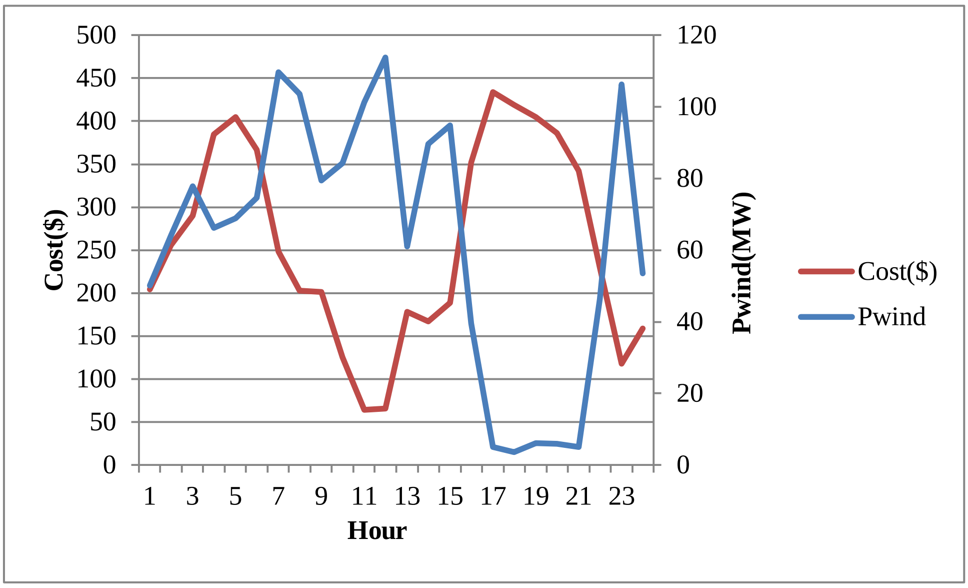

Figure 4.34: The Relation Between Production Costs Performance and the Wind Performance During 24 Hours (Case 4).

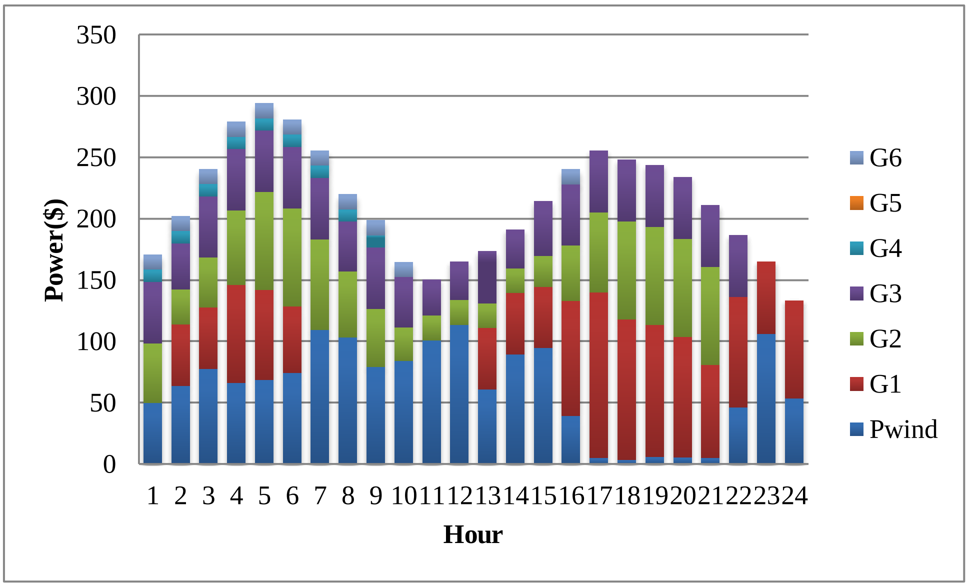

Figure 4.35: The UC and Power Dispatch in the IEEE 30-bus Test System (Case4).

4.2.5 Analyzing the Uncertainty of Wind Energy by Using DP Method in the Case of (IEEE 30-Bus System)

After applying UC over four different cases by using DP approach in the case of IEEE 30-buses system, the changing of wind power values causes changing in the production cost as a result of changing in generators commitment to satisfy the demand. Figure 4.36 shows the production costs performance for the four cases during the 24 hours. Figure 4.37 comparing the total production cost between the four cases.

