

NEURAL NETWORK PREDICTIVE CONTROL BASED POWER SYSTEM STABILIZER

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The present paper investigates the power system stabilizer based on neural predictive control for improving power system dynamic performance over a wide range of operating conditions. In this study a design and application of the neural network model predictive controller (NN-MPC) on a simple power system composed of a synchronous generator connected to an infinite bus through a transmission line is proposed. The synchronous machine is represented in detail, taking into account the effect of the machine saliency and the damper winding. Neural network model predictive control combines reliable prediction of neural network model with excellent performance of model predictive control using nonlinear Levenberg-Marquardt optimization. This control system is used the rotor speed deviation as a feedback signal. Furthermore, the used performance system of the proposed controller is compared with the system performance using conventional one (PID controller) through simulation studies. Digital simulation has been carried out in order to validate the effectiveness proposed NN-MPC power system stabilizer for achieving excellent performance. The results demonstrate that the effectiveness and superiority of the proposed controller in terms of fast response and small settling time.

KEYWORDS: Power system stabilizer, NN_MPC control and single synchronous machine infinite bus systems

LIST OF SYMBOLS

H	Inertia constant of the machine, in second	X_{kd}	The d-axis damper winding self reactance, in p.u.
i_d	d-axis armature current, in p.u.	X_{kq}	The q-axis damper winding self reactance, in p.u.
i_f	Field winding current, in p.u.	X_q	q-axis synchronous reactance, in p.u.
i_{kd}	d- and q-axis damper winding currents, in p.u.	X'_d	d-axis transient reactance, in p.u.
i_q	q-axis armature current, in p.u.	X''_d	d-axis subtransient reactance, in p.u.
r_e	Series resistance of transmission system, in p.u.	δ	Rotor displacement angle, in radian
r_f, r_m	Field and armature resistance, in p.u.	ω	Rotor instantaneous angular velocity, in rad./sec
T_e	Machine electromagnetic torque, in p.u.	ω_o	Rotor synchronous speed, in rad/sec

T_m	Shaft torque, in p.u.	Ψ_d	The d-axis armature flux linkage in p.u.
V_f	Field voltage, in p.u.	Ψ_f	The field winding flux linkage in p.u.
V_t	Machine terminal voltage, in p.u.	Ψ_{kd}	The d-axis damper winding flux linkage in p.u.
X_d	d-axis synchronous reactance, in p.u.	Ψ_{kq}	The q-axis damper winding flux linkage in p.u.
X_e	Series reactance of transmission system, in p.u.	Ψ_q	The q-axis armature flux linkage in p.u.

1. INTRODCION

Power system stabilizers (PSSs) have been widely used as supplementary controllers to provide extra damping for synchronous generators in electrical power system. Conventional power system stabilizer (CPSSs) are used to damp out small signal oscillations and they are designed based on a model which is linearized around a particular operating point. Conventional design tunes the gain and time constants of the PSS, which are mostly lead-lag compensator, using modal frequency techniques [1-3]. The feedback signal is subtracted from the reference to determine the error signal. Due to the complexity of the mathematics, the conventional control methods were used mostly for single-input-single-output system. Modern control methods were extremely successful because they could be efficiently implemented on computers, they could handle multi-input-multi-output system, and they could be optimized [4-7]. With the development of numerical algorithms for solving linear matrix inequality (LMI) problem in the last few years, the LMI approach has emerged as a useful tool for solving a wide range variety of control problems.

Predictive control is now widely used in industry and a large number of implementation algorithms. Most of the control algorithms use an explicit process model to predict the future behavior of a plant and because of this, the term model predictive control (MPC) is often utilized [8-10]. The most important advantage of the MPC technology comes from the process model itself, which allows the controller to deal with an exact replica of the real process dynamics, implying a much better control quality. The inclusion of the constraints is the feature that most clearly distinguishes MPC from other process control techniques, leading to a tighter control and a more reliable controller. Another important characteristic, which contributes to the success of the MPC technology, is that the MPC algorithms consider plant behavior over a future horizon in time. Thus, the effects of both feed forward and feedback disturbances can be anticipated and eliminated, fact, which permits the controller to drive the process output more closely to the reference trajectory.

Several versions of MPC techniques are model algorithmic control (MAC) [11], dynamic matrix control (DMC) [12], and internal model control (IMC) [13]. Although the above techniques differ from each other in some details, they are fundamentally the same, because all of them are based on linear process modeling.

The Neural Network Model Predictive Control (NN-MPC) is another typical and straightforward application of neural networks to nonlinear control. When a neural network is combined with MPC approach, it is used as a forward process model for the

prediction of process output [14,15]. Neural network model predictive control has been applied on the process control as chemical, industry applications. But, applying MPC on power system stability and control is still very slightly used [16-19].

The main objective of this study is to investigate the application of neural network model predictive controller on the single synchronous machine connected to an infinite bus power system. The system is modeled and the NN-MPC is designed and applied on the system. A comparison between the system performance obtained when using the proposed NN-MPC controller and the performance obtain using PID controller at different operating conditions is presented and evaluated for power system. The feasibility and effectiveness of the proposed controller have been demonstrated through computer simulations. Simulation results have NN-MPC proved that the proposed controller can give better overall performance. Simulation results show also that the NN-MPC gives promising results.

2. POWER SYSTEM MODEL

Figure 1 shows a synchronous machine with salient poles and damper windings represented in rotating d-q axis coordinates. The coordinates are fixed on the rotor and rotate with it. The non-linear differential equations of unsaturated salient pole synchronous machine can be expressed as [1]

$$\frac{1}{\omega_o} \dot{\Psi}_f = V_f - r_f \cdot i_f \tag{1}$$

$$\frac{1}{\omega_o} \dot{\Psi}_d = V_{td} + r_m \cdot i_d + \frac{\omega}{\omega_o} \Psi_q \tag{2}$$

$$\frac{1}{\omega_o} \dot{\Psi}_{kd} = -r_{kd} \cdot i_{kd} \tag{3}$$

$$\frac{1}{\omega_o} \dot{\Psi}_q = V_{tq} + r_m \cdot i_q - \frac{\omega}{\omega_o} \Psi_d \tag{4}$$

$$\frac{1}{\omega_o} \dot{\Psi}_{kq} = -r_{kq} \cdot i_{kq} \tag{5}$$

$$\dot{\delta} = \omega - \omega_o \tag{6}$$

$$\dot{\omega} = \frac{\omega_o}{2H} (T_m - T_e) \tag{7}$$

The non-linear differential equations described above from Eqns. (1-7) can be linearized around an operating point become linearized algebraic equations as follows:

$$\Delta T_e = \Psi_{do} \Delta i_q + I_{qo} \Delta \Psi_d - \Psi_{qo} \Delta i_d - I_{do} \Delta \Psi_q \tag{8}$$

$$\Delta v_{td} = V_b \cos \delta_o \Delta \delta + r_e \Delta i_d - x_e \Delta i_q \tag{9}$$

$$\Delta v_{tq} = -V_b \sin \delta_o \Delta \delta + r_e \Delta i_q + x_e \Delta i_d \tag{10}$$

