Optimal Active Power Dispatch Combining Network Flow and Interior Point Approaches

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Abstract

In this paper, the optimal active power dispatch is formulated as a network flow optimization model and solved by interior point methods. The primal-dual and predictor-corrector versions of such interior point methods are developed and the resulting matrix structure is explored. This structure leads to very fast iterations since it is possible to reduce the linear system either to the number of buses or to the number of independent loops. Either matrix is invariant and can be factored off-line. As a consequence of such matrix manipulations, a linear system which changes at each iteration has to be solved; its size, however, reduces to the number of generating units. These methods were applied to IEEE and Brazilian power systems and the numerical results were obtained using a C implementation. Both interior point methods proved to be robust and achieved fast convergence in all instances tested.

Keywords

Optimal active power dispatch, Optimal power flow, Interior point methods, Network flow model.

I. Introduction

Active power dispatch in electric energy systems has traditionally been formulated by optimal power flow (OPF) problems. These problems have been widely used in the solution of various applications involving the analysis and operation of power systems, such as economic dispatch [1], generation and transmission reliability analysis [2], [3], security analysis [4], generation and transmission expansion planning [5], unit commitment [6], and short term generation scheduling [7], [8]. Depending on the specific application involved, different degrees of detail for generation and transmission systems are represented, with the DC power flow formulation being the most common representation for the transmission system.

Some of these optimal active power dispatch problems have been formulated using network flow models [1], [5], [7], [8], [9], [10], [11], [12] as an alternative to classical optimal active power dispatch based on nodal formulation. One advantage of this approach is that power flows are explicitly represented in the model, which allows the handling of capacities directly imposed on the transmission variables. This feature also enhances speed of contingency studies [11] and is suitable for the representation of transmission line control devices, such as FACTS [9].

The solution of these network flow models did not use interior point methods, although such methods have been successfully used to solve various power system applications [13], such as OPF problems [14], unit commitment [6], reactive power dispatch [15], loss minimization [16], security analysis [17], optimal spot pricing [18], dynamic economic dispatch with ramping constraints [19] and have proved to be quite efficient and robust, especially for solutions involving large-scale applications [13].

The main specific contribution of this paper is the combination of the network flow approach with interior point methods through an efficient computational implementation to solve the optimal active power dispatch problem. The approach aggregates the modeling abilities of network flow with the efficiency and robustness of interior point methods providing new insight into their integration. It takes advantage of the special structure of the network flow model by reducing the linear system matrix to a single dimension, either of the number of buses, or of the number of independent loops. This reduction, after the application of the interior point method to the network flow formulation, seems to be more efficient than the classical approach based on nodal formulation, since no additional functional constraints are needed to cope with transmission limits [19]. Furthermore, both matrices are invariant during all interior point iterations and can be factored off-line. An efficient heuristic is implemented to obtain a sparse matrix for the Kirchhoff loop law, and it is also computed off-line.

Numerical results involving IEEE test systems and the Brazilian power system are reported. A sensitivity study was performed using the IEEE 30-bus test system to highlight the nature of the solution and the influence of the various parameters. The primal-dual and predictor-corrector versions of interior point methods were both tested and the results compared. The results showed that both proposed methods for all tests converge after very few iterations, indicating a robust and efficient tool for optimal active power dispatch, suitable for applications where optimal dispatch is largely used, such as security dispatch [20] and short term generation scheduling [8].

The paper is organized as follows: Section II describes the network flow approach to the optimal active power dispatch problem. Section III presents interior point methods developed to solve the problem in primal-dual and predictor-corrector versions. Implementation details and matrix structure manipulations are highlighted in Section IV, as well as, the heuristic used to obtain the reactance matrix. Finally, Section V presents the numerical results and Section VI states the conclusions.

