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TECHNICAL NOTE

Qualitative and quantitative approaches to analyse reliability of a mechatronic system: a case

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Abstract The main research intent of this paper is to introduce the use of fault tree analysis (FTA) and failure mode and effects analysis (FMEA) in conjunction to analyse the risk and reliability of a complex mechatronic system in both qualitative and quantitative manner. The major focus is on handling imprecise and vague information with the help of fuzzy synthesis of information. A complex mechatronic system, i.e. modular automated production system (MAPS), composed of mechanical, electronic, and embedded software subsystems is considered to study the reliability aspects using hybrid FTA. From the results, it is found that the proposed approach models both subjective issues such as human errors along with hardware failures. The in-depth analysis and prioritizing of failure modes using a risk ranking approach based on fuzzy inference system and grey relation approach not only integrate expert judgment, experience, and expertise in more flexible and realistic manner, but also address the limitations associated with traditional procedure of FMEA.

Keywords System · FTA · FMEA · Fuzzy · Failure rate · Reliability · RPN

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Introduction

Every technological system where “mechanics”, “electronics”, and “control” harmonize in a mutually supportive way to the overall performance belongs to the family of the “mechatronics” systems. For instance, in the field of Flexible Automation, i.e. robotics, machine tools or machining centres, automated guided vehicle systems and automated storage and retrieval systems (Ferretti et al. 2004). The word, mechatronics, is composed of “mecha” from mechanism and “tronics” from electronics and was probably first created by a Japanese engineer in 1969 (Kyura and Oho 1996). According to Bolton (2010) “A mechatronics system is not just a marriage of electrical and mechanical systems and is more than just a control system; it is a complete integration of all of them”. New developments in these traditional disciplines are being absorbed into mechatronics design at an ever increasing pace. It appears that modern concurrent engineering design practices, now formally viewed as part of the mechatronics specialty, are natural design processes. What is evident is that the study of mechatronics provides a mechanism for researchers interested in understanding and explaining the engineering design process to define, classify, organize, and integrate many aspects of product design into a coherent package. Generally, a mechatronic product has various design characteristics such as (a) more precise and accurate, (b) cost effective and more efficient, (c) more reliable, (d) more flexible and functional, (e) less mechanically complex, safer, and more environment friendly, etc. In view of its multi-domain nature, design of a mechatronic system is a challenging task (Silva and Behbahani 2012). The responsibility of equipment designers and manufacturers has increased manifold with twin objectives: (a) to minimize the probability of failure and (b) to design the features that lead to unsafe operator practices. According to Amerongen (2003) and Thramboulidis (2005), the concurrent integration between mechanical, electrical, and automation and control design subdisciplines is a fundamental research problem in the field of mechatronics.

Recent publications in the area of mechatronics propose consideration of risk and reliability assessment methods to ascertain functional behaviour of components to meet safety requirements.

Sierla et al. (2012) in their paper introduced a risk analysis methodology that can be applied at the early concept design phase, whose purpose is to identify fault propagation paths that cross disciplinary boundaries, and determine the combined impact of several faults in software-based automation subsystems, electric subsystems, and mechanical subsystems. Further, Sierla and Bryan (2014) extended the work and transformed functional failure identification and propagation (FFIP) approach to safety analysis of a product line. Yiannis et al. (2011) developed a computerised tool called Hierarchically Performed Hazard Origin & Propagation Studies ('HiP-HOPS'), which helps in automatic synthesis of system information using fault trees and failure modes and effects analysis tools. Follmer et al. (2012), in their article, outlined the significance of system-level modelling and simulation for design of multi-disciplinary mechatronic systems. Claudia and Matthias (2011) conducted component-based hazard analysis for complex mechatronic system used in rail cab by specifying the architecture of components, their ports and connectors. For each component, they determined the flaws and built a failure propagation model (as a set of fault trees), which relates failures at the ports of the components with internal errors. Coulibaly and Ostrosi (2011) proposed a framework for mechatronic systems reliability assessment at early stage of the design process. They focused on complex mechatronic systems consisting of subsystems made of mechanical components, electronic devices, and software modules. Gietelink et al. (2009) recommended the use of fault tree analysis (FTA) and failure mode effect and criticality analysis (FMECA) in the requirements and specification phase of a product design. Kumar and Yadav (2012) evaluated system reliability using intuitionistic fuzzy fault tree analysis. Isermann (2008) recognized the need to integrate methods such as FTA and failure mode and effects analysis (FMEA) for mechatronic systems. For safety-related systems, a hazard analysis with risk classification has to be performed, e.g. by stating quantitative risk measures based on the probability. Brooke and Paige (2003) illustrate application of fault tree to the design and analysis of security-critical systems. Mihalache et al. (2004, 2006) in their work stated the importance of reliability evaluation of mechatronic systems. They provided an application to a vehicle Antilock Brake System (ABS).

Based upon the above studies in general, the authors believe that system risk and reliability assessment (SRRA) is a fundamental research problem in the field of mechatronics for the following reasons (Chen et al. 2009; Zhong et al. 2010; Sierla et al. 2012; Khalaj et al. 2013; Rao and Naikan 2014).

1. Functional dependency: Functionality and sequential dependency are the primary concerns of designers. A failure might be caused by more than one mutually dependent event such as shared causes, exclusive events during designing large complex systems, with focus on electrical, mechanical, pneumatic, hydraulic, and software types of failures.
2. Uncertainty: While modelling the reliability and safety aspects of systems, one comes across different uncertainties which can be grouped with regard to their causes into two types: (a) aleatory and (b) epistemic uncertainties. Aleatory uncertainty is caused by random variations in samples and is also known as stochastic, type A or irreducible uncertainty. Epistemic uncertainty is caused by lack of knowledge about a system or phenomenon and is also known as subjective, type B or reducible uncertainty. Different mathematical tools can be used to treat these two types of uncertainties, the most common being probability theory for treatment of aleatory uncertainty and fuzzy logic theory for treatment of epistemic uncertainty.

In the context of industrial competiveness estimating the reliability of mechatronic products is of crucial interest and an important research issue. Numerous authors studied the importance of risk and reliability assessment of mechatronic products using the data of subsystems/components/parts and provided valuable advice for performing functional failure analysis of mechatronic systems. However, well-established integrated framework which takes into account vague, imprecise, and subjective issues in complex mechatronic system is still missing and is a source of concern which needs to be addressed. In the words of Zhong et al. (2010) "the attempt to improve system reliability makes the task of system reliability assessment an ongoing research topic". In the system reliability and safety assessment, the focuses are not only the risks caused by hardware or software, but also the risks caused by ''human error" (Cheng et al. 2010). A number of methods for reliability assessment such as FTA (Kumar and Yadav 2012; Gharahasanlou 2014), failure mode effect and criticality analysis (FMECA) (Sharma et al. 2008), Petri nets (Adamyan and He 2004), Markov analysis (Sharma 2008; Tewari et al. 2012) have been developed to model and estimate system reliability using the data of components. The non-probabilistic/inexact reasoning methods study problems which are not probabilistic but cause uncertainty due to imprecision associated with the complexity of the systems as well as vagueness of human judgment. Indeed, this uncertainty is common in a mechatronic system and none of the previous research has addressed such type of uncertainties in mechatronic systems. These methods are still developing and often use fuzzy sets, possibility theory and belief functions. Introduced by Zadeh (Zimmermann 1996), Fuzzy set theory is used to deal with problems in which the absence of sharply defined criteria is involved and has been considered in literature by various researchers as a modelling language to approximate situations in which fuzzy phenomena and criteria exist. The imprecise parameters can be expressed as fuzzy numbers and the variability is characterized by the membership function (MF) which may be triangular or trapezoidal as the most common MF types used in reliability application are triangular or trapezoidal functions (Yadav et al. 2003). As an emerging methodology, it helps to incorporate imprecision and subjectivity into the model formulation and solution process. By allowing for imprecision in the model, fuzzy logic opens the possibility for the inclusion of imprecise inputs and imprecise thresholds (Homayouni et al. 2009).

