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Fuzzy Logic-Based Fault Detection in Industrial Production Systems: A Case Study

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Abstract: The burgeoning application of artificial intelligence (AI) technologies for the diagnosis and detection of defects has marked a significant area of interest among researchers in recent years. This study presents a fuzzy logic-based approach to identify failures within industrial systems, with a focus on operational anomalies in a real-world context, particularly within the competitive landscape of Omar Benamour, in Al-Fajjouj region, Guelma, Algeria. The analysis has been started with the employment of the Activity-Based Costing (ABC) method to identify the critical machinery within the K-short dough production line. Subsequently, an elaborate failure tree analysis has been conducted on the pressing machine, enabling the deployment of a fuzzy logic approach for the detection of failures in the dough cutter of AMOR BENAMOR's K production line press. The effectiveness of the proposed method has been validated through an evaluation conducted with an authentic and real-time data from the facility, where the study took place. The results underscore the efficacy of the fuzzy logic approach in enhancing fault detection within industrial systems, offering substantial implications for the advancement of defect diagnosis methodologies. The study advocates for the integration of fuzzy logic principles in the operational oversight of industrial machinery, aiming to mitigate potential failures and optimize production efficiency.

Keywords: Fault detection; Failure probability; Fuzzy logic; Membership function; Fuzzification; Fuzzy rules; Defuzzification; Industrial systems

1 Introduction

The technological development of production technologies has led to the emergence of highly complex and dynamic industrial systems. Any industrial system can go directly from a normal operating mode to a defective mode in correspondence to a change or a stop in the industrial system ability to perform the production function. To avoid this problem, a systematic maintenance strategy can be followed through designing the system support, according to a certain pre-determined time period. Since this strategy requires a complete or a partial termination of the production system, it has a practical drawback, which in turn leads to a decrease in the productivity of the industrial system [1, 2]. To achieve this objective, it is necessary to find intelligent predictive technology that helps make decisions related to maintenance without the need to stop the production process [3, 4]. One of these techniques is the fuzzy logic technique. The intrinsic advantages of logic flow, according to the modeling approach, can be summarized in three points: reducing development cost [5], implementation and maintenance. The fact that in most organizations 60 to 80% of the physical activity provides maintenance makes the last feature the most important [6]. In general, system experts compare decision aid systems [7, 8], as well as traditional approaches [9, 10] and models based on flow logic or flow models [11], which have different properties:

• A strong reasoning engine.

• It is possible to abandon a prototype with significant delay [11].

• Adapting and auto regulator.

• Systems are designed to extend support in the face of contradictions [12] and the presence of ambiguous or imprecise information [13].

• The models are used for non-linear problems and their stability is enhanced in such contexts [14].

This study aims at developing the fuzzy logic technique in the field of diagnosis [15, 16], specifically detecting real industrial faults in compliance and dynamism and how to deal with them. For this purpose, the Omar Ben

Omar Industrial Foundation, Guelma, Algeria, was proposed in this field of application, in particular, and circulated to institutions. In the industrial sector that practices the same activity, this introduction and case study can be summarized in the following dimensions; in order to achieve this objective, special attention is paid to the short pasta manufacturing process and the production line equipment (Line K) is analyzed, due to its specificity, which allows us to classify it, according to its criticality. Then, the functional or structural failure of the cash machine (press) is analyzed. Finally, fuzzy logic technology is developed. The study ends with a comprehensive conclusion summarizing the carried-out work as well as the alleged future work in this field.

2 Case Study

As a part of the case study, the authors of this study are interested in the K production line for 4000 kg/h short pasta from the AMOR BENAMOR mill company in the wilaya of Guelma. The K line has an immediate availability and a fairly well-known stock level, due to an increase in consumption by Algerian customers. The current production capacity of the company is shown in Table 1.

Table 1. Current production capacity of the company

Production	Actual Capacity (kg/h)
Short pasta	A line capacity of 6500
	Three lines with a capacity of 3500
Long pasta	A capacity line of 3000
Special pastas	A line capacity of 3000

It is made up of 8 pieces of equipment, as shown in Figure 1. The coding of the short pasta pattern K is shown in Table 2.

