

## A neural regulator for efficient control of electric vehicle motors

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### Abstract

**INTRODUCTION:** A number of promising designs of electric vehicles use separate wheeled motors. In this case, an important task of designing a power supply system is to provide effective control of electric motors and battery charge / discharge modes.

**OBJECTIVES:** The paper considers the problem of determining optimal coefficients of the electric motor proportional-integral (PI) controller and their influence on the power distribution in the electric vehicle on-board power supply system.

**METHODS:** It is proposed to implement separate adaptive control of electric motors, taking into account conditions of operating, road surface, and other factors. There are introduced two options for the motor controller implementation: an adaptive PI-controller and an intelligent PI-controller with an adaptive observer based on a neural network.

**RESULTS:** The simulation results show that the adaptive PI-controller provides a reduction in the transient duration, but insufficient energy efficiency. Intelligent PI controller on the base of neuroregulator provides 2 times reduction of transition time, reduction of energy losses and engine overshoot.

**CONCLUSION:** The use of the neuroregulator makes it possible to automatically select and adjust PI controller coefficients. In addition, the proposed control method reduces inrush currents and torque spikes, that prolongs the service life of mechanical components. During motor operation, the neural network can continue learning and adjusting PI-controller coefficients to changes in operating conditions (for example, seasonal) and motor parameters. Assumed outcomes of this solution will be improving electric vehicle characteristics, increasing mileage and battery life time, and prospective transition to an electronic differential.

**Keywords:** Energy optimization, nature-inspired computing techniques, neural network electric vehicle, PI-regulator, neural observer, embedded systems, adaptive control, method, model.

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### 1. Introduction\*\*

Air pollution from internal combustion engines and oil resources depletion stimulates the development and implementation of electric vehicles. Electric cars are

designed to be energy efficient and environmentally friendly. These requirements are interconnected. Disposing of rechargeable batteries and manufacturing new ones is also detrimental to the environment. The battery life of industrial electric vehicles is quite short and does not usually exceed three years [1, 2]. A battery life depends not only on the distance of run but also on the mode of operation. Efficiency of an on board power system ensures not only low power consumption, but also a long battery life.

The indicator of power control efficiency is specific energy intensity, or energy consumption per kilometre (kW\*h/km) [1, 2]. In this case, we take into account one-charge distance, including regenerative braking. Equally important is to ensure a long battery life [1]. One of the promising ways to achieve required

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characteristics is separate adaptive control of wheel motors, when each wheel operates in an individual mode. This is especially important, for example, in the case of skidding or sliding of one of the wheels when a car is in the starting mode. Using adaptive control for each wheel increases power reserve and the battery life. It also improves the electric vehicle performance in general. Distributed drives make it possible to eliminate the mechanical differential. This simplifies the mechanical layout of the power train and, as a result, reduces the vehicle weight and maintenance cost.

Since the operational mode of a power supply system depends on operating conditions, road conditions, and charging and discharging modes of batteries, adaptive control is required to ensure efficient operation. Adaptive control involves changing the current and voltage coefficients of electric motor regulators, control of recovery and battery charging modes.

## 2. Related work

Adaptive control and monitoring of wheel motors for electric vehicles are recognized as one of the promising directions of electric vehicle development [3]. A number of studies [4, 5, 6] present the comparative analysis of adaptive control algorithms which are used in sensorless control systems for alternating current electric motors.

An adaptive method based on determining the rotational speed and active resistance of the stator is described in [7]. A feature of the method is the use of a state observer as a part of the adaptive control system. The state observer is an adjustable real-time model of the controlled object that allows estimating unknown values from known parameters. This model can be implemented in coordinates convenient for the motor controller synthesis. The use of an observer does not complicate the control system. This approach makes it possible to control a motor without additional test inputs. However, it does not support adjusting observer parameters and, as a result, current surge protection in the case of motor speed reduction. The effect of motor magnetization is not taken into account. In addition, this method is applicable to a single type of electric motors.

In [8], it was proposed to use the electric motor itself as a reference model for an observer, and the full-order model of electromagnetic processes as an adjustable model. The article describes a new regulator adjusting law based on analysis of its stability. The experimental study confirmed applicability of the proposed approach. However, it does not ensure stable motor operation in the generation mode, and the suggested method of adjusting observer parameters has no theoretical justification.

