Derivation of Fuzzy Diagnosis Rules for Multifunctional Fuel Cell Systems

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Abstract

This paper presents a model-based approach for the derivation of fuzzy diagnosis rules. These are used to classify data of faulty system behavior in order to identify root causes. The data is gained from an extended simulation model of a multifunctional fuel cell system for aircraft use. Faulty behavior is implemented into each component and a bottom up simulation is carried out. The data gained is classified according to root causes. This means that each data vector is assigned to a class representing one type of simulated fault. The classified data is then fed into an evolutionary optimization procedure. There it is weighted and separated into training and validation data.

Inside the optimization procedure, the structure of the fuzzy diagnosis rule is represented by a chromosome that has a discrete and a real valued part. The discrete part describes the selection of a signal and the real valued part states parameters of the membership function for each signal. Based on training data, a genetic algorithm optimizes both parts and a set of optimal binary and real valued parameters is gained. By that, one fuzzy diagnosis rule at a time is identified that best fits a set of fitness functions. On basis of this rule, weights of the training data are updated afterwards. This is done in order to guide the genetic algorithm in the next run to data vectors that are not covered effectively yet. Each run of the algorithm gives a new fuzzy diagnosis rule. The performance of the set of all rules that are gained so far is evaluated by use of validation data. Subsequently, a new run is started. This process continues until a stop criterion is reached. A set of optimal fuzzy diagnosis rules is gained in the end.

1. Introduction

The increasing scarcity of resources and growing demands on the European aviation's social, economical and environmental impact have led to the formation of scenarios and goals for the years 2020 (European Commission, 2001) and 2050 (European Commission, 2011). Besides a drastic reduction of greenhouse gases and noise, low door-to-door travel times, low accident rates, and a reliable transport function at low operating costs are demanded. In more detail, all European flights should arrive within one minute of the planned arrival time. Comparing this goal with data of the year 2012 (European Organisation for the Safety of Air Navigation, 2013b), 16.7% of all European flights had a delay of more than fifteen minutes. This was mainly due to technical issues (European Organisation for the Safety of Air Navigation, 2013a), which caused maintenance actions to happen and high cost to arise. The fulfillment of the future goals for European air traffic is thus far from being reached. This is even intensified with respect to new complex technologies to be integrated into the system's architecture of future aircraft.

An approach of current research deals with the integration of fuel cells (FC) on board of short range aircraft. FC enable the generation of electrical power without the emission of greenhouse gases and noise. In order to use these ecological benefits, a current concept consists in the replacement of the Auxiliary Power Unit (APU). The APU is a combustion engine that is mainly used to deliver electrical power during ground phase. However, the provision of the same amount of power using FC results in a highly increased system weight. Hence, in order to make sure, that the use of FC is not only ecologically beneficial, but also economically feasible, the integration of FC has to be done in a multifunctional way. This means that all products of the FC have to be used. By that, FC do not only deliver electrical power, but also oxygen depleted air for tank inerting and fire suppression, as well as process water (Enzinger, 2010).

A simplified integration of FC into an aircraft architecture on basis of an Airbus A320 is shown in Figure 1. In this concept, FC are used to provide electrical power during ground operation for the conventional on-board systems as well as for an electrical taxiing system. Another product of the electrochemical process is humid oxygen depleted air. This is cooled down, dried and used for kerosene tank inerting. The resulting heat flow is conducted to the wing's leading edge for anti-icing and the water is fed to the on board water system. A complex system architecture and many challenges arise thereby.

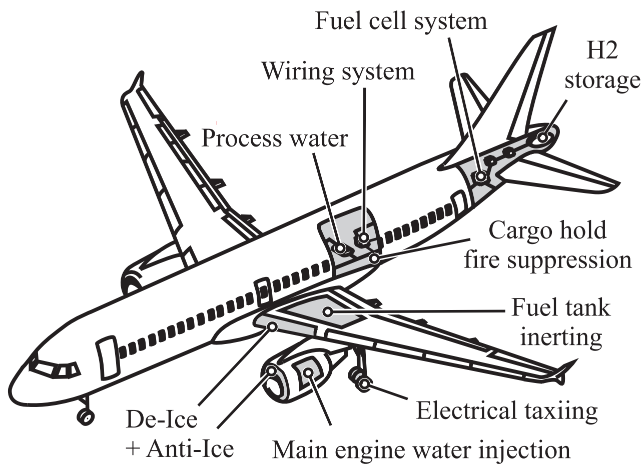

Figure 1. Integration of fuel cell technology into the overall aircraft systems architecture.

Summarizing the current status, FC on board of future aircraft can drastically reduce the emission of greenhouse gases and noise, and contribute to the fulfillment of future goals of European air traffic. This is achieved beneficially by a multifunctional integration strategy. However, the complex system architecture and the ambitious operational goals for the year 2050 lead to many challenges. Without proving that a multifunctional fuel cell system (MFFCS) can be operated and maintained beneficially there will be no chance to bring it on board of future aircraft. Hence, efficient health management functions are required. Tasks to be performed are reasoning about causes and effects, and early failure detection amongst others. This leads to challenges like optimal sensor placement, and the definition of built-in-test procedures. Handling these issues in a manual way is laborious, cost intensive and prone to human errors. A systematic and model-based development process is therefore needed. This is addressed in this paper in terms of fuzzy diagnosis rules. These are used for inferring causes of detected failures and malfunctions as a new type of a built-in-test procedure.

This paper is organized as follows. In Section 2, the concept of fuzzy diagnosis rules is introduced and motivated. A model-based approach to gain an optimized set of rules is shown in Section 3. Results of a study on a multifunctional fuel cell system are depicted in Section 4. The content of the paper is summarized in Section 5 and an outlook on open topics is given.

2. MOTIVATION

A multifunctional fuel cell system has to function efficiently, but also to be operated economically. Hence, a poor availability of operation can be a major drawback for a successful integration on board of future aircraft. Due to that, there is a distinct need to detect failures and malfunctions as early as possible, and identify root causes to an adequate level, so that economic damage can be avoided. These actions can be supported by means of a diagnosis function that works with diagnosis rules (Modest & Thielecke, 2012). These consist of a premise holding an indicator, and a conclusion suspecting or clearing candidates of root causes. In order to clarify this concept, basics are explained in the following.

