

STUDY OF UNIT COMMITMENT WITH LOAD FORECASTING THROUGH NEURAL NETWORK

A Dissertation submitted in fulfillment of the requirements for the Degree
of

MASTER OF ENGINEERING *in* **Power Systems**

Submitted by

Isha Arora
801441011

Under the Guidance of
Ms. Manbir Kaur
Associate Professor, EIED



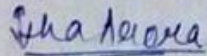
2016

Electrical and Instrumentation Engineering Department
Thapar University, Patiala
(Declared as Deemed-to-be-University u/s 3 of the UGC Act., 1956)
Post Bag No. 32, Patiala – 147004
Punjab (India)

DECLARATION

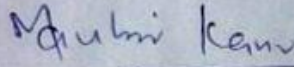
I hereby certify that the work which is presented in dissertation entitled, "STUDY OF UNIT COMMITMENT WITH LOAD FORECASTING THROUGH NEURAL NETWORK", in partial fulfillment of the requirements for the award of the degree of Master of Engineering in Power Systems, submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of Ms. Manbir Kaur. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

Place: Patiala
Date: 8.7.2016

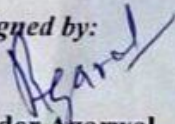

Isha Arora
Isha Arora
Roll No.: 801441011

It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

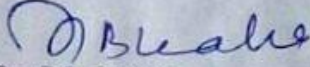
Date: 8.7.2016


Ms. Manbir Kaur
Associate Professor
Electrical & Instrumentation Engineering Department
Thapar University, Patiala

Countersigned by:


Dr. Ravinder Agarwal

Head
Electrical & Instrumentation Engineering Department
Thapar University,
Patiala


Dr. S.S. Bhatia

Dean (Academic Affairs)
Thapar University,
Patiala

CERTIFICATE

Certified that the dissertation entitled, "STUDY OF UNIT COMMITMENT WITH LOAD FORECASTING THROUGH NEURAL NETWORK", which is being submitted by Isha Arora in fulfillment of the requirements for the award of the Master of Engineering in Power Systems, to Thapar Institute of Engineering & Technology University, Patiala, is a bona-fide record of the candidate's own work carried out by her under my supervision and guidance. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other university or institute for award of any degree.

Place: Patiala
Date: 8.7.2016


Supervisor

ACKNOWLEDGEMENT

I would wish to express my gratitude to Ms. Manbir Kaur, Associate Professor, Electrical and Instrumentation Engineering Department. I acknowledge the support, the encouragement extended by her. Thank you for being kind and benevolent. I am really very fortunate to have the opportunity to work with her.

I would like to thank Dr. Ravinder Agarwal, Head of the Department, EIED, for his continuous inspiration during this time. I am very much thankful to all the department staff who have contributed directly or indirectly towards my thesis work. I would like to thank Thapar University, Patiala for providing all the necessary facilities for successful completion of this work.

I am also thankful to all those researchers whose work has been consulted, utilized and cited in my dissertation.

I would like to pay my regards to my parents and family for their contribution, love and everlasting support.

All above, I extend my indebtedness to thee 'ALMIGHTY' for all His graces and kindness.

Isha Arora
801441011

TABLE OF CONTENTS

	Page
DECLARATION	i
CERTIFICATE	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF ABBREVIATIONS	ix
ABSTRACT	x
CHAPTER-1 INTRODUCTION	1-7
1.1 Overview	1-2
1.1.1 Load forecasting	1
1.1.2 Unit Commitment	2
1.2 Literature Survey	2-7
1.3 Objectives	7
1.4 Gap of study	7
1.5 Organization of the Work	7
CHAPTER - 2 MEDIUM TERM LOAD FORECASTING	8-12
2.1 Overview	8
2.2 Classification of Load Forecasting	8-9
2.3 Factors Affecting Load Forecast	9-11
2.4 Medium Term Load Forecast	11
2.5 Applications of Medium Term Load Forecast	11-12
2.6 Accuracy of Medium Term Load Forecast	12
2.7 Medium Term Load Forecasting Techniques	12
CHAPTER - 3 MEDIUM TERM LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK	13-23
3.1 Introduction	13-15
3.2 Components of Artificial Neural Network	15-19
3.3 Network Architecture	19-20

TABLE OF CONTENTS (Continued)

	3.3.1	Multilayer Feed forward Networks	20
	3.3.2	Recurrent Networks	20
3.4		Back Propagation Algorithm	21-23
	3.4.1	Back propagation algorithm for multi-layer feed forward networks	21-22
	3.4.2	Back propagation algorithm for layer recurrent networks	22-23
3.5		Forecasting Accuracy	23
CHAPTER – 4		SIMULATION AND RESULTS FOR LOAD FORECASTING	24-36
	4.1	Problem Formulation	24
	4.2	Selection of Network Configuration - Structure Learning	24-31
	4.2.1	Solution Methodology	27-31
	4.3	Parameter Learning	31-36
	4.3.1	Case 1: Hourly Load Forecasting	31-32
	4.3.2	Case 2: Weekly Load Forecasting	32-34
	4.3.3	Case 3: Weekly Load Forecasting	34-36
CHAPTER - 5		UNIT COMMITMENT	37-48
	5.1	Introduction	37-38
	5.2	Consideration of Unit Commitment	38-39
	5.3	Constraints in Unit Commitment	39-41
	5.3.1	Type of Unit	39
	5.3.2	Units' minimum and maximum generation limits	39
	5.3.3	Units' minimum up and minimum down time limits	40
	5.3.4	Units' Initial Status	40
	5.3.5	Crew Constraints	40
	5.3.6	Start-up Cost	40
	5.3.7	Production Cost	40

TABLE OF CONTENTS (Continued)

5.3.8	Generation Emission	41
5.3.9	Spinning Reserve	41
5.4	Formulation of Unit Commitment	41-43
5.4.1	Power balance constraint	42
5.4.2	Spinning reserve constraint	42
5.4.3	Unit Generation Limits	42
5.4.4	Units' minimum up/down time	42
5.5	Dynamic Programming	43-46
5.5.1	Introduction	43
5.5.2	Dynamic Programming Approaches	43-44
5.5.2.1	Forward direction	43
5.5.2.2	Backward direction	44
5.6	Unit Commitment Scheduling Using Dynamic Programming Approach	44-48
CHAPTER - 6	RESULTS - UNIT COMMITMENT	49-60
6.1	Test Case 1	50-53
6.2	Test Case 2	51-56
6.3	Emission Constrained Single Objective Problem	56-60
6.3.1	Single Objective - Minimising Production Cost	57-58
6.3.2	Single Objective - Minimising Emission	59-60
CHAPTER - 7	CONCLUSION AND FUTURE WORK	61-62
7.1	Conclusion	61
7.2	Future Work	61
REFERENCES		63-69
PUBLICATIONS		70
APPENDIX		71-76

LIST OF TABLES

Table No.	Caption	Page
1	Day type and respective status	25
2	MSE and Time Elapsed for Different ANN Structures	31
3	Nomenclature of Input Neuron for case - 1	33
4	Nomenclature of Input Neuron for case - 2	34
5	MSE obtained for 100 epochs for case - 2	35
6	Nomenclature of Input Neuron for case - 3	36
7	MSE obtained for 100 epochs for case - 3	37
8	Forecasted load demand for test case - 1	49
9	Forecasted load demand for test case - 2	49
10	Data of 5 generating units for test case -1	50
11	List of feasible states for 7 th hour for 2 nd combination of constraints for test case - 1	50
12	Commitment schedule for 5 units over 24 hour load pattern for test case - 1	51
13	Hourly schedule and operating costs for 2 nd combination of constraints for test case - 1	52
14	Results obtained for each combination for test case -1	53
15	Data of 10 generating units for test case - 2	53
16	Commitment schedule for 10 units over 24 hour load pattern for test case - 2	54
17	Hourly schedule and operating costs for 2 nd combination of constraints for test case - 2	55
18	Results obtained for each combination for test case -2	56
19	Data of 10 Generating Units	56
20	Hourly Generation Levels of Units	57
21	Hourly Production Cost and Emission	58
22	Hourly Generation Levels of Units	59
23	Hourly Production Cost and Emission	60

LIST OF FIGURES

Figure No.	Caption	Page
1	Wind speed variation all through a year	9
2	Temperature variation all through a year	9
3	Load curves	10
4	Load patterns	11
5	Multi-layer Feed forward network	14
6	Process flowchart of modelling using ANN	15
7	Basic Structure of an Artificial Neuron	16
8	Layer recurrent network	20
9	MSE for topology T1	27
10	MSE for topology T2	27
11	MSE for topology T3	27
12	MSE for topology T4	27
13	MSE for topology T5	28
14	MSE for topology T6	28
15	MSE for topology T7	28
16	MSE for topology T8	28
17	MSE for topology T9	28
18	MSE for topology T10	28
19	MSE for topology T11	29
20	MSE for topology T12	29
21	MSE for topology T13	29
22	MSE for topology T14	29
23	MSE for topology T15	29
24	MSE for topology T16	29
25	MSE for different network combinations	30
26	Training time for different network combinations	32
27	Mean Squared Error (MSE) for case 1	33
28	Mean Squared Error (MSE) with 15 hidden neurons for case 2	34
29	Mean Squared Error (MSE) with 18 hidden neurons for case 2	35
30	Mean Squared Error (MSE) with 21 hidden neurons for case 2	35
31	Mean Squared Error (MSE) for different number of hidden neurons for case 3	37
32	Unit Commitment via forward dynamic programming	48

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
UC	Unit Commitment
MTLF	Medium Term Load Forecasting
FFD	Feed forward Network
LRT	Layer Recurrent Network
MSE	Mean Squared Error
DP	Dynamic Programming
IEEE	The Institute of Electrical and Electronics Engineers

ABSTRACT

Unit commitment scheduling of power system depends upon the prediction of the load demand, load demand trend, availability of generating units, minimum and maximum generating capacity of the units, minimum up and down time of the generators and initial status of units. As per the past experiences of various power system utilities, different commitment schedules of units' can lead to huge difference in total operating cost incurred. Prediction of future load trends is quite essential for optimal decisiveness in power system operation and planning. Accurate hourly and daily load demand prediction holds an important role for appropriate scheduling of units. The medium term load forecasting is applied for the scheduling of annual maintenance, scheduling of fuel supplies, load dispatch, planning of generation shifting etc.

This work presents dynamic programming forward approach to perform the unit commitment with medium-term load forecast, obtained through training of neural network.

Both structure learning and parameter learning procedures are applied to train the neural network. The input data is constituted of historic weather sensitive parametric quantities i.e. temperature, humidity, wind speed, hour of the day, day type (weekday, weekend, holiday), month of the year and hourly load demand data.

For structure learning, a relative study on the multi-layer feed forward networks and recurrent networks has been executed. The performance of the network configurations is judged based on the mean square error and training time. For the optimally chosen network, parameter learning is carried out using supervised learning and the results attained are reported.

Unit commitment is carried out on all thermal units. Conventional forward approach dynamic programming technique is implemented on different test cases with forecasted load demand to generate optimal solutions. The integration of neural network based load forecasting with unit commitment scheduling is carried out with an objective to improve the quality of solution of unit commitment generation.

Keywords—Artificial neural networks; Constraints; Dynamic programming; Forecasting; Load; Mean square error (MSE); Network architecture; Unit commitment; Weather parameters.

CHAPTER 1

INTRODUCTION

1.1 Overview

Electric utilities run the power grid to deliver power to consumers world-wide. Economic operation has become quite significant with growing uncertain load demands, open access policies, deregulated market structures, leading to increased need of planning operation and management of the system. Load forecasting is crucial constituent of power system planning and operation [1]. As the power corporations are proceeding towards open deregulated markets, unit commitment scheduling is the best alternative for providing secure and cost-effective power to customers.

1.1.1 Load forecasting

Load forecasting, primarily refers to predicting electric demand and energy, is being practised across all sections of the power industry that are generation, transmission, distribution.

It is useful in making important decisions related to load management, economical planning, unit commitment, spinning reserve allocation, voltage control, development of infrastructure. Utilities always confront the challenge of meeting the increasing load demands while maximizing their short-term and long-term usable efficiency. While load forecasting provides a vital contribution to reliable and economic systems operations leading to revenue generation, incorrect load estimates can result in equipment failures or even system-wide blackout [2].

Presently, with the advancement of smart grid technologies, load foretelling is of even more significance due to its applications in the preparation of demand side management, distributed generation, etc. The accuracy of load forecasting is influenced by many factors such as, geographic diversity, data quality, weather factors, time factors and customer distribution. Although many techniques have been established, studied and executed to load forecasting, still it remains a very demanding issue as it is devoid of any systematic outlook or some benchmark method, hence, making the load forecasting problem quite complex.

1.1.2 Unit Commitment

Unit Commitment (UC) aims toward minimising overall production cost while satiating numerous equality and inequality constraints such as reserve requirements of the system,

generating limits of units, ramp limits of units, operating costs, start-up costs of units and shut down costs of units. Optimum scheduling of units enhances reliability of the power system and can lead to cost savings [3]. It is used to determine the day wise scheduling of the available units.

Since UC of thermal units is based on forecasted load, accurate load prediction is of quite significance for optimum planning and functioning of power system. Inaccurate load predicting can cause improper commitment schedule of units that is, under forecasting may lead to purchasing power from markets at increased rates or over forecasting may result in unnecessary scheduling of generating units.

1.2 Literature Survey

In this section, literature on electric load forecasting and unit commitment is studied and briefly reported.

Hong *et al.* [4] have proposed a naïve linear regression based benchmark model for load forecasting. The model developed incorporates various qualitative and quantitative factors such as customer count, weather variables like hourly temperature, hourly load and calendar variables suchlike hour, day and month.

Wang *et al.* [5] have implemented this regression model and presented weather station selection system to decide number of and which weather stations to use for area of interest, considering temperature as the most significant weather variable for load forecasting.

Garg *et al.* [6] have proposed fuzzy based model for forecasting rice production, emphasizing the influence of trend and seasonal variations. The model can be used as reliable means for analysing and forecasting crop production.

Artificial Neural Networks (ANNs) learns to perform required tasks using specific training algorithms. ANNs are able to define non-linear relation that persists between historical load data K. Methaprayoon *et al.* [7] have developed model for short term load forecasting built on artificial neural network, and it has been utilised for resource planning and unit commitment. The results depict that ANN forecasting model provides solution with better accuracy and model can be modified as per the utility's requirements.

Falvo *et al.* [8] have reported a method for medium term load forecasting ANN based that is a multi-layer perceptron via feed forward error back propagation algorithm, giving the results for monthly maximum demand and monthly energy consumption of a municipal locality.

Yun Lu [9] has presented a neural network based load forecasting method. The results have shown that ANN method provides basis for improving forecasting accuracy as well as studying effect of various load factors such as weather parameters, date type variables.

Afrah Nazir [10] has evaluated different type of neural networks and carried out comparative analysis on the basis of mean square error results, classification rate and training time of the networks.

Sharif *et al.* [11] have applied set of independent feed-forward neural networks to forecast the load of each hour during a day. The range of training data set is adjusted to reduce the error of forecasted hourly loads of the upcoming hours.

Papalexopoulos *et al.* [12] have reported that ANN model provides accurate load predictions under a huge variety of power system operating conditions. It has been shown that ANNs are capable of integrating weather and random effects affecting load efficiently with load patterns.

Adepoju *et al.* [13] have illustrated the application and efficiency of ANNs for load forecasting of the Nigerian power system. Number of nodes in hidden layer has been varied to evaluate the difference between performances of various networks.

Zarezadeh *et al.* [14] have come up with ANN method to estimate hourly average electricity price for Iran's electricity markets, as forecasting has become quite important for present day's deregulated electricity markets. Six different ANN structures are designed and then compared to access better results. The study concluded that for forecasting electricity prices ANNs perform better in comparison with traditional regression models.

Feilat *et al.* [15] have presented neural network based approach for medium term load forecasting of distribution system of Al-Dakhiliya, comprising of historical monthly load data, temperature, wind speed and humidity. The performance of neural networks have been matched with the classical multiple linear regression models and established that results obtained by ANN more sensible and satisfactory. There is great potential in utilisation of weather ensemble predictions in ANN load forecasting technique has been reported by Taylor *et al.* [16].

Salama *et al.* [17] have carried out the forecasting for medium term by implementing ANN technique. The forecasting has been conducted for one year and five year period. It has been concluded that weather condition is one of the most significant criteria that affects medium term load forecasting but lack of input variables of network structures, sometimes lead to incorrect results.

Park *et al.* [18] have proposed that the ANN method is suitable to incorporate the relation among the temperature and load pattern of training data sets to predict the future load patterns. Also it has been reported that use of other weather variables such as cloud coverage, wind speed in addition to temperature would generate improved results.

Khotanzad *et al.* [19] have described ANN based short term load forecasting system that is presently being used by various utilities across USA and Canada. The system developed has provided insight into the structure learning of ANNs. It has been concluded that the huge adoption of this ANN system is a strong proof of neural network technique's better performance and edge over the earlier conventional tools being used for forecasting.

Atiya *et al.* [20] have applied ANNs to predict the flow of the river Nile in Egypt, which is helpful in agricultural water management and safety from water shortages or flood destruction.

Lu *et al.* [21] have made a comparison of ANN based forecasting model with the statistical forecasting methods and have reported that ANN based models are quite helpful, effective means for load forecasting and provide more promising results in load prediction.

Peng *et al.* [22] have developed a neural network strategy that consists of combination of linear and nonlinear terms to correlate past load and temperature inputs to the forecasted output.

Al-Saba *et al.* [23] have depicted the implementation of the ANN to long period load forecasting. The model has been used to predict the annual peak demand and energy requirements of a Middle Eastern utility. It has been concluded the ANN technique yields accurate results comparatively than other statistical forecasting approaches.

Unit Commitment

Unit commitment planning of utility depends on load pattern, forecasted demand, capacity and availability of generators. Saksornchai *et al.* [24] have described the practise to improve the unit commitment scheduling by means of the correct hour-ahead and day-ahead outcomes from the neural network built load predicting program in SCADA and EMS.

Kerr *et al.* [25] have laid emphasis on the necessity to determine unit commitment scheduling form economic viewpoint in power system operations, have discussed different aspects of UC, various operating restrictions, and prepared solution methodology to solve UC problem.

Snyder *et al.* [26] have presented a dynamic programming formulation for unit commitment issue. The results are tested on medium size utility. España *et al.* [27] have proposed mixed integer linear programming approach of scheduling of thermal units. Results have shown that the proposed formulation enhances the convergence speed, reduces computational time while achieving better quality solutions.

Sen *et al.* [28] have presented the purpose of UC and discussed the unit commitment issue along with various objective functions, constraints and different approaches to solve the unit commitment scheduling problem.

Lee [29] has demonstrated method to solve the fuel constrained unit commitment for Oklahoma utility. Various fuel constraints, minimum up time and minimum down time constraints, initial condition of units have been considered in the system to determine short-term UC schedule.

Vemuri *et al.* [30] have given a general method of solving UC with fuel constraints in consideration. Lagrangian Relaxation technique has been used to solve the fuel dispatch and UC problem. The method has been implemented with hourly and daily periods for 10 units in southwest U.S. utility's EMS.

Lee *et al.* [31] have presented a thermal UC approach for multi-area interconnected power systems. Spinning reserve requirements, time constraints are taken into account. The method has been used to obtain near optimal multi-area commitment schedule resulting in significant cost savings.

Ma *et al.* [32] have incorporated optimal power flow along with transmission security and voltage constraints in the UC problem formulation. The efficiency of the method is demonstrated on a 36-unit system in the IEEE-118 bus network.

Gjengedal [33] has presented approach to solve the emission constrained UC problem. The approach deduces the least cost solution for meeting daily and weekly emission targets. It is solved on the basis of Lagrangian Relaxation algorithm, considering variable emission during start-up, operation, shut-down of generating units.

