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A Novel Approach for TCSC-Based Supplementary Damping Controller Design Using Multi-Objective Optimization Technique

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Abstract
Design of an optimal controller requires optimization of multiple performance measures that are often noncommensurable and competing with each other. Design of such a controller is indeed a multi-objective optimization problem. Being a population based approach; Genetic Algorithm (GA) is well suited to solve multi-objective optimization problems. This paper investigates the application of GA-based multi-objective optimization technique for the design of a Thyristor Controlled Series Compensator (TCSC)-based supplementary damping controller. The design objective is to improve the power system stability with minimum control effort. The proposed technique is applied to generate Pareto set of global optimal solutions to the given multi-objective optimization problem. Further, a fuzzy-based membership value assignment method is employed to choose the best compromise solution from the obtained Pareto solution set. Simulation results are presented to show the effectiveness and robustness of the proposed approach.

Keywords-*multi-objective optimization, genetic algorithm, pareto solution set, thyristor controlled series compensator, power system stability*

I. Introduction

Real world problems often have multiple conflicting objectives competing with each other. For example, while designing a control system, we would usually like to have a high-performance controller, but we also want to achieve desired performance with little control efforts (cost). Optimization of multiple performance measures which are noncommensurable and competing with each other is in reality a multi-objective optimization problem. In multi-objective optimization problems generally there is no single solution that is the best when measured on all objectives. Hence several trade-off solutions (called the *Pareto optimal set*) are usually preferred [1]. Control systems optimization problems involving the optimization of multiple objective functions require high computational time and effort [2, 3]. As conventional techniques are difficult to apply, modern population based heuristic optimization techniques are preferred to obtain Pareto optimal set [4].

Recent development of power electronics introduces the use of Flexible AC Transmission Systems (FACTS) controllers in power systems [5]. Thyristor Controlled Series Compensator (TCSC) is one of the important members of FACTS family that is increasingly applied with long transmission lines by the utilities in modern power systems [6-11]. The majority of the control methodologies presented in literature employ single objective optimization technique to get the desired performance. This paper proposes to use a multi-objective optimization technique for the optimal TCSC-based controller design.

There are two general approaches to multiple objective optimizations. One approach to solve multi-objective optimization problems is by combining the multiple objectives into a scalar cost function, ultimately making the problem single-objective prior to optimization. However, in practice, it can be very difficult to precisely and accurately select these weights as small perturbations in the weights can lead to very different solutions. Further, if the final solution found cannot be accepted as a good compromise, new runs of the optimiser on modified objective function using different weights may be needed, until a suitable solution is found. These methods also have the disadvantage of requiring new runs of the optimizer every time the preferences or weights of the objectives in the multi-objective function change [4]. The second general approach is to determine an entire Pareto optimal solution set or a representative subset. Pareto optimal solution sets are often preferred to single solutions because they can be practical when considering real-life problems, since the final solution of the decision maker is always a trade-off between crucial parameters [12].

In this paper, the design problem of a TCSC is formulated as a multi-objective optimization problem. Genetic Algorithm- based multi-objective optimization method is adapted for generating Pareto solutions in designing a TCSC-based controller. The design objective is to get maximum damping (performance) with minimum control effort (cost). Further a fuzzy based membership function value assignment method is employed to choose the best compromise solution from the obtained Pareto set. Simulation results are presented under various loading conditions and disturbances to show the effectiveness and robustness of the proposed approach.

II. Modeling The Power System With TCSC

The single-machine infinite-bus (SMIB) power system installed with a TCSC, shown in Figure 1 is considered in this study. In the Figure, X_T and X_L represent the reactance of the transformer and the transmission line respectively; V_T and V_B are the generator terminal and infinite bus voltage respectively.

In the design of electromechanical mode damping stabilizer, a linearized incremental model around an operating point is usually employed. The Phillips-Heffron model of the power system with FACTS devices is obtained by linearizing nonlinear equations of the power system around an operating condition [12].

