Обычно необходимо несколько запросов. Большая часть этих запросов будет отражена первой нейронной сетью, так как они будут содержать признаки атаки. Еще не малую часть закроет вторая нейронная сеть, которая видит результаты действий в выводе. Однако, не стоит забывать о том, что небольшое количество запросов, которые еще не являются атакой в строгом понимании этого слова, могут дать дополнительные данные в руки атакующего или произвести небольшие изменения. Именно от таких случаев нужно защитить пользователя выпуском патча.

Заключение

В работе систем обнаружения вторжений важным критерием является высокая точность распознавания вредоносного запроса. Несмотря на полученные в [2] качественный классификатор, всегда существует опасность пропустить слабо коррелирующий признак атаки и выдать атакующему определенную часть информации. Для решения данной проблемы необходимо контролировать не только то, что поступает на вход приложению, но и реакцию приложения на полученный запрос.

Предложенный алгоритм позволяет избежать ложных срабатываний системы и исключить атаку на нее за счет дополнительной проверки данных детектором, который ищет признаки исключений и вывода ошибок, а также сигнатуры запрещенного контента, а также проверки на наличие кодов ошибки от 400 до 500.

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УДК 62-933.6:004

AUTOMATIC CONTROL OF PARAMETERS OF A NON-STATIONARY OBJECT WITH CROSS LINKS

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Abstract: Many objects automatic control unsteady. This is manifested in the change of their parameters. Therefore, periodically adjust the required parameters of the controller. This work is usually carried out rarely. For a long time, regulators are working with is not the optimal settings. The consequence of this is the low quality of many industrial control *systems. The solution problem is the use of robust controllers. ACS with traditional PI and PID controllers have a very limited range of normal operation modes due to the appearance of parametric disturbances due to changes in the characteristics of the automated unit and changes in the load on it. The situation is different when using in the architecture of artificial neural network controllers. It is known that when training a neural network, the adaptation procedure is often used. This makes it possible to greatly expand the area of normal operating modes of ACS with neural automatic regulators in comparison with traditional linear regulators. It is also possible to significantly improve the quality of control (especially for a non-stationary multidimensional object), provided that when designing the ACS at the stage of its simulation in the model of the regulatory object model, an adequate simulation model of the executive device. It is also possible to significantly improve the quality of control (especially for a non-stationary multidimensional regulatory object model, an adequate simulation model of the executive device. Especially actual implementation of all these requirements in the application of electric actuators. This article fully complies with these requirements. This is what makes it possible to provide a guaranteed quality of control in non-stationary ACS with multidimensional objects and cross-links between control channels. The possibility of using a known hybrid automatic regulator to stabilize the parameters of a two-channel non-stationary object with two cross-linked. A simulation control system under the action of the object coordinate and parametric perturbations. The simulation showed that the quality control is not reduced.*

Keywords: automatic control system (ACS), adjustable object (AO), model.

Formulation of the problem

The problem of constructing ACS for stabilizing the parameters of the AO is considered. This article should be considered as a continuation of [1]. In it, it was noted that the PI and PID regulators do not compensate well enough for the changes in the parameters of the AO. Therefore, periodic adjustment of these controls is required.

In the case of multi-loop ACS, the number of which increases, the adjustment of regulators is a rather complex engineering task that requires a lot of time.The reasons for the poor quality of ACS regulation with linear PID controllers are several when used.The main ones are: the settings of the regulator of each circuit depend significantly on the characteristics of other circuits, including the settings of the regulators in these circuits.If one circuit is not correctly tuned in a multidimensional system, then most often this is reflected in the appearance of periodic oscillations of the same frequency with different amplitudes and phases in all interconnected circuits.To determine in this case the outline with the "regulator-culprit" of poor performance in the whole ACS is not a very simple task.In the case of multidimensional AO with a large number of cross-links, this leads to a decrease in the quality of control.

Lowering the severity of this problem can be achieved through the use in the ACS of hybrid regulators [1], in the structure of which artificial neural networks are used.Such regulators, when applied in local single-loop ACS, have pronounced properties of robust ones.How much these properties are retained in cases where the AO has two adjustable variables with cross links between the control channels is the subject of consideration in this work.From the solution of the problem posed, the task of parametric identification of the AO is deliberately excluded, since the synapse coefficients of the neural networks of the regulators are not fundamentally related to its parameters, and hence the synapse coefficients are usually not optimal with respect to the original (presumed) values of the parameters of the AO control channels. Of course, that the work related to identifying the characteristics of a real AO is mandatory.

