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Neural Controller Based on Plant's Inverse Model

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ABSTRACT

This paper present a neural controller based on inverse model of a considered plant, with application to excitation control of a synchronous generator connected to a power system. Theoretical basis and practical implementation aspects are described. A simulation study that confirms the obtained result of such a control strategy is performed.

KEYWORDS: process identification, recurrent neural network, training method, neural controller, synchronous generator

1. INTRODUCTION

The basics principle of the process control using a controller that models the inverse dynamics of a process is represented in figure 1. In many cases, the identification of an inverse model of a considered process represents a viable solution to design a control strategy. The design and identification of an inverse model of a certain process is conditioned by the existence of an input-output bijective function.

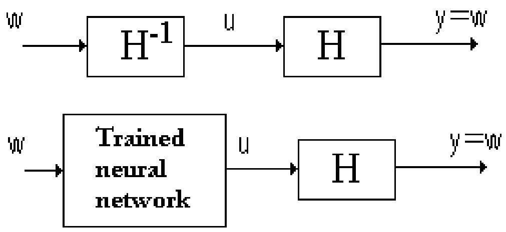

Fig. 1 Control with inverse model

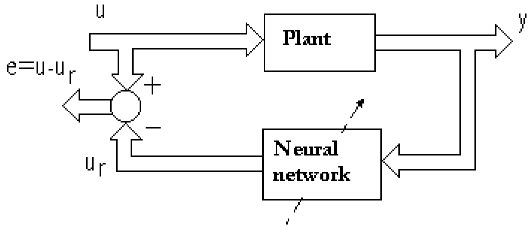

Fig. 2 Inverse model identification

The basic scheme used for the inverse model determination of a process is depicted in figure 2. The neural network receives as input the process's output variable (y), and the process's input variable (u) represents the output data which has to be learned by the network during the training process [1].

The process's input signal (used at the neural network training) is a normally distributed stochastic signal, which represents the deviation of input variable in relation with a fixed value of a stationary regime functioning (taking into consideration the fact that the considered process is a synchronous generator).

The 3000 pairs of input-output [*u(t)-ur(t), y(t)*] are forming the network learning data set, used to identification of a neural model that approximates the inverse dynamic process's characteristic. A larger palette of input signal's amplitude automatically yields up for an increase of sample set data, and consequently a larger amount of data that should be "learned" by the considered neural network.

The considered neural network used for identification (learning) of the process's inverse model is a recurrent network having one hidden layer with 20 neurones (the neurones have a sigmoid tangent activation function).

By using a trained recurrent neural network, which models the process's inverse characteristic, as a controller in a similar systemic configuration with the one presented in figure 1, practically an open-loop control structure is implemented [2].

Such control structure is totally inadequate for the control of a process with a complex dynamic, as the case of a synchronous generator connected to a power system, permanently perturbed by a multitude of factors (including a random noise) [3].

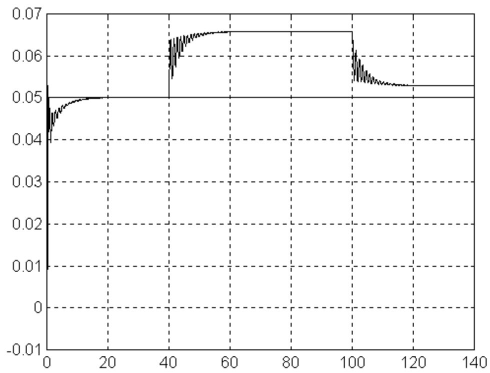

Fig. 3 Change of process output (without the rejection of perturbations)

As an example, in figure 3 is represented the control system's output based on the recurrent neural controller, which approximates the process's inverse model, under the following synchronous generator operating conditions:

- at *t=0* time moment occurs a 5 % step reference variation;
- at *t=40* [sec.] time moment the mechanical torque (as a perturbation) shows a 10% decrease (active power unload);
- at *t=100* time moment, a supplementary local consumer is connected.

There can be noticed that the neural controller responses adequate to a reference variation (lead the process output to the new desired output value), but it is completely non-sensitive to the action of the disturbing factors. All graphical representations have the time axis scaled in seconds.

2. DESIGN OF NEURAL CONTROLLER BASED ON INVERSE MODEL

The proposed solution consists into the addition of a supplemental component in order to complete the recurrent neural network architecture (that models the process's inverse dynamics). This component has as input variable the error between the reference value and the controlled output variable (closing the loop of control structure). The objective of the supplementary component is to adapt the *bias* factor of the final neurone representing the output layer. This structure implements a mechanism that rejects the perturbation's effect (the output error becomes zero), practically having the role of an external integrating loop. The generalised neural controller's structure is presented in figure 4 (for the considered plant -synchronous generator modelled as a 4^{th} order system -, with the particular values n=m=4 and N=20). The tuning mechanism of the final neurone *bias* implements the following relation: $BIAS(t+1) = BIAS(t) + k[w(t) - y(t)]$, where $BIAS(0)$ is initialised with a value $bias_0$

obtained through an off-line network training process and the *k* constant can be calculated off-line, by performing some tests.

