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Design of general LQR-ANN-controller of „crane-load" system. Part 2

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Abstract. The second part of the article presents the training mechanism of an artificial neural network (ANN), the structure of which was developed in the previous study. A significant amount of training data (85451 training pairs), the size of the bach (2000), the number of training rounds (500000), as well as the depth of the ANN allowed us to obtain a fairly low training loss ($1.52 \cdot 10^{-6}$) and validation loss ($1.99 \cdot 10^{-6}$). In addition, for almost the entire test data the ANN showed a high-quality prediction of the coefficients of the optimal controller. This statement was supported with the maximum and root-mean-square prediction errors. However, individual values of the coefficient prediction errors doubt the quality of the optimal control of the system's motion. In order to assess this quality for these cases, the worst result in terms of prediction error was studied. This allowed us to establish that the deviation of the coefficients (the maximum value is 7.86%) does not cause a significant deviation of the dynamics of the "crane-load" system from that obtained by using the optimal coefficients of the linear-quadratic controller. For this purpose, graphical dependencies of the phase portrait of the pendulum oscillations of the load, the control function, the driving force, and the speed of the crane movement were built and analyzed.

The article notes one of the advantages of the obtained ANN – the speed of obtaining optimal control. It follows from the fact that access to the ANN requires significantly fewer computational resources than those required for solving the Riccati equations.

The final part of the article provides recommendations for implementing the obtained results in practice. They consist of the fact that the input vector, which contains the normalized values of the load mass, the length of the flexible suspension, and the control weight coefficient, is transmitted to the input of the ANN. This allows us to obtain the predicted values of the coefficients of the optimal controller. In the further, they are used to find the optimal control strategy. The latter, in turn, is implemented by means of controlled electric drive mechanisms of the crane.

Keywords: crane, solutions set, neural network training, testing, optimal control.

INTRODUCTION

One of the important issues in crane exploitation is connected with the design of crane control strategies. In the first part of the study, we focused on the optimal in the sense of LQR-criterion controls. The articles, that refer to the intelligent approaches, are stressed in the current study. Generally speaking, the term „intelligent" includes a plethora of methods. Among them, we pointed to artificial neural networks (ANN).

In the scientific work [1] fuzzy-logic (FL), adaptive neuro fuzzy inference system (ANFIS), and ANN were exploited to control the gantry crane described with the nonlinear pendulum model. The set of indicators (settling time, load position overshoot, and steady-state error) approved the superiority of ANFIS over ANN, which may be explained by the simple structure of the latter (only one hidden layer).

In the study [2] a deep learning-based container crane control model was designed. It outputs the signal of force, that governs the movement of the trolley and hoist. Inputs of ANN are target position, initial position, and weight of the load. The study results were approved with the numerical simulation.

A sensorless anti-swing control method for automatic gantry cranes is designed in the study [3]. Based on ANN the soft sensor is developed to implement the anti-swing policy of the crane movement. The ANN is a multi-layer perceptron (as a soft sensor), its exploitation provides a sensorless method to control load oscillations.

A similar approach is developed in the work [4]. The obtained in the study ANN was compared with the previously developed non-linear crane controller. The authors concluded, that the proposed control law refers to good tracking of load movement including its oscillations suppressing. Another positive feature of the developed ANN – it does not require the specific values of crane parameters, i.e. volume of the efforts of crane modeling is not significant.

PURPOSE OF THE PAPER

The paper's purpose is to obtain properly trained ANN, which can predict the gains values of optimal (by LQR-criterion) controller of crane dynamical system.

RESEARCH RESULTS

The first stage of the study is connected with its structure design. We used deep ANN, which includes 4 hidden layers of neurons. Each of the hidden layers has fifty neurons, the output layer includes 5 neurons – as the length of the output vector G=$(G_1, G_2, G_3, G_4, G_5)^T$.

Three neurons form the input layer - as the number of inputs in the training pairs $(\tilde{m}_{2,i},\ \tilde{l}_i,\ \tilde{\delta}_i)^T \to \tilde{\mathrm{G}}_i$. The general view of the developed ANN is shown in Fig. 1.

