GENERATION AND LOAD SHEDDING SCHEDULING FOR DEMAND SIDE BIDDING

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(with Specialization in Power Systems Engineering)

By

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in this Dissertation Thesis entitled, **"Generation and Load Shedding Scheduling for Demand Side Bidding"**, in partial fulfillment of the requirements for the award of the degree of **Master of Technology** in **Electrical Engineering** with specialization in **Power System Engineering**, submitted in the **Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee,** is an authentic record of my own work carried out during the period from June 2006 to June 2007 under the supervision of **Dr. J. D. Sharma**, Professor and **Shri. Bharat Gupta**, Assistant Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee, India.

The matter embodied in this Dissertation Thesis has not been submitted by me for award of any other degree or diploma.

Date: 19th JUNE, 2007

Place: ROORKEE.

(Patel Mepal Kantibhai)

CERTIFICATE

This is to certify that the above statements made by the student are correct to the best of my knowledge.

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ABSTRACT

In most instances, consumers have very little influence on the design of electricity market. Most electricity markets do not treat consumers as a genuine demand side capable of making rational decisions but simply as a load that need to be served under all conditions. If the demand side is allow for participating in the market then it would make electricity market more efficient and more competitive.

With keeping this in mind, a market model has been proposed and analyzed in which both generators and consumers are participants; with energy and reserve are jointly dispatched. A simultaneous market for reserve considers spinning reserve from generators and interruptible loads. It is all about encouraging flexibility in the use of electricity by demand-side.

Traditional formulation of the scheduling problem is not valid when load reduction is available. So, a composite model for optimal generation and load shedding scheduling is developed here. The market structure considered as a competitive power pool which accepts bids from both the generators and the consumers for energy and reserve and these form the objective function of the scheduling problem. This is minimized subject to several operating constraints. This formulation results into a mixed-integer nonlinear optimization problem which is solved using a new approach based on Hybrid Particle Swarm Optimization (HPSO) method. For handling the system constraints in HPSO, a method based on preserving feasibility of solution is applied.

An approach based on the combination of Artificial Neural Network (ANN) and PSO is proposed to solve the scheduling problem. The extra scheduling introduced by demand side bidding in the reserve offers significant gains in economic efficiency.

CONTENTS

n_g	=	No. of generating units
n_l	=	No. of consumers
T	=	Scheduling period in hours (h)
a_i, b_i, c_i	=	Fuel cost coefficients of generating unit i (mu/MWh^2, mu/MWh, mu/hr)
d_j, e_j	=	Bid function coefficients of customer j (mu/MWh^2, mu/MWh)
$PG_i^{\max}$	=	maximum generation limit of i^{th} unit (MW)
$PG_i^{\min}$	=	minimum generation limit of i^{th} unit (MW)
$PL_j^{\max}$	=	maximum consumption limit of j^{th} load (MW)
$PL_j^{\min}$	=	minimum consumption limit of j^{th} load (MW)
DG_i	=	Rate offered by the ith generating unit to provide reserve (mu/MWh)
DL_j	=	Rate offered by the jth consumer to provide reserve (mu/MWh)
ϕ_i	=	Fraction of the available capacity of unit i that is offered as reserve
δ_j	=	Fraction of the load to be curtailed by load j for providing reserve
$REQRES_h$	=	Reserve requirement for hour h (MW)

Continuous Variables

PG_{ih}	=	Power output of generating unit i for hour h (MW)
PL_{jh}	=	Power consumption of customer j for hour h (MW)
PL_{jh}^{sd}	=	Power consumption reduced by customer j for hour h (MW)

Binary Variables

UG_{ih}	=	ON/OFF status of generating unit i at hour h '1' when ON; '0' when OFF
UL_{jh}	=	status of customer j at hour h '1' if customer is selected to buy; otherwise '0'

ULR_{jh} = '1' if customer j is called to provide reserve at time h
'0' if customer j is not called to provide reserve at time h

For Particle Swarm Optimization:

x_i = Particle variables

V_i = Particle velocity

ω = Inertia weight

c_1 = Coefficient of the self-recognition component

c_2 = Coefficient of the social component

r_1, r_2 = Random numbers between [0,1]

$k_{\max}$ = Maximum no. of iterations

$\omega_{\max}$ = Maximum value of inertia weight

$\omega_{\min}$ = Minimum value of inertia weight

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CHAPTER – 1
INTRODUCTION

Today electric industry in the whole world is undergoing through the major changes, like De-regulation, Unbundling, Restructuring, etc. The former vertically integrated electric utility, which performed all the functions involved in power – generation, transmission, distribution and retail sales is disaggregating into separate companies devoted to each function. The major objective of this reform is to create a competition in electric power industry. The competition has changed the way of electricity trading. And this has paved the way for Demand Side Bidding (DSB). DSB offers the opportunity for consumers to receive financial compensation for making short-term changes to their electricity consumption. By rescheduling loads, consumers may help to maintain a balance between electricity supply and demand, reducing the amount of generation and other important implications can be achieved.

With the competition in the electricity industry, the issue of energy market design becomes a fundamental problem. In this work, a competitive power pool is considered which accepts bids from the supply and the demand side for energy as well as reserve. Two markets are accessible in this system: energy market and reserve market. These markets are generally the responsibility of the system operator who manages set amounts of particular services based on bids from generators and demand side bidders that can supply them. In many electricity markets, energy and reserve are often traded and scheduled in separate markets [11]. In such cases, only the generators submit reserve offers from which the system operator allocates the required amounts; usually in a sequential manner after the energy market has been cleared. In order to avoid the market inefficiencies created by this type of sequential model, energy and reserve are scheduled simultaneously [10, 12].

In this dissertation work, we have proposed and analyzed a market model in which both generators and consumers (demand side) are participants in a joint energy and reserve market. In this, the products are energy as well as the reserve margins. From the perspective of the producers, spinning reserve is provided by those generating units that are committed. From the point of view of the consumers, the fact that the demands are elastic within some limits offers partial natural reserve. However, for coming emergency states under which the system operator would have to rebalance power, some consumers may be willing to curtail their consumption beyond their elastic limits with some financial reimbursements. This readiness provides additional reserve which is considered as spinning reserve.

The main function of the market operator is to minimize the combined cost of the total generated energy and of the reserve provided by generators and consumers, as well as to maximize the total benefit obtained by the consumers. This scheduling is done for 24 hours time horizon on hourly basis. This multiperiod scheduling problem of 24 hours is decomposed in 24 problems for each hour as shown in Fig. 1.

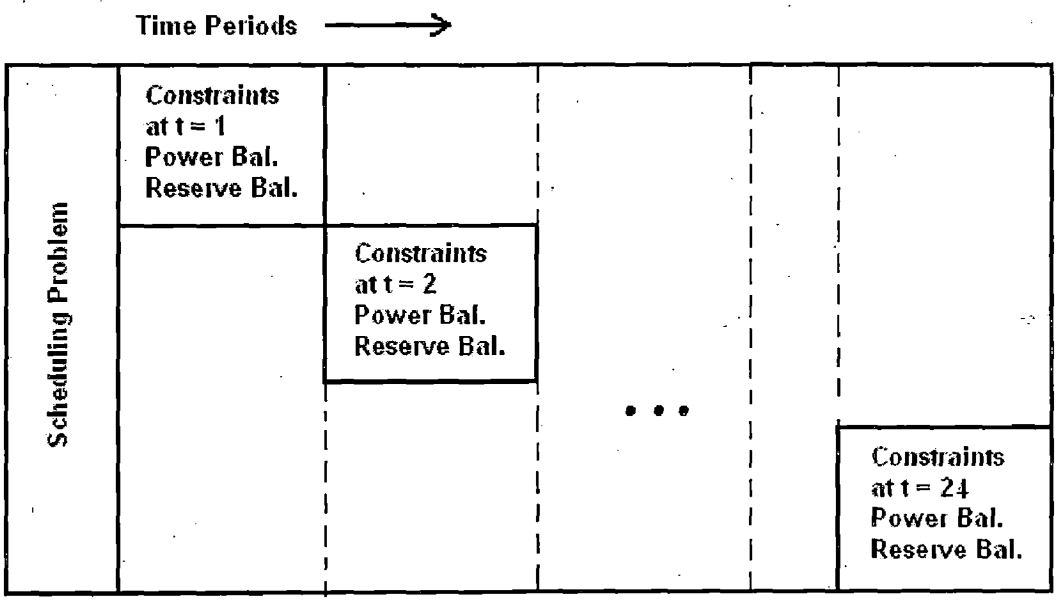


Fig. 1 Structure of Scheduling Problem

This generation and load shedding scheduling problem is a mixed-integer nonlinear optimization problem with constraints. The exact solution of the problem cai be obtained at a cost of excessive time requirement for realistic power system. A surve of literature on generation scheduling problem reveals that many numerical optimizatio techniques like priority list method, dynamic programming, mixed-integer programming simulated annealing, genetic algorithm, etc., applied to solve this kind of problem. Her hybrid particle swarm optimization based method is presented for solving the above sai scheduling problem.

The particle swarm optimization (PSO), which mimics social behavior is an optimization technique developed by Kennedy and Eberhart [15]. It has been reported that the PSO is suitable for minimization of nonconvex and continuous functions and can find a global minimum of nonconvex function with high certainty. But there are many practical optimization problems having continuous as well as binary or discrete variables. The proposed scheduling problem also having binary variables indicating ON/OFF status of generators and the consumers who shows their willingness for load curtailment. To handle discrete and binary variables, Kennedy and Eberhart has proposed discrete binary version of particle swarm algorithm. Here to solve the mixed-integer nonlinear scheduling problem, HPSO is used which is a blend of binary particle swarm optimization (BPSO) and real coded particle swarm optimization (RCPSO) running simultaneously. The scheduling problem with DSB providing reserve is solved using HPSO methodology. The obtained results show HPSO as a competent and very efficient method.

There are certain customers which cannot provide the total demand reduction. If they will curtail their load at certain timeslots then the same amount of load they will recover during other timeslots. One particular case with load reduction and load recovery is also considered here with the proposed scheduling problem.

An approach based on Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO) for scheduling problem is also presented. It is applied for the scheduling without considering DSB. In this method, firstly ANN will be trained with the known schedule for different load profiles. After providing training, if unknown load profile is presented to the neural network (NN), it will give the status of generators. This status information will be used by the RCPSO and the optimal generation is obtained.

CHAPTER – 2
LITERATURE REVIEW

There are handful literatures available highlighting the demand side participation into the electricity market and assessment of the influence of it on various market parameters. The literatures relevant to this dissertation work are summarized below.

Eric Hirst and Brendan Kirty [1] states that customer participation is must in bulk-power markets; otherwise these markets will not be truly competitive, and the expected benefits of competition will not be realized. The combination of retail competition, wholesale competition and improved technologies will greatly expand the type and magnitude of price responsive demand. Permitting and encouraging retail consumers, especially residential consumers, to participate will greatly improve economic efficiency, discipline market power and improve reliability. Also strategically timed demand reductions decrease the need to build new generation and transmission facilities which may improve environmental equality. Retail consumer response to price volatility help lower the size of price spikes. The cost, designing and installing metering, communication and computing technologies represent important barriers to these programs.

The IEA report [2] illustrates the steps that need to be taken in order to ensure that Demand-Side Bidding (DSB) schemes are successful. It shows how to gain an understanding of the opportunities for DSB in the electricity market and indicates the factors that need to be taken into consideration when implementing new DSB schemes. This guide provides the background information about the concept of DSB and why it is important in the operation of competitive electricity markets, the benefits of DSB and drivers for DSB. It also provides the information about step-by-step implementation of DSB and illustrates by building up complete examples of DSB in operation. The IEA survey [3] shows that most market participants view DSB favorably, mainly due to improved market liquidity and an improved choice of products in the electricity market. The survey also highlights the main barriers that prevent the development and introduction of successful DSB products in the participating countries. These barriers range from technical barriers to ignorance whereby market participants do not fully understand the financial and environmental benefits of DSB products. A study of electrical technologies in the domestic, commercial, and industrial sectors is also required in order to determine which technologies can be controlled in ways suitable for use in DSB schemes.

Deniel Kirschen [4] discusses the unusual economic characteristics of the demand for electrical energy and show that the short run price elasticity of the demand for electricity is small. He has identified the barriers to enhance the elasticity of demand and finds the benefits of overall increment in demand elasticity in term of reduction in the magnitude and number of price spikes. He also outlines the tools for consumers and retailers to help consumers by taking the opportunities offered by competitive markets. Deniel Kirschen et. al. [5] has proposed the method of modeling the elasticity of the demand for electricity and incorporated it in scheduling and pricing program.

R. S. Rassenti et. al. [6] define the market power in a sealed bid offer market and outlines the market structure. They analyze the effect of introducing the demand side bidding on the market price with and without the presence of market power. They have observed primary effects of demand side bidding above the one sided market as : prices will be lower and more competitive; price volatility, as represented by high incidence of price spikes, will be drastically eliminated and reduce the need for reserve supplies of generator capacity.

Goran and Daniel [7] demonstrated that demand side bidding and other forms of flexible generation can cause sharp and unwanted price increase if the production schedule is established on the basis of minimization of the total production cost. Load scheduling program completely ignores the load recovery which is preceded followed by load reduction periods. The formation of optimum scheduling problem should accommodate the effect of demand side bidding. This paper provides the framework for consideration of DSB in terms of load/generation balance formulation. The role of DSB in daily scheduling needs to be carefully analyzed as it changes total electricity production cost. For that purpose, a composite model for optimal generation and demand reduction scheduling is presented by G. Strbac et. al. in [8]. An augmented scheduling formulation capable of dealing with supply side and demand side bidders simultaneously has been developed. It also includes the influence of DSB on total production costs, system marginal price profile and benefit allocation between producers and consumers.

S. B. Philpott and E. Pitterson [9] presented a model of a purchaser of electricity bidding into a wholesale electricity market that operates a day ahead of dispatch. They first formulate the model for single purchaser, then extending the model to n purchasers and finally a simple model where one generator and one purchaser bidding strategically. They find that nearly in all models purchaser should bid for less than their expected demand.

Jing Wang et. al. [10] proposed a market model that includes demand side reserve offers where energy and reserve are jointly dispatched. Generators and consumers can present offers and bids on various distinct products like, energy, up spinning, down spinning and standby reserve. They have considered single period scheduling where the objective function is to minimize cost of generated energy, cost of reserve and maximize the load benefit function. The numerical analysis presented in this paper emphasized the influence and benefits of demand side reserve offers.

S. S. Oren [11] explored the alternative market of reserve in parallel with energy market, as the case in many established energy markets, where reserve market is cleared in a sequential manner after the energy market has been cleared. In order to avoid market inefficiencies created by such type of model, a simultaneous clearing of energy and energy market is proposed by X. Ma and D. Sun [12]. Adoption of joint dispatch based market clearing methodology has provided best tradeoff between allocation of limited capacity among energy and reserve.

B. J. Kirby [13] recommends Power system operators and power market designers to encourage responsive loads to participate in reserve market since their participation will increase reliability and reduce cost to all power system customers. The primary analysis shows that load response is likely to be a faster and more effective than generation response for providing reserve.

A variety of metaheuristic, heuristics and mathematical programming techniques within a hybrid framework have been proposed by Keshav P. Dahal et. al. in [14]. All the proposed methods use genetic algorithm with other classical techniques, but the methodology provided to handle generation scheduling problem with metaheuristic approach is astonishing.

