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PSO-ANN Approach for Transient Stability Constrained Economic Power Generation

Ayman Hoballah, *Graduate Student Member, IEEE,* and István Erlich, *Senior Member, IEEE*

Abstract--This paper presents an approach to solve the online transient stability constrained power generation (TSCPG) by a mixture of a modified particle swarm optimization (PSO) and artificial neural network (ANN). This mixture (PSO-ANN) has been used as optimization tool to guarantee searching the optimal solution within the hyperspace reducing the time consumed in the computations and improving the quality of the selected solution. TSCPG is formulated as a nonlinear constrained optimization problem subject to load flow equations, power system capacity requirements and power system transient stability behavior. The critical clearing time (CCT) at the critical contingency is considered as an index for transient stability. The rescheduling process based on the generation companies (GENCOs)/consumer's bids is used as a remedial action to direct system operation in the direction of transient stability enhancement. The goal of the approach is to minimize the opportunity cost payments for GENCOs/consumers backed down in generation/consumption and the additional cost for GENCOs/consumers increased their generation/consumption in order to enhance system transient stability. The proposed approach provides a fast and accurate tool to evaluate continuous online adaptation for the power system operation to enhance system transient stability.

***Index Terms*— Optimization methods, Power system transient stability, Power generation economics, Power generation scheduling.**

I. Introduction

With increasing the electric power system size, the power system transient stability is having a significant importance in power system operations. Therefore, power system operators should consider not only economic load dispatch but also on-line transient stability aspects [1]. It means that after the disturbances the power system must be able to surviving and moving into an acceptable steady-state condition that meet all established limits. Transient stability assessment becomes a major concern because a fault or loss of a large generator can lead to large electromechanical oscillations between generating units that may rise to loss synchronism. TSCPG is a nonlinear constrained problem subject to load flow equations and power system capacity requirements. The solution difficulty comes from the variety of control variables and constraints and the time consumed in transient stability computation. This paper presents a methodology for continuously checking the transient stability conditions of generators and generation rescheduling process is used to enhance system transient stability. Active power rescheduling required for transient stability enhancement considered as market. Participants in this market offer their bids by specifying up or down generation/load capability and the corresponding costs. The main objective in this research is to make a correction in power generation schedule to ensure power system transient stability with minimizing the additional costs for increased generation and the opportunity cost for reduced power infeed respectively. The problem is formulated as constrained global optimization and solved by a mixture of PSO and ANN. The basic and modified PSO has used to solve many of complex nonlinear optimization problems in power system such as economic dispatch [2-3], FACTS sizing and allocation [4], dynamic security border identification [5], and others. To shorten the calculation time required for transient stability analysis, a trained neural network is used to estimate the CCT. CCT characterizing transient stability is considered as an additional constraint within the optimization process.

Ayman Hoballah is with the Institute of Electrical Power Systems, University of Duisburg-Essen, Germany (e-mail: ayman.hoballah@uni-due.de)

István Erlich is the head of the Institute of Electrical Power Systems, University of Duisburg-Essen, Germany (e-mail: istvan.erlich@uni-due.de)

II. Market Formulation for Transient Stability Enhancement

A. Rescheduling Costs

In a pool-based market, the energy is optimally allocated among suppliers/consumers based on volunteer energy bids. In the real-time dispatch setting, these energy allocations should be adjusted to assure standard system security level. To satisfy all constraints with rescheduling, a participant whose energy is backed down should be paid opportunity cost for reduction in power generation/consumption. In addition, a participant whose energy is increased will be paid the cost of additional energy generation based on MCP and may be additional cost is required to apply the required increase in generation/consumption. The primary goal of this work is to investigate the energy market co-optimization in the setting of a pool-based market organization for acceptable transient stability level. Of particular interest is the extra cost payments minimization for energy under rescheduling process. The authors of this paper suggest a marked base approach. According to this, all participants in rescheduling market submit their offers to increment and/or decrement power generation/consumption from the base energy market cleared quantity. The participant bids include limits of change and the corresponding cost function. There are many strategies for bidding such as single or multi-block bidding, linear bidding or others. Figure 1 shows linear bid strategy for opportunity cost for a reduction in generation and additional cost beside market clearing price for increase in generation more than the dispatched power. Money flow chart according to the

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rescheduled power generation is shown in figure 2.