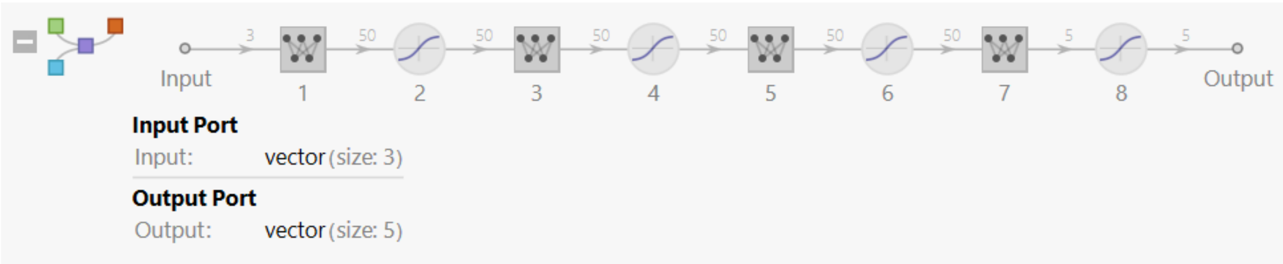

Fig. 1. Scheme of the developed ANN structure

However, the analyzed works are based on numerical simulations, they lack practical approval of the research results. Thus, their outputs should be considered as important but only as an intermediate stage of the development procedure.

One of the scientific works worth mentioning [5] reveals the used approaches, where ANN has been applied for crane control problems. Amon them: combination with classical controllers to improve the control strategies [6-8] and design control operators [9], estimate the impacts, that affect the crane dynamics [9], and crane modelling [10], etc.

In the first part of the investigation, the set of LQR-problem solutions was obtained. This makes it possible to use it in order to train the ANN and test its ability to properly predict the values of optimal controller gains. The current study is dedicated to the described approach.

The number of hidden layers and neurons in them is grounded by the requirement of good approximation of the available data. This structure is obtained by multiple testing of trial ANNs. The selected ANN variant (Fig. 1) is the best one in the sense of the „structure simplicity – good prediction ability" trade-off.

The next step is ANN training, which is carried out with ADAM optimizer [11].

The most important indicators of ANN training procedure, which influence the quality of ANN training, are given in Table 1.

Table 1. Numerical values of ANN training procedure

Parameter	Value
Bach size	$2 \cdot 10^3$
Training rounds	$5 \cdot 10^5$
Final training loss function value	$1.52 \cdot 10^{-6}$
Final validation loss function value	$1.99 \cdot 10^{-6}$
Total training time	$2.52 \cdot 10^4$

Again, the bach size and training rounds parameters were selected empirically.

In order to indicate the dynamics of ANN training, the corresponding plot was built (Fig. 2). It is clear (Fig. 2) that the dramatic reduction of loss function was in the early stage of the ANN training (approximately on the first 10^5 iterations). Further iterations did not bring much improvements. We have decided to preserve the obtained result.

The analysis of the presented plots (Fig. 3) indicates, that most values of the errors are located around the horizontal axis, i.e. they are very low in values. The number of spikes in plots (Fig. 2) doesn't exceed 20. Thus, the number of relatively big errors is quite small.

In order to make the analysis more complete, the indicators were calculated (Table 2).

