An Intelligent System Supporting a Forklifts Maintenance Process

Katarzyna Antosz[(✉)] and Dorota Stadnicka

Faculty of Mechanical Engineering and Aeronautics, Rzeszow University of Technology,
Rzeszów, Poland
{katarzyna.antosz,dorota.stadnicka}@prz.edu.pl

Abstract. A maintenance process of forklifts presented in this work is realized by a service organization which delivers services for several companies that use forklifts. In the work, the fuzzy logic was implemented to assess the risk of failures for different groups of forklifts. The results of the analysis are to be taken into consideration by the service company in the decision making process. The plan of maintenance activities for each client's forklifts can be developed and adequate maintenance activities can be indicated for each group on the basis of the risk of failures.

Keywords: Maintenance · Fuzzy logic · Intelligent system · Frequency of maintenance tasks

1 Introduction

A maintenance process made by a service organization on machines being used in different organizations is difficult. It is even more difficult because of different conditions that can be included in a service contract [1]. Additionally, when it comes to the servicing organizations, two different situations can appear. A servicing company can be a producer of a machine [2] or an organization only delivering maintenance services.

It is not only a matter of distance between a service organization and the locations of serviced machines, but there are also other factors which make the process difficult.

Undoubtedly, the most important is the proper planning of the maintenance activities, which should be made on the basis of a machine exploitation. Therefore, the right communication between machines owners and a service organization is very important in order to plan the maintenance process in a collaborative way. For example, in the work [3] the authors propose such a collaborative maintenance planning system.

Another factor is a company engagement in the autonomous maintenance. In some organizations the autonomous maintenance can be performed properly. Other organizations do not undertake any autonomous maintenance activities even to keep their own machines clean.

The next problem is connected to financial issues. Sometimes, even if a company knows that some maintenance activities should be undertaken, it is not willing to pay a service organization at a certain time, and it postpones the actions what in consequence

may lead to failures. It can be related to the importance of machines for companies. Sometimes even the same machine can have different importance for different companies. Therefore, a maintenance service company should perform the machines categorization with the participation of the owner of the serviced machines. The results of the machines categorization will be the basis for the decision about maintenance activities which should be undertaken to keep the risk of failures on the established level. It will also help in the spare parts management [4, 5] as well as the management of maintenance employees and their workplace [6–8].

Therefore, the main issue is connected to the risk of failures assessment. The failures may interrupt the production process and generate costs connected not only with failures elimination, but also with production disruptions. In the work [9], the authors propose to use ontologies and multi-agent systems as an approach for disruptions and risks monitoring. The system was designed to support a decision making process.

Various situations may arise depending on a company, a branch, a product, a company financial situation, consequences of a machine failure, etc. In some cases the results of machines failures are connected only with financial losses, in other cases the consequences of failures may influence e.g. the environment or people's safety.

The author of the paper [10] proposes to use a multicriteria decision making approach to improve maintenance policies in a healthcare organization where the condition of healthcare equipment may influence human life.

In turn, in the work [11], the authors incorporated machine learning techniques together with the distributed learning and hierarchical analytical approaches to explore historical and real-time data concerning railway conditions and to predict failures. However, for example in the manuscript [12], a combined data mining-based methodology for the condition-based maintenance, which considers the condition monitoring data and historical maintenance management data, is presented. In the paper [13], the importance of predictive maintenance as well as its impact of machine operation and manufacturing equipment throughout the years was presented. The authors of the work [14] propose the policies for preventive replacement of machines components for complex process plants, where the tracking of each component is difficult. In the paper [15, 16], a novel degradation prediction approach based on the condition monitoring signals and evaluation of the risk in production systems with a parallel reliability structure is presented. However, such sophisticated analytical systems are not always justified.

Simply, the risk of failures can be calculated with the use of the data collected in a maintenance process, for example on the basis of the machine age and its working hours. Nevertheless, knowing that in different companies the autonomous maintenance and general utilization of machines can be on a different level, the risk can be also different even if the input data are similar. For that reason, in this work the authors propose to use the fuzzy logic to calculate the risk of failures for the machines used in different companies.