Lee *et al.* [34] have proposed method for multi-area UC based on sequential commitment process. DC power flow model has been used to depict the inter-area transmission interconnection. The effectiveness of the method has been demonstrated on a four-area sample structure.

Sheble' *et al.* [35] have applied various optimisation techniques to obtain the solution of thermal UC problem. Techniques have been compared over short-term period considering various constraints such as crew constraints, minimum up and down time constraints.

Gjengedal *et al.* [36] have put forward efficient method to resolve the multi-objective UC problem. The method given is capable of handling numerous constraints such as variable start-up or shut-down costs, emission constraints, minimum up-down time limits. The solution based on Lagrangian Relaxation method finds both minimum emission and minimum cost unit commitment for a power system.

Park *et al.* [37] have proposed a modified DP solution to work out the UC problem, while incorporating production cost and start-up cost constraints of generating units. The analysis made has concluded that modified DP is more effective than standard DP for huge scale power system as combinations of state of generators increases exponentially.

Handschin *et al.* [38] have described a technique for unit commitment scheduling taking into account energy constraints derived from long-term optimisation. Pandžić *et al.* [39] have presented transmission restrained UC formulation. Results have shown that stochastic unit commitment is the most effective way of handling wind uncertainty.

Kanchev *et al.* [40] have proposed 24 hour ahead power planning for microgrid using UC by dynamic programming approach, and the system considered is comprised of twelve PV based generators and three micro gas turbines.

Singhal *et al.* [41] have put forward the solution for large scale UC problem based on the dynamic programming, minimal total cost has been identified that incorporates costs related to start-up /shut down of units and production costs of generating units.

Pang *et al.* [42] have compared the performance of various methods to resolve the UC problem based on economic schedules and computing time. The modelling of inter-area flow network has also been presented considering transmission constraints.

Kaddah *et al.* [43] have presented a proposed solution for UC issue applied on multi-area framework comprised of storage units, conventional and renewable energy sources. The multi constrained multi objective problem is aimed at obtaining minimal total operating cost. The solution methodology based on dynamic programming and neural network has been executed on standard IEEE 30 bus two-area system.

1.3 Objectives

The objective of the study is to perform unit commitment of thermal units based on medium term load forecast. ANNS approach is used to conduct medium term load forecasting by incorporating weather parameters such as temperature, wind speed, humidity. The work presented is carried out in following steps:

1. Data Collection for load forecasting.

2. Structure learning to optimally choose network among different network architectures.
3. Parameter learning on the selected network using error-back propagation algorithm.
4. Unit commitment scheduling for forecasted load pattern using dynamic programming.

1.4 Gap of Study

Different works are described in literature survey about the unit commitment but the work on this topic that marked as gap of study is given below:

- Unit commitment results are computed for variable reserve requirement of the system.
- Comparison had been made between 2 single objective problems considering emission constraints of the test system.

1.5 Organization of the Work

The dissertation is organized into seven chapters. The contents of these chapters are summarized as:-

Chapter 1 includes the introduction of the load forecasting, unit commitment, brief summary of literature review and objectives of the work.

Chapter 2 introduces the medium-term load forecasting problem and covers the factors affecting load forecasting.

Chapter 3 deals with the theoretical concepts of artificial neural network technique.

Chapter 4 contains the proposed technique for medium term load forecasting by utilising ANN model.

Chapter 5 provides with the knowledge about unit commitment and dynamic programming approach used to solve the unit commitment scheduling problem.

In chapter 6, the results of unit commitment problem are reported.

In Chapter 7, the summary of conclusion and the future work are presented.

CHAPTER 2

MEDIUM TERM LOAD FORECASTING

2.1 Overview

Load forecasting has been a significant practice in electrical utilities since 20th century. For operation to be effective, economical and safe the day-to-day load demand of the customers must be recognised beforehand accurately. Load forecasting is the central and crucial criterion for attaining the aim of optimum planning and functioning of power system. The accurateness of load prediction has substantial effects on cost incurred for power system operation, generation and maintenance. Forecasting errors generally are the source of vastly increased operating costs. Therefore, accuracy in load prediction is quite significant. Both under forecasting and over forecasting affect the outcomes of operation economically. Utility that under-forecasts its load, may be impelled to purchase energy from the market at heavier rates; or a utility that over-forecasts the load, generates more energy than needed, leads to wastage of energy and resources . Accurate prediction models for load demand are substantial for the utilities' functioning and planning, as energy producers, finance companies, and numerous contributors in electricity generation, transmission and distribution markets. Setting up forecast models on the basis of available data to improve forecast accuracy has been an important topic for load forecasting in power system. In the past years, the power industry has gone innovative and is moving towards open markets. With the development of Smart Grid, due demand response and distributed generation, the usual obstacles to load forecasting persist and are further complicated.

2.2 Classification of Load Forecasting

The forecasting horizon ranges from hours to days to several years to several decades. Various methods are developed and are being used to model the load pattern to find out the future load growth. The natures of the forecasts are dissimilar as well. For example, for a specific area, it is feasible to foresee the following day load demand with an accuracy of around 1-3%. However, it is impossible to foresee the following year peak demand with the same accuracy since precise long term weather forecasts are not accessible.

Based on the time horizon, mainly, Load forecast is mainly divided into 3 categories-

- Short term load forecast ranging from period of one hour to a week. It is used for day-to-day system management, contingency analysis and security assessment [44].

- Medium term load forecast requires load forecast to be done for period of few days to few weeks or few months. It is being carried out for fuel supplies scheduling, scheduling maintenance of units, generation optimization.
- Long term load forecast for period of more than a year. It is performed to plan for the future needs for expansion, machinery purchasing, investment planning.

2.3 Factors Affecting Load Forecast

The exactness of load forecast has an important impact on load forecast and on power system operation, as power system functioning and control is quite responsive to forecasting errors. The essential parameters that affect the load forecast are:

(i) Weather: Weather is the main factor influencing load demand. The change of the weather leads to variation in the consumers comfort level and also in the consumption by few appliances like heater, air conditioner and refrigerator. In the regions of large meteorological deviations in summer and winter, the load patterns vary tremendously. Usually load consumption is higher when there is rise or fall in temperature from a base level.

The most important weather parameters affecting load variations are –

- Cloud coverage
- Humidity
- Sunlight Intensity
- Temperature
- Wind speed

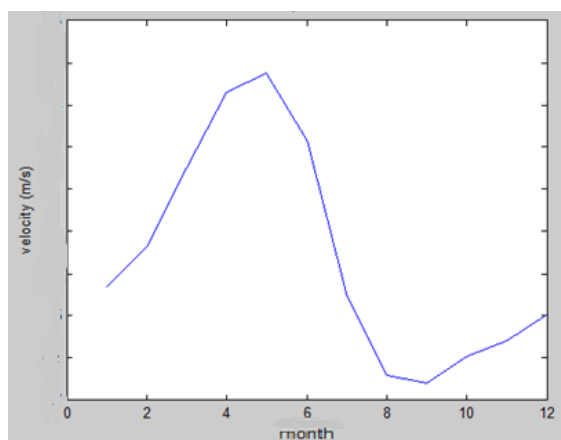


Fig. 1 Wind speed variation all through a year

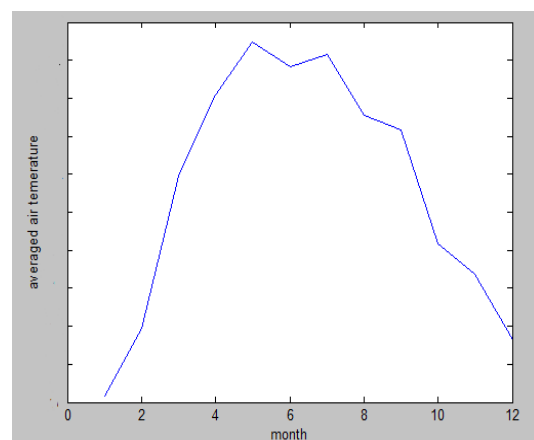


Fig. 2 Temperature variation all through a year

Temperature, wind speed and humidity are usually taken into account for load prediction.

(ii) Time aspect: Time aspect includes factors such as the hour of the day, the day of the week, and the month of the year. Weekdays and weekends load trend vary substantially. Load consumption is different on weekdays as compared with weekends and holidays. This is specifically true during the summer period. Holidays are more complex to forecast than non-holidays due to their relative limited occurrence. Consumer's daily life activities greatly influence the load deviation with time. The weekend or holiday load pattern is usually lesser than the weekday pattern, because of the reduction in operational load. The time of start and end of shifts, beginning of the session of educational institutes also contribute to the important variation of the previous load frames. Periodicity is additional characteristic of the load pattern. There exists periodicity in hourly, daily, weekly, yearly load patterns.

(iii) Economic system: Economic parameters, like the extent of industrialisation, tariff rate and load administering strategies have powerful influence on the system load rise/decay pattern. With the recent inclination towards deregulation of electricity industry, load forecasting has gained more importance.

(iv) Consumer category: Most electrical companies handle consumers of different sorts like residential, commercial and industrial. The electricity consumption trend is different for consumers that belong to distinct categories but is somewhat alike for consumers in each category.

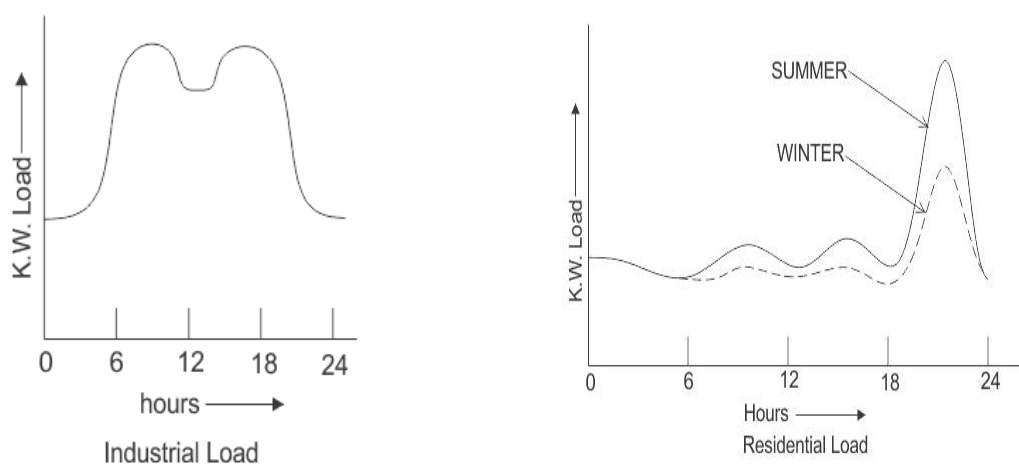


Fig. 3 Load curves

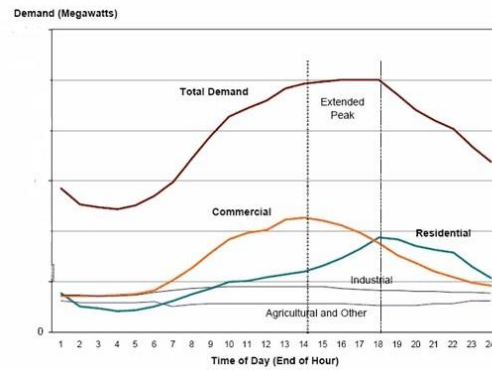


Fig. 4 Load patterns

2.4 Medium Term Load Forecast

The word “medium” implies forecasting period of the order of few days or few weeks or few months or even a year. The medium load forecasting (MTLF) is used to decide the capability of generation, transmission and distribution system, the yearly maintenance scheduling etc. It is of importance both for energy manufacturers to figure out the operation planning of the generation (refilling of thermal power plants, hydro resources managing, maintenance planning etc.) and for transmission and distribution companies to plan the extension of transmission and distribution systems’ capacity in order to reassure the energy and demand in the time period. For medium term load forecasting, the prime parameters are climatological and casual. The impact of monetary factors is unimportant due to the time period which is so brief for the economics effects to be experienced. The meteorological variables that are more firmly correlative to load are temperature and humidity, due to their straightaway impact on major sectors of the end usages, as heating and cooling loads [45].

2.5 Applications of Medium Term Load Forecast

Medium term load forecast is an essential part in the formation of economic and optimal operational policies for the power system .The primary goal of the MTLF is to produce the load forecasts for:

- Generation, transmission and distribution capacities of system
- Outage and maintenance planning
- Fuel supply scheduling

The principal task of medium term load prediction is to optimize generation that contributes towards most economical functioning of system. The load prediction is needed for allocating fuel and maintenance scheduling. Medium term load forecast are used mainly to assist in unit commitment decisions. Correct MTLF gives utilities data to better design power generation

extension (or purchase), plan maintenance actions, execute system betterments and prepare cost effective fuel buying policies. MTLF statistics can be efficiently utilized by the deregulated companies to assist the enhancement of their transmission network hence providing consumers with better service.

2.6 Accuracy of Medium Term Load Forecast

The calculation of the accuracy of framework needs that the forecast computational error, i.e., the deviation of forecasted value of the load from the true value of the load, be resolved at a piece time interval of the predicting duration. However, the realistic forecast error will be governed greatly by the category of load, which is its combination of residential, industrialized, and commercial constituents, its geographic position and distribution, and also the time of year. The load pattern should be anticipated beforehand so as to have enough power generation to satisfy the load requirements. Overestimating may lead to starting-up of too many units and result in an unneeded surge in the reserve and the operating expenditures. Underestimating load forecast fails to cater the required spinning reserve and stability to the power system, which may cause the breakdown of the power system network. Load estimation errors can produce insignificant unit commitment results. Therefore accurate predicting of the load is a crucial component in power system. Both positive and negative forecasting errors give rise to raised operating costs. Reduction in the mean forecasting errors can result in hundreds to thousands to even millions of rupees savings [46].

2.7 Medium Term Load Forecasting Techniques

A wide diversity of statistical and artificial intelligent approaches have been formulated for medium term load forecasting that comprises of methods applying regression, statistical time series models, similar day approach, artificial neural networks, expert systems, fuzzy logic methods.[47].

CHAPTER 3

MEDIUM TERM LOAD FORECASTING USING ARTIFICIAL NEURAL NETWORK

3.1 Introduction

Neural networks are an assuring modern generation of information handling systems that depict the capability to learn, recollect, and generalise from training information or data. ANNs are models that are built to make use of structural instructions similar to that of human brain. ANNs are effective at tasks suchlike pattern matching and sorting, optimization, vector quantization, function estimation, information clustering.

ANNs have huge amount of tremendously inter-connected processing components (nodes or units or neurons) that generally undergo parallel operation and are assembled in regular architectures. The connecting weights support the knowledge. These models have acquired the learning and logically thinking attributes of human brains. ANNs bear the capability to learn and design a complicated nonlinear mapping through a set of input/output patterns. The neural network, via conditioning course, learns the purposeful connection between the network inputs and outputs [48].

Neural networks are simple, but robust, compelling and adjustable means for predicting, as long as there is sufficient information for training, decent choice of the input–output patterns, an apt number of hidden nodes and plenty computing resources accessible. Also, ANNs have the familiar benefits of being capable to proximate any nonlinear mathematical function and have ability to resolve complications where the input–output relationship is neither well specified nor straightforwardly estimable, because ANNs are information driven.

Generally, the ANN maps input details to predict load demands. The input data are previous load patterns and parameters, which have impact the realistic load demand. During conditioning, characteristics from the historical data are recorded into the network's input layer. The node actuation in input layer is fed ahead via the network and the net results are analysed with respect to the actual load values.

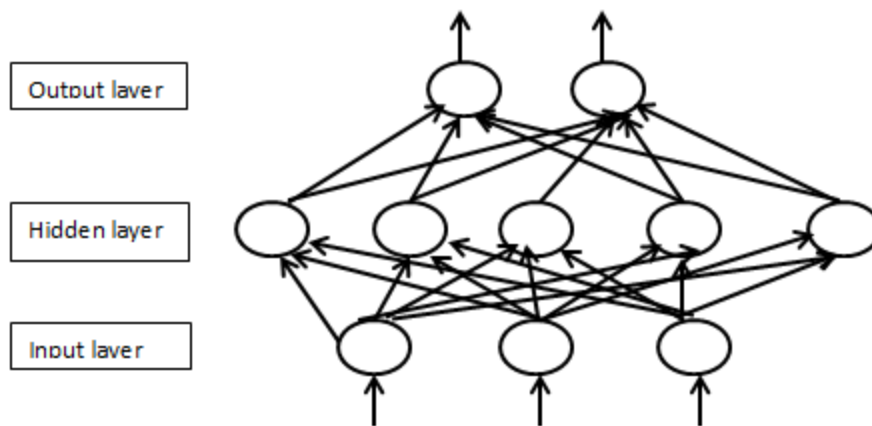


Fig.5 Multi-layer Feed forward network

In employing a neural network to load estimating, one must select the configuration (e.g. feed forward or feedback), the count and connectivity of layers and neurons, usage of bidirectional or unidirectional connections.

Benefits of ANN

1. They can achieve complicated input-output mappings without definitive programming and determine both linear and nonlinear relationships.
2. ANNs are information driven system and do not need restraining presumptions about the type of the key model.
3. ANN can anticipate the pattern which is not given during training (generalization) [49].
4. ANN is effective at training huge scale of patterns because of its parallel processing ability.
5. They are enormously powerful computational tools.
6. Capability to discover all potential interactions between predictor variables.

The architecture of a neural network is fixated for a learning procedure. However, a fixated design may not result in the best performance within the training span provided. If the neural network design is too complex, the training span will have to be stretched, and accordingly the execution costs will be more. Fig. 6 depicts the process flowchart of modelling utilising ANN [50].

