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Briefly, the proposed methodology can be described:

• Construction of the computational model to system simulation;
• Simulations for validation;
• Construction of response surfaces using artificial neural networks trained with points obtained through Sobol;
• Optimization utilizing genetic algorithms with the aid of response surfaces.

The methodology proposed is applied and it is presented the results for two case studies, one for the dynamic positioning of a vessel modeled with one degree of freedom (longitudinal movement) and another with three degrees of freedom (motion in the plane).

2. PID CONTROLLER

A representation of a PID controller can be seen in Fig. 1. The controller is called Proportional-Integral-Derivative in function of the application of these 3 operations on the input signal to form the output signal. Usually the control loop uses a line of negative feedback to form the error signal, which is the difference between a reference signal (final system state) and the sign that indicates the current state.

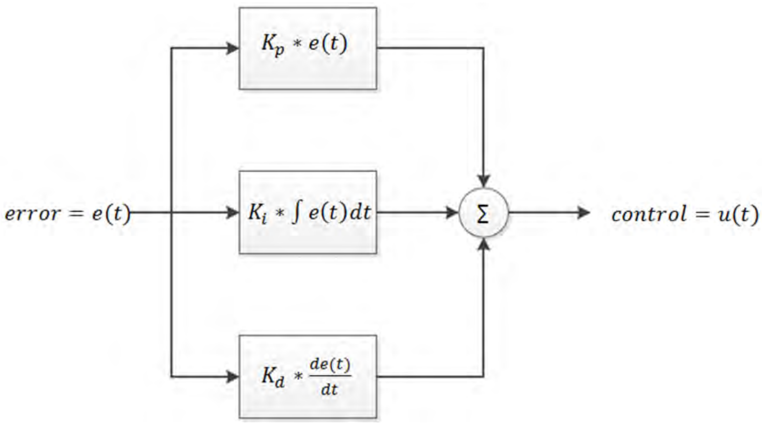

Figure 1. PID Controller Diagram

The proportional term K_P, or proportional gain, comes through the overall control of the error signal by multiplying it. The integral term K_I, or integral gain, reduces the steady state error by offsetting low frequency, applying the time integration in the error signal. The derivative term K_D, or derivative gain, improves the control performance in the transitional regime, through compensation for high frequency, applying the time derivative of the error signal (Ang et ali. 2005).

As a practical matter, each has a direct effect on the behavior of the control signal in a stable plant. However, are closely related to each other, so only the determination of all parameters simultaneously can achieve satisfactory performance conditions.

The mathematical operation applied can be seen in Eq. 1, and the composition of the error signal in Eq. 2, where r (t) is the reference signal and x (t) is the current position signal.

$$u(t) = K_P * e(t) + \int_0^t K_I * e(\tau)d\tau + K_D * \frac{de(t)}{dt} \quad (1)$$

$$e(t) = r(t) - x(t) \quad (2)$$

There are various techniques for simple tuning of PID controllers, most manufacturers already sells the product accompanied by a manual that presents such techniques. However, they usually present performance inefficient and often not feasible.

3. OPTIMIZATION

One can define the optimization process as the automatic, systematic and directed search to obtain the best solution within the universe of existing solutions (Tancredi, 2008). Often, obtaining the minimum of a function analytically is very complicated, impractical or impossible, as is the case of many engineering problems.

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To solve the optimization problem is defined a parameter space, composed by:

• Design variables: essentially, the parameters of the controller;
• Objective function: in the PID controller are used the maximum overshoot and the settling time, what characterize a multi-objective problem;
• Constraints: eventually it is possible establish the maximum overshoot as a constraint of the process in a mono-objective approach.

The recent work (Ye et ali., 2010) describes how the last decade established engineering designs with new technological advances, more complex and bold, with high criteria requirements and various limitations, restrictions and nonlinearity. The genetic algorithms are very adapted at this scenario and are used in many recent works involving optimization in engineering, especially when is not easy to evaluate the gradient of function.