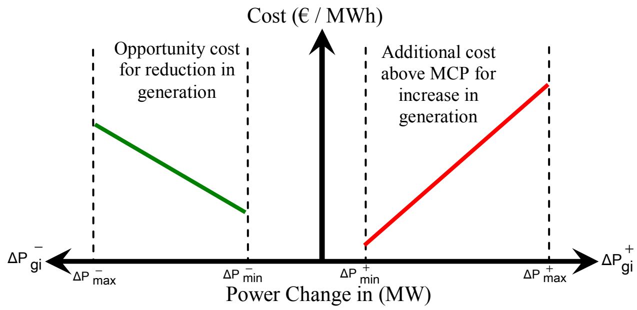

Figure 1: Opportunity and additional costs for generation changes

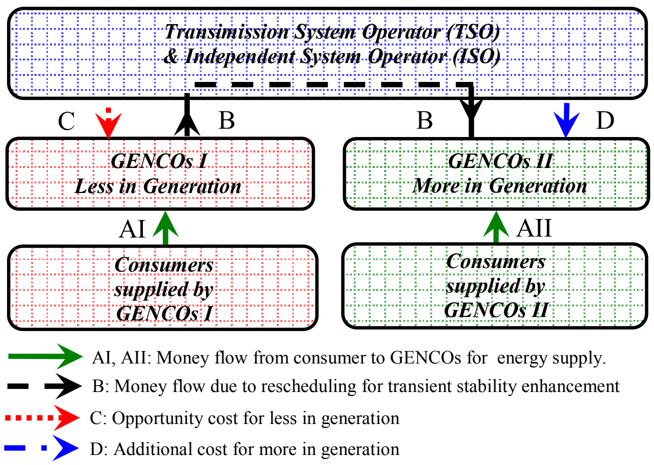

Figure 2: Money flow to enhance transient stability using generation rescheduling

Based on generation and consumption bids in energy market, market cleared to specify power schedule and then money flow from consumers to GENCOs (money flow AI and AII). The rescheduling process will shift part of generated power from GENCOs I to GENCOs II in order to enhance transient stability and hence part of money (AI) will be transferred from GENCOs I to GENCOs II (money flow B). GENCOs I will be paid opportunity cost (C) for loss in generation based on shifted power according to the offered bids. GENCOs II have the chance to ask for additional payment (D) beside that for the shifted power recognized based on MCP (B). This charge is paid for additional costs and also for the willingness increasing the power generation in a very short duration time. Consumers also can be participating in the auction by increase or decrease consumption with acquiring opportunity costs. The target of optimization process is to adjust the operating point to enhance system transient stability considering system constraints with minimum payments.

B. Problem Formulation

The objective function aims to minimize the costs associated with power rescheduling to obtain feasible power system operating point with an acceptable transient stability level. The required transient stability level is taken into consideration as a constraint. The objective function based on opportunity and additional costs can be mathematically formulated as:

$$Min \quad Costs = \sum_{i=1}^{N_{d1}} f_i\left(\Delta P^{+}_{gi}\right) + \sum_{j=1}^{N_{d2}} f_j\left(\Delta P^{-}_{gj}\right) \tag{1}$$

Subject to:

Power flow constraints

$$\boldsymbol{h}(\boldsymbol{x})=0 \tag{2}$$

$$\boldsymbol{g}(\boldsymbol{x})\leq 0 \tag{3}$$

Transient stability constraint

$$CCT \geq CCT_{min} \tag{4}$$

where f is the cost function based on bidding strategies of participants in rescheduling process, ΔP is the change in scheduled power from initial operating point based on market clearance, N_{d1} and N_{d2} are the number of participants whose energy is increased and decreased respectively, $\boldsymbol{h}$ represents power balance equations at all nodes, $\boldsymbol{g}$ represents voltage and current limitations within the grid, $\boldsymbol{x}$ is the vector of control variables including transformer taps, load variations and generated active and reactive power. The CCT is limited by acceptable minimum limit, CCT_{min}.

