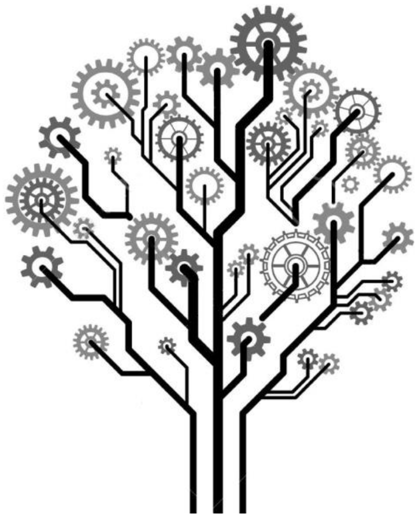

Machinery failure assessment through pattern recognition of energy consumption

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Thesis to obtain the Master of Science Degree in

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ABSTRACT

The purpose of the thesis was to develop a fault detection system of a fan based on pattern recognition in energy consumption. The aim of the system is to detect abnormal conditions in ventilation systems in buildings, which result in the increase of the energy costs and the decrease of indoor air quality.

The first step of the process involved building the laboratory stand required for the data acquisition. Recorded data included energy consumption of the fan and ambient air temperature. The analysis of the energy consumption curves indicated that power requirements change within the daily cycle. The changes in temperature, which affect the air density, were the main factor causing the daily load fluctuation.

Secondly, measurements were performed during normal and faulty operating conditions. The examined states include clogged air intake area and fault causing additional friction between a shaft and housing. The analysis of results indicated that energy consumption varies depending on working conditions.

The failure assessment was based on damage sensitive features extracted from the dataset and the set of selected features include average load, time of record and standard deviation. The failure assessment was performed with two methods: decision trees and neural networks. Both algorithms were suitable for the given problem and had similar overall classification accuracy. Algorithms were highly efficient in predicting clogged air intake area (more than 80%), but the fault causing extra friction was rarely detected - the malfunction was correctly classified only in 16% of cases. The main advantage of using the decision trees its clear structure which is easy to understand, while the neural network is highly efficient due to the utilisation of nonlinear function and its flexibility in the learning process.

RESUMO

Esta tese apresenta o desenvolvimento de um sistema de detecção de falhas baseado no reconhecimento de padrões de consumo energético para o caso de estudo de um ventilador. O objetivo do sistema é permitir a deteção de falhas nos sistemas de ventilação de edifícios, conhecendo apenas o seu consumo energético. Estas falhas conduzem a um aumento dos custos energéticos e à diminuição da qualidade do ar interior.

A primeira etapa do processo envolveu a construção de uma instalação experimental, necessária para a aquisição de dados e indução de falhas. Os dados adquiridos incluíam o consumo energético do ventilador e a temperatura ambiente. A análise das curvas de potência mostra que consumo de energia varia ao longo do dia fundamentalmente devido às flutuações na temperatura ambiente, que afetam a densidade do ar e a respectiva carga na ventoinha.

Posteriormente, foram realizadas medições em condições de funcionamento nominais e defeituosas (com falhas). Os estados defeituosos examinados incluem: entradas de ar obstruídas e falhas causadas por excesso de atrito entre o eixo e a armadura. A análise dos resultados mostra que o consumo de energia varia consoante as condições de trabalho.

A avaliação de falhas baseou-se na análise de características extraídas do conjunto de dados adquiridos durante os ensaios, tais como: a carga média, o desvio padrão e hora de aquisição. A avaliação de falhas foi realizada utilizando dois métodos: árvores de decisão e redes neuronais. Ambos os algoritmos são considerados adequados para o problema em estudo e apresentam desempenhos semelhantes na classificação de padrões. Os algoritmos foram altamente precisos na deteção da falha "entrada de ar obstruída", no entanto a falha causada por fricção adicional no eixo raramente foi detetada. A principal vantagem do uso das árvores de decisão é a sua estrutura clara e de fácil compreensão, por outro lado as redes neuronais são altamente eficientes devido à utilização de funções não-lineares e à flexibilidade no processo de aprendizagem.

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Chapter 1

Introduction

The ventilation and air-conditioning systems are widely used in buildings located in developed countries and it is predicted that these systems continue to grow rapidly in developing countries. However, the installations are often designed and/or commissioned incorrectly. This situation leads to abrupt or gradual system degradation resulting in excessive energy consumption and high maintenance cost.

One way to detect operation problems in the ventilation and air-conditioning installations is to apply fault detection and diagnosis methodologies. These systems are utilised to detect any abnormal conditions and then diagnoses and determine the causes. Automated fault detection and diagnosis has been intensively developed as embedded intelligence for two main reasons: improve safety and decrease operational cost.

In ventilation and air-conditioning applications fault detection and diagnosis is mainly used to improve equipment efficiency, thermal comfort, indoor air quality and proper maintenance scheduling. Fault detection is performed with the use of sensors monitoring the equipment operation and a system which diagnoses problems and recommends actions.

1.1 Background

The increase in the world electricity consumption has been observed during the last decades and the demand is predicted to grow continuously over the next years. In the OECD countries, electricity consumption almost tripled over the last 40 years, for an average annual growth rate of 2.5% [1]. Part of the increase is attributable to rising GDP per capita as well as the development of the commercial and public services sectors and the multiplication of small appliances in offices and homes. One of the main drivers of energy consumption increase is the high demand of heating, ventilating and air conditioning (HVAC) systems. The impact of HVAC technology on peak demand is even of greater consequence. In result, in the well-developed countries, the peak consumption is observed not only during the winter time but also in the summer due to widely used air conditioning installations. The air conditioning and ventilating technology will be the main interest area of this work.

In the context of growing electricity demand, the global energy market faces the challenge of developing technologies that will increase energy savings in appliances usage. In the terms of HVAC systems, energy savings will be obtained mainly through optimal control and early fault detection. The decrease in energy consumption and operation cost with proper comfort level can be reached together with well-organized maintenance, fast detection of faults and best use of equipment's performances. As a result, not only energy and comfort are aspects taken into consideration, but also performance and reliability of ventilating and air-conditioning devices. Suitable control of working parameters in the HVAC systems is necessary to achieve this goal.

1.2 Introduction to fault diagnosis

A failure is typically an event that is characterised by the temporary or permanent termination of the ability of a machine to perform a required function. The machine failure is usually characterised by an abnormal condition or by a fault pattern. Malfunctions in ventilating and air conditioning systems may occur in many components [2]. The typical faults include wear of fan bearings, clogged filters, or malfunction in temperature, pressure, and humidity controllers [3]. Faults result in inefficient usage of energy, cause loss of quality in the device service and shorten the remaining useful life of machine components. If the loss of quality is within an acceptable range of tolerance, the device needs to be repaired, but when it is out of range, the fault may result in the breakdown of the whole installation. Therefore, the early fault detection in machinery is important for the system security and presents an advantageous economic reason. The fault diagnosis system will support better prioritisation of the maintenance schedule and will allow localisation of quality losses [2].

Various methods can be used to identify a process fault. The development of computational intelligence and sensor technology enables the usage of a real-time fault diagnosis system monitoring the operation of components. Such system allows to detect, locate and predict the presence of the defects and it can be achieved through online analysis of the electrical energy intake of machine tools. As defects develop, the machine abnormal behaviours are automatically monitored, logged and analysed to identify the need for the maintenance.

1.3 Motivation

The benefits from the application of early fault detection systems in the air conditioning and ventilation installations will be the following:

- energy savings through early detection of inefficiently operating processes and faster location of faults;
- increased quality of living, e.g. faults can be detected before they affect the indoor air quality,
- reduction of cost and inconvenience of users as a result of scheduled and planned beforehand maintenance [5],
- increase in safety, as detecting the faults early decreases the risk of personal injuries, as improperly operating processes may cause a health risk,
- optimisation of the supply chain – the early fault detection allows to properly plan replacement and purchase of the equipment, which operates with a fault [3].

In this work, the measurement of energy consumption is proposed as the base parameter for the faults detection. As a result, the energy audit can be also used as a source of valuable information. Analysis of device energy consumption helps to identify energy wastages, indicate necessity of energy savings or estimate the financial impact of the energy conservation projects.

1.4 Market size

Three-quarters of American households use air conditioning systems and it accounts for 16% of all household electricity demand. This number results in total energy consumption of household air conditioners equal to 183 TWh per year. The electricity usage is significantly higher when demand of all devices used in public and industrial sector is also taken into account. In the OECD countries residential air conditioning is estimated to account just for 6.4% of electricity usage and in European countries, as the percentage of households with air-conditioning systems is lower than 2% [4]. However, the service sector in 2012 in Europe consumed 209 TWh of energy for cooling [6]. The amount of energy used for cooling and ventilation in both (residential and service) sectors will significantly increase in Europe and other regions (Asia, Latin America or even Africa) if there is an uptake of American usage patterns. Added to this, the demand for air-conditioning systems is predicted to increase due to progressing climate change.

According to the data published within the project Energy Efficiency of Room Air Conditioners supported by the European Commission, it is predicted that by the year 2020 up to 70% of households in Lisbon will use air conditioning systems [4]. Together with the service and industrial sector, the number of air conditioning devices installed is already vast but it is going to increase, which implies a big market potential in the sector of HVAC systems.

1.5 Thesis structure

The thesis is organised into following six chapters:

- *Chapter 2* briefly describes the history of development of model-based and process history based methods of the fault detection. It focuses then on the description of processes, which are necessary for the proper development of failure diagnosis systems. The chapter is terminated with two examples of real-world application of the fault detection algorithms,
- The methodology of the fault detection system, which is a subject of the thesis, is presented in *Chapter 3*,
- *Chapter 4* provides the description of the laboratory stand designed for the fan fault diagnosis together with the analysis of power consumption during the various operating conditions. The chapter discusses also the effect of the most common malfunction on the fan energy requirements,
- The different models are examined in *Chapter 5* in order to find the most efficient algorithm for the fault detection problem of the case study. The final part of the chapter compares the two techniques that were applied: decision tree and neural network,
- Conclusions of the investigations are drawn in *Chapter 6*, which summarises the main findings and proposes work that could be done in the future.

Chapter 2

Literature review

The chapter provides a brief description of the history and the evolution of fault detection systems in industrial processes over the last three decades. The progress enabled advent of automation and development of computational intelligence. Due to the broad scope of the processes using fault diagnosis, various computer-aided approaches have been developed over the years.

The description of the possible choice of methods is provided with the distinction between the methods that require accurate process models and the methods based on the process history. The crucial problem of the model-based approaches is the generation of an accurate analytical model, which in industrial applications is often unrealistic due to the processes complexity. Therefore, the alternative are the methods which do not assume any form of analytical model and rely only on the process history information. They cover a wide variety of techniques such as the early attempts using fault trees and digraphs, knowledge-based systems and neural networks in more recent studies. The models based on the historical records are often applied in the fault detection systems.

The chapter discusses also the steps which are necessary to undertake in order to develop a complete fault detection algorithm and is finishes with a description of two case studies. Examples of real world applications include the study of a drill wear estimation and the fan fault detection system based on the vibration analysis.

2.1 Model – based method

The development of model - based fault detection systems began at various places in the early 1970s. Beard and Jones reported, for example, the “failure detection filter" approach for linear systems [7]. The developed procedures were also applied to fault identification in the jet engines and to leak detections. The summary of the early attempts is given by Willsky in 1976 and the first book on model – based methods for fault detection with specific application to chemical processes was published by in 1978 [8]. Nowadays, the interest in theory and applications of model – based fault detection methods continues to grow, because of economical and safety related matters. In particular, well-established theoretical developments can be seen in many contributions published in the International Federation of Automatic Control Congresses and in the research of Isermann and Simani [9]. These methods require an analytical model of the process, usually involving time-dependent differential equations. As a result, faults are an intrinsic part of the model and deviations from the expected values are recorded in a residual vector which represents the health state of the structure. An important drawback of model-based approaches is the necessity to establish an analytical model of the process which is a nontrivial problem. In real-world applications, the availability of an analytical model is often unrealistic or the derived models are inaccurate due to the complexity of the process, so the false diagnosis can implemented by inappropriately designed models [10].

2.2 Process history based method

The recent development of the computational intelligence enables the application of the alternative, model - free methods in cases where an analytical model is not available. In industrial processes, model – free fault detection is possible with the use of pattern recognition techniques based on the process history data. Pattern recognition algorithm assign a class label to a sample of measured data, usually from a finite set. In the case of damage identification, the measured data or the derived features could be vibration mode shapes, full-field thermoelastic data, scattered wave profiles, energy consumption, etc. The appropriate class labels would encode damage information (e.g. type and location). Each possible fault class should usually have a training set of measurement vectors or features that are associated uniquely with it. In order to carry out the pattern recognition, it is required to build a statistical model of the data, for example, to characterise their probability density function. This approach depends on the use of machine learning algorithms [11].

Many pattern recognition algorithms work by training a model while knowing beforehand the true label for each data set. Such a type of learning algorithm is called supervised learning and it is applied for example in the neural networks. The network performs the learning process – the measurement data is introduced in the algorithm and asked to produce the correct class label; if the result differs from the desired label, the network is corrected. In order to build a complete fault detection algorithm, it is necessary to provide a significant number of labelled examples data for each of the considered process classes, which is a fundamental drawback of the model-free approach. If only a small number of patterns are available in the training phase, the statistical classifiers might be misled and very sensitive to noise or classify data in the wrong manner [11].

Ideally, the complete fault detection algorithm provides information over five different levels:

1. Detection: qualitative indication that damage might be present in the structure,
2. Localisation: information about the probable position of the damage,
3. Classification: information about the type of damage,
4. Assessment: estimation of the damage extent,
5. Prediction: information about the safety of the structure, for example, estimates a residual lifetime.

The development of a complete fault detection systems requires several steps. A general pattern recognition paradigm for fault detection can be defined through the integration of the following procedures: operational evaluation, acquisition, normalisation, cleaning, compression and fusion of data, feature selection and statistical modelling for the feature discrimination. The procedures are necessary for a proper fault diagnosis and will be shortly described. *Figure 1* presents a schematic overview of the design process, highlighting the most important steps.

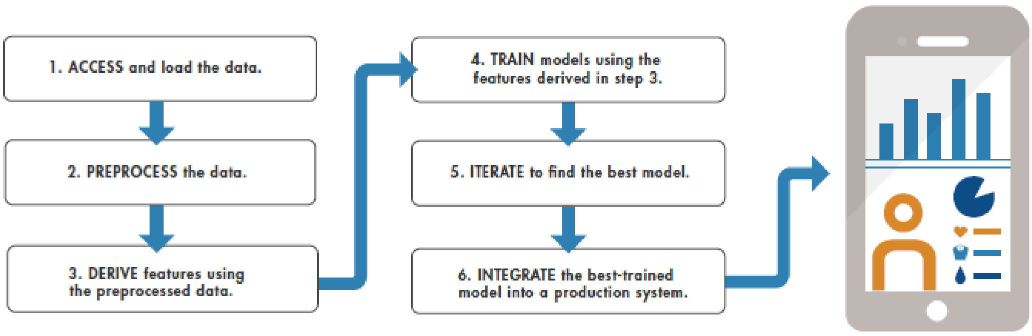


Figure 1 Design process of fault detection algorithm with the use of machine learning techniques [13]

2.2.1 Operational evaluation

The operational evaluation procedure provides information on the implementation of a damage identification process. Firstly, the economic and life-safety benefits are evaluated, in the next step damage possibilities of the system are identified. During the evaluation process, operational and environmental conditions of the system are defined, as well as the limitation of data acquisition should be investigated. It is recommended to set the limitations on what will be monitored and how the monitoring will be accomplished. The operational evaluation process tries to tailor the damage identification to features that are unique to the system and attempts to exploit unique features of the damage that are to be detected.

2.2.2 Acquisition, normalisation and cleaning of data

The data acquisition process involves selecting the excitation methods, the sensor types, their number and locations, and the data acquisition, storage, and communications hardware. This part of the process is application-specific. Economic considerations play a major role in making decisions regarding the data acquisition hardware to be used for the fault identification. The interval at which data should be collected is another consideration that must be addressed. For many industrial processes, it may be necessary to collect data continuously at relatively short time intervals.

In real-world processes, parameters are often measured under varying operational and environmental conditions, therefore ability to normalise the data becomes very important for the damage detection. Without this, changes in the measured response caused by different conditions may be mistaken as a faulty process. Thus, it might be necessary to perform additional measurements to provide information on data normalisation and the need for this should be considered in the operational evaluation stage [11].

Data cleaning is the process of detecting, correcting or removing inaccurate records from a record set. It refers to identifying incorrect or irrelevant parts of the data and then replacing, modifying, or deleting the dirty or coarse data. After cleaning, a data set should be consistent with other similar data sets in the system. The actual process of data cleaning may involve removing typographical errors or validating and correcting values against a known list of entities. Some solutions clean data by cross-checking with a validated data set [14] or the process is based on knowledge gained by the individuals involved with the data acquisition - for example, an inspection of the test setup may reveal that a sensor was loosely mounted and it is recommended to delete a certain set of data from the feature selection process. Signal processing techniques such as filtering and resampling can also be thought of as data cleaning procedures.

An important part of data cleaning procedure is to detect outliers. Outliers are the values in data set that deviate significantly from the majority of observations. They may be generated by a different mechanism corresponding to normal data, for example, due to sensor noise, process disturbances, instrument degradation or human-related errors. Dataset contaminated with outliers can lead to model misspecification, biased parameter estimation, and incorrect analysis results, therefore it is important to indicate them during the data processing. Most of outlier detection methods are based on an underlying assumption of identically and independently distributed values, where the location and the scatter are the two most important statistics for data analysis in the presence of outliers. The sample mean and standard deviation give a good estimation of data location and scatter. However, for a small data set or for the data set containing outliers of extreme values, the sample mean and standard deviation may deviate significantly. It can lead to masking problems – the less extreme outliers will not be detected because of the high value of standard deviation. Thus, to robustly estimate the location and the scatter, often other methods are introduced, like median and the median absolute deviation [15].

2.2.3 Compression and fusion of data

The measurement technologies required to perform fault detection inevitably produce large amounts of data. Therefore, the aim of the compression process is to reduce the dimension of the processed data. A condensation is advantageous and necessary when comparisons of many feature sets are obtained over the lifetime of the system. It is also recommended to develop robust data reduction techniques, which will be sensitive to features of the most significance. Data fusion is the process of combining information from multiple sources to enhance the credibility of the damage detection process. The fusion process may combine data from spatially distributed sensors and data of heterogeneous type. Data fusion is closely related to the previous processes of data processing: normalisation, cleaning and compression [11].

2.2.4 Feature extraction

The part of the fault detection process that receives most of the attention in the technical literature is the identification of data features. The advancement of signal processing technology and a better understanding of the dynamics of a physical process contributes to obtain features that are more effective, accurate, and reliable for the diagnosis that allows to distinguish between undamaged and damaged states of the investigated structure.

A damage sensitive feature is some quantity extracted from the measured system that indicates the presence of a fault in a structure. In some cases, raw data measurements or only the calculation of simple key features is sufficient to obtain accurate diagnostic conclusions. However, in many situations, sensitive features are not easily extracted and further processing of features is necessary. This is especially true when features related to machinery faults are dynamic and of large amount, with some being redundant but not easily discriminated from each other. [12]

Features vary considerably in their complexity, from the simple standard deviation of a data set or a maximum peak to peak value, to the more complex statistical tools like principal component analysis. Ideally, the feature set is low-dimensional and highly sensitive to the condition of the structure and those should be the main criteria during the feature selection process. Usually, a degree of signal processing is also required to extract effective features. Inherent to this process are the mathematical operations, a fusion of data from multiple sensors and the use of a priori engineering judgement [10][11].