The genetic algorithm is inspired by the mechanism of natural selection, where in each one of the iteration of the process, the algorithm works with a population of potential solutions, called chromosomes, representatives of a particular combination of input parameters. From this, then the objective function is calculated and the process of natural selection is applied. This procedure permits that the design problem evolves to a consistent and coherent optimum solution.

Genetic algorithms are very versatile and its application is found in many works about tuning of PID controllers (Lopez, 2008 and Marangoni et ali. 2010).

4. RESPONSE SURFACE

The response surface technique is widely employed in optimization processes of engineering, where the search process uses the fact that the response surface represents the physical processes and models constructed with low computational cost.

In some cases, the use of response surface are the only way viable to the optimization process, especially when obtaining the objective function requires the time domain simulation of the system, which often has a high computational cost (Bo et al. 2,005). In the traditional approach, it is used a set of points that are used as a pattern to be training the response surface to represent the phenomenon.

The artificial neural networks are widely used as a tool for the construction of the surface, particularly when working with nonlinear systems and complex analytic representation. When working with this type of case and compared with other techniques, the neural networks has great merit, who, through study and training of the same, is able to capture the complex relationship between input and output, saving and storing patterns, allowing output to obtain untested values (Hanyum et al., 2009). The technique used is called Multi-Layer Perceptron, using exponential functions, reproduces the complex relationships of a neural network, such as our brain, creating relationships between inputs and outputs - design variables and objective functions.

There are several different topologies of neural network configuration with different number of inputs, outputs, and intermediate layers. Each topology is best suited for a particular behavior of the mapped function. For example, functions and nonlinear chaotic behavior need more hidden layers to be represented faithfully. In Fig. 2 is shown a generic configuration with 2 hidden layers and 4 neurons in each layer, where each circle represents a neuron with activation function.

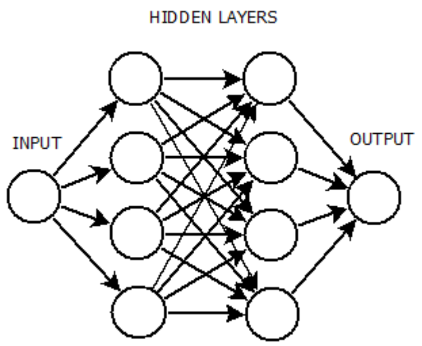

Figure 2. Generic Topology for Neural Network

The response surface was constructed using a pre-selected group of points obtained by the technique Sobol (Bratley et al., 1988). The technique is part of a group called *quasi-random* and has a uniform distribution in design space.

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5. METHODOLOGY

The method comprises the following steps:

• Development of mathematical model - the current approach of the proposed methodology requires modeling the system of interest to be controlled. In this paper are presented two cases where the system was modeled using the MatLab Simulink tool, that permits the evaluation of the performance attributes of the controller.
• Tests and simulations - testing and simulations in the time domain models built to verify its operation and establish the values obtained at the outputs for a given set of values placed as input;
• Construction of response surfaces - based in the database of simulations in the time domain obtained in the previous step, construct the response surfaces that represent the phenomenon and reduces the number of time domain simulation, improving the optimization process speed;
• Optimization process – with the response surfaces constructed in the previous step, perform the optimization to determine the parameters of the controller;
• Interpretation of results - theoretical verification process and results. In this step is verifies the consistence and coherence of the results, including the alimentation of the process with a new response surface creation.

5.1 Case Study: SPD for a vessel with a degree of freedom

In this section is presented the example the application of the methodology proposed in this article. The theoretical and practical aspects for the construction of the model can be found in the bibliography (Tannuri, 2009. Bray, 1998. Augustine, 2009).

The dynamic positioning system (DPS) is the system that controls the ship position in the horizontal plane by means of a propulsion active (Bray, 1998). It consists of a complex system with multiple sensors (GPS, sonar, anemometers, gyroscopes), actuators (main, azimuth and side thrusters), and a central processor that implements the control algorithm and serves as interface to the human operator (Tannuri, 2009). Between the various types of controllers used in DPS, the PID controllers are very commonly applied. However the correct tuning for optimal performance is very difficult in function of high complexity and non-linearity of the system, especially if are considerate the environment's forces. The simplified block diagram of the system considerate is shown in Fig. 3.