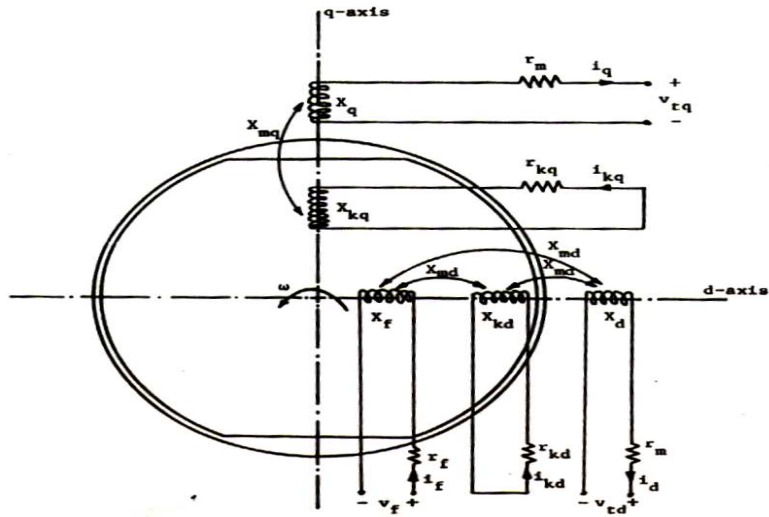


Fig. 1 : Representation of synchronous machine in d-q axis coordinate

The relation between fluxes and currents can be derived from the following matrix [1],

$$\begin{bmatrix} \Delta\Psi_f \\ \Delta\Psi_d \\ \Delta\Psi_{kd} \\ \Delta\Psi_q \\ \Delta\Psi_{kq} \end{bmatrix} = \begin{bmatrix} x_f & -x_{md} & x_{md} & 0 & 0 \\ x_{md} & -x_d & x_{md} & 0 & 0 \\ x_{md} & -x_{md} & x_{kd} & 0 & 0 \\ 0 & 0 & 0 & -x_q & x_{mq} \\ 0 & 0 & 0 & -x_{mq} & x_{kq} \end{bmatrix} \begin{bmatrix} \Delta i_f \\ \Delta i_d \\ \Delta i_{kd} \\ \Delta i_q \\ \Delta i_{kq} \end{bmatrix} \tag{11}$$

From Eqn. (11), the currents can be derived as a function of fluxes. These yields

$$\Delta i_f = a_6 \Delta\Psi_f + a_7 \Delta\Psi_{kd} + a_8 \Delta\Psi_d \tag{12}$$

$$\Delta i_d = a_3 \Delta\Psi_f + a_4 \Delta\Psi_{kd} + a_5 \Delta\Psi_d \tag{13}$$

$$\Delta i_{kd} = c_1 \Delta\Psi_f + c_2 \Delta\Psi_{kd} + c_3 \Delta\Psi_d \tag{14}$$

$$\Delta i_q = b_1 \Delta\Psi_q + b_2 \Delta\Psi_{kq} \tag{15}$$

$$\Delta i_{kq} = b_3 \Delta\Psi_q + b_4 \Delta\Psi_{kq} \tag{16}$$

The linearized model for this system can be written in the state space form as::

$$\dot{x} = Ax + B_{11}u + B_{22}\Delta T_m \tag{17}$$

$$y = Cx + Du + \theta$$

Where;

$$A = \begin{bmatrix} -w_o r_f a_6 & -w_o r_f a_8 & -w_o r_f a_7 & 0 & 0 & 0 & 0 \\ w_o a_3 (r_e + r_m) & w_o a_5 (r_e + r_m) & w_o a_4 (r_e + r_m) & w_o (1 - x_o b_1) & -w_o x_e b_2 & w_o V_b \cos \delta_o & \Psi_{qo} \\ -c_1 w_o r_{kd} & -c_3 w_o r_{kd} & -c_2 w_o r_{kd} & 0 & 0 & 0 & 0 \\ w_o x_e a_3 & (w_o x_e a_5 - w_o) & w_o x_e a_4 & b_1 w_o (r_e + r_m) & b_2 w_o (r_e + r_m) & -w_o V_b \sin \delta_o & -\Psi_{do} \\ 0 & 0 & 0 & -b_3 w_o r_{kq} & -b_4 w_o r_{kq} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ \frac{w_o a_3 \Psi_{qo}}{2H} & \frac{-w_o}{2H} (I_{qo} - \Psi_{qo} a_5) & \frac{w_o a_4 \Psi_{qo}}{2H} & \frac{w_o}{2H} (I_{do} - \Psi_{do} b_1) & \frac{-w_o b_2 \Psi_{do}}{2H} & 0 & 0 \end{bmatrix}$$

$x = [\Delta\Psi_f \quad \Delta\Psi_d \quad \Delta\Psi_{kd} \quad \Delta\Psi_q \quad \Delta\Psi_{kq} \quad \Delta\delta \quad \Delta\omega]^T$, are the system states

u is the control signal

θ = is the sensor noise

$B_{11} = [w_o \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0]^T$, is the input vector

$B_{22} = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad w_o / 2H]^T$, is the disturbance vector

