

Intelligent flux monitoring system using fuzzy logic: Flow-fault detection and time-to-empty validity assessment

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ABSTRACT

This research aims to develop an intelligent flux monitoring system using fuzzy logic to support continuous flux discharge and assess the operational validity of time-to-empty (TTE) estimation during abnormal flow conditions. The problem addressed is the reduced reliability of conventional physics-based TTE estimation when the monitored system operates under faulty conditions, including supply-tube blockage, nozzle error and unstable flow. The study proposes a hybrid fuzzy-deterministic framework in which fuzzy logic functions as a diagnostic layer that complements the conventional mass-flow relationship. The framework uses flux tank weight and flux flow rate as measured inputs, whereas supply-tube-blockage and nozzle-error indicators are treated only as external reference labels for validation. The experimental record contains 500 observations sampled at 60-s intervals over 8 h 19 min, comprising 454 normal observations, 30 supply-tube-blockage observations and 16 nozzle-error observations. The Mamdani fuzzy inference system uses explicitly defined membership functions, a 16-rule base, minimum AND/implication, maximum aggregation and centroid defuzzification. All labelled fault observations have zero recorded flow, whereas normal observations range from 3.652 to 6.539 g/s; consequently, the fuzzy classifier and a fixed-flow threshold both achieve 100% sample-level accuracy on the available record. Deterministic TTE is defined as $1000 W/(60 Q)$ min for $Q > 0$ and is treated as invalid when the fuzzy diagnostic index indicates abnormal flow. Using an empirical within-run depletion horizon derived from the tank-weight trajectory, normal-condition deterministic TTE gives MAE = 215.48 min, RMSE = 248.85 min and MAPE = 86.49%. These values are within-run consistency diagnostics rather than independent predictive-accuracy estimates because the reference is derived from the same experiment and the recorded flow channel has an unresolved scale discrepancy. The results support the use of fuzzy logic as an interpretable flow-fault and TTE-validity gate, while independent TTE accuracy, physical sensor-noise robustness, fault-type isolation and PCB-quality improvement require calibrated and repeated experiments.

Keywords: fault detection, flow stability, flux monitoring system, fuzzy inference system, Mamdani, time-to-empty validity.

INTRODUCTION

Flux monitoring systems play a critical role in industrial processes where consistent material flow is required to maintain product quality, system reliability and production continuity. In printed circuit board (PCB) production, stable flux delivery is particularly important because flow interruption can affect process quality and lead to unplanned downtime. One important function of such monitoring systems is the estimation of time-to-empty (TTE), which supports material replenishment planning, predictive maintenance and process optimisation. The present study evaluates the flux-delivery subsystem and does not directly measure PCB defect rate, rejection rate, soldering quality, rework frequency, production yield or downtime.

Conventional TTE estimation is usually derived from deterministic mass-flow relationships. These models are effective when the system operates under steady and predictable conditions, but their performance deteriorates when the measured flow is affected by uncertainty, sensor noise or mechanical faults. Industrial flow systems are frequently exposed to disturbances such as partial blockage, valve irregularity and nozzle error, which can alter the observed flow rate without accurately representing the true material availability in the tank [1, 2].

A key limitation of deterministic models is their limited adaptability to ambiguous operating states. For example, when a blockage occurs, the flow rate can become very low even though the tank still contains sufficient material. A physics-based model that relies heavily on instantaneous flow may therefore misinterpret the event as material depletion or produce unstable TTE predictions [3]. This creates a practical need for a diagnostic method that can reason under uncertainty and distinguish between true depletion and abnormal flow behaviour.

Fuzzy logic, introduced by [34], provides a suitable framework for this type of industrial diagnostic problem because it represents variables through degrees of membership rather than rigid binary classes. This allows uncertain conditions such as “low flow”, “high tank weight” and “possible blockage” to be represented in a form that resembles engineering judgement. Recent applications show that fuzzy systems are useful in control, monitoring and fault-diagnosis environments where data may be incomplete, noisy or imprecise [5, 6].

Therefore, research devoted to the integration of fuzzy logic with physics-based flux monitoring is relevant because it may support fault detection, improve interpretation of unstable TTE values and provide a practical decision-support mechanism for real-time industrial monitoring [7].

