24th COBEM - 2017

24th ABCM International Congress of Mechanical Engineering
December 3-8, 2017, Curitiba, PR, Brazil

COBEM-2017-0506
NEURO-FUZZY CONTROL AND DIFFERENTIAL EVOLUTION IN THE COMPENSATION OF THE ACTUATORS' DEAD ZONE OF A TWO-WHEELED VEHICLE

Bruno Luiz Pereira
Leonardo Sanches
José Jean-Paul Zanlucchi de Souza Tavares
Universidade Federal de Uberlândia, Faculdade de Engenharia Mecânica, MG, Brazil
brunolp.meca@gmail.com, lsanches@ufu.br, jean.tavares@ufu.br

Abstract. *Dead zone nonlinearity of electrical motor influences the stabilization and oscillation of mechanical systems, such as two-wheeled inverted pendulum vehicles. Based on the intelligent control techniques, this article proposes the development of a neuro-fuzzy controller method for the refereed vehicle, considering the nonlinearity of its actuators and using the differential evolution as optimization method to determine the controller parameters. A simulation analysis shows the influence of dead zone and points out that neuro-fuzzy controller is able to deals with it.*

Keywords: *Neuro-Fuzzy System, Differential Evolution, Intelligent Control, Two-Wheeled Vehicle, Dead Zone.*

1. INTRODUCTION

The study of control methodologies applied to two-wheeled vehicles is widely performed (Juang and Lum, 2013; Bonafilia *et al*., 2014; Pereira *et al*., 2016) due to the nonlinearity characteristic of the robot, being applied in this way in the benchmarkings survey regarding the efficiency of controllers applied to nonlinear systems.

Actuators of two-wheeled vehicles, usually equipped with DC motors, are also subject to nonlinearities among which we can mention slack, saturation and dead zone. The latter, caused by the Coulomb friction, exerts a strong influence on the dynamic behavior of these systems with respect to their stabilization and the increase of their oscillation amplitude (Peng and Dubay, 2011).

The increase of the processing capacity of the microcontrollers together with the inefficiency of the classical controllers in nonlinear and high complexity processes makes possible the use of optimization and intelligent control techniques in the design of controllers for these types of systems (Grabowski *et al*., 2008; Han, Lin, and Chang, 2013; Jang, 1992).

Thus, this work proposes the analysis of the dead zone influence on the dynamics of a two-wheeled inverted pendulum vehicle, controlled from a neuro-fuzzy controller whose parameters are obtained through the differential evolution algorithm from the simulation of the vehicle operation conditions, considering the knowledge of the plant's dynamic behavior and the dead zone of its actuators.

2. TWO-WHEELED INVERTED PENDULUM VEHICLE

In Bonafilia *et al*. (2014), a two-wheeled inverted pendulum vehicle, Fig. 1, is modeled, where x is the vehicle position, $\dot{x}$ is its translation speed, θ measures the inclination angle of the vehicle, $\dot{\theta}$ the variation of the inclination angle in time and u is the supply voltage of the two DC motors. Equation (1) presents the system dynamic model.