An adaptive control based on the fuzzy logic is introduced in [6]. However, the effectiveness of the proposed method was not analyzed for cases of an asynchronous electric motor control, non-stationarity of motor parameters as well as variations in the equivalent inertia moment of the motor.

Genetic algorithms show good results in regulating the rotating speed of an asynchronous electric motor [8].

However, it is necessary to preprocess a large amount of data using wavelet filtering to increase the genetic algorithm convergence. The experimental study shows that the use of a genetic algorithm in power control systems leads to self-oscillations, which causes a significant error in observer's control signals, especially in start and brake modes.

A hardware-software control system with an observer is described in [7]. The observer is used in a sensorless control system of an asynchronous electric motor. It is implemented as a library routine for the Texas Instruments TMS processor. The control algorithm is based on minimizing the objective function of adjusting variables. Reactive power is not measured; it is calculated (recovered) using the measured value of the electromotive force. In turn, the adjusting law of the sensorless observer uses reactive power to recover motor speed.

The review shows that observer-based control systems are a promising solution for electric motor control systems. The observer makes it possible to determine motor operating mode parameters such as the current vector, the wheel speed, power consumption, etc., for different transient processes. This allows taking into account the "history" of effects of road conditions, transported cargo weight etc. on transient processes and battery current consumption. In the case of separate control of wheel motors, the controller takes into account the difference in tire-road adhesion on different sides of the vehicle. This prevents wheel slippage and maintains the optimal mode of the motor operation. As a result, an observer-based control system increases the motor energy efficiency. However, the corresponding algorithms for the observer and the control system as a whole have not yet been developed.

## 3. Proposed solution

It is proposed to build the motor control system based on a proportional integral (PI) controller using an observer. The receding horizon control (RHC) strategy [9] is chosen to perform the predictive control. According to this strategy, the observer predicts the reaction of the controlled object over a certain time interval in the future. The prediction of the current, voltage and motor speed is performed taking into account previous data, transients, and the system robustness. The task of the motor control system is to generate control signals in such a way as to minimize the objective function. The fitness function is the difference between the output signals of a real controlled object and an ideal model [7, 10].

To build the control system, a vector control method [4, 11, 12–16] was chosen. The choice is due to the fact that the method makes it possible to control not only the magnitude and frequency of the supply voltage, but also the phase. This allows the system to control the speed and torque on the motor shaft independently. The use of vector equations to calculate adjustable variables ensures the adjustment accuracy and fully corresponds to the problem being solved.

To study the introduced solution, the model of the power supply system with adaptive control was developed using the Matlab modelling environment (Figure 1).