The technical contribution of this research lies in combining a transparent deterministic mass-flow TTE calculation with a graded Mamdani consistency gate that evaluates whether measured flow is physically consistent with the remaining tank content. The blockage and nozzle-error labels are excluded from the fuzzy inputs and are used only for validation. This architecture permits direct comparison with a fixed-threshold rule and separates abnormal-flow detection from numerical TTE calculation.

The integration of fuzzy logic with the conventional mass-flow relationship provides an interpretable framework for distinguishing normal depletion from abnormal flow interruption. The current experiment is treated as a proof-of-concept; claims of general diagnostic superiority, improved TTE accuracy or improved PCB production quality require independent validation under partial faults, calibrated sensors and production-quality measurements.

BACKGROUND

Recent studies on industrial monitoring and control have emphasised the difficulty of maintaining reliable model performance under uncertain operating conditions. Robust control and mass-flow control approaches have been used to manage disturbances and uncertainty, but these approaches normally depend on accurate process assumptions and may still be sensitive to operating deviations that fall outside the nominal model boundary [8]. This leaves unresolved the problem of identifying faults when the measured output flow no longer reflects the actual material state in the tank.

Hybrid approaches combining physics and data-driven reasoning have been proposed for failure prediction because purely physics-based formulations may not capture all degradation or fault patterns in complex systems [9]. Model-based fault diagnosis and fault-tolerant control have also been applied to process systems and chemical reactors, showing that fault isolation can improve system safety and operational reliability [10, 11]. However, many such approaches require

detailed process models, sufficient labelled fault data or computational frameworks that may be difficult to implement in simple real-time flux monitoring units.

Knowledge-based and logic-based diagnostic methods provide an alternative route for interpreting abnormal process behaviour. [12] highlighted the value of model- and knowledge-based approaches in process fault diagnosis, while [13] demonstrated logic-based probabilistic fault detection and tracking in process systems. Nevertheless, the unresolved issue remains how to express practical operator knowledge, such as the relationship between high tank weight and low discharge, in a form that can be directly used for TTE correction and fault warning.

Fuzzy logic has been widely used for uncertainty handling because it allows process states to be expressed as linguistic classes. Studies involving fuzzy computing, fuzzy control and fuzzy-set-based robustness indicate that fuzzy systems can improve interpretability when process measurements are uncertain or nonlinear [14–16]. In addition, fuzzy logic controllers have been reviewed as effective decision mechanisms in hybrid energy and storage systems, reinforcing their suitability for multi-condition engineering problems [17, 18].

For industrial fault detection, fuzzy approaches have been applied to HVAC systems and electrical equipment, where the main advantage lies in identifying abnormal patterns without requiring

complete mathematical descriptions of every fault condition [19, 20]. Time-series anomaly detection studies further show that temporal patterns can strengthen fault identification when instantaneous measurements are insufficient [21]. However, the specific use of fuzzy logic as a complementary diagnostic layer for flux TTE prediction in PCB production remains insufficiently addressed.

Data quality is another unresolved aspect. Industrial datasets often contain missing values, inconsistent formats and noisy measurements. Pre-processing methods such as imputation, scaling and fuzzy clustering for missing data are important for maintaining diagnostic model reliability [22, 23]. The effect of membership functions and defuzzification methods must also be considered because fuzzy outputs can vary depending on the selected inference and defuzzification structure [24].

Based on the literature, the unresolved problem is that conventional TTE models and many existing diagnostic methods do not adequately handle the combined effects of flow interruption, remaining tank mass and uncertain fault states in a practical flux monitoring system. This creates the need for a fuzzy-logic-enhanced framework that can interpret abnormal flow behaviour and support more reliable TTE prediction without replacing the underlying physics-based model.

Studies directly related to PCB flux application and soldering-process monitoring show that fluxing parameters influence selective-soldering

Table 1. Comparison with closely related flux, PCB-monitoring and fuzzy diagnostic work