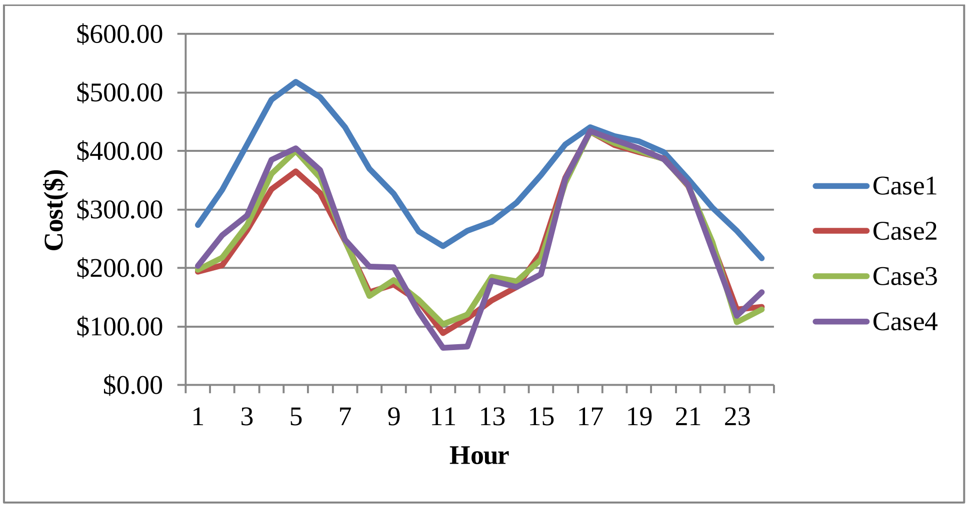

Figure 4.36: Production Costs Performance for the Four Cases During 24 H by DP.

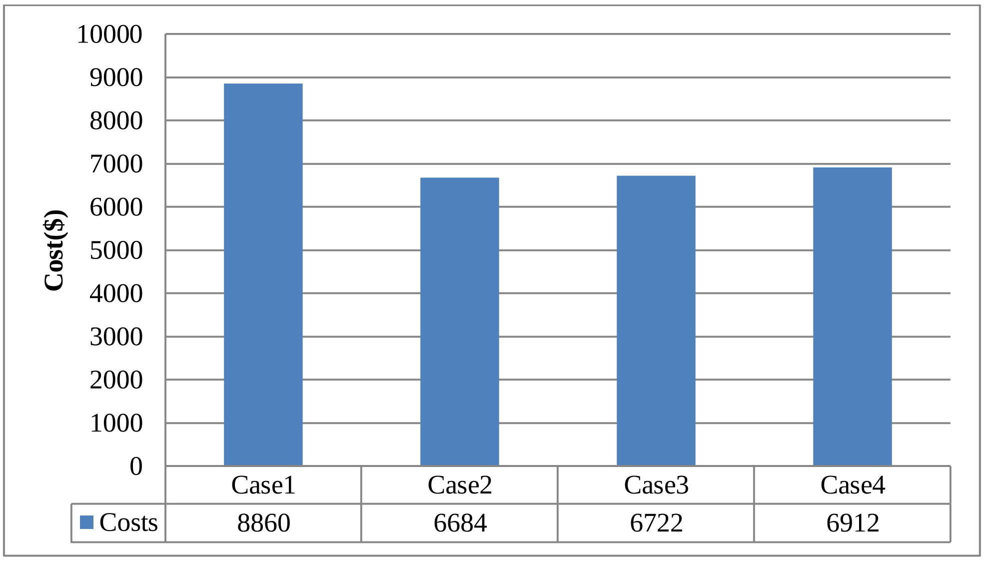

Figure 4.37: Comparison Between the Total Production Costs for the Four Cases by DP.

Chapter 5

CONCLUSION

UC is a complex integrational optimization problem in the power systems. A previous knowledge about generation which have to be committed among available ones to satisfy the load demand not only reduces the generation cost but also helps the system operators in its smooth running. However the UC problem has become more monotonous with the integration of renewable energy in the power network. With the growing concern towards utilizing the renewable sources for producing power, this task has become an interesting task ahead of power engineers today.

In this thesis, UC is applied to two case studies: IEEE 6-bus system which includes three thermal units in addition to one wind farm and IEEE 30-bus system which includes six thermal units plus one wind farm. In the beginning a neural network approach is used to forecast day ahead of the wind power performance then by using Weka program and the forecasted results of the neural network, many scenarios of wind power are generated, two different scenarios are selected randomly to study the uncertainty of the renewable energy. In the first case study two different optimization methods are used to plan day ahead performance of the generators which are GA and DP. The result shows that DP method outperforms GA method under different scenarios of output wind power. Then in the case of IEEE 30-buses DP approach is applied to plan day ahead commitments of the network. Many constraints are taken into account during the optimization techniques such as: maximum and minimum generation limits, minimum down-up time, and the ramp rates limit.

