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INNOVATION FOR SECURE AND
EFFICIENT TRANSMISSION GRIDS
CIGRÉ Belgium Conference
Crowne-Plaza – Le Palace
Brussels, Belgium | March 12 - 14, 2014

Parallel Computing and Localization Techniques for Faster Power System Dynamic Simulations

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SUMMARY

Dynamic simulation studies are used to analyze the behavior of power systems after a disturbance has occurred. This type of simulation is essential when the system is operating close to its stability limits or its behavior is dictated by complex control and protection schemes modifying its trajectory. These simulations can be computationally very demanding, especially if performed over a time interval of several minutes. In this paper, new shared-memory parallel computing techniques to increase the performance of large-scale power system dynamic simulations are described. The algorithms presented achieve this by utilizing the parallel processing resources available in modern, inexpensive, multi-core machines. In addition, the localized response of power systems after a disturbance is exploited to further accelerate simulations without decreasing accuracy. The medium-scale model of a real power system and a realistic large-scale test system have been used for the performance evaluation of the proposed methods.

KEYWORDS

time-domain simulation, localization, Schur-complement, parallel computing, OpenMP

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1 Introduction

Dynamic simulation studies are used to analyze the trajectory of the system over a specific time period after a disturbance (instead of focusing on the final, presumably stable steady state as considered in static security assessment). This type of simulation is essential when the system is operating close to its stability limits or the outcome is dictated by complex control and protection schemes modifying its trajectory [1].

The biggest disadvantage of dynamic simulations is their large computational cost. Large-scale power systems may need hundreds of thousands of stiff, non-linear, hybrid, Differential and Algebraic Equations (DAEs) to be modeled [2]. Simulating such a system in detail with present-day dynamic simulation software proves to be a challenge [3].

The emergence of parallel computing architectures along with parallel numerical methods and simulation algorithms, resulted in a great boost of the simulation performance. Algorithms or numerical methods considered inefficient at some point in time proved highly efficient under the scope of parallel computation, while new algorithms and numerical methods were developed to fully exploit parallelization [4]. The most prominent of these algorithms are inspired from the field of Domain Decomposition Methods (DDMs) .

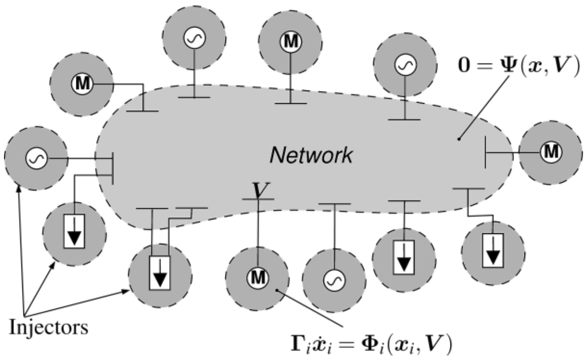

Figure 1 Decomposed System

In this paper we present a parallel domain decomposition-based algorithm for dynamic simulation of large-scale electric power systems. The proposed algorithm allows the acceleration of the simulations in two ways. First, shared-memory parallel programming techniques are employed to exploit the parallelization opportunities of a simple domain decomposition. The latter is based on the partitioning of a large-scale power system into the network and the individual injectors (synchronous machines, compensators, loads, etc.) connected to it (Figure 1). The solution of the decomposed system is achieved through a Schur-complement-based elimination procedure that allows the independent treatment of injectors [5]. Hence, independent processing of the injectors (such as formulation of DAE systems, discretization, formulation of linear systems for Newton method, solution of linear systems, check of convergence, etc.) can be parallelized.

Second, the idea of localization is exploited to further accelerate the simulation procedure. The concept of localization results from the observation that in large power systems a disturbance very often affects a limited number of components while the remaining are only slightly impacted [6]. So, during the simulation, components marginally participating to the system dynamics are characterized as *latent* and their dynamic models are replaced by much simpler equivalents. At the same time, components with significant dynamic activity are characterized as *active* and their original dynamic models are used. Based on a robust, run-time-based criterion, components switch status between active and latent to increase performance while retaining high accuracy.