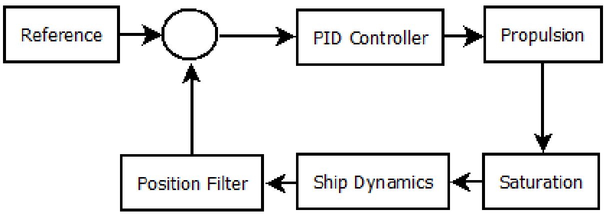

Figure 3. Block Diagram - Simplified SPD System

The simulations in time domain are done to a reference signal of 24 m and it was considered a pipe launcher vessel, whose constructive characteristics used in analysis are listed in Table 1.

Table 1. Vessel Parameters for a degree of freedom

Parameter	Value (Unit)
Mass M	$1.72 * 10^7$ *kg*
Length L	22 *m*
Additional Mass M_{11}	1.72×10^6 *kg*
Damping c_{11}	$1.00 * 10^4$ *Ns / m*
Maximum Thrust Saturation	$8.52*10^5$ *N*

Each block of Fig. 3 is represented by a differential equation. The propulsion block is represented by Eq. 3, the block ship dynamics is represented by Eq. 4 and the filtered position is represented by Eq. 5. All the equations are shown in the form of Laplace transform, normally used in control applications.

$$T(s) = \frac{1}{10*s+1} \qquad (3)$$

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$$S(s) = \frac{1}{(M+M11)*s^2+c11*s} \tag{4}$$

$$F(s) = \frac{1}{3*s+1} \tag{5}$$

The methodology proposes the optimization of performance parameters (Fig. 4), which are in this case, the 2% settling time t_s and the maximum overshoot M_p. The settling time is measured from the beginning of the reference signal until the time when the output signal varies within a range of ± 2% of the reference. The maximum overshoot is the ratio between the maximum amplitude of the output and the reference signal.

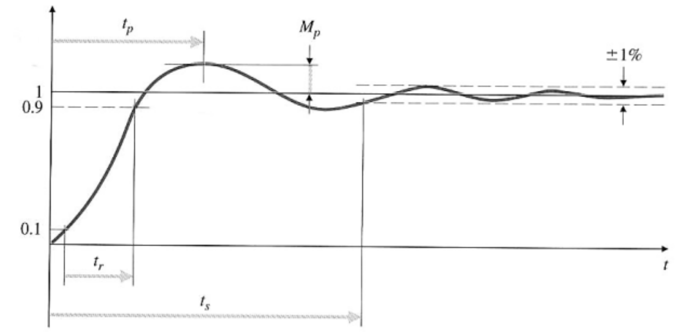

Figure 4: Parameters of controller performance

Using a technique for automatic tuning, there was obtained the benchmark parameters for the PID controller: Kp = $1.3*10^4$, Ti = $4.2 * 10^4$ and Td = $5.7*10^1$, resulting in a overshoot of 5% and a settling time of 500 s.

A neural response surface was training with the results of time domain simulation for some points defined by Sobol technique. To verify the consistence of the response surfaces, the comparison between the results obtained with simulation and with neural network is shown in Fig. 4, where the horizontal axis represents the response of the neural network and the vertical axis represents the response of the simulation. The closer to forming a straight 45 degrees to the horizontal, better is the representation of the phenomenon done by the neural response surface.

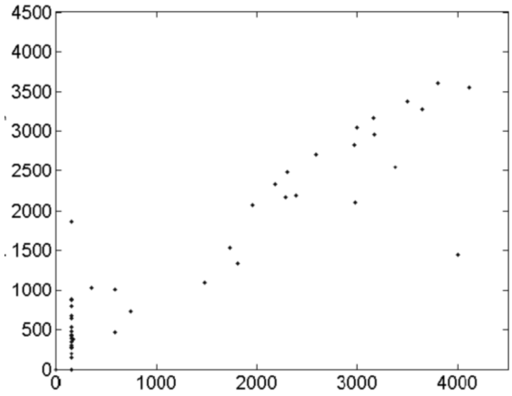

Figure 4. Comparison between the Neural Network and the Simulation for the settling time

Lastly, it was applied the optimization process with several percentage participations of neural networks. The proposed algorithm applies the optimization process combining the results obtained by the neural network with the result obtained by simulation, using the best of each model, as processing time in the first and the precision of the second.

