A Framework for Enhancement of Power System Dynamic Behavior

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

***Abstract*--Grid operation under market competition forces systems closer to their instability boundaries, and operating decisions must be based on accurate online system identifications. This paper presents a new framework for online power system dynamic stability enhancement with a new rescheduling market construction. The approach is to solve the online transient and oscillatory stability constrained economic power system operation by a mixture of a modified particle swarm optimization (PSO) and artificial neural network (ANN). The problem is formulated as nonlinear constrained optimization problem and PSO has been used as optimization tool to guarantee searching the optimal economic solution within the available hyperspace reducing the time consumed in the computations by using ANN to assess power system dynamic stability. The rescheduling process based on the generation companies (GENCOs)/consumer's bids is used as a remedial action to maintain system operation away from the limits of system stability. The goal of the approach is to minimize the opportunity cost payments for GENCOs/consumers backed down in generation/load and the additional cost for GENCOs/consumers increased their generation/load in order to enhance system dynamic stability. The critical clearing time (CCT) at the critical contingency is considered as an index for transient stability. System minimum damping of oscillation (MDO) is considered as indicator for oscillatory stability. The proposed framework is examined on a 66-bus test system.**

***Index Terms*-- Power system dynamic stability, Power generation economics, Power system transient stability**

I. Introduction

THE dynamic problems associated with power system operation increase with increasing the load exchanges among large interconnected power systems. The coordination of available energy sources to meet the forecasted demand for maximum economic benefits as a consequence of deregulation of the electric power industry push the system to its stability limits and increase the importance of system dynamic for safe operation of a large power grid. Power system operators should consider not only economic load dispatch but also on-line dynamic stability aspects [1]. Of particular interests in this paper are transient stability and small signal stability. Transient stability assessment (TSA) 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 [2].

With the deregulation of electricity markets, the utilities are allowed to participate outside their traditional stability borders to maximize their income, thus critical oscillatory modes appear after small disturbances. Oscillations limit the amount of power that can be transferred and may lead to power system breakup and outage. The oscillatory stability assessment (OSA) can be characterized in terms of mode parameters, e.g. frequency and damping of oscillations.

Independent system operator is the responsible of a secure real time system operation; 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. For safe system operation, several dynamic stability cases need to be run in a very short period of time (10-20 minutes) using online data to initiate preventive control actions. Thus system operators need different computational tools for system stability assessment. These tools must be accurate and fast for online application.

ANN has been recently applied in several power system problems to shorten the calculation time required. ANN is presented as accurate tool for TSA and OSA of large-scale power systems because ANN can be trained to map the power system operating conditions in order to simulate the dynamic system behavior [3-5]. In this paper ANN designed to be a robust assessment tool for TSA and OSA which can deal with all expected changes in power distributions and system topology.

In [6], the authors present a new methodology for continuously checking the transient stability conditions of generators and generation rescheduling process is used to enhance system transient stability. In the paper the work is extended to include oscillatory stability enhancement beside transient stability enhancement during system operation considering system topology changes. Power rescheduling as remedial action for stability enhancement considered as market. In this market, GENCOs and consumers can participant in the market by offering their energy bids. These bids should specify up or down generation/load capability and the corresponding compensation costs.

The main objective of this research is to enhance system dynamic stability by a proper shift in power generation/load schedule with a minimum compensation costs. These costs include the additional costs for increased generation and the opportunity cost for reduced power in-feed. The problem is

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)

formulated as constrained global optimization and solved by a mixture of PSO and ANN. Operating limits based on current conditions used to achieve the required online power system dynamic stability. CCT characterizing transient stability and MDO characterizing oscillatory stability are considered as additional constraints within the optimization process and estimated using offline trained ANN.

II. Study Power System

The implementation of the proposed framework is illustrated through the Power Stability Test 16-machine network (PST16) [5]. The single line diagram of the test system is shown in Fig. 1. The test system contains 66-bus and is divided into three areas (A, B and C) connected through tie lines. It is developed based on characteristic parameters of European power system to study different kinds of stability problems. The generators are considered hydropower and thermal power types and consist of number of blocks as shown in Fig. 1. The generator models are 5th order model with detailed exciter and governing systems.

