J. Automation & Systems Engineering 3-1 (2009): 26-40

Regular paper

JASE
Journal of Automation
& Systems Engineering

Neuronal Control of an Artificial Swells Generation System

Raouf Ketata, Sofiène Hermi and Taieb Ben Romdhane

This paper tries a neuronal approach to control a non linear complex system used for the generation of artificial swells. Artificial Neuronal Networks (ANN), as universal approximator especially for non linear functions, are used in modeling and controlling the swells generator using a non linear model, that of Pierson MOSKOWICH, which represents well the Mediterranean swell behavior. The proposed structure is composed of two units: the first is referred to as Neuronal Supervisor (NS) for priming the swells generation system and the second as Neuronal Control by Internal Model (NCIM) dedicated to command the same system. So, the latter unit contains an Inverse Model (IM) as a regulator, a Direct Model (DM) as a predictor, and a low-pass filter expected to reduce the modeling errors. After adopting a judicious choice of the structure parameters, the obtained results have well confirmed the ANN importance as a universal approximator characterized by the learning capability.

Keywords: Swells Generator; Pierson MOSKOWICH Spectrum; Function Approximation; Neuronal Control and Modeling.

1. INTRODUCTION

The development of intelligent systems such as fuzzy system theory, neuronal networks, and neuro-fuzzy networks, is attracting increasingly the attention of many researchers. In particular the number of industrial applications using Artificial Neuronal Networks (ANN) has been increasing over the last decades [1, 8, 9, 14, and 18]. Indeed, the ANN has been applied in many engineering fields for example system identification, adaptive control…etc. Moreover, many researches have been made in order to discuss the stability and robustness of neuronal control systems. W. Frey et al suggest a neuro-fuzzy supervisory control system for industrial batch processes [24], C.-F. Juang et al give us a recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithms [1], also C. Li et al present self-organizing neuro-fuzzy system for control of unknown plants [2], M. Fazle Azeem et al describe a Structure Identification of Generalized Adaptive Neuro-Fuzzy Inference Systems [15].

In this way, neuronal modeling and control of non linear systems by ANN has been the subject of many research works; this is due principally to ANN great capability of learning, approximation, and generalization with fewer experimental data [13, 16, and 25]. Artificial swells generation system is developed to control oceanic waves in order to protect maritime coasts.

S. Mottelet [20] study the controllability and stabilization of a canal with wave generators, in the same context, we tried to propose integrate neuronal networks to control and supervise artificial swells generation system. Being one of the best universal approximators

Research Unit on Intelligent Control, Design and Optimization of Complex System (ICOS), University of Sfax, National School of Engineers of Sfax, Tunisia. Raouf.Ketata@insat.rnu.tn
Department of Instrumentation and Physical Engineering, National Institute of Applied Sciences and Technologies (INSAT), Tunis, Tunisia. HermiSofiene@yahoo.fr, BENROMDHANE.T@planet.tn

[12], the ANN can reproduce swells behavior faithfully taking into consideration electrical and mechanical constraints and limits of the generation system: limit frequencies, displacements, acceleration, torque, etc.

The development of this survey will be divided into two parts. The first part will deal with the design and generation of digital commands of the random swells generator in conformity with Pierson MOSKOWICH energy spectrum. The second part will be dedicated to the development of a control law permitting the regulation of canal-generated swells according to the energy spectrum parameters initially adopted. T. Ben Romdhane et al [21, 22, and 27] gave us a detailed survey about the design and control of the swells generation system.

2. SYSTEM'S NEURONAL MODELING AND CONTROL

In this paper, it is difficult to discuss all neuronal network structures e.g. the multilayer network of back- propagation type, the Hopfield networks, the Kohonen auto-organizer cards, and the recurrent neuronal networks. To that effect, Multilayer Perceptron (MLP) presents many advantages [23] such as the learning capability concerning the approximation of non linear and relatively complicated functions according to the structure presented by Fig. 1 [19, 25]. Network parameters are adjusted in a view to produce an output similar to that of the unknown function – the input being the same for both systems. In case the unknown function can represent the controlled system, the corresponding neuronal network uses the part of a predictor. Moreover, this function can represent the inverse of a controlled system of which the neuronal network is a regulator.

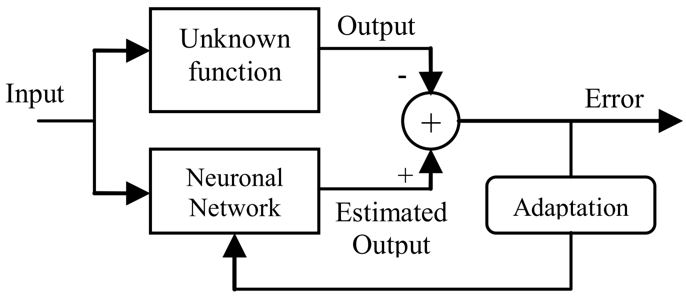

Fig. 1. Neuronal approximation of unknown function.

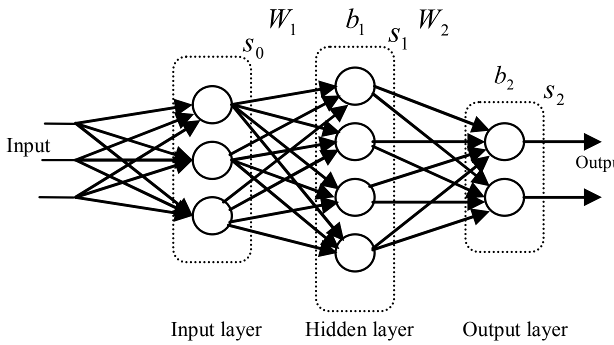

Fig. 2. MLP structure.

2.1. Multilayer Perceptron Architecture

The perceptron is generally organized into three layers as Fig. 2 shows. The first layer (input layer) links the input data to the following layer (hidden layer). Similarity, this latter is connected to the last layer (output layer) producing the MLP outputs. Many research studies [23, 26] have shown that a MLP of three layers is sufficient to approximate the majority of complicated functions. This limitation of layers number to three prompts us to choose carefully the number of hidden layer neurons, so that we guarantee a good network convergence.

