Vibration Anomaly Detection Using Multivariate Time Series

Crina Deac, Gicu Călin Deac, Radu Constantin Parpala, Cicerone Laurentiu Popa, and Constantin-Adrian Popescu

***Abstract*—The paper presents a set of deep learning algorithms for detecting vibration anomalies in bearings using multivariate time series on datasets provided by Case Western Reserve University. The study considers a problem of multiclassification of the condition of the bearings depending on the type of defect, but also on the degree of defect, considering only punctual defects in an incipient phase. Once the data sets are correctly labeled and the algorithms are trained on this data, they can accurately predict the type and the size of defect. The model with the best results in the set is RNN - CNN (Recurrent Neural Network with Convolutions) giving an accuracy greater than 97% in all (load) cases.**

***Index Terms*—DNN, CNN, RNN, LSTM, anomaly detection, fault diagnosis, deep anomaly detection, vibration analyses condition monitoring, Industry 4.0.**

I. Introduction

Vibration analysis plays a critical role in the condition-based maintenance of rotating equipment. The vibration signals can be interpreted to provide early indicators of developing problems. Variations in vibration characteristics over time are key indicators of the state of a machine's mechanical health.

Conditions that cause abnormal vibration, other than the normal signature of a machine vibration, could be imbalance, misaligned races, poor lubrication, loose parts, damage to the gear or damage to the rolling element bearing, all these generating specific signature in the vibration signal [1].

The features in the time domain, extracted from vibration signal for anomaly detection are root-mean-square (RMS), peak, kurtosis, crest factor, impulse factor, shape factor or clearance factor of vibration signals [2] which are good indicators for incipient faults, but as the defects increases and spreads along the surface, these indicators values return to the normal level, because the vibration signal becomes random, the imperfection simply becomes slightly smoother and the amplitude can reduce over time. Instead, in the frequency domain, as the defect becomes severe, features such as energy and RMS of the spectral difference (Rdo) indicates a fault that exists [3].

Envelope analysis can separate the vibration of a defective bearing from the vibration generated by the other machine elements, by progressively filtering out unwanted parts of the vibration spectrum until the signal of a bearing defect can clearly be seen. [4].

Envelope analysis demodulates the vibration signals at the resonance that the impulse excited, extracts out the periodic excitation of the resonance and the frequency extracted is the frequency of the impulse, which is the characteristic bearing defect frequency, by this, localizing the component of the defect in the bearing. The purpose is not only localizing the incipient defects but maximize the useful service life of bearings by delaying their replacement after detecting an incipient fatigue defect (spall or wear). This means to monitor the defect size.

There are many methods for this [5]. One of the methods is vibrational jerk method, by differentiating the acceleration data provided by the accelerometer. In this way the entry/exit points are better detectable. The time span between these two events is correlated with the spall size.

This approach is recently developed using a Savitzky-Golay differentiator (SGD) that transform the acceleration response to a jerk response having a better energy balanced excitation for the entry into the spall / exit from the spall events, when crossing the defect, making them better recognizable in comparison to raw acceleration responses [6]. The fault size on the jerk response is computed by the time difference between the entry and exit peaks after appropriate scaling on the bearing geometry, the sampling frequency, and the rotational speed.

Furthermore, for multiple and severe defects, a new technique based on monitoring the bearing unbalance is used [6].

Vibration measurement is done with sensors that need to be mounted properly, the most reliable sensor for vibration monitoring is usually the accelerometer, because it has a wide frequency range, a wide dynamic range, also measuring the combination vibration/temperature. The signal processing techniques applied to accelerometer measurements, like acceleration integrated to velocity allows low-frequency measurement, while high frequency acceleration signals processed by using acceleration enveloping technique is useful for determining repetitive impact type vibrations generated by rolling bearing defects, lack of lubrication or gear faults [1].

Deep learning has demonstrated a lot of success in learning feature representations from different types of raw data for anomaly detection, showing tremendous capabilities in learning expressive representations of complex data such as temporal data and high-dimensional data, depending only on the temoral coherence of the raw times series.

Utilizing labeled data to learn expressive representations of normality/abnormality is crucial for accurate anomaly

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The anthers are with University "Politehnica" of Bucharest, Rumania (e-mail: george.deac@impromedia.ro, crina.deac@impromedia.ro, radu.parpala@gmail.com,laur.popa79@gmail.com,popescuadrian_c@yahoo.com).

