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A MODEL OF AN INTELLIGENT AUTOMATION SYSTEM FOR MONITORING OF SENSOR SIGNALS WITH A NEURAL NETWORK IMPLEMENTATION

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Abstract

The automation systems today combine the capabilities of AI to process large databases in real-time work, aiming to predict equipment or machine failures. Essential to the reliable and efficient operation of automated systems is the application of AI to monitor their current state. Tracking the status of the sensors in each cycle of machine operation through neural networks would provide an adaptive reflection of faulty or correct behaviour of the automated system. The present study presents a model of an intelligent automation system for monitoring the sensor signals with a neural network implementation. An algorithm for working in two basic modes of a programmable logic controller in this integration is proposed. The neural network is trained with a large number of combinations of sensory signals, corresponding to states of correct behaviour and system faults. Depending on the classification accuracy or currently occurring wrong sensor signals, a retraining method is developed for both modes of operation. The main purpose of the research is to show the effectiveness of the method for classifying the sensor behaviour, in terms of dynamic reaction of the system. The obtained results are discussed and a proposal is made for further development of the research.

Keywords: Automated control; Sensor signals; Neural network; Classification; Programmable logic controller.

1. Introduction

AI (artificial intelligence) automation systems provide real-time integration of PLCs (Programmable Logic Controller) and AI data processing capabilities. Gradually, automation will begin to replace human cognitive abilities, providing greater speed, accuracy and consistency of operations. Implementing machine learning and artificial intelligence is a key stone of contemporary innovations in production automation as discussed in [1]. Several forward-thinking organizations and institutions are paying attention to convergent automation and cognitive technologies by investing in their development of such systems [2].

As manufacturers begin to embed intelligence into automation systems such as PLCs, SCADA (Supervisory Control and Data Acquisition), etc., this new wave of cognition is now a fact of in industrial automation. This evolution of PLCs makes and evolves them as part of a robust, flexible and supportive AI system that exhibits intelligent capabilities. The

Working Paper of 34th DAAAM Symposium

future is open to machines that can operate on their own with little manual intervention, have computing capabilities on demand, and can autonomously optimize the resources and processes involved in automated production. The large number of PLC manufacturers that apply unified and standardized methods and integrated tools to ensure the functionality of controllers, as well as their integration with neural networks in hardware or cloud-based platforms, have allowed the application of AI at different levels in the hierarchical structure of control systems - field level, control level and management level [3] [4].

Tracking the status of the sensors in each cycle of machine operation through neural networks would provide an adaptive reflection of faulty or correct behaviour of the automated system. The present study presents a model of an intelligent automation system for monitoring the sensor signals with a MLP (Multi-Layered-Perceptron) neural network implementation. The objective of the study is to show how the neural network can be trained to recognize combinations of sensory signals, corresponding to states of correct behavior and system faults, as well as to dynamically retrain itself with currently emerging new states. An algorithm for working in two basic modes (off-line and on-line) of a programmable logic controller in this integration is proposed. The neural network is trained with a large number of combinations of sensory signals, corresponding to states of correct behaviour and system faults. Depending on the classification accuracy or currently occurring wrong sensor signals, a retraining method is developed for both modes of operation. The main purpose of the research is to show the effectiveness of the method for classifying the sensor behaviour, in terms of dynamic reaction of the system. The obtained results are discussed and a proposal is made for further development of the research.

