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Prediction of Compressed Air Demand Depending on the Type of Production with the Use of Neural Networks

Kamil Kasprzyk[1,2], Adam Gałuszka[1*]

[1] Department of Automatic Control and Robotics, Silesian University of Technology, Gliwice, Poland
[2] Marani Sp. z o.o., Zabrze, Poland
* Corresponding author's e-mail: adam.galuszka@polsl.pl

ABSTRACT

Compressed air systems are commonly used in industrial plants to produce the compressed air required for the facility's daily operations. Since air compressors consume more electricity than any other type of facility equipment, an optimization of the efficiency of compressed air system operation cycles is essential for energy savings. In this article the demand for compressed air in production plants with different operating characteristics is analyzed. It is checked how the neural network identified for a given plant would work in the case of another plant with a different needs while predicting compressed air demand, which is understood as a prediction of compressor on/offs. The simulation results based on real data indicate possible decisions that improve system efficiency. LSTM network seems to be well suited for identification achieving best results on dedicated object used for training. Cooperation of neural network updated in real time with supervisory controller may achieve little margain error and provide accuarte control system decision support.

Keywords: compressed air, neural networks, deep learning, demand prediction, optimization

INTRODUCTION

Compressed air systems are widely used in industrial plants to produce the compressed air necessary for the daily operation of the facility. Recent research has drawn attention to the importance of energy efficiency in industrial systems powered by compressed air. Much of the research focuses on identifying factors that affect efficiency, such as temperature, air humidity, pressure, as well as the wear rate of the compressor and system components. The introduction of new technologies and solutions, such as heat recovery systems, compressed air regeneration and control of the air compression process, can significantly improve the energy efficiency of installations. The studies also emphasize the role of plant maintenance and upkeep activities, such as regular cleaning and replacement of air filters and prevention of air leaks. The conclusion of this research is that measures must be taken to improve the energy efficiency of industrial compressed air facilities, which will help reduce costs and greenhouse gas emissions.

Since air compressors consume more electrical energy than any other type of facility equipment [1], an optimized and efficient compressed air system is essential to achieve energy savings. There are usually multiple approaches to improve the performance of a compressed air system. They are summarized in [2], they are as follows: minimize energy losses during distribution, reduce air losses in the system (such as air leaks and overpressure), optimize the air demand by minimizing the required optimal flow and pressure and choose the best energy-efficient compressor. For example in [3] a new approach is proposed for evaluation of the energy efficiency of compressed air systems based on a six-step local methodology for energy benchmarking. On the other hand [4] proposes a new simulation and optimization model to increase energy efficiency in the facility by determining the optimal location of the air compressor. In turn, in [5] the authors review various methods of energy consumption optimization, particularly noting system analysis and harmonization of production and consumption, loss minimization (leakage prevention strategy, leakage identification and quantification), filter pressure drop reduction opportunities, and a group of methods for optimizing pneumatic control optimization of pneumatic control: by-pass control, PWM control, and use of exhaust air. It should be noted here that according to [6], in addition to energy savings, increasing the energy efficiency of compressed air systems can bring other significant benefits to the company. Energy-saving measures mean a high level of their monitoring and proper maintenance. This leads to fewer production equipment failures, avoidance of wasted raw materials or other inputs, a longer life cycle for pneumatic equipment, and greater reliability of the entire system. Reducing energy consumption will also result in fewer emissions of hazardous substances and pollutants, reducing the impact on the environment. Often these benefits are more valuable than the energy savings.

CONTRIBUTION

In this work we focus on one of the stages of developing an intelligent master control of compressors, from different manufacturers, operating in different industrial plants in different configurations with different characteristics of air demand. We assume that the developed algorithm for predicting the moments of activation of compressors will be able to learn the characteristics of operation of a given plant, which will allow to minimize the activation of compressors, the tangible benefit of which will be significant savings in electricity as well as in material consumption, while ensuring a constant pressure that allows the customer to work. The problems of high current energy prices and increasingly difficult availability of consumables cause a strong demand for the introduction of intelligent control systems based on more advanced solutions than the algorithms found in compressed air stations. What would be required now would be a control system that takes into account what has happened in the past and what we can expect in similar conditions. The algorithm will have to work with already existing control system solutions enabling integration in the Industry 4.0 concept.