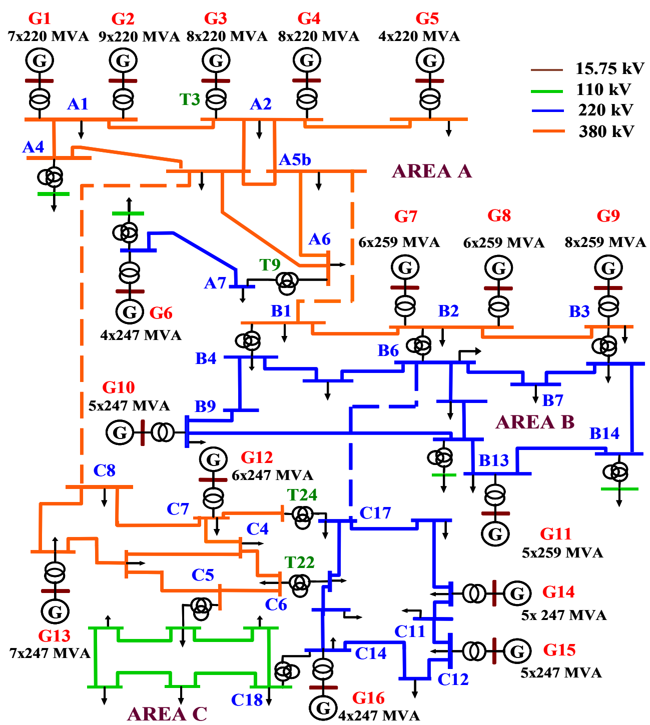

Fig. 1. Single line diagram of the sixteen-machine, 66-bus test system

Estimation of time varying dynamics using ANN introduce dependency on the data used in calibration that is not valid after change in system topology, for example, a line disconnection. To enhance the ability of ANN to deal with such situations, system topology and power distribution are considered to be changed during preparing Input/output patterns for ANN training. Table I lists the terminals of the disconnected transmission lines and Table II lists the name of disconnected generators.

TABLE I
Disconnected Transmission Lines During Topology Changes

Case	1	2	3	4	5
Disconnected Transmission Line Terminals	Base case	A5b/A6	B13/B14	B13/ B14 B4/ B9	C4 / C7

TABLE II
Disconnected Generators During Network Changes

Case	6	7	8	9
Disconnected Generators Name	G1-G2	G7-G8	G13	G1-G2-G7-G8- G13

III. Grid Dynamic Behavior Evaluation

A. Transient Stability Analysis

The power system transient stability analysis leads to the solution of nonlinear systems set of differential algebraic equations. Time domain simulation (TDS) provides an accurate calculation by solving these equations through step-by-step integration by producing time response of all state variables. Transient stability is based on coherent behavior of generators relative rotor angles procured from time domain simulation outputs. Under credible contingencies, if the relative angles enlarge gradually, after pre-defined accepted value generators no longer considered operated synchronously and , the system will lose its synchronism, otherwise it remain stable with a certain stability margin. The CCT is the maximum time duration that a fault may occur in power systems without failure in the system so as to recover to a steady state operation. CCT associated with each fault is a dynamic attribute for power systems which can be used as indicator for TSA. The time needed by relays to clear fault should be less than CCT to consider the system is transiently stable. Time domain simulations considering several contingencies at each operating point were carried out for the purpose of gathering CCT. The modeling and simulation results for load flow and corresponding CCT calculations were done by using the simulation package 'Power System Dynamics (PSD)' [7].

B. Small Signal Stability Analysis

Modal analysis of a set of differential equations is used to provide considerable insight into the stability properties of the system. In the investigation of OSA, the system equations are used to investigate the stability of the system by calculating the eigenvalues of the modified state matrix [8]. It requires data about complete system description, load flow analysis, linearization around current operating point, state space model formulation, and then parameters estimation. Due to the time varying and strong nonlinear dynamics in large power systems, it requires significantly large computational effort.

Dynamic behavior associated with major disturbances such as three phase short circuit is a good source of information concerning system oscillations and the control system responses. The time responses of electrical signals are used to calculate the eigenvalues of the monitored system using ringdown analysis (Prony analysis) or normal operation analysis [9]. Prony analysis is a curve-fitting methodology that extends Fourier analysis by directly estimating the frequency, damping, strength, and relative phase of the modal components present in a recorded signal [10]. In this paper, Prony analysis is applied to the generators active power as signals that seem to be the most sensitive in use for determination of mode parameters. From a systems view this choice is sensible in that an oscillation is due to a power imbalance at the swinging generators. Dynamic system identification toolbox (DSI) is used to identify system oscillation and damping during injected probing signals [11]. In this paper, DSI is used to identify MDO to account the system response for change in fault location. In order to improve significantly the electromagnetic mode identification; a probing signal should be injected at certain location with a proper duration. In this paper three phase short circuit is applied at pre-selected fault location with different fault duration to investigate the system response. Fig. 2 shows the MDO calculated at different contingencies and fault durations. The calculated values likely remains constant with 1-millisecond fault duration and thus the minimum damping at pre-selected fault location with 1-millisecond is considered as OSA during optimization process.

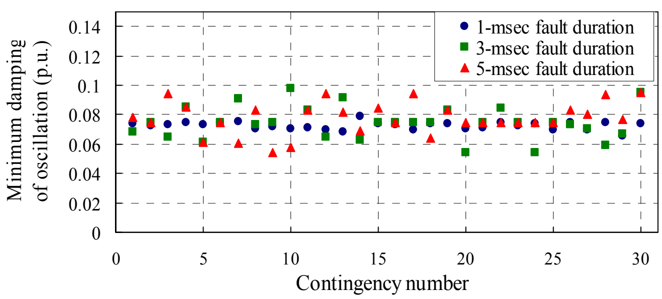

Fig. 2. MDO calculated from the time response

Fig. 3 shows the time response of generators active power due to a single step fault at bus B6 in area B and Fig. 4 presents the comparison between the real system data relative to the identified system data using DSI based Prony analysis toolbox. The observed inter-area oscillation mode with 0.87 Hz and approximately 7.5% damping ratio is characterized. As seen in Fig. 3, Generators in area A oscillate in anti-phase with generators at area B and area C.

