Chapter

Quality Determination of Hydraulic Pumps with Adaptive Fuzzy Pattern Classifiers to Reduce the Risk for Quality Management

Amir Nemati, Elif Öztürk, Steffen F. Bocklisch and Welf-Guntram Drossel

Abstract

Automated production of complex assemblies such as hydraulic pumps also requires reliable detection of defects utilizing functional tests. In principle, this is a classification task in good/bad, which, however, is often not to be made sharply but should provide gradations for detailed error analysis. From this, conclusions can be drawn, for example, about the type or location of the defects, wear, or aging of components in the production chain. A high-dimensional vector of data from static or dynamic measurements including is generally available as the basis for the fault detection model. Modeling such complex nonlinear systems under various load conditions with dynamic test procedures leads to uncertainties that should also be reflected in the diagnostic model. For this, the design of the classification model (the classifier) should be largely automatic during the training phase for time and cost reasons. In addition, online updating under actual operating conditions is also often desired. These challenging goals can be met through the artificial intelligence (AI) methodology of fuzzy pattern classification. This chapter deals with the development of a fuzzy classifier for the application case of the final inspection of hydraulic axial piston pumps. The focus is on the automatic training of the classifier employing a new adaptation procedure and permanently (until termination) evaluates the resp. current classifier using performance measures. Using real experimental data, the procedure and the step-by-step adaptation results for different links between the current classification model and the new data are presented and compared.

Keywords: fuzzy pattern classification, adaptive fuzzy pattern classifiers, hydraulic pump, quality control, productivity improvement

1. Introduction

Today, in the various industrial sectors, the primary objective of each industrial unit is to improve the quality level of the products manufactured. More confidence in the equipment used is one of the requirements that the designer must consider as one of the basic objectives of any system, which is achieved through the timely detection of defects. Designers face the challenge of designing diagnostic systems that must be robust to faults within the system and resistant to uncertainties in the system. The uncertainties introduced by modelings, such as linearizing nonlinear systems and process parameter variations, cause the diagnostic system to fail and generate false alarms [1, 2].

Due to the numerous advantages of hydraulic drives over other drives, such as reliability, low power consumption, precise controllability, and high performance, such assembly systems are increasingly used. In the hydraulic industry, the hydraulic pump is the central part of hydraulic systems, responsible for generating flow and pressure in the process. In general, defects in hydraulic pumps can cause severe and irreparable damage, requiring costly repair and overhaul. Therefore, diagnosis, detection, and repair of defects in the pump components are crucial at the initial stage. The operation of hydraulic pumps is affected by various factors such as friction, adhesion, incompressible fluid, and internal and external leakage. Therefore, hydraulic pumps have nonlinear behavior and are complex nonlinear systems with multiple inputs and multiple outputs whose input and output behavior cannot be described by physical exact mathematical models. Therefore, theoretical modeling would only be an inaccurate model of the system. Since we need to simplify the input data, we are often forced to accept a certain degree of inaccuracy and uncertainty in mathematical models, which then cannot achieve acceptable results for the dynamic behavior of the systems [3, 4]. In such situations, a data-based controlled nonlinear black-box system provides a reasonable approximation to nonlinear systems. In these approaches, models are built based on the process's measured input and output data, requiring little or no physical or formal information [3]. The literature shows that black-box models, such as neural networks and fuzzy logic-based models, are widely used to build fault diagnostic models from measured input/output data [5–7]. These approaches perform better than statistical models [1] and mathematical equations [3].

For the prediction of hydraulic pump failure, the correct and accurate categorization of faults is essential because various factors affect the failure of the hydraulic pump. The fault categories can be understood as classification. Qualitative variables are considered, and the classification approach can be used for qualitative variables. Various approaches to classify data sets include regression, artificial neural networks, probability, and fuzzy approaches. However, these classification approaches are static, and the nature of static classification leads to several primary principle weaknesses on the user's side [8, 9].

1. The first issue is that these static classifications cannot adapt to the current user data stream that occurs in real systems. A comprehensive data set that covers all features of the system (big data), which is often required, is costly and time-consuming, complicated, and often impossible to achieve.

2. The second point is that the flow of new, unclassified, and unlabeled data requires a new classification that an expert or supervising supervised person has not provided. So the user's need may change, and the classifier should keep up with this need and automatically add a new class to its database.

Therefore, the goal is to develop a new method for automatic modeling in real-world situations and also with online data streams. The technical term for this category is Evolving Classification [10]. Evolving classifications can adaptively update their structures, components, and parameters according to the requirements of new process characteristics, system behavior, and operational and environmental conditions. These systems support modeling arbitrary scenarios of data flow, online measurements, and dynamic data whose nature and characteristics change over time. The main features of the evolving classifications are as follows [11]:

1. The learning process can be started from scratch, and the system can learn the classes required by the user without an initial learning phase.

2. Input samples can form new classes without losing previous knowledge, that is, or forgetting previous classes that the classifier has not currently seen.

3. Unlike traditional approaches, these evolving classification systems may have little or no learning phase.

The research work presented in this paper deals with axial piston pump. Specifically, a subset of these pumps of the variable displacement pump type was selected for the study. The axial piston hydraulic pump was designed and optimized for demanding heavy industry and shipping use. Thus, this type of pump, this axial piston pump in swash plate design in an open circuit with pressure ratings up to 420 *bar* and high speeds offers the user a high productivity and power density. The axial piston hydraulic pump is characterized by high conversion flexibility [12].

The main objective of this work is to provide a new fuzzy pattern classification approach [13] that works automatically, online, and without the presence of users. This classification method is applied to the final inspection and testing of hydraulic axial piston pumps.

2. Principles of pumps and axial piston hydraulic pumps

Nowadays, power transfer at low cost and high precision is desired in many processes. Hence, the use of pressure fluid in the transmission and control of power in all branches of the industry is expanding. Fluid power is separated into two categories: hydraulic and pneumatic. Pneumatic systems are used where relatively low forces (about one ton) and high-mobility speed are required (such as in systems that are used in drive robots). In pneumatic systems, compressible fluids such as air are used. In cases where high power and precisely controlled speeds (such as hydraulic jacks, brakes, and hydraulic steering) are needed, hydraulic systems are used. The advantages of hydraulic systems to mechanical and electronic systems are a simple design, power increase capability, simplicity and accuracy of control, flexibility, high efficiency, and reliability. Hydraulic systems are highly regarded in many industrial applications, such as industrial robot control, industrial machinery, automobile industry, hydraulic suspension systems, mechanical power transmission systems, and aerospace industries. Other advantages of hydraulic systems, compared to other mechanical systems, are the need for fewer actuator components and the achievement of high power and high-power movement at any point due to high-pressure flow in the tubes and hoses. In other mechanical systems, it is used to transmit power from components such as a cam, gear, lever, or clutch. As the heart of the hydraulic system, the pump converts the mechanical energy supplied by electric motors or internal combustion to hydraulic energy. The pump in a hydraulic cycle increases fluid energy to be used in the desired position. Hydraulic systems are based on Pascal's law. Like many mechanical systems, the disadvantages of hydraulic systems are their nonlinear and similar behavior. Several factors affect the operation of hydraulic systems, such as friction, adhesion, incompressible fluid, and internal and external leakage [14, 15].

The hydraulic axial piston pump is a type of hydraulic pump that has two fixed axial piston pumps and a variable axial piston pump. The multi-piston pump is used for mechanized hydraulic systems and can produce a more uniform flow of fluid. **Figure 1** shows the hydraulic axial piston pump. In the hydraulic axial piston pump type, the pistons are parallel to the central axis of the pump. The pistons are located around the central axis of the pump and in the circle's environment. The primary axial piston pump is based on the motion of the piston and the piston inside the cylinder that operates the suction and pressure of fluid in every move. In other words, the pump converts the rotary motion of the input shaft to the piston's back-and-forth linear motion. By embedding a mechanism for changing the angle of the back of the pistons, the displacement volume of a pump can be changed. This mechanism changes each piston movement's course, and the pump's discharge rate is adjusted by changing the angle between the two pump axes. There is no discharge at zero angles, and the maximum discharge is obtained at the maximum angle. Axial piston pumps are high-pressure pumps. Depending on the type of controller each pump has, the flow changes uniformly and continuously.

The pumps used in this work are axial piston pumps with a swash plate designed and optimized for demanding use in heavy-duty industrial and marine applications. With pressure ratings of up to 420 *bar* and high-speed ratings, this open circuit, swashplate-type axial piston pump provides its users high productivity and power density.