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detection. The proposed models are supervised learning models that recognizes the normal and fault data having a good accuracy in classification, learning directly from the raw time series data supplied by the accelerometers. The only condition is to have correct labeled examples. It should be noted that in practice limited anomaly examples may come from different anomaly classes, being not labeled in the supervised dataset, this scenario is fundamentally different from the general learning, in which the limited examples are class-specific and assumed to share the same class structure [2]. The trained model would assign one of the assumed classes for that anomaly eventually. In our following tests, all wrong predictions have been assigned to different classes associated with defects but not to the class representing the normal behavior, the models being able to discern the normal behavior quite well (99% accuracy).

The presented method is for point anomalies - bearing defects in incipient phases, and cannot be used for group anomalies, also focuses on detecting anomalies from single data sources, not from multiple heterogeneous data sources.

A previous study [9] validated the CNN and DNN models to classify and predict normal and defect status on the same dataset - Case Western Reserve University- considered in the current study, containing several types of defect but without considering the size of the defect and used univariate timeseries. C. Lu et al. propose a hierarchical convolutional network on the same open-source dataset, using a one-dimensional Multi-Scale Deep Convolutional Neural Network model and obtaining 92,60% accuracy with 90% training sample percentage [10], while [11] presents a convolutional neural network-based approach using data from multiple sensors getting 99,40% with 70% training sample percentage. [12] obtained an accuracy of 94,75% on the same CWRU dataset modeling a Deep RNN.

II. Data Preparation

We will validate deep learning neural network-based techniques for diagnosing failures using multivariate time series obtained from datasets provided by Case Western Reserve University (CWR) [8] The bearing dataset was acquired on a test stand which consists of a 2hp motor, a torque transducer, dynamometer, and control electronics. The test bearings support the motor shaft. Single point faults were introduced using electro-discharge machining to the test bearing (B1) having fault diameters of 0.007” and 0.021” at two different rotations: 1797 rpm, motor load (HP) 0 and 1772 rpm, motor load (HP) 1. [9]

In the outer raceway the faults are placed relative to the load zone of the bearing to affect the vibration response of the system, respectively in the drive end bearing (B1), in the load zone (6 o’clock), orthogonal to the load zone (at 3 o’clock) and opposite (at 12 o’clock) to the load zone, also punctual faults of 0.007” and 0.021” were placed in the B1, in the inner raceway and in the rolls.

The fan end bearing B2 is considered normal, without defect in our study, but the proposed model could very well assume defects in B2, this implying adding more labels – indicatives of defects in the fan end (B2) - to the samples that will be formed.

Data was acquired at a sampling rate of 12,000 samples/second for both bearings, by using accelerometers attached to the motor housing with magnetic bases in the position of 12 o’clock at both, the drive end (B1) and fan end (B2), for each rotational speed. Datasets, comprising accelerations in the drive end (B1) and fan end (B2), where separately considered for two fault diameters 0.007” and 0.021”, in two different load cases- motor Load 0 hp and motor Load 1 hp, for 5 types of faults: in the inner race, in the ball and 3 faults types in the outer race: centered, orthogonal, opposite and also two dataset for the normal behavior at each load, resulting 11 classes in the end. This means the study will be done for each specific load (Load 0 and Load 1) using 11 datasets each one (11 timeseries), a total of 22 datasets provided by CWR. Next, the time series will be formed segmented in samples to feed the proposed models. A total of 1464427 data points included in all those 11 files will make up the buffer size of our dataset in the study for Load 0.

At Load 0, the rotational speed of the engine is 1797 rotations per minute (RPM) and as the sampling rate is 12000/s, it means 12000 data points recorded in a second and 30 Rot/s with 400 data points contained in a rotation period. At Load 1, the rotational speed is 1772 rotations per minute (RPM) at the same sampling rate, meaning 29.53Rot/s, so for both cases the rotational speed will be approximated at 30 per second. When local defects occur on the outer/inner raceway and rolling element (cracks, spalls), the interaction between the raceway and rolling element results in time-varying and non-uniform discontinuous contact forces that generate a specific signature in the vibration signal.