The work presented in this paper unifies and extends our previous works reported in [5], [7] and [8]. It provides a more robust and accurate localization criterion, additional performance analysis of the parallel algorithm and more comprehensive simulation results.

The paper is organized as follows. In Section 2 the modeling formulation is presented. In Sections 3 and 4, the proposed parallel solution algorithm and the localization technique are detailed, respectively. Our simulation results are reported in Section 5 and followed by closing remarks in Section 6.

2 Power System Modeling

Any power system can be decomposed into the network and the remaining components, as sketched in Figure 1. For reasons of simplicity, all components connected to the network, producing or consuming power are called *injectors*. On the one hand, each injector *i* is described by a system of non-linear DAEs [2]:

$$\mathbf{\Gamma}_i \dot{\mathbf{x}}_i = \mathbf{\Phi}_i(\mathbf{x}_i, \mathbf{V}) \tag{1}$$

where $\mathbf{V}$ is the vector of network voltage variables, $\mathbf{x}_i$ is the state vector containing differential and algebraic variables of the *i*-th injector and $\mathbf{\Gamma}_i$ is a diagonal matrix with:

$$(\mathbf{\Gamma}_i)_{\ell\ell} = \begin{cases} 0 & \text{if the } \ell\text{-th equation is algebraic} \\ 1 & \text{if the } \ell\text{-th equation is differential.} \end{cases}$$

On the other hand, the linear algebraic network equations are described by:

$$\mathbf{0} = \mathbf{D}\mathbf{V} - \mathbf{I} = \mathbf{D}\mathbf{V} - \sum_{i=1}^{n} \mathbf{C}_i \mathbf{x}_i = \mathbf{g}(\mathbf{x}, \mathbf{V}) \tag{2}$$

where **D** includes the real and imaginary parts of the bus admittance matrix, **I** is the vector of rectangular components of the bus currents and $\mathbf{C}_i$ is a trivial matrix with zeros and ones whose purpose is to extract the injector current components from $\mathbf{x}_i$.

3 Parallel Solution Algorithm

For the purpose of numerical simulation, the injector DAE systems (1) are algebraized using a differentiation formula (such as Trapezoidal Rule, Backward Differentiation Formula, etc.) to get the corresponding non-linear algebraized systems:

$$\mathbf{0} = \mathbf{f}_i(\mathbf{x}_i, \mathbf{V}), \quad i = 1, \dots, n \tag{3}$$

At each discrete time-step the non-linear algebraized injector equations (3) are solved together with the network equations (2), using Newton method, to compute the state vectors $\mathbf{x}$ and $\mathbf{V}$. At the *k*-th Newton iteration, the following linear equations have to be solved:

$$\mathbf{A}_i \Delta\mathbf{x}_i + \mathbf{B}_i \Delta\mathbf{V} = -\mathbf{f}_i(\mathbf{x}_i^{k-1}, \mathbf{V}^{k-1}), i = 1, \dots, n \tag{4}$$

$$\mathbf{D}\Delta\mathbf{V} - \sum_{i=1}^{n} \mathbf{C}_i \Delta\mathbf{x}_i = -\mathbf{g}(\mathbf{x}^{k-1}, \mathbf{V}^{k-1}) \tag{5}$$

The solution of the system (4)-(5) is computed using a domain decomposition-based algorithm [5] exploiting the partitioning of Figure 1. In brief, the injector equations (4) are solved with respect to $\Delta\mathbf{x}_i$ and introduced in (5) to obtain the following reduced system:

$$(\mathbf{D} + \sum_{i=1}^{n} \mathbf{C}_i \mathbf{A}_i^{-1} \mathbf{B}_i)\Delta\mathbf{V} = -\mathbf{g}(\mathbf{x}^{k-1}, \mathbf{V}^{k-1}) - \sum_{i=1}^{n} \mathbf{C}_i \mathbf{A}_i^{-1} \mathbf{f}_i(\mathbf{x}_i^{k-1}, \mathbf{V}^{k-1}) \tag{6}$$

This reduced system is then solved to obtain the voltage correction, $\Delta\mathbf{V}$ which is back substituted in (4) to get the state corrections $\Delta\mathbf{x}_i$.