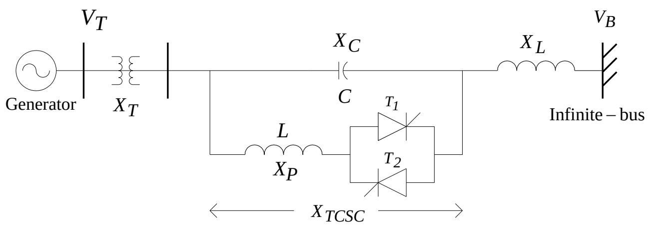

Figure 1. Single machine infinite bus power system with TCSC

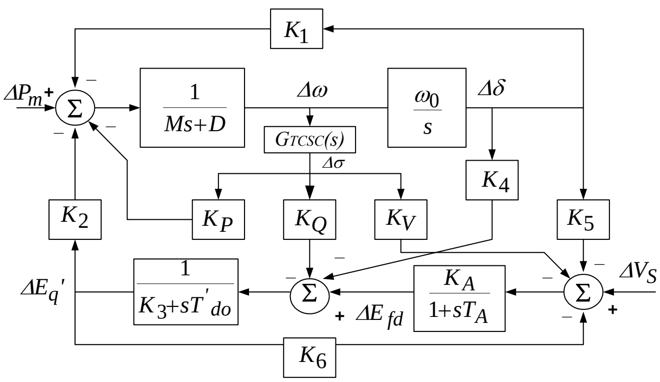

Figure 2. Modified Phillips-Heffron model of SMIB with TCSC

The linearized expressions are as follows [10]:

$$\dot{\Delta\delta} = \omega_b \Delta\omega$$

$$\dot{\Delta\omega} = [-K_1\Delta\delta - K_2\Delta E_q' - K_P\Delta\sigma - D\Delta\omega]/M$$

$$\dot{\Delta E_q'} = [-K_3\Delta E_q' - K_4\Delta\delta - K_Q\Delta\sigma + \Delta E_{fd}]/T_{d0}'$$

$$\dot{\Delta E_{fd}}' = [-K_A(K_5\Delta\delta + K_6\Delta E_q' + K_V\Delta\sigma) - \Delta E_{fd}]/T_A$$

Where,

$$K_1 = \partial P_e/\partial\delta,\ K_2 = \partial P_e/\partial E'_q,\ K_P = \partial P_e/\partial\sigma$$

$$K_3 = \partial E_q/\partial E'_q,\ K_4 = \partial E_q/\partial\delta,\ K_Q = \partial E_q/\partial\sigma$$

$$K_5 = \partial V_T/\partial\delta,\ K_6 = \partial V_T/\partial E'_q,\ K_V = \partial V_T/\partial\sigma$$

(1)

The notations in equation (1) for the variables and parameters described are standard and defined in the nomenclature. For more details, the readers are suggested to refer [1, 12]. The Phillips-Heffron model of the SMIB system with TCSC is obtained using the linearized equations. The corresponding block diagram model is shown in Figure 2.

III. PROBLEM FORMULATION

A. *TCSC Controller Structure*

The commonly used lead–lag structure is chosen in this study as a TCSC controller. The structure of the TCSC controller is shown in Figure 3. It consists of a gain block with gain K_T, a signal washout block and two-stage phase compensation block. The phase compensation block provides the appropriate phase-lead characteristics to compensate for the phase lag between input and the output signals. The signal washout block serves as a high-pass filter, with the time constant T_{WT}, high enough to allow signals associated with oscillations in input signal to pass unchanged. Without it steady changes in input would modify the output. From the viewpoint of the washout function, the value of T_{WT} is not critical and may be in the range of 1 to 20 seconds [13].

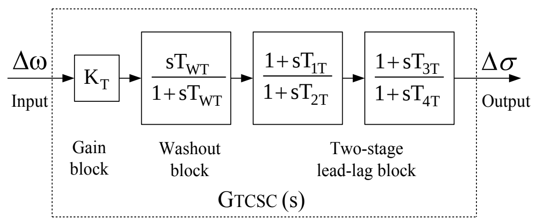

Figure 3. Structure of TCSC-based Controller

B. *Objective Function*

It is worth mentioning that the proposed controller is designed to damp power system oscillations with minimum control effort following a disturbance. The tuning of lead-lag controller is done, by optimizing the error signal and the control signal values simultaneously. The objective is formulated as the minimization of function *F* given by:

$$F = (F_1, F_2) \tag{2}$$

Where, $F_1 = \int_0^{t_1} e^2(t)\,dt$ and $F_2 = \int_0^{t_1} u^2(t)\,dt$

In the above equations, '*e*' is the error signal i.e. changes in the speed deviation and '*u*' is the TCSC control out put i.e. changes in the conduction angle of the TCSC controller and t_1 is the time range of the simulation. For the objective function calculation, the time-domain simulation of the power system model is carried out for the simulation period.