2. State of the Art

In the field of automation, more and more manufacturers of control equipment are developing the capabilities of AI to work together with PLCs as the main devices in the control systems. With the introduction of the S7-1500 TM neural processor (NPU) module for the Simatic S7-1500 controller and ET 200MP I/O system, Siemens has integrated AI into the controller itself. The S7-1500 TM NPU module is suitable for use at the field level in the control structure, as well as wherever reliable, fast, deterministic and real-time solutions are required [5]. The S7-1500 TM NPU module works using a trained neural network and stored knowledge on an SD card. Users can connect Gigabit Ethernet and USB 3.1 compatible sensors, such as cameras and microphones, to the module's integrated interfaces. CPU data transmitted from the backplane can also be used as input data. The processing results are then evaluated in the processor program [6]. The TM NPU transfers the result of the processing operation to the CPU via the backplane bus. The CPU then allows further evaluation to reflect the results in the user program. But the typical area of application is a visual quality check in production plants, with an implemented application shown in [6]. But no examples have been published for implementations with digital sensory input signals and transferring the results from the neural module to the CPU via the backplane bus. The Allen-Bradley Control Logix and Compact Logix controllers support machine learning and artificial intelligence only through the integration of third-party software tools. They implement cloud based Neural network technologies, but in the field of energetics [7]. The AC500 PLC series of ABB, features an integrated AI controller that can be programmed using MATLAB and Simulink3, but with no examples with AI applications and integration through PROFINET bus, protocol that efficiently manages Inputs and Outputs exchange between the controller and I/O Devices in real-time operation [8] [9]. The iQ-R Series PLCs of Mitsubishi Electric, support machine learning and artificial intelligence through the integration of third-party software tools. The iQ-F series is an all-in-one programmable controller that can be used for stand-alone applications or networked system applications, but the proposed applications are addressed only for Data and statistical analysis [10]. The Modicon M580 controller of Schneider Electric supports machine learning and artificial intelligence through the integration of third-party software tools. This feature allows the controller to perform mostly advanced analytics and predictive maintenance [11]. The authors Marugán, A.P. & Márquez, F.P.G. present a method based on neural networks for a dynamic generation of a control strategy, but not based on input sensor signals. It suggests that the thresholds used for generating alarms can vary and, therefore, the control of the wind turbine will be adapted to each specific wind turbine [12]. Wang, W., Harrou, F. § Bouyeddou, B. propose an application of a neural network for recognition of various heterogeneous cyberattacks, also working at the SCADA level [11]. It is reasonable due to the fact, that these attacks are carried out at the management level. Both methods given in [11] and [12] work on SCADA management level, which does not imply efficient operation in terms of speed in the exchange of data between the PLC, the neural module and the input-output data.

In this study a model of an intelligent automation system for monitoring of sensor signals with a MLP neural network implementation is presented. It shows how the neural network can be trained to recognize combinations of sensory signals, corresponding to states of correct behavior and system faults, as well as to dynamically retrain itself with currently emerging new sensory states. The emphasis is on the training and retraining of the MLP network in the two main modes off-line and on-line. Depending on the classification accuracy or currently occurring wrong sensor signals, a retraining method is developed for both modes of operation. The main purpose of the research is to show the effectiveness of the method for classifying the sensor behaviour, in terms of dynamic reaction of the system. In this way, the dynamics in the changes of input combinations will be correctly classified by the MLP NN, especially after long-term operation of the automatic complex, when the majority of sensory combinations unforeseen in the training data would occur. A number of input training data representing real sensor signals were used in the experiment. The obtained results show very good

Working Paper of 34th DAAAM Symposium

adaptability and accurate classification of the neural network when tested with a large sample of dynamically changing input data.

3. Description of the proposed conceptual system model

The proposed conceptual system model is presented in Figure 1. The data of connected sensors and the data from the user program of the CPU is processed with a high data throughput/high data rate through neural network in the MLP NN. The sensors are connected via Gigabit Ethernet and USB 3.1 to the integrated I/O (Input/Output) interfaces of the module. The MLP NN transfers the result of the corresponding processing operation to the CPU via the backplane and PROFINET bus. The CPU then allows further evaluation to take place in the user program and the PLC outputs to the actors. Displaying the current results on the HMI (Human Machine Interface) device. After the model is trained, it is exported in a format that is compatible with the MLP NN module. The trained neural system is exported/loaded to the SD card of the module. The system works in two base modes - off-line and on-line mode. The following is an exposition of the proposed functional algorithm.