II. Optimal Active Power Dispatch Model

A series of papers has been published using network flow model approaches for solving active power dispatch problems. Such models differ mainly in terms of the degree of accuracy used in the representation of the transmission system. The simplest model considers only the first Kirchhoff law (node law), ignoring the second Kirchhoff law (loop law) [1], [9]. The solution of such a model can yield quite different results from the DC load flow solution. Other network flow models based on the least effort criterion enforce the second Kirchhoff law by using a quadratic function of the power flows weighted according to branch reactances [12]. It can, however, be shown that the solution of such models are DC load flow solutions only when transmission constraints are not active [11]. The most accurate models [7], [8], [11] represent the second Kirchhoff law by additional linear constraints and assure total equivalence with the DC load flow solution. This paper adopts such an accurate network flow model to represent the transmission system; it is stated as follows:

$$\min \quad \phi(f,p) \tag{1}$$

$$\text{s. t} \quad Af = p - l, \qquad Xf = 0 \tag{2}$$

$$f^{min} \leq f \leq f^{max}, \quad p^{min} \leq p \leq p^{max} \tag{3}$$

where: $\phi(f,p)$ is the objective function to be minimized; A represents the network incidence matrix; X represents the network loop reactance matrix; l represents the active load vector; and f^{max}, f^{min}, p^{max} and p^{min} are bounds for the active power flow, f, and generation, p, variables.

This set of constraints is linear, where (2) represents DC load flow equations and (3) represents the bounds for active power flow and generation.

The objective function used in the model is a weighted combination of two separable quadratic functions

$$\phi(f,p) = \alpha\phi_l(f) + \beta\phi_g(p) \tag{4}$$

where α and β are weight constants. This is a general function in the sense that it can represent most of the objectives traditionally used in literature to dispatch active power. The quadratic function $\phi_l(f)$ can be associated with active power losses in the transmission system, whereas the function $\phi_g(p)$ can represent both generation costs in thermal generating units and hydro generation loss [8]. These functions are generally written as follows:

$$\phi_l(f) = \frac{1}{2} f' R f, \qquad \phi_g(p) = \frac{1}{2} p' Q p + c_p' p$$

where, R is the diagonal resistance matrix, and Q and c_p are the diagonal matrix of quadratic coefficients and the coefficient of the linear term for generation cost, respectively.

III. Solution Technique

In order to simplify the notation, let us assume that the lower bounds in (3) are all zero and that $\alpha = \beta = 1$ in (4).

The dual problem for the optimal active power dispatch formulation (1)–(3) is given by [21]:

$$\begin{aligned} \max \quad & d'y - (f^{max})'w_f - \tfrac{1}{2} f'Rf - (p^{max})'w_p - \tfrac{1}{2} p'Qp \\ \text{s. t} \quad & B'y + z_f - w_f - Rf = c_f, \\ & -y(p) + z_p - w_p - Qp = c_p \\ & (z_p, w_p) \geq 0, (z_f, w_f) \geq 0 \end{aligned}$$

where $B = \begin{pmatrix} A \\ X \end{pmatrix}$; $d = \begin{pmatrix} -l \\ 0 \end{pmatrix}$; z_f and z_p are slack variables; and $y(p)$ are the entries on the dual vector y associated with generation buses.

The optimality conditions for primal and dual problems are given by primal and dual feasibility and the complementarity conditions:

$$\begin{cases} F z_f = 0, & W_f s_f = 0 \\ P z_p = 0, & W_p s_p = 0 \end{cases}$$

where, s_p and s_f are slack variables for the bound constraints on active power generation and transmission, respectively. Moreover, the notation $F = diag(f)$ for diagonal matrices formed by vectors is introduced.

A. Primal-Dual Interior Point Methods

The majority of primal-dual interior point methods can be seen to be variants of the application of the Newton method to optimality conditions. The following outlines a framework for such methods, with the notations $x = (f, p, s_f, s_p)$ and $t = (z_f, z_p, w_f, w_p)$ being used:

Given y^0 and $(x^0, t^0) > 0$.

