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COMPARISON OF GENETIC ALGORITHM AND NEURAL NETWORK APPROACHES FOR THE PROGNOSIS OF MECHANICAL IDLE RUNNING LOSSES IN AGRICULTURE TRACTOR TRANSMISSION

Summary. An experimental investigation of mechanical idle running losses in an agriculture tractor transmission was used to collect a wide range of data. The influence of the engine rotation speed, the number of switched-on gears, and the oil level in the transmission gearbox on the idle running losses was determined. Adequate regression models in cases of switched-on and switched-off PTO were received. A genetic algorithm was used to optimize mathematical models obtained using regression analysis. A feed-forward artificial neural network was also developed to estimate the same experimental data for mechanical idle running losses in transmission. A back-propagation algorithm was used when training and testing the network. A comparison of the correlation coefficient, reduced chi-square, mean bias error, and root mean square error between the experimental data and fit values of the obtained models was made. It was concluded that the neural network represented the mechanical idle running losses in tractor transmission more accurately than other models.

1. INTRODUCTION

Due to the presence of a power take-off (PTO) shaft and the requirement for technological speeds, agricultural tractors have two-flow transmissions and a large number of gears with widely varying gear ratios. This implies a large number of gear poles, through which the working and technological gears are realized. As a result, these transmissions are highly complex and cause substantial idle run losses [4, 5]. Two-flow hydro-mechanical transmissions are also widely used in agricultural tractors for the same reasons [17].

Various studies have been devoted to the study of losses in mechanical transmissions. The analysis of these works shows that almost all studies consider the losses in the transmission as a whole and multiply the elements' efficiency [13-16].

Some experimental data were obtained in [5]. The results concern idle losses under various conditions and regimes. The problems of the influence of the engaged gear and the engine speed on idle run losses have not been sufficiently studied. Therefore, studies are needed to extend the knowledge and clarify the influence of main factors.

Different innovative mathematical tools for benchmarking transmissions of transport vehicles have been used [18], and an integral criteria system for comparisons of stepless transmission alternatives has been developed.

Numerous studies in various fields have applied the methods of artificial intelligence by using genetic algorithms (GAs) and artificial neural networks (ANNs) to model processes.

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The GA is a search method and optimization technique for obtaining an optimal value of a complex objective function by simulating the evolutionary process based on genetics, crossover, and mutation. The GA is a stochastic method for solving optimization problems with and without constraints.

Today, GAs are used for many automotive purposes to optimize the transmission element and characteristics [1, 2]. A GA was used in [1] to optimize a spiral bevel gear. A nonlinear optimization problem was solved using three objective functions, five design variables, and 11 constraints concerning a bevel gear. The aim of this study was to optimize the weight, cone distance, and efficiency in three cases. The simulation was commented on, and the results were validated with data from the literature.

In [2], a GA was used to improve the efficiency of a hydro-mechanical continuous variable transmission at the design stage. The research considered an optimization design method. The improvement of efficiency, fast determination of parameters, and completion of requirements were the main criteria. Thanks to the GA, higher speed and accuracy of the algorithm were achieved. The transmission with optimized parameters had indicators that met the requirements of the vehicle, improved transmission efficiency, and provided advice for determining the shifting points of a variable gearbox.

One other use of a GA in mechanical engineering is described in [6]. This work reviewed GAs designed to solve complex problems in material science and manufacturing. The authors commented that the GA is a multi-path algorithm that searches many peaks in parallel, avoids local minimums, and can be used for multi-objective optimizations.

Ying Sun et al. [7] applied a GA in the field of mechanical optimization design. As a kind of brand-new random optimization method, the GA has been widely used in many cases for mechanical optimization design. This work analyzed the principle, makeup, and characteristics of the GA. The optimization steps during mechanical design are presented. The trends of using GA in a mechanical optimization design were analyzed.

Neural networks are extremely suitable for identifying objects for which classical mathematical approaches are not easily applicable. They predict one or more output variables for the corresponding one or more input variables. Neural networks allow the processing of a large volume of data for nonlinear systems, especially when the physical quantities describing the process are multiconnected. In the field of automotive technology, attempts have been made to use this approach for a long time, but they are rare.