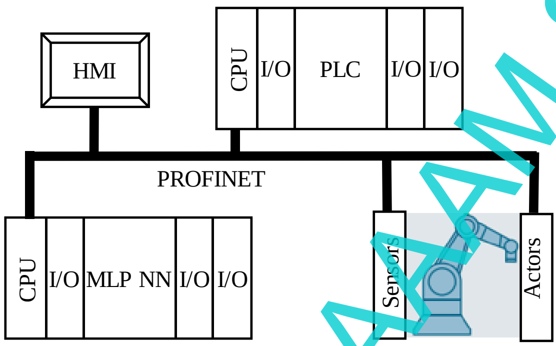

Fig. 1. Conceptual system model

3.1. Proposed functional algorithm

Off-line mode:

1. Train the MLP with a large sample of combined sensor data for both classes - "normal values" and "incorrect values";
2. Test the MLP NN, submitting large sample of combined sensor data of both classes, that did not participate in the training phase. If the classification accuracy is under 80%, optimize the MLP NN parameters: increase the number of neurons in the hidden layer, reduce the preset MSE (Mean Square Error) training error;
3. Add the misclassified sensor combinations to the training sample, assigning the correct class and train the MLP NN again;
4. Download of the obtained matrix of weight coefficients (the trained knowledge base) in the SD card of the NN hardware module.

On-line mode:

1. In real-time operation, the current combination of sensor values is fed within each cycle (current state of the automaton complex) to the inputs of the trained MLP NN and to the PLC.
2/a If any of the sensor values are out of range in the current program input combination and the MLP NN does not correctly classify it as the "incorrect values" class,
2/b or all the sensor values are within the allowable range in the current program input combination, but the MLP NN does not correctly classify it as class "normal values".
In this case, the current misclassified input sensor combination is added to the training sample of sensor combinations as the right corresponding class, and the off-line training mode is set again.
3. Update the obtained matrix of weight coefficients (the trained knowledge base) in the SD card of the NN hardware module and continue in on-line mode.

In this way, the dynamics in the changes of input combinations will be correctly classified by the MLP NN, especially after long-term operation of the automatic complex, when the majority of sensory combinations unforeseen in the training data would occur.

4. Experimental data and results

To conduct the experiment, water pump sensor data, freely available in the open platform for datasets *Kaggle* [13], were used. The training file of the neural network includes the values of 49 sensors with levels corresponding to normal operation of the sensors, as well as those outside their operating range that occurred during real emergency situations. Included are 300 combinations of actual „normal values“ during operation and 300 combinations of „incorrect values“.

Working Paper of 34th DAAAM Symposium

These values are grouped in the training file into two classes of sensor signal combinations, the class "normal values" and class "incorrect values". Figure 2 represents the first 300 correct and the next incorrect combinations of sensor values for three of the sensors.

