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- Artificial Intelligence (AI)-

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APPLICATION OF ARTIFICIAL INTELLIGENCE IN FACTORY MAINTENANCE

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Abstract: *The work that will be presented in the rest of the document deals with the application of artificial intelligence AI, neural networks, machine learning on machine maintenance, which is a key resource for production in industry. It is a specific machine that must not have an interruption longer than 30 minutes during one shift. Due to the specific nature of the job of inserting fresh air into the blast furnace, the machine must work continuously during the entire furnace operation campaign. This campaign can last up to 12 months. By looking at the situation before the introduction of AI into the system, it was established that the stoppage is mainly caused by damage to the rolling bearings, which are the basis for starting the fan turbines. Further research led to the startling conclusion that bearings ran shorter when they were more lubricated than when they were not lubricated at all. Based on these observations, it was decided that it is necessary to create a program that will collect data on the sensors and based on this data, create an AI that will decide when and how much it is necessary to lubricate the bearings. The advantages of the system are related to the application of algorithms that significantly improve the efficiency of the software in the maintenance application, which significantly reduces the downtime of the machine, and increases its timeliness, availability and efficiency. The method* *of learning with incentives was applied. The program receives data from the sensors (pressure, temperature, vibrations and ultra sound), then performs an action on the machine via the actuator. The machine returns feedback via sensors to the program, which corrects the settings depending on the results (good or bad). The goal is for the program to learn during operation to have as high a percentage of good results as possible. Due to the complexity of the machine, there are limited limit values in the program, so that the program cannot cause damage to the machine during learning. The research results are presented using statistical methods in the paper.*

Specifically, the paper deals with the application of the Convolutional neural network CNN. The data measured on the sensors are sent to the database located on the server. The program groups this data and selects them based on the results - good and bad. The data is then used to train the network and create an optimal algorithm that, with its timely actions, should extend the service life of the rolling bearings on the machine, which is a key resource for the complete production of the factory. Based on the learning, the AI can generate reports based on which the procurement and replacement plan of critical components can be planned. By using the mentioned solution, the service life of the rolling bearings was increased by 20%, while the emergency outages of the plant were reduced to 0. The advantage of the used solution is reflected in high timeliness, availability, reliability, since there were no emergency outages since the implementation of the mentioned solution.

Keywords: *Artificial intelligence (AI), Convolutional neural network CNN, sensors, database, server.*

PRIMENA VESTACKE INTELIGENCIJE U ODRZAVANJU FABRIKE

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Apstrakt: *Rad koji ce biti predstavljen u nastavku dokumenta bavi se prime-nom veštačke inteligencije AI, neuronskih mreža, mašinskog učenja na odrzavanju mašine koja je kjucni resurs za proizvodnju u industriji.Radi se o specificnoj masini koja u toku jedne smene ne sme imati prekid veci od 30min. Zbog specificnosti posla ubacivanje svezeg vazduha u visoku pec masina mora da radi kontinulno tokom cele kampanje rada peci. Ova kampanja moze da traje i do 12 meseci. Sagledavanjem stanja pre uvodjenja AI u sistem ustanovili smo da do zastoja uglavnom dolazi zbog ostecenja kotrljajucih lezajeva koje su osnov za pokretanje turbina ventilatora. Daljim istrazivanjima dosli smo do zapanjujucih zakljucaka da su lezajevi krace radili kada su bili vise podmazani nego kada uopste nije ni bilo podmazivanja. Na osnovu ovih zapazanja odlucili smo da je potrebno napraviti program koji ce vrsiti prikupljanje podataka na senzorima i na osnovu ovih podataka uraditi AI koja ce odlucivati kada i koliko je potrebno podmazati lezajeve. Prednosti sistema se odnose na primenu algoritama koji znatno poboljšavaju efikasnost softwera u aplikaciji održavanja čime se znatno smanjuje vreme otkaza mašine, a povećava njena ažurnost, dostupnost i efikasnost. Primenjena je metoda učenja uz podsticaje. Program prima podatke sa senzora (pritisak, temperatura, vibracije i ultra zvuk), zatim preko aktuatora vrši akciju na mašini. Mašina vraća povratnu informaciju* *preko senzora programu, koji koriguje podešavanja u zavisnosti od rezultata (dobri ili loši). Cilj je da program tokom rada nauči da ima što veći procenat dobrih rezultata. Zbog složenosti mašine u programu su ograničene granične vrednosti tako da program ne može da prouzrokuje oštećenje mašine prilikom učenja. Rezultati istraživanja prikazani su statističkim metodama u radu.*

Konkretno rad se bavi primenom neuronske mreze Convolutional neural network CNN. Podatke izmerenih na senzorima salju se u bazu podatka koja se nalazi na serveru. Program grupise ove podatke i selektuje ih na osnovu rezultata dobri I losi. Podaci se zatim koriste da se izvrsi ucenje mreze i napravi optimalan algoritam koji ce svojim pravovremenim akcijama treba da produzi radni vek kotrljajucih lezajeva na masini koja predstavlja kljucni resurs za kompletnu proizvodnju fabrike. Na osnovu ucenja AI moze da vrsi generisanje izvestaja na osnovu kojih se moze planirati nabavka I plan zamene kriticnih komponenata. Upotrebom pomenutog resenja radni vek kotrljajucih lezajeva je povecan za 20%, dok su havarijski ispadi postrojenja svedeni na 0. Prednost upotrebljenog resenja ogleda se u velikoj azurnosti, dostupnosti pouzadnosti posto nije bilo havarijskih ispada od implementacije pomenutog resenja.