III. PROPOSED SOLUTION

The proposed algorithm schematic diagram is shown in Figure 3. F(x) is the normalized constraint-fitness function. In the proposed approach, trained ANN is used to estimate CCT based on pre-selected features. Control variables are used to adjust the operating point in the direction of TSCPG. PSO is used as optimization tool to obtain the optimal value of control variables to enhance system transient stability with minimum cost. The major parts of the proposed algorithm are summarized as follows:

A. CCT estimation Using ANN

Power system transient stability analysis investigates the time response of the rapidly changing electrical components of a power system to a sequence of credible disturbances. Transient stability analysis involves repeatedly solving large, very sparse, time varying non-linear systems over thousands of time steps. Time domain simulation (TDS) provides an accurate calculation of power system transient stability but it is very time consumption and can not be applied in online optimization applications. In order to reduce the time consumed, ANN can be trained to map the power system operating conditions in order to simulate the dynamic system behavior in particular to estimate CCT as indicator for system transient stability. ANN is trained offline based on a given operation states so that the heavy computational burden is avoided in online optimization process and thus allows transient stability assessment performed in a very short time. Accurate selection of input variables is the key to the success of ANN applications. A large number of patterns are generated by perturbing both real and reactive loads randomly in a wide range of loading and optimal power flow solutions are used to adjust each operating point and generate the ANN input features. Feature selection is used to select features which contain valuable information that efficiently represents all system data. Input features are selected in two steps. First step to characterize the severity of faults to the generators, TDS is used to calculate the voltage drop at generator terminals immediately after fault occurrence. According to our experience this feature is the most important for CCT assessment by ANN and therefore the voltage drop at all generator terminals are preferred ANN inputs.

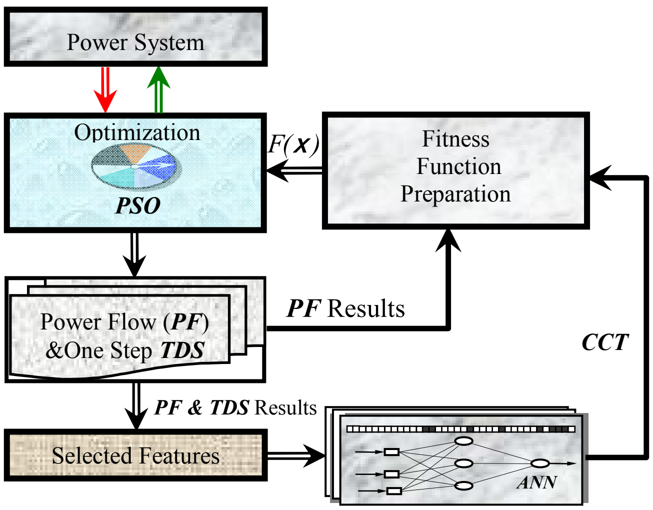

Figure 3: The schematic diagram of the proposed approach

Second step features from the load flow data, in particular demand and generation levels, power flow through transmission lines and tap changer transformer settings are pre-selected by applying a systematic feature selection. The Euclidean distance based clustering is used to group the system features into a certain number of clusters such that features in a cluster have similar characteristics and then one feature from each cluster picked out as a selected feature. A multilayer feed-forward structure with the back-propagation training network is implemented to relate the selected features and the corresponding CCT of the most critical contingency. The training algorithm used is the Levenberg-Marquardt algorithm because it provides fast convergence. MATLAB neural network toolbox is used as a computing tool. All information about trained ANN is saved to be used through the simulation process.

B. Swarm Optimization and Constraints Handling

PSO is a population based optimization technique was introduced by Kennedy and Eberhard in 1995 to simulate the bird flock and is used to solve many optimization problems [6]. The particles update their directions and positions as:

$$\begin{aligned} \boldsymbol{v}^{k+1} &= w^k \boldsymbol{v}^k + c_1 r_1 (\boldsymbol{x}_l^k - \boldsymbol{x}^k) + c_2 r_2 (\boldsymbol{x}_g^k - \boldsymbol{x}^k) \\ \boldsymbol{x}^{k+1} &= \boldsymbol{x}^k + \chi \boldsymbol{v}^{k+1} \\ w^k &= w_{max} - (w_{max} - w_{min})\left(\frac{k}{max\,iteration}\right) \end{aligned} \tag{5}$$