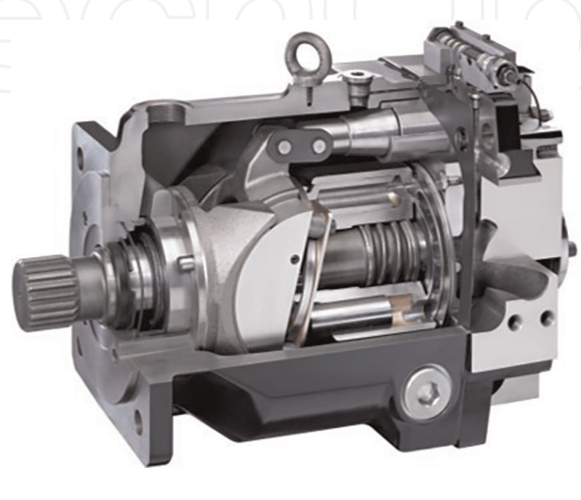

Figure 1.
Hydraulic axial piston pump [16].

As a standard, every swashplate-type axial piston pump comes with an integrated pre-compression volume, which ensures low ripple operation. A wide range of displacements and control options allows for various applications such as primary metal refining/processes, machine tools, marine, oil gas and power generation. The displacement for this pump ranges from 16 cm^3/rev to 360 cm^3/rev. These pumps are classified into five frame sizes according to the displacement. Each frame size can generate the discharge rate concerning the value of the swashplate angle. In **Table 1** and **Figure 2**, all types of frame size and their output flow are expressed.

The advantages of a swashplate-type axial piston pump include the following:

- Operating pressures of up to 350 *bar* (continuous) or 420 *bar* (intermittent) and high-power density.
- Accurate, high dynamic controls
- Outstanding response characteristics and productivity improvements.
- Excellent suction characteristics, high self-priming speeds, and increased productivity.

Frame size	Displacement [cm^3/rev]
1	16, 20, 23, 28
2	32, 40, 46
3	63, 80, 92
4	140, 180
5	270

Table 1.
Physical conditions and characteristics of the pumped fluid.

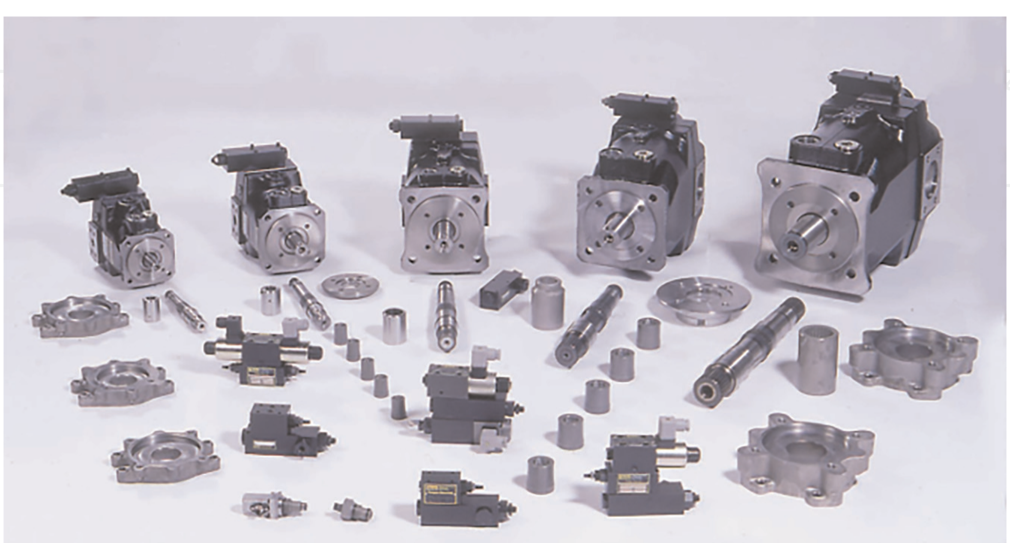

Figure 2.
Axial piston pumps with five different frame sizes [16].

There are several approaches to determining the quality of products or detecting defects and their classification. Product quality is diagnosed by processing multiple measurements using data analysis or logical reasoning links. It is also another way to compare real actual data and mathematical models of hydraulic pumps. However, creating a mathematical model is difficult because the pump system has considerable nonlinearities in parameters.

Another approach is to develop an intelligent system that learns the behavior of the hydraulic pump. Fuzzy pattern classification can be referred to as an approach to developing intelligent systems [13, 17].

3. Theoretical basis and methodology

Human intelligence has creativity, skill, awareness, intuition, and emotion. Intelligence is the ability to understand, think, and learn. The question is how to model this human ability and demonstrate it in a way that has computational efficiency. Traditional artificial intelligence and various mathematical and analytical tools for characterization, description, and analysis of systems attempted to simulate such intelligent behavior in systems requiring accurate and comprehensive representation of knowledge. With the increase in the complexity of dynamic systems, the traditional modeling techniques could not satisfy the needs any further and fall short in managing such processes, mainly because these methods were especially suitable for linear systems and could not solve problems in nonlinear systems. Hence, new tools for nonlinear systems should be developed that, on the one hand, can learn or deal with new and unknown situations and, on the other hand, can predict future events accurately enough for proper decision-making. This system, capable of understanding and predicting the environment or processes and its changes, can be called an intelligent system.

Computational intelligence means extracting intelligence, knowledge, and algorithms. Intelligent systems, in principle, provide free models for dynamic systems through the approximation of functions and/or mapping. Additionally, computational characteristics, such as accuracy, flexibility, and ease of implementation, are also of utmost importance in an intelligent system. Intelligent techniques have been applied, especially in uncertain, complex, nonlinear, time-varying, and randomly targeted processes. These models are not comparable to traditional mathematical modeling techniques mainly because [18]:

- The mathematical description of the processes is extraordinarily complex.
- Evaluation of these models is difficult and expensive.
- There is uncertainty in process operations.
- Nature often has a nonlinear process and random distribution.

The significant challenge in computational intelligence and one of the distinctive criteria for classification models is whether the system can continually learn from the incoming stream of data [19]. When human learning is considered, it is observed that the learning process is incremental. Human learns concepts from the environment and refines these concepts from facts, new observations, and new information in an increasing manner. For two primary reasons, humans need to learn continuously [20].

- The continuous flow of information.
- Limited memory and information processing.

Nowadays, with the massive increase in the speed of data collection, the goal of processing data is not only to achieve the least possible error, as it always was, but to do so in the shortest possible time. However, traditional approaches for training machine learning models fall short in this aspect since most of the learning algorithms in computational intelligence are batch learning or optimization, which are very costly and very slow in the data flow. The use of these algorithms is very challenging, especially in an online process, due to the sensitivity of the parameters in these algorithms, which makes it difficult in many cases to maintain accuracy.

Batch learning does not provide the possibility to learn continuously. Therefore, the system must be trained using all the available data, hence the requirement for a lot of computing time and resources. That is why this learning is done offline. In the presence of new data or facing an ever-changing environment, the models that are trained offline need to be trained again. Such a process, in which the system is stopped, trained again, and replaced as a new one, obviously cannot be done during system execution. Consequently, if the available data, a collection of the recently obtained and already existing data, are immense in size, the system should be trained from scratch and then replace the older version, which was trained by the previously available data. This, of course, would require a lot of resources, such as computational power from CPUs, memory space, disk space, etc., and would probably take hours to be done [19].

Because of the need for new techniques to continuously improve the performance of models with the flow of new data, incremental or online learning techniques are proposed. Incremental learning is, in fact, a method in advanced modeling [11, 21]. An incremental learning system is especially beneficial for computers with limited resources or systems that need to adapt quickly to the current data. In an online system, there is no need to keep the data after training; the data can be discarded and, as a result, save memory space. These systems are mostly suitable for large data, where storing them in the device's memory is neither a valid nor practical option.

Three important aspects of incremental learning are as follows [20].

1. How to adapt the previously learned knowledge to the currently received data and use the new raw data for learning.
2. How the accumulated experience and knowledge over time can support and further benefit future decision-making processes.
3. How classes can be produced, merged, or divided based on the dynamic nature of environmental changes.

3.1 Fuzzy computational

To counter complexity in modeling and solving new issues in physics, engineering, medicine, biology, and many other sciences, creating and developing new computational methods more closely aligned with human thinking is required. Artificial intelligence aims to match a computer system's behavior and response to the patterns in which humans behave and respond. In reality, many concepts which humans use are perceived as imprecise, unclear, and vague. Though words and concepts such as hot, cold, long, short, old, young, and so on do not refer to exact numbers, the human mind immediately understands everything with fantastic flexibility and uses them for decisions and conclusions. At the same time, the machine is precise and only understands numbers. The purpose of new methods in computer science is to learn these abilities from human beings and then to teach them to machines as closely as possible [22].