In the words of Khalaj et al. (2013) "Existing risk in production systems has a direct relationship with unreliability of these systems. Under such circumstances, the approach to maximize the reliability should be replaced with a risk-based reliability assessment approach". To this effect in the study, authors make use of FTA and FMEA, to perform risk-based reliability assessment of a complex mechatronic system, i.e. modular automated production system, by incorporating fuzzy methodology. Various mechanical, electronic, and embedded software subsystems are considered to estimate the reliability of mechatronic system. By estimating the failure rate of components, the reliability values for all the subsystems comprising MAPS are computed. As reliability evaluation of mechatronic systems requires the modelling of failure behaviour of different components, authors made use of Mil HDBK-217F and NPRD 95 sources for calculation of failure rate of different mechanical and electronic components.

The main features of the proposed approach in contrast with those of other existing methods are as follows:

- For performing FTA, the proposed approach has capabilities to handle both qualitative and quantitative data. In conventional FTA, the basic events are normally associated with hardware failures only. However, in highly automated mechatronics systems, people are still the key component in the system. According to Lee et al. (1988), depending upon the degree of human involvement in the system, the human component is responsible for 20–90 % of the failures in many systems. Thus, the evaluation of vague, imprecise, and subjective issues such as human errors in complex mechatronic system is the major concern which needs to be addressed.
- For performing FMEA, the proposed approach handles limitations of traditional FMEA procedure to obtain risk priority number (RPN). The main disadvantage of RPN approach is that various sets of input terms, i.e. O_f, S, O_D may produce an identical value, however, the risk implication may be totally different which result in high-risk events may go unnoticed. For instance, consider two different events having values of $O_\mathrm{f} = 6$, $S = 4$, $O_\mathrm{d} = 5$ and $O_\mathrm{f} = 2$, $S = 10$, $O_\mathrm{d} = 6$, respectively. Both these events will have a total RPN value of 120; however, the risk implications of these two events may not necessarily be the same which may result in high-risk events may go unnoticed which are addressed by using fuzzy inference system (FIS) and grey relation analysis (GRA) by the authors.

The paper is organized as "Introduction" section presents introduction to mechatronics and literature review concerning reliability analysis of mechatronic systems. "System risk and reliability assessment (SRRA) methods" section presents brief account of FTA and FMEA as SRRA methods used in the study. "Illustrative case" section presents introduction to different modules of modular automation production system (MAPS) followed by FTA and FMEA by the proposed fuzzy and grey approach, and finally "Conclusion" section summarizes the conclusions from the study.

System risk and reliability assessment methods

The study makes use of FTA and FMEA well-known failure analysis techniques for system analysis. Both tools are long established. FMEA was formally introduced at Grumman Aircraft Corporation in the 1950s, and FTA in the 1960s—and both have been employed in a number of different areas, including the aerospace, nuclear power, and automotive industries (Sharma et al. 2005, 2008; Chin et al. 2008, 2009; Hauptmanns (2004, 2011; Guimaraes et al. 2011). Fault trees are graphical representations of logical combinations of failures, and show the relationship between a failure or fault and the events that cause them. A fault tree normally consists of a top event, which is typically a system failure, connected to one or more basic events via a system of logical gates, such as AND and OR. Basic events are usually either component failures or events expected to happen as part of the normal operation of the system. Today, FTA is widely used in various fields of technology, mainly in aerospace, chemical, and nuclear industries, and it is finding its way into many other fields such as robotics, rail transportation, and car industries (Majdara and Toshio 2009).

Failure mode and effects analysis is a very powerful and effective analytical tool, which is widely used in engineering projects to examine possible failure modes and eliminate potential failures during system design. In particular, it provides design engineers with quantitative or qualitative measures necessary to guide the implementation of corrective actions by focusing on the main failure modes and its impact on the products (Xiao et al. 2011). In an FMEA, the basic process consists of compiling lists of possible component failure modes (all the ways in which an entity may fail), gathered from descriptions of each part of the system, and then trying to infer the effects of those failures on the rest of the system. There are number of criteria to evaluate these effects, such as severity, probability, and detectability, and often these criteria are then combined into an overall estimate of risk (Wang et al. 2009; Xiao et al. 2011). There are two phases in FMEA.

- Phase I: It is concerned with identification of the potential failure modes and their effects. It includes defining the potential failures of product's component, subassemblies, final assembly, and its manufacturing processes.
- Phase II: It is concerned with obtaining scores for probability of occurrence of failure (O_f), severity (S), and chance of the failure being undetected (O_d) and computing RPN, i.e. RPN = $O_f.S.\ O_d$

In the study, the RPN approach is used to rank the failure causes associated with system components. Table 1 presents the scale used to compute the RPN scores.

Illustrative case

A modular automation production system has been investigated using hybrid FTA and FMEA. It has the following nine subsystems.

- Subsystem I, belt conveyer: An electro pneumatic controlled linear actuator transfers the material from conveyer to the front of linear pick and place unit.
- Subsystem II, horizontal transfer unit: An electro pneumatic controlled linear actuator transfers the material from conveyer to the front of linear pick and place unit.
- Subsystem III, linear pick and place unit: An electro pneumatic controlled vertical and horizontal arm transfers the material from horizontal transfer unit to six station rotary indexing table using an angular gripper.
- Subsystem IV, six station rotary indexing table: It is used to index and transfer components between stations (filling station, capping station and rotary pick and place unit).
- Subsystem V, filling module: The filling module is used to transfer the filling material to the container present in the rotary table, when the table indexes towards the station. It is an electro-pneumatic control system.
- Subsystem VI, capping module: The function of capping module is to close the material filled container present in the rotary indexing table with caps when table indexes towards this station. It is an electro-pneumatic control system.
- Subsystem VII, rotary pick and place unit: The function of rotary pick and place arm is to transfer the work piece from rotary indexing table to weighing module. It is an electro-pneumatic system where the movement is controlled by a linear and rotary actuator with the help of angular gripper.
- Subsystem VIII, weighing station: The function of weighing station is to weigh the material and display the value.
- Subsystem IX, palletizer assembly unit: The function of palletizer assembly unit is to pick and place the work piece from weighing station to 24 position pallets.