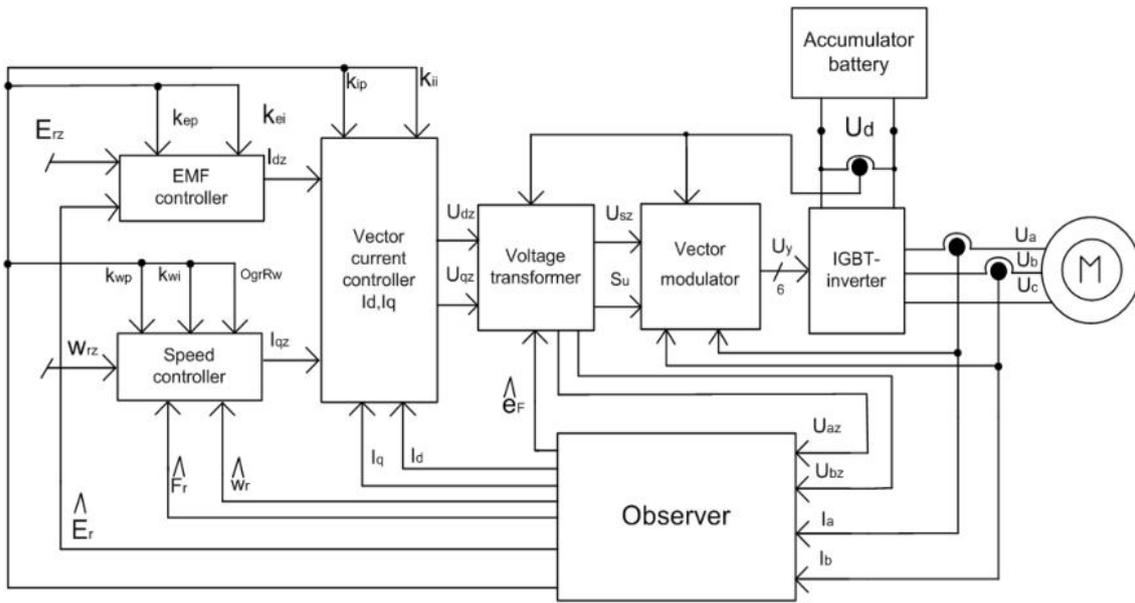


Figure 1. Structural diagram of the vector PI controller with an observer

The following indicators are proposed to evaluate the control system quality:

- peak currents in motion,
- transient time,
- rotor speed,
- magnetic flux,
- resistance moment on the motor shaft.

The observer can be implemented in various ways. First, the control unit model based on a non-adaptive observer was studied. Two operation laws of observer were considered.

In the first case, the motor speed was determined as the derivative of the angle, and the angle was calculated by equation (1) [16].

$$\hat{\theta}_\varphi = \int \omega_\varphi dt + \theta_{\varphi 0} \quad (1)$$

where  $\hat{\theta}_\varphi$  is the recovered angle,  $\Psi_{R\alpha}$  and  $\Psi_{R\beta}$  are  $\alpha$  and  $\beta$  projections of the rotor magnetic flux, respectively.

In the second case, the motor speed was determined according to expression (2), and the angle was calculated as an integral of the speed [16].

$$\omega_\varphi = \frac{1}{K_p + K_i/s} (W_{rz} - \omega_\varphi) + \omega_\varphi \quad (2)$$

where  $\omega_\varphi$  is the recovered rotational speed,  $K_p$  and  $K_i$  are proportional and integral coefficients respectively,  $I_{qz}$  and  $I_{dz}$  are increment of the current on axis  $\alpha$  and  $\beta$  respectively.

Simulation results are shown in Figure 2.

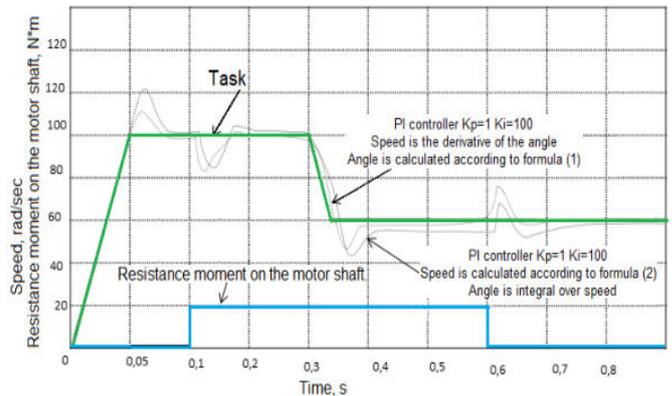


Figure 2. Motor simulation results for two laws of PI controller operation

PI controller coefficients are usually preselected automatically or manually. This is a non-trivial task, because it is difficult to preset the coefficients optimally. For example, Figure 2 shows that there is an integral error in determining rotor rotation angles, regardless of the method of determining the speed and angle. This is because integral coefficient  $K_i$  in expression (2) is not optimal for this mode.

In addition, in expressions 1 and 2, the value of the rotor flux is actually non-linear. This leads to an increase in the control error. Another limitation of this model is that simulating reverse motion downhill requires an additional identification signal in the stator circuit. There is also no way to determine the coefficients of the controller for starting the engine in this mode, since expression 2 should only generate positive and non-zero speed values for the proper functioning of the system. This complicates the

determination of speed.4. PI controller based on an adaptive observer

The next step aimed at improving the effectiveness of the control system is the introduction of an adaptive observer (Figure 3).