In the case study presented in this paper, the maintenance process of forklifts undertaken by a service organization is realized to keep the forklifts ready to work. The forklifts are used in different companies and the service organization undertakes maintenance activities in various locations. In order to plan the activities, it is appropriate to predict failures to prevent them by undertaking adequate actions. In the presented case study,

the risk of failures was calculated for forklifts on the basis of the data collected in a maintenance process. In order to calculate the risk, the data concerning the age of forklifts as well as the number of their working hours were taken into consideration. The risk was assessed with the use of a simple method which takes into account the collected data. Then, the fuzzy logic was incorporated into the calculations. Finally, the percentage of preventive and corrective maintenance activities for the forklifts with medium and high risk of failures was presented on the basis of the historical data.

2   A Case Study

2.1   Structure of Forklifts Classification

The forklifts which are the subject of the following analyses can be classified according to different criteria, such as: a type of a forklift (diesel, hydraulic, electric), a brand (b_1, b_2, …, b_n), a model (m_1, m_2, …, m_n), a year of production (age <10, 10–20, >20 years) and working hours (millage <10,000, 10,000–20,000, >20,000). The data obtained during the own study as well as the data from [17] were used for the analysis.

2.2   Analyses of the Frequency of Maintenance Activities

In order to identify the frequency of maintenance tasks (*MT*) the gathered data were analysed. With the purpose of analysing the frequency of *MT,* two criteria were examined. The first is the age of a forklift (*AoF*) and the other is the number of working hours (*NoWH*). It was observed that the *AoF* is in the range of 5–31 years, and *NoWH* is in the range of 1,346–29,100 h. These criteria were divided into three categories – *Low (L), Medium (M)* and *High (H)* (Table 1).

Table 1.   Criteria classification.

Range			
Category	L - Low	M - Medium	H - High
Age of forklift (AoF) [years]	<10	10–20	>20
Number of working hours (NoWH) [hours]	<10,000	10,000–20,000	>20,000

For the groups created with the use of these categories of the criteria, the frequency of maintenance tasks (*FoMT*) in the analysed group of forklifts was calculated by means of the formula (1). The results of the calculations are presented in Table 2.

$$FoMT = \frac{NoMT_C}{\sum NoMT} \tag{1}$$

where: *FoMT* – the frequency of maintenance tasks,

NoMTc – a number of maintenance tasks in each category (in relation to *AoF* and *NoWH*),

$\sum NoMT$ – the sum of all (number) maintenance tasks in the analysed period of time.

Table 2. Frequency of maintenance tasks of analysed forklifts.

Age of forklift (AoF) [years]		L	M	H
Number of working hours (NoWH) [hours]	L	0.24	0.42	0.02
	M	0.08	0.18	0.02
	H	0	0.04	0

Based on the experience of both the maintenance personnel and authors, it was assumed that if *FoMT* is less than 0.20 the frequency is Low, if *FoMT* ranges between 0.20–0.40 the frequency is Medium, and for more than 0.40 the frequency is High (Table 3). In Table 4 the risk level for each category is presented.

Table 3. The categories of FoMT.

The category	L	M	H
The values	<0.20	0.20–0.40	>0.40

Table 4. The level of FoMT.

Age of forklift (AoF) [years]		L	M	H
Number of working hours (NoWH) [hours]	L	M	H	L
	M	L	L	L
	H	L	L	L

There is no problem in estimating the level of *FoMT* if the values of both, the age of a forklift (*AoF*) and the number of working hours *(NoW*H) are in the middle of each range. However, if the value falls to the border of a particular range, then there is a high possibility of making suboptimal classification the level of *FoMT*. In addition, such uncertainty creates significant variability in the analysis depending on the available information, knowledge and experience. In order to cater these circumstances, it is vital to use a fuzzy logic-based approach for enhancing the level of *FoMT*.

2.3   Fuzzy Logic in Support of FoMT Determination

The illustrative case presented in this work uses a Mamdani-type fuzzy inference process.

This type of Fuzzy Interference System was used because it is based on the expertise and experience of an operator of the system. Mamdani systems are the most intuitive and easy to understand. The general scheme of the system of inference presented for the analysed example is shown in Fig. 1.
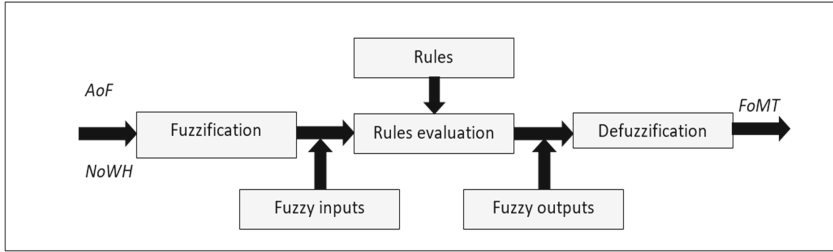
Fig. 1. Fuzzy Interference Process.

