Fuzzy modeling of dependability optimization for supporting the production-quality strategies - case study in technical field

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Abstract: this work treats dependability from a functional (systemic) standpoint, which implies meeting a function required within an input/output system. This approach is demanded and necessary within technical equipment design stages, and is an integrant part of systems integrity design methodology. Designing the system integrity includes design criteria for reliability, availability, maintainability and safety of any system and equipment. The combination of these four concepts leads to the necessity of a comparative and integrative methodology that should ensure a good systems design, with required integrity values that can be computed easily, analyzed the most complete possible, and with the possibility to be modified accordingly. During the recent years, artificial intelligence techniques have been developed for dependability, that make use of: statistic methods (necessary for the realization of an operation history), deterministic mathematic algorithms (to determine the exact solutions when these can be determined and are required and the time resource is not critical), heuristic artificial intelligence methods (that can provide good quality solutions when time is a critical resource) - neuronal networks, genetic algorithms (to determine predicted or extreme values for system variables), as well as fuzzy methods for systems in which the system variables change within certain values intervals. All these techniques offer a global image of the artificial intelligence modelling (AIM) in designing the reliability, availability, maintainability and safety, in order to offer a continuous design feedback mean during the entire engineering design process. In this work, we shall develop a fuzzy model for a technical process and will compare our results with the results supplied by mathematical, neuronal and genetic models applied to the same system. The qualitative comparison of models will be completed with their quantitative comparison, by analyzing the complexity of algorithms and execution time. The utility of this work consists in the implementation of an interdisciplinary tool easy to apply to technical systems with measurable dependability variables that can provide during the flow sheet, the values requested from technical and economic standpoint.

1. Introduction
The mathematical theory of fuzzy logic is present in all the engineering fields, due to the similitude with human reasoning and to the fact that it can be applied on operational management systems with few input- output information or with combined quantitative- qualitative information [1-3]. On the other side, coming into prominence of this modelling technique, alongside with other mathematic [4], statistic or heuristic modelling techniques occurred also due to the fact that this type of method can reason with imprecise information using its own construction rules in a simple implementation. The uncertainty character of this method can be annulled by comparing its results with those obtained by
other algorithms [5, 6]. The difficulty in implementation of a fuzzy system for modeling derives from
the fact that there is no clear mathematical methodology for building up the membership functions and
adjustment of the rules that connects the input and the output data, this stage being the prerogative of
those proficient in the specific of the problems to be solved [7].

Modelling based on fuzzy rules of “if-then” type, mainly adequate for the implementation of
discrete qualitative models constitute a strong instrument in mixed modelling systems (neuronal
modelling + fuzzy modelling). This type of neuro-fuzzy modelling combines the “learning”,
“generalization” and “prediction” characteristics of neuronal networks with the synthesis of
knowledge in the development of fuzzy rules, less sensitive to the variations of the dynamic system
parameters to be modelled.

2. Method and problem

2.1. The optimization method based on fuzzy logic

L. Zadeh created the foundation of the fuzzy logic by extending the set theory, a theory that fixes
exclusively an element from a set or outside it [8]. The fuzzy logic describes a set \( A \) through a
membership function \( m_A(x) \) defined on a “universe of discourse” that takes values within the interval
\([0, \alpha]\), the function value indicating the degree of membership of the \( x \) value in the \( A \) set. For
consistency, the range of \( A \) set values is scaled within the interval \([0, 1]\); the value 1 indicates that the
element \( x \) is a member of the set \( A \); value 0 indicates that \( x \) is not a member of the set \( A \), and an
intermediate value characterizes the membership degree of \( x \) within the set \( A \). These intermediate
values represent the difference between the fuzzy set and the classical set from set theory. The choice
of this membership set is subjective, as everybody can axiomatically fix a membership function and
modify it in terms of the characteristics of the modelled system. This characteristic of the fuzzy
modelling represents an advantage within the class of approximate methods of technical systems
modelling [9, 10].