2.2.5 Statistical modelling using machine learning techniques

The development of statistical models for fault detection is concerned with the implementation of algorithms that operate over the extracted features to quantify the damage state of the structure. As it was mentioned in *Chapter 2.1*, the functional relationship between the selected features and the state of the structure is often difficult to define based on model-based engineering analysis procedures. Therefore, in process history based methods, machine learning techniques are used to derive statistical models. The machine learning algorithms used in model development usually fall into two categories. When the training data is available from both the undamaged and damaged structure, supervised learning algorithms are applied - group classification and regression analysis are primary examples of such algorithms. Unsupervised learning problems arise when only data from the undamaged structure is available for training. Outlier or novelty detection methods are the primary class of algorithms used in this situation. All these algorithms use statistical distributions of the measured or derived features to enhance the damage detection process.

When an unsupervised learning is applied, statistical models can typically be used to detect the existence and sometimes the location of the fault. With the application of supervised learning mode, it can be possible to determine the type, extent of damage and the remaining useful life of the structure [11].

2.2.6 Selecting the threshold value

The statistical modelling process allows to select the threshold value for alarms and warnings. If the thresholds are too tight, then several false alarms are issued, but if the thresholds are too low, then equipment or system failures can go undetected. Therefore, the model should be developed in the way that minimises false diagnoses. In the fault detection process, incorrect diagnoses fall into two categories:

- false-positive damage indication (an indication of damage when none is present),
- false-negative damage indication (no indication of damage when damage is present).

The diagnostic systems can weigh the costs of each type of error differently. Protective monitoring refers to the case when damage-sensitive features are used to identify impending failure and shut the system down or alter its use before catastrophic failure results. In this case, the statistical models are used to establish absolute values or thresholds on acceptable levels of feature change. Predictive monitoring refers to the case where one identifies trends in data features that are then used to predict when the damage will reach a critical level. This type of monitoring is necessary to develop cost-effective maintenance planning. In this case, statistical modelling is used to quantify uncertainty in estimates of the feature's time rate of change [11].

2.3 Case studies

Early detection and diagnosis of process faults during systems operation helps to avoid abnormal event progression and reduces productivity losses. Since the increase in process reliability and economical gains are significant, there is a considerable interest in the field of fault detection from industrial practitioners as well as academic researchers. Therefore, the description of numerous case studies of fault detection systems can be found in the literature, but only few of them describes the problem of fault detection in ventilating systems. The next chapters provide descriptions of two examples of studies performed on the identification and fault diagnosis that are relevant for this thesis: the first case, where energy consumption is used to detect failures in a certain system, which is relevant from the methodology perspective; and a second case, where the faults of a ventilation system are detected using acoustic sensors, which is relevant from the application perspective.

2.3.1 Drill wear estimation based on the spindle motor consumption

The drilling operation is a fundamental machining process and it is widely used in the automobile, aircraft, and other industries. Drill wear has a bad effect on the surface finish and the dimensional accuracy of the workpiece, and leads to drill failure and workpiece damage. Therefore, there is a need for a reliable real-time measurement of drill wear to control the quality of automatic drilling operations. The research on this topic was performed in the Mechanical Department of Pusan National University. A common method for measuring drill wear in the real time is to detect it indirectly from physical changes caused by drilling, such as cutting force, motor current, sound and vibration. Of these signals, cutting force, measured using a tool dynamometer, is the most accurate, but this method is more suitable for the laboratory than to real production. In the study, motor current was chosen as a base parameter, due to its characteristics. Measurements of motor current are less expensive, more durable and more flexible [16].

In the study, the drill wear is estimated based on the value of torque. To perform the estimation, several parameters need to be given: drill geometry, cutting conditions, and material hardness. Additionally, a motor power-torque model needs to be established to describe a relation between torque, friction and power consumption. The model allows to calculate the drilling power consumed by the drilling torque, by subtraction the tare power component from the total motor power detected. The tare component is responsible for overcoming the viscous and coulomb frictions to maintain the desired spindle speed. The total motor current measurement was performed through the load meter built into the controller. The signal was processed through a low-pass filter to eliminate high-frequency noise. The filtered signal was sampled at a rate of 500 Hz and averaged at every hole made by the device. To compare the obtained results, the drill wear was measured using a tool microscope when a prescribed number of holes has been made.

Figure 2 shows a comparison of the progressive wear patterns read at the microscope (*Figure 2*) and those calculated based on the estimated torque (*Figure 3*). The estimated wear is in close agreement with the measured wear and has a maximum error below 0.02 mm. Since the flank wear of 0.18 mm can be recommended as a criterion for drill replacement, the error is of lower importance. Therefore, the spindle motor power can be used as a reliable monitoring signal of drill wear [16].

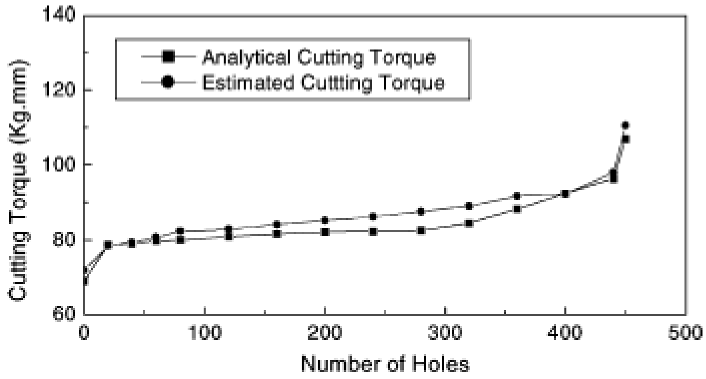


Figure 2 Analytical and estimated cutting torque [16]

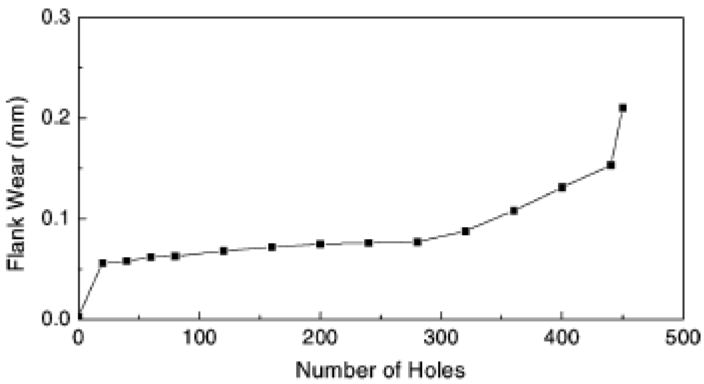


Figure 3 Flank wear [16]

Experiments were also conducted under various cutting conditions to evaluate the performance of the proposed method. A drill diameter varied in the range of 4 to 6 mm and a cutting velocity changed from 2800 to1900 rpm. The measurements were also performed for the various feed rates. For the all the proposed conditions, the method worked well. The study concluded that the drill wear can be estimated accurately based on the real-time measurements of spindle motor power consumption.

2.3.2 Fan faults detection methods based on vibration analysis

The recent studies on fan fault detection based on the noise and vibration analysis were performed in Mechatronics Engineering Department of Erciyes University, Turkey. The main goal of the research was to show the effectiveness of the acoustic emission technique compared to the vibration signal analysis to detect different fan faults. The study aimed to determine the possible faults that may occur in the system by the acoustic properties of signals. For this purpose, a computer cooling fan with seven blades was used for the experimental measurement. Artificial fan faults such as broken fan blades, deformed blade shape, bearing faults, lubrication problems, cracked part at the root of the fan blades are considered and outlined in Figure 4. Both vibration and acoustic measurements were performed to evaluate the system responses [17].

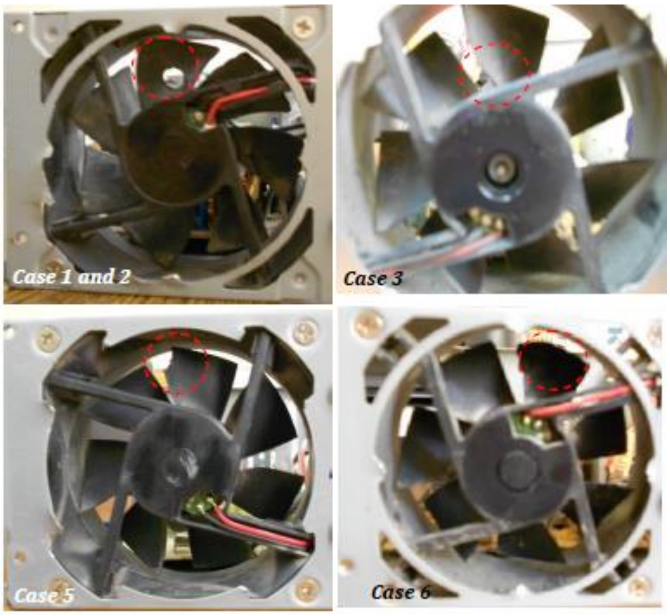


Figure 4 Artificial fan faults: hole in a blade (case 1, 2), blade fault (case 3, 5), blade shape deformation (case 6)[17]

Vibration and acoustic signals were measured simultaneously with the use of an acoustic sensor with a preamplifier (4189-A-021) and an accelerometer (B&K 4514B). Other noise sources from the surroundings were isolated from the experimental system. Measurements were performed for the healthy and defective work of a fan working in same conditions for all investigated cases. *Figure* 5 presents the sample results for the case 1 (blade with a hole of 4 mm diameter).

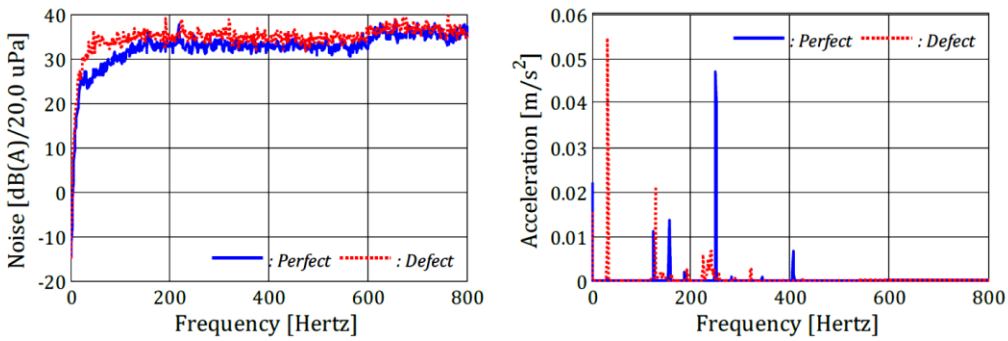


Figure 5 Noise and vibration signal data for a fan during healthy and faulty working conditions[17]

Based on the results analysis, the authors came to the conclusion that depending on the fault type, different methods for fault detection are suitable. In the case of blade faults, the vibration measurements gave the best results. On the contrary, the bearing faults and lubrication problem were detected during noise signal analysis.

Moreover, noise measurements do not require a contact with examined devices, thus sensors can be installed everywhere within the system. Conversely, a vibration sensor must be located on a bearing. The study concluded that in order to detect all the examined faults, both vibration and noise analysis have to be performed [17].

Chapter 3

Methodology

As stated in *Chapter 2*, the development of a complete fault detection system involves several steps including, data acquisition and pre-processing, feature extraction and statistical modelling. The following chapter describes in detail the steps which are undertaken to develop the fault detection algorithm of this thesis. The sequence of the work is presented in the diagram below.

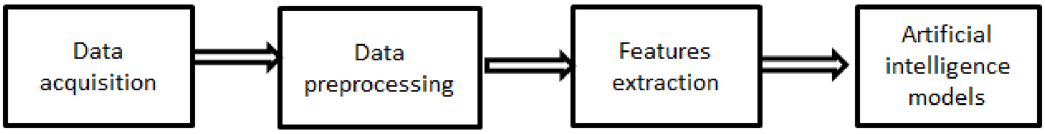


Figure 6 - Sequence of development of a fault detection system

The first step involves the data acquisition and pre-processing, which is a crucial part of development of model – free methods. The process description includes the information of measurements methodology and the outliers' detection. The chapter discusses the choice of extracted features for the investigated algorithm and provides a description of the artificial intelligence models that are chosen to classify the data within the fault detection system. Two methods characterised by different features are selected: decision tree and neural network. The decision tree algorithm is easy to understand and has the clear relationship between input and output, thus it is selected as the first model to perform the classification task. After the model evaluation, the set of the input variables resulting in the best model performance is used for the development of the neural network algorithm. The network is chosen as the second investigated model since it has a black box learning approach and does not have a clear relationship between inputs and outputs. On the other hand, the advantage of this method is the possibility of using nonlinear boundaries, which results in a high efficiency of classification.

3.1 Acquisition and cleaning of data

The development of a fault diagnosis system with the use of supervised learning techniques requires data acquisition. The process is application-specific and usually involves recording signals such as vibration, temperature, pressure and energy usage because they are easy to acquire. Signal data are typically of large amount and require pre-processing before feeding into the next processing stage, the feature extraction. For the subject of this work two types of signals are recorded from meters: energy consumption and temperature in the room.

Energy consumption measurements involve the application of two devices: the single-phase electronic energy meter (type: EMDIN01) and the EOT module, which transmits data to the cloud service using Wi-Fi connection. The measurements sampling rate is 9 min and records are collected on the online platform my.eot.pt. The platform enables direct and real-time access to energy consumption data. Temperature measurements are performed with the use of EOT Temperature Meter at the sampling rate of 1 min. The device uses a temperature sensor to perform measurements and sends data through a wireless connection to a cloud service online [18]. *Table 1* presents the technical specification of the described devices.

Table 1 Technical specification [18][19]

Energy meter	Type	EMDIN01	
	Voltage	230 V	
	Current	5 (40) A	
	Power consumption	<= 0.4 W	
	Frequency	50/60 HZ	
	Accuracy class	1.0	
	Display mode	LCD 5+2 digits=99999.99	
	Temperature range	-20 to 65°C	
EOT module	Power	5 V DC, 1 A	
	Communication	Wi-Fi 802.11b/g/n 2.4GHz	
	Range	<=500 meters	
	Material	PLA and Acrylic	
EOT Temperature Meter	Operational Range	-55 to 125°C	
	Resolution	0.0625°C	
	Precision	±0.5°C	
	Casing of sensor	30 mm tubular stainless steel	
	Power	5 V DC, 1 A	
	Communication	Wi-Fi 802.11b/g/n 2.4GHz	
	Range	<=500 meters	

In the given work, the cleaning procedure of data is limited to detecting outliers - values in the data set that deviate significantly from most of observations. Deviations might be caused by a sensor noise, process disturbances or human-related errors. The majority of the outliers' detection methods are based on the two important statistics: location and scatter. The sample mean (3.1) and standard deviation (3.2) give a good estimation of those features [13]:

$$\bar{a} = \frac{1}{n}\sum_{i=1}^{n} a_i \tag{3.1}$$

$$Sd = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - \bar{a})^2} \tag{3.2}$$

In the applied procedure, outliers are detected with the use of the standard deviation method. The method indicates that measurements outside intervals may be considered as outliers. The range of the interval is calculated as the triple value of the standard deviation [20].

3.2 Feature extraction

Identifying a significant number of indicators from a large amount of signal data is challenging and has been a focal point in the domain of fault diagnosis. For some applications, one or two key features can help to reach diagnostic conclusions directly without further calculations. More often, sensitive features are not straightforward to obtain and processing further the extracted features is necessary. In any case, feature extraction plays an important role in effective fault diagnosis and it is a crucial aspect of pattern recognition. It is desirable that the features extracted from the sensory signal are sensitive to machinery abnormal behaviour and robust to the varying machinery operating conditions and background noise. Algorithms for extracting features from a large amount of signal data should also be in inexpensive in computations [12].

In the given example of fault diagnosis, the statistical parameters are extracted from the dataset over a certain time period, which is established beforehand. The following parameters are calculated: standard deviation (3.1), average value (31), and peak to peak value (3.3) defined as:

$$Pp = \frac{1}{2}\left(max_{i=0}^{n-1} a_i - \ min_{i=0}^{n-1} a_i\right) \tag{3.3}$$

The mean value reflects the average energy consumption of the fan over the investigated time period, the standard deviation measures the dispersion of the dataset and the peak-to-peak value indicates the absolute amplitude level of the energy consumption fluctuations.

3.3 Artificial intelligence methods

Features extracted from the sensory signals are usually not direct indicators ready for reaching diagnostic conclusions. Further analysis and fusion of the extracted features are necessary so that a combined effect can be obtained to indicate the machinery health condition. Such a process is usually nonlinear due to the complex relations among many extracted features [12]. To overcome the problem of handling a great amount of data, several decision support systems are applied. Algorithms are required to consider the ill-structure of predictive data resulting in high uncertainty of the diagnosis process. To find an effective solution, several paradigms coming from the machine-learning field can be applied to a variety of situations, and with diverse requirements and problem characteristics (data mining, supervised, unsupervised, expert knowledge, reinforcement learning). Some of the mentioned methods have developed into robust tools that can be used for the modelling of several kinds of classification problems, such as monitoring and diagnosis. Artificial neural networks and induction trees are examples of successful algorithm paradigms [21].

3.3.1 Decision trees

The example of a statistical model which can be used for fault detection system is a decision tree. This is a method for approximating discrete-valued target functions in which the learned function is represented by a decision tree algorithm. A tree structure is among the most popular of inductive inference algorithms and has been successfully applied to a broad range of tasks. Decision trees classify instances by sorting them from the root to some leaf node, down the tree. Each node in the tree specifies a test of some attribute and each branch descending from the node corresponds to one of the possible values of that attribute. An instance is classified by starting at the tree root, testing the attribute specified by each node and moving down the tree branch corresponding to the output value in the given test [22]. The example of a structure of a decision tree is shown in *Figure* 7.

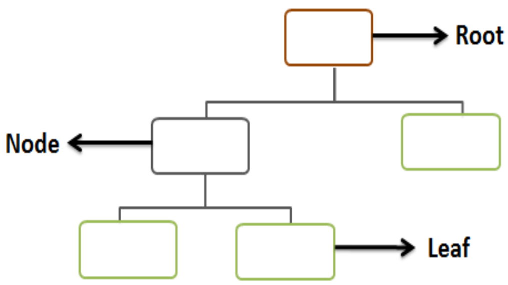


Figure 7 Decision tree structure

The learning process of decision trees begins with searching for the attribute, which should be tested at the root of the tree. Therefore, each instance attribute is evaluated using a statistical test to determine how well it alone classifies the training dataset. The best attribute is selected and used as the test at the root node of the tree. A node is then created for each possible value of this attribute, and the training examples are sorted to the appropriate descendant node. The whole process is then repeated using training examples associated with each descendant node to select the best attribute to test at that point in the tree.

To find a good description of the worth of an attribute, the quantity called information gain is defined. Information gain measures how well a given attribute separates the training examples according to their target classification. The information gain is defined precisely, with a measure commonly used in information theory, called entropy, that characterises the impurity of an arbitrary collection of examples. The entropy is 0 if all members belong to the same class and the entropy is 1 when the collection contains an equal number of positive and negative examples. The information gain is the expected reduction in entropy caused by partitioning the examples according to this attribute [22].

There are many are many possible trees that can be learned from a sample data set. It is recommended to use the less complex tree since they are more general and tend to be more accurate. The complexity of a tree is measured by one of the following metrics: the total number of nodes, total number of leaves, tree depth and the number of attributes used [23]. Too complex structures may lead to data overfitting. Overfitting the training data is an important issue in decision tree learning. In general, training examples are only a sample of all possible instances. Therefore, it might happen that addition of branches to the tree that improves the performance on the training dataset will decrease the performance on other instances outside this set [22]. The issue of overfitting data is visualised in *Figure 8*.

