Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 3188 – 3200

doi:10.3906/elk-1608-147

Dynamic security enhancement of power systems using mean-variance mapping optimization

Cavit Fatih KÜÇÜKTEZCAN, Veysel Murat İstemihan GENÇ*
Department of Electrical Engineering, Faculty of Electrical and Electronics, İstanbul Technical University, İstanbul, Turkey

Received: 12.08.2016 • **Accepted/Published Online:** 23.12.2016 • **Final Version:** 30.07.2017

Abstract: In this paper, a preventive control action that involves both generation rescheduling and load curtailment is proposed for enhancing the dynamic security of large interconnected power systems. The control action is formulated as a security-constrained optimization problem that is solved by mean-variance mapping optimization (MVMO) integrated with a self-adaptive penalization technique and artificial neural networks to develop a fast and effective methodology. The proposed methodology is applied to a 16-generator 68-bus test system to solve the security-constrained optimization problem with both continuous and discrete decision variables. To find a proper and cost-effective solution for the control actions within an acceptable time, dynamic security assessment methodology based on artificial neural networks is integrated into the optimization process for predicting the violations of security constraints brought about by the candidate solutions. The proposed method effectively integrates a variety of popular heuristic optimization algorithms, including MVMO, differential evolution, particle swarm optimization, genetic algorithms, big bang–big crunch, and artificial bee colony. MVMO outperforms all the others in various aspects such as reliability and robustness.

Key words: Power system security, preventive control, generation rescheduling, load curtailment, heuristic optimization, mean-variance mapping optimization, dynamic security assessment

1. Introduction

When a power system is operated under stressed conditions that are close to security limits, it becomes vulnerable to some contingencies that may cause loss of synchronism and even cascading blackouts. For such an insecure operating point (OP), the system operator can apply preventive control actions to move the system to an OP where it can withstand critical contingencies.

In this paper, a method that combines both generation rescheduling and load curtailment approaches [1] is proposed as a preventive control to restore the security of the system. Small-signal angle stability, static security constraints related to voltage regulation, and thermal capabilities of system components are also considered while restoring security against transient instabilities. Within the security region constrained by both dynamic and static security limits, the power generation and consumption in the system is rescheduled such that the cost related to the changes in generation and consumption is optimized. Thus, the preventive control is designed through the formulation and solution of a security-constrained optimization problem. Various optimal power-flow methods solving the preventive control problem against transient instabilities can be found in [2,3]. Due to the size of real power systems, the optimization problem involves a multidimensional search space with many

*Correspondence: gencis@itu.edu.tr

continuous and discrete control variables as well as a large number of equality and inequality constraints, leading to the existence of many local optimum solutions. In addition, constraints related to the dynamic security of the system are highly nonlinear and sometimes too complex to be defined mathematically. Therefore, conventional optimization methods may not always converge to a satisfactory solution for the optimization problem to be dealt with. Heuristic optimization methods do not guarantee global optimum solutions, but they provide satisfactory solutions in a reasonable time for complex and high-dimensional optimization problems. They have been applied to various optimization problems such as unit commitment, economic emission dispatch, and reactive power control [4–6].

In this study, a novel optimization method called mean-variance mapping optimization (MVMO) is proposed for the first time to solve the security-constrained optimal preventive control action problem of large interconnected power systems. Despite its similarities to some of the popular heuristic methods, the uniqueness of the MVMO is the use of a special mapping function to mutate candidate solutions according to the statistics of the best candidate solutions. MVMO has shown promising performance in some other optimization problems of power systems [7–9].

Extensive time domain simulations (TDSs) require a significant amount of time and make optimization methods impractical for very large power systems when these methods fail to converge in an acceptable amount of time. Direct methods do not require solving differential equations as in TDSs, but modeling limitation is the main drawback of this type of method for large-scale power systems [10]. Moreover, fast pattern recognition tools can be used to predict the dynamic behavior of the system for dynamic security assessment (DSA) during optimization [11]. In this work, for increasing the DSA speed of candidate solutions during optimization, multilayer perceptrons (MLPs) are used to predict stability indices, instead of TDSs and small-signal stability analyses. In addition, self-adaptive penalization [12] is applied to decrease the number of function evaluations required to reach feasible solutions, even if the initial set of candidate solutions is composed of only infeasible solutions.

2. Methodology and problem definition

2.1. Security enhancement via preventive control

In this study, a preventive control action that involves both generation rescheduling and load curtailment is proposed for enhancing the dynamic security of large interconnected power systems against credible contingencies. Generation rescheduling is considered an effective preventive control action to restore and enhance system security by shifting the generation among controllable generators [13]. Additionally, in the case an insecure OP is detected, the system operator can also request some available loads to curtail their demand [14]. This load-curtailment action can be integrated with generation rescheduling as a whole to shape the power-flow patterns within the network in such a way that the stability of the system is preserved in the case of any critical contingency.

2.2. Control variables of the optimization problem

Angle stability of the system is strongly related to the active power flows through the transmission lines. The active power flows can be controlled by changing the active power generated and consumed at some projected points within the network of the power system that might be deregulated, where these control actions are limited by predetermined contracts. Beside generation rescheduling, load curtailment is applied at the consumer side to increase the flexibility of changing the active power flow, but this action is limited by the amount of available load that can be curtailed.