Due to the normalization of the membership function values within the interval \([0,1]\), confusion
appears between these and the values of a probability function. Yet, between the two notions (fuzzy
number and probability), there are two differences. The first difference is that the values given by a
fuzzy membership function cannot be denied, unlike the probability \( p \) attached to an event \( (1 - p = probability of the denied event) \) and the second difference is that, once an occurred, the
probability notion no longer exists, while the membership function supplies a membership value [11,
12].

The fuzzy logic includes other two new notions, as compared to classical set theory: the linguistic
variable and the linguistic value. The first notion represents a characteristic, property or attribute
attached to an object, and the second notion represents an adjective or an adverb that is associated with
the linguistic variable [13].

The graphics of the membership functions can intersect each other, such that a value on the field of
definition can take \( n \) specific values, corresponding to \( n \) membership functions, thus falling into \( n \)
classes of values (figure 1). In a fuzzy system, the following relation (equation (1)) is satisfied [14]:

\[
\forall x \in X, \sum_{i=1}^{n} m_A(x) = 1
\]  

Where \( X \) is the field of definition (the universe of discussion), and \( n \) is the number of values
classes.

Namely, in a modelling system based on fuzzy logic, there are three stages (figure 1) [15,16]:
- Fuzzification stage in which one associates to the exact values of the input parameters, the values
supplied by the membership functions.
- Inference stage, in which, based on linguistic rules, the input variables are linked to the output
variables (qualitative connections are realized between combinations of input and output parameters at
the set level).
Defuzzification stage, in which the fuzzy values are converted into exact values for the parameters of the modeled system.

Respecting the general structure of a fuzzy system, in this paper we will use a Mamdani structure (figure 1).

Knowledge base comprises [17]:

- Fuzzy sets that codify the fuzzy sets of quantitative or qualitative values of the input parameters.
- Fuzzy sets that codify the fuzzy sets of qualitative or qualitative values of the output parameters.
- Fuzzy rules base that realizes the inference of fuzzy values of the output variables from the fuzzy values of the input variables.

![Figure 1. Structure of a Mamdani fuzzy logic system.](image)

2.2. Introduction of optimization problem – technical system - honing machine

The works [18, 19] realize an optimization of the reliability (parameter characterized by mean time between failure - MTBF) and maintenance (parameter estimated through the mean time to repair - MTTR) parameters in terms of production and quality strategies. This work realizes a fuzzy modelling to determine the production and quality parameters (dependent parameters) in terms of reliability and maintainability parameters (independent parameters).

The target problem consists in the determination of the best production and quality values when one knows the values of technical systems reliability and maintainability.

This complementary problem has been analyzed from the standpoint of its importance in the works [20, 21], the modelling approaches being those specific to artificial intelligence (neuronal networks and genetic algorithms).

These approaches will be analyzed from two standpoints:

- From the standpoint of results, these will be compared with the results of fuzzy model.
- Modelings specific to mathematic and artificial intelligence fields will supply additional information for the determination of fuzzy rules.

The optimization problem is given by the relation \((P, Q) = f(M, F)\) [22, 23]. It is worth noticing that fuzzy modelling does not supply a multivariable polynomial function and values for production and quality for known values of maintenance and reliability.

2.3. Quantitative data for modeling

The data are obtained by summarizing the information obtained from honing machine computer, recorded for 6 months, and are synthesized in the following values: MTBF- mean team between failure, MTTR- mean time to repair, P - production and Q - quality (see table 1).

The honing process represents a fine chip removing processing of rotary swivel channels for car injection pumps. The Op 150C machine is supplied by the operator with coarse parts from the previous washing operation. The supply is executed by the operator on machine feed bend. Once in the station, the robot from this machine takes the parts over and set them on supports in honing stations. After the part is processed in the six honing stations, it is taken over at the discharge point by the robot, which carries it to leak test station. The role of this station is to test for contingent leaks in the case that the honing operation went wrong. In this way, we can make the difference between the “ok parts” and “nok parts”. After the Leak test station responds if the part is ok, the robot takes over the
part and put it on the evacuation band, whence the operator will take it over and place it in special boxes. In case that the part is considered nok by the Leak test station, the robot will carry it to the scrap box. According to the production plan, the maximum production volume that can be processed in this station is of 120 pieces/hour (960 pieces/8 hours) if the machine has down-times [5, 7].