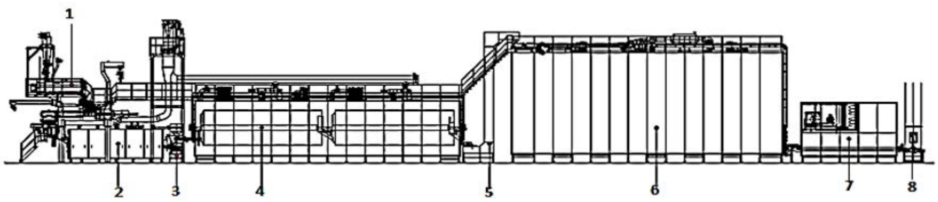

Figure 1. A descriptive diagram of the short pasta production line K

Table 2. Coding of the short pasta diagram

Index	1	2	3	4	5	6	7	8
Equipment	The press	The trabatto	Elevator 01	Pre-dryer	Bucket elevator 02	Dryer	The cooler	Bucket elevator 03

In order to quantify the equipment criticality in the production process of line K, an ABC analysis method has been used through taking the number of breakdowns for each machine as a criterion with four years of experience feedback [17], as shown in Table 3. According to the above table, the following diagram (Figure 2) has been constructed

Table 3. ABC table of K line machines

Machines	Number of Failures	Cumulative Number of Failures	Proportion of the Number of Failures (%)	Proportion of the Cumulative Number of Failures (%)
The press	137	137	59.31	59.31
The silo	25	162	10.82	70.13
The pre-dryer	21	183	9.09	79.22
The dryer	18	201	7.79	87.01
The trabatto	12	213	5.19	92.21
Elevator 01	6	219	2.60	94.81
Bucket elevator 03	5	224	2.16	96.97
Bucket elevator 02	4	228	1.73	98.70
The cooler	3	231	1.30	100.00

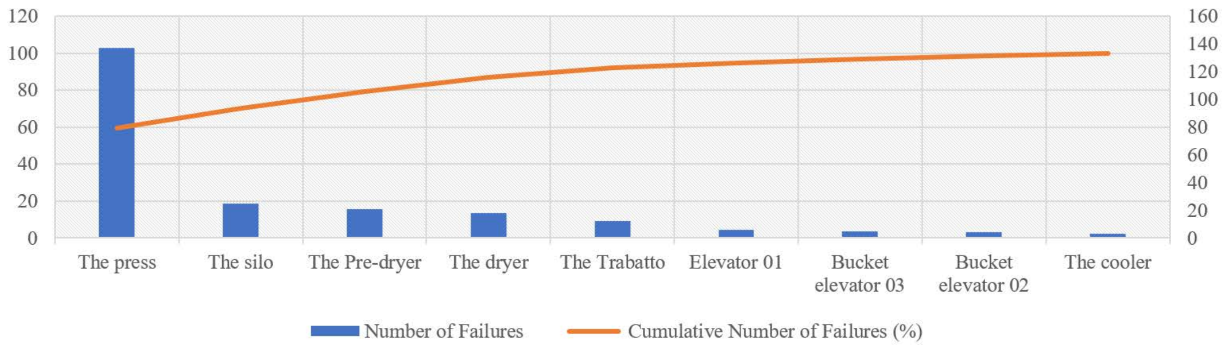

Figure 2. ABC diagram of K line machines

According to the ABC analysis on the K line equipment, the chosen press is classified in zone A, and has a high percentage of breakdowns estimated at 59.31%. Table 4 shows the ABC table of the press. Figure 3 shows the ABC diagram of the press. In addition, the production process of the K line is a shop-type flow. Therefore, the press is a bottleneck machine. The press fault tree is presented in Figure 4. ABC analysis has been applied to the most sensitive part of production line K, which is the press, in order to know precisely at which level to apply fuzzy logic. The figure illustrates the results of the ABC analysis on the press components.