where k is the current iteration, $\boldsymbol{\chi}$ is the constriction factor to control the particles diversity and ensure convergence. c_1 and c_2 are the two positive factors called acceleration coefficients, allowing particles to account particle's individual experience and interaction between particles; $\boldsymbol{v}^k$ and $\boldsymbol{x}^k$ are the actual velocity and position vectors; r_1 and r_2 are two randomly generated numbers drawn uniformly from the interval [0, 1]; $\boldsymbol{x}_l$ is the local best position vector that the particles had; $\boldsymbol{x}_g$ is the global best particle position in the swarm; w^k is inertia weight to control the influence of the previous velocity on the velocity vector update [7]. The motion of particles through hyperspace is governed by their past individual experiences as well as the interaction between particles and their neighborhood experiences to search for the optimal or near optimal position. Constraints handling method is a highly important. In [8] a self adaptive penalty function based algorithm for constrained optimization has developed to achieve this target and will be used in this paper. A new fitness function consists of normalized fitness-constraint function for constraints handling is formulated and can be expressed as:

$$\boldsymbol{F(x)} = \boldsymbol{D(x)} + \boldsymbol{\varphi(x)} \tag{6}$$

where $\boldsymbol{D(x)}$ is called distance value which used to comparing infeasible individuals in the absence of feasible individuals.

$$\boldsymbol{D(x)} = \begin{cases} \vartheta(\boldsymbol{x}) & if\ r_f = 0 \\ \sqrt{\boldsymbol{fn}(\boldsymbol{x})^2 + \vartheta(\boldsymbol{x})^2} & if\ r_f \neq 0 \end{cases} \qquad r_f = \frac{number\ of\ feasible\ solutions}{swarm\ size} \tag{7}$$

where $\boldsymbol{fn(x)}$ is the normalized objective cost function and $\boldsymbol{\vartheta(x)}$ is the sum of the average normalized violation in each constraint. $\boldsymbol{\varphi}(\boldsymbol{x})$ is the penalty function which used to identify the best infeasible individuals. However by using a self adaptive penalty, any number of constraints can be handled and the infeasible particles are used to force the swarm into feasible space.

C. Power Rescheduling and Optimization Process

Generation rescheduling as well as consumption variation are used as an important preventive control action to improve transient stability [9]. The purpose of TSCPG is to find the optimal amount of rescheduled power between generators/consumers with minimum payments. The rescheduling scheme should make all potentially critical contingencies completely stable at the same time. The optimization sequence can be summarized as follows: For each new operating point, the power system subjected to a set of selected critical contingencies. The trained ANN is used to estimate CCT and all contingencies are ranked based on their corresponding CCT in order to select the most sever contingency with minimum CCT. When the minimum CCT is less than a desired minimum CCT limit, it is considered as a critical contingency. Power rescheduling depends on the original generation/consumption levels from energy market clearance and the participants bid offers is used to improve transient stability. PSO is used to solve the TSCPG problem to adjust the operating point with minimum cost. The population has a number of particles and each particle consists of a dimensional vector $\boldsymbol{x}$, where $\boldsymbol{x}$ is the vector of control variables including change in rescheduled active (Δp) and reactive (Δq) power and transformer tap settings (Δt).

$$\begin{aligned} &\boldsymbol{x}^T = [\Delta \boldsymbol{p}^T \ \ \Delta \boldsymbol{q}^T \ \ \Delta \boldsymbol{t}^T], \ \ \Delta \boldsymbol{p}^T = [\Delta p_1, \Delta p_2, \cdots, \Delta p_{Np1}] \\ &\Delta \boldsymbol{q}^T = [\Delta q_1, \Delta q_2, \cdots, \Delta q_{Np2}], \ \ \Delta \boldsymbol{t}^T = [\Delta t_1, \Delta t_2, \cdots, \Delta t_{Nt}] \end{aligned} \tag{8}$$

where N_{p1} and N_{p2} are the number of participants in active and reactive power rescheduling, Nt is the number of transformer taps.

The optimization process continued until stopping criteria reached. Two stopping criteria are used in this approach; first, the movement of the global best fitness is observed and a certain threshold number used to terminate the program. Second, the distance between the global best and each individual is observed and the optimization is terminated if the maximum distance is below a defined threshold value.