The results of optimization process for each participation of neural network can be seen in Fig. 5, where the horizontal axis represents the settling time and the vertical axis represents the maximum overshoot. The curve of optimal solutions is called the Pareto Frontier. The percentage of the legend indicates the participation of the simulation in time domain. For example, one percentage of 100% means that all the evaluation is performed using simulation in time domain, while 50% indicates that half of results are evaluated with neural network.

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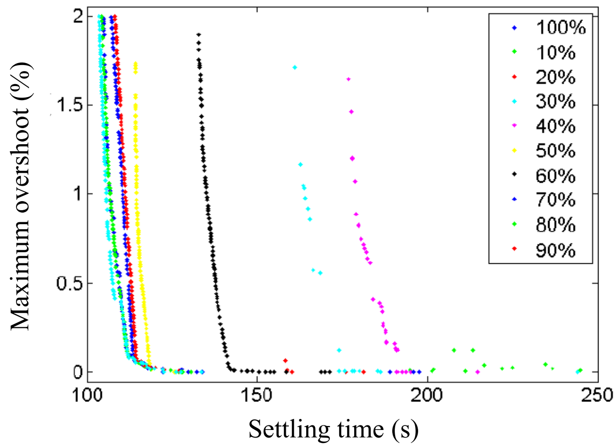

Figure 5. Pareto Frontiers the maximum overshoot (vertical axis) and settling time (horizontal axis) for different percentages of time domain simulations in optimization process

The best results were obtained with a higher percentage of participation of simulations in time domain, however, the computational cost in obtaining results using neural network was lower, as shown in Table 2. It is possible a reduction of approximately 50% in time consuming of the optimization process for get results as good as the results achieved without the neural response surface use.

Table 2. Performance table for different percentages of time domain simulations in optimization process

Simulation in time domain (%)	Time (minutes)	Performance increase (%)
0	1.73	89
10	6.84	55
20	6.11	60
30	7.09	54
40	8.02	47
50	11.10	27
60	11.40	25
70	13.40	12
80	14.10	7
90	13.00	15
100	15.26	-

In relation of the system trajectory, in Fig. 6 is shown a comparison of the trajectories for the different percentages of participation of simulations in time domain. Each trajectory represents a point with less than 5% of overshoot of each one of the Pareto Frontiers shown in Figure 5.

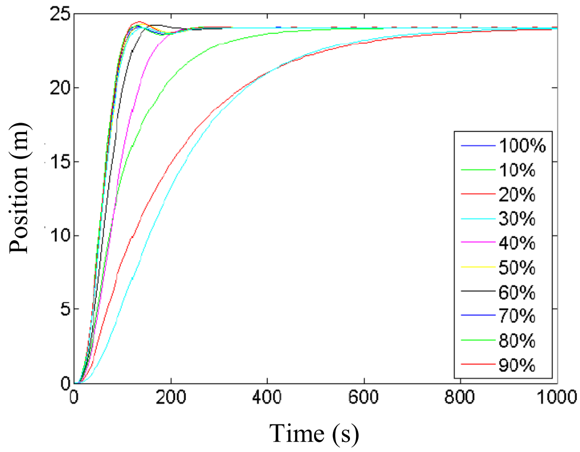

Figure 6. Comparison of trajectories for different percentages of participation of simulations in time domain.

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5.2 Case Study: SPD for a vessel with three degrees of freedom

The second case analyzed is similar to the first one, and the block diagram of the system for three degrees of freedom is shown in Fig. 7. The system is more complex than the first one, with greater interdependence between the directions of movement, differential equations with feedback of each direction and nine control parameters to be set: three parameters of PID controllers, one for each direction, in this case, the displacement in the longitudinal direction X, transverse movement Y and rotation around Z, ψ.