Table 1. Determination of quantitative indices concerning the system reliability.

| No. of week | Stops | Shutdown time (min) | Operational time (min) | Pieces/h | Pieces/week | Ra (microM) | MTBF (min) | MTTR (min) |
|-------------|-------|---------------------|------------------------|---------|-------------|-------------|------------|------------|
| 1           | 5     | 76                  | 10004                  | 65      | 10838       | 0.011       | 2001       | 15.2       |
| 2           | 3     | 401                 | 9679                   | 75      | 12099       | 0.123       | 3226       | 133.7      |
| 3           | 1     | 125                 | 9955                   | 105     | 17421       | 0.234       | 9955       | 125.0      |
| 4           | 2     | 37                  | 10043                  | 88      | 14730       | 0.055       | 5022       | 18.5       |
| 5           | 2     | 155                 | 9925                   | 85      | 14060       | 0.163       | 4963       | 77.5       |
| 6           | 1     | 45                  | 10035                  | 108     | 18063       | 0.024       | 10035      | 45.0       |
| 7           | 5     | 78                  | 10002                  | 67      | 11169       | 0.013       | 2000       | 15.6       |
| 8           | 1     | 35                  | 10045                  | 105     | 17579       | 0.231       | 10045      | 35.0       |
| 9           | 0     | 0                   | 10080                  | 114     | 19152       | 0.010       | 10080      | 0.0        |
| 10          | 2     | 625                 | 9455                   | 108     | 17019       | 0.212       | 4728       | 312.5      |

The novelty consists in supervised determination of the rules and membership functions. This technique is taken over from the stage of neuronal networks training stage and can become a methodology to create the rule base and defuzzification procedure. Namely, the technique permits to choose functions number, to adjust them and to refine the inference rules, such that the values of output parameters modelled by the fuzzy system to coincide with the measured outputs of the modelled system, at the application of the input patterns.

The methodology of fuzzy system training consists in adjustment of the values supplied through the determination of the number of membership functions on inputs and outputs, and of the knowledge base. Fine adjustment of these values by modifying the functions graphics and adding other input parameters.

3. Method implementation and application
One determines for each measured parameter, the minimum and maximum values, and the values ranges are fragmentized in three proportional intervals, according to table 2.

Table 2. Measured values for the technical system.

| Production | Roughness | Reliability (MTBF) | Maintenance (MTTR) |
|------------|-----------|--------------------|--------------------|
| min        | 10834     | 0.011              | 1642               |
| max        | 19152     | 0.321              | 10080              |

| Variation | Values | Values | Variation | Values | Variation | Values |
|-----------|--------|--------|-----------|--------|-----------|--------|
| Small     | 13607  | N3     | 0.114     | Small  | 4455      | Small  | 104    |
| Normal    | 16379  | N4     | 0.218     | Normal | 7267      | Normal | 208    |
| High      | 19152  | N5     | 0.321     | High   | 10080     | High   | 313    |

The knowledge base includes 9 rules and is presented in table 3. The rules were constructed by considering variables interdependences; an increased maintenance determines an increased roughness (high quality) and a relatively low production, while an increased reliability determines a high production and a normal or small (N3) roughness [5, 7].
Table 3. The rules set.

| Reliability | and | Maintenance | => | Production | Roughness |
|-------------|-----|-------------|----|------------|-----------|
| Small       | Small| Small       | N5 |            |           |
| Normal      | Small| Normal      | N4 |            |           |
| High        | Small| Normal      | N3 |            |           |
| Normal      | Normal| Normal      | N5 |            |           |
| High        | Normal| Normal      | N4 |            |           |
| High        | Normal| High        | N3 |            |           |
| High        | Small| High        | N5 |            |           |
| High        | Normal| High        | N4 |            |           |
| High        | High  | High        | N3 |            |           |

The structure modelling technique based on fuzzy system is shown in figure 2.