With the current concentration on integration of wind energy based power generation into the network, the study provides an effective solution for UC for the systems having wind plants among their generation and it will help the power utilities in their consideration for taking over new tools/solutions while incorporating the wind energy in the power generation billfold.

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APPENDIX

GA Matlab Code for IEEE 6-Bus for The First Hour.

```
%% main code of UC PROBLEM
objfcn1= @UCproblema;
objfcn2= @UCproblemb;
objfcn3= @UCproblemc;
objfcn4= @UCproblemd;
nvars=3;
%% Generators limits
LBa=[90 10 10];
UBa=[220 100 20];
LBb=[90 10 0];
UBb=[220 100 0];
LBc=[90 0 10];
UBc=[220 0 20];
LBd=[90 0 0];
UBd=[220 0 0];

%%  wind= 0
consfcna1=@ucconstrainta1;
consfcnb1=@ucconstraintb1;
consfcnc1=@ucconstraintc1;
consfcnd1=@ucconstraintd1;
[a1,fvala1]=ga(objfcn1,nvars,[],[],[],[],LBa,UBa,consfcna1);
[b1,fvalb1]=ga(objfcn2,nvars,[],[],[],[],LBb,UBb,consfcnb1);
[c1,fvalc1]=ga(objfcn3,nvars,[],[],[],[],LBc,UBc,consfcnc1);
[d1,fvald1]=ga(objfcn4,nvars,[],[],[],[],LBd,UBd,consfcnd1);
%% forecasted wind value=45.41
consfcna1s1=@ucconstrainta1s1;
consfcnb1s1=@ucconstraintb1s1;
consfcnc1s1=@ucconstraintc1s1;
consfcnd1s1=@ucconstraintd1s1;
[a1s1,fvala1s1]=ga(objfcn1,nvars,[],[],[],[],LBa,UBa,consfcna1s1);
[b1s1,fvalb1s1]=ga(objfcn2,nvars,[],[],[],[],LBb,UBb,consfcnb1s1);
[c1s1,fvalc1s1]=ga(objfcn3,nvars,[],[],[],[],LBc,UBc,consfcnc1s1);
[d1s1,fvald1s1]=ga(objfcn4,nvars,[],[],[],[],LBd,UBd,consfcnd1s1);
%% sinario 1 wind=47.0564
consfcna1s2=@ucconstrainta1s2;
consfcnb1s2=@ucconstraintb1s2;
consfcnc1s2=@ucconstraintc1s2;
consfcnd1s2=@ucconstraintd1s2;
[a1s2,fvala1s2]=ga(objfcn1,nvars,[],[],[],[],LBa,UBa,consfcna1s2);
[b1s2,fvalb1s2]=ga(objfcn2,nvars,[],[],[],[],LBb,UBb,consfcnb1s2);
[c1s2,fvalc1s2]=ga(objfcn3,nvars,[],[],[],[],LBc,UBc,consfcnc1s2);
[d1s2,fvald1s2]=ga(objfcn4,nvars,[],[],[],[],LBd,UBd,consfcnd1s2);
%% sinario 2 wind=50.15
consfcna1s3=@ucconstrainta1s3;
consfcnb1s3=@ucconstraintb1s3;
consfcnc1s3=@ucconstraintc1s3;
consfcnd1s3=@ucconstraintd1s3;
[a1s3,fvala1s3]=ga(objfcn1,nvars,[],[],[],[],LBa,UBa,consfcna1s3);
[b1s3,fvalb1s3]=ga(objfcn2,nvars,[],[],[],[],LBb,UBb,consfcnb1s3);
[c1s3,fvalc1s3]=ga(objfcn3,nvars,[],[],[],[],LBc,UBc,consfcnc1s3);
[d1s3,fvald1s3]=ga(objfcn4,nvars,[],[],[],[],LBd,UBd,consfcnd1s3);

%% Comparing UC results
z1=[a1 fvala1;b1 fvalb1;c1 fvalc1;d1 fvald1]
z1s1=[a1s1 fvala1s1;b1s1 fvalb1s1;c1s1 fvalc1s1;d1s1 fvald1s1]