Only the availability of such reliable information allows a priori to assess the possibility of using a hybrid controller for control. For this evaluation, it is necessary to know its area of normal work [1].

The most difficult question when using neural networks in automatic regulators is their training (even in the version of single-loop ACS). Using the same algorithm for Back Propagation Algorithm is problematic due to the presence in the simulation models of the AO and the controller of quite numerous links of transport lag and other various nonlinear links.

Main part

The simulation model of a two-channel ACS, in which the AO has two cross-links, is implemented in the MATLAB environment using the Simulink software packages and is presented in Figure 1.

Parameters of coupling coefficients of neural networks of both hybrid regulators have the same numerical values: $k1 = -0.2$; $k2 = 2.8$; $k3 = 0.5$; $k4 = -2$, that is, they correspond to the regulator parameters in [1]. Nevertheless, it is appropriate to recall that in vector notation this can be represented in the following form:

$$U = f[(k1x1 + k2x2 + k3x3 + k4x4)]k5 = f[(-0.2x1 + 2.8x2 + 0.5x3 - 2x4)]0.75. \qquad (1)$$

Here, $x1$, $x2$, $x3$, $x4$ are the signals of the setpoint, the sensor of the controlled parameter, the dynamic error of the contour and its coordinate disturbance, respectively;

U – signal at the output of the neural network of the regulator. Activation functions are linear with constraints; the coefficient of proportionality is 0.75.

Subsystem1 and Subsystem5 provide normalization of signals of regulators. Subsystem4 and Subsystem7 are generators of coordinate perturbations, which are necessary for simulation of ACS.

The control part of the ACS does not use corrective circuits that compensate for both cross-links in the AO and for changing the parameters of its control channels.In addition, corrective connections between regulators, so common to traditional ACS with linear regulators, are not used either.The simulation model of the AO with two internal cross-links (Subsystem3) is shown in Figure 2.

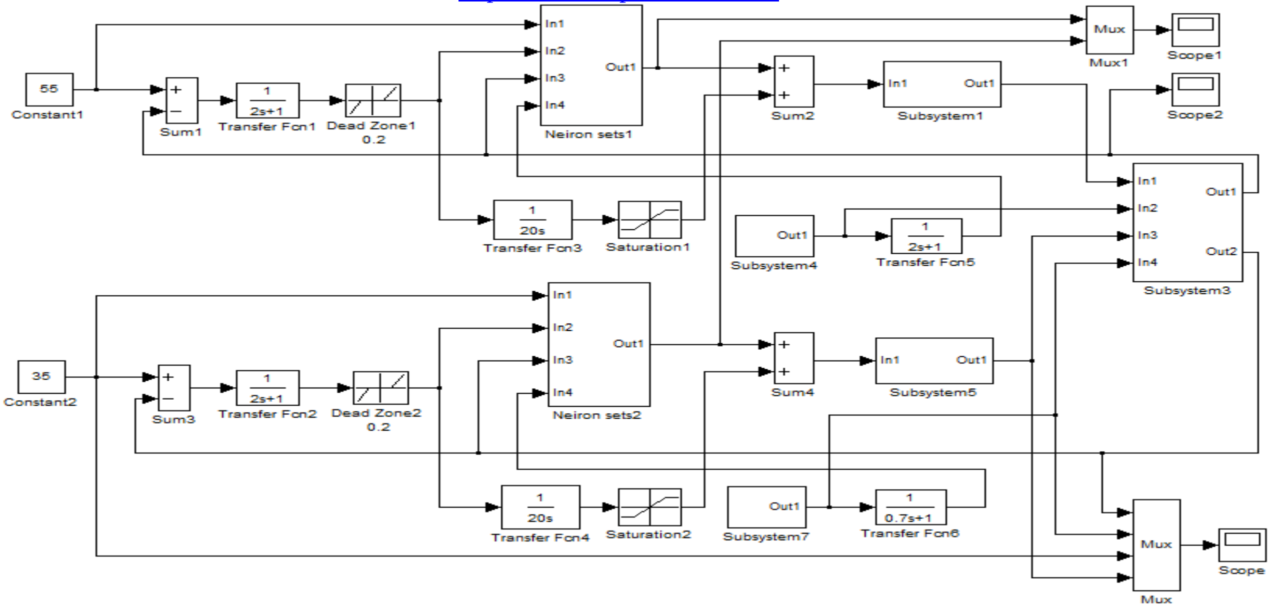

Fig. 1 – Structural diagram of the ACS simulation model in the MATLAB environment