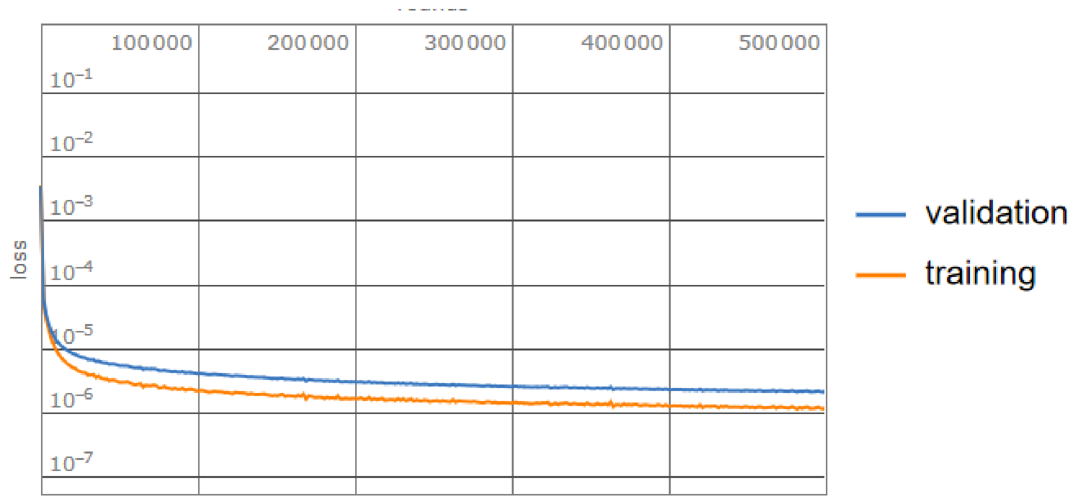

Fig. 2. Plots of loss function reduction on the training set (orange curve) and on the validation set (blue curve)

The obtained values of ANN weights are presented in the external file „Weights of trained ANN.txt”. It may be downloaded by the link [12].

All the biases of the ANN are equal to zero.

In order to estimate the prediction abilities of the ANN the test set was exploited. For this purpose, we fed the testing set data to the ANN input and obtained some output. The absolute error is the deviation of the outputted value and the value in the test data. The relative estimation is obtained by multiplying by 100%:

$$\Delta G = \left(\mathrm{ANN}((\tilde{m}_{2,i},\ \tilde{l}_i,\ \tilde{\delta}_i)^T) - \tilde{G}_i\right)100\% = (\Delta G_1,\ \Delta G_2,\ \Delta G_3,\ \Delta G_4,\ \Delta G_5), \quad (1)$$

where $\Delta G_1 \ldots \Delta G_5$ – errors, each of which corresponds to the optimal controller gain (in percentage units).

The calculated dot-plots for each of the errors are given in Fig. 3.

Table 2. Numerical values of ANN testing errors, %

The corresponding controller gain	Value	
	RMS*	max**
G_1	$7.73 \cdot 10^{-2}$	2.03
G_2	$7.62 \cdot 10^{-2}$	1.86
G_3	$6.52 \cdot 10^{-2}$	2.37
G_4	$7.07 \cdot 10^{-2}$	2.16
G_5	$1.79 \cdot 10^{-1}$	7.86

* root-mean-square value;

** maximal value of the errors module

The analysis of the data given in Table II shows, that RMS values are very small. The maximal error indicator is in the range 1.86…7.86%. Here we should note, that the maximal value of error (7.86%) corresponds to the G_5 gain. For this gain, we may stress five errors, that are bigger than 4% (Fig. 3, e).