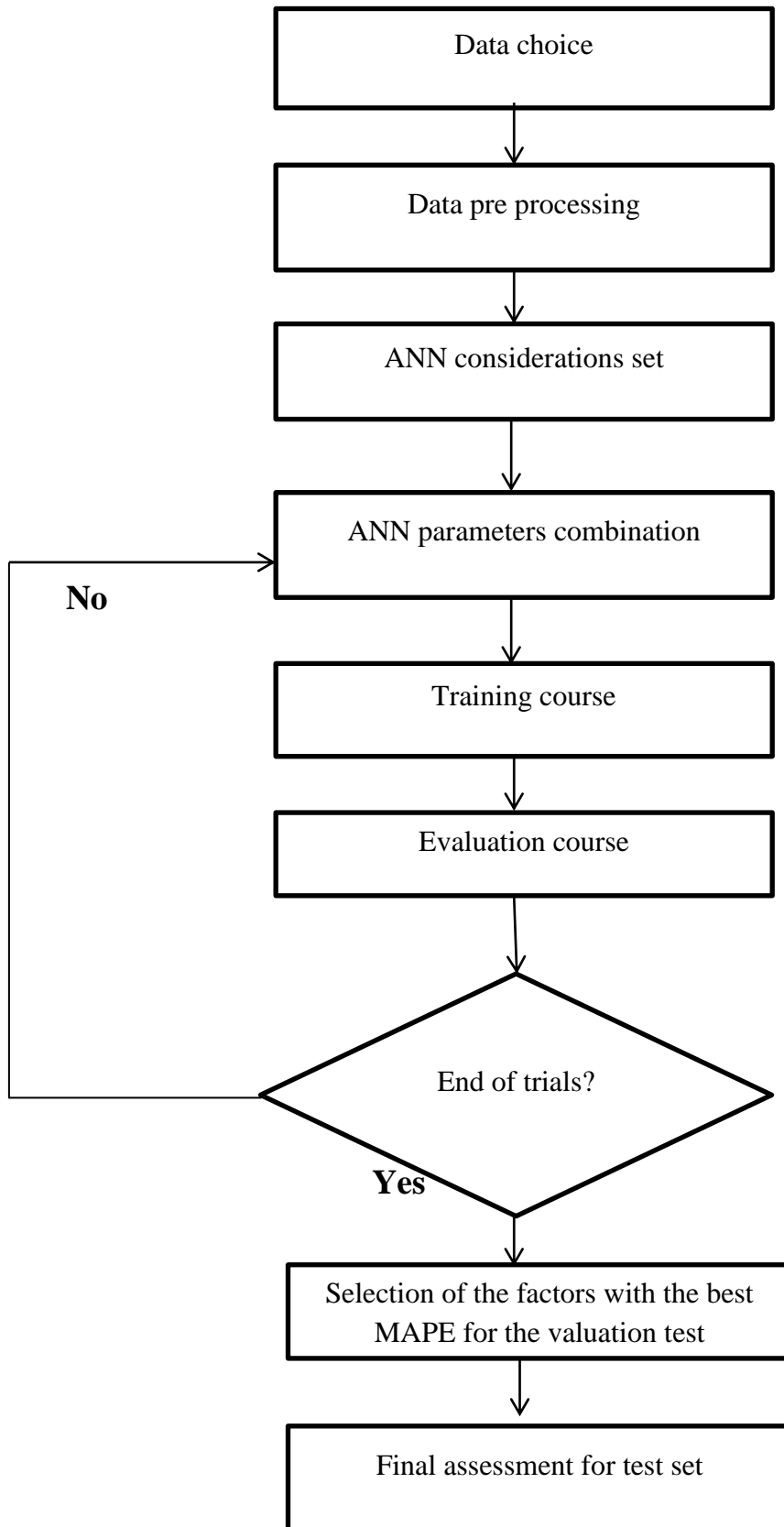


Fig. 6 Process flowchart of modelling using ANN

3.2 Components of Artificial Neural Network

The artificial neural network is composed of some main components. These components are compiled as [51]:-

- Processing Element(Neuron)
- Weighting Elements
- Summation (Addition) Function
- Activation Function
- Output Function
- Error and Back-propagated Value
- Learning Function

Processing Element (Artificial Neuron): Neuron is the basic building segment of an ANN. The fundamental composition of an artificial neuron is shown in Fig.7 In this framework, the connecting weights are modified between the neurons. Node a_i yields node inputs O_{qi} while the network is presented to input pattern q . Each and every input is multiplied by a connecting weight w_{ij} , where w_{ij} is the contact between neurons a_i and a_j . The connecting weights represent the strength of the impact of each of the previous nodes. After the multiplication, values are added, producing net_{qj} . A bias value θ_j is incorporated in the summation to counterbalance the fundamental level of the input to the energising function, $f(net_{qj})$ that produces the output O_{qj} . In order to set up a bias value θ_j , the bias term can come out as an input from a different node with a constant value (a value of +1 usually). Each node needing a bias value will be associated with the same bias node. The bias values are then self-modified as the other nodes learn, without requiring any additional considerations.

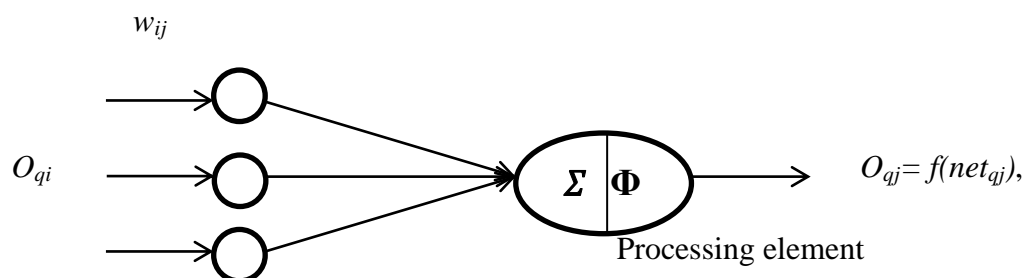


Fig. 7 Basic Structure of an Artificial Neuron

In computing the outcome of the node, the activation function may be of the kind of a threshold function, if a threshold level is attained, the result of the node is +1 and 0 contrarily. The numerous activation functions like hyperbolic tangent, ramp, sigmoidal etc. can be employed.

When a model is designed for particular application, learning of model is carried out by utilising input patterns and correspondent desired outputs till it learns to associate a specific input with an output. A network is conditioned until the variation in connecting weights in a training cycle achieves a minimal value. After training, a model is confirmed by determining whether it generates correct output or not.

Successful functioning of load interpreters applying ANN involves relevant training data set and training principle. It should consider all series of the input samples adequately to produce the network information to observe and generalize the associations among the parameters in the problem [52].

Weighting Elements: A neuron encounters many inputs concurrently. Each input possess its own weight which yields the input influence that it requires on the processing component's summation function. These weights execute the similar kind of function as do the changing synaptic strengths of biologic neurons. In both cases, some inputs are considered more significant than others so that they have a bigger impact on the processing component as they aggregate to produce a neural reaction. These strengths can be adjusted in response to several training data sets and as per network's particular topography or through its learning principles.

Summation (Addition) Function: Firstly the weighted aggregate of all of the inputs is calculated in a processing component's operation. This simple addition function is obtained by multiplying each element of the input by the correspondent element of the w_{ij} matrix and then summing up all the products. So, the input to the node of succeeding layer is a single value, not a multi-dimensional array.

Activation Function: The activation function is indicated by $\Phi (\cdot)$. After addition each processing component has to produce an activation value as a mathematical function of its net via an activation function or transfer function.

Generally used activation functions are:

- Step function
- Ramp function
- Threshold function
- Sigmoidal function

- Unipolar sigmoidal function

$$f(x) = \frac{1}{1 + e^{-x}} \quad (1)$$

- Bipolar sigmoidal function

$$f(x) = \frac{1 - e^{-x}}{1 + e^{-x}} \quad (2)$$

x denotes the net additive value obtained after multiplication of the input patterns with respective weights.

Output Function: Every processing component is permitted one output signal which it may send to hundreds of other nodes. Usually, the output is right away equivalent to the activation function's outcome. Nodes are allowed to contend with one another, hindering processing components unless they have sufficient strength. Competition can take place at one or both of two levels. Firstly, competition finds out which artificial node will be active, or gives an output. Secondly, competitive inputs help specify which processing component will take part in the learning or adaption process.

Error and Back-Propagated Value: The disagreement between the actual output and the target output is computed. This raw error is then altered by the error function to match specific network configuration. Most of the fundamental configurations utilise this error directly, but some use squared error while preserving its sign and other criterion to alter the raw error to match with their particular purposes. The node's error is then by and large transmitted into the learning function of another processing component. Generally, this back-propagated value, undergoes scaling by the learning function, is multiplied by the incoming weights to change them before the succeeding learning cycle.

Learning Function: The intent of the learning function is to change the variable linking weights on the inputs of each processing components as per some neural based algorithm. Generally, the weight updation is given as,

$$\Delta w_{ij} = \eta \Delta E \quad (3)$$

Δw_{ij} = change in the weight linking a_i and a_j neuron

η = learning constant

$\Delta E = \frac{\partial E}{\partial w_{ij}}$ That is, derivative of energy function

Learning Rules: Normally, learning rules are categorised into 3 classes: supervised learning, reinforced learning and unsupervised learning.

In supervised learning, every time when input is employed to a neural network the correspondent output response of the network is provided. Hence the value what it should be producing as output is already mentioned.

But in few circumstances only less elaborated information is accessible for example, the outcome is 'too high', learning based on this type of critic knowledge is known as reinforcement learning. It is a kind of supervised learning since the network still acquires some feedback from its surroundings.

In unsupervised learning, no feedback is available from the surroundings to state what the results should be or whether they are right. The network must find out for itself patterns, characteristics, classes in the input data and cipher for them in output.

3.3 Network Architecture

Network comprises of a set of extremely interconnected processing components such that each component output is linked up through weights, to other components or itself. Layer of the nodes can be created by combining one processing component with other. Inputs can be joined with these nodes via numerous weights, leading in a series of outputs, one per neuron. This leads to a *single layer feed forward network*. Further various layers can be interconnected to frame a *multi-layer feedforward network*, The layer that encounters inputs is known as *input layer*. The outputs of the network are yielded from the *output layer*. Any layer enclosed by the input and output layers is known as a *hidden layer* because it is interior to the network and has no straight link with the exterior surroundings. There may be zero to various hidden layers in a neural network. The network is stated as *fully connected* if each and every output from a layer is linked to every neuron in the succeeding layer. When outputs are directed backwards as input to either same or previous layer neurons, the network is called a feedback network. Feedback networks that consist of closed loops are known as *recurrent networks*. The development of network model calls for determination of different

model parameters such as input variables, incoming patterns, algorithm, transfer function, and topography.

3.3.1 Multilayer Feedforward Networks (FFD)

The other class of a feed-forward neural network (one being single layer feedforward network) differentiates itself by the existence of one or more than one hidden layers, whose computing units are likewise known as hidden nodes. The purpose of hidden node is to step in between the input and the system output in some helpful way. By adding up more hidden layers, the network is capable of determining high order statistics. The input signal is employed to nodes in the second layer. The outcome of second layer is utilised as inputs to the third layer, and so on for the remaining network. Multi-layer feed-forward networks are the recognized and extensively used type of neural network.

3.3.2 Recurrent Networks (LRT)

A recurrent neural network has leastwise one feedback loop. It may be composed of a single layer of nodes with every neuron serving its outcome back to the inputs of every other neuron. Self-feedback refers to condition where the outcome of a node is served backwards into its own input. The existence of feedback loops has a thorough influence on the learning ability of the structure and on its operation. Contrary to feed-forward neural networks, recurrent networks can utilise their internal memory to work on arbitrary series of inputs.

In such networks, self-loops and backward links between the neurons are permitted. The advantage of these networks is that smaller structures may contribute towards the functionality of much bigger feed-forward networks. In layer recurrent networks, in extension to data in the data set, every step has an additional input from the hidden state h_{i-1} from the prior step.

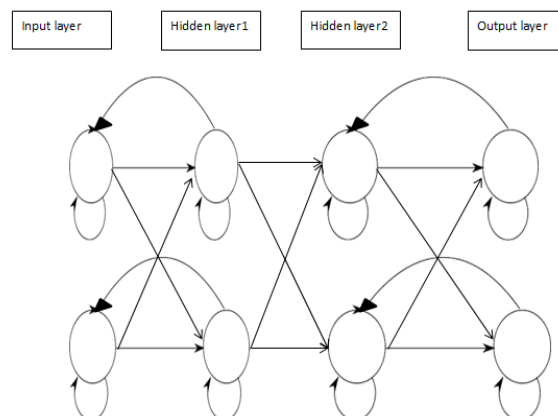


Fig.8 Layer recurrent network

3.4 Back Propagation Algorithm

The back propagation algorithm is one of the most vital historic developments in ANNs. It is good at generalisation. This learning algorithm is used to networks containing processing components with continuous differentiable functions. The algorithm offers a process for altering the weights in a network to categorise the given inputs correctly. The base for this weight update algorithm is the gradient descent method [51].

3.4.1 Back propagation algorithm for multi-layer feed forward networks

Consider a network with M feed forward layers, $m= 1, 2, \dots, M$,

$net_i^{k,m}$ - Net input from i^{th} unit in m^{th} layer for k^{th} pattern,

$y_i^{k,m}$ - Output of the i^{th} unit in m^{th} layer for k^{th} pattern,

w_{ij}^m - Connection weights between i^{th} node of m^{th} layer to j^{th} node of $m-1^{th}$ layer for k^{th} pattern.

Input: A set of training vector x^k with the target output d^k for $k=1 \dots p$.

Step 1 (Initialisation): Choose learning rate $\eta > 0$ and E_{max} (maximum tolerable error). Initialize the weights to small random values. Set $E=0$ and $k=1$

Step 2 (forward propagation): Propagate the signal forward through the network using

$$y_i^{k,m} = a(net_i^{k,m}) = a\left(\sum_j w_{ij}^m y_j^{k,m-1}\right) \quad (4)$$

for each neuron ($i=1 \dots n$) and layer until the outputs of the M^{th} output layer, $y_i^{k,M}$ have all been obtained, where $a(.)$ denotes the activation function of corresponding layer.

Step 3 (Output error measure): Figure out the error value and error signals δ_i^M for the output layer for $i=1 \dots n$

$$E = \frac{1}{2} \sum_{i=1}^n (d_i^{k,M} - y_i^{k,M})^2 \quad (5)$$

$$\delta_i^M = (d_i^{k,M} - y_i^{k,M}) a'(net_i^M) \quad (6)$$

Step 4 (Error back propagation): Transmit the errors backward to update the weights w_{ij} and calculate the error signals δ_i for the previous layers:

$$\Delta w_{ij}^m = \eta \delta_i^{m-1} y_j \quad (7)$$

For m^{th} layer,

$$w_{ij}^q{}^{\text{new}} = w_{ij}^q{}^{\text{old}} + \Delta w_{ij}^q \quad (8)$$

Step 5(One epoch looping): Check whether the complete set of training data has been cycled once. If $k < p$, then $k = k + 1$ and go to step 2; else, go to step 6.

Step 6 (Total error checking): Check whether the current total error is tolerable: If $E < E_{\text{max}}$, then dismiss the training process and output the final weights; otherwise, $E = 0$, $k = 1$, and start the training epoch by going to step 2.

End algorithm.

3.4.2 Back propagation algorithm for layer recurrent networks

Step 1: Find the value y_i of recurrent back propagation network

$$y_i = a(h_i) = a\left(\sum_j w_{ij} y_j + x_i\right) \quad (9)$$

Where $h_i = \sum_j w_{ij} y_j + x_i$ is the net input to the node i when the network is at the attractor.

Step 2: Error Calculation: Calculate the error of each node

$$E = \frac{1}{n} \sum_{k=1}^n E_k^2 \quad (10)$$

$$\text{Where } E_k = \begin{cases} d_k - y_k, & \text{if } k \text{ is an output node} \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

d_k = desired output of k^{th} input pattern

y_k = actual output of k^{th} input pattern

n = total number of input training patterns

$$\Delta w_{pq} = -\eta \frac{\partial E}{\partial w_{pq}} = \eta \sum_k E_k \frac{\partial y_k}{\partial w_{pq}} \quad (12)$$

$$\frac{\partial y_i}{\partial w_{pq}} = a'(h_i) [\delta_{ip} y_q + \sum_j w_{ij} \frac{\partial y_j}{\partial w_{pq}}] \quad (13)$$

$$\sum_j L_{ij} \frac{\partial y_j}{\partial w_{pq}} = \delta_{ip} a'(h_i) y_q \quad (14)$$

Where

$$L_{ij} = \delta_{ij} - a'(h_i) w_{ij} \quad (15)$$

$$\frac{\partial y_k}{\partial w_{pq}} = [L^{-1}]_{kp} a'(h_p) y_q \quad (16)$$

Step 3: Weight update: Update the weights of the network using equations:

$$\Delta w_{pq} = \eta \sum_k E_k [L^{-1}]_{kp} a'(h_p) y_q = \eta \delta_p y_q \quad (17)$$

Δw_{pq} = change in weight connecting pth and qth neuron

Where

$$\delta_p = a'(h_p) \sum_k E_k [L^{-1}]_{kp} \quad (18)$$

δ_p is the error signal for pth neuron.

3.5 Forecasting Accuracy

To assure the model accuracy, the comparative error between the forecasted load demand and the actual load consumed are attained regularly. A positive error value suggests over forecasting, that means that the forecasted load is more than the actual demand. On the other hand, a negative error suggests under forecasting, where the forecasted load value is less as compared to the actual load consumption [53].

CHAPTER 4

SIMULATION AND RESULTS FOR LOAD FORECASTING

4.1 Problem Formulation

The work here has been focused on the analysis of performance of artificial neural network model to carry out hourly and weekly load forecasting.

Load forecasting employing neural networks is carried out in different stages:

1. Selection of optimal architecture
2. Training of patterns
3. Validation and testing.

Learning of a neural network can be done in different ways. A network can be trained by carrying out structure learning or parameter learning or both simultaneously or separately. Structure learning involves varying the topology or the basic structure of the network. It is executed by either adding or eliminating existing connections, varying number of processing elements, modifying connection type that is feed forward network of feedback network, network with self-loops etc. Parameter learning is carried out by controlling the set of weights or by modifying learning constants or type of activation function used. Here, the different topologies undergo structure learning and then the optimal selected network undergoes parameter learning using back propagation algorithm.

4.2 Selection of Network Configuration - Structure Learning

Major factors which have impact on load consumption are recognised. Number of input parameters rely on number of effective parameters considered such as weather data, load data, time factor. The impact of different combinations of multilayer networks, hidden layers and hidden nodes on the forecasting errors is analysed. The relative accuracy of different types of neural network architectural combinations is estimated.

The hidden nodes of hidden layer permit ANN to capture the pattern in the data, and perform non-linear mapping between input and output variables. Number of neurons in hidden layer has an impact on the learning capability of the model and the complexity of neural model changes with it. Number of neurons in the hidden layers should be cautiously chosen, as too

many neurons result in the problem of overfitting,, that leads to loss of generalizing capability. With too many trainable units, the network fails to learn the training data and performs very badly on the testing data. Whereas, if the number of neurons in hidden layer are not sufficient, it may be difficult for the network to train according to the historical data.

Real time data includes

- Weather data
 - Temperature of hour of the day
 - Humidity of hour of the day
 - Wind speed of hour of the day
- Calendar variables
 - Hour of the day
 - Day of the week
 - Month of the year
- Hourly load demand

Data used to perform load forecasting is compiled from Jodhpur State Load Dispatch and Communication Centre, Rajasthan Vidyut Parasaran Nigam (JVN) from March, 2012 – April, 2012. The training data considered is given in Appendix that consists of temperature (°C), humidity (%), wind speed (km/h) and load (MW) information.

Neural network model prepared has a single input layer with number of input neurons as per the number of input variables. As the required output is forecasted load data, model has one output layer with single node.

Three categories of day type that is, weekdays, weekends and holidays have been considered in the study as the load consumption is not same on working day as compared to weekends, and holidays [54]. Status of days is regarded as tabulated in table 1.

Table 1
Day Types and Respective Status

Day type	Status
Weekday	1
Weekend	0.5
Holiday	0.1

Hour variable refers to hour of the day as load keeps on varying during the day from one hour to another.

The size of hidden layer is usually attained using hit and trial method. The number of hidden neurons is started off as a fraction, that is, 2/3 the size of the input layer [55]. If the network fails in converging to a minimal error or a specific solution, more hidden neurons are added. If the network starts to converge, addition of few more neurons is attempted, and finally settles down on the size based on overall performance of the network. The number of hidden layer neurons can be modified for different performance of the network. Topology of network can be altered depending on number of hidden layers, number of neurons in hidden layer.

Activation Function

Continuous differential function is being used. “tansig” has been used as the transfer function for different networks considered. It is sigmoidal activation function that gives value between -1 to +1 (bipolar) and 0 to 1 (unipolar)

$$a(f) = \frac{2}{1 + e^{-\lambda f}} - 1 \quad (19)$$

$$a(f) = \frac{1}{1 + e^{-\lambda f}} \quad (20)$$

$a(f)$ denotes the activation function,

f denotes the net additive value,

λ denotes steepness of curve.

The performance of a forecasting model is usually evaluated by some accuracy measure.

Evaluation criteria considered is:

- Mean squared error: Mean Square Error (MSE) is the squared prediction error. Lesser the MSE the better the classification rate of the network, this means less number of false classification.

$$MSE = \frac{1}{n} \sum_{i=1}^n (d_i - y_i)^2 \quad (21)$$

d_i = target output over the i^{th} input pattern

y_i = actual output of the i^{th} input pattern

n = total input pattern count

- Training time: Training time is the time taken to train the network according to the parameters set for training. It is measured in seconds.

4.2.1 Solution Methodology

In order to find the optimal network architecture, for the data set being considered, several combinations are evaluated. These combinations included networks with different number of hidden layers, different number of units in each layer and different types of connections (unidirectional or bidirectional).