![Figure 2](image)

Figure 2. The structure of modelling technique.

Membership functions are presented in figure 3.

![Figure 3](image)

Figure 3. Membership functions.
By applying the input patterns on the fuzzy system, one can determine modelling errors for the output parameters (table 4).

### Table 4. Computed values and error determination before fuzzy system training.

| Production (No. pcs/week) | Quality (Ra, roughness classes) | Measured | Modelled | Relative error | Measured | Modelled class | Class error |
|---------------------------|---------------------------------|----------|----------|----------------|----------|----------------|-------------|
| Measured X1000            |                                 |          |          |                |          |                |             |
| 10838                     | 1.19                            | 9.80     |          |                | 0.011    | N3             | N5 Error    |
| 12099                     | 1.2                             | 0.82     |          |                | 0.123    | N4             | N4 Ok       |
| 17421                     | 1.87                            | 7.34     |          |                | 0.234    | N5             | N5 Ok       |
| 14730                     | 1.46                            | 0.88     |          |                | 0.055    | N3             | N5 Error    |
| 14060                     | 1.42                            | 1.00     |          |                | 0.163    | N4             | N4 Ok       |
| 18063                     | 1.86                            | 2.97     |          |                | 0.024    | N3             | N5 Error    |
| 11169                     | 1.19                            | 6.54     |          |                | 0.013    | N3             | N5 Error    |
| 17579                     | 1.87                            | 6.38     |          |                | 0.231    | N5             | N5 Ok       |
| 19152                     | 1.88                            | 1.84     |          |                | 0.010    | N3             | N5 Error    |
| 17019                     | 1.63                            | 4.22     |          |                | 0.212    | N4             | N3 Error    |

When modelling the production parameter, the relative errors between the measured and modelled values are smaller than 10%, which leads to the fact that the number of membership functions, their definition intervals, their shape and the fuzzy rule set were well inspired chosen [24].

In the case of the quality parameter, (Ra), important errors appeared in the classification of modelled values, compared with computed values. These errors appear especially at high quality class (N_3 = Ra small), which leads to modifications of membership functions for the quality parameter. The errors appeared at the modelling of roughness class N3 are due to the fact that machine downtimes were used for simple (non-invasive) interventions, such as “robot restart”, 230 V fuse - burnt” or “ip setting and subnet network plate”. These interventions do not correct the functionally right behaviour of the machine.

In order to correct the “fuzzy system behaviour” on this segment of the quality parameter, a new input parameter – “intervention time”- was introduced, with the limits [0...300], with two membership functions (figure 4).

![Figure 4. Intervention time membership function.](image)
### Table 5. Set of additional rules.

| Reliability | Maintenance and | Intervention time | => | Production | Quality |
|-------------|-----------------|-------------------|----|------------|---------|
| Small       | Small           | Small             |    | Small      | N3      |
| Normal      | Small           | Small             |    | Small      | N3      |
| High        | Small           | Small             |    | Normal     | N3      |
| Normal      | Small           | Normal            |    | Normal     | N3      |
| High        | Small           | High              |    | N3         |
| Normal      | Small           | High              |    | High       | N3      |
| High        | Small           | High              |    | High       | N3      |

### Table 6. Computed values and error determination after fuzzy system training.

| Production (No. pcs/week) | Quality (Ra, roughness classes) |
|---------------------------|---------------------------------|
| Measured Values | Modelled X1000 | Relative error | Modeled Values | Measured Class | Modeled Class | Class error |
| 10838 | 1.19 | 9.80 | 0.056 | N3 | N3 | Ok |
| 12099 | 1.20 | 0.82 | 0.132 | N4 | N4 | Ok |
| 17421 | 1.87 | 7.34 | 0.242 | N5 | N5 | Ok |
| 14730 | 1.46 | 0.88 | 0.057 | N3 | N3 | Ok |
| 14060 | 1.42 | 1.00 | 0.201 | N4 | N4 | Ok |
| 18063 | 1.86 | 2.97 | 0.056 | N3 | N3 | Ok |
| 11169 | 1.19 | 6.54 | 0.057 | N3 | N3 | Ok |
| 17579 | 1.87 | 6.38 | 0.255 | N5 | N5 | Ok |
| 19152 | 1.88 | 1.84 | 0.056 | N3 | N3 | OK |
| 17019 | 1.63 | 4.22 | 0.207 | N4 | N4 | Ok |