During the iteration of applied heuristic methods to the optimization problem, some other constraints, such as steady-state voltage limits at each bus, must also be taken into account. While the voltages at the generator buses are directly controlled by automatic voltage regulators, transformers with tap changers can be controlled to attain a desired voltage regulation over all the other buses. This will introduce discrete control variables to the problem, and thus any candidate solution of the optimization problem of generation rescheduling and load curtailment combined with control of tap changers is represented as $u = [\Delta P_G \ \Delta P_L \ \Delta T_{Tap}]$, where ΔP_G and ΔP_L are the vectors of changes (continuous variables) in the active power of generation and consumption of controlled generators and loads, respectively, and ΔT_{Tap} is the vector of the changes (discrete variables) in the tap position of controlled transformers.

2.3. Objective function of the optimization problem

The aim of preventive control is to specify the OP by changing the power generated and consumed by the participants to enhance dynamic security of the system. To satisfy the security constraints, when power consumption of any participant is reduced, they should be paid an opportunity cost for reduction in consumption. In addition, if a system operator increases the power generation of any supplier, they should be paid an additional cost for increasing generation. The objective in the optimization problem is to minimize extra payment. It is assumed that opportunity costs and additional costs are required for a participant's active power rescheduling, and no cost is defined for other control variables such as transformer tap-settings and rescheduling of reactive power sources. The objective function with properly chosen constants a_i, b_i, c_i, and d_i can be formulated as

$$f(x,u) = \sum_{i=1}^{N} a_i \Delta P_i^{+} + b_i (\Delta P_i^{+})^2 + \sum_{i=1}^{N} c_i \Delta P_i^{-} + d_i (\Delta P_i^{-})^2, \tag{1}$$

where ΔP_i^{+} and ΔP_i^{-} are the increments and decrements, respectively, in power generation and consumption of N participants in the market.

2.4. Constraints of the optimization problem and penalization

The optimization problem involves a large number of equality and inequality constraints, where the equality constraints are the power flow equations. Denoting the voltage phasor at the ith bus by $V_i e^{j\theta_i}$,

$$P_{Gi} - P_{Li} - V_i \sum_{k=1}^{N_{bus}} V_k Y_{ik} \cos(\theta_i - \theta_k - \alpha_{ik}) = 0 \tag{2}$$

$$Q_{Gi} - Q_{Li} - V_i \sum_{k=1}^{N_{bus}} V_k Y_{ik} \sin(\theta_i - \theta_k - \alpha_{ik}) = 0 \tag{3}$$

P_{Gi} and Q_{Gi}: The active and reactive power generation at the ith bus.

P_{Li} and Q_{Li}: The active and reactive power consumptions at the ith bus.

$Y_{ik} e^{j\alpha_{ik}}$: (i,k)th entry of the admittance matrix of the network.

N_{bus}: The number of buses in the network.

The magnitude of the voltage at each bus is maintained within the acceptable ranges $V_{i_{\min}} < V_i < V_{i_{\max}}$, where $V_{i_{\min}}$ and $V_{i_{\max}}$ are lower and upper limits for the ith bus voltage. The thermal limits on the transmission lines are defined as $|\mathbf{S}_{ij}| < |\mathbf{S}_{ij}|_{th}$, where $|\mathbf{S}_{ij}|$ represents the apparent power transferred from the ith bus to the jth bus and $|\mathbf{S}_{ij}|_{th}$ is the given thermal limit. The constraint of transient stability is based on the critical clearing time (CCT) of the faults assumed in contingencies, denoting the CCT for contingency m by CCT_m, $CT_m < CCT_m$, where CT_m is the clearing time of the acting circuit breakers. The constraint of small-signal stability is based on damping of the electromechanical modes, $\xi_{\min} < \xi$, where ξ is the damping ratio of the most critical mode and $\xi_{\min}$ is its lower bound. The penalty function for the infeasible solutions is the weighted sum of violations, which are the distances of the unsatisfying variables to their limits,

$$p\left(x,u\right) = w_1 \sum_{i=1}^{N_{bus}} v_{U,i} + w_2 \sum_{i=1}^{N_{line}} v_{T,i} + w_3 \sum_{i=1}^{N_{cont}} v_{C,i} + w_4 v_D \tag{4}$$

$v_{U,i}$: The violation due to the voltage limits of ith bus.

$v_{T,i}$: The violation due to the thermal limit of ith transmission line.

$v_{C,i}$: The violation due to the transient stability limit for ith critical contingency.

v_D : The violation due to small-signal stability of the system.

N_{line}: The number of lines in the network.

N_{cont}: The number of critical contingencies in the system.

The weight of each violation is represented by w_i. These values are specified after experimenting and evaluating the constraint violations during a number of simulations. Depending on the variation among the different types of violations, these numbers are normalized in such a way that all types of constraints have almost the same priority.

The performance of static penalization is sensitive to the selected parameters [15]. To discard the selection of a large set of parameters, an adaptive penalization technique is used in this study [12]. This technique does not need parameter tuning and has the ability to set the penalized fitness function at different stages of the optimization. The fitness evaluation function is $e\left(x\right) = d\left(x\right) + p(x)$, where $p(x)$ is the penalty term. The distance term is

$$d(x) = \begin{cases} v'(x) & \text{if } \ r_f = 0 \\ \sqrt{f'\left(x\right)^2 + v'(x)^2} & \text{otherwise} \end{cases}, \tag{5}$$

where r_f represents the feasibility rate of the population. The normalized values of the violations and objective functions are represented by $v'(x)$ and $f'(x)$, respectively [12].