Some of the first applications were to predict tire properties and vehicle dynamics. El-Gindy and Palkovich used an ANN to describe tire characteristics. They developed the so-called neuro-tyre [11], and they further used this model in studies of vehicle dynamics [10].

In [10], after reviewing and analyzing the existing and possible applications of ANN in automotive systems, it was concluded that such systems' use in vehicle systems was low. There are new developments in the field of ANN for alternative approaches for modeling the dynamics of cars, and this method can be useful in nonlinear areas at the limits of characteristics.

In [11], the trajectory stability of a three-axle truck was studied based on an ANN model of a pneumatic tire. The ANN yielded good results, and the authors pointed out that this is a competitive and accurate approach to tire modeling in car simulations in general, including while braking.

The applicability of ANNs for modeling the characteristics of tires under the action of dynamically changing vertical loads was also tested. The neuro-tyre developed by this method may involve more complex connections than would be achieved for a tire model, developed by conventional methods. There are no theoretical limits on the number of connections that can be modeled.

In the same period, an ANN was used to optimize the mechanical design [8]. Shioutsuka developed adaptive control of a driving system based on an ANN [12].

The possibilities of driving a car with four steerable wheels were studied [12]. An ANN was used to describe the behavior of a tire at different speeds and under different traction conditions. The ANN described the behavior of the tire for several values of side sleep and speed. The model estimated the tire load in real time.

Currently, ANNs are used in processes of control [9] and even internal combustion engine emissions prediction [3].

The aims of the present article are to model mechanical idle running losses in an agriculture tractor mechanical transmission, to then optimize the mathematical model by using a GA, to develop an artificial neural network, and, finally, to compare the obtained models.

2. EXPOSITION

2.1. Method and results

A two-flow mechanical transmission for a wheeled agricultural tractor was chosen as the object of study. It consisted of two branches, one of which drove the wheels while the other transmitted the power to the two PTO shafts (rear and side). There was a two-flow clutch, which transmitted torque from the engine to the gear box and PTOs. The basic gearbox had 7+1 gears and full reverse of the rotation. The second power flow gave the possibility to switch on/switch off every rear or side PTO shaft as independent or synchronic.

Fig. 1 shows the kinematic scheme of the experimental installation.

The system could examine the losses independent of the load (idle running losses) by measuring the resistance torque M_c, which the transmission generates when rotating. It consisted of the tractor transmission 1, the driving motor 2, the measuring device scale 3, and the measuring lever 4. It was possible to realize all operating modes of the transmission without load. Electric motor 1 generated driving torque, which was transferred to the input shaft of the transmission, clutch, and gearbox. The resistant torque during rotation, at switched gear and constant engine speed, was registered through the corpus of the electric motor 2 as reactive torque *Mc*. It was indicated by the scale 3.

The experiments were performed in different variants of operating conditions to reveal the quantitative influence of engine speed, oil level in the gearbox, and transmission gear number (characterized by the gear ratio). The experiments were repeated in two modes: with rear and side PTO on and off.

For each series, at every gear, tests were performed at seven different constant speeds of the input shaft of the gearbox (clutch shaft). The limits of the tractor engine speed varied from the minimum stable to the nominal one. Measurements of the resistance torque at each regime (combination of the operating conditions) were repeated three times.

The values of the controlled input factors are as follows:

- for the input shaft speed of rotation – $200, 400, 600, 800, 1000, 1200$ and $1400\ min^{-1}$;
- for the oil level in the gearbox $-35, 50, 65\ mm$;
- for the number of the engaged gear without the gear engaged (marked "0") and at the first, third, fifth, and seventh gears engaged.

The mechanical losses were estimated by the value of the resistance torque M_c of the transmission of the respective mode and operating conditions. A significant amount of experimental data was obtained [4], the processing of which allowed some analyses and conclusions to be made. Fig. 2 presents the graphical dependences for the idle losses in the studied agriculture tractor transmission. A graphic summarizes results from all experiments.