IV. MULTI-OBJECTIVE OPTIMIZATION

A Multi-objective Optimization Problem (MOP) differs from a single-objective optimization problem because it contains several objectives that require optimization. In case of single objective optimization problems, the best single design solution is the goal. But for multi-objective problems, with several and possibly conflicting objectives, there is usually no single optimal solution. Therefore, the decision maker is required to select a solution from a finite set by making compromises. A suitable solution should provide for acceptable performance over all objectives [14-15].

A general formulation of a MOP consists of a number of objectives with a number of inequality and equality constraints. Mathematically, the problem can be written as [16]:

$$\text{minimize/maximize } f_i(\mathbf{x}) \quad \text{for } i = 1, 2, \ldots, n. \tag{3}$$

Subject to constraints:

$g_j(\mathbf{x}) \leq 0 \qquad j = 1, 2, \ldots, J$

$h_k(\mathbf{x}) \leq 0 \qquad k = 1, 2, \ldots, K$

where

$f_i(\mathbf{x}) = \{ f_1(x), \ldots f_n(x)\}$

n = number of objectives or criteria to be optimized

$\mathbf{x} = \{x_1, \ldots, x_p\}$ is a vector of decision variables

p = number of decision variables

There are two approaches to solve the MOP. One approach is the classical weighted-sum approach where the objective function is formulated as a weighted sum of the objectives. But the problem lies in the correct selection of the weights or utility functions to characterise the decision-makers preferences. In order to solve this problem, the second approach called Pareto-optimal solution can be adapted. The MOPs usually have no unique or perfect solution, but a set of non-dominated, alternative solutions, known as the Pareto-optimal set. Assuming a minimisation problem, dominance is defined as follows:

A vector $\mathbf{u}=(u_1,\ldots,u_n)$ is said to dominate $\mathbf{v}=(v_1,\ldots,v_n)$ if and only if $\mathbf{u}$ is partially less than $\mathbf{v}$ ($\mathbf{u}$ p< $\mathbf{v}$),

$$\forall\ i\ \varepsilon\{1,\ldots,n\},\ u_i \leq v_i \wedge \exists\ i\ \varepsilon\{1,\ldots,n;\ u_i < v_i \tag{4}$$

A solution $x_u\ \varepsilon\ U$ is said to be Pareto-optimal if and only if there is no $x_v\ \varepsilon\ U$ for which $\mathbf{v} = \mathbf{f}(x_v) = (v_1,\ldots,v_n)$ dominates $\mathbf{u} = f(x_u) = (u_1,\ldots,u_n)$.

The ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations reinforces the potential effectiveness of GA in optimization problems. Although, the conventional GA is also suited for some kinds of multi-objective optimization problems, it is still difficult to solve those multi-objective optimization problems in which the individual objective functions are in the conflict condition.

Being a population based approach; GA is well suited to solve MOPs. A generic single-objective GA can be easily modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA exploits structures of good solutions with respect to different objectives to create new non-dominated solutions in unexplored parts of the Pareto front. In addition, most multi-objective approach does not require the user to prioritise, scale, or weigh objectives. In this paper, real-coded genetic algorithm (RCGA) optimization technique has been used to solve the given MOP problem. A brief overview of RCGA has been provided in the next section.

V. REAL CODED GENETIC ALGORITHM

Recently, Genetic Algorithm (GA) appeared as a promising evolutionary technique for handling the optimization problems [17]. GA has been popular in academia and the industry mainly because of its intuitiveness, ease of implementation, and the ability to effectively solve highly nonlinear, mixed integer optimisation problems that are typical of complex engineering systems. It has been reported in the literature that Real-Coded Genetic Algorithm (RCGA) is more efficient in terms of CPU time and offers higher precision with more consistent results. Implementation of GA requires the determination of six fundamental issues: chromosome representation, selection function, the genetic operators, initialization, termination and evaluation function. Brief descriptions about these issues are provided in the following sections.