The penalty function $p(x)$ is used to provide proper fitness value for infeasible solutions in different stages of the optimization. In early iterations, populations involve only infeasible solutions ($r_f = 0$) and violation is more important than the objective function, infeasible solutions with low violations being subjected to less penalization than other solutions. Then the algorithm starts to find feasible solutions in addition to infeasible ones, infeasible solutions with low objective function values being subject to less penalization than infeasible solutions with high objective function values. Details are given in [12]. In later iterations, the population consists of feasible individuals and penalization becomes passive, because $v^{'}\left(x\right) = p\left(x\right) =$, resulting in $e\left(x\right) = f\left(x\right)$ for all individuals.

2.5. Dynamic security assessment by artificial neural networks

During optimization, violations of inequality constraints related to steady-state quantities, such as the generator outputs, the amounts of load curtailments, the steady-state bus voltages, and the power flows through transmission lines, are easily calculated by power-flow calculations. On the other hand, calculation of violations related to transient and small-signal stability constraints is a time-consuming task. In this study, these stability-related violations for each candidate solution are predicted by offline trained artificial neural networks (ANNs) to speed up the optimization procedure. In this study, a commonly used ANN for engineering applications, MLP [16], is chosen.

Since MLPs need supervised learning, they require a knowledge base (KB) that includes different examples of the system behavior to be learned. A part of this KB is used to optimize the structure of the MLP with a k-fold cross-validation process and to train the MLP with optimum structure. The MLP structure is optimized by determining the best number of hidden neuron and input features via the methodology given in Figure 1. The procedure is repeated for each MLP that is designed to predict the CCT for a particular contingency and the damping ratio of the most critical electromechanical mode. Before starting the procedure given in Figure 1, the feature selection method RReliefF [17] is used to rank a large number of features in the KB and to determine the most relevant ones to both transient and small-signal angle-stability indices.

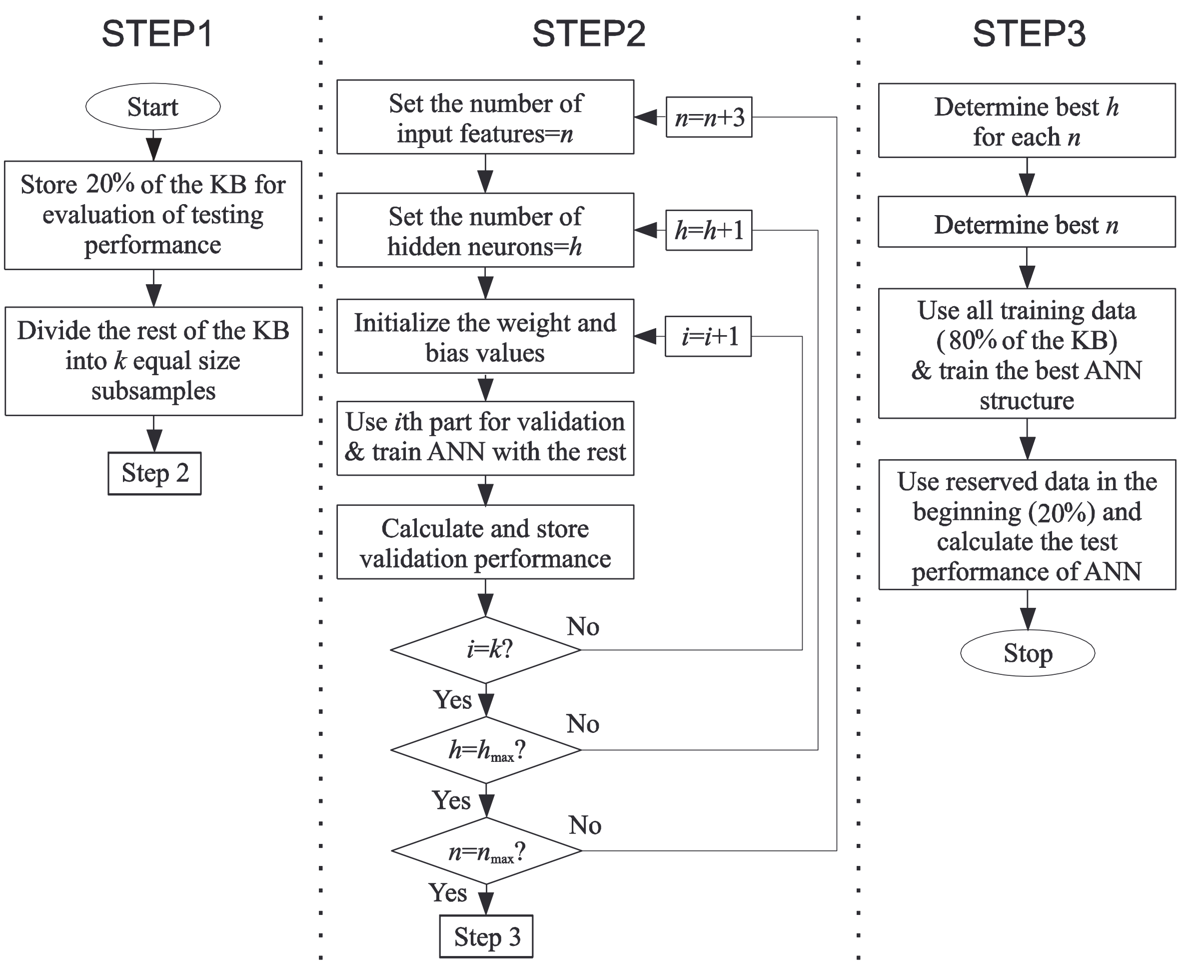

Figure 1. MLP design methodology.