While this DDM-based algorithm is numerically equivalent to a simultaneous Newton scheme applied to equations (4)-(5), it provides access to the individual injector models and allows their separate and independent treatment. This feature is exploited to parallelize the calculations and accelerate the simulation. In particular, the discretization and algebraization of (1), the computation of the contributions to (6) and the final solution of the injectors to determine $\Delta\mathbf{x}_i$ are parallelized as shown in the shaded blocks of Figure 2.

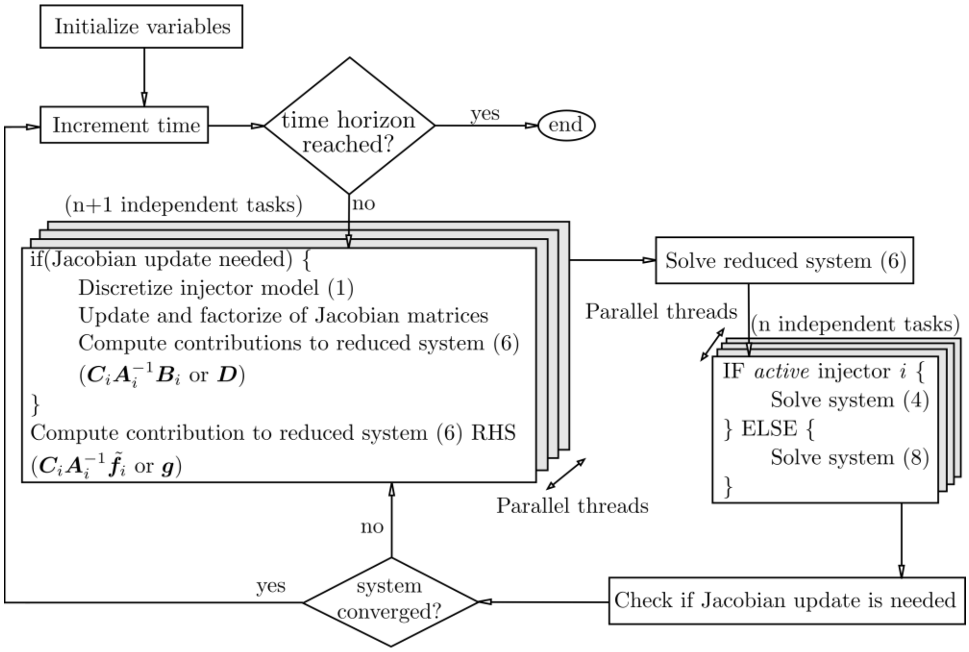

Figure 2 DDM-based Parallel Algorithm with Localization

4 Localization Technique

The goal of this technique is to detect, during the simulation, which injectors are marginally participating to the system dynamics (*latent*) and replace their dynamic models (1) with much simpler sensitivity-based linear models. At the same time, the full dynamic model is used for a component which exhibits significant dynamic activity (*active*).

The sensitivity-based linear model used is derived from the injector linearized equations (4) when ignoring the internal dynamics, that is $\mathbf{f}_i(\mathbf{x}_i^{k-1}, \mathbf{V}^{k-1}) \simeq \mathbf{0}$, and solving for the state variation $\Delta\mathbf{x}_i$:

$$\Delta\mathbf{x}_i \simeq -\mathbf{A}_i^{-1}\mathbf{B}_i\Delta\mathbf{V} \tag{7}$$

The corresponding current variation $\Delta\mathbf{I}_i$ can be formulated as:

$$\Delta\mathbf{I}_i = -\mathbf{E}_i\mathbf{A}_i^{-1}\mathbf{B}_i\Delta\mathbf{V} = -\mathbf{G}_i\Delta\mathbf{V} \tag{8}$$

where $\mathbf{E}_i$ is a trivial matrix with zeros and ones whose purpose is to extract the injector current variations from $\Delta\mathbf{x}_i$ and $\mathbf{G}_i$ is the sensitivity matrix relating the current with the voltage variation.