J. Kennedy and R. Eberhart [15] have introduced the concept for the optimization of nonlinear functions using particle swarm methodology. They have briefly reviewed the stages of its development from the social simulation to optimizer. They have also described the relationship of Particle Swarm Optimization (PSO) with Genetic Algorithm and Evolutionary Programming. Moreover, they have shown many models to implement it and discussed one of the models in more details showing the success of their new concept. But the major limitation of this algorithm was, it can only handle continuous variables. However, many practical problems frequently encounter discrete variables as well as continuous variables, and they cannot be solved using the continuous-valued particle swarm algorithm. In [16], J. Kennedy and R. Eberhart have provided the revision of particle swarm algorithm from continuous to a discrete operation.

S. Kitayama et. al. [17] have suggested the PSO for mixed discrete nonlinear problems. The penalty function approach to handle the discrete design variables is employed, in which discrete design variables are handled as the continuous ones by penalizing it. A useful method to determine the penalty parameter of penalty term for the discrete design variables is proposed.

T. O. Ting et. al. [18] have presented a new approach via hybrid particle swarm optimization (HPSO) scheme to solve the unit commitment problem which is a mixed-integer nonlinear problem. The proposed HPSO is the mixture of binary PSO and continuous PSO. Integer variables are handled by the binary PSO and the continuous variables are handled by the real-valued PSO and both are running concurrently.

Evolutionary computation techniques have received a lot of attention regarding their potential as optimization techniques. However, these cannot make a significant breakthrough in the area of nonlinear programming due to the fact that they did not address the issue of constraints in the systematic way. Several methods were proposed by Michalewicz [19] for handling constraints by evolutionary computation techniques. Most of them are based on the concept of penalty functions, which penalize infeasible solutions.

X. Hu and R. Eberhart [20] have presented PSO algorithm for constrained nonlinear optimization problems. Here constrains handled by preserving feasibility strategy which keeps only feasible solutions for further processing. G. Coath and S. K. Halgamuge [21] presented a comparison of two constrained handling methods used in the application of PSO to the real world constrained nonlinear optimization problems. The two methods considered are the application of non-stationary multi-stage penalty functions and preservation of feasible solutions. The paper concludes that the choice of constraint handling method is very problem dependent.

CHAPTER – 3
DEMAND SIDE BIDDING

3.1 WHAT IS DEMAND SIDE BIDDING?

Demand Side Bidding (DSB) is a mechanism that enables the demand side (consumers) to actively participate in the trading of electricity, by offering to undertake changes to their normal pattern of consumption in return for financial reward. The financial reward can be in the form of reduced electricity prices or via a direct payment for electricity they have 'not consumed' or even an availability payment for the promise of being available to make a consumption change at an agreed time.

3.2 PARTICIPANTS IN DEMAND SIDE BIDDING

Many different parties are involved in demand side bidding. Each of the main participants is briefly explained in the following sections.

3.2.1 Demand Side Bidders

Demand side bidding relates to participation in electricity trading by consumers of electricity. Therefore, an electricity consumer represents the demand side bidder. If a consumer sells a block of electricity then they are required to switch off the necessary equipment to fulfill their commitment. In this way, a demand side bidder sells non-consumption of electricity; they have the option to consume.

3.2.2 Demand Side Aggregators

In order for a consumer to engage in DSB, it is necessary to use the services provided by a demand side aggregator. A demand side aggregator is defined as an organization that co-ordinates DSB by more than one participant.

In practice, it is not feasible for one electricity consumer to offer DSB products in the electricity wholesale market because the administrative cost and complexity would be too high. In particular, it would require an investment in electricity trading systems for submitting bids and receiving notification of acceptance. However, an aggregator can play an extremely useful role in facilitating DSB amongst many consumers by combining numerous minor bids together to form a major bid that can be traded in the wholesale electricity market. Any organisation can act as a demand side aggregator.

3.2.3 Demand Side Buyers

A demand side buyer is essentially a purchaser of demand side bids. Such purchasers are those organisations that are involved in the wholesale electricity market and have a need to balance electricity supply and demand or maintain the quality and security of supply. In particular, electricity suppliers, generators, the System Operator and network companies all represent potential demand side buyers.

3.3 CATEGORIES OF DEMAND SIDE BIDDING

DSB can take many forms, each known as a DSB 'product'. The DSB products have been broadly divided into the following categories:

Table-I

Categories of DSB Products

Characteristics	DSB Category	Main Features
DSB requiring consumers to alter their electricity demand	Ancillary Services	DSB to maintain quality.
	Transmission/Distribution constraints	DSB to solve network constraints
	Balancing Market	DSB for electricity balancing
	Spot Markets	DSB for access to spot market
DSB involving the bulk purchase of electricity	▪ Spot Markets ▪ Bilateral Contracts ▪ Supply Contracts	DSB for price setting

The main difference between these products is the time that bids are offered and accepted in the market place, as indicated in Fig. 2 below. For example, demand bids may be agreed several months or years in advance under supply contracts, but the actual demand shift required under ancillary services may not be known until a few minutes or even seconds ahead the time of delivery.

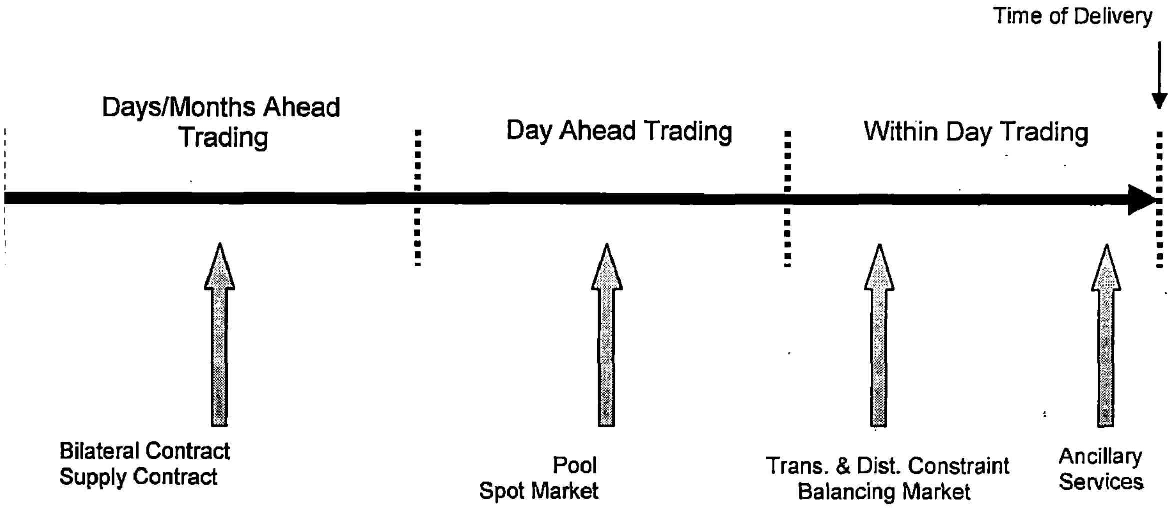


Fig. 2 Time Scale for bids of different DSB products

DSB products can exist between the consumer and almost any of the other market participants, as suggested by the schematic shown in Fig. 3.

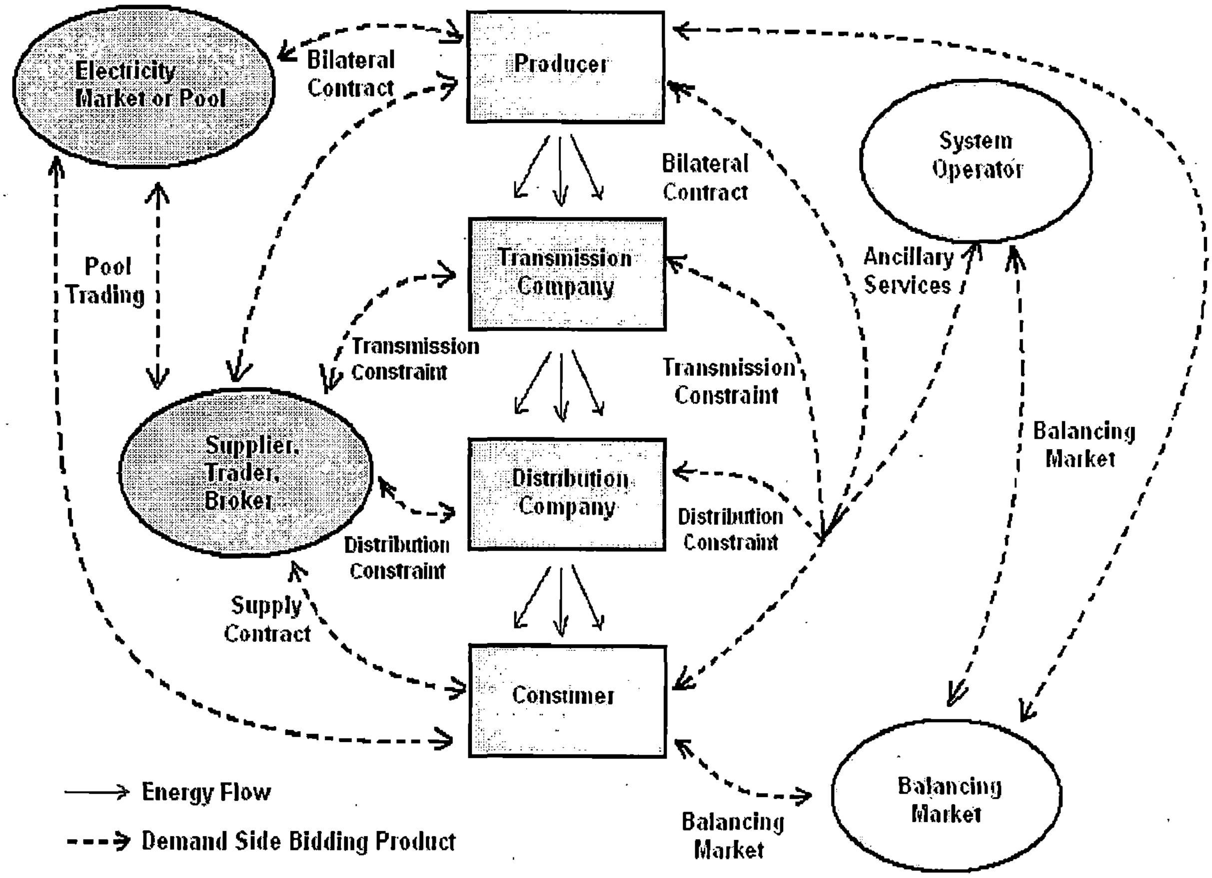


Fig. 3 Schematic showing possible DSB products between the market participants [3]

3.4 GENERIC REQUIREMENT FOR DSB

Invariably, Control, Metering and Communication technologies are required in order to make DSB happen. In very general terms making and delivering demand side bid involves the following steps:

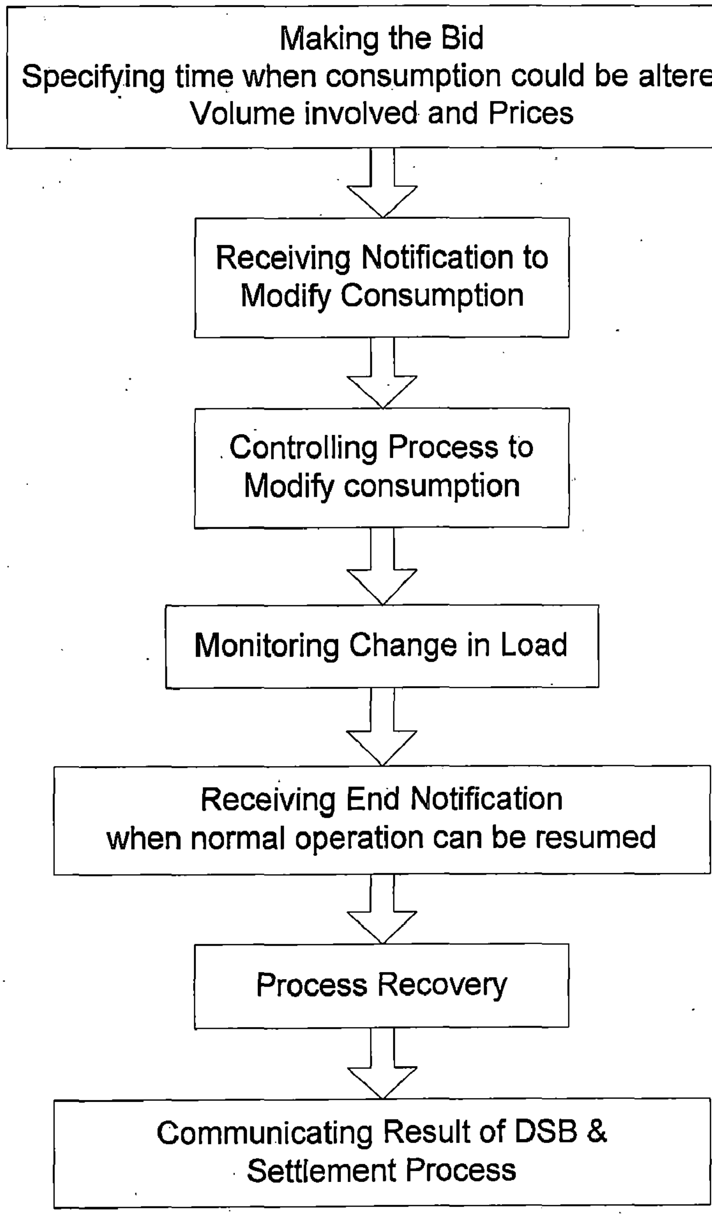


Fig. 4 Steps for making and delivering Demand Side Bids

The actual detail of each of these steps will depend on the kind of DSB product. In some cases, sophisticated electronics and associated software is required, in others it might involve little more than a phone call.

3.4.1 Control Equipment

The function of the control equipment is to effect the necessary change in electricity consumption. Thus, the control equipment should be able to switch on and off the relevant electrical load, whether this is to execute an agreed load schedule, or to make rapid changes in response to some predetermined signal. Thus one major difference in control between the various DSB products relates to the speed or notice required for switching and whether the control is manual or automatic. Allowing consumers to control their load manually requires a method of communicating the need to shift demand to the consumer. This can operate successfully with large consumers, but is not likely to be successful with domestic consumers who may be unable or unwilling to change their demand upon request. The results of the surveys also show that domestic consumers are unwilling to accept any interruption to their supply if it means a loss of comfort or service. This suggests that domestic consumers need technology that automates the demand shifting process without any loss of comfort.

In the category of DSB - to maintain quality of supply, load reduction must be rapid and consequently control is usually automatic. In many of the other DSB products, the control requires the schedule of the load and it will execute that schedule.

3.4.2 Monitoring Equipment

In terms of monitoring, or metering, the equipment must be able to verify that a consumer has switched off the necessary load for the required duration. High speed real time monitoring of individual resources is necessary for large resources such as generators and very large loads.

3.4.3 Communication Equipment

Communication between the DSB buyer and responsive load is required for sending the notification to modify or end of the consumption, to access the performance after the fact, set payments, etc. The DSB buyer cannot deal with the large number of individual sources via individual phone calls and that the communication requirements would be overwhelming. Communication technologies such as radio, internet, pagers, that support group notification, are better than the technologies that exclusively support individual communication, such as telephones. A requirement for individual communication may make sense only for the largest resources. The type of communication, the speed and the amount of data transferred are different for each DSB product.

There will be the costs involved with providing these technologies and these must be defined before the implementation of DSB. For consumers with large demands for electricity, the financial benefits of DSB products will outweigh the additional costs for these technologies. For example, large consumers are often already required to have half-hourly or hourly metering, and thus there are only modest additional costs associated with monitoring their demand bids. However, the additional costs of metering, telemetry, communication and monitoring for smaller consumers would far outweigh any benefits they may receive.