The article presents results of deep learning and machine learning methods enabling prediction of the demand for compressed air depending on the type of production, using real time data acquisitioned at company Marani sp. z o.o. and Matlab Deep Learning Toolbox. The idea of applying neural network techniques to prediction of air demand is not new in the literature, e.g. in the [7, 8] authors are predicting air demands understood as a prediction of an amount of air. In this work the compressed air demand is understood as a prediction of compressor on/offs.

CLASSIFICATION OF MEASUREMENT DATA

Data for the study was collected in the same time intervals from 3 production plants carrying out 3 types of activity with different working characteristics within 48 hours from the start of the production in a given week. The samples were collected at equal intervals of 20 seconds. Plants will be marked as:

- A – a plant with 11 screw compressors with a total capacity of about 2.6 MW,
- B – a plant with 7 screw compressors with a total capacity of 1.8 MW,
- C – a plant with 3 screw compressors with a total capacity of 0.23 MW.

Each plant is equipped with a supervisory master controller which carries out cascade control. The task of each controller is to select the right number of machines depending on exceeding of the lower or upper limit of the working pressure so that the pressure is maintained within the required range. There is no feedback on the number of pneumatic devices concurrently operating within the air network therefore the controllers make their decisions based on the pressure measurement in the installation at a point that reflects the actual demand. Decision limits of the working pressure of supervisory controllers are presented in Table 1.

Each plant has also a different demand for compressed air. The Figure 1 shows the pressure course in the period under study of which 90% will be the basis for neural networks training.

Table 1. Decision limits of the working pressure of supervisory controllers

No.	Plant	Lower working pressure limit [bar]	Upper working pressure limit [bar]	Range [bar]
1	A	6.35	6.75	0.40
2	B	5.05	5.35	0.30
3	C	6.40	6.80	0.40

Production plants work specifics

Production plants A and C are characterized by high variability due to frequent exceeding of the lower and upper operating pressure limits when the supervisory controllers have to decide whether to start or stop supplying compressed air. Analyzed plants have at least one machine with a frequency converter whose task is to reduce pressure fluctuations and minimize the number of compressors in operation. The Figure 2 shows one hour of operation for plant B. Green color indicates that the machine was running in loaded state providing compressed air. Yellow color indicates idle run (unloaded) during which the machine was ready for compression.

Neural network selection

Observing the course of the pressure we can notice that the value of pressure at a given moment of time will be influenced by the previous sample as well as the course of the current characteristic up to the sample point. It was decided to use a network based on LSTM long-term memory cells [9, 10]. The optimization problem is formulated as a minimization of the objective function [11] that corresponds to error of pressure prediction. These networks are successfully used in many areas of deep learning including image identification and speech recognition. For the