The mathematical coefficients a_1, a_2, \dots , and c_3 can be summarized as follows [2]:

$$a_1 = x_f x_d x_{kd} / x_{md} - x_{md} x_f - x_{kd} x_{md} + 2x_{md}^2 - x_{md} x_d$$

$$a_2 = (x_f x_{md} - x_{md}^2 - x_f x_d + x_d x_{md})$$

$$a_3 = ((x_{md} - x_d) / a_2) (1 - ((x_f x_d x_{kd} / x_{md} - x_{kd} x_f + x_{md}^2 - x_{md} x_d) / a_1))$$

$$a_4 = \frac{-1}{a_2} \{x_f / x_{md} (x_{md} - x_d) + (x_d x_f / x_{md} - x_{md}) [(x_f x_d x_{kd} / x_{md} - x_{kd} x_f + x_{md}^2 - x_{md} x_d) / a_1]\}$$

$$a_5 = \frac{-1}{a_2} \{(x_{md} - x_f) ((x_f x_d x_{kd} / x_{md} - x_{kd} x_f + x_{md}^2 - x_{md} x_d) / a_1)\}$$

$$a_6 = 1/x_f + a_3 x_{md} / x_f - x_{md} / x_f (x_{md} - x_d) / a_1$$

$$a_7 = a_4 x_{md} / x_f - x_{md} / x_f \{ (x_d x_f / x_{md} - x_{md}) / a_1 \}$$

$$a_8 = a_5 x_{md} / x_f - x_{md} / x_f \{ (x_{md} - x_f) / a_1 \}$$

$$b_1 = x_{mq}^2 / (x_q (x_{mq}^2 - x_{kq} x_q)) - 1/x_q$$

$$b_2 = -x_{mq} / (x_{mq}^2 - x_{kq} x_q)$$

$$b_3 = -b_2$$

$$b_4 = -x_q / (x_{mq}^2 - x_{kq} x_q)$$

$$c_1 = (x_{md} - x_d) / a_1$$

$$c_2 = (x_d x_f / x_{md} - x_{md}) / a_1$$

$$c_3 = (x_{md} - x_f) / a_1$$

3. MODEL BASED PREDICTIVE CONTROL

MBPC is a name of several different control techniques. All are associated with the same idea. The prediction is based on the model of the process, as it is shown in Fig. 2.

The target of the model-based predictive control is to predict the future behavior of the process over a certain horizon using the dynamic model and obtaining the control actions to minimize a certain criterion, generally [10]:

$$J = \sum_{k=N_1}^{N_2} \left(M(t+k) - Y_m(t+k) \right)^2 + \sum_{k=1}^{N_u} \left(\lambda_k \Delta U_n(t+k) \right)^2 \quad (18)$$

Signals $M(k+t)$, $Y_m(k+t)$, $u(k+t)$ are the t -step ahead predictions of the process output, the reference trajectory and the control input, respectively. The values N_1 and N_2 are the minimal and maximal prediction horizon of the controlled output, and N_u is the prediction horizon of the control input. The value of N_2 should cover the important part of the step response curve. The use of the control horizon N_u reduces the computational load of the method. The parameter λ represents the weight of the control signal. At each sampling period only the first control signal of the calculated sequence is applied to the controlled process. At the next sampling time the procedure is repeated. This is known as the receding horizon concept.

The controller consists of the plant model, the optimization block, objective function and prediction block as shown in Fig. 2. The input and output constraints are:

$$\begin{aligned} u_{\min} &\leq u_i \leq u_{\max}, & i = 0, \dots, N_2 - 1 \\ \Delta u_{\min} &\leq \Delta u_i \leq \Delta u_{\max}, & i = 0, \dots, N_2 - 1 \\ y_{\min} &\leq y_i \leq y_{\max}, & i = 1, \dots, N_2 \end{aligned}$$

The ability to handle constraints is one of the key properties of MBPC and also causes its spread, use, and popularity in industry. MBPC algorithms are reported to be very versatile and robust in process control applications.

4. NEURAL NETWORK PREDICTIVE CONTROL

Neural networks have been applied very successfully in the identification and control of dynamic systems. The universal approximation capabilities of the multilayer perception make it a popular choice for modeling of nonlinear systems and for implementing of nonlinear controllers. The unknown function may correspond to a controlled system, and the neural network is the identified plant model. Two-layer networks, with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer, are universal approximations. The prediction error between the plant output and the neural network output is used as the neural network training signal. The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The structure of the neural network plant model is given in the Fig. 3, where $u(t)$ is the system input, $yp(t)$ is the

plant output, $ym(t)$ is the neural network model plant output, the blocks labeled TDL are tapped delay lines that store previous values of the input signal, $IW_{i,j}$ is the weight matrix from the input j to the layer i . $LW_{i,j}$ is the weight matrix from the layer j to the layer i .