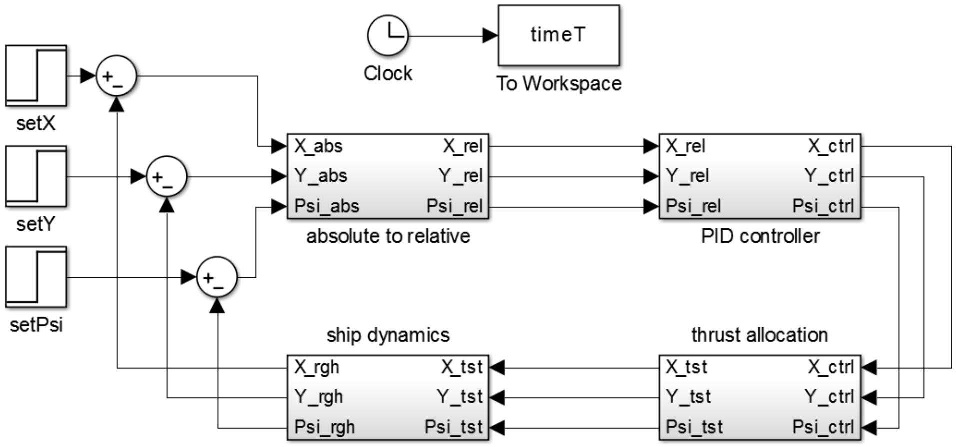

Figure 7. Block diagram of the system

The step type entries (setX, setY and setPsi) represent the positions where you want to go with the boat, which are subtracted from the signal of the current position x(t) in a negative feedback for each of three directions, resulting in the error signal e(t).

This error signal is then passed by the block "absolute to relative" that convert the coordinates from referential of ship to the absolute referential.

The error signal in the new coordinate system then passes in the block "PID controller". There is a block PID Controller for each direction, each one with three design variables, totalizing nine design variables.

In the block "thrust allocation" applies the saturation limit of the thrusters, which is a limit of maximum physical thrust possible for each direction considered.

Finally, the signal enters the block "ship dynamics" that implements the vessel dynamics. Each subsystem performs calculations that define the acceleration in a particular direction given the effort and other velocity components in other directions.

This recursive calculation is performed with the Simulink model, allowing the simulation in the time domain to the trajectory of the vessel. The acceleration obtained in each direction is integrated to obtain velocity, that is then passed on to the absolute coordinate system, where it is again integrated to obtain the current position of the vessel, repeating the cycle simulation.

The characteristics of the vessel simulated are listed in Table 3 and correspond to a model of a platform supply vessel.

Table 3. The characteristics of the vessel

Parameter	Value
Mass M	52.5 kg
Inertia I_Z	4.63 kg.m
Length L	178e-2 m
Breadth B	29e-2 m
Draft T	12e-2 m
Additional Mass M_{11}	5.25 kg
Additional Mass M_{22}	26.25 kg
Additional Mass M_{66}	8.51 kg.m
Additional Mass M_{26}	0 kg.m
Center of Gravity x_g	0 m

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In the Eq. 6 to 8 are presented the laws that govern the dynamics of the vessel. It is important to observe the dependence between each of the directions, which reflected the determination of control parameters, since the PID controller gains in one direction affects the performance of other directions.

$$(M + M_{11}) * \ddot{x}_1 - (M + M_{22}) * \dot{x}_2 * \dot{x}_6 - \left(M * x_g + M_{26}\right) * \dot{x}_6^2 = F_{1t} + F_{1e} \quad (6)$$

$$(M + M_{22}) * \ddot{x}_2 + \left(M * x_g + M_{26}\right) * \ddot{x}_6 + (M + M_{11}) * \dot{x}_2 * \dot{x}_6 = F_{2t} + F_{2e} \quad (7)$$

$$(I_Z + M_{66}) * \ddot{x}_6 + \left(M * x_g + M_{26}\right) * \ddot{x}_2 + \left(M * x_g + M_{26}\right) * \dot{x}_1 * \dot{x}_6 = F_{6t} + F_{6e} \quad (8)$$

In the dynamics equations, the terms x_1, x_2 and x_6 represent the generalized coordinates in the x, y, ψ, respectively, and the terms F_{it} F_{ie}, represent the environment forces and the thrusters in each of the directions. Lastly, the terms M_{ij}, represents the additional hydrodynamic mass of the hull.