Table 4. ABC table of the press

Machines	Number of Failures	Cumulative Number of Failures	Proportion of the Number of Failures (%)	Proportion of the Cumulative Number of Failures (%)
Dough cut	57	57	41.61	41.61
Vacuum system	19	76	13.87	55.47
Dough-cutting mat	13	89	9.49	64.96
Compression screw	12	101	8.76	73.72
Mixing water	10	111	7.30	81.02
Semolina cyclon	8	119	5.84	86.86
Stirrer	8	127	5.84	92.70
Centrifugal	7	134	5.11	97.81
Doser	2	136	1.46	99.27
The head	1	137	0.73	100.00
Limiter	0	137	0.00	100.00

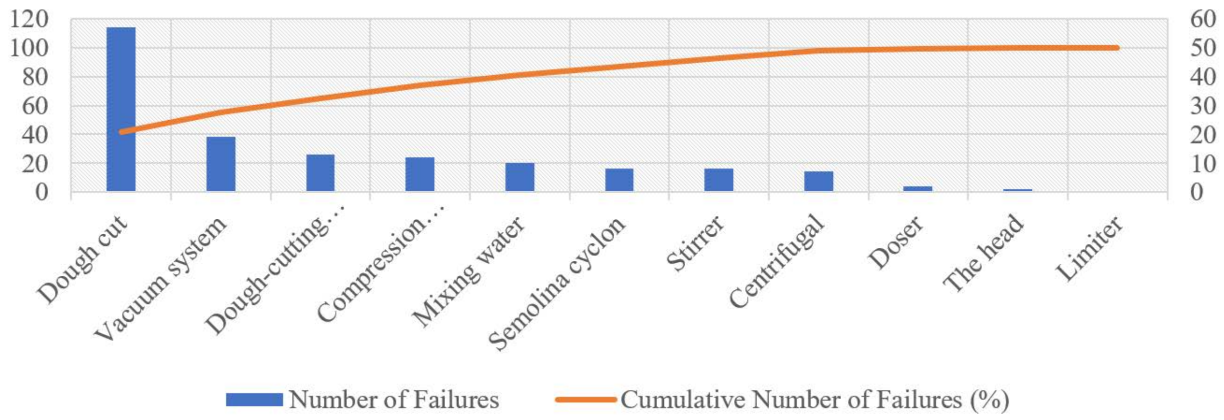

Figure 3. ABC diagram of the press

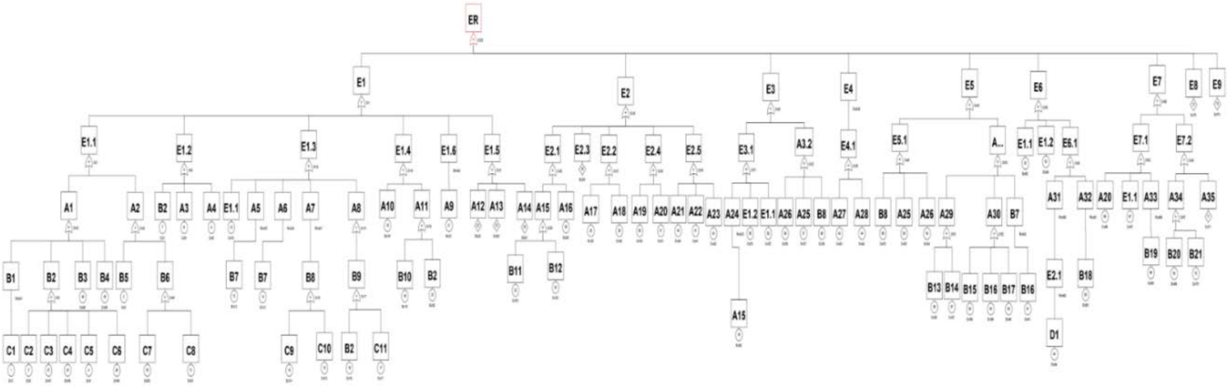

Figure 4. Press failure tree

According to the ABC analysis of the press equipment, the dough-cutting equipment has been chosen for both. It is classified in zone A, and has a high breakdown percentage, estimated at 41.61%. Besides, it is highly sensitive, and has a repetitive type of failure. Therefore, the dough cutter has been chosen as the studied system in Figure 5. Failure probabilities are shown in Table 5.

In this application, membership functions need to be defined for each fuzzy subset of the three variables in Figure 6 and Table 6. Figure 7 shows the final function after the aggregation of fuzzy rules using a cut method.