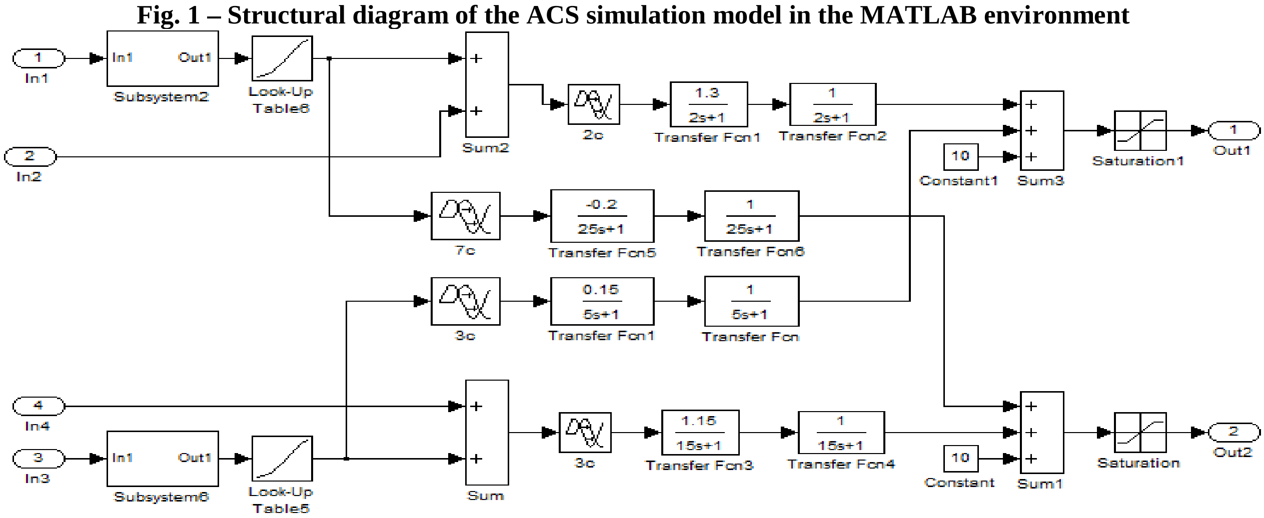

Fig. 2 – Simulation model of the controlled AO in its original form

The Subsystem2 and Subsystem6 of the AO model display the dynamic properties of the proportional-action constant-speed motor actuator [1].

The results of the ATS simulation with the characteristics of the AO corresponding to Figure 2 are shown in Figure

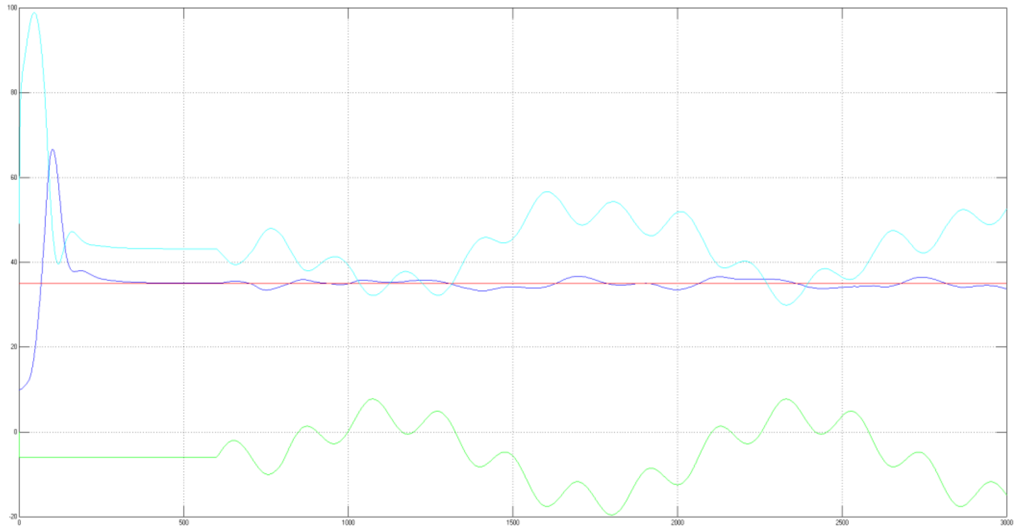

Fig. 3 – Graphical results of ACS modeling on the second channel

In the conditions of simultaneous action of two disturbances on the second channel (along the control and cross-connection channels), the dynamic control error does not exceed 1.5%. In this case, the dynamic control error in the second circuit does not exceed 2.5%.