3.5 SPINNING RESERVE BY DEMAND SIDE

Here, the application of DSB in the category of ancillary services is studied, particularly for providing reserve: a contingency need to be available in the case of unexpected changes to demand or available generation. The electric power system is unique in that it must match aggregate production and consumption instantaneously and continuously. Several types of controllable reserves are maintained to help the system operator to achieve this required generation-load balance. Contingency reserves restore the generation-load balance after the sudden unexpected loss of a major generator or transmission line.

Traditionally, spinning reserve has been supplied from generators. The responsive loads can also be considered as the reserve provider. While responsive load can theoretically provide almost any service the power system requires, most loads are best suited to provide reserve. The basic idea of providing spinning reserve from load is rapidly curtailment of load.

Power system operators and power market designers should be motivated to encourage loads to participate in reserve markets because their participation will increase reliability and reduce costs to all power system customers. When loads provide spinning reserve, generation is freed up to provide energy. This increases generation supply, which reduces the energy-clearing price for everyone. Similarly, increasing the resource pool for contingency reserves necessarily reduces their costs to the system. The faster response offered by some loads further increases reliability. Finally, encouraging retail loads to provide reserves reduces the market power, in both energy and ancillary service markets, that some generators might have otherwise. Providing spinning reserve is a better match to the natural capabilities of many loads.

3.6 VIEWS TOWARDS DSB

While increased market efficiency, improved network operation and the possibility of environmental benefits are important, the main drivers for DSB as far as consumers are concerned is the ability to earn additional income or reduce market exposure costs. Not only does this additional income offset energy costs, but it can also be used to fund more traditional energy savings measures. For example, one company in the UK has used the income derived from participation in DSB to invest in high efficiency motors and drives, which will lead to savings in energy costs in the long-term.

However for the consumers who are manufacturers, any income derived from DSB is of secondary importance to the production process. Manufacturers are generally of the opinion that the 'process is king,' and participation in DSB is only possible if it does not have a significant impact on production rates. For example, in the case of cement manufacturing, interruptions to the crushing and milling operations will not have an impact on production because the crushed materials are stored prior to use. Similarly, a short interruption to the supply of an arc furnace does not have a significant impact on production rates.

Other processes cannot be interrupted once started, and therefore, have a much more limited potential for DSB schemes. For example, the start of batch processes can often be delayed to avoid use of high cost electricity. However, many processes are run on a 24 hours per day, 7 days per week basis to minimize costs and maximize production, thus providing only limited potential to participate in DSB. Thus consumers with these types of processes are largely restricted to participation in DSB categories that allow access to market prices. For those cases where it is impossible to interrupt the electrical supply under any circumstances without causing significant production losses, DSB can still be an option if the manufacturers use their standby generation capacity.

In recent years, DSB has been restricted primarily to large consumers, for example those of energy intensive industries. However, participation in DSB is not, and should not be restricted to these consumers. Encouraging wider participation from all consumers is seen as the next step for DSB.

CHAPTER – 4

PROBLEM FORMULATION

The scheduling of generators and loads in a centralized electrical power system is formulated as a mixed integer problem. The solution of this kind of scheduling problems involves the determination of on or off status of the generating units in each time interval; yes or no kind of status showing readiness of the demand side for load curtailment; and economic dispatch (ED) for each generator in a power system at each time interval in the scheduling period. ED is continuous problem which determines the allocation of the system load and reserve requirement to the generating units. It requires the simultaneous consideration of these decisions. Of course, this is a large problem, manifesting itself mathematically as a mixed-integer problem. In general, the scheduling problems are highly constrained and combinatorial in nature, and continue to present a challenge for efficient solution techniques.

4.1 PROBLEM DESCRIPTION

The market structure considered is a competitive power pool with centrally optimized scheduling. This accepts bids from both the supply and the demand side for energy and reserve and this form the criteria for optimum scheduling subject to a variety of operational constraints. The total generation must meet the demand; moreover there must be a certain level of reserve capacity available. Individual generating units are characterized by constraints including the maximum and minimum generation levels. Individual loads are also characterized by maximum and minimum load limits. Consumers are ready to curtail their consumption to participate in the reserve market. There are also set limits on the reduction of load, which will not allow any consumer to curtail its consumption more than its specified limit.

4.2 MATHEMATICAL FORMULATION

This section presents generation scheduling with demand side bidding as a mixed-integer nonlinear problem. As both generators and consumers are submitting bid in the pool for energy, the general supply and demand curves are shown in Fig. 5.

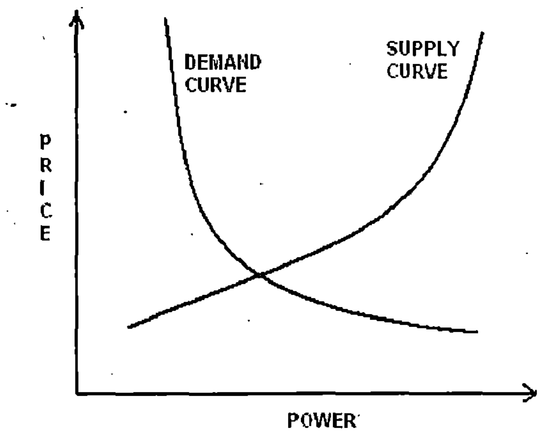


Fig. 5 Supply and Demand curve

4.2.1 Supply Side

Generator i bids in a supply curve for each time period h with coefficients a_i, b_i and c_i. The cost of energy associated with generator i at time h is then

$$UG_{ih}\,(a_{ih}\,PG_{ih}^2 + b_{ih}\,PG_{ih} + c_{ih}) \tag{4.1}$$

For reserve, the generator bids a price per MWh, DG_i. The reserve price DG_i will reflect the generators` estimates of their opportunity costs and the wear and tear caused by the units being available to provide reserve. The cost for reserve associated with generator i at time h is then

$$UG_{ih}\,DG_i\,RGEN_{ih} \tag{4.2}$$

The reserve characteristic used here is,

$$RGEN_{ih} = \phi_{ih}\,(PG_i^{\max} - PG_{ih}) \tag{4.3}$$

The generators quote the value of ϕ_i relevant to their unit. The value of ϕ_i will vary depending on the timeframe within which reserve is required, but will always less than or equal to 1.

4.2.2 Demand Side

An elastic load, customer j, bids in quadratic demand curve with coefficients d_j and e_j. Then customer j at time h is willing to pay,

$$UL_{jh}\,(-d_{jh}\,PL_{jh}^2 + e_{jh}\,PL_{jh}) \tag{4.4}$$

This is also called as bid benefit power function for the load. It is analogues to the cost of the supplier.

A customer that can interrupt load and wishes to bid into the reserve market bids with a price DL_j per MWh. The cost for reserve associated with customer j at time h is

$$ULR_{jh} DL_j \, PL_{jh}^{sd} \tag{4.5}$$

4.2.3 Formulation of Optimization Problem

The main function of the market operator is to minimize the combined cost of the total generated energy and of the reserve provided by producers and consumers, as well as to maximize the total benefit obtained by the consumers.

The objective function to be minimized:

$$\begin{aligned}&\sum_{h=1}^{T}\sum_{i=1}^{ng} UG_{ih}\,(a_{ih}\,PG_{ih}^2 + b_{ih}\,PG_{ih} + c_{ih}) - \sum_{h=1}^{T}\sum_{j=1}^{nl} UL_{jh}\,(-\,d_{jh}\,PL_{jh}^2 + e_{jh}\,PL_{jh})\\ &+\sum_{h=1}^{T}\sum_{i=1}^{ng} UG_{ih}\,DG_i\,\phi_{ih}\,(PG_i^{\max} - PG_{ih}) + \sum_{h=1}^{T}\sum_{j=1}^{nl} ULR_{jh}\,DL_j\,PL_{jh}^{sd}\end{aligned} \tag{4.6}$$

Owing to the operational requirements, the minimization of the objective function is subject to the following constraints:

(a) *Equality Constraints*

(1) Power Balance Constraint

Assuming that the transmission losses are neglected, in each time period total generation should be equal to total demand.

$$\sum_{i=1}^{ng} UG_{ih}\,PG_{ih} = \sum_{j=1}^{nl} UL_{jh}\,PL_{jh}, \qquad i = 1, \ldots, n_g; j = 1, \ldots, n_l \quad h = 1, \ldots, T \tag{4.7}$$

(b) *Inequality Constraints*

(2) Reserve Constraint

In each time period, reserve provided by generators and consumers should be more than or equal to the reserve required in that particular period.

$$\sum_{i=1}^{ng} UG_{ih}\, \phi_i\, (PG_i^{\max} - PG_{ih}) + \sum_{j=1}^{nl} ULR_{jh}\, PL_{jh}^{sd} \geq REQRES_h, \tag{4.8}$$

$$i = 1, \ldots, n_g;\ j = 1, \ldots, n_l;\ h = 1, \ldots, T$$

(3) Generation Limit Constraint

For each generator, its generated power should be limited within the upper and lower bounds.

$$UG_{ih} PG_i^{\min} \leq PG_{ih} \leq UG_{ih} PG_i^{\max},\ \forall i,\ h = 1, \ldots, T \tag{4.9}$$

(4) Load Limit Constraint

For each load, its demand requirement should be limited within the upper and lower bounds.

$$PL_j^{\min} \leq PL_{jh} \leq PL_j^{\max},\ \forall j,\ h = 1, \ldots, T \tag{4.10}$$

(5) Load Shedding Constraint

For each load, its load curtailment capacity should be limited within the upper and lower bounds.

$$PL_{jh}\, \delta_j \leq PL_{jh}^{sd} < PL_{jh},\ \forall j,\quad h = 1, \ldots, T \tag{4.11}$$

Here a consumer can provide a proportion δ_j $(\delta_j \leq 1)$ of the level they are dispatched at as reserve. $(PL_j \delta_j)$ term denotes the lower limit to which the j^{th} load is willing to curtail itself to provide reserve. If $\delta_j = 0$, means that the load is willing to curtail demand by the full amount.

Here, the value of $UL\,[\in(0,1)]$ for all customers and for each time period is considered as 1, indicating that all the loads are participating into the market for all time. Also the value of ϕ_i is kept constant for i^{th} generator during all time period.

CHAPTER – 5

PARTICLE SWARM OPTIMIZATION

PSO was formulated by Edward and Kennedy in 1995 [15]. The thought process behind the algorithm is inspired by the behavior of social insects such as fish schools and bird flocks. In general, this is done by mimicking the behavior of the biological creatures within their swarms and colonies. Particle swarm optimization, also commonly known as PSO, mimics the behavior of a swarm of birds or a school of fish. If one of the particles discovers a good path to food the rest of the swarm will be able to follow instantly even if they are far away in the swarm. Swarm behavior is modeled by particles in multidimensional space that have two characteristics: a position and a velocity. These particles wander around the hyperspace and remember the best position that they have discovered. They communicate good positions to each other and adjust their own position and velocity based on these good positions.

PSO is a population-based optimization tool, which could be implemented and applied easily to solve various function optimization problems, or the problems that can be transformed to function optimization problems. As an algorithm, the main strength of PSO is its fast convergence, which compares favorably with many global optimization algorithms like Genetic Algorithms (GA), Simulated Annealing (SA) and other global optimization algorithms. For applying PSO successfully, one of the key issues is finding how to map the problem solution into the PSO particle, which directly affects its feasibility and performance. PSO is powerful, easy to understand, easy to implement and computationally efficient.

Some characteristic of PSO which are common to other metaheuristic methods are as follows:

- It is applicable to the nondifferentiable optimization problems as it does not require the gradient information of functions.
- Compared with one point search method, it utilizes multi point search.
- Provide a list of optimum variables, not just a single solution.

5.1 A THUMBNAIL SKETCH OF PSO

The PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions. They move iteratively through the n-dimension problem space to search the new solutions, where the fitness of each particle can be calculated as the certain qualities measure. Each particle has a position represented by a position-vector x_i (i is the index of the particle), and a velocity represented by a velocity-vector V_i. Each particle remembers its own best position found so far in the exploration. This position is called personal best and is denoted by *pbest*. Additionally, among these pbests, there is only one particle that has the best fitness, called the global best and is denoted by *gbest*. At (k +1) iteration, the update of the velocity from the previous velocity to the new velocity is determined by Eq. (5.1). The new position is then determined by the sum of the previous position and the new velocity by Eq. (5.2).

$$V_i^{k+1} = \omega\, V_i^k + c_1 r_1 (gbest - x_i^k) + c_2 r_2 (pbest - x_i^k) \tag{5.1}$$

$$x_i^{k+1} = x_i^k + V_i^{k+1} \tag{5.2}$$

Velocity updates are influenced by both the gbest solution associated with the lowest fitness value ever found by a particle and the pbest solution associated with the lowest fitness in the present population. If the pbest solution has a fitness value less than the fitness value of the current global solution, then the pbest solution replaces the gbest solution. The particle velocity is reminiscent of local minimizers that use derivative information, because velocity is the derivative of position. In order to guide the particles effectively in the search space, the maximum moving distance during each iteration must be clamped in between the maximum velocity [$-Vmax$, $Vmax$].

5.2 PARAMETERS OF PSO

5.2.1 Inertia weight (ω)

The role of inertia weight ω, in Eq. (5.1), is considered critical for the convergence behavior of PSO. The inertia weight is employed to control the impact of the previous history of velocities on the current one. Accordingly, the parameter

ω regulates the trade-off between the global and the local exploration abilities of the swarm. A large inertia weight facilitates global exploration while a small one tends to facilitate local exploration, i.e., fine tuning the current search area. The suitable value of inertia weight results in a reduction of the number of iterations required to locate the optimum solution.

However, some experiment results indicates that it is better to initially set the inertia to a large value, in order to promote global exploration of the search space, and gradually decrease it to get more refined solutions [17]. Thus, an initial value around 0.9 and gradually reducing towards 0 can be considered as a good choice for ω. The inertia term decreases gradually during the search iteration k by,

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{k_{\max}} \times k \tag{5.3}$$

5.2.2 Cognitive Parameter (c_1) and Social Parameter (c_2)

The parameters $c1$ and $c2$, in Eq. (5.1), are not critical for the convergence of PSO. However, proper fine-tuning may result in faster convergence and alleviation of local minima. These coefficients are recommended to keep the following relationship.

$$c_1 + c_2 \leq 4 \tag{5.4}$$

As default value, usually, $c_1 = c_2 = 2$ are used.

5.2.3 Population Size

PSO is a population based stochastic optimization technique. It will work effectively with the moderately sized population. A large population will search the space more completely, but at the higher computational cost. Generally, the population size in PSO is taken in between 20-50.

5.3 BASICS OF BINARY PSO

The original version of PSO operates on real values. However, many practical problems frequently encounter discrete/integer variables as well as continuous variables, and they cannot be solved using the continuous-valued particle swarm algorithm. J. Kennedy and R. Eberhart [16] have provided the revision of particle swarm algorithm from continuous to a discrete binary operation, where particle swarm can take on values of 0 and 1 only.

Binary version of PSO is the probability of individual's deciding yes or no, true or false, or making some other binary decision. Thus a particle moves in a state space restricted to zero and one on each dimension, where each V_i represents the probability of bit x_i taking the value 1. The velocity V_i will determine a probability threshold. If V_i is higher, the individual will more likely to choose 1, and lower value favors the 0 choice. In other words, if $V_i = 0.20$, then there is a 20% chance that x_i will be 1, and 80% chance it will be 0.