The modeling and simulation results for load flow and CCT calculations are accomplished using the simulation package 'Power System Dynamics (PSD)' [10]. The used code for PSO was implemented in MATLAB software.

IV. NUMERICAL EXAMPLE

The implementation of the proposed approach for TSCPG is illustrated through the PST sixteen-machine 66-bus power system [11]. The PST Test System is a stressed system designed for power system stability investigation. The single line diagram of the test system is shown in figure 4.ANN with three layers; input layer-one hidden layer-output layer has been used. The number of input neurons depends on the total number of selected features. The optimal number of neurons in the hidden layer has been estimated based on trial method. The number of output neurons is equal to 1 for CCT estimation. ANN is trained by input/output patterns. Two hundred different operating conditions within loading level from 60% to 130% of their base case operating point are used to extract the input/output patterns and three-phase short circuit is simulated at selected twenty critical points in the retained network. The optimal number of selected feature with minimum error is 25 features from 258 features. These features include generators power, lines power, loads power and transformers taps in addition to 16 features voltage drop for a single step 10 milliseconds fault at generator terminal voltages (ΔV) and so the ANN input pattern consists of 41 variables and these features are listed in table I.

TABLE I
ANN PERFORMANCE BASED ON ESTIMATION ERROR

Experimental selected features	Features selected by systematic clustering		
	Generators power	Transmission lines power	Transformer taps
ΔV at all generator terminal voltages with single step fault	QG2-QG4 QG9-PG13 QG13-QG14 PG15	PA5b/B1 - PB7/B8 PC16/C17 - PC17/C9 PC21/C22 - QA2/A5a QA5a/A6 - QB8/B14 QC4/C6 - QC9/C10 QC10/C11 - QC12/C13	T1-T3 T11-T13 T14-T22

TABLE II
ANN PERFORMANCE BASED ON ESTIMATION ERROR PREDICTING CCT

RMSE (sec)	*MAE (sec)*	*Emax (%)*	*Emin (%)*	*MAPE (p.u.)*
0.012	0.0103	6.40	-7.10	0.082

Table II presents the performance of the ANN in terms of mean absolute error (*MAE*), maximum percentage error (*Emax*), minimum percentage error (*Emin*), mean absolute percentage error (*MAPE*) and root mean square error (*RMSE*). The error definitions are given in equation (9). The estimation error in percentage is shown in figure 5.