Table 1 Scale to measure FMEA inputs

Linguistic terms	Symbol	Score/rank no.	MTBF	Occurrence rate (%)	Severity effect	Likelihood of non-detection (%)
Remote	− −	1	>3 years	<0.01	Not noticed Slight annoyance to operator	0–5
Low	−	2	1–3 years	0.01–0.1		6–15
		3				16–25
Moderate	+	4	4–1 years	0.1–0.5	Slight deterioration in system performance	26–35
		5				36–45
		6				46–55
High	++	7	2–4 months	0.5–1	Significant deterioration in system performance	56–65
		8				66–75
Very high	+++	9	<2 months	>1	Production loss and non-conforming products	76–85
		10				86–100

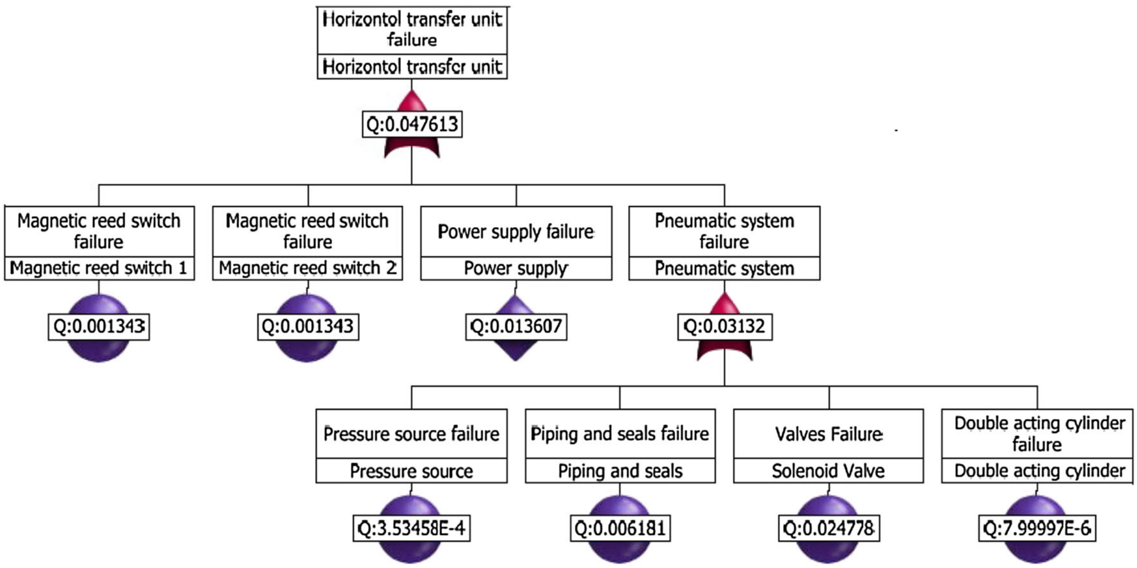

Fig. 1 Fault tree analysis (FTA) diagram for horizontal transfer unit

Fault tree for MAPS

Fault tree diagram has been prepared individually for each of the subsystem of MAPS. Each event is partitioned into other combination of events further down the tree until a basic event which can be assigned an independent probability is reached. Where appropriate, the branch of tree is terminated by an event for which the required failure rate data is available. In this particular case, the model is simple, because all the variables are combined by an OR gate. The NRPD 95 and Mil HDBK-217F are the sources that have been used. The assessment of failure using FTA tells about problem areas and can prove useful in improving the reliability of system, thus reducing possibility of accidents resulting from hardware failure. Figure 1 presents FTA of horizontal transfer unit.

Sample calculations for horizontal transfer unit

First step in the FTA is calculation of failure rate depending on application environment. NPRD95 (1995) and MIL-HDBK-217F (1990) have been used to calculate the failure rates. The details are given in Table 2.

Table 3 presents the calculations of failure probability of different components of horizontal transfer unit. The same procedure is adopted for different modules and failure rate of each of the module is calculated. The results for different modules are shown in Table 4.

Table 2 Failure rate of different components

Component	Failure rate at 25 °C (faults/10^6 h)
DC electric motor	9.2
Sensor, photoelectric	3.885
Magnetic reed switch	1.344
Piping and seals	6.2
Valve, solenoid	25.09
Sensor, inductive	3.6
Pressure source	0.35352
Cylinder	0.080
Resistance	0.26
Relay	1.2
Display screen	0.14
Bearing	1.65
Shaft	1.0038
Coupling	0.928
Stepper motor	9.2
Lead screw	1.0
Power supply	13.7

Source: NPRD 95, Mil HDBK

Estimation of failure rate for human errors

According to Lee et al. (1988), depending upon the degree of human involvement in the system, the human component is responsible for 20–90 % of the failures in many systems. Thus, failure rate for human errors, i.e. incorrect operation and careless operation is calculated using fuzzy set theory, as in literature, fuzzy set theory is widely used as tool for dealing with linguistic expressions which are used for denoting human-related subjective events.

Steps for calculation of fuzzy failure rate

Step 1: Linguistic assessment for human performance and vague events is conducted by expert elicitation which involves maintenance and reliability experts. A five-point linguistic rating scale is used (i.e. very low, low, medium, high, and very high) for assessment. Figure 2 shows the fuzzy MF for linguistic assessment of human performance.

Step 2: Linguistic assessments, i.e. very low, very low, very low, very low, low for careless operation are obtained through five experts as shown in Table 5. These assessments are transformed into fuzzy number with the help of fuzzy MFs and finally aggregation of the experts' opinions into one fuzzy number.

Now, since these two fuzzy numbers are not of same type (i.e. one is trapezoidal and other is triangular), we use α-cut addition and the single fuzzy number so obtained is presented as

Table 3 Calculation of failure probability of different components

S. no.	Failure description	Failure rate
1	Double acting cylinder failure	0.008
2	Magnetic reed switch 1 failure	1.344
3	Magnetic reed switch 2 failure	1.344
4	Piping and seals failure	6.2
5	Pressure source failure	0.3535
6	Solenoid valve failure	25.9
7	Power supply failure	13.7

Source: NPRD 95, Mil HDBK

For magnetic reed switch

Failure rate (using Mil HDBK-217F)

$\lambda_p = \lambda_b \times \pi_c \times \pi_u \times \pi_q \times \pi_e$ failures/10^6 h

$=0.02 \times 8.4 \times 4 \times 1 \times 2$

$=1.344$

Probability of failure $(Q) = 1 - e^{-(1.344 \times 1{,}000)}$

$= 0.00134$

$$f_W(z)\begin{cases} \dfrac{z-0.05}{0.075} & 0.050 < z < 0.125 \\ 1 & 0.125 < z < 0.175\,. \\ \dfrac{0.3-z}{0.125} & 0.175 < z < 0.300 \end{cases}$$

Step 3: Conversion of fuzzy number into fuzzy possibility score

By using Chen and Hwang (1992) right and left fuzzy ranking method, fuzzy possibility score so obtained is 0.1915

Step 4: Transformation of FPS into fuzzy failure rate.

Fuzzy failure rate is defined as

Here $k = \left[\frac{1-0.1915}{0.1915}\right]^{\frac{1}{3}}(2.301) \Rightarrow k = 3.7.$ So, $\mathrm{FFR} = 1/10^{3.7}$ $\mathrm{FFR} = 2.13 \times 10^{-4}$failures/h Table 6 presents values of fuzzy failure rate for human error induced because of incorrect and careless operations.

Figure 3 presents the complete FTA for MAPS showing the failure rate of all the modules along with human error failure rate due to careless and incorrect operations.