The resistant torque *Mc* depended nonlinearly on the input shaft speed *n*. The relationship was parabolic. The character was different depending on the oil level. At low levels, the curves were close to a linear character, but at high oil levels, the dependence was strongly parabolic

With an increase in the oil level, the idle run losses at the same gear increase were also nonlinear. However, the influence of the engaged gear was the strongest.

In the engaged mode, PTO losses also increased significantly. Due to high oil levels, including in torque transfer more gear poles, the hydraulic component of resistant torque *Mc* increased nonlinearly with the gear number.

Obviously, it is difficult to model the experimentally obtained results, and new approaches have to be researched and used.

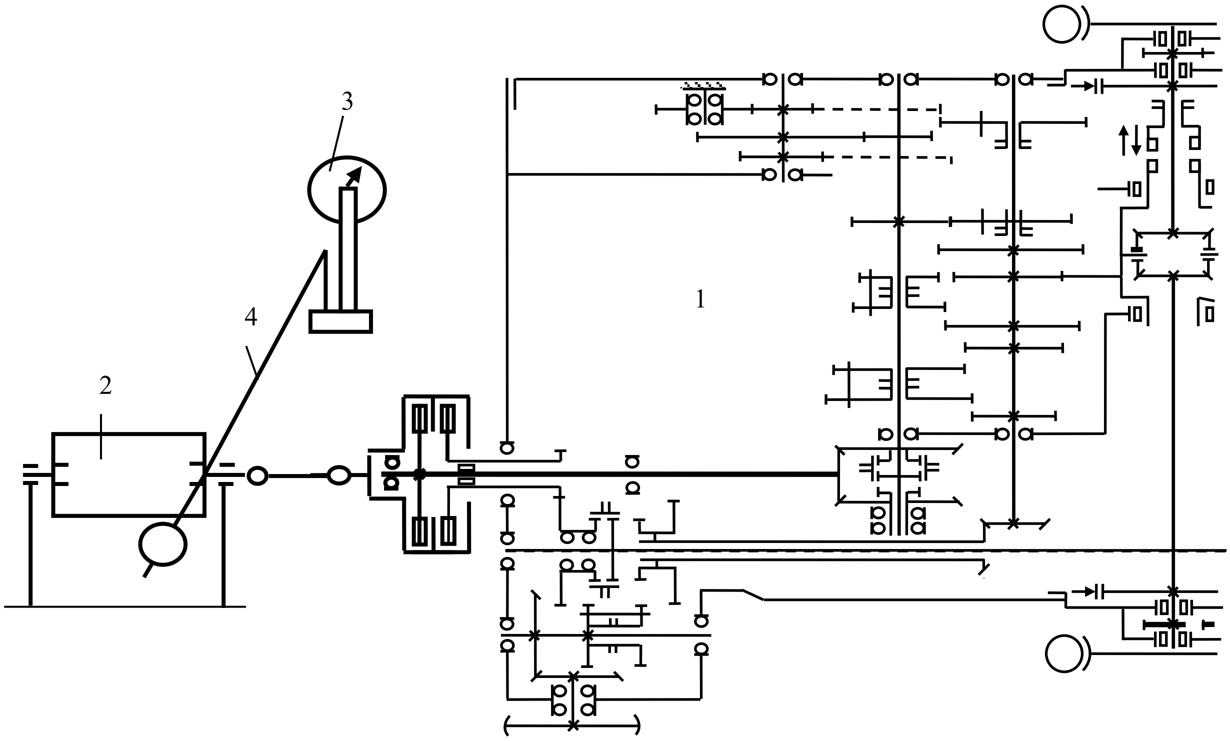

Fig. 1. Scheme of experimental installation: 1 – tractor transmission, 2 – driving electric motor, 3 – measuring scale, 4 – measuring lever

2.2. Theoretical consideration

The classic approach for modeling the experimental data is regression analysis. In some cases, when the real dependence of the obtained experimental data and controllable factors is complex, it is difficult to find an appropriate model that provides sufficient accuracy.

When building the model of the mechanical idling losses in the agriculture tractor transmission, the following input independent variables (controllable factors) were selected:

x_1 - speed of rotation of the input shaft, min^{-1};

x_2 - oil level in the gearbox, mm;

x_3 - number of the engaged gear.