Study / approach	Domain	Method / output	Validation focus	Limitation relative to this study
Tasevski and Papazoska [35]	Selective soldering fluxing	DOE/process-parameter optimisation	Flux-process capability	No fault or TTE-validity diagnosis
Martinez-Viol et al. [19]	HVAC	Fuzzy early fault detection	Fault-detection case study	No material-depletion or TTE coupling
Ma et al. [27]	Gas turbine	FIS under measurement uncertainty	Fault diagnosis under uncertain measurements	Different sensing and fault context
Kizito et al. [31]	Automobile	Mamdani rule-based diagnosis	Interpretable rule reasoning	Mamdani inference itself is established
Ulger et al. [37]	PCB/SMT solder joints	Inspection survey and labelled dataset	Defect-oriented quality evaluation	Downstream quality inspection rather than flux delivery
Chang and Chang [39]	Process control loops	Fuzzy IF-THEN diagnosis	Simulation-based fault diagnosis	Uses richer process fault-propagation information
Cheded and Doraiswami [40]	Process safety	Hybrid model-free + model-based FDI	Simulation and physical process evaluation	Richer hybrid framework than the two-sensor flux unit
Pfab et al. [41]	SMT/PCB production	AOI production dataset	132-day labelled quality/false-call data	Direct quality labels are required for PCB-quality claims
Present study	PCB flux-delivery monitoring	Mamdani consistency gate + deterministic/conditional TTE	Class metrics, threshold benchmark and TTE consistency	Fault-type isolation and external TTE validation remain outstanding

process behaviour. Tasevski and Papazoska [35] used designed experiments to optimise fluxing parameters on a selective soldering machine, while Vesely et al. [36] quantified no-clean flux spatter during soldering. Ulger et al. [37] reviewed PCB solder-joint inspection and provided a labelled defect dataset, and Pfab et al. [41] reported a 132-day automated-optical-inspection dataset from SMT production. These studies establish the process relevance of flux delivery and also show that claims concerning final PCB quality require direct downstream quality indicators.

Fuzzy fault diagnosis is well established in other process domains. Martinez-Viol et al. [19] applied fuzzy logic to HVAC early fault detection, Ma et al. [27] examined fuzzy inference under measurement uncertainty in gas-turbine diagnosis, and Kizito et al. [31] implemented Mamdani reasoning for automobile fault detection. Chang and Chang [39] developed fuzzy IF-THEN fault diagnosis for process control loops, while Cheded and Doraiswami [40] integrated model-free and model-based fault-diagnosis layers. Consequently, Mamdani inference itself is not claimed as the novelty; the contribution considered here is the use of a graded fuzzy output as a validity gate for a deterministic flux TTE calculation. Table 1 summarises the application domain, diagnostic method and output, validation focus, and principal limitation of each selected study.

MATERIALS AND METHODS

Research focus, hypothesis, assumptions and simplifications

The research focuses on a flux monitoring system designed to continuously measure tank weight and flux flow rate for evaluating material availability and estimating the system's TTE. The system integrates weight-based monitoring and flow-rate measurement to support real-time assessment of material depletion during operation. The main research hypothesis is that a fuzzy-logic diagnostic layer can identify complete abnormal flow-interruption events and determine when a deterministic TTE value should be treated as invalid, without assuming superiority over a fixed-threshold detector.

The study adopted the following assumptions: the measured tank weight and flow rate represent the principal observable variables of the system;

fault states can be interpreted from deviations between expected and observed flow behaviour; and common operating anomalies can be represented using linguistic fuzzy classes. The main simplification is that the current model focuses on supply tube blockage and nozzle error as representative fault modes, while gradual mechanical wear and long-term component degradation are reserved for future work.

Three evaluation questions are considered: (1) can abnormal-flow events be detected from tank availability and flow without using the reference fault labels as fuzzy inputs; (2) how does fuzzy validity gating affect interpretation of deterministic TTE under normal and zero-flow conditions; and (3) does the fuzzy gate provide an empirical advantage over a transparent fixed-threshold detector on the available dataset?

Experimental data collection and pre-processing

Data were obtained from a physical bench-scale flux monitoring rig consisting of a nominal 20-kg flux supply tank on a weighing platform with a digital weight monitor. The available dataset is one continuous sequence from 1 January 2025 00:00 to 08:19, sampled at 60-s intervals (0.01667 Hz), giving 500 observations over 499 min (8 h 19 min). The record contains 454 normal observations, 30 supply-tube-blockage observations and 16 nozzle-error observations. No independent run or replicate identifier is encoded, so the 500 observations are treated as a time-ordered record rather than 500 independent experimental repetitions.