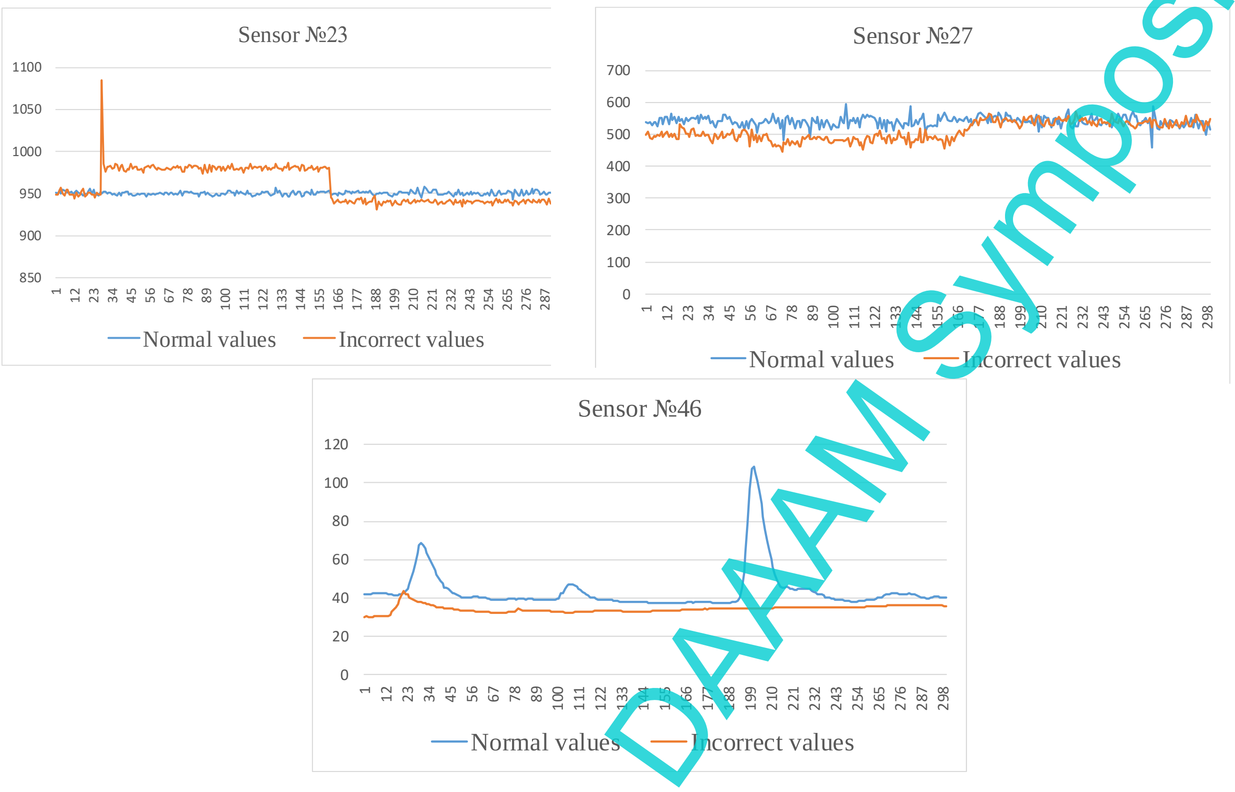

Fig. 2. 300 trained sensor values for classes "Normal values" and "Incorrect values" for three of the sensors

The trained neural network is of the MLP type with a 49-20-2 structure (49 input neurons, 20 neurons in the hidden layer and two neurons in the output layer - corresponding to the two defined classes of sensory signals - "normal values" and "incorrect values"). The MLP structure was trained until reaching 0.1% MSE in the output layer. This was achieved after 12354 iterations. A tangent hyperbolic activation function was applied to all three layers of the MLP structure and a standard Backpropagation training algorithm was applied.