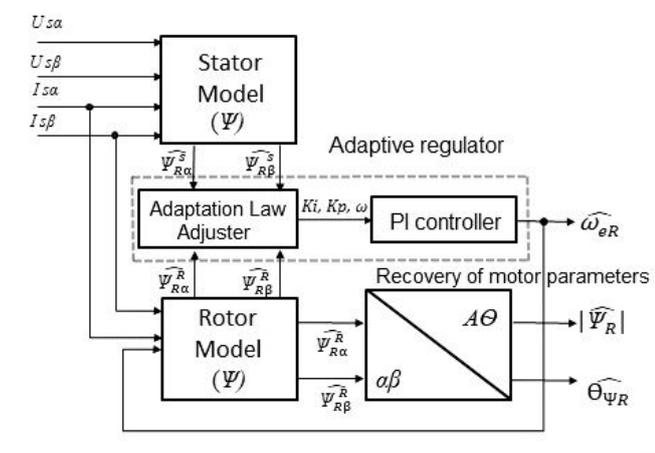


Figure 3. Structural diagram of the adaptive regulator

Adaptation of the observer is performed by a module called the “Adaptation Law Adjuster”. It compares magnetic flux of the model and generates the speed estimation signal. The PI-controller uses this signal as an adapting signal. The function of converting compared vector quantities (in this case, fluxes) into a scalar signal of speed estimation at the controller output is called the adaptation law.

The model of the described system was developed and simulated in Matlab. The case study included applying a load corresponding to the movement of the M1 class car in the urban cycle according to [2].

The following values were observed: motor currents ( $I$ ), transient times ( $t$ ), motor speed ( $\omega$ ), and load moment on the shaft ( $M$ ). An example of experimental results is shown in Figure 4.

It can be seen that the adaptive controller shows satisfactory results in terms of the transient time in the case of changing the motor speed. The task was to increase the motor speed from 0 to 100 rad/s; after one second, the speed should be reduced to 50. Achieving the required speed took 0.5 s. After that, the motor gained speed up to 105 rad/s, then the speed error decreased to zero within 0.5 seconds. Thus, in this experiment, the overshoot error does not exceed 5 %, which corresponds to the average value of the entire series of experimental studies [14].

However, the diagram analysis shows that the used PI control methods do not exclude current surges. For example, a current surge occurred when a reduction in motor speed from 100 to 50 rad/s was performed in accordance with the task (Figure 4, Graph 2, the time period from 1.01 to 1.2 s.). Due to this surge about 15 V of battery power were wasted. Since an intermittent cycle of motion is typical for urban traffic, such a useless consumption of battery power leads to a significant decrease in the distance on one charge.

### 5. Intelligent PI controller based on a neuroregulator

Studies of the developed model show that the choice of PI controller coefficients at the stability boundary of the system makes it possible to reduce the transition time, improve important control characteristics, such as accuracy and stability, and, as a result, reduce energy consumption and decrease currents that destroy the battery.