An indicator of a diagnosis rule can have the discrete values $\{-1, 0, 1\}$ representing the colors $\{\text{Low}, \text{Nominal}, \text{High}\}$. An example is given in Figure 2 where two signals are shown. E001 represents a measurement of fuel cell current, and TX3A represents a measurement of air temperature. At the instant of time t_F a failure at the component level is simulated. A change in system behavior can be observed afterwards. This change is evaluated with respect to thresholds and persistence times. By that, at the instant of time $t_{D,1}$ the indicator E001 gets the color Low, and at the instant of time $t_{D,2}$ the indicator TX3A gets the color High.

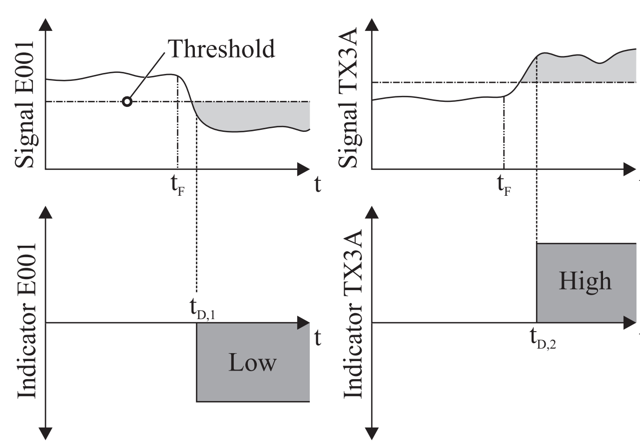

Figure 2. Measurements of faulty behavior and indicators with discrete values.

The indicators are used to match premises of two types of discrete diagnosis rules. These are *suspect* and *clear* rules where the first one has the following form:

$$\text{if E001 = Low then suspect } \{\text{LRU A,.., LRU K}\}. \quad (1)$$

Suspect rules are used as starting point of the reasoning process. By means of this type of rule a set of potential root causes, e.g. a line replaceable unit (LRU) or a specific failure mode on the component level, is generated and hypotheses are gained. These hypotheses can fully explain the indicator color. In order to test the necessary condition for the particular hypothesis, further indicators and clear rules are used. These have the following form:

$$\text{if TX3A = High then clear } \{\text{LRU C, LRU D, LRU E}\}. \quad (2)$$

By means of several clear rules the necessary condition for all the suspected candidates is tested so that the final diagnosis is inferred. According to the required level of detail, this can be a set of components including the real root cause. However, requiring a very detailed level of isolation, e.g. having a final diagnosis of only one suspect, could lead to a high amount of indicators needed and by that to many sensors to be integrated into the system. An approach for avoiding this necessity can consist in using indicators having not only discrete but *fuzzy* values. By that, not only exceeding of a threshold is taken into account but also the level of exceedance. An example for that is shown in Figure 3.

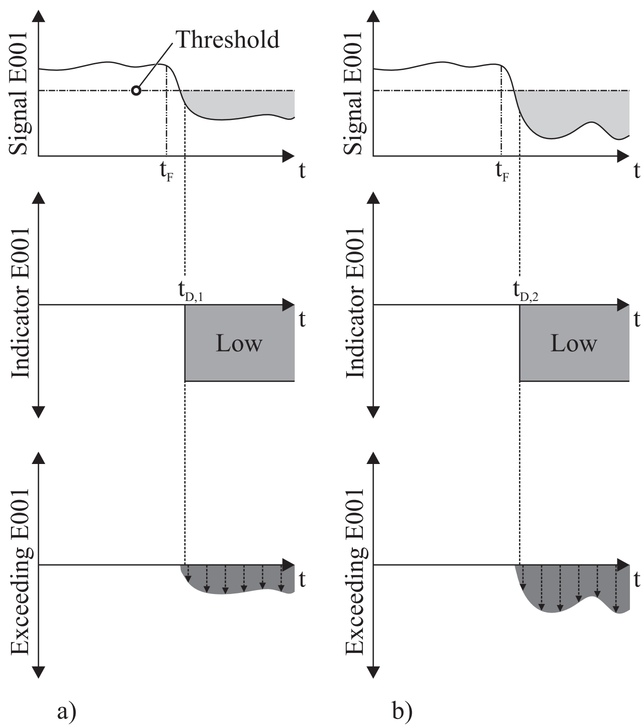

Figure 3. Taking into account the level of exceedance of a threshold for discrimination between failures. a) Failure A. b) Failure B.

In the example, there are two failures simulated. These lead to the same indicator color which is $E001 =$ Low. Based only on this information, the root cause can't be inferred exactly. However, taking into account the level of exceeding of the threshold, now offers the possibility to discriminate between the failures. The level of absolute exceeding of the threshold for *Failure A* is smaller than for *Failure B*. These levels are used to derive several fuzzy sets that are then used as the premise of a diagnosis rule whose conclusion is a suspected component. This states a *fuzzy diagnosis rule*. An example looks like follows:

$$\begin{aligned} &\text{if E001 = Low with Exceeding = } a^1_{E001} \\ &\text{then suspect LRU A with certainty } \epsilon_{LRUA}. \end{aligned} \quad (3)$$

In Equation 3, the term a^1_{E001} is a fuzzy set that is related to the exceeding of a threshold. With respect to the pattern, that matches the premise, the rule's conclusion is the suspect LRU_A with certainty degree ϵ_{LRUA}. Compared to Equation 1 only one suspect is left. *Clear* rules are omitted in this new concept. In the next section, a model-based approach to derive the required fuzzy sets in an optimized way and gain a set of fuzzy diagnosis rules is presented.

