Control of Direct Current Motor by Using Artificial Neural Networks in Internal Model Control Scheme

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In this research, control of the Direct Current motor is accomplished using a neuro controller in the Internal Model Control scheme. Two Feed Forward Neural Networks are trained using historical input-output data. The first neural network is trained to identify the object's dynamic behavior, and that model is used as an internal model in the control scheme. The second neural network is trained to obtain an inverse model of the object, which is applied as a neuro controller. Experiment is conducted on the real direct current motor in laboratory conditions. Obtained results are compared to those achieved by implementing the Direct Inverse Control method with the same neuro controller. It was demonstrated that the proposed control method is simple to implement and the system robustness is achieved, which is a great benefit, aside from the fact that no mathematical model of the system is necessary to synthesize the controller of the real object.

Keywords: *Internal model control, direct inverse control, DC motor, artificial neural networks, neuro controller*

1. INTRODUCTION

A direct current (DC) motor represents a power actuator that converts electrical into mechanical energy [1]. It is often utilized in various industries where wide speed ranges are required, such as for robotic manipulators, overhead cranes, guided vehicles, cutting tools, electrical traction, etc. The fundamental reason for this is that DC motors are highly adaptable when it comes to speed control, and they have excellent characteristics such as high starting, accelerating, and retard torque, high response performance, etc. [2].

Numerous techniques are available for controlling a DC motor's angular velocity. Undoubtedly, using classical PID-like controllers is one of the most common techniques due to their simplicity, ease of installation, and cost-effectiveness. Adjustment of parameters for PID-like controllers can rely on classical methods such as Ziegler-Nichols and Chien-Hrones-Reswick [3], but other methods can also be used [4]. For dealing with the same task, the adaptive PID controller demonstrated its superiority over the conventional PID controller, which is proved in [5].

After Lotfi A. Zadeh introduced fuzzy logic concepts [6], control theory underwent a significant change. Fundamentally, fuzzy logic enables the processing of multiple potential truth values through a single variable represented with linguistic value. Fuzzy logic controllers (FLC) can be used to control the speed of DC motors. For example, it was demonstrated in [7] that FLC represents a better option than traditional PID controllers. A comparison between PID, FLC, and fuzzy PID controllers revealed that fuzzy PID guarantees superior performance to the other two controllers [8]. An even better solution can be produced by applying an adaptive fuzzy PID controller [9]. A different approach for implementing fuzzy logic speed controllers is offered in [10], where the authors developed fuzzy logic microcontroller and suggested using it since it is easy to implement and requires a few inexpensive components.

The development of artificial intelligence paved the way for the advancement of engineering in general. It has found purpose in a variety of fields, such as for heating energy consumption prediction [11], predicting kinematic errors solution in the five-axis machine [12], modeling of machining parameters [13], optimization of traditional Montenegrin chair [14], etc. An example of the use of the artificial neural network (ANN) in the domain of speed control can be found in [15], where ANNs are trained to estimate speed and control the DC motor. It was shown that by using ANN, calculating the motor parameters can be avoided in modeling the system, and ANN can replace the speed sensors in the control system models. Additionally, the neuro controller achieved a remarkable advantage compared to the conventional one. Compared with FLC, where both controllers performed well, the ANN controller reacted faster on the speed adjusting, and the settling time was lower [16]. Adaptive neural speed controller can be applied as well [17].

The technique combining fuzzy logic and ANNs implies using an adaptive neuro-fuzzy inference system (ANFIS) for object control. In control system metrics, including overshoot, undershoot, steady state error, rise, settling, and recovery time, the ANFIS controller outperforms conventional PI, fuzzy-tuned PID, and Fuzzy Variable Structure controller [18].