In sum, the particle swarm formula:

$$V_i^{k+1} = \omega\, V_i^k + c_1 r_1 (gbest - x_i^k) + c_2 r_2 (pbest - x_i^k) \tag{5.5}$$

remains unchanged, except that now x_i, *pbest* and *gbest* are integers in $\{0,1\}$ and V_i, since it is a probability, needs to stay in the range [0.0, 1.0]. One straightforward function for accomplishing V_i as probability threshold is common in neural networks. The function is called the sigmoid function and is defined as follows:

$$s(V_i) = \frac{1}{1+\exp(-V_i)} \tag{5.6}$$

The function forces its input into the requisite range and has properties that make it agreeable to be used as a probability threshold. The new position is then determined by the following rule:

If $(rand() < sV_i)$ *then* $x_i = 1$;

else $x_i = 0$

According to this rule, a random number is generated between [0, 1]. x_i is set to 1 if the random number is less than the value from the sigmoid function, otherwise x_i is set to 0.

Similar to continuous valued particle swarm algorithm, in a binary PSO also *Vmax* is set to limit the range of V_i. A large *Vmax* value results in a low frequency of changing state of x_i, whereas a small value increases the frequency of bit flipping. In practice, *Vmax* is set at $\pm$ 4.0, so that there is always a good chance that ample number of bits will change their states.

5.4 CONSTRAINTS SATISFACTION

The key point in the constrained optimization process is to deal with the constraints. Many methods are proposed [19] for handling constraints, such as methods based on penalty functions; methods based on preserving feasibility of solutions; method that make a clear distinction between feasible and infeasible solution; and other hybrid methods. The most straightforward method is one based on preserving feasibility of solutions. The same is applied here in the solution approach.

When implementing this technique into the PSO, the initialization process involves forcing all particles into the feasible space before any evaluation of the objective function has begun. Upon evaluation of the objective function, only particles which remain in the feasible space are counted for the new *pbest* and *gbest* values. The idea here is to accelerate the iterative process of tracking feasible solutions by forcing the search space to contain only solutions that do not violate any constraints.

5.5 HPSO AS SOLUTION METHODOLOGY

As explained in chapter 4, the scheduling problem considered in this work has both continuous and binary variables. To handle both types of variables, hybrid particle swarm optimization method is adopted. HPSO is the blend of real coded PSO (RCPSO), for solving economic dispatch for generation and load, and binary PSO (BPSO), for finding ON/OFF status of generators and consumers. The generalized structure of HPSO applied for the problem solution is shown in Fig. 6.

In our case, the scheduling problem is formulated for 24 hour operating time period. To solve this multiperiod problem, 'divide and conquer' strategy is used; where the problem is solved for each hour.

BPSO initialize the particle swarm with 1 and 0, indicating the ON/OFF status of generators, randomly. This binary information is send to RCPSO. RCPSO produces generation value for each generator randomly, within their maximum and minimum limits. With the ON/OFF status and generation value available, load balance constraint is checked. In order to decrease the pressure of constraint violation error, a set of major feasible solutions that satisfy the power demand is generated before evaluation of the fitness function (Eq. (4.6)). This assures that the PSO explores in a feasible environment,

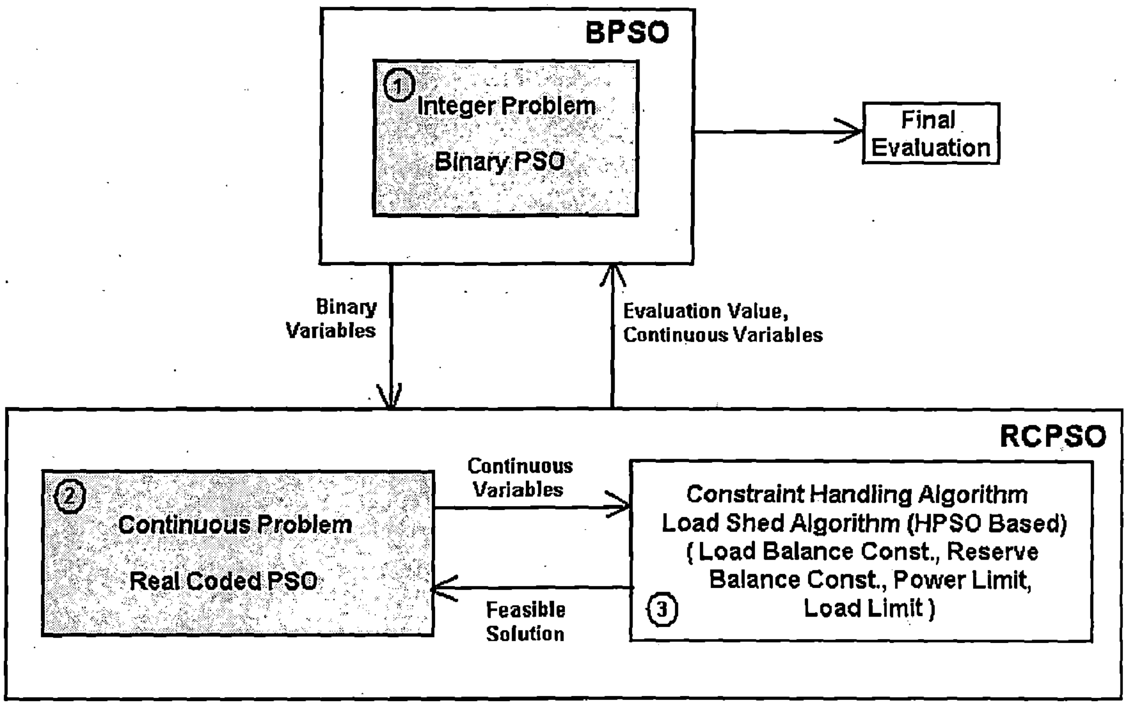


Fig. 6 Structure of the HPSO approach

which reduces the computation time as well as improves the quality of the solution [18]. The pseudo code below illustrates the process whereby the feasible power values are generated based on its demand.

Do while *Demand is not met*

    If total power generated < Demand ***then***

        For *i = 1 to TotalGen*

            Set available generators to operate at maximum capacity.

            Once the total power generated is greater than the demand, minus the error from the current generator in order to exactly meet the demand.

            Check the range.

If exceed maximum or minimum limit, re-initialize randomly within power limits of a generator.

***Next** i*

Else if** total power generated > Demand **then

***For** i = TotalGen to 1 step -1*

Set available generators to operated at minimum capacity.

Once the total power generated is less than the demand, add the error to the current generator in order to exactly meet the demand.

Check the range.

If exceed maximum or minimum limit, re-initialize randomly within power limits of a generator.

Next i

End If

Loop

The *gbest* value of the RCPSO symbolizes generation value corresponding to the binary string indicating ON/OFF status, with minimum operating cost and also satisfying the demand balance constraint. Now the reserve constraint is checked. If the required reserve is not met with the online generator units, then load shedding algorithm is followed.

The load shedding algorithm also uses the concept of HPSO. Here BPSO is used for selecting the loads to participate in load shedding procedure to satisfy the reserve requirement and RCPSO is used to decide the optimum amount of load shed value. Here also a set of major feasible solutions that satisfy the reserve requirement is generated before evaluation of the load curtailment cost. The pseudo code below illustrates the process whereby the feasible load shed values are generated based on reserve requirement.

***Do while** ResDemand is not met*

If** total load shed < ResDemand **then

***For** i = 1 to TotalLoad*

Set available loads to curtail upto maximum capacity.

Once the total load shed is greater than the reserve demand, minus the error from the current load in order to exactly meet the reserve demand.

Check the range.

If exceed maximum or minimum limit, re-initialize randomly within limits of a load shed.

Next i

Else if** total load shed > ResDemand **then

***For** i = TotalLoad to 1 step -1*

Set available loads to curtail at minimum capacity.

Once the total load shed is less than the reserve demand, add the error to the current load in order to exactly meet the reserve demand.

Check the range.

If exceed maximum or minimum limit, re-initialize randomly within limits of a load shed.

Next i

End If

Loop

After satisfying demand and reserve constraint, again optimal schedule with modified load pattern is obtained. With all optimal values of binary and continuous variables, the main objective function is evaluated and this cost is sent back to the main BPSO. BPSO will find the optimal value of the objective function using swarm algorithm. To get the better results more iteration should perform. Here, each hour will have its own minimum cost value, and the total cost will be the summation of the hourly-based costs.

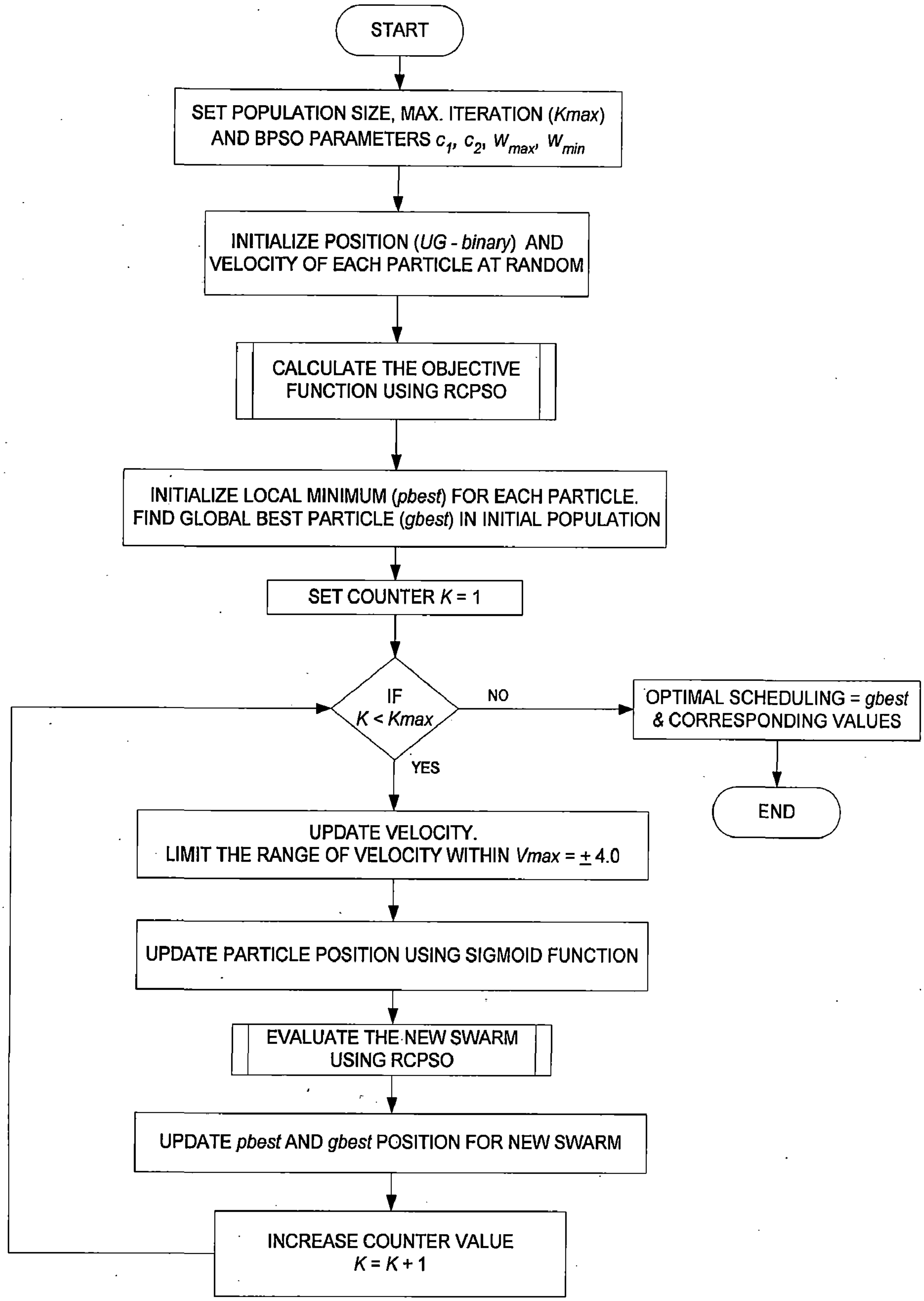


Fig. 7 Flowchart for BPSO

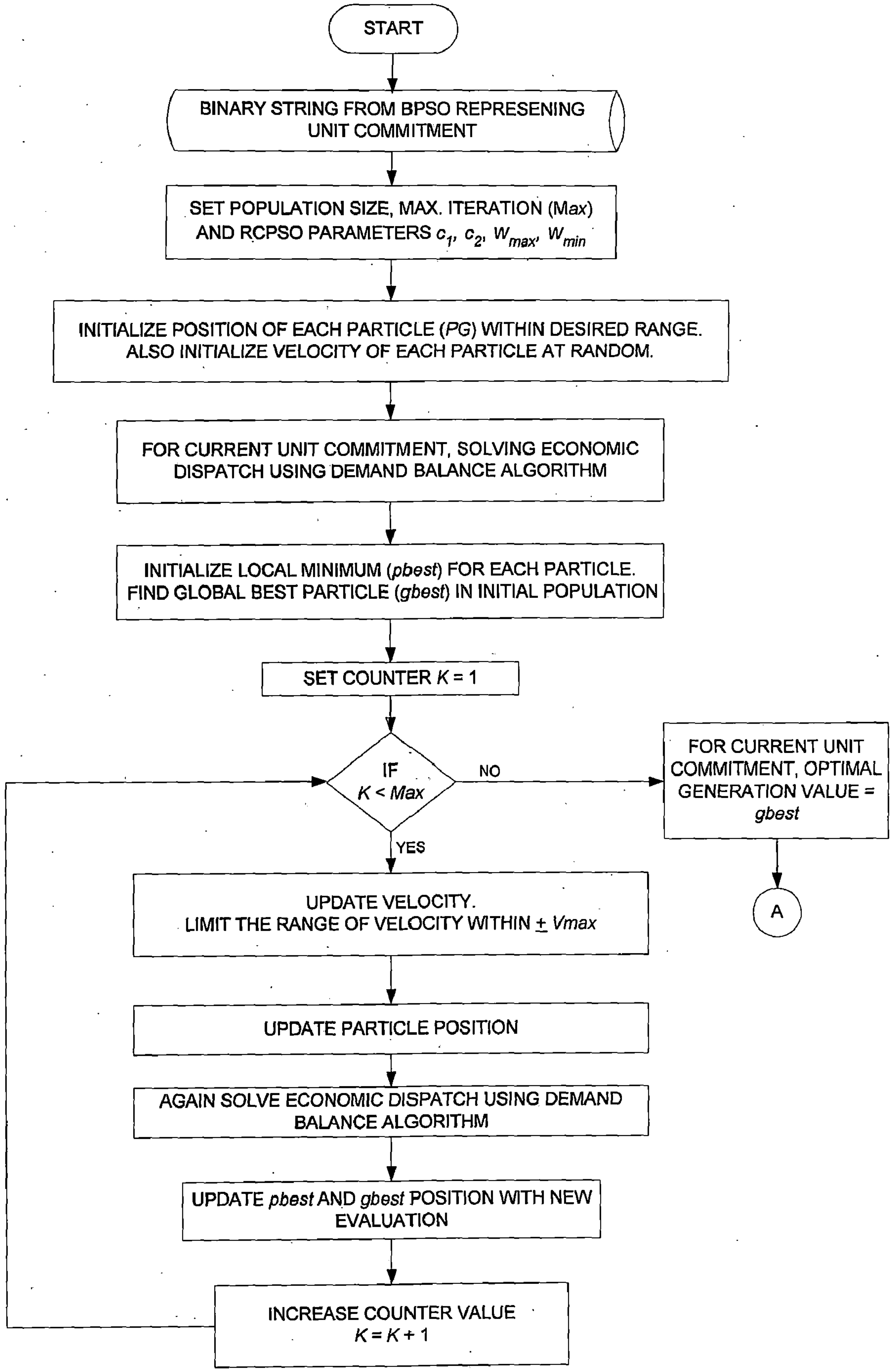


Fig. 8 Flowchart for RCPSO (*Cont.*)