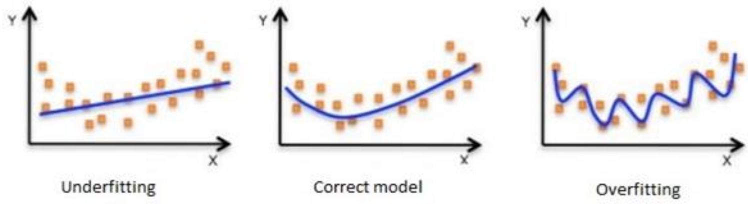


Figure 8 Overfitting problem

When overfitting problem occurs, a statistical model can describe error or noise instead of the underlying relationship between attributes. It is a common issue, when a model is excessively complex, such as having too many parameters relative to the number of observations. To control the depth and complexity of a decision tree, it is recommended to specify a maximum number of splits or branch points [24].

3.3.2 Artificial Neural Network

An Artificial Neural Network (ANN) is a mathematical model that simulates the structure and functionalities of biological neural networks. The basic component of a model is an artificial neuron, which illustrates a mathematical function of three simple sets of rules: multiplication, summation and activation. At the beginning of a computational process, the neuron inputs are weighted - every input value is multiplied by individual weight. In the next step, summation of weighted input signals is performed. The obtained sum is projected on an activation function, the so-called transfer function and at the end an artificial neuron passes the information via outputs. The process of information flow in the artificial neuron is depicted in *Figure 9* [25].

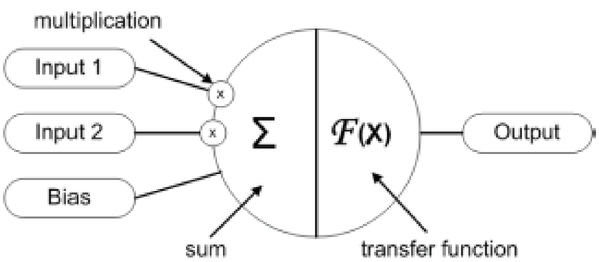


Figure 9 Artificial neuron: working principle[25]

The output value from the artificial neuron is described by the mathematical function:

$$y_i(k) = F\left(\sum_{i=0}^{m} w_i(k) \cdot x_i(k) + b\right) \tag{3.4}$$

where:

- $w_i(k)$ - input value in the discrete time k,
- $x_i(k)$ - weight value in the discrete time k,
- b – bias,
- F – transfer function,
- $y_i(k)$ - output value in the discrete time k.

As seen from a model of an artificial neurone and its equation (3.4), the unknown variable is the transfer function. Transfer function defines the properties of artificial neurons and the choice of a function is based on the problem that the artificial neural network is required to solve. In most applications, the transfer functions are chosen from the following set: Step function, Linear function and Non-linear (Sigmoid) function.

Step function is a binary function that has only two possible output values - this means that if the input value meets a specific threshold, the output value results in one value (e.g. one) and when the specific threshold is not meet, the value is equal to another value (e.g. zero). When this type of transfer function is used, the artificial neuron is called perceptron.

In the case of a linear transfer function, the artificial neuron is doing a linear transformation over the sum of weighted inputs and bias. When non-linear functions are used the most common choice is the sigmoid function. Sigmoid function has an easily calculated derivate, which can be important when calculating weight updates in the artificial neural network.

Sigmoid neurons are often used for pattern recognition problems. Therefore, in this work, the neural network created for a fault detection uses the Log – Sigmoid function (*Figure 10*) as an activation function. The Log – Sigmoid function generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity [26]. The Log – Sigmoid function is characterised by following:

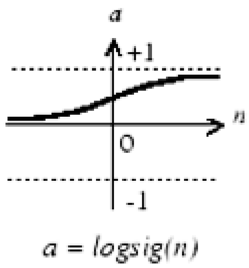


Figure 10 Log- Sigmoid transfer function [26]

The working principle of individual elements of the network is not complicated - neurons read an input, process it, and generate an output. The calculation power of the model occurs when basic blocks are interconnected into artificial neural networks. ANNs are capable of solving complex real-life problems by processing information in a non-linear, distributed, parallel and local way. The way that individual artificial neurons are interconnected is called the architecture or topology of an artificial neural network and the group of individual neurons is called a layer. Interconnections can be done in different ways resulting in numerous possible topologies. They that are divided into two basic classes: feed-forward (FNN) and recurrent (RNN) topology of an artificial neural network *(Figure 11*). In the RNN topology information flows not only in one direction but also can be transmitted backwards [25].

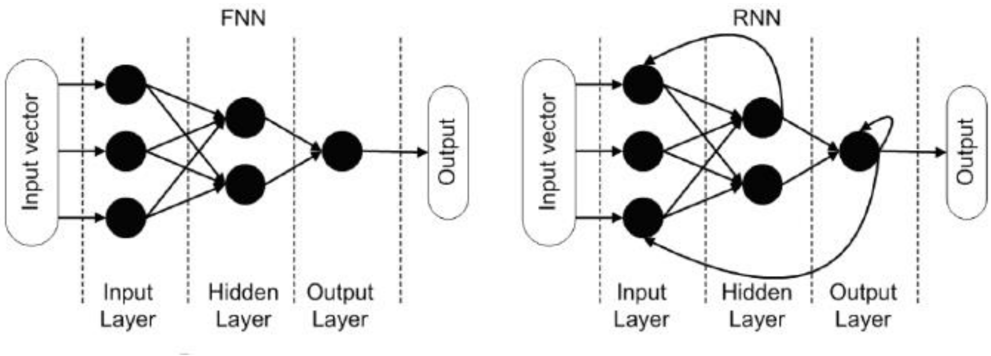


Figure 11 Feed-forward and recurrent topology of an artificial neural network [25]

The neural network which is a subject of this work has a feed-forward architecture. In that case, information flows from inputs to outputs in only one direction (represented by the model on the left side of *Figure 11)*. The applied network has an input and output layer and more than one hidden layer of sigmoid neurons, which allows to learn nonlinear relationships between input and output vectors. During the training process, the internal structure of the network is changed based on the information flowing through the model. The network tries to achieve proper output response in accordance with input signals by the adjustment of weights and biases.

The neural network is trained through the supervised learning paradigm. Supervised learning is a machine learning technique that sets parameters of an artificial neural network from training data. The task of the learning artificial neural network is to set the value of its parameters for any valid input value after having seen the output value. The training data consist of pairs of input and desired output values that are traditionally represented in data vectors. Once the network is trained, the validation of a model is required using the data set that has not been introduced to artificial neural network while learning.

Chapter 4

Laboratory facility

Development of a fault detection system of a fan using a history based method and supervised learning algorithm requires two types of datasets. Measurements need to be performed during the proper working conditions and while the fan is operating with different types of faults. To collect data of those two types, a low scale laboratory stand was designed and built. The chapter provides the scheme and description of the designed installation and discusses the fault types, which may occur during the fan exploitation.

Measurements results of the fan power consumption are examined for the various condition: the normal and the faulty operating state. To look for the patterns in the fan energy consumption, a periodicity analysis is performed and the causes of load fluctuations are investigated. The understanding of changes in the fan load during the normal work is necessary for the well-designed fault detection system. The chapter is terminated with the analysis of the changes in the fan energy requirements when the device is subjected to the different types of malfunction. Two types of fault are under examination: the fault in the air intake area and the fault causing additional friction between blades and housing.

4.1 Description and scheme of a stand

The laboratory stand consists of two fans and variable sensors, which measure, process and send the data to the cloud. The lower fan (number 9 in the scheme) is subjected to different types of faults, while the second one is working in the correct manner and it is used as a model device during fans performances comparison. Fans require connection to the grid for the power supply. The energy consumption is measured collectively for both fans by a energy meter, which displays a result based on current and voltage. Data is sent by a wire to the smart meter EnergyOT and transmitted to the cloud service. The results are available for online monitoring in the website: www.my.eot.pt. [18]. The EnergyOT module requires direct current, therefore an AC/DC transformer is installed before the device. In case there is the need to measure the energy consumption of another device, a power socket is available in the stand. The whole installation is protected with circuit breakers, which are also used for switching on fans. Additionally, measurements of temperature are performed with EOT Temperature Meter and are sent through a wireless connection directly to a cloud service online. *Figure 12* shows the scheme of installation and *Table 2* describes presented components.

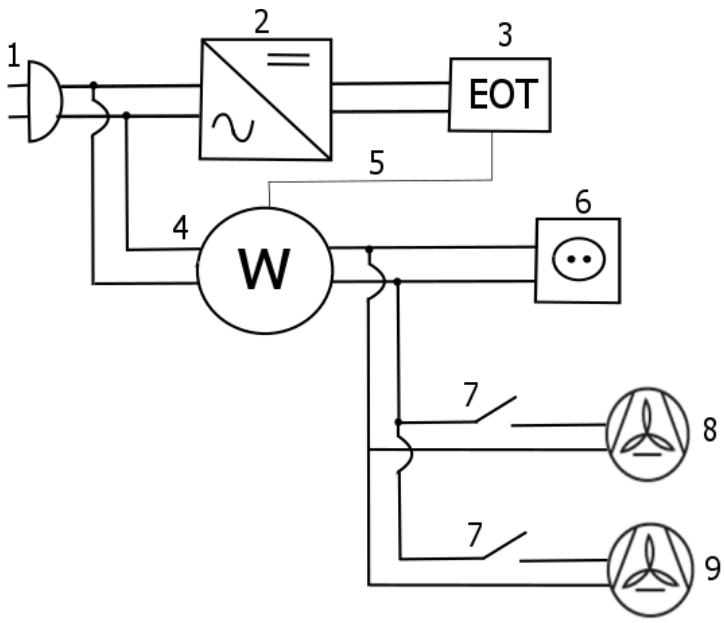


Figure 12 The scheme of the laboratory stand

Table 2 Components of the laboratory stand

1	Plug to the grid
2	AC/DC transformer
3	EnergyOT Smart Meter
4	Watt-hour meter
5	Wire connection
6	Power socket
7	Circuit breaker
8	Fan I
9	Fan II

After designing process, the stand was built in a laboratory of Instituto Superior Técnico. A wooden frame was shaped with the use of a digital cutter. The process is depicted in *Figure 13*.

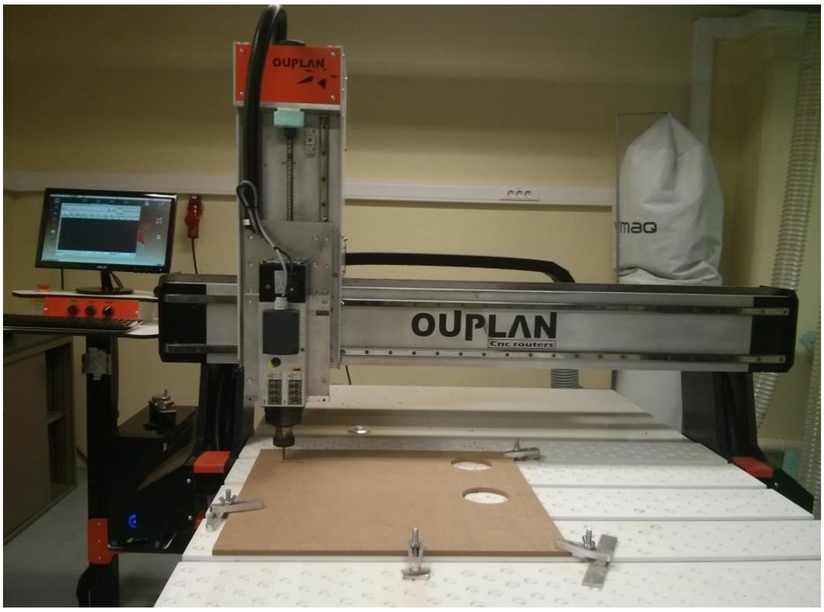


Figure 13 Building process of the laboratory stand

In the next step, all devices were placed in the wooden frame and connected with cables according to the designed scheme. *Figure 14* shows a picture of a ready for tests stand.

Figure 14 Ready installation

4.2 Fan performance without fault

In the first stage of data acquisition, the performance of a fan without any fault was examined. To register changes in the power consumption, the fan was working continuously for twenty-one days. The graph below (*Figure 15*) presents the obtained measurements records.

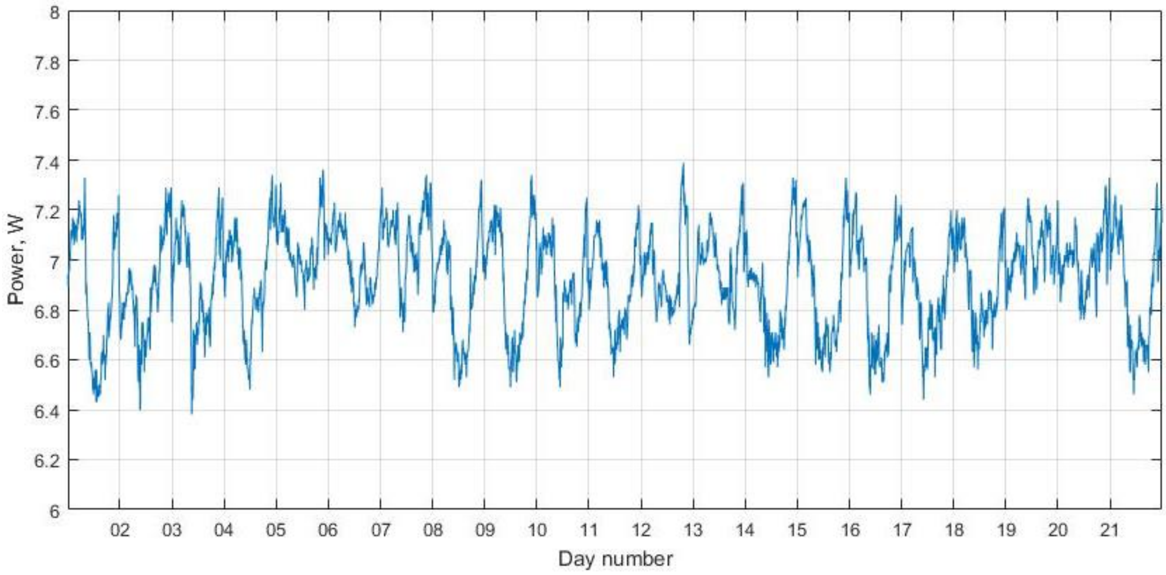


Figure 15 Daily changes in power consumption of a fan

The figure shows, that the power consumption of the fan fluctuates, with a minimum and maximum value equal to 6.4 W and 7.4 W respectively. The average value is equal to 6.9 W. We can observe, that during weekends, namely during days of number: 5, 6, 12, 13, 19, 20, the power characteristics have different shape than during weekdays. This leads to the conclusion, that ambient conditions in the office influence the power requirements of the fan.

The shape of the graph indicates that the power consumption may change in a daily cycle, but it is difficult to characterise oscillatory behaviour in the data since the current signature is recorded in a time domain. To determine if the signal is periodic in the different cycles, a spectral analysis was performed. This is a mathematical operation, which with the use of Fourier transform extracts the frequency information from the time domain and transforms it into the frequency domain [22]. Such analysis allows detecting cyclic behaviour in the data, by observing peaks at the frequencies corresponding to these periodicities [28].

A spectral analysis of power consumed by the fan is performed for a time period of twenty-one days and it is shown in *Figure 16*. On the graph, a significant increase in magnitude is observed at the frequency corresponding to 7 cycles per week. This information leads to the conclusion that power consumption is characterised by a daily cycle.

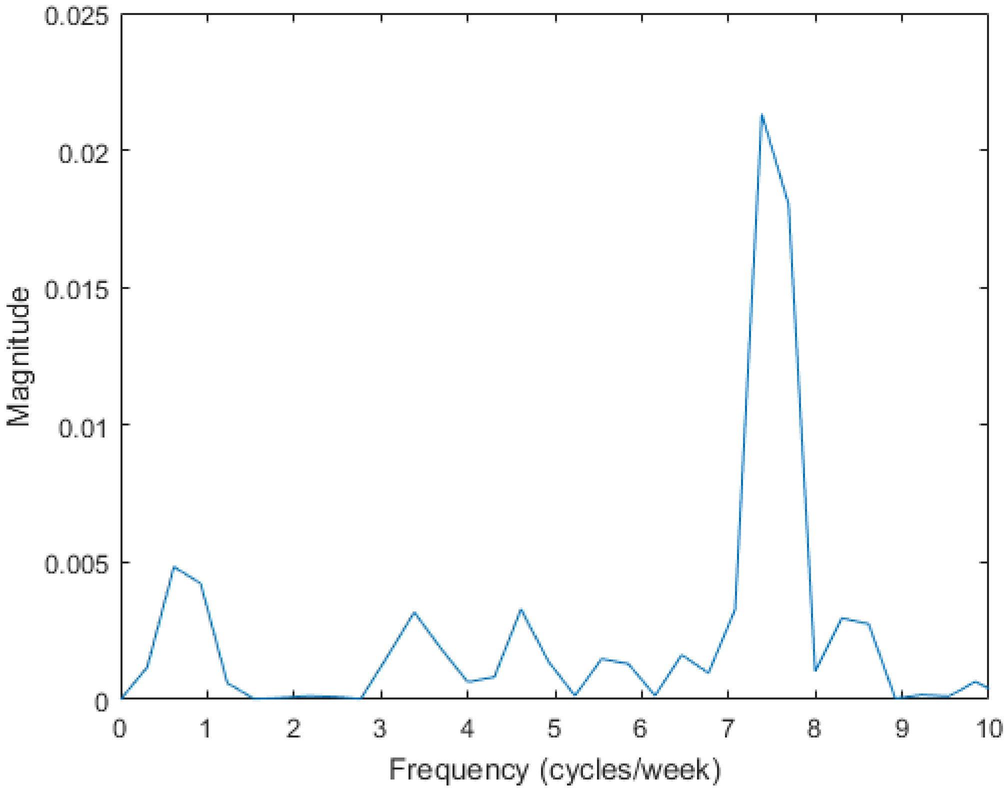


Figure 16 Frequency analysis

The spectral analysis indicates that changes in the power consumption occur within a daily pattern. Therefore, the weekly measurements results of power were disaggregated. *Figure 17* compares used electricity for each day separately, in order to prevent clear view of the graph characteristic of only twelve days is displayed.