### 4. Fuzzy modelling analysis and results comparison

Fuzzy modelling is compared with the results supplied by other two types of modelling [25, 26]: the mathematical one and the evolutional one based on genetic algorithms (table 7, table 8).

Sum values in the last line of table 7 and table 8 show a better modelling of fuzzy implementation than other modelling (mathematical and genetic).

We took into account 4 indicators: complexity of modelling structures and easiness in designing them, easiness in model utilization, results quality and modelling generality.

From the standpoint of structure complexity, fuzzy modelling implies to create a much more complex system, through an “inspired” selection, validated then in the stage of training the number, type and shape of membership functions and of the set of rules respectively. The increased complexity of the fuzzy system also derives from the fact that it supplies simultaneously values for output parameters in terms of the input vectors \( (P, Q) = f(M, R) \), while the mathematical modelling supplies one statistic polynomial multi-variable function (whose coefficients are determined using the **least-squares method**) for each of the output parameters. The evolutionary modelling, performed by means of the Solver tool from the MS Excel package, is situated, from complexity standpoint, between the mathematical and the fuzzy modelling. This determines, through an evolutional (iterative) algorithm,
solutions for the coefficients of the regression functions of the parameters $P$, $Q$ in terms of independent parameters $M$, $R$.

**Table 7.** Measured, computed values and modelling differences for production.

| MTBF (min) | MTTR (min) | Production measured | Evolutionary modelling | Mathematical modelling | Fuzzy modelling |
|------------|------------|---------------------|------------------------|------------------------|----------------|
|            |            | Prod. modelled | Absolute diff. | Ampl (%) | Prod. modelled | Absolute diff. | Ampl (%) | Prod. modelled | Absolute diff. | Ampl (%) |
| 2001       | 15.2       | 10838             | 8780                  | 2058                  | 19.0           | 4560           | 6278                  | 57.9             | 1.19           | 1062         | 9.8        |
| 3226       | 133.7      | 12099             | 11345                 | 754                   | 6.2            | 5400           | 6699                  | 55.4             | 1.2            | 99           | 0.8        |
| 9955       | 125        | 17421             | 14567                 | 2854                  | 16.4           | 17288          | 133                    | 0.8              | 1.87           | 1279         | 7.3        |
| 5022       | 18.5       | 14730             | 9027                  | 5703                  | 38.7           | 14748          | 18                     | 0.1              | 1.46           | 130          | 0.9        |
| 4963       | 77.5       | 14060             | 12356                 | 1704                  | 12.1           | 14040          | 20                     | 0.1              | 1.42           | 140          | 1.0        |
| 10035      | 45         | 18063             | 14325                 | 3738                  | 20.7           | 17970          | 93                     | 0.5              | 1.86           | 537          | 3.0        |
| 2000       | 15.6       | 11169             | 5700                  | 5469                  | 49.0           | 11009          | 160                    | 1.4              | 1.19           | 731          | 6.5        |
| 10045      | 35         | 17579             | 17694                 | 115                   | 0.7            | 18131          | 552                    | 3.1              | 1.87           | 1121         | 6.4        |
| 10080      | 0.1        | 19152             | 12236                 | 6916                  | 36.1           | 18825          | 327                    | 1.7              | 1.88           | 352          | 1.8        |
| 4728       | 312.5      | 17019             | 14543                 | 2476                  | 14.5           | 17043          | 24                     | 0.1              | 1.63           | 719          | 4.2        |
| Sum        |            | 31787             | 14304                 | 6170                  |

