A Gradient-Based Approach for Power System Design Using Electromagnetic Transient Simulation Programs

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Abstract--Digital simulation platforms, such as electromagnetic transient simulation programs, are instrumental in the analysis and design of modern power networks. Use of very accurate models for various network elements as well as efficient solution methods provides their users with a powerful means for studying the short-term transient behavior of a network with a great deal of accuracy; however, it also increases the computational intensity of these programs. Such intensities are severely amplified in design problems, where selection and tuning of the design parameters requires several successive simulations. The computational burden of simulation-based designs can be drastically reduced by interfacing nonlinear optimization algorithms with transient simulation programs. This paper extends the optimization-based approach by introducing a method for interfacing gradient-based optimization algorithms, i.e., the ones that need first order derivatives as well as objective function evaluations. The paper describes the method of interfacing, including the calculation of partial derivatives and determination of the step length parameter. The paper also discusses the inherent parallel nature of the proposed tool and proposes a method for exploiting this feature. Usefulness of the method is manifested through the example of an HVDC control system design using PSCAD/EMTDC simulation program.

Keywords: Optimization, transient simulation, gradient-based methods, HVDC.

I. Introduction

ELECTRIC power networks exhibit complicated dynamic behavior due to the presence of nonlinear and frequency-dependent elements. The increasing application of high power switching systems has further exacerbated the severity of nonlinear phenomena in power systems. This increasing complexity limits the application of many of the conventional analytical design procedures, and necessitates the use of specialized tools and techniques to capture the relevant transients and interactions.

Transient simulation tools, which use detailed modeling and solution techniques and therefore provide an accurate representation of the short-term transient behavior of power systems, are finding numerous applications in the design of power networks with various switching and nonlinear elements. Conventional design procedures used in these tools are essentially based on generating (on a random or sequential basis) a large collection of candidate design parameter sets and simulating the network for each of the sets [1]. Eventually the parameter set that yields the most suitable performance (according to the specified design objectives) is selected.

Since transient simulation is a slow and computationally demanding procedure, the conventional design procedure mentioned above is not entirely suitable for today's design problems, which involve multiple variables and multiple objectives. In such cases the computational burden of the conventional approach becomes prohibitively large.

Recently heuristic non-linear optimization techniques have been successfully used to steer the multiple-runs, and the method appears to result in orders of magnitude reduction in computer resources [2,3]. The most prominent feature of this tool is its capability of finding the optimal setting of design parameters (at least locally) even for the cases where no explicit representation of the design objective function in terms of design parameters is available.

This paper extends the optimization-based approach by including gradient-based methods [4]. At first glance these methods appear to be potentially inferior to heuristic methods due to the requirement of calculating derivatives numerically. However they still often result in quick convergence and give uniformly good performance regardless of the number of variables to be optimized. This latter feature becomes very essential when dealing with design in which a large number of parameters are to be optimized simultaneously.

In the sections to follow, the paper covers, in detail, the method devised for interfacing an emtp-type simulation program with the Cauchy gradient-based optimization algorithm, and addresses the methods used for numerical calculation of the gradients as well as an intermediate stage for determination of the step length parameter used in the Cauchy optimization method. The paper also discusses a number of practical issues such as the efficiency and suitability of the proposed tool in comparison with other optimal design methods. It also investigates the parallelism of the algorithm and proposes methods for the implementation of the tool on parallel processing platforms.

The approach is illustrated using an example, in which the control parameters are optimally selected for an HVDC transmission system based on the detailed CIGRE HVDC Benchmark model represented in the PSCAD/EMTDC

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simulation program.

II. Optimization-Enabled Transient Simulation

The underlying concept of optimization-enabled transient simulation is to use a dedicated optimization algorithm in conjunction with a simulation program so that search for the optimal parameter set is enhanced. Fig. 1 shows the schematic diagram of the interface between a generic (non-gradient-based) optimization algorithm and a simulation program. The objective function (OF) evaluated through simulation is designed by the user and encapsulates the design objectives. Evaluation of the OF (in this case through simulation) yields a figure of merit for the performance of the system under the current parameter set and is a measure of the conformity of the actual performance of the system with the design objectives.