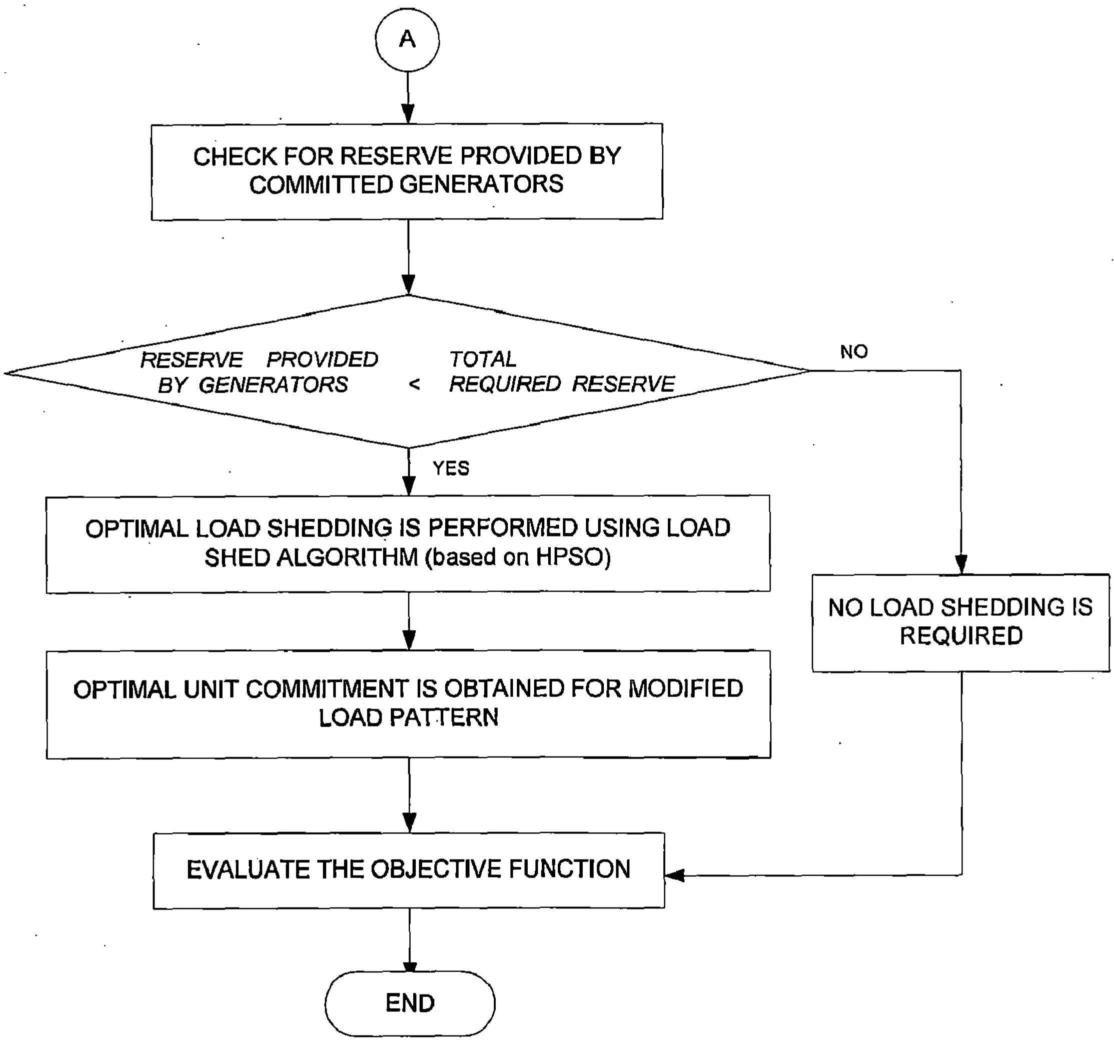


Fig. 8 Flowchart for RCPSO

CHAPTER – 6
HYBRID ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks (ANN) are nonlinear information processing devices, which are built from interconnected elementary processing devices called neurons. This paradigm has been motivated by the kind of computing performed by the human brain. It resembles the brain in two respects:

- Knowledge is acquired by the network through a learning process.
- Inter-neuron connection strengths known as synaptic weights are used to store the knowledge

ANN is composed of highly interconnected neurons working in union to solve specific problems. ANNs learn by examples. They can therefore be trained with known examples of a problem to acquire knowledge about it. There are various learning mechanism exist to enable the ANN acquire knowledge. Based on these learning mechanisms and other features, ANN architectures have been classified into various types. Once appropriately trained, the network can be put to effective use in solving 'unknown' or 'untrained' instances of the problem.

Here, a methodology is proposed where ANN is used in conjunction with PSO, which is termed as hybrid artificial neural network (HANN).

6.1 MODEL OF AN ARTIFICIAL NEURON

The behavior of a biological neuron has been represented by a simple model as shown in Fig 9. Every component of the model bears a direct analogy to the actual constituents of a biological neuron and hence is termed as artificial neuron. It is the model which forms the basis of ANNs.

Here, $x_1, x_2, \ldots, x_n$ are the n inputs to the artificial neuron and $w_1, w_2, \ldots, w_n$ are the weights attached to the input links. The total input I received by the summation junction of artificial neuron is

$$I = w_1x_1 + w_2x_2 + \ldots + w_nx_n$$

$$= \sum_{i=1}^{n} w_ix_i \tag{6.1}$$

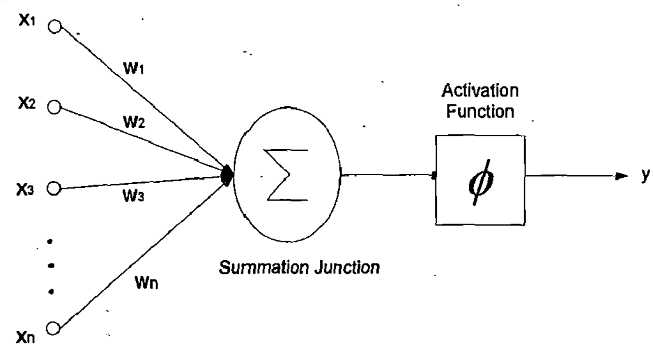


Fig 9 Simple model of an artificial neuron

To generate the final output y, the sum is passed on to a function called Activation Function or Transfer Function (ϕ).

$$y = \phi(I) \tag{6.2}$$

6.2 BUILDING BLOCKS OF ANN

The basic building blocks of ANN are:

1. Training or Learning
2. Architecture
3. Activation Function

All these are discussed in brief below.

6.2.1 Training Or Learning

The method of setting the value for the weights enables the process of training or learning. The process of modifying the weights in the connections between network layers with the objective of achieving the expected output is called training a network. Training methods used in ANN can be broadly classified into three basic types: Supervised Training, Unsupervised Training and Reinforcement Training. However, Supervised and Unsupervised training methods are used in most applications.

There are certain set of well defined rules are available for the solution of a training or learning problem, which are called as the learning rules. Each learning rule differs from the other in the way in which the adjustment of a synaptic weight of a neuron is formulated. Also, the manner in which a neural network is made up of a set of interconnected neurons relating to its environment is also to be considered. There are various learning rules are available, such as Hebbian Learning Rule, Delta Learning Rule, etc.

6.2.2 Network Architecture

One of the basic building blocks of ANN is the network architecture. The arrangement of the neurons into layers and the pattern of connection within and in-between layers are generally called as the architecture of the neural network. ANN architectures have been broadly classified as single layer feed forward network, multilayer feed forward network and recurrent network. Over the years, several other ANN architectures have been also evolved.

Here, a three layer feed forward network is used. The three layers are input, hidden and output layers. There are various methods available to decide the number of layers as well as number of neurons in each layer. But here trial and error method is used to decide the structure of the network. The presented structure provides minimum time for the training.

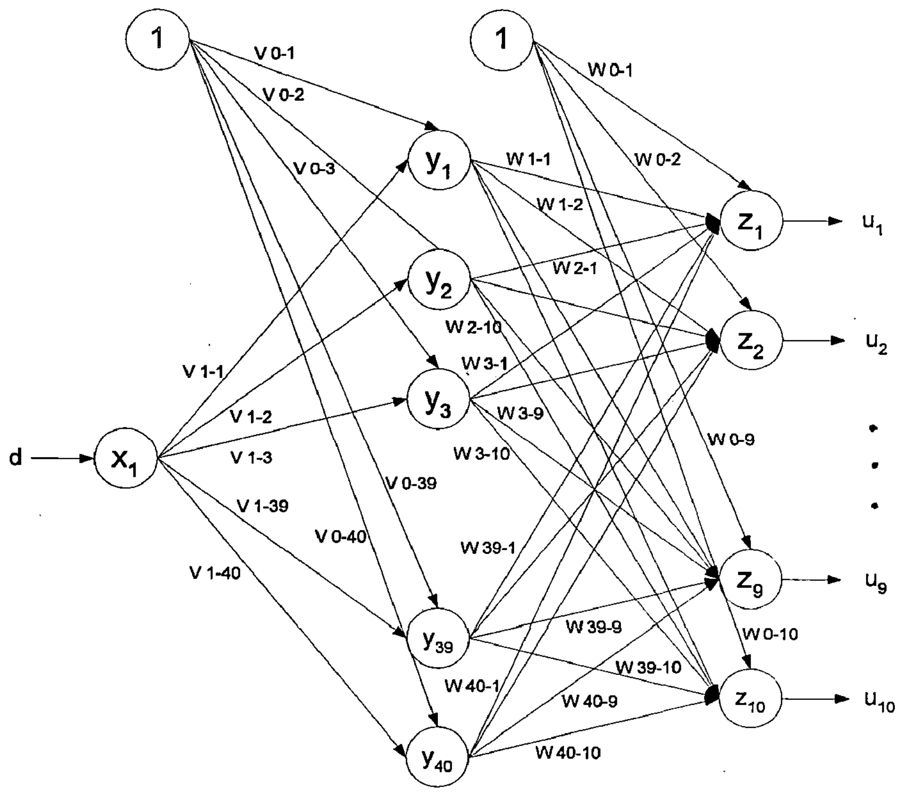
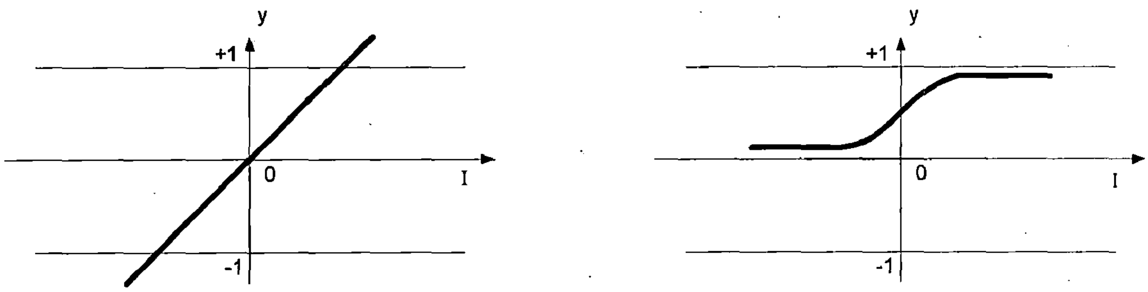


Fig. 10 Structure of the neural network

6.2.3 Activation Function

The activation function is used to calculate the output response of a neuron. The sum of the weighted input signal is applied with an activation to obtain the response. For neurons in same layer, same activation functions are used. These may be linear as well as nonlinear activation functions. A few linear and nonlinear activation functions are binary step function, sigmoidal function, linear function, hyperbolic tangent function, etc. Here, sigmoidal function used in input and hidden layer, linear function is used in output layer.



(a) *linear* (b) *sigmoidal*

Fig. 11 Activation functions for NN

6.3 SOLUTION METHODOLOGY

A three layer feed forward network is used to decide the ON/OFF status of generators for scheduling purpose without considering DSB. The input layer of the ANN is configured to adapt a load profile. The inputted load values are to be normalized using the following expression:

$$Dn_j = \frac{D_j - D_{min}}{D_{max} - D_{min}} \times 0.8 + 0.1 \tag{6.3}$$

where, j = index of hour

D_j = demand at j^{th} hour

Dn_j = normalized value of demand at j^{th} hour

D_{max} = maximum value of demand among all the pattern

D_{min} = minimum value of demand among all the pattern

The neurons in the output layer provide the commitment st corresponding to the load value. A committed schedule contains ON/OFF states of generator that is one or zero.

Proper training is the vital part of the application of ANN. For training purpose, a set of load profiles and their corresponding commitment schedules are to be determined. Each pair of the load profile and its commitment schedule is referred to as input/target data pair. These input/target data pairs are generated using HPSO based methodology as shown in Fig. 12. The theoretical background of HPSO is already described in chapter-4 with the relevant flowcharts.

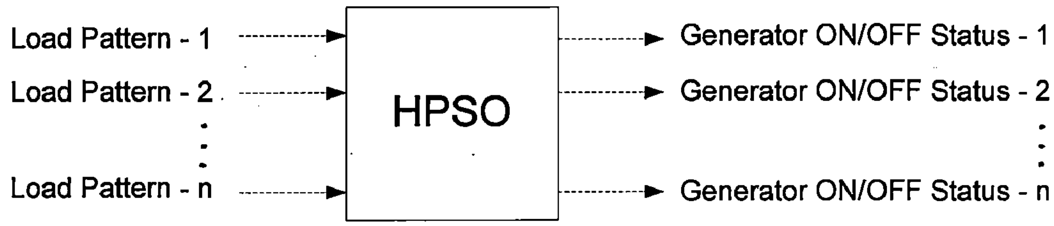


Fig. 12 Pattern generation for ANN training

For the given load profile, HPSO will provide ON/OFF status of generators as well as generation value of each generator. For training the neural network, only generators ON/OFF status are to be considered. The back propagation algorithm (BPA) is used for the training of proposed NN. The procedural steps of BPA are described as follows:

Step :1 Initialize the weights to small random values.

Feed Forward

Step:2 Each input unit receives the input signal, applies activation function and transmits the output signals to hidden layer. (

Step:3 Each hidden unit sums its weighted input signals, applies activation function and sends the output signals to the output layer.

Step:4 Each output unit sums its weighted input signals and applies its activation function to calculate the output signals.

Error Back Propagation

Step:5 Each output unit receives a target pattern corresponding to an input pattern, from which error information term is calculated.

Updation of weight and bias

Step-6 Each output unit updates its weights and bias using the error information term obtained from the step-5.

Error Back Propagation

Step-7 Each hidden unit sums its delta inputs from units in the layer above and the error information term is calculated.

Updation of weight and bias

Step-8 Each hidden unit updates its weights and bias using the error information term obtained from the step -7.

Step-9 Test the stopping condition. Repeat steps 2-8 until the convergence criterion is not satisfied.

After providing training, the base load profile is to be presented to the network. The network will give the generators status at the output neurons according to the knowledge gained during training. To get the generation value corresponding to the ON/OFF status, real coded PSO method is used. The flowchart for the proposed methodology is shown in Fig. 13. The RCPSO uses the generators status on hourly basis and gives generation value for each generator using particle swarm optimization method.

The proposed HANN methodology is tested on the small system comprising 10 generators and 6 loads without considering DSB. Here to train the network, one hundred load patterns for 24 hours are used. These training patterns are generated using HPSO method. The HPSO takes approximately 2-3 minutes time for one hour scheduling. This difficulty is overcome by using HANN. Due to ANN's learning and generalization ability, it will give scheduling for 24 hours within few second computing time. Also the obtained results are very encouraging which proves this method as the efficient and competitive.