MLP training with one hidden layer is carried out by the back propagation algorithm. The unused part of the KB is used to test the performance of the trained MLP. The designed MLPs are used for the DSA of the system operating at the candidate solutions during optimization. Thus, they must be capable of recognizing the changes in the loading level and topology, and should be trained by a KB including all possible OPs of various loading levels and topologies.

2.6. Mean variance mapping optimization

The unique feature of the MVMO algorithm is the transformation used for mutating the solutions based on mean-variance of the archive that involves n best solutions [18]. Mapping function h is used to transform random variable x_i^* into x_i, which is concentrated close to its mean value. The function h is defined by mean $\bar{x}$ and shape s.

$$s_i = -ln(v_i) f_s \tag{6}$$

v_i: The variance of the ith variable of candidate solutions in the archive.

f_s: The factor that changes the shape of the function h.

The function h is computed as

$$h\left(\bar{x}_i, s_{i1}, s_{i2}, x_i\right) = \bar{x}_i\left(1 - e^{-x_i s_{i1}}\right) + \left(1 - \bar{x}_i\right) e^{(x_i - 1) s_{i2}} \tag{7}$$

$\bar{x}_i$: The mean of the ith element of the solution vector in the archive.

$\bar{x}$ and s determine the characteristic of h. They are calculated by using n best solutions stored in the archive. Then the ith variable of candidate solution x is used to calculate

$$x_i = h_x + \left(1 - h_1 + h_0\right) x_i^* - h_0, \tag{8}$$

where x_i^* is a random variable generated by uniform distribution and h_0, h_1, and h_x are the outputs of h with different inputs such that

$$h_0 = h\left(x_i = 0\right), \quad h_1 = h\left(x_i = 1\right), \quad h_x = h\left(x_i = x_i^*\right) \tag{9}$$

x_i is always generated between 0 and 1. During the fitness evaluation, the solution vector is denormalized to its original value. The variance and mean values are computed after the archive is filled up. Before this stage, s_{i1} and s_{i2} are equal to 0. Generally, the size of the archive is selected between 2 and 5 for satisfactory results. Increasing the size of the archive causes more conservative convergence behavior. The first position of the archive is reserved for the best solution reached. Selected parents and variables are updated by using the mapping function. To determine the variables to be updated, there are four different alternatives: random selection, neighbor group selection, neighbor group selection, and sequential selection of the first variable then selection of the rest randomly. The steps of MVMO are given below:

(1) Randomly initialize an initial solution vector x between 1 and 0.

(2) Denormalize x and evaluate the fitness function.

(3) Update the archive if x is better than any solution in the archive.

(4) Compute mean and variance based on the updated archive.

(5) Select parents and m variables of them to create new solutions.

(6) Apply the mapping function to the selected m variables of parents (mutation).

(7) Set remaining variables to new solutions (crossover).

(8) Repeat steps (2) to (7) until stopping criterion is satisfied.

3. Results

The proposed methodology is applied to a 16-generator 68-bus test system [19] shown in Figure 2. Each generator, which is modeled by the two-axis model of order 6, is equipped with a static exciter of order 1 and a power system stabilizer of order 3 [20]. The generators are driven by speed governor turbine units of order 3. The system operates at an initial insecure OP due a set of 12 critical contingencies (Figure 2). Each critical contingency is a three-phase fault at one end of a transmission line cleared by the removal of the faulted line well after its critical clearing time (Table 1). The selected control (decision) variables of the optimization problem are the outputs of all generators, P_{Gi}, $i = 1,\ldots,16$, active power demands given as P_{Lj}, $j = 1,\ldots,8$, and tap changer positions of the 19 transformers shown in Figure 2. The loads to be curtailed for the preventive control are selected according to the results of a feature-selection procedure, RReliefF, that determines the loads to which the stability index for each critical contingency is sensitive. These effective loads to be curtailed are located close to the line where the critical contingencies occur (Figure 2). Thus, the curtailment of these loads can change the relevant interface flows and enhance the security of the system.

Table 1. Critical clearing time (CCT) and clearing time (CT) of critical contingencies.

Contingency	1	2	3	4	5	6	7	8	9	10	11	12
CCT (cycle)	7	7.3	7	6.9	6.6	5.8	4.9	4.1	5.6	5.5	1.9	4.4
CT (cycle)	9	9	9	9	9	8	7	7	8	8	5	7

3.1. Dynamic security assessment by ANN

For training and performance testing of MLP, a KB consisting of 1500 different instances (OPs) at various loading levels (75%–125%) and with 45 different topologies of the system is generated by DSATools [21]. Instances are represented by 377 features, which are the active and reactive power outputs of all generators, the active and reactive power flows through the transmission lines, the magnitudes and phase angles of the bus voltages, the active and reactive power demands at all load buses, and the stability index values.