3. FUZZY DIAGNOSIS RULES

Fuzzy diagnosis rules are used to match and classify faulty system behavior during operation. Knowledge about this behavior is gained on basis of an extended system model. This enables the simulation of failures at component level. Effects at system level are gained through different types of sensors and are structured in a matrix format. This is shown in Section 3.1. The effects are evaluated by using fuzzy inference. The basics are presented in Section 3.2. There, matching degree and membership function are explained and it is shown which parameters have to be determined for the derivation of fuzzy diagnosis rules. These parameters are gained in an optimized way on basis of an evolutionary optimization procedure. This is introduced in Section 3.3. The entire process for the derivation of fuzzy diagnosis rules is shown in Section 3.4.

In general, a fuzzy diagnosis rule should have the following structure:

$$\begin{aligned} &\text{if } f^v_i = A_i \text{ with Exceeding = } a_i \\ &\text{and ... and } f^v_j = A_j \text{ with Exceeding = } a_j \\ &\text{then suspect } FM_x \text{ with certainty } \epsilon_{FM_x}. \end{aligned} \quad (4)$$

The premise of the rule makes use of features f^v_i of the ith dimension of the feature vector f^v. These are matched to colors A_i that belong to a predefined color space, and fuzzy sets a_i. Both are conjunct for a set of features. Each of the fuzzy sets is characterized by a membership function that determines the degree of each input f^v_i belonging to the specific fuzzy set a_i. This structure is used to assign features to a class FM_x that belongs to the set of all the failures FM that are taken into account. This is done with certainty ϵ_{FM_x}.

In order to determine the required features f^v_i and the parameters of the fuzzy sets a_i, data about faulty behavior is required. This is gained on basis of an extended system model which is shown in the next section.

3.1. Extended system model

In order to derive fuzzy diagnosis rules, data about faulty system behavior is required. This data is gained from an extended simulation model which is based on a dynamic nominal system model (Grymlas & Thielecke, 2013). This has been derived by using the *Matlab* toolbox *Simscape*. This allows for an a-causal modeling of physical behavior using equations. An overview of the model is given in Figure 4.

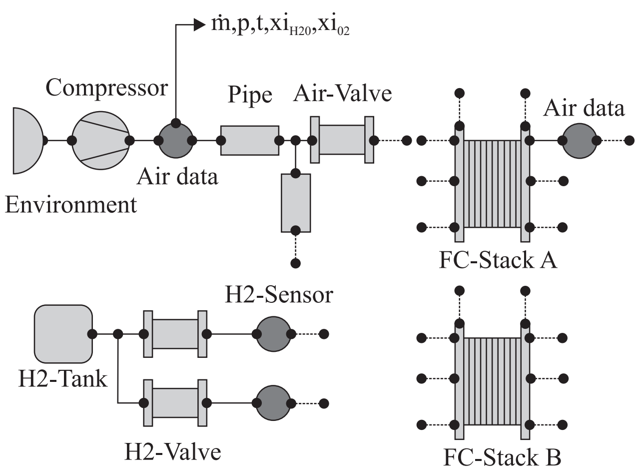

Figure 4. Extended system model of a MFFCS.

The system model consists of two fuel cell stacks that are supplied with pressurized air by a compressor and with hydrogen by a H_2 tank. Different pipes and valves are used for transportation and control. The oxygen depleted air of both fuel cell stacks is merged, transported and separated for further tasks. This could be kerosene tank inerting and cargo fire suppression. Processing the air is done by using pipes and valves. The hydrogen that has not been used in the electrochemical process inside the fuel cells is fed back to the hydrogen supply. Pumps, valves and pipes are used therefore.

The nominal system model is extended with faulty behavior on the component level. Examples are leakages of pipes, jamming of valves and dedicated failure modes of fuel cells. An example of a failure model of a pipe of the air supply is shown in Figure 5.

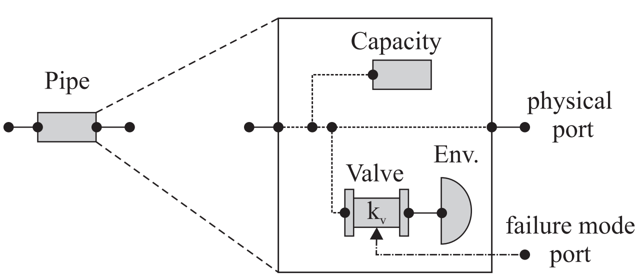

Figure 5. Failure model of a pipe.

The failure model of the pipe consists of a block representing the pipe's capacity and a valve that is connected to the environment. The integration into the overall model is done by using three ports. Two of them are physical conserving and bidirectional whereas the failure mode port is directional. By means of a time controlled failure signal, the valve can be opened in order to simulate a leakage. This is done by adapting the specific flow coefficient k_v that is influencing the mass flow $\dot{m}_{air}$ through the valve (Herwig, 2006). This is shown in Equation 5.

$$\dot{m}_{air} = k_v \cdot \sqrt{\frac{\rho_{air,in} \cdot p_{air,out}}{T_{air,in}} \cdot (p_{air,in} - p_{air,out})}. \quad (5)$$

After implementing all failure modes in the overall model, a bottom up simulation is carried out. The respective effects of each failure are observed by using sensors, that have been placed at several positions inside the model. An example is shown in Figure 4. By means of air data sensors, information about mass flow, pressure, temperature as well as 0_2 and $H_2 0$ fractions are gained. These values are evaluated with respect to thresholds like it is shown in Equation 6. This approach is used in order to increase the distance between the data sets of all the failure modes which facilitates the classification in later steps.

$$p_{FC1,in}* = \frac{p_{FC1,in} - \text{thresh.}_{p_{FC1,in}}}{\text{thresh.}_{p_{FC1,in}}}. \quad (6)$$

An example of how the evaluated effects of different failure modes look like is depicted in Figure 6. There, data is shown for 12 failures of the air supply system of both the fuel cell stacks. Only 7 data lines can be seen. This is due to the fact of overlapping failure modes showing the same effect. This is the case for different levels of friction of air pipes for this particular feature.