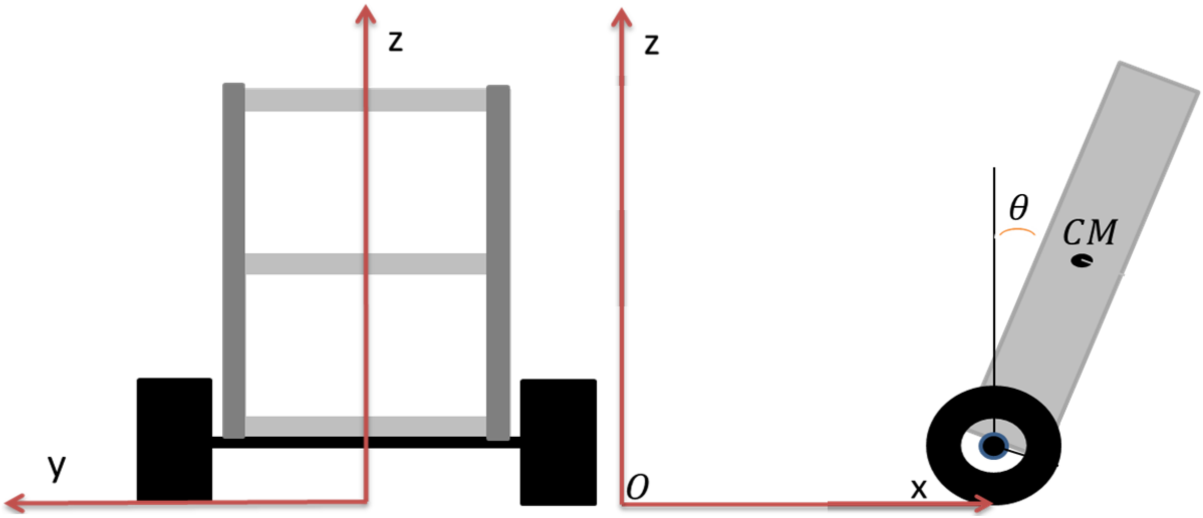


Figure 1. Two wheeled inverted pendulum vehicle representation.

$$\dot{\xi} = A\xi + Bu \tag{1}$$

where:

$$\xi = \left[x \; \dot{x} \; \theta \; \dot{\theta}\right]^T$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & \alpha_M & \beta_M & -r\alpha_M \\ 0 & 0 & 0 & 1 \\ 0 & \gamma_M & \delta_M & -r\gamma_M \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & \alpha_M \varepsilon_M & 0 & \gamma_M \varepsilon_M \end{bmatrix}^T$$

being:

$$\alpha_M = \frac{2(Rb - K_e K_m)(M_b L_m^2 + M_b r L_m + J_b)}{R(2(J_b J_w + J_w L_m^2 M_b + J_b M_w r^2 + L_m^2 M_b M_w r^2) + J_b M_b r^2)}$$

$$\beta_M = \frac{-L_m^2 M_b^2 g r^2}{J_b(2J_w + M_b r^2 + 2M_w r^2) + 2J_w L_m^2 M_b + 2L_m^2 M_b M_w r^2}$$

$$\gamma_M = \frac{-2(Rb - K_e K_m)(2J_w + M_b r^2 + 2M_w r^2 + L_m M_b r)}{Rr(2(J_b J_w + J_w L_m^2 M_b + J_b M_w r^2 + L_m^2 M_b M_w r^2) + J_b M_b r^2)}$$

$$\delta_M = \frac{L_m M_b g(2J_w + M_b r^2 + 2M_w r^2)}{2J_b J_w + 2J_w L_m^2 M_b + J_b M_b r^2 + 2J_b M_w r^2 + 2L_m^2 M_b M_w r^2}$$

$$\varepsilon_M = \frac{K_m r}{Rb - K_e K_m}$$

The description and the adopted values of the parameters involved in the process are presented in Tab. 1:

Table 1. System Parameters.

Parameters	Description	Value
M_b	Vehicle structure mass	1.304 kg
M_w	Vehicle wheels mass	0.031 kg
J_b	Vehicle structure moment of inertia in relation to its center of mass	0.00480 kgm^2
J_w	Wheel moment of inertia in relation to its center of mass	0.00003 kgm^2
r	Wheel radius	0.032 m
L_m	Distance from wheel axle to the vehicle center of mass	0.0748 m
K_e	Ratio between the counter-electric force generated by the engine and its speed	0.3400 Vs/rad
K_m	Ratio between the torque generated by the motor and its armature current	0.3373 Nm/A
R	Motors electrical resistance	0.93 Ω
b	Constant related to the motors viscous friction	0.0001 Nms/rad
g	Gravity acceleration	9.81 m/s^2

In order for the dynamic model could be used in simulations of the mechanism operation, Eq. (1) is discretized considering a zero-order holder, as described below:

$$\xi_{k+1} = G\xi_k + Hu_k \tag{2}$$

in which:

$$G = e^{AT_s} \tag{3}$$

$$H = A^{-1}(e^{AT_s} - I)B \tag{4}$$

where T_s is the sampling time and I is the identity matrix.

