A TIME-DOMAIN APPROACH TO TRANSMISSION NETWORK EQUIVALENTS VIA PRONY ANALYSIS FOR ELECTROMAGNETIC TRANSIENTS ANALYSIS

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Abstract: This paper presents a method of obtaining transmission network equivalents from the network's response to a pulse excitation signal. Proposed method is based on modal decomposition representation for the large-scale interconnected system. In this framework we use Prony analysis to identify the network function of the system and to decompose the large system into a parallel combination of simple first-order systems. As a result network function of the transmission network can be identified easily, and Thevenin-type of discrete-time filter model can be generated. It can reproduce the driving-point impedance characteristic of the network. Furthermore proposed model can be implemented into the EMT system in a direct manner. The simulation results with the full system representation and the developed equivalent system showed a good agreement.

Keywords: Network Function, Modal Decomposition, Prony Analysis, Electromagnetic Transients.

I. Introduction
It is required in electromagnetic transients studies to represent the complex power system in great detailed manner[1-5]. Whereas routine load-flow and fault level studies in power system are widely carried out for networks of several hundred nodes, it is seldom feasible to base electromagnetic transient analysis on this scale of explicit network representation. Thus almost invariably, it is required to represent networks, or given part of networks, in a reduced form.

The equivalent for the electromagnetic transient analysis requires the ability to reproduce the original system's effects on the transient signal accurately. The transient signals are of very short duration and have a broad range of frequencies. The frequency dependence and distributed nature of the network components, especially those of the transmission lines, are the typical characteristics that exert a great effect on the generation and propagation of the transient signals. Thus, to satisfy the fundamental requirement, the equivalent system must be generated by an appropriate method that can fully reflect those major characteristics into the equivalent.

The conventional short-circuit impedance, calculated at power frequency, cannot reproduce the reduced network's behavior because this form of equivalent is of lumped parameter form and it is therefore unable to take into account those characteristics of the transmission line. To improve the shortcomings A. S. Morched and V. Brandwajn proposed a method of constructing equivalent that approximates the frequency response of the network[4]. In this frequency domain method the system to be reduced is represented by an approximated rational network function. The approximated network function is determined in frequency domain via iterative nonlinear curve fitting procedure.

This paper describes a new time-domain method of obtaining transmission network equivalents from the network's response to a pulse excitation. Proposed method is based on modal decomposition representation for the interconnected system. It is the Prony analysis that makes the framework of modal decomposition feasible. With Prony analysis we can analyze the system response and identify a rational network function in simple fraction expansion form. As a result, we can decompose the large system into a parallel combination of simple first-order systems and consequently Thevenin-type of discrete-time filter model can be obtained in easy and simple way. This model has optimal low-order. It can reproduce the driving-point impedance characteristics of the network and can be implemented in a direct manner into the EMT system or any other time-domain digital simulator. The simulation results with the full system representation and the developed equivalent system showed a good agreement. In the paper, the proposed reduction method will be described only for the single-phase equivalent model. However, the same approach can be extended to generate 3-phase equivalent easily by modal transform[1-5].

II. Network Function
Consider the system shown in Fig. 1.

![Fig. 1. External system, study system and boundary bus.](image)

In Fig. 1, the overall system consists of two parts; the study system and the external system. Because of the close electromagnetic influence, the model appropriateness for the study system may have a serious effect on the accuracy of the simulation results. Thus the study system must be modeled in great detailed manner. On the other hand, in
transient analysis it is the transient signals at the boundary bus that are of great importance while those in the external system are of no interest. So, the external system can be replaced by an equivalent.