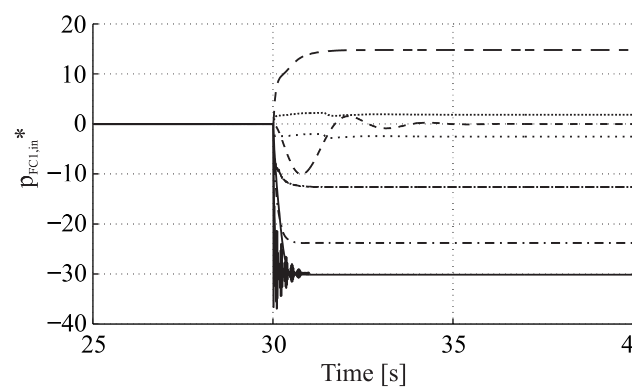

Figure 6. Data of faulty system behavior.

Each line in Figure 6 represents one failure mode that has been simulated. This will be explained in more detail in Section 4.1. In the next steps, it will be worked with the respective failure data. Therefore, the data is transferred into a matrix format which is shown in Table 1.

All available data is sampled at fixed instances of time by using a unique time vector for all failure modes. At each step of sampling, all features f_i^v, e.g. $p_{FC1,in}*$ and $T_{FC1,in}*$, are aggregated in a row of the matrix. Hence, a row always holds a vector of features f^v for a specific failure mode. The type of failure mode is represented by the *Class* variable in the last column. This procedure is done for all sampling points and repeated for all failure modes. The respective data is concatenated in the end.

The class variable c has a range from one to 12 which represents 12 failure modes that are taken into account in this study. The task of the fuzzy diagnosis rule is to classify the data vectors f^v so that the correct conclusion, meaning the correct class c can be inferred. This is done by using fuzzy inference which is explained in the next section.

Index	$p_{FC1,in}*$	**...**	$T_{FC1,in}*$	**Class c**
1	14.8043	...	57.7561	1
2	14.8043	...	57.7561	1
3	14.8042	...	57.7561	1
...				
543	26.1362	...	11.0998	2
544	26.1362	...	11.0998	2
545	26.1362	...	11.0999	2
...				
4000	-12.6088	...	11.0999	12

Table 1. Classified data of faulty system behavior.

3.2. Fuzzy Inference

Fuzzy inference is used by a set of fuzzy diagnosis rules in order to match features and derive conclusions. It is based on fuzzy sets in the rule's premise. These sets can be formulated by using two different approaches. The first one is descriptive with a linguistic variable from a color space. This means that each rule uses the same color for a given feature if it is in a certain range. An example would be a range of $[0.1..0.4]$ for feature f_1^v which could be assigned to the color Low. A drawback is that the range is fixed and holds for all rules. Hence, the second approach is approximative where each rule is allowed to define its own fuzzy sets rather than using predefined colors. This means that each rule can work with its own range of feature values. Although this shows a lack of interpretability, it offers more granularity and by that leads to better results. This approach is used in this study.

The matching degree $\mu_n(f^v)$ of a fuzzy diagnosis rule n and feature vector f^v states the compatibility between f^v and the premise. It is defined as follows (Cox, 1994):

$$\mu_n(f^v) = \prod_{i=1}^{N} \mu_i^n(f_i^v). \quad (7)$$

In Equation 7, the term $\mu_i^n(f_i^v)$ is the membership grade of rule n in dimension i of the feature vector f^v. This is implemented as a double sided *Gaussian* membership function having the form (Cox, 1994):

$$\mu_i^n(f_i^v) = \begin{cases} \exp\{\frac{-(f_i^v - m_l^{n,i})^2}{(\sigma_l^{n,i})^2}\}, & f_i^v < m_l^{n,i}, \\ 1, & m_l^{n,i} \leq f_i^v \leq m_r^{n,i}, \\ \exp\{\frac{-(f_i^v - m_r^{n,i})^2}{(\sigma_r^{n,i})^2}\}, & f_i^v > m_r^{n,i}. \end{cases} \quad (8)$$

In Equation 8, the terms $m_l^{n,i}$ and $m_r^{n,i}$ are the centers of the left and right Gaussian functions with widths $\sigma_l^{n,i}$ and $\sigma_r^{n,i}$. This applies for rule n and feature i.

During derivation of the fuzzy rule base, the rule consequent c_n of rule n has to be determined. This is done by calculation of the dominating class c of all the classes F among all instances f^v with class label c^f which are covered by the rule's premise:

$$c_n = \arg\max_{c=1:F} \sum_{f^v, c^f = c} \mu_n(f^v). \quad (9)$$

The approach of Equation 9 is called maximum voting scheme. It uses overlapping and cooperating fuzzy sets rather than only maximum matching.

After having fixed all rule consequents c_n and having derived the entire rule base, Equation 9 is adapted to have the form:

$$c_{max} = \arg\max_{c=1:c_n} \sum_{n, c_n = c} \mu_n(f^v). \quad (10)$$

Based on Equation 10, inferring a solution to the classification problem by using the derived rule base is again done by using maximum voting. This time however, the decision is made by summing up the matching degrees $\mu_n(f^v)$ for one given feature vector f^v and the conclusion c_n of rule n. The maximum argument then gives the overall conclusion c_{max}.

The degree of certainty ϵ of correct classification of class c is calculated as the ratio of the sum of matching degrees $\mu_n(f^v)$ for $c = c_{max}$ and all available feature vectors f^v referred to the overall matching degree, irrespective of the rule's consequent:

$$\epsilon_c = \frac{\sum_{f^v, c = c_{max}} \mu_n(f^v)}{\sum_{f^v} \mu_n(f^v)}, \; \mu_n(f^v) > 0. \quad (11)$$

In order to identify those parameters of the fuzzy inference so that the desired behavior of correct classification with a high degree of certainty is achieved during operation, fuzzy modeling is used. This can be done manually but is complex and prone to failure. The use of automatic approaches for the derivation of membership functions and rule base is motivated thereby.

In literature there are mostly non technical but medical and geographical approaches that use evolutionary algorithms to automatically and optimally construct rule base and membership functions (Herrera, Lozano, & Verdegay, 1995) (Andres Pena-Reyes & Sipper, 1999) (Gonzles & Francisco, 1997) (Stavrakoudis, Theocharis, & Zalidis, 2009). An overview is given in the next section and one approach is chosen.