The operation of the fuzzy inference consists of the following steps:

1. **Fuzzification** of input values, and thus the calculation of the degree of the inputs membership to each of the terms.
2. **Rules evaluations.** Determination of the degree of fulfilment of each rule. On this stage the fuzzy input variables are entered. These values carry out a logical operation. As a result the changing shape of the membership function is obtained. To change the shape, the levels of the condition are determined. Besides, each of the rules has a declared weight between 0 and 1, which expresses its validity. As the output of this stage we get fuzzy.
3. **Defuzzification** is the combination of all individual collections created (by cutting or rescaling) in the previous step for each rule. These sets are combined into one fuzzy set. It is a determination of the values for each of the output of the fuzzy set [18].

In this case the membership functions are established with respect to the ranges of the *AoF* and *NoWH*, which were developed by engaging maintenance experts. The input data used for the analysis must be quantitative [19–21] or qualitative and judgmental (i.e. linguistic) [22]. Additionally, using the corresponding membership function, the user is more confident that the input parameter is located in the central part of the range than at the edges. In this article, the authors incorporated the functions of Gaussian membership, as in the works [19–21, 23], to minimize the difference between the practical application and mathematical modelling which is defined by the Eq. (2):

$$\text{Gaussian } (x; sigm, c) = e^{\dfrac{-(x-c)^2}{2\sigma^2}} \tag{2}$$

where c represents the centre and *sigm* determines the width of the membership functions. In order to determine the membership functions, the Gaussian combination membership (GCMF) (i.e. 'gauss2mf'), which is accessible in MATLAB (R2012a), was used [24]. The function "gauss2mf" is a combination of two parameters [i.e. ($c, sigm$)] indicated in the Eq. (3). It follows the syntax from Mathworks [25]:

$$y = gauss2mf\left\{x, \left[sigm\_(1)\, c\_(1)\, sigm\_(2)\, c\_2\right]\right\} \tag{3}$$

This function, 'gauss2mf', is a combination of the two of these parameters. The first function, defined by *sigm1* and *c1*, determines the profile of the left-most curve.

The other function defined by *sigm2* and *c2* determines the profile of the right-most curve. Whenever *c1* < *c2*, the "gauss2mf" function reaches the maximum value of 1. Otherwise, the maximum value is less than one [25]. The parameters are listed in the order [*sigm1, c1, sigm2, c2*]. Additionally, other parameters were selected (Table 5).

Table 5. Parameters of the fuzzy logic system.

The parameter	AND	OR	Implication	Aggregation	1 Defuzzification
The values	Min	Max	Min	Max	Centroid

A fuzzy rule base was developed with a table-look-up approach (Table 4). The simulator tool of MATLAB Fuzzy Toolbar (R2012a) was used to execute the suggested fuzzy inference process in Matlab program [24].

2.4   Analysis, Results and Discussion

Figure 2 illustrates Matlab R2012a based fuzzy logic designer used for calculating frequency of MT in relation to *AoF* and *NoWH*.
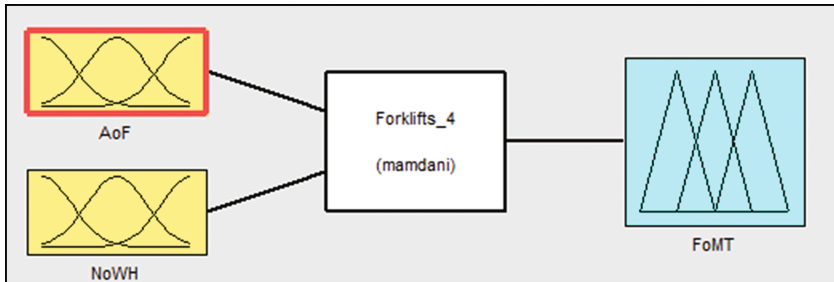

Fig. 2.   Fuzzy logic designer

Using the level of frequency of MT (see Table 6), a rule base was developed (see Fig. 3). The Gaussian combination memberships for the *AoF, NoWH* are illustrated in Figs. 4 and 5 respectively.

