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ENHANCING LOAD DISPATCH PERFORMANCE THROUGH TRANSIENT STABLITY BASED UCP THROUGH ROTOR ANGLE

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***Abstract*— Traditional security-constrained unit commitment (SCUC) considers only static security criteria, which may however not ensure the ability of the system to survive dynamic transition before reaching a viable operating equilibrium following a large disturbance, such as transient stability. This paper proposes attract able mathematical model for transient stability-constrained unit commitment (TSCUC) and a practical solution approach. The problem is modeled without explicit differential-algebraic equations, reducing the problem size to one very similar to a conventional SCUC. The whole problem is decomposed into a master problem for UC and a range of sub problems for steady-state security evaluation and transient stability assessment (TSA).Additional constraints including Benders cut and so-named stabilization cut are generated for eliminating the security/stability violations. The extended equal-area criterion (EEAC) is used for fast TSA and analytically deriving the stabilization cut, where in multiple contingencies having common instability mode can be simultaneously stabilized by one cut.**

***Index Terms*— security-constrained unit commitment (SCUC), transient stability-constrained unit commitment (TSCUC), transient stability assessment (TSA), extended equal-area criterion (EEAC).**

INTRODUCTION

In the short-term, typically considered to run from twenty-four hours to one week, the solution of the unit commitment problem (UCP) is used to assist decisions regarding generating unit operation. In a regulated market, a power generating utility solves the UCP to obtain an optimal schedule of its units in order to have enough capacity to supply the electricity demanded by its customers. The optimal schedule is found by minimizing the production cost over the time interval while satisfying the demand and a set of operating constraints. The minimization of the production costs assures maximum profits because the power generating utility has no option but reliably supply the prevailing load. The price of electricity over this period is predetermined and unchanging; therefore, the decisions on the operation of the units have no effect on the firm's revenues. As deregulation is being implemented in various regions of the United States, the traditional unit commitment problem continues to remain applicable for the commitment decisions made by the Independent System Operator (ISO). The ISO resembles very much the operation of a power generating utility under regulation. The ISO manages the transmission grid, controls the dispatch of generation, oversees the reliability of the system, and administers congestion protocols. The ISO is a non-profit organization. Its economic objective is to maximize social welfare, which is obtained by minimizing the costs of reliably supplying the aggregate load. Under deregulation, the UCP for an electric power producer will require a new formulation that includes the electricity market in the model. The main difficulty here is that the spot price of electricity is no longer predetermined but set by open competition. Thus far, the hourly spot prices of electricity have shown evidence of being highly volatile. The unit commitment decisions are now harder and the modeling of spot prices becomes very important in this new operating environment. Different approaches can be found in the literature in this regard.

Stochastic model for the UCP have introducing in the uncertainty of the load and prices of fuel and electricity are modeled using a set of possible scenarios. The challenge here is to generate representative scenarios and assign them appropriate probabilities. Allen and Ilic have proposed a stochastic model for the unit commitment of a single generator. They assume that the hourly prices at which electricity is sold are uncorrelated and normally distributed. In Tseng uses Into processes to model the prices of electricity and fuel in the unit commitment formulation. The purpose of this project is to present a new formulation to the UCP suitable for an electric power producer in a deregulated market and consider computationally efficient procedures to solve it. We express the UCP as a stochastic optimization problem in which the objective is to maximize expected profits and the decisions are required to meet operating constraints such as capacity limits and minimum up and down time requirements. We show that when the spot market of electricity is included, the optimal solution of a UCP with M units can be found by solving M uncoupled sub-problems. A sub-problem is obtained by replacing the values of the Lagrange multipliers by the spot market prices of electricity. The volatility of the spot market price of electricity is accounted for by using a variation of the stochastic model proposed by Ryan and Maunder. The model, which is referred to as the probabilistic production-costing model, incorporates the stochastic features of load and generator availabilities. It is often used to obtain approximate estimates of production costs. This model ignores the unit commitment constraints and assumes that a strict predetermined merit order of loading prevails. This implies that a generator will be dispatched only when the available unit immediately preceding it in the loading order is working at its full capacity. We believe that this model provides a good approximation to the operation of an electricity market such as the California market in which no centralized unit commitment decisions are taken. The model captures the fundamental stochastic characteristics of the system. At any moment, a power producer may not be fully aware of the exact characteristics of the units comprising the market at that particular time. But it is likely to posses' information about the steady state statistical characteristics of the units participating in the market. Ryan and Mazumdar's probabilistic production costing model can be used to provide a steady- state picture of the market.

The hourly spot market price of electricity is determined by the market-clearing prices. The market-clearing price can be shown to be the variable cost or bid of the last unit used to meet the aggregate load prevailing at a particular hour. This unit is called the marginal unit. We determine the probability distribution of the hourly market-clearing price based on the stochastic process governing the marginal unit, which depends on the aggregate load and the generating unit availabilities. We model the aggregate load as a Gauss-Markov stochastic process and use continuous-time Markov chains to model the generating unit availabilities. We assume that the information on mean time to repair, mean time to failure, capacity, and variable operating cost of each unit participating in the market required to characterize these processes is available. We use probabilistic dynamic programming to solve the stochastic optimization problem pertaining to unit commitment. The results of the report on the accuracy and computational efficiency of several analytical approximations as compared to Monte Carlo simulation in estimating probability distributions of the spot market price for electric power. The firefly algorithm (FA) is a met heuristic algorithm, inspired by the flashing behaviour of fireflies. The primary purpose for a firefly's flash is to act as a signal system to attract other fireflies. XinShe Yang formulated this firefly algorithm by assuming.