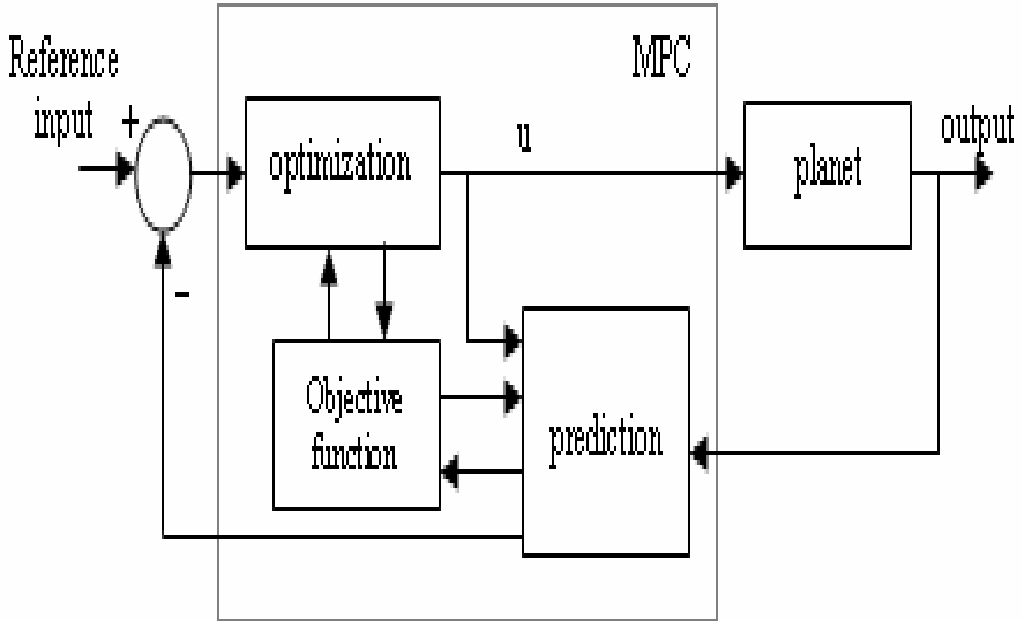


Fig. 2. Classical model-based predictive control scheme

This network can be trained off-line in batch mode, using data collected from the operation of the plant. The procedure for selecting the network parameters is called training the network. The Levenberg-Marquardt (LM) algorithm is very efficient for training. The LM algorithm is an iterative technique that locates the minimum of a function that is expressed as the sum of squares of nonlinear functions. It has become a standard technique for nonlinear least-squares problems and can be thought of as a combination of steepest descent and the Gauss-Newton method [17]. When the current solution is far from the correct one, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Gauss-Newton method.

Assumed functional relation which maps a parameter vector $P \in R^m$ to an estimated measurement vector $\hat{x} = f(p), \hat{x} \in R^n$. An initial parameter estimate p_0 and a measured vector x are provided, and it is desired to find the vector \hat{p} that best satisfies the functional relation f , i.e. minimizes the squared distance $e = x - \hat{x}$. The basis of the LM algorithm is a linear approximation to f in the neighborhood of p . For a small $\|\delta_p\|$, a Taylor series expansion leads to the approximation

$$f(P + \delta_p) \approx f(P) + J\delta_p \text{ where } J \text{ is the Jacobi matrix } \frac{\partial f(P)}{\partial P}. \text{ Like all non-linear}$$

optimization methods, LM is iterative: initiated at the starting point p_0 , the method produces a series of vectors p_1, p_2, \dots , that converge towards a local minimize \hat{p} for f . Hence, at each step, it is required to find the δ_p that minimizes the quantity $\|e - J\delta_p\|$. The sought δ_p is thus the solution of a linear least-square problem: the minimum is attained when $J\delta_p - e$ is orthogonal to the column space of J . This leads to $J^T(J\delta_p - e) = 0$ which yields δ_p as the solution of the normal equations:

$$J^T J \delta_p = J^T e \quad (19)$$

The matrix $J^T J$ in the left hand side of Eqn. (19) is the approximate Hessian, i.e. an approximation to the matrix of second order derivatives. The LM method actually solves a slight variation of Eqn. (19), known as the augmented normal equations $N\delta_p = J^T e$, here the off-diagonal elements of N are identical to the corresponding elements of $J^T J$ and the diagonal elements are given by $N_{ii} = \mu + [J^T J]_{ii}$. The strategy of altering the diagonal elements of $J^T J$ is damping and is referred to the damping term. If the updated parameter vector $p + \delta_p$ with δ_p computed from Eqn. (19) leads to a reduction of the error e , the update is accepted and the process repeats with a decreased damping term. Otherwise, the damping term is increased, the augmented normal equations are solved again and the process iterates until a value of δ_p that decreases error is found.

In LM, the damping term is adjusted at the following conditions are met. Each iteration to assure a reduction in the error e . The LM algorithm terminates when at least one of

1. The magnitude of the gradient of $e^T e$, i.e. $J^T e$ in the right hand side of Eqn. (19), drops below a threshold ϵ_1 .
2. The relative change in the magnitude of δ_p drops below a threshold ϵ_2 .
3. The error $e^T e$ drops below a threshold ϵ_3 .
4. A maximum number of iterations k_{max} is completed.

If a covariance matrix Σ for the measured vector x is available, the minimum is found by solving a weighted least squares problem defined by the weighted normal equations:

$$J^T \Sigma J \delta_p = J^T \Sigma e \quad (20)$$

Model predictive control using a neural network model for single-input, single-output systems has been studied by a few researchers and is outlined. For multivariable systems, the neural network MPC strategy was described using three fixed MLP models. The same strategy is used in our system using two MLP models with an adaptive model as shown in Fig.4.