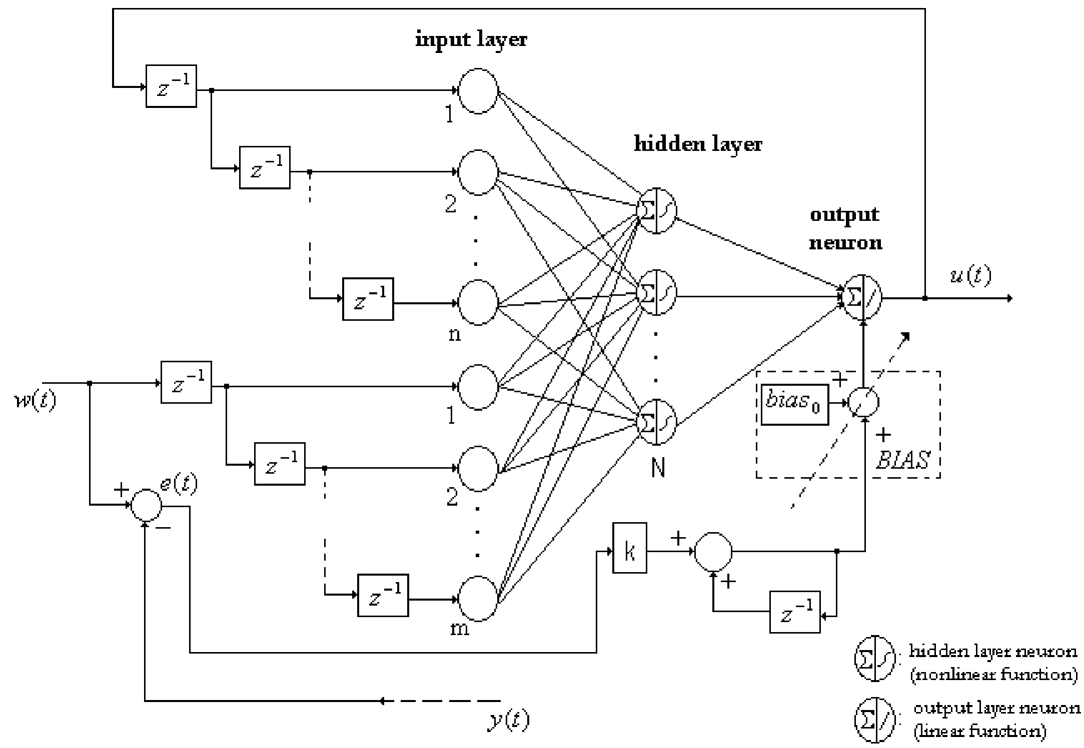

Fig. 4 Neural controller with tuning of final neurone *bias*

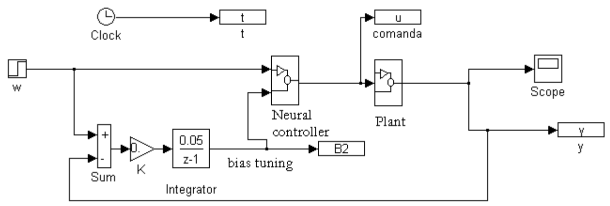

Fig.5.a. The Simulink model of the neuronal control structure

The implementation and simulation of the neuronal control structure was done in Matlab – Simulink. The Simulink models of the generalised neuronal control structure and the corresponding subsystems are presented in figures 5.a,b,c.

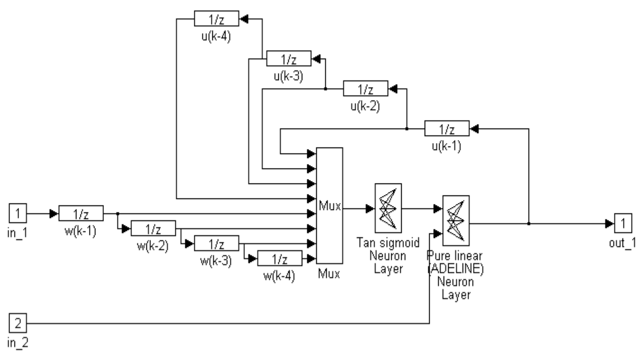

Fig.5.b. The Simulink model of neuronal controller subsystem

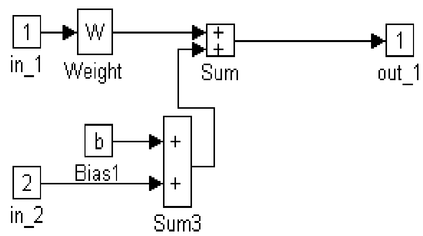

Fig.5.c The Simulink model of final neurone's subsystem (ADALINE)

3. STUDY CASE

In the same conditions of reference modification and perturbation's actions (already stated), for which have been obtained unsatisfactory results as presented in figure 3, the new control structure (completed with the final neurone's bias tuning mechanism) shows a much better response (as depicted in figures 6 and 7). There can be noticed a rejection of the perturbation's effect (modification of mechanical torque, the connection of additional consumers).