I. Inference Analysis

In the short-term, typically considered to run from twenty-four hours to one week, the solution of the unit commitment problem (UCP) is used to assist decisions regarding generating unit operations. In a regulated market, a power generating utility solves the UCP to obtain an optimal schedule of its units in order to have enough capacity to supply the electricity demanded by its customers. The optimal schedule is found by minimizing the production cost over the time interval while satisfying the demand and a set of operating constraints. The minimization of the production costs assures maximum profits because the power generating utility has no option but to reliably supply the prevailing load. The price of electricity over this period is predetermined and unchanging; therefore, the decisions on the operation of the units have no effect on the firm's revenues. As deregulation is being implemented in various regions of the United States, the traditional unit commitment problem continues to remain applicable for the commitment decisions made by the Independent System Operator (ISO). The ISO resembles very much the operation of a power generating utility under regulation. The ISO manages the transmission grid, controls the dispatch of generation, oversees the reliability of the system, and administers congestion protocols. The ISO is a non-profit organization. Its economic objective is to maximize social welfare, which is obtained by minimizing the costs of reliably supplying the aggregate load. Under deregulation, the UCP for an electric power producer will require a new formulation that includes the electricity market in the model. The main difficulty here is that the spot price of electricity is no longer predetermined but set by open competition. Thus far, the hourly spot prices of electricity have shown evidence of being highly volatile. The unit commitment decisions are now harder and the modeling of spot prices becomes very important in this new operating environment. Different approaches can be found in the literature in this regard. Takriti . We have introduced a stochastic model for the UCP in which the uncertainty in the load and prices of fuel and electricity are modeled using a set of possible scenarios. The challenge here is to generate representative scenarios and assign them appropriate probabilities. Allen and Iliac have proposed a stochastic model for the unit commitment of a single generator. They assume that the hourly prices at which electricity is sold are uncorrelated and normally distributed. In Tseng uses Ito processes to model the prices of electricity and fuel in the unit commitment formulation.

The purpose of this project is to present a new formulation to the UCP suitable for an electric power producer in a deregulated market and consider computationally efficient procedures to solve it. We express the UCP as a stochastic optimization problem in which the objective is to maximize expected profits and the decisions are required to meet operating constraints such as capacity limits and minimum up and down time requirements. We show that when the spot market of electricity is included, the optimal solution of a UCP with M units can be found by solving M uncoupled sub-problems. A sub-problem is obtained by replacing the values of the Lagrange multipliers by the spot market prices of electricity. The volatility of the spot market price of electricity is accounted for by using a variation of the stochastic model proposed by Ryan and Maunder. The model, which is referred to as the probabilistic production-costing model, incorporates the stochastic features of load and generator availabilities. It is often used to obtain approximate estimates of production costs. This model ignores the unit commitment constraints and assumes that a strict predetermined merit order of loading prevails. This implies that a generator will be dispatched only when the available unit immediately preceding it in the loading order is working at its full capacity. We believe that this model provides a good approximation to the operation of an electricity market such as the California market in which no centralized unit commitment decisions are taken. The model captures the fundamental stochastic characteristics of the system. At any moment, a power producer may not be fully aware of the exact characteristics of the units comprising the market at that particular time.

But it is likely to posses' information about the steady state statistical characteristics of the units participating in the market. Ryan and Mazumdar's probabilistic production costing model can be used to provide a steady- state picture of the market. The hourly spot market price of electricity is determined by the market-clearing prices. The market-clearing price can be shown to be the variable cost or bid of the last unit used to meet the aggregate load prevailing at a particular hour. This unit is called the marginal unit. We determine the probability distribution of the hourly market-clearing price based on the stochastic process governing the marginal unit, which depends on the aggregate load and the generating unit availabilities. We model the aggregate load as a Gauss-Markov stochastic process and use continuous-time Markov chains to model the generating unit availabilities. We assume that the information on mean time to repair, mean time to failure, capacity, and variable operating cost of each unit participating in the market required to characterize these processes is available. We use probabilistic dynamic programming to solve the stochastic optimization problem pertaining to unit commitment. We also report results on the accuracy and computational efficiency of several analytical approximations as compared to Monte Carlo simulation in estimating probability distributions of the spot market price for electric power.