2.2. Multilayer Network Learning

Neuronal function approximation requires a practical method permitting the determination of the appropriate network parameters represented by weights and biases. Generally, the gradient back-propagation method is the most used to network learning.

This method, which is based on gradient descent algorithm, allows the updating of weights by minimizing a cost function generally chosen of the quadratic type given by the expression (1):

$$J = \frac{1}{2}(d - s)^2 \tag{1}$$

In every layer, the weights are given by expressions (2).

$$w_{i,j}(t+1) = w_{i,j}(t) - \eta . \frac{\partial J}{\partial w_{i,j}(t)} \tag{2}$$

$$b_{i,j}(t+1) = b_{i,j}(t) - \eta . \frac{\partial J}{\partial b_{i,j}(t)} \quad i, j = 1,\ 2\ and\ 3$$

With d is the desired output, s the neural model output, and η denotes learning rate (lower than 1).

2.3. Neuronal Control Structures

ANN are used for systems control according to different structures: predictive, reference model, with internal model [7, 16]…etc

Seeing its advantages, we have chosen the internal model structure to control the swells generation system. The general structure of such control system is represented in Fig. 3 [5, 11].

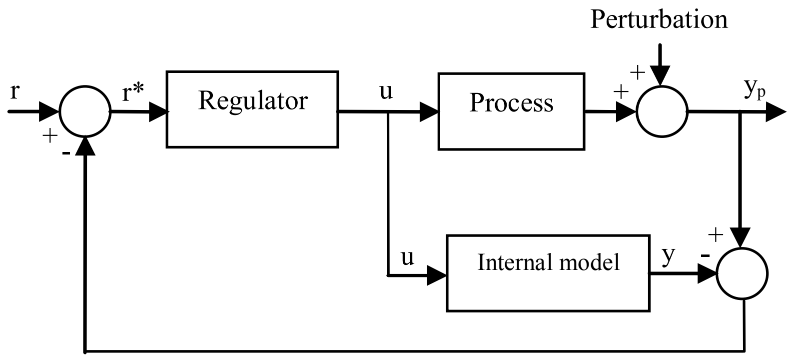

Fig. 3. Control Structure Using Internal Model.

We note that:

- r : reference signal (set point)
- y_p : process output

- y : internal model output
- u : control signal delivered by the neuronal regulator
- r^* : regulator input.

This control structure preserves the advantages of classical feedback control. In fact, it allows compensating the unknown or unmeasured perturbations as well as the modeling errors.

It is so easy to conceive the regulator synthesis since the stability conditions of the global system are those of an open loop control.

Both parts of this structure are based on ANN (MLP type). The Direct Model (DM) type acts as the process predictor. The Inverse Model (IM) imposes the dynamics of the system. The regulator learning is based on the IM of the predictor, as long as it is stable, for the real system of swells generation is stable. Internal model control using neural networks is reviewed by E. Haber Rodolfo et al [6], I. Rivals [10], J. Alvarez [11], and D.C. Psichogios [4].

3. PRESENTATION OF SWELLS CANAL SYSTEM

The oceanic waves have been being studied for a long time. Studies were authorized for the control of these waves and consequently for the development of their spectrum models. In fact, the objective of these studies is the protection of the maritime coasts. Indeed, to that effect, a miniature system allowing describing, as faithfully as possible, the oceanic waves behavior is needed. This system appears under the canal form permitting the swells generation. Research tasks have been undertaken for the design of a supervision and control model of our system.

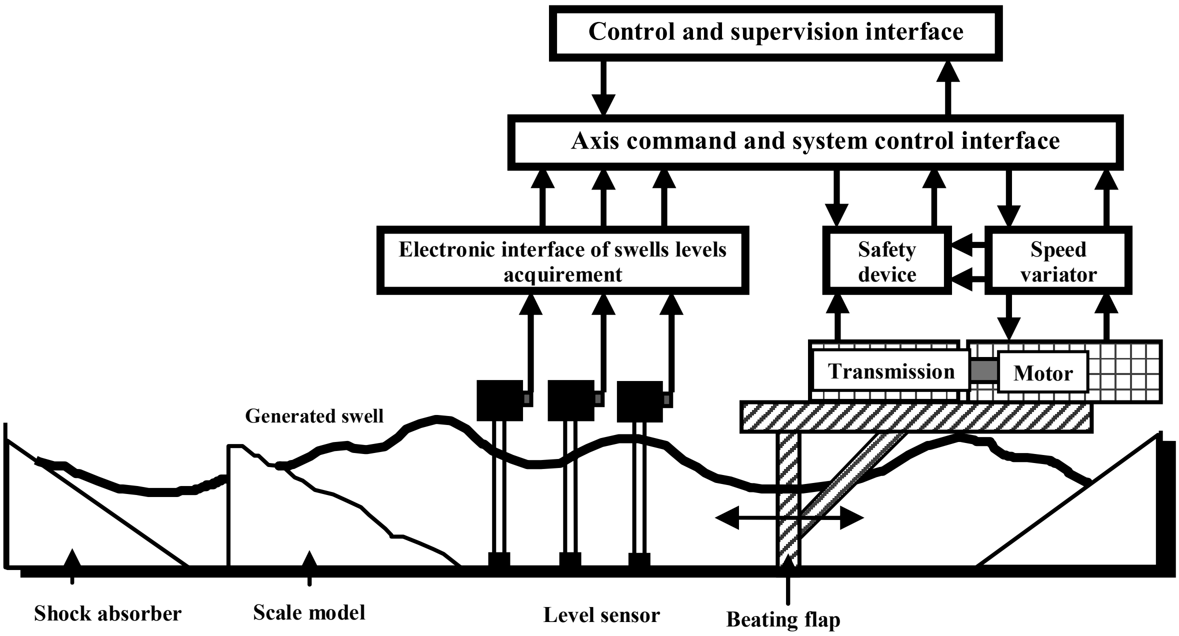

Fig. 4. Swells canal system.