Failure mode and effects analysis

FMEA analysis has been done for all mechanical, electrical, and electronic components of a complex mechatronic system. Table 7 presents the details of FMEA analysis. The numerical values of RPN number are obtained by multiplying FMEA parameters, i.e. O_f, S, and O_d. From the table it is observed that a failure mode F_{15} with high severity, low rate of occurrence, and moderate detectability (7, 3, and 4, respectively) have lower RPN (84) than F_{11}, where all the parameters are moderate (4, 5, and 5 yielding an

Table 4 Failure rate and probability for different modules of MAPS

S. no.	Item	Temperature (°C)	Failure rate/10^6 h	Failure probability
1	Belt conveyer	25	26.78	0.026
2	Horizontal transfer unit	25	48.78	0.048
3	Linear pick and place unit	25	32.4	0.11
4	Six station rotary indexing table	25	115.31	0.032
5	Filling module	25	48.14	0.047
6	Capping module	25	81.42	0.078
7	Rotary pick and place unit	25	124.92	0.118
8	Weighing station	25	15.85	0.015
9	Palletizer assembly unit	25	110.93	0.104

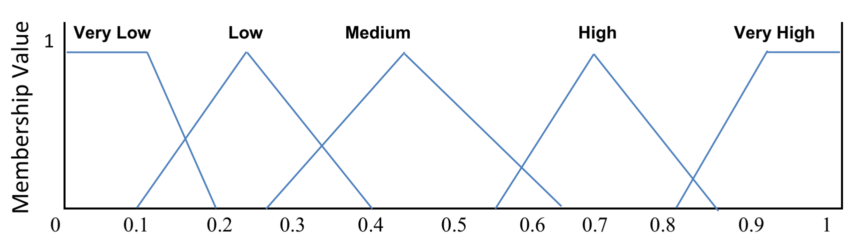

Fig. 2 Fuzzy membership function for linguistic assessment of human performance

Table 5 Linguistic assessments and fuzzy membership function

S. no.	Linguistic assessment	Fuzzy membership function
Expert I	Very low	$f_{\mathrm{VL}}(x)\begin{cases}1 & 0<x<0.1\\ \frac{0.2-x}{0.1} & 0.1<x<0.2\\ 0 & \text{otherwise}\end{cases}$
Expert II	Low	$f_{L}(x)\begin{cases}\frac{x-0.1}{0.15} & 0.1<x<0.25\\ \frac{0.4-x}{0.15} & 0.25<x<0.40\\ 0 & \text{otherwise}\end{cases}$
Expert III	Very low	$f_{\mathrm{VL}}(x)\begin{cases}1 & 0<x<0.1\\ \frac{0.2-x}{0.1} & 0.1<x<0.2\\ 0 & \text{otherwise}\end{cases}$
Expert IV	Very low	$f_{\mathrm{VL}}(x)\begin{cases}1 & 0<x<0.1\\ \frac{0.2-x}{0.1} & 0.1<x<0.2\\ 0 & \text{otherwise}\end{cases}$
Expert V	Very low	$f_{\mathrm{VL}}(x)\begin{cases}1 & 0<x<0.1\\ \frac{0.2-x}{0.1} & 0.1<x<0.2\\ 0 & \text{otherwise}\end{cases}$

Table 6 Fuzzy failure rate for human error

	Incorrect operation	Careless operation
Fuzzy failure rate, FFR (failures/h)	2.13×10^{-4}	0.69×10^{-4}

RPN of 100) even though F_{15} should have a higher priority for corrective action. Also, with respect to F_{12}, $F_{13,}$ and F_{14} which are represented with same linguistic terms, i.e. moderate, high, and high, respectively, produce different RPN. Such type of limitations of traditional FMEA is addressed by using fuzzy and grey approaches.

Fuzzification

Fuzzification refers to transformation of crisp inputs into a membership degree, which expresses how well the input belongs to the linguistically defined terms. To represent input variables (O_{f}, S, and O_{d}) graphically, trapezoidal MF is used which are consistent with the definitions of probability of failure occurrence, severity, and non-detectability used in the study as depicted in Table 1. To represent output variable, risk priority graphically both triangular and trapezoidal MFs are used. Multiple experts with different degree of competencies are used to construct the MF. The descriptive terms describing the output MF are not important, minor, low, moderate, important, and very important (Fig. 4a, b).

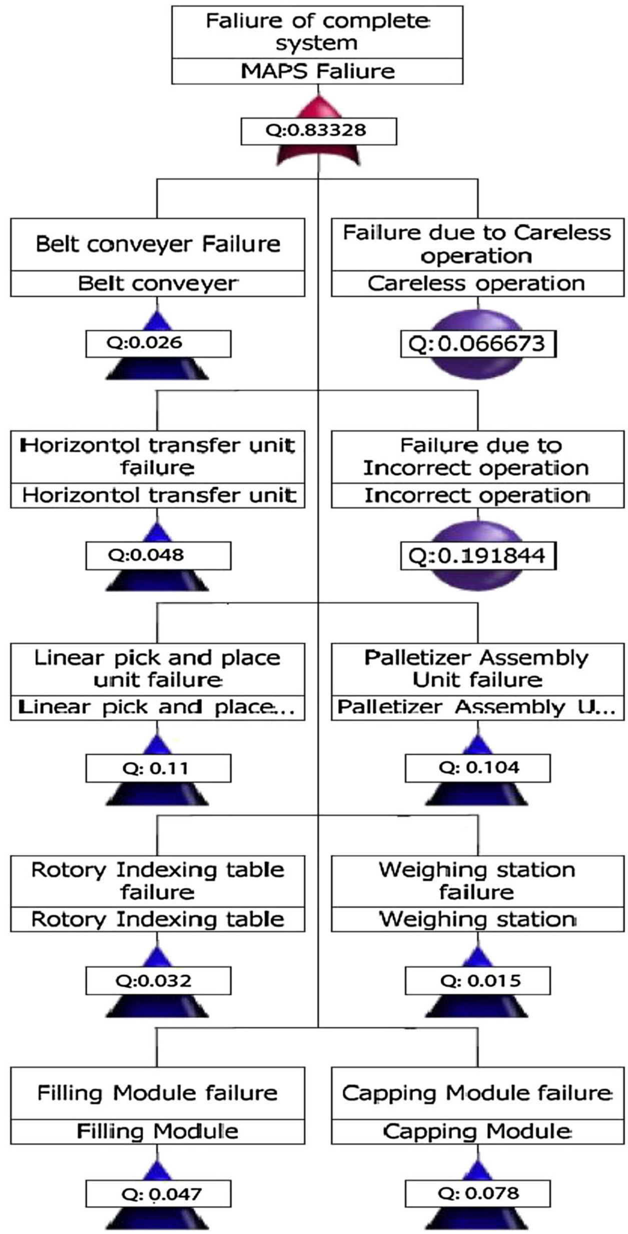

Fig. 3 Hybrid FTA of MAPS

Fuzzy rule base

The fuzzy inputs, i.e. O_{f}, S, O_{d}, are evaluated in fuzzy inference engine, which makes use of well-defined rule base. In the study, based on the MFs of 3 input variables O_{f}, S, O_{d} with 5 fuzzy sets in each, a total of 125 rules can be generated. However, these rules are combined (wherever possible) and the total number of rules in rule base is reduced to 30. The format of rules framed in the study is shown in Fig. 5.