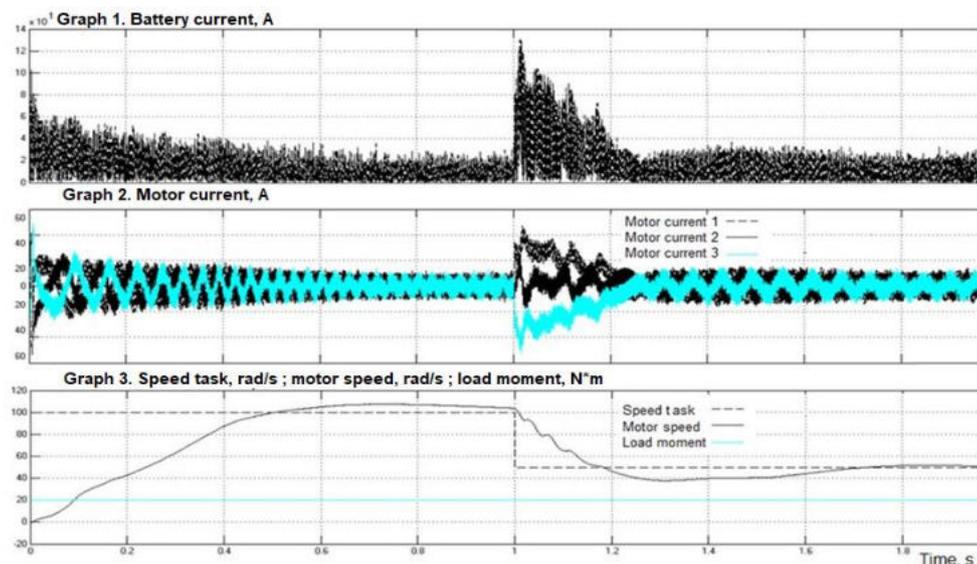
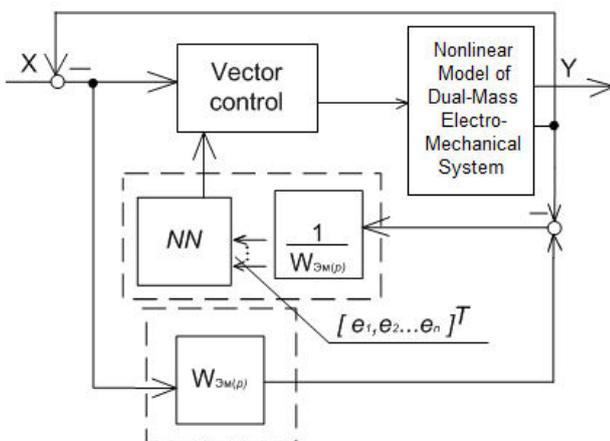


Figure 4. Transients in the power supply system and the electric motor controlled by the adaptive PI controller

To increase the efficiency of the controller, its coefficients should be adjusted taking into account individual engine instance characteristics and their changes during operation. One of the promising ways to implement an intelligent adaptive module for selecting and adjusting the PI controller coefficients is to use neural networks as an adaptive observer [17–22]. This approach is expected to increase motor control efficiency and battery life, motor operating stability, and possibly overall performance of the control system.

The task of the neuroregulator in this system is to minimize deviations of the rotor speed ( $\omega_r$ ) and stator current ( $I_s$ ) from ideal values by adjusting the PI controller coefficients. The functional diagram of the adaptive regulator learning is shown in Figure 5.



**Figure 5.** Structural diagram of the adaptive neuroregulator learning

It includes: a model of a dynamic object with a feedback on deviation with a real object, an identifier of the object parameters (the motor EMF, rotor current, magnetic flux, and speed).

The choice of a dual-mass electromechanical system (DMEMS) is because the torque transmission uses a mechanical gear motor variator for matching rotational speeds of the motor shaft and the drive wheel. In many cases, this kinematic scheme contains elastic elements [23]: long shafts, torsions, elastic couplings, etc. Mechanical systems with elastic links are usually reduced to dual-mass mechanical systems. This is especially true for electric motors operating in intensive dynamic modes, typical for electric vehicles. To build the adaptive neural observer, it is proposed to use a multilayer neural network with delay lines, trained using error back propagation [22].

The network has three levels and uses two delay lines to take into account previous values of rotor speed and stator current of the electric motor. Delay lines are introduced to analyze time sequences that describe the motor operation. To reduce noise, the control object output is averaged. The output signal from the control object enters the input layer of the neural network in the next clock cycle.

The disadvantage of applying untrained neural networks is the absence of a priori knowledge about the control object. It is proposed to carry out preliminary neural network training. A neural network training sample is prepared with the use of the ideal mathematical model of the motor. The model describes the dependence of the rotor speed, stator current, and the motor shaft torque on the selected PI controller coefficients [9].

After training, the neural network was integrated into the adaptive control module. Modelling and testing the control system with the neuroregulator was performed under the same conditions as the conventional adaptive observer. Simulation results are shown in Figure 6.