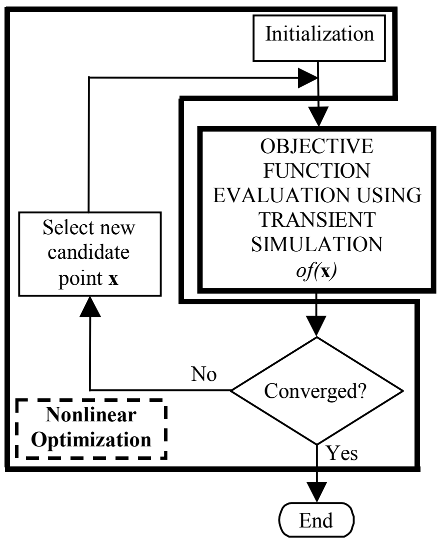


Fig. 1. Schematic diagram of the optimization-enabled transient simulation.

The authors have already implemented this concept using a number of non-gradient-based optimization algorithms (such as the nonlinear Simplex optimization method and genetic algorithms) along with the PSCAD/EMTDC simulation program and have used the combined tool for the optimal design of some nonlinear systems [2,5]. It has been shown that the new tool is orders of magnitude faster than the conventional multiple-run approach in converging to the optimum (at least a local one) while it also produces results of much accuracy.

The complexity of nonlinear and switching systems (such as power electronic devices) often prohibits a closed form representation of the OF in terms of the design variables, and for that reason the non-gradient-based optimization algorithm, which depend only on the OF evaluations, are primarily chosen to be interfaced. Non-gradient-based algorithms lend themselves to a relatively straightforward implementation and have a fairly good performance in terms of their rate of convergence to the optimum.

Gradient-based algorithms, on the other hand, are more complicated as they require partial derivatives of the OF as well as OF evaluations. Lack of an analytical representation of the OF in terms of individual design parameters prohibits the analytical evaluation of the OF derivatives and therefore, numerical methods are to be used for their calculation. Although this seems to be a major drawback (as it is prone to numerical inaccuracies), they have prominent features that provide incentive for their re-consideration: (i) they are inherently robust with regard to the number of parameters to be optimized, and (ii) regardless of how far the staring point might be from a local optimum, they still establish a trajectory of parameter sets with steadily decreasing OF evaluations (in a minimization problem). In other words, gradient-based algorithms, if properly implemented, can optimize an OF with virtually any number of variables starting from an arbitrarily selected initial point.

In the following, the fundamental aspects of a gradient-based algorithm are reviewed; numerical methods developed for the calculation of the derivatives and other intermediate steps are also described.

III. Gradient-Based Optimization Algorithms

Consider a generic minimization problem stated as follows.

$$\begin{aligned}&\text{Minimize } f(\mathbf{x})\\&\mathbf{x}=(x_1,x_2,\cdots,x_N)\\&\text{subject to given constraints}\end{aligned} \tag{1}$$

where the parameter set $\mathbf{x}$ contains the design parameters to be (optimally) determined by the optimization algorithm and $f(\mathbf{x})$ is the OF.

In gradient-based optimization algorithms, the selection of a new parameter set is carried out based on the OF evaluation at the current point as well as first (and sometimes higher) order derivatives. The general iteration formula in a generic gradient-based algorithm is as follows.

$$\mathbf{x}^{(k+1)}=\mathbf{x}^{(k)}+\alpha^{(k)}\mathbf{s}(\mathbf{x}^{(k)}) \tag{2}$$

where $\mathbf{x}^{(k)}$ and $\mathbf{x}^{(k+1)}$ are current and new parameter sets, respectively. $\mathbf{s}(\mathbf{x}^{(k)})$ is the search direction in the N-dimensional space, and $\alpha^{(k)}$ is the length of the step in that direction. The search direction $\mathbf{s}(\mathbf{x}^{(k)})$ is determined using gradient information at the current point $\mathbf{x}^{(k)}$. The most straightforward approach to choose the search direction is to use the direction of the largest descent based on the local information at $\mathbf{x}^{(k)}$. It can be shown that such a direction is the opposite of the gradient of the objective function at $\mathbf{x}^{(k)}$. The iteration formula will therefore be as follows.