Ključne reči: *Veštačka inteligencija (AI), convolutional neural network CNN, senzori, baza podataka, server.*

INTRODUCTION

The work was created as a result of research and problem solving on industrial maintenance of production equipment (machines). Namely, it is a specific type of production that is carried out in a blast furnace. The main problem occurred due to the failure of the ball-roller bearings on the housings of the shaft for introducing fresh air into the furnace. During activation, the flow and amount of fresh air must be continuous and must not be interrupted. All interruptions must not be longer than 45 minutes (replacement of housing, motor, switching to generator in case of power failure). Longer holdings would lead to the appearance of flue gases, which puts the entire factory at risk due to the high possibility of explosion. The production process in this furnace during activation lasts for months, and just for shutting down the furnace, a minimum time of 20 days is required. In the event of a breakdown, equipment maintenance workers access emergency maintenance. From the contingency plan, they receive a list of parts that must be changed and change the parts or activate the power supply unit. The contingency plan, which is an integral part of the maintenance procedures, describes and explains in detail the replacement and procurement of parts for critical machines and equipment. Problems arose frequently. It happened that during the campaign, which lasted 9 months, the number of interventions on this part of the machine reached up to 15 replacements, which is as much as 1.66 times a month, and this represents a serious problem due to the constant engagement of the maintenance service (which must perform 24-hour monitoring during operation of the furnace), the cost of spare parts, as well as damage that occurs when the air supply is interrupted (the material in the furnace loses its properties, so it is destroyed or used as a product of lower quality). Factory losses resulting from these accidents are quite large.

1. INVESTIGATION OF THE CAUSES WHICH LEAD TO MACHINE FAILURE

It is approached to find the root cause of the problem leading to increased machine failure. The quality of the procured parts was also taken into account. Parts from various renowned world manufacturers (SKF, FAG, NKL, etc.) were changed, but there was no improvement. Figure 1 shows the number of cancellations by month. From the figure, it can be seen that in the initial phase of heating the furnace, there was no emergency outage. As the furnace worked longer, the outages happened more and more often.

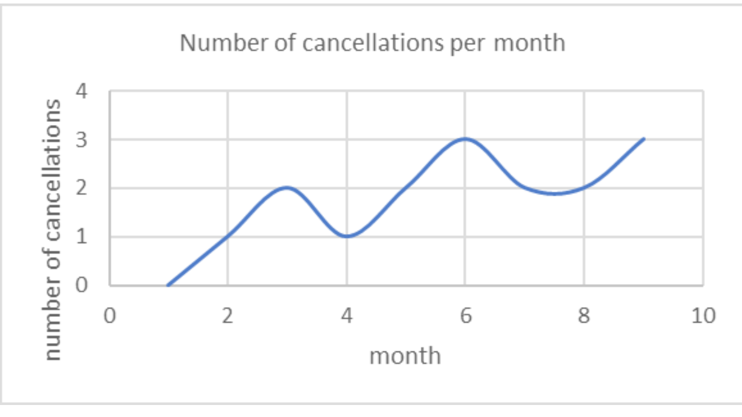

Figure 1. Number of cancellations per month (Source: Miljan Miletic, 2016.)

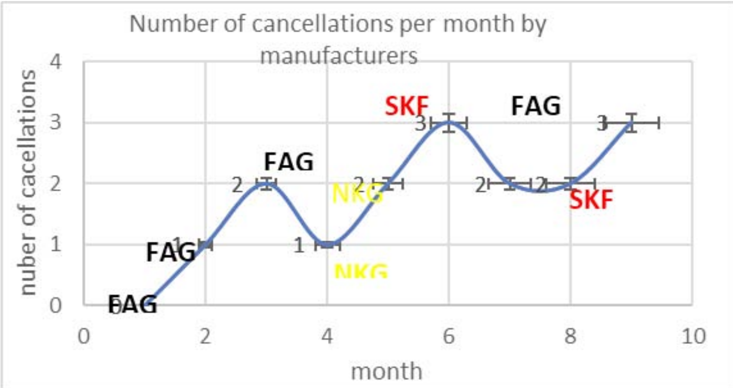

Figure 2. Number of cancellations by bearing manufacturers
(Source: Miljan Miletic, 2017.)

It was not possible to determine from the figure what causes the failures. The second figure shows the dates when emergency parts were replaced. There was no rule that one manufacturer's bearings and housings would last longer than another. Please note that only original quality parts were installed. Since it was not possible to find a problem from these monitoring, it is moved on to measuring various parameters that could be the cause of these anomalies. It was necessary to perform temperature measurements on the bearing housings, vibration measurements, grease pressure measurements in the housing, as well as shaft speed measurements. All probes and transmitters are connected to a programmable logic controller - PLC, which sends data to an application written in programming language "Python". This application processes the obtained values (values range from 0 - 5V or 4 - 20 ma), converts the values into temperature, pressure, frequency and enters the data into a MySQL database. Updating and entering new data is done every 5 minutes.

PLC - This device is used to collect and process data from the sensor, which it sends to the application on the computer through the communication port, and the computer enters the data into the database. The principle was used in the work. Figure 3 shows the block diagram of the machine line for introducing fresh air into the furnace. The mounting locations of temperature sensors (temp 1, temp2, temp3), vibration sensors and pressure sensors (pressure gauges 1 and 2) are shown.