3. ACTUATORS' DEAD ZONE

The dead zone of an actuator (Fig. 2) is characterized as the range(s) in which the variation of the input variable has no influence on the system output response. In (Peng and Dubay, 2011), an actuator that presents this nonlinearity is modeled by Eq. (5):

$$y = \begin{cases} f_n(u), \; u \leq \delta_n \\ 0, \; \delta_n < u < \delta_p \\ f_p(u), \; u \geq \delta_p \end{cases} \tag{5}$$

where u is the control action applied to the actuator, y is the actuator torque, $f_n(u)$ and $f_p(u)$ are functions that relate the control action to the actuator output and the parameters δ_n and δ_p determine the dead zone size.

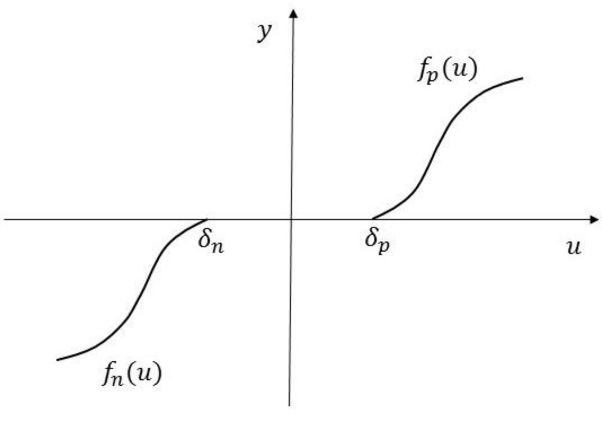


Figure 2. Dead zone representation.

The parameters δ_n and δ_p are difficult to obtain because they change as a function of the loads to which the actuators are subjected, and are also a function of their mechanical wear.

In the present paper, the DC motors of the two-wheeled vehicle are subjected to the dead zone effect, and in order to add the effect of this nonlinearity in the dynamic modeling indicated in Eq. (2), it is considered $|\delta_n| = |\delta_p| = \delta$ in Eq. (5). Thus, the control action perceived by the system dynamics and used as input signal in Eq. (2), u_k, is modeled from Eq. (6):

$$u_k = \begin{cases} u_k^0, & u_k^0 \leq -\delta \\ 0, & -\delta < u_k^0 < +\delta \\ u_k^0, & u_k^0 \geq +\delta \end{cases} \tag{6}$$

where u_k^0 is the control action actually applied on the vehicle's engines and δ is the mechanism dead zone amplitude.

4. NEURO FUZZY SYSTEM

The adaptive neuro-fuzzy system (Jang, 1992a; Jang, and Sun, 1995), also known as ANFIS, arose from the merging of artificial neural networks ANN with the Fuzzy Inference System FIS. In this way, the ANFIS inherits the FIS structure, that is, it contains the fuzzification process, a rule base of type *If* ... *Then*, a fuzzy inference machine and the defuzzification; but with the same structure representation, learning capacity and adaptation of ANN through the adjustment of the parameters related to the fuzzy system.

Figure 3 sketches the structure representation of a neuro-fuzzy system that uses the fuzzy inference method of Takagi-Sugeno (Chen, Lin, and Lin, 2008), where the variables $I_i(k), i = 1, \dots, n$, are the process inputs in iteration k; $MF_{ij}, i = 1, \dots, n,\ j = 1, \dots, m$, are the membership functions associated with the input variables; $R_L, L = 1, \dots, R$, are the rules belonging to the ANFIS rule base and f_L , $L = 1, \dots, R$, are the functions that relate the input variables to the output variable $O(k)$.