3.3. Optimization Procedure

As a form of an evolutionary algorithm, the genetic algorithm (GA) is used in this study. The GA is an iterative procedure that uses a population of individuals where each individual is represented by a genome. This encodes a solution inside a given problem space that comprises all feasible solutions to the problem under study (Coello, Lamont, & van Veldhuizen, 2007). In general, the GA always starts with an initial population of individuals and evolves towards optimized individuals by using genetic operators inspired by nature. For details please refer to (Coello et al., 2007).

In literature there are basically three approaches for using genetic algorithms to derive parameters of membership functions and fuzzy rules (Michalewicz, 1996) (Gonzles & Francisco, 1997). These are explained briefly in the following.

The Michigan Approach In the Michigan approach, each individual of the GA represents a single rule and respective membership functions. The fuzzy inference system is represented by the entire population of individuals. Due to the fact that several rules participate in the inference process the active rules are in constant competition for the best action to be proposed and cooperate to form an efficient fuzzy rule-based system. The cooperative-competitive nature of this approach is one drawback as it complicates the decisions on which of the rules are ultimately responsible for an optimal behavior. By that an effective policy to build adequate fitness values is necessary (Michalewicz, 1996).

The Pittsburgh Approach In the Pittsburgh approach, each individual of the GA represents a candidate for the entire fuzzy rule-based system. This means that it holds a predefined number of rules with respective membership functions. Genetic operators are used to generate new generations of the entire system. A benefit of this approach is that an evaluation is easily possible as the entire system is encoded in one individual. A major drawback though is a high computational cost as well as the fact that the number of rules has to be defined in advance.

The Iterative Rule Learning Approach In the Iterative Rule Learning approach each individual represents a single rule of the rule base to be derived. The GA is used sequentially to determine a single optimal rule in each run. This is a partial solution to the entire problem. In order to solve that, the GA is used in an iterative manner in order to discover new rules and check each time if all cost and performance criteria are already fulfilled. If this is the case the process stops. In order to prevent the discovery of redundant rules there are approaches to remove covered data sets as well as to penalize covered data sets (Gonzles & Francisco, 1997). The benefit of this approach is that it combines the benefits of the Michigan and the Pittsburgh approaches which is the speed and the simplicity of defining and applying optimization criteria.

The iterative rule learning approach is chosen in this study. This generates one rule at a time in an iterative manner. The rule is represented by a genome. This is a finite set of symbols which is split into a real valued part representing parameters of the membership function and a binary valued part representing the features that are chosen. An example is depicted in Equation 12.

$$[|\ \underbrace{0\,|\,1}_{\text{Binary part}}\ ||\underbrace{m_l^1|\ \Delta m^1|\ \sigma_l^1|\ \sigma_r^1|\ m_l^2|\ \Delta m^2|\ \sigma_l^2|\sigma_r^2}_{\text{Real-valued part}}] \qquad (12)$$

In Equation 12, a genome is shown that represents a fuzzy diagnosis rule. There are two features available where the first one is not active in the current case. Each binary value is related to four real valued parameters. These are part of the membership function and have been introduced previously. The parameter Δm^1 is the difference between the left and right center of the Gaussian membership function:

$$\Delta m^1 = m_r^1 - m_l^1, m_r^1 > m_l^1.$$

An important aspect of the iterative rule learning approach is the penalization of covered data sets. The approach of *Boosting* is applied for that, as proposed in (Stavrakoudis et al., 2009). Basically this means, that initially all data sets are weighted with a single factor w^{f_v}. This can be a value of one. After each run of the GA, the rule error of the current rule is determined for each feature vector f^v. Features that are classified correctly are reduced in their weight whereas misclassified features keep their former weight. For more details please refer to (Hastie, Tibshirani, & Friedman, 2009).

The weights w_{f_v} are included in the fitness function of the GA where the overall fitness function consists of three sub functions. These are introduced in the following.

The set of fuzzy diagnosis rules should exhibit a low rate of misclassification. This is taken into account using the factors ω^+ and ω^-.

$$\omega^+ = \sum w_{f_v} \cdot \mu_n(f^v), \forall f^v \exists\, c_{f^v} = c^n. \qquad (13)$$

$$\omega^- = \sum w_{f_v} \cdot \mu_n(f^v), \forall f^v \exists\, c_{f^v} \neq c^n. \qquad (14)$$

By means of Equation 13, a weighted sum of membership grades is gained for those features that are classified correctly. Misclassified features are taken into account by means of Equation 14.

Using ω^+, the class coverage is defined as first factor f_1 of the overall fitness function:

$$f_1 = \frac{\omega^+}{\sum w_{f_v}}, \forall f^v \, \exists \, c_{f^v} = c^n. \tag{15}$$

Using Equation 15, correctly classified features are taken into account. In order to have a rule that supports a high amount of feature vectors f^v, factor n is defined as the ratio of ω^+ related to the sum of the weights of all features covered by the rule, independent of the class label:

$$n = \frac{\omega^+}{w_{f_v}}. \tag{16}$$

By means of Equation 16 the class support f_2 is defined as follows:

$$f_2 = \begin{cases} 1, & \text{if } n > k_{cov} \\ n/f_{cov}, & \text{otherwise.} \end{cases} \tag{17}$$

By using the factor f_2 the generality of the rule is enforced. Depending on the number of classes, a value of $f_{cov} \in [0.2, 0.5]$ is proposed in (Stavrakoudis et al., 2009). As a last factor the rule consistency is introduced. This means that the rule should not only possess a high number of correct classification but likewise a low number of misclassification. This is addressed by means of factor f_3:

$$f_3 = \begin{cases} 0, & \text{if } k_c \cdot \omega^+ < \omega^- \\ (\omega^+ - \omega^-/k_c)/\omega^+, & \text{otherwise.} \end{cases} \tag{18}$$

A value of $f_c \in [0, 1]$ is proposed in (Stavrakoudis et al., 2009). All factors are normalized so that the overall fitness function is defined as the product of f_1, f_2 and f_3:

$$f = f_1 \cdot f_2 \cdot f_3. \tag{19}$$

3.4. Fuzzy Diagnosis Rule Generation Algorithm

The previous sections introduced basics of fuzzy inference and an optimization procedure that is used to train fuzzy diagnosis rules. These tasks are integrated into an algorithm that is explained in the following. An overview is given by Figure 7.