Number of neurons in hidden layer has been changed from 5 to 10 to 15 and so on, and number of hidden layers in the network is changed from 1 to 2. Two network configurations have been considered that is, multi-layer feed forward network and recurrent network. The effects of change in number of nodes and layers on the performance of two network types have been analysed.

Fig. 9 to fig. 24 shows the MSE for different configurations L refers to number of hidden layers and N refers to number of hidden nodes in each hidden layer.

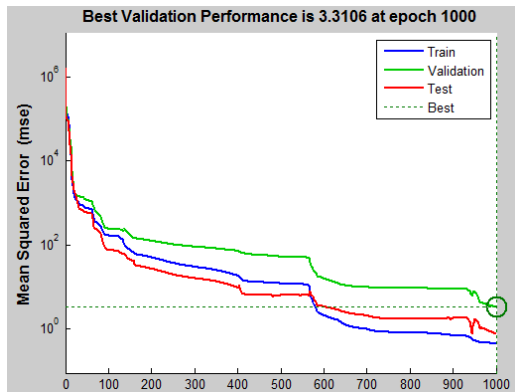


Fig. 9 Case (T1): FFD, L=1, N=5

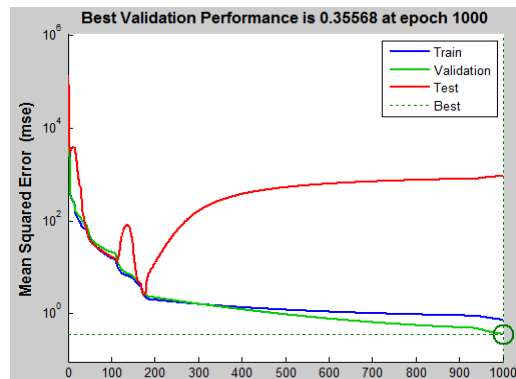


Fig. 10 Case (T2): FFD, L=1, N=10

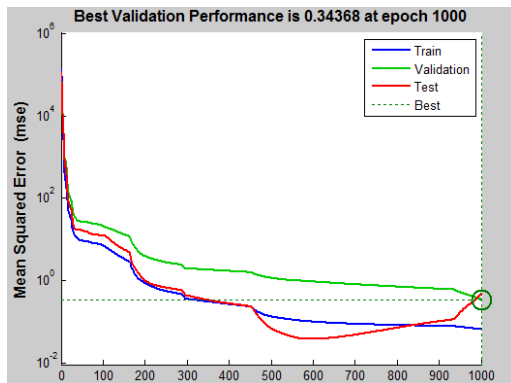


Fig. 11 Case (T3): FFD, L=1, N=15

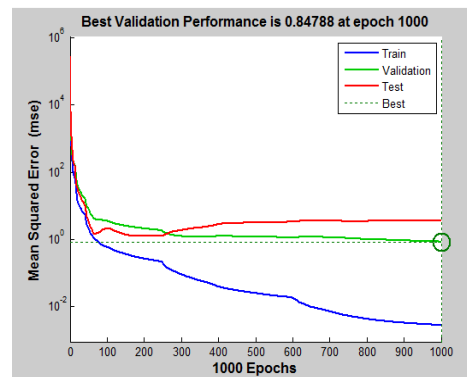


Fig. 12 Case (T4): FFD, L=1, N=21

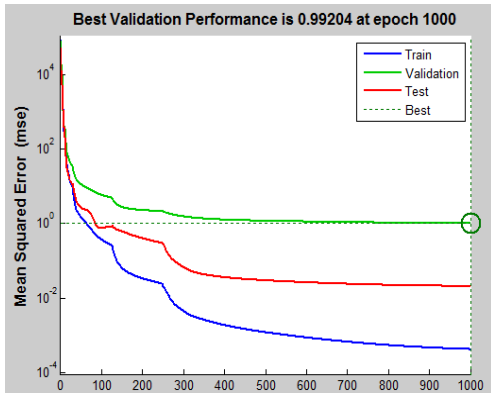


Fig. 13 Case (T5): FFD, L=2, N=5

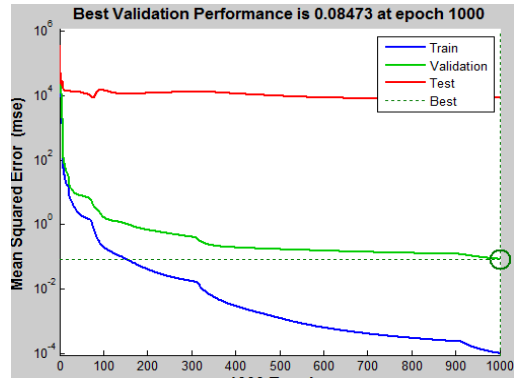


Fig. 14 Case (T6): FFD, L=2, N=10

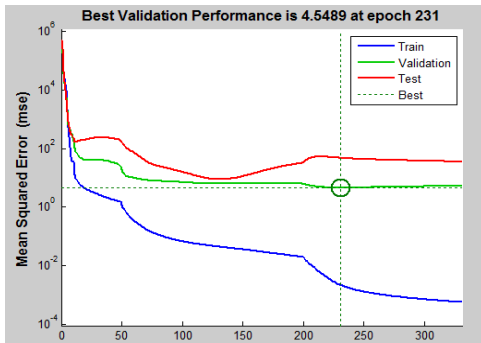


Fig 15 Case (T7): FFD, L=2, N=15

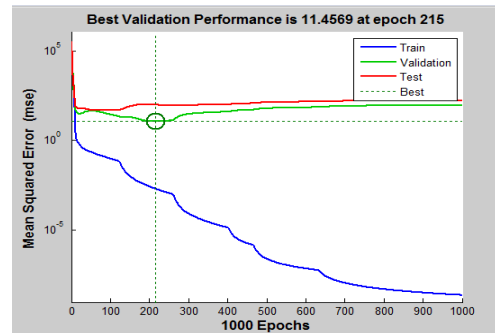


Fig. 16 Case (T8): FFD, L=2, N= 21

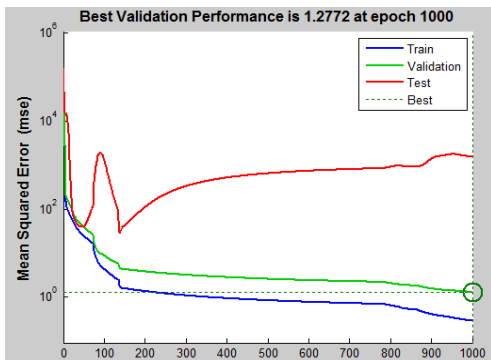


Fig.17 Case (T9): LRT L=1, N=5

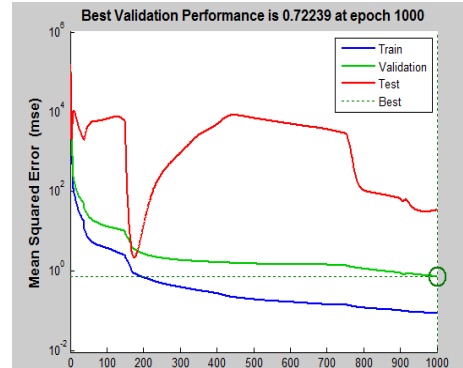


Fig. 18 Case (T10): LRT, L=1, N=10

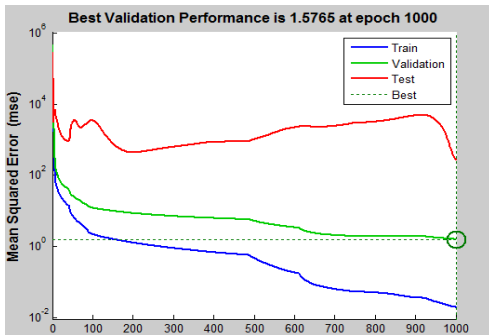


Fig. 19 Case (T11): LRT, L=1, N=15

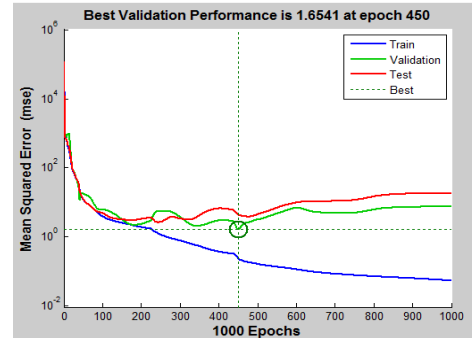


Fig. 20 Case (T12): LRT, L=1, N=21

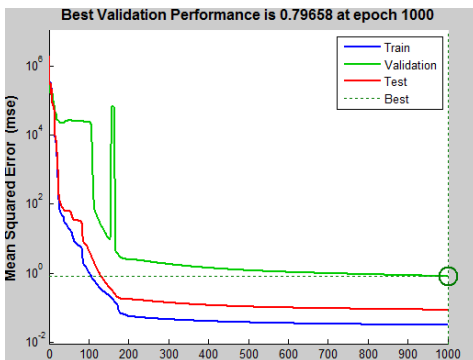


Fig. 21 Case (T13): LRT, L=2, N=5

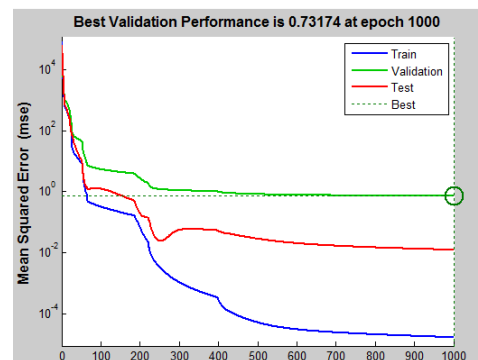


Fig. 22 Case (T14): LRT, L=2, N=10

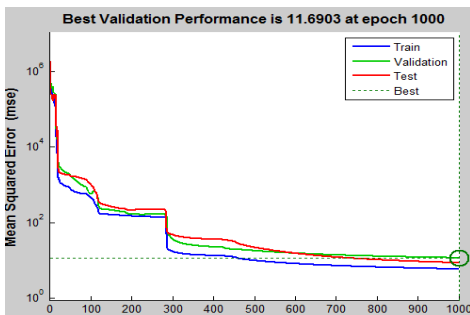


Fig. 23 Case (T15): LRT, L=2, N=15

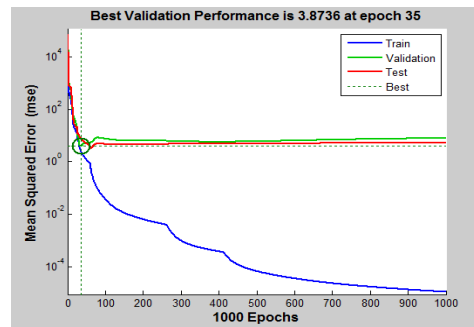


Fig. 24 Case (T16): LRT, L=2, N=21

The network is said to generalize well when it sensibly interpolates input patterns that are new to network. Network with too many trainable parameters for the given amount of training data set learn well but do not generalise well. This phenomenon is usually called over fitting. Training error is presented in blue, validation error in red, both as a function of the number of training cycles. If the validation error increases (positive slope) while the training error gradually declines (negative slope) then a circumstance of over fitting may have

followed. The best foretelling model would be where the validation error has its global minimum.

It is noticed that as the choice of number of hidden neurons is close to three times the number of input neurons, the system starts to overfit. The analysis of different network architectures is confined to 21 hidden neurons.

The results of comparison of the different neural networks the basis of these performance evaluation criteria as depicted in fig. 9 to fig. 24 are tabulated in Table 2, where L represents number of hidden layers and N represents number of hidden nodes in each hidden layer in corresponding configuration:

Each network configuration undergoes 1000 epochs.

Fig. 25 and 26 shows the performance of suggested network topographies in terms of Mean Squared Error (MSE) and training time when trained over 1000 epochs. T1, T2 ...T16 are different topology configurations formed by changing L and N for FFD network and LRT network as per fig. 9 to fig. 24.

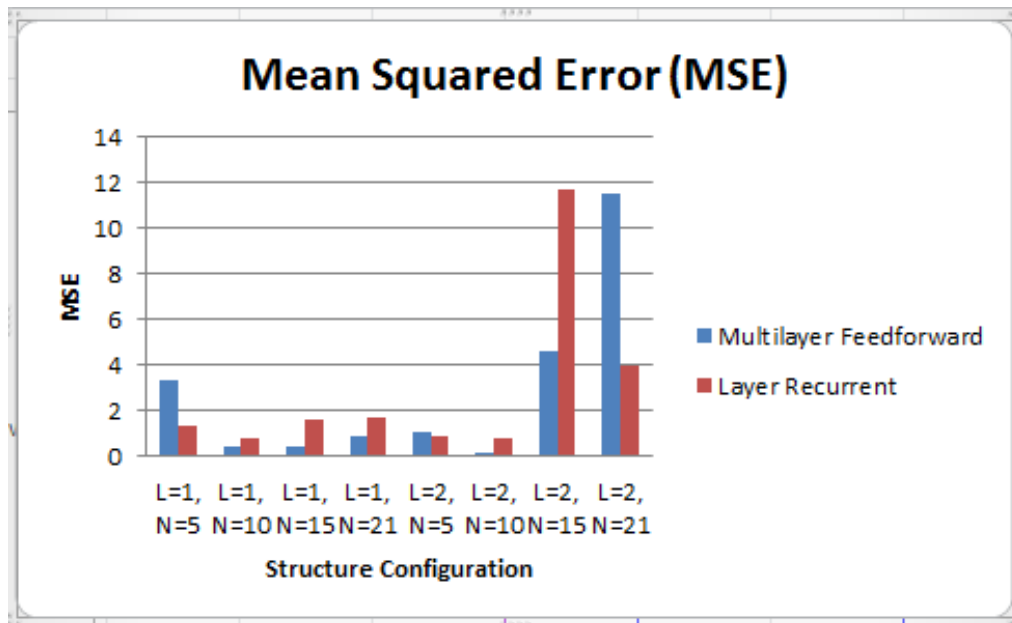


Fig. 25 MSE for different network combinations

Table 2
MSE and Time Elapsed for Different ANN Structures

Topology No.	Type	L	N	MSE	Time(sec)	Structure
T1	FFD	1	5	3.3106	22	
T2	FFD	1	10	0.35568	20	
T3	FFD	1	15	0.34368	27	
T4	FFD	1	21	0.84788	30	Overfit
T5	FFD	2	5	0.99204	25	Overfit
T6	FFD	2	10	0.08473	34	Overfit
T7	FFD	2	15	4.5489	60	Overfit
T8	FFD	2	21	11.4569	111	Overfit
T9	LRT	1	5	1.2772	20	
T10	LRT	1	10	0.72239	34	Overfit
T11	LRT	1	15	1.5765	103	Overfit
T12	LRT	1	21	1.6541	234	Overfit
T13	LRT	2	5	0.79658	24	
T14	LRT	2	10	0.73174	148	Overfit
T15	LRT	2	15	11.6903	610	Overfit
T16	LRT	2	21	3.8736	1560	Overfit

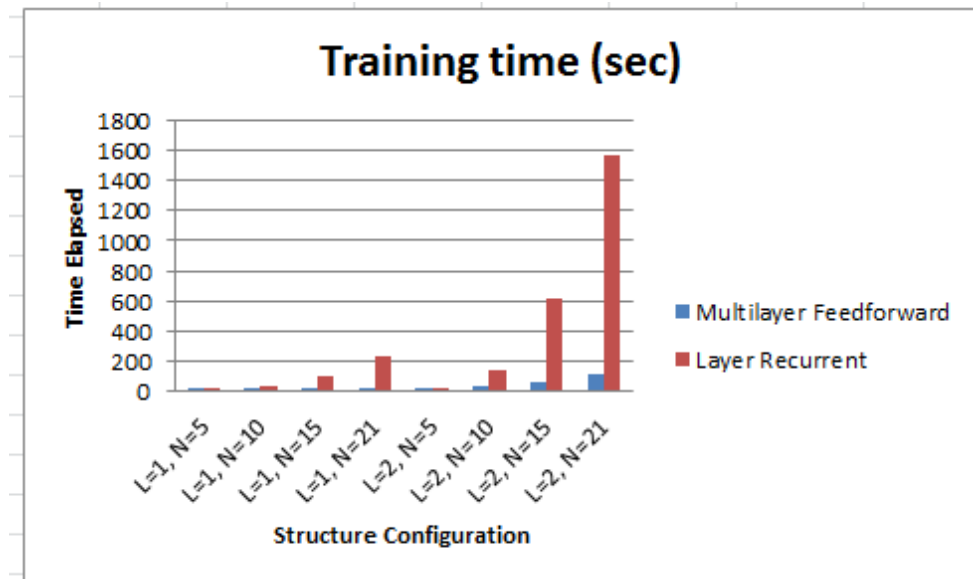


Fig. 26 Training time for different network combinations

So, from the table we see that although the least mean square error is achieved in the case of feed forward network with 2 hidden layers, each having 10 neurons, but the network is over-fitted.

Feed forward network with single layer and 15 neurons has attained a more optimised value as compared to the feed forward network with single hidden layer and 10 neurons in it, about 3% better result, also the difference in time consumed in training by two networks is not that vast, so for the given data set, the preferred network would be multi-layer feed forward network configuration, having one input layer, one output layer and one hidden layer with 15 neurons in it. So, from the above outcomes conclusion drawn is that the multi-layer feed-forward networks consume less amount of time in training of the data in comparison with recurrent networks.

4.3 Parameter Learning

The network selected from the previous section that is, multi-layer feed-forward network with one hidden layer is utilised for conducting parameter learning. Error back propagation algorithm is applied to train the network to perform hourly and weekly load forecasting.

4.3.1 Case 1: Hourly Load Forecasting

The parameter learning is conducted on the optimal selected network configuration to predict hourly loads. The nomenclature of 7 input neurons considered is listed in Table 3.

Table 3
Nomenclature of Input Neuron

Neuron No.	Parameter	Notation
1	Temperature	T
2	Wind Speed	W
3	Humidity	H
4	Month	M
5	Day type	d
6	Hour Variable	t
7	Hourly load	L(t,d,w)

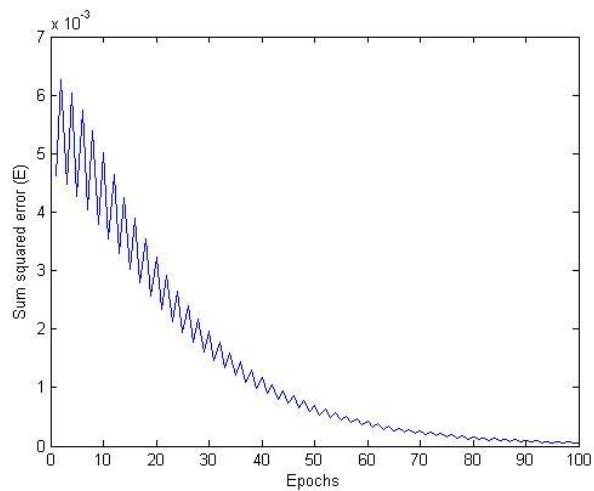


Fig. 27 Mean Squared Error (MSE)

4.3.2 Case 2: Weekly Load Forecasting

In test case 2, the parameter learning is performed to predict weekly loads by taking into account 9 input neurons namely, hourly load at a specific hour, in a week before and after, in add-on to weather, load and calendar variables, as listed in Table 4.

The parameter learning is carried out examining different number of neurons in hidden layer that are, 15, 18 and 21.