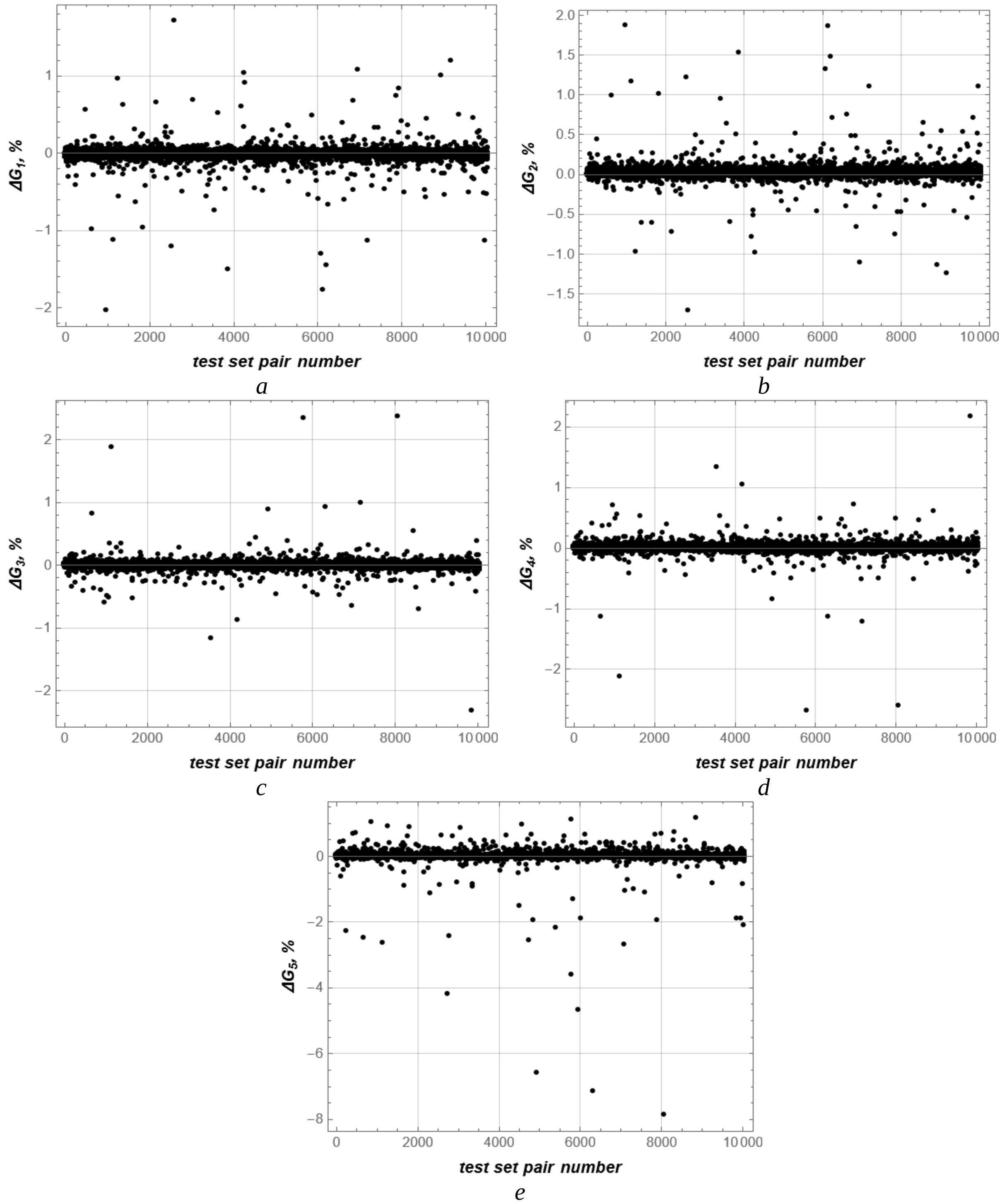

Fig. 3. Plots of dot functions of errors of ANN predictions for each of the controller gains

The provided analysis supports the previous conclusion – the overall quality of the prediction of controller gains coefficients is quite high. However, the biggest error value indicates, that the output control may be deteriorated – particularly for the considered case. In order to figure out whether it's true or not we found the values of predicted by ANN coefficients $G_1 \ldots G_5$ for the case of the mentioned biggest error. They are given in Table 3.

The data in Table 3 clearly indicate, that for all coefficients but G3 the true and predicted values are very close to each other. However, the coefficient G_3 changes in the range from -367057 to 21294. Thus, the difference between true (LQR) and predicted by ANN values of coefficient G_3 is minor.

Table 3. Numerical values of predicted by ANN coefficients and the true coefficients

The controller gain	Coefficients' values	
	true	predicted
G_1	294780	292542
G_2	-294773	-294477
G_3	3240.94	7844.62
G_4	629223	624158
G_5	5.79141	5.68504

In the built below plots (Fig. 4) the deviations, which are caused by the difference in control functions, are minor (gray plots in Fig. 3 present the differences of the functions multiplied by 10; black plots refer to LQR-optimal control; subscripts „ANN" and „LQR" correspond to the method of coefficients calculation: via Riccati equation solution or via ANN application). Indeed, the deviations of the coefficients do not cause a significant deterioration of the optimal control strategy. Thus, we can conclude that the developed in the study ANN may be exploited as a general predictor of optimal control coefficients.

One of the benefits of ANN application is connected with the small duration of optimal coefficients calculation. Involving the calculation resources of PC (Intel Core i3, 2.13GHz, 8Hb RAM) the average duration of the current LQR problem solving equals 0.00220 seconds, and the duration of access to developed ANN is 0.00025 seconds, which is by order smaller. Thus, there is no need to use big computational resources to implement the ANN function in the control system of the crane.

The concluded part of the study is devoted to the problem of implementation of the optimal control, that is derived from the trained ANN. We may propose a scheme, that illustrates the concept of ANN application (Fig. 4).

According to the proposed scheme, the first step is setting the parameters of the system (weight of the load, length of the cable) and crane mode to perform (acceleration/deceleration, value of weight coefficient δ, final positions, and velocities of the load). This step must be carried out with proper sensors. The higher level control system for the final position and velocities of the load or references of their changes over time is mandatory.