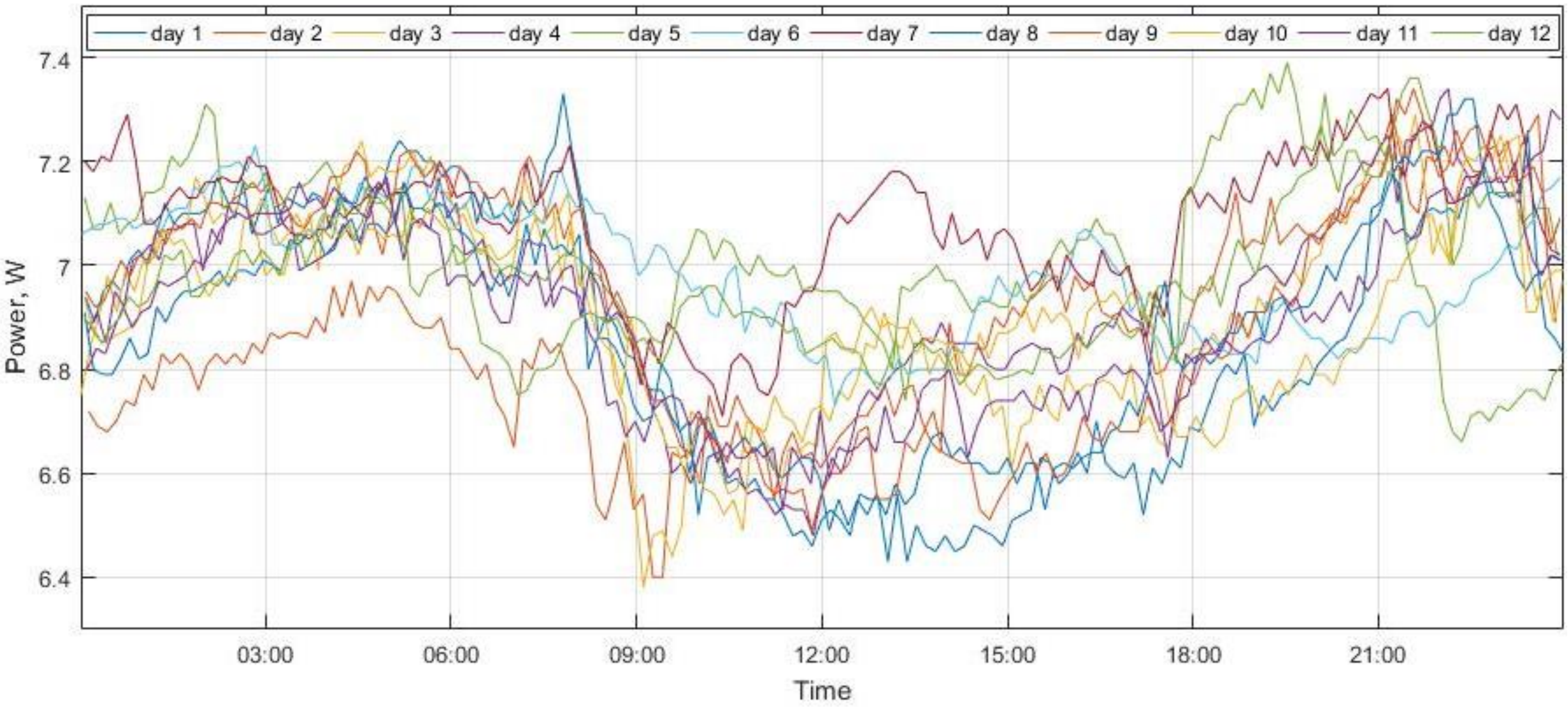


Figure 17 Daily disaggregated electricity consumption

Based on data presented in the graph, it can be observed that the power consumption varies in a similar way every day. The load of the fan decreases during daytime and after 18:00 starts to increases. The highest value of power is observed during night hours and usually oscillates between 7 W and 7.4 W.

To understand the reasons of daily fluctuations in fans load, the working principles of a device were analysed. The fan is a constant volume machine. Therefore, when operating at constant speed it will deliver the same flow at standard density air (ρ =1.2 kg/m^3) as it will deliver with another value of density air (ρ_c). In the result, regardless of air conditions, the flow rate (Q) remains constant. Pressure (p_c) and power requirements (P_c), however, change proportionally with density [30]:

$$Q_c = Q \tag{4.1}$$

$$p_c = p \cdot \frac{\rho_c}{\rho} \tag{4.2}$$

$$P_c = P \cdot \frac{\rho_c}{\rho} \tag{4.3}$$

The temperature in the surroundings of the test stand changes from night to daytime thus affecting the air density. The correlation between those two quantities is shown in the graph below (*Figure 18*). It can be seen, that changing the temperature notably influences the air density and in result, according to the equation (4.3), it affects also the power consumption.

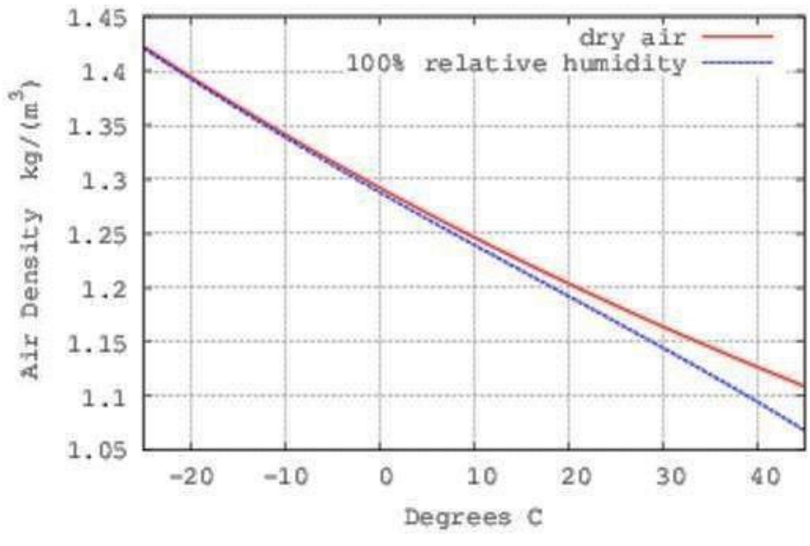


Figure 18 Temperature influence on air density [29]

To understand how energy consumption depends on the room temperature, the daily power measurements were complemented by the information obtained with the use of EOT Temperature Meter. *Figure 19* compares power and temperature measurements for the time period of 12 days.

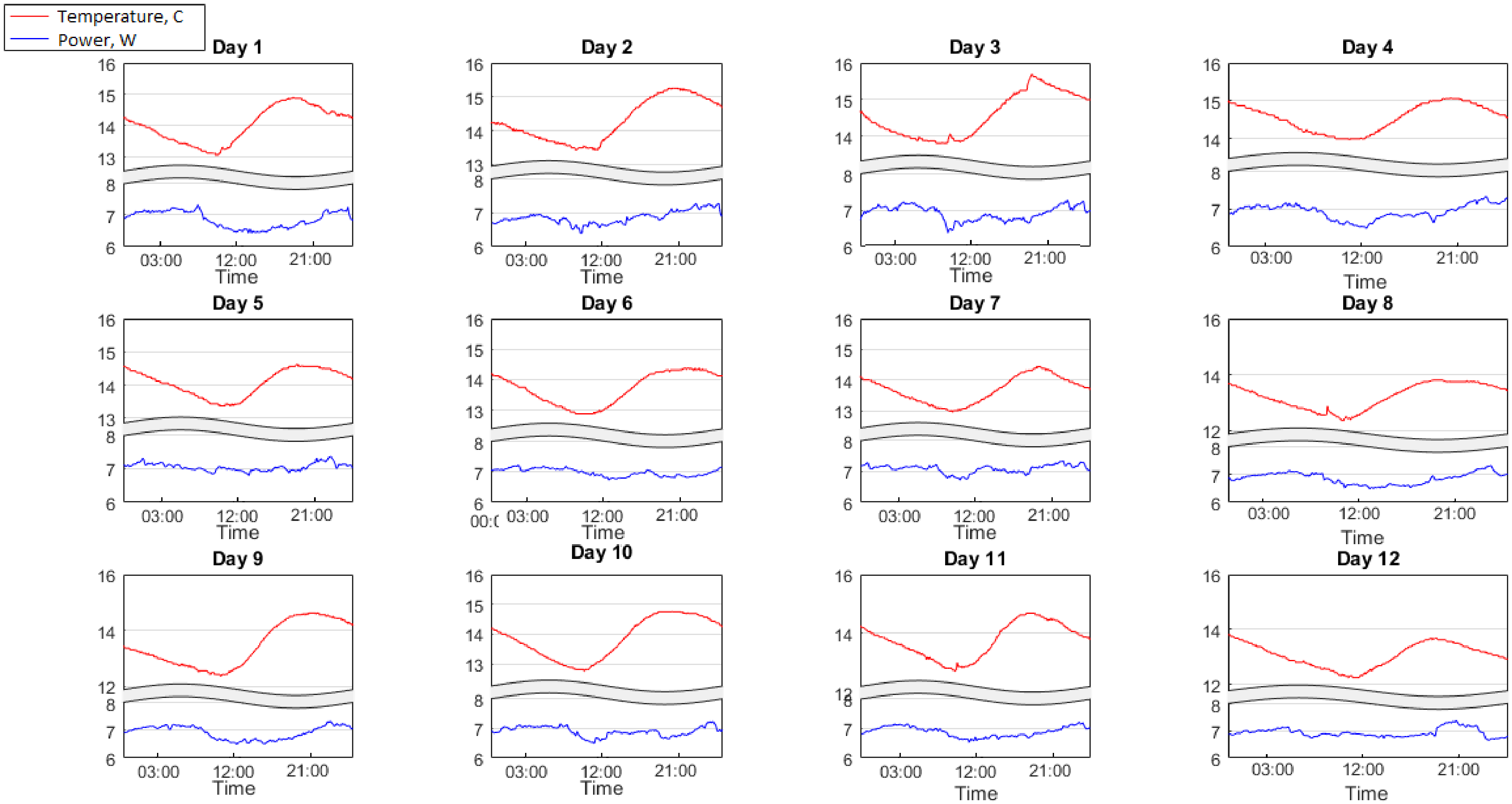


Figure 19 Correlation between fan power consumption and ambient temperature

According to the graphs, the temperature in the room varies from 12°C to 15°C. The graphs indicate that during night hours, when the temperature drops (resulting in higher air density), an increase in the power consumption is registered. It can be particularly observed during the first, fourth, ninth and eleventh day.

The power consumption of a fan, which operates without any fault varies in the range 6.4 W to 7.4 W. Based on the obtained results, temperature change is said to be the main factor causing the daily power consumption fluctuation. The natural variation in the fan performance due to the different air conditions should be taken into consideration during the process of fault detection and diagnosis.

4.3 Comparing the performance of two fans

Chapter 4.2 discussed the performance of a fan without any operating fault. However, the application of the collected data in the universal fault diagnosis system requires to analyse if different models of the same type of fan have similar patterns in terms of daily power consumption. To compare the performances of two fans installed in the laboratory stand, a set of measurements was carried out. For the reliability of the test results, it is required, that fans operate with the similar air conditions. To meet this requirement, fans were working alternately during daytime. Power consumption and temperature data was acquired for the time period of two days. To compare the performances of fan I and fan II operating under similar working conditions, a graph of power consumption in a function of the temperature was plotted (*Figure 20*).

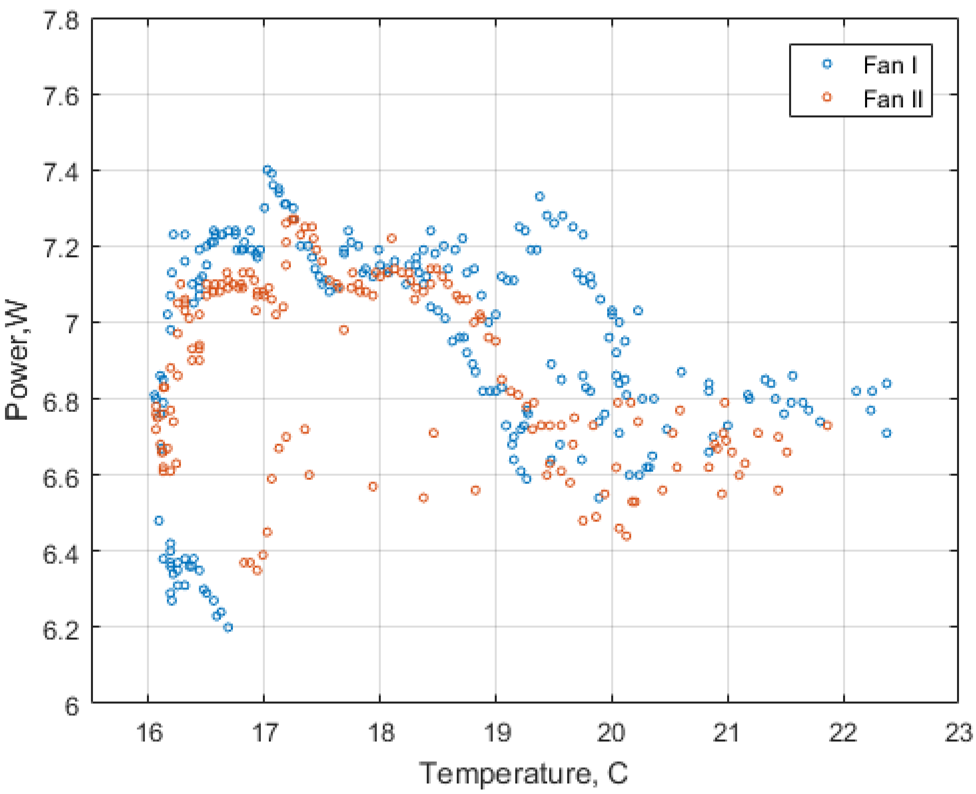


Figure 20 Comparison in fans performance: power consumption in the function of temperature

The power consumption of both fans is similar for the same working conditions; only a few measurements points of the fan II do not match the general model. Based on the obtained results, we can conclude that fans of the same type are characterised by the similar pattern of power consumption. *Figure 20* indicates also that energy usage starts to decrease when ambient temperature exceeds 18°C, which is consistent with the correlation discussed in *chapter 4.2*.

4.4 Faulty working conditions

4.4.1 Clogging

One of the typical faults in ventilation systems is the clogging of air intake area. To simulate such operating conditions in the laboratory stand, different areas of intake surface were covered with duck type: a quarter, a half, three-quarters and a whole surface. *Figure 21* presents pictures of different cases of air intake clogging.

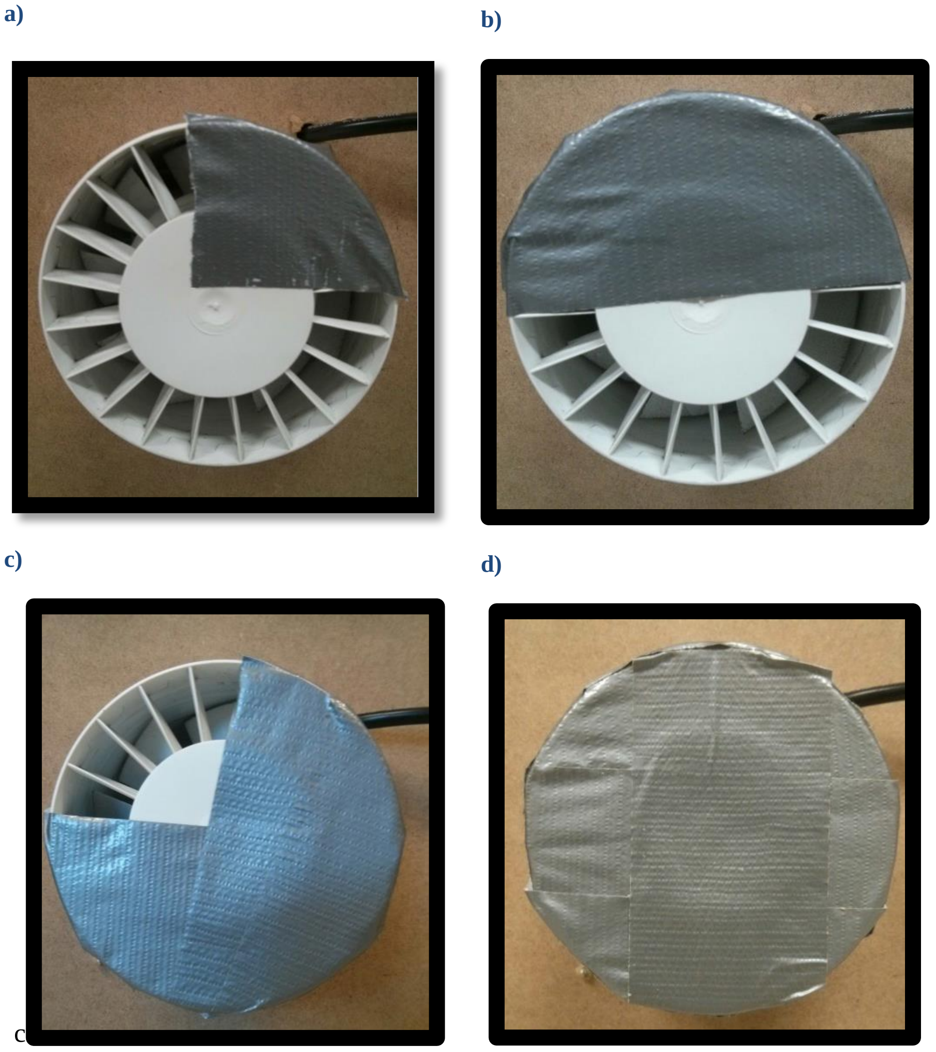


Figure 21 Faults in the surface of air intake, different areas clogged: a)quarter b) half c)three-quarters d)whole surface

For each type of fault depicted in the figure above, measurements were run for 60 hours. During the tests, both fan's load and temperature were recorded. The figure below presents the energy requirements of the fan subjected to the fault of clogged air intake area.