We assume that the external system is linear and time-invariant (LTI) and the only interaction between the external system and the study system comes from the transient voltage/current at the boundary bus. Note that we make no assumptions concerning the study system; it may be nonlinear and/or time-varying. In this case the transient voltage and current signal will not be affected if the external system is replaced as Fig. 2 by either a Thevenin equivalent or Norton equivalent.

\[ H_a(s) = \sum_{k=1}^{n} \frac{R_k}{s - p_k} \]

or equivalently in z-domain

\[ H_a(z) = \sum_{k=1}^{n} \frac{R_k}{1 - \lambda_k z^{-1}} \lambda_k = \exp(p_k t) \]

due to the following facts;

i) The time-domain conversion is immediate and as a result the impulse response of modal decomposition form can be obtained in a direct manner as follows;

\[ h_a(t) = \sum_{k=1}^{n} R_k \exp(p_k t) \]

or

\[ h_a(t) = \sum_{k=1}^{m} A_k \exp(-\sigma t) \cos(\omega_k t + \phi_k) \]

ii) By this modal decomposition the large systems can be decomposed into a parallel combination of simple first-order systems. System reduction problems may become easier in this framework. In such cases we can reduce the dimension of the system by ignoring all the minor modes.

iii) Information included in the response of the system due to some excitation signal can be used for the identification of the rational function. This is very meaningful with a view point that we can identify the model in time-domain not in frequency-domain.

There is an additional attraction. This fraction expansion form makes it possible to use a powerful versatile time-domain signal analysis technique, namely Prony analysis.

III. Prony Network Function Identification Method

Prony signal analysis

Prony analysis is a technique of analyzing signals to determine modal, damping, phase and magnitude information contained in the signal[7,9-12]. It is an extension of Fourier analysis in that damping information as well as frequency information is obtained. The Prony analysis gives an optimal fit in the least-squared-error (LSE) sense to an output signal \( y(t) \) in the form

\[ y(t) = \sum_{i=1}^{n} B_i \exp(\lambda_i t) \]

or equivalently in z-plane

\[ Y(z) = H(z)U(z) = \sum_{i=1}^{n} \frac{B_i z}{\lambda_i z - \lambda_i} \]

In this equation \( H(z) \) is the network function of the external system, \( U(z) \) is the transform of any excitation signal, and \( Y(z) \) is that of the corresponding output signal at the boundary bus. If the response \( y(t) \) is recorded as \( y_{(k)} = y(k\Delta t), \quad k = 1, 2, \ldots, N \) then the 3-step Prony analysis identifies the \( n \) distinct eigenvalues (\( \lambda_i \)'s) and signal residues (\( B_i \)'s) according to the following procedure.

Step I. Linear prediction model (LPM) construction.

Assume that the sampled signal \( y(k) \) can be described by the linear prediction equation.
\[ y(k) = a_1 y(k - 1) + a_2 y(k - 2) + \cdots + a_n y(k - n) \]  

Then applying (7) repeatedly to form

\[
\begin{bmatrix}
  y(n) \\
  y(n-1) \\
  y(n-2) \\
  \vdots \\
  y(N-1)
\end{bmatrix}
\begin{bmatrix}
  a_1 \\
  a_2 \\
  \vdots \\
  a_n
\end{bmatrix} =
\begin{bmatrix}
  y(n+1) \\
  y(n+2) \\
  \vdots \\
  y(N)
\end{bmatrix}
\]

or

\[ X \Theta = Z \]  

we can obtain the least squares estimator \( \hat{\Theta} \) for the unknown coefficients \( \theta_i \)'s as

\[ \hat{\Theta} = (X^T X)^{-1} X^T Z \]

(9)

(\( X^T \) : Moore-Penrose pseudo-inverse of matrix \( X \))

Step II. Characteristic polynomial root finding for the eigenvalue \( \lambda_i \).

By finding the roots of the characteristic polynomial associated with the LPM

\[ z^n - (a_2 z^{n-1} + a_2 z^{n-2} + \cdots + a_n) = 0 \]

we can obtain the eigenvalues of the system, i.e., \( \lambda_i \)'s.

Step III. Signal Residue Estimation.