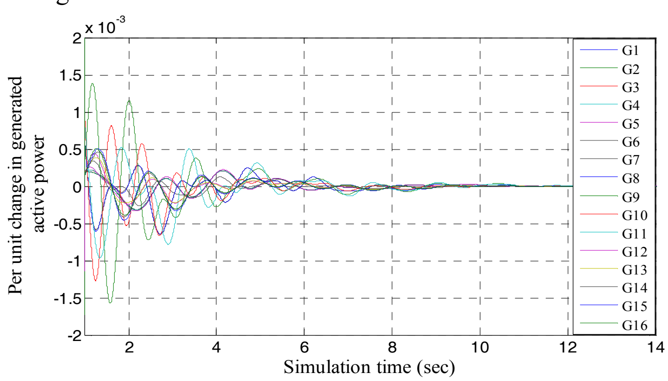

Fig. 3. Time response due to 1-millisecond short circuit at bus B6

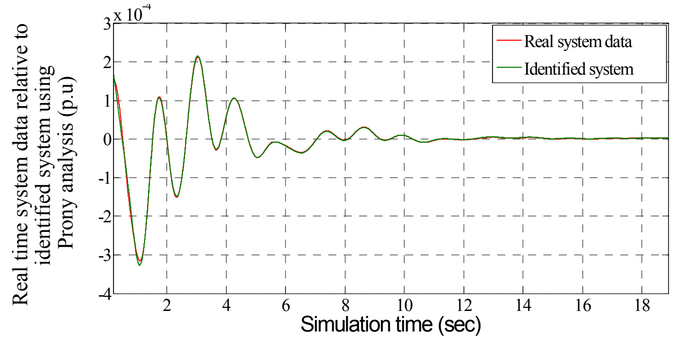

Fig. 4. Active power deviation relative to identified data using Prony analysis

DSI is an efficient method for OSA but consumes time in input data preparation and additional cure required for accurate estimate of system modes such as proper choice of number of sample points and sampling ratio for proper signal to noise ratio [10]. Thus it is not suitable for on-line applications. Off-line trained ANN can be used to predict the MDO based on the current operating point as indicator for OSA. Detection of low damping can then alarm operators or enables special protection schemes or adjust the rescheduling process to enhance system stability.

C. *ANN for TSA and OSA*

Two ANN are used in TSA and OSA. The generation of input/output patterns for ANN training is achieved by randomly varying the loads in wide range in each expected system configuration. Optimal power flow is used to adapt the generation depending on the required power and produce the required system information. At each operating point, TDS is used to calculate CCT and DSI is used to identify the MDO at pre-selected credible set of contingencies. The lowest values are selected as targets for ANN. Fig. 5 presents the block diagram of the main steps in ANN modeling process.

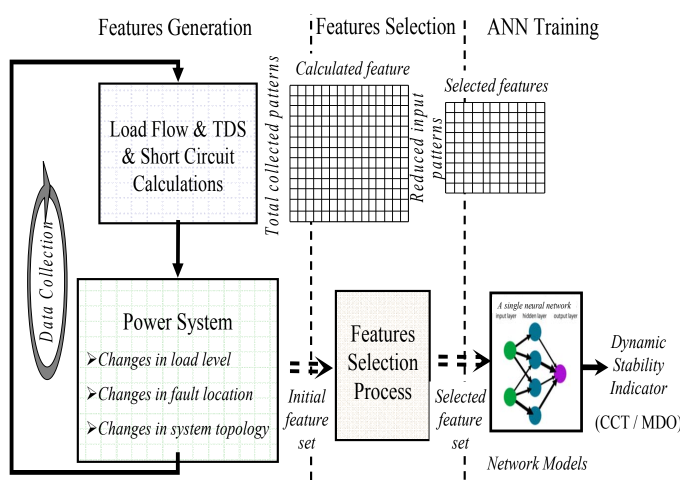

Fig. 5. Main steps in ANN modeling

Feature selection is necessary to reduce the large number of available features in power system and select the most valuable information contents that efficiently represent the entire system. Initial feature sets are pre-selected based on engineering judgment before feature selection process. The initial feature sets include load flow information such as bus voltages, generator powers, line flows, transformer powers, transformer tap sittings and demands. For dynamic stability assessment the ANN should be able to follow the changes in load levels, changes in power distribution, changes in system topology and ability for evaluating system dynamic behavior independent on fault location. In order to achieve this goal, Final features are selected in two stages as follows: First stage: Initial feature set is selected based on the knowledge of the power system using power flow results, TDS and short circuit analysis. Second stage: In this stage, the input features are selected in three steps to improve the accuracy of ANN in TSA and OSA. *First step*: To characterize the severity of faults to the generators and detect the fault location, the voltage drop at generator terminals immediately after a single step short circuit are preferred ANN inputs. As seen in Fig. 6, when a three phase fault occurs at bus A1 in area A of PST16 the nearest generators get more response as indication of fault location.