The scientific laws of Newtonian physics and mechanics are all based on old logic. Old logic can only express two attitudes: white and black, yes and no, bright and dark, one and zero, true and false. In general, variables in nature or calculations are of two types:

Quantitative values can be expressed in a given number, and qualitative values are expressed from a feature. These two values can be converted. Since the human mind operates with other logic and adapts decisions, formulating and developing new logic and the multivalued requirement, fuzzy logic is one of them. Following the first fuzzy set theory by Professor Lotfi Zadeh [23] in 1965, a new calculation appeared on the scene. This theory was developed to compensate for the inadequacy of the Boolean logic to describe many real-world issues. Classical math operations recognize only 0 and 1. Much real-world data is inaccurate and has uncertainties, so classical logic cannot cite the fact in this respect. Fuzzy logic presents a systematic concept for investigating uncertainty both quantitatively and qualitatively. Fuzzy theory is for applications with uncertain conditions and utilizes linguistic variables [18, 24].

One of the critical issues in fuzzy logic is distinguishing it from the theory of probabilities in mathematics. Often, the fuzzy theory is confused with the probability theory. However, these two concepts are entirely different from each other. Fuzzy logic deals with inaccurate facts and refers to the limits and levels of reality. However, probability theory is the theory of random events and discusses the chance of an event occurring. When the predicted event occurs, the theory is assumed to be accurate [25].

The main difference between fuzzy logic and neural networks is the data used. In other words, neural networks are based on data-driven modeling, but fuzzy models are knowledge-based. Data-driven models are any form of mathematical model extracted or learned from data. Knowledge-based models are extracted from the experience of experts, operators, and users working on the system [11, 18].

3.2 Fuzzy pattern classification (FPC)

Fuzzy pattern classification is suitable for complex issues, including technical and non-technical, and can provide support for control or decision support. Fuzzy patterns are modeled using multidimensional fuzzy membership functions, specified in a dimensional feature space representing the measured variables or characteristics. Compared to other approaches, the fuzzy pattern is a sign of parallel and non-sequential. One classifier can comprise some patterns, which are all semantically interpretable. Fuzzy pattern classifiers can be modeled using a knowledge-based approach or data-driven approach or as a combination of both [10, 13]. Fuzzy classification is a method for describing classification systems of observations defined as feature vectors in feature space of one or more dimensional (n-dimensional) Euclidean space. Compared to other methods, this model allows modeling interdependencies of the variables by rotating the multi-axis system within the entire coordinate system. Therefore, the correlation between input variables can be discussed. Fuzzy pattern classification can also be designed and modeled as a data-driven or knowledge-based approach or a combination of both [13]. The following is a discussion of the one-dimensional and multi-dimensional membership functions appropriate for the fuzzy pattern classification.

3.2.1 One-dimensional membership functions (MF)

Fuzzy pattern classification is based on an asymmetric membership function that differentiates between left and right function branches. This is a generalized potential function of the Aizerman's model and the Bocklisch model is similarly used to describe niches in ecology [16]. It has been proven that Aizermans modified function is very suitable for describing very high-dimensional membership functions (practical to 100 dimensions). Eq. (1) defines the one-dimensional asymmetric membership function type for the variable u.

$$\mu(u) = \begin{cases} \dfrac{a}{1 + \left(\dfrac{1}{b_l - 1}\right)\left(\frac{r-u}{c_l}\right)^{d_l}} & u < r \\ \dfrac{a}{1 + \left(\dfrac{1}{b_r} - 1\right)\left(\frac{u-r}{c_r}\right)^{d_r}} & u \geq r \end{cases} \tag{1}$$

Besides the mathematical model of this function, the following semantic meaning can be assigned to the parameters. This function is based on a set of eight parameters:

The parameter r denotes the representative position of the MF, which can be determined in various ways, for example, as the center of gravity of the objects constituting the class, as the arithmetic mean, or as a reference point. The maximum value of the membership parameter a of this unimodal MF is assigned to r. The membership parameter $a \geq 1$ can indicate the weight or authenticity of a class. The membership parameter can indicate the weight or authenticity of a class. The parameters c_l and c_r ($c_{l/r} > 0$) are the class information that contains the position of the farthest object from the center in projection to the axis. Therefore, parameter c represents the greatest distance of an observed object from r. As shown in **Figure 3**, c_l and c_r characterize a fuzzy pattern class's left- and right-sided expansions. Both parameters represent the range of a class. The parameters b_l and b_r ($0 < b_{l/r} \leq 1$) are factors that determine the value of the MF at the sharp boundaries $c_{l/r}$ of the fuzzy pattern class. The parameters d_l and d_r ($d_{l/r} \geq 2$) determine the form of the function and carry information about the object distribution in the corresponding class. In special cases the amount for $d_{l/r} \to \infty$ changes to a sharply described class (red color in **Figure 4**) [3, 13].

3.2.2 Multidimensional membership functions

The previous considerations only focused on the presentation of fuzzy pattern classification in one-dimensional (feature) space $\mathbb{R}^1$. The fuzzy potential function points to the theoretical possibility of multidimensional membership functions. Hence, one-dimensional membership functions define the membership function in N-dimensional space $\mathbb{R}^N$ Therefore, the exceptional advantage of the potential function is that a suitable conjunctive combination of several fuzzy sets/logic can be used to obtain a multivariate membership function in parametric form [3, 13]. The normalized function ($a = 1$) with N dimension is given by

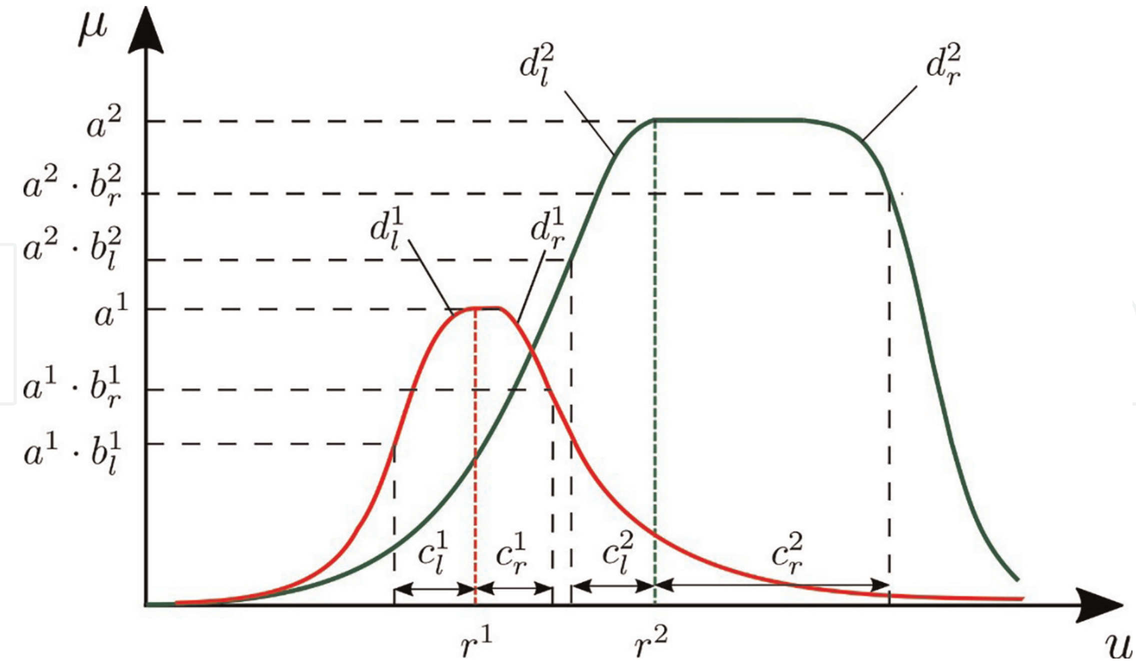

Figure 3.
Two one-dimensional asymmetric membership functions with different parameters [3].

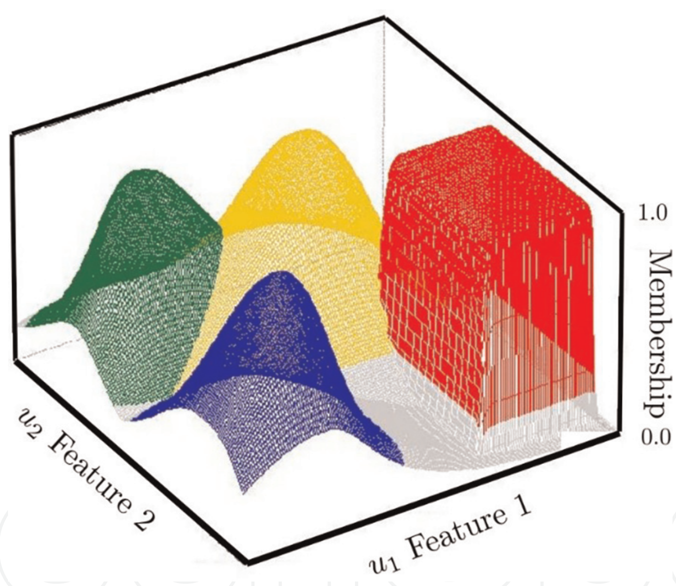

Figure 4.
Illustration of two-dimensional MFs for four classes [3].

$$\mu(\underline{u}) = \frac{1}{1 + \left(\frac{1}{N} \cdot \sum_{n=1}^{N} \sigma_n\right)} \tag{2}$$

where j belonging to number of features (n = 1,2,3,..., N; N = the number of dimension). Therefore, σ_j denoted by

$$\sigma_n = \begin{cases} \left(\dfrac{1}{b_{l,n}} - 1\right)\left(\frac{r_n - u_n}{c_{l,n}}\right)^{d_{l,n}} & u_n < r_n \\ \left(\dfrac{1}{b_{r,n}} - 1\right)\left(\frac{u_n - r_n}{c_{r,n}}\right)^{d_{l,n}}, & u_n \geq r_n \end{cases} \tag{3}$$

Figure 4 illustrates the basic join operation for two-dimensional fuzzy pattern classes.