The case of simultaneous action of three perturbations on the second channel of the AO is investigated. As a third factor, there will be significant parametric changes in the first channel. The dynamic control error (as seen in Figure 4) in the second contour of the AO has not changed: 1.5%. The dynamic control error in the primary circuit decreased, falling to 2%.

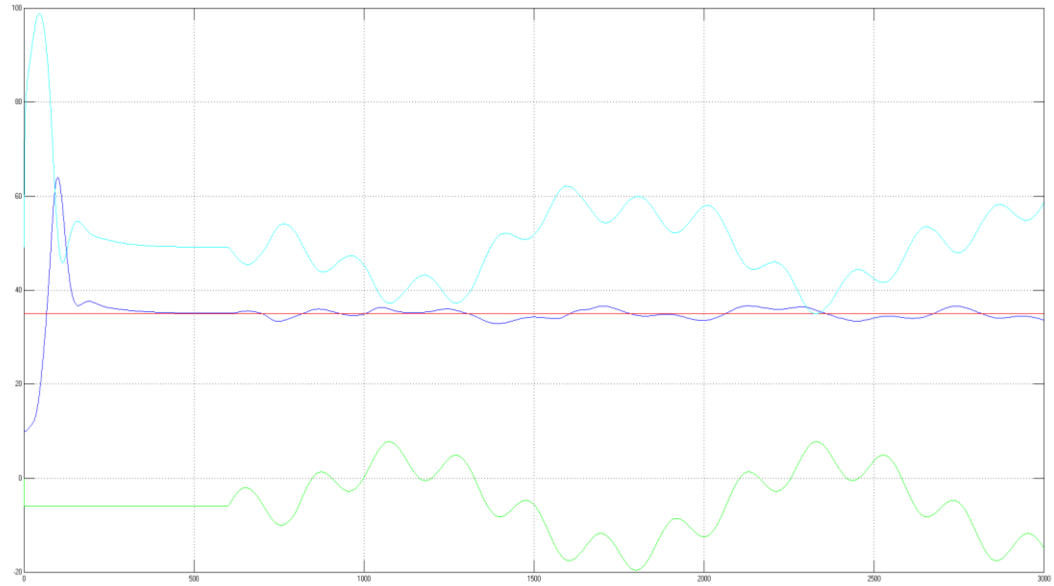

Fig. 4 – Graphical results of ATS modeling on the second channel (first channel: k = 0.6; T1 = T2 = 6 s; τ = 6 s; second channel: k = 1.15; T1 = T2 = 15 s; τ = 3 s)

It remains to consider the variant of simultaneous action of four perturbations on both channels. As the fourth factor, simultaneous parametric changes will occur in both control channels of the AO.

The graphical results of the simulation are shown in Figure 5.