Particular MLPs are generated to predict the CCT for each contingency. According to the results of feature selection process, most of these selected features are active power flows through the transmission lines that are topologically closer to the location where the related critical contingency occurs. By using a training set consisting of 1200 instances, the 10-fold cross validation procedure is applied to determine the optimum number of input features (n_{best}) and the neurons in the hidden layer (h_{best}) of the MLP. For each MLP structure implemented, the resulting mean absolute error (MAE) is used for a comparison.

$$MAE(\%) = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_i^* - y_i|}{y_i}, \tag{10}$$

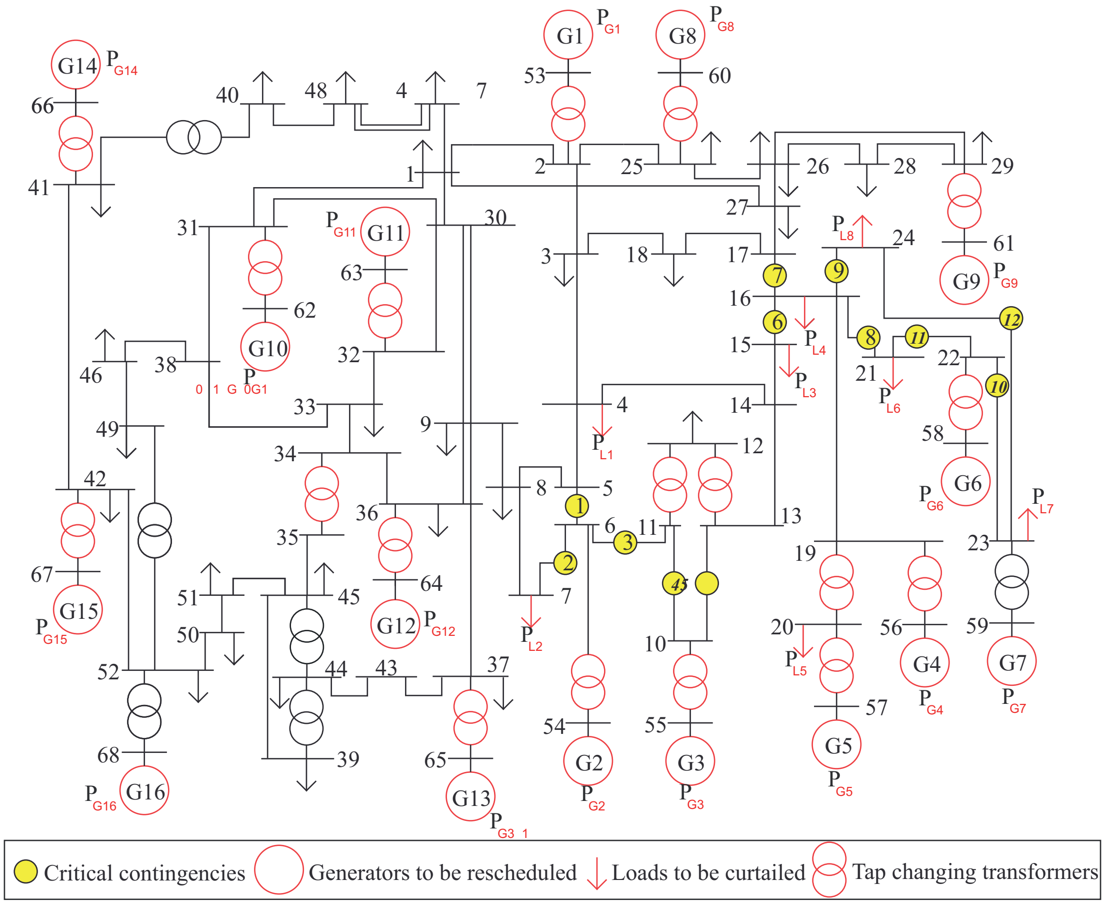

Figure 2. The 16-generator 68-bus power system.

where N is the number of instances and y_i and y_i^* are the CCTs calculated by TDS and predicted by the ANN, respectively. As an example, the results of the MLPs to predict CCT for contingency number 4 are given in Figure 3a. The best MLP structure (number of input features and hidden neurons) for each contingency is found as the MAEs in a test set consisting of 300 instances are compared. The results for all contingencies are given in Table 2, whereas a scatter diagram for the best MLP structure found for contingency number 4 is plotted in Figure 3b. The best ANN designed to predict the minimum damping has 48 inputs and 8 hidden neurons, and the MAE for this MLP structure is 0.5034%. The results show that the optimum ANNs can map the security boundary quite accurately. Thus, the designed ANNs can be used to detect the security violations of the candidate solutions obtained during the optimization.

Table 2. ANN performances with the optimum parameters.