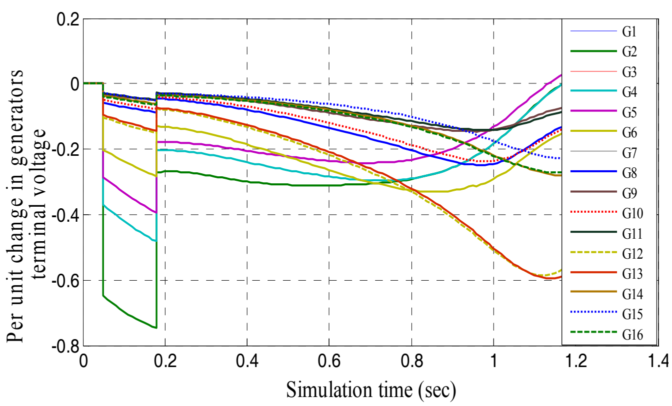

Fig. 6. Voltage drops at generator terminals immediately after a single step short circuit at bus A1 in PST16 test system

Second step: To characterize the change in power distribution due to change in the portion of areas in power generation, an Area Power Generation Distribution Factor (APGDF) for each area is used. This factor depends on the summation of generated energy in each area related to the summation of the total energy capacity of connected generators.

$$\boldsymbol{APGDF} = \frac{\sum_{i=1}^{N_k} \boldsymbol{H}_i \cdot \boldsymbol{P}_{gi}}{\sum_{i=1}^{N_k} \boldsymbol{H}_i \cdot \boldsymbol{S}_{gi}} \tag{1}$$

where; $\boldsymbol{H}$ is the generator inertia constant, $\boldsymbol{P}$ active power in MW, $\boldsymbol{S}$ is generator capacity in MVA and $\boldsymbol{Nk}$ is the number of generators in area $\boldsymbol{k}$

Third step: To characterize the varying in load levels and power flow through transmission lines during operating point adjustments, a systematic feature selection algorithm, in our case k-means clustering algorithm, is used to select the most important features from the initial selected sets of features.

Selected features used to train the ANN for TSA and OSA are listed in Table III; these features reflect the system configuration, pre-contingency operating conditions, fault locations and severity of the disturbances.

TABLE III
FEATURES SELECTED FOR TSA AND OSA USING ANN

Name of Features	Selected Features for TSA & OSA
Terminal voltage drop	ΔV of all generators after a fault
Area power generation distribution factor	APGDF for each Area
Generator power	Qg3 - Qg6 - Pg8 - Pg9 - Qg13 - Pg14
Magnitude of bus voltage	VA4 - VA7 - VB7 - VC6 - VC8
Transformer taps	T24 - T22 - T9
Tie-line power	PA5b/B1 - PB6/C17 - QB6/C17
Loads power	PA2 - PA7 - PB3 - PC4 - PC7 - PC14 - QB1 - QB2 - QC12 - QC18

A multilayer feed-forward structure with the back-propagation training network is implemented to relate the selected input features and the corresponding CCT and MDO of the most critical contingency. The training algorithm used is the Levenberg-Marquardt algorithm. MATLAB neural network toolbox is used to implement ANN. All information about trained ANN is saved to be used through the simulation process.

IV. PROPOSED ALGORITHM

A. *Market Formulation*

The main target in the proposed algorithm is to investigate the energy market co-optimization based on extra cost payments minimization of energy under rescheduling process to enhance system dynamic stability considering system constraints. The proposed algorithm schematic diagram is shown in Fig. 7. As a responsibility of ISO in real time power system operation, system dynamic stability should be evaluated nearly at every 15 minutes. When the dynamic stability limits are violated, a counter measures are required to enhance the dynamic stability for a secure operation.

In the paper, we suggest a new rescheduling market construction to reallocate the energy among suppliers and consumers who participate in the market by placing optional energy bids to enhance the power system dynamic stability. This market is a separate market established after the energy market clearance.

In this market, all GENCOs and consumers have equal chance to participate with volunteer energy bids to increase or decrease their scheduled level (generation/load) based on energy market clearance. Based on the required cost for control variables, the optimization starts with low cost control variables to minimize the required payments.