$$\mathbf{x}^{(k+1)}=\mathbf{x}^{(k)}-\alpha^{(k)}\nabla f(\mathbf{x}^{(k)}) \tag{3}$$

where $\nabla f(\mathbf{x}^{(k)})$ is the gradient of the objective function at $\mathbf{x}^{(k)}$, and it is obtained from the following formula.

$$\nabla f=[\frac{\partial f}{\partial x_1}\quad\frac{\partial f}{\partial x_2}\quad\cdots\quad\frac{\partial f}{\partial x_N}]^T \tag{4}$$

The formula of (3) is known as the Cauchy optimization method. The algorithm can be stopped when the gradient (derivative) becomes smaller than a pre-specified threshold (ε).

Having found the gradient of the OF at the current point, one can observe that $f(\mathbf{x}^{(k+1)}) = g(\alpha^{(k)})$, and as such the step length parameter can determine how much the OF is decreased as a result of the current iteration. The step length parameter $\alpha^{(k)}$ is usually chosen to minimize the objective function at the new point. Should an explicit representation of the objective function in terms of design parameters be available, the parameters $\mathbf{s}(\mathbf{x}^{(k)})$ and $\alpha^{(k)}$ can be obtained using partial derivatives and a single variable optimization, respectively (see below for details). However, lack of such an explicit mathematical representation leaves the designer with the only feasible approach being the use of numerical techniques to determine search direction and step length.

A. Numerical Calculation of Partial Derivatives

The gradient vector given in (4) is formed by calculating individual partial derivatives. They can be calculated using the following formula.

$$\frac{\partial f}{\partial x_j}(\mathbf{x}^{(k)}) = \frac{f(\mathbf{x}^{(k)} + \mathbf{h}_j) - f(\mathbf{x}^{(k)} - \mathbf{h}_j)}{2h} \tag{5}$$

where h is an adequately small increment; the vector $\mathbf{h}_j$ is defined as follows.

$$\mathbf{h}_j = \begin{bmatrix} \underbrace{0 \;\cdots\; 0}_{1 \text{ to } j-1} & h & \underbrace{0 \;\cdots\; 0}_{j+1 \text{ to } N} \end{bmatrix}_{1\times N} \tag{6}$$

Note that (5) practically yields the average of the right- and left-hand derivatives of the OF at the current point. Technically the increment h has to be vanishingly small; however, to avoid numerical inaccuracies, h is practically chosen to be a small fraction (e.g. 5%) of the corresponding $x_j^{(k)}$. Although this is not necessarily extremely small, it still results is a fair approximation of the derivatives.

Note that the calculation of each partial derivative using (5) requires two OF evaluations (in this case through simulation). In an N-variable optimization problem, $2N$ simulations are required merely to obtain the gradient vector. Compared to a non-gradient-based approach, this can be an unfavorable property as the number of intermediate simulations quickly grows with the number of parameters; however, the inherently faster convergence of the gradient-based algorithms is expected to partially compensate for the (potentially large) number of intermediate steps.

B. Determination of the Step Length Parameter

Theoretically, the step length parameter $\alpha^{(k)}$ can be determined to result in the largest decrease in the OF during the evolution from $\mathbf{x}^{(k)}$ to $\mathbf{x}^{(k+1)}$. To do so, one needs to have a closed form representation of $f(\mathbf{x}^{(k+1)}) = g(\alpha^{(k)})$ and to use a single-variable optimization method to find $\alpha^{(k)}$ to minimize $g(\alpha^{(k)})$. In nonlinear circuits, such as the ones encountered in power systems, an analytical expression for $g(\alpha^{(k)})$ is often prohibitively difficult to obtain, limiting the application of analytical optimization methods to find the optimal value of the $\alpha^{(k)}$.