Table 6.   The percentage of maintenance tasks.

Type of maintenance		Preventive Maintenance (PM)	Corrective Maintenance (CM)
Level of FoMT	M	24%	76%
	H	18%	82%

Figure 6 illustrates a rule view and an example calculation of the frequency of maintenance tasks (*FoM*T) for forklifts. The calculation was carried out for the *AoF* = 15 and *NoWH* = 19,500 h. The frequency rank estimated by the fuzzy inference process is 0.183. The corresponding linguistic value is L (using the membership function in Fig. 5). This linguistic value shall be used for the organisation of the range and types of
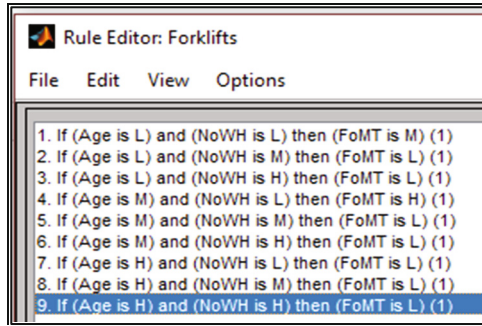
Rule Editor: Forklifts

File   Edit   View   Options

1. If (Age is L) and (NoWH is L) then (FoMT is M) (1)
2. If (Age is L) and (NoWH is M) then (FoMT is L) (1)
3. If (Age is L) and (NoWH is H) then (FoMT is L) (1)
4. If (Age is M) and (NoWH is L) then (FoMT is H) (1)
5. If (Age is M) and (NoWH is M) then (FoMT is L) (1)
6. If (Age is M) and (NoWH is H) then (FoMT is L) (1)
7. If (Age is H) and (NoWH is L) then (FoMT is L) (1)
8. If (Age is H) and (NoWH is M) then (FoMT is L) (1)
9. If (Age is H) and (NoWH is H) then (FoMT is L) (1)
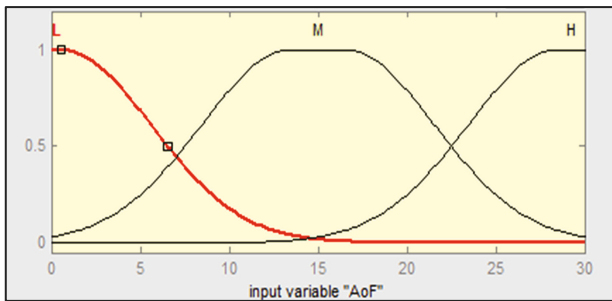
Fig. 3. A rule base.

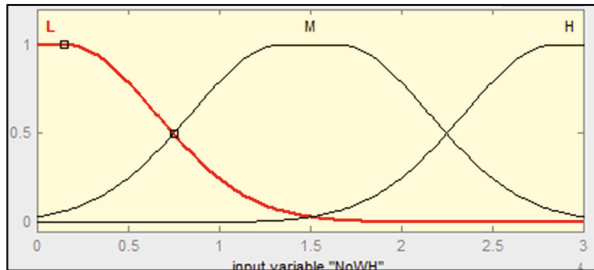**Fig. 4.** Gaussian combination membership of *AoF*.

Fig. 5. Gaussian combination membership of *NoWH*

maintenance tasks for forklifts (i.e. forklifts with high frequency of MT will be given a main priority).

Figure 7 illustrates three dimensional (3D) risk (*FoMT*) profiles in relation to *Ao*F and *NoWH*.
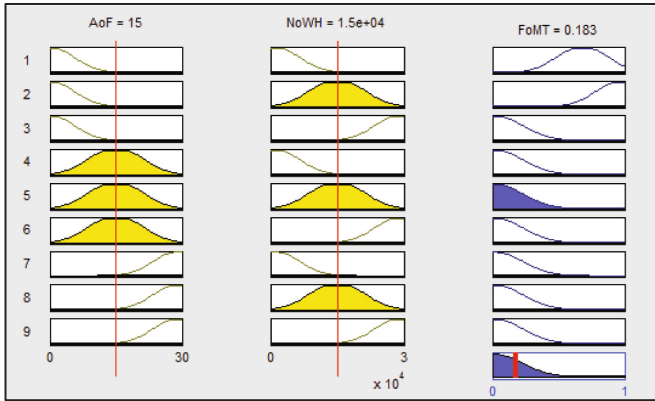
Fig. 6. Calculations [$FoMT = 0.183$ for $AoF = 15$ and $NoWH = 15{,}000$] and rule view.
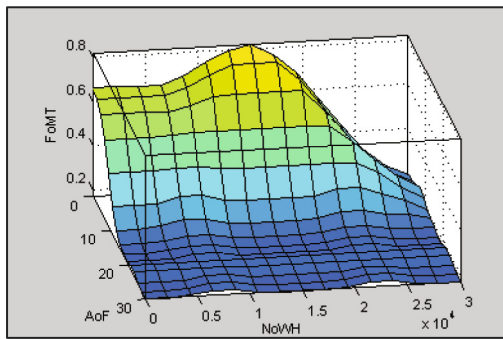