It can be observed the signature of the vibration specific to each type of defect and size and how the defect in one bearing induces vibrations in the second bearing without defect through the shaft (Fig. 1 and Fig. 2)

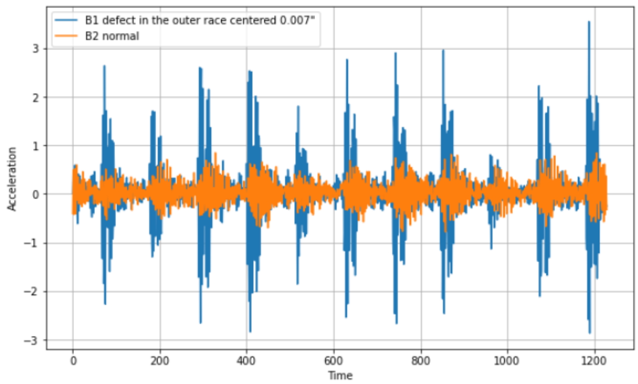

Fig. 1. Drive end bearing B1 with outer race centered defect, 0.007”, Fan end bearing B2 normal, at Load 0.

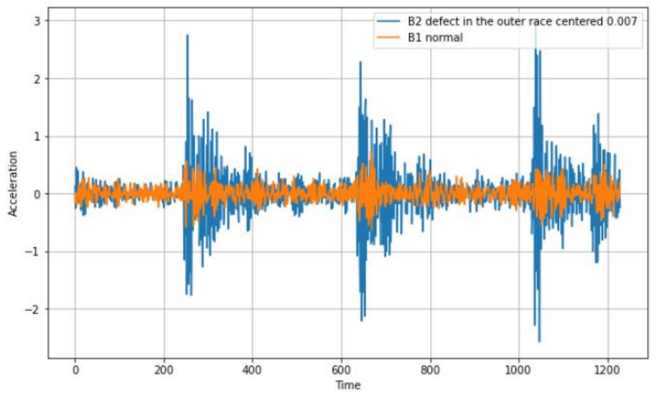

Fig. 2. Fan end bearing B2 with outer race centered defect, 0.007”,drive End bearing B1 normal, Load 0.

Vibrational signal has an amplitude of maximum 0.3 for the normal behavior in both B1 and B2 and increases in amplitude in B1 when the defect occurs in it, becoming greater than 2. At the same time, the vibration in B2 increases in amplitude until 0.5-0.8

One can be seen that the same type of defect at the same size of 0.007" in the outer race, center to the load zone, when it occurs in B2 has another signature and frequency than in B1. On the other hand, as the size of the defect increases in B1, at 0.021", the signature of the vibration under the same defect type is changing (Fig. 2).

The defect in the role at 0.007" size diameter was the most difficult to be learned by the models, maybe because the amplitude varies between the normal limits, while at 0.021" it reaches more than 1.

III. Defining, Training and Testing Models

For each load we tried to define and train several models. For some models, a change in structure, a larger number of layers, or a larger number of training epochs was required, when switching from Load 0 to Load 1, to obtain comparable results, but the best models worked the same for both cases.

The first two models that were tried for both load cases were those from [9], a CNN and a DNN model, but this time receiving a separate input type. Then another 4 models had been chosen and presented in the following. The metrics for evaluating all the models are categorical accuracy, loss and the score F1.

A. Model CNN – Convolutional Neural Network

The CNN network composed from two sequences of two convolutional 1D layers with 12 filters, and kernel size of 5, separated by a max-pooling layer and finalized with a global average pooling layer and a dense layer of 11 units for the output, received a bidimensional input this time. The activation function in the layers is the rectified linear unit (ReLU) and in the final layer it is the Softmax.

At Load 0, the model has been trained for 700 epochs, with a best learning rate for start of 2e-4, but at Load 1 the model needed 1000 epochs to get the plateau and accuracy to start saturating, and a best learning rate of 1e-4 was set.

The accuracy on the test dataset was 94,10% with a score F1 = 0.96 at Load 0, respectively 92,14% with a score F1 = 0.94 at Load 1.

One notice that defect in the roller was the least detected defect by the CNN model, al Load 1 only in percent of 57% (Recall = 0.57 for Label 5 - defect in the roller 0.007") and from total predicted Label 10:defect in the roller 0.021" – only 62% was true (Precision =0.62), then Label 4 (defect in the outer race opposite 0.007") was correct detected in percent of 75%, the rest are well classified and the general result could be considered very good.