On the other hand there are optimization methods that do not require an OF in closed form and can be technically applied to find the optimal value of the $\alpha^{(k)}$; however, an underlying assumption in these algorithms is the unimodality of the OF [4], which cannot be guaranteed in our case. Therefore, instead of trying to optimize the step length parameter at the current point (to obtain the smallest $f(\mathbf{x}^{(k+1)})$), a sub-optimal value for the $\alpha^{(k)}$ is used. The algorithm used to obtain this sub-optimal value is given below.

1 $\alpha^{(k)} = \alpha_0$
2 $\mathbf{x}_{test1} = \mathbf{x}^{(k)} - \alpha^{(k)} \nabla f(\mathbf{x}^{(k)})$
3 IF $f(\mathbf{x}_{test1}) < f(\mathbf{x}^{(k)})$
4     $\mathbf{x}_{test2} = \mathbf{x}^{(k)} - 1.5\alpha^{(k)} \nabla f(\mathbf{x}^{(k)})$
5   IF $f(\mathbf{x}_{test2}) < f(\mathbf{x}^{(k)})$
6         $\alpha^{(k)} = 1.5\alpha^{(k)}$
7   ELSE
8         $\alpha^{(k)} = \alpha^{(k)}$
9   END
10 ELSE
11     $\mathbf{x}_{test2} = \mathbf{x}^{(k)} - 0.5\alpha^{(k)} \nabla f(\mathbf{x}^{(k)})$
12   IF $f(\mathbf{x}_{test2}) < f(\mathbf{x}^{(k)})$
13         $\alpha^{(k)} = 0.5\alpha^{(k)}$
14   ELSE
15         $\alpha^{(k)} = 0.25\alpha^{(k)}$
16   GOTO 2
17   END
18 END

Algorithm 1. Determination of the step length parameter

The underlying idea in this algorithm is to find a value for the step length so that $f(\mathbf{x}^{(k+1)}) < f(\mathbf{x}^{(k)})$. Note that this value does not necessarily result in the largest decrease, hence a sub-optimal value.

C. Interfacing the Parts

Having devised methods for the numerical calculation of partial derivatives as well as the step length parameter, one can interface them with a transient simulation program to form the combined (gradient-based) optimization-enabled transient simulation. Fig. 2 shows a schematic diagram of the combined tool.

IV. Case Study

This section demonstrates the use of the proposed combined tool in the control system design for an HVDC system. The study is based on the CIGRE HVDC Benchmark [6] model developed in the PSCAD/EMTDC transient simulation program. Fig. 3 shows a schematic diagram of the system along with its control system; the parameters to be optimized are the proportional gain (K_{r1}) and integral time constant (T_{r1}) on the rectifier side (current controller) and proportional gain (K_{i2}) and integral time constant (T_{i2}) for the inverter side (extinction angle controller).

Other parameters of the system are listed in Table I.