Using the roots of step II as the complex modal frequencies for the signal, we can determine the signal residues for each mode according to the linear equation.

\[
\begin{bmatrix}
  \lambda_1 \\
  \lambda_2 \\
  \vdots \\
  \lambda_n
\end{bmatrix}
\begin{bmatrix}
  B_1 \\
  B_2 \\
  \vdots \\
  B_n
\end{bmatrix} =
\begin{bmatrix}
  y(1) \\
  y(2) \\
  \vdots \\
  y(m)
\end{bmatrix}
\]

or

\[ AB = Y \]  

(11)

Then the least squares estimator for the signal residue vector \( B \) is given by

\[ \hat{B} = (A^T A)^{-1} A^T Y \]  

(12)

SVD and model identification in step I: Since the matrix \( X \) in step I usually become rank deficient and noise corrupted the Moore-Penrose pseudo inverse computation must be based on the SVD (singular value decomposition) and only this SVD guarantees numerically reliable result. Furthermore by SVD we can identify the appropriate model order easily. These desirable features of the SVD are summarized as follows[8,9,11].

First, SVD gives a good index for the model order identification. This index makes it possible to identify the effective model order \( p \) of the response, thus of the network function. The singular values of \( X \) are the positive square roots of the nonzero eigenvalues of \( X^T X \). The number of nonzero singular values is equal to the rank of the matrix. It is known that the singular values and singular vectors of a matrix are relatively insensitive to perturbations in the entries of the matrix, and to finite precision errors. Therefore, the singular value distribution is a good indicator of the numerical rank of \( X \). The singular values that should have been zero will be small in the presence of finite precision errors in their computation, and the rank of the matrix can be reliably estimated by counting the significantly large singular values only.

Second, the presence of additive white noise perturbations on the matrix has little effect on the principal singular vectors. This is because such perturbations result in a dominantly diagonal perturbation of \( X^T X \) which has little effect on the eigenvectors of \( X^T X \), and hence on the singular vectors of \( X \). Therefore, the singular vectors of the perturbed matrix corresponding to the dominant singular values will be a good estimate of the singular vectors of the original, noise-free matrix, and its span will be a good approximation to the range space of the original matrix. The SVD is thus a numerically reliable and robust means for estimating the signal and noise spaces from the white-noise-corrupted data.

Polynomial root finder in step II: Since the order of the characteristic polynomial becomes very large, numerically stable efficient algorithm needs to deal with the nonlinearity and ill-condition of the polynomial. Recently a new powerful algorithm has been developed.[13] It is the circular arithmetic algorithm. This new method finds all roots of the polynomial simultaneously and therefore there is no necessity for the root-polishing that is the basic drawback of traditional algorithms such as Laguerre method, Jenkins-Traub method. Because it has the property of parallelization and the convergence rate of cubic order it can be a powerful method. In appendix A we give a brief description about circular arithmetic algorithm and represent a new method of getting initial guess.

QR decomposition in step III: The LSE method used here to evaluate \( B \) employs QR decomposition. This is because QR method gives \( B \) in fewest possible nonzero components form when matrix \( A \) is not of full rank. Using this distinctive feature further reduction can be attained by ignoring all the modes of near-zero signal residue.

Choice of the excitation signal

Network function identification using Prony analysis needs the output response of the external system due to some excitation signal. In this case the choice of an appropriate excitation signal is very important. Since the objective of the injected excitation signal is to stimulate all modes of the external system within a selected range of frequencies the signal itself must have a band-broad frequencies. Short-duration pulse signal can be such an excitation signal and pulse of duration 1 is the ideal excitation signal, i.e., impulse signal.

In this paper, voltage response to the current pulse excitation was used for driving-point impedance function identification. Since the power system, in generally, is inductive the voltage response to the current excitation will have smaller DC offset term, which may cause bias error in estimated results.

The response data for Prony analysis was calculated by EMTP. In such a case, sampling time step \( \Delta t \) determines the frequency range to be considered according to Nyquist's criterion. Injected current pulse was generated using two unit step source in EMTP as[2]

\[ i(k \Delta t) = u_0 k \Delta t + u_1 (k - 1) \Delta t \]  

(13)
Network function identification by Prony analysis

It is important to note that Prony analysis results in a residue and eigenvalue decomposition of an output signal not the network function. But, as shown in appendix B, the network functions can be obtained for the chosen input excitation signal[11].