Fig. 7. 3D profile.

Based on the manufacturing company risk philosophy, it is possible to prioritize: 1. *AoF*, 2. *NoWH* or any other sequence.

Knowing the level of *FoMT* it would be good to know what kind/type of maintenance tasks the company will have to perform. That is why, the data collected of the maintenance of forklifts were analysed. The type of activities implemented was specified. Two types of maintenance tasks were defined: preventive and corrective maintenance. Table 6 shows the percentage of operations for these types of tasks for the levels of M and H of *FoMT*.

In this case study, a significant share of CM in relation to PM is noticed. The share of CM increases for a high level of *FoMT*. It may indicate the possibility of planning of more preventive actions to prevent failures. Unfortunately, the companies possessing forklifts are not willing to increase preventive activities, even if the risk of failures increases. However, a service company can be prepared for any additional maintenance tasks. On the basis of the machine categorization results, made together with an owner on a forklift, it may try to justify the necessity of undertaking preventive actions.

3   Conclusions

A maintenance process of forklifts presented in this work is characterized by a high share of corrective actions in comparison to preventive actions. The historical data can be used in the fuzzy logic programming, and then to present the risk of forklifts failures. The main reason why the fuzzy logic was implemented is that different forklifts owners treat forklifts in different ways. Therefore, even if there are two the same branches, the same models, at the same age, and forklifts used in a similar way (similar millage), the risk of failures can be different. The fuzzy logic implementation for the assessment of the risk of forklifts failures and for the maintenance tasks (preventive and corrective) prediction, as it is known to the authors, hasn't been done so far. The issue is interesting because, probably in many cases, it will be a service maintenance organization which will try to convince an owner of a forklift that it will be justified to undertake preventive actions, instead of corrective actions. It is worth emphasizing that many of the companies which cooperate with a case study service organization are SME with only one or two forklifts. Therefore, keeping their forklifts in a working order should lie in their interest. Using the presented concept, a service organization can calculate the risk of failure for each forklift and plan corrective and preventive actions. Obviously, it is impossible to predict exactly how many failures will happen on a particular forklift. However, the outputs of the analysis can be taken into account, for example in planning of human resources which are to be engaged in the maintenance tasks.

In the future work, the authors would like to integrate the presented concept with machines categorization.

References

1. Kumar, R., Markeset, T., Kumar, U.: Maintenance of machinery: negotiating service contracts in business-to-business marketing. Int. J Serv. Ind. Manuf. **15**(3-4), 400–413 (2004)
2. Juściński, S., Piekarski, W.: Logistic management of an authorized service for agricultural tractors and machines. Eksploatacja i Niezawodnosc (Maint. Reliab.) **2**(38), 23–33 (2008)
3. Wan, S., Li, D.B., Gao, J., Roy, R., Tong, Y.F.: Process and knowledge management in a collaborative maintenance planning system for high value machine tools. Comput. Ind. **84**, 14–24 (2017)
4. Cheng, C.Y., Prabhu, V.: Evaluation models for service oriented process in spare parts management. J. Intell. Manag. **23**, 1403–1417 (2012)
5. Carpentieri, M., Guglielmini, A.N., Mangione, F.: A Life cycle cost framework for the management of spare parts. In: Advances in Life Cycle Engineering for Sustainable Manufacturing Businesses, pp. 473–478. Springer, London (2007)
6. Colen, P.J., Lambrecht, M.R.: Cross-training policies in field services. Int. J. Prod. Econ. **138**, 76–88 (2012)
7. Loewenstern, D., Pinel, F., Shwartz, L., Gatti, M., Herrmann, R., Cavalcante, V.: A learning feature engineering method for task assignment. In: Proceedings of the 13th IEEE/IFIP Network Operations and Management Symposium, pp. 961–967 (2012)
8. Jasiulewicz-Kaczmarek, M., Drożyner, P.: Preventive and pro-active ergonomics influence on maintenance excellence level. In: Robertson, M.M. (ed.) Ergonomics and Health Aspects, HCII 2011. LNCS, vol. 6779, pp. 49–58. Springer, Berlin (2011). ISBN 978-3-642-21715-9