A. Formulation

We consider the situation in which an electric power producer owns a set of M generating units and needs to determine an optimal commitment schedule of its units such that the profit over a short period of length T is maximized. Revenues are obtained from fulfilling bilateral contracts and selling electric power, at spot market prices, to the power pool. It is assumed that the electric-power company is a price taker. If at a particular hour the power supplier decides to switch on one of its generating units, it will be willing to take the price that will prevail at this hour. We also assume that the power supplier has no control over the market prices and the M generating units will remain available during the short time interval of interest. In determining an optimal commitment schedule, there are two decision variables which are denoted by $P_{k,t}$ and $v_{k,t}$. The first variable denotes the amount of power to be generated by unit k at time t, and the latter is a control variable, whose value is "1" if the generating unit k is committed at hour t and "0" otherwise. The cost of the power produced by the generating unit k depends on the amount of fuel consumed and is given by a known cost function

$$CF_k(p) = a_k + b_k p + c_k p^2$$

Where p is the amount of power generated. The start-up cost, which for thermal units depends on the prevailing temperature of the boilers, is given by a known function $S_k(x_{k,t})$. The value of $x_{k,t}$ specifies the consecutive time that the unit has been on (+) or off (-) at the end of the hour t. In addition, a generating unit must satisfy operating constraints. The power produced by a generating unit must be within certain limits. When the *kth* generating unit is running, it must produce an amount of power between P_k^{min} and P_k^{max} (MW). If the generating unit is off, it must stay off for at least t_k^{dn} hours, and if it is on, it must stay on for at least t_k^{up} hours. The objective function is given by the sum over the hours in the interval $[0,T]$ of the revenue minus the cost. The revenue is obtained from supplying the bilateral contracts and by selling to the power pool at a price of m_t per MWH the surplus energy E_t (if any) produced in each hour t. The cost includes the cost of producing the energy, buying shortfalls (if needed) from the power pool, and the startup costs. Defining the supply amount stipulated under the bilateral contract by l_t (MWH) and by R (\$/MWH) the price, the objective function (maximum total profit) is given by:

$$\max_{v_{k,t}P_{k,t}E_t}\left\{\sum_{t=1}^{T}\left\{l_t R - m_t E_t - \sum_{k=1}^{M}\left[CF_k(P_{k,t}) + S_k(x_{k,t})(1-v_{k,t-1})\right]v_{k,t}\right\}\right\}$$

A positive value of E_t indicates that E_t megawatts hour are bought from the power pool and a negative value indicates that $-E_t$ megawatts hour are sold to the pool. Since the quantity $l_t R$ is a constant, the optimization problem reduces to:

$$\max_{v_{k,t}P_{k,t}E_t}\left\{\sum_{t=1}^{T}\left\{-m_t E_t - \sum_{k=1}^{M}\left[CF_k(P_{k,t}) + S_k(X_{k,t})(1-v_{k,t-1})\right]v_{k,t}\right\}\right\}$$

subject to the following constraints (for $t=1,\ldots,T$ and $k=1,\ldots,M$)

Load: $E_t + \sum_{K=1}^{M} V_{k,t}P_{k,t} = l_t$

Capacity limits: $v_{k,t}P_k^{min} \le P_{k,t} \le v_{k,t}P_k^{max}$

Minimum down time: $v_{k,t} \le 1 - I(-t_k^{dn} + 1 \le x_{k,t-1} \le -1)$

Minimum up time: $v_{k,t} \ge I(1 \le x_{k,t-1} \le t_k^{up} - 1)$

where $I(x) = \begin{cases} 0 & \text{if } x \text{ is false} \\ 1 & \text{if } x \text{ is true} \end{cases}$

$P_{k,t} \ge 0$ and E_t unrestricted in sign

$v_{k,t} = \{0,1\}$

After substituting in the objective function the value of $E_t = I_t - \sum_{k-1}^{M} v_{k,t}P_{k,t}$, obtained from Equation 4, we re-write Equation 3 as follows:

$$\max_{v_{k,t}P_{k,t}E_t}\left\{\sum_{t=1}^{T}\left\{-m_t\left[l_t - \sum_{k=1}^{M}P_{k,t}v_{k,t}\right] - \sum_{k=1}^{M}\left[CF_k(P_{k,t}) + S_k(x_{k,t})(1-v_{k,t-1})\right]v_{k,t}\right\}\right\}$$

which after removing constant terms is equivalent to:

$$\max_{v_{k,t}P_{k,t}}\left\{\sum_{t=1}^{T}\left\{\sum_{k=1}^{M}\left[m_t P_{k,t} - CF_k(P_{k,t}) + S_k(x_{k,t})(1-v_{k,t-1})\right]v_{k,t}\right\}\right\}$$

Subject to the operating constraints. Because the constraints refer to individual units only, the advantage of Equation 9 is that the objective function is now separable by individual units. The optimal solution can be found by solving M de-coupled sub-problems. Thus, the sub-problem D_k for the k^{th} unit (k=1,..,M) is:

$$\max_{v_{k,t}P_{k,t}}\left\{\sum_{t=1}^{T}\left\{m_t P_{k,t} - CF_k(P_{k,t}) + S_k(x_{k,t})(1-v_{k,t-1})\right\}v_{k,t}\right\}$$

Subject to operating constraints of the *kth* unit. Equation is similar to the sub-problem obtained in the standard version of the UCP excepting that the value of the Lagrange multipliers are now replaced by the spot market price of electricity.