To classify each injector into *active* or *latent*, a simple and fast to compute metrics is used, originating from real-time digital signal processing [8]. In particular, an injector is declared latent when both its active (P_i) and reactive (Q_i) powers have "not changed significantly for some time" or, in other words, exhibit small variability. As the P_i and Q_i values are discretized in time, traditional methods for analyzing time series data can be employed to characterize their variability over a pre-specified, moving, time window.

The choice of using a moving time window and not the entire history aims at disregarding the oldest "behavior" of an injector and involving only recently observed dynamics. The main characteristics extracted from the time series are the sample average value and standard deviation. The latter is the measure of volatility that shows how much dispersion exists from the average. A small standard deviation indicates that the data points tend to be very close to the average.

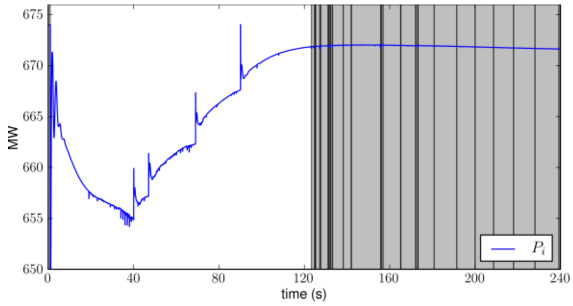

Figure 3 Injector Active Power Output

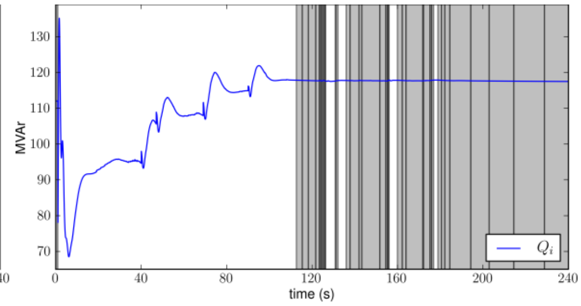

Figure 4 Injector Reactive Power Output

Consequently, a standard deviation of P_i and Q_i concurrently smaller than a tolerance ϵ_L, is a good indication that the *i*-th injector exhibits low dynamic activity and can be considered latent. Figure 3 and Figure 4 show respectively P_i and Q_i of a power plant during a dynamic simulation. The grey shaded areas in each figure show that the standard deviation calculated over a 20 s time-window is smaller than ϵ_L=0.1 MW/MVAr. Thus, in the areas where *both* figures are grey the *i*-th injector is declared *latent* and the model (7) is used to represent it. In the remaining areas the injector is *active* and the full dynamic model (1) used. The vertical black lines show the moments when the power plant switches from active to latent and vice-versa. It is worth noting that even towards the end of the simulation, the power plant is switched back to active mode due to the its dynamic response.

The observation time-window and the tolerance ϵ_L are selected to obtain the desired balance between accuracy and speed. First, the observation time-window needs to be big enough to avoid a very localized observation window which can cause a huge number of switching between modes. At the same time, extensively increasing the observation time-window could lead to loss of performance as events that appeared "far" in the past will be taken into account. In practice, an observation window of 15-25 s is satisfactory when simulating system responses for a time-horizon of few minutes.

Second, the localization tolerance ϵ_L defines the amount of deviation accepted in the system's accuracy. Increasing the tolerance value provides more acceleration but could deteriorate accuracy. In practice, a tolerance value ϵ_L <0.5 MW/MVAr has shown to retain full accuracy of the dynamic simulation while providing sufficient performance [8].

5 Simulation Results

The DDM-based algorithm sketched in Figure 2 with the localization technique have been implemented in the RAMSES software, developed at the University of Liège. RAMSES uses the OpenMP application programming interface for parallelization, which allows the simulation to be executed on inexpensive multi-core computers. All the simulation results have been obtained using a 24-core AMD Opteron Interlagos desktop computer running Debian Linux.