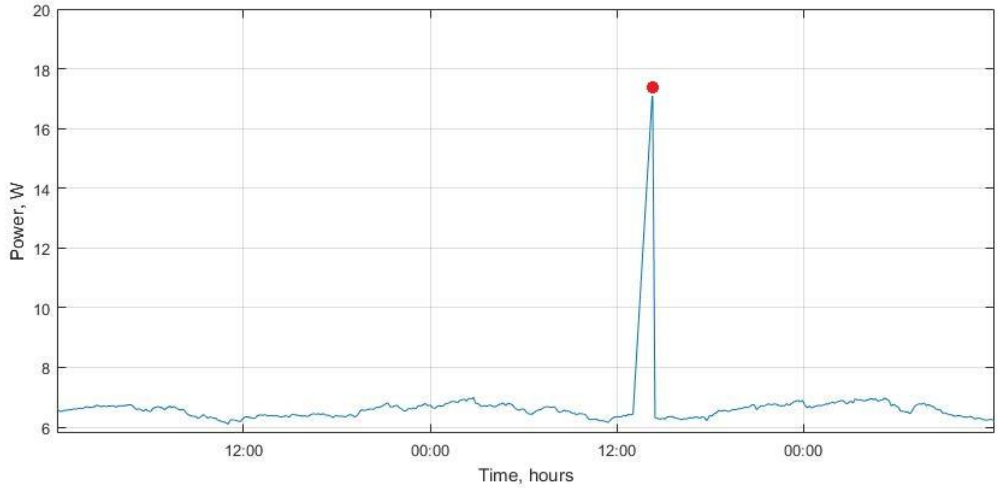
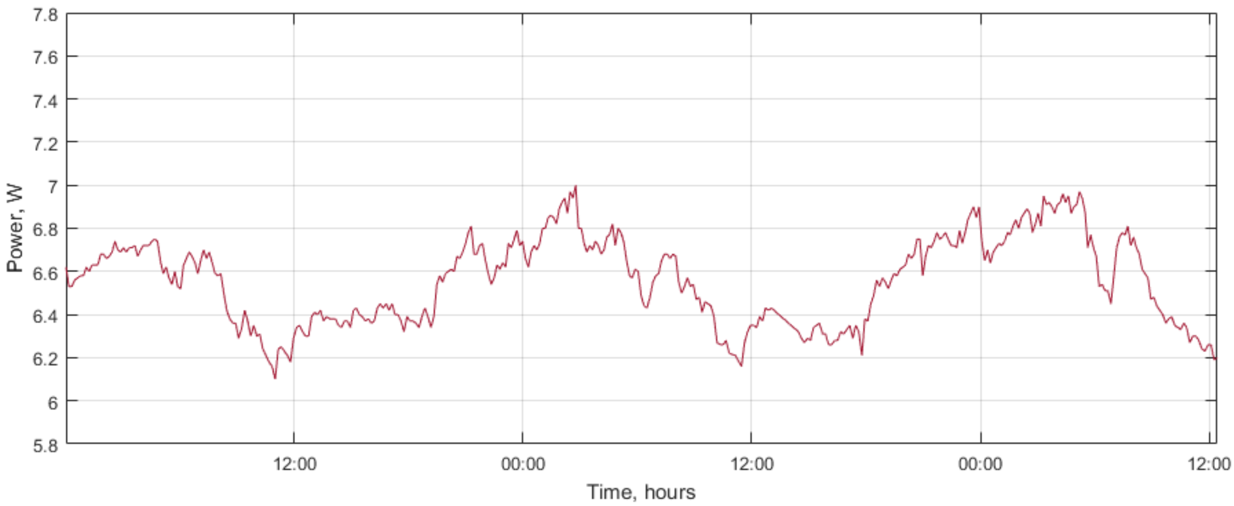


Figure 22 Detected outlier

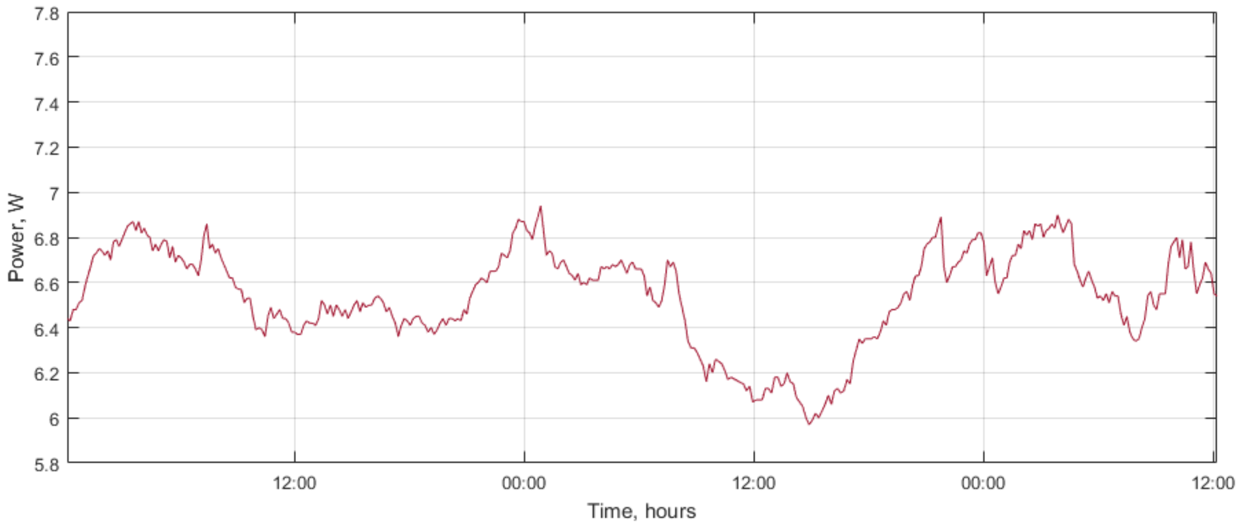
It can be observed, that around 2 pm during the day of measurements, the unexpectedly high value of power consumption (17.3 W) was recorded. Since such observation point is significantly distant from all other records it is considered as an outlier. Outliers should be removed from the dataset because they affect the training process of the applied algorithms and can lead to the misclassification of proper data records. The outliers were removed from the all measurements dataset with the method discussed in *Chapter 3.1*.

After the outliers' removal, the analysis of the fan energy requirements during the faulty operating condition was performed. The plots of the power consumption (as it is the base parameter for the fault detection algorithm) are presented *Figure 23* for each of the considered cases.

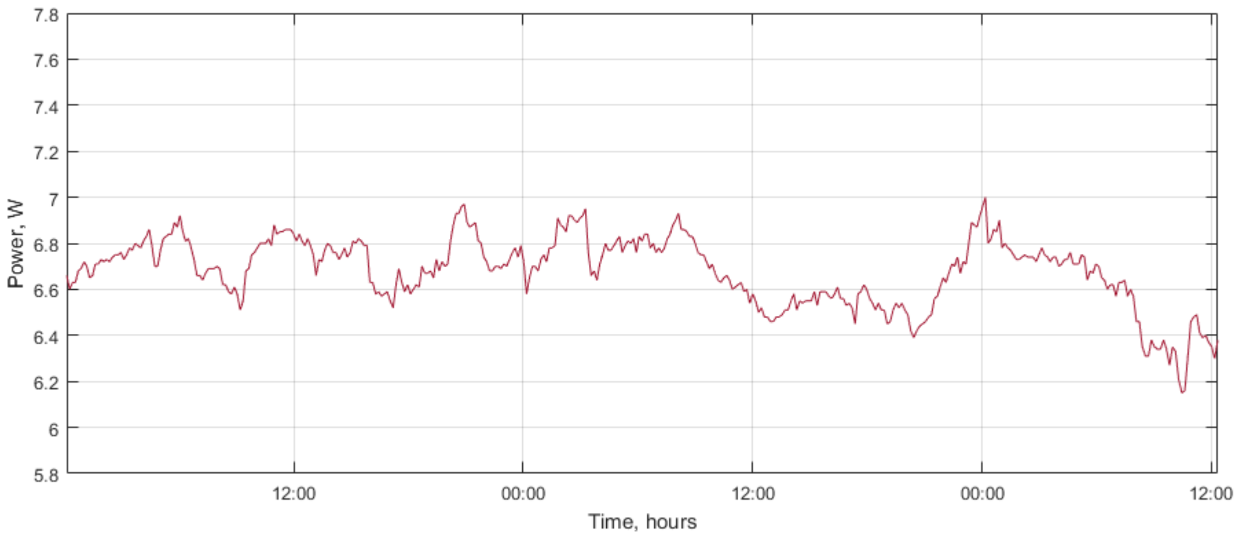
a) Quarter of the air intake area clogged



b) Half of the air intake area clogged



c) Three-quarters of the air intake area clogged



d) Whole air intake area clogged

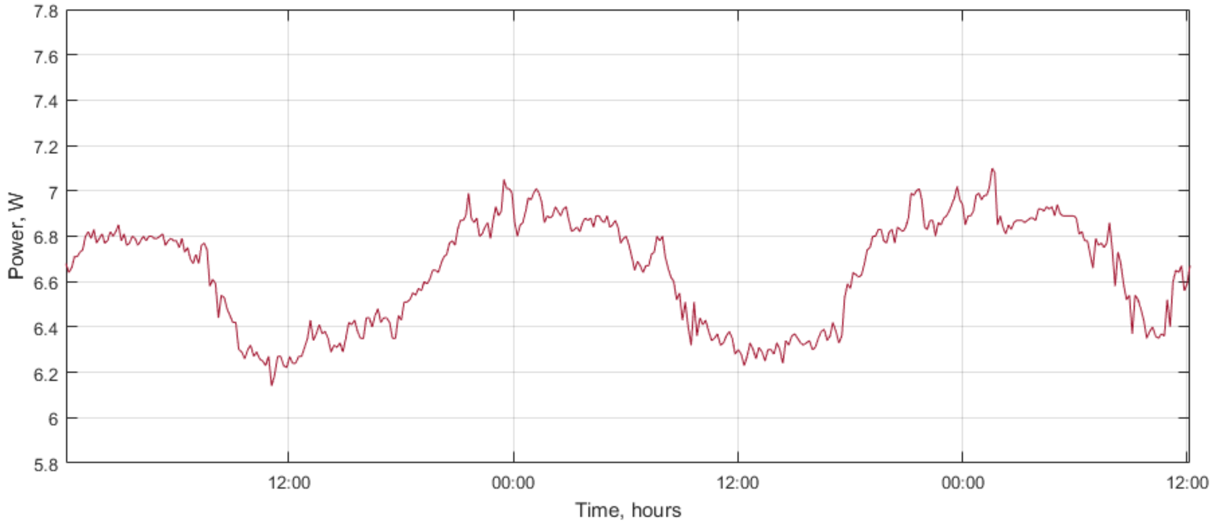


Figure 23 Power consumption of a fan subjected to the different faults of the air intake area

The plots indicate that power consumption of a faulty fan oscillates, having a minimum and maximum value of 6 W (case b) and 7.1 W (case d). The average load for “a”, “b”, “c”, and “d” case is equal to 6.56 W, 6.55 W, 6.68 W and 6.55 W respectively. It can be observed that the power consumption decreases in comparison to the fan performance without any failure, which has a mean load equal to 6.9 W. The reason to this decrease is a change in the work which needs to be done by the blades of a fan. Due to clogged intake area, a flow rate of air drops, therefore we observe a decrease in a power used by a motor to overcome air resistance. However, the mean load in the case “c” (three-quarters of air intake area are clogged) has the highest value. The obtained result indicates that there is no proportional correlation between amount of clogged area and decrease in power requirements - all investigated cases are characterized by a similar pattern of a power consumption. Lack of the noticeable correlation between different ratios of clogged air intake areas and load of a fan could be caused by the limited accuracy of the power meter and by the changing conditions of the ambient air. It is worth to underline that the work of a fan subjected to a fault is also characterised by a daily pattern of energy consumption, having the minimum load around the noon and the maximum consumption during night hours. Those daily changes in the power requirements prove that device is sensible to ambient air conditions, especially temperature.

4.4.2 Bearing wear and misalignment

Another example of the most common malfunctions that occur in the ventilating systems is the wear and misalignment of bearings. Such fault can lead to the situation where the bearing axis is not perpendicular to the housing bore. The shaft and housing are then both distorted cyclically during rotation, which results in additional friction [31]. To simulate such working conditions, additional material was mounted on the fan housing, which is depicted in *Figure 24*. As a result, every rotation of a shaft led to the interaction between material and rotating blades, causing additional resistance.

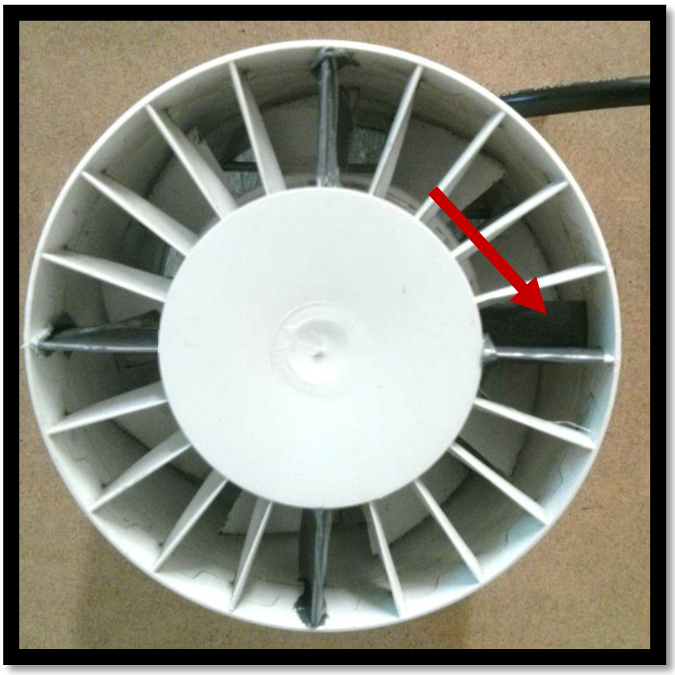


Figure 24 Fan operating with additional friction

Similarly to the tests ran with clogged air intake area, the fan was operating with a condition causing additional friction for 60 hours. During this period, the temperature and energy consumption was measured; *Figure 25* presents the records of a fan load.

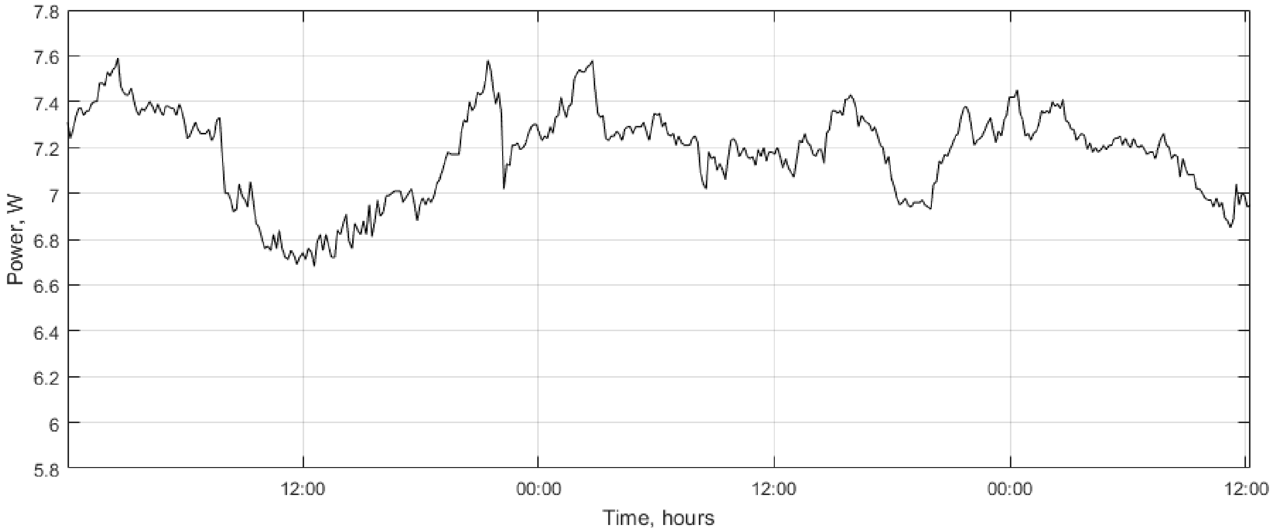


Figure 25 Changes in the fan energy consumption while operating with additional friction

The graph indicates that a fan operating in conditions simulating bearing malfunction faces the increase in the energy consumption. The minimum recorded value is equal to 6.7 W, 0.7 W higher than in the case of a fan operating with an air intake fault. The mean value of power consumption is 7.18 W and this is significantly higher than the previous records. The increase in the power requirements is caused by the necessity to overcome additional friction by the fan motor. Some of the energy was also dissipated causing the sound effect.

In order to visualise the differences between performances of a fan subjected to the various working condition, the plot below (*Figure 26*) gathers all power consumption characteristics discussed in *chapter 4*.

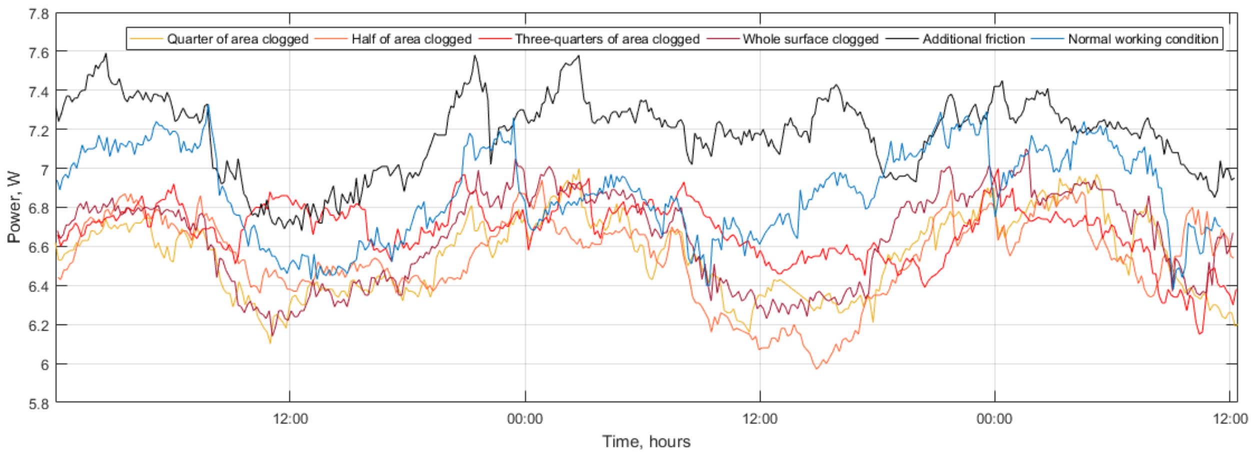


Figure 26 Power consumption of a fan operating in different conditions

Based on the graph, we can draw the conclusion that the energy consumption varies depending on the fan working condition. The energy required to run a fan without any failure (indicate by a blue line in the graph) changes during a day. The different conditions of ambient air are said to be the main reason of daily fluctuations. When the motor is forced to overcome additional friction (black line), the required energy increases. However, there are periods throughout the day, where the lines in the graph overlap with each other, meaning that both working states are characterised by the same power requirements. Contrary to the bearing fault, which simulates the additional friction caused by a bearing malfunction, the clogging area of the air intake results in the energy consumption decrease. It can be observed that the plots of the fan load for different ratios of clogged surface have a similar shape, which makes them difficult to unambiguously identify for any pattern recognition algorithm. Additionally, also in the case of the fault in the air intake surface, there are periods during a day when the power requirement is similar to the normal working conditions.

Chapter 5

Results and discussions

The preceding chapter has focused on the first part of fault diagnosis system: acquisition of data for both, normal and faulty, operating states. The next step of the process includes making an accurate assessment of the malfunction, based on extracted features. The algorithm can learn relationships from the data sets and assign a damaged state to a given set of features. The features are formed from measurements, which are sensitive to the malfunction. Once the features have been established, the map between the values and the diagnosis is constructed with the use of two different methods: decision tree and neural network. The use of those pattern recognition techniques offers the unique possibility to automate the fault detection process.

In order to develop the most efficient algorithm, several decision trees models with different input values are examined. The possible choice of inputs includes power measurements, period of the day and ambient air temperature. The another variable in the model is time over the features are extracted. The examined models are also characterised by different complexity levels of the tree structure, which is assessed by the maximum number of splits. After the evaluation of the decision tree performance, the model based on the neural network is developed. The efficiency in the prediction of the fan working state is evaluated on a dataset different from the training dataset. The final part of the chapter compares the accuracy in data classification and general features of two developed models.

5.1 Decision tree

In order to train the decision tree algorithm, a large dataset with historical records is required. For the given fault detection algorithm, the total number of days when the measurements were performed is equal to 46. *Table 3* presents detailed information of the data acquisition process.

Table 3 Details of recorded data

Working state of a fan	Days of measurements
No fault	21
Fault in the intake area	16
Work with additional friction	9
Days in total	46

Total number of measurement points (power)	7420
Number of detected and removed outliers	5
Total number of measurement points (temperature)	67267

The records were divided into two different sets: 5/6 of total data available was used for the model training and the rest of records were used to evaluate the model performance. Test data was extracted from 6 different points of the total dataset to ensure proper diversity of records used for the model evaluation. In the result of a division, the training dataset contained 6175 measurements points of a fan load.

For this work, decision tree models were trained with the use of the application Classification Learner included in the software MATLAB R2016a. The application allows to classify data using supervised machine learning techniques and it is a part of the Statistic and Machine Learning toolbox. Classification Learner processes data using several models including decision trees, discriminant analysis, logistic regression classifiers, support vector machines, nearest neighbour classifiers and ensemble classifiers.

In the first step of the decision tree model development, the input values and the complexity of the structure have been defined. For the given case, the possible input data includes fan load, period of the day and ambient air temperature. Moreover, the features of power consumption data (standard deviation, mean value, peak to peak value) are calculated over time, which is also set beforehand. The complexity of the decision tree model is measured by the maximum number of splits, which can vary from 4 to 100. The several models with different structures were developed to compare their accuracy in classification.

5.1.1 Model I

In the first of the considered models, the input data includes average load, peak-to-peak value and standard deviation. The features were calculated for every 2 hours of measurements, resulting in 492 observations obtained from the whole database; among them, 404 points were used for the model training. *Figure 27* visualises the input data as a scatter plot between average load and standard deviation of power measurements during the period of two hours. The graph indicates that yellow observation points, which represent a fault in the intake air area, are characterised by a lower value of the average load, while in the case of majority of red points (fan work with extra friction), the average load has values higher than 7 W.