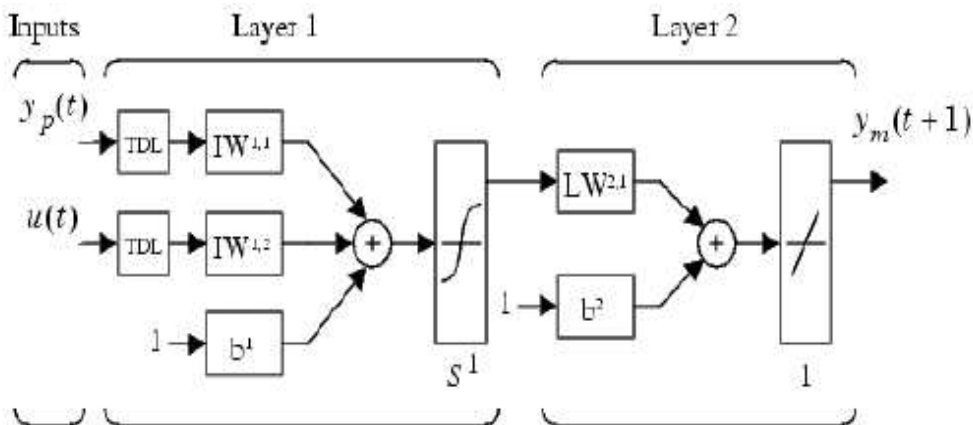


Fig. 3: Structure of the neural network plant model

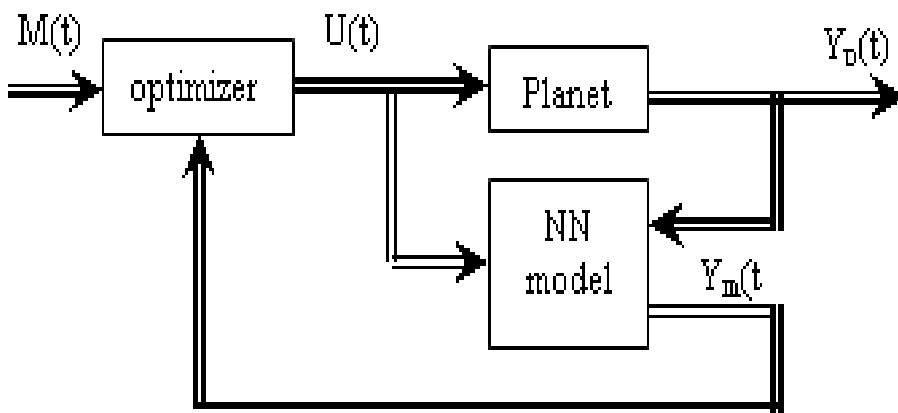


Fig.4: Multivariable NN MPC control strategy

5. PID POWER SYSTEM STABILIZER

PID controllers are dominant and popular and, have been widely used because one can obtain the desired system responses and they can control a wide class of systems. This may lead to the thought that the PID controllers give solutions to all requirements, but unfortunately, this is not always true [18]. In this work, the PID optimal tuning method used is found in Ref. [19]. In this method, the parameters of PID controller satisfying the constraints correspond to a given domain in a plane. The optimal controller lies on the curve. The design plot enables the identification of the PID controller for desired robust conditions, and in particular, gives the PID controller for lowest sensitivity. By applying this method, trade-off among high frequency sensor noise, low frequency sensitivity, gain and phase margin constraints are also directly available.

The transfer function of a PID controller is given by:

$$K(s) = K_p \left(1 + \frac{1}{T_I s} + T_D s \right) \tag{21}$$

where K_p , $\frac{K_p}{T_I}$ and $K_p T_D$ represent the proportional, integral and derivative gains

of the controller respectively. Define $\omega_n = \frac{1}{\sqrt{T_I T_D}}$ and $\zeta = \frac{1}{2} \sqrt{\frac{T_I}{T_D}}$ as the controller's

natural frequency and the damping coefficient, respectively. Then the PID transfer function can be written as:

$$K(s) = K_p \frac{\omega_n^2 + 2\zeta\omega_n s + s^2}{2\zeta\omega_n s} \tag{22}$$

The optimal PID controller parameters values were: $K_p = 22$, $T_I = 0.6$ and $K_D = 12$

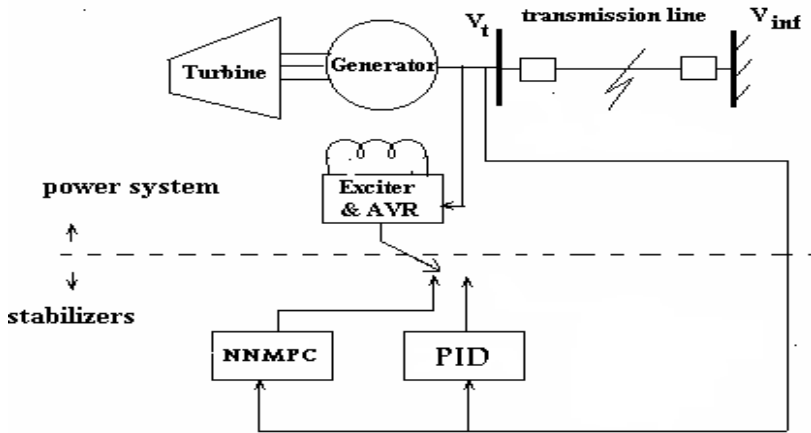


Fig. 5: Schematic diagram of power system model with different power system stabilizers

6. SIMULATION RESULTS AND DISCUSSION

The objective of this control is to stabilize the power system performance and minimize the deviation between the actual and reference field voltage. The cost function of Eqn. (18) will have the following form for the proposed system:

$$J = \sum_{k=N_1}^{N_2} \left(V_f(t+k) - V_{fpred}(t+k) \right)^2 + \sum_{k=1}^{N_u} \left(\lambda_k V_{fref}(t+k) \right)^2 \tag{23}$$

the constraints are chosen such that, the output voltage is normalized to be 1, corresponds to output voltage. Thus,

$$V_{ref} - \epsilon \leq u_p \leq V_{ref} + \epsilon .$$

The controller using a neural network model to predict future power system responses and potential control signals is designed. Then, an optimization algorithm related to Eq. (23) computes the control signals that optimize future plant performance. The neural network plant model was trained using the Levenberg–Marquardt algorithm. The training data were obtained from the model of the power system model (1–7). The used model predictive control method was based on the receding horizon technique. The neural network model predicted the plant response over a specified time horizon. The predictions were used by a numerical optimization program to determine the control signal that minimizes performance criterion over the specified horizon. The controller was implemented using Matlab/Simulink software program.

Choosing power system parameters as given in Ref. [2] in a pu.as follows:

$$\begin{aligned}
 X_f &= 1.1, & X_d &= 1.2, & X'_d &= 0.291, & X_{kd} &= 1.1, & X_{md} &= 1.0, & X_q &= 0.8 \\
 X_{kq} &= 0.8 & X_{mq} &= 0.6, & r_m &= 0.01, & r_{kd} &= 0.02, & r_{kq} &= 0.04, & r_f &= 0.0011 \\
 T'_{do} &= 2.65, & H &= 3.0, & T_{mo} &= 0.01, & r_e &= 0.0, & x_e &= 0.4, & w_o &= 377.0
 \end{aligned}$$

Applying the proposed NNMPC and PID controller to the power system under study as shown in Fig. 5. Fig. 6 shows the rotor speed deviation response due to 0.1pu. step disturbance at 0.5 lag power factor load with both PID and NN-MPC controller. Fig. 7 depicted the rotor speed deviation response due to 0.1pu. step disturbance at -0.5 lead power factor load with both PID and NN-MPC controller. Fig.8 shows the rotor speed deviation response due to 0.1pu. step disturbance at 0.8 lag power factor load with both PID and NN-MPC controller. Also, Fig. 9 shows the rotor speed deviation response due to 0.1pu. step disturbance at -0.8 lead power factor load with both PID and NN-MPC controller. Moreover, the rotor speed deviation response due to 0.1pu. step disturbance at 0.8 lag power factor load with PID and NN-MPC controller with 20% increase in X_f and X_d . is shown in Fig. 10. Fig. 11 depicted the rotor speed deviation response due to 0.1pu. step disturbance at -0.8 lead power factor load with PID and NN-MPC controller with 20% increase in X_f and X_d . Fig. 12 shows the rotor speed deviation response due to 0.1pu. step disturbance at -0.6 lead power factor load with PID and NN-MPC controller with 20% increase in X_f and X_d . Furthermore, the maximum overshoot (MP), settling time (T_s) and steady state error (e_{ss}) are calculated in table 1 at different operating point.