The well-known, simultaneous Very DisHonest Newton (VDHN) algorithm applied to the original system (1), (2) is used for comparison [9]. The Jacobian matrix is updated and factorized only if the system has not converged after three Newton iterations at any discrete time instant. This update strategy gives the best performance for the following test-cases.

5.1 Case 1: 2204-bus System

This section reports on results obtained with the medium-size model of a real system including 2204 buses, 2919 branches and 135 power plants each with a detailed representation of the synchronous machine, its excitation system, automatic voltage regulator, power system stabilizer, turbine and speed governor. The model also includes 976 dynamically modeled loads. The resulting DAE system has 11774 states.

The disturbance consists of a short circuit lasting seven cycles, cleared by opening a line. The system is simulated over a period of 240 s with a time step size of one cycle. The system evolves in the long term under the effect of 1076 LTCs, 24 automatic shunt compensation switching devices as well as OvereXcitation Limiters (OXL). The observation time window chosen for the localization technique is 20 s and the latency tolerance ϵ_L =0.1 MW/MVAr.

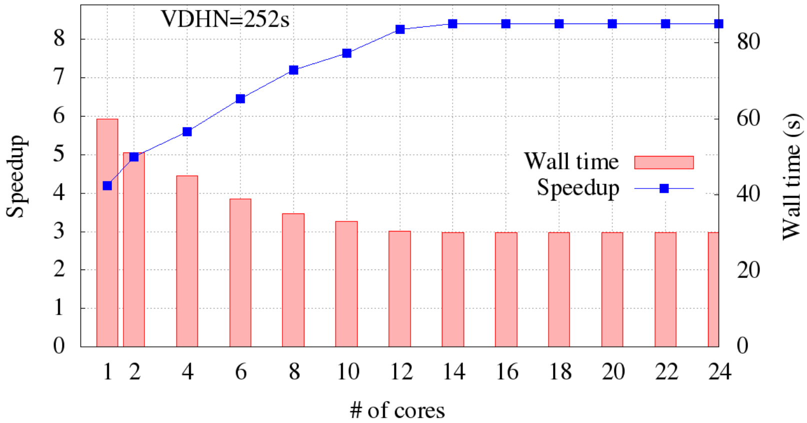

Figure 5 Case 1: Execution Time and Speedup

Figure 5 shows the speedup gained by the presented algorithms. While the benchmark VDHN algorithm takes 252 s to simulate the disturbance, the DDM-based algorithm on a single core is four times faster, finishing in 60 s. The speedup when executing on a single core stems from the localization technique described in Section 4. When more cores are used, the presented algorithm is up to 8.5 times faster, finishing in 30 s.