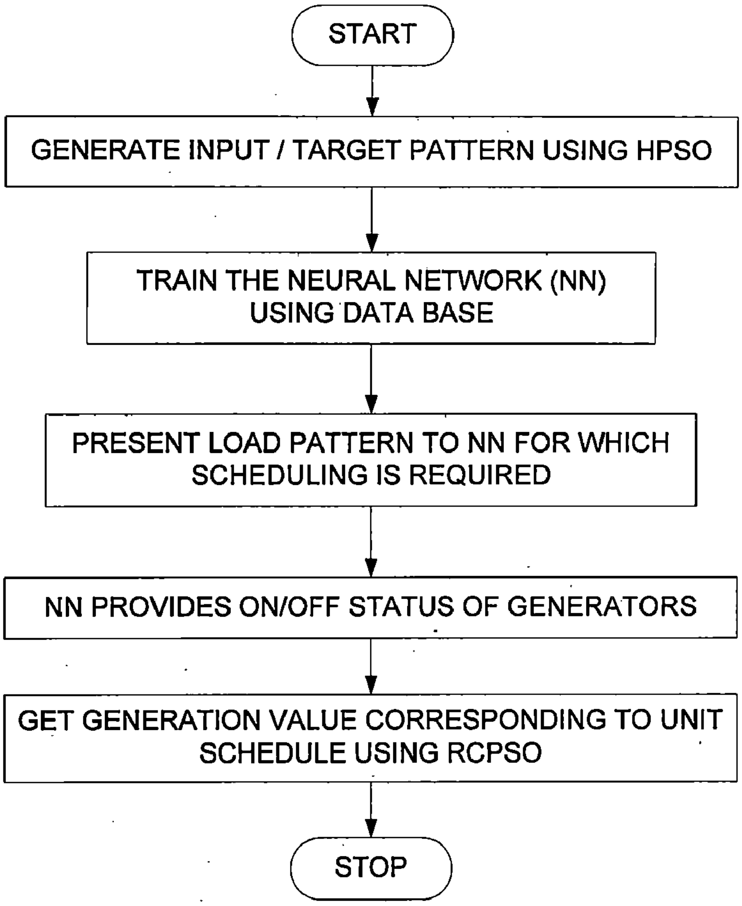


Fig. 13 Flowchart for scheduling using HANN

CHAPTER – 7
RESULT & DISCUSSION

To demonstrate the application of the developed method, a sample power system comprising 10 thermal generators and 6 loads are considered. The system data is provided in Appendix – A. Moreover, all the six loads are ready to curtail their demand up to their minimum limit as and when required.

Case - 1

In this case, the application of DSB for providing reserve is studied. onventionally, spinning reserve has been supplied from generators. The responsive ads can also be considered as the reserve provider. Responsive load has the potential to a more reliable supplier of reserves.

For the scheduling problem considered here, supply side as well as demand side into the market for energy as well as for reserve. If generators provide the reserve uirement, then they will get the payment as per their bids. Similarly, if consumers will vide the reserve by reducing load then they are also received payment according to r bid amount. The proposed method is applied to the system considered, and the ılts are shown in Table-II and III.

The total cost after considering DSB is 214097.17 mu (1 mu = 45 Rs.). If the e load profile for 24 hours is scheduled without considering DSB, then its overall cost ıes out to be 261126.38 mu which is 47029.21 mu more than the scheduling cost of system with considering DSB. The scheduling without considering DSB is given in le-IV. It indicates that these responsive loads could be excellent providers of spinning rve. When loads provide spinning reserve, generation is freed up to provide energy h reduces the overall cost. This in turn also reduces the energy price for those umers which are not participating into the DSB scheme.

The obtained result show the general validity of the method used. The algorithm ccessful in committing and dispatching generation and load and in providing reserve ompetitive framework. All schedules referred feasible, near optimal solution.

Table-II Scheduling with considering DSB

	ON/OFF Status of Generators										Generators Output (MW)										Modified Load (MW)	Cost (mu/Hr)
Hour	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10		
1	1	0	1	1	0	0	0	0	0	0	455	0	97.11	110.83	0	0	0	0	0	0	662.93	5324.97
2	1	0	1	1	0	0	0	0	0	0	455	0	114.46	110.44	0	0	0	0	0	0	679.90	5533.32
3	1	1	1	0	0	0	0	0	0	0	455	278.98	116.02	0	0	0	0	0	0	0	850.00	7126.53
4	1	1	1	0	0	0	0	0	0	0	455	338.33	121.93	0	0	0	0	0	0	0	915.26	7263.23
5	1	1	1	0	0	0	0	0	0	0	455	396.10	84.90	0	0	0	0	0	0	0	936.00	7548.48
6	1	1	1	1	0	0	0	0	0	0	455	377.20	119.07	118.00	0	0	0	0	0	0	1069.27	8463.37
7	1	1	1	1	0	0	0	0	0	0	455	381.42	120.31	123.15	0	0	0	0	0	0	1079.87	8864.12
8	1	1	1	1	0	0	0	0	0	0	455	455	130	82.89	0	0	0	0	0	0	1122.88	8864.07
9	1	1	1	1	1	0	0	0	0	0	455	455	130	130	54.59	0	0	0	0	0	1224.59	10450.29
10	1	1	1	1	1	0	0	0	0	0	455	455	130	130	100.2	0	0	0	0	0	1270.20	10989.19
11	1	1	1	1	1	0	0	0	0	0	455	455	130	130	136.40	0	0	0	0	0	1306.40	11199.76
12	1	1	1	1	1	1	1	0	0	0	455	455	130	130	157.82	61.32	24.54	0	0	0	1413.68	13442.45
13	1	1	1	1	1	0	0	0	0	0	455	455	130	130	111.26	0	0	0	0	0	1281.26	11073.80
14	1	1	1	1	1	0	0	0	0	0	455	455	130	130	55.45	0	0	0	0	0	1225.45	10498.95
15	1	1	1	1	0	0	0	0	0	0	455	446.57	92.71	119.07	0	0	0	0	0	0	1113.35	9071.46
16	1	1	1	1	0	0	0	0	0	0	455	307.22	129.49	127.39	0	0	0	0	0	0	1019.10	8798.99
17	1	1	1	0	0	0	0	0	0	0	455	336.03	124.37	0	0	0	0	0	0	0	915.40	7688.33
18	1	1	1	1	0	0	0	0	0	0	455	375.60	126.19	91.33	0	0	0	0	0	0	1048.18	8730.88
19	1	1	1	1	0	0	0	0	0	0	455	435.19	129.85	94.13	0	0	0	0	0	0	1114.17	8830.32
20	1	1	1	1	1	0	0	0	0	0	455	455	130	130	100.20	0	0	0	0	0	1270.20	10911.38
21	1	1	1	1	1	0	0	0	0	0	455	455	130	130	51.23	0	0	0	0	0	1221.23	10432.78
22	1	1	1	1	0	0	0	0	0	0	455	362.24	107.21	124.32	0	0	0	0	0	0	1048.76	8802.46
23	1	1	1	0	0	0	0	0	0	0	455	310.63	117.99	0	0	0	0	0	0	0	883.62	7286.49
24	1	1	0	0	0	0	0	1	0	0	455	335	0	0	0	0	0	10	0	0	800.00	6901.55

Table-III Load Shedding ...

	Load Shedding Status						Amount of Load Shed (MW)						Total Load Shed (MW)
Hour	1	2	3	4	5	6	1	2	3	4	5	6	
1	1	0	0	0	0	0	37.07	0	0	0	0	0	37.07
2	1	1	0	0	0	0	40	30.10	0	0	0	0	70.10
3	0	0	0	0	0	0	0	0	0	0	0	0	0.00
4	1	0	0	0	0	0	34.74	0	0	0	0	0	34.74
5	1	0	0	0	0	0	64.00	0	0	0	0	0	64.00
6	1	0	0	0	0	0	30.73	0	0	0	0	0	30.73
7	1	0	0	0	0	0	70.13	0	0	0	0	0	70.13
8	1	0	0	0	0	0	77.12	0	0	0	0	0	77.12
9	1	0	0	0	0	0	75.41	0	0	0	0	0	75.41
10	1	1	0	0	0	0	104	25.8	0	0	0	0	129.80
11	1	1	0	0	0	0	114	29.6	0	0	0	0	143.60
12	1	0	0	0	0	0	86.32	0	0	0	0	0	86.32
13	1	0	0	0	0	0	118.74	0	0	0	0	0	118.74
14	1	0	0	0	0	0	74.55	0	0	0	0	0	74.55
15	1	0	0	0	0	0	86.65	0	0	0	0	0	86.65
16	1	0	0	0	0	0	30.90	0	0	0	0	0	30.90
17	1	1	0	0	0	0	72	12.6	0	0	0	0	84.60
18	1	0	0	0	0	0	51.82	0	0	0	0	0	51.82
19	1	0	0	0	0	0	85.83	0	0	0	0	0	85.83
20	1	1	0	0	0	0	115	14.8	0	0	0	0	129.80
21	1	0	0	0	0	0	78.77	0	0	0	0	0	78.77
22	1	0	0	0	0	0	51.24	0	0	0	0	0	51.24
23	1	0	0	0	0	0	16.38	0	0	0	0	0	16.38
24	0	0	0	0	0	0	0	0	0	0	0	0	0.00

Table-IV Scheduling without considering DSB

Hour	ON/OFF Status of Generators										Generators Output (MW)										Cost (mu/Hr)
1	1	1	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	5745.80
2	1	1	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	5758.04
3	1	1	1	0	0	0	0	0	0	0	455	278.98	116.02	0	0	0	0	0	0	0	7126.53
4	1	1	0	1	0	1	0	0	0	0	455	363.44	0	106.11	0	25.45	0	0	0	0	8238.16
5	1	1	0	0	1	1	0	0	0	0	455	443.31	0	0	78.70	22.99	0	0	0	0	8440.83
6	1	1	0	1	1	1	0	0	0	0	455	455	0	130	27.97	32.03	0	0	0	0	9742.25
7	1	1	1	1	1	0	0	0	0	0	455	455	110.42	103.44	26.14	0	0	0	0	0	10306.90
8	1	1	1	1	1	1	0	0	0	0	455	455	130	105.19	26.96	27.85	0	0	0	0	11292.18
9	1	1	1	1	1	1	1	0	0	0	455	455	130	126.78	75.27	24.24	33.71	0	0	0	12771.78
10	1	1	1	1	1	1	1	1	1	0	455	455	130	130	121.85	42.89	29.75	19.12	16.39	0	15343.69
11	1	1	1	1	1	1	1	1	1	1	455	455	130	130	158.41	34	25.44	26.33	24.67	11.16	16728.11
12	1	1	1	1	1	1	1	1	1	1	455	455	130	130	162	46.35	31.53	35.87	12.79	41.46	17193.79
13	1	1	1	1	1	1	1	1	1	0	455	455	130	130	98.97	48	39.31	22.03	21.69	0	15710.63
14	1	1	1	1	1	1	1	0	0	0	455	455	130	130	77.31	20.10	32.59	0	0	0	12814.46
15	1	1	1	1	1	1	0	0	0	0	455	455	130	92.63	25.28	42.09	0	0	0	0	11606.75
16	1	1	0	1	0	1	1	0	0	0	455	434.53	0	110.35	0	22.94	27.18	0	0	0	9719.53
17	1	1	0	0	1	1	0	0	0	0	455	437.54	0	0	66.11	41.35	0	0	0	0	8688.77
18	1	1	0	1	1	1	0	0	0	0	455	455	0	130	37.24	22.76	0	0	0	0	9774.10
19	1	1	1	1	1	1	0	0	0	0	455	455	118.02	107.29	26.09	38.60	0	0	0	0	11303.80
20	1	1	1	1	1	1	1	1	1	0	455	455	130	130	124.70	31.26	25.20	21.44	27.41	0	15304.31
21	1	1	1	1	1	1	1	0	0	0	455	455	130	130	68.28	34.40	27.32	0	0	0	12694.21
22	1	1	0	1	1	1	0	0	0	0	455	452.24	0	129.30	43.47	20	0	0	0	0	9858.26
23	1	1	0	0	0	1	0	1	0	0	455	399.12	0	0	0	35.35	0	10.53	0	0	8061.93
24	1	1	0	0	0	0	0	1	0	0	455	335	0	0	0	0	0	10	0	0	6901[illegible]

Pricing has not been considered. Here the results are affected by many variables including the bids and offers, the reserve target and the constraints.

Case - 2

In this case, load curtailment capability of the consumers is analyzed where load reduction and load recovery are explicitly considered. The demand curtailed during any time period can be recovered in the course of off peak hours. The demand recovery can be prior to or followed by load curtailment hour.

As per the demand profile shown in Appendix-A, the system has the peak demand at the 12th hour. Here one particular instance is considered where Load-1, 2 and 3 each will provide 40 MW load curtailment at the 12th hour. So total 120 MW load will be curtailed during 12th hour. During off peak hours, which are at 16th, 17th and 18th hours, each load will recover the same amount of load which they have curtailed. The modified load profile is shown in Table-V.

The scheduling results with hourly cost for the base case are already shown in Table-IV. The scheduling with the load reduction as well as load recovery is shown in the Table-VI. Total cost with base case is 261126.38 mu while the cost with load reduction and recovery is 260295.67 mu. The cost values of the specified hours are depicted in Fig. 14. The difference in the total cost is 830.71 mu as a result of the load redistribution. It shows that the overall scheduling cost will be reduced with this kind of DSB scheme where load can recover its demand which it has curtailed during the peak hours of the same day.

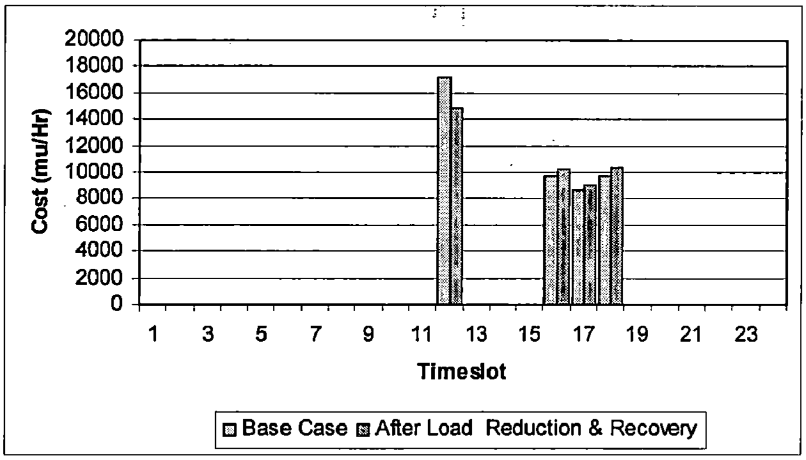


Fig. 14 Cost with load reduction and load recovery

Table-V

Modified Load Profile with DSB

Hour	Base Load Profile (MW)	Modified Load Profile (MW)	Hour	Base Load Profile (MW)	Modified Load Profile (MW)
1	700	700	**13**	1400	1400
2	750	750	**14**	1300	1300
3	850	850	**15**	1200	1200
4	950	950	**16**	1050	1090
5	1000	1000	**17**	1000	1040
6	1100	1100	**18**	1100	1140
7	1150	1150	**19**	1200	1200
8	1200	1200	**20**	1400	1400
9	1300	1300	**21**	1300	1300
10	1400	1400	**22**	1100	1100
11	1450	1450	**23**	900	900
12	1500	1380	**24**	800	800

Case – 3

The process of generation scheduling with HPSO methodology and only considering generators for providing reserve takes approximately 2-3 minutes for one hour scheduling. To overcome this difficulty, the neural network is used. Here, one hundred load patterns for 24 hours are generated (tabulated in Appendix-B). For each load profile, HPSO methodology is used to find generators status without considering DSB.