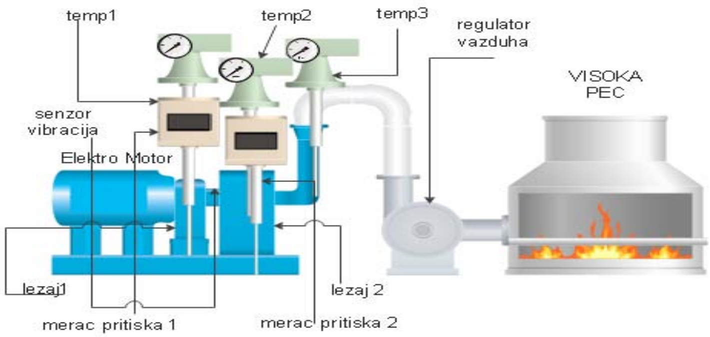

Figure 3. Block diagram of the machine (Source: Miljan Miletic, 2018.)

All the devices listed above are attested and have a certificate of compliance with Serbian and European standards. The results of the measurements collected from the sensors after processing are forwarded by the PLC to the application in the programming language "Python", which reads the values of voltage, current, frequency and converted scaled values from the communication ports and sends them to the application in the programming language "PHP", and then this application writes the data into the MySQL database . Figure 4 represents an application written in the "Python" program, which writes data into the MySQL database. The picture shows the connection string for connecting to the database, as well as the fields that need to be entered in the database.

temperature.py - C:\Users\x\Dropbox\30.6.2017 lm\phyton\temperature.py (3.6.4)

File Edit Format Run Options Window Help

```
import MySQLdb

db= MySQLdb.connect(host="localhost", user="root", passwd="",
db="trayal")
try:
     datum = raw_input("Unesi datum: ")
     if title == "" :
         exit
     temperatura1 = raw_input("Unesi vrednost za temperaturu1: ")
     if title == "" :
         exit
     temperatura2 = raw_input("Unesi vrednost za temperaturu2: ")
     if title == "" :
         exit
     temperatura3 = raw_input("Unesi vrednost za temperaturu3: ")
     if title == "" :
         exit
print "datum: [" +  + "]"
print "temperatura1: ["+  + "]"
print "temperatura2: ["+  + "]"
print "temperatura3: ["+  + "]"


cursor = db.cursor()

stmt = "INSERT INTO temperature (datum, temperatura1, temperatura2, temperatura3
stmt = stmt + datum
stmt = stmt + "', '"
stmt = stmt + temperatura1
stmt = stmt + "', "
stmt = stmt + temperatura2
stmt = stmt + "', "
stmt = stmt + temperatura3
stmt = stmt + "', "

cursor.execute(stmt)
print "Record added!"

cursor.close ()
db.commit ()
```

Ln: 1 Col: 0

Figure 4. Python application for entering data into the database (Source: Miljan Miletic, 2017.)

Figure 5 presents a program that displays temperature values for the day and time. Data is entered into the database every 5 minutes. The application is written in the programming language "PHP" and has automatic generation of graphs for each day from which deviations and critical temperatures can be seen. Temperatures 1 and 2 represent the values on the ball bearing housings, while temperature 3 represents the measured value of the temperature on the shaft towards the fan. The same application was made for the other sensors that were used on the machine.

DOBILI STE PODATKE :
ZA DATUM:20170427

Temperatura1	Temperatura2	Temperatura3	Datum
33.000399520575	33.001015415859	32.606979314701	2017-04-25 11:59:10
33.639632441071	32.954860149543	33.238591504816	2017-04-25 12:04:05
33.000399520575	32.447152220068	32.606979314701	2017-04-25 12:09:05
34.678385936876	33.370257546386	34.264961313753	2017-04-25 12:14:05
33.719536556133	32.908704883227	33.31754302858	2017-04-25 12:19:05
37.395125848981	35.031847133758	36.949313121743	2017-04-25 12:24:05
36.276468238114	35.67802086218	35.843991789042	2017-04-25 12:29:05
39.073112265282	37.985784177975	38.607295120796	2017-04-25 12:34:05
36.356372353176	34.431828671651	35.922943312806	2017-04-25 12:39:05

Figure 5. The PHP application displays temperatures by input time (Source: Miljan Miletic, 2017.)

1.1. Analysis of results after measurement

By studying the obtained values (all parameters were obtained after measurements after the installation of new bearings) it was concluded that the temperature on the housings, vibrations and grease pressure increase sharply after 10 days after installation. The figures show the values for one month after changing the casing and bearings. Figure 6 shows the results of temperature measurements at all three measuring points for 30 days, and figure 7 presents data for all types of measurements - pressure, temperature, oscillations for 30 days. From figure 6, it can be seen that the temperatures measured on the bearing housings (temperature 1 and temperature 2) change suddenly every 10 days, while temperature 3 (the temperature measured on the shaft to the fan) is constant and does not change when temperature 1 and temperature 2. The same observation for pressure values, the oscillation in figure 7 can be seen that it happens every 10 days. By carefully studying these events, it was established that the housing and bearings are lubricated every 10 days. By checking the maintenance procedures and looking at the lubrication charts on this machine, the lubrication time was changed due to frequent failures and replacement of bearings and housings (in earlier years, especially during the time of sanctions, quality parts could not be procured, so bearing lubrication was frequent).

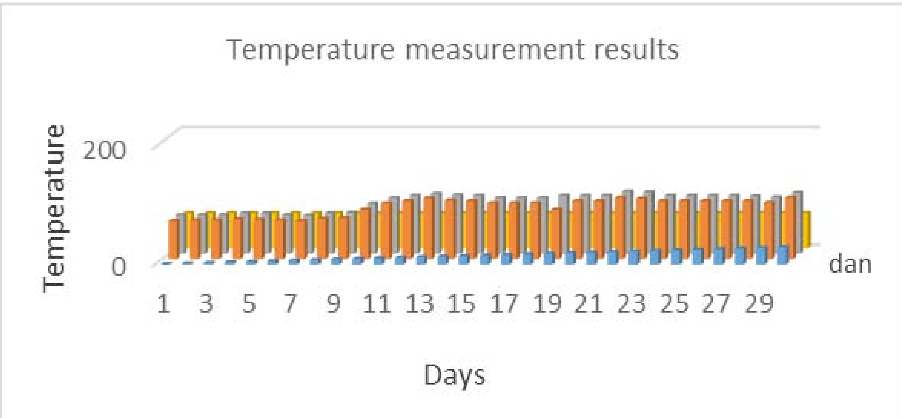

Figure 6. Display of measurement results per day (Source: Miljan Miletic, 2017.)