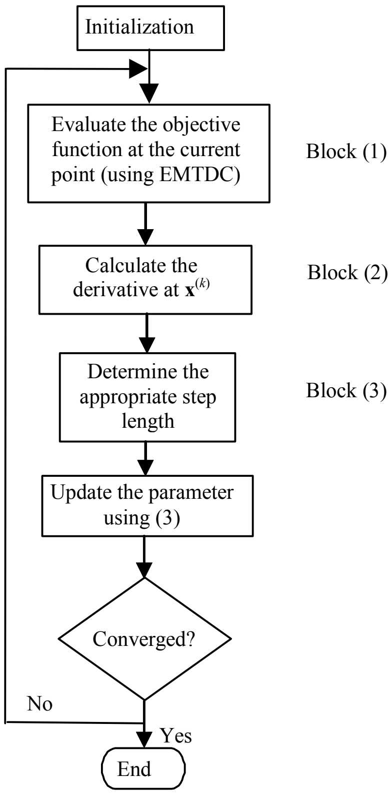


Fig. 2. Interface between the optimization algorithm and transient simulation

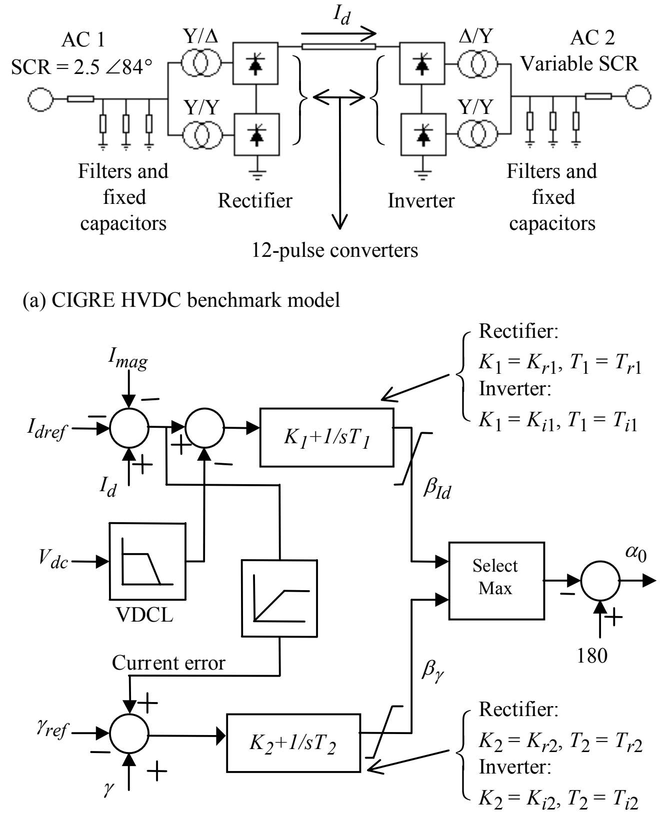
TABLE I
DATA PERTINENT TO THE CIGRE HVDC BENCHMARK MODEL

Rectifier side		
AC system	Transformers (each)	
373.3 kV, SCR = 2.5@84°	600 MVA, 211.3/345 kV, 18%	
Inverter side		
AC system	Transformers (each)	
222.3 kV, SCR = 3.0@81°	600 MVA, 206.5/230 kV, 18%	
Filters and fixed capacitors (MVAR) (for both sides)		
11-th harmonic	13-th harmonic	Fixed capacitors
250	250	150
DC link		
DC line resistance	Rated dc voltage (rectifier side)	Rated dc current
5 Ω	500 kV	2 kA

The objective of the design is to select the values of the control system parameters so that the small signal dynamics of the dc line current is optimized around its nominal operating point, i.e. the deviation between the I_{dref} and actual I_d is minimized. The test on the system comprises a -20% step change in the current order (from 1.0 pu to 0.8 pu), followed by another +20% change to return the system to its nominal operating point.

The optimization OF used for the design is given as follows.

$$ISE(K_{r1}, T_{r1}, K_{i2}, T_{i2}) = 1000 \int_{0.8}^{3.0} (1 - \frac{I_d}{I_{dref}})^2 \, dt \qquad (7)$$



(a) CIGRE HVDC benchmark model

(b) Converter control system

Fig. 3. Schematic diagram of the HVDC system

Note that the OF given in (7) penalizes any deviation between the reference and actual values of the dc line current; should the two signals be matching at all times, the ISE attains its minimum possible value of zero. The objective of the design, therefore, is to find the control system parameters so that the ISE is minimized, indicating a close match between the reference and actual values of the dc current.

Table II summarizes the optimization results obtained using the combined tool. The table shows the pre-optimized parameter set as well as the optimized set along with their respective OF evaluations, which indicate a significant decrease in the ISE evaluation. The corresponding dynamic responses of the dc current are shown in Fig. 4.