For $k = 0, 1, 2, \ldots$, do

(1) Choose $\sigma^k \in [0, 1)$ and set $\mu^k = \sigma^k(\frac{\gamma^k}{n})$ where, n is the dimension of x and $\gamma^k = (x^k)' t^k$.

(2) Compute the Newton search directions $(\Delta x^k, \Delta y^k, \Delta t^k)$.

(3) Choose an appropriate step length to remain interior

$\alpha^k = \min(1, \tau^k \rho_p^k, \tau^k \rho_d^k)$ where $\tau^k \in (0, 1)$,

$$\rho_p^k = \frac{-1}{\min_i\left(\frac{\Delta x_i^k}{x_i^k}\right)} \quad \text{and} \quad \rho_d^k = \frac{-1}{\min_i\left(\frac{\Delta t_i^k}{t_i^k}\right)}.$$

(4) Form the new iterate

$(x^{k+1}, y^{k+1}, t^{k+1}) = (x^k, y^k, t^k) + \alpha^k(\Delta x^k, \Delta y^k, \Delta t^k)$.

The step length for both primal and dual variables is the same, because for quadratic problems primal variables appear in the dual problem constraint set. The parameters σ and τ and the starting point are discussed later. Newton search directions are defined by the following linear system[1]:

$$\begin{cases} A\Delta f - \Delta p = -l - Af + p \equiv r_i \\ X\Delta f = -Xf \equiv r_v \\ \Delta f + \Delta s_f = f^{max} - f - s_f \equiv r_f \\ \Delta p + \Delta s_p = p^{max} - p - s_p \equiv r_p \\ B'\Delta y + \Delta z_f - \Delta w_f - R\Delta f = r_y \\ -\Delta y(p) + \Delta z_p - \Delta w_p - Q\Delta p = r_g \end{cases} \tag{5}$$

$$\begin{cases} Z_f\Delta f + F\Delta z_f = \mu e - FZ_f e \equiv r_{z_f} \\ Z_p\Delta p + P\Delta z_p = \mu e - PZ_p e \equiv r_{z_p} \\ W_f\Delta s_f + S_f\Delta w_f = \mu e - S_f W_f e \equiv r_{w_f} \\ W_p\Delta s_p + S_p\Delta w_p = \mu e - S_p W_p e \equiv r_{w_p} \end{cases} \tag{6}$$

where e is the column vector composed exclusively of ones, $r_y \equiv c_f - B'y - z_f + w_f + Rf$ and $r_g \equiv c_p + y(p) - z_p + w_p + Qp$.

B. The Predictor-Corrector Method

For the predictor-corrector approach [22], two linear systems have to be solved. First the *affine directions* $(\Delta\tilde{x}, \Delta\tilde{y}, \Delta\tilde{t})$ are computed by solving (5) and (6) for $\mu = 0$. The

[1]From now on, the superscript k will be omitted to provide a cleaner notation.

search directions are then given by solving (5) and the following:

$$\begin{cases} Z_f \Delta f + F \Delta z_f = \mu e - F Z_f e - \Delta \tilde{F} \Delta \tilde{Z}_f e \equiv \tilde{r}_{z_f} \\ Z_p \Delta p + P \Delta z_p = \mu e - P Z_p e - \Delta \tilde{P} \Delta \tilde{Z}_p e \equiv \tilde{r}_{z_p} \\ W_f \Delta s_f + S_f \Delta w_f = \mu e - S_f W_f e - \Delta \tilde{S}_f \Delta \tilde{W}_f e \equiv \tilde{r}_{w_f} \\ W_p \Delta s_p + P_f \Delta w_p = \mu e - S_p W_p e - \Delta \tilde{S}_p \Delta \tilde{W}_p e \equiv \tilde{r}_{w_p}. \end{cases}$$