The presented methodology was applied again and the auto tuning method was used as a comparison with the results obtained by the optimization process.

A neural response surface was training with the results of time domain simulation for some points defined by Sobol technique. The distribution of the Sobol points in 3D space defined by 3 of the design variables can be seen in Fig. 8.

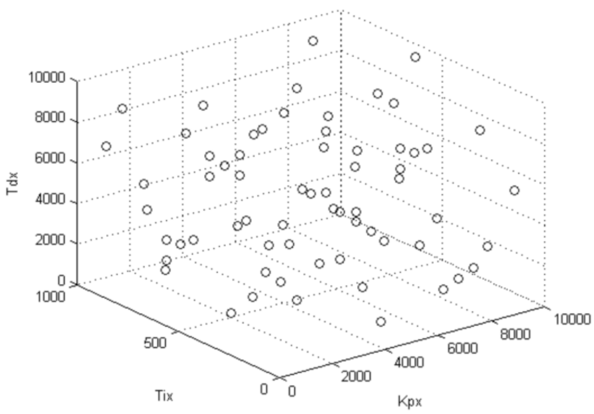

Figure 8. Point distribution using Sobol

Using the results obtained in the previous case, the optimization process was done with 30% of the evaluations using the neural response surface trained.

The final results are presented in Fig. 9 to. 11, where the blue curve is the benchmark, obtained by the auto tuning method, the red curve represents the result for the optimization with 30% of the participation of neural response surface and the curve in cyan represents the optimization only with simulation in time domain.

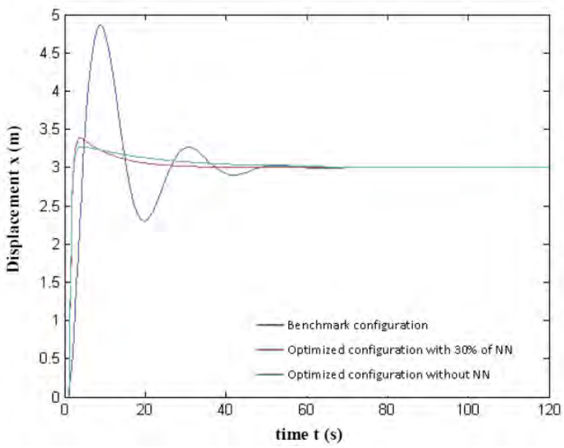

Figure 9. Result comparison in X displacement (m) in function of the time (s)

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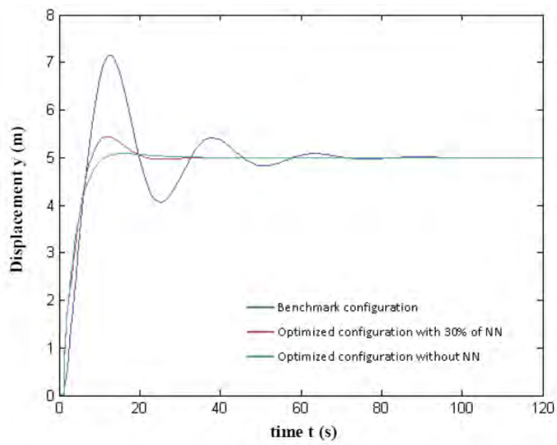

Figure 10. Result comparison in Y displacement (m) in function of the time (s)