According to the form of the experimental dependences for the influence of the engine speed, the oil level, the number of the engaged gear, and the state of the PTO on the resistance torque M_c in the tractor transmission, the adopted polynomial model of the second degree took the following form [5]:

$$Y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{23}x_2x_3 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 \quad (1),$$

where b_i are the regression coefficients and the output parameter of the model is $Y = M_c$.

The best equation to define the mechanical losses at idle had to be selected after analyzing the following factors:

- the correlation coefficient R;
- the reduced chi-square χ^2;
- the mean bias error MBE;
- the root means square error $RMSE$.

The abovementioned indicators were calculated as follows:

$$R = \frac{N\sum_{i=1}^{N} Y_{M,i}Y_{e,i} - \sum_{i=1}^{N} Y_{M,i}\sum_{i=1}^{N} Y_{e,i}}{\sqrt{\left(N\sum_{i=1}^{N} Y_{M,i}^2 - \left(\sum_{i=1}^{N} Y_{M,i}\right)^2\right)\left(N\sum_{i=1}^{N} Y_{e,i}^2 - \left(\sum_{i=1}^{N} Y_{e,i}\right)^2\right)}}, \quad (2)$$

$$\chi^2 = \frac{\sum_{i=1}^{N}\left(Y_{e,i} - Y_{M,i}\right)^2}{N-n}, \quad (3)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{e,i} - Y_{M,i}\right| , \quad (4)$$

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left(Y_{e,i} - Y_{M,i}\right)^2\right]^{\frac{1}{2}} , \quad (5)$$

where $Y_{e,i}$ is the experimentally determined resistance torque for the ith measurement, $Y_{M,i}$ is the model-determined resistance torque for the respective measurement, N is the number of observations, and n is the number of constants.