Recently, the usage of metaheuristic optimization algorithms in finding optimal controller parameters has been growing. Metaheuristic algorithm can be defined

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as a form of stochastic optimization that is not dependent on the surface gradient for optimization [19]. Inspiration for developing a new algorithm can usually be found in nature, evolution, society, etc. In [20], Archimedes Optimization Algorithm (AOA), Dispersive Flies Optimization (DFO), and Particle Swarm Optimization (PSO) algorithms served for tuning optimal gain parameters of conventional PID controllers. It was shown that AOA-PID and DFO-PID are more convenient for speed control of DC motors than PSO-PID and PID tuned via the Ziegler-Nichols method. Fuzzy controllers can be optimized likewise. Fuzzy PD and PID controllers were optimized via PSO, Cuckoo, and Bat algorithms [21], and the controller optimized with the bat search algorithm achieved the best performance. The advantages of PSO and the Gravitational Search Algorithm were combined to develop the fuzzy PI controller parameters for the DC motor [22].

Internal Model Control (IMC) is a control technique often used to control industrial processes, and it can be applied to both linear and nonlinear systems. The reason for common usage is founded in the fact that compensation for the effect of disturbances on the system can be achieved using a simple control scheme containing a controller and an internal model that simulates the controlled object's behavior. In theory, by using the IMC scheme, perfect control is possible. IMC strategy can be implemented to tune the parameters of the PID controller to control brushless DC motors, like in [23].

Model-based fuzzy controller with a fuzzy dynamic model in the IMC scheme demonstrated good robust performance in controlling flow rate [24]. Also, it was shown that this control method could be used with ANNs to control the class of nonlinear systems [25].

In this research, the ANN approach is used in the Internal Model Control scheme to control the DC motor's angular velocity. The first ANN is trained for the identification of the object, and it is used as an internal model, while the second ANN is trained to represent an inverse model of the system, which is later utilized as the controller. Obtained results are compared to results obtained using Direct Inverse Control (DIC) strategy with an ANN controller.

2. SYSTEM DESCRIPTION

The real-life system, Quanser SRV02 Rotary Servo Base Unit [26], is used in this study.

The Servo plant includes DC motor placed in a solid aluminum frame with a planetary gearbox. The motor also has an internal gearbox that drives external gears. There are two available external loads: a disk and a bar. Their purpose is to vary the moment of inertia [26]. In this work, the disk load is attached to the load gear of the object. This object is shown in Figure 1.

The well-known equation that describes the dynamic behavior of the used DC motor and whose schematic model is represented in figure 2 is [27]:

$$J_{eq}\frac{\mathrm{d}\omega_l(t)}{\mathrm{d}t}+B_{eq,v}\omega_l(t)=A_m V_m(t). \quad (1)$$

In (1) ω_l denotes the angular velocity of the load shaft, and V_m is motor voltage; the rest of the parameters can be calculated using the following equations.

$$J_{eq}=\eta_g K_g^2 J_m + J_l, \quad (2)$$

$$B_{eq,v}=\frac{\eta_g K_g^2 \eta_m k_t k_m + \left(\eta_g K_g^2 B_m + B_l\right) R_m}{R_m}, \quad (3)$$

$$A_m=\frac{\eta_g K_g \eta_m k_t}{R_m}. \quad (4)$$

In equations (2), (3), and (4), symbols η_g, K_g, J_m, J_l, η_m, k_t, k_m, B_m, B_l, and R_m, represent gearbox efficiency, the gear ratio of the motor's gear train, motor shaft moment of inertia, moment of inertia of the load, the motor efficiency, current-torque constant, back electromotive motor constant, viscous friction acting on the motor shaft, viscous friction acting on the load shaft and motor resistance, respectively.

Figure 1. Quanser SRV02 system with external gears [26]

Finally, by choosing output variable $y=\omega_l$ and input variable $u=V_m$ linear model of the system is:

$$J_{eq}\dot{y}(t)+B_{eq,v}y(t)=A_m u(t). \quad (5)$$

The linear model does not describe the dynamical behavior of the object completely well because it needs to pay attention to the major nonlinear effect, such as the speed dependant friction, dead zone, and backlash. The nonlinear mathematical model of the system, which takes friction into account, is of the form [28]:

$$J\dot{y}(t)+By(t)+T_{st}\left(y(t)\right)=A_m u(t). \quad (6)$$

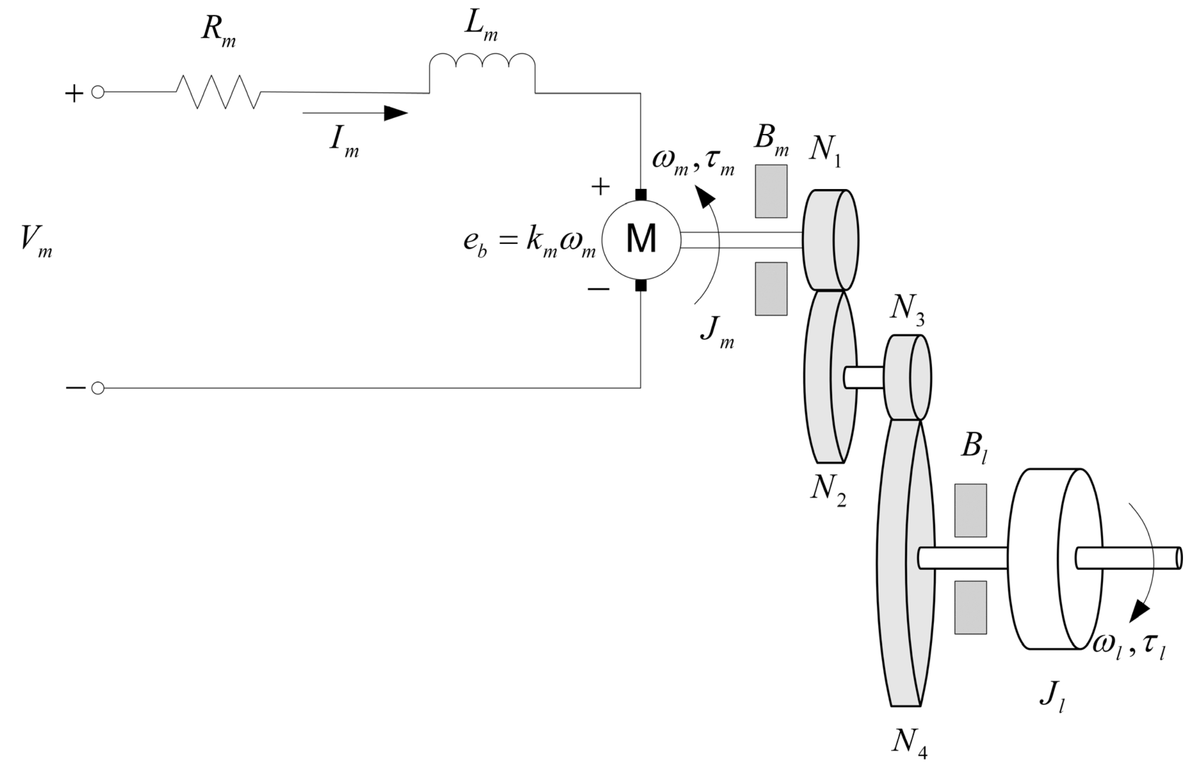

Figure 2. Schematic representation of DC motor [27]

The total moment of inertia reflecting the output shaft is labeled as *J*, while *B* is the equivalent damping term where the linear viscous friction has already been comprehended. Addition, that represents the nonlinear part of the friction torque, T_{st} is [28]:

$$T_{st}\left(y\right) = 0.0174\,\mathrm{sgn}\left(y\right) + 0.0087 e^{\left(-\frac{y}{0.064}\right)}\,\mathrm{sgn}\left(y\right). \quad (7)$$

However, the mathematical model of the object is not used in this research to obtain results. It is served only as foreknowledge about the object to determine the object's difference equation, which is used for setting inputs and output of ANNs, which will be explained in the continuation of the paper.

3. ANN INTERNAL MODEL CONTROL STRATEGY

The prime characteristic of the IMC strategy is that it should achieve system robustness. A well-known sch–eme that illustrates the IMC strategy is shown in Figure 3.