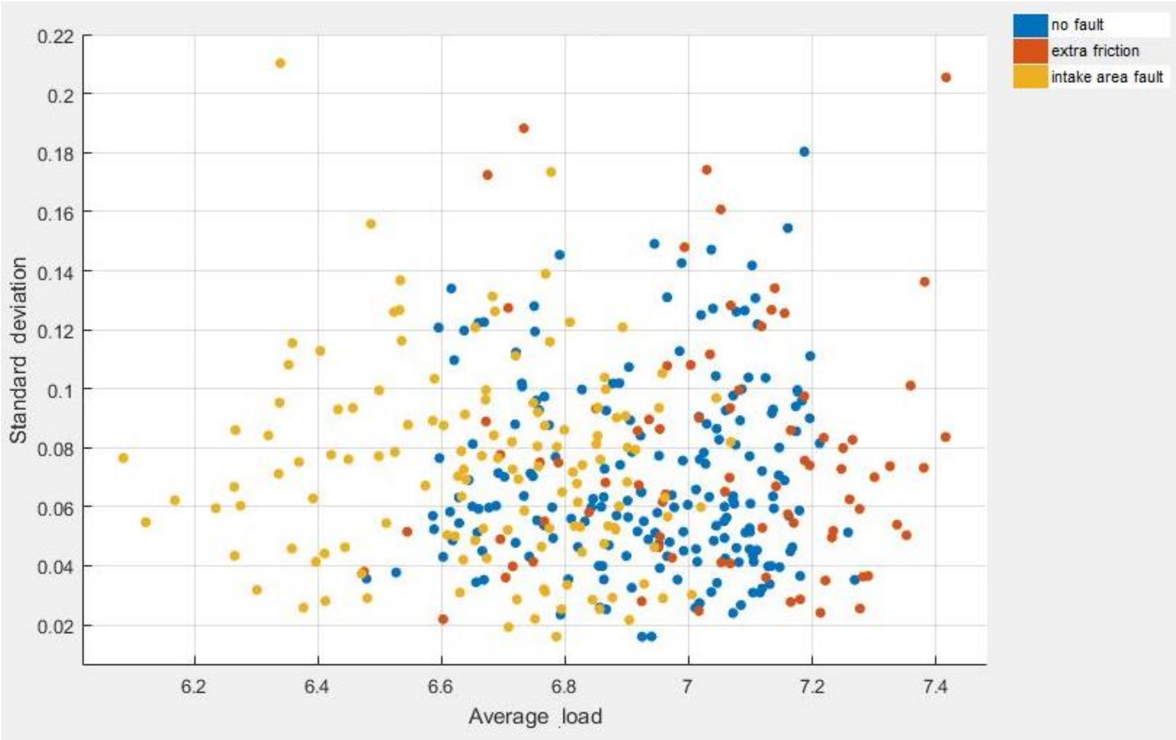


Figure 27 Original dataset for the model I

Based on the input data, the model of a simple decision tree was trained. The training time was 0.398 s and the prediction speed is estimated to be 14000 obs/sec. The model is characterised by the simplest structure of the decision tree, which is limited by the maximum number of splits equal to 4. *Figure 28* presents the structure of the tree. It can be seen, that model of the simple structure takes into consideration only average load as a decision attribute.

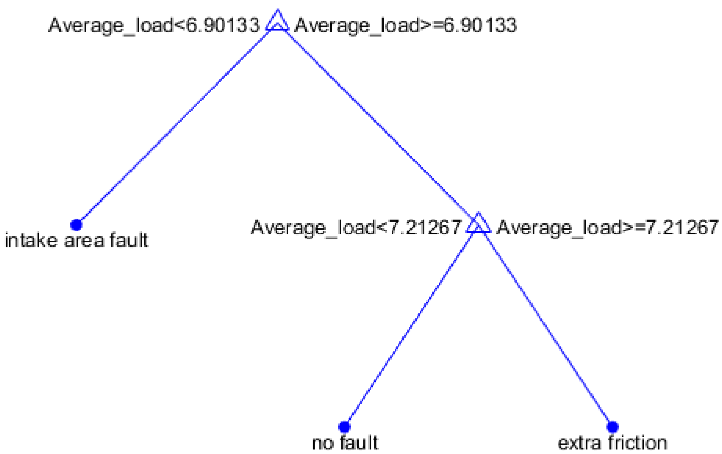


Figure 28 Structure of the decision tree, model I

The accuracy of the developed model was evaluated within the tool Application Learner as **62.1 %.** In total, 251 observation were correctly classified. The largest number of errors occurs between the classes "intake area fault" and "no fault". The fault in the air surface area is detected in 60 observation, while the true working state is normal operating conditions. The detailed results of the observations misclassification are presented in *Figure 29*.

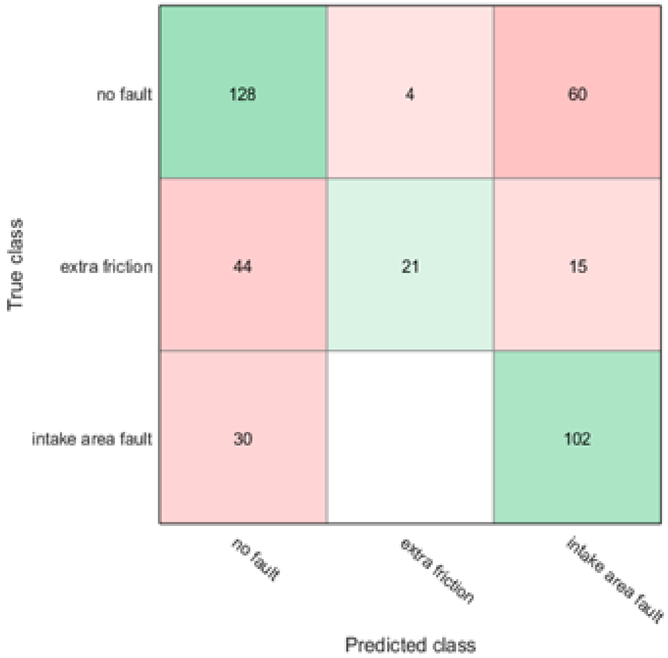


Figure 29 Confusion matrix, model I

During the evaluation process, the the test data (not used for the algorithm training) was used by model I to predict the operating state of a fan. In the next step, model predictions were compared with the true working class (*Figure 30*).

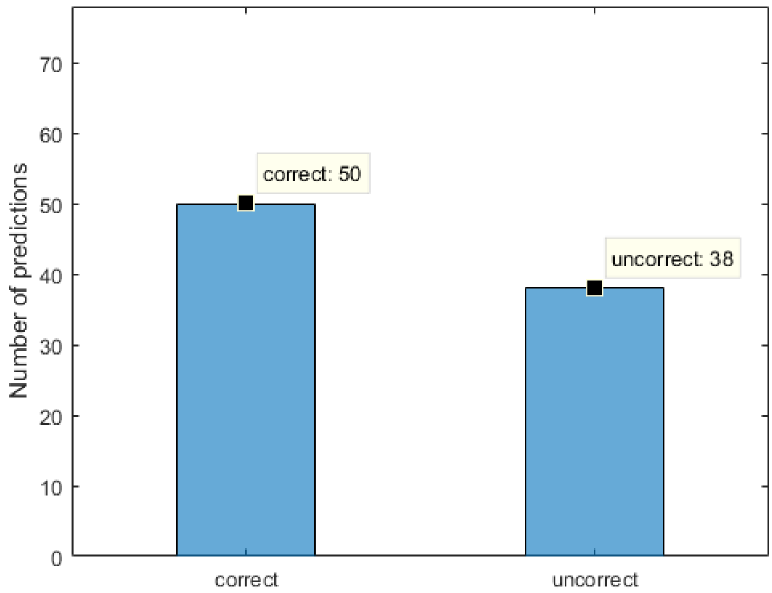


Figure 30 Evaluation of the model performance, model I

The algorithm correctly classified working state of the 50 observations, resulting in a prediction accuracy of **57%**, which is comparable with the 62.1% of the training set. The low value of the performance efficiency indicates that models with different input data and structure should be considered.

5.1.2 Model II

To improve the accuracy of data classification, a model II - with different input values and more complex tree structure - was designed. The features of power consumption changes are calculated over a shorter period, in comparison to the previously examined model. Features are extracted every 40 min from the database of measurements, which resulted in 1237 observations points used for the training and 244 used for the model evaluation. The tree structure of the model II is more complex, with a maximum number of splits equal to 20.

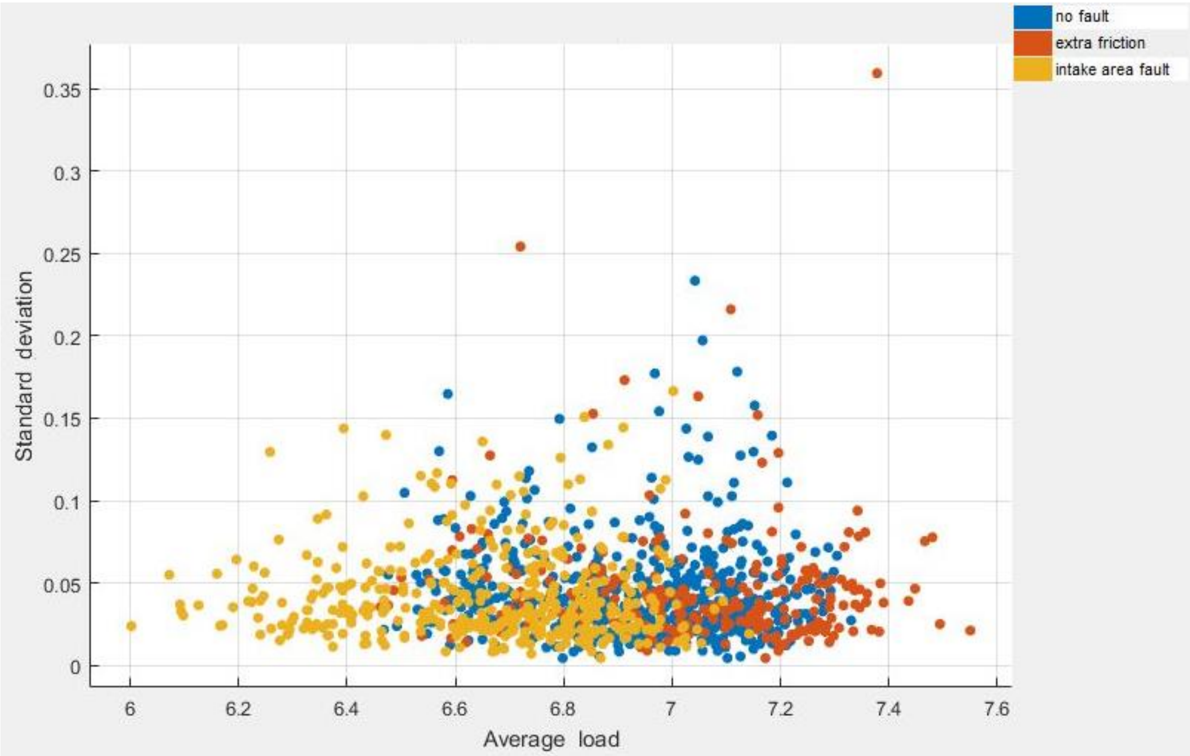


Figure 31 Original dataset for the model II

The input data for the algorithm training is presented in *Figure 31*. It can be seen that, similarly to the graph of the model I (*Figure 27*), the points which describe the fault of the extra friction are clustered in the right part of the graph and the points which represent a fault in the air intake area are characterised by a lower value of the average load. However, the overall set of points available for model training is larger than in the previous case. Based on the input data, the new model was trained as a medium complex decision tree. *Figure 32* presents the schematic diagram of the algorithm structure. In the more complex tree structure, values of standard deviation and average load are considered as decision attributes. Some of the detailed values of those quantities, which are taken in the consideration during a classification process, are not displayed in the figure to preserve the clear structure of the diagram.

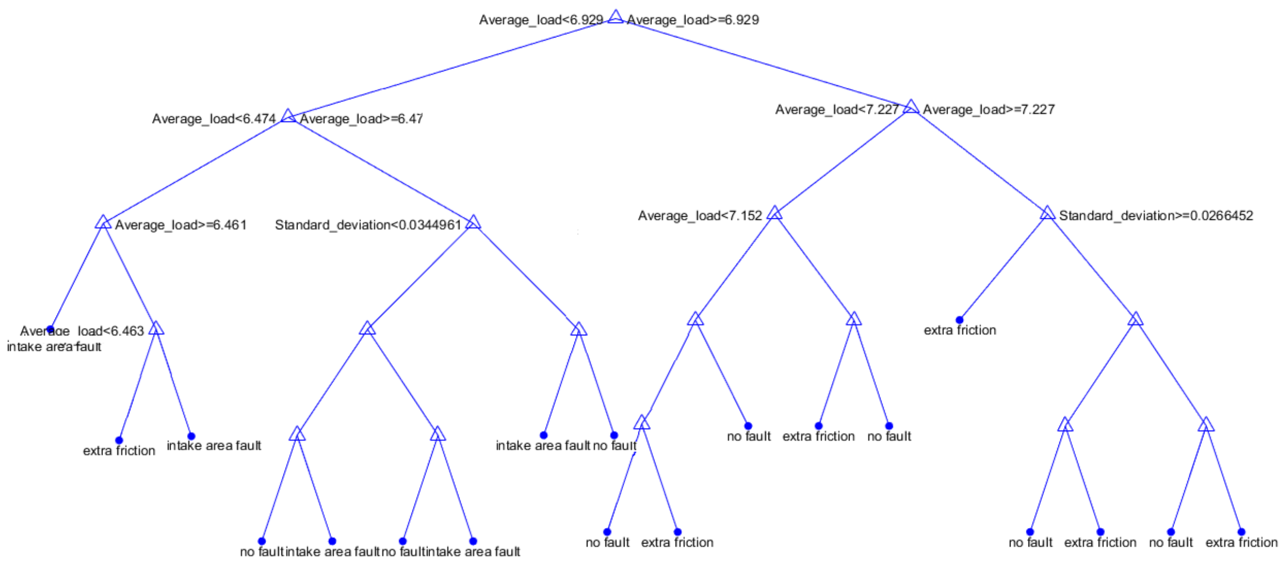


Figure 32 Structure of the decision tree, model II

It can be observed that in this more complex tree structure, both average load and standard deviation are the decision attributes. For such model, the software estimated accuracy of classification to be **60.5 %,** with the number of correct perditions equal to 749. The most common misclassified classes were again "fault in the intake area" and "no fault", with the total number of wrong prediction equal to 277 (*Figure 33*).

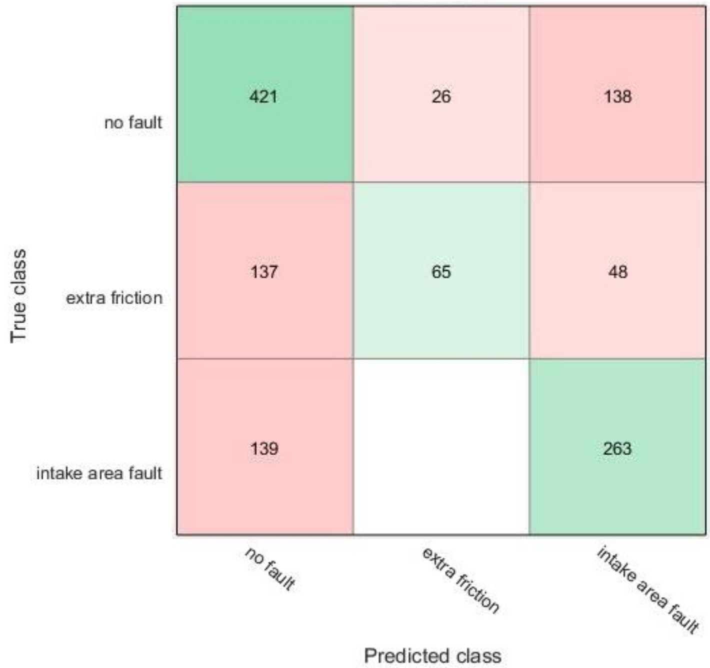


Figure 33 Confusion matrix, model II

The model evaluation was also performed on the 244 data points excluded from training set. The number of correct prediction is equal to 145, resulting in the algorithm accuracy of **59.4%** (*Figure 34*), which again is comparable to the accuracy with the training data**.** Classification efficiency is 2 percentage points higher than in the case of previously evaluated model, but the results show that the use of a more complex tree structure and the reduction of period over which features were calculated lead only to a small improvement of the model performance.

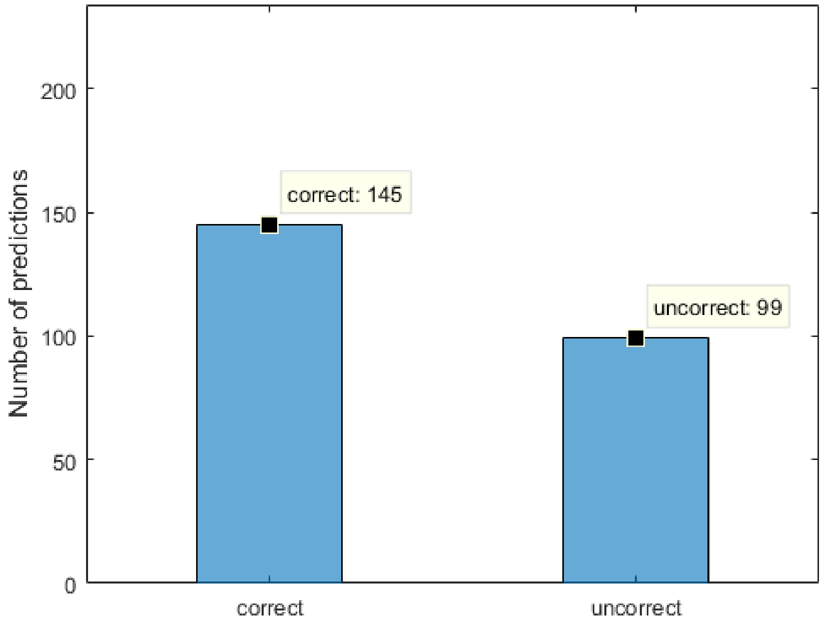


Figure 34 Evaluation of the model performance, model II

5.1.3 Model III

In the studies carried out in *Chapter 4,* fluctuations with a daily cyclic behaviour in the fan load fluctuations were observed: during daytime, the power consumption is lower than in the night hours. Therefore, it was decided to include information about the period of the day when the measurements were performed in the next model. The features were calculated every 40 min, which results in the training set consisting of 1237 observation points. *Figure 35* presents the observations included in the training set in a form of the scatter plot between the average load in the period of the day.