Suppose in (6) that the single rectangular pulse of height $U_0$ is applied at time $k=1$ and the time $k=\text{d}+1$ is the first sample value for which the input is no longer being applied. In this case, the network function residues $R_k$ can be obtained from signal residues $B_k$ as follows (refer to appendix B)

$$R_k = \frac{B_k}{1 - \lambda_k \cdot \alpha_k}$$

(14)

Procedure for the network function identification

The following steps outline the system excitation and network function identification procedure.

1. Disconnect the study subsystem from the external system.
2. Turn off all the sources in the external system.
3. Inject the excitation pulse signal into the boundary bus and compute the corresponding response by EMTP.
4. Identify the network function with calculated response using Prony analysis as follows.

   1) With the initial guess of linear prediction order $n$, calculate the singular value distribution of $X$ in (8) and determine the effective model order $p$. The p-rank approximation is obtained by retaining the p dominant singular values and corresponding singular vectors.

   2) Estimate the characteristic polynomial coefficient($\lambda_k$).

   3) Find the roots of the characteristic polynomial and calculate the least squares estimate for the signal residues($B_k$).

   4) Calculate the network function residues($R_k$) using the signal residues.

5. Then the minimum order model is obtained by ignoring all the modes of near-zero network function residues.

IV. Equivalent System

With the identified network function the equivalent system can be realized in an easy and direct manner. Generated model has Thevenin-type structure and duplicates the driving-point impedance characteristics of the external system.

Equivalent Impedance Model

If we choose the current as the input excitation, the output corresponds to the voltage. In this case the network function, estimated in $z$-plane with order $q$, will be the driving-point impedance function, $Z_d(z)$.

$$Z_d(z) = \sum_{k=1}^{q} \frac{R_k}{z - \lambda_k} = \sum_{k=1}^{q} \frac{R_k}{1 - \lambda_k z^{-1}}$$

(15)

To avoid complex arithmetic operation in (15), Equation (15) is rearranged below by combining the complex conjugate terms together as

$$Z_d(z) = \sum_{k=1}^{q} \left( \frac{R_k}{1 - \lambda_k z^{-1}} - \frac{R_k^*}{1 - \lambda_k^* z^{-1}} \right)$$

$$= \sum_{k=1}^{r} \left( \frac{d_k + e_k z^{-1}}{1 + a_k z^{-1} + b_k z^{-2}} \right)$$

(16)

where

$$a_k = -(\lambda_k + \lambda_k^* k)$$

$$b_k = \lambda_k \cdot \lambda_k^*$$

$$c_k = R_k + R_k^* = 2 \text{Re}(R_k)$$

$$e_k = -(R_k \lambda_k + R_k^* \lambda_k^*)$$

$$= -2 \text{Re}(R_k \lambda_k)$$

(17)

(18)

(19)

(20)

If $R_k$ and $\lambda_k$ are real number in (15) then

$$a_k = -\lambda_k$$

$$b_k = R_k$$

$$c_k = e_k = 0$$

(21)

(22)

(23)

Now let

$$V_k(z) = Z_k(z) \cdot I(z) = \left( \frac{d_k + e_k z^{-1}}{1 + a_k z^{-1} + b_k z^{-2}} \right) \cdot I(z)$$

(24)

then (24) can be expressed in time-domain

$$v_k(n) + a_k v_k(n-1) + b_k v_k(n-2) = d_k(n) + e_k(n-1)$$

(25)

The difference equation (25) can be rewritten in compact form as

$$v_k(n) = d_k(n) + \text{hist}_k(n-1)$$

$$\text{hist}_k(n-1) = e_k(n-1) - a_k v_k(n-1) - b_k v_k(n-2)$$

(26)

(27)

By the definition of the driving-point impedance

$$V(z) = Z(z) \cdot I(z) = \sum_{k=1}^{r} Z_k(z) \cdot I(z) = \sum_{k=1}^{r} V_k(z)$$