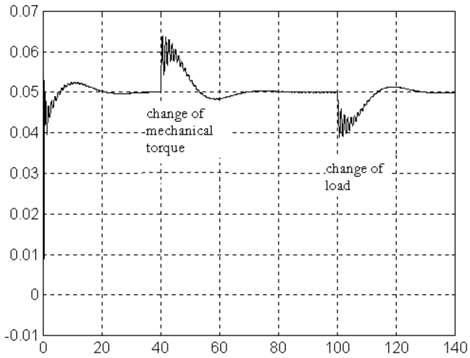

Fig. 6 Change of process output (structure with *bias* tuning)

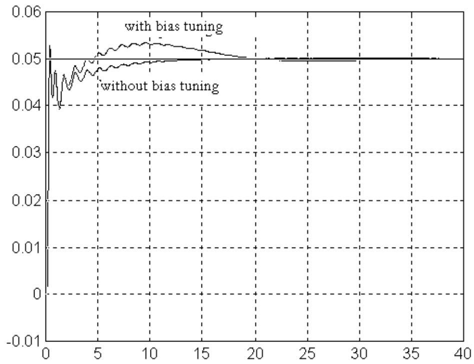

Fig. 7 Compared changes of process outputs (structure with and without *bias* tuning)

In figure 7 is presented the control system's response at a reference modification, in the case of additional tuning mechanism usage, comparatively to the situation without the usage of this mechanism. To such operating conditions (change of reference) the differences between the controlled output are small.

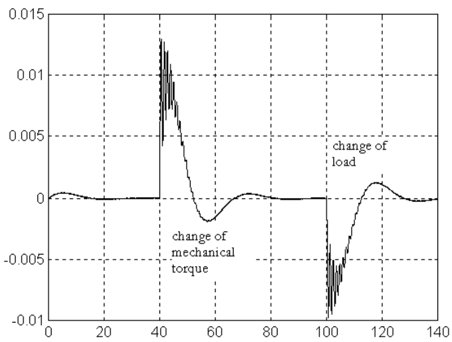

Fig.8.a. Change of process output

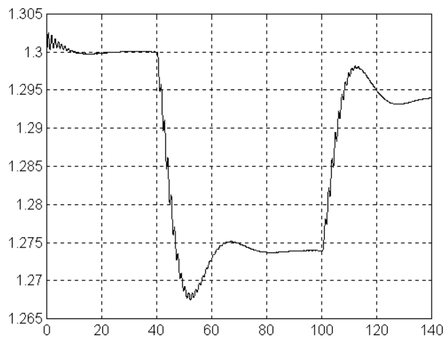

Fig.8.b. Controller output

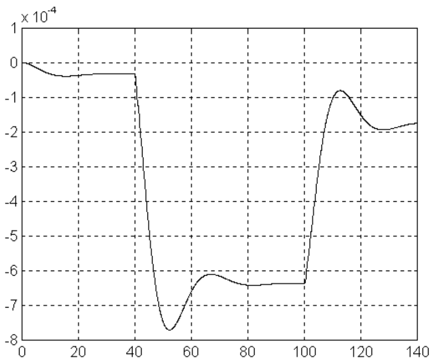

Fig.8.c. Tuned *bias* factor

The figures 8.a,b,c present the controlled output (with perturbation rejection), the controller output and respectively the *bias* evolution of final neurone placed on output layer. There can be noticed a relatively reduced dynamic of the controller output.

Although the new neuronal structure rejects the perturbation, as a fact to the on-line tuning of the final neurone *bias*, the performances of this control structure (in the case of an synchronous generator connected to a power system) are relatively poor comparatively with those conferred by a classic self-tuning control (overshoots/undershoots with higher amplitude, longer period of transient regimes). [4] The control structure is viable, but its practical implementation depends on the process's characteristics and on the imposed controlled output's performances.

4. CONCLUSION

The recurrent neural controller (including the tuning mechanism of the output neurone *bias*), presented in this paper with application to excitation control of a synchronous generator, could be implemented in a simply manner and with relatively good results, proved by computer simulation. An adequate choice of initial *BIAS* factor value can optimise the neural control system performances.

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