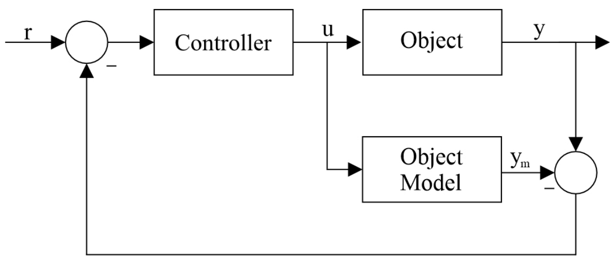

Figure 3. General Internal Model Control diagram

There are three main properties of IMC strategy [25]:
Property 1 – Stability: Suppose that the model of the object is perfect. The closed-loop system is also stable if the object and the controller are input-output stable.
Property 2 – Perfect control: Suppose that the controller and inverse model are equal and that the closed-loop system is stable. In that case, control of the system will be perfect.
Property 3 – Zero offset: Suppose that the closed loop system is stable and the steady state controller gain equ–als the inverse of the model gain. Then the offset-free control is reached for asymptotically constant signals.

A deeper analysis of the IMC approach can be found in [29].

IMC strategy with ANNs implies that trained ANNs are used as controllers and object models in the control scheme. There are two steps in implementing this method – identification of the object and iden–tification of the inverse model. Object identification involves training the ANN to predict output from the real object so that it can be used as an object model in the scheme, while identification of the inverse model serves to learn ANN to predict object input and be treated as an inverse controller. The paper further discusses the application of this control method to the specific DC motor case.

3.1 Feedforward ANN model

Feedforward neural network (FFNN) is a simple ANN with a well-known architecture composed of neurons arranged in input, hidden, and output layers. It is often used to control different objects and processes, function approximation, prediction, classification, etc. Classical learning process of FFNN is based on the back-propagation algorithm. For example, deeper information about FFNN can be found in [30].

In this research, two FFNNs were trained to satisfy the IMC scheme. Both models have only one hidden layer with a difference in the number of neurons. Model of the object has 6 neurons, and the inverse model has 7 neurons in the hidden layer. Training was offline with historical input-output data. Levenberg-Marquardt algo–rithm, which promises fast convergence, is used in mo–del training. Mean Squared Error (MSE) is defined as the objective function. Learning rate is set to 0.001. Mentioned parameters are kept the same in both of the training processes.

3.2 Object identification

Object identification is conducted via a model where the output from the object is predicted based on input and output from the previous moment.

DC motor that is considered in this research belongs to single-input-single systems. According to equation (6) it can be represented via the following difference equation:

$$y(k+1) = f\left[y(k), u(k)\right]. \tag{8}$$

Based on (8), neural network output can be desc–ribed as:

$$y_m(k+1) = N_1\left[y(k), u(k)\right], \tag{9}$$

where N_1 represents a trained neural network for object identification. Structural diagram that describes the training process of the feedforward model for this particular object is given in figure 4.

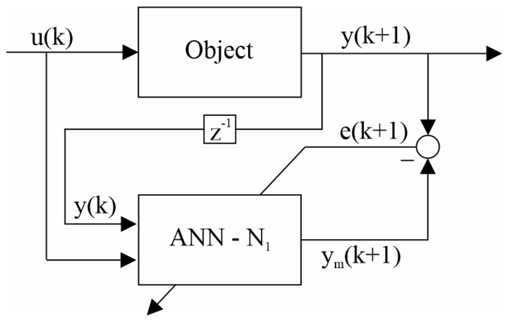

Figure 4. Identification of considered object using ANN

4. IDENTIFICATION OF INVERSE OBJECT

Obtaining an inverse model means that ANN should be trained to predict the input of an object, i.e., control signal based on previous output and input signals.

In our case, ANN marked with N_2, is trained to give output u_m based on the following expression:

$$u_m(k) = N_2\left[y(k), y(k+1)\right]. \tag{10}$$

A structural diagram of training ANN to represent an inverse model of the user object is shown in figure 5.