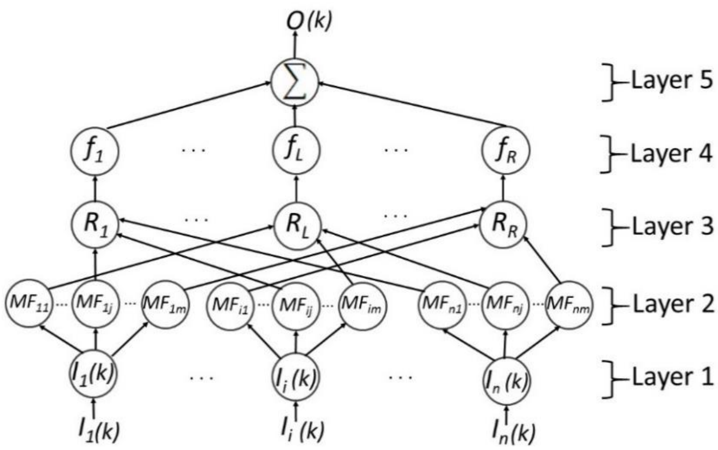


Figure 3. Neuro-fuzzy system representation.

Considering that the fuzzy inference method used is the first order Takagi-Sugeno, the functions f_L are then given by:

$$f_L = w_{0L} + w_{1L} I_1 + \cdots + w_{iL} I_i + \cdots + w_{nL} I_n \tag{7}$$

The parameters w_{iL} are weights whose values are obtained from some optimization method that minimizes the cost function Cf related to the process. Section 5 deals with differential evolution, used as a method to find the appropriate weights for ANFIS.

5. DIFFERENTIAL EVOLUTION

Differential evolution is an algorithm developed by Storn and Price (1996) that aims to minimize functions, which may be nonlinear and non-differentiable. The method is able to reach the global optimum value more easily and quickly than other classical and heuristic methods.

The method has a search engine that is based on the differential mutation operator (vector sum), Eq. (8):

$$V = I_n + F(I_m - I_p) \tag{8}$$

where V is a vector representing an individual that is candidate to belong to the population, I_n, I_m e I_p are randomly chosen individuals that belong to this population, and F is a factor called disturbance factor.

Differential evolution is an evolutionary method, and thus it repeats iteratively from the differential mutation operator until some predetermined stop condition is satisfied.

6. METHODOLOGY

The neuro-fuzzy controller in this paper, named as Differential Evolution and Dynamical Model Based Neuro-Fuzzy Controller (DEDMNF), is obtained by simulating the operating conditions of the two-wheeled vehicle, taking into account the dynamic model presented in Eq. (2) and the dead zone of its actuators.

The simulation for the vehicle at the operating conditions is described below:

- The vehicle operation is simulated for $\mathrm{T_t} = 20\ s$ with a sampling time $\mathrm{T_s} = 0.005$ s;
- The vehicle is assumed, initially, at rest and only with an inclination angle θ_0;
- The accelerometer is corrupted by zero mean white noise and standard deviation σ_{acc}
- Both θ_k and $\Delta\theta_k$ are corrupted respectively by zero mean white noise and standard deviation σ_θ and $\sigma_{\Delta\theta}$;
- Disturbances (e.g., impulse functions) are applied to the system inclination angle θ_k, with intensity i_θ and repeated n_{id} times;
- The mentioned above disturbances and noises are applied until the simulation time $\mathrm{T_p}, \mathrm{T_p} < \mathrm{T_t}$. It's verified the controller ability to reject the system external disturbances;
- The determination of the kinematic structure properties at time kT_s is given by Eq. (2);
- If the value of the control action calculated by the controller at time k, u_k, is contained in the interval $-\delta < u_k < +\delta$, it is necessary that it be equal to zero, according to Eq. (6), so as to account for the effect of the engines dead zone on the vehicle dynamic behavior in the simulation;

The simulation is reproduced for each possible solution found from the differential evolution method, in which is used 40 vectors, 50 iterations, the disturbance factor equal to 0.4 and unitary crossing rate. In this process, it seeks to minimize the cost function Cf associated with the process, Eq. (9):