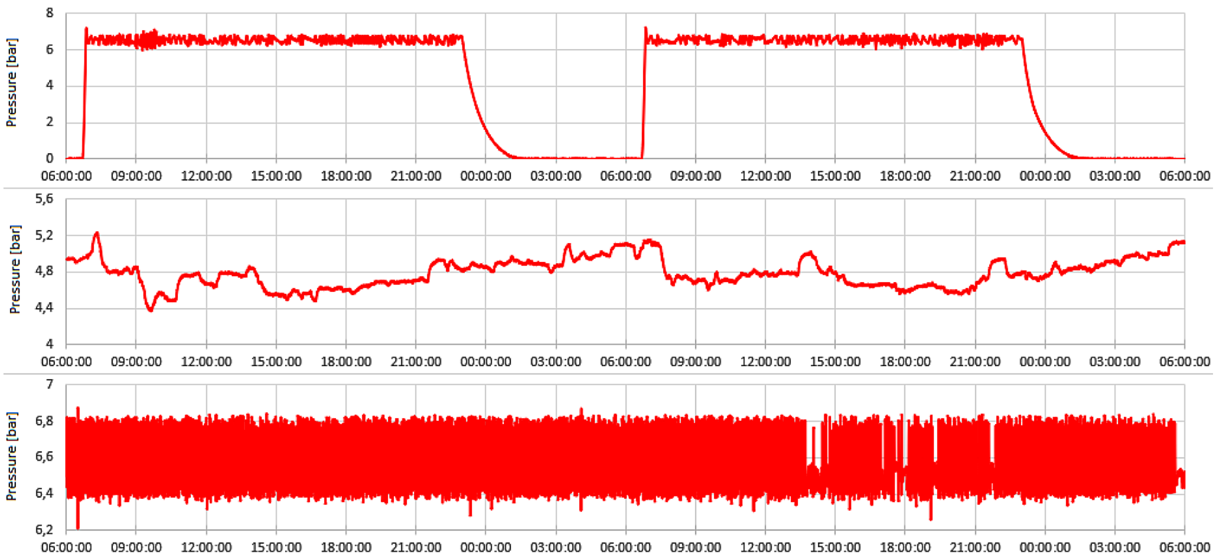

Figure 1. Pressure characteristics of the of production plants, successively from the top marked as A, B, C

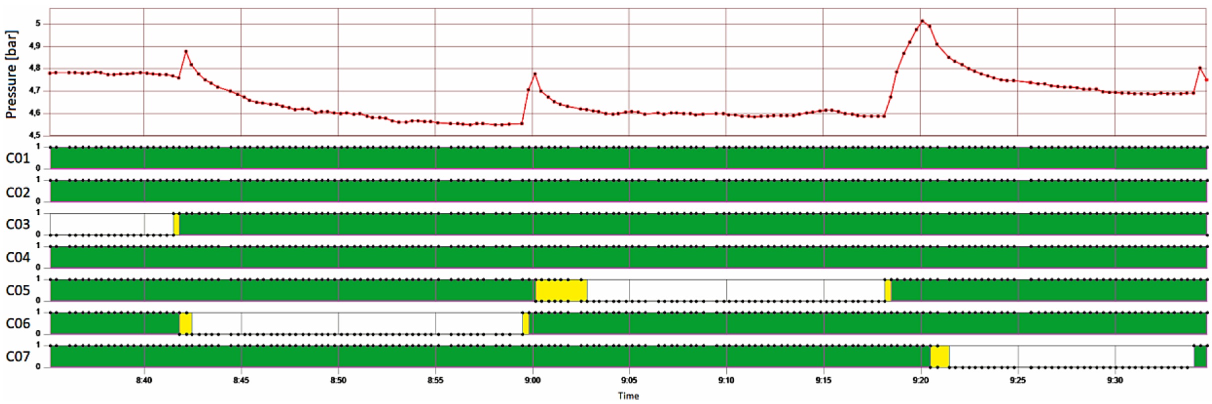

Figure 2. Example of hourly run for plant B with compressor states

analysis training was done on a set of 90% of the gathered samples for a given plant and prediction was done on the last 10% which corresponds to the time horizon of approx. 5 hours. The ADAM stochastic optimization algorithm was used to train the network and the learning was performed over a period of 250 epochs.

We will evaluate the results in two cases:

- I – when as the input data for the recursive neural network we will use following samples from prediction and use them to predict the future in the time horizon of the test set,
- II – when as the input data for the recursive neural network we will use real time samples, this situation would correspond to the actual use of the neural network in industry when new data would arrive and would be used for prediction.

Evaluation reference point for all studies will be the element of the root mean square error which was calculated for the neural network for a given case. We will also pay attention to other features in the database of collected samples that may have influenced the result and present more interesting cases from the considered ones.

DEMAND PREDICTION

Plant A

Plant A is the only plant that was stopped twice in the test data set which should affect the neural network response. The test data set for which the prediction was made was stopped at the time of the study.

In Figure 3 it is observed that the neural network predicts the occurrence of underpressure in the system but we could consider this as a situation in which machines would most certainly not work. Neural networks trained on a working system have an understandable difficulty in predicting a stop which in their cases does not occur.

In Table 2 it is noticed that best result was achieved for dedicated neural network used for training however RMSE for Type I is still high (result of 1.4 is not sutiable for production prediction). In case of Type II using real time data provided higher accuracy with low RMSE which is promising in case of decision support.

Table 2. RMSE for neural networks of different types for plant A

No.	Neural network	RMSE Type I Prediction	RMSE Type II Prediction
1	A	1.4081	0.071762
2	B	7.5381	0.10211
3	C	4.6636	4.7826

Plant B

The figure 4 shows the predicted characteristics for plant B where we have the case in which the pressure most of the time remains below the lower setpoint limit of the pressure and its changes are caused by minor changes in compressed air demand. Unlike other cases the upper pressure limit border is not exceeded and therefore there is no typical "saw" like trend of the pressure supply.