3.3 Adaptive fuzzy pattern classification (AFPC)

As previously explained, some classification systems can be designed dynamically. These systems can modify classifications automatically during the operation phase and online. These systems can adjust their parameters continuously to improve system performance or change their structure for new classes. For these systems, two types of incremental learning algorithms can be presented: algorithms for incremental parameter learning and algorithms for incremental structure learning. The system is considered at the beginning of the learning process for incremental learning of the parameters, and the system parameters are learned according to the new data. Such algorithms are considered "adaptation" algorithms, and the classifications whose parameters change based on new data are called "adaptive classifiers." In incremental structure learning, parameters and classification structures change; they are called "evolving classifiers." Adaptive classifiers can modify their parameters based on the new process's demand characteristics, the system's behavior, and operational and environmental conditions. These systems can support modeling any scenario for data flow, online measurements, and dynamic data whose nature and characteristics change over time. Continuous adaption capability is essential for two reasons [10, 11]:

1. New data samples are related to the specific context in the real world, which can improve classification and differentiate it.

2. The storage of information and learning data is not required for classification consistency. Therefore, the classification can be set up with a small dataset and improve system performance.

3.3.1 Adaption of parameter $\boldsymbol{a}$

The parameter a, as already explained, represents a measure of the "weight" of a class. This "weight" is limited upwards by a value max which is determined individually ($a_{max} = 10$). The parameter a is a function of the number of N_k objects belonging to a class. For the total number of objects belonging to the classifier, a is defined as

$$a_k = a_{max} \cdot \left(1 - \left(\frac{a_{max} - 1}{a_{max}}\right)^{N_k}\right) \tag{4}$$

The dynamic of the evolvement can be changed using the weight of the transition patterns $N_k \geqslant 1$ depending on the membership function parameter a, which represents the number of data points that created the patterns in the past [10, 13].

3.3.2 Adaption of parameter $\boldsymbol{r}$

Adapting the r values leads to modification of the fuzzy pattern's position in the coordinate system. The new position of r, called $r_n^{(k,new)}$, with n representing the index of the dimension and with $k = 1, 2, 3, \dots, K$; whereby K is the number of classes, is defined for each additional data value x_n through the weighted arithmetic mean:

$$r_n^{(k,new)} = \frac{N_k}{N_k+1} \cdot r_n^{(old)} + \frac{1}{N_k+1} \cdot x_n \tag{5}$$

The dynamic of the evolvement can be changed using the weight of the transition patterns $N_k \geqslant 1$ with N_k depending on the membership function parameter a, which represents the number of data points that created the patterns in the past [10, 13].

3.3.3 Adaption of parameter $\mathbf{c}_{l/r}$

Adapting the $c_{l/r}$ values leads to modification of the fuzzy pattern's boundary of the class. The new $c_{l/r}$ boundary $c_{((l/c),n)}^{(k,new)}$, with n representing the index of the dimension and k representing the number of classes, is defined for each additional data value x_n.

$$c_{(l/c),n}^{(k,new)} = \begin{cases} c_{(l/n)}^{(k,new)} = \dfrac{N_k}{N_k+1} \cdot c_{l/n}^{(old)} + \dfrac{1}{N_k+1} \cdot x_n \\ c_{(r/n)}^{(k,new)} = \dfrac{N_k}{N_k+1} \cdot c_{r/n}^{(old)} + \dfrac{1}{N_k+1} \cdot x_n \end{cases} \tag{6}$$

To adapt the parameter $c_{l/r}$, first, it must be determined that the new point in each dimension, in what position of the new parameter $r_n^{(k,new)}$, is in the same dimension.

After determining the position of the new point, the new parameter $c_{l/r}$ is calculated from Eq. (6). At this phase, we introduced two approaches for adaptation and evaluated their results.

I: To adapt the parameter $c_{l/r}$, first, in each dimension the new point must be determined, at what position of the old parameter c is in the same dimension. Then, if the corresponding object is out of range, that is, it is smaller than the left c parameter or greater than the c right parameter, then adaptation is done for the c parameter. II: The $c_{l/r}$ parameter is compatible with all objects (see scenarios II and III in Section 5.1 and results in Section 5.2).

4. Experiments on an axial piston pump and data collection

The level and complexity of product reliability and safety requirements have been increasing in many industrial fields. Complying with such demands requires various tests and evaluations at each stage of production, from research and development of materials to evaluating finished products. Dynamic testing is used to measure product behavior and response characteristics and structural members in response to environmental changes, for instance, through the internal analysis of excitation vibration, pressure, and the temperature source transfer path of the piston pump. In order to make the product work reliably and safely, it is essential to ensure that the system has excellent dynamic attributes. Therefore, dynamic analysis and design of mechanical products and equipment are necessary to satisfy the requirements of static and dynamic characteristics of the mechanical structure.

4.1 Hydraulic pumps testing machine

Any pump, regardless of its type and size, should be tested in different methods throughout the operation. If done otherwise, there is no way of knowing if all the requirements and needs of the user will be met. Therefore, the type of test and how to use it depends on the ultimate goal of the application. The performance test of the axial piston pump is done after assembly completion to prove that the pump has the required specifications based on requests. The performance test is performed after completing quality control inspections, such as mechanical and tolerance tests. These tests are a benchmark for the acceptability of the pump. Therefore, testing machine (see **Figure 5**) in laboratory has been developed with the ability to test rotational speeds up to 3000 *rpm*, a torque of 5000 *Nm*, a pressure of up to 450 *bar*, and a flow of 500 *liters/min*. The hydraulic pump is fixed with the help of fixators on the work table so that it does not move and vibrate during the hydrological pump test. After setting the values based on the pump controller and test program, the device is turned on through the touch screen. The main factors affecting the pump's operation are suction, discharge, and speed. Secondary factors affecting the performance of pumps include physical and climatic variables such as temperature, viscosity, density, and turbulence in the pumped liquid. At the pump outlet, a pressure gauge measures the output pressure, the average of the piston pressures in the pump. There are also sensors for measuring the outlet flow and rotational speed of the electromotor in the testing machine. The circuit of the test station is closed. This means the fluid is pumped from the reservoir and returned to the reservoir again after leaving the pump and passing through the equipment and filters.

In this work, the standard controllers from Parker Hannifin [16] are selected for testing, and in these controllers, there are two plans for the axial hydraulic pump, full stroke, and zero stroke. In the full stroke plan, four features are measured at three levels of pressure, and in the zero stroke plan, five features are measured at the three levels of pressure (see sections 4.1.1 and 4.1.2). The characteristics of the pumped fluid and the physical conditions are defined in **Table 2**.

4.1.1 Full stroke in axial piston pumps

In the axial piston pumps, the generated flow volume Q depends on the displacement swash plate. In other words, the displacement value is proportional to the

Figure 5.
Axial piston pumps test bench [16].

Hydraulic fluid	Hydraulic oil, Group HLP
Viscosity class	ISO VG 46
Viscosity class of the hydraulic fluid	$v = 46 \pm 5\ mm^2/s\ in\ 40°C$
Temperature of the hydraulic fluid	$t = 50 \pm 2°\ C$
Purity level of the hydraulic fluid	18/16/13 according to ISO 4406

Table 2.
Physical conditions and characteristics of the pumped fluid.

change in the angle between the swashplate and the axis of the pistons. In the full stroke, four features (see **Table 3**) are measured at three levels of pressure, 100, 200, and 300 *bar*. When the test machine is turned on, the hydraulic oil pressure is increased to 100 *bar* (set value) within four seconds, and it stays at this level for five seconds. Then, the actual feature values are determined by the sensors every second and stored. After the recording of these values, the hydraulic oil pressure increases to 200 *bar* (set value) in four seconds. At this step, the oil pressure stays at the value of 200 *bar*, and over five seconds, the values of the features are measured every second by the sensors. This process is repeated for a pressure of 300 *bar* (set value). When the measurement is finished, the pressure value is reduced from 300 *bar* to zero. **Figure 6** shows the pressure variations according to the time in the full stroke plan.