Table 4
Nomenclature of Input Neurons

Neuron No.	Parameter	Notation
1	Temperature	T
2	Wind Speed	W
3	Humidity	H
4	Month	M
5	Day type	d
6	Hour Variable	t
7	Hourly load	$L(t,d,w)$
8	Hourly load, week before	$L(t,d,w-1)$
9	Hourly load, week after	$L(t,d,w+1)$

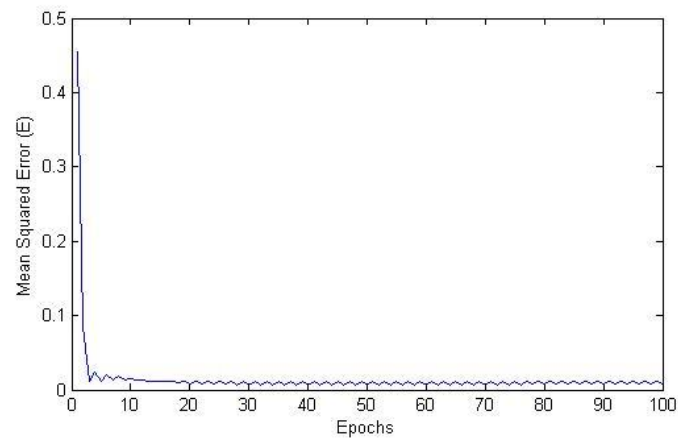


Fig. 28 Mean Squared Error (MSE) with 15 hidden neurons

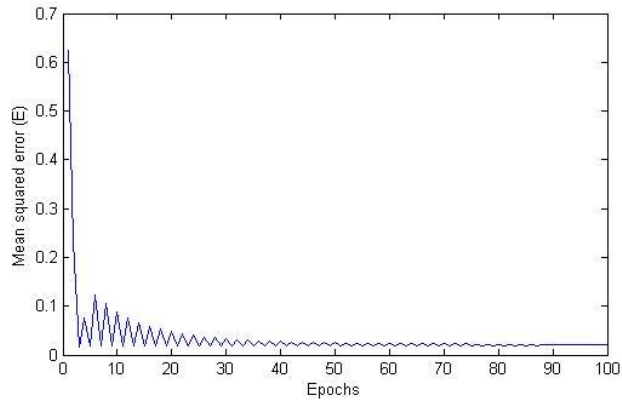


Fig. 29 Mean Squared Error (MSE) with 18 hidden neurons

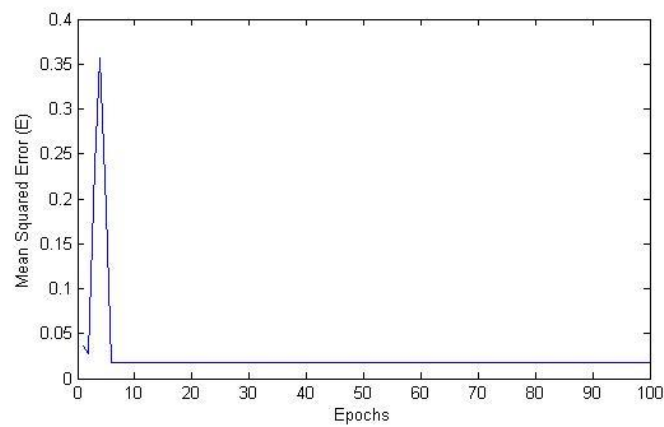


Fig. 30 Mean Squared Error (MSE) with 21 hidden neurons

For 100 epochs, MSE attained for different number of hidden neurons is as tabularized in Table 5.

Table 5
MSE Obtained for 100 Epochs

Case	Number of neurons	MSE
1	15	0.006
2	18	0.0214
3	21	0.0181

The multilayer feed forward network with 15 hidden neurons is accounted as the optimum network due to the least Mean Squared Error (MSE).

4.3.3 Case 3: Weekly Load Forecasting

In this case, the parameter learning is performed to predict weekly loads by taking 15 input nodes namely, temperature at a specific hour, in a week before and after, humidity at a specific hour, in a week before and after, wind speed at a specific hour, in a week before and after, hourly load at a specific hour, in a week before and after, in addition to previously considered weather, load and calendar variables, as tabularized in Table 6.

Table 6
Nomenclature of Input Neurons

Neuron No.	Parameter	Notation
1	Temperature	T
2	Wind Speed	W
3	Humidity	H
4	Month	M
5	Day type	d
6	Hour Variable	t
7	Hourly load	L(t,d,w)
8	Temperature, week before	T(t,d,w-1)
9	Temperature, week after	T(t,d,w+1)
10	Wind Speed, week before	W(t,d,w-1)
11	Wind Speed, week after	W(t,d,w+1)
12	Humidity, week before	H(t,d,w-1)
13	Humidity, week after	H(t,d,w+1)
14	Hourly load, week before	L(t,d,w-1)
15	Hourly load, week after	L(t,d,w+1)

The parameter learning is carried out considering different number of neurons in hidden layer that are; 15, 25, 30, 35 and 45.

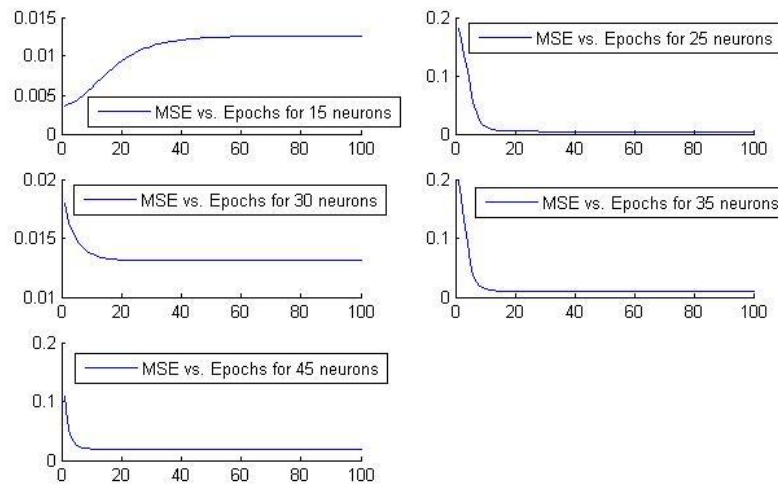


Fig. 31 Mean Squared Error (MSE) for different number of hidden neurons

For 100 epochs, MSE achieved for different number of hidden neurons is as tabularised in Table 7.

Table 7
MSE Obtained for 100 Epochs

Case	Number of neurons	MSE
1	15	0.0126
2	25	0.004
3	30	0.0131
4	35	0.01
5	45	0.0189

Therefore, it is deduced from fig. 27 and Table 6 that minimal Mean Squared Error (MSE) is achieved with 25 hidden neurons.

The testing of the network is carried out on 10% of the training data. The results incurred justify the network arrangement as optimal for the case considered in this work

CHAPTER 5

UNIT COMMITMENT

5.1 Introduction

Unit commitment (UC) is a non-linear, mixed integer large scale optimization problem to schedule the functioning of the generating units of a power system, at minimum operating cost while meeting the load demand, reserve requirement, equality and inequality restraints. Unit commitment is crucial for the system's stability and also helpful in utilizing the available resources judiciously. UC problem is dynamic process; the generation schedule is always varying as per the different load and network topography [56]. The economic dispatch problem comes up with the optimal output power over shorter time periods i.e., real time or hourly, whereas, unit commitment provides the solution over daily or weekly time period. Also the economic dispatch problem doesn't not affect the unit's commitment i.e., units are not turned on or off, it just modifies the power production levels of units. In huge power systems, UC problem handles large generating plants varying from hundreds to thousands of megawatts. The intricacies involved in the UC problem raise exponentially with the number of generating units.

It is not worthy to run all the existent units during the entire time horizon, as at each time period there will be specific load levels [57]. The operation of generators is bounded by a set of constraints. Generators cannot be turned on or off instantly and their output power cannot overstep certain limits. This might restrict the power production in a system at certain period of time, causing an inflexible operation. Therefore, it is crucial to commit the units in advance to fulfil the load demand and reserve requirements constantly.

Many utilities' daily load patterns show variations from hour to hour, among weekdays, weekends or holidays, less consumption at midnight or early morning as compared to rest of the day. If sufficient generation to satisfy the peak demand is kept on-line throughout the day, there is a possibility that some of the generating units would be operating nearly at their minimum generating limit during the off peak hours. The difficulty faced by the system operator is to decide in advance which units should be made offline, which units to start-up, when to link them to network, sequence in which operational units should be shut down and for how long. The process of estimating this and making decisions is known as Unit Commitment and the generating units when planned for connection with the system is

reported as committed. That is the unit is brought up to the speed, synchronised with the system and connected so that it can deliver power to the network. In power system operation, it is important to satisfy the load demand at minimum operating cost using optimal combination of different generating plants. The UC program is employed to get the optimal day-to-day commitment schedule of generators. UC problem is regarded as best alternative of delivering power to customers in economic and secured manner, also leading in great savings for power utilities [58]. So, the main objective of UC scheduling problem is to obtain minimum total cost of system while meeting all equipment and operating constraints. For commitment scheduling, availability of generators, generator, power systems and network constraints are recognised. For instance, depending on load, there is a possibility to release some of the units for timely maintenance [59]. Constraints associated with generators are maximum and minimum generating limits, start-up time, minimum up time, minimum down time, each generator's reserve commitment, ramp rate limits. Power system constraints consist of entire system's reserve requirements, area regulation and power exchange agreements with other utilities [60]. Network constraints include restrictions on flow on lines and interfaces, import and export restraints, which are limits on net generation in or out of a particular area. The line flow and interface limits need to be fulfilled for a given set of unit and network contingencies.

5.2 Consideration of Unit Commitment

Utilities have hourly, daily and weekly load variation that may differ from peak-hour load to off peak hours such as early morning load hours. If all the generating units are on-line throughout the complete day, then many of these units would be running at their minimum power capacities during early morning hours. Rather than operating many of these at minimum power, it may be more cost-effective to shut them down overnight.

Therefore, economic choices must be made such as the choice of units that need to be shutdown, the hour of day when they are to be shut down and the hour of the next day when they need to be brought on-line again. In addition to the economic conditions for start-up and shut down, other factors must be analysed that refer to utility operable strategies, operating constraints of the units, and utility system's stability and consistency. All these discussions are part of the study of unit commitment.

A basic rule in developing an introductory commitment is that the most cost-effective operation tends to prevail when the fewest number of generators are online. The average

operating cost per MWh is the product of fuel cost times the average heat rate added to operating and maintenance costs. A system with numerous generating units could operate all of them to meet every single load demand. Since the net output power from all of the generators must equalise the load, many of the units could be operating at low-power output, resulting in low operating cost. On the other hand, the system could start up only sufficient units to serve the load demand.

The minimal operating costs commitment strategy is to commit the minimum amount of capacity for usage. As commitment with a least number of operating generators inclines to be more economical, we must now determine which units are effective ones to commit for each hour. As a prior step, a list is prepared that arranges the units' as per full-load hourly fuel cost per MW. The list is reviewed, for given time period in sequence from lowest to highest \$/MWh, committing sufficient units to satisfy the load. Such classification can be used as primary step of commitment to reduce the over-all start-up costs of units, the costs inculcated with fetching units from off-line to operating terms. Start-up costs are costs linked with providing energy to bring the unit to working state.

Also it is required to ensure that sufficient generators are online to serve the load under normal as well as faulty conditions such as unit outages or transmission line failures. Future load demand needs to be predicted several hours ahead or days or weeks in advance, so that the thermal UC schedule can be developed that could assure system reliability.

5.3 Constraints in Unit Commitment

Various constraints can be incorporated in the UC problem. Every single unit, power system, network, stability and reliability conditions affect scheduling of the units.

5.3.1 Type of Unit

Utilities have three main types of generators such as base load plants or must-run units, mid load plants or cycling units, peaker plants. Base load plants are units that must be on-line, if available, because of operating, economic and reliability conditions. Cycling units are the one that cycle on/off, and are subjected to minimum up and minimum down time constraints. Peaker plants are used only for peak load hours, and start up quickly, and are not governed by minimum up and minimum down time constraints.

5.3.2 Units' minimum and maximum generation limits

The generation limits depict the minimum loading below which it is not economical to operate the unit, and maximum loading above which the unit should not be loaded.

Thermal units normally require crew to operate them, specifically during turn on or off. A thermal unit experiences slow temperature changes, that is time period of few hours is needed to bring the it on-line. As a consequence of this, various constraints come up in the operation of unit such as:

5.3.3 Units' minimum up and minimum down time limits

An operating unit cannot be shut down immediately. Also there is a minimum time before a de-committed unit is brought back to operation.

5.3.4 Units' Initial Status

The initial status of a unit, if is positive, denotes the number of hours for which is already up and, if negative, indicates the number of hours for which the unit has already been shut down. The initial statuses of the units affect the start-up costs of the units. Also the positive/negative status of the unit is significant to determine whether the new state violates the minimum up and minimum down time constraints or not.

5.3.5 Crew Constraints

If a plant has 2 or more units, they cannot be acted on at the same time, as there are not sufficient crew members to handle the units while starting them up.

5.3.6 Start-up Cost

As the thermal unit experiences slow temperature and pressure changes, a definite amount of energy must be spent to bring the generator on-line. The energy does not lead to any MW production but is accounted in the UC problem as Start-up Cost [61].

5.3.7 Production Cost

The production cost is the cost of fuel incurred by the set of operating units to satisfy the load.

$$F(P_{i,t}) = a_i + b_i P_{i,t} + c_i P_{i,t}^2 \quad (22)$$

Here, $P_{i,t}$ is the power produced by unit i at time t , and a_i, b_i, c_i are the fuel cost coefficients of the i^{th} unit

5.3.8 Generation Emission

$$F_e(P_{i,t}) = \alpha_i + \beta_i P_{i,t} + \gamma_i P_{i,t}^2 \quad (23)$$

Here, $P_{i,t}$ is the power produced by unit i at time t , and $\alpha_i, \beta_i, \gamma_i$ are the emission coefficients of the i^{th} unit.

5.3.9 Spinning Reserve

Spinning Reserve is defined as the total sum of all generating units integrated with the system, minus the load demand catered and the losses incurred. Spinning Reserve has to be certain given percentage of predicted load demand. There must be sufficient spinning reserve to cover any deficit in generation. Spinning reserve should also be capable of making up losses of heavily loaded unit in given time period.

5.4 Formulation of Unit Commitment

The primary objective of UC scheduling problem is to attain least possible total cost of system under consideration while fulfilling all machine and functioning constraints. Cumulative production cost of power generation constitutes units' generation cost, start-up, shutdown costs, and maintenance costs.

$$TC = \sum_{t=1}^T \sum_{i=1}^N (S_{i,t} F(P_{i,t}) + U_{i,t} SC_i + V_{i,t} SD_i) \quad (24)$$

Where,

TC = total production cost

$i = i^{\text{th}}$ generating unit

N = total generating units

T = time horizon considered

t = each time interval

$F(P_{i,t})$ = units' generation cost

$U_{i;t} = 1$ if i^{th} unit is started at 't' and 0 otherwise

$SC_i =$ start-up cost of unit i when it is shut down for $(t-1)$ hours

$V_{i;t} = 1$ if i^{th} unit is shut down at 't' and 0 otherwise

$SD_i =$ shut down cost of unit i

The target of UC problem to minimise overall production cost of system is subjected to various operational and unit constraints, studied above are expressed as follows

5.4.1 Power balance constraint

$$\sum_{i=1}^N (P_{i,t}) = Load_t \quad (25)$$

Where, $Load_t =$ Load at t timespan

5.4.2 Spinning reserve constraint

$$\sum_{i=1}^N S_{i,t} SR_i \geq R_t \quad (26)$$

Where,

$SR_i =$ Spinning reserve portion served by unit i in system

$R_t =$ Spinning reserve necessity at t time interval

5.4.3 Unit Generation Limits

$$P \min_i \leq P_{i,t} \leq P \max_i \quad (27)$$

Where,

$P \min_i =$ Minimum output power i

$P \max_i =$ Maximum output power i

5.4.4 Units' minimum up/down time

$$U_{i,t} H_{i,(t-1)} \geq MDT_i \quad (28)$$

$$V_{i,t}H_{i,(t-1)} \geq MUT_i \quad (29)$$

Where,

MUT_i = Minimum up time of unit i

MDT_i = Minimum down time of unit i

Various techniques have evolved to perform unit commitment. These techniques range from simple rules to quite complex methods. Various programming practices are utilised to obtain the status of generating units for example lagrangian relaxation method, dynamic programming, genetic algorithm etc. Dynamic programming divides a complete problem into smaller sub-problems and entire time horizon into intervals. It then inspects every potential state in each interval. The prime advantage of this technique is significant reduction in the dimensionality of the problem. The scheduling issue varies substantially from system to system depending on availability of units, combination of units and generator's and network's constraints. Several approaches being used generally to find the commitment schedule are priority list order, dynamic programming, lagrangian relaxation method, particle swarm optimisation. In modern day's deregulated markets, it has become quite substantial to accomplish least possible production cost using several effectual optimising schemes. Dynamic Programming is one of the approaches which produce the optimal outcomes.

5.5 Dynamic Programming

5.5.1 Introduction

Dynamic Programming (DP) is significant optimisation technique with immense application areas. It is an approach for working out an intricate and elaborated problem by splitting it into a cluster of simple subproblems, resolving each of those subproblems once and then storing their solutions in a memory-based arrangement. DP technique is mostly used for optimisation. It explores the formerly solved subproblems and then integrates their solutions therefore providing the best solution of the problem considered.

The terminology *dynamic programming* in the first instance was employed in the 1940s by Richard Bellman to elucidate the technique of working out the problems where one calls for finding the best outcomes one after another. Subproblems are solved by further breaking them into sub-sub parts and, so on, until simpler case is reached which can be solved in constant time.

Dynamic Programming mechanism for unit commitment scheduling scrutinizes every potential state in each and every time interval. The dimensionality of the problem is eminently reduced which is the prime advantage of this approach. Also DP has ability of maintaining solution feasibility [62].

5.5.2 Dynamic Programming Approaches

The search technique for the outcome can be either in forward or backward manner. The entire time period is divided into intervals, solving each interval at a time.

5.5.2.1 Forward direction

The procedure runs from foremost time interval to the hindmost, former status of units can be covered at each time interval and time intervals or stages are solved until overall optimal solution is obtained. The recursive process is usually based on forward direction method [63].

5.5.2.2 Backward direction

In this, the first time interval to be analysed is the final interval of the problem and the process moves in the backward direction until whole time period is covered.

5.6 Unit Commitment Scheduling Using Dynamic Programming Approach

Dynamic programming disintegrates a problem into series of simpler and smaller problems, and optimal solution to the main problem is evolved step-by-step by resolving these sub-problems. The stages of DP are defined as intervals of the complete time period considered for analysis. Each stage generally exhibits hourly operation and states of the units that are to be scheduled are stored for each and every hour in the pattern of an array.

For unit scheduling, DP approach inspects every potential state in each time interval and feasibility check is conducted. Some of the states being infeasible are neglected right away.

For generating the list of the states, 2 strategies are basically utilised here. First is priority list method in which each state has one more committed generator in comparison with previous state. Hence, N combinations of units are possible, where N is total count of units. Units are systematically organised as per their full load average cost in ascending order [64]. The second strategy used is complete enumeration (CE), in which there are $2^N - 1$ potential combinations of units and the minimal expensive generating unit is committed first.

The recursive equation to determine the least cost in hour T with state combination S is,

$$F_{cost}(T, S) = \min[P_{cost}(T, S) + TR_{cost}(T-1, L : T, S) + F_{cost}(T-1, L)] \quad (30)$$

Where,

$F_{cost}(T; S)$ = minimal total cost to reach state(T,S)

$P_{cost}(T; S)$ = production cost for state (T,S)

$TR_{cost}(T-1; L : T; S)$ = transition cost from state (T-1,L) to state (T,S)

The step-by-step course of DP is as follows:

Consider set of N generating units to be committed over H hour period, divided into time intervals, such as, $T = 1 \dots H$, $i=1 \dots N$.