In case of Figure 4 neural network was not able to provide accurate prediction of observed pressure however in case of Figure 5 different

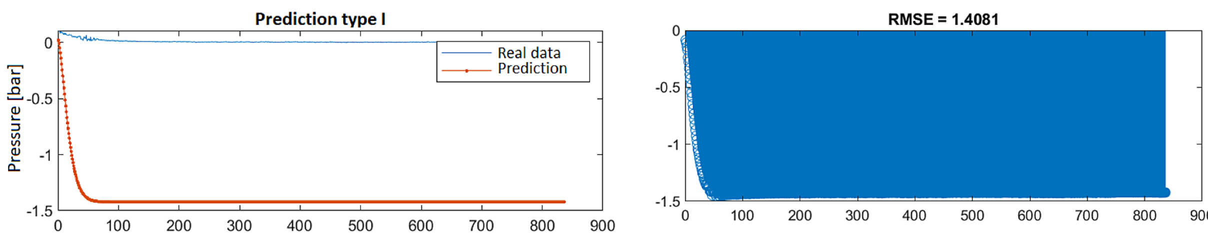

Figure 3. Type I prediction for plant A

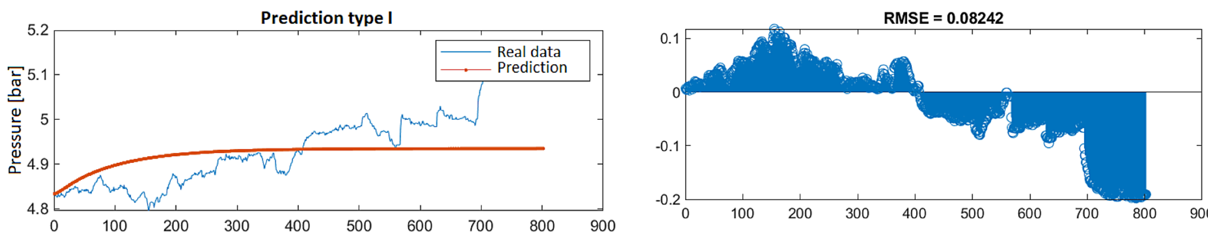

Figure 4. Type I prediction for plant B

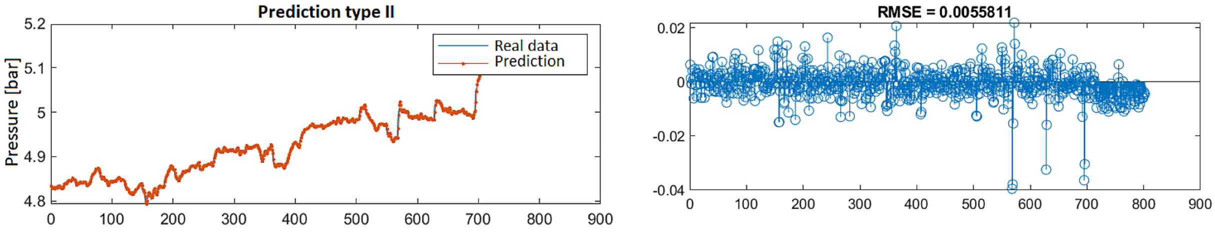

Figure 5. Type II prediction for plant B

methodology resulted with amlost perfect fit for the task.

What could be expected is confirmed in Table 3 and lowest RMSE was achieved for dedicated network however other competitors are not far behind. Neural network A was second best but RMSE for Type II could provide accurate prediction and step into the future which may be useful for production needs. Type I prediction in all cases was much less accurate and dedicated neural network seems to be the best solution.

Table 3. RMSE for neural networks of different types for plant B

No.	Neural network	RMSE Type I Prediction	RMSE Type II Prediction
1	A	0.12919	0.066176
2	B	0.08242	0.005581
3	C	0.27448	0.175130

Plant C

The plant is characterized by very high pressure variability. In this case there are quite large deviations while e.g. in the case of prediction type I we can assume that the predicted pressure will remain within the set borders while burdened with a fairly large error. In the case of type II we will get a significant improvement, but high volatility will still cause some unpredictability of the trend.