A model of a MFFCS is used to gain data of faulty system behavior. This is split into training data (TD) and validation data (VD), where TD is used for training of rules and VD for testing the current performance of classification. The rule base is initially empty. According to the iterative rule learning approach, one fuzzy diagnosis rule is trained at a time by using the fitness function from Equation 19 for evaluation. In a post processing step, the binary part of the genome is analyzed further. All non zero entries are sequentially set to zero and it is checked if the fitness value remains constant. If this is the case, there is no need for the related feature. Hence, the total number of required features and sensors can be reduced. By means of VD, the current performance is tested. If it is above an initial threshold and higher than the previous performance, the rule is accepted and added to the rule base. In a *boosting* step, the current rule error is calculated on basis of the misclassified data, and the weights of TD are updated. The process continues in a loop until a stop criterion is reached. In the current case this is the number of runs of the algorithm. In the future, this can also be coupled to the performance. If the process stops, all genomes are transformed into the structure of Equation 4 and a fuzzy diagnosis rule base is gained.

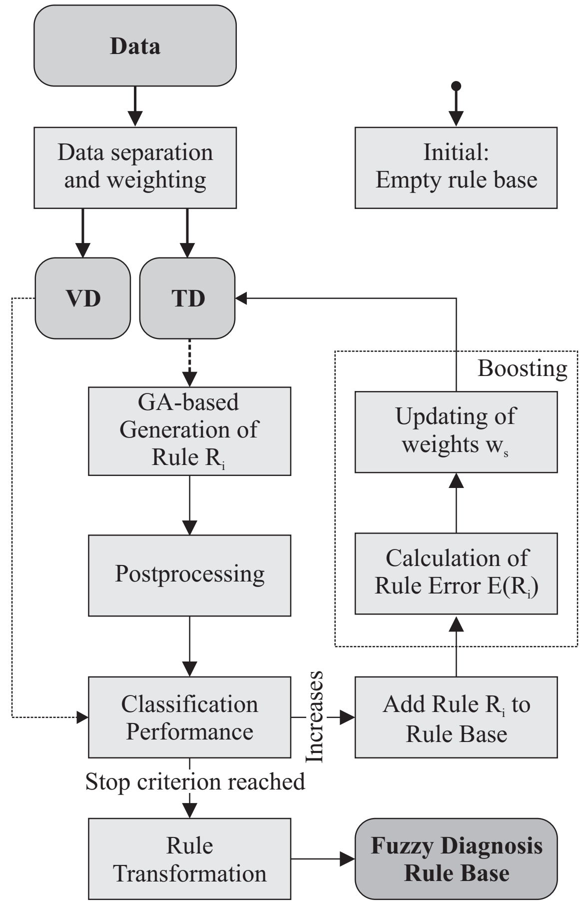

Figure 7. Process for the derivation of optimized fuzzy diagnosis rules.

4. RESULTS

This section depicts the results that are obtained by applying the algorithm from Section 3.4 to a MFFCS. In Subsection 4.1, failure modes that have been taken into account are highlighted and sensors are shown that provide data about faulty system behavior. Afterwards, in Subsection 4.2 results of the optimization procedure are discussed and examples of the derived rule base are presented.

4.1. Failure modes

In the current study, 12 different failure modes have been taken into account. These are given by six components where each component contains two failure modes. These components are part of the air supply of both the fuel cell stacks as it is shown in Figure 8. An overview of the failure modes is depicted in Table 2.

Component	Failure Mode	Class. c
Compressor	Increased friction	1
	Jamming	2
Pipe A	Increased leakage	3
	Highly increased leakage	4
Pipe B	Increased leakage	5
	Highly increased leakage	6
Pipe C	Increased leakage	7
	Highly increased leakage	8
Air-Valve A	Jamming in closed position	9
	Jamming in half opened position	10
Air-Valve A	Jamming in closed position	11
	Jamming in half opened position	12

Table 2. Failure modes that have been taken into account.

In order to detect the failure modes and classify the related data, 10 sensors Si have been placed in the system. These provide 12 measurements as shown in Figure 8. Measurements range from pressure p of air and hydrogen, mass flow $\dot{m}$, electrical current I to the fraction of oxygen x_{02} and gaseous water x_{H20} in the air. By means of the optimization procedure, those features are identified that are really needed for data classification.

4.2. Fuzzy diagnosis rule base

In total, 250 runs of the fuzzy diagnosis rule generation algorithm have been performed and a classification performance of 99.2% has been reached. This is achieved by 15 rules. These are split into three rules that are used for inference of classification 3, two rules for classification 4 and one rule for every other classification. Measurements of current by means of sensors $S3$ and $S7$ as well as measurement of mass flow $\dot{m}$ by means of sensor $S9$ are not required to achieve the result. After termination of the algorithm all rules are transformed into the format shown in Equation 4. In order to clarify the result, an example is given in the following.

Two rules are used for inferring a highly increased leakage of pipe A which is class 4. These are the rules 8 and 11 of the rule base. Rule 8 uses three features. These are provided by sensors 4, 6 and 9. Rule 11 uses one feature which is provided by sensor 9. The structure of rule 8 is shown in Equation 20 and the structure of rule 11 in Equation 21.

$$\begin{aligned} \text{Rule 8: if } & S4 : x_{H20}* = High \text{ with Exceeding} = a_4^8 \\ & \text{and } S6 : p* = Low \text{ with Exceeding} = a_6^8 \\ & \text{and } S9 : p* = Low \text{ with Exceeding} = a_9^8 \\ & \text{then suspect } c = 4 \text{ with certainty } \epsilon_4. \end{aligned} \tag{20}$$

In a cooperative manner, rule 11 supports the inference of the conclusion of rule 8.

$$\begin{aligned} \text{Rule 11: if } & S9 : p* = Low \text{ with Exceeding} = a_9^{11} \\ & \text{then suspect } c = 4 \text{ with certainty } \epsilon_4. \end{aligned} \tag{21}$$

Both the rules use the feature $S9 : p*$ which is shown in Figure 9. There are depicted effects which are based on a simulation of an increased leakage and a highly increased leakage of pipe A. At an instant of time $t_F = 30s$ those failures are activated. Based on that, a decrease of $S9 : p*$ can be observed that is followed by an increase which is based on control action.