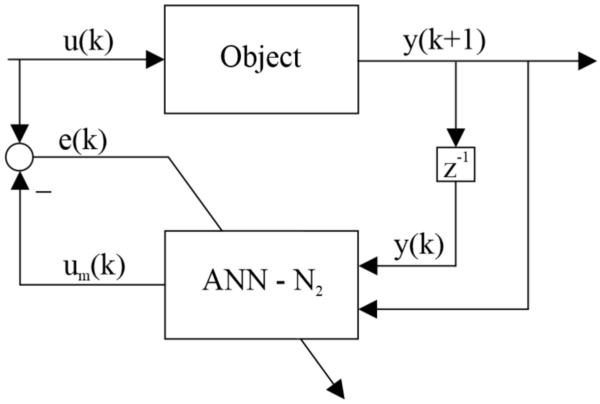

Figure 5. Obtaining an inverse model of the DC motor

5. IMPLEMENTATION OF IMC SCHEME ON DC MOTOR

Finally, after training FFNN models, the IMC strategy is adapted to suit the object used in this research. Detailed structural diagram of the proposed IMC method, which shows appropriate input signals in the identified object model, neuro controller, and the real object, DC motor, is shown in Figure 6.

6. DIRECT INVERSE CONTROL METHOD

The DIC method implies using an inverse model as a neuro controller. It is a simple method where the inputs in the controller are desired output values and outputs from the object.

In our research, the DIC method is compared with IMC to investigate the performance of the proposed IMC method. The Neuro controller used in DIC is the same as in the IMC scheme. Figure 7 shows a detailed structural diagram of DIC adapted to the specific case of DC motor control.

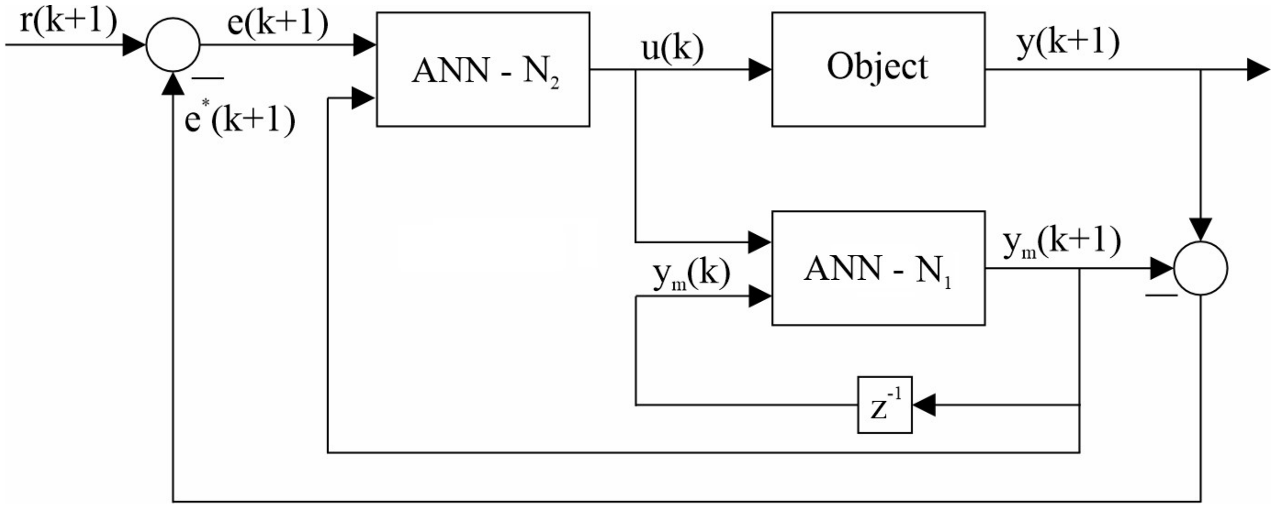

Figure 6. Structural diagram of adapted IMC scheme

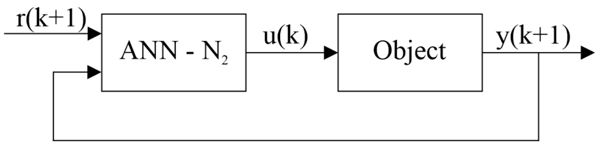

Figure 7. Structural diagram of adapted DIC scheme

7. EXPERIMENTAL RESULTS AND DISCUSSION

This section is split into two parts. The first is presented results after training FFNNs used in IMC strategy. The second subsection refers to the presentation and com– parison of the results obtained by implementing two different control strategies.