B. Stochastic Formulation of the sub-problem

We next consider the value of the spot market price of electricity, m_t, which is determined by the market-clearing price, as a random variable. When the optimization sub-problem is being solved for a particular unit, we assume that the market, which includes the M-1 units owned by the power producer solving the problem, consists of N generating units ($N>>M$). The generating unit for which the sub-problem is solved is excluded from the market. We assume that the unit commitment decisions for any one unit have a negligible effect on the determination of the marginal unit of the market for a given hour. To model the market-clearing price, we assume that the generators participating in the market are brought into operation in an economic merit order of loading. The i^{th} unit in the loading order has a capacity c_i (MW), variable energy cost d_i ($/MWH), and a forced outage rate q_i. Under the assumption of economic merit order of loading, the market-clearing price at a specific hour t, is equal to the operating cost ($/MWH) of the last unit used to meet the load prevailing at this hour. The last unit in the loading order is called the marginal unit and is denoted by $J(t)$. The market-clearing price, m_t, is thus equal to $d_{J(t)}$. The values of $J(t)$ and $d_{J(t)}$ depend on the prevailing aggregate load and the operating states of the generating units in the loading order.

We write the objective function of the sub-problem for one of the M generating units as follows:

$$\text{Maximum profit} = \underset{v_i,p_i}{\text{Max}} \sum_{t=1}^{T} \{P_t d_{j(t)} - CF(P_t) - S(x_T)[1-v_{t-1}]\} v_t$$

subject to the operating constraints: capacity limits, minimum up time, and minimum down time.

C. Probabilistic Dynamic Programming Solution

The maximum profit over the period T (Equation 11) is a random variable because the hourly market-clearing price is a random variable. We assume that at the time of the decision, hour zero, the marginal unit and the load for all the hours before hour zero are known. We denote the marginal unit at time zero by j_0, and solve the sub-problem by maximizing the conditional expected profit over the period T. We express the objective function as:

$$\text{Max}E[profit\, j_0] = \underset{v_i P_i}{\text{Max}} \sum_{t=1}^{T} \{P_t E[d_{J(t)} | j_0] - CF(P_t) - S(x_t)(1-v_{t-1})\} v_t$$

This equation is subject to the same operating constraints described earlier. We use probabilistic dynamic programming to solve this optimization problem. We define the function $g_t(v_t,j)$ by the following equation:

$$g_t(v_t,j) = \underset{P_t}{\text{Max}} \{[P_t d_j - CF(P_t)] v_t\} \quad 0 < t \le T$$

This function denotes the maximum profit at hour t given that at this hour the jth unit is determining the market-clearing price and the generator to be scheduled is in the operating state v_t. We also define the recursive function $F_t(x_t)$ to be the optimum expected profit from hour t to hour T of operating the generator that is in state x_t at time t. Thus, the expression for hour zero is:

$$F_0(x_0) = \underset{v_1}{max}\{F_1(x_1) - v_1[1-v_0]S(x_1)\}$$

and for hour t ($0<t<T$) the expression is given by the following recursive relation:

$$F_t(x_t) = \underset{v_{t-1}}{max} \left\{ \begin{matrix} F_{t+1}(x_{t+1}) - v_{t+1}[1-v_t]S(x_{t+1}) + \\ \sum_{j=1}^{N} Pr[J(t) = j \,|\, J(0) = j_0] g_i(v_{i,}j) \end{matrix} \right\}$$

Setting the expected incoming profit at time T+1 to be zero ($F_{T+1}(x_{T+1})=0$), we obtain the boundary condition for the last stage $t = T$ to be:

$$F_t(x_T) = \sum_{j=1}^{N} Pr[J(t) = j \,|\, J(0) = j_0]\, g_T(v_T,j)$$

The initial conditions are given by the initial state of the generator x_0 and v_0, and the marginal unit at hour zero j_0. Consequently, the optimal schedule is given by the solution of $F_0(x_0)$. To solve the problem, the following conditional probabilities need to be computed.

$$Pr[J(t) = j \,|\, J(0) = j_0] = \frac{Pr[J(t)=j \text{ and } j(0)=j_0]}{Pr[J(0)=j_0]}$$

Thus, the joint probability distribution of J (0) and $J(t)$, and the marginal probability distribution of $J(0)$ are needed.