The measured features include:

Symbol	Unit	Feature
P	[*bar*]	outlet pressure
VM1	[*l*/*min*]	outlet flow
VM2	[*l*/*min*]	leak oil flow
NM1	[*rpm*]	electromotor rotational speed

Table 3.
The feature definition for the full stroke plan.

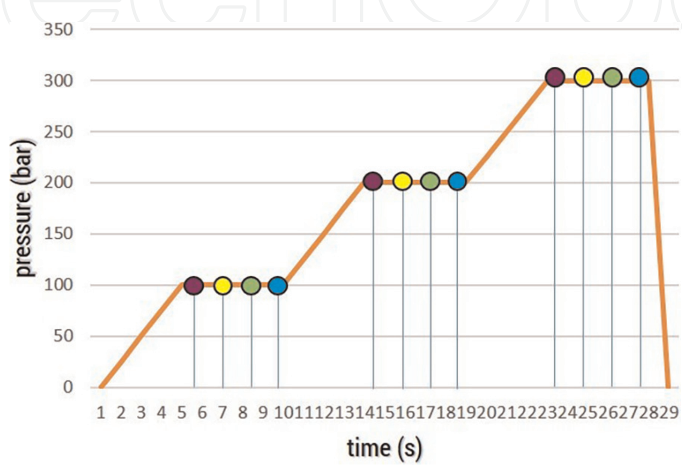

Figure 6.
Pressure vs. time curve for the full stroke plan.

4.1.2 Zero stroke in axial piston pumps

After completing the measuring in the full stroke plan, the test program enters a new phase called the zero stroke plan. The goal of the zero stroke plan is to measure five features (see **Table 4**) at the three levels of pressure 350, 200, and 100 *bar*. **Figure 7** shows the pressure variations over time in the zero stroke plan.

In this process, the hydraulic oil pressure is increased to 350 *bar* (set value) within four seconds and stays at this level for five seconds. Then, the actual feature values are measured by sensors every second and stored. After storing these values, the hydraulic pressure of the oil is decreased to 200 *bar* within four seconds. Afterward, the oil pressure stays at the value of 200 *bar* for five seconds, and the values of the features are measured by the sensors every second. This process is repeated for 100 *bar* oil pressure, too. In the end, the oil pressure is reduced to zero. At this point, the process of testing a hydraulic piston pump is finished.

The measured features include:

Symbol	Unit	Feature
P	[*bar*]	outlet pressure
ΔP	[*bar*]	Pressure difference between output and control
VM1	[*l/min*]	outlet flow
VM2	[*l/min*]	leak oil flow
NM1	[*rpm*]	electromotor rotational speed

Table 4.
The feature definition for the zero stroke plan.

4.2 Data collection and data labeling

In the database, there may be corrupt data such as I. Failure to store data. II. There needs to be more compatibility between the data. Therefore, the quality of these data should be checked. Preprocessing can eliminate inappropriate and corrupt data. In this way, the desired output can be obtained from the data. After data acquisition and

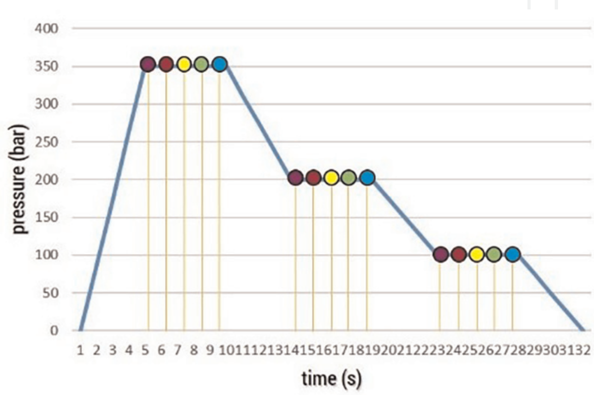

Figure 7.
Pressure vs. time curve for the zero stroke plan.

merging, data preparation was started. The next step was data cleaning. Collected data usually has three significant breaches: some data is noisy, there are some missing values, or in some cases, there is an inconsistency within the data, so data cleaning, to treat missing values and possibly inconsistent data, is necessary. After cleaning the data, selecting features was started. This process will discuss which plans are selected and how they can be prepared for the labeling phase. The full stroke and the zero stroke plans were selected among different plans. Then, the full stroke set values 100, 200, and 300 *bar* and the zero stroke set values 350, 200, and 100 *bar* were selected. In the end, the results were used in the labeling step. Due to the use of a supervised learning approach, it is essential to determine the appropriate label. At this step, labeling means evaluating data. The process of labeling receives data from the previous step includes the two plans: full stroke and zero strokes. It should be noted that all pumps tested in this work were in good condition. According to frame size, displacement, and the set values of this plan (see **Table 5**), the number of 18 classes was defined by the expert for full and zero stroke.

Depending on the available dataset, the classifier design can be considered as supervised learning for fuzzy pattern classification. This work has a set of labeled objects with known class membership. About 70% of this set is extracted and applied to obtain a classifier. These objects build the training set. The remaining objects, whose correct class assignments are also known, are referred to as the sets for adaptation and are used to validate the adaptive classifier's performance.

Class	Frame size	Displacement [cm^3/rev]	Set value full stroke	Set value zero stroke
1	3	60	100	350
2	3	80	100	350
3	3	92	100	350
4	4	140	100	350
5	4	180	100	350
6	5	270	100	350
7	3	60	200	200
8	3	80	200	200
9	3	92	200	200
10	4	140	200	200
11	4	180	200	200
12	5	270	200	200
13	3	60	300	100
14	3	80	300	100
15	3	92	300	100
16	4	140	300	100
17	4	180	300	100
18	5	270	300	100

Table 5.
The labeled dataset for the full stroke and zero stroke plan.

5. Results and discussion

5.1 Introduction

In this section, the fuzzy pattern classification and adaptive fuzzy pattern classification algorithms developed in this work are evaluated, and their performances are presented. For the fuzzy modeling, the axial piston pump test data was used. Two full stroke plans and zero stroke plans were used for tests on pumps, which aim to model the data obtained from these two test plans. The modeling is based on supervised learning. So, for each test plan, the 18 classes were defined (see **Table 5**).

Since the validity of any model computed in the research needs to be estimated, the division of the samples into the three training, fitting, and testing datasets was applied to measure and verify the accuracy of the models. For learning the fuzzy model, three scenarios are considered:

Scenario I: About 70% of the data was used for fuzzy modeling as a basic model. Therefore, 15% of the data (testing data respectively, the last 15% of saved data.) was used to evaluate the accuracy of the models.

Scenario II: Models obtained from scenario one were applied to an adaptive algorithm. Therefore, 15% of the data (adaption data) was used to adapt the model's parameters from the scenario I and to obtain the new pattern with the new parameters. In order to evaluate the accuracy of a new fuzzy pattern obtained from an adaptive algorithm, it has been used of the data (test data).

Scenario III: In this scenario, as in scenario II, 15% of the data is used in the basic model adaptation process, and 15% is used as test data to evaluate the adaption model. The difference in this scenario is that only the objects that are outside the scope of any classifier are included in the adaptation process.

The training phase was defined with initial values ($b_{l/r}$ = 0.5, $d_{l/r}$ = 2) and is used for the fuzzy pattern classification for all classes.

5.2 Evaluation of the fuzzy pattern classification and adaptive fuzzy classification

Figure 8 shows the membership values of the test data (15%) for full stroke, set value pressure 100 *bar*, and for different scenarios. As you can see, in class 1 and scenario I, the membership value, in other words, the accuracy of the basic model, has improved to 0.81 and after the adaptation process according to scenario.

II: to 0.84 and scenario III to 0.86. In class 6, these improvements and changes are more, and in class 3, these changes are much less. However, in these classes, it is more accurate after adapting the model. As it is clear from diagram 8, scenario II in classes 2, 4, and 5 has less compliance than the other two scenarios, but overall, scenario III shows a useful improvement considering the small number of data.

Figure 9 shows the membership values for different frame sizes for full stroke at a pressure of 200 bar. As can be seen in **Figure 9**, class 8 has the most changes to increase the accuracy of the base model after adaptation, and these results can be seen in classes 7 and 12. In classes 9 and 10, the changes after adaptation are almost negligible, while these classes display more than 95% accuracy after adaptation.