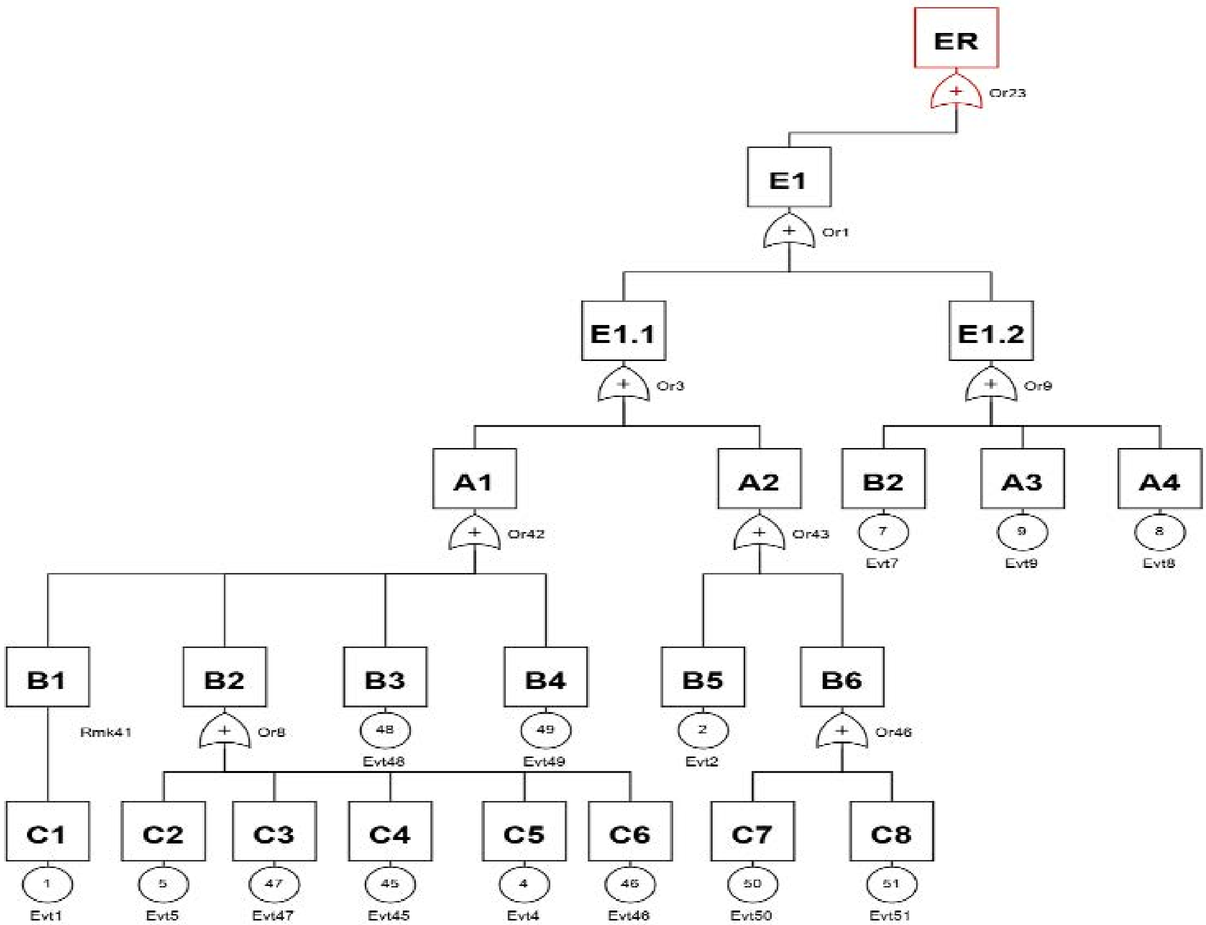

Figure 5. Designation of the part chosen to apply fuzzy logic

Table 5. Failure probabilities

Minimal Cut	Event Symbol	Probabilities
Loss of Dough Cutting Function	A14	4.5589604780138515E-4
	A13	1.1599993271493858E-6
	A12	4.498987651857522E-4
	E1.5	1.8698251658977316E-4
	A4	3.49938757145174E-4
	A3	4.498987651857522E-4
	B2	1.0999395022182057E-4
	E1.2	3.3994220655009233E-4
	C1	1.1999280028796022E-4
	B1	2.2997355202769576E-4
	B3	9.99999949513608E-8
	C6	9.99999949513608E-8
	C5	5.19998648007558E-6
	C4	3.999999920178965E-8
	C3	4.199991180064977E-6
	C2	6.999997550494186E-7
	B2	4.199991180064977E-6
	A1	1.9999979999907325E-6
	C8	4.498987651857522E-4
	C7	1.0999395022182057E-4
	B6	4.199991180064977E-6
	B5	1.399999020046394E-6
	A2	1.9999979999907325E-6
	E1.1	1.1399935020195429E-5