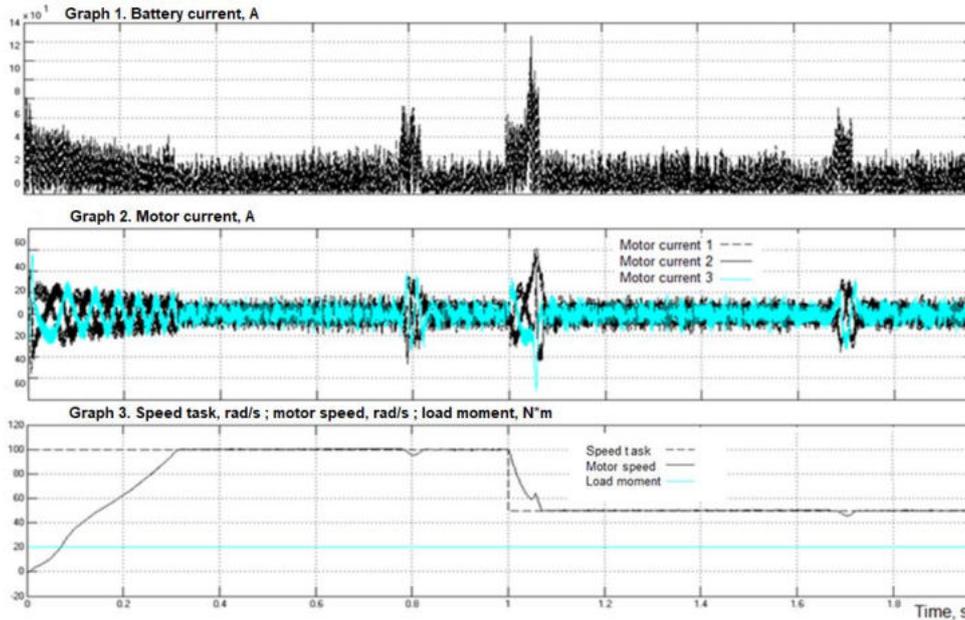
Diagrams show that in the case of task to increase the motor speed from 0 up to 100 rad/s the transient time is reduced from 0.6 to 0.3 seconds due to the prediction of the electric motor reaction. Thus, the use of the neuro-regulator provided the motor speed stabilization 2.1 times faster. In the case of the task on decreasing the rotor speed from 100 down to 50, the transient time is also reduced. As a result, useless energy consumption has declined too. The adaptive coefficient regulation with the use of the neuroregulator eliminates overshoot of the motor speed. Therefore, it can be concluded that the use of a neuroregulator makes the system more stable regardless of the trajectory and traffic conditions of electric vehicles.

To verify coefficient adjustment and the PI controller stability, there are set artificially into the current measurement channels to simulate the 15% increasing in the resistance of rotor and stator windings due to temperature changes. In Figure 6, the results of introducing disturbance can be observed at 0.8 and 1.7 seconds. As it can be seen in Figure 6, the neural network-based adaptive controller successfully compensated the parameter instability.

During the motor operation, the neural network continues to train and adjust PI controller coefficients obtained within pre-training. The neuroregulator provides adjusting PI controller coefficients in real time. This allows PI controller to take into account the control object nonlinearity. In addition, neuron networks allow changing the control law by means of correction of neuron weights and displacements without a significant change in the control system structure.

## Evaluation of the energy efficiency of the proposed solution

It is assumed that the proposed solution will provide higher energy efficiency compared to an unregulated PI controller due to faster achievement of the optimal range of slip values.



**Figure 6.** Transients in the power supply system and the electric motor controlled by the intelligent adaptive PI controller with the neuro-regulator

The possibility to influence on the electric motor slip through increasing the rotor speed is described by the following expression [24]:

$$s = \frac{\omega_0 - \omega}{\omega_0} \quad (3)$$

where  $\omega_0$  is the nominal value of the stator field revolutions,  $\omega$  is the rotor speed,  $\omega_{eff}$  is the effective stator field speed.

Losses for the induction motor are added up from [24]:

$$P_{loss} = P_{var} + P_{const} \quad (4)$$

where  $m$  is the number of stator winding phases,  $R_1, R_2$  are active resistances of stator and rotor winding circuits respectively,  $\Delta P_v$  are variable losses,  $\Delta P_c$  are constant losses, described by expression:

$$P_{const} = \Delta P_c \quad (5)$$

Variable losses can also be expressed through losses in the rotor, which are connected with electromagnetic power and slip as:

$$P_{var} = \frac{M^2 s}{\omega_0} \quad (6)$$

where  $s$  is the slip relative to the ideal idle speed  $\omega_0$ ,  $M$  is the electromagnetic moment.