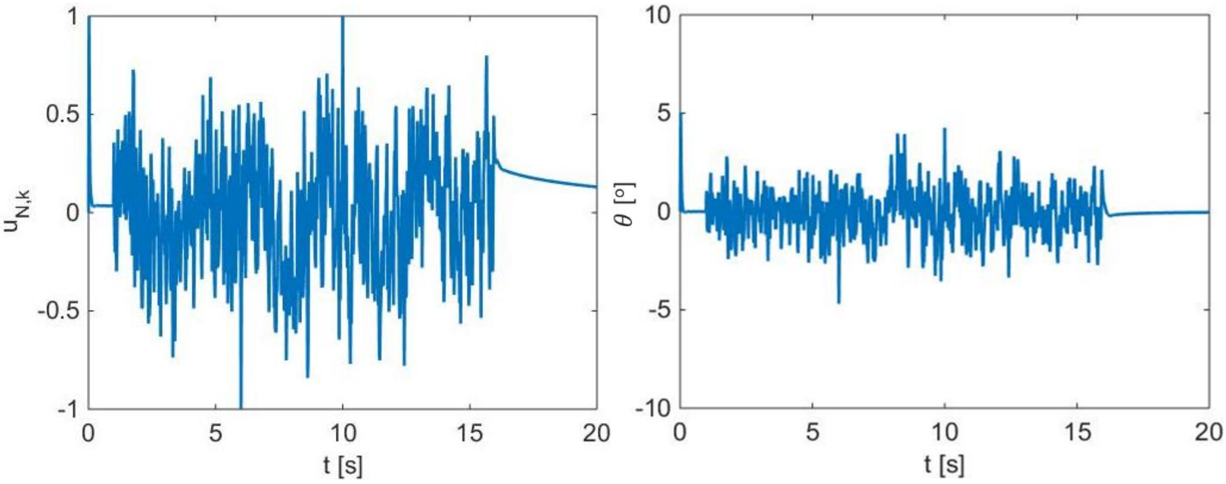
$$Cf = \frac{\sum_{k=1}^{k_{\max}} \lambda_1(u_k)^2 + \lambda_2(\theta_k - \theta_{ref})^2 + \lambda_3(\Delta\theta_k - \Delta\theta_{ref})^2}{k_{max}} \tag{9}$$

where θ_{ref} is the reference inclination angle, considered null, $\Delta\theta_{ref}$ is the reference inclination angle variation, also considered null, and the constants λ_1, λ_2 and λ_3 are used in the imposition of priorities in the cost function minimization procedure. The constant λ_1 is linked to the control effort and the system energy efficiency, while the constants λ_2 and λ_3, as they are related respectively to the inclination angle and the variation of the inclination angle, are linked to the minimization of the vehicle oscillation amplitude. In order to prioritize the control effort minimization and the system energy efficiency maximization, the values of λ_1, λ_2 and λ_3, respectively and by trial and error, are equal to 20, 2 and 0.5.

7. RESULTS AND DISCUSSIONS

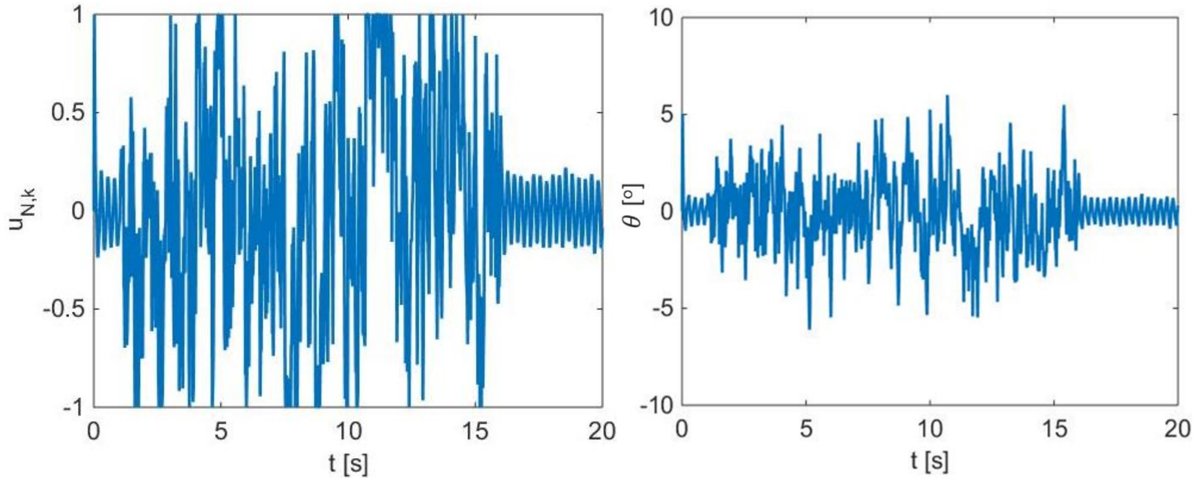
In order to analyze the influence of the dead zone on the plant response and the ability of the neuro-fuzzy structure to control a system subjected to this nonlinearity, simulations of the two-wheeled vehicle operation are performed, using the model presented in Eq. (2), and varying the value of the dead zone amplitude δ.