Cont.	1	2	3	4	5	6	7	8	9	10	11	12
n_{best}	45	27	27	33	39	57	57	57	51	45	45	51
h_{best}	12	15	15	12	9	8	6	9	8	13	8	10
MAE (%)	0.57	0.71	0.8	0.66	0.48	1.46	0.94	1.37	1.05	0.99	1.61	0.98

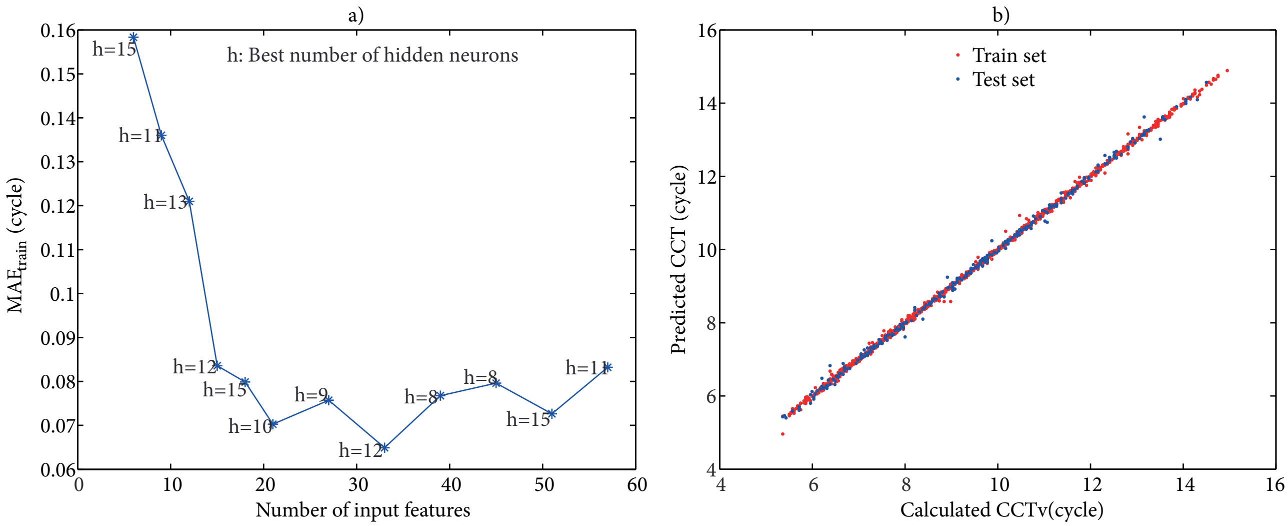

Figure 3. a) Training performance of MLP structures implemented for contingency number 4. b) Scatter diagram of the best MLP structure selected for contingency number 4.

3.2. Optimization for preventive control

The performance of the MVMO method is compared with a variety of popular heuristic optimization methods, genetic algorithms in [22], differential evolution in [23], big bang–big crunch (BB-BC) in [24], particle swarm optimization (PSO) in [25], and artificial bee colony in [26]. To investigate the robustness of the methods to the randomness in their steps, the process of each optimization method is repeated 30 times. Each optimization attempt involves 8050 function evaluations. The results associated with the final solutions and with the first feasible solutions (*feas1*) during the optimization are given in Table 3. $f_{\min}, f_{avg}$, and f_{std} are the minimum, average, and standard deviation of the final objective function values obtained in each optimization method over multiple runs. $k_{feasible}$ and $t_{feasible}$ are the average number of function evaluations and the time required to reach the first feasible solution, respectively. $f_{feasible}$ is the average of $f(x,u)$ of the first feasible solutions. During the computation of penalty function, the weight of each violation is selected as $w_1 = 500$, $w_2 = 1$, $w_3 = 10$, and $w_4 = 200$.

Table 3. Results for the optimization methods.

Method	$f_{\min}$(\$/h)	f_{avg}(\$/h)	f_{std}(\$/h)	$k_{feasible}$	$t_{feasible}$ (min)	$f_{feasible}$ (\$/h)
GA	15,630.02	19,634.21	2830.1	660.1	3.30927	85,560.73
DE	15,840.05	17,771.48	1496.08	520.6	2.60047	90,148.32
BB-BC	17,129.32	19,853.53	1502.4	368.3	1.836342	106,411
PSO	15,266.61	17,032.52	1052.52	344.7	1.715885	128,170
ABC	15,202.31	16,743.23	878.13	720.2	3.599039	95,790.55
MVMO	14,622.5	15,975.09	766.31	1090.4	5.452486	74,342.83

All optimization methods start the searching process with randomly created solutions by considering upper and lower limits of control variables. While all of the solutions within the initial and some number of subsequent populations are infeasible with respect to a large number of constraints, all methods have the ability to reach feasible solutions in less than 6 min on a workstation with an Intel Core i5 3.2 GHz microprocessor (Table 3).

During the first stage of optimization where the population involves only infeasible solutions, the main target is not the minimization of the objective function, but reaching a feasible solution. BB-BC and PSO are the fastest algorithms to reach feasible solutions, and the average objective function values of the first feasible solutions, $f_{feasible}$, are much higher than the ones for final solutions, f_{avg} (Table 3). In the second stage of the algorithms, while the number of feasible solutions increases, their objective function values are improved. Although BB-BC is one of the fastest algorithms during the first stage, it is not so successful at improving the objective function value. Considering $f_{\min}$, MVMO outperforms the other algorithms. In addition, f_{avg} and f_{std} show that MVMO is the most reliable and the most robust algorithm against the randomness in these algorithms. Although MVMO requires a large number of function evaluations to reach a feasible solution, better solutions with lower $f_{feasible}$ values are found by MVMO when compared to the other algorithms.

Figure 4 shows the minimization of the objective function during the execution of each optimization method. The values at each iteration are calculated as the averages of the objective function values of the best solutions obtained in 30 individual runs of each optimization method. The reason for fluctuation of the objective function values of best individuals in the earlier iterations is the priority given to feasibility instead of objective function value. After the first feasible solution is obtained, objective function values of the best solutions start to decrease.