Table 1; The time settling and step- characteristic of different controller

	Vt=1 pu. , Pf=0.8 Lag power factor load		Vt=1 pu. , Pf= -0.5 Lead power factor load	
	With PID control	With NN-MPC	With PID control	With NN-MPC
<i>MP</i>	0.029	0.008	0.028	0.012
<i>T_s</i>	9.0	1.0	9.0	0.9
<i>e_{SS}</i>	0	0	0	0

Where; MP is the maximum peak; T_s is the settling time, e_{ss} is the steady state error

It is clear that from the above figures that the overshoot, undershoot with less time settling of the time response system in case of the proposed NNMPC controller are shorter and smaller than the case of PID controller. From table 1, the settling time with PID controller is 9 Sec. but with the proposed NNMPC is 1 Sec. Moreover, the steady state error is zero in both PID and NNMPC controllers.

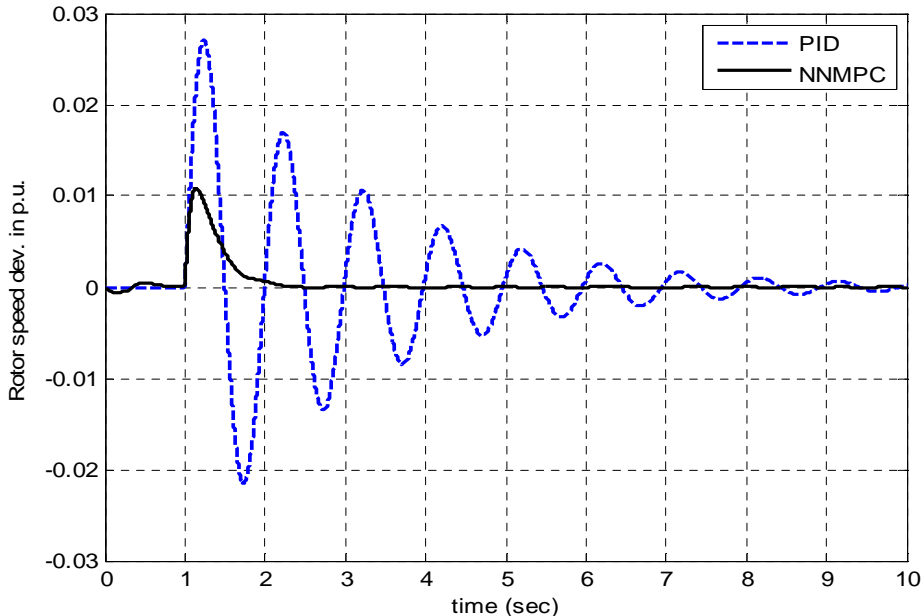


Fig. 6: Rotor speed deviation response due to 0.1pu. step disturbance at 0.5 lag power factor load with PID and NN-MPC controller.

7. CONCLUSIONS

The scope of this paper is to investigate the potential improvements that can be achieved using neural network predictive control methodologies for the design of power system stabilizer. To validate the effectiveness of the proposed controller, a comparison among the PID controller and the proposed NN-MPC controller is obtained. Both the proposed NN-MPC and PID with the single synchronous machine connected to infinite bus power system is evaluated when both load and parameters changed. From the simulations results, it is seen that the proposed controller is robust and gives good transient as well as steady -state performances. The digital simulation results validate the effectiveness and powerful of the proposed NN-MPC controller compared with the PID stabilizer in terms of fast power system mechanical oscillation damping over a wide range of operating conditions and variations in system parameters. The time settling with the proposed NN-MPC stabilizer is smaller than the corresponding value with PID stabilizer. The maximum over and under shoot with the proposed NN-MPC stabilizer is less than the corresponding value with PID controller.

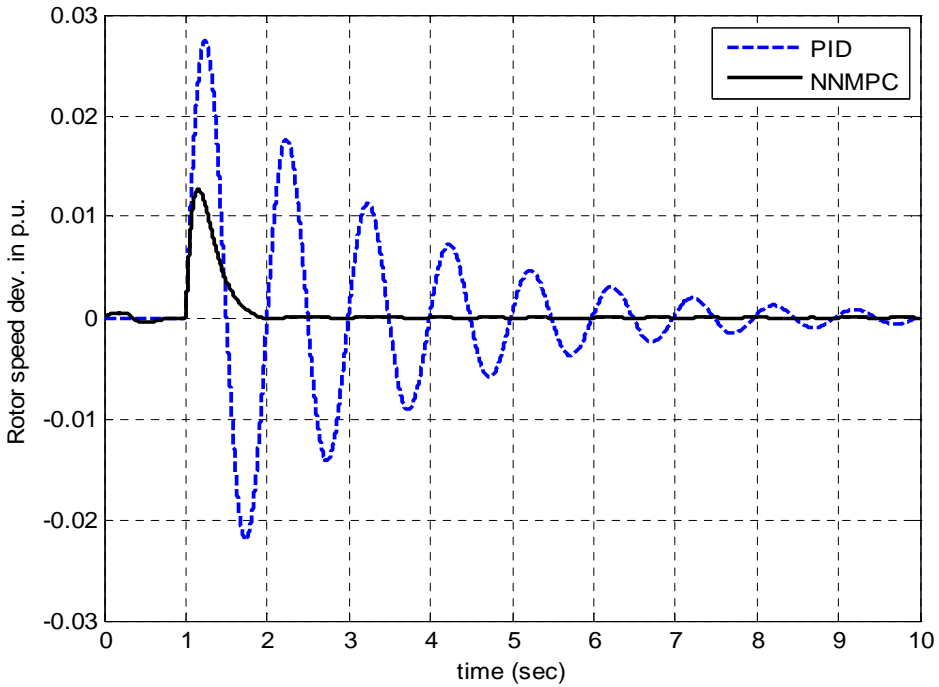


Fig. 7: Rotor speed deviation response due to 0.1pu. step disturbance at -0.5 lead power factor load with PID and NN-MPC controller.