The  $K_i$  and  $K_p$  adjusting performed by the neural network allows optimizing the rotor speed at start-up, operation in static mode and transient processes of an induction motor, thereby affecting the motor slip. Setting the

optimum slip value  $s$  makes it possible to reduce the current consumption [24].

The motor operation in the section of the mechanical characteristic corresponding to the motor slips exceeding the critical value occurs only in transient conditions. Therefore, the equation of mechanical characteristic in most cases can be simplified by replacing the working section with a segment of a straight line passing through the origin [24].

The critical motor slip is determined by the expression:

$$s_{crit} = \frac{R_2}{\omega_0} \quad (7)$$

In transient modes, variable losses depend on time, and their value is an integral function. In the general case, energy losses during the transition process  $t_{tp}$  are equal:

$$E_{loss} = \int_0^{t_{tp}} P_{loss} dt \quad (8)$$

Figure 7 shows the dependence of motor losses on slip. Point 1 corresponds to the critical slip calculated in accordance with expression (8) for the motor with the power of 5.5 kW, and efficiency  $\eta = 86\%$ . Point 2 corresponds to the optimal slip and its setting time is halved from 0,6 to 0,3 s. This result is obtained by optimization using the proposed neuroregulator.

As can be seen in the figure, the difference in instantaneous power loss between the points exceeds  $d\Delta P = 300 W$ . This is approximately 25% of variable motor losses.

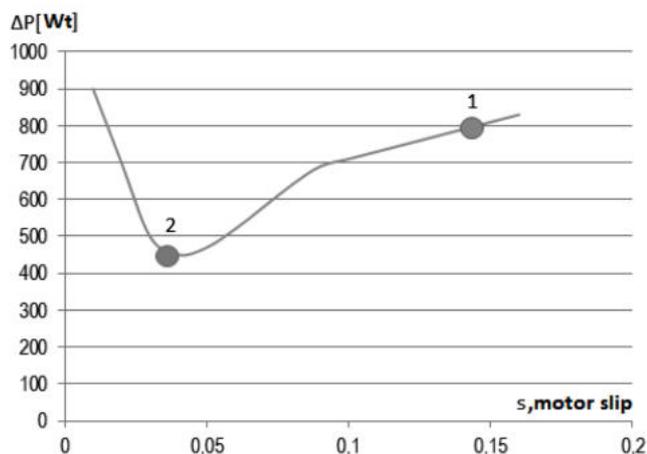


Figure 7. Dependence of motor losses on slip

Losses on the motor slip depend on the setting time of the slip point. To ensure high efficiency, the motor should operate at the rated load with low slip, that is, the motor should have a small critical slip. Transient losses obtained for the motor with a neuroregulator is integrated according to expression (8). Results prove reduction of resulting losses compared with a non-adaptive PI controller by an average of 36%. This confirms the increase in electric motor energy efficiency as a result of using the proposed solution.

## 6. Conclusion

The simulation results show that the use of the proposed intelligent adaptive PI controller provides a significant reduction in motor energy losses. In addition, the proposed method of determining PI-controller coefficients reduces the inrush currents and torque spikes, which prolongs the service life of mechanical components. The use of a neuroregulator makes it possible to select PI controller coefficients automatically.

During further motor operation, the neural network can continue to learn and adjust the PI-controller to changes in operating conditions (for example, seasonal) and motor parameters.

Our next steps in future research will be to improve controlling of the combined power source for an electric vehicle consisting of a supercapacitor and a battery. We assume that the suggested system will provide more data for the adaptive operation of the charge-discharge device of the electric vehicle power supply. It can also improve the efficiency of the recovery (recuperation) mode. This will allow getting more energy from the motor in different driving modes, depending on the angle of descent (rise) of an electric vehicle on the track. Assumed outcomes of this solution will be improving electric vehicle characteristics, increasing mileage and battery life time, and prospective transition to an electronic differential.

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