7.1 Obtaining identified and inverse object model

The dataset used for FFNNs training is a collection of previous readings of the object's input and output signal values obtained in laboratory conditions. Input in the ob– ject is a random signal whose values go between -10 V and 10 V and change every 0.5 s. Time duration for obta– ining the dataset is 200 s with fixed step time $T = 0.002$ s.

The diagram that shows obtained output from a noncontrolled DC motor and output predicted via FFNN is given in figure 8, and a high coincidence of these two signals can be noticed. The best value of the MSE in validation during the training process is 0.0096123.

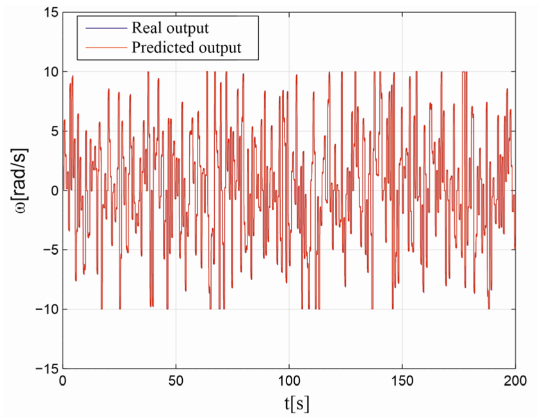

Figure 8. Training results of the identified object model

Figure 9 is a given graph, after training the inverse model, that shows input in the object (which is the output of the inverse model) and predicted input via FFNN based on the value of the output signal from the object. The best MSE value is 0.28553.

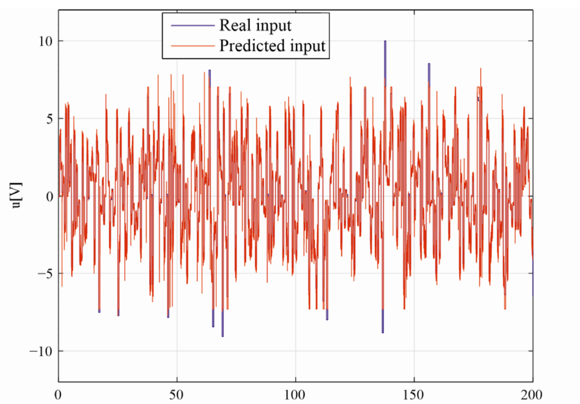

Figure 9. Results after training the inverse object model

7.2 Comparison of the obtained results by using IMC and DIC strategies

There are three following cases of comparison between DIC and IMC methods whose results are shown in the continuation of the paper.

Case 1: In the first case, the desired output is a step signal with a value of 5 rad/s.

Case 2: In the second case, models are tested when disturbance acts on the object. The disturbance arises at 0.5 s and lasts till 1 s. Desired output is the same as in the first case.

Case 3: The third case of comparison is an examination of how our models behave when the desired output is a sinusoidal signal with an amplitude 5 rad/s and a frequency of 0.04 rad/s.

Integral Square Error (ISE) is used as a performance index, and this criterion can be described via the following expression:

$$ISE = \int_0^{\infty} e^2(t)\,dt \tag{11}$$

A moving-average filter reduces noise in all res– ponse and control signals. It can be described with the difference equation (12) where the length of average, *N*, is set to 5, *y[n]* is the current output, *x[n]* is the current input, *x[n-1]* is the previous input, etc.