(28)

equivalently in time-domain

$$v_k = \sum_{k=1}^{r} v_k \left[ k \right]$$

(29)

we can obtain the resultant equation via collecting all the delay terms together and denote them by Hist(n-1) as follows

$$v(n) = Z_{eq}(n) + \text{Hist}(n-1)$$

$$Z_{eq} = \sum_{k=1}^{r} d_k$$

(30)

(31)

$$\text{Hist}(n-1) = \sum_{k=1}^{r} \text{Hist}_k(n-1)$$

(32)

This is the equation of a discrete-time Thevenin equivalent to the zero-input external system (Fig. 3). Equation (26), (27) are actually equivalent to two convolutions, denominator for $v$ and numerator for $i$, with the driving-point impedance characteristic of the system. The driving-point impedance represents the time-domain effects caused by the frequency dependent and distributed parameter elements.
The response data were recorded in finite length of $10^{-6}$ digit so the numerical noise to this finite precision extend can be expected. The response and the estimated result by the proposed method are shown in Fig. 6. In the estimated model, its resultant order $q$ after Prony step III was 70. The estimated error was about 4.36e-4, which was defined by

$$\text{error} = \sqrt[2]{\frac{\sum_{k=1}^{N} (\nu(k) - \bar{\nu}(k))^2}{\sum_{k=1}^{N} \nu(k)^2}}$$

(33)

where $\nu(k)$ is the EMTP response and $\bar{\nu}(k)$ is estimated value.

The network function identification refers to the choice of the model order $p$. Thus, first of all, the distribution of the singular values in Prony step I was calculated. In Fig. 7 several cases of the distribution, which correspond to different LPM order $n$, are denoted. From this Fig. 7 it can be confirmed that SVD give a good index for the model order identification.

V. Validation of Equivalent

In order to validate the proposed reduction method

- comparison of the step responses between the full representation and equivalent model
- calculation of the open-end voltages of the two models due to the energization of the transmission line

were carried out. The single-phase test system considered is shown in Fig. 5 where the study system consists of the open-ended 200 Km transmission line. The remaining part of the network constitutes the external system. To generate the equivalent, voltage response of the external system to the current pulse excitation at node 4 was calculated using EMTP. In the simulation, the lines are all represented by distributed parameter line model and sampling time step $\Delta t$ was 1.0 $\times$ $10^{-4}$ [s]. With this $\Delta t$, frequency range up to 5 kHz can be considered.

Fig. 6. Voltage response to the current pulse excitation

Fig. 7. Singular value distribution in Prony step I.

Fig. 8. Estimation errors to the different model order.
Because the response data were recorded in finite precision correspond to $10^{-6}$ digit, the singular values about this magnitude after 74th exhibit a unique tendency and show a sharp distinction. By ignoring the singular values smaller than 74th the minimal order $p$ of the equivalent model was determined directly. With reference to Fig. 8, in which the estimation errors of the Prony results due to the different model order are presented, it is evident that the proposed method gives the best minimum-order model.

A comparison of the responses of the external system and that of the equivalent due to the step input at the boundary bus is shown in Fig. 9. The shown results demonstrate the ability of the developed equivalent to reproduce the original network's transient behavior. In the figure, $p$ and $q$ are denote, respectively, the identified order in Prony step II and the order of the equivalent system after ignoring near-zero residue terms. Only the model that has its order lower than 74 reveals inferior accuracy.

In Fig. 10, the line energization voltage at bus 4 from EMTP simulation using the full system and that of our program are shown. It is evident that the output of the developed equivalent and that of the original system show a good agreement.

VI. Conclusion

A time-domain reduction method for electromagnetic transients analysis is presented. The response of the external system to a short duration pulse excitation signal is utilized to identify a discrete-time equivalent filter model for the system. The equivalent model is determined by the transfer function identification technique based on the Prony analysis. The validity of the proposed method is verified by comparing

- the step responses at the boundary bus
- transients due to the line energization of an open-ended line

using the full system and its equivalent.

VII. References


Appendix A. Circular arithmetic algorithm for polynomial root-finding.