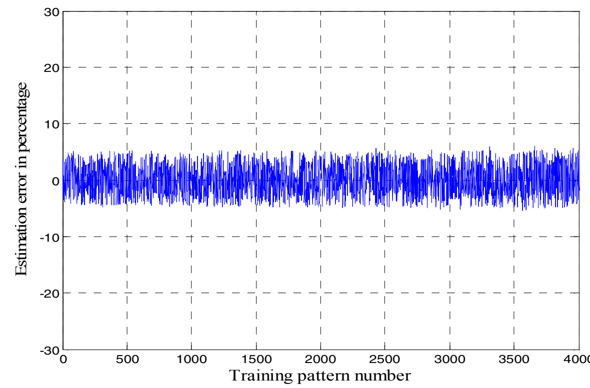

Figure 5: Percentage error in CCT estimation using ANN

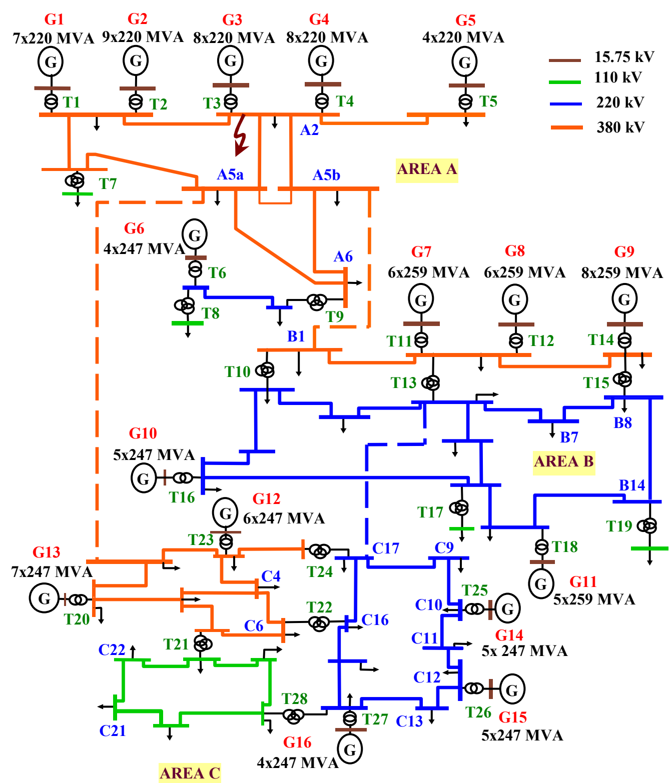

Figure 4: The sixteen-machine, 66-bus single line diagram

Figure 6 shows the linear regression plot between CCT calculated by TDS and CCT estimated by ANN with an average regression 0.99.

$$MAE = \frac{1}{N_d} \sum_{k=1}^{N_d} \left| y_k - \tilde{y}_k \right|$$

$$MAPE = \frac{1}{N_d} \sum_{k=1}^{N_d} \left| \frac{y_k - \tilde{y}_k}{y_k} \right| \qquad (9)$$

$$RMSE = \sqrt{\frac{1}{N_d} \sum_{k=1}^{N_d} \left(y_k - \tilde{y}_k \right)^2}$$

Where y is the calculated CCT by TDS; $\tilde{y}$ is the estimated CCT using ANN; N_d is the number of input patterns.

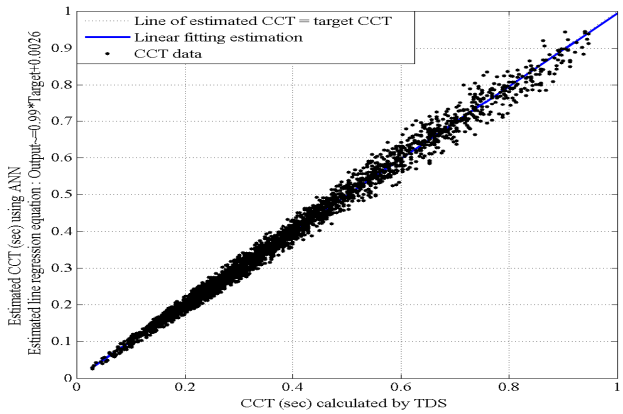

Figure 6: The linear regression between targets CCT calculated by TDS relative to CCT estimation using ANN: Regression = 0.99

During simulation, all GENCOs are assumed to provide obligatory reactive power service to support the grid voltage. within certain acceptable limits without additional costs. In this test system, all generators are assumed to participate in rescheduling process and each generator submits linear bids for up and down rescheduling and change limits ($\Delta P_{\min}$ and $\Delta P_{\max}$). The linear bids can be defined as follows:

$$f = \begin{cases} f_u = \alpha_u + \beta_u \left|\Delta P^{+}\right| & \Delta P^{+}_{min} < \Delta P < \Delta P^{+}_{max} \\ f_d = \alpha_d + \beta_d \left|\Delta P^{-}\right| & \Delta P^{-}_{min} < \Delta P < \Delta P^{-}_{max} \end{cases} \quad (10)$$

The opportunity and additional cost coefficients and power generation limits are shown in Table III. The minimum up and down acceptable change in generations are assumed to be 25 MW for all generators and the maximum change is governed by generation limits for each generator. The system has 60 control variables; these variables contain 16 active generated power, 16 reactive generated powers and 28 transformers-tap settings. The step size for adjusting transformers-tap setting is 0.005 per unit for their adjustable voltage range between 0.90 and 1.10 per unit. Figure 7 shows the system is unstable 100 milliseconds fault at Bus A2.