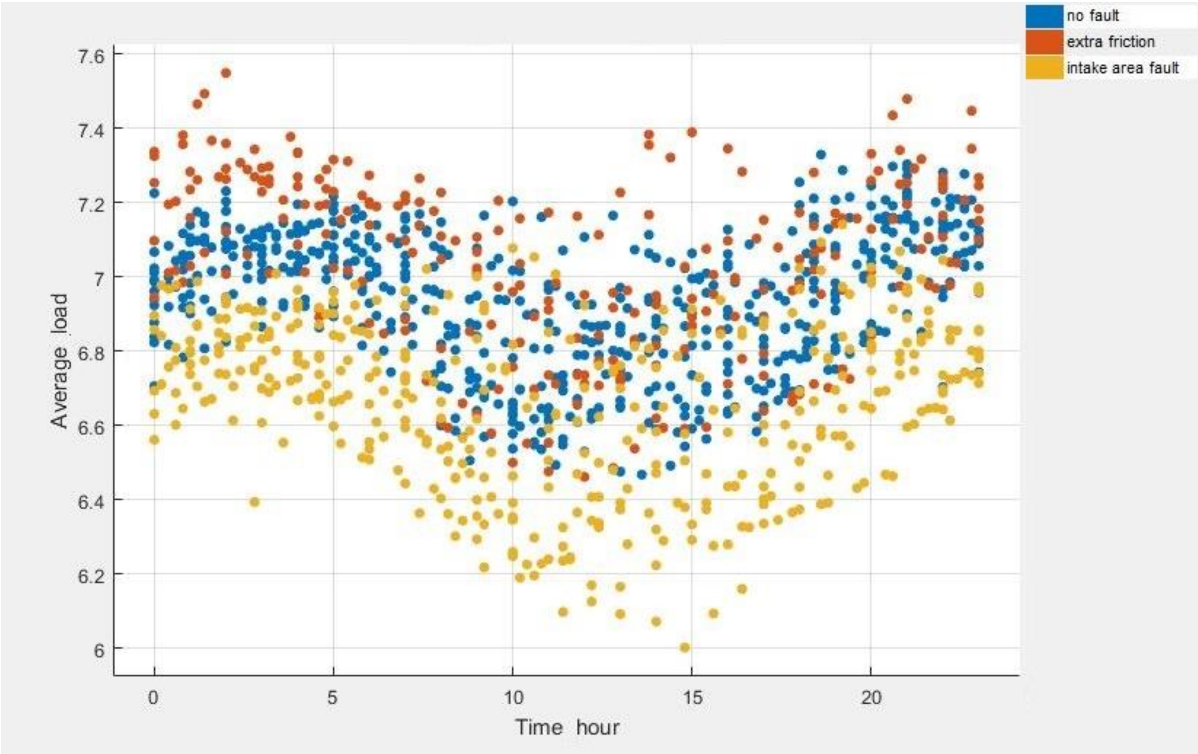


Figure 35 Original dataset for model III, average load in the function of time

It can be observed that the points of each considered class are gather in different layers along the graph, which enables a better distinction between fan operating conditions. Model III has a medium complex structure tree, limited by the maximum number of splits equal to 20. The tree structure is presented in *Figure 36*. Some detailed values of attributes are not displayed in order to preserve clear view of the figure.

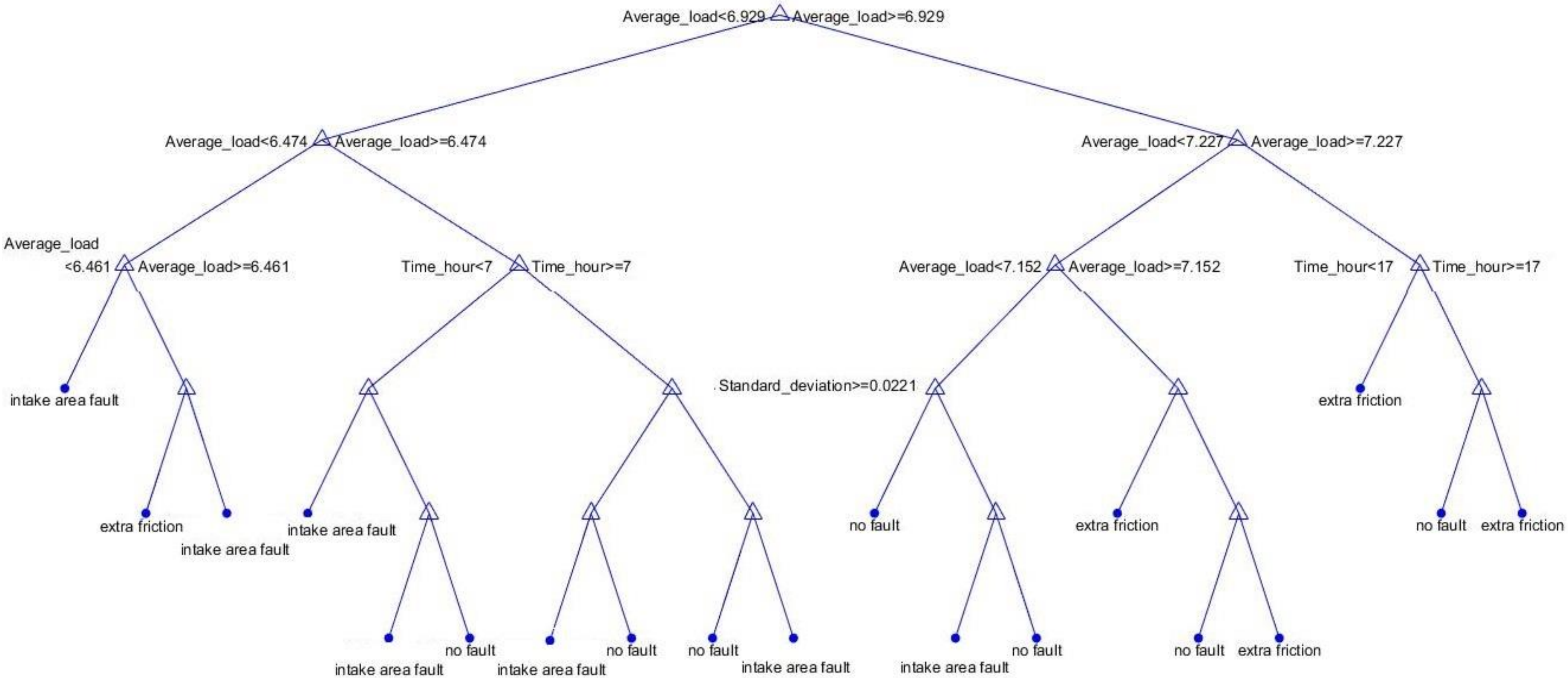


Figure 36 Structure of the decision tree, model III

The developed algorithm during data classification takes into account three attributes: average load, period of the day and standard deviation. The peak-to-peak value is not included in the tree structure, therefore calculations of this feature are redundant. The model efficiency was evaluated by the software at the level of **67.3 %**, which means that for 833 from 1237 observation points, the class was predicted correctly. *Figure 37* presents detailed information on data misclassification.

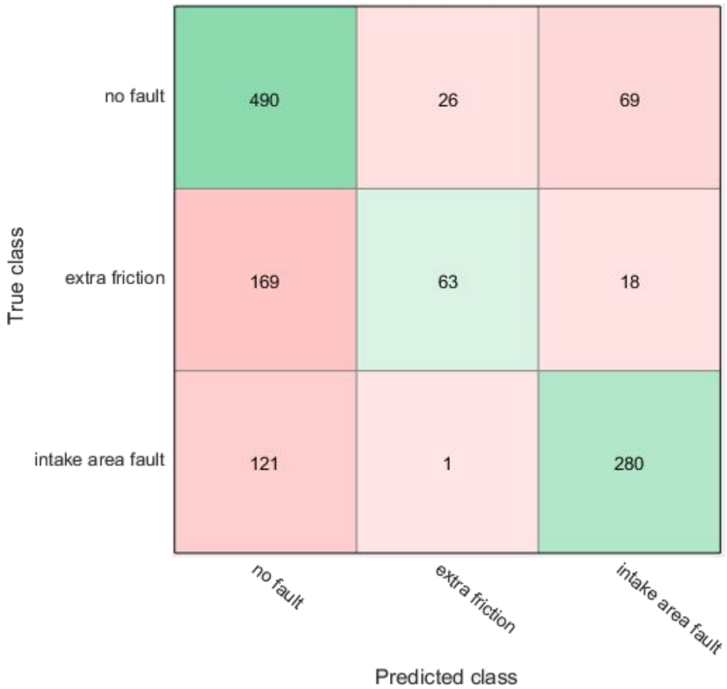


Figure 37 Confusion matrix, model III

The figure indicates that a high level of misclassification is observed between classes: “no fault” and “extra friction”. Including information about the period of the day significantly improved the efficiency in distincting a “fault in the intake air area” and the lack of fault. The total number of false predictions is 190 and is 87 lower than in the case of the previously developed model.

The model performance was also evaluated on the test data set. The algorithm correctly predicted the operating state of a fan in the case of 167 observations from the total of 244 observations. Therefore, the accuracy model is **68.4 %,** which confirms the significant improvement in the performance (9 percentage points in comparison to the previously evaluated model II).

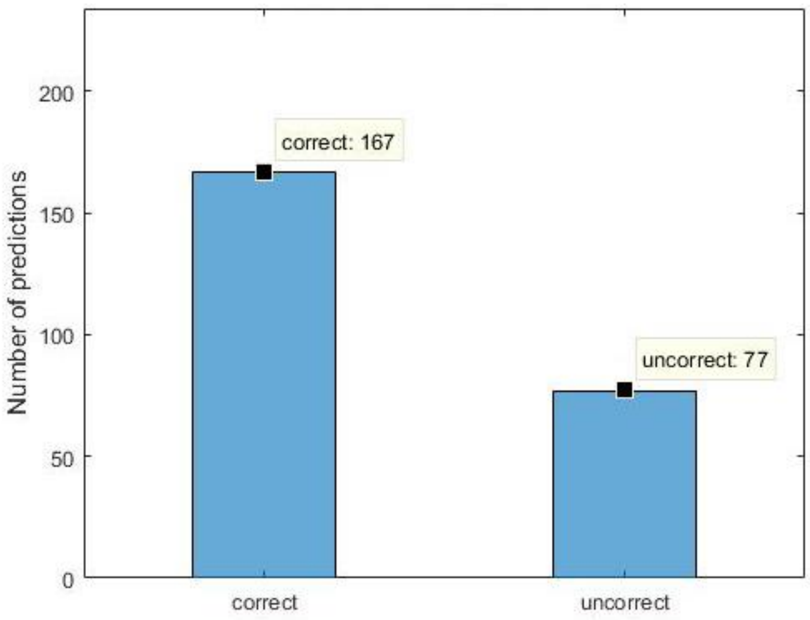


Figure 38 Evaluation of the model performance, model III

The detailed statistics of the correct predictions are presented in *Figure 39*. It can be observed that the states "normal operating condition" and "fault in the intake air area" are classified with the highest accuracy. Conversely, efficiency in detecting the fault caused by the additional friction is very poor. The malfunction was correctly classified only in the case of 16% from all observations characterised by this type of the fault.

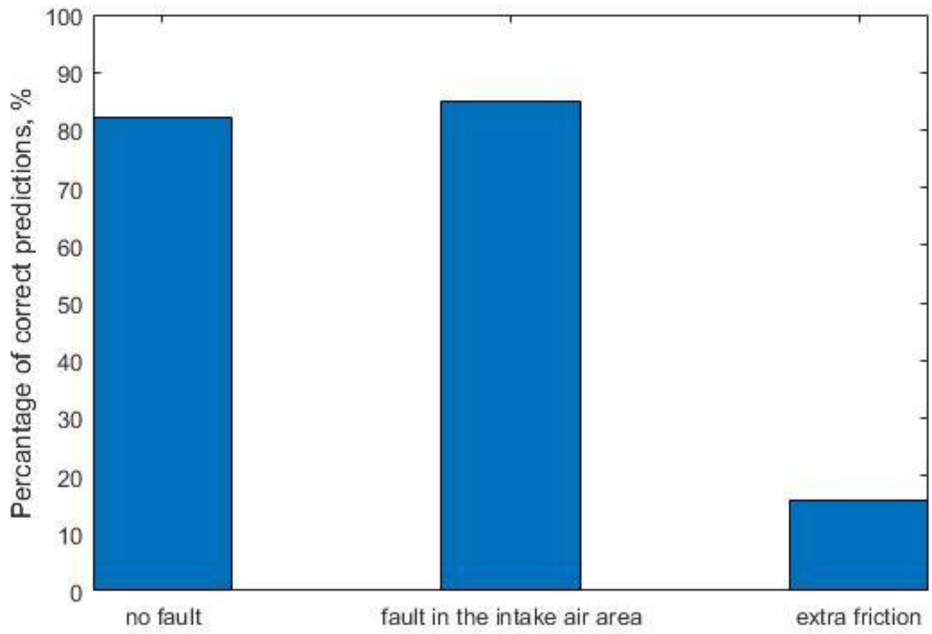


Figure 39 Statistics of the model correct data classification

5.1.4 Model IV

In the next step of the model optimisation process, it was decided to examine how the complexity of the tree structure affects the classification efficiency. Therefore, the input variables and the training data set are identical to previous case (model III, *Figure 35*). However, the decision tree architecture is more complex. The structure of model IV is limited to the maximum number of splits equal to 100. The decision tree is presented in *Figure 42*; detailed values of branch nodes and some leaf nodes are not displayed to present a clear overview.

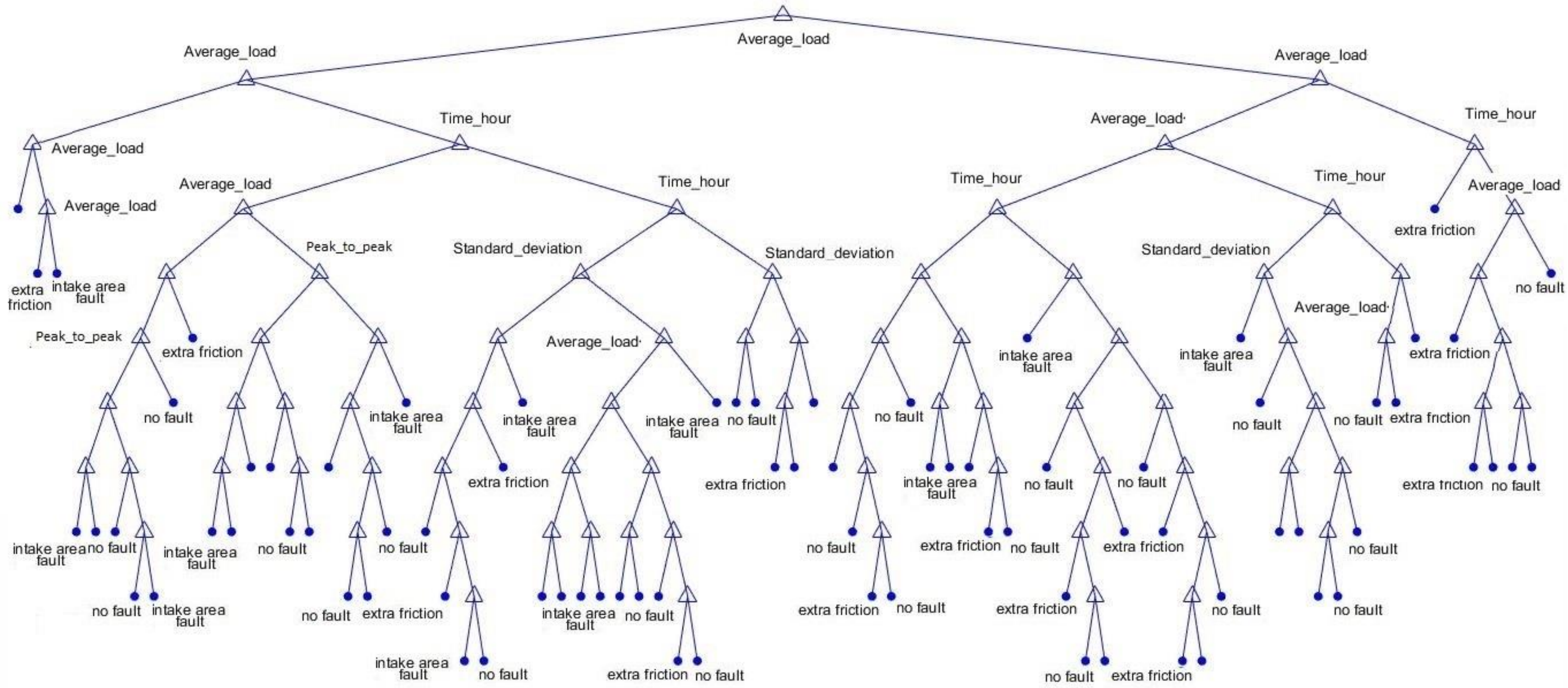


Figure 40 Structure of the decision tree, model IV

After training of the algorithm, the model efficiency was evaluated as **62 %.** The accuracy in the data classification for all investigated classes has decreased in comparison to the model III (*Figure 41*). Overall, 767 observations were correctly predicted, thus the number of false predictions is 66 higher than in the previously examined algorithm.

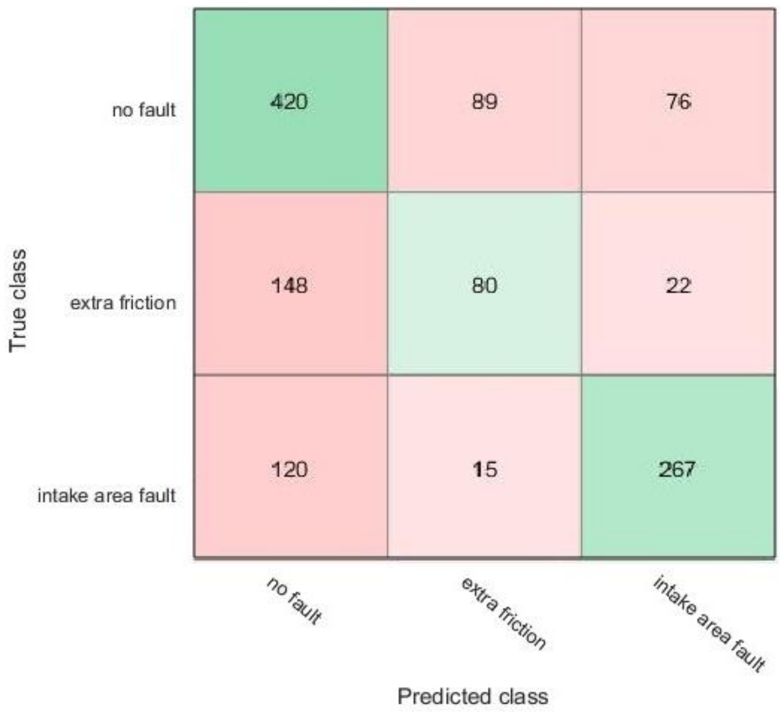


Figure 41 Confusion matrix, model IV

The evaluation of algorithm performance on the test data set also proved to achieve a lower classification accuracy. *Figure 42* presents a bar chart of predictions on the fan operating state. 153 observation points were classified correctly, which corresponds to a model efficiency equal to **62.7 %.**

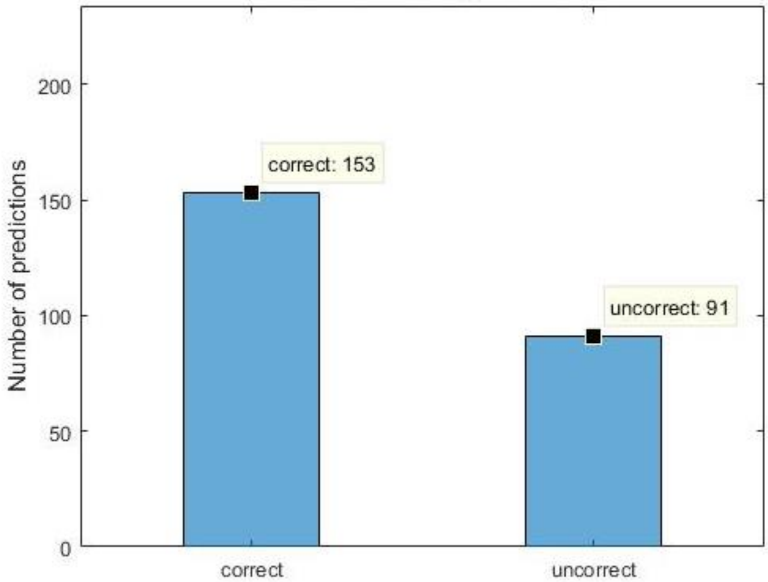


Figure 42 Evaluation of the model performance, model IV

The observed decrease in the accuracy of data classification indicates that the model is too complex with respect to the size of the training data. Therefore, for the given algorithm, it is recommended to limit the tree architecture with the maximum number of splits equal to 20 or to increase the size of the training set by acquiring a larger dataset of measurements performed in the laboratory stand.