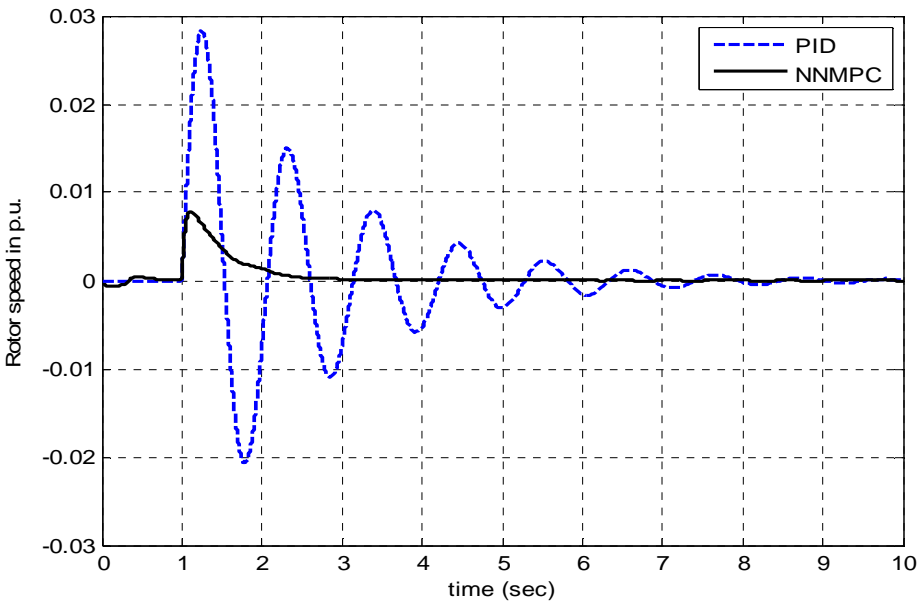


Fig. 8: Rotor speed deviation response due to 0.1pu. step disturbance at 0.8 lag power factor load with PID and NN-MPC controller.

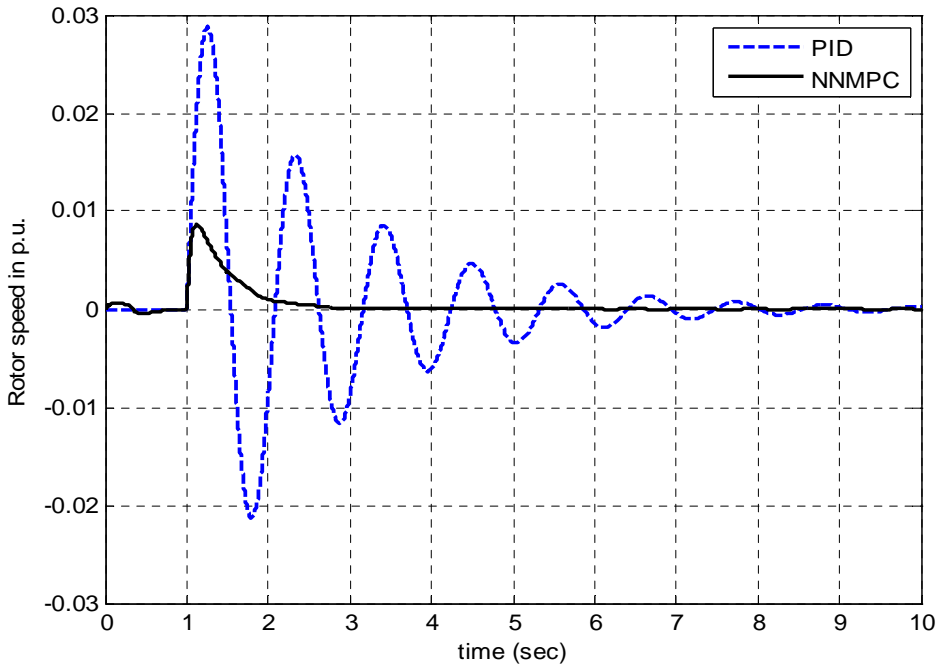


Fig. 9: Rotor speed deviation response due to 0.1pu. step disturbance at -0.8 lead power factor load with PID and NN-MPC controller.

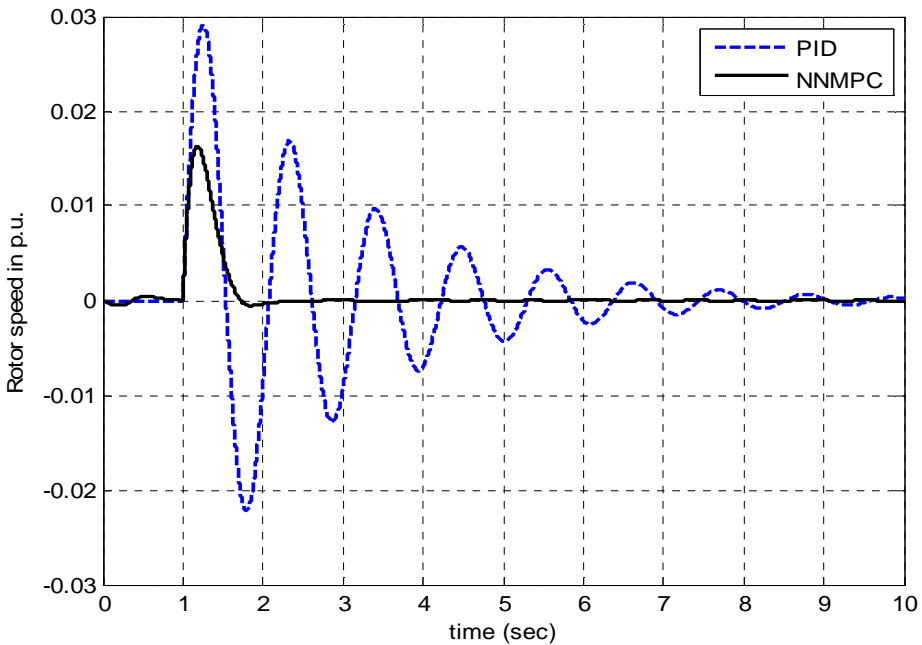


Fig. 10: Rotor speed deviation response due to 0.1pu. step disturbance at 0.8 lag power factor load with PID and NN-MPC controller with 20% increase in X_f and X_d .