Confusion matrix indicates the same, column 10, indicates the total number of samples classified as Label 10, it is the label more week detected by CNN, only 169 are corrected identified, 26 are actually Label 4, 73 are actually Label 5 and 5 samples are belonging to Label 9.

B. Model DNN – Deep Neural Network

The second model, DNN network, composed from 5 stacked layers in Load0 case, received a concatenate input like tensors B1+B2 of shape 200 (data points).

After only 500 epochs the training model obtained 100% categorical accuracy on the training dataset, 92% accuracy on validation dataset and 89.36% on test dataset at Load 0, keeping the same worst detection for Label 5 defect in the roller 0.007" (Recall = 0.48), followed by a poorer detection for Label 7 (defect in the outer race centered 0.021") with a Recall of 0.73, the rest of the labels being well detected (Recall > 0.84).

The same architecture at Load 1 did not give the same good results. Even increasing the number of layers and the number of units from 100 to 400 in two layers, the model did not improve too much, the categorical accuracy got saturated after 600 epochs becoming 100% on the training dataset and the result on the validation dataset was only 80,68%, while on the test dataset got 78,76%.

DNN detected worst on data at Load 1, the defect in the roller 0.007" Label 5 was detected only in percent of 26% (Recall 0.26), then the defect in the roller 0.021" Label 10 in percent of 36% and Label 9 - defect in the outer race opposite in proportion of 46%. At Load 0, excepting Label 5 (detected 48%), all other classes were well detected.

C. Model RNN – Recurrent Neural Network

The third model is RNN which is a neural network which uses recurrent layers. This sequentially processes sequence of inputs, sequences of quarts of rotations. We build an RNN that contains four recurrent layers and a final dense layer which will serve as the output for those 11 classes. The model will be fed with batches of sequences and it will output a batch of forecasts.

The full input shape when RNN is used is three-dimensional: the first dimension is the batch size (set in our study to 20), the second is the time steps or the number of the features (we have a window size of 100 points in time which are features, meaning a quart of rotation) and the third is the dimensionality of the inputs at each time step (in our case, dimensionality is 2, because we have a bidimensional tensor with data from B1 and B2)

At Load 0, the model was trained over 500 epochs after choosing a best learning rate for start of 4e-6, until the loss and the categorical accuracy got the plateau, the categorical accuracy achieved on the training set was 99.91% and on the validation dataset 93,96%.

Testing on the test dataset, the categorical accuracy got 90.82% still smaller than CNN which remains the best model until this phase. At Load 1, in the same configuration of the model, it needed 1000 epochs for training which last more than 4 hours until the saturation of the metrics. The values received for the categorical accuracy were 99,89% on the training dataset and 89,98% on the validation dataset. When tested on test dataset it was obtained less than at Load 0, only 89,12%

This model obtained the worst detection in Label 5 in the Load 1 case, the precision is almost 0.05, this meaning from the total predictions for Label 5 only 0,5% was true and from the confusion matrix it is seen that this percent represents exactly one sample that was correct identified for this class. The rest of the labels were almost entirely detected, this giving the score still higher to the model. Next, we will try to improve this model by adding some convolutions and see if they will help better in the learning process.

D. Model RNNCNN – Recurrent Neural Network with Convolutions

We have constructed an RNNCNN model by alternating two sequences of two recurrent layers followed by two convolutions 1D, the first two convolutions have a max-pooling layer of 3 (reducing three times the quantity of the parameters) and the next two convolutions are followed by a global average pooling layer, then the last layer of the model which is a Dense of 11 units for predicting the 11 classes.

We kept 12 filters with a kernel of 5 for each convolution and changed the number of memory-cells from 100 to 50, because 100 cells overfitted the model. The results obtained were remarkable.

After selecting the best start learning rate (ex. 1e-5 for Load 1and 7e-5 for Load 0), the model was trained over 1000 epochs in both load cases.

A total accuracy of 99.75% was obtained on training dataset and 98,40% on the validation dataset at Load 0, and a total accuracy of 100% on training dataset and 96,62% on the validation dataset at Load 1.

When evaluating on test dataset, a very well accuracy of 98,54% was achieved at Load 0, respectively 97,33% at Load 1, with this result surpassing all other tried models.