The normalized control action $u_{N,k}$ and the vehicle inclination angle θ obtained during the simulation, that also is used in the obtainment of the DEDMNF controller parameters, are presented below, where in Figs. 4a and 4b is considered δ = 0 V, δ = 0.6 V in Figs. 5a and 5b, δ = 1.2 V in Figs. 6a and 6b, and δ = 1.8V in Figs. 7a and 7b.



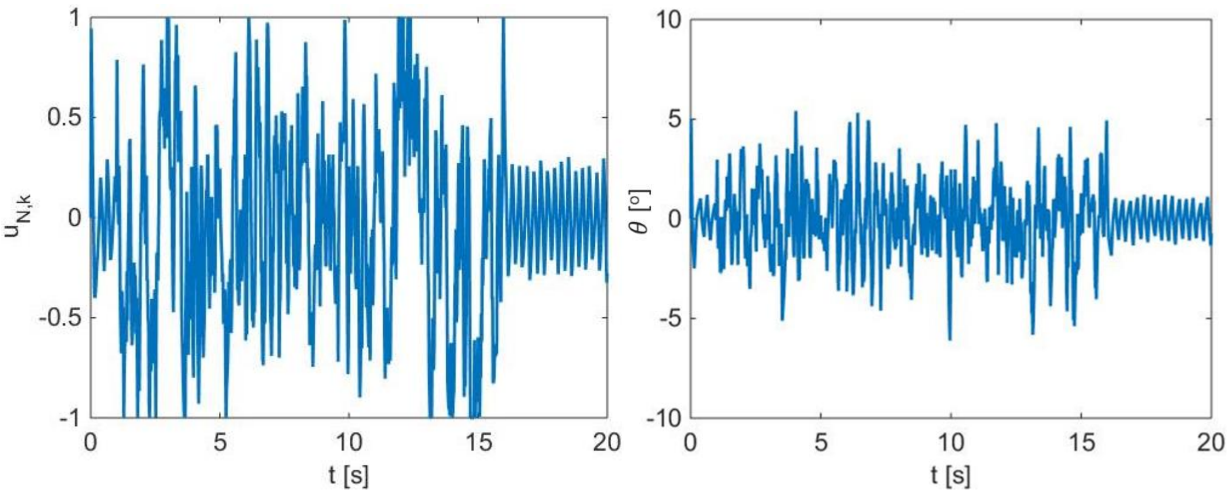
(a) (b)

Figure 4. Vehicle (a) input and (b) output for δ = 0 V.