Physically, swells canal system (Fig. 4) is characterized by a canal of 37.5 m of length integrating the mockup of the port to control. To generate waves in this canal, a beating flap driven by a servomechanism is used. This latter is controlled by an axis command card which assures the automatic control of positions and the security check. This card is supervised from a microcomputer allowing the generation of digital commands and the exploitation of measured swells in the canal. The characteristics of the swells generator are inspired from research works made on the swells canal system by T. Ben Romdhane et al [21, 22, and 27].

3.1. Generation of tasks and task graph

For the swells generation, we have used Pierson MOSKOWICH spectrum given by the expression (3) and represented by the Fig. 5. This spectrum is characterized by the amplification constant α, the gravity constant g, the central frequency f_p, and the extreme frequencies $f_{\min}$ and $f_{\max}$ of the spectrum.

$$S(f) = \alpha . g^2 [2\pi]^{-4} f^{-5} \exp\left[\left(-\frac{5}{4}\right)\left(\frac{f}{f_p}\right)^{-4}\right] \tag{3}$$

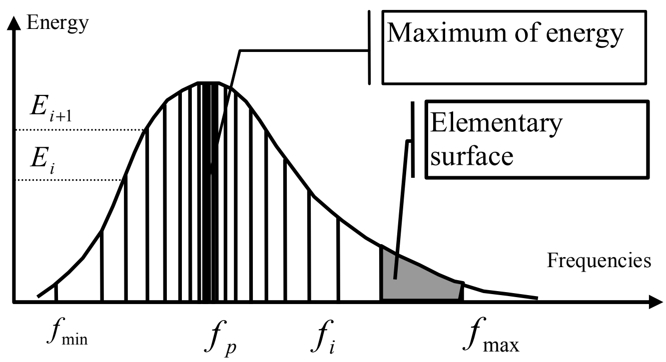

Fig. 5. Pierson MOSKOWICH Spectrum.

3.2. Command Parameters

To elaborate the digital commands for the swells generation within the canal, we have used the BORMAN method. It consists of subdivising the energy spectrum into elements of equal surfaces. Referring to the oceanic waves study, the chosen command parameters are the average period T_m and the average height H_m [27].

These parameters are described by the expressions (4) and (5).

$$T_m = \left(\frac{2}{5\pi}\right)^{\frac{1}{4}} \frac{1}{f_p} \left[\frac{\exp\left(-\frac{5}{64} f_p^4\right) - \exp\left(-\frac{5.10^4}{64} f_p^4\right)}{erf\left(\sqrt{\frac{5.10^4}{64} f_p^2}\right) - erf\left(\sqrt{\frac{5}{64} f_p^2}\right)}\right]^{\frac{1}{2}} \tag{4}$$

$$H_m = \alpha \frac{(2\pi)^{-3}}{5} g^2 \frac{1}{f_p^2} \left[\exp\left(-\frac{5}{64} f_p^4\right) - \exp\left(-\frac{5.10^4}{64} f_p^4\right)\right]^{\frac{1}{2}} \tag{5}$$

NB: $erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} . dt$;

Taking into account system constraints, studies of the influence of these variables f_p, $f_{\min}$, and $f_{\max}$ on the command parameters (T_m and H_m) gave the results of the Table 1.

Command parameters expressions were thus defined; it remains to determine the central frequency f_p and the amplification constant α according to the Pierson MOSKOWICH spectrum. So, we must search f_p and α according to H_m and T_m.

3.3. Swells Generation

The phases of swells generation are resumed in the organization chart of Fig. 6. Indeed, the first step is the introduction of averages parameters H_m and T_m by the operator. Next, the calculated parameters f_p and α of P.MOSKOWICH Spectrum are used to reconstitute the spectrum. With this spectrum and using the BORMAN method, the digital commands for swells generation will be deduced. These digital commands allow the control of the generation system through axis command and system control interface.

Table 1. Study Results.

Parameters	Domains	unit
$f_{\max}$	2	Hz
$f_{\min}$	0.2	Hz
f_p	0.3 - 0.6	Hz
T_m	1 – 1.9	S
H_m	4 - 13	Cm

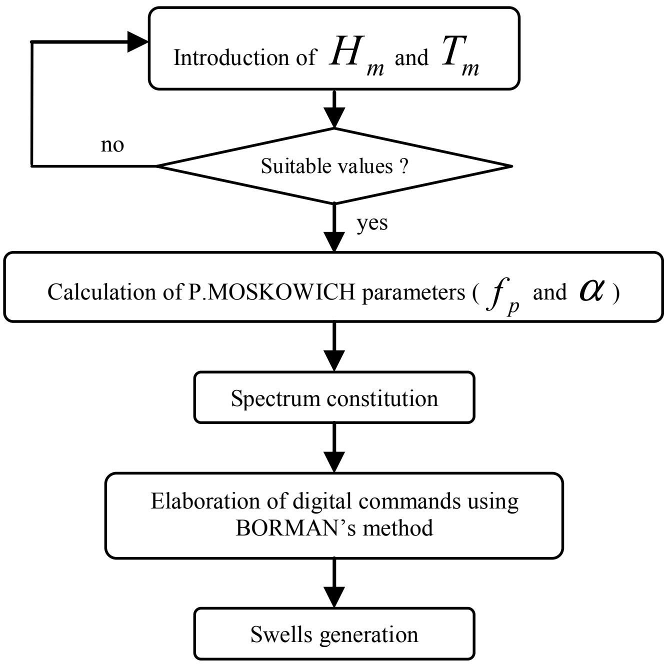

Fig. 6. Organization Chart of Swells Generation.

The major problem lies in the determination of appropriate spectrum parameters (α and f_p) from the averages parameters (T_m and H_m) introduced by the operator. This brings us to an imprecise and uncertain modeling of the system to control. To resolve this problem, it is suitable to use a heuristic method like the neuronal networks.