C. Implementation Issues

The parameters τ and σ have fixed values: $\tau = 0.99995$ and $\sigma = n^{-\frac{1}{2}}$. For the predictor-corrector approach, the perturbation is given by the equation: $\mu = (\frac{\tilde{\gamma}}{\gamma})^2(\frac{\tilde{\gamma}}{n^2})$, where $\tilde{\gamma} = (x + \Delta\tilde{x})'(t + \Delta\tilde{t})$. In both versions, however, if $\gamma < 1$ then $\mu = (\frac{\gamma}{n})^2$. The following starting point is suggested:

let $y^0 = 0$; $f^0 = s_f^0 = \frac{f^{max}}{2}$; $p^0 = s_p^0 = \frac{p^{max}}{2}$;

$z_f^0 = w_f^0 = (R + I)e$; $z_p^0 = w_p^0 = e$.

IV. Linear System Solution

Since both linear systems share the same matrix, the following discussion will consider only the system involving (5) and (6). The dimension of this linear system can be reduced by substitutions involving various sets of variables without changing the sparse pattern of the matrix. First, slack variables are eliminated:

$$\begin{aligned} \Delta z_f &= F^{-1}(r_{z_f} - Z_f \Delta f); \\ \Delta z_p &= P^{-1}(r_{z_p} - Z_p \Delta p); \\ \Delta w_f &= S_f^{-1}(r_{w_f} - W_f \Delta s_f); \\ \Delta w_p &= S_p^{-1}(r_{w_p} - W_p \Delta s_p); \end{aligned}$$

$$\Delta s_f \;=\; r_{s_f} - \Delta f; \quad \Delta s_p = r_{s_p} - \Delta p$$

reducing (5) to

$$\begin{cases} A\Delta f - \Delta p = r_i \\ X\Delta f = r_v \\ B'\Delta y - D_f \Delta f = r_a \\ -\Delta y(p) - D_p \Delta p = r_b \end{cases} \tag{7}$$

where,

$D_f = F^{-1}Z_f + S_f^{-1}W_f + R$, $D_p = P^{-1}Z_p + S_p^{-1}W_p + Q$, $r_a = r_y - F^{-1}r_{z_f} + S_f^{-1}r_{w_f} - S_f^{-1}W_f r_f$

and

$r_b = r_g - P^{-1}r_{z_p} + S_p^{-1}r_{w_p} - S_p^{-1}W_p r_p$. Note that only inverse diagonal matrices are involved. Now the active power generation and transmission variables in (7) can be eliminated: $\Delta f = -D_f^{-1}(r_a - B'\Delta y)$ and $\Delta p = -D_p^{-1}(r_b + \Delta y(p))$, giving rise to

$$(BD_f^{-1}B' + D)\Delta y = r \tag{8}$$

where $r = \begin{pmatrix} r_i \\ r_v \end{pmatrix} + BD_f^{-1}r_a - Dr_b$, and D is a diagonal matrix with nonzero entries corresponding to the generation buses given by D_p^{-1}. Again, only inverse diagonal matrices are involved.

A. Exploiting the Sparse Pattern of the Matrix

The fact that adding any canonical column e_j to B gives a square nonsingular matrix is crucial. This feature can be used to reduce the computational work per iteration of the interior point methods. Let us consider the matrix $\tilde{B} = [B \; e_j]$. The linear system in (8) can be rewritten as follows:

$$(\tilde{B}\tilde{D}_f^{-1}\tilde{B}' + \tilde{D})\Delta y = r \tag{9}$$

where $\tilde{D}_f^{-1}$ contains an extra diagonal entry (jj) taken from D in order to form $\tilde{D}$. The solution of (9) is then obtained in two steps. First a linear system with matrix $\tilde{B}\tilde{D}_f^{-1}\tilde{B}'$ is solved very efficiently since only the diagonal matrix $\tilde{D}_f$ changes from one iteration to the next, and $\tilde{B}$ is square. Thus, only a single factorization of $\tilde{B}$ is necessary, and this can be computed off-line. Actually, this factorization is even less demanding to compute as will be shown later.