z1s2=[a1s2 fvala1s2;b1s2 fvalb1s2;c1s2 fvalc1s2;d1s2 fvald1s2]
z1s3=[a1s3 fvala1s3;b1s3 fvalb1s3;c1s3 fvalc1s3;d1s3 fvald1s3]
```

```
z1s4=[a1s4 fvala1s4;b1s4 fvalb1s4;c1s4 fvalc1s4;d1s4 fvald1s4]
z1s5=[a1s5 fvala1s5;b1s5 fvalb1s5;c1s5 fvalc1s5;d1s5 fvald1s5]
result=[d1 fvald1 d1s1 fvald1s1 d1s2 fvald1s2 d1s3 fvald1s3 d1s4
fvald1s4 c1s5 fvalc1s5]

%% fitness function
function a= UCproblema (x)
 a =
(176.9+13.5*x(1)+0.0004*x(1)^2+100)*1.2469+(129.9+32.6*x(2)+0.001*x(
2)^2+300)*1.2461+(137.4+17.6*x(3)+0.005*x(3)^2)*1.2462;
end

function b= UCproblemb (y)
y(3)=0;
 b =
(176.9+13.5*y(1)+0.0004*y(1)^2+100)*1.2469+(129.9+32.6*y(2)+0.001*y(
2)^2+300)*1.2461;

end

function c= UCproblemc (z)
z(2)=0;
 c =
(176.9+13.5*z(1)+0.0004*z(1)^2+100)*1.2469+(137.4+17.6*z(3)+0.005*z(
3)^2)*1.2462;

end

function d= UCproblemd (w)
w(2)=0;
w(3)=0;
 d= (176.9+13.5*w(1)+0.0004*w(1)^2+100)*1.2469;

end
%% forcasted wind =0
function [c,c_eq]= ucconstrainta1(x)
 c=[];
c_eq=[x(1)+x(2)+x(3)-219.19-3.5];


end

function [c,c_eq]= ucconstraintb1(y)
y(3)=0;
 c=[];
c_eq=[y(1)+y(2)-219.19-3.5];


end

function [c,c_eq]= ucconstraintc1(z)
z(2)=0;
 c=[];
c_eq=[z(1)+z(3)-219.19-3.5];


end
```

```
function [c,c_eq]= ucconstraintd1(w)
w(2)=0;
w(3)=0;
 c=[];
c_eq=[w(1)-219.19-3.5];


end

%% sinario 1 wind=45.41
function [c,c_eq]= ucconstrainta1s1(x)
 c=[];
c_eq=[x(1)+x(2)+x(3)+45.41-219.19-3.5];


end

function [c,c_eq]= ucconstraintb1s1(y)
y(3)=0;
 c=[];
c_eq=[y(1)+y(2)+45.41-219.19-3.5];


end

function [c,c_eq]= ucconstraintc1s1(z)
z(2)=0;
 c=[];
c_eq=[z(1)+z(3)+45.41-219.19-3.5];


end

function [c,c_eq]= ucconstraintd1s1(w)
w(2)=0;
w(3)=0;
 c=[];
c_eq=[w(1)+45.41-219.19-3.5];


end
%% sinario 2 wind=47.0564
function [c,c_eq]= ucconstrainta1s2(x)
 c=[];
c_eq=[x(1)+x(2)+x(3)+47.0564-219.19-3.5];


end

function [c,c_eq]= ucconstraintb1s2(y)
y(3)=0;
 c=[];
c_eq=[y(1)+y(2)+46.0564-219.19-3.5];


end
```

```
function [c,c_eq]= ucconstraintc1s2(z)
z(2)=0;
 c=[];
c_eq=[z(1)+z(3)+46.0564-219.19-3.5];


end

function [c,c_eq]= ucconstraintd1s2(w)
w(2)=0;
w(3)=0;
 c=[];
c_eq=[w(1)+46.0564-219.19-3.5];


end

%% sinario 3 wind=50.15
function [c,c_eq]= ucconstrainta1s3(x)
 c=[];
c_eq=[x(1)+x(2)+x(3)+50.15-219.19-3.5];


end

function [c,c_eq]= ucconstraintb1s3(y)
y(3)=0;
 c=[];
c_eq=[y(1)+y(2)+50.15-219.19-3.5];


end

function [c,c_eq]= ucconstraintc1s3(z)
z(2)=0;
 c=[];
c_eq=[z(1)+z(3)+50.15-219.19-3.5];


end

function [c,c_eq]= ucconstraintd1s3(w)
w(2)=0;
w(3)=0;
 c=[];
c_eq=[w(1)+50.15-219.19-3.5];


end
```