Table 7 RPN calculation for different failure modes of MAPS components

S. no.	Component	ID and failure mode		Effect on component	O_f	S	O_d	RPN
1	Cylinder	F_{11}	Radial expansion	Loss of air	4	5	5	100
		F_{12}	Wear	Contamination of air	5	8	8	320
		F_{13}	Leakage	Loss of air	5	7	8	280
	Piping and seals	F_{14}	Seepage	Gradual loss of air	6	7	8	336
		F_{15}	Rupture	Loss of air	3	7	4	84
2	Ball bearing	F_{21}	Wear	Vibration	7	6	8	336
		F_{22}	Race fracture	Vibration	3	8	5	120
		F_{23}	Flaking	Bearing surface turns into irregular particles	6	8	7	336
		F_{24}	Seizing	Overheating	4	6	7	168
		F_{25}	Creeping	Slipping of race on mounting	5	8	4	120
3	Mechanical relay	F_{31}	Spurious trip	Relay malfunction	3	6	7	126
		F_{32}	Short	Malfunction	5	7	8	280
	Lead screw	F_{33}	Backlash	Loss of power	3	7	5	105
	Belt	F_{34}	Excessive wear	Reduction in strength	6	8	8	384
		F_{35}	Fatigue	Slipping of belt	5	8	8	320
4	Electric motors	F_{41}	Winding failure	Motor halts	4	5	5	100
		F_{42}	Bearing failure	Power loss	6	7	5	210
		F_{43}	Overload	Overheating	5	6	5	150
		F_{44}	Short circuit	Malfunction	4	6	5	120
		F_{45}	Mechanical damage	Motor stops working	7	6	8	336
		F_{46}	Rotor deflection	Non uniform wear of rotor	6	8	7	336
		F_{47}	Short between coils	Hardware failure	4	7	5	140
5	Resistor	F_{51}	Overheating	Hardware failure	6	8	5	240
		F_{52}	Open	Malfunction	7	6	5	210
	Solenoid valve	F_{53}	Overheating	Oxidation of coil	6	7	6	252
		F_{54}	Work hardening	Sensitivity reduced	6	6	6	216
		F_{55}	Crack	Loss of signal	3	6	5	90
6	Inductive sensor	F_{61}	Winding failure	Hardware failure	2	6	7	84
		F_{62}	Hysteresis	Sensitivity reduced	3	8	5	120
		F_{63}	Drift	Bad response	3	6	6	108
		F_{64}	Noise	Vibration	4	9	8	288
	Photoelectric sensor	F_{65}	Loss of signal	Fault reading	3	7	6	126
		F_{66}	Sensor bias	Fault reading	4	9	6	216
		F_{67}	Drift	Output change cont.	5	6	8	240
		F_{68}	Noise	Signal loss	4	6	8	192
		F_{69}	Hysteresis	Fatigue	4	7	5	140
	Magnetic reed switch	F_{70}	Sticking	Sensitivity reduction	3	5	8	120
		F_{71}	Missing	Malfunction	7	6	3	126

Fuzzy inference system and defuzzification

By using the inference mechanism, an output fuzzy set is obtained from the rules and the input variables. Figure 6 shows the schematic representation of the fuzzy reasoning mechanism (Mamdani approach) with two rules. First, the numerical input variables (occurrence, severity) are fuzzified using appropriate MFs. Then, the min operator is used for the conjunction and for the implication operations. The outputs (individual fuzzy sets) are aggregated by using the max operator, and finally the aggregated output is defuzzified using centroid method to obtain crisp FRPN ranking from the fuzzy conclusion set. Figure 7 presents FRPN output for two failures modes F_{13} and F_{14} which are represented with same linguistic terms, i.e. moderate, high and high, respectively, and produce same

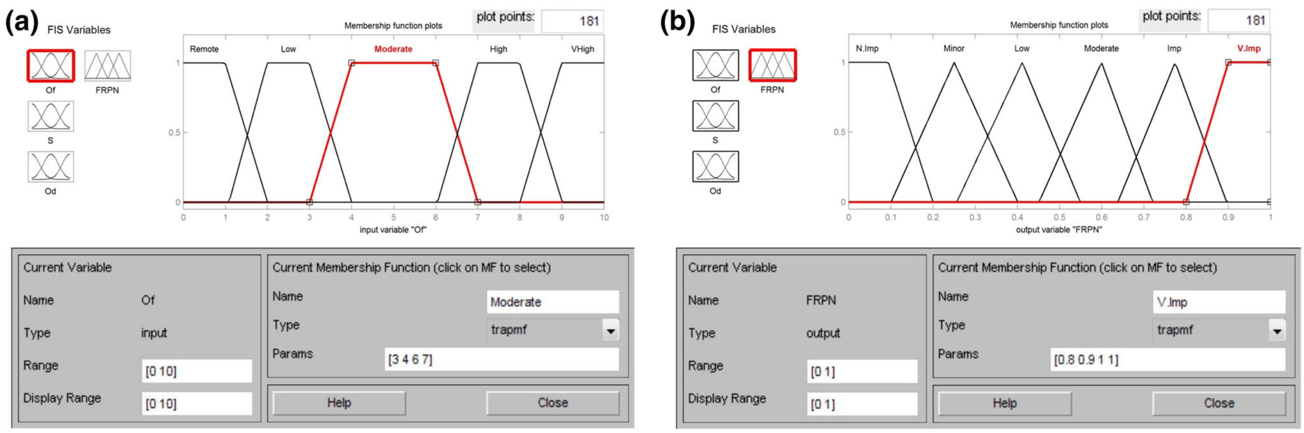

Fig. 4 Linguistic representation plots. **a** O_f, S and O_d; **b** risk priority

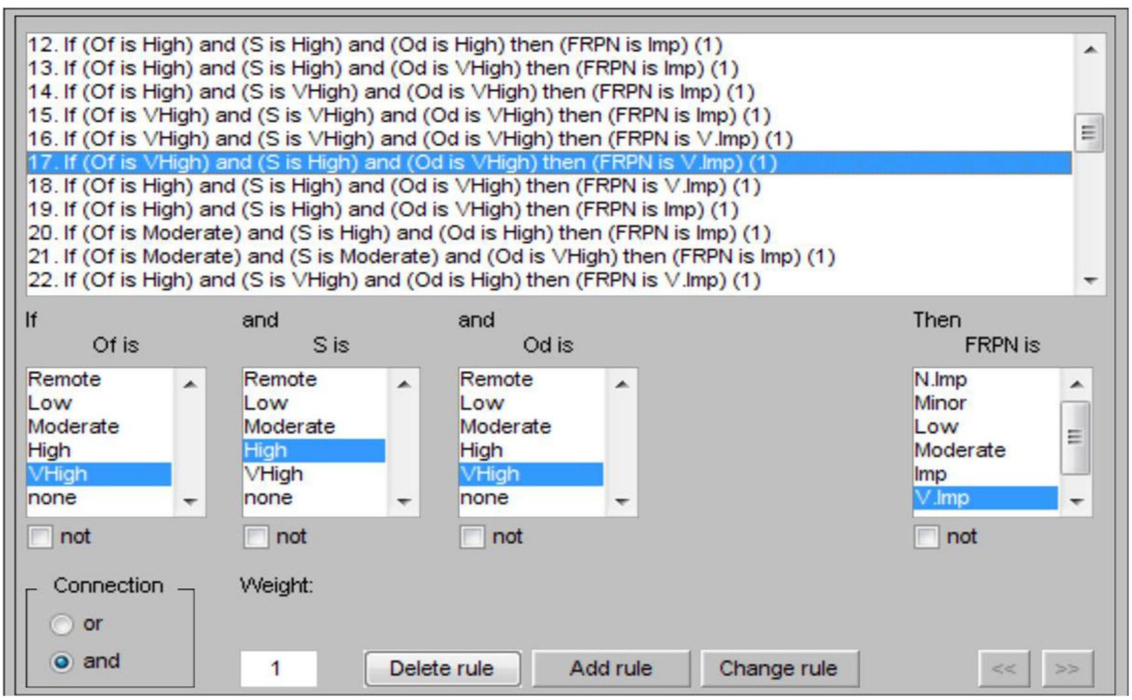

Fig. 5 Format of rules framed on fuzzy inference system

RPN FRPN, i.e.0.664. The FRPN results for all failure modes with respect to different components, i.e. mechanical, electrical, and electronic so obtained are presented in Table 9.