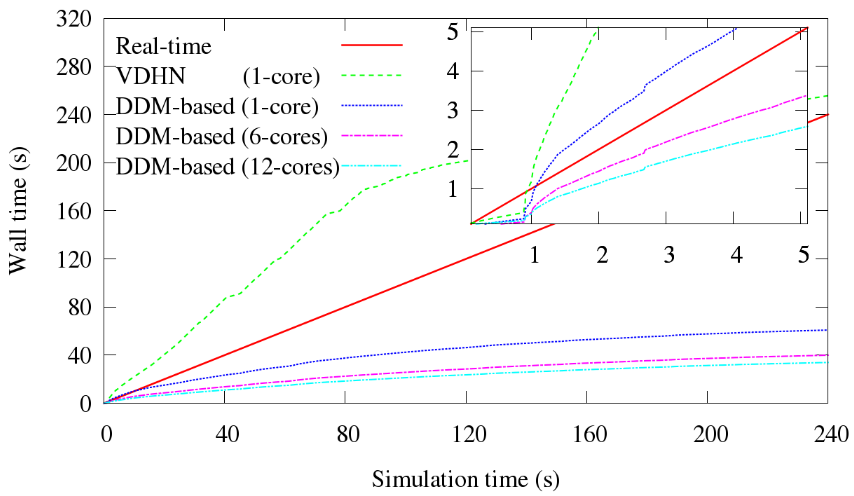

Figure 6 Case 1: Real-time Performance

Furthermore, Figure 6 shows the real-time simulation capabilities of the algorithm. The real-time line in the figure shows the limit of faster than real-time execution. The VDHN and the DDM-based algorithm on a single core are slower than real-time as they cross the real-time line (lagging) at some point. The presented algorithm using six or more cores is faster than real-time during the whole simulation. Such simulations could be used to anticipate the system evolution after a disturbance has occurred (look-ahead capability [10]). They could find application in training system operators, real-time testing of control algorithms (software in the loop), etc.

5.2 Case 2: 15226-bus System

This section reports on results obtained with the large-scale test-system, representative of the continental European main transmission grid, set up in the context of the FP7 European PEGASE project [11]. The variant considered includes 15226 buses, 21765 branches and 3483 power plants with a detailed representation of each synchronous machine, its excitation system, automatic voltage regulator, power system stabilizer, turbine and speed governor. The model also includes 7211 dynamically modeled loads, thus summing to 10694 injectors. The resulting DAE system has 146239 differential and algebraic states.

The disturbance consists of a busbar fault, lasting five cycles, that is cleared by opening two double-circuit lines. The system is simulated over a period of 240 s with a time step size of one cycle. The system evolves in the long term under the effect of LTCs as well as OXLs. The observation time window chosen for the localization technique is 20 s and the latency tolerance ϵ_L =0.1 MW/MVAr.

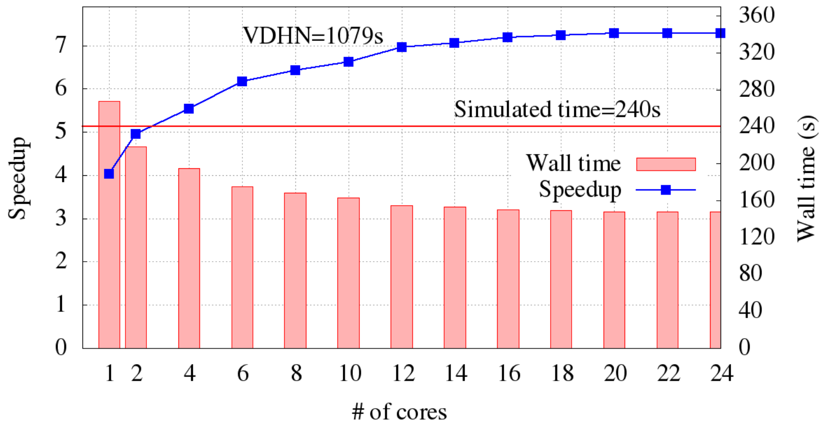

Figure 7 Case 2: Execution Time and Speedup

Figure 7 shows the speedup gained by the proposed algorithm. While the VDHN algorithm takes 1079 s to simulate the disturbance, the presented algorithm on a single core is four times faster, finishing in 270 s. The speedup when executing on a single core stems from the localization technique described in Section 4. When increasing the number of cores used, the proposed algorithm is up to 7.2 times faster, finishing in less than 150 s.