To simultaneously obtain all zeros $\lambda_i$ of a real coefficient polynomial

$$p(z) = z^n + a_1 z^{n-1} + \ldots + a_n$$

the circular arithmetic algorithm (or improved Newton process) is a recommended solution method.

$${z}_i^{(k+1)} = {z}_i^{(k)} - \frac{1}{A(z_i^{(k)}) - D(z_i^{(k)})}$$

$$A(z_i^{(k)}) = \frac{p'(z_i^{(k)})}{p(z_i^{(k)})}$$

$$D(z_i^{(k)}) = \sum_{j=1}^{n} \frac{1}{z_i^{(k)} - z_j^{(k)}}$$

where $k$ denotes the iteration step. Because it has the property of parallelization and the convergence rate of cubic order the improved Newton process can be a powerful method. The method, although used in serial way, is superior to the Laguerre’s or Jenkins-Traub method and this superiority may be more remarkable by adopting parallel processing.

However, its applications are still restricted considerably because of the difficulty of getting safe initial approximation solutions $z_i^{(0)}$ of zeros $\lambda_i$ ($i = 1, 2, \ldots, n$). So, in order to increase the practical efficiency of the algorithm, we represent a simple and effective method of getting the initial guesses.

From the relation between the roots and coefficients of the polynomial (A.1)

$$\sum_{i=1}^{n} \lambda_i = -a_1$$

$$\prod_{i=1}^{n} \lambda_i = (-1)^n a_n$$

we know that arithmetic mean of the location of all the roots equals to $(-a_1 / n, 0)$ and geometric mean of the distances from origin to the root equals to $|\lambda|^{1/n}$.

Let

$$t = z + \frac{a_1}{n}$$

$$\hat{\lambda}_i = \lambda_i + \frac{a_1}{n}$$

then we can obtain the following equation.

$$p(z) = q(t) = \prod_{i=1}^{n} (t - \hat{\lambda}_i)$$

$$= t^n - (\sum_{i=1}^{n} \hat{\lambda}_i) t^{n-1} + \ldots + (-1)^n \prod_{i=1}^{n} \hat{\lambda}_i$$

Therefore since

$$\sum_{i=1}^{n} \hat{\lambda}_i = \sum_{i=1}^{n} (\lambda_i + \frac{a_1}{n}) = 0$$

$$(-1)^n \prod_{i=1}^{n} \hat{\lambda}_i = q(0) = p(x)_{x=-a_1/n}$$

we may expect statistically all the roots of $q(t)$ to be on the circle that has its center at 0 and radius of $|q(0)|$. Thus for the polynomial $p(z)$ of (A.1) we can make the initial guess for the $z_i^{(0)}$ of zeros $\lambda_i$ by taking n evenly distributed points on the circle that has its center at $(-a_1 / n, 0)$ and radius of $|p(-a_1 / n)|^{1/n}$ in complex plane. By this method we can solve the characteristic equations (of order from 60 to 150), on an average, in 10-15 iteration steps.

Appendix B. Transfer function identification using Prony result

Suppose in (6) that the single rectangular pulse of height $U_0$ is applied at time $k=1$ and the time $k=d+1$ is the first sample value for which the input is no longer being applied. In this case, $d$ is the pulse duration. The $z$-transform of this input is

$$U(z) = \frac{U_0}{z - 1} \left(1 - z^{-d}\right) = U_0 \sum_{i=1}^{d} z^{-i}$$

Applying this input to a linear network function in partial-fraction expansion form

$$H(z) = \sum_{i=1}^{n} \frac{R_i z}{z - \lambda_i}$$

yields the output signal $Y(z)$.
\[ Y(z) = H(z) \cdot U(z) = U(z) \sum_{i=1}^{n} \frac{R_{i} z}{z - \lambda_{i}} \]
\[ = U_{0} \sum_{j=1}^{d} z^{-j} \sum_{i=1}^{n} \frac{R_{i} z}{z - \lambda_{i}} \]  
(B.3)