Figure 10 shows the membership values for full stroke and in 300 *bar*. As you can see, in class 14, in other words, in scenario I, the basic model has a low accuracy of about 10%. In contrast, after adaptation and with a limited number of objects, the model's accuracy has improved. Also, in other classes, except class 17, we see an

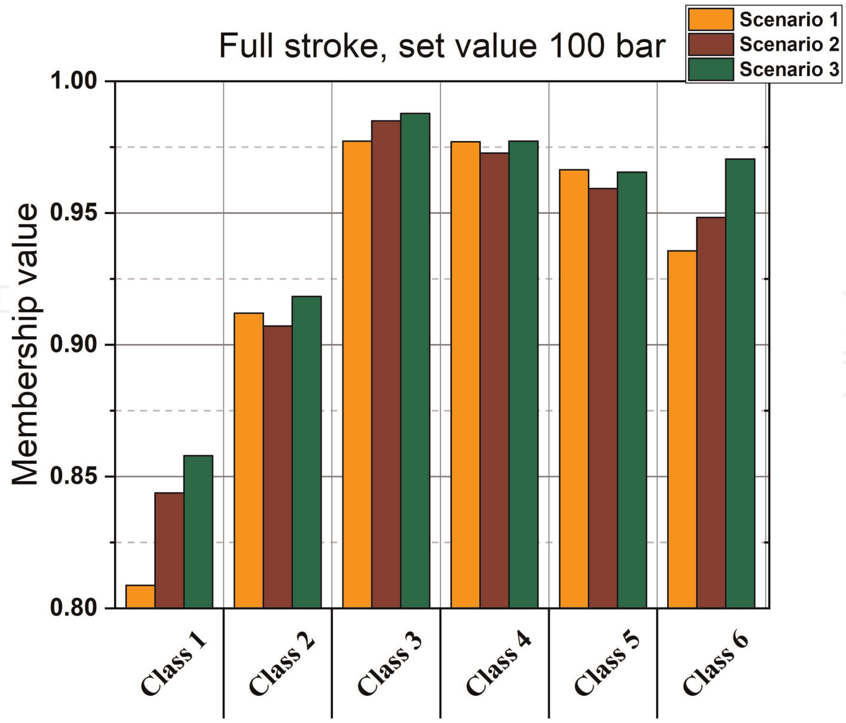

Figure 8.
Accuracy of different scenarios for full stroke in set value 100 bar *by testing data.*

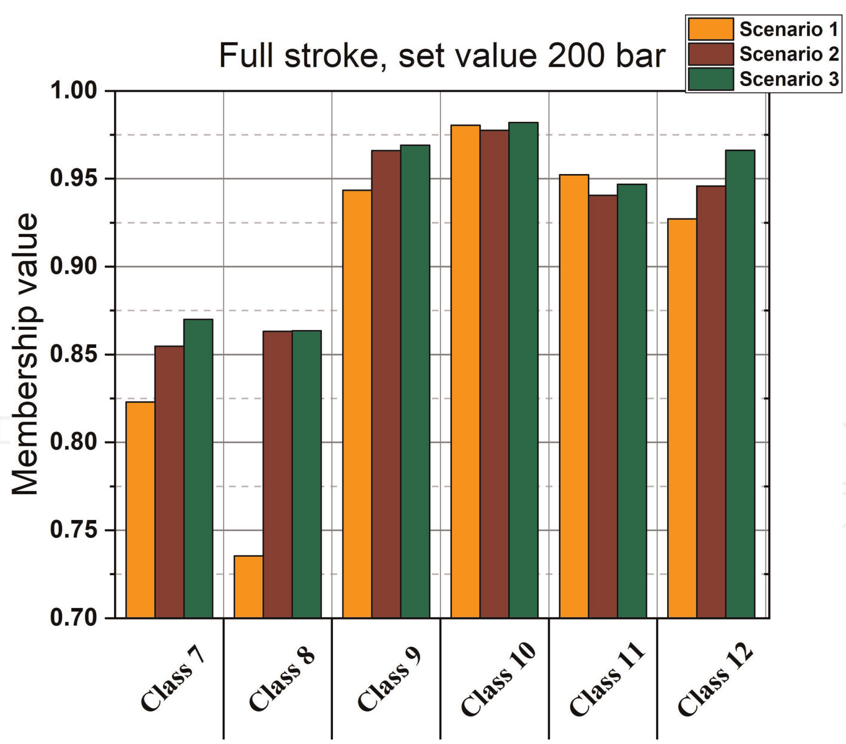

Figure 9.
Accuracy of different scenarios for full stroke in set value 200 bar *by testing data.*

increase in accuracy in the model after adaptation, and this accuracy is more than 80% in all classes except class 14.

Figures 11–13 show the membership values of test data for zero stroke at pressures of 350, 200, and 100 *bar*. As it is evident in these figures, in frame size 5 (see **Table 1**),

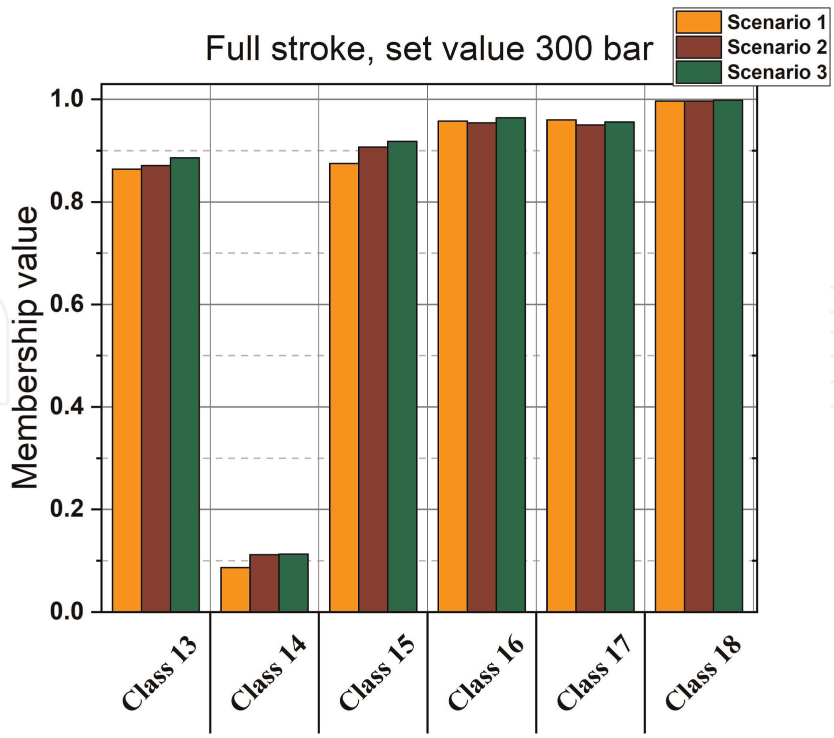

Figure 10.
Accuracy of different scenarios for full stroke in set value 300 bar *by testing data.*

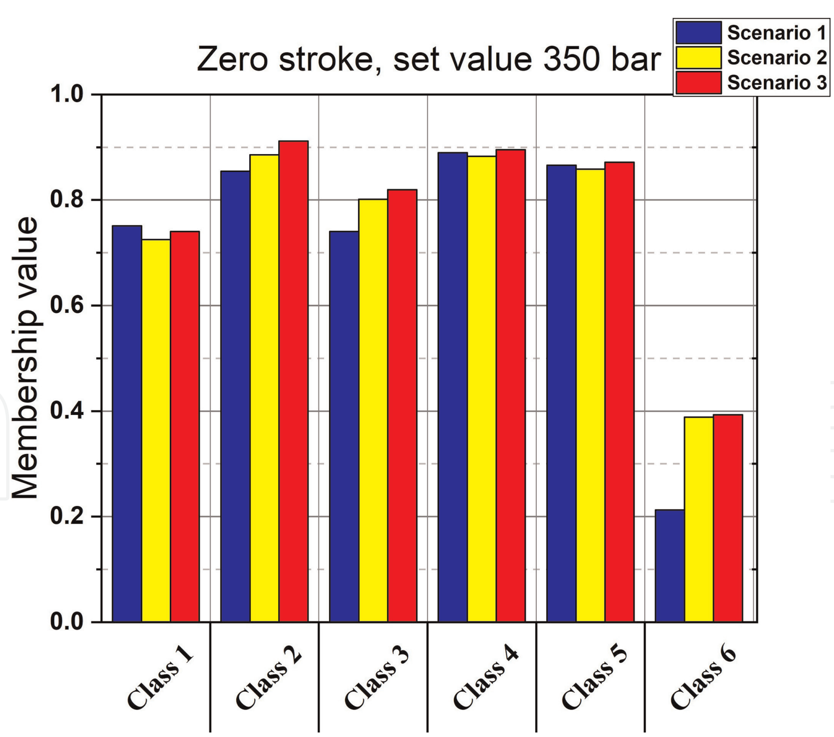

Figure 11.
Accuracy of different scenarios for zero stroke in set value 350 bar *by testing data.*

in other words, classes 6, 12, and 18, the accuracy of the basic model, in other words, scenario I, is in the range of 0.21 to 0.41, which after the adaptation of these models, there is a significant improvement that they show from 0.39 to 0.65. As discussed in the zero plane test and Section 4.1.2, the tested pumps are suddenly pressurized to