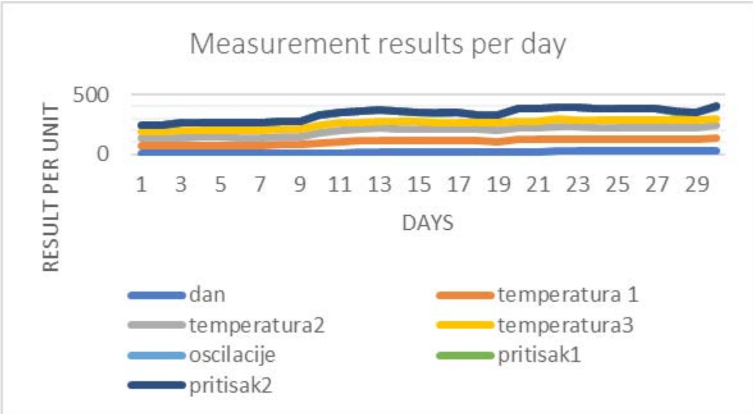

Figure 7. Display of measurement results (temperature, pressure, oscillations) per day (Source: Miljan Miletic, 2017.)

Frequent lubrication of bearings and housings leads to faster damage. By checking the factory data of the ball bearings, it was found that the factory prescribed a significantly longer time between lubrication. From their advice, it is better not to lubricate the bearings than to be lubricated more than necessary. After each lubrication, the values of temperature, vibration and pressure in the housings increased. Due to the addition of excess fat, the pressure increases. A greater load is created on the bearing balls, there is a sudden heating and a significant shortening of the service life of the bearings. The next step is to change the time between lubrication according to the factory instructions of the bearing manufacturer (each manufacturer prescribes the time when control and lubrication should be performed). After this, a check and verification will be carried out based on the value got from the measurements.

1.2. Analysis of results obtained after lubrication time corrections

After corrective measures were taken to change the lubrication time of the bearings, by replacing new housings, shafts and bearings (bearings manufactured by SKF were installed), we started re-measurements. The new campaign started in the 5th month of 2017 and ended at the end of the 12th month, so there are reliable, comparable results with the previous campaign that lasted 9 months. Figure 8 presents data for each measurement per month, as well as the number of cancellations in a given month. The figure shows a significant reduction in cancellations compared to the previous campaign. In the previous campaign, there were 16 dismissals, while in this one, the number of dismissals is 5. This is a much better result; the number of equipment failures is reduced to 31.2%, but the reasons for equipment failures will be checked and it will be tried to reduce them. Figure 9 shows the results of measurements collected from the sensors for one month.

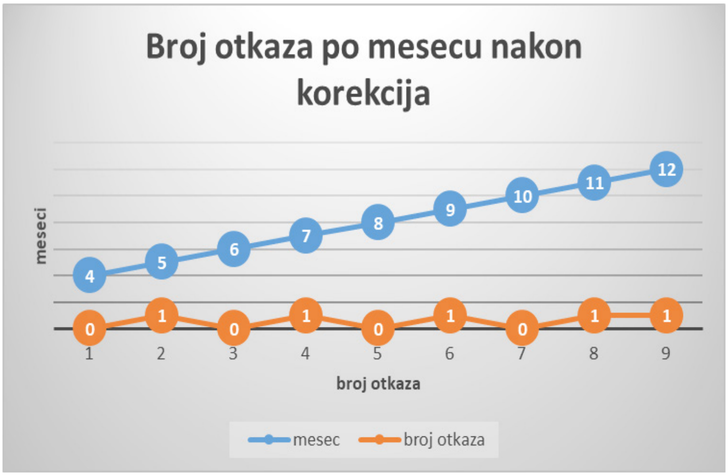

Figure 8. Cancellations by month after correction (Source: Miljan Miletic, 2017)

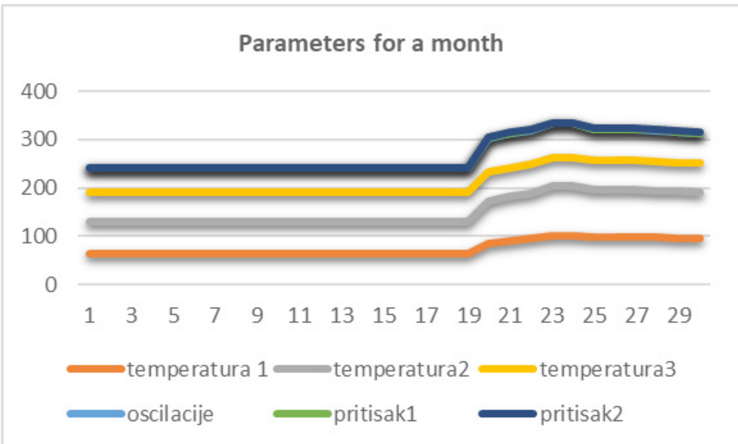

Figure 9. View measurements for a month (Source: Miljan Miletic, 2017.)