Figure above demonstrates that neural network learned pressure sequence characteristics however being more careful on top and bottom pressure borders which resulted with conclusion that pressure should be somewhere between 6.40 bar and 6.70 bar which is not far from supervisory controller setup. Since a lot of peak points where missed RMSE varies a lot and is quite high yet still accomplishing not bad average.

Figure 7 shows results with very accurate pressure characteristics. Maximum and minimum points of real time data seem to be followed by predticiton trend. If we assume that pressure may be unpredictible this date may oppose this thesis however still there is some shifting in data which results with lower then Figure 6 RMSE and three times lower average RMSE.

Table 4 also confirms that best results where achieved for neural network dedicated however other results are not much off the grid. In case of Type II results where almost three times worse, in case of type I deviation was much lower. Type I in

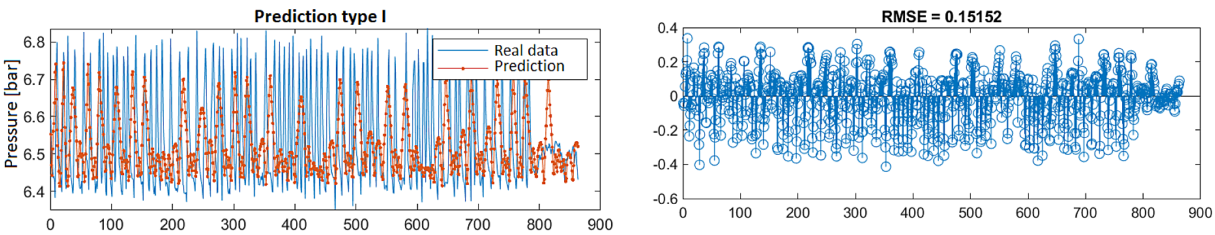

Figure 6. Type I prediction for plant C

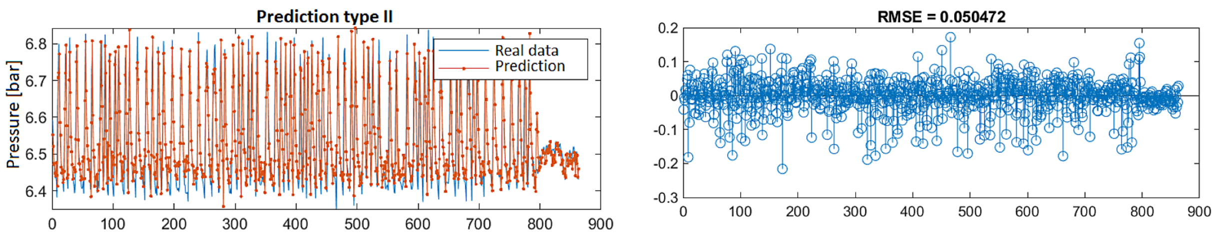

Figure 7. Type II prediction for plant C

Table 4. RMSE for neural networks of different types for plant C

No.	Neural network	RMSE Type I Prediction	RMSE Type II Prediction
1	A	0.17323	0.167870
2	B	0.23768	0.144180
3	C	0.15152	0.050472

case of Plant A may be a good option. Maybe it is possible to provide some trained network which could provide not the best results but still usable.

CONCLUSIONS

The LSTM network is well suited for the identification of considered pressure characteristics providing long-term modelling while offering a relatively small error. If the deviation of the expected pressure would not exceed 0.15 bar the decision made would have a positive impact on the energy efficiency of the system allowing to limit the number of machines in operation. It would be enough to consider prediction in the range in example of 10 minutes by updating samples of input data.

In the case of type I long-term prediction it turns out that we can get acceptable results with small deviations for each of the learned neural networks except the case of stopped system. For type II predictions when we were constantly updating input data with the measurement data the networks defined for a given plant type worked best.

In the examples considered a dedicated network always offered the best results. The use of the recursive LSTM network together with the network update based on real time measurement data would give a sufficient margin of error to support the supervisory controllers in making decisions regarding the control of air compressors between the working pressure limits. The next step in the analysis would be to check the operation of the neural network in real time.

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