Input:

$Pmin_i, Pmax_i$ – minimum and maximum capacities of generator i, $i=1 \dots N$

SC_i – start-up cost of generator i

MUT_i, MDT_i – minimum up and minimum down time of unit i

a_i, b_i, c_i - fuel coefficients of generator i

$Load_T$ – load at T^{th} time interval

InS_i – initial state of unit i

$$InS_i = \begin{cases} 1, & \text{if unit is committed} \\ 0, & \text{if unit is decommitted} \end{cases} \quad (31)$$

InS - Set of initial state of the generating units.

$U_{i:T} = 1$ if i^{th} unit is started at 'T' and 0 otherwise

$V_{i:T} = 1$ if i^{th} unit is shut down at 'T' and 0 otherwise

Step 1: Generate all possible states

Priority list method: number of possible states =N

Complete enumeration method: number of possible states = 2^N-1

Step 2: For $T= 1: H$. Find feasible states for each hour. State is feasible for time interval T , if

$$S_{i,T}P_{i,T} = Load_T + R_T \quad (32)$$

Where,

$P_{i,T}$ = power generated by unit i during T^{th} interval

$S_{i,T}$ = status of unit i during T^{th} interval

R_T = reserve requirement of system at T^{th} interval

S is the array of states of N units

i/T	$T=1$	$T=2$	$T=...$	$T=H$
$i=1$	$S_{1,1}$	$S_{1,2}$		$S_{1,N}$
$i=2$	$S_{2,1}$	$S_{2,2}$		$S_{2,H}$
.....				
$i=N$	$S_{N,1}$	$S_{N,2}$		$S_{N,H}$

Step3: Checking for possibility of transition

For all the feasible states S at T time interval, check if transition is possible to state S in time interval T from state L in time interval $T-1$, subjected to

$$U_{i,T}H_{i,(T-1)} \geq MDT_i \quad (33)$$

$$V_{i,T}h_{i,(T-1)} \geq MUT_i \quad (34)$$

Checking if any unit i has been ON less than MUT_i or OFF less than MDT_i

Compute the minimum operating cost in hour T among all possible combinations.

$$F_{cost}(T, S) = \min[P_{cost}(T, S) + TR_{cost}(T-1, L: T, S)] \quad (35)$$

Step 4: Calculating transition costs: Transition costs are calculated only for the possible transitions in on-going time interval.

$$F_{cost}(T, S) = \min[P_{cost}(T, S) + TR_{cost}(T-1, L: T, S) + F_{cost}(T-1, L)] \quad (36)$$

Total cost incurred is determined that is addition of transition charges, production cost and total cost at previous hour. This process is followed for all the previous hour states.

Step 5: Saving lowest operating cost: The total costs are then organised and least of them are stored.

Step 6: Completing entire time period: Check whether entire time horizon is covered.

If $T < H$, $T=T+1$,

Go to step 2, otherwise proceed to step 6.

Step 7: Commitment Schedule: The optimal commitment schedule of generating units is traced. ON/OFF status of the units is noted.

End algorithm once optimal results for H^{th} interval are obtained.

Fig. 32 depicts the process flow diagram of unit commitment via forward dynamic programming.

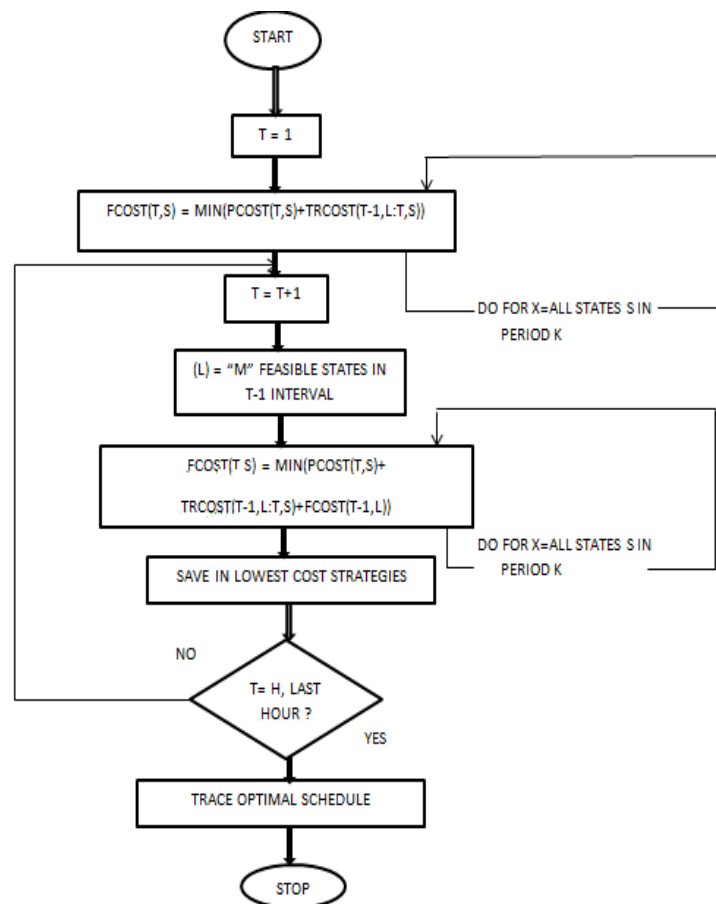


Fig. 32 Unit Commitment via forward dynamic programming [63]

CHAPTER 6

RESULTS – UNIT COMMITMENT

The previous chapter provides insight into the issue of unit commitment and dynamic programming approach for UC problem formulation. Unit commitment scheduling is executed for the forecasted 24-hour load demand pattern. The performance has been analysed for 5 generator and 10 generator set. Different combinations are formed depending upon the consideration of constraints such as; minimum up/down time, reserve requirements and method used for arranging units that is priority list or complete enumeration method and further comparison is made amongst them based on total operating cost achieved.

Unit commitment for test case 1 is carried out for the load demand as tabulated in table 8 and for test case 2 it is performed for the demand as tabularized in table 9.

Table 8
Forecasted Load Demand

Hour	Forecasted demand (MW)	Hour	Forecasted demand (MW)	Hour	Forecasted demand (MW)
1	1061.55	9	1248.95	17	1021.125
2	1455.25	10	1014.3	18	1006.95
3	1050.525	11	1112.475	19	977.55
4	1005.9	12	1053.675	20	1042.65
5	986.025	13	1386.75	21	949.725
6	1007.475	14	1174.95	22	978.075
7	1265.75	15	1087.275	23	1100.925
8	1067.85	16	982.8	24	1050.525

Table 9
Forecasted Load Demand

Hour	Forecasted demand (MW)	Hour	Forecasted demand (MW)	Hour	Forecasted demand (MW)
1	2123.1	9	2497.9	17	2042.25
2	2910.5	10	2028.6	18	2013.9
3	2101.05	11	2224.95	19	1955.1
4	2011.8	12	2107.35	20	2085.3
5	1972.05	13	2773.5	21	1899.45
6	2014.95	14	2349.9	22	1956.15
7	2531.5	15	2174.55	23	2201.85
8	2135.7	16	1965.6	24	2101.05

The outcomes of respective test cases are discussed as:

6.1 Test Case 1

5 available generation units have been considered for assessment to serve 24-hour load trend as given in table 8. Minimum and maximum limits of power generation (P_{min_i} , P_{max_i}), start-up cost (SC_i), fuel coefficients (a_i , b_i , c_i) and minimum up/down times (MUT_i , MDT_i) of units are as tabulated in table 10. The reserve requirement of the total system for each specific hour is taken as 10% of the system load during that hour.

Table 10
Data of 5 Generating Units

Unit	P_{min_i} (MW)	P_{max_i} (MW)	SC_i (\$)	a_i (\$/hr)	b_i (\$/MW ² hr)	c_i (\$/MW ² hr)	MUT_i (hr)	MDT_i (hr)
1	30	100	2050	820	9.023	0.00113	5	4
2	130	400	1460	400	7.654	0.00160	3	2
3	165	600	2100	600	8.752	0.00147	2	4
4	130	420	1480	420	8.431	0.00150	1	3
5	225	700	2100	540	9.223	0.00234	1	3

In this test case, different combinations of the constraints considered have been made, that is whether the constraint is incorporated or not for example, minimum up/down time constraints are regarded or neglected, complete enumeration (CE) or priority list scheme is utilized, reserve requirements are considered or neglected.

Table 11 exhibits list of all feasible states, optimal chosen state, the status of 5 generating units in optimal state ('1' for committed unit and '0' for de-committed unit) corresponding to 7th hour and cost attained in this interval. This outcome is shown for the case when minimum up and minimum down time restraints are accounted, complete enumeration scheme is utilised and reserve requirements of the system are abandoned that is the number second combination from the different combinations of the constraints as listed in table 14.

Table 11
List of Feasible States for 7th Hour for 2nd Combination of Constraints

Hour	Load	Feasible States	Optimal State	Optimal State Status	Operating Cost
				Units ON/OFFF	
7	1265.75	21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32	23	0 1 1 1 0	12737

Table 12 summarizes the commitment schedule of units and based on this the total cost of power production over the entire 24-hour period is computed and is shown in table 13. Detailed results have been depicted for the second combination of constraints out of 8 as listed in table 14. Here, 1 denotes that unit is committed and 0 states that unit is de-committed.

Table 12
Commitment Schedule for 5 Units Over 24 Hour Load Pattern

Hour	Load demand (MW)	Units' Status				
		Unit 1	Unit 2	Unit 3	Unit 4	Unit 5
1	1061.55	0	1	0	1	1
2	1455.25	0	1	0	1	1
3	1050.525	0	1	0	1	1
4	1005.9	0	1	0	1	1
5	986.025	0	1	1	1	0
6	1007.475	0	1	1	1	0
7	1265.75	0	1	1	1	0
8	1067.85	0	1	1	1	0
9	1248.95	0	1	1	1	0
10	1014.3	0	1	1	1	0
11	1112.475	0	1	1	1	0
12	1053.675	0	1	1	1	0
13	1386.75	0	1	1	1	0
14	1174.95	0	1	1	1	0
15	1087.275	0	1	1	1	0
16	982.8	0	1	1	1	0
17	1021.125	0	1	1	1	0
18	1006.95	0	1	1	1	0
19	977.55	0	1	1	1	0
20	1042.65	0	1	1	1	0
21	949.725	0	1	1	1	0
22	978.075	0	1	1	1	0
23	1100.925	0	1	1	1	0
24	1050.525	0	1	1	1	0

Table 13
Hourly Schedule and Operating Costs for 2nd Combination of Constraints

Hour	Unit (MW)					Demand (MW)	Start-Up Cost(\$)	Production Cost(\$)
	1	2	3	4	5			
1	0	400	0	420	241.55	1061.55	3580	10848
2	0	400	0	420	635.25	1455.25	0	15286
3	0	400	0	420	230.525	1050.525	0	10734
4	0	400	0	380.9	225	1005.9	0	10300
5	0	400	241.9318	344.9318	0	986.025	2100	10020
6	0	400	187.475	420	0	1007.475	0	10223
7	0	400	445.75	420	0	1265.75	0	12737
8	0	400	283.2576	384.5924	0	1067.85	0	10799
9	0	400	428.95	420	0	1248.95	0	12568
10	0	400	194.3	420	0	1014.3	0	10288
11	0	400	305.7955	406.6795	0	1112.475	0	11228
12	0	400	276.0985	377.5765	0	1053.675	0	10663
13	0	400	566.75	420	0	1386.75	0	13976
14	0	400	354.95	420	0	1174.95	0	11835
15	0	400	293.0682	394.2068	0	1087.275	0	10985
16	0	400	240.303	342.497	0	982.8	0	9989
17	0	400	259.6591	361.4659	0	1021.125	0	10353
18	0	400	186.95	420	0	1006.95	0	10218
19	0	400	237.6515	339.8985	0	977.55	0	9940
20	0	400	270.5303	372.1197	0	1042.65	0	10558
21	0	400	223.5985	326.1265	0	949.725	0	9677
22	0	400	237.9167	340.1583	0	978.075	0	9944
23	0	400	299.9621	400.9629	0	1100.925	0	11117
24	0	400	274.5076	376.0174	0	1050.525	0	10633
Total Cost								270598

In Table 14, the results corresponding to each combination are tabulated, where Y stands for the constraint is considered and N stands for that particular constraint is not considered. Here, the total cost (TC) denotes the total cost incurred at the end of 24 hour time horizon.

Table 14
Results Obtained for Each Combination

S. No.	Combination of constraints			Total Cost (TC) (\$)
	MUT/MDT	CE	Reserve	
1	Y	Y	Y	275341
2	Y	Y	N	270598
3	Y	N	Y	297411
4	Y	N	N	288085
5	N	Y	Y	272689
6	N	Y	N	270125
7	N	N	Y	293491
8	N	N	N	288085

6.2 Test Case 2

Commitment scheduling of generating units is carried out to serve 24-hour load pattern pertaining to table 9.

The test data for this case is composed of 10 available thermal units. The reserve requirement for each specific hour of the system in totality is taken as 10% of the system load during that hour. Table 15 comprises details of 10 units, that is minimum and maximum limits of power generation (P_{min_i} , P_{max_i}), start-up cost (SC_i), minimum up/down times (MUT_i , MDT_i) and fuel coefficients (a_i , b_i , c_i).

Table 15
Data of 10 Generating Units

Unit	P_{min_i} (MW)	P_{max_i} (MW)	SC_i (\$)	MUT_i (hr)	MDT_i (hr)	a_i (\$/hr)	b_i (\$/MW.hr)	c_i (\$/MW ² hr)
1	30	100	2050	5	4	820	9.023	0.00113
2	130	400	1460	3	2	400	7.654	0.00160
3	165	600	2100	2	4	600	8.752	0.00147
4	130	420	1480	1	3	420	8.431	0.00150
5	225	700	2100	1	3	540	9.223	0.00234
6	50	200	1360	2	2	175	7.054	0.00515
7	250	750	2300	3	4	600	9.121	0.00131
8	110	375	1370	1	3	400	7.762	0.00171
9	275	850	2200	4	3	725	8.162	0.00128
10	75	250	1180	2	1	200	8.149	0.00452

Identical to test case 1, different combinations of constraints have been enumerated and corresponding outcomes are expressed.

For the complete enumeration method, during the load period of 24-hours, in all there are $(2^{10} - 1 = 1023)$ states possible. That is, for each hourly interval there are total 1023 states and out of these possible states DP will automatically pick out that state which has minimal production cost and this process will carry on upto the load demand period of 24 hours.

Elaborated results have been shown for the second combination out of total 8 combinations as listed in table 18.

Table 16 shows the hourly status of the generating units over the 24-hour period for test case 2, where ‘1’ states unit is committed and ‘0’ presents the de-committed unit.

Table 16
Commitment Schedule for 10 Units Over 24 Hour Load Pattern

Hour	Load Demand (MW)	Units' Status									
		1	2	3	4	5	6	7	8	9	10
1	2123.1	0	1	0	1	0	1	0	1	1	1
2	2910.5	0	1	0	1	0	1	1	1	1	1
3	2101.05	0	1	0	0	0	1	1	1	1	1
4	2011.8	0	1	0	0	0	1	1	1	1	1
5	1972.05	0	1	0	0	0	1	1	1	1	1
6	2014.95	0	1	0	0	0	1	1	1	1	1
7	2531.5	0	1	0	0	0	1	1	1	1	1
8	2135.7	0	1	0	0	0	1	1	1	1	1
9	2497.9	0	1	0	0	0	1	1	1	1	1
10	2028.6	0	1	0	0	0	1	1	1	1	1
11	2224.95	0	1	0	0	0	1	1	1	1	1
12	2107.35	0	1	0	0	0	1	1	1	1	1
13	2773.5	0	1	0	1	0	1	1	1	1	1
14	2349.9	0	1	0	1	0	1	1	1	1	1
15	2174.55	0	1	0	1	0	1	0	1	1	1
16	1965.6	0	1	0	1	0	1	0	1	1	1
17	2042.25	0	1	0	1	0	1	0	1	1	1
18	2013.9	0	1	0	1	0	1	0	1	1	1
19	1955.1	0	1	0	1	0	1	0	1	1	1
20	2085.3	0	1	0	1	0	1	0	1	1	1
21	1899.45	0	1	0	1	0	1	0	1	1	1
22	1956.15	0	1	0	1	0	1	0	1	1	1
23	2201.85	0	1	0	1	0	1	0	1	1	1
24	2101.05	0	1	0	1	0	1	0	1	1	1

Load distribution among the units and total cost incurred by unit commitment of 10 units over 24-hour duration for the load demand as tabulated in table 2 is as summarized in table 17 for second combination of constraints that is, minimum up/down time constraints considered, complete enumeration method used and reserve requirements neglected; out of 8 combinations as listed in table 18.

Table 17
Hourly Schedule and Operating Costs for 2nd Combination of Constraints

Hour	Unit (MW)										Demand (MW)	Start-up Cost (\$)	Production Cost(\$)
	1	2	3	4	5	6	7	8	9	10			
1	0	400	0	404.1279	0	200	0	375	578.6649	165.3078	2123.1	3680	20680
2	0	400	0	420	0	200	446.7150	375	831.7944	236.9905	2910.5	2300	29007
3	0	400	0	0	0	200	278.3597	375	659.4931	188.1972	2101.05	0	20859
4	0	400	0	0	0	200	250	375	612.0407	174.7593	2011.8	0	19985
5	0	400	0	0	0	200	250	375	581.0631	165.9869	1972.05	0	19600
6	0	400	0	0	0	200	250	375	614.4955	175.4545	2014.95	0	20016
7	0	400	0	0	0	200	464.4391	375	849.9337	242.1272	2531.5	0	25201
8	0	400	0	0	0	200	293.3386	375	674.8231	192.5384	2135.7	0	21201
9	0	400	0	0	0	200	449.9141	375	835.0683	237.9176	2497.9	0	24858
10	0	400	0	0	0	200	250	375	625.1331	178.4669	2028.6	0	20149
11	0	400	0	0	0	200	524.95	375	475	250	2224.95	0	22088
12	0	400	0	0	0	200	281.0831	375	662.2804	188.9865	2107.35	0	20921
13	0	400	0	420	0	200	387.4914	375	771.1826	219.826	2773.5	1480	27608
14	0	400	0	394.8612	0	200	250	375	567.8061	162.2327	2349.9	0	23416
15	0	400	0	420	0	200	0	375	606.3907	173.1593	2174.55	0	21178
16	0	400	0	407.7223	0	200	0	375	417.5308	165.3469	1965.6	0	19176
17	0	400	0	420	0	200	0	375	459.15	188.1	2042.25	0	19904
18	0	400	0	420	0	200	0	375	447.742	170.258	2013.9	0	19634
19	0	400	0	402.8878	0	200	0	375	436.682	140.682	1955.1	0	19077
20	0	400	0	420	0	200	0	375	492.6993	197.6007	2085.3	0	20316
21	0	400	0	420	0	200	0	375	303.7266	200.7234	1899.45	0	19553
22	0	400	0	403.3712	0	200	0	375	371.7082	206.0706	1956.15	0	19087
23	0	400	0	420	0	200	0	375	627.6659	179.1841	2201.85	0	21444
24	0	400	0	395.3205	0	200	0	375	568.3444	162.3851	2101.05	0	20468
Total Cost													518966

The total cost incurred over 24-hour period for different combinations of constraints is as tabularized in table 18, where Y stand for the particular constraint is incorporated and N stands for the constraint is neglected.

Table 18
Results Obtained for Each Combination

S. No.	Combination of constraints			Total Cost (TC) (\$)
	MUT/MDT	CE	Reserve	
1	Y	Y	Y	521892
2	Y	Y	N	518966
3	Y	N	Y	566675
4	Y	N	N	563912
5	N	Y	Y	521019
6	N	Y	N	518966
7	N	N	Y	566400
8	N	N	N	563912

It is seen from table 14 and table 18 that minimal total operating cost is attained using complete enumeration scheme for ordering of units as compared to priority list method. Also, it analyses 2^N-1 states whereas, latter method analyses N states leading to suboptimal results.