$$y[n] = \sum_{i=0}^{N-1} x[n-i] \tag{12}$$

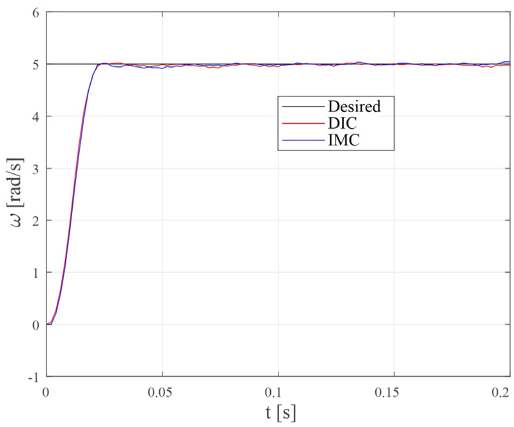

Figure 10. System response to the step input signal

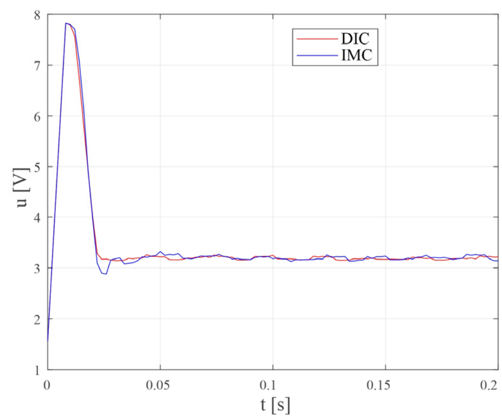

Figure 11. Control signal to step input

Figure 10 shows the system response in the first testing case. Both of the used models work similarly, and the desired velocity value is achieved quickly. Control signal for this case is given in figure 11.

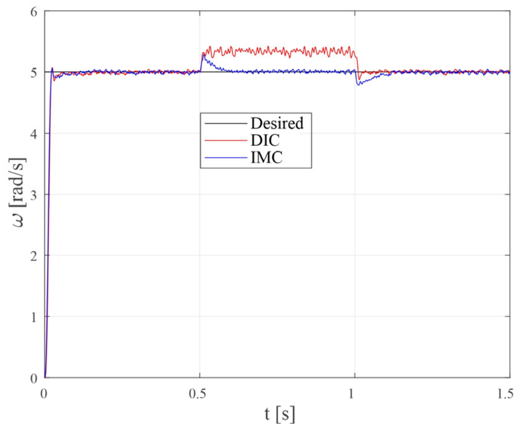

Figure 12. System response to the step input signal with disturbance

The system response to step signal with disturbance for both controlling methods is given in figure 12. It is clear that the IMC method ensures that the neuro controller reacts in a way that balances the impact of the disturbance, while the controller in DIC cannot handle the disturbance. Suitable control signal for this case can be seen in figure 13.

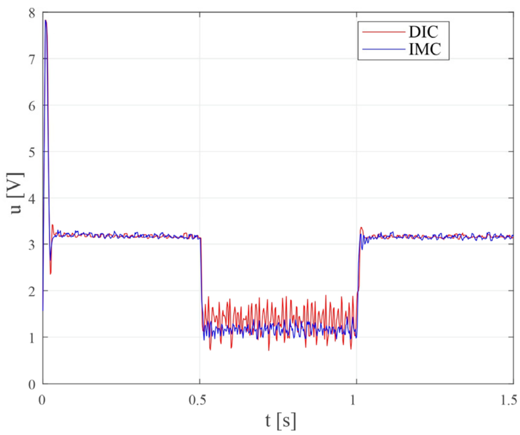

Figure 13. Control signal to step input with disturbance

Finally, output signals for sinusoidal desired velocity are given in figure 14.

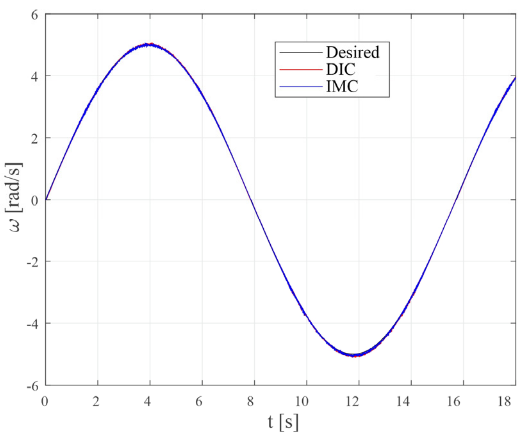

Figure 14. System response to the sinusoidal input signal

Figure 15 shows the control signal in the third com–parison case.