Grey relation analysis

Based on the steps discussed in "Appendix", grey theory approach is applied to prioritize the causes identified in the FMEA process. The MF for each linguistic term associated with (O_f), (S), and (O_d) are defined (which are same as that used in used in FIS). Then, using Chen's ranking (1992), defuzzification is carried out. The defuzzified values so obtained for linguistic terms used in MFs are presented in Table 8.

These values are used to generate the comparative series. For instance, for motors, the series obtained is represented using matrix (Eq. 1a). The symbols on left-hand side of matrix represent the linguistic terms assigned to failure causes and numerical values on right-hand side represent the corresponding defuzzified values. Similar series can be obtained for other components of MAPS.

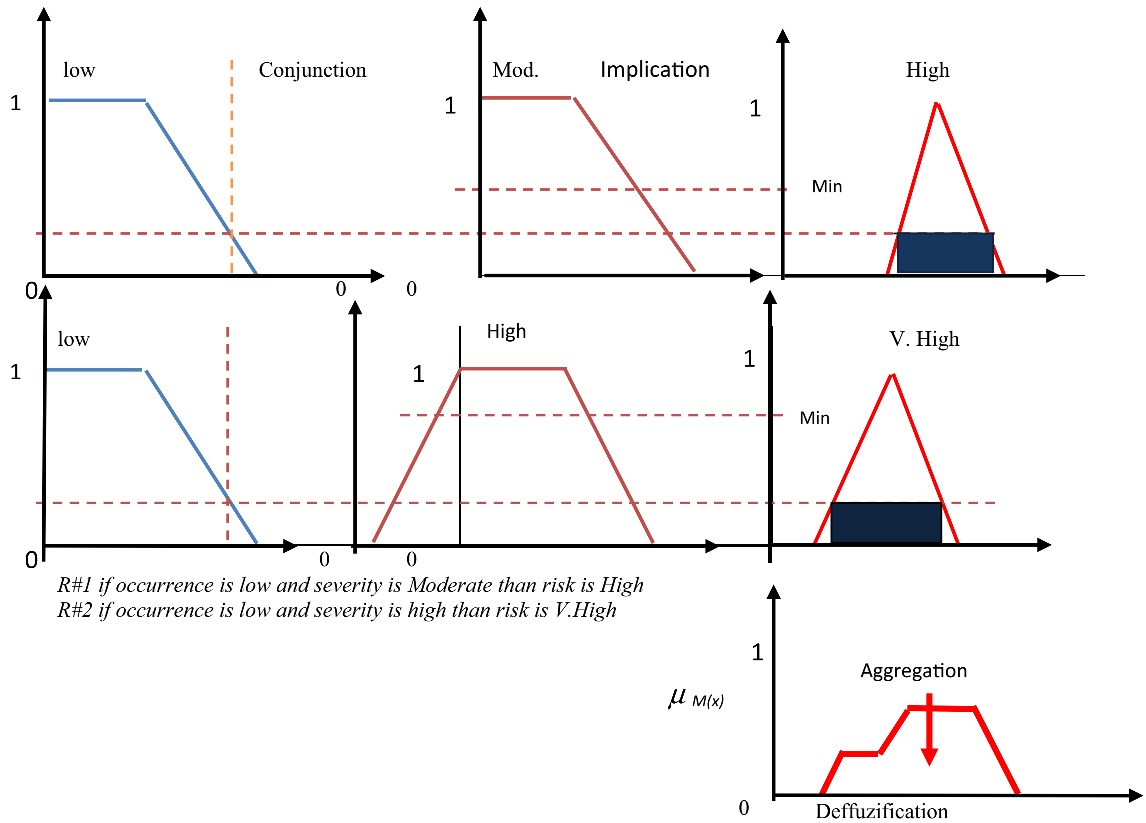

Fig. 6 Illustration of fuzzy reasoning mechanism

$$\begin{bmatrix} + & + & + \\ + & ++ & + \\ + & + & + \\ + & + & + \\ ++ & + & ++ \\ + & ++ & ++ \\ + & ++ & + \end{bmatrix} = \begin{bmatrix} 0.6240 & 0.6240 & 0.6240 \\ 0.6240 & 0.7272 & 0.6240 \\ 0.6240 & 0.6240 & 0.6240 \\ 0.6240 & 0.6240 & 0.7272 \\ 0.7272 & 0.6240 & 0.7272 \\ 0.6240 & 0.7272 & 0.7272 \\ 0.6240 & 0.7272 & 0.6240 \end{bmatrix} \tag{1a}$$

Then standard series (Eq. 1b) for motors is generated by determining the optimal level of O_f, S, and O_d (as in FMEA, smaller the RPN number, the lesser the risk; therefore standard series should consists of the lowest level of linguistic terms describing the three variables), which is remote in the study with a defuzzified value 0.1409, as such the value 0 (lowest possible value) is taken to represent the term remote.

$$\begin{bmatrix} -- & -- & -- \\ -- & -- & -- \\ -- & -- & -- \\ -- & -- & -- \\ -- & -- & -- \\ -- & -- & -- \\ -- & -- & -- \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{1b}$$

To obtain the grey relation coefficient using Eq. (4), the difference between the standard and comparative series is computed which is equal to comparative series. Using the value of the grey relation coefficient and introducing a weighting factor for all three linguistic variables, the degree of grey relation for each failure cause is calculated. The degree represents the ranking order of each failure cause. In the study, the weighting factor (β_k), for the linguistic variables O_f, S, and O_d, is determined using AHP analysis. The experts were asked to make comparisons between occurrence (O_{w1}), severity (S_{w2}), and non-detectability (O_{w3}). The values provided by them are: (O_{w1}) versus (S_{w2}) = 60:40; (S_{w2}) versus (O_{w3}) = 30:70, and (O_{w3}) versus (O_{w1}) = 60:40, respectively.