6.3 Emission Constrained Single Objective Problem

In this test system, emission coefficients of generating units have also been considered to solve UC problem. Test system is composed of 10 available units to serve 24 - hour load trend as given in table 8. Here, the emission constrained problem is solved to obtain optimal net operating cost and optimum emission of generators for the complete time horizon. Minimum and maximum generating limits, start-up cost cold and hot, initial status, minimum up/down time, fuel coefficients, emission coefficients of units are considered for evaluation [65].

Table 19
Data of 10 Generating Units

Unit	P_{min_i} (MW)	P_{max_i} (MW)	a_i (\$/hr)	b_i (\$/MW.hr)	c_i (\$/MW ² hr)	α_i (lb/hr)	β_i (lb/MW.hr)	γ_i (lb/MW ² hr)
1	100	1500	0	0.814	0.008	24.3	-.81	0.0036
2	100	300	0	1.3804	0.0014	27.03	-.1	0.0035
3	40	200	0	1.5662	0.0016	27.03	-.5	0.033
4	40	170	0	1.6069	0.0016	22.07	-.3	0.0034
5	2	240	0	1.5662	0.0016	24.3	-.81	0.038
6	1	120	0	1.7422	0.0018	27.023	-.5	0.033
7	1	100	0	1.7755	0.0018	29.04	-.03	0.0034
8	20	100	0	1.7422	0.0018	29.03	-.02	0.0039
9	60	570	0	1.1792	0.0012	27.05	-.3	0.003
10	30	250	0	1.6947	0.0017	22.07	-.25	0.0034

Minimum/maximum generating capacities (P_{min_i} , P_{max_i}), cost coefficients (a_i , b_i , c_i), emission coefficients (α_i , β_i , γ_i) of units are as tabulated in table 19. In first test case, operating cost is minimised and in second test case, emission of generation is minimised.

6.3.1 Single Objective - Minimising Production Cost

Power generated by units to cater the load demand is as listed in table 20. Emissions are calculated corresponding to these generation levels and are tabulated along with optimised operating cost in table 21.

Table 20
Hourly Generation Levels of Units

Hour	Load Demand (MW)	Unit's Generation (MW)									
		1	2	3	4	5	6	7	8	9	10
1	2123.1	764.566	234.609	147.221	134.502	147.221	81.974	72.724	81.974	357.544	100.765
2	2910.5	978.684	300	200	170	240	120	100	100	500.289	201.528
3	2101.05	760.587	232.336	145.231	132.512	145.231	80.201	70.956	80.201	354.892	98.894
4	2011.8	744.483	223.133	137.179	124.46	137.179	73.048	63.798	73.048	344.155	91.316
5	1972.05	737.311	219.035	133.593	120.874	133.593	69.86	60.61	69.86	339.374	87.94
6	2014.95	745.051	223.458	137.463	124.745	137.463	73.301	64.051	73.301	344.534	91.583
7	2531.5	843.446	279.684	186.661	170	186.661	117.032	100	100	410.131	137.887
8	2135.7	766.84	235.908	148.357	135.639	148.357	82.984	73.734	82.984	359.06	101.836
9	2497.9	835.378	275.073	182.627	169.908	182.627	113.446	100	100	404.752	134.09
10	2028.6	747.515	224.865	138.695	125.976	138.695	74.395	65.145	74.395	346.176	92.742
11	2224.95	782.944	245.111	156.409	143.691	156.409	90.142	80.892	90.142	369.796	109.415
12	2107.35	761.724	232.985	145.8	133.081	145.8	80.711	71.461	80.711	355.65	99.429
13	2773.5	921.321	300	200	170	225.599	120	100	100	462.047	174.534
14	2349.9	805.522	258.012	167.698	154.98	167.698	100.177	90.926	99.999	384.848	120.04
15	2174.55	773.5	239.914	151.862	139.144	151.862	86.099	76.849	86.099	363.733	105.135
16	1965.6	736.147	218.37	133.011	120.292	133.011	69.343	60.093	69.343	338.598	87.393
17	2042.25	749.978	226.273	139.926	127.208	139.926	75.49	66.24	75.49	347.818	93.901
18	2013.9	744.862	223.35	137.369	124.65	137.369	73.217	63.967	73.217	344.408	91.4939
19	1955.1	734.252	217.287	132.064	119.345	132.064	68.501	59.251	68.501	337.335	86.501
20	2085.3	757.746	230.712	143.81	131.092	143.81	78.942	69.692	78.942	352.997	97.557
21	1899.45	724.211	211.549	127.043	114.324	127.043	64.038	54.788	64.038	330.641	81.776
22	1956.15	734.442	217.396	132.158	119.439	132.158	68.585	59.335	68.585	337.461	86.59
23	2201.85	778.776	242.729	154.325	141.607	154.325	88.289	79.039	88.289	367.017	107.453
24	2101.05	760.587	232.336	145.231	132.512	145.231	80.206	70.956	80.206	354.892	98.894

Table 21
Hourly Production Cost and Emission

Hour	Load Demand (MW)	Production Cost(\$) (x10 ³)	Emission (lb) (x10 ³)
1	2123.1	3.4780	3.8178
2	2910.5	5.1913	7.6726
3	2101.05	3.4332	3.7395
4	2011.8	3.2531	3.4332
5	1972.05	3.1736	3.3023
6	2014.95	3.2594	3.4437
7	2531.5	4.3347	5.5665
8	2135.7	3.5037	3.8631
9	2497.9	4.2622	5.3753
10	2028.6	3.2868	3.4895
11	2224.95	3.6870	4.1934
12	2107.35	3.4460	3.7617
13	2773.5	4.8719	6.9544
14	2349.9	3.9475	4.6856
15	2174.55	3.5832	4.0047
16	1965.6	3.1607	3.2814
17	2042.25	3.3142	3.5357
18	2013.9	3.2573	3.4402
19	1955.1	3.1398	3.2476
20	2085.3	3.4012	3.6842
21	1899.45	3.0296	3.0722
22	1956.15	3.1419	3.2509
23	2201.85	3.6394	4.1062
24	2101.05	3.4332	3.7395
Total		86.2289	98.6612

6.3.2 Single Objective - Minimising Emission

Power generated by units to equate the load demand is as listed in table 22. Production costs are calculated corresponding to these generation levels and are tabulated along with optimised emission levels in table 23.

Table 22
Hourly Generation Levels of Units

Hour	Load Demand (MW)	Unit's Generation (MW)									
		1	2	3	4	5	6	7	8	9	10
1	2123.1	522.962	300	52.353	170	49.544	52.353	100	100	525.888	250
2	2910.5	1089.1	300	114.1	170	103.2	114.1	100	100	570	250
3	2101.05	514.188	300	51.396	170	48.713	51.396	100	100	515.358	250
4	2011.8	478.671	300	47.522	170	45.348	47.522	100	100	472.738	250
5	1972.05	462.853	300	45.796	170	43.849	45.796	100	100	453.756	250
6	2014.95	479.924	300	47.658	170	45.467	47.658	100	100	474.242	250
7	2531.5	800.426	300	82.622	170	75.83	82.622	100	100	570	250
8	2135.7	527.976	300	52.9	170	50.019	52.9	100	100	531.905	250
9	2497.9	774.834	300	79.83	170	73.405	79.83	100	100	570	250
10	2028.6	485.356	300	48.251	170	45.981	48.251	100	100	480.761	250
11	2224.95	566.938	300	57.151	170	53.71	57.151	100	100	570	250
12	2107.35	516.694	300	51.67	170	48.95	51.67	100	100	518.366	250
13	2773.5	984.748	300	102.73	170	93.292	102.73	100	100	570	250
14	2349.9	662.108	300	67.533	170	62.726	67.533	100	100	570	250
15	2174.55	543.436	300	54.587	170	51.483	54.587	100	100	550.457	250
16	1965.6	460.286	300	45.516	170	43.606	45.516	100	100	450.676	250
17	2042.25	490.788	300	48.844	170	46.496	48.844	100	100	487.279	250
18	2013.9	479.506	300	47.613	170	45.427	47.613	100	100	473.741	250
19	1955.1	456.107	300	45.06	170	43.21	45.06	100	100	445.662	250
20	2085.3	507.919	300	50.712	170	48.119	50.712	100	100	507.837	250
21	1899.45	433.962	300	42.644	170	41.112	42.644	100	100	419.087	250
22	1956.15	456.525	300	45.106	170	43.25	45.106	100	100	446.163	250
23	2201.85	554.299	300	55.772	170	52.513	55.772	100	100	563.493	250
24	2101.05	514.187	300	51.396	170	48.713	51.396	100	100	354.892	250

Table 23
Hourly Production Cost and Emission

Hour	Load Demand (MW)	Production Cost (\$) ($\times 10^3$)	Emission (lb) ($\times 10^3$)
1	2123.1	3.6378	2.2638
2	2910.5	5.2751	6.1116
3	2101.05	3.5928	2.1994
4	2011.8	3.4150	1.9527
5	1972.05	3.3379	1.8501
6	2014.95	3.4212	1.9610
7	2531.5	4.4279	3.8405
8	2135.7	3.6636	2.3013
9	2497.9	4.3596	3.6772
10	2028.6	3.4480	1.9974
11	2224.95	3.8468	2.5798
12	2107.35	3.6056	2.2176
13	2773.5	4.9524	5.1997
14	2349.9	4.0724	3.0315
15	2174.55	3.7441	2.4197
16	1965.6	3.3255	1.8339
17	2042.25	3.4749	2.0343
18	2013.9	3.4191	1.9582
19	1955.1	3.3054	1.8078
20	2085.3	3.5610	2.1542
21	1899.45	3.2004	1.6745
22	1956.15	3.3074	1.8104
23	2201.85	3.8015	2.5055
24	2101.05	3.5928	2.1994
Total		89.7882	61.5815

Here, from the comparison of 2 cases, we see that optimising emission level decreases the emission by approximate $37(\times 10^3)$ lb per day whereas optimising total operating cost leads to about $3(\times 10^3)$ \$ savings per day.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

The major task of an electric utility is to accurately foretell load requirements at all times. Outcomes acquired from load forecasting procedure are used to perform unit commitment of thermal units.

Neural Networks can estimate a function without mathematically identifying the functions that relate inputs to outputs. In this study, load forecasting based on neural network approach is carried out by executing structure and parameter learning.

Hourly and weekly load data has been considered to perform medium term load forecasting expending weather inputs as temperature, humidity, wind speed and calendar variables as hour of the day, day type (weekday, weekend, and holiday) and month of the year. Here, the optimisation of the neural network architecture is done by conducting competitive analysis based on mean square error and training time, by changing network configurations, varying number of neurons in hidden layer and number of hidden layers.

It is concluded from structure learning for the data under inspection, the most preferred network is the multi-layer feed forward network with one input layer, one output layer, and one hidden layer. The optimally selected network further undergoes parameter learning using error back propagation algorithm.

Unit commitment of thermal units using dynamic programming is conducted on two sets of 24-hour forecasted loads. Various constraints like minimum up/down time, start-up costs of units and reserve requirements of the system are taken into consideration. It is concluded that complete enumeration scheme for ordering of generating units is more optimal than priority list method, as complete enumeration not only inspects all of the 2^N-1 potential states but also result in lower operating cost. However, the computation time for CE method was quite enormous. In priority list method, there are more numbers of generators committed, leading to generators operating at their nearly minimum generating levels resulting in decrease in efficiency of the system.

7.2 Future Work

The mean square error in the load prediction can further be reduced if more number of input patterns is used to train the neural network.

The error further can even be lowered by utilising hybrid systems that is neural networks along with fuzzy system.

Additional information like weather parameters such as cloud coverage, solar radiation intensity, rainfall etc. can be incorporated in the model for more precise results.

Unit commitment scheduling can be formulated for hydro units, solar power generating units, wind power generating units, considering the uncertainties associated with the solar radiation intensity, wind speed etc. Various other constraints such as ramp-rate limits, fuel constraints, costs involved in shut down of units can be considered along with for more optimal scheduling of generating units. Numerous hybrid algorithms like neural networks, particle swarm optimisation can be incorporated for more accurate results.

REFERENCES

- [1] T. Senjyu, H. Takara, K. Uezato and T. Funabashi, "One-Hour-Ahead Load Forecasting Using Neural Network", *IEEE Transactions on Power Systems*, vol. 17, no. 1, pp. 113–118, 2002.
- [2] Z.H. Osman, M.L. Awad and T.K. Mahmoud, "Neural network based approach for short-term load forecasting" *2009 IEEE/PES Power Systems Conference and Exposition*, pp. 1–8. DOI:10.1109/PSCE.2009.4840035
- [3] S.U. Rani and C.H.P. Raju, "A Solution to Unit Commitment Problem via Dynamic Programming and Particle Swarm Optimization" *International Journal of Current Engineering and Technology*, pp. 1495-1503, 2013.
- [4] T. Hong, P. Wang, and H. Lee Willis, "A Naïve Multiple Linear Regression Benchmark for Short Term Load Forecasting," presented at Power Energy Society General Meeting 2011 *IEEE*, no. 2, pp. 1–6, 2011.
- [5] T. Hong, P. Wang, and L. White, "Weather station selection for electric load forecasting," *International Journal of Forecasting*, *ELSEVIER*, vol. 31, no. 2, pp. 286–295, 2015.
- [6] B. Garg, M. M. S. Beg, and A. Q. Ansari, "Fuzzy time series model to forecast rice production," *2013 IEEE International Conference on Fuzzy Systems*, pp. 1–8, 2013.
- [7] K. Methaprayoon, C. Yingvivatanapong, W. Lee and J. Liao, "An Integration of ANN Wind Power Estimation Into Unit Commitment Considering the Forecasting Uncertainty", *IEEE Transactions on Industry Applications*, vol. 43, no. 6, pp. 1441-1448, 2007.
- [8] M. C. Falvo, R. Lamedica, S. Pierazzo, and A. Prudenzi, "A Knowledge Based System for Medium Term Load Forecasting," *2005/2006 IEEE/PES Transmission and Distribution Conference and Exhibition*, pp. 1291–1295, 2006.
- [9] Y. Lu, "Short-term load forecasting method based on structural neural network," *2008 IEEE 7th World Congress on Intelligent Control and Automation*, no. 8, pp. 4434–4438, 2008.

- [10] A. Nazir, "A Comparative Study of Different Artificial Neural Networks Based Intrusion Detection Systems," *International Journal of Scientific and Research Publications*, vol. 3, no. 7, pp. 1–15, July 2013.
- [11] S. S. Sharif and J. H. Taylor, "Real-Time Load Forecasting by Artificial Neural Networks," *2000 IEEE Power Engineering Society Summer Meeting*, vol. 01, pp. 496–501, 2000.
- [12] D. Alex and S. Hao, "An Implementation of a neuronal network based load forecasting model for the EMS," *IEEE Transactions on Power Systems*, vol. 9, no. 4, pp. 1956–1962, 1994.
- [13] G. Adepoju, S. O. A. Ogunjuyigbe, and K. O. Alawode, "Application of neural network to load forecasting in Nigerian electrical power system," *The Pacific Journal of Science and Technology*, vol. 8, no. 1, pp. 68–72, 2007.
- [14] M. Zarezadeh, A. Naghavi, and S. F. Ghaderi, "Electricity price forecasting in Iranian electricity market applying Artificial Neural Networks," *2008 IEEE Electrical Power & Energy Conference*, pp. 1–6, 2008.
- [15] E. A. Feilat, and M. Bouzguenda, "Medium-Term Load Forecasting Using Neural Network Approach," *2011 IEEE/PES Conference*, pp. 1–5, 2011.
- [16] J. W. Taylor and R. Buizza, "Neural Network Load Forecasting With Weather Ensemble Predictions," *IEEE Transactions on Power Systems*, vol. 17, no. 3, pp. 626–632, 2002.
- [17] H. A. E. Salama, A.F.A. EL-Gawad, S.M. Sakr, E.A. Mohamed and H.M. Mahmoud, "Applications On Medium-Term Load Forecasting For Loads And Energy Scales By Using Artificial Neural Network," *2009 IET/CIRE*, pp. 8–11, 2009.
- [18] D. C. Park, R. J. Marks, L. E. Atlas, and M. J. Damborg, "Electric Load Forecasting Using An Artificial Neural Network," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 442–449, 1991.
- [19] A. Khotanzad, R. Afkhami-Rohani, T. Lu, A. Abaye, M. Davis, and D. J. Maratukulam, "ANNSTLF – A Neural-Network-Based Electric Load Forecasting System," *IEEE Transactions on Neural Networks*, vol. 8, no. 4, pp. 835–846, 1997.

- [20] A. F. Atiya, S. M. El-shoura, S. I. Shaheen, and M. S. El-sherif, "A Comparison Between Neural-Network Forecasting Techniques — Case Study : River Flow Forecasting," *IEEE Transactions on Neural Networks* , vol. 10, no. 2, pp. 402–409, 1999.
- [21] C. N. Lu, H. T. Wu and S. Vemuri, "Neural Network Based Short Term Load Forecasting," *IEEE Transactions on Power Systems*, No. 1, vol. 8, no. 1, pp. 336–342, 1993.
- [22] T. M. Peng, N. F. Hubele and G. G. Karady, "Advancement In The Application Of Neural Networks For Short-Term Load Forecasting," *IEEE Transactions on Power Systems*, vol. 7, no. 1, pp. 250-257, 1992.
- [23] T. Al-saba and I. El-amin, "Artificial Neural Networks As Applied To Long-Term Demand Forecasting," *Artificial Intelligence In Engineering, ELSEVIER*, vol. 13, April 1998, pp. 189–197, 1999.
- [24] T. Saksornchai, W. J. Lee, K. Methaprayoon, J. R. Liao, and R. J. Ross, "Improve the unit commitment scheduling by using the neural-network-based short-term load forecasting," *IEEE Transactions On Industrial Applications*, vol. 41, no. 1, pp. 169–179, 2005.
- [25] R. H. Kerr, J. L. Scheidt, A. J. Fontana and J. K. Wiley, "Unit Commitment," *IEEE Transactions On Power Apparatus And Systems*, vol. PAS-85, no. 5, pp. 417–421, 1966.
- [26] W. L. Snyder, H. D. Powell and J. C. Rayburn, "Dynamic Programming Approach to Unit Commitment," *IEEE Transactions on Power Systems*, no. 2, pp. 339–348, 1987.
- [27] G. Morales-españa, J. M. Latorre, and A. Ramos, "Tight and Compact MILP Formulation for the Thermal Unit Commitment Problem," *IEEE Transactions On Power Systems*, vol. 28, no. 4, pp. 4897–4908, 2013.
- [28] S. Sen and D. P. Kothari, "Optimal Thermal Generating Unit Commitment : A Review," *Electrical Power and Energy Systems, ELSEVIER*, vol. 20, no. 7, pp. 443–451, 1998.
- [29] F. N. Lee, "A Fuel-Constrained Unit Commitment Method," *IEEE Transactions On Power Systems*, vol. 4, no. 3, pp. 1208–1218, 1989.
- [30] S. Vemuri and L. Lemonidis, "Fuel Constrained Unit Commitment," *IEEE Transactions on Power Systems*, vol. 7, no. 1, pp. 410–415, 1992.