It can be concluded from the graph that sudden changes in temperature, pressure and oscillation values began to occur on the 20th day of the month. From the values in figure 9, it can be concluded that the maintenance service started lubricating the bearings. This can be seen from the parameters. After lubrication, the pressure increased to a value of 1.12 bar, and the previous value was 0.12 bar. The increase in pressure due to excessive lubrication was also reflected in other values, the oscillation temperatures increased. The machine broke down in the campaign twice as a result of excessive lubrication. Although workers were informed and trained not to perform lubrication, they did so twice. The other three failures that occurred in other months are a direct consequence of insufficient lubrication, since the pressure in the bearing housings dropped to 0. It should be noted that the working conditions in this plant are extremely bad - due to the climatic conditions, the plant operates at a temperature of -20 to + 40^{o}C. The environment is quite dirty from the dust that occurs during the combustion process in the furnace, various metal filings and other industrial dust. This significantly affects the shortening of the life of the seals - searings on the bearing housings, and as a result there is a loss of grease and the penetration of dust into the bearings, during which they quickly suffer and the housing and shaft are damaged. In the next chapter, it will be explained how this problem was solved by replacing certain parts and using artificial intelligence on a machine that will learn by itself depending on the parameters it receives from the sensors.

2. ARTIFICIAL INTELLIGENCE AND CNN NETWORKS

In this part of the work, the solution to the problem of machine failure will be explained in detail using artificial intelligence, neural networks and machine learning. Neural networks have an incredibly high ability of adaptation, universal approximation, which was used to research the development of artificial intelligence on this system. An intelligent machine learning system is capable of adapting to an unknown or partially known System framework. On the system previously used, the bearing housings and bearings were replaced with new oil-lubricated ones. The oil is located in a tank in which a temperature gauge, cooling radiator and heaters for reheating the oil for starting at low temperatures are installed. The approximation performed by neural networks led to the result that the ideal oil temperature for lubricating bearings is 78-82^{o}C. By using a temperature regulator, we were able to maintain that value within a range of ±0.5^{o}C. The system is controlled by a PLC device that receives input information from probes, performs processing, and then forwards the data to the computer. The computer enters all data into the database. Machine learning uses data obtained from the system and determines further action based on it. It always keeps the temperatures on the bearings and the temperature of the oil in the tank in the ideal range. The computer sends feedback to the PLC controller, which commands the actuators through the output ports. Actuators are electromechanical, electropneumatic or electrohydraulic devices that convert the electrical information they receive from the PLC controller from the output ports to perform certain actions for which they are intended. Pressure gauges send a pressure value. After receiving information from the computer, the PLC opens or closes the valves for oil flow into the bearing housing. Each valve is special. Machine intelligence decides when, which and how much to open or close. All other sensors (vibration and ultrasonic) work on the same principle - they send information to the PLC controller, and the machine learning algorithm decides on further action. The machine learning method with incentives was applied to this system. This learning works on the principle of receiving information from the sensor, then using the actuator to perform an action, feedback, i.e. it receives information feedback from the sensor and then receives praise for doing well or punishment for having to correct parameters. Of course, due to the importance of this machine, key decisions were limited. The algorithm has been set a minimum and maximum threshold beyond which it must not move in order not to endanger the entire system.[1]

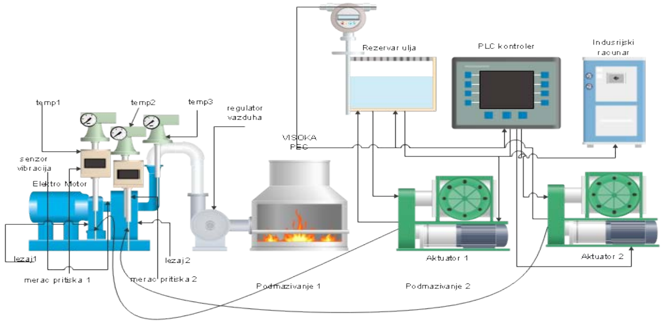

Figure 10. Sketch of the applied intelligent system on the machine
(Source: Miljan Miletic, 2020.)

Maintenance workers can no longer lubricate the bearings. Their only duty is to check the alarms. A new application has been introduced into the maintenance procedure, which alerts the manager and the maintenance worker to check the oil level in the tank, replace the oil with a new one after the prescribed time, or replace the housing or bearings in the event of a breakdown. All messages sent by the system are recorded in the database and reports are printed to the maintenance manager who has a detailed view of what is happening with the machine. In the maintenance procedure, machine chart and lubrication, the type of lubrication and time were replaced, as well as training on working on the new system. After the changes and putting the system into operation for the last two campaigns, which lasted 9 months each, there was not a single failure of the machine. Figures 11 and 12 show the parameters obtained from the probes. From these graphs it can be concluded that in these two campaigns of eight months each there was not a single failure of the machine or the control system.

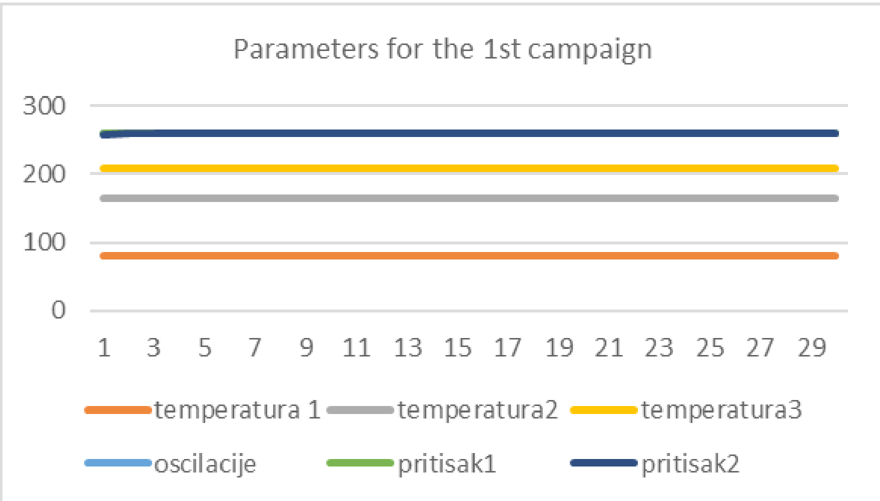

Figure11. Parameters for the first campaign (Source: Miljan Miletic, 2020.)