TABLE II
OPTIMIZATION RESULTS

Initial parameter set				
K_{r1}	T_{r1}	K_{i2}	T_{i2}	ISE
8.1	0.01	2.5	0.04	124.86
Optimized parameter set				
K_{r1}	T_{r1}	K_{i2}	T_{i2}	ISE
1.33	0.0029	0.67	0.027	0.88

As seen the pre-optimized parameter set has resulted in severe sustained current fluctuations, whereas the optimized parameter set causes a smooth tracking of the reference current with very desirable steady state performance as well. The entire design is carried out in 430 simulations, which compared to a conventional multiple-run, shows orders of magnitude savings in terms of the simulation intensity (note that with only 10 steps for each of the 4 variables in this example, the conventional multiple-run requires $10^4 = 10,000$ simulations).

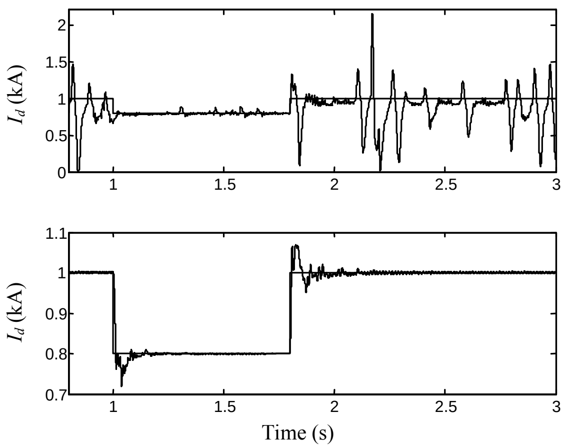


Fig. 4. Dynamic response of the system (top: pre-optimized parameter set; bottom: optimized parameter set)

V. Parallelism of the Algorithm

The study presented in this paper shows that gradient-based optimization algorithms can be efficiently used in conjunction with a transient simulation program for the optimal design of complex systems. However, further examination of the routines used for numerical calculation of derivatives and also determination of an appropriate step length reveals that a large number of intermediate simulations are to be carried out to find the gradient as well the step length merely to enable finding a new parameter set (see (3)). Although gradient-based algorithms are generally expected to be able to find the optimum in a fewer number of iterations than non-gradient-based algorithms, these intermediate simulations, which are necessitated by the absence of an explicit objective function, can severely impact the performance of these algorithms. For example a gradient-based algorithm may be able to find the optimum of a function in handful of iterations as in (3), but note that in a 5-variable optimization problem for instance, each of the iterations will require 10 simulations to find the gradient as well as a number of simulations to determine the step length required. The combined number of these simulations may become so large that they degrade the performance of gradient-based algorithms to below that of non-gradient-based ones. However, it is easy to note that the numerical evaluation of derivatives as presented in (5) is an inherently parallel procedure, because it involves independent function evaluations that can be carried out on different processors. Therefore, in an N-dimensional problem, for which $2N$ objective function evaluations are required to calculate the gradient, each of these evaluations can be assigned to a different processor and the final results are sent back to the main processor, which does the job of calculating the partial derivatives and forming the gradient. Exploiting this inherent parallelism can significantly speed up the process of optimization and therefore enhances the design loop by lowering the burden on the main processor.

VI. Conclusions

The paper extended the concept of the optimization-enabled transient simulation to include part of the powerful family of gradient-based optimization algorithms. It was shown that despite unavailability of an explicit OF in terms of design parameters, it is possible o deploy numerical techniques for the calculation of the derivatives as well as determination of the step length parameter. The paper proposed and implemented a method for interfacing these algorithms with a transient simulation program and used it for the optimal control system design for an HVDC system. Despite the intermediate simulations required for the implementation of the algorithm, the example case showed that the optimization-based approach is still orders of magnitude faster than a conventional multiple-run and yields results of much higher accuracy as well. The paper also investigated the parallel nature of the algorithm that can be used on parallel processors to expedite the design process.

VII. References

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VIII. Biographies

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