A. Chromosome representation

Chromosome representation scheme determines how the problem is structured in the GA and also determines the genetic operators that are used. Each individual or chromosome is made up of a sequence of genes. Various types of representations of an individual or chromosome are: binary digits, floating point numbers, integers, real values, matrices, etc. Generally natural representations are more efficient and produce better solutions. Real-coded representation is more efficient in terms of CPU time and offers higher precision with more consistent results.

B. Selection function

To produce successive generations, selection of individuals plays a very significant role in a genetic algorithm. The selection function determines which of the individuals will survive and move on to the next generation. A probabilistic selection is performed based upon the individual's fitness such that the superior individuals have more chance of being selected. There are several schemes for the selection process: roulette wheel selection and its extensions, scaling techniques, tournament, normal geometric, elitist models and ranking methods.

The selection approach assigns a probability of selection P_j to each individuals based on its fitness value. In the present study, normalized geometric selection function has been used. In normalized geometric ranking, the probability of selecting an individual P_i is defined as:

$$Pi = q^{'}(1-q)^{r-1} \tag{5}$$

$$q^{'} = \frac{q}{1-(1-q)^{P}} \tag{6}$$

Where,

q = probability of selecting the best individual

r = rank of the individual (with best equals 1)

P = population size

C. Genetic Operators

The basic search mechanism of the GA is provided by the genetic operators. There are two basic types of operators: crossover and mutation. These operators are used to produce new solutions based on existing solutions in the population. Crossover takes two individuals to be parents and produces two new individuals while mutation alters one individual to produce a single new solution. The following genetic operators are usually employed: simple crossover, arithmetic crossover and heuristic crossover as crossover operator and uniform mutation, non-uniform mutation, multi-non-uniform mutation, boundary mutation as mutation operator. Arithmetic crossover and non-uniform mutation are employed in the present study as genetic operators. Crossover generates a random number r from a uniform distribution from 1 to m and creates two new individuals by using equations:

$$x_i' = \begin{Bmatrix} x_i, if\ i < r \\ y_i\ otherwise \end{Bmatrix} \tag{7}$$

$$y_i' = \begin{Bmatrix} y_i, if\ i < r \\ x_i\ otherwise \end{Bmatrix} \tag{8}$$

Arithmetic crossover produces two complimentary linear combinations of the parents, where r = U (0, 1):

$$\bar{X}' = r\bar{X} + (1-r)\bar{Y} \tag{9}$$

$$\bar{Y}' = r\bar{Y} + (1-r)\bar{X} \tag{10}$$

Non-uniform mutation randomly selects one variable j and sets it equal to a non-uniform random number.

$$x_i' = \begin{Bmatrix} x_i + (b_i - x_i)\ f(G) & if\ r_1 < 0.5, \\ x_i + (x_i + a_i)\ f(G) & if\ r_1 \geq 0.5, \\ x_i, & otherwise \end{Bmatrix} \tag{11}$$

Where,

$$f(G) = (r_2(1 - \frac{G}{G_{\max}}))^b \tag{12}$$

r_1, r_2 = uniform random nos. between 0 to 1.

G = current generation.

G_{max} = maximum no. of generations.

b = shape parameter.

D. Initialization, termination and evaluation function

An initial population is needed to start the genetic algorithm procedure. The initial population can be randomly generated or can be taken from other methods. GA moves from generation to generation until a stopping criterion is met. The stopping criterion could be maximum number of generations, population convergence criteria, lack of improvement in the best solution over a specified number of generations or target value for the objective function. Evaluation functions or objective functions of many forms can be used in a GA so that the function can map the population into a partially ordered set.