The recognition of the defect in the roller 0.007” Label 5 has been improved, getting a Recall of 87% at Load 1 and 99% at Load 0.

LSTM neural networks will be further tested to see if more than 97% total accuracy can be achieved. LSTM learns better long-temp temporal dependencies than RNN which have feedback loops in the recurrent layer to maintain the information in the cell memory over time. LSTM network is an RNN type that stores information in the memory cell for many, many timesteps using special units. The number of units is the size (length) of the internal state vector.

Each unit can be seen as a standard LSTM unit, having a cell and three gates, input gate, output gate and forget gate, which regulate the flow of information into and out of the cell, controlling when information enters the memory, when it’s output, and when it’s forgotten. In this way data from an earlier window can have a great impact on the overall projection, than RNNs.

A sequential model which is a linear stack of layers is used, two LSTM layers, one containing 20 units and another one with 10 units, followed by a Dense layer with 100 units and the output layer of 11 units. A greater number of units did not help the training, overfitted the model, even when tried to add a dropout layer after each LSTM layer to avoid overfitting. After choosing the best learning rate for start, 1e-4 for Load 1 datasets and 4e-5 for Load 0, model needed more than 1000 epochs to fit, and more than 4 hours to train and the accuracy obtained was 95,6% on the training dataset, 87,30% on the validation at Load 0, and only 82% on the training dataset and 71,69% on the validation dataset at Load 1. On evaluation, the total accuracy obtained on test dataset was 79% at Load 0 and 65,52% at Load 1.

The model did not detect at all the defect in the roller at 0.007” at every Load, but it seems once the defect becomes bigger it could be detected by all the models (Recall = 0.84 for Label 10 at Load 1 and 0.90 at Load 0, the percent at detection being very well at 0.021”). Also, defect detection in the outer race, centered and opposite to the load zone and inner race were poor at Load 1 (Label 4,6 and 7).

The next tests with LSTM will consist of adding convolutions to see if the learning process could be improved.

E. Model LSTMCNN – Long Short-Term Memory with Convolutions

The sixth’s model added convolutions to LSTM layers and alternated sequence of LSTM and 1D convolution layers followed by a global average pooling and a dense layer for the output.

1300 epochs were necessary to train the model until the accuracy and loss got the plateau and accuracy touched 95,23% on training dataset and 90,63% on validation dataset at Load 0, respectively 89,58% and 84,02% at Load 1 having a start learning rate of 5e-5. The convolutions increased significantly the score F1 of LSTM from 0.68 to 0.85 in Load 1 case.

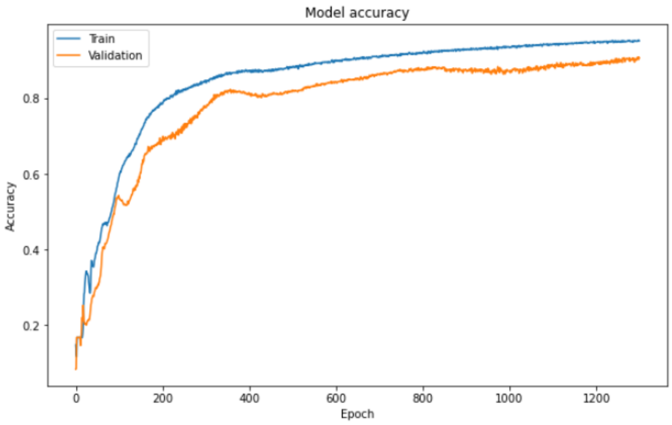

Fig. 3. Loss variation during 1300 epochs over training and validation dataset, load 0, LSTMCNN model.

The convolutions enhanced the detection in Labels 5,6 and 7 and, at evaluation on dataset the accuracy obtained was 87,35% at Load 0 and 84,18% at Load 1.