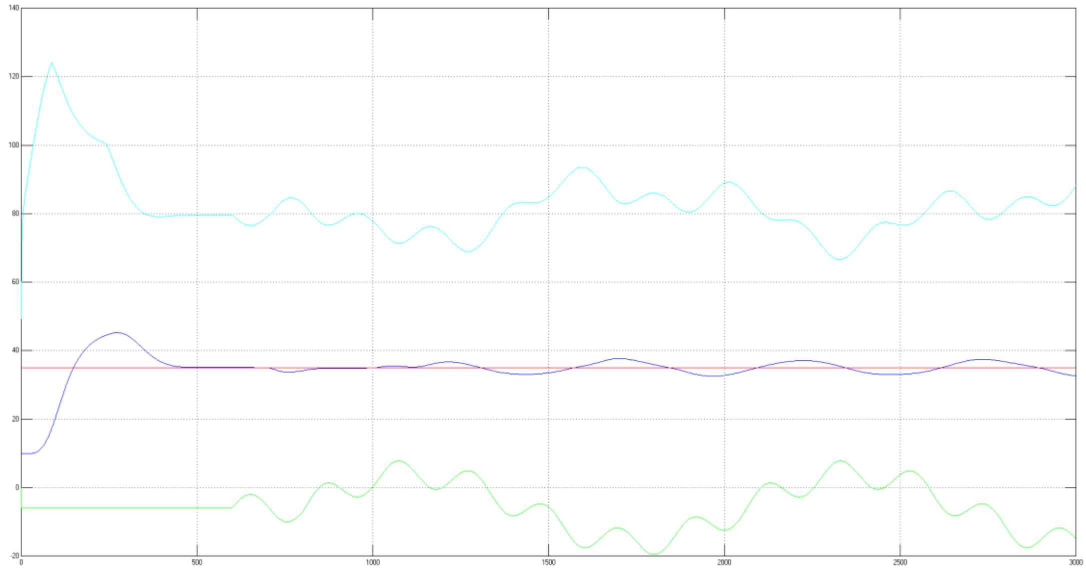

Fig. 5 – Graphical results of ACS modeling on the second channel (first channel: k = 0.6; T1 = T2 = 6 s; τ = 6 s; second channel: k = 0.5; T1 = T2 = 25 s; τ = 7 s)

As can be seen from Fig.5, under the conditions of simultaneous action of four large disturbances on both channels, the dynamic control error in the second circuit does not exceed 2%. In this case, the dynamic control error in the primary circuit dropped to 1.0% (Scope2).

Figure 6 also shows the change in the signals U1 and U2, formed by neural networks of regulators and displayed by Scope1.

Conclusions

1. Under conditions of wear and aging of the AO, accompanied by significant changes in its static and dynamic characteristics, and with significant disturbances in both control channels, there is no decrease in the quality of regulation. Consequently, there is no need to reconfigure the regulators.

2. There is no need to retrain the neural networks of regulators in those cases when the parameters of the control channels of the AO correspond to the area of normal operation of the hybrid regulator.

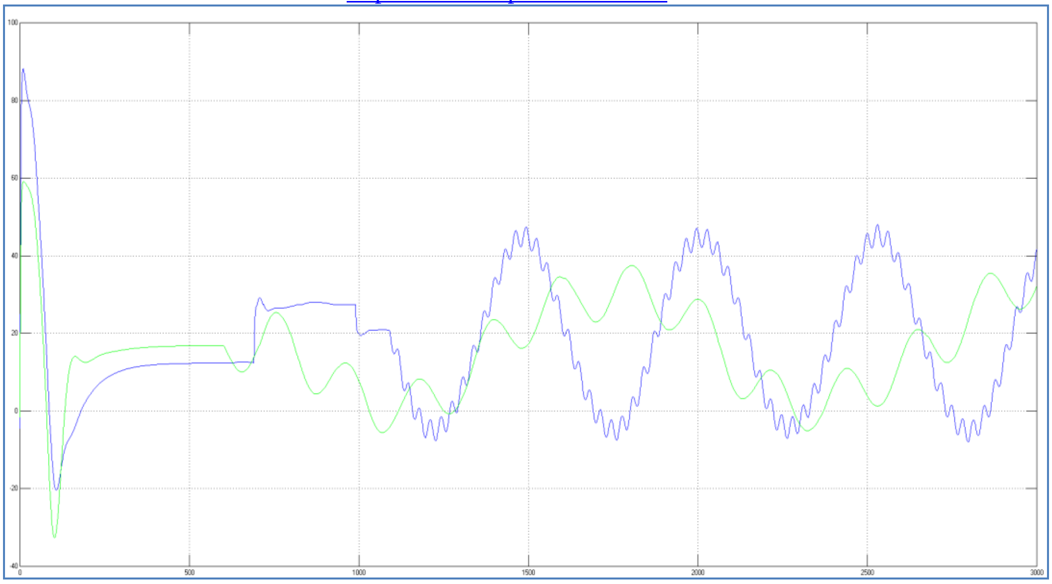

Fig. 6 – Signals U1 and U2 at the outputs of neural networks (first channel: k = 0.6; T1 = T2 = 6 s; τ = 6 s; second channel: k = 1.15; T1 = T2 = 15 s; τ = 3)

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Цитата номеру:

« I seem to have been only like a boy playing on the seashore, and diverting myself in now and then finding a smoother pebble or a prettier shell than ordinary, whilst the great ocean of truth lay all undiscovered before me »

— Isaac Newton