TABLE III
GENERATORS CAPACITY AND COST COEFFICIENT FOR 16-MACHINES SYSTEM

Generator name	Pgmax MW	Pgmin MW	α_u €/MWh	β_u €/MWh	α_d €/MWh	β_d €/MWh
G1	1500	400	0.254	10	0.102	5
G2	1500	400	0.256	5	0.113	3
G3	1650	550	0.246	4.5	0.15	3.5
G4	1650	550	0.232	8	0.124	2
G5	600	250	0.258	8.9	0.114	5.9
G6	700	250	0.27	7	0.184	4
G7	1500	400	0.263	6	0.192	3
G8	1500	400	0.244	4	0.196	5
G9	2000	400	0.252	5	0.121	3
G10	1150	450	0.276	8	0.18	2
G11	1250	350	0.258	5.8	0.185	2.8
G12	1650	500	0.262	2.6	0.118	3.6
G13	1450	500	0.264	6.4	0.109	3.4
G14	1250	250	0.228	6.28	0.19	3.28
G15	1200	350	0.256	8.56	0.113	5.56
G16	950	350	0.25	5	0.108	2.5

In order to satisfy minimum CCT limit, a re-dispatch is necessary to improve system transient stability, where some of the expensive generating units must be re-dispatched to satisfy all constraints as well as transient stability. Table IV and table V present the value of transformers tap settings and active power generation before and after rescheduling process using PSO respectively. According to the results, there are four generators will not participate in rescheduling process because the required change less than the minimum limit of change during the optimization process. The uniform market clearing price, in which all suppliers are paid the same price without considering transient stability into account, is considered as an initial power flow operating point. The initial CCT corresponds to critical contingency with three phase short circuit at bus A2 is 48.9 milliseconds where the required minimum limit of CCT is 150 milliseconds as a common limit for all circuit-breakers.

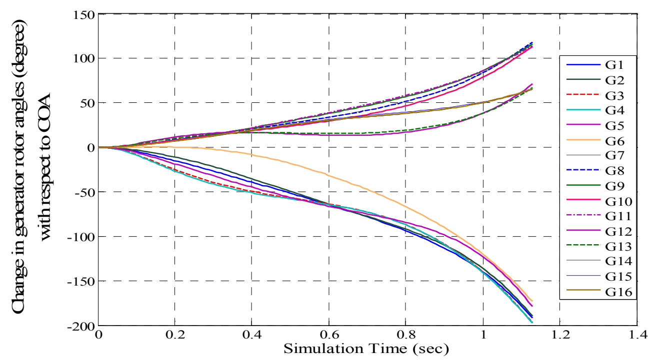

Figure 7: Dynamic response with 100 milliseconds fault before rescheduling.

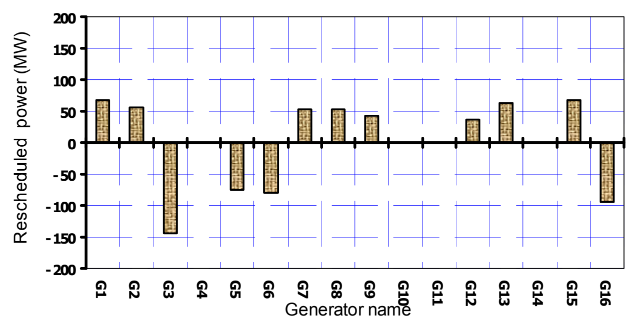

Figure 8: The change in generation levels after rescheduling process

TABLE IV
PER UNIT TRANSFORMERS-TAP CONTROL VARIABLES

Transformer name	Taps before rescheduling	Taps after rescheduling	Transformer name	Taps before rescheduling	Taps after rescheduling
T1	1.025	0.96	**T15**	1.005	1.0
T2	1.025	0.95	**T16**	0.995	1.01
T3	1.025	1.005	**T17**	0.975	1.05
T4	1.025	1.05	**T18**	1.01	1.025
T5	1.02	1.03	**T19**	0.985	1.05
T6	0.95	0.96	**T20**	1.035	1.0
T7	0.995	0.975	**T21**	1.005	1.005
T8	0.985	1.04	**T22**	1.03	1.005
T9	0.955	1.005	**T23**	1.02	1.04
T10	1.015	1.02	**T24**	1.025	1.05
T11	1.02	1.02	**T25**	1.01	0.975
T12	1.02	1.02	**T26**	1.01	1.0
T13	1.005	1.02	**T27**	1.015	0.97
T14	1.02	1.05	**T28**	1.0	1.045

After rescheduling, the transient stability enhanced and the total opportunity cost required to be paid to suppliers is 15822.3 €/h. The change in generation levels after rescheduling process is shown in figure 8.