(3.11)

D. Stochastic Model for the Market-Clearing Price

The stochastic model of the market-clearing price uses the production- costing model proposed by Ryan and Mazumdar . This model has been used in estimating the mean and variance of production cost and marginal cost of a power generating system.

i. Stochastic model of the market

For a market with N generating units, the model uses the following assumptions:

1. The generators are dispatched at each hour in a fixed, pre-assigned loading order, which depends only on the load and the availability of the generating units. Operating constraints such as minimum up time, minimum down time, spinning reserve, and scheduled maintenance are not considered.
2. The ith unit in the loading order has a capacity c_i (MW), variable energy cost d_i ($/MWH), mean time to failure λ_i^{-1}, mean time to repair μ_i^{-1}, and a forced outage rate, q_i, $i=1,2,...,N$.
3. After adjusting for the variations in the ambient temperature and periodicity, the load at time t, $u(t)$, is assumed to follow a Gauss-Markov process [16,17] with $E[u(t)]=u_t$ and Cov $[u(r), u(t)]=\sigma_{r,t}$, where u_t and $\sigma_{r,t}$ are assumed to be known. (Data analysis given in [13] validates this assumption.)
4. The operating state of each generating unit i follows a two-state continuous-time Markov chain, $Y_i(t) = \{0,1\}$, with failure rate λ_i and repair rate μ_i. The forced outage rate q_i is related to these quantities by the equation $q_i = \lambda_i/(\lambda_i + \mu_i)$.
5. For $i \neq j$, $Y_i(r)$ and $Y_j(t)$ are statistically independent for all values of r and t. Each $Y_i(t)$ is independent of $u(t)$ for all values of t.

ii. Probability distribution of the marginal unit.

To derive an analytical expression for the probability mass function of the marginal unit at time t, we first note that $Pr[J(t) = j] = Pr[J(t) > j - 1] - Pr[J(t) > j]$ and that the events $J(t) > j$ and $u(t) - \sum_{i=1}^{j} c_i y_i(t) > 0$ are equivalent. Thus, the following equality holds:

$$Pr[J(t) > j] = Pr\left[u(t) - \sum_{i=1}^{j} c_i y_i(t) > 0\right]$$

Therefore, to obtain the probability mass function of *J*(*t*), the probability that $u(t) - \sum_{i=1}^{j} c_i Y_i(t)$ is greater than zero for all values of *j* needs to be computed.

iii. Bivariate Probability distribution of the marginal unit

An analytical approximation for the bivariate probability mass function of *J*(*r*) and *J*(*t*), needed for evaluating Equation, requires the following development. Writing

$$Pr[J(r) = m \,\&\, J(t) = n] = pr[J(r) > m - 1 \,\&\, J(t) > n - 1]$$
$$-Pr[J(r) > m \,\&\, J(t) > n - 1]$$
$$-pr[J(r) > m - 1 \,\&\, J(t) > n]$$
$$+Pr[J(r) > m \,\&\, J(t) > n]$$

And observing that the events $\{u(r) - \sum_{i=1}^{m} c_i y_i(r) > 0 \,\&\, u(t) - \sum_{i=1}^{n} c_i y_i(t) > 0\}$ and $\{J(r) > m \,\&\, J(t) > n\}$ are equivalent, we obtain the following equality

$$P_r[J(r) > m \,\&\, J(t) > n] = P_r\left[u(r) - \sum_{i=1}^{m} c_i y_i(r) > 0 \,\&\, u(t) - \sum_{i=1}^{n} c_i y_i(t) > 0\right]$$

Therefore, to compute the bivariate probability mass function of *J*(*r*) and *J*(*t*) the probability that $\{u(r) - \sum_{i=1}^{m} c_i y_i(r) > 0 \,\&\, u(t) - \sum_{i=1}^{n} c_i y_i(t) > 0\}$ needs to be evaluated for all values of *m* and *n*.

The computational effort in evaluating equations depends on the many values that the expression $\sum_{i=1}^{j} c_i Y_i(t)$ can take, which in the worst case is 2^N (when $j=N$). Thus, the computational time increases exponentially as *N* increases and it would make an exact computational procedure prohibitive for large *N*. In our numerical examples, we have used three approximation methods: the normal, Edge worth and Monte Carlo approximations. The Edge worth approximation is known in the power system literature as the method of cumulates. We also attempted the use of the large deviation or equivalently, the saddle point approximation method but it turned out to be prohibitively time-consuming for very large systems.

E. *Solution of the probabilistic unit commitment problem: a numerical example*

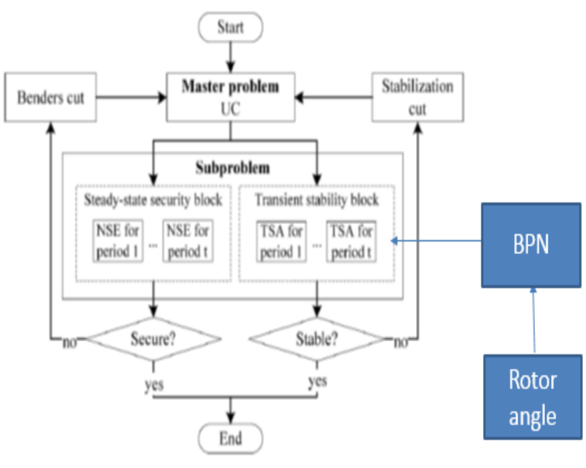
For our purpose, we assume that a complete description of the electricity market is given by the data concerning the *N* power generators that comprise the market, historical data of the aggregate load, and the hourly temperature forecast for the day of trading. The description of the power generators includes the order in which they will be loaded by the ISO, their capacities, energy costs, mean times to failure, and mean times to repair. The data for the aggregate load gives the historically forecast ambient temperature and the corresponding load for each hour in the region served by the marketplace. In this example, a data set that gave the actual ambient temperature and the corresponding load for each hour in a region covering the Northeastern United States during the calendar years 1995 and 1996 was used.