The second step uses the Sherman-Morrison-Woodbury formula [23] to obtain Δy:

$$\begin{aligned} Z &= (\tilde{B}^{-1}E)'\tilde{D}_f(\tilde{B}^{-1}E) \\ v &= (\tilde{B}\tilde{D}_f^{-1}\tilde{B}')^{-1}r \\ \Delta y &= v - (\tilde{B}\tilde{D}_f^{-1}\tilde{B}')^{-1}E(\tilde{D}^{-1} + Z)^{-1}E'v \end{aligned}$$

where the matrix E is given by the canonical vectors corresponding to the nonzero entries of the diagonal matrix $\tilde{D}$. Therefore, the matrix $(\tilde{B}^{-1}E)$ is determined by the network and can be computed off-line as well.

Given Z, $(\tilde{D}^{-1} + Z)$ can be computed without much computational effort. Moreover, the Cholesky method can be used to factor it. The size of this matrix corresponds to the number of generating units minus one. Furthermore, no matrix-vector multiplication with either E or E' involves floating point operations.

B. Use of Spanning Trees

It is possible to permute the columns of $\tilde{B}$, obtaining the following:

$$\tilde{B}C = \begin{bmatrix} T & e_j & N \\ X_T & 0 & X_N \end{bmatrix} \tag{10}$$

where T is a spanning tree for the network and N contains its remaining branches. Moreover, the rows of $[T\ e_j]$ can be reordered to obtain a triangular matrix. Eliminating the variables corresponding to this matrix yields a linear system with the matrix $X_N - X_T[T\ e_j]^{-1}N$. The size of this matrix corresponds to the number of independent loops, and it can also be factored off-line.

C. Computing a Loop Reactance Matrix

The sparsest reactance matrix results from the use of the smallest independent loops. This is called the canonic loop set. Building the matrix in this way provides the additional advantage of the presence of a maximum of two nonzero entries for each branch in the reactance matrix for planar networks. Moreover, always choosing the same orientation results in a network incidence matrix.

Since no efficient algorithm for determining the canonic loop set is known, an heuristic has been developed which considers the network to be a spanning tree joined by additional branches. Such a structure yields a reactance matrix with a pattern that can be efficiently exploited. When the network incidence matrix is split in this way, the reactance matrix block corresponding to the additional branches (X_N) is diagonal since each branch belongs to a unique loop. Therefore, eliminating X_N in (10) yields the reduced matrix ($[T\ e_j] - NX_N^{-1}X_T$), with a size corresponding to the number of buses. Yet another advantage of this choice is revealed when the reduced matrix is multiplied by $[T\ e_j]^{-1}$, yielding the matrix $I + sign(X_T)'X_T$, which is positive definite and symmetric in structure. A similar structure exists for $X_N - X_T[T\ e_j]^{-1}N$, which becomes $X_N + X_T sign(X_T)'$. Observe that numerical stability is not an issue for pivot selection and that there are efficient methods for the factorization of such matrices [23].

This heuristic works for any spanning tree. However, the sparse pattern of the reactance matrix depends on the tree. In this paper, the spanning tree is built starting from the bus with largest degree as root and all the adjacent buses as its children. The bus with the next largest degree connected to the tree is then chosen from the remaining ones. The procedure is repeated until there are no remaining buses. In this way, the distance from the root to the leaves tends to be small as are the loops given by the branches out of the tree.

V. Numerical Results

All the experiments were carried out on a Sun Ultra-1 station using the IEEE standard for floating point arithmetic double precision and tolerance was set to the square root of machine epsilon. The method described here was implemented in the C programming language.

The main goal of the experiments was to show the advantages of the method in relation to both speed and robustness. In all experiments $f^{min} = -f^{max}$ was used for active power flow and $p^{min} = 0$ for active power generation. In order to simplify the interpretation of the results, only pure quadratic cost functions for generation were used, i. e., $c_p = 0$, and the quadratic coefficients were the same for all units, with the exception of Unit 3, which costs double the others, and Unit 1 with generation costs only half as large.