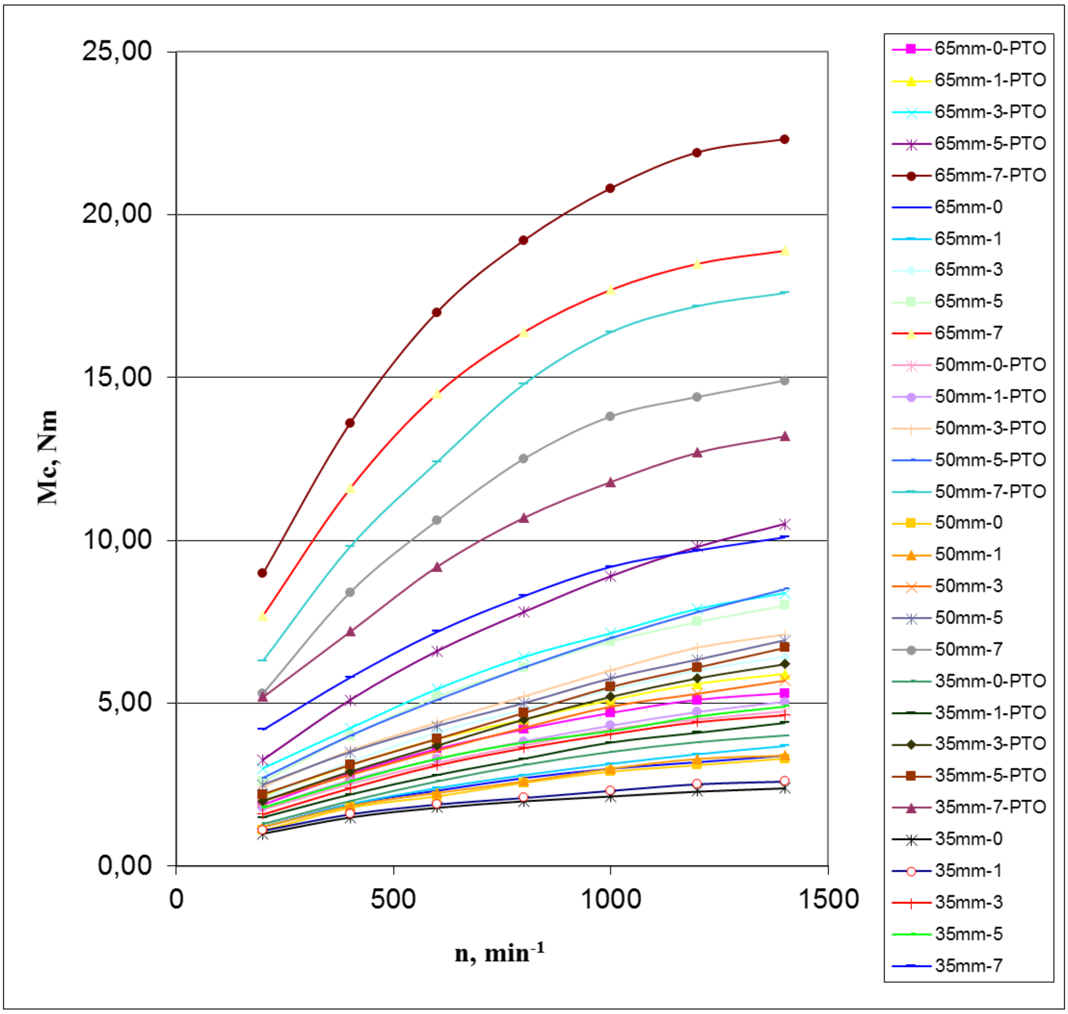

Fig. 2. Experimental data for the influences of engine speed, transmission oil level, number of switched-on gears, and PTO state on the resistance torque M_c in tractor transmission

Three models describing experimental data of idle running of an agriculture tractor transmission were built and compared using regression analysis, GA, and ANN. The accuracy of each model was estimated through characteristics (2) … (5).

3. MODELS AND DISCUSSION

3.1. Regression models using MATLAB

The Optimization package of MATLAB was used to obtain the regression models. The problem of finding the regression models was solved using the lsqcurvefit function, which determines the parameters of a given function describing the experimental data by the method of least squares.

The form of the regression equation is similar to (1).

The results were strongly influenced by the state of the PTO. In the processing and regression analysis, the data were divided into two groups: with the PTO on and off.

The following equation for the condition with the PTO off was obtained:

$$M_c = 1.9203 - 1.6605x_3 + 9.1171.10^{-5}x_1x_2 + 7.2119.10^{-4}x_1x_2 + 0.0162x_2x_3 - \\ -1.5310.10^{-6}x_1^2 - 3.4332.10^{-4}x_2^2 + 0.2314x_3^2. \quad (6)$$

The equation for the condition with the PTO on was as follows:

$$M_c = 2.7871 - 2.6937x_3 + 0.0008x_1x_3 + 0.0282x_2x_3 + 1.0597.10^{-6}x_1^2 + \\ +0.2809x_3^2\,. \quad (7)$$

The values of correlation coefficient R, reduced chi-square χ^2, mean bias error MBE, and root mean square error $RMSE$ with PTO off and on are shown in Tab. 1 and Tab. 2, respectively.

The results of the regression analysis show that for the cases of PTO on and off, according to the degree of influence, the factors can be arranged in the following order: gear number, speed, and oil level. All three factors influenced the resistance torque M_c nonlinearly, which is evident from the regression equations and Fig. 2.

3.2. Mathematical model optimized using the GA

The GA was used to determine the resistance torque M_c for all experimental data when the PTO was switched off and on. As unknown variables, it was considered to be the coefficients of the regression equations. The objective function is as follows:

$$J = \frac{0.25}{R} + 0.25\chi^2 + 0.25MBE + 0.25RMSE. \quad (8)$$

The objective function had to be saved in M-file to minimize the fitness function. It was necessary to pass a function handle as the first argument to the GA function, as well as to specify the number of variables as the second argument. There was no need to manually input any other restrictive condition.