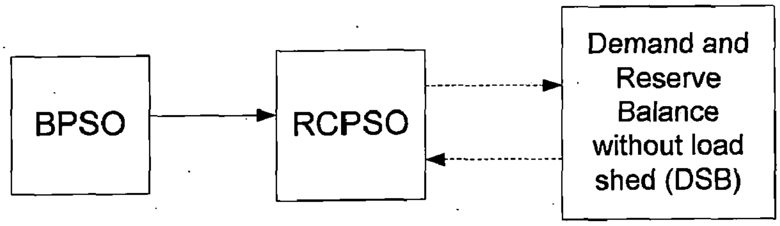


Fig. 15 HPSO method without DSB

Table-VI Scheduling with Load Reduction and Load Recovery

Hour	ON/OFF Status of Generators										Generators Output (MW)										Cost (mu/Hr)
1	1	1	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	5745.80
2	1	1	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	5758.04
3	1	1	1	0	0	0	0	0	0	0	455	278.98	116.02	0	0	0	0	0	0	0	7126.53
4	1	1	0	1	0	1	0	0	0	0	455	363.44	0	106.11	0	25.45	0	0	0	0	8238.16
5	1	1	0	0	1	1	0	0	0	0	455	443.31	0	0	78.70	22.99	0	0	0	0	8440.83
6	1	1	0	1	1	1	0	0	0	0	455	455	0	130	27.97	32.03	0	0	0	0	9742.25
7	1	1	1	1	1	0	0	0	0	0	455	455	110.42	103.44	26.14	0	0	0	0	0	10306.90
8	1	1	1	1	1	1	0	0	0	0	455	455	130	105.19	26.96	27.85	0	0	0	0	11292.18
9	1	1	1	1	1	1	1	0	0	0	455	455	130	126.78	75.27	24.24	33.71	0	0	0	12771.78
10	1	1	1	1	1	1	1	1	1	0	455	455	130	130	121.85	42.89	29.75	19.12	16.39	0	15343.69
11	1	1	1	1	1	1	1	1	1	1	455	455	130	130	158.41	34	25.44	26.33	24.67	11.16	16728.11
12	1	1	1	1	1	1	1	1	1	0	455	455	130	84.61	131.57	21.86	40.76	29.36	31.84	0	14925.43
13	1	1	1	1	1	1	1	1	1	0	455	455	130	130	98.97	48	39.31	22.03	21.69	0	15710.63
14	1	1	1	1	1	1	1	0	0	0	455	455	130	130	77.31	20.10	32.59	0	0	0	12814.46
15	1	1	1	1	1	1	0	0	0	0	455	455	130	92.63	25.28	42.09	0	0	0	0	11606.75
16	1	1	1	1	0	1	0	0	0	0	455	455	113.00	44.90	0	22.11	0	0	0	0	10206.18
17	1	1	0	1	1	0	0	0	0	0	455	417.04	0	117.77	50.19	0	0	0	0	0	9079.87
18	1	1	1	1	1	0	0	0	0	0	455	424.94	124.32	101.93	33.80	0	0	0	0	0	10334.00
19	1	1	1	1	1	1	0	0	0	0	455	455	118.02	107.29	26.09	38.60	0	0	0	0	11303.80
20	1	1	1	1	1	1	1	1	1	0	455	455	130	130	124.70	31.26	25.20	21.44	27.41	0	15304.31
21	1	1	1	1	1	1	1	0	0	0	455	455	130	130	68.28	34.40	27.32	0	0	0	12694.21
22	1	1	0	1	1	1	0	0	0	0	455	452.24	0	129.30	43.47	20	0	0	0	0	9858.26
23	1	1	0	0	0	1	0	1	0	0	455	399.12	0	0	0	35.35	0	10.53	0	0	8061.93
24	1	1	0	0	0	0	0	1	0	0	455	335	0	0	0	0	0	10	0	0	6901.55

A total of these one hundred patterns are used in the training set. The training set is presented to the three layer feed forward network. The structure of the neural network used in this case is shown in Fig. 10. Total load for each hour is provided as the input d to the neural network and ten neuron outputs $u_1, u_2, \ldots, u_{10}$ from the output layer give the values between 0 and 1. So it is assumed that the value below 0.5 is zero and the value above 0.5 is one. The Mean Square Error for the given training set after 2000 epoch comes out to be 0.04998.

The base load profile shown in Fig. A.1 is considered for finding the performance of trained network. The corresponding unit commitment generated by ANN is given in Table VII. This takes approximately one second computing time. When these results are compared with the result shown in Table III, they are found to be very similar.

The ON/OFF status of generators, obtained from ANN, is applied to real coded particle swarm optimization method and the cost of each hour is obtained as shown in Table VII.

Table-VII Scheduling for Base Load Profile using HANN

Hour	ON/OFF Status of Generators										Generators Output (MW)										Cost (mu/Hr)
1	1	1	0	0	0	0	0	0	0	0	455	245	0	0	0	0	0	0	0	0	5745.80
2	1	1	0	0	0	0	0	0	0	0	455	295	0	0	0	0	0	0	0	0	5758.04
3	1	1	1	0	0	0	0	0	0	0	455	287.45	107.55	0	0	0	0	0	0	0	7144.57
4	1	1	0	1	0	1	0	0	0	0	455	415.49	0	58.44	0	21.07	0	0	0	0	8241.69
5	1	1	1	1	1	0	0	0	0	0	407.49	419.09	0	129.52	43.89	0	0	0	0	0	8819.74
6	1	1	0	1	1	1	0	0	0	0	455	448.30	42.08	66.28	32.89	55.45	0	0	0	0	10195.73
7	1	1	1	1	1	0	0	0	0	0	455	455	130	84.48	25.52	0	0	0	0	0	10308.74
8	1	1	1	1	1	1	0	0	0	0	455	387.95	120.11	87.41	120.62	28.90	0	0	0	0	11335.95
9	1	1	1	1	1	1	1	0	0	0	455	455	115.32	64.54	143.07	30.36	36.71	0	0	0	13147.84
10	1	1	1	1	1	1	1	1	1	0	455	455	130	130	99.04	72.62	27.53	16.78	14.04	0	15332.48
11	1	1	1	1	1	1	1	1	1	1	455	455	130	130	105.10	51.38	41.29	46.38	16.71	19.14	16892.37
12	1	1	1	1	1	1	1	1	1	1	455	455	130	130	157.40	40.33	72.37	27.75	10.36	21.79	17127.19
13	1	1	1	1	1	1	1	1	1	0	455	455	130	130	99.22	29.62	35.58	12.27	53.32	0	15778.85
14	1	1	1	1	1	1	1	0	0	0	455	455	130	130	68.50	20.91	40.59	0	0	0	12882.95
15	1	1	1	1	1	1	0	0	0	0	455	455	130	66.87	57.04	36.10	0	0	0	0	11703.96
16	1	1	0	1	0	1	1	0	0	0	455	434.53	0	110.35	0	22.94	27.18	0	0	0	9753.25
17	1	1	1	1	1	0	0	0	0	0	455	334.25	61.34	110.99	38.42	0	0	0	0	0	9210.66
18	1	1	0	1	1	1	0	0	0	0	455	371.76	104.17	101.05	48.02	20	0	0	0	0	10127.29
19	1	1	1	1	1	1	0	0	0	0	455	327.81	127.69	128.24	123.61	37.65	0	0	0	0	11419.39
20	1	1	1	1	1	1	1	1	1	0	455	455	130	130	77.25	33.42	75.71	31.68	11.94	0	15709.51
21	1	1	1	1	1	1	1	0	0	0	455	455	130	100.81	44.20	63.31	51.68	0	0	0	13062.83
22	1	1	0	1	1	1	0	0	0	0	455	426.84	42.23	65.70	77.53	32.71	0	0	0	0	10528.42
23	1	1	0	0	0	1	0	0	0	0	455	421.99	0	0	0	23.01	0	0	0	0	8281.69
24	1	1	0	0	0	0	0	0	0	0	455	345	0	0	0	0	0	0	0	0	6960.00

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Table A.3
Load Demand and Reserve Requirement for 24 Hr

Hour	Demand (MW)	Reserve (MW)	Hour	Demand (MW)	Reserve (MW)
1	700	70	**13**	1400	140
2	750	75	**14**	1300	130
3	850	85	**15**	1200	120
4	950	95	**16**	1050	105
5	1000	100	**17**	1000	100
6	1100	110	**18**	1100	110
7	1150	115	**19**	1200	120
8	1200	120	**20**	1400	140
9	1300	130	**21**	1300	130
10	1400	140	**22**	1100	110
11	1450	145	**23**	900	900
12	1500	120	**24**	800	800

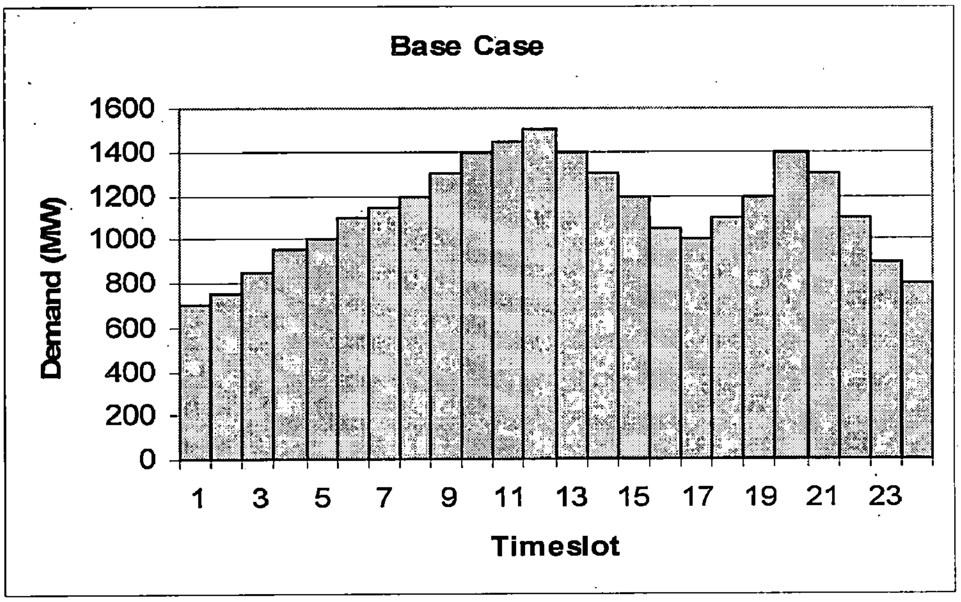


Fig A.1 Load Profile

APPENDIX – B

Training Pattern

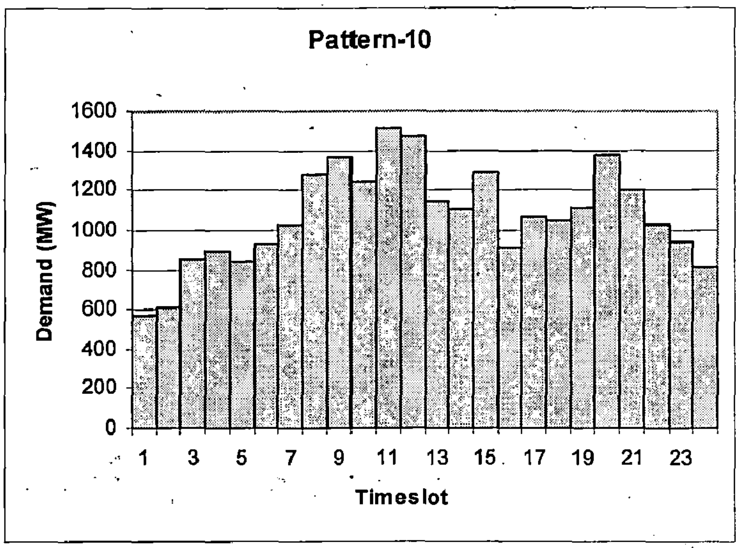
Hour	Load Pattern																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	715	660	760	590	615	720	665	700	610	570	720	655	695	590	750	715	600	600	710	640
2	690	640	720	630	730	600	710	650	790	610	690	800	710	740	770	700	810	750	650	770
3	900	740	810	860	890	700	930	785	630	855	840	820	880	690	790	715	710	830	840	720
4	935	760	940	1025	1000	950	860	760	670	890	890	900	870	910	950	900	970	1030	840	790
5	710	1050	840	950	690	735	1070	850	650	845	1090	1030	890	970	900	800	1070	850	1050	920
6	1160	1090	1090	1200	790	970	760	1035	850	930	1090	1040	1030	1110	900	1060	900	1200	1100	980
7	1040	810	960	720	1190	915	1240	980	1110	1030	1170	1160	1120	1140	1110	1130	930	1000	920	1210
8	1170	950	1090	760	1030	1110	1160	910	1250	1280	1060	1120	1060	1280	1060	1270	1070	1000	1110	1140
9	1050	910	1200	920	1100	1035	1040	1270	1340	1365	1200	1070	1060	1050	1370	1170	1340	1110	1250	1090
10	1160	1250	1100	1045	1290	1400	930	1370	1290	1240	1390	1430	1360	1520	1290	1400	1200	1420	1240	1240
11	1360	1380	1420	990	1500	1370	1230	1400	1060	1510	1280	1370	1450	1470	1550	1460	1400	1270	1370	1490
12	1570	1410	1550	1050	1550	1140	1430	1270	1525	1470	1520	1430	1570	1490	1550	1340	1560	1490	1530	1430
13	1240	1490	1355	1370	1195	1500	1190	1290	1190	1140	1490	1250	1390	1160	1480	1440	1400	1200	1320	1530
14	1100	1160	1200	1300	1360	1050	1100	980	1050	1110	1400	1100	1360	1270	1290	1120	1260	1220	1190	1360
15	1070	800	1045	1170	1220	1070	1115	910	950	1290	1155	1300	1120	1300	1280	1250	1120	1270	1180	1310
16	1140	735	1130	1070	1000	910	1090	710	945	910	1040	1090	1080	1100	1120	960	1020	940	1150	960
17	700	940	790	1000	690	870	830	1030	970	1070	1060	970	870	1050	1000	1080	900	1020	950	980
18	970	1120	870	1140	1210	720	1130	1060	1150	1050	1080	1160	1090	1200	1140	910	990	1010	1100	1130
19	1170	1200	1250	1290	1070	1040	1250	1125	1020	1120	1250	1220	1070	1120	1050	1170	1220	1110	1070	1020
20	1410	1480	1250	1260	1265	1180	1270	1390	1500	1375	1440	1460	1320	1340	1240	1460	1300	1360	1460	1370
21	1210	1040	1300	1240	1120	1265	1090	1325	1335	1205	1360	1140	1200	1290	1150	1210	1150	1240	1190	1320
22	980	1140	1090	925	970	1080	1030	820	880	1025	1110	1090	1060	1190	1120	1070	1150	1200	1100	970
23	925	815	940	860	910	855	840	780	825	940	950	980	960	820	830	910	990	940	880	870
24	850	815	870	730	690	700	800	750	740	810	740	780	860	750	760	840	745	880	770	820