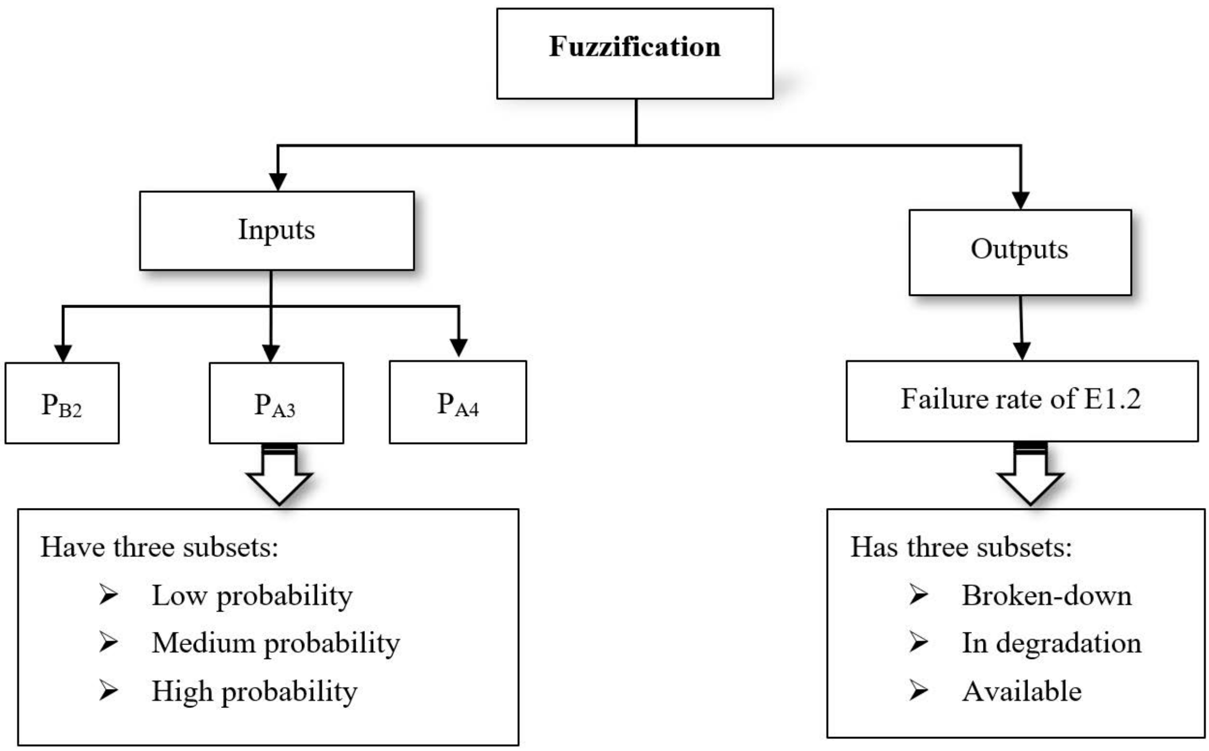

Figure 6. Fuzzification diagram

Table 6. Fuzzification settings

Linguistic Variable	Linguistic Value Membership Function	Linguistic Value Membership Class
Probability of failure of B2 $(\mathrm{P}_{\mathrm{B2}})$	Low	[9e-05 0.0001]
Probability of failure of A3 $(\mathrm{P}_{\mathrm{A3}})$	Average	[9e-05 0.0003]
Probability of failure of A4 $(\mathrm{P}_{\mathrm{A4}})$	Strong	[9e-05 0.0005]
The Universe of Speech		
[0.0001 0.0005] for inputs and outputs	Available	[-0.0001 0.0001 0.0002]
	Degrading	[0.0002 0.0003 0.0004]
	Broken	[0.0004 0.000508 0.00055]