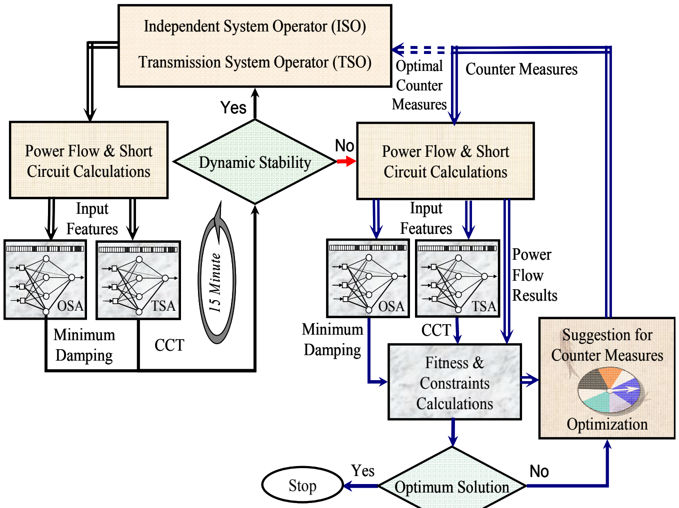

Fig. 7. The schematic diagram of the proposed approach

In the market, a participant whose energy is backed down should be paid an opportunity cost for reduction in power generation/load level. On the other hand, a participant whose energy is increased will be paid the cost of increase in generation/load level based on market clearing price (MCP) and may be additional costs required to execute the required change. The GENCOs and consumers are not participate in the market will be treated financially based on energy market clearance. Cash flow block diagram according to the new rescheduling process is shown in Fig. 8.

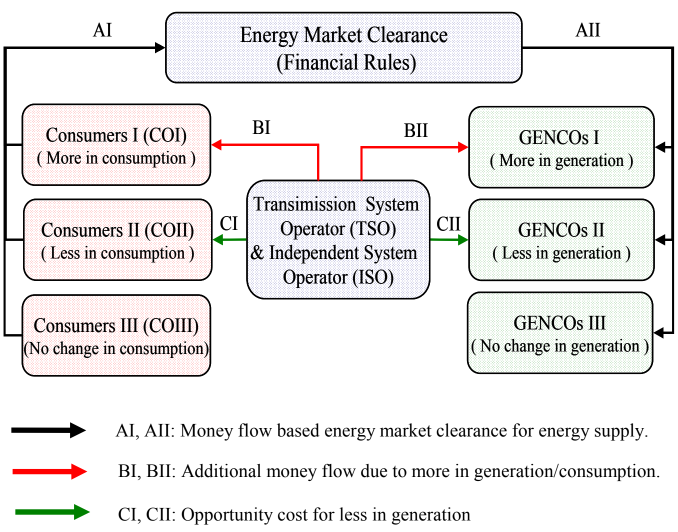

Fig. 8. Money flow to enhance transient stability using generation rescheduling

Based on energy market clearance, market cleared to specify power schedule and corresponding money flow from consumers to GENCOs (money flow AI and AII). The new rescheduling process will shift part of generated power from GENCOs I to GENCOs II and may be change in energy consumption of consumers I and consumers II in order to enhance dynamic stability. Additional costs are paid to GENCOs I and consumers I to increase in scheduled generation/load level. In the same time, opportunity costs will be paied to GENCOs II and consumers II for less in generation/load level.

B. Problem Formulation

The participants in the market submit their volunteer energy bids including limits of change and the corresponding cost functions. These offered biddings can be implemented with any acceptable form such as linear bid strategy as shown in Fig. 9. Multi-stage linear biding is offered for opportunity cost required for a reduction in generation with the limits (ΔP^-_{min} , ΔP^-_{max}) and additional cost beside market clearing price for increase in generation more than the dispatched power within limits (ΔP^+_{min} , ΔP^+_{min}).

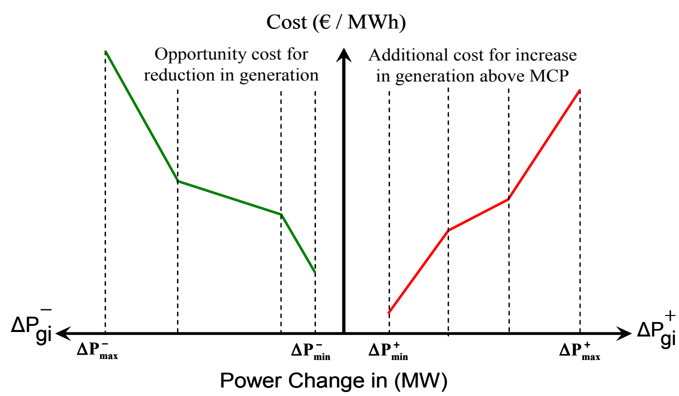

Fig. 9. Opportunity and additional costs for generation changes

The problem is formulated as cost minimization objective function. The target is to minimize the costs associated with power rescheduling to obtain feasible power system operating point with an acceptable dynamic stability level. The required transient stability level and the acceptable MDO are taken into consideration as constraints. The objective function based on opportunity and additional costs can be mathematically formulated as [6]:

Minimize:

$$Costs = \sum_{i=1}^{N_{d1}} f_i\left(\Delta P^+_{gi}\right) + \sum_{j=1}^{N_{d2}} f_j\left(\Delta P^-_{gj}\right) \qquad (2)$$

Subject to:

Power flow constraints

$$h(x) = 0 \qquad (3)$$

$$g(x) = 0 \qquad (4)$$

Transient stability constraint

$$CCT \geq CCT_{min} \qquad (5)$$

$$\xi \geq \xi_{min} \qquad (6)$$

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, 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 $\boldsymbol{CCT_{min}}$ is the acceptable minimum CCT limit. ξ is the system damping and ξ_{min} is the minimum acceptable system damping.