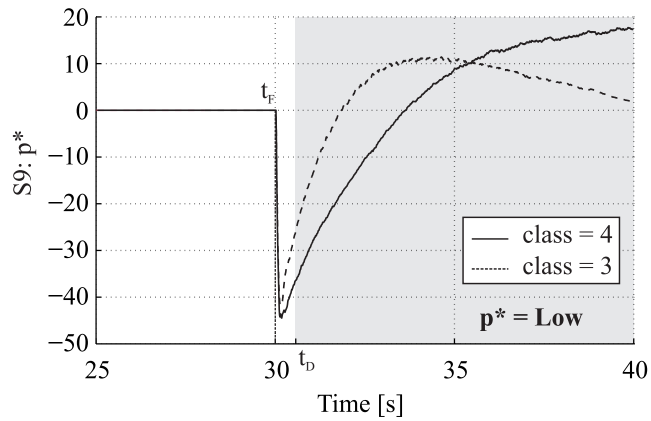

Figure 9. Effects of increased and highly increased leakage of pipe A.

At time t_D both the failures are detected by means of indicator color $S9 : p* = Low$. Inferring the root cause starts at this moment. For this task, only a small part of the data range is used by the fuzzy sets a_9^8 and a_9^{11}. This is shown in Figure 10 where a detailed view of Figure 9 is given.

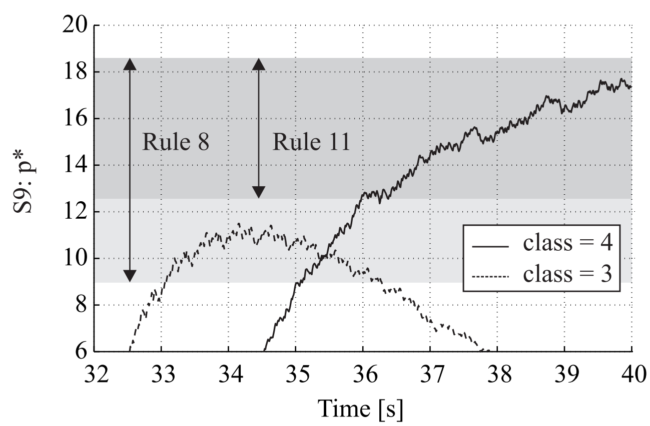

Figure 10. Detailed view of effects increased and highly increased leakage of pipe A.

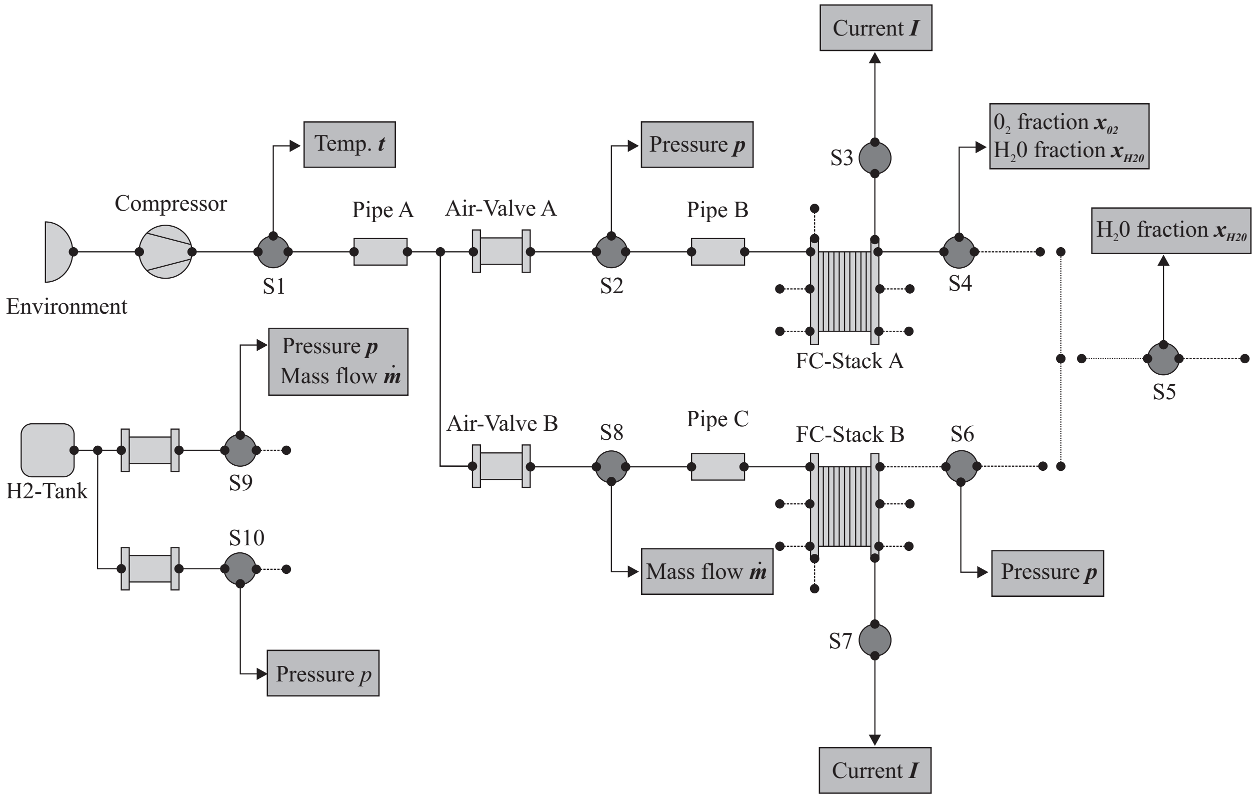

Figure 8. Sensor locations and components with faulty behavior that have been taken into account in the study.

Rule 8 uses a data range that covers data for both classes 3 and 4. The result that can be inferred is not sufficient so that rule 11 is used for support. The respective data range covers a part of the data range of rule 8 but only the part that is unique for class 4.