- UCP had been handled with Binary neighborhood field optimization (BNFO) algorithm multiple constraints
- Power Balance Constraint
- Spinning Reserve Constraint
- Capacity Limit
- Unit Minimum ON/OFF Durations
- Unit Ramp Constraints

The time consumption of the algorithm is around 0.9s. Transient stability is calculated in multiple discrete periods. Load angle has not been considered for UCP decision and economical load dispatch has not been performed before UCP decision are the problems in the existing inferences.

II. Operational Analysis

The existing system works towards the identification of load angle and hence the frequency of the generator based on which UCP is performed.



BNN simply takes the objective functions as mentioned in the

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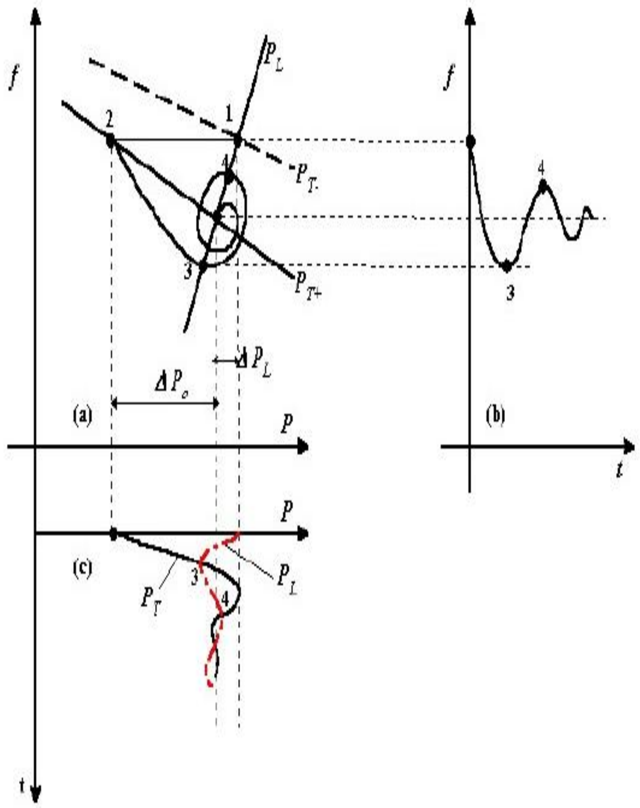
previous slides and based on the a minimization or maximization at a particular load conditions. A weight values are constructed based in if loops. When the set of rules increases , the decision will be correct.

A. Frequency Variations

System frequency is one of the most important single variables indicating the viability of operating of a power system [Kni01]. Acceptable deviations of frequency set by utilities are different, for instance ± 75mHz in UCPTE, and ± 100mHz for the Great Britain and Nordel. The North American standards require that frequency deviations should be corrected within 30 seconds. Many utilities use automatic generator control (AGC) to maintain frequency at the specified value. AGC is an example of a multi-level control system, which includes primary, secondary and tertiary frequency control. Primary control is decentralized because it is installed in power plants situated at different geographical locations. The purpose of primary control is to halt the frequency drop or increase due to the active power imbalance, eliminate frequency variations and bring frequency to a constant value. Secondary control is a centralized function, which changes the electrical outputs of the generators involved in secondary control in order to bring frequency back to the value it had before the imbalance. Finally, tertiary control is driven by economic dispatch. It is centralized but does not require a response as fast as secondary control. Two very important points are the minimum frequency value (Fig. 3.1b point 3) and the maximum generator output (Fig 3.1c, point 4). The former can be used to determine activation of under frequency load shedding, while the latter indicates the maximum spinning reserve required to stop the frequency drop.