Each observation contains timestamp, flux tank weight W (kg), recorded flux flow rate Q (labelled g/s), a binary supply-tube-blockage indicator and a binary nozzle-error indicator. Normal operation is defined when both indicators are 0; blockage is defined when `supply_tube_blockage` = 1 and `nozzle_error` = 0; nozzle error is defined when `nozzle_error` = 1 and `supply_tube_blockage` = 0. No observation contains both fault labels simultaneously. The 30 blockage observations form 27 contiguous labelled episodes, whereas the 16 nozzle-error observations form 16 one-minute episodes. All 46 labelled fault observations have $Q = 0$, while all normal observations have $Q \geq 3.651557$ g/s.

No missing values occur in the 500-row record. Raw weight and flow values are retained for descriptive analyses. For fuzzy inference, tank

availability is calculated as $A = \text{clip}(100 W/20, 0, 100)\%$, so small readings outside the physical 0-20 kg interval are bounded only for tank-percentage and TTE calculations. No z-score standardisation is applied because the fuzzy variables are defined directly on their physical universes. The blockage and nozzle-error labels are excluded from the fuzzy inputs and are introduced only after inference for validation. The physical bench-scale monitoring arrangement used for the experimental record is shown in Figure 1. The rig specifications, operating conditions, sampling information, process properties, and metrological limitations are consolidated in Table 2.

The process sheet specifies 40-70 mL/min and a flux density of $0.790 \pm 0.005 \text{ g/cm}^2$, corresponding to approximately 0.527-0.922 g/s. The normal tank-weight trajectory gives a depletion rate of 0.6671 g/s, which lies within this converted range; however, the recorded normal flow channel averages 5.0044 while being labelled g/s. Because no calibration equation, duty-cycle factor or sensor scaling is supplied, the recorded flow channel is retained as recorded for classification but is not assumed to be a traceably calibrated mass-flow measurement for absolute TTE accuracy claims.

The dataset identifies each observation as normal operation, supply-tube blockage, or nozzle error through the available fault-status labels. However, the supporting documentation does not provide detailed information on how the blockage and nozzle-error conditions were physically introduced during the experiment, including their severity, duration, or repetition procedure. Therefore, these fault-status labels are used only as reference classes for evaluating the fuzzy diagnostic system. A more detailed fault-generation procedure should be documented in future experimental work to support independent replication.

Fuzzy logic model development

The fuzzy logic model was developed to detect abnormal discharge by analysing the consistency between tank availability and recorded flow behaviour. The operational inputs are tank availability A (%) and recorded flux flow rate Q (g/s). The supply-tube-blockage and nozzle-error indicators are reference labels used only for validation and are not supplied to the fuzzy inference system. The output is a continuous diagnostic index D on $[0,100]$, interpreted through the linguistic classes Normal, Warning and Abnormal. A rule-based framework was formulated using

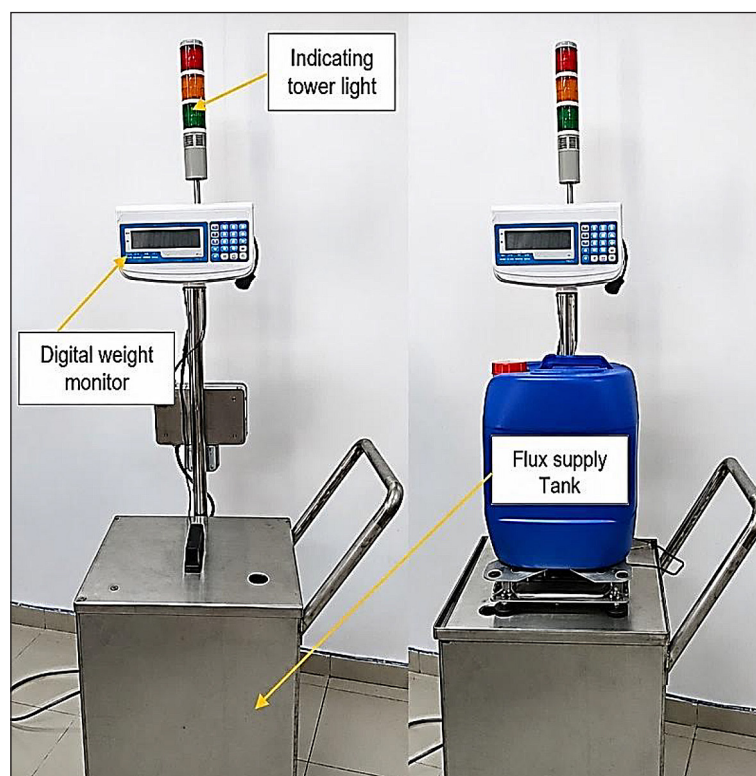


Figure 1. Flux monitoring system setup

Table 2. Experimental and process information available for the flux monitoring test