4. PROPOSED CONTROL STRUCTURE

The proposed structure (Fig. 7) is principally composed of a supervision unit and regulation unit. The first unit intervenes to prime the system by generating the initial data. Whereas, the second unit intervenes to control the system by imposing its dynamics. Such a control structure is that of the neuronal control according to internal model (NCIM).

The installed filter is of the first-class and low-pass type; it introduces a stabilizing action.

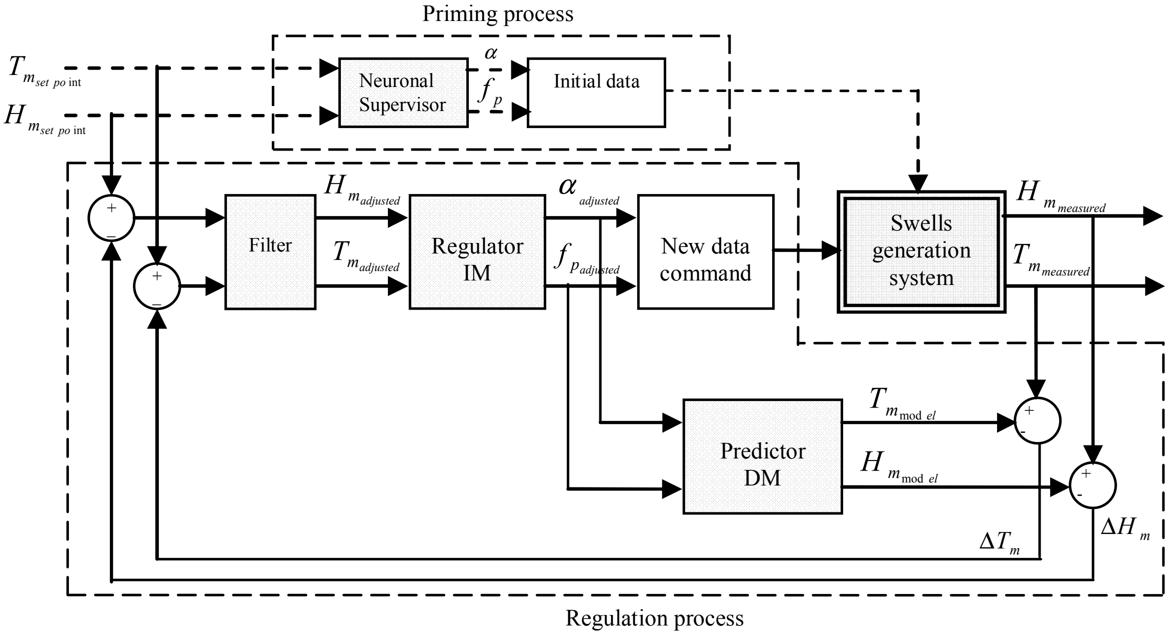

Fig. 7. The Control Structure of the Generation System.

The neuronal supervisor model describes the relation between the P.MOSKOWICH variables (α and f_p) and the control parameters (T_m and H_m). The conceived model is based on ANN. The neuronal model has, as inputs, the average period T_m and the average height H_m . It generates the suitable parameters of P.MOSKOWICH spectrum: α and f_p . This model is given by the Fig. 8.

Referring to the relation (4) and (5), it would be simple to determine f_p according to T_m , then deduce the amplification constant α using the expression (6).

$$\alpha = \frac{H_m(consigne)}{H_m\left(\alpha = 1, f_p\right)} \tag{6}$$

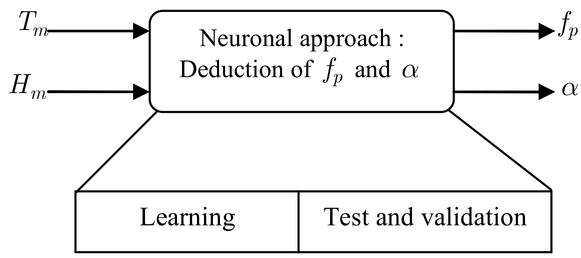

Fig. 8. Deduction of P.MOSKOWICH Parameters.

Whereas for the regulation process, we have firstly to conceive the DM of generation system reproducing the system behavior as faithfully as possible. This results in a model allowing to approximate $T_m = F_1(f_p)$ and $H_m = F_2(f_p, \alpha = 1)$. Secondly, we conceive the neuronal regulator. It is to be noted that the estimation of regulator parameters is giving by using the controlled system model DM.

Finally, we discuss the importance of the installed filter which permits the filtering of error signal, imposes perturbation rejection dynamics, and reduces the influence of model uncertainties on the control [17]. The filter must preserve the system dynamics; we have to choose its parameters judiciously. For this reason, we have chosen a first class and low-pass filter described by the relation (7) (the z transformation of filter transfer function). By changing the static gain G of the filter, the filter pole must satisfy the stability condition ($a < 1$).

$$F(z) = \frac{G}{z + a} \tag{7}$$

The adjustment of filter parameters is fixed by minimizing the gap between the system output and set point.

5. SIMULATION RESULTS

The control of the swells generation system requires, the design of ANN used for the supervisor, DM, and the IM, on the one hand; and a good choice of the low-pass filter, on the other hand.

5.1. Neuronal networks structure

The design of neuronal networks (neuronal supervisor, direct model, regulator network) composes through two phases:

- The choice of the network design.
- Network learning.

For the neuronal supervisor as well as the IM, the chosen ANN is a MLP composed of an input layer characterizing the control parameter T_m, a hidden layer, and an output layer characterizing the central frequency f_p (Fig. 9).