5.1.5 Model V

During the process of data acquisition, measurements of the fan load and ambient air temperature were performed. So far, input variables of models included only the power consumption and the period of use. Model V was developed to investigate if the addition of the temperature measurement improves the algorithm efficiency. The dataset used for the training is identical to the one previously used to obtain model III (*Figure 35*), but the set of input variables is extended with the average value of air temperature.

After adding the average temperature to the input variables, three different tree structures were trained: simple, medium and complex. The simple tree architecture was evaluated as the most efficient, with a classification accuracy of **81.1 %.** The detailed information on the data classification is presented in *Figure 43*. The figure indicates that the "fault in the air intake area" was detected for almost all cases. Similarly, the majority of observations of the class 'no fault' were classified correctly.

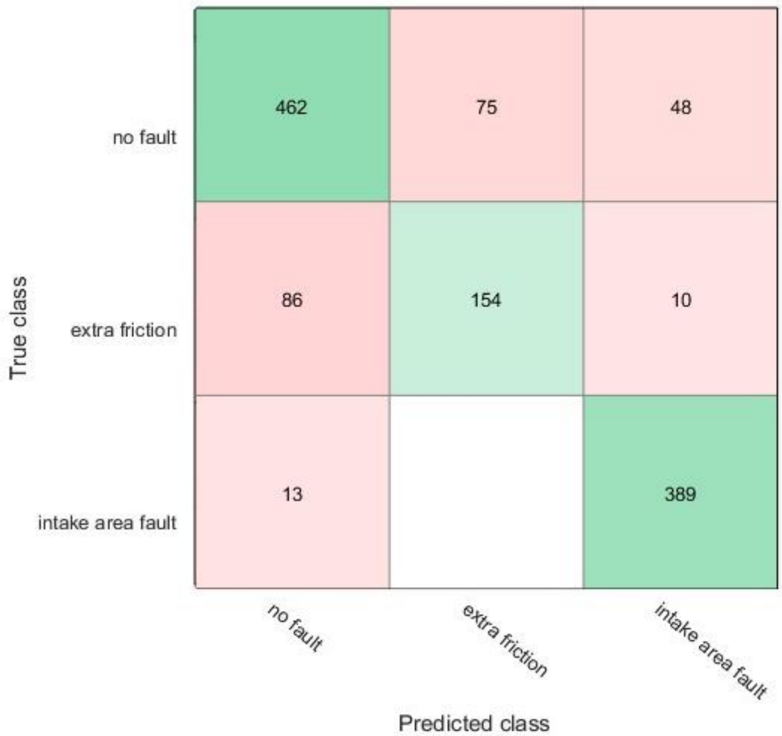


Figure 43 Confusion matrix, model V

To investigate the cause of the significant improvement in the classification accuracy, the decision tree structure (*Figure 44*) was examined. The figure indicates that after the algorithm training, the air average temperature was chosen as the attribute which classifies in the best way the training dataset (root node). However, as discussed in *chapter 4.2*, the air temperature influences only daily fluctuations in the fan power consumption and those temperature changes are of lower importance for the fault detection algorithm. Therefore, the choice of average air temperature as the main attribute is incorrect. The high classification accuarcy is caused by the change of ambient coniditions during the measurments of different operating condtions of a fan. The measurements of the fault causing additional friction were performed during the winter time, when the ambient temperature was lower, while the other experiments were performed during the warmer time of the year.

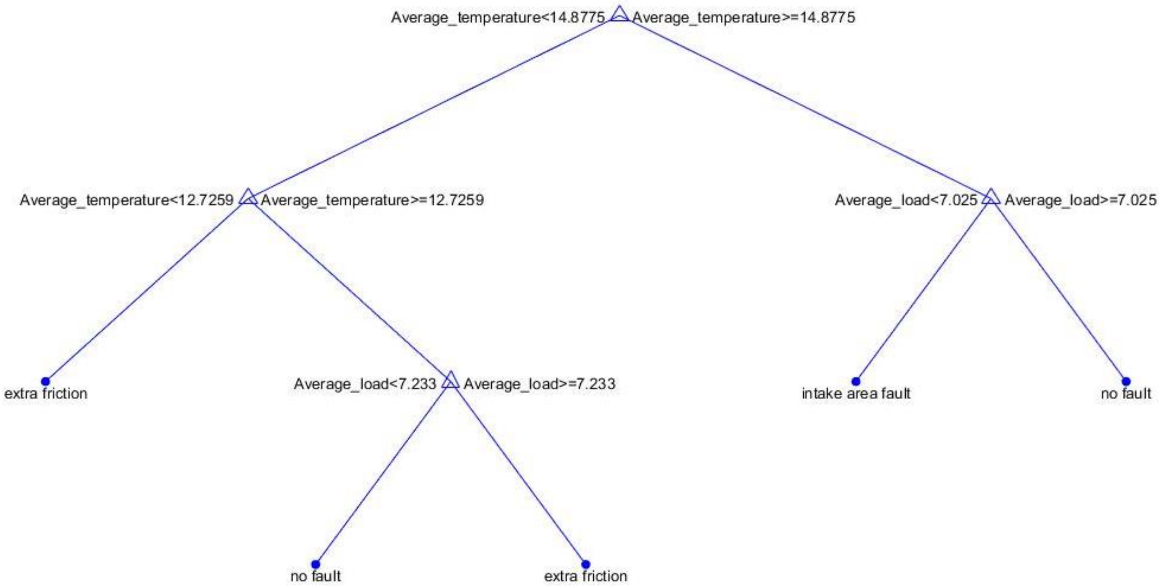


Figure 44 Structure of the decision tree, model V

For this reason, including information about ambient temperature significantly improves the accuracy in classification for a particular dataset. The algorithm became tailored fit to the specific sample, but it does not reflect overall population. [32] In the general case, the correlation between the average air temperature and the presence of a fault (which was detected by the algorithm) does not exist. Therefore, the developed model is incorrect and it will lead to the wrong conclusions.

5.2 Neural network

Artificial neural networks is another example of a computational approach widely applied for the pattern recognition. The algorithm based on the neural networks was developed to examine the efficiency in the fan fault detection. The network was trained using the same dataset using the Neural Network Pattern Recognition toolbox, which is included in the MATLAB software. The obtained accuracy in the classification is then compared with the efficiency of the decision tree model.

The designed network consists of the input layer fed with 4 input variables, 10 hidden layers of neurons and the output layer. The network inputs were chosen based on the model III of the decision tree, which was characterised by the best performance. Therefore, the 4 input quantities include average load, period of the day, standard deviation and peak-to-peak value. The calculations of features were performed over the time period of 40 min, which results in a training set consisting of 1237 observations and a test set of 244 observations. The result of the output layer of the neural network is a prediction on the fan operating state from the three investigated classes: no fault, fault in the input area and fault causing extra friction. The network architecture is presented in *Figure 45*.

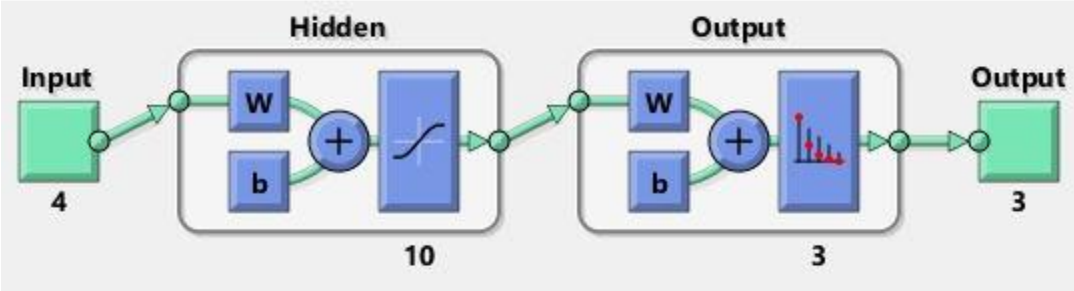


Figure 45 Network architecture

The activation function used in the network is the non-linear Log – Sigmoid function. The function generates outputs between 0 and 1, which allows to estimate how probable is the prediction of the particular fan working state for each case. The network has the feed-forward architecture, i.e. the information flows from the inputs to outputs in only one direction.

After the network training, the efficiency was evaluated at the level of **70%**. Overall, 372 observations were classified incorrectly and the highest misclassification was present between the classes "extra friction" and "no fault" (*Figure 46*).

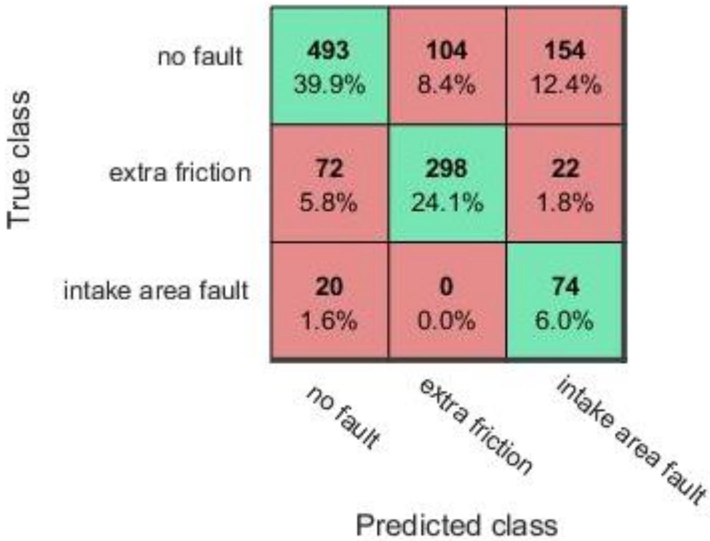


Figure 46 Confusion matrix, neural network

The neural network accuracy of classification was also evaluated on the data external to the training set. As the output, the neural network determines the probability distribution between classes of the given observation point. For this work, the class with the highest probability was chosen as the network prediction, what lead to the results presented in *Figure 47*. From the data set consisting of 244 points, 172 events were predicted correctly. The classification accuracy is high and equals to **70.5 %.**

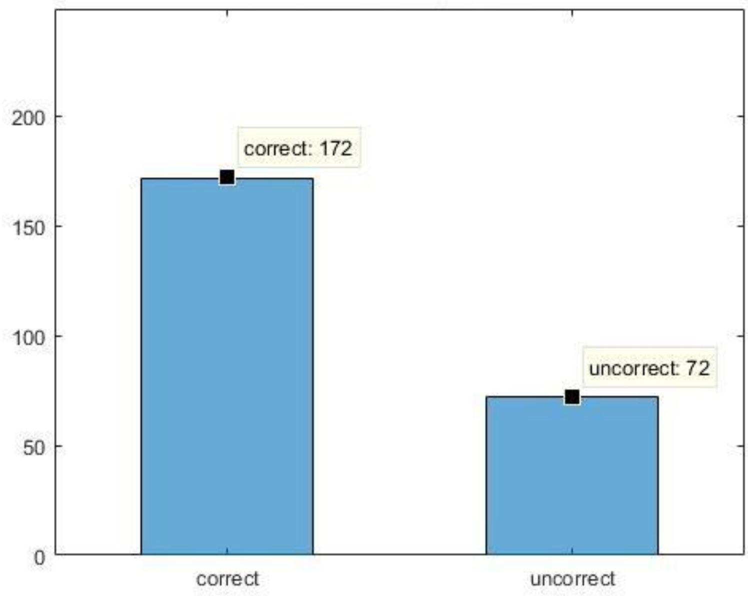


Figure 47 Evaluation of the model performance, neural network

The detailed information on the model performance is presented in *Figure 48*. The graph indicates that, similarly to the decision tree model, the highest classification accuracy is observed for the classes “no fault” and “fault in the intake air area”. The malfunction causing additional friction was predicted correctly only in 15% of the cases.

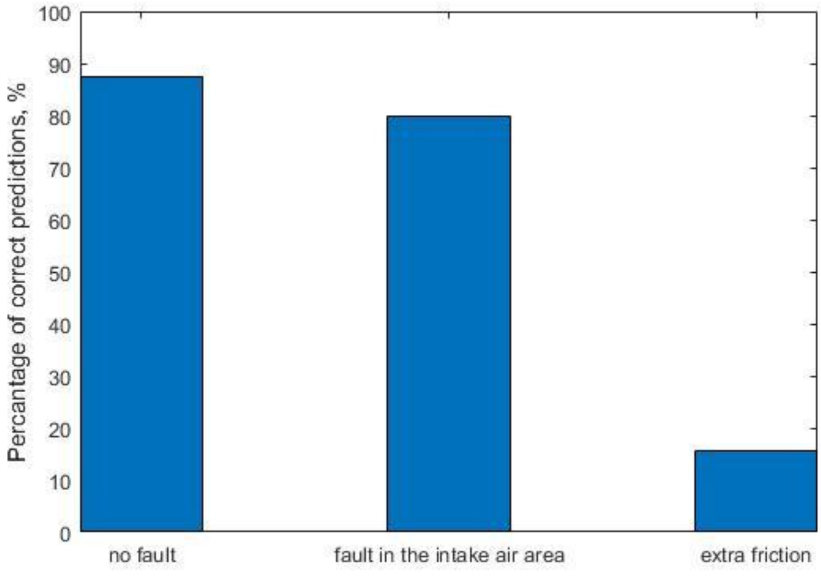


Figure 48 Statistics of the model correct data classification, neural network

5.3 Discussion of the results

In *Chapter 5.1* several decision tree models analysed to select an algorithm characterised by the best performance. The Table 4 compares the characteristics and classification accuracies of all developed models.

Table 4 Summary of the decision tree models characteristic

Model	Inputs	Time period over which features are extracted	Complexity of the tree structure	Accuracy: training dataset	Accuracy: test dataset
I	Power measurements	120 min	Simple (maximum 4 splits)	62.1%	57%
II	Power measurements	40 min	Medium (maximum 20 splits)	60.5 %	59.4 %
III	Power measurements, period of the day	40 min	Medium (maximum 20 splits)	67.3 %	68.4 %
IV	Power measurements, period of the day	40 min	Complex (maximum 100 splits)	62 %	62.7 %
V	Power measurements, period of the day, temperature	40 min	Simple (maximum 4 splits)	81 %	The model is incorrect, efficiency has not been evaluated

Based on the obtained results for the given dataset, the most efficient and correct model has following characteristics:

- Inputs: power measurements and period of the day,
- Extracted features: average load, average hour and standard deviation,
- Time period over which features are extracted: 40 min,
- Complexity of the tree structure: medium (maximum 20 splits).
- Overall accuracy of data classification: 67.3 % (training set) and 68.4 %(test dataset).

The original set of the features includes peak to peak value. The analysis of the tree structure indicates that the value is not selected as the attribute in the tree node, therefore the extraction of this feature is redundant and unnecessary, as it requires additional computational memory.

The characteristics of the most efficient decision tree model are selected as the entry parameters for the neural network algorithm. The neural network performance was better than the decision tree algorithm in both cases: with the training sets and with the test dataset (external to the training). However, since the difference in classification accuracy is small (two percentage points only), both methods, decision tree and neural network were considered to be suitable for the given problem. It is important to underline that the algorithms rarely detected the fault causing extra friction during the fan operation. This leads to the conclusion that not all malfunctions are possible to diagnose with the use of pattern recognition based on the energy consumption.

The high efficiency of the neural network model is caused by the utilisation of nonlinear functions and adaptive learning. The flexibility in learning is particularly useful when new data is continuously introduced to model. The neural network is capable of reflecting the information of the new instances on the model very efficiently just by changing the weight values. The advantage of the algorithm is also the form of prediction – results are presented in the form of probability distribution. On the other side, the neural network represents the black box learning approach. The relationship between input and outputs cannot be visualised and analysed in the way it is possible with the decision tree algorithm. Moreover, neural networks take more time to be trained and evaluated.

The decision tree model is characterised by being easy to understand and having a clear relationship between input and output. The clear and easy to follow the tree structure enables to analyse the process of data classification and identify errors or wrong assumptions within the process, as it happened for Model V. Decision trees are also fast to be trained and power – efficient. However, their work principle is the simple data division, which can result is a worse classification accuracy. Conversely to the neural networks, decision trees algorithms are not suitable for applications which require constant updates of the model. If new data includes some exceptional situation, it will be necessary to train the algorithm one more time.

Chapter 6

Conclusions

The thesis aimed to develop a fault detection system of a fan based on the pattern recognition of its energy consumption. The development of a fault detection system with the use of a history based method and supervised learning algorithm requires large datasets of measurements for both normal and faulty operating conditions. For this purpose, a laboratory stand was built and that allowed to acquire data of both states. However, in real world application, acquisition of large datasets of measurements carried out during operation with all possible machinery failures is often unrealistic. Moreover, the dataset used for the algorithm training should include records performed during various ambient conditions. The incomplete training dataset can lead to poor efficiency in fault detection and results in the need to perform constant updates. The acquisition of large and complete dataset is a significant drawback of fault detection system based on the process history method.

Another important issue during the system development is the choice of features extracted from the dataset and the algorithm input values. The feature selection is often not a straightforward task. The extracted features should be damage sensitive and robust to the varying machinery operating conditions and background noise. On the other hand, it is recommended to perform computations in an inexpensive way due to the large size of signal data. The choice of the algorithm inputs should also be done carefully in order to prevent the overfitting problem. The developed model should not be tailored fit to the specific sample, but should reflect the overall population of events.

The analysis of developed models leads to several conclusions. Both examined algorithms - decision tree and neural network - had a similar overall accuracy in the prediction of the operating state, thus both methods are suitable for the given classification problem. The developed algorithms were characterised by the high efficiency in the prediction of "clogged air intake area" fault, but the fault causing extra friction was rarely detected. Therefore, not all malfunctions of the fan are possible to diagnose with the use of pattern recognition of the energy consumption. For this type of failures, it is recommended to apply a method that is more damage sensitive (e.g. vibration analysis).

Both algorithms - decision tree and neural network - were trained with the use of the Statistics and Machine Learning toolbox and Neural Network Pattern Recognition toolbox. The applications are included in the MATLAB 2016a software. The software is characterised by the user-friendly structure and interface and also by the broad scope of available documentation. The main advantage of the decision trees includes the clear and easy to understand structure, which enables to identify errors or wrong assumption. On the other hand, the neural network is highly efficient due to the utilisation of nonlinear function and flexibility in learning.

6.1 Future work

While carrying out the investigations described in this thesis, it became apparent that there is still lots of work that could be done to develop a complete fault detection system. To improve the performance of the already developed algorithms, the training dataset should be extended by a greater amount of measurements carried out in the various conditions. The set of possible faults could also include different types of common fan malfunction, for example, blade failures. Moreover, it is recommended to investigate the possibility of implementing algorithms in a real-time fault detection system. In that case, the developed models will be connected to the online platform: www.my.eot.pt. The models will continuously process the data sent by the energy meters in order to detect device malfunctions. The work could be also expanded with measurements carried out in the big, industrial ventilation system, where the failure detection is of high importance and results in both economic and comfort gains.

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