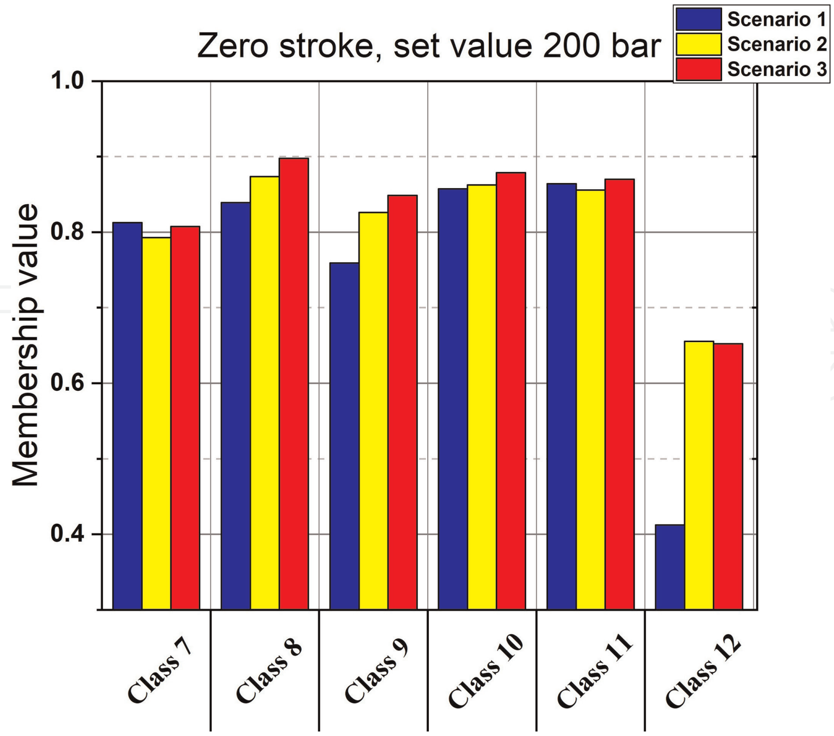

Figure 12.
Accuracy of different scenarios for zero stroke in set value 200 bar *by testing data.*

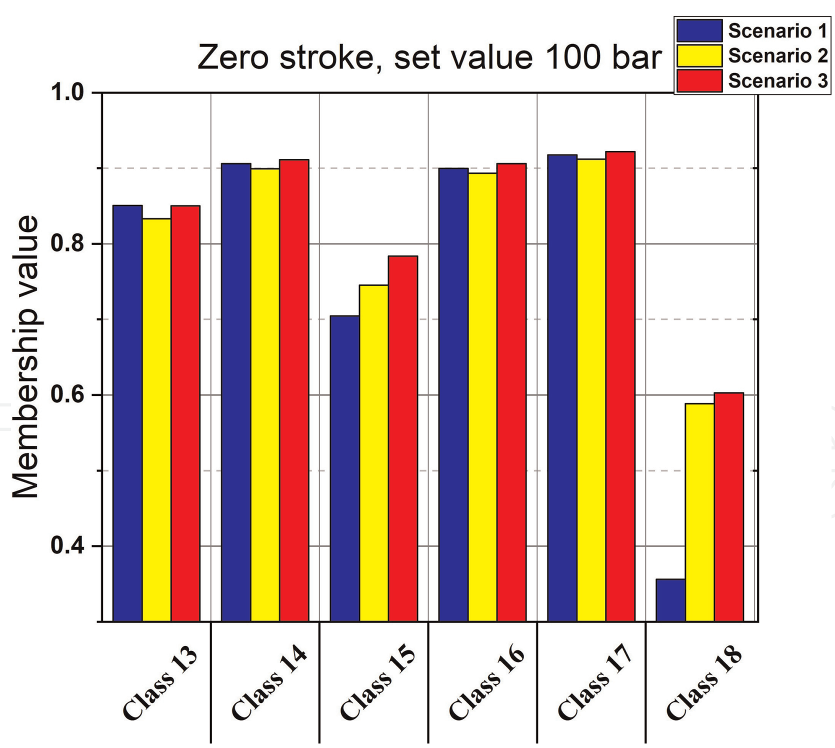

Figure 13.
Accuracy of different scenarios for zero stroke in set value 100 bar *by testing data.*

350 *bar* from a static state within a few seconds. In this case, the data dispersion is almost high, and the system faces uncertainty because the oil pressure needs time to reach equilibrium. The thing to think about in this process is that the fuzzy model has

displayed a stable state with appropriate accuracy concerning this uncertainty. Also, the accuracy of the model has improved after adaptation.

5.3 Evaluation of the adaptive fuzzy classification process

One of the questionable points in the adaptation process is how accurate the adapted model of each adaptation step is to the test data, whether the model's accuracy has continually improved during the adaptation process or exhibits other results.

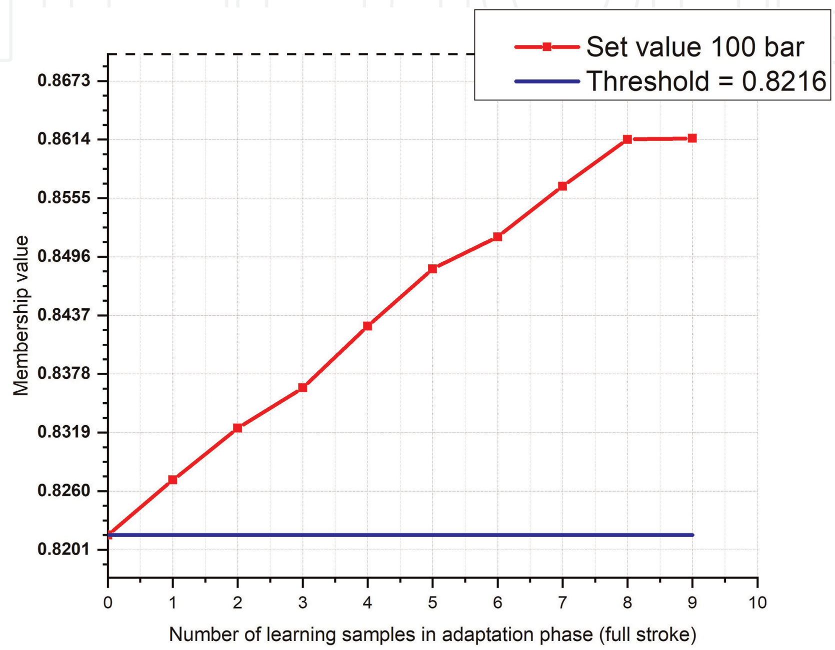

Figure 14.
Example of each adaptation step for full stroke of class 1 in set value 100 bar.

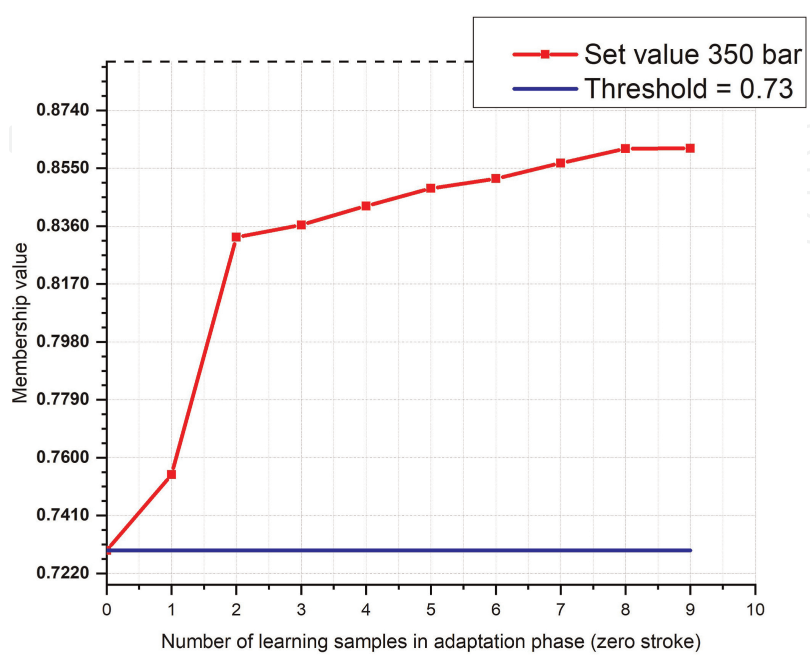

Figure 15.
Example of each adaptation step for zero stroke of class 2 in set value 350 bar.