The obtained equations are as follows:

- when PTO is switched off

$$M_c = 2.9 - 2.6726x_3 + 8.0927.10^{-5}x_1x_2 + 6.0845.10^{-4}x_1x_2 + 0.0271x_2x_3 - \\ - 2.10^{-6}x_1^2 - 7.10^{-4}x_2^2 + 0.2834x_3^2 \quad (9)$$

- when PTO is switched on

$$M_c = 3.1441 - 3.2507x_3 + 0.0009x_1x_3 + 0.0306x_2x_3 + 1.10^{-6}x_1^2 + 0.3344x_3^2. \quad (10)$$

Regarding the above equations, R, χ^2, MBE, and $RMSE$ were optimized for the models by applying a GA with the PTO off and on (as shown in Tab. 1 and Tab. 2, respectively). Obviously, the accuracy of the mathematical model optimized by GA and evaluated by the statistical indicators χ^2, MBE, and $RMSE$ was much better than that of regression analysis.

3.3. Artificial neural network model

The most popular networks for process modeling are multi-layer perceptrons, also known as multi-layer feed-forward networks. These networks consist of identical neurons organized in layers (an input layer, an output layer, and one or more hidden layers). The first task in artificial neural network development is to find the best network architecture. It is necessary to determine the number of hidden layers, the number of neurons in hidden layers, transfer functions, and the training algorithm. In this study, an ANN was developed using MATLAB's neural network toolbox. The trial-and-error approach with iteration technique was used to build the ANN. The training, validating, and testing procedures were performed by using the data randomly selected from experimental data. The back-propagation method was used to train the neural network. Three neurons were used in the input layer; these corresponded to engine frequency, engine oil level, and the number of switched-on gears. The output layer had one neuron representing the resistance torque M_c in the tractor transmission.

A range of training tests was done with two hidden layers (each having different neuron numbers) to determine the optimum number of the hidden layers and the number of neurons within each hidden layer. In the first and second hidden layers, there were 40 neurons and 25 neurons, respectively, and Tangent sigmoid activation functions were used. The schematic block diagram of the ANN is shown in Fig. 3. The accuracy of the trained network was measured by the mean square error (*MSE*). The optimum hidden layer and optimum neuron number within each layer were determined as the minimum value of *MSE* reached.

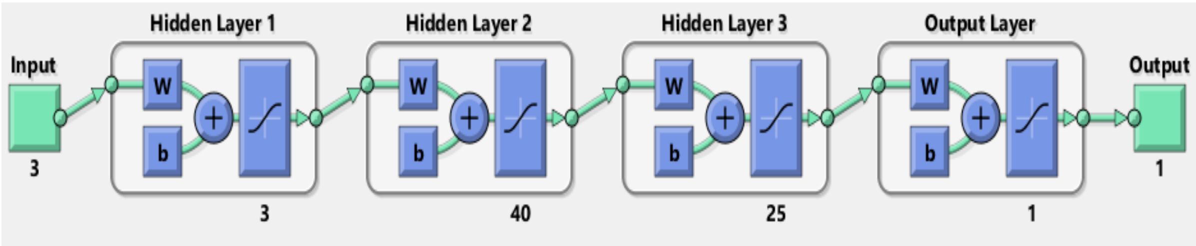

Fig. 3. Model of an ANN

The correlation coefficient, reduced chi-square χ^2, mean bias error MBE, and root mean square error $RMSE$ with the PTO off and on in the ANN model are shown in Tab. 1 and Tab. 2, respectively. It can be seen that the correlation coefficient was the highest for the model developed using the ANN. The accuracy of describing the experimental data—assessed by the statistical indicators, reduced chi-square χ^2, mean bias error MBE, and root mean square error $RMSE$—for the ANN was the highest.

Fig. 4 and Fig. 5 show a comparison between the experimental (shown with the symbol "*") and the predicted (shown with "○") values of the resistance torque M_c, with PTO off and on, respectively, using a neural network. Each of the three groups of five series points presents a separate oil level. Each of the series in a group represents one gear number (0, 1, 3, 5, or 7).

The results show that the experimental data are best described by the neural network model.