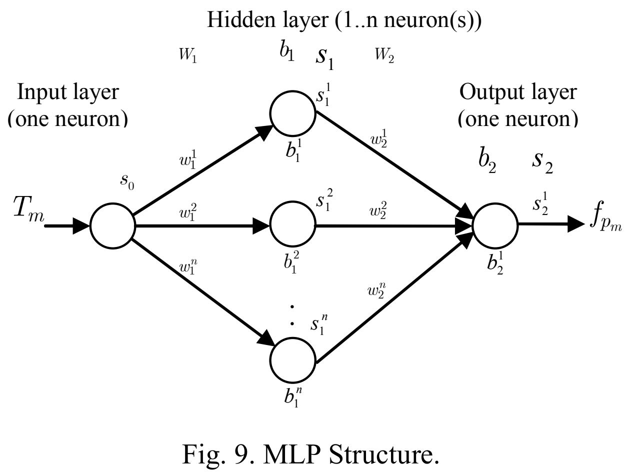

Fig. 9. MLP Structure.

The DM is different in the inversion of the input and the output of the MLP: f_p as input and T_m as output.

We note that:

- s_i *(i = 0, 1, 2)* : output vector of the different layers
- b_i *(i = 1, 2)* : biases vector of the hidden and output layer
- W_i *(i = 1, 2)* : weights vector between layers.

The network learning is supervised using the gradient back-propagation algorithm and minimizing the quadratic error.

5.2. Neuronal Modeling

The Organization Chart of Fig. 10 shows the different phases of the conception of the neuronal model to approximate f_p according to T_m.

To choose the network design, two surveys were proposed considering two influence factors, that is:

- Influence of the neurons activation function type.
- Influence of neurons number.

From the obtained results, we found that:

- The activation functions of the sigmoid logarithmic type are the least appropriate to approximate the central frequency. In fact, the representative curves of f_{p_m} give relatively important gaps (between 1.45×10^{-5} and 2.45×10^{-5} Hz) compared with T_m according to f_p.
- The neuron number of the hidden layer has an influence on the precision of simulation results (f_{p_m} compared with f_p).

The most interesting case is given by the choice of the following parameters (Fig. 11-13):

- The type of the chosen activation function is:
- Linear for the input and output layers;
- Hyperbolic sigmoid tangent « Tansig » for the hidden layer.
- The neurons number (N) of the hidden layer as well as passage number (N_p) were chosen as follows:
- For the DM: $N = 3$, $N_p = 2000$;
- For the IM: $N = 3$ or $N = 5$, $N_p = 2000$;

5.2.1 *Neuronal supervisor*

After the choice of neuronal model parameters (activation function and neurons number), the neuronal supervisor will be given by the Fig. 11. To compare the results of the obtained model with those of the expression, we have illustrated some values in Table 2.

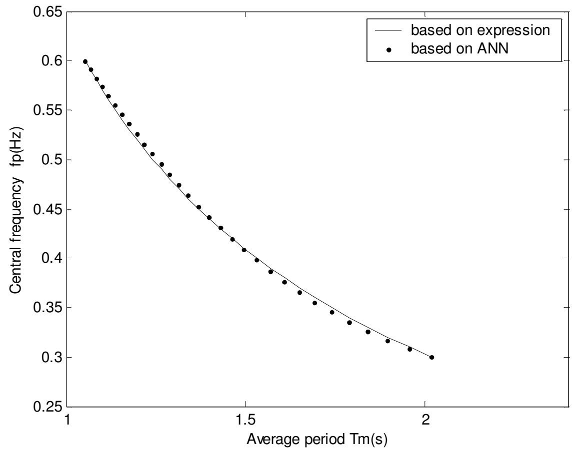

Fig. 11. Variation of f_p According to T_m .