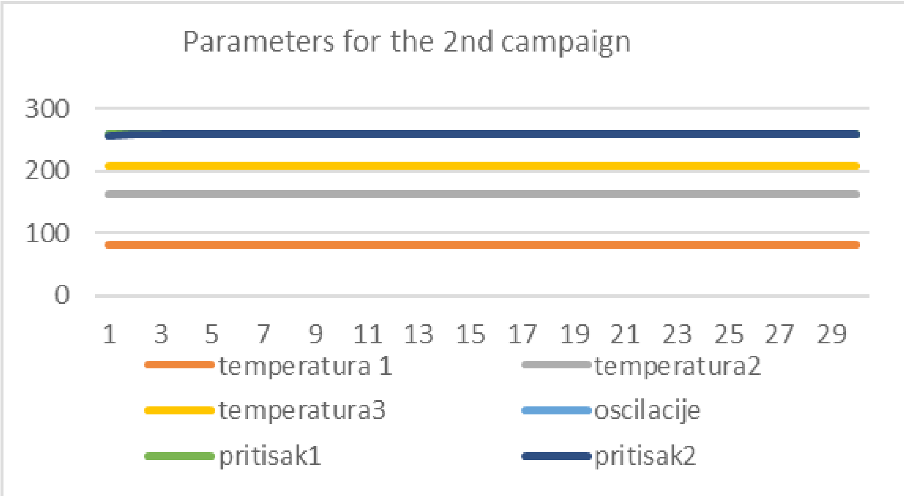

Figure 12. Parameters for the second campaign (Source: Miljan Miletic, 2020.)

DNNs have the ability to characterize and classify signals in the audio domain with significant levels of robustness, because audio events have specific spectro-temporal shapes. It is well known, also, that using DNN as a black box for audio processing is very unsatisfactory. For the development of better models and network architectures, as well as the determination of hyperparameters, a clear understanding of how and why DNNs can learn from audio signals and their representations, such as spectrogram-based images, is essential.[2]

A network often used for AI-based audio processing is CNN. According to some research on deep learning models from the literature, CNN outperforms other models in image and video data processing. For this reason, CNN is increasingly popular in artificial intelligence-based audio processing [3-6], which can be said to be insensitive to sample position in spectrogram-based images [7] and recognized as a suitable technique for spectrogram image feature classification [3]. CNN can effectively exploit the invariance existing in spectrograms for its convolutional and pooling operations [8]. CNN has the ability to achieve translational invariance and tolerance to minor differences in data patterns [9].

Using CNN, a large number of parameters of a fully connected neural network can be reduced [10]. Sparse connectivity and shared weights in CNNs facilitate network optimization by reducing the number of parameters and the risk of overloading [11]. Convolutional and pooling layers are the two basic layers in a CNN, while the final layers are typically fully connected layers. Looking at spectrogram-based image binning, the general conclusion is that the effects are different for binning along frequency and time. Practice has shown that performance usually degrades when combining frequencies [12].

A CNN with a sequential processing pipeline (linear stack of layers) was developed and implemented in the Python programming language for the use case of classifying an asynchronous motor into two classes - OK and NOK in case of any fault or failure manifesting as a change in the sound generated by that asynchronous motor. The network consists of the following layers: convolutional, activation, pooled and dropout in a convolutional network block followed by a fully connected network. Table 1 shows the convolutional, maximum pooling, smoothing and fully connected layers of the developed CNN network with the number of parameters. This kind of network architecture with a large number of parameters was chosen due to research phases in which the resolution of the parameters will be reduced by specific quantization algorithms.

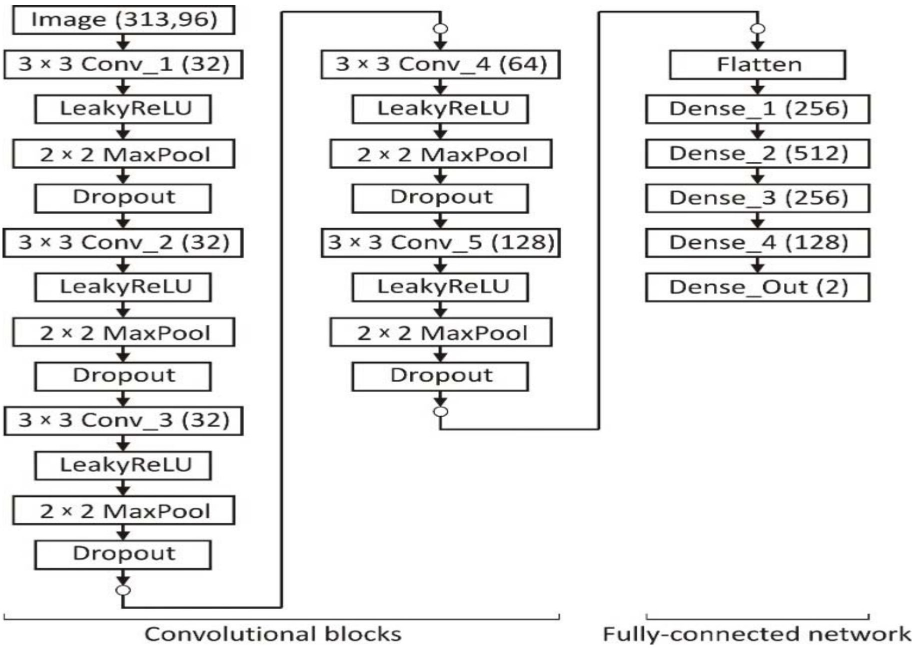

Figure 13. Architecture of the CNN developed for the target use case of classifying asynchronous motors [2]