Parameter	Value / status	Use in analysis
Experiment type	Bench-scale physical monitoring rig	Defines current validation scope
Nominal container mass	20 kg	Tank availability calculation
Specified volumetric flow	40–70 mL/min	Process-sheet context
Recorded raw flow channel	0–6.53944 g/s	Used as recorded for classification
Spray pressure	2–4 bar	Context only; not recorded per sample
Nozzle	Single needle, 1.3 mm	Context only
Temperature / humidity	25–30 °C / 40–60%RH	Context only; not recorded per sample
Flux density	0.790 +/- 0.005 g/cm ³	Unit-consistency check
Viscosity	Not available in the current documentation	Not included in the present analysis
Weight-sensor model/range/accuracy/resolution/response time	Not available in the current documentation	Not included in the present analysis
Flow-sensor model/range/accuracy/resolution/response time	Not available in the current documentation	Not included in the present analysis
Calibration and measurement uncertainty	Not available in the current documentation	Measurement uncertainty was not quantified
Sampling interval / frequency	60 s / 0.01667 Hz	Temporal and ACF analysis
Archive structure	One continuous 500-sample session	Run/replicate IDs not encoded
Normal weight-depletion rate	0.040025 kg/min = 0.6671 g/s; R ² = 0.99957	Weight-time regression
Raw normal flow-channel mean	5.0044 (record labelled g/s)	About 7.50 x weight-derived depletion rate

observed system behaviour and process knowledge. The complete rule base is the Cartesian combination of four tank-availability sets and four flow sets (16 rules). Stopped flow at low, medium or high tank availability produces an Abnormal output, whereas stopped flow at near-empty tank availability produces a Warning because true depletion becomes plausible. Reduced/low flow at medium or high tank availability also produces an Abnormal response. Nominal flow maps to Normal severity across tank-availability levels.

The fuzzy output represents the likelihood or severity of a fault condition. It can be used to

trigger warnings, support maintenance decisions or modify the interpretation of TTE prediction [32]. For validation, $D \geq 60$ is classified as Abnormal and $D < 60$ as non-fault. The threshold is fixed between the Warning set centre and the onset of the Abnormal set and is not tuned using the reference fault labels. The corresponding membership functions for tank availability, recorded flow rate and the diagnostic index are illustrated in Figure 2.

The numerical universes of discourse and membership-function parameters used for tank availability, recorded flow, and the diagnostic index are specified in Table 3.

Table 3. Universe of discourse and complete membership-function parameters

Variable	Universe	Linguistic set	Shape	Parameters
Tank availability A (%)	[0,100]	Near-empty	Trapezoidal	[0, 0, 0.5, 1.0]
		Low	Trapezoidal	[0.5, 2, 20, 35]
		Medium	Trapezoidal	[20, 35, 65, 80]
		High	Trapezoidal	[65, 80, 100, 100]
Flow Q (g/s)	[0,6.6]	Stopped	Trapezoidal	[0, 0, 0.05, 0.5]
		Low	Triangular	[0.2, 1.5, 3.8]
		Nominal	Trapezoidal	[3.5, 4.2, 5.8, 6.3]
		High	Trapezoidal	[5.8, 6.2, 6.6, 6.6]
Diagnostic index D	[0,100]	Normal	Trapezoidal	[0, 0, 20, 35]
		Warning	Triangular	[25, 50, 75]
		Abnormal	Trapezoidal	[65, 80, 100, 100]