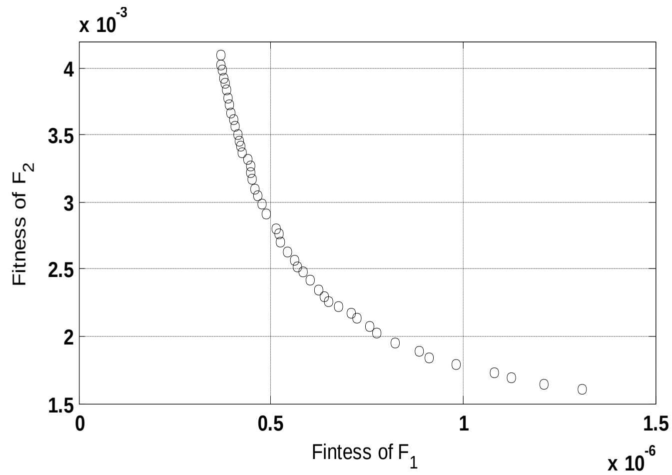

Figure 4. Pareto optimal solution surface

VI. Results And Discussions

The objective function given by equation (2) is evaluated by simulating the system dynamic model considering a 10 % step increase in mechanical power input (ΔP_m) at t = 1.0 sec. For the implementation of RCGA normal geometric selection is employed which is a ranking selection function based on the normalized geometric distribution. Arithmetic crossover takes two parents and performs an interpolation along the line formed by the two parents. Non uniform mutation changes one of the parameters of the parent based on a non-uniform probability distribution. This Gaussian distribution starts wide, and narrows to a point distribution as the current generation approaches the maximum generation. Using the above approach the final Pareto solution surface is obtained as shown in Figure 4 where the Pareto solutions are shown with the marker 'o'.

A. Best Compromise Solution

In the present paper, a Fuzzy-based approach is applied to select the best compromise solution from the obtained Pareto set. The *j*-th objective function of a solution in a Pareto set f_j is represented by a membership function μ_j defined as [18]:

$$\mu_j = \begin{cases} 1, & f_j \le f_j^{\min} \\ \dfrac{f_j^{\max} - f_j}{f_j^{\max} - f_j^{\min}}, & f_j^{\min} < f_j < f_j^{\max} \\ 0, & f_j \ge f_j^{\max} \end{cases} \tag{13}$$

Where $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values of the j-th objective function, respectively.

For each solution i, the membership function μ^i is calculated as:

$$\mu^i = \frac{\sum_{j=1}^{n} \mu_j^i}{\sum_{i=1}^{m} \sum_{j=1}^{n} \mu_j^i} \tag{14}$$

Where, n is the number of objectives functions and m is the number of solutions. The solution having the maximum value of μ^i is the best compromise solution.

Using the above approach the best compromise solution is obtained as:

K_T =38.278, T_{1T} =0.5632s, T_{2T} =0.2646s, T_{3T} =0.1013 s and T_{4T} =0.1549 s.

B. Simultion Results

In order to verify the effectiveness of the proposed approach, the performance of the proposed TCSC controller is tested for different loading conditions. The mechanical power input to the generator is increased by 5 % at t =1.0 sec at nominal loading condition (Pe=0.9 pu). The system response for the above contingency is shown in Figures 5 and 6. For comparison, Figures 5 and 6 show the response when the best compromise solution is used (shown in the Figures in solid lines) and also when the other two solutions from the Pareto set are used (shown in dotted and dashed lines). It can be seen from Figures 5 and 6 that when both the