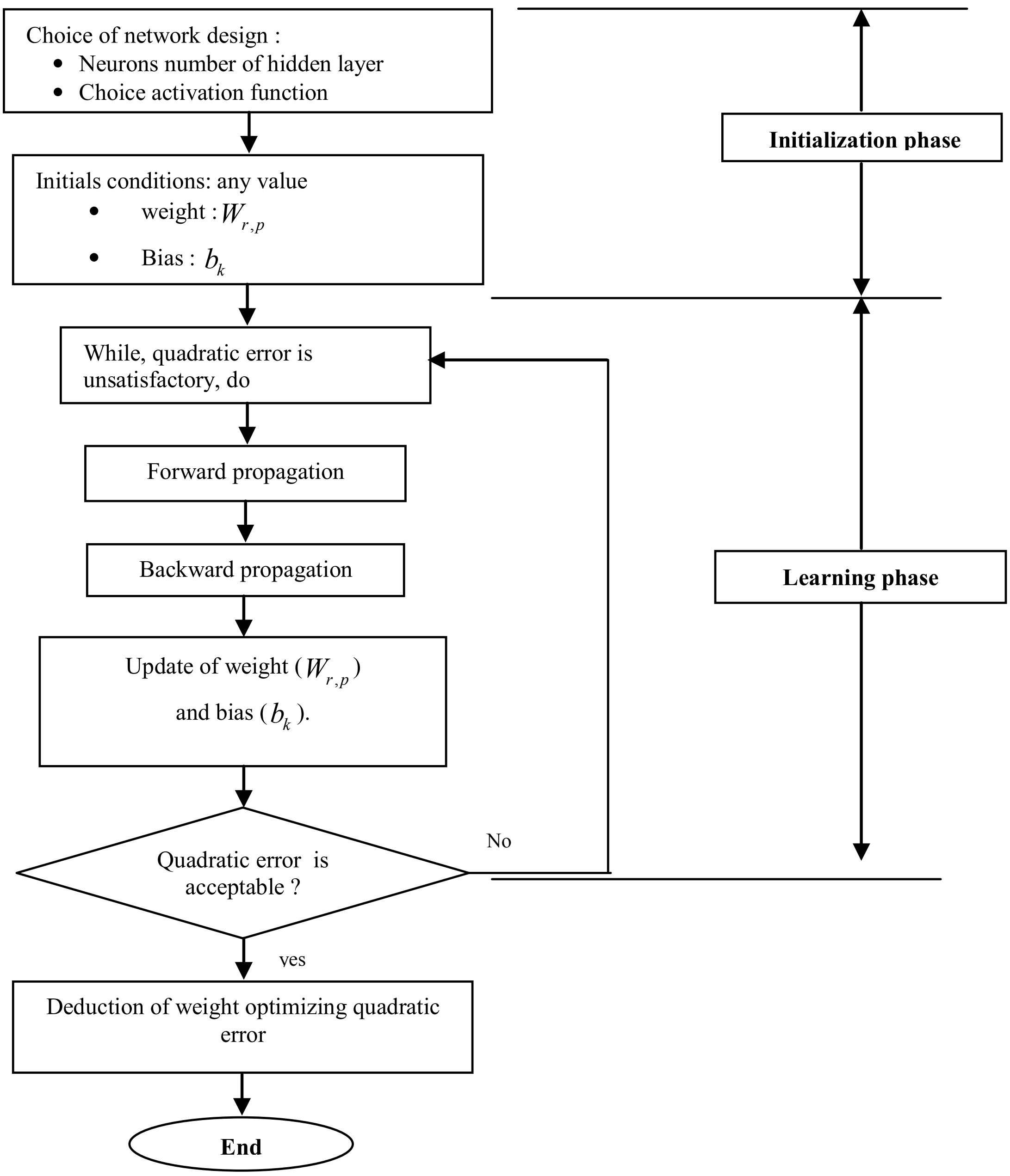

Fig. 10. Design of Neuronal Model.

Table 2. Identification of Central Frequency f_p .

Average period T_m (s)	$f_{p_{expression}}$ (Hz) based on expression	$f_{p_{ANN}}$ **(Hz) based on ANN**	$\left\|f_{p_{expression}} - f_{p_{ANN}}\right\|$ (Hz)
1.7	0.35	**0.3456**	0.0044
1.5	0.40	**0.3976**	0.0024
1.3	0.45	**0.4516**	0.0016
1.2	0.50	**0.5044**	0.0044
1.3	0.55	**0.5542**	0.0042
1.0	0.60	**0.6001**	0.0001

5.2.2 *Neuronal predictor*

The neuronal predictor models the average period T_m and average height H_m according to the central frequency f_p . The results of this modeling are showed in the Fig. 12.

The noticed gap is due to physical constraints (tolerance intervals f_p , H_m , and T_m). Since, the expressions modeling the generation process are approximate; this gap doesn't have a great influence on the system dynamics since it is reduced by a low-pass filter.

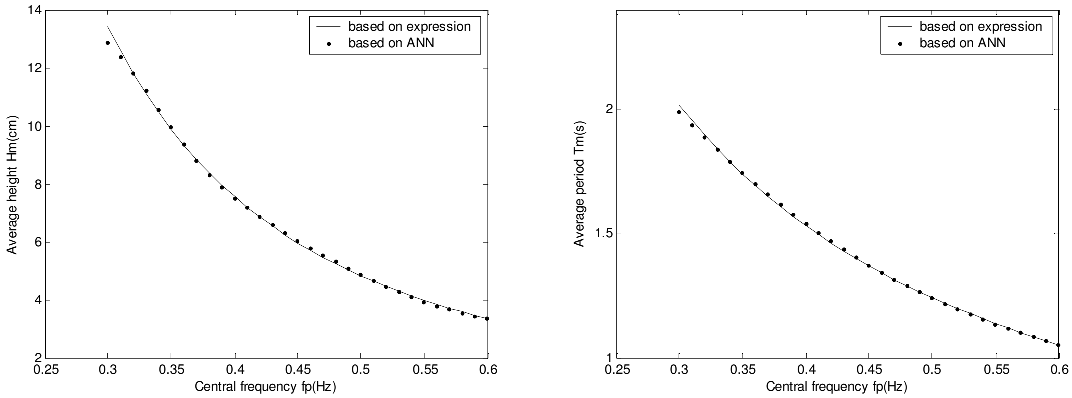

Fig. 12. Generation Process Modeling: DM.

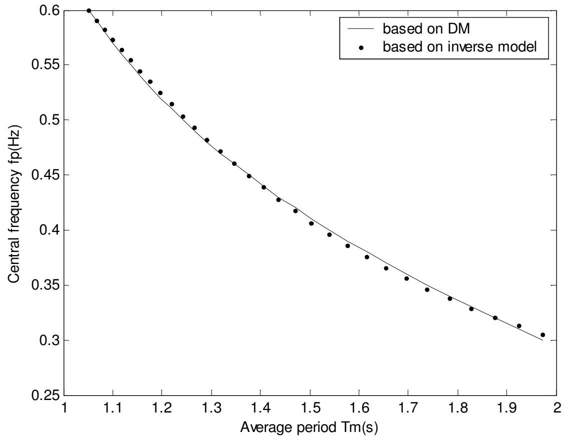

Fig. 13. Inverse Model of Generation Process: IM.

5.2.3 *Neuronal regulator*

The inverse model of the predictor is presented in Fig. 13. The noticed difference is due to modeling errors stored.

After determining the DM and IM, we will adjust the filter parameters to guarantee the system dynamics. To do so, two conceivable cases have been studied to reduce static error: filter with random parameters and filter with adjusted parameters.

Afterwards, we will show the influence of filter parameters choice on the regulation of the global system.

i) Random parameters

Firstly, we choose random values of filter parameters as $G_t = 2$ and $a_{1t} = -0.02$ (filter stabilizing the average period T_m) and $G_h = 1.05$ and $a_{1h} = -0.02$ (filter stabilizing the average height H_m). For the set point values $T_{m_{set\,po\text{int}}} = 1.2\ s$ and $H_{m_{set\,po\text{int}}} = 10\ cm$, the regulation of system outputs is illustrated in the Fig. 14.

According to the simulation of average period and average height, we notice that the NCIM regulation of these parameters converges.

We observe that the last iterations of regulation are characterized by a difference between the set point value and the generation value (gap of 0.78 s for the average period and gap of 1.2 cm for the average height). In fact, this gap is due to the precision quality of the DM compared with the real process of swells generation and the variation of propagation duration between the swell generated at the beginning and that from the regulation.

Moreover, we notice that the time of average period convergence is near to that of the average height. The Table 3 illustrates the convergence time of the parameters T_m and H_m.