The network input is a log-mel spectrogram with dimensions 96 × 313, which means there are 96 mel bands and 313 time frames. The convolutional block consists of five convolutional layers, the filter size is 3 × 3 in each layer, and the number of filters is 32, 32, 32, 64, and 128.

Layer (type)	Output shape	Number of parameters
conv2d (Conv2D)	(None, 96, 313, 32)	320
max_pooling2d (MaxPooling2D)	(None, 48, 157, 32)	0
conv2d_1 (Conv2D)	(None, 48, 157, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 24, 79, 32)	0
conv2d_2 (Conv2D)	(None, 24, 79, 32)	9248
max_pooling2d_2 (MaxPooling2D)	(None, 12, 40, 32)	0
conv2d_3 (Conv2D)	(None, 12, 40, 64)	18496
max_pooling2d_3 (MaxPooling2D)	(None, 6, 20, 64)	0
conv2d_4 (Conv2D)	(None, 6, 20, 128)	73856
max_pooling2d_4 (MaxPooling2D)	(None, 3, 10, 128)	0
flatten (Flatten)	(None, 3840)	0
dense (Dense)	(None, 256)	983296
dense_1 (Dense)	(Non, 512)	131584
dense_2 (Dense)	(None, 256)	131328
dense_3 (Dense)	(None, 128)	32896
dense_4 (Dense)	(None, 2)	258
Total params/trainable params: 1,390,530		
Non-trainable params: 0		

Table 1 Layers, output shapes and numbers of parameters of the developed CNN obtained directly from Python [2]

To keep input and output the same size, padding is applied. Each convolutional layer follows the activation layers, using a ReLu leaky activation function with a slope coefficient set to 0.03. The next layer after the activation layer is a maximum pooling layer of a 2 × 2 pooling window shape. The last layer before the next convolutional layer is a dropout layer, with the node rate set to zero 10%. This set of layers (convolutional, activation, maximum pooling layer and dropout layer) is repeated five times making up the convolutional block of the developed CNN.

After the convolution block, its output is first smoothed in a smoothing layer, followed by a fully connected network. This network consists of four hidden fully connected layers and a fully connected output layer. The number of outputs from the hidden fully connected (dense) layers is 256, 512, 256 and 128. The fully connected output layer has 2 outputs since there are two classes of asynchronous motors (OK and NOK motors) for the target application case.

The developed CNN was applied to the labeled data obtained from audio signals of asynchronous motors containing a total of 668 samples, i.e. 281 samples of the OK type and 387 samples of the NOK type. For this purpose, series of 64 and 30 epochs are used for training. Since the data set here is small, k-fold cross-validation is applied, where k=10. Figures 14 and 15 show the training and validation accuracies, as well as the loss for a well-performing model. A clear trend of improvement in training and validation accuracy, as well as reduction in training and validation loss, is shown. The achieved accuracy on the test set of 67 samples is 0.866, while the test loss is 0.325. Table 2 provides data on precision, recall, F1 score, and support (number of samples from the test set), with "Macro avg" and "Weighted avg" associated with unweighted and weighted performance metrics.

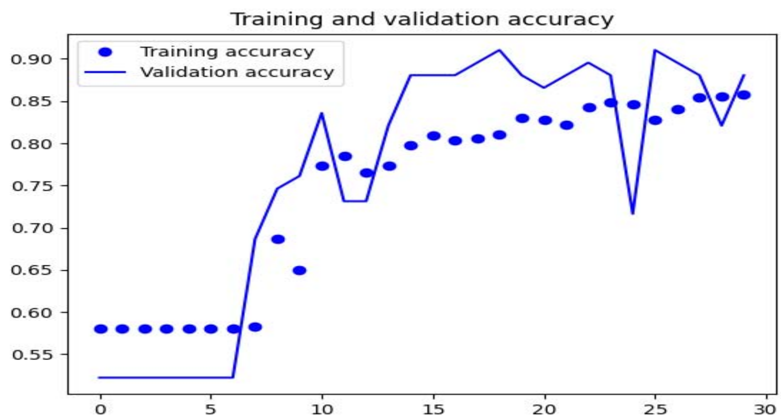

Figure 14. Training and validation accuracy through 30 epochs when the developed CNN is applied to the set of acquired labeled sounds of asynchronous motors with two classes – OK and NOK motors [2]