9. Bayar, N., Darmoul, S., Hajri-Gabouj, S., Pierreval, H.: Using immune designed ontologies to monitor disruptions in manufacturing systems. Comput. Ind. **81**, 67–81 (2016)
10. Carnero, M.C., Gomez, A.: A multicriteria decision making approach applied to improving maintenance policies in healthcare organizations. BMC Med. Inform. Decis. Mak. **16**, 47 (2016). doi:10.1186/s12911-016-0282-7. Springer, London
11. Li, H.F., Parikh, D., He, Q., Qian, B.Y., Li, Z.G., Fang, D.P., Hampapur, A.: Improving rail network velocity: a machine learning approach to predictive maintenance. Transp. Res. Part C **45**, 17–26 (2014)
12. Galar, D., Gustafson, A., Tormos, B., Berges, L.: Maintenance decision making based on different types of data fusion. Eksploatacja i Niezawodnosc (Maint. Reliab.) **2**, 135–144 (2012)
13. Chiribau, O., Ferent, S., Pura, A., Ciupan, C.: Maintenance service of machine-tools and manufacturing equipment. In: Proceedings of the 1st International Conference on Quality and Innovation in Engineering and Management (QIEM), Romania, pp. 243–248 (2011)
14. Das, A.N., Acharya, D.: Age replacement of components during IFR delay time. IEEE Trans. Reliab. **53**(3), 306–312 (2004)
15. Chen, X., Xu, D., Xiao, L.: Joint optimization of replacement and spare ordering for critical rotary component based on condition signal to date. Eksploatacja i Niezawodnosc (Maint. Reliab.) **19**(1), 76–85 (2017)
16. Burduk, A., Chlebus, E.: Evaluation of the risk in production systems with a parallel reliability structure. Eksploatacja i Niezawodność (Maint. Reliab.) **2**, 84–95 (2009)
17. Walat, T.: Identyfikacja oraz eliminacja nieprawidłowości w eksploatacji urządzeń transportu bliskiego z zastosowaniem nowoczesnych metod zarządzania (in Polish). Diploma thesis (2015). Supervisor Antosz, K., Rzeszów
18. Ross, T.: Fuzzy Logic in Engineering Applications, 3rd edn. Wiley, Singapore (2010)
19. Ratnayake, R.M.C, Antosz, K.: Development of risk matrix and extending risk based maintenance analysis with 'fuzzy logic'. In: Proceedings of the 7th International Conference on Engineering, Project, and Production Management, EPPM 2016, Białystok, Poland, 21–23 September, 2016. Not published
20. Ratnayake, R.M.C., Antosz, K.: Risk based maintenance assessment in the manufacturing industry: minimisation of suboptimal prioritisation. Manag. Prod. Eng. Rev. **8**(1), 38–45 (2017)
21. Ratnayake, R.M.C.: Knowledge based engineering approach for subsea pipeline systems' FFR assessment: a fuzzy expert system. TQM J. **28**, 40–61 (2016)
22. Antonelli, D., Stadnicka, D.: Classification and efficiency estimation of mistake proofing solutions by Fuzzy Inference. In: IFAC Conference on Manufacturing Modelling, Management and Control. IFAC-PapersOnLine, Troyes, France, 28–30 June 2016, vol. 49(12), pp. 1134–1139 (2016)
23. Tay, K.M., Lim, C.P.: On the use of fuzzy inference techniques in assessment models: part II: industrial applications. Fuz. Opti. Dec. Mak. **3**, 283–302 (2008)
24. Matlab, MATLAB 7.12.0 (R2012a): Fuzzy logic Toolbox, 1984–2012 The MathWorks, Inc. (2012)
25. Mathworks: Fuzzy inference system modelling: Gaussian combination membership function (2014). www.mathworks.se/help/fuzzy/gauss2mf.html. Accessed 10 Feb 2017