Table 1

Statistical performance of the models obtained by regression analysis, model optimized by GA and ANN (PTO switched off)

Model	R	χ^2	MBE	$RMSE$
Regression analysis	0.9604	1.8249	0.9334	1.2984
Model optimized by GA	0.9632	1.3230	0.8414	1.1056
ANN	0.9986	0.0464	0.1107	0.2353

Table 2

Statistical performance of the models obtained by regression analysis, model optimized by GA and ANN (PTO switched on)

Model	R	χ^2	MBE	$RMSE$
Regression analysis	0.9604	1.7596	1.6590	1.2880
Model optimized by GA	0.9615	1.7273	1.6286	1.0604
ANN	0.9915	0.3704	0.2010	0.6086

4. CONCLUSIONS

The losses in a mechanical agriculture tractor transmission were studied, and experimental data were obtained, which made it possible to assess the influence of the input shaft speed, the number of gears engaged, and the oil level on idle running losses.

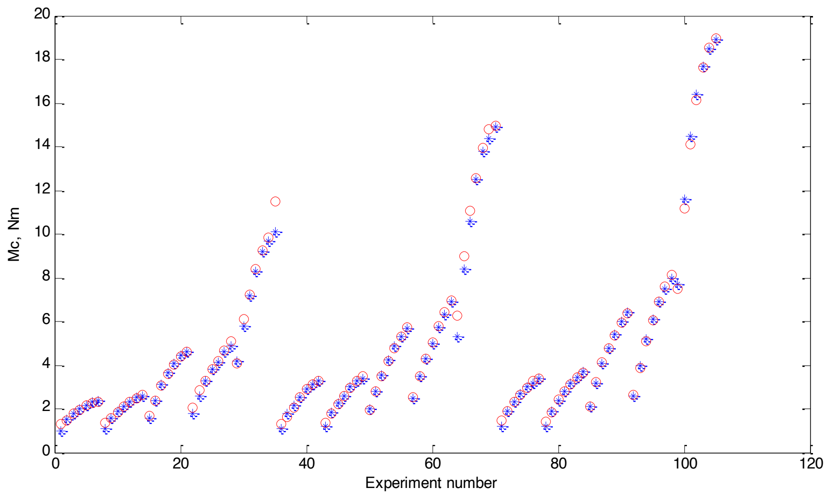

Fig. 4. Comparison between the experimental (*) and predicted (○) values of the resistance torque M_c with PTO switched off

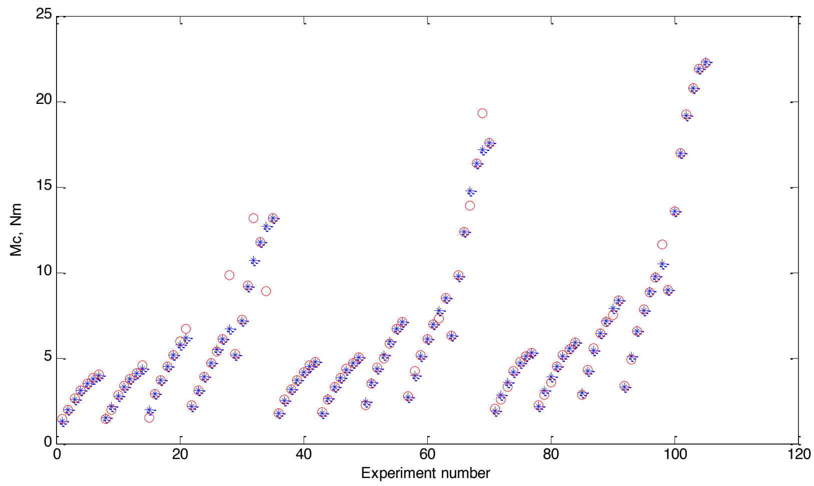

Fig. 5. Comparison between the experimental (*) and predicted (○) values of the resistance torque M_c with PTO on

The adequate regression models for the cases with PTO shafts on and off were developed with different tools and compared. According to the degree of influence, the studied factors can be arranged in the following sequence: gear number, speed, and oil level.

The highest correlation coefficient R and the lowest reduced chi-square χ^2, mean bias error MBE, and root mean square error $RMSE$ values when the PTO is switched off and on were obtained using the neural network. Compared with the other models (the regression equation and the model optimized by GA, the ANN model described the whole range of experimental data more accurately; specifically, the root means square error $RMSE$ was 2 to 5-6 times lower than the relative values for other models.

The ANN model could also be retrained, and the range of experimental conditions could be expanded by adding new sets of experiments.

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