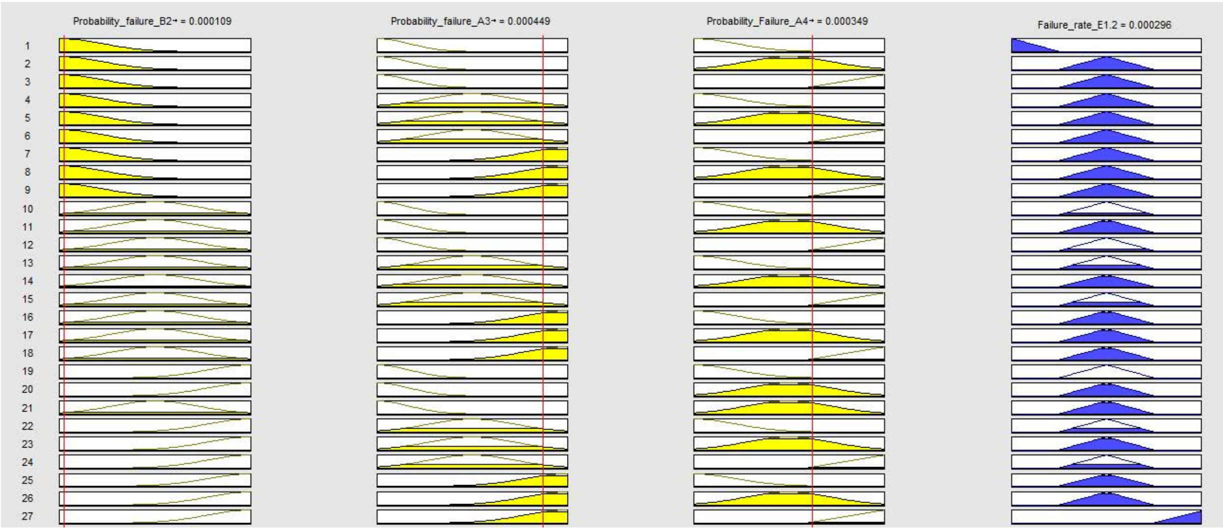

Figure 7. Final function after aggregating fuzzy rules using a cut method

3 Computational Experiments

Figure 8 presents the relationship between the failure rates A4 and A3 used for the degradation of E1.2 attributed to the paste cutting system:

• It can be noted that when the failure rate of the couple (A4 and A3) is strictly less than 3×10^{-4}, the system is always in operation or completely available. As the failure rate reaches its maximum, the dynamic behavior of the system becomes more stable.

• When the failure rate of the couple (A4 and A3) is greater than 3×10^{-4}, the two components (A3 and A4) are degraded successively up to a failure rate of 4.5×10^{-4} torque, and the system is deteriorating (failing).

• Finally, when the failure rate of the couple (A4 and A3) is greater than 4.5×10^{-4}, t, the system enters the faulty phase, i.e., component E1.2 does not work or it's completely broken down.

The failure rate of component E1.2 is stochastically dependent on the torque of the components (A4 and A3). The transition from failure A3, which is the lack of oil, influences the movement towards a more degraded status. That is the lack of lubrication, which is a factor contributing to the lowering of the capacity of the system and the increase of degradation rate of the affected E1.2 component. Therefore, the prognostic agent of component A4, which is the gears, is responsible for updating the shape parameter over time, depending on the established preventive maintenance program of the gears [18].

Figure 9 presents the relationship between the B2 bearing failure rates and the A3 lack of oil used for the degradation of E1.2 attributed to the paste cutting system.

• It can be noted that when the failure rate of the couple (B2 and A3) is strictly less than 3×10^{-4}, the system is always in operation or fully available. When the failure rate is at its maximum, the dynamic behavior of the system becomes more stable.

• When the failure rates of the couple (B2 and A3) are greater than 3×10^{-4}, the two components (B2 and A3) are gradually degraded up to a failure rate of 4.2×10^{-4} of the torque, and the system is degrading (failing). When the value exceeds 4.2×10^{-4}, the system is suddenly degraded until it reaches the maximum value.

• When the component torque failure rates (B2 and A3) reach the maximum value 5×10^{-4}, the system does not work or completely fails.