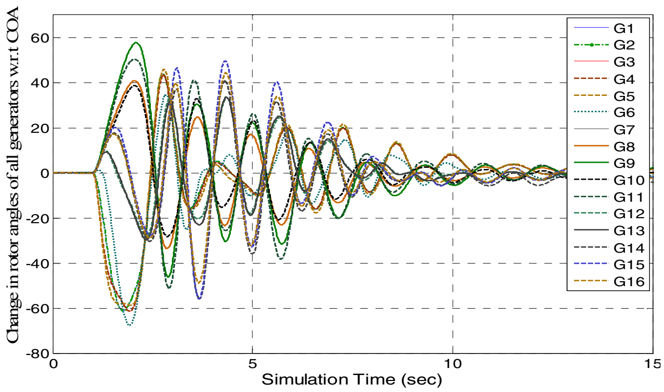

Figure 9: Dynamic response with 150 milliseconds fault after rescheduling.

TABLE V
POWER GENERATION (MW) BEFORE AND AFTER RESCHEDULING PROCESS

Generator name	Generation before rescheduling	Generation after rescheduling	Generation change	Opportunity costs (€/h)
G1	1008.98	1076.4	67.41	1411.46
G2	1003.77	1056.3	52.52	786.85
G3	1043.43	900	-143.43	3588.20
G4	1101.05	1101.05	0.00	0.00
G5	600	525.4	-74.6	1074.56
G6	700	620.8	-79.2	1470.96
G7	972.10	1025.2	53.096	1059.99
G8	1044.71	1097.9	53.18	902.80
G9	1376.60	1419.6	43	680.94
G10	915.24	915.24	0.00	0.00
G11	984.21	984.21	0.00	0.00
G12	982.15	1018.5	36.35	440.73
G13	969.57	1032.3	62.73	1440.43
G14	1000.00	1000.0	0.00	0.00
G15	994.40	1062.7	68.30	1778.89
G16	1018.77	924.9	-93.87	1186.39

Figure 9 shows the dynamic response during 150 milliseconds fault at the critical bus after rescheduling. This figure shows that the system is transiently stable at the critical contingency and the approach able to get a new operating point that enhances the system transient stability.

V. Conclusion

Transient stability constrained power generation based on PSO-ANN is proposed and tested in this paper. A market for active power rescheduling is implemented to enhance system transient stability. Participants introduce their offers and PSO-ANN is used as optimization tool to find a solution of online TSCPG problem with minimum payments for participants in the market. A mixture of TDS and ANN is applied in order to reduce the time consumption during the repeatedly transient stability calculation. ANN is a very fast tool for CCT estimation compared to TDS but should be trained carefully over a wide hyperspace in order to avoid over-fitting. The ANN is trained once for a given power system for any expected situation and then used for any load condition in the system. The results emphasize PSO capability of handling nonlinear mixed-integer optimization problems with complex objective function and constraints such as rescheduling process for transient stability enhancement. The results show that the PSO-ANN proposed method is successfully able to adjust system operating point to improve system transient stability with minimum cost during rescheduling process.

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VII. Biographies

Ayman Hoballah (GSM'2009) received the B.Sc. and M.Sc. degrees in electrical engineering from the Tanta University, Egypt in 1996 and 2003. Since 1998, he has been with the Electrical Power Department, Faculty of Engineering, University of Tanta/Egypt. He started his Ph.D. in the university Duisburg- Essen, Germany in 2007 supported by an Egyptian government scholarship. His Ph.D. thesis focuses on power system transient stability.

István Erlich (1953) received his Dipl. Ing. degree in electrical engineering from the University of Dresden/Germany in 1976. After his studies, he worked in Hungary in the field of electrical distribution networks. From 1979 to 1991, he joined the Department of Electrical Power Systems of the University of Dresden again, where he received his PhD degree in 1983. In the period of 1991 to 1998, he worked with the consulting company EAB in Berlin and the Fraunhofer Institute IITB Dresden respectively. During this time, he also had a teaching assignment at the University of Dresden. Since 1998, he is Professor and head of the Institute of Electrical Power Systems at the University of Duisburg-Essen/Germany. His major scientific interest is focused on power system stability and control, modeling and simulation of power system dynamics including intelligent system applications. He is a member of VDE and senior member of IEEE.