To answer this question, the new model should be evaluated with test data for each object participating in the adaptation process and compared with the reference or threshold value. The result of this study is shown in **Figures 14** and **15**. In these graphs, the blue lines are the reference values and, in other words, the thresholds displayed for class 1 in plan five and class 2 in plan six based on strategy III. The red lines show each stage's adaptation process and the model's accuracy. It can be seen from these graphs that the adapted models have improved compared to the threshold. So that in plan five and **Figure 14**, the model's accuracy has improved from 0.82 to 0.86, and this value in plan six and **Figure 15** is from 0.73 to 0.86. It should be noted that the number of objects during the adaptation process was 9.

6. Conclusion and future work

The primary goal of this work is to provide a new method for the final inspection and testing of hydraulic axial piston pumps working automatically and online without the user's presence. Motivated by the increasing need for flexible classifiers that can be automatically adapted continuously to cope with dynamic work environments in the context of Industry 4.0 and 5.0, this work proposed an adaptive fuzzy pattern classification algorithm, which can model nonlinear and complex relationships between empirical input and output data with precise accuracy. This algorithm can adapt models to real situations and with online streams of data. The performance test of the axial piston pump is done to verify that the pump has the required specifications based on requests. These tests are a benchmark for the acceptability of the pump. In this work, the pump data from the good situation are tested for four months. In the standard controllers, there are two application plans: full stroke and zero stroke for the axial hydraulic pump. In the full stroke, four features are measured at 100, 200, and 300 *bar* pressure levels. In the zero stroke plan, five features are measured at 350, 200, and 100 *bar* pressure levels. The axial piston pumps range the displacement from 16 cm^3/rev to 360 cm^3/rev. According to frame size, displacement and the set values of each plan are defined as the number of 18 classes out of 448 pumps.

The parameters of a class are composed of position parameters and shape parameters. The strategy to update the initially static fuzzy pattern classifier to changes in the fuzzy pattern classifier parameter is to the classifier from the sequence of the object.

In the scenario I, to evaluate the accuracy of the models in both test plans, 70% of the data (learning data) and 15% of the data (testing data) were used. In scenarios II and III, 70% of the data was used as a basic model for fuzzy modeling. Therefore, 15% of the data was used to adapt and 15% to evaluate the accuracy of the models.

As can be seen from the results, the model's accuracy improves with the adaption process and increasing number of samples. These results show that the models can be improved significantly when using adaptation/ evolution based on new measurements.

Similar to the parts presented in this work, our standpoint can be divided into application and theoretical perspectives.

As future applications, we present here the essential points:

- In the tested pumps, two pumps were found with faults whose data can be defined and modeled as fault classes in the future.

- These pumps can be controlled online by defining classes in a microcontroller, connecting with axial piston pumps, and defining fault classes.

- It is possible to transmit this concept and approach to other technical applications, such as machine tools, forming and pressing machines, surface analyses.

As future theoretical works, we present below the direct signs that we consider to improve our approach:

- For a better classification of the complex features according to the analysis results, the model always requires an adjustment of the combination of all parameters. Therefore, adapting the remaining class parameters $(b_{l/r}, d_{l/r})$ is required.

- An evolving fuzzy pattern classification can update structural components on demand based on new system behavior and operating conditions. Evolving structure is a theoretical complex that should be researched in the future.

Author details

Amir Nemati[1], Elif Öztürk[1,2]*, Steffen F. Bocklisch[1] and Welf-Guntram Drossel[1,3]

1 Chemnitz University of Technology, Chemnitz, Saxony, Germany

2 Institute of Machine Tools and Manufacturing, ETH Zurich, Zurich, Switzerland

3 Fraunhofer Institute for Machine Tools and Forming Technology, IWU, Chemnitz, Saxony, Germany

*Address all correspondence to: oeztuerk@inspire.ethz.ch

References

[1] Helwig N, Pignanelli E, Schutze A. Condition monitoring of a complex hydraulic system using multivariate statistics. In: 2015 IEEE International Instrumentation and Measurement Technology Conference (I2MTC) Proceedings. Pisa, Italy: IEEE; 2015. pp. 210-215

[2] Helwig N, Pignanelli E, Schütze A. D8.1 - detecting and compensating sensor faults in a hydraulic condition monitoring system. In: Proceedings SENSOR 2015. Nürnberg, Germany: AMA Service GmbH, Von-Münchhausen-Str. 49, 31515 Wunstorf, Germany; 2015. pp. 641-646

[3] Nemati A, Jäckel M, Bocklisch SF, Drossel W-G. Fuzzy pattern modeling of self-pierce riveting for data from experiments and computer simulations. International Journal of Advanced Manufacturing Technology. 2022;**122**: 2203-2216. DOI: 10.1007/s00170-022-09914-6

[4] Baur M, Bocklisch SF. Similarity based local model approach for nonlinear modelling. In: 2001 European Control Conference (ECC). Porto: IEEE; 2001. pp. 3905-3910

[5] Chao Q, Gao H, Tao J, et al. Fault diagnosis of axial piston pumps with multi-sensor data and convolutional neural network. Frontiers of Mechanical Engineering. 2022;**17**:36. DOI: 10.1007/s11465-022-0692-4

[6] Xiao C, Tang H, Ren Y, Kumar A. Fuzzy entropy assisted singular spectrum decomposition to detect bearing faults in axial piston pump. Alexandria Engineering Journal. 2022;**61**: 5869-5885. DOI: 10.1016/j.aej.2021.11.019

[7] Tang S, Yuan S, Zhu Y, Li G. An integrated deep learning method towards fault diagnosis of hydraulic axial piston pump. Sensors. 2020;**20**:6576. DOI: 10.3390/s20226576

[8] Almaksour A. Incremental learning of evolving fuzzy inference systems: application to handwritten gesture recognition. Machine learning [cs.LG]. INSA de Rennes, (Doctoral dissertation). 2011

[9] Dougherty G. Pattern Recognition and Classification. New York, New York, NY: Springer; 2013

[10] Bocklisch F, Bocklisch SF, Beggiato M, Krems JF. Adaptive fuzzy pattern classification for the online detection of driver lane change intention. Neurocomputing. 2017;**262**:148-158

[11] Lughofer E. Evolving Fuzzy Systems – Methodologies, Advanced Concepts and Applications. Berlin, Heidelberg: Springer; 2011. DOI: 10.1007/978-3-642-18087-3

[12] Kayani OK, Sohaib M. Generic Simulation Model Development of Hydraulic Axial Piston Machines.

[13] Bocklisch SF. Prozessanalyse mit unscharfen Verfahren. Berlin: Verlag Technik; 1987

[14] Ivantysyn J, Ivantysynova M. Hydrostatische Pumpen und Motoren: Konstruktion und Berechnung. Vogel Buchverlag; 1993. Available from: https://books.google.ch/books?id=e1w7AAAACAAJ

[15] Eifler W, Küttner K-H. Küttner Kolbenmaschinen: [Kolbenpumpen, Kolbenverdichter, Brennkraftmaschinen] ; mit 40 Tabellen sowie zahlreichen

Übungen und Beispielen mit Lösungen, 7., neu bearb. Aufl. Wiesbaden: Vieweg + Teubner; 2009

[16] https://www.parker.com

[17] Bocklisch F, Bocklisch SF, Krems JF. Sometimes, often, and always: Exploring the vague meanings of frequency expressions. Behavior in Research. 2012; **44**:144-157. DOI: 10.3758/s13428-011-0130-8

[18] Siddique NH, Adeli H. Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks, and Evolutionary Computing. Chichester, West Sussex, United Kingdom: John Wiley & Sons; 2013

[19] Géron A. Hands-on Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. Sebastopol, CA: O'Reilly Media; 2017

[20] Ade RR, Deshmukh PR. Methods for incremental learning: A survey. International Journal of Data Mining & Knowledge Management Process. 2013; **3**:119-125. DOI: 10.5121/ijdkp.2013.3408

[21] Read J, Bifet A, Pfahringer B, Holmes G. Batch-incremental versus instance-incremental learning in dynamic and evolving data. In: Hollmén J, Klawonn F, Tucker A, editors. Advances in Intelligent Data Analysis XI. Berlin Heidelberg, Berlin, Heidelberg: Springer; 2012. pp. 313-323

[22] Buckley JJ, Eslami E. An Introduction to Fuzzy Logic and Fuzzy Sets. Heidelberg: Physica-Verlag HD; 2002

[23] Zadeh LA. Fuzzy sets. Information and Control. 1965;**8**:338-353. DOI: 10.1016/S0019-9958(65)90241-X

[24] Kacprzyk J, Pedrycz W. Springer Handbook of Computational Intelligence. Berlin Heidelberg, Berlin, Heidelberg: Springer; 2015

[25] Angelov PP. Handbook on Computational Intelligence. New Jersey: World Scientific; 2016