**Table 8.** Measured, computed values and modelling differences for quality.

| MTBF (min) | MTTR (min) | Quality measured | Evolutionary modelling | Mathematical modelling | Fuzzy modelling |
|------------|------------|------------------|------------------------|------------------------|----------------|
|            |            | Quality modelled | Absolute diff. | Ampl (%) | Quality modelled | Absolute diff. | Ampl (%) | Quality modelled | Absolute diff. | Ampl (%) |
| 2001       | 15.2       | 0.011            | 0.010                 | 0.001                | 9.1            | 0.01           | 0.002                 | 20.0             | 0.012          | 0.001         | 9.091       |
| 3226       | 133.7      | 0.123            | 0.090                 | 0.033                | 26.8           | 0.14           | 0.013                 | 10.5             | 0.132          | 0.009         | 7.317       |
| 9955       | 125        | 0.234            | 0.160                 | 0.074                | 31.5           | 0.24           | 0.005                 | 2.3              | 0.242          | 0.008         | 3.419       |
| 5022       | 18.5       | 0.055            | 0.043                 | 0.012                | 22.1           | 0.07           | 0.018                 | 32.0             | 0.057          | 0.002         | 3.636       |
| 4963       | 77.5       | 0.163            | 0.154                 | 0.009                | 5.5            | 0.14           | 0.023                 | 14.1             | 0.201          | 0.038         | 23.313      |
| 10035      | 45         | 0.024            | 0.032                 | 0.008                | 33.3           | 0.03           | 0.010                 | 41.7             | 0.020          | 0.004         | 16.667      |
| 2000       | 15.6       | 0.013            | 0.015                 | 0.002                | 15.4           | 0.01           | 0.004                 | 29.3             | 0.016          | 0.003         | 23.077      |
| 10045      | 35         | 0.231            | 0.240                 | 0.009                | 3.9            | 0.10           | 0.128                 | 55.5             | 0.255          | 0.024         | 10.390      |
| 10080      | 0.1        | 0.01             | 0.012                 | 0.002                | 20.0           | 0.01           | 0.005                 | 50.0             | 0.011          | 0.001         | 10.000      |
| 4728       | 312.5      | 0.212            | 0.212                 | 0.000                | 0.0            | 0.21           | 0.002                 | 1.1              | 0.207          | 0.005         | 2.358       |
| Sum        |            | 0.1499           | 0.21                  | 0.10                 |

The 2\textsuperscript{nd} assessment criterion: in terms of setting and adjusting of the modelling structures, the fuzzy modelling proves to be of a remarkable simplicity in its utilization and in supplying the output values with evolutilional mathematical modelling. This fact is also the result of immediate supply of the results, as compared to the delay of evolutilional modelling (one runs through a number of stages until the sequence convergence or until the stop condition is satisfied).

The 3\textsuperscript{rd} criterion: the fuzzy system is superior to other modelling at this criterion too, as it supplies qualitative solutions (as one can see in table 7 and table 8) that reveals the errors in approximating the output parameters. This is not surprising, since a fuzzy system, well-built and trained within the entire output parameters definition interval will supply clear, good quality values of the output parameters.
for any input pattern. One must also specify that in mathematical modelling based on the least squares method, errors can appear due to singularity of the matrix of the target system.

From the standpoint of the 4th criterion, the fuzzy system has adaptive characteristic superior to the other modelling types, by its easiness in modifying the limits of system parameter definition. This characteristic makes the fuzzy modelling a flexible tool, applicable in various types of problems from different technical fields, applied on systems whose parameters change their variation limits.

5. Conclusions
Fuzzy modelling system proves to be a flexible tool, with an important characteristic of generalization of the application on different technical systems, with easiness in the process of internal structure modification to correct the outputs, which represents a high adaptability level. Moreover, this adaptability characteristic supports an automatic adjustment, by combining the fuzzy system with self-adaptive artificial intelligence systems (neuronal networks).

Thus, the neuro-fuzzy modelling annuls the only negative element of the fuzzy modelling – the determination of fuzzy system internal structure and its adjustment, by automating this process. This type of modelling will be implemented and applied on technical system from 9 mechanic field, and the results of this modelling type will be analyzed.

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