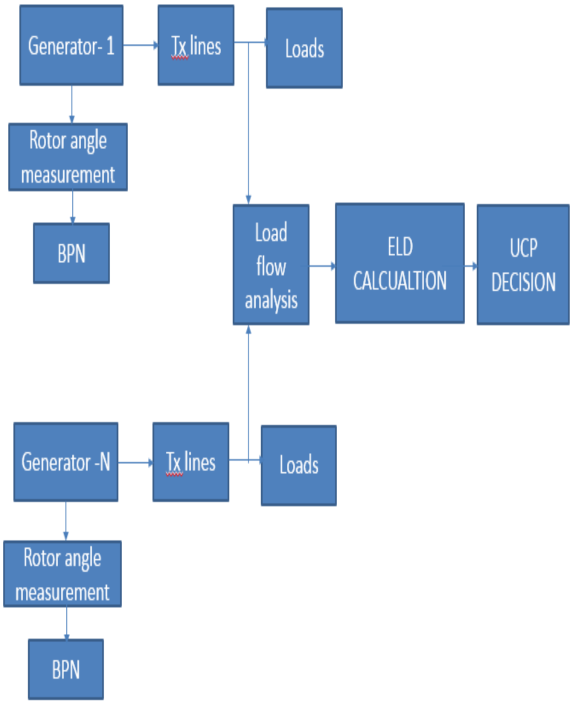
B. Frequency collapse

Fig showed that the power output of turbine is frequency dependent. This might cause a significant frequency drop when the frequency is much lower than the nominal frequency. Sometimes, it might lead a power system to a frequency collapse. The generator characteristics shown in Fig. are assumed to be straight lines. In reality the mechanical driving power delivered by turbines depends on the frequency deviation and the lines shown in Fig. are not straight. The system generator characteristics are likely to have the shape shown in Fig. However, for small frequency deviations the linear assumption is valid. On the other hand, for large frequency deviations this assumption is not valid because the deterioration in the performances of the boiler feed pumps caused by these variations can reduce the mechanical power. The deterioration effect is shown in Fig .Special attention should be devoted to the lower part of characteristic P_{T+}, which shows how an equivalent generator characteristic can be affected by the deterioration of the performances of the boiler feed pumps. Thus, the intersections of the load characteristic P_L with the generator characteristic P_{T+} are points s and u (see Fig.). The former is stable, while the latter is an unstable point. Point s is locally stable, as for any disturbance within the vicinity of this point the system returns to point s. The region in which this condition holds is referred to as the area of attraction. The lower point u is locally unstable, as any disturbance within the vicinity of this point will result in the system moving away from the equilibrium point. As in Fig. , if a loss of generation



occurs the operating point moves from 1 to 2. The significant difference between the generation and load produces an initial rapid drop in frequency. As the difference between load and generation reduces, the frequency drop slows down and the turbine power trajectory *f*(P_T) approaches the equilibrium point s. However, the trajectory *f*(

P_T) might enter the area of repulsion of point u. In that case it will be forced away and the system will suffer a frequency collapse.



Implemented Block Diagram

```
NG =

     4
```

Bus number: 1

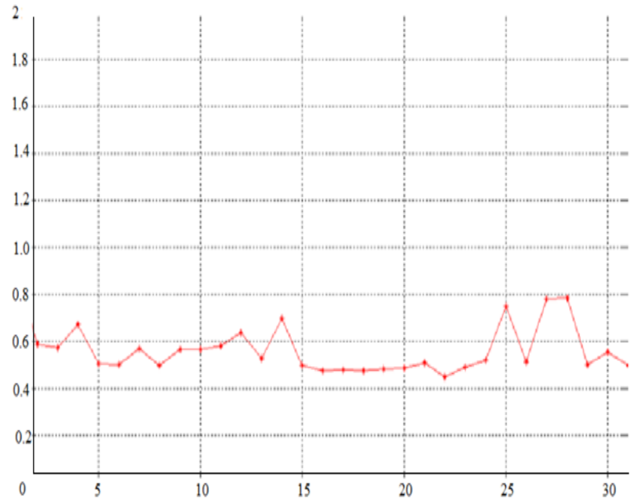
State No.	MW min	MW max	Units 1	2	3	4
1	0.0	0.0	0	0	0	0
2	52.0	60.0	0	0	0	1
3	50.0	80.0	1	0	0	0
4	102.0	140.0	1	0	0	1
5	49.0	250.0	0	1	0	0
6	48.0	300.0	0	0	1	0
7	101.0	310.0	0	1	0	1
8	99.0	330.0	1	1	0	0
9	100.0	360.0	0	0	1	1
10	98.0	380.0	1	0	1	0
11	151.0	390.0	1	1	0	1
12	150.0	440.0	1	0	1	1
13	97.0	550.0	0	1	1	0
14	149.0	610.0	0	1	1	1
15	147.0	630.0	1	1	1	0
16	199.0	690.0	1	1	1	1

Interval Results:

Hour	Demand	Tot.Gen	Min MW	Max MW	ST-UP Cost	Prod.Cost	F-Cost	State	Generators
0	-	-	97	550	0	0	0	13	0 1 1 0
1	450	450	97	550	0	9208	9208	13	0 1 1 0
2	530	530	97	550	0	10648	19857	13	0 1 1 0
3	600	600	149	610	0	12462	32319	14	0 1 1 1
4	540	540	97	550	0	10828	43147	13	0 1 1 0
5	400	400	97	550	0	8308	51455	13	0 1 1 0
6	280	280	97	550	0	6186	57641	13	0 1 1 0
7	290	290	97	550	0	6360	64001	13	0 1 1 0
8	500	500	97	550	0	10108	74110	13	0 1 1 0
9	450	450	97	550	0	9208	83318	13	0 1 1 0
10	530	530	97	550	0	10648	93966	13	0 1 1 0
11	600	600	149	610	0	12462	106428	14	0 1 1 1
12	540	540	97	550	0	10828	117257	13	0 1 1 0
13	400	400	97	550	0	8308	125565	13	0 1 1 0
14	280	280	97	550	0	6186	131751	13	0 1 1 0
15	290	290	97	550	0	6360	138111	13	0 1 1 0
16	500	500	97	550	0	10108	148219	13	0 1 1 0
17	450	450	97	550	0	9208	157428	13	0 1 1 0
18	530	530	97	550	0	10648	168076	13	0 1 1 0
19	600	600	149	610	0	12462	180538	14	0 1 1 1
20	540	540	97	550	0	10828	191366	13	0 1 1 0
21	400	400	97	550	0	8308	199675	13	0 1 1 0
22	280	280	97	550	0	6186	205860	13	0 1 1 0
23	290	290	97	550	0	6360	212220	13	0 1 1 0
24	510	510	97	550	0	10288	222509	13	0 1 1 0
25	500	500	97	550	0	10108	232617	13	0 1 1 0
26	500	500	97	550	0	10108	242726	13	0 1 1 0

Elapsed time: 0.2116 sec.