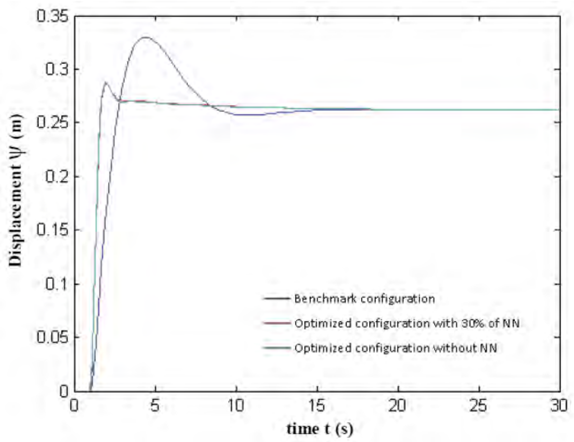

Figure 11. Result Comparison in ψ displacement (rad) in function of the time (s)

The final results comparison is shown in Table 4.

Table 4: Comparison of Approaches: PID Parameters

Parameter	Optimized with 30% of Neural Network	Optimized without Neural Network	Benchmark configuration
Kpx	9,6	5,6	5,0
Kix *	0,0	0,0	2,0
Kdx	67,0	87,0	10,0
Kpy	6,3	5,3	5,0
Kiy *	0.0	0,0	2,0
Kdy	27,0	28,7	10,0
Kpψ	6,1	5,9	5,0
Kiψ *	0,0	0,0	2,0
Kdψ	43,4	39,4	10,0
T_s x (s)	29,4	18,4	45,2
T_s y (s)	19,8	18,7	55,0
T_s ψ (s)	7,5	6,6	8,3
M_p x (%)	9,9	16,5	62,0
M_p y (%)	9,9	9,4	43,0
M_p ψ (%)	8,9	10,1	26,0
Computational Cost (minutes)	20,3	28,3	5,0

* Fixed as suggestion of Bezerra et al (2012).

6. CONCLUSIONS

It was presented in this paper a methodology for defining the PID parameters for optimal performance of a system. The performance parameters chosen were the maximum overshoot and settling time. However, it is possible to use many other performance parameters, which does not alter the methodology proposed, only the function used in the optimization process.
As previously described, the methodology proposed involves:

• Construction of the computational model to simulation of the system;
• Simulations for validation;
• Construction of Response Surfaces using Neural Networks trained with points chosen by the Sobol algorithm;
• Optimization using genetic algorithms with response surfaces for performance improvement

As example of application, this methodology was applied in the determination of the optimal parameters of the PID controller for the dynamic positioning system of a ship. The results show a considerable increase in processing speed, through the employ of Neural Networks and Sobol techniques, which proved efficient to scan the space and represent the phenomenon. In this case the methodology proposed had a gain of 30% in computational cost in relation of the traditional approach.

Once the methodology is consolidated, the next step is the employ this procedure in the optimization of a system with six degrees of freedom, totalizing 18 design variables.

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8. REFERENCES

Agostinho, A. D., “Controle por Modos Deslizantes Aplicado a Sistemas de Posicionamento Dinâmico” <Sliding mode control applied to dynamic positioning systems>. Master's Dissertation, Escola Politécnica da Universidade de São Paulo, São Paulo, Brasil, 2009.

Anjum, M. F., Tasadduq, I. and Tasadduq, K., “Response surface methodology: A neural network approach”, European Journal of 12 Operational Research, Vol. 101, Issue 1, pp. 65-73, 1997.

Arulmozhiyal, R.; Kandiban, R., "Design of Fuzzy PID controller for Brushless DC motor," Computer Communication and Informatics (ICCCI), 2012 International Conference on , vol., no., pp.1,7, 10-12 Jan. 2012a.

Arulmozhiyal, R., "Design and Implementation of Fuzzy PID controller for BLDC motor using FPGA," Power Electronics, Drives and Energy Systems (PEDES), 2012 IEEE International Conference on , vol., no., pp.1,6, 16-19 Dec. 2012b.