The second step involves the ANN, it is fed with the input vector and returns the optimal (for particular values of input vector) gains of the controller. This makes it possible to design the optimal controller (the third step).

The last step is connected with the application of the optimal law, i.e. optimal control signal is sent to the controlled drive (for instance, varied-frequency drive). The drive produces the needed electromagnetic torque, which, in turn, governs the dynamical system „crane-load" movement.

CONCLUSIONS

In the article, further investigation provides the development and testing of ANN. The latter is a general approximator of the LQR-problem solutions domain. The second part of the study shows the training of ANN, its validation, and testing procedures. The corresponding indicators (training and validation losses) indicate, that the training was successful. The testing procedure revealed the good quality of optimal coefficients' prediction as well. The worst prediction, made with ANN, corresponds to almost no deviation from the optimal dynamics of the system „crane-load" movement.

The obtained from the study results (ANN with complete information: structure, tensors

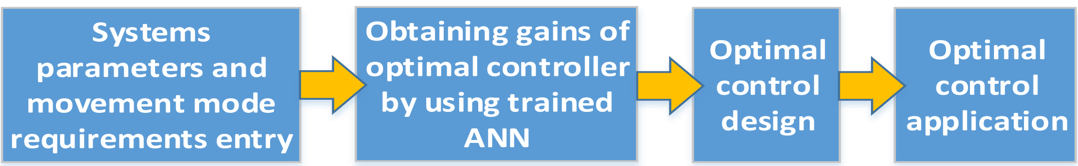

Fig. 4. The scheme of developed ANN application in the practice of crane exploitation

of weights, and matrix of biases) are downloaded to the external resource. This made it possible for the implementation of developed ANN in the crane control system, which may suppress load pendulum oscillations in an optimal manner with a wide variety of load mass and length of load suspension (cable).

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Розробка узагальненого лінійно-квадратичного нейрорегулятора системи „кран-вантаж”. Частина 2

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Анотація. У другій частині статті представлено механізм навчання штучної нейронної мережі (ШНМ) структура якої була розроблена у попередньому дослідженні. Значний обсяг навчальних даних (85451 навчальних пар), величина пакету навчання (2000), кількість раундів навчання (500000), а також глибина ШНМ дозволили отримати досить низьку похибку навчання ($1{,}52\cdot10^{-6}$) та валідації ($1{,}99\cdot10^{-6}$). Крім того, майже на всій тестовій вибірці ШНМ також показала досить якісне передбачення коефіцієнтів оптимального регулятора. Для цього були розраховані максимальні та середньоквадратичні похибки прогнозування.

Однак, окремі значення похибок прогнозування коефіцієнтів поставили під сумнів якість оптимального регулювання руху системи. Для того, щоб оцінити цю якість було вивчено найгірший у сенсі похибки прогнозування результат. Це дозволило встановити, що відхилення величин коефіцієнтів (максимально на 7,86%) не спричиняє значного відхилення динаміки руху системи „кран-вантаж” від того, що отримано за допомогою оптимальних коефіцієнтів лінійно-квадратичного регулятора. Для цього побудовано та проаналізовано графічні залежності фазового портрету маятникових коливань

вантажу, функції керування, рушійного зусилля та швидкості руху крана.

У статті відмічена одна із переваг отриманої ШНМ – швидкодія отримання оптимального керування. Вона випливає із того, що доступ до ШНМ потребує значно менших обчислювальних ресурсів, аніж ті, що потрібні для розв'язання рівнянь Ріккаті.

У заключній частині статті наведено рекомендації стосовно реалізації отриманих результатів на практиці. Вони полягають у тому, що на вхід ШНМ передають вхідний вектор, що містить нормовані значення маси вантажу, довжини гнучкого підвісу та коефіцієнта ваги керування. Це дозоляє отримати прогнозні значення коефіцієнтів оптимального регулятора. У подальшому їх використовують для відшукування оптимальної стратегії керування. Остання, в свою чергу, реалізується засобами керованих електроприводних механізмів крана.

Ключові слова: вантажопідйомний кран, множина розв'язків, тренування штучної мережі, тестування, оптимальне керування.