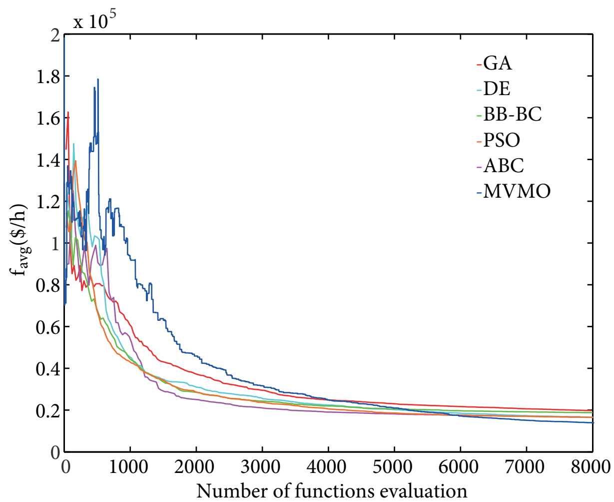

Figure 4. Average convergence behavior of the optimization methods.

Figure 5 shows the final values of ΔP_G and ΔP_L, respectively, for the best solutions achieved in each optimization method among the multiple runs performed. At the optimal solutions, dynamic security of the system is restored mostly by shaping the active power flows through the lines that are close to the location of the contingency. Additionally, the optimal changes in the tap changer positions ΔT_{Tap}, which do not affect the objective function in Eq. (1), are quite effective in satisfying the constraints related with the steady-state voltages.

Using the method proposed in the study with the dedicated computational power, it takes approximately 40 min for the optimization methods, which start with randomly generated initial populations, to converge in 8050 function evaluations. If ANNs were not utilized, the same process would require about 16 h.

The optimization methods are also applied to the same test system under 4 insecure initial OPs with different loading levels and topologies (Table 4), where OP_1 corresponds to the original insecure point taken

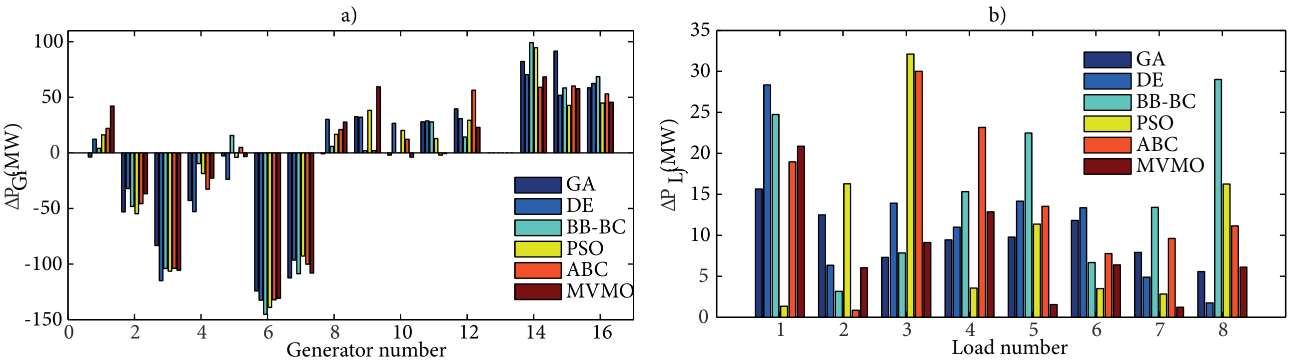

Figure 5. a) The optimum generation rescheduling for different methods. b) The optimum load curtailment for different methods.

previously. Table 4 also shows the average of objective function values obtained by the optimization methods, each of which is run 30 times. As expected, compared to the original OP, the cost of rescheduling is found to be larger for each new OP, which has a higher loading level and a line outage.

Table 4. Optimization results for initial OPs with various loading levels and line outages.

Initial insecure OPs	OP_1	OP_2	OP_3	OP_4
Loading level (%)	111	112	115	120
Line outage between buses	-	17–27	4–14	8–9
GA, f_{avg}($/h)	19,634.21	27,463.33	33,931.45	38,457.29
DE, f_{avg}($/h)	17,771.48	20,571.14	24,032.18	23,960.57
BB-BC, f_{avg}($/h)	19,853.53	22,259.03	26,657.22	35,541.79
PSO, f_{avg} ($/h)	17,032.52	21,622.24	25,845.7	31,320.23
ABC, f_{avg}($/h)	16,743.23	20,583.97	24,423.62	26,916.07
MVMO, f_{avg}($/h)	15,975.09	20,074.37	22,990.92	23,864.53

The proposed methodology can be applied to a real power system considerably larger than the test system studied. In this case, the number of critical contingencies and possible network topologies might be quite large and the TDSs to be performed for an excessively large number of OPs can be quite demanding. This could be exacerbated if the number of system components and the complexities in their models are increased. Therefore, more computational effort might be required for all the offline tasks in the proposed methodology. However, most of this burden can be shared by multiple computers and the method can be made feasible for larger and more complex systems. Among the online tasks, the computational burden due to DSA by ANN during the optimization is directly dependent on the number of critical contingencies. In addition, for larger systems, the size of the search space can be higher due to the number of controllable system components. However, all of the online tasks can be accomplished in a feasible time by a single modern computer, despite the implications of having a large system under study.