ISE values for all three comparison cases are given in table 1. It can be noticed that values are approximate when the object is not affected by a disturbance. When disturbance appears, the ISE value is significantly lower when IMC is used. However, ISE is slightly lower in those cases when applied in the DIC method.

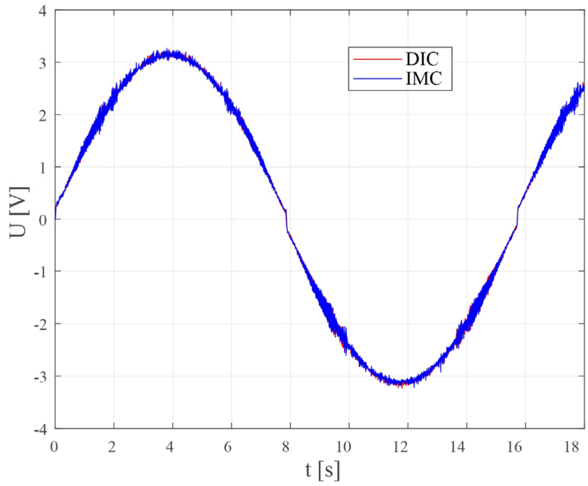

Figure 15. Control signal to a sinusoidal input

Table 1. ISE value

ISE	Case 1	Case 2	Case 3
DIC	0.1361	0.2505	0.0716
IMC	0.1463	0.1539	0.0767

8. CONCLUSION

This study proposes an artificial intelligence approach to automatic control. The IMC strategy is adapted for controlling the real DC motor using two FFNNs. In addition, DIC is implemented for the same purpose, and the same ANN model is used as a neuro controller. There are several inferences from this research.

The fact that mathematical equations that describe the object's dynamic behavior are not required for controller synthesis is a significant benefit provided by the usage of ANN for control.

Both methods are easy to implement, but it is crucial to obtain identified and inverse models that are good representations of the real system. For this purpose, it is necessary to train a few ANN with variations in learning parameters, which can refer to a number of neurons, hidden layers, learning rate, etc. Sometimes using diffe–rent ANN models brings better solutions. In this resea–rch, FFNNs were acceptable for dealing with the set task.

When it comes to the comparison of DIC and IMC strategies, it is obvious that in the cases when the object is not affected by disturbance, both of them give similar results. Although ISE criteria stand out for DIC, the difference in ISE values is diminutive. A huge diffe–rence between these methods occurs when disturbance affects DC motors. Then, the controller in the DIC strategy cannot compensate for the effect of the distur–bance, while the controller in the IMC scheme success–fully deals with the disturbance. In that case, the diffe–rence in ISE values is noticeably greater.

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УПРАВЉАЊЕ МОТОРА ЈЕДНОСМЕРНЕ СТРУЈЕ КОРИШЋЕЊЕМ ВЕШТАЧКИХ НЕУРОНСКИХ МРЕЖА У УПРАВЉАЧКОЈ ШЕМИ СА УНУТРАШЊИМ МОДЕЛОМ

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У овом истраживању је остварено управљање мотором једносмерне струје коришћењем неуро-контролера у управљачкој шеми са унутрашњим моделом. Две неуронске мреже без повратних веза су обучене на основу прикупљених улазно-излазних података. Прва неуронска мрежа је обучена за идентификацију динамичког понашања објекта и тај модел је коришћен као унутрашњи модел у шеми управљања. Друга неуронска мрежа је обучена у циљу добијања инверзног модела објекта, који је примењен као неуро-контролер. Експеримент је спроведен на реалном систему – мотору једносмерне струје у лабораторијским условима. Добијени резултати су упоређени са резултатима постигнутим имплементацијом методе директног инверзног управљања са истим неуро-контролером. Показало се да је предложени метод управљања једноставан за имплементацију и да је постигнута робусност система, што поред чињенице да није потребан математички модел да би се пројектовао контролер за управљање стварним објектом, представља велику предност.