An interesting aspect of rules 8 and 11 is that both use data of the hydrogen supply in terms of $S9 : p*$ in order to infer failures of the air supply. They don't use the feature $S2 : p*$ that has been shown in Figure 6 as an illustrative example of raw data of faulty behavior. Based on only $S2 : p*$ it was obvious that both the classes 3 and 4 could not be inferred as the effects overlap. By means of the rule generation algorithm this result is confirmed and optimal features are gained for separation. Instead of using $S2 : p*$ the feature $S9 : p*$ is more valuable although not a part of the air supply. If the rules would have been created in a manual way, this feature would therefore probably not be used although giving good results. Furthermore, a manual generation of the fuzzy sets in an optimized way would have been hardly possible.

5. CONCLUSION

Multifunctional system concepts and ambitious goals for the future of European air traffic require powerful health management technologies to ensure a safe operation and a high availability. This paper introduced a model-based approach for the derivation of fuzzy diagnosis rules for multifunctional fuel cell systems. These rules are used for the inference of root causes of detected failures and malfunctions. A fast and reliable troubleshooting is gained by that. In order to clarify the background of the paper, the concept of a multifunctional fuel cell system has been explained in detail in the beginning. The importance of dealing with health management functions has been emphasized and the general concept of fuzzy diagnosis rules has been introduced afterwards. Subsequently, a novel approach to derive a fuzzy rule base was depicted. An extended system model has been used to gain knowledge about effects of failures and malfunctions. These effects have been allocated a unique class label which represents the underlying root cause. Data of faulty system behavior was gained and stored in a matrix. In an evolutionary optimization procedure, fuzzy sets have been trained on basis of the matrix data so that the correct class label can be inferred. Based on a case study, a rule base of 15 rules has been derived in the end. An example illustrated two rules and showed that the novel approach gives valuable results. Compared to other classification procedures, a traceable and human interpretable approach has been introduced.

The case study of this paper dealt with the air supply system of two fuel cell stacks. The approach has also been applied to the entire multifunctional fuel cell system including the fuel cell stacks. However, in order to clarify the basic approach and the general procedure to derive the rule base, only a small part of all failure modes and malfunctions has been dealt with in the case study. A further paper on the application of the approach on specific fuel cell failures is in progress and will come in future. Furthermore, in future work, the proposed approach could be extended to also deal with early failure detection as a first step of prognosis. Degraded behavior can be simulated therefore in different levels up to failures and malfunctions. The respective data can then be dealt with by using the approach described in this paper.

NOMENCLATURE

A	color variable
I	current
N	Number of rules
R	Rule
a	fuzzy set
m	mass
m_l	left center of Gaussian function
m_r	right center of Gaussian function
T	temperature
c	class variable
p	pressure
f^v	feature vector
f	fitness function
h	height
i	dimension
k_v	specific flow coefficient
x	fraction
ϵ	certainty factor
μ_n	matching degree of rule n
ρ	density
σ	width
ω	classification factor

REFERENCES

Andres Pena-Reyes, C., & Sipper, M. (1999). A Fuzzy-Genetic Approach to Breast Cancer Diagnosis. *Artificial Intelligence in Medicine*, *17*(2), 131–155.

Coello, C. A. C., Lamont, G. B., & van Veldhuizen, D. A. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems* (2nd ed.). Boston and MA: Springer Science+Business Media, LLC.

Cox, E. (1994). *The Fuzzy Systems Handbook: A Practitioner's Guide to Building, Using, and Maintaining Fuzzy Systems*. San Diego, CA, USA: Academic Press Professional, Inc.

Enzinger, M. (2010). *Technology Programmes-Multifunctional Fuel Cell Application.* Hamburg.

European Organisation for the Safety of Air Navigation. (2013a, March). *Coda Digest - Delays to Air Transport in Europe - Annual 2012* (Tech. Rep.). Brussels, Belgium: Eurocontrol-Central Office for Delay Analysis.

European Organisation for the Safety of Air Navigation. (2013b, May). *Performance Review Report - An Assessment of Air Traffic Management in Europe during the Calender Year 2012* (Tech. Rep.). Brussels, Belgium: Eurocontrol-Performance Review Commission.

European Commission. (2001, January). European Aeronautics: A Vision for 2020. *Report of the group of personalities*.

European Commission. (2011). Flightpath 2050 - Europe's Vision for Aviation. *Report of the high level group on aviation research*.

Gonzles, A., & Francisco, H. (1997). Multi-Stage Genetic Fuzzy Systems based on the Iterative Rule Learning Approach. *Mathware and Soft Computing*, *4*(3), 233–249.

Grymlas, J., & Thielecke, F. (2013). Virtual Integration and Testing of Multifunctional Fuel Cell Systems in Commercial Aircraft. *SAE International Journal of Aerospace*, *6*(2), 746–760.

Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). New York: Springer.

Herrera, F., Lozano, M., & Verdegay, J. L. (1995). Generating Fuzzy Rules from Examples using Genetic Algorithms. *Fuzzy Logic and Soft Computing*, *4*, 11–20.

Herwig, H. (2006). *Strömungsmechanik: Eine Einführung in die Physik und die mathematische Modellierung von Strömungen* (2nd ed.). Berlin: Springer.

Michalewicz, Z. (1996). *Genetic Algorithms + Data Structures = Evolution Programs* (3rd ed.). Berlin: Springer.

Modest, C., & Thielecke, F. (2012). A Design Methodology of Optimized Diagnosis Functions for High Lift Actuation Systems. In I. Roychoudhury, J. R. Celaya, & A. Saxena (Eds.), *Proceedings of the Annual Conference of the Prognostics and Health Management Society 2012* (pp. 233–248). PHM Society.

Stavrakoudis, D., Theocharis, J., & Zalidis, G. (2009). Genetic Fuzzy Rule-based Classifiers for Land Cover Classification from Multispectral Images. In S. G. Tzafestas & K. P. Valavanis (Eds.), *Applications of Intelligent Control to Engineering Systems* (Vol. 39, p. 195-221). Dordrecht: Springer Netherlands.

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