4. Discussion

In this study, an efficient methodology is proposed for enhancing the dynamic security of power systems by means of a preventive control action that involves both generation rescheduling and load curtailment. This study shows the ability and applicability of the applied heuristic optimization methods to solve the security constrained optimization problem thus formulated. The results of the optimization methods applied to a test system are compared and MVMO outperforms all the others in various aspects such as reliability and robustness. The proposed methodology in which the ANN-based DSA is utilized during the optimization process significantly reduces the time required for predicting the violations of the security-based constraints. Although the use of ANNs enhances the applicability of the heuristic optimization methods, a considerable number of iterations to reach the optimum solution may be needed when the initial populations start with only infeasible solutions. This problem is solved by using the self-adaptive penalization method, which accelerates the determination of feasible solutions.

Acknowledgment

This work was supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under grant number 114E157.

References

[1] Wehenkel L, Pavella M. Preventive vs. emergency control of power systems. In: Proceedings of the IEEE Power Systems Conference and Exposition; 2004; New York, NY, USA: pp. 1665-1670.

[2] Nguyen TB, Pai MA. Dynamic security-constrained rescheduling of power systems using trajectory sensitivities. IEEE T Power Syst 2003; 18: 848-854.

[3] Ruiz-Vega D, Pavella M. A comprehensive approach to transient stability control: part I-near optimal preventive control. IEEE T Power Syst 2003; 18: 1446-1453.

[4] Li YF, Pedroni N, Zio E. A memetic evolutionary multi-objective optimization method for environmental power unit commitment. IEEE T Power Syst 2013; 28: 2660-2669.

[5] Jadoun VK, Nikhil G, Niazi KR, Swamkar A. Modulated particle swarm optimization for economic emission dispatch. Int J Elec Power 2015; 73: 80-88.

[6] Kılıç U, Ayan K. Artificial bee colony algorithm based optimal reactive power flow of two-terminal HVDC systems. Turk J Elec Eng & Comp Sci 2016; 24: 1075-1090.

[7] Wildenhues S, Rueda JL, Erlich I. Optimal allocation and sizing of dynamic var sources using heuristic optimization. IEEE T Power Syst 2014; 30: 2538-2546.

[8] Rueda JL, Cepeda JC, Erlich I, Echeverríab D, Argüellob G. Heuristic optimization based approach for identification of power system dynamic equivalents. Int J Elec Power 2015; 64: 185-193.

[9] Chamba MS, Ano O, Reta R. Application of hybrid heuristic optimization algorithms for solving optimal regional dispatch of energy and reserve considering the social welfare of the participating markets. Swarm Evol Comput 2016; 28: 161-171.

[10] Fouad AA, Vittal V. Power System Transient Stability Analysis Using the Transient Energy Function Method. Upper Saddle River, NJ, USA: Prentice Hall, 1991.

[11] Kucuktezcan CF, Genc I. A new dynamic security enhancement method via genetic algorithms integrated with neural network based tools. Electr Pow Syst Res 2012; 83: 1-8.

[12] Tessema B, Yen GG. A self-adaptive penalty function based algorithm for constrained optimization. In: Proceedings of the IEEE Congress on Evolutionary Computation; 2006; Canada: pp. 246-253.

[13] Pavella M, Ernst D, Ruiz-Vega D. Transient Stability of Power Systems: A Unified Approach to Assessment and Control. Boston, MA, USA: Kluwer Academic Publishers, 2000.

[14] Kehler JH. Procuring load curtailment for grid security in Alberta. In: Proceedings of the IEEE Power and Energy Society Winter Meeting; 2001; Columbus, OH, USA: pp. 234-235.

[15] Michalewicz Z. Genetic algorithms, numerical optimization and constraints. In: Proceedings of the 6th International Conference on Genetic Algorithms; 1995; San Mateo, CA, USA: pp. 151-158.

[16] Haykin S. Neural Networks – A Comprehensive Foundation. Upper Saddle River, NJ, USA: Prentice Hall, 1998.

[17] Kononenko I. Estimating attributes: analysis and extensions of relief. In: Proceedings of the European Conference on Machine Learning; 1994; Catania, Italy: pp. 171-182

[18] Erlich I, Venayagamoorthy GK, Nakawiro W. A mean-variance optimization algorithm. In: Proceedings of the IEEE World Congress on Computational Intelligence; 2010; Spain: pp. 1-6.

[19] Rogers G. Power System Oscillations. Boston, MA, USA: Kluwer Academic Publishers, 2000.

[20] Sauer PW, Pai MA. Power System Dynamics and Stability. Upper Saddle River, NJ, USA: Prentice Hall, 1998.

[21] Powertech Labs Inc. TSAT User Manual. Surrey, BC, Canada, 2014.

[22] Goldberg DE. Genetic Algorithms in Search, Optimization and Machine Learning. Boston, MA, USA: Addison-Wesley, 1989.

[23] Storn R, Price K. Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. J Global Optim 1997; 11: 341-359.

[24] Erol OK, Eksin I. A new optimization method: big bang-big crunch. Adv Eng Softw 2006; 37: 106-111.

[25] Kennedy J, Eberhart RC. Swarm Intelligence. San Francisco, CA, USA: Morgan Kaufmann Publishers, 2001.

[26] Karaboga D, Akay B. A comparative study of artificial bee colony algorithm. Appl Math Comput 2009; 214: 108-132.