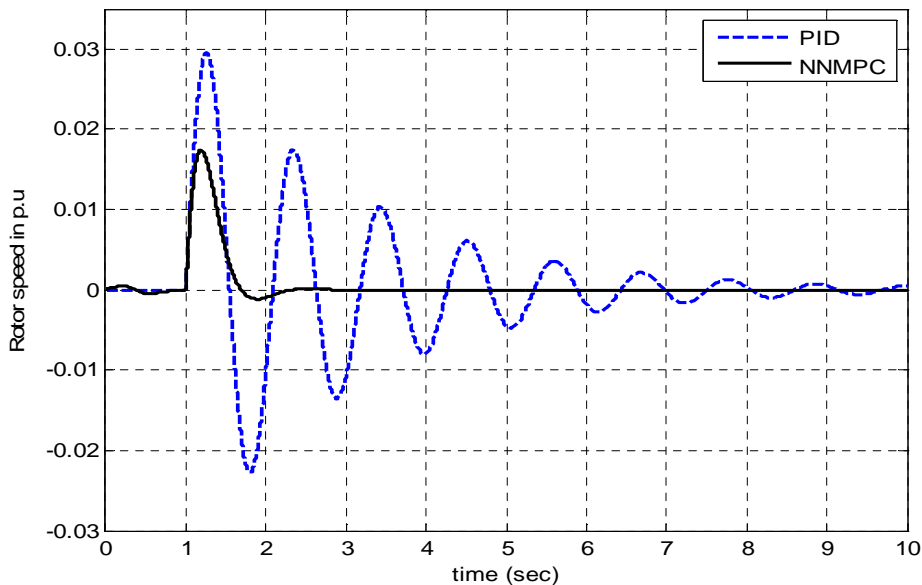


Fig. 11: Rotor speed deviation response due to 0.1pu. step disturbance at -0.8 lead power factor load with PID and NN-MPC controller with with 20% increase in X_f and X_d .

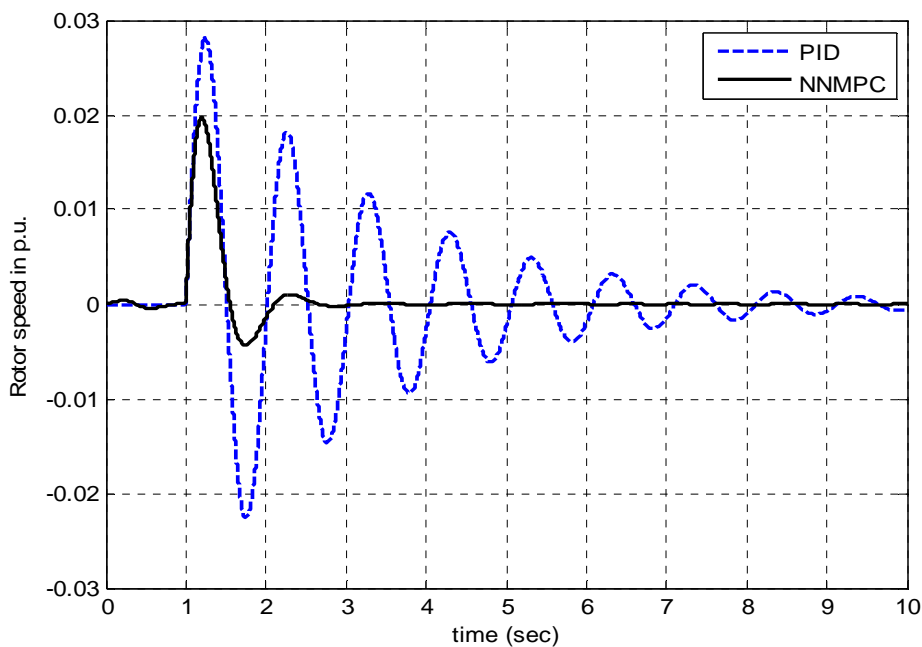


Fig. 12: Rotor speed deviation response due to 0.1pu. step disturbance at -0.6 lead power factor load with PID and NN-MPC controller with with 20% increase in X_f and X_d .

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مثبت نظام كهربائي معتمد على التحكم بشبكة الأعصاب التنبؤية

البحث الحالي يقوم بفحص مثبت النظام الكهربائي مستندا على التحكم التنبؤي بشبكة الأعصاب الاصطناعية لتحسين أداء النظام الكهربائي الديناميكي على تشكيلة واسعة من حالات التشغيل، إقترحت هذه الدراسة تصميم وتطبيق جهاز سيطرة الشبكة العصبية النموذجي التنبؤي (NN-MPC) على نظام كهربائي بسيط متكون من مولد متزامن موصل إلى حافلة لانهائية خلال خط نقل، إن الماكينة المترامنة ممثلة بالتفصيل مع الأخذ في الحسبان تأثير بروز اقطاب الماكينة و القطب الملفوف، التحكم بالشبكة العصبية النموذجية التنبؤية (NN-MPC) تدمج تنبؤ موثوق من الشبكة العصبية بالأداء الممتاز من السيطرة التنبؤية النموذجية باستخدام طريقة ليفن مارك الاخطية النموذجية، استعملت هذه السيطرة إنحراف سرعة الدوران كإشارة مرجعية، نتائج المحاكاة الرقمية تظهر بأن مثبت نظام الشبكة العصبية النموذجي التنبؤي المقترح الكهربائي يمكن أن يُنجز أداء جيد على نطاق واسع من حالات التشغيل، زيادة على ذلك، أداء جهاز السيطرة المقترح تم مقارنته بجهاز سيطرة معتمد على PID تقليدي خلال دراسات المحاكاة، النتائج المكتسبة توضح التأثير الكبير وتفقو جهاز السيطرة المقترح من ناحية الرد السريع ووقت الاستقرار الصغير.