- [31] F. N. Lee and Q. Feng, "Multi-area unit commitment," *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 591-599, 1992.
- [32] H. Ma and S.M. Shahidehpour, "Unit Commitment with Transmission Security and Voltage Constraints," *IEEE Transactions on Power Systems*, vol. 14, no. 2, pp. 757-764, 1999.
- [33] T. Gjengedal, "Emission Constrained Unit-Commitment (ECUC)," *IEEE Transactions on Energy Conversion*, vol. 11, no. 1, pp. 132-138, 1996.
- [34] F. N. Lee, J. Huang and R. Adapa, "Multi-Area Unit Commitment Via Sequential Method And a DC Power Flow Network Model," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 279-287, 1994.
- [35] G. B. Sheble' and G. N. Fahd, "Unit Commitment Literature Synopsis," *IEEE Transactions on Power Systems*, vol. 9, no. 1, pp. 128-135, 1994.
- [36] T. Gjengedal, S. Johansen and O. Hansen, "Economic-Environmental Unit Commitment (EEUC)- A Multicriteria Approach," *IEEE/CMPEUR*, pp. 59-64, 1992.
- [37] J. Park, S. Kim, G. Park, Y. Yoon, and S. Lee, "Modified Dynamic Programming Based Unit Commitment Technique," *IEEE/PES*, no. 2, pp. 1-7, 2010.
- [38] E. Handschin and H. Slomski, "Unit Commitment in Thermal Power Systems with Long-Term Energy Constraints," *1989 IEEE/PICA*, pp.211-217, 1989.
- [39] H. Pandžić, Y. Dvorkin, T. Qiu, Y. Wang, and D. S. Kirschen, "Toward Cost-Efficient and Reliable Unit Commitment Under Uncertainty," *IEEE Transactions on Power Systems*, vol. 31, no. 2, pp. 970-982, 2016.
- [40] H. Kanchev, B. Francois and V. Lazarov, "Unit Commitment by Dynamic Programming for Microgrid Operational Planning Optimization and Emission Reduction," *2011 IEEE/ACEMP* pp. 502-507, 2011.
- [41] P. K. Singhal and R. N. Sharma, "Dynamic Programming Approach for Large Scale Unit Commitment Problem," *2011 IEEE/CSNT* pp. 714-717, 2011.

- [42] C. K. Pang, G. B. Sheble' and F. Albuyeh, "Evaluation of Dynamic Programming Based Methods and Multiple Area Representation for Thermal Unit Commitments," *IEEE Transactions on Power Apparatus and Systems*, vol. 1, no. 3, pp. 1212–1218, 1981.
- [43] S. S. Kaddah, K. M. Abo-Al-Ez, T. F. Megahed, and M. G. Osman, "Probabilistic Unit Commitment In Multi-Area Grids With High Renewable Energy Penetration By Using Dynamic Programming Based On Neural Network," 2015 *IET/RPG*, pp. 1–6, 2015.
- [44] V. Ferreira and A. da Silva, "Toward Estimating Autonomous Neural Network-Based Electric Load Forecasters", *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1554-1562, 2007.
- [45] M.C. Falvo, R. Lamedica and A. Prudenzi, " Meteorological Parameters Influence for Medium Term Load Forecasting", 2005/2006 *IEEE/PES Transmission and Distribution Conference and Exhibition*, pp. 1296 - 1301, 2006.
- [46] W. Dai and P. Wang, "Application of Pattern Recognition and Artificial Neural Network to Load Forecasting in Electric Power System", 2007 *IEEE/ICNC*, vol. 1, pp. 381 – 385.
- [47] M. Ghiassi, H. Saidane and D. Zimbra, "A dynamic artificial neural network model for forecasting time series events", *International Journal of Forecasting*, vol. 21, no. 2, pp. 341-362, 2005.
- [48] T. Yalcinoz and U. Eminoglu, "Short term and medium term power distribution load forecasting by neural networks," *Energy Conversion & Management, ELSEVIER*, vol. 46, no. 9–10, pp. 1393–1405, 2005.
- [49] M.P. Darji, V.K. Dabhi and H.B. Prajapati, "Rainfall Forecasting Using Neural Network : A Survey," 2015 *IEEE/ICACEA*, pp. 706-713
- [50] K. Anand, B. Barik, K. Tamilmannan and P. Sathiya, "Artificial neural network modeling studies to predict the friction welding process parameters of Incoloy 800H joints", *Engineering Science and Technology, an International Journal*, vol. 18, no. 3, pp. 394-407, 2015.
- [51] C. Lin CT and C. Lee CSG, *Neural Fuzzy Systems*. Upper Saddle River, NJ: Prentice Hall PTR. 1996.

- [52] S.M. Badran and O.B. Abouelatta, "Forecasting Electrical Load using ANN Combined with Multiple Regression Method", *CICEM*, vol. 2, pp. 52-58.
- [53] M. Khamis, Z. Baharudin, N. Hamid, M. Abdullah, S. Yunus, "Electricity Forecasting for Small Scale Power System using Fuzzy Logic", *International Power Engineering and Optimization Conference*, vol.1, pp. 1040-1045, 2011.
- [54] G. Panchal, A. Ganatra, Y.P. Kosta and D. Panchal, "Behaviour Analysis of Multilayer Perceptrons with Multiple Hidden Neurons and Hidden Layers," *International Journal of Computer Theory and Engineering*, vol. 3, no. 2, April 2011.
- [55] N. Kandil, R. Wamkeue, M. Saad and S. Georges, "An Efficient Approach for Short term Load Forecasting using Artificial Neural Networks," *2006 IEEE International Symposium on Industrial Electronics*, vol. 3, pp. 1928-1932, July 2006.
- [56] P.K. Singhal and R.N. Sharma, "Dynamic Programming Approach for Solving Power Generating Unit Commitment Problem," *IEEE/ICCCT*, pp. 298-303, 2011.
- [57] M.Z. Kamh, A.Y. Abdelaziz, S.F. Mekhamer and M.A.L. Badr, "Modified Augmented Hopfield Neural Network for Optimal Thermal Unit Commitment, *2009 IEEE/PES* pp. 1 - 8, 2009.
- [58] B.F. Hobbs, S. Jitrapaikulsarn, S. Konda, V. Chankong, K.A. Loparo and D.J. Maratukulam, "Analysis of the Value for Unit Commitment of Improved Load Forecasts," *IEEE Transactions on Power Systems*, vol. 14, no. 4, pp. 1342-1348, November 1999.
- [59] D.K. Ranaweera, G.G. Karady and R.G. Farmer, "Economic impact analysis of load forecasting," *IEEE Transactions on Power Systems*, vol. 12, no. 3, pp. 1388 – 1392, DOI: 10.1109/59.630486, 1997.
- [60] A.I. Cohen, V. Brandwajn and S.K. Chang, "Security Constrained Unit Commitment for Open Markets," *1999 IEEE/PICA*, pp. 39 – 44, DOI: 10.1109/PICA.1999.779383, 1999.
- [61] Y.R. Guo, Y.H. Wu, J.R. Zhang and J.D. Ren, "Improved PSO Approach for the Solution of Unit Commitment Problem," *International Conference on Artificial Intelligence and Industrial Engineering*, Atlantis Press, pp. 510-513, 2015.
- [62] C.A. Li, R.B. Johnson and A.L. Svoboda, "A New Unit Commitment Method," *IEEE Transactions on Power Systems*, vol. 12, no. 1, pp. 113-119, 1997.

[63] A. Wood and B. Wollenberg, *Power Generation, Operation and Control*, New York: Wiley, 2013.

[64] T.J. Manetsch, "An Approach to Optimal Planning For SO₂ Emission Compliance," *IEEE Transactions on Power Systems*, vol. 9, no. 4, pp. 1921-1926, 1994.

[65] I. J. Raglend and N. P. Padhy, "Solutions to Practical Unit Commitment Problems with Operational, Power Flow and Environmental Constraints," *IEEE Power Eng. Soc. Summer Meet*, 2006.

PUBLICATIONS

1. Isha Arora and Manbir Kaur, "Weather Sensitive Medium Term Load Forecasting Using Artificial Neural Network", National Conference on Advanced Computational Methods in Electrical Engineering (ACMEE-2016).
- 2 Isha Arora and Manbir Kaur, "Unit Commitment Scheduling by Employing Artificial Neural Network Based Load Forecasting", *Computers and Electrical Engineering*, (communicated).

APPENDIX

Following data sets are considered comprising of hourly temperature, humidity, wind speed and load demand values on specific dates mentioned.

T	T ₁	T ₂	T ₃	T ₄	H ₁	H ₂	H ₃	H ₄	W ₁	W ₂	W ₃	W ₄
1	25	19	19	26	29	26	37	13	24	13	0	7
2	24	19	18	25	31	26	36	14	23	15	0	4
3	23	19	18	23	34	28	47	15	22	19	0	3
4	22	18	17	22	36	34	44	16	20	17	0	2
5	22	18	15	22	39	34	41	17	20	15	0	1
6	21	17	16	21	41	37	46	19	19	19	0	4
7	21	17	14	21	43	39	46	16	21	17	0	6
8	21	17	13	21	44	37	46	17	22	17	0	9
9	22	17	16	21	43	35	50	17	23	22	0	8
10	23	18	18	22	42	33	47	16	24	19	13	8
11	25	19	21	26	37	29	39	16	26	20	11	8
12	27	20	24	29	31	18	31	14	28	28	11	8
13	29	22	25	30	27	19	31	12	29	24	9	8
14	30	26	27	33	23	19	28	11	30	20	9	8
15	31	28	27	34	20	20	26	11	31	20	9	9
16	32	28	27	34	18	19	23	12	29	17	13	9
17	32	28	28	35	17	19	22	12	28	19	9	9
18	31	29	27	36	18	20	19	13	27	19	9	10
19	30	29	27	37	18	20	17	13	22	17	17	12
20	28	28	25	37	20	20	18	12	18	15	9	13
21	27	28	24	37	22	20	15	12	13	15	4	14
22	25	28	23	33	24	20	18	12	10	9	0	15
23	24	27	19	31	26	21	18	12	8	13	6	16
24	22	27	20	28	29	26	18	12	8	13	9	16

T₁, H₁, W₁ – Temperature, humidity, wind speed for 5th March

T₂, H₂, W₂ – Temperature, humidity, wind speed for 12th March

T₃, H₃, W₃ – Temperature, humidity, wind speed for 19th March

T₄, H₄, W₄ – Temperature, humidity, wind speed for 26th March

T	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆	L ₇	L ₈
1	2022	1944	2144	1939	2111	2121	1817	1807
2	2010	1922	2134	1909	2078	1995	1800	1777
3	2001	1904	2108	1880	2046	1952	1916	1749
4	1916	1785	2067	1773	1948	1862	1873	1678
5	1821	1702	1997	1749	1830	1799	1793	1763
6	1919	1832	2024	1862	1924	1978	1837	1985
7	2030	2070	2198	2134	2042	2168	2182	2209
8	2034	2138	2262	2162	2169	2156	2129	2162
9	1998	2107	2245	2103	2089	2129	2019	2060
10	1932	2017	2182	2059	1951	2098	1945	1888
11	2119	2007	2133	2100	1969	2031	2010	1881
12	2007	2071	2103	2072	2095	2002	2011	1910
13	2070	2047	2230	2120	2205	2024	2014	1891
14	2238	2036	2120	2009	2032	2029	1956	1847
15	2071	1969	2004	1898	2009	1993	1788	1806
16	1872	1866	2061	1892	1969	1933	1916	1736
17	1945	1833	1985	1872	1995	1800	1889	1699
18	1918	1677	1816	1704	1845	1713	1813	1538
19	1862	1594	1676	1611	1771	1597	1747	1567
20	1986	1824	1865	1790	1866	1770	1877	1500
21	1809	1774	1792	1809	1799	1764	1811	1352
22	1863	1845	1938	1839	1857	1874	1861	1371
23	2097	2034	2000	1872	2142	1896	2017	1448
24	2001	2113	2160	1856	2225	1941	1837	1395

L₁ - Load for 5th March

L₂ - Load for 12th March

L₃ - Load for 19th March

L₄ - Load for 26th March

L₅ - Load for 14th March

L₆ - Load for 21st March

L₇ - Load for 28th March

L₈ - Load for 4th April

T	T ₁	T ₂	T ₃	T ₄	H ₁	H ₂	H ₃	H ₄	W ₁	W ₂	W ₃	W ₄
1	19	13	28	30	30	38	15	20	0	17	19	18
2	18	12	27	29	32	38	18	21	0	17	13	18
3	18	10	26	28	32	37	34	22	0	16	11	18
4	17	10	25	28	34	36	35	23	6	16	9	18
5	15	10	25	28	39	35	35	24	0	16	6	17
6	16	9	25	28	42	34	36	26	7	16	0	17
7	14	9	26	28	51	35	37	27	0	16	6	17
8	13	9	26	27	59	38	37	30	0	16	17	16
9	16	10	27	28	48	38	38	29	0	15	9	16
10	18	12	30	28	46	37	35	28	7	16	13	15
11	21	16	31	30	38	34	29	26	7	16	7	15
12	24	18	33	31	27	31	28	24	6	16	4	14
13	25	24	34	33	18	27	24	21	4	16	7	12
14	27	25	34	34	15	25	26	18	7	17	6	10
15	27	25	35	36	15	23	27	16	9	17	9	9
16	27	25	35	35	17	25	25	16	9	17	19	8
17	28	25	35	35	15	30	20	16	9	17	13	8
18	27	25	34	35	17	37	25	15	13	17	11	8
19	27	20	33	34	17	42	24	16	7	16	6	11
20	25	18	33	34	19	26	23	15	11	16	7	14
21	24	17	32	33	22	26	22	15	7	15	7	17
22	23	16	31	33	23	24	21	16	7	15	7	17
23	19	14	30	32	28	28	20	16	0	15	0	16
24	19	13	30	31	28	51	20	18	0	15	6	16

T₁, H₁, W₁ – Temperature, humidity, wind speed for 14th March

T₂, H₂, W₂ – Temperature, humidity, wind speed for 21st March

T₃, H₃, W₃ – Temperature, humidity, wind speed for 28th March

T₄, H₄, W₄ – Temperature, humidity, wind speed for 4th April

T	T ₁	T ₂	T ₃	T ₄	T ₅	H ₁	H ₂	H ₃	H ₄	H ₅	W ₁	W ₂	W ₃	W ₄	W ₅
1	15	25	25	27	32	31	20	9	21	21	6	5	12	9	5
2	15	25	24	26	31	31	21	10	23	20	4	8	12	6	5
3	16	25	24	25	30	27	24	11	25	19	4	11	12	4	3
4	13	25	23	25	30	36	28	11	27	24	0	14	12	3	2
5	11	25	23	25	29	38	30	12	29	22	0	14	12	3	2
6	12	25	23	25	29	35	31	12	31	26	0	14	12	2	2
7	10	25	23	25	28	43	33	13	32	33	0	14	13	3	3
8	15	25	23	25	28	31	34	14	26	31	7	14	13	4	3
9	17	21	23	26	31	30	38	14	24	26	9	14	13	5	3
10	18	25	24	27	29	30	36	14	23	37	11	14	13	5	3
11	20	25	25	28	30	28	34	12	21	30	13	14	13	6	3
12	21	25	26	29	32	29	31	11	18	25	11	14	13	6	5
13	23	26	28	31	36	20	28	9	16	16	11	14	11	5	5
14	25	28	30	33	37	15	24	8	13	12	9	14	10	5	6
15	25	29	31	34	39	15	20	7	12	10	6	13	9	4	8
16	26	30	31	34	41	16	18	8	12	18	6	13	9	4	8
17	25	30	30	33	40	17	17	8	12	8	4	13	9	4	10
18	24	30	30	33	39	16	17	8	12	9	4	13	9	4	10
19	23	30	29	32	38	19	17	9	13	9	0	12	10	5	10
20	19	29	29	30	36	24	18	9	15	9	0	11	12	6	11
21	20	28	28	30	35	23	19	10	14	10	2	10	13	8	10
22	20	28	28	30	34	23	19	10	15	10	9	9	14	9	10
23	19	27	27	30	34	24	20	11	16	10	9	8	14	10	10
24	17	27	26	29	32	27	20	12	17	11	11	8	15	11	10

T₁, H₁, W₁ – Temperature, humidity, wind speed for 10th March

T₂, H₂, W₂ – Temperature, humidity, wind speed for 17th March

T₃, H₃, W₃ – Temperature, humidity, wind speed for 24th March

T₄, H₄, W₄ – Temperature, humidity, wind speed for 31st March

T₅, H₅, W₅ – Temperature, humidity, wind speed for 7th April

T	L ₁	L ₂	L ₃	L ₄	L ₅	L ₆	L ₇	L ₈	L ₉
1	2137	2019	1917	1801	1701	1944	2144	1939	1691
2	2108	2054	1983	1790	1662	1922	2134	1909	1584
3	2094	2058	1976	1866	1614	1904	2108	1880	1535
4	1988	1959	1904	1830	1583	1785	2067	1773	1476
5	1874	1891	1850	1797	1653	1702	1997	1749	1588
6	1814	2023	1923	1847	1898	1832	2024	1862	1711
7	2011	2114	2049	2084	2113	2070	2198	2134	1718
8	2230	2248	2165	1984	2090	2138	2262	2162	1748
9	2193	2193	2091	2059	1962	2107	2245	2103	1702
10	1975	2064	2000	2004	1736	2017	2182	2059	1671
11	1956	2141	2063	2039	1738	2007	2133	2100	1689
12	2052	2164	2081	2066	1819	2071	2103	2072	1874
13	2039	1997	2079	2054	1875	2047	220	2120	1991
14	2007	1985	2078	2067	1831	2036	2120	2009	2021
15	1870	1891	1942	1892	1831	1969	2004	1898	1810
16	1811	2023	1815	1957	1770	1866	2061	1892	1654
17	1811	2037	1828	1944	1638	1833	1985	1872	1538
18	1722	1906	1798	1832	1572	1677	1816	1704	1430
19	1637	1778	1698	1732	1470	1594	1676	1611	1322
20	1788	1914	1856	1838	1591	1824	1865	1790	1517
21	1707	1873	1833	1813	1586	1774	1792	1809	1526
22	1845	2013	1839	1785	1539	1845	1938	1839	1505
23	2090	1900	1886	1900	1670	2034	2000	1872	1594
24	1942	2026	1873	1876	1756	2113	2160	1856	1647

L₁ - Load for 10th March

L₂ - Load for 17th March

L₃ - Load for 24th March

L₄ - Load for 31st March

L₅ - Load for 7th April

L₆ - Load for 11th March

L₇ - Load for 18th March

L₈ - Load for 25th March

L₉ - Load for 8th April

T	T ₁	T ₂	T ₃	T ₄	H ₁	H ₂	H ₃	H ₄	W ₁	W ₂	W ₃	W ₄
1	18	26	25	30	28	25	9	36	11	7	14	0
2	18	26	24	29	30	26	11	31	15	9	14	0
3	18	26	24	28	30	28	12	27	15	12	14	0
4	13	26	24	28	30	29	13	35	13	12	14	0
5	13	25	24	28	44	30	14	29	6	12	13	0
6	13	25	24	27	41	32	15	31	9	12	12	0
7	16	25	24	25	39	34	16	40	7	12	12	0
8	18	25	24	25	41	38	17	35	9	11	11	2
9	18	25	24	28	34	36	17	28	13	10	10	3
10	20	25	24	29	32	34	16	42	19	10	9	3
11	21	26	25	30	32	31	14	34	19	10	9	3
12	23	27	27	32	30	28	12	28	15	10	8	5
13	25	9	28	37	31	23	11	15	17	10	7	3
14	27	31	30	39	25	19	9	12	13	10	6	5
15	26	32	31	40	18	17	9	10	15	10	5	6
16	26	32	31	40	13	16	9	14	15	10	5	5
17	27	32	31	31	15	16	9	21	13	10	6	3
18	26	31	31	30	13	16	9	21	11	10	7	5
19	26	30	30	30	12	17	10	19	13	8	9	5
20	29	29	29	30	13	18	10	18	9	7	10	5
21	29	28	29	31	13	19	10	17	7	5	12	5
22	29	28	29	28	16	20	11	21	9	5	13	6
23	28	27	28	29	20	21	11	21	13	5	13	6
24	27	27	27	30	21	22	12	22	13	5	14	8

T₁, H₁, W₁ – Temperature, humidity, wind speed for 11th March

T₂, H₂, W₂ – Temperature, humidity, wind speed for 18th March

T₃, H₃, W₃ – Temperature, humidity, wind speed for 25th March

T₄, H₄, W₄ – Temperature, humidity, wind speed for 8th April