Figures 1 and 2 show the results for the IEEE30 test system using the predictor-corrector method. Limits on power generation and flow were settled large enough to lead to optimal solutions with no active bounds. In all cases, the running time was about 0.01 seconds, and the method took 7 iterations for the first experiment and 6 iterations for all others. Fig. 1 shows the output for three different situations in terms of weight coefficients:

1. The consideration of only transmission power loss ($\alpha = 1$ and $\beta = 0$) (T);

2. The consideration of only generation costs ($\alpha = 0$ and $\beta = 1$) (G);

3. Consideration of transmission and generation costs (T&G).

The consideration of a single aspect led to a drastically different solution, since the cheapest generating Unit (1) is located at some distance from the loads, whereas the expensive one (3) is located close by.

The T&G situation adopts the weights $\alpha = mc$ and $\beta = 1$, where mc is the marginal cost of the generating units in situation G. Since none of the units reaches its bound and

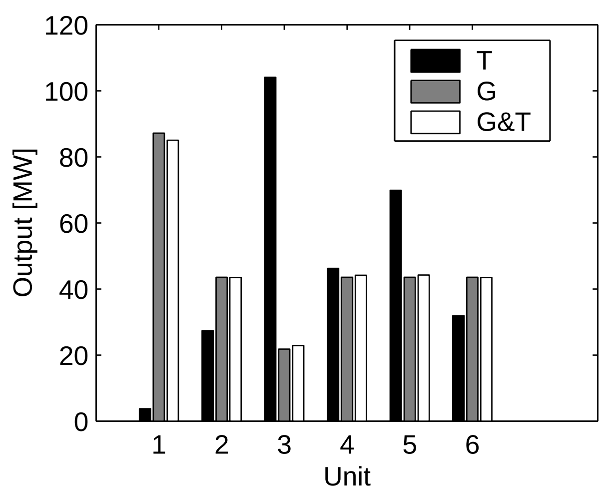

Fig. 1. Active Power Dispatch for different weights – no binding constraints

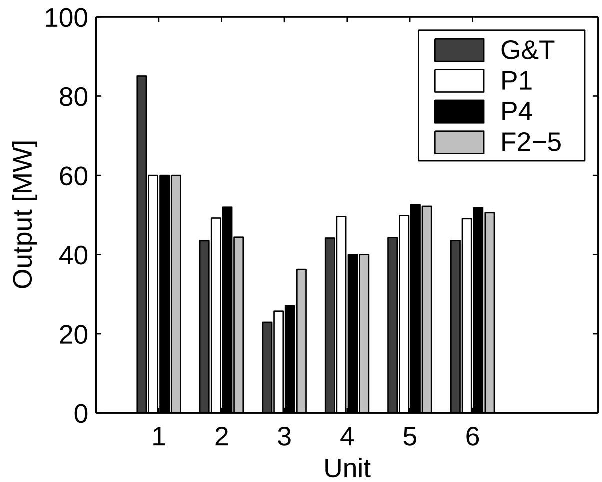

Fig. 2. Active Power Dispatch – binding constraints

losses are not considered in the power balance equation, all units have the same marginal cost. The choice of the weights aims to transform transmission loss (MW) into monetary units ($) so that the first term in the objective function represents the cost of generating the loss. This solution is similar to that considering only generation costs, which suggests that transmission costs are dominated by generation costs. This is due to the fact that transmission loss constitutes only a small fraction of the total generation, usually around 5%. The compound solution is used as a yardstick in Fig. 2.