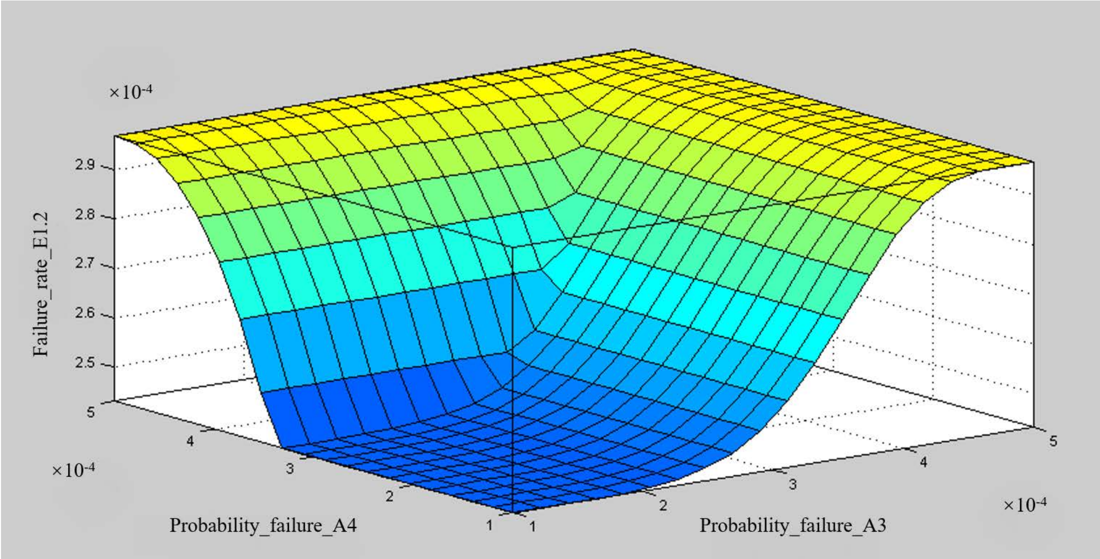

Figure 8. Area between A3/A4

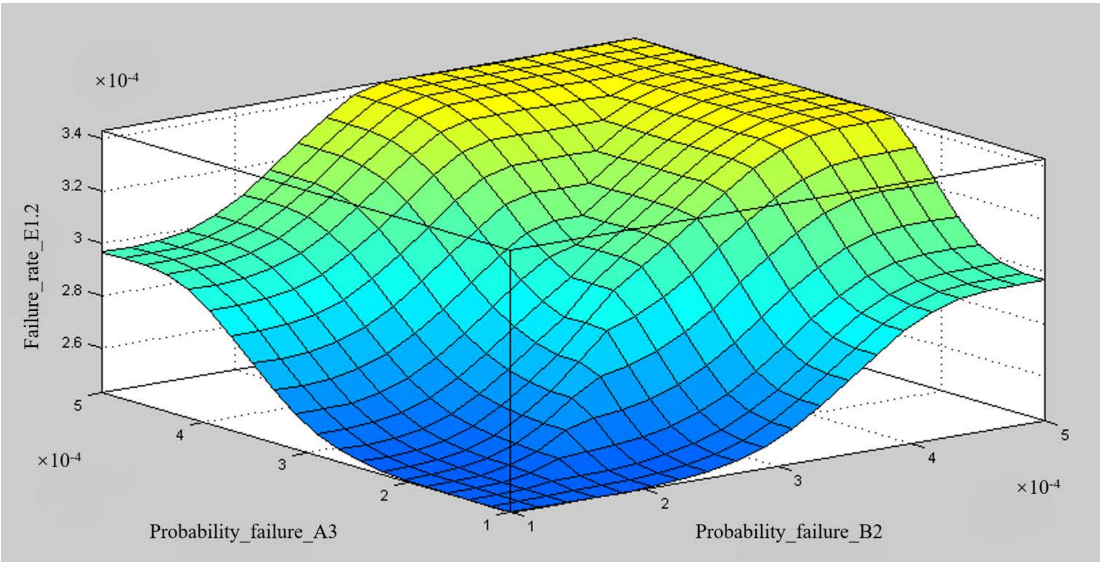

Figure 9. Area between A3/B2

The failure rate of component E1.2 is stochastically dependent on the torque of the components (B2 and A3). The transition from failure A3 (lack of oil) influences the movement towards more degraded status, and affects the degradation rate of component E1.2. Therefore, component prognosis agent B2 is responsible for updating the shape parameter over time based on the established bearing component preventive maintenance program [19, 20].