Based on these comparisons, the AHP analysis is carried out which gives coefficients as $\beta_f = 0.21$, $\beta_s = 0.48$, $\beta_d = 0.31$, respectively. The degree of grey relation is then calculated by using Eq. (10). For instance, for failure cause F_{42} the grey output is obtained as:

$$0.21 \times 0.624 + 0.48 \times 0.503 + 0.31 \times 0.624 = 0.5650$$

The values of grey output for all failure modes is computed and presented in Table 9 (Column 6). The comparative results of FMEA obtained through traditional,

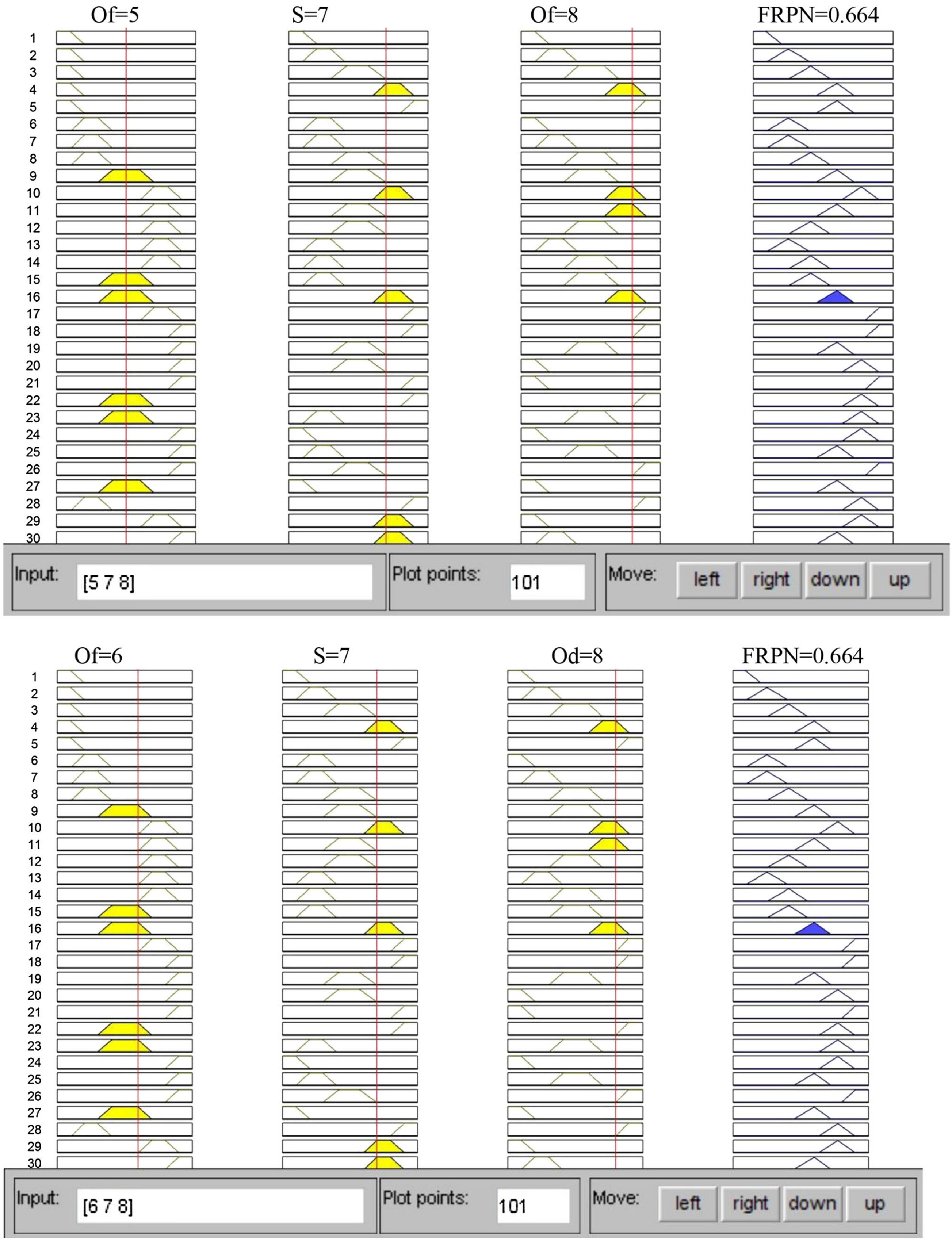

Fig. 7 Fuzzy inference system output for failure modes F_{13} and F_{14}

Table 8 Defuzzified values for linguistic terms

Linguistic term	Remote	Low	Moderate	High	Very high
Symbol	− −	−	+	++	+++
Defuzzified values	0.1409	0.2920	0.6240	0.7272	0.9090

Table 9 Traditional, fuzzy and grey results

ID failure mode	Traditional RPN output	Traditional ranking	Fuzzy (FIS) output	Fuzzy ranking	Grey output	Grey ranking
F_{11}	100	4	0.511	3	0.6240	3
F_{12}	320	2	0.664	1	0.5284	1
F_{13}	280	3	0.664	1	0.5284	1
F_{14}	336	1	0.664	1	0.5284	1
F_{15}	84	5	0.533	2	0.6060	2
F_{21}	336	1	0.636	2	0.5610	2
F_{22}	120	4	0.601	4	0.6060	4
F_{23}	336	1	0.664	1	0.5284	1
F_{24}	168	3	0.617	3	0.5864	3
F_{25}	120	4	0.597	5	0.6240	5
F_{31}	126	4	0.521	3	0.6274	2
F_{32}	280	3	0.664	1	0.5284	1
F_{33}	105	5	0.533	2	0.6060	3
F_{34}	384	1	0.664	1	0.5284	1
F_{35}	320	2	0.664	1	0.5284	1
F_{41}	100	6	0.597	4	0.6240	4
F_{42}	210	2	0.627	3	0.5650	3
F_{43}	150	3	0.597	4	0.6240	4
F_{44}	120	5	0.597	4	0.6240	4
F_{45}	336	1	0.636	2	0.5610	2
F_{46}	336	1	0.644	1	0.5284	1
F_{47}	140	4	0.627	3	0.5650	3
F_{51}	240	2	0.6270	1	0.5650	1
F_{52}	210	4	0.6010	2	0.5985	2
F_{53}	252	1	0.6270	1	0.5650	1
F_{54}	216	3	0.5551	4	0.6844	4
F_{55}	90	5	0.5793	3	0.6649	3
F_{61}	84	9	0.319	8	0.6654	9
F_{62}	120	7	0.333	6	0.6060	5
F_{63}	108	8	0.313	9	0.6649	8
F_{64}	288	1	0.679	1	0.4962	1
F_{65}	126	6	0.333	6	0.6060	5
F_{66}	216	2	0.659	2	0.5337	2
F_{67}	240	3	0.617	3	0.5864	4
F_{68}	192	4	0.617	3	0.5864	4
F_{69}	140	5	0.431	4	0.5650	3
F_{70}	120	7	0.321	7	0.6274	6
F_{71}	126	6	0.411	5	0.6590	7

fuzzy and grey approach are presented jointly in Table 9 with respective priorities.

It is evident from the comparative results (Table 9) that in traditional FMEA, events with same linguistic terms produce different RPN, but the fuzzy and grey methods produce identical ranking. For instance, F_{12}, F_{13}, and F_{14}, where O_f, S, and O_d are described by moderate, high, and high, respectively, the defuzzified output is 0.664 and the grey relation output is 0.5284, for all the three events. This entails that these three events should be given the same priority for attention. The RPN method, however, produces an output of 320, 280, and 336 for these events and ranks them at 1st, 2nd, and 3rd place, respectively. Also, failure mode F_{15} with high severity, low rate of occurrence, and moderate detectability (7, 3, and 4, respectively) having lower RPN (84) than F_{11} where all the parameters are moderate (4, 5, and 5 yielding an RPN of 100) have been ranked with higher priority for corrective action by both fuzzy and grey methods.