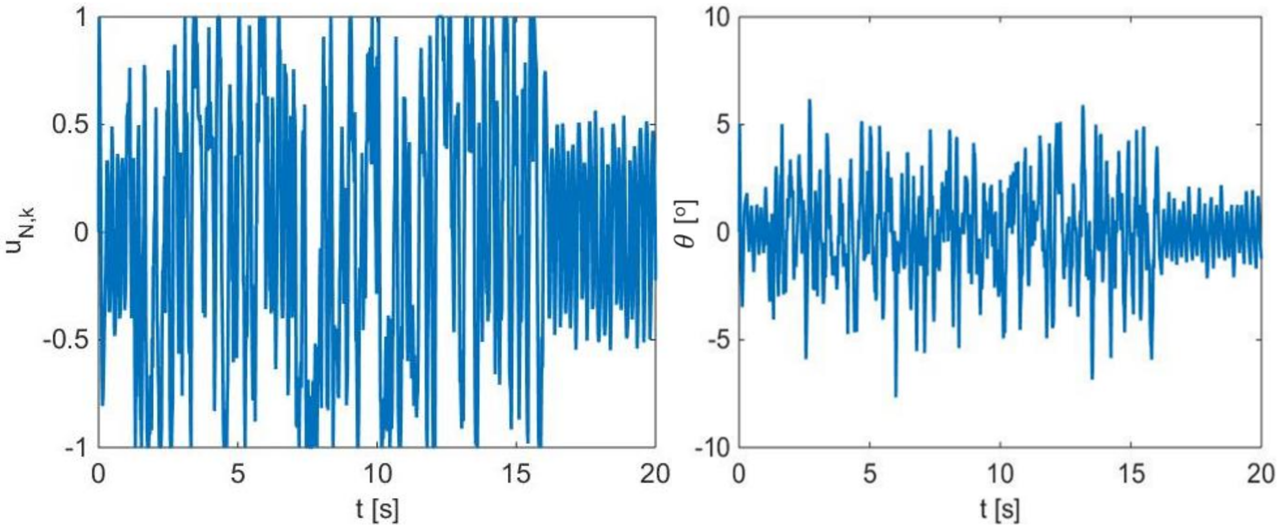
(a) (b)

Figure 5. Vehicle (a) input and (b) output for δ = 0.6 V.



(a) (b)

Figure 6. Vehicle (a) input and (b) output for δ = 1.2 V.



(a) (b)

Figure 7. Vehicle (a) input and (b) output for δ = 1.8 V.

From Figs. 4, 5, 6 and 7, it is possible to verify that as the amplitude of the actuators dead zone increases, plant oscillation also increases, which is in agreement with the conclusion drawn in Peng and Dubay (2011). There is, however, no evidence that the neuro-fuzzy controller is not able to control a system corrupted by such nonlinearity.

Table 2 shows the mean and standard deviation values of the control action and inclination angle as a function of δ, obtained from the simulations.

Table 2. Controller performance as a function of δ.

δ $[V]$	$\overline{u_N}$	s_{u_N}	$\bar{\theta}$ [°]	s_θ [°]
0	0.035	0.275	-0.059	1.110
0.6	0.017	0.485	-0.014	1.713
1.2	-0.041	0.443	0.002	1.733
1.8	0.013	0.574	0.026	2.101

From the values presented in Tab. 2, statistical tests (Montgomery, 2004) are performed in order to analyze, with a certain level of statistical confidence, the effect of the dead zone on the vehicle performance and the neuro-fuzzy controller capacity to make the system to follow the predetermined reference value.

For the statistical analysis of the dead zone effect, from F Snedecor statistical distribution, two hypotheses are elaborated:

- **Null hypotheses:** The vehicle response variance is insensitive to the existence of dead zone in the actuators;
- **Alternative hypotheses:** The vehicle response variance is greater when the actuators present dead zone.

The null hypothesis was rejected for any analyzed $\delta \neq 0$ with a 95% confidence level, which indicates that the dead zone actually contributes to the increase of the system oscillation amplitude around the reference value.

For the statistical test of the DEDMNF controller ability to make the system follow the predetermined reference value, from t Student statistical distribution, 2 hypotheses are elaborated:

- **Null hypotheses:** The vehicle response mean is equal to the zero reference value when using DEDMNF controller;
- **Alternative hypotheses:** The vehicle response mean is different from the zero reference value when using DEDMNF controller.

For any value of δ analyzed, the null hypothesis was not rejected with a 95% confidence level, that is, there is no indication that DENFNF controller is not able to statically stabilize the inclination angle of the two wheeled inverted pendulum vehicle.