4 Conclusions

Complex industrial processes present highly non-linear dynamics and have a large number of variables. Therefore, sometimes it is difficult to obtain an accurate mathematical model to detect abnormal situations. Fuzzy logic technology has proven its effectiveness in detecting and predicting malfunctions before industrial systems stop. On the other hand, precautions for detection are necessary. Their performance depends strongly on a good selection of parameters and mastery of the process to be implemented. The authors are particularly interested in presenting the fuzzy approach within Omar Bin Omar and applying this approach to the K production line. First, the criticality of the machines on the K production line has been analyzed. Then, a fault tree has been developed to determine the causal relationships between malfunctions, failures and errors related to the critical machine. The ABC method has been used to find the most sensitive component of the press, the dough cutter, to which fuzzy logic could be applied. Finally, a fuzzy approach was applied to dough pieces in order to better detect anomalies as well as potential predictors of downtime and recovery. The obtained results are very satisfactory. This study can be generalized to institutions that contain the same industrial activity. As for future related studies, this approach could be generalized to all workshops in the factory. The idea of applying fuzzy logic to separate regulators is perhaps complicated and difficult to set up, but the simulation remains convincing. For the Omer ben Omor company, it is more interesting to have a fuzzy system of control, supervision, diagnosis and continuous maintenance than a system based on the stabilization of a complicated industrial system, which makes it difficult to control these parameters.

Data Availability

Not applicable.

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Conflicts of Interest

The authors declare no conflict of interest.

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Nomenclature

ER	Press stop
E1	**Dough cutting stop**
E1.1	Engine problem
A1	Mechanical problem
B1	Operational overloads
C1	Heated engine
B2	Bearing problem
C2	Completed lifespan
C3	Faulty assembly
C4	Misalignment of motor drive shaft
C5	Inadequate or incorrect lubrication
C6	Faulty assembly
B3	Misalignment
B4	Shaft imbalance (the center of mass located outside the axis of rotation)
A2	Electric problem
B5	Broken engine
B6	Voltage imbalance
C7	Degradation of insulation
C8	Increased operating temperatures
E1.2	Reducer problem
A3	Lack of oil
A4	Pinion tooth breakage
E1.3	Carpet problem
A5	Torn carpet
B7	Paste leak
B8	PLC system problem
C9	Program loss
C10	Grilled pile
A6	Offset rug
A7	Backward walking mat
A8	Roller lock
B9	Bearing problem
C11	Breakage of the bearing body
E1.4	Knife problem
A10	Rotation sensor problem
A11	Friction problem
B10	Support vibration problem
E1.5	Sensor problem
A12	Rotation sensor problem
A13	Left-right motion sensor problem
A14	Up-down motion sensor problem
E1.6	Heat problem
A9	Burn resistance

E2	**Vacuum system shutdown**
E2.1	Jam
A15	Lack of water
A16	Excess water
B11	Screw lock
B12	Vacuum blocking
E2.2	Problem with lid not closing
A17	Security problem
A18	Lack of vacuum pressure
E2.3	Vacuum pump problem
E2.4	Vacuum pallet deformation
A19	Detachment
A20	A strange body
E2.5	Probe alarm
A21	Adjustment
A22	Calibration of the probe
A23	Probe not functional
E3	**Stopping the screw**
E3.1	Blocking the screw
A24	Dry product
A3.2	Rotation sensor
A25	Wire torn
A26	Distortion or position shift
E4	**Mixing water system shutdown**
E4.1	Valve problem
A27	Torn sleeve
A28	Stop positioned (open-closed)
E5	**Semolina cyclone stop**
E5.1	Product presence sensor
E5.2	Door problem
A29	Joint tearing
B13	Bad quality
B14	Lifespan completed
A30	Security problem
B15	Safety hook not working
B16	Deformation of the door
B17	Fixing problem
E6	**Agitator stop**
E6.1	Agitator axis problem
A31	Blocked
D1	Excess quantity of product
A32	Axis broken
B18	Poor quality of raw material
E7	**Centrifuge stop**
E7.1	Blocking i.e. a rotation problem
A33	Deformation of the door axis - centrifuge
B19	Friction between the axis and the screw
A7.2	Problem with the centrifuge safety door
A34	Blocking of the safety axis
B20	Dust
B21	Lack of voltage (voltage less than 24 v)
A35	Electrical problem (cut, voltage, etc.)
E8	**Dosing stop**
E9	**Head stop**