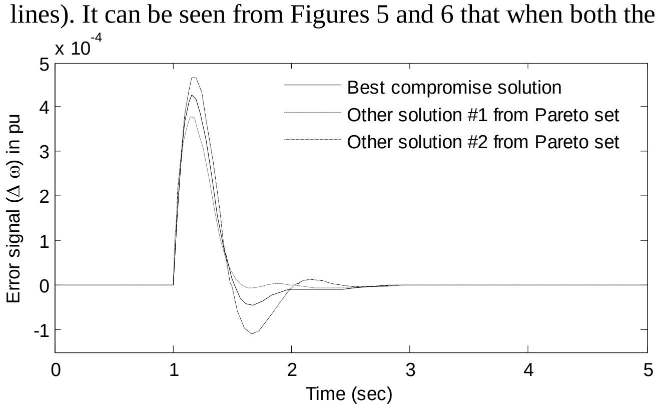

Figure 5. System error response for disturbance in P_m

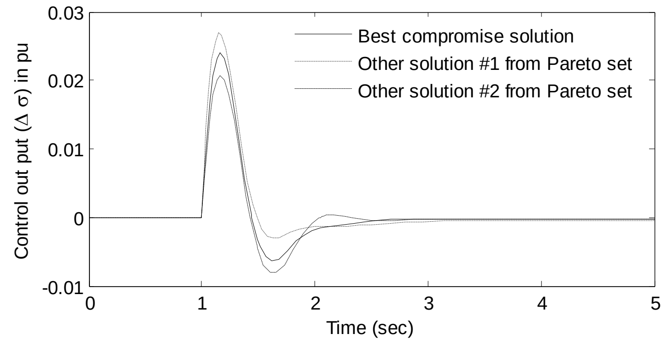

Figure 6. System control output response for disturbance in P_m

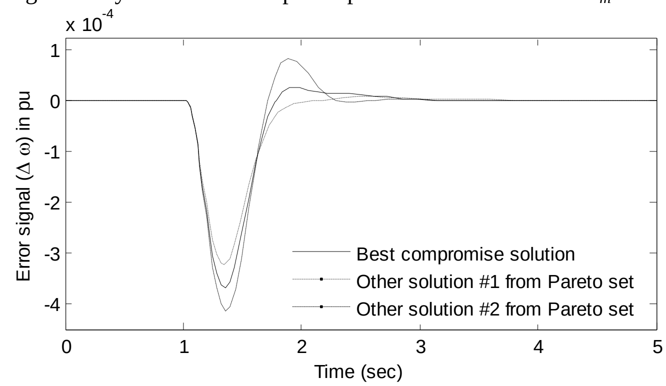

Figure 7. System error response for disturbance in V_{ref}

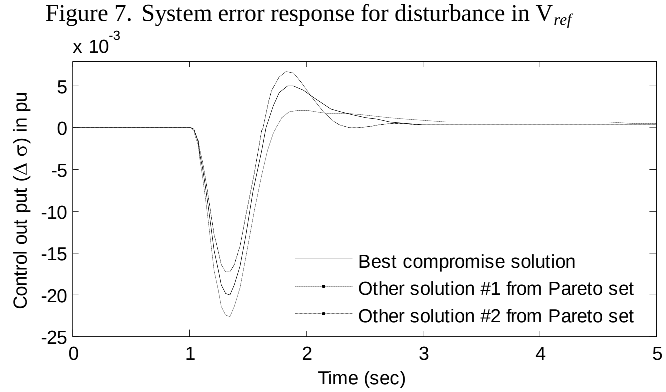

Figure 8. System control output response for disturbance in V_{ref}

error and control out put is considered, the proposed best compromise is the best choice.

To test the robustness of the proposed controller the loading condition is changed to light loading condition (Pe=0.4 pu) and a 5 % step increase in reference voltage is considered at t = 1.0 sec. The system responses for the above cases are shown in Figures 7-8. It can be seen from these Figures that proposed controller is robust and works effectively under various operating conditions and disturbances. Also it can be seen that when both the objectives are considered the proposed approach gives a better response.

VII. CONCLUSIONS

In this study optimal design of a TCSC-based controller is presented and discussed. The design objective is to improve the stability of a power system with minimum control effort. A real-coded genetic algorithm based solution technique is applied to generate a Pareto set of global optimal solutions to the given multi-objective optimization problem. Further, a fuzzy-based membership value assignment method is employed to choose the best compromise solution from the obtained Pareto solution set. Simulation results are presented at various loading conditions and disturbances to show the effectiveness and robustness of the proposed approach.

The proposed method is valuable for the design of the interactive decision making. The decision makers can choose from the solutions in the Pareto-optimal set to find out the best solution according to the requirement and needs as the desired parameters of their controllers. The results show that evolutionary algorithms are effective tools for handling multi-objective optimization where multiple Pareto-optimal solutions can be found in one simulation run.

APPENDIX

Static System data: All data are in pu unless specified otherwise.

Generator:

$M = 9.26$ s., $D = 0$, $X_d = 0.973$, $X_q = 0.55$, $X'_d = 0.19$, $T'_{do} = 7.76$, $f = 60$, $V_T = 1.05$, $X_{TL} + X_T = 0.997$, *Excitor:* $K_A = 50$, $T_A = 0.05$ s

TCSC Controller: $X_{TCSC0} = 0.2169$,

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