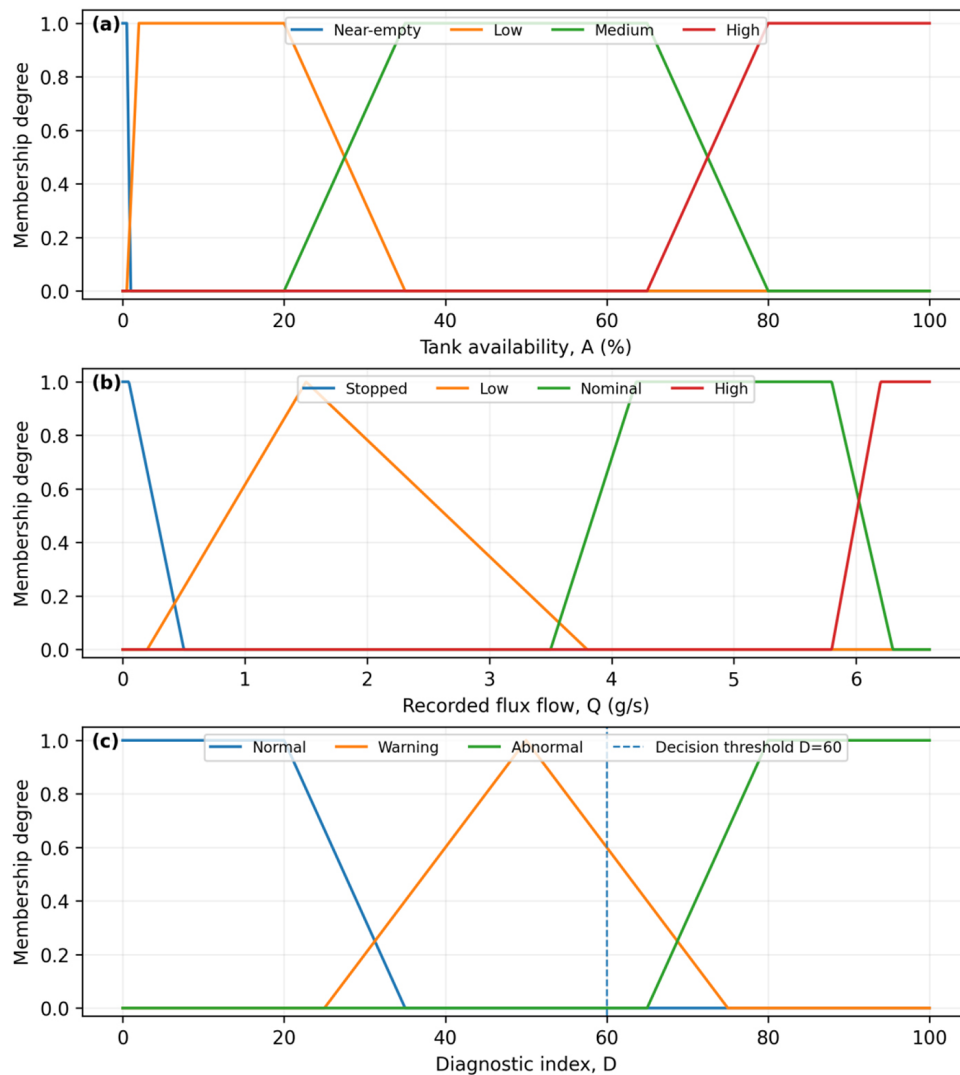


Figure 2. Membership functions for tank availability, recorded flow rate and fuzzy diagnostic index

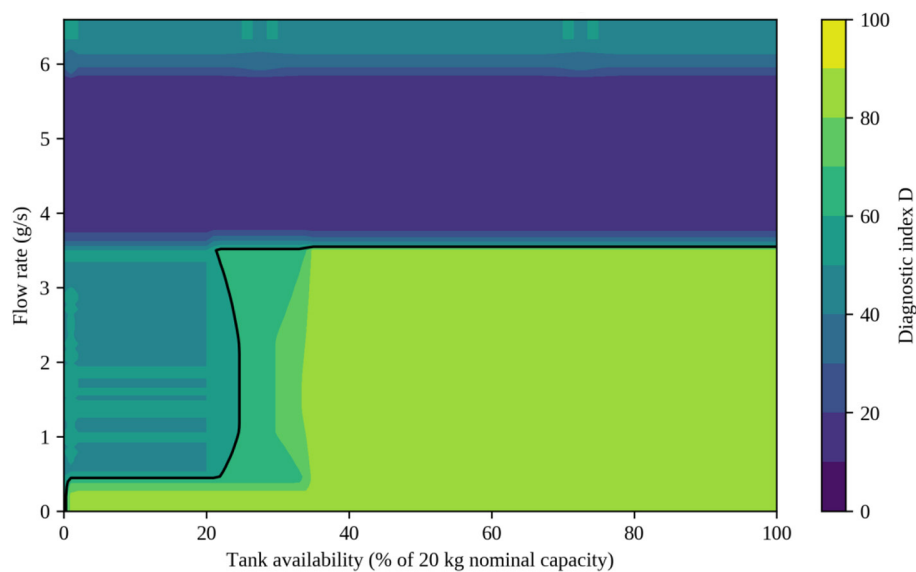
Following the variable definitions, the complete 16-rule Mamdani rule base used to map tank-availability and flow states to the diagnostic output is listed in Table 4. The inference operators, aggregation method, defuzzification procedure, decision threshold, and software implementation are summarised in Table 5. Worked inference example 1: for $W = 10$ kg ($A = 50\%$) and $Q = 0$, the Medium + Stopped rule produces an Abnormal output and the centroid is $D = 85.92$. Worked inference example 2: for $W = 10$ kg and $Q = 5$ g/s, the Medium + Nominal rule dominates and the centroid is $D = 14.08$. Across the complete dataset, normal samples produce $D = 14.08$ – 50.00 , blockage samples $D = 69.78$ – 85.92 and nozzle-error samples $D = 85.09$ – 85.92 . The resulting Mamdani decision surface and the $D = 60$ decision contour are presented in Figure 3.