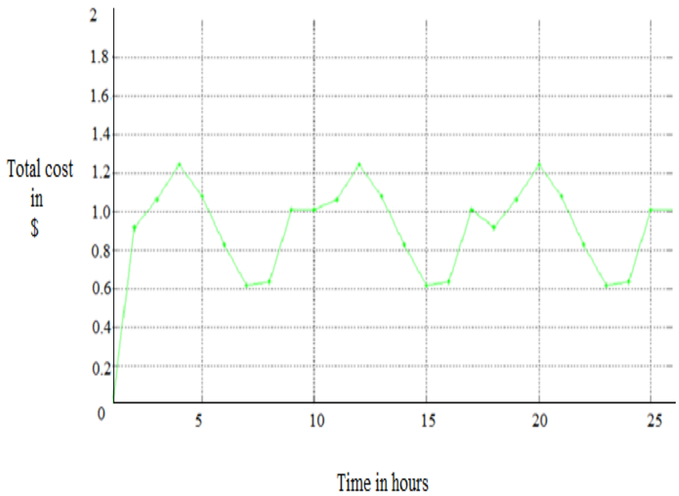
UCP Output



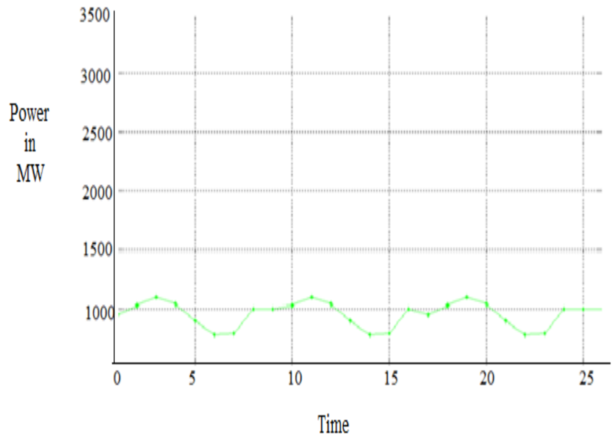
Optimizing time taken for each bus

X axis bus no

Y axis time in sec



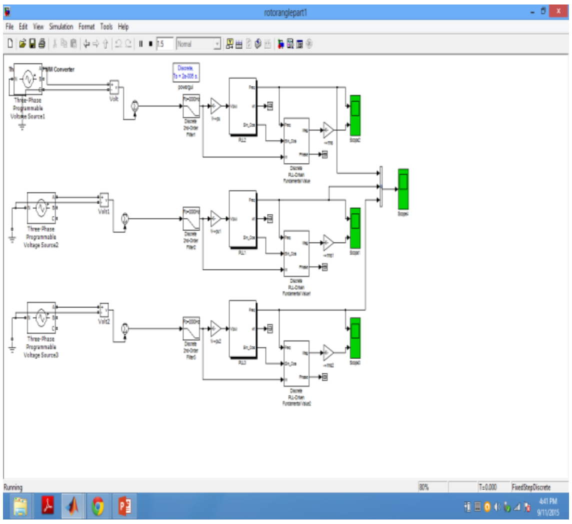
Total cost for each interval

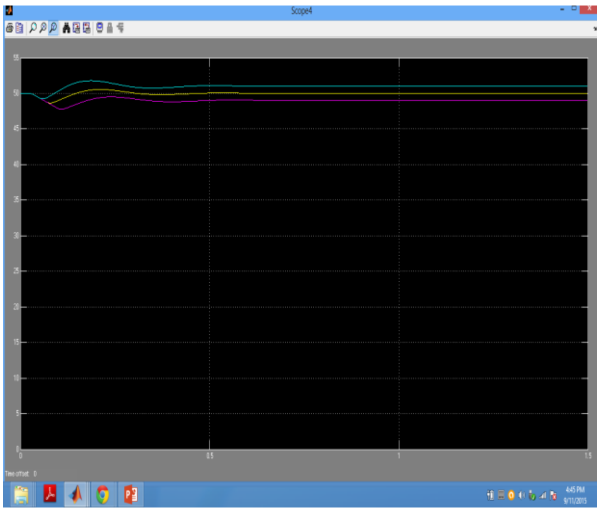


Power Transferred

III. Simulation Results

In order to perform rotor angle based UCP, the first step is to measure the rotor angle. The simulation model is shown below.





Rotor angle of a three phase system

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