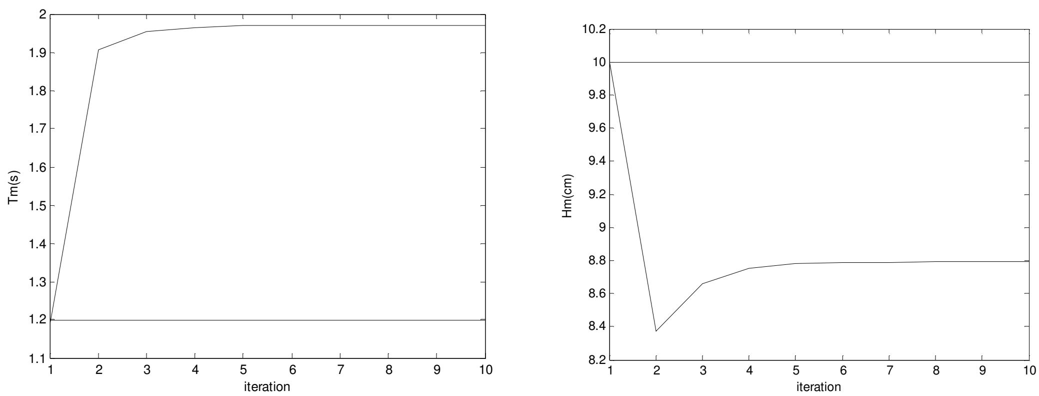

Fig. 14. Neuronal Regulation of Average Outputs with Random Filter Parameter.

Table 3. Simulation Results.

Set point	System output	Convergence time	Gap between set point and output
$T_{m_{set\,po\text{int}}} = 1.2\ s$, and $H_{m_{set\,po\text{int}}} = 10\ cm$	T_m	5 iterations	0.7708 s
	H_m	6 iterations	1.209 cm

These results show the presence of a noticeable gap between the set point and the output system. This choice of filter parameters doesn't give the acceptable precision of the system, so it has been necessary to adjust these parameters to attain the desired performances.

The obtained results are not acceptable; this control type which is too much excited can damage the system. So, it is preferable to adjust the filter parameters.

ii) Adjusted parameters

To resolve this problem, we have elaborated an algorithm determining the pair (G, a) to minimize the gap between the set point and the generation system output. The strategy of this algorithm says that for every introduced set point, we have to vary the gain G and the pole a within a clearly defined interval until finding the appropriate values to minimize the gap.

Let us take the example of the previous set point ($T_{m_{set\,po\text{int}}} = 1.2\ s$ and $H_{m_{set\,po\text{int}}} = 10\ cm$), the adjusted filter parameters would be $G_t = 1.013$; $G_h = 1.004$; $a_{1t} = -0.002$ et $a_{1h} = -0.001$. This choice gives the results of Fig. 15 and Table 4.

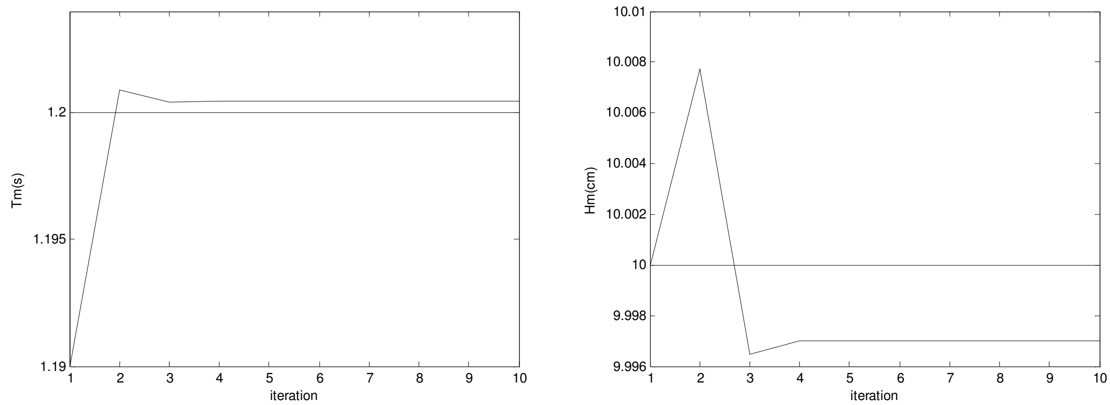

Fig. 15. Neuronal Regulation of Average Output with Adjusted Filter Parameters.

Table 4. Influence of Filter Parameters.

Set point	System output	Convergence time	Gap between set point and output
$T_{m_{set\,po\text{int}}} = 1.2\ s$ and $H_{m_{set\,po\text{int}}} = 10\ cm$	T_m	3 iterations	4.5×10^{-4} s
	H_m	4 iterations	0.003 cm

Referring to the obtained results in the Tables 3 and 4, we notice that with a good choice of filter parameters, we can ameliorate the convergence time and the precision of the system outputs. Moreover, the gap between the set point and the system output becomes infinitesimal (4.5×10^{-4} s for T_m and 0.003 cm for H_m). So, with a stable filter, we can assure the stability of the global system in addition to a well stable control.

6. CONCLUSION

For the control of the swells generation system, an approach based on the use of the neural networks had been proposed and confirmed. The structure thus proposed consists of a regulation unit accompanied with a supervisor allowing the priming of the system. For this structure, the chosen neural network type is that of multilayer perceptron with the back-propagation gradient method for the weights updating. Obtained results for the direct model and inverse model have well proved that the best reproduction of the swells generation process behavior is represented by Pierson Moskowich's model.

The choice of the filter is sensible. Indeed, it must limit the perturbation and not the system dynamics. For the proposed structure, obtained results confirm the system requirements when imposing its dynamics. Moreover, the simulations made with the proposed regulator show that the latter assures the system convergence. Results and performances given by the neuronal control, relying on the NCIM, are acceptable. Thus, we can generate a command law against perturbation while the model reflects as faithfully as possible the swells generation process. Then, the control quality depends essentially on the real process modeling, since every model always presents an error compared with the real system. This situation has an influence on the rapidity and the convergence gap.