V. Counter Measures and Optimization Process

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 [12]. PSO is used as optimization tool to obtain the optimal counter measures to enhance system dynamic stability with minimum cost. During the optimization process, the particles move through hyperspace defined by the limits of the control variables and updated to satisfy all constraints. Constraints handling method is a highly important. In [6] a self adaptive penalty function based algorithm for constrained optimization in implemented to achieve this target and is used in this paper.

The ISO has to check the dynamic stability each 15 minutes; if system is stable, energy schedule from energy market directed to real time application else optimization start to search about proper remedial actions. Participant's bids should be submitted and objective function formulated. The population in PSO is initiated with a dimensional vector $\boldsymbol{x}$, where $\boldsymbol{x}$ is the vector of control variables including change in rescheduled active and reactive power (Δq, Δp) of all participants in the market in addition to all online available control variables such as transformer tap settings (Δt) and FACTS devices to control the injected reactive power.

$$\begin{aligned} \boldsymbol{x}^T &= [\Delta \boldsymbol{p}^T \ \Delta \boldsymbol{q}^T \ \Delta \boldsymbol{t}^T] \\ \Delta \boldsymbol{p} &= [\Delta p_1, \Delta p_2, \cdots, \Delta p_{Np1}] \\ \Delta \boldsymbol{q} &= [\Delta q_1, \Delta q_2, \cdots, \Delta q_{Np2}] \\ \Delta \boldsymbol{t} &= [\Delta t_1, \Delta t_2, \cdots, \Delta t_{Nt}] \end{aligned} \tag{7}$$

where Np1 and Np2 are the number of participants in active and reactive power rescheduling, Nt is the number of transformer taps.

For each particle in the population, the load flow is used to adjust the operating point and the power system subjected to a set of selected critical contingencies as described before. Based on the selected features, offline trained ANNs are used to estimate CCT and minimum damping of system oscillations. After ranking, when the minimum CCT and/or damping ratio are less than the desired values, it considered as constraints violation during optimization. Thus the constrained objective function is formulated and velocities and positions of particles are updated. The optimization process continued until reach the stopping criteria in the direction to enhance the system dynamic stability with minimum cost. The final solution should make all potentially critical contingencies completely stable at the same time. The used code for PSO was implemented by MATLAB software.

VI. Numerical Results

A. Performance Evaluation of ANN in TSA and OSA

The ability of ANN for TSA considering system topology changes and change in power distributions is presented in [4]. Fig. 10 presents randomly selected three operating points for each case study presented in Table I, II during testing with unforeseen set of input/output pattern.

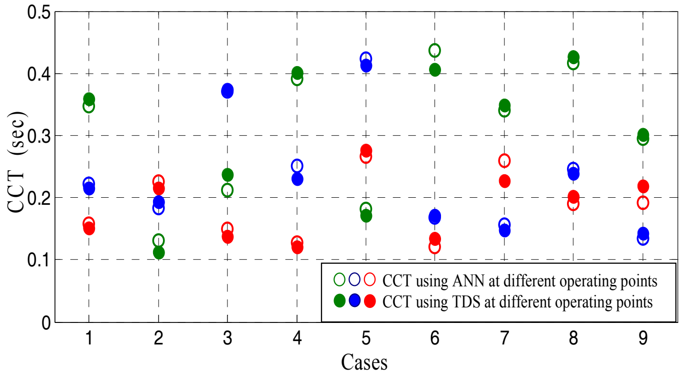

Fig. 10. CCT estimated by ANN as indicator for TSA relative to CCT calculated by TDS

The same procedure described in [4] is used to model ANN for OSA. A single hidden layer feed-forward structure ANN trained using beck-propagation is used for OSA. ANN is used to map the relation between the selected features listed in Table III and the MDO calculated by DSI at each operating point as described in section III. The number of neurons in input layer is equal to the number of selected features. The output layer contains one neuron related to the target OSA. The number of neurons in the hidden layer is selected to minimize the root mean square error (RMSE) between the estimated damping ratio by ANN and the target damping ratio estimated by DSI. Fig. 11 shows the target percentage damping ratio relative to estimated values at randomly selected 50 unforeseen operating points to test the ability of ANN in OSA.

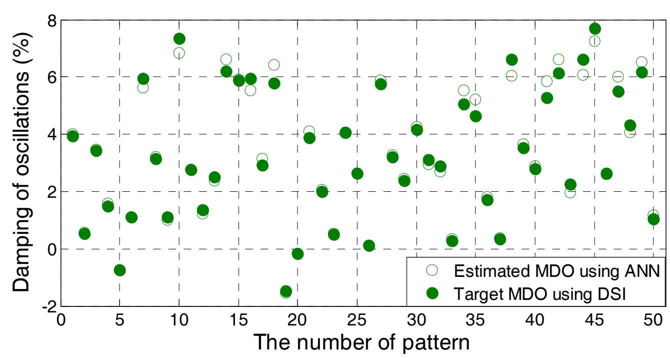

Fig. 11. The percentage minimum damping estimated by ANN relative to target minimum damping calculated by DSI

Fig. 12 shows a randomly selected three operating point for each case in Table I, II.