The inverse z-transform gives the following sampled output signal

\[ y(k) = U_{0} \sum_{j=1}^{d} \left\{ \sum_{i=1}^{n} R_{i} \left( \lambda_{i} \right)^{k-j} \right\} u_{s}(k-j) \]  
(B.4)

where \( u_{s}(k-j) \) is the unit step function. This expression is actually a discrete time convolution of the sampled input signal with the system impulse response. When the input is no longer being applied to the system i.e. \( k \geq d \) and \( u_{s}(k-j) = 1 \), the output can be expressed as

\[ y(k) = U_{0} \sum_{i=1}^{n} R_{i} \left( \lambda_{i} \right)^{k} \frac{d}{d} \sum_{j=1}^{d} \left( \lambda_{i} \right)^{-j} \]
\[ = U_{0} \sum_{i=1}^{n} R_{i} \left( \lambda_{i} \right)^{k} \left( \frac{1-\lambda_{i}^{-d}}{1-\lambda_{i}} \right) \]  
\[ k \geq d \]  
(B.5)

By equating (B.5) and (5) the network function residues \( R_{i} \) can be obtained from signal residues \( B_{i} \) as

\[ R_{i} = \frac{B_{i}}{U_{0} \left( \frac{\lambda_{i} - 1}{1 - \lambda_{i}^{-d}} \right)} \]  
(B.6)

Above result mainly suggested by reference [12].
Discussion

Francisco de León (Instituto Politécnico Nacional, Mexico): I would like to congratulate the authors for their very interesting contribution to the computation of equivalent circuits for the simulation of electromagnetic transients via Prony analysis. The authors’ comments on the following remarks would be greatly appreciated.

The calculation and use of equivalent circuits for the computation of electromagnetic transients has been a prolific research topic for the last few years. For statistical analysis, an external equivalent circuit is useful only when the cpu time invested in the computation of the equivalent circuit plus the cpu time of performing a number of the simulations (typically 100) is smaller than the time of performing the same number of simulations with the complete system. Unfortunately, the authors did not provide the cpu times and one cannot fully assess the usefulness of their equivalent network. Will the authors kindly provide the cpu times?

In my experience only a relatively small part of the entire system has an important influence in the transient and, therefore, should be modeled to the detail (using frequency dependent models). Another region has some influence and can be treated with a model of reduced order. As the transient penetrates into the system, the modeling requirements are less demanding. In fact, there is a practical maximum distance away from the switching node where a simple 60 Hz (multi-port three-phase) Norton equivalent would be enough to represent the system behind. Have the authors looked at the problem of the maximum region that should be represented in full detail?

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Jun-Hee Hong and Jong-Keun Park: The authors wish to thank Mr. Francisco de Leon for his interest in our paper. The authors would like to respond to his useful comments as follows:

1. On an IBM PC with i80486 DX2 microprocessor, the model preparation for the 3-phase external network equivalent took 59.2 seconds of CPU time, of which 41.6 seconds is required by the Prony analysis to obtain the equivalent model parameters for the ground- and aerial-mode.

Once the model is available, the line energization simulation run for 2 cycle( 33.3ms) using the equivalent takes only 0.53 second of CPU time. The corresponding time using the full system representation (with frequency-dependent, transposed lines in the external system) in ATP is approximately 19.8 seconds. It is, therefore, expected that the use of the developed equivalent will save overall computing time when a large number of simulations for study of transient phenomena involving switchings in the study system are carried out.

2. Although the choice of the extent of the network to be represented is largely judgmental, we can follow the guidelines by A. S. Morched and V. Brandwajn in their earlier contribution[1].

The external network can be split into two parts. A part is the part to be replaced by the developed equivalents. This part extends to the bus bars where the reflection from the far ends of externally connected lines would not reach the transients location within the period of interest. Sometimes this part may be subject to practical restrictions. For example, in the RTDS(Real-Time Digital Simulator) case, this part must extend only to the bus bars that can be represented within the RTDS capability.

The second part is the part external to this part and the study system. This should be replaced by the surge impedances, produce the power frequency equivalents of the remaining network.

REFERENCE


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