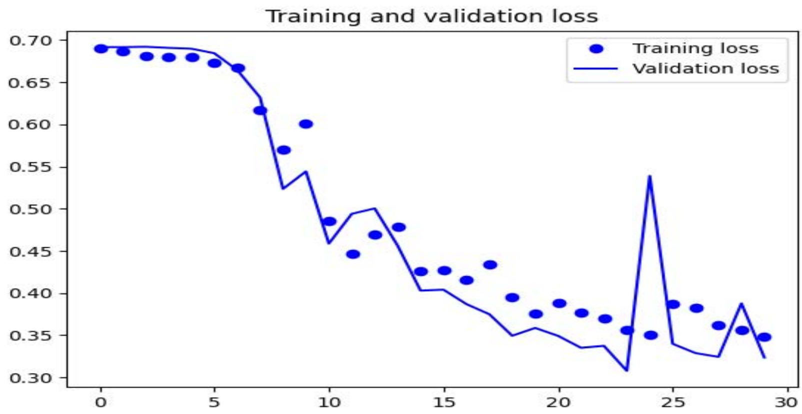

Figure 15. Training and validation loss through 30 epochs when the developed CNN is applied to the set of acquired labeled sounds of asynchronous motors with two classes – OK and NOK motors [2]

Class	Precision	Recall	F1-score	Support
Class 0	0.92	0.86	0.89	42
Class 1	0.79	0.88	0.83	25
Accuracy		0.87		67
Macro avg	0.85	0.87	0.86	67
Weighted avg	0.87	0.87	0.87	67

Table 2 Precision, Recall, F1 score and number of test samples (support) achieved by applying the developed CNN on acquired set of labeled sound samples of asynchronous motors (class 0 is related to NOK motors, class 1 is related to OK motors) [2]

CONSLUSION

This work confirms and justifies the research methods, the use of artificial intelligence and machine learning to solve the problem of frequent machine failures, as well as great economic justification. The system paid for itself many times over after the first campaign, primarily due to the quality of the product - there is no more waste or scrap. The operation of the factory is significantly more flexible due to the quality of the products that it can now deliver in the appropriate time and quantity without paying fines due to delays, because they primarily export their goods. Savings were achieved on spare parts of housings, bearings, searings and shafts. The savings on lubricating greases for lubrication is quite large. After installing this system, there is no more grease leakage, so it is a great advantage in terms of protecting the environment from harmful substances, and the price for disposal and destruction of these greases is reduced. There was also a great saving in the time of maintenance workers who are currently in deficit, and are engaged in other more complex tasks. The presented machine learning solution gave excellent results in practice. This work confirmed the justification of the introduction of artificial intelligence in various areas of the industry due to significant savings of material resources, protection of the work and environment, reduction of the workload of maintenance workers who are currently in deficit primarily due to migration qualified, professional workforce in the field of machine and equipment maintenance.

REFERENCES:

1. Ćirić, D.G. Perić, Z.H.; Vučić, N.J.; **Miletić, M.P**. Analysis of Industrial Product Sound by Applying Image Similarity Measures. Mathematics 2023, 11, 498. https://doi.org/10.3390/math11030498**For a journal paper:** author(s), (year). paper title, journal name (italic), volume and issue numbers, page numbers(inclusive). (Miriyala, K. and Harandi, M. T. (1991) Automatic derivation of formal software specifications from informal descriptions, IEE E Transactions on Software Engineering, Vol. 17, no.2, pp. 1126-1142.)
2. Dejan Ćirić, Marko Janković, **Miljan Miletić**, "Sound Based DC Motor Classification by a Convolution Neural Network" *Proceedings of 57rd International Scientific Conference on Information, Communication and Energy Systems and Technologies - ICEST*, pp. 1-4, North Macedonia, Ohrid, June 16 - 18, 2022, Publisher: IEEE, ISBN: 978-1-6654-8500-5.
3. A. Khamparia, D. Gupta, N. G. Nguyen, A. Khanna, B. Pandey, P. Tiwari, "Sound Classification Using Convolutional Neural Network and Tensor Deep Stacking Network", IEEE Access, vol. 7, pp. 7717-7727, Jan. 2019.
4. J. Lee, J. Park, K. L. Kim, J. Nam, "Sample-level Deep Convolutional Neural Networks for Music Auto-tagging Using Raw Waveforms", Sound Music Comput. Conf., Espoo, Finland, 5–8 Jul. 2017.

5. J. Schlüter S. Böck, "Improved Musical Onset Detection with Convolutional Neural Networks", IEEE Int. Conf. Acoust. Speech Sig. Proc. (ICASSP), pp. 6979–6983, Florence, Italy, 4-9 May 2014.
6. Z. Ouyang, H. Yu, W-P. Zhu, B. Champagne, "A Fully Convolutional Neural Network for Complex Spectrogram Processing in Speech Enhancement", IEEE Int. Conf. Acoust. Speech Sig. Proc. (ICASSP), Brighton, UK, 12–17 May 2019.
7. Y. Zeng, H. Mao, D. Peng, Z. Yi, "Spectrogram Based Multi-Task Audio Classification", Multimedia Tools App., vol. 78, no. 3, pp. 3705-3722, 2019.
8. J. Pons, O. Slizovskaia, R. Gong, E. Gomez, X. Serra, "Timbre Analysis of Music Audio Signals with Convolutional Neural Networks", arXiv:1703.06697, 2017.
9. O. Abdel-Hamid, A. Mohamed, H. Jiang, L. Deng, G. Penn, D. Yu, "Convolutional Neural Networks for Speech Recognition", IEEE/ACM Trans. Audio Speech Lang. Proc., vol. 22, no. 10, pp. 1533-1545, 2014.
10. Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, "Gradient-based Learning Applied to Document Recognition", Proc IEEE, vol. 86, no. 11, pp. 2278-2324, 1998.
11. I. J. Goodfellow, Y. Bengio, A. Courville, Deep Learning (Adaptive Computation and Machine Learning Series), MIT Press, 2016.
12. M. Espi, M. Fujimoto, K. Kinoshita, T. Nakatani, "Exploiting Spectro--temporal Locality in Deep Learning Based Acoustic Event Detection", EURASIP J. Aud., Speech, Music Proc., article no. 26, 2015.