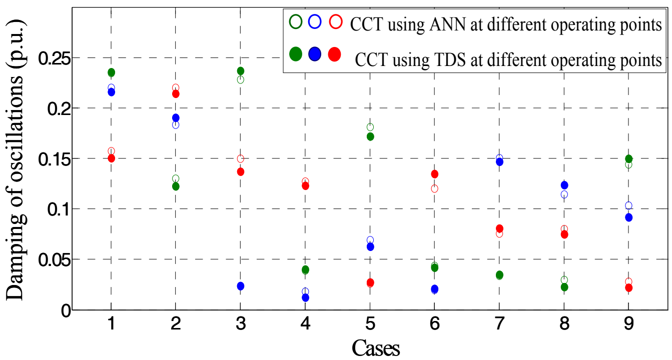

Fig. 12. Min. damping estimated by ANN as indicator for TSA relative to estimated values by DSI

The ANN performances are evaluated using average estimation error (AE), standard deviation (σ) and mean absolute percentage error (MAPE) between estimated minimum damping using trained ANN and target value estimated by DSI. The definitions are given as follow:

$$RMSE = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}\left(y_k - \tilde{y}_k\right)^2} \tag{8}$$

$$E_k = \left(\frac{y_k - \tilde{y}_k}{y_k}\right) \tag{9}$$

$$AE = \frac{1}{N_d}\sum_{k=1}^{N_d} E_k \tag{10}$$

$$\sigma = \sqrt{\frac{1}{N_d}\sum_{k=1}^{N_d}\left(E_k - AE\right)^2} \tag{11}$$

$$MAPE = \frac{1}{N_d}\sum_{k=1}^{N_d}\left|E_k\right| \tag{12}$$

where y is the calculated CCT by TDS; ỹ is the estimated CCT using ANN; Nd is the number of input patterns.

The results provide the suitability of ANN in TSA and OSA with a reasonable degree of accuracy. Table IV summarize the performance evaluations of ANN in TSA and OSA

TABLE IV
PERFORMANCE OF ANN IN TSA AND OSA

	AE (%)	σ (%)	*MAPE* (%)
TSA using ANN	-0.1343	7.088	3.467
OSA using ANN	-0.3520	6.400	4.520

B. Application of the Proposed Approach

The implementation of the proposed approach is illustrated through the PST16 presented in section II. A highly stressed operating point is selected to investigate the suitability of the proposed framework in dynamic stability enhancement. The uniform market clearing price, in which all suppliers are paid the same price without considering dynamic stability into account, is considered as an initial schedule. In this operating point, the CCT if found to be 82.5 millisecond with a three phase fault at bus A2 in area A and the corresponding minimum damping of oscillation is 1%. The target for a dynamic stable system operation is assumed to be 150 milliseconds as a common for all circuit-breakers in the system and the acceptable sufficient MDO is 4%. To enhance the system dynamic stability, a new market implemented and GENCOs and consumers are asked to submit their energy bids. All GENCOs are assumed provide the reactive power service to support the grid voltage without additional costs and participate in the market.

The opportunity and additional cost coefficients and power generation limits are presented in Table V The minimum up and down acceptable change in generations are assumed to be 20 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 and no cost variables including 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.

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

Generator name	**Pgmax MW**	**Pgmin MW**	α_u **€/MWh**	β_u **€/MWh²**	α_d **€/MWh**	β_d **€/MWh²**
G1	1500	300	0.124	6	0.102	2
G2	1500	300	0.116	5	0.0913	1
G3	1650	450	0.136	4.5	0.13	3.5
G4	1650	450	0.132	8	0.114	2
G5	600	150	0.125	9	0.114	5.9
G6	700	150	0.17	7	0.184	4
G7	1500	300	0.121	6	0.1922	3
G8	1500	300	0.144	4	0.196	5
G9	2000	300	0.152	5	0.121	3
G10	1150	350	0.146	8	0.15	2
G11	1250	250	0.158	5.8	0.125	2.8
G12	1650	400	0.162	2.6	0.118	3.6
G13	1450	400	0.164	6.4	0.109	3.4
G14	1250	150	0.128	6.28	0.19	3.28
G15	1200	250	0.156	6.56	0.1134	5.56
G16	950	250	0.12	5	0.108	2.5

Table VI and Table VII present the value of transformers tap settings and active power generation before and after rescheduling process using PSO respectively. According to the results after rescheduling process, there are three generators will not participate in rescheduling process to satisfy the required minimum limit of change. During the simulation, the required dynamic stability limits are considered as constraints beside all system limits. After rescheduling, the dynamic stability enhanced and the required limits are satisfied. The total opportunity and additional costs required to be paid to participants in the market is 18733.12

€/h. the new CCT is 165.5 milliseconds with 4.63% MDO.