From the table it is observed that a failure cause F_{22} with high severity, low rate of occurrence, and moderate detect ability (8, 3, and 5, respectively) have same RPN (120) to that of F_{25} where all the parameters are moderate ($O_f = 5$, $S = 6$, and $O_d = 4$) yielding an RPN of 100. Both are ranked same at 4th position but fuzzy and grey methods produce different results and ranks them differently. The effect of the weighting coefficient considered in grey analysis can be visualized in grey output results. The grey theory ranks cause F_{22} higher than that of F_{25} if severity is considered as an important factor. Failure modes F_{21} and F_{23} represented by different sets of linguistic terms produce an identical RPN, i.e. 336 and are ranked at position 1, however, the risk implication for both the causes may be totally different. This limitation of traditional FMEA is handled by using both grey and fuzzy methods as they ranks F_{23} higher than F_{21} by considering severity as one of the main contributor.

The failure modes under mechanical components F_{32}, F_{34}, and F_{35}, where O_f, S, and O_d are described by moderate, high, and high, respectively, produces different RPN numbers, i.e. 280, 384, and 320, respectively, and are ranked differently at 3rd, 1st, and 2nd place, respectively. On the other hand, FIS (0.664) and grey relation methodology (0.5284) produce similar output and rank them identically at position 1. This entails that these three events should be given the same priority for attention.

F_{41}, F_{43}, and F_{44} represented by same set of linguistic terms, i.e. moderate, moderate, and moderate, but produce different traditional RPN number, i.e. 100, 150, and 120 and are ranked at 6th, 3rd, and 5th position, respectively. On the other hand, fuzzy and grey methods rank all these causes at same position, i.e. 4th and 3rd position by addressing the inherent limitation. Failure modes F_{45} and F_{46} represented by different sets of linguistic terms, i.e. high, moderate, high and moderate, high, high produce an identical RPN, i.e. 336 and are ranked at position 1, however, the risk implication for F_{46} is high. This limitation of traditional FMEA is handled by using both grey and fuzzy methods as they rank F_{46} higher than F_{45} by considering severity as one of the main contributor.

The failure modes F_{51} and F_{53} represented by same linguistic terms produce different RPN, i.e. 240 and 252 using traditional FMEA and are ranked 2nd and 1st position, respectively, which could be misleading. On the other hand, both grey and fuzzy approaches produce same output and same rank.

F_{62} and F_{65} represented by same linguistic terms, i.e. low, high, moderate produce different RPN, i.e. 120 and 126 and are ranked at 6th and 7th positions, which could be misleading. Both fuzzy and grey approaches produce same results and hence identical ranking for them. Also F_{68} and F_{69} where O_f, S, and O_d are described by same linguistic terms, i.e. moderate, moderate, high produce different RPN and ranking, but the fuzzy and grey outputs for both failure modes are identical. This entails that these causes should be given the same priority for attention.

Conclusion

The paper presents the application of hybrid FTA and failure mode effects analysis, as failure analysis techniques to examine the risk and reliability needs of a complex mechatronic system, i.e. Modular Automated Production System (MAPS), which consists of mechanical, electronic and embedded software subsystems. The application of hybrid FTA not only helps to analyse the probabilities associated with hardware components of the system, but also helps to evaluate probability of failures resulting from human errors in complex mechatronic system. From the results, it is found that the proposed approach models both subjective issues such as human errors along with hardware failures. The thorough analysis and prioritizing of failure causes of different components of a mechatronic system using a risk ranking approach based on fuzzy rule based inference system and grey relation approach not only integrate expert judgment, experience and expertise in more flexible and realistic manner, but also address the disadvantages associated with traditional procedure of FMEA. In the GRA, the introduction of weighting coefficient provides the analyst with enough flexibility to decide which factor among O_f, S, and O_d is more important to the analyst, the outcome of which will provide valuable information with respect to risk associated with the system components. The results obtained from the proposed approach are in agreement with the other works in the literature (Chang et al. 1999; Ho and Liao 2011; Majdara and Toshio 2009; Xiao et al. 2011) in which authors have used fuzzy set theory and grey methodology to address the research issues in different fields of engineering.

From the study, we can conclude that owing to its sound logic, efficacy in quantifying the vagueness and imprecision in human judgment, the fuzzy methodology can be used as an effective tool by the engineers to assess the risk and reliability needs of mechatronic products. The analyst can use linguistic variables to assess the events and failure possibility of events can be approximated by well-defined MFs which can handle imprecise and vague information more precisely.

Appendix

The main steps involved in Grey approach are:

Step 1: Formulation of comparative series

The comparative series also known as information series are used to represent various linguistic terms and decision factors in the form of a matrix (Eq. 1)

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} x_1(1) & x_1(2) & \ldots\ldots & x_1(k) \\ x_2(1) & x_2(2) & \ldots\ldots & x_2(2) \\ \vdots & \vdots & \ldots\ldots & \vdots \\ x_n(1) & x_n(2) & \ldots\ldots & x_n(k) \end{bmatrix} \tag{1}$$

The linguistic terms describing the decision factors may be remote, low, fairly low and moderate. For instance, if $x_i = \{x_1 (1), x_1 (2),\ldots, x_1 (k)\}, \{x_2 (1), x_2 (2),\ldots, x_2 (k)\}$, etc. are the linguistic terms (decision factors), then $\{x_1, x_2,\ldots, x_n\}$ are the potential failure modes or failure causes of FMEA.

Step 2: Formulation of standard series

The standard series is an objective series that reflects the ideal or desired level of all the decision factors and can be expressed as Eq. (2)

$$x_0 = [x_0(1), x_0(2), x_0(k)]. \tag{2}$$

Step 3: Obtain difference between the two series

To determine the degree of grey relation, the difference between the two series, D_0, (comparative and standard series) is calculated and expressed as

$$D_0 = \begin{bmatrix} \varDelta_{01}(1) & \varDelta_{01}(2) & \varDelta_{01}(3) & \varDelta_{01}(k) \\ \varDelta_{02}(1) & \varDelta_{02}(2) & \varDelta_{03}(3) & \varDelta_{02}(k) \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \varDelta_{02}(k) \\ \varDelta_{0m}(1) & \varDelta_{0m}(2) & \varDelta_{0m}(3) & \varDelta_{0m}(k) \end{bmatrix} \tag{3}$$

where $\varDelta 0j(k) = \left\| x_0(k) - x_j(k) \right\|$

Step 4: Compute grey relation coefficient

To compare the decision factors with standard series, a relationship has to be established. This relationship is known as grey relation coefficient and is expressed as

$$\gamma(x_0(k), x_i(k)) = \frac{\min_i \min_k |x_0(k) - x_j(k)| \varsigma \max_i \max_k |x_0(k) - x_j(k)|}{|x_0(k) - x_j(k)| + \varsigma \max_i \max_k |x_0(k) - x_j(k)|} \tag{4}$$

where x_0 (k) is the min or max value from the standard series and x_j (k) is the min or max value from the comparative series and ς an identifier, $\varsigma \in (0, 1)$ only affecting the relative value of risk without changing the priority; generally taken as 0.5

Step 5: Determine degree of relation

The degree of relation $[\Gamma(x_i, xj)]$ denotes the relationship between the potential causes and the optimal value of the decision factors and is expressed as Eq. (5).

$$\Gamma\left(x_i, x_j\right) = \sum_{k=1}^{n} \beta_k \gamma\left\{x_i(k).x_j(k)\right\}, \text{ With } \Gamma\left(x_i, x_j\right) = \sum_{k=1}^{n} \beta_k \gamma\left\{x_i(k).x_j(k)\right\} \tag{5}$$

where (β_k) the weighting coefficient of the decision factors

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