Finally, we can say that the system remains subject to development in order to improve results already obtained. Other approaches like those of genetic algorithms and expert systems can be envisaged.

References

[1] C.-F. Juang, A TSK-Type Recurrent Fuzzy Network for Dynamic Systems Processing by Neural Network and Genetic Algorithms, IEEE Transaction on Fuzzy System, Vol. 10, pp. 155 – 170, 2002.

[2] C. Li and C.-Y. Lee, Self-Organizing Neuro-Fuzzy System for Control of Unknown Plants, IEEE Transaction Fuzzy System, Vol. 11, pp. 135 – 150, 2003.

[3] C. Alippi, C. Russis de and V. Piuri, A neural-network based control solution to air-fuel ratio control for automotive fuel-injection systems, IEEE Transaction on System Man and Cybernetics, Vol. 33, pp. 259–268, 2003.

[4] D.C. Psichogios and L.H. Ungar, Direct and indirect model based control using artificial networks, Industrial and Engineering Chemistry Research, Vol. 30, pp. 2564-2573, 1991.

[5] E. Coulibaly, S.Maiti and C. Brosilow, Internal Model Predictive Control, Automatica, Vol. 31, No. 10, pp. 1471-1482, 2005.

[6] E. Haber Rodolfo and R. Alique José, Nonlinear internal model control using neural networks: an application for machining processes, Neural Computing and Applications, Vol. 13, pp. 47-55, 2004.

[7] F.N. Chowdhury, P. Wahi, R. Raina and S. Kaminedi, A survey of neural networks applications in automatic control, Proceeding of the 33rd Southeastern Symposium on System Theory, pp. 349 -353, 2001.

[8] G. Colin, Y. Chamaillard, G. Bloch, G. Corde and A. Charlet, Linearized neural predictive control. A turbocharged SI engine application, IEEE Transaction Neural Networks, Vol. 18, pp. 1101-1114, 2007.

[9] H. Guido, S.G. Shuzhi and G. Guoxiao, Practical Implementation of a Neural Network Controller in a Hard Disk Drive, IEEE Transaction Control System Technology, Vol. 13, pp. 146 -154, 2005.

[10] I. Rivals and L. Personnaz, Non-linear Internal Model Control Using Neural Networks: Application to Processes with Delay and Design Issues, IEEE Transaction Neural Networks, Vol. 11, pp. 80-90, 2000.

[11] J. Alvarez, An internal model controller for nonlinear systems, Proceeding of the 3rd European Control Conference, Rome, Italy, September, pp. 301-306, 1995.

[12] K. Hornik, M. Stinchcombe and H. White, Multilayer feedforward networks are universal approximators, Elsevier Science Ltd., Neural Networks Vol. 2, pp. 359-366, 1989.

[13] K.S. Narendra and S. Mukhopadhyay, Adaptive control of nonlinear multivariable systems using neural networks, Elsevier Science Ltd., Neural Networks, Vol. 7, pp. 737-752, 1994.

[14] M. Beham and D. Yu, Modeling a variable valve timing spark ignition engine using different neural networks, Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, Vol. 218, pp. 1159–1171, 2004.

[15] M. Fazle Azeem, M. Hanmandlu and N. Ahmad, Structure Identification of Generalized Adaptive Neuro-Fuzzy Inference Systems, IEEE Transaction on Fuzzy System, Vol. 11, pp. 666 – 681, 2003.

[16] M. Norgaard, O. Ravn, N.K. Poulsen and L.K. Hansen, Control with neural network, Networks for Modelling and Control of Dynamic Systems, Springer-Verlag, London, pp. 121-204, 2000.

[17] M. Campi, W.S. Lee and D.O.Anderson, New filters for internal model control design, International Journal of robust and nonlinear control, Vol. 4, pp. 757-775, 1994.

[18] R.-J. Wai and H.-H. Chang, Backstepping Wavelet Neural Network Control for Indirect Field-Oriented Induction Motor Drive, IEEE Transaction on Neural Networks, Vol. 15, pp. 367 – 382, 2004.

[19] S. Ferrari and R.F. Stengel, Smooth Function Approximation Using Neural Networks, IEEE Transaction Neural Networks, Vol. 16, pp. 24- 38, 2005.

[20] S. Mottelet, Controllability and stabilization of a canal with wave generators, SIAM Journal on Control and Optimization, Vol. 38, pp. 711-735, 2000.

[21] T. Ben Romdhane, M. KsourI and R. Ketata, Intégration d'un Système de Commande d'axe pour la reproduction des vagues océaniques dans un canal à houles, C2MNI6 Tunis, Novembre, 1998.

[22] T. Ben Romdhane, R. Ketata and M. Ksouri, Approche basée sur la logique floue pour la conception des consignes de commande d'un générateur de vagues aléatoires, JTE'98, Hammamet, Tunisia, Novembre, 1998.

[23] T. Kim and T. Adalı, Approximation by Fully Complex Multilayer Perceptrons, Neural computation, Vol. 15, pp. 1641-1666, 2003.

[24] W. Frey, M. Sajidman and H.-B kuntze, A Neuro-Fuzzy Supervisory Control System for Industrial Batch Processes, The Ninth IEEE International Conference on Fuzzy System, Vol. 1, pp. 116 – 121, 2000.

[25] Y. Mizukami, Y. Wakasa and K. Tanaka, A proposal of neural network architecture for non-linear function approximation, Pattern Recognition, ICPR2004, Proceeding of the 17th International Conference, Vol. 4, pp. 605 – 608, 2004.

[26] M.R. Gallagher, Multi-Layer Perceptron Error Surfaces: Visualization, Structure and Modelling, Ph.D. Thesis, University of Queensland, Department of Computer Science and Electrical Engineering, 2000.

[27] T. Ben Romdhane, La conception et la mise en œuvre d'un système de conduite et de supervision d'un générateur de houles : canal à houles, Ph.D. Thesis, National school of Engineering in Tunis (ENIT), Tunisia, 1997.