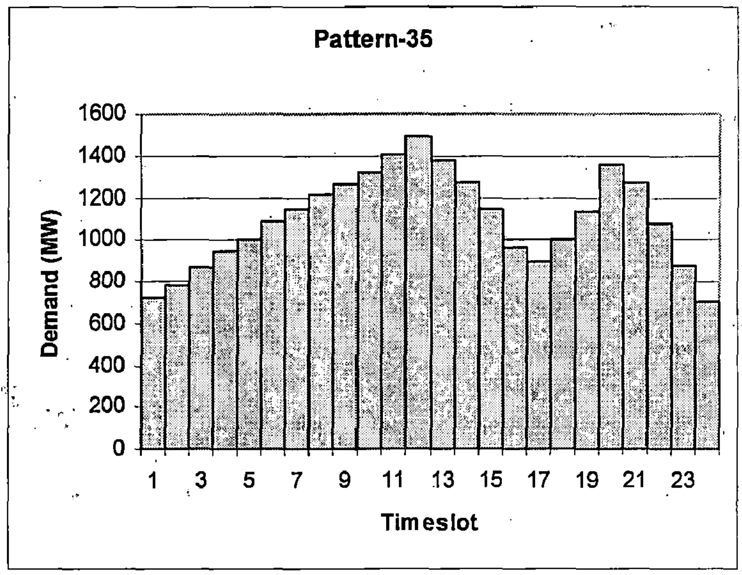
Hour	Load Pattern																			
	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	710	630	690	715	740	690	680	650	720	745	640	760	640	680	720	740	670	630	650	650
2	730	700	740	800	810	740	750	700	790	820	680	810	690	740	780	810	720	680	720	690
3	810	690	810	860	840	890	910	800	830	840	720	860	740	810	870	890	770	740	790	730
4	860	770	880	920	900	950	960	900	890	910	780	930	850	890	940	960	840	800	880	790
5	930	840	960	990	1000	1050	1060	950	970	990	870	1010	930	960	1000	1040	920	910	960	880
6	1020	910	1070	1080	1100	1120	1150	1050	1040	1080	960	1090	1120	1050	1090	1130	1010	980	1050	970
7	1110	990	1150	1160	1190	1170	1200	1100	1110	1140	1070	1180	1190	1120	1150	1180	1070	1050	1120	1080
8	1190	1040	1210	1240	1270	1220	1290	1150	1190	1210	1140	1230	1260	1190	1210	1250	1120	1130	1180	1150
9	1250	1130	1280	1300	1340	1290	1350	1250	1280	1290	1210	1300	1330	1270	1260	1320	1230	1190	1250	1220
10	1330	1260	1360	1420	1430	1370	1430	1350	1370	1350	1310	1400	1410	1360	1320	1410	1320	1220	1340	1320
11	1420	1340	1410	1480	1470	1480	1510	1400	1430	1410	1390	1510	1520	1430	1410	1490	1380	1370	1420	1400
12	1530	1420	1490	1550	1530	1560	1570	1450	1500	1490	1470	1560	1560	1510	1490	1560	1440	1450	1500	1480
13	1450	1360	1410	1470	1460	1500	1490	1350	1410	1420	1390	1420	1500	1450	1380	1470	1330	1370	1400	1400
14	1360	1250	1330	1350	1370	1400	1380	1250	1320	1310	1270	1340	1390	1320	1270	1290	1260	1240	1300	1280
15	1240	1170	1220	1240	1290	1280	1300	1150	1240	1190	1150	1260	1200	1190	1150	1140	1130	1100	1200	1160
16	1100	1020	1080	1100	1140	1150	1150	1000	1100	1050	1010	1130	1040	1010	960	980	1000	980	1050	1020
17	1050	960	1010	970	1080	1090	1000	950	1040	980	950	1080	980	950	900	910	950	930	1000	960
18	1150	1060	1110	1070	1180	1190	1100	1050	1140	1080	1050	1180	1080	1050	1000	1010	1050	1030	1100	1060
19	1240	1170	1230	1120	1320	1280	1200	1150	1230	1190	1160	1300	1200	1180	1140	1170	1160	1190	1200	1170
20	1440	1370	1430	1320	1520	1480	1400	1350	1420	1400	1370	1500	1390	1350	1360	1320	1400	1370	1400	1380
21	1330	1260	1340	1240	1400	1350	1300	1250	1310	1300	1260	1390	1270	1260	1270	1240	1300	1260	1300	1270
22	1140	1070	1140	1070	1200	1160	1100	1050	1140	1120	1040	1150	1040	1050	1080	1100	1090	1050	1100	1050
23	950	870	950	880	1000	960	900	850	960	930	830	940	860	840	880	900	850	820	900	840
24	840	790	710	750	900	840	800	750	840	810	710	830	740	720	700	800	750	690	800	720

Hour	Load Pattern																			
	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
1	720	640	700	725	750	700	690	660	730	755	650	770	650	690	730	750	680	640	660	660
2	740	710	750	810	820	750	760	710	800	830	690	820	700	750	790	820	730	690	730	700
3	820	700	820	870	850	900	920	810	840	850	730	870	750	820	880	900	780	750	800	740
4	870	780	890	930	910	960	970	910	900	920	790	940	860	900	950	970	850	810	890	800
5	940	850	970	1000	1010	1060	1070	960	980	1000	880	1020	940	970	1010	1050	930	920	970	890
6	1030	920	1080	1090	1110	1130	1160	7060	1050	1090	970	1100	1130	1060	1100	1140	1020	990	1060	980
7	1120	1000	1160	1170	1200	1180	1210	1110	1120	1150	1080	1190	1200	1130	1160	1190	1080	1060	1130	1090
8	1200	1050	1220	1250	1280	1230	1300	1160	1200	1220	1150	1240	1270	1200	1220	1260	1130	1140	1190	1160
9	1260	1140	1290	1310	1350	1300	1360	1260	1290	1300	1220	1310	1340	1280	1270	1330	1240	1200	1260	1230
10	1340	1270	1370	1430	1440	1380	1440	1360	1380	1360	1320	1410	1420	1370	1330	1420	1330	1230	1350	1330
11	1430	1350	1420	1490	1480	1490	1520	1410	1440	1420	1400	1520	1530	1440	1420	1500	1390	1380	1430	1410
12	1540	1430	1500	1560	1540	1570	1560	1460	1510	1500	1480	1570	1570	1520	1500	1570	1450	1460	1510	1490
13	1460	1370	1420	1480	1470	1510	1500	1360	1420	1430	1400	1430	1510	1460	1390	1480	1340	1380	1410	1410
14	1370	1260	1340	1360	1380	1410	1390	1260	1330	1320	1280	1350	1400	1330	1280	1300	1270	1250	1310	1290
15	1250	1180	1230	1250	1300	1290	1310	1160	1250	1200	1160	1270	1210	1200	1160	1150	1140	1110	1210	1170
16	1110	1030	1090	1110	1150	1160	1160	1010	1110	1060	1020	1140	1050	1020	970	990	1010	990	1060	1030
17	1060	970	1020	980	1090	1100	1010	960	1050	990	960	1090	990	960	910	920	960	940	1010	970
18	1160	1070	1120	1080	1190	1200	1110	1060	1150	1090	1060	1190	1090	1060	1010	1020	1060	1040	1110	1070
19	1250	1180	1240	1130	1330	1290	1210	1160	1240	1200	1170	1310	1210	1190	1150	1180	1170	1200	1210	1180
20	1450	1380	1440	1330	1530	1490	1410	1360	1430	1410	1380	1510	1400	1360	1370	1330	1410	1380	1410	1390
21	1340	1270	1350	1250	1410	1360	1310	1260	1320	1310	1270	1400	1280	1270	1280	1250	1310	1270	1310	1280
22	1150	1080	1150	1080	1210	1170	1110	1060	1150	1130	1050	1160	1050	1060	1090	1110	1100	1060	1110	1060
23	960	880	960	890	1010	970	910	860	970	940	840	950	870	850	890	910	860	830	910	850
24	850	800	720	760	910	850	810	760	850	820	720	840	750	730	710	810	760	700	810	730

Hour	Load Pattern																			
	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
1	740	660	720	745	770	720	710	680	750	775	670	790	670	710	750	770	700	660	680	680
2	760	730	770	830	840	770	780	730	820	850	710	840	720	770	810	840	750	710	750	720
3	840	720	840	890	870	920	940	830	860	870	750	890	770	840	900	920	800	770	820	760
4	890	800	910	950	930	980	990	930	920	940	810	960	880	920	970	990	870	830	910	820
5	960	870	990	1020	1030	1080	1090	980	1000	1020	900	1040	960	990	1030	1070	950	940	990	910
6	1050	940	1100	1110	1130	1150	1180	1080	1070	1110	990	1120	1150	1080	1120	1160	1040	1010	1080	1000
7	1140	1020	1180	1190	1220	1200	1230	1130	1140	1170	1100	1210	1220	1150	1180	1210	1100	1080	1150	1110
8	1220	1070	1240	1270	1300	1250	1320	1180	1220	1240	1170	1260	1290	1220	1240	1280	1150	1160	1210	1180
9	1280	1160	1310	1330	1370	1320	1380	1280	1310	1320	1240	1330	1360	1300	1290	1350	1260	1220	1280	1250
10	1360	1290	1390	1450	1460	1400	1460	1380	1400	1380	1340	1430	1440	1390	1350	1440	1350	1250	1370	1350
11	1450	1370	1440	1510	1500	1510	1540	1430	1460	1440	1420	1540	1550	1460	1440	1520	1410	1400	1450	1430
12	1560	1450	1520	1560	1560	1570	1560	1480	1530	1520	1500	1570	1510	1540	1520	1570	1470	1480	1530	1510
13	1480	1390	1440	1500	1490	1530	1520	1380	1440	1450	1420	1450	1530	1480	1410	1500	1360	1400	1430	1430
14	1390	1280	1360	1380	1400	1430	1410	1280	1350	1340	1300	1370	1420	1350	1300	1320	1290	1270	1330	1310
15	1270	1200	1250	1270	1320	1310	1330	1180	1270	1220	1180	1290	1230	1220	1180	1170	1160	1130	1230	1190
16	1130	1050	1110	1130	1170	1180	1180	1030	1130	1080	1040	1160	1070	1040	990	1010	1030	1010	1080	1050
17	1080	990	1040	1000	1110	1120	1030	980	1070	1010	980	1110	1010	980	930	940	980	960	1030	990
18	1180	1090	1140	1100	1210	1220	1130	1080	1170	1110	1080	1210	1110	1080	1030	1040	1080	1060	1130	1090
19	1270	1200	1260	1150	1350	1310	1230	1180	1260	1220	1190	1330	1230	1210	1170	1200	1190	1220	1230	1200
20	1470	1400	1460	1350	1550	1510	1430	1380	1450	1430	1400	1530	1420	1380	1390	1350	1430	1400	1430	1410
21	1360	1290	1370	1270	1430	1380	1330	1280	1340	1330	1290	1420	1300	1290	1300	1270	1330	1290	1330	1300
22	1170	1100	1170	1100	1230	1190	1130	1080	1170	1150	1070	1180	1070	1080	1110	1130	1120	1080	1130	1080
23	980	900	980	910	1030	990	930	880	990	960	860	970	890	870	910	930	880	850	930	870
24	870	820	740	780	930	870	830	780	870	840	740	860	770	750	730	830	780	720	830	750

Hour	Load Pattern																			
	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
1	730	650	710	725	760	710	700	670	740	755	660	780	660	700	740	760	690	650	670	670
2	750	720	760	820	830	760	770	720	810	840	700	830	710	760	800	830	740	700	740	710
3	830	710	830	880	860	910	930	820	850	860	740	880	760	830	890	910	790	760	810	750
4	880	790	900	940	920	970	980	920	910	930	800	950	870	910	960	980	860	820	900	810
5	950	860	980	1010	1020	1070	1080	970	990	1010	890	1030	950	980	1020	1060	940	930	980	900
6	1040	930	1090	1100	1120	1140	1170	1070	1060	1100	980	1110	1140	1070	1110	1150	1030	1000	1070	990
7	1130	1010	1170	1180	1210	1190	1220	1120	1130	1160	1090	1200	1210	1140	1170	1200	1090	1070	1140	1100
8	1210	1060	1230	1260	1290	1240	1310	1170	1210	1230	1160	1250	1280	1210	1230	1270	1140	1150	1200	1170
9	1270	1150	1300	1320	1360	1310	1370	1270	1300	1310	1230	1320	1350	1290	1280	1340	1250	1210	1270	1240
10	1350	1280	1380	1440	1450	1390	1450	1370	1390	1370	1330	1420	1430	1380	1340	1430	1340	1240	1360	1340
11	1440	1360	1430	1500	1490	1500	1530	1420	1450	1430	1410	1530	1540	1450	1430	1510	1400	1390	1440	1420
12	1550	1440	1510	1570	1550	1560	1570	1470	1520	1510	1490	1560	1550	1530	1510	1560	1460	1470	1520	1500
13	1470	1380	1430	1490	1480	1520	1510	1370	1430	1440	1410	1440	1520	1470	1400	1490	1350	1390	1420	1420
14	1380	1270	1350	1370	1390	1420	1400	1270	1340	1330	1290	1360	1410	1340	1290	1310	1280	1260	1320	1300
15	1260	1190	1240	1260	1310	1300	1320	1170	1260	1210	1170	1280	1220	1210	1170	1160	1150	1120	1220	1180
16	1120	1040	1100	1120	1160	1170	1170	1020	1120	1070	1030	1150	1060	1030	980	1000	1020	1000	1070	1040
17	1070	980	1030	990	1100	1110	1020	970	1060	1000	970	1100	1000	970	920	930	970	950	1020	980
18	1170	1080	1130	1090	1200	1210	1120	1070	1160	1100	1070	1200	1100	1070	1020	1030	1070	1050	1120	1080
19	1260	1190	1250	1140	1340	1300	1220	1170	1250	1210	1180	1320	1220	1200	1160	1190	1180	1210	1220	1190
20	1460	1390	1450	1340	1540	1500	1420	1370	1440	1420	1390	1520	1410	1370	1380	1340	1420	1390	1420	1400
21	1350	1280	1360	1260	1420	1370	1320	1270	1330	1320	1280	1410	1290	1280	1290	1260	1320	1280	1320	1290
22	1160	1090	1160	1090	1220	1180	1120	1070	1160	1140	1060	1170	1060	1070	1100	1120	1110	1070	1120	1070
23	970	890	970	900	1020	980	920	870	980	950	850	960	880	860	900	920	870	840	920	860
24	860	810	730	770	920	860	820	770	860	830	730	850	760	740	720	820	770	710	820	740





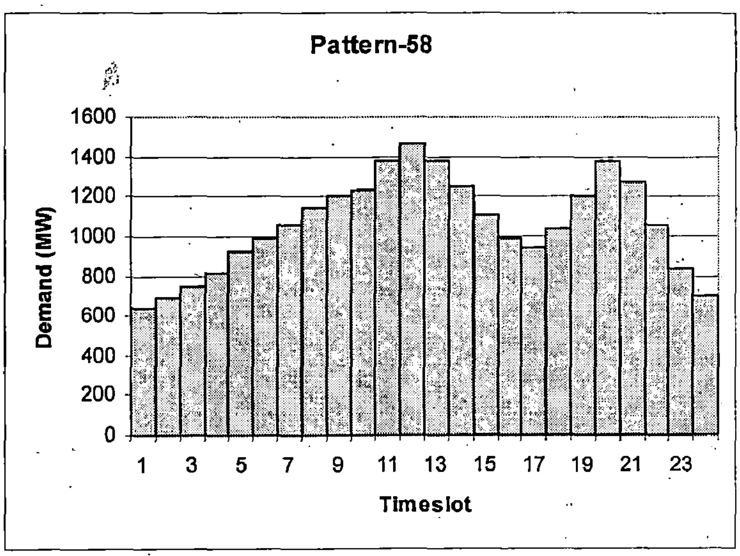


Fig. B-1 Graphical presentation of different Load Patterns