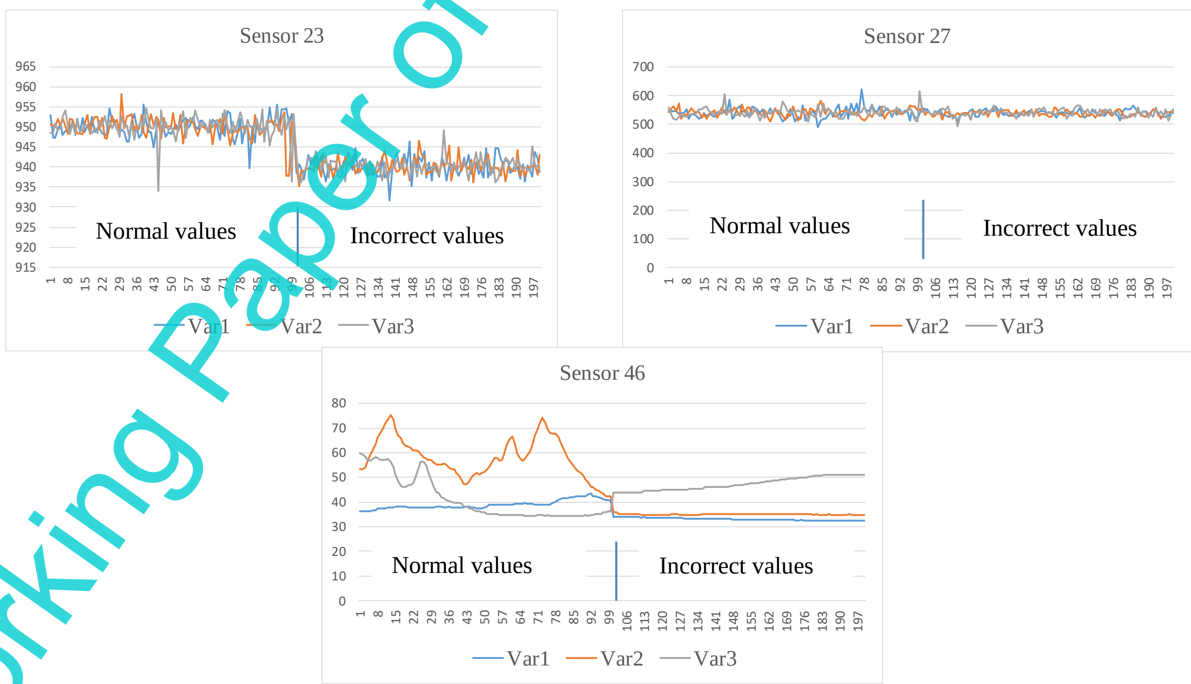

Fig. 3. 100 different instances for each of the three variants in the test phase

Working Paper of 34th DAAAM Symposium

In the test phase, when performing steps 2 and 3 in the off-line mode and steps 2a and 2b in the on-line mode of the algorithm, three variants of combinations of sensor signals for both classes, which did not participate in the training sample, were applied. For each of the 49 sensors, 100 different instances were selected for each of the three variants for class “Normal values” and the next 100 - for class “Incorrect values”. They are represented in Figure 3.

4.1. *Test results*

The next section presents the results of testing the trained MLP NN before and after retraining in steps 2 and 3 in off-line mode and steps 2a and 2b in on-line mode. The graphs show the ideal values set in the training phase for the two