In order to verify the performance of the method under more strict conditions, a series of experiments was conducted in which more tightly bound constraints were added to the system. Thus, in Fig. 2 the maximum output of Unit 1 was lowered to 60MW (P1). All other units increased their output according to their cost function. In the same figure, the upper bound of Unit 4 was set to 40MW (P4) and with the remaining units again having to compensate for this load in respect to cost. Thus Unit 3, which involved greater cost, made only a minor contribution. Fig. 2 also shows the output in the situation in which

TABLE I

EFFECT OF BINDING CONSTRAINTS – IEEE30

Binding	Iterations	Time (sec.)
0	5	0.01
1	5	0.01
2	5	0.01
3	5	0.01
4	7	0.02
5	8	0.02

TABLE II

PRIMAL-DUAL VERSUS PREDICTOR-CORRECTOR – IEEE118

Binding	PD	PC	PD	PC
Generation	100%		110%	
Constraints	25		28	
Iterations	10	7	11	7
Time (sec.)	0.12	0.09	0.13	0.09

branch 2-5 has an upper bound of 40MW (F2-5). In this situation, the optimization method alleviates the overloaded transmission line by increasing the output of Unit 3 while decreasing the output of Unit 2. Table I exhibits the performance of the method for different stress levels. In all situations, there were 2 binding unit power constraints, and the number of transmission lines at maximum loading (under Binding) ranged from zero to five. No difficulty in achieving convergence was found in the experiments. The number of iterations increased from 5 for the less stressed systems to 8 for the one with more binding constraints.

TABLE III

ITERATION COUNT AND CPU TIME (SECONDS)

Problem	Bus	Load (MW)	Iterations	Time
IEEE	30	283	5	0.01
IEEE	118	4242	7	0.09
SSE	1654	32326	6	2.29
SSE	1732	35658	6	2.45
Brazil	1993	40155	6	2.36

Finally, in order to simulate the situation of a heavily loaded system, all units were given a bound of 50MW, resulting in a capacity slightly above the basic load of 283.4MW. In this solution, all units achieved this bound, with the exception of Unit 3, with an output of 33.4MW.

Table II provides a comparison between the primal-dual (PD) and predictor-corrector (PC) methods for the IEEE 118-bus test system under two different load scenarios, where the total load was 100% and 110% of the IEEE 118-bus basic load, respectively. These loads represent 80% and 88% of the employed system capacity, respectively, thus allowing the study of the interior point methods on problems involving larger loads. There are a large number of binding unit power output constraints in this two scenarios, 25 and 28, respectively, for system with 53 generating units. In both situations, the predictor-corrector method resulted in a better performance than did the primal-dual approach;

moreover, it required less computational time, even considering the extra computational effort necessary for each iteration.

Table III shows the number of iterations and the running time for several systems. Systems SSE 1654 and SSE 1732 are two representations of the South – Southeast Brazilian power system, and Brazil 1993 is a representation of the Brazilian interconnected power system. The number of iterations remained small and the processing time increased slowly with the number of buses. It must be pointed out that these results were similar to those presented in Table I for IEEE 30-bus test system and Table II for IEEE 118-bus test system in relation to number of binding constraints.

VI. Conclusions

In this paper optimal active power dispatch was formulated as a network flow optimization model and solved by interior point methods. One advantage of the network flow modeling approach is that transmission capacities and loss are neatly handled since power flows are explicitly represented. Moreover, the specific structure of the model is suitable for applying interior point methods, which leads to very fast iterations since most of the computational work can be performed off-line.

The first of the advantages of these methods is that they tend to be rapid, due to a limited number of iterations necessary, which in no case exceeded 8 for the predictor-corrector variant, even for loaded systems, and very fast iterations. Thus, Brazilian power systems can be determined in less then 2.5 seconds. The second advantage involves robustness, since this method obtains convergence in very few iterations without presenting numerical instability, even for a tolerance tighter than that expected in practice with loaded systems.

The predictor-corrector variant was also shown to provide a performance superior to that of the standard primal-dual method. Given the superior performance of the approach proposed here, its implementation is being adapted for application to the predispatch problem.

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