TABLE VI
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	0.960	T15	1.005	1.002
T2	1.000	0.950	T16	0.995	1.025
T3	1.025	1.025	T17	0.975	1.00
T4	1.050	1.025	T18	1.025	1.025
T5	1.030	1.000	T19	0.985	1.025
T6	0.950	1.025	T20	1.025	1.000
T7	0.995	1.000	T21	1.005	1.005
T8	0.985	1.020	T22	1.030	1.030
T9	0.955	1.005	T23	1.020	1.020
T10	1.015	1.030	T24	1.050	1.025
T11	1.020	1.020	T25	1.025	0.975
T12	1.020	1.020	T26	1.025	1.000
T13	1.025	1.005	T27	1.050	0.970
T14	1.020	1.020	T28	1.025	1.050

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

Generator name	Generation before rescheduling	Generation after rescheduling	Generation change	Opportunity costs (€/h)
G1	1108.984	1176.4	67.415	834.729
G2	1083.778	1060.3	-23.478	-31.399
G3	1143.438	1020.5	-122.938	2697.347
G4	1001.055	1121.055	120	1545.6
G5	600.000	515.4	-84.6	1315.052
G6	700.000	650.8	-49.2	642.197
G7	972.104	1105.1	132.992	3681.074
G8	1044.719	1127.3	82.580	1312.386
G9	1276.600	1399.7	123.1	2918.887
G10	915.240	915.24	0.00	0.00
G11	984.210	984.21	0.00	0.00
G12	982.150	1018.8	36.651	312.912
G13	969.570	1032.5	62.932	1090.063
G14	1000.000	1000.00	0.00	0.00
G15	994.400	1082.3	87.900	1556.942
G16	1118.770	1002.6	-116.170	1748.098

VII. CONCLUSION

A new framework for enhancement of power system dynamic stability based on PSO-ANN is developed and tested in this paper. A new market for active power rescheduling is implemented to enhance system dynamic stability. In the market, participants introduce their offers and PSO-ANN is used as optimization tool to find a solution to enhance online dynamic stability with minimum payments for participants in the market. ANN is implemented as a robust tool for TSA and OSA reducing the time consumed during repeatedly calculations of TSA and OSA. ANN is a very fast tool for TSA and OSA estimations compared to traditional methods but should be trained carefully over a wide hyperspace in order to achieve high accuracy of estimation. 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 dynamic stability enhancement. The results show that the new framework can be applied in the real time power system operation to adjust system operating point for system dynamic stability enhancement with minimum cost during a rescheduling process.

VIII. REFERENCES

[1] H. R. Cai, C. Y. Chung and K. P. Wong, "Application of Differential Evolution Algorithm for Transient Stability Constrained Optimal Power Flow," *IEEE Trans. on Power Systems*, vol. 23, no. 2, pp. 719–728, May. 2008.

[2] J. F. Hauer, F. J. Hughes, D. Trudnowski, G. Rogers, J. Pierre, L. Scharf and W. Litzenberger, "A Dynamic Information Manager for Networked Monitoring of Large Power Systems," Tech. Rep. WO 8813-01, EPRI. 42, 1998.

[3] Yakout Mansour, Ebrahim Vaahedi and M. El-Sharkawi, "Dynamic Security Contingency Screening and Ranking using Neural Networks", IEEE Trans. on Neural Networks, Vol. 8, No. 4, pp. 942-950, May 1997.

[4] A. Hoballah and I. Erlich, "Transient Stability Assessment using ANN Considering Power System Topology Changes," ISAP 2009, Power & Energy Society, November 2009, Curitiba, Brazil

[5] Simon P. Teeuwsen, Istvan Erlich and Mohamed A. El-Sharkawi, "Neural Network based Classification Method for Small Signal Stability Assessment," *IEEE PowerTech*, Bologen, Italy, June, 2003.

[6] A. Hoballah and I. Erlich, "PSO-ANN approach for transient stability constrained economic power generation," PowerTech2009 IEEE Bucharest, pp. 1 – 6, July 2009

[7] István Erlich, "Analysis and simulation of dynamic behavior of power system," Postdoctoral lecture qualification, Dept. of electrical engineering, Dresden University, Germany, 1995.

[8] I. Erlich and A. Fischer, "Fast Assessment of Small-Signal Osillatory Stability in Large Interconnected Power Systems," Balkan Power Conference BPC, June 2002 Belgrade, Yugoslavia.

[9] J. Hauer, C. Demeure, and L. Scharf, "Initial results in Prony analysis of power system response signals," IEEE Transactions on Power Systems, vol. 5, no. 1, 1990

[10] J. Hauer, "Application of Prony analysis to the determination of modal content and equivalent models for measured power system response," IEEE Trans. Power System., 1991, 6, (3), pp. 1062–1068.

[11] Available: www.naspi.org/resources/archive/archiveresources.stm

[12] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," Proc. IEEE International Conference on Neural Networks, 1995, IEEE Service Center Piscataway, NJ, pp. IV: pp. 1942–1948, Aug. 2004.

IX. BIOGRAPHIES

Ayman Hoballah 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 the 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.