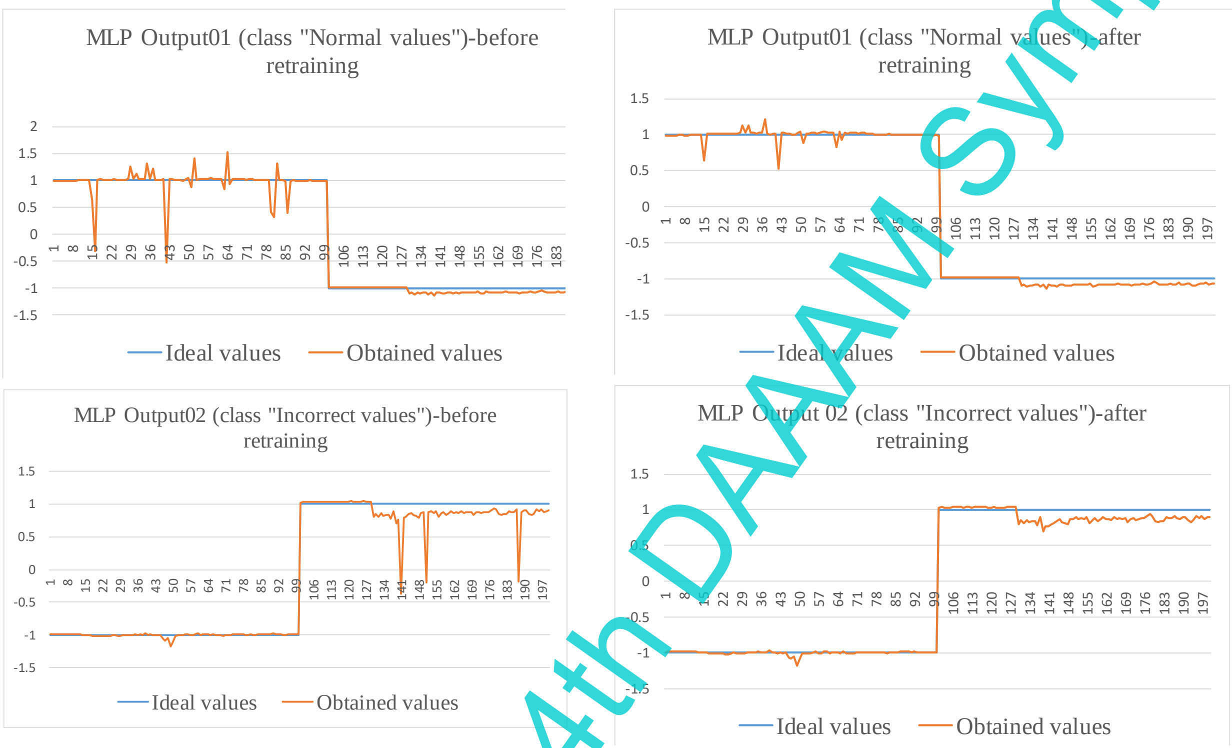

Fig. 4. MLP NN outputs in test phase before and after retraining

classes "Normal values" and "Incorrect values", as well as the values obtained in the testing phase. Graphs for one of the three variants tested are presented in Figure 4. The effect of retraining is visible, whereby there are no misclassified input combinations in the "after retrained" plots. The two misclassified "normal values" sensor combinations in output 1 and the three misclassified "incorrect values" sensor combinations in output 2 are recognized correctly after retraining the neural network.

4.2. *Classification results*

The results of the classification before and after the retraining of the MLP NN are presented in Table 1. The classification accuracy was calculated as the number of incorrectly classified input sensor combinations in on-line mode/the total number of tested combinations in each of the three sample variants. After the retraining proposed in steps 2a and 2b of the algorithm, the neural network is dynamically retrained. In this way, the dynamics in the changes of input combinations will be correctly classified by the MLP NN , especially after long-term operation of the automatic complex, when the majority of sensory combinations unforeseen in the training data would occur.

MLP NN - Classification accuracy [%]					
Variant1		Variant2		Variant3	
Before retraining	After retraining	Before retraining	After retraining	Before retraining	After retraining
95%	100%	91%	100%	87%	100%

Table 1. Presentation of classification accuracy

Working Paper of 34th DAAAM Symposium

5. Conclusion

The proposed conceptual model and algorithm for dynamic retraining of the neural network is tailored to the specifics of data exchange in an automated PLC control system and operation of an integrated hardware module with neural networks. The main benefits and contributions of this study are as follows:

1. The application of deep learning and NN retraining enables adaptive self-tuning of the control system at the field communication level;

2. By statistically accumulating and storing sensor combinations corresponding to incorrect sensor values or wrong sensor combinations, it would be more difficult to determine wrong combinations by searching the accumulated database. It is much more efficient to update the database by retraining, as shown in the proposed algorithm;

3. The dynamics in the changes of input combinations will be correctly classified by the MLP NN, especially after long-term operation of the automatic complex, when the majority of sensory combinations, unforeseen in the training data would occur;

4. If the art of the sensor signals need to be changed, retraining can be easily performed without significantly changing the algorithm itself. The presented results and the achieved high classification accuracy after retraining for all three investigated variants show a good generalization of the method;

5. The proposed method can be easily integrated in different real automated systems, supporting standard communication protocols and data exchange, between the neural module and PLC.

As a future development and continuation of the research, extended testing of the method with a large number of different sensor combinations in learning differente structures of the MLP NN, aiming to minimize the number of neurons in the inner hidden layer, can be indicated. This would speed up the real-time operation of the neural network in the hardware module. Additional implementation and testing of the model in the Siemens S7-1500 TM NPU modules is also pending.

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