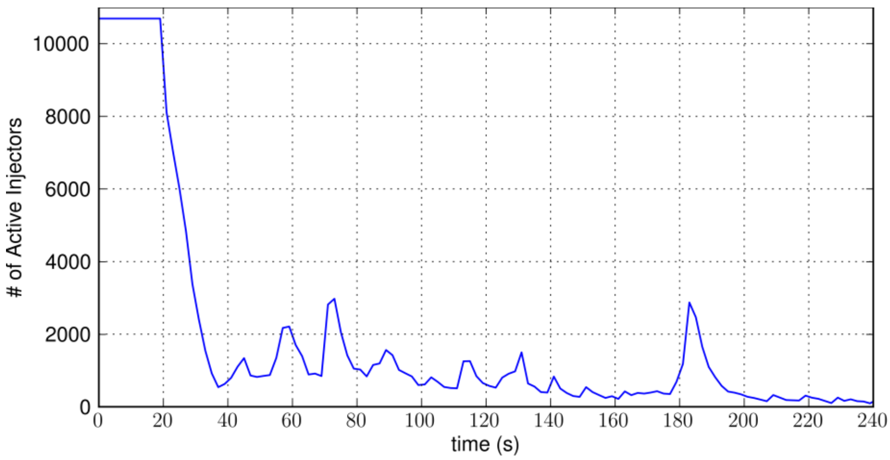

Figure 8 Case 2: Number of Active Injectors

Figure 8 shows the overall injector activity during the simulation. Significant activity is observed during the first 20 s with almost all injectors remaining active. Following, the number of active injectors is significantly decreased, only to rise again when devices with larger response time (e.g. LTC, OXL, etc.) start acting. This pattern continues until around 200 s. In the final period, all most injectors become latent as the system has almost reached its final equilibrium point.

6 Conclusion

Power systems with high percentage of renewable energy sources operating closer to their stability limits, post-disturbance control schemes and active demand response are among the reasons why dynamic simulations are becoming indispensible. This rising need for simulating larger and more detailed power system models is constantly increasing the computational burden and execution time of dynamic simulations.

This paper presents a domain decomposition-based algorithm that exploits parallel computing and localization techniques to accelerate dynamic simulations while retaining full accuracy of the solution. The performance of the presented algorithm was demonstrated on a 2204-bus medium-scale model of a real system and a 15226-bus large-scale test-system. The algorithm shows high speedup ratios in both system simulations, with the medium-scale system being simulated at faster than real-time levels. The corresponding software runs on inexpensive multi-core computers, and distributes the computational effort over the various processors in a totally automatic manner.

REFERENCES

[1] D. Koester, S. Ranka, and G. Fox, "Power systems transient stability-a grand computing challenge," Northeast Parallel Architectures Center, Syracuse, NY, Technical Report 1992.

[2] P. Kundur, *Power system stability and control*. New York: McGraw-hill, 1994.

[3] S.K. Khaitan and A. Gupta, Eds., *High Performance Computing in Power and Energy Systems*.: Springer Berlin Heidelberg, 2013.

[4] R.C. Green, Lingfeng Wang, and M. Alam, "High performance computing for electric power systems: Applications and trends," in *Proc. IEEE PES General Meeting*, San Diego, 2011, pp. 1-8.

[5] P. Aristidou, D. Fabozzi, and T. Van Cutsem, "Dynamic Simulation of Large-scale Power Systems Using a Parallel Schur-complement-based Decomposition Method," *to appear in IEEE Transactions on Parallel and Distributed Systems*, 2013.

[6] V. Brandwajn, "Localization Concepts in (In)-Security Analysis," in *Proc. IEEE PES PowerTech Conference*, Ahtens, 1993, pp. 10-15.

[7] D. Fabozzi, A.S. Chieh, B. Haut, and T. Van Cutsem, "Accelerated and Localized Newton Schemes for Faster Dynamic Simulation of Large Power Systems," *to appear in IEEE Transactions on Power Systems*, 2013.

[8] P. Aristidou, D. Fabozzi, and T. Van Cutsem, "Exploiting Localization for Faster Power System Dynamic Simulations," in *Proc. IEEE PES PowerTech Conference*, Grenoble, 2013.

[9] D. Tylavsky, A. Bose, F. Alvarado, R. Betancourt, and K. Clements, "Parallel processing in power systems computation," *IEEE Transactions on Power Systems*, vol. 7, no. 2, pp. 629 –638, may 1992.

[10] S. Jin, Z. Huang, R. Diao, D. Wu, and Y. Chen, "Parallel implementation of power system dynamic simulation," in *Proc. IEEE PES General Meeting*, Vancouver, 2013.

[11] (2013, January) Pan european grid advanced simulation and state estimation (PEGASE). [Online]. http://www.fp7-pegase.eu/