F. Models Summary Score

TABLE I: MODELS SUMMARY

Model	Total Accuracy on test dataset Load 0	F1 on test dataset Load 0	Total Accuracy on test dataset Load 1	F1 on test dataset Load 1
1. CNN	94%	0.96	92%	0.94
2. DNN	89%	0.93	79%	0.82
3. RNN	90%	0.94	89%	0.91
4. RNNCNN	98,50%	0.99	97,35%	0.98
5. LSTM	79%	0.85	66%	0.68
6. LSTMCNN	86,61%	0.91	82.29%	0.85

Table I presents a summary of the scores for each of the 6 models in the table. The best models are RNNCNN and CNN. A function in python is written (4) to do a weighted average elementwise between the models’ predictions for each class to see if the score could be improved. The function takes as argument an array containing the best models and the test dataset. For Load 0, the mediation model obtained the maximum accuracy of 97,94% and a score F1=0,987 on two models: CNN and RNNCNN, which nod exceeded RNNCNN, at Load 1 the mediation slightly enhanced the accuracy to 98,19% (Table II).

TABLE II: BEST MODELS SUMMARY

Best Model	Accuracy test dataset Load 0	F1 test dataset Load 0	Accuracy test dataset Load 1	F1 test dataset Load 1
RNNCNN	**98,50%**	0.990	97,35%	0.980

Average Model (model1, model4)	97,94%	0.987	**98,19%**	0.987

IV. Conclusion

We succeed to obtained models that detected very well 5 types of defects at two size diameters, having a labeled bidimensional dataset - a multivariate time series (B1, B2)- containing 11 Labels and defects only in B1, B2 being normal. Also, these models detected very well the normal behavior (B1 normal, B2 normal). Further tests were done on multivariate timeseries (B1, B2) with B1 normal and B2 containing defects, on the 6 models. The normal behavior in B1 was not recognized in this case, because of the defect in B2 and the vibration influence in B1. This means B2 (fan end bearing) has a different signature in vibration on diameters sizes 0.007" and 0.021", influences B1 normal and it is required that a separate model to be trained for defects only in B2 or another approach, to extend the labeling in the models proposed, with defects in B2. On the other hand, in the bearings there are many diameters' defects sizes that should be labeled, and a better approach would be to train models that are able to detect "defect intervals" or classes of defects. Many industrial partners maybe are not interested to know exactly the fault size but an interval of the defect size or at least one-two-three categories for each defect type: incipient phase, medium, advanced. It is interesting to see if neural network models could identify common features in such a categorization.

Conflict of Interest

The authors have no conflicts of interest to declare.

Author Contributions

The authors have equal contribution for this paper.

All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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Crina-Narcisa Deac (Georgescu) was born in Baia Mare in 1973. She is Ph.D student at University "Politehnica" of Bucharest, master's degree in Training Techniques in the Virtual Environment at University "Politehnica" of Bucharest 2016, matematician, University of North Baia Mare (1997). She is an entrepreneur working at Impro-Media SRL (https://impromedia.eu) as cofounder and CEO. She has published some articles and books in VR, AR, and predictive maintenance topics.

Gicu-Calin Deac was born in Baia Mare in 1970. He is a PhD student at University "Politehnica" of Bucharest, master's degree in Training Techniques in the Virtual Environment at University "Politehnica" of Bucharest 2016, dipl. Engineer, University of North Baia Mare (1995). He is an entrepreneur working at Impro-Media SRL (https://impromedia.eu) as cofounder and CTO. He has published some articles and books in VR, AR and IIoT topics.

Constantin Radu Parpala is a lecturer at University Politehnica of Bucharest, Faculty of Industrial Engineering and Robotics, with a PhD in industrial engineering. He has published over 40 papers in scientific journals and conference proceedings. He participated as a researcher in more than 10 research projects. His main fields of interest include but are not limited to: IoT, IIoT, manufactuing processes, design, FEM, industry 4.0, databases.

Cicerone Laurentiu Popa is an associate professor at University Politehnica of Bucharest, Faculty of Industrial Engineering and Robotics, with a PhD in industrial engineering. He has published over 50 papers in scientific journals and conference proceedings. He was project manager in the project *Selective waste collection integrated system for a smart city* – SMARTCOLLECT (2016-2018) and participated as a researcher in over 12 research projects. Research topics: industrial engineering, waste management, material flow management, smart cities, Industry 4.0.

Constantin Adrian Popescu is an lecturer at University Politehnica of Bucharest, Faculty of Industrial Engineering and Robotics, with a PhD in industrial engineering. He has published over 20 papers in scientific journals and conference proceedings and participated as a researcher in several research projects.

His research topics are industrial engineering, logistics, sensors, data acquisition, programmable logic controllers.