Bezerra, M. V. O.; Tancredi, T. P.; Morishita, H. M. “Aplicação de Superfícies de Resposta para Otimização dos Parâmetros de Controle de um Sistema de Posicionamento Dinâmico” <Application of Response Surface to Optimization of Control Parameters of a Dynamic Positioning System>. 24º Congresso Nacional de Transporte Aquaviário, Construção Naval e Offshore. Rio de Janeiro, Brasil, 2012.

Bray, D. “Dynamic Positioning”. The Oilfield Seamanship Series, Volume 9, Oilfield Publications Ltd. 1998.

K. H. Ang, G. Chong, and Y. Li , “PID Control System Analysis, Design, and Technology,” IEEE Trans. Contr. Syst. Technol., vol. 13, no. 4, pp. 559-576, July 2005.

Bo Ping Wang; Zhen Xue Han; Xu, L.; Reinikainen, T., "A novel response surface method for design optimization of electronic packages," Thermal, Mechanical and Multi-Physics Simulation and Experiments in Micro-Electronics and Micro-Systems, 2005. EuroSimE 2005. Proceedings of the 6th International Conference on , vol., no., pp.175,181, 18-20 April 2005.

Fernandes, R. F. “Identificação Remota de Plantas Industriais Utilizando Tecnologias OPC e CyberOPC” <Remote identification of industrial plants using OPC and CyberOPC technology>. Master's Dissertation, Escola de Engenharia da Universidade de São Carlos, São Carlos, Brasil, 2009.

Hanyun Wen; Jie Hu, "Research on Multidisciplinary Design Optimization Based Response Surface Technology of Artificial Neural Network," Genetic and Evolutionary Computing, 2009. WGEC '09. 3rd International Conference on , vol., no., pp.510,514, 14-17 Oct. 2009

Kiam Heong Ang; Chong, G.; Yun Li, "PID control system analysis, design, and technology," Control Systems Technology, IEEE Transactions on , vol.13, no.4, pp.559,576, July 2005

ISSN 2176-5480

Vasu Murthy, B.; Kumar, Y.V.P.; Kumari, U.V.R., "Application of neural networks in process control: Automatic/online tuning of PID controller gains for ±10% disturbance rejection," Advanced Communication Control and Computing Technologies (ICACCCT), 2012 IEEE International Conference on , pp.348,352,. 2012.

Rubaai, A.; Castro-Sitiriche, M.J.; Ofoli, A., "DSP-Based Implementation of Fuzzy-PID Controller Using Genetic Optimization for High Performance Motor Drives," Industry Applications Conference, 2007. 42nd IAS Annual Meeting. Conference Record of the 2007 IEEE , vol., no., pp.1649,1656, 23-27 Sept. 2007.

Tancredi, T. P. "Otimização Multidisciplinar Distribuída Aplicada a Projetos de Engenharia" < Multidisciplinary distributed optimization applied to engineering projects>. phD Thesis, Escola Politécnica da Universidade de São Paulo. São Paulo, Brasil, 2008.

Tannuri. E. A. "Desenvolvimento de Metodologia de Projeto de Sistema de Posicionamento Dinâmico Aplicado a Operações em Alto-Mar" < Development of a new methodology for offshore dynamic positioning system design>. phD Thesis, Escola Politécnica da Universidade de São Paulo. São Paulo, Brasil, 2002.

Tannuri, E. A., "Sistema de Posicionamento Dinâmico: Projeto, Análise e Novos Desenvolvimentos" <Dynamic Positioning System: design, analysis and new developments>. phD Thesis, Escola Politécnica da Universidade de São Paulo, São Paulo, Brasil, 2009.

Ye Fei; Haiyang Yu; Jiang Xueshou, "An improved Constrained Optimization Genetic Algorithm," Intelligent Computing and Intelligent Systems (ICIS), 2010 IEEE International Conference on , vol.2, no., pp.435,439, 29-31 Oct. 2010.

Ziegler, J. G.; Nichols, N. B., "Optimum Settings for Automatic Controllers". Comitte on Industrial Instruments and Regulators of the Process Industries Division.Annual Meeting, New York, N. Y., December 1-5, 1942.

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