8. CONCLUSIONS

This article presented a neuro-fuzzy controller named as Differential Evolution and Dynamical Model Based Neuro-Fuzzy Controller (DEDMNF). DEDMNF parameters were obtained through the differential evolution algorithm from the simulated response of the vehicle at its operational condition, taking into account the knowledge of the plant's dynamic behavior and the dead zone of its actuators.

In fact, the dead zone of the DC motors of two-wheeled inverted pendulum vehicles causes the appearance of nonlinear effects, affecting the responses and reducing its controllability. The greater amplitude of the actuators dead zone, the greater the amplitude of the vehicle oscillation around the pre-determined reference position.

By knowing the actuators' dead zone amplitude δ and the dynamic model of the system, it is possible to develop a neuro-fuzzy controller that takes into account the nonlinearity in question and is able to statically stabilize the two-wheeled inverted pendulum vehicle inclination angle. With 95% of confidence level, there is no indication that DENFNF controller is not able to statically stabilize the inclination angle of the two wheeled inverted pendulum vehicle affected by the dead zone effects.

9. FURTHER WORK

It is proposed to perform bench tests for the experimental validation of DENFNF controller applied in the dead zone effect compensation in two-wheeled inverted pendulum vehicles.

10. ACKNOWLEDGEMENTS

The authors acknowledge the Brazilian funding agencies CNPq, FAPEMIG and CAPES for the financial support for the development of this work.

11. REFERENCES

Bonafilia, B. et al. Self-balancing two-wheeled robot. p. 1-11, 2014.

Chen, C. H., Lin, C. J. and Lin, C. T. "Nonlinear System Control Using Adaptive Neural Fuzzy Networks Based on a Modified Differential Evolution". IEEE Transactions on Systems , Man, and Cybernetics — Part C: Aplications and Reviews. Taiwan, v. 39, n. 4, p. 459-473, 2008.

Grabowski, P. Z. et al. "A Simple Direct-Torque Neuro-Fuzzy Control of PWM-Inverter-Fed Induction Motor Drive", IEEE Transactions on Industrial Electronics. Poland, v. 47, n. 4, p. 863-870, 2008.

Han, M. F., Lin, C. T. and Chang, J. Y. "Differential Evolution With Local Information for Neuro-Fuzzy Systems Optimisation". Knowledge-Based Systems. Taiwan, v. 44, p. 78-89, 2013.

Jang, J. S. R. and Sun, C. T. "Neuro-Fuzzy Modeling and Control". Proceedings of the IEEE. UC Berkeley, v. 83, n.3, p. 378-406, 1995.

Jang, J. S. R. "Fuzzy Controller Design without Domain Experts". IEEE International Conference on Fuzzy Systems. Berkeley, p. 289-296, 1992a.

Jang, J. S. R. "Self-Learning Fuzzy Controllers Based on Temporal Back Propagation". IEEE Transactions on Neural Networks. UC Berkeley, v. 3, n. 5, p. 714-723, 1992b.

Juang, H. S. and Lum, K. Y. "Design and Control of a Two-Wheel Self-Balancing Robot using the Arduino Microcontroller Board". 10th IEEE International Conference on Control and Automation (ICCA), China, p. 634-639, abr. 2013.

Montgomery, D. C. Diseño y análises de experimentos: Versión Autorizada en Español, 2 ed. Arizona, EUA: Limusa Wiley, 2004, 686 p.

Peng, J. and Dubay, R. "Identification and Adaptive Neural Network Control of a DC Motor System With Dead-Zone Characteristic", ISA Transactions. Canada, v. 50, n. 4, p. 588-598, 2011.

Pereira, B. L. et al. "Two-Wheeled Vehicle Control Using Neural Network and Differential Evolution". Postgraduate Symposium in Mechanical Engineering of Federal University of Uberlandia (POSMEC), Brazil, p. 1-7, 2016.

Storn, R. and Price, K. "Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces", Journal of Global Optimization. Netherlands, v. 11, p. 341-359, 1996.

12. RESPONSIBILITY NOTICE