Table 4. Complete 16-rule Mamdani rule base

Rule	Tank availability	Flow	Output
1	Near-empty	Stopped	Warning
2	Near-empty	Low	Warning
3	Near-empty	Nominal	Normal
4	Near-empty	High	Warning
5	Low	Stopped	Abnormal
6	Low	Low	Warning
7	Low	Nominal	Normal
8	Low	High	Warning
9	Medium	Stopped	Abnormal
10	Medium	Low	Abnormal
11	Medium	Nominal	Normal
12	Medium	High	Warning
13	High	Stopped	Abnormal
14	High	Low	Abnormal
15	High	Nominal	Normal
16	High	High	Warning

Table 5. Inference, aggregation, decision and implementation configuration

Item	Specification
AND operator	Minimum
OR operator	Maximum (defined for completeness; no OR antecedent is required)
Rule implication	Minimum clipping
Aggregation	Maximum across rule consequents
Defuzzification	Centroid / centre of area
Decision gate	$D \geq 60 \rightarrow$ Abnormal; $D < 60 \rightarrow$ non-fault
Software	Python 3.13.5; NumPy 2.3.5; pandas 2.2.3; SciPy 1.17.0; Matplotlib 3.10.8
Implementation	Custom vectorised max-min Mamdani evaluator; deterministic grid-based centroid over D in $[0, 100]$
Decision-threshold rationale	$D = 60$ fixed a priori between Warning centre (50) and Abnormal onset (65); not tuned on reference labels


Figure 3. Mamdani diagnostic decision surface, the $D = 60$ contour representing the abnormal-flow classification boundary

Deterministic and fault-gated time-to-empty calculation

For a calibrated physical mass-flow Q in grams per second and remaining tank mass W in kilograms, deterministic instantaneous TTE is calculated as $TTE_{det} \text{ (min)} = 1000 W / (60 Q) = 16.6667 W / Q$ for $Q > 0$. The factor 1000 converts kilograms to grams and the factor 60 converts seconds to minutes. At $Q = 0$, deterministic TTE is undefined and is not interpreted as normal tank depletion.

For fault-gated evaluation, the fuzzy diagnostic index first determines whether the current state is abnormal. When $D < 60$ and $Q > 1$ in the recorded flow channel, the instantaneous Q is used. When $D \geq 60$, Q is replaced by Q_{valid} , defined as the median of the preceding 10 valid

non-fault flow observations available causally in the sequence. The resulting conditional TTE represents the replenishment horizon that would apply if flow were restored to the recent valid rate; it is not the actual time-to-empty while flow remains stopped.

A normal-record linear fit of tank weight versus elapsed time gives a fitted zero-mass crossing at $t = 499.35$ min. An empirical within-run reference is therefore defined as $TTE_{ref}(t) = 499.35 - t$ minutes. MAE, RMSE and MAPE are calculated against this empirical reference; MAPE excludes reference horizons below 1 min. Because TTE_{ref} is derived from the same continuous experiment rather than an independent measurement, these error metrics are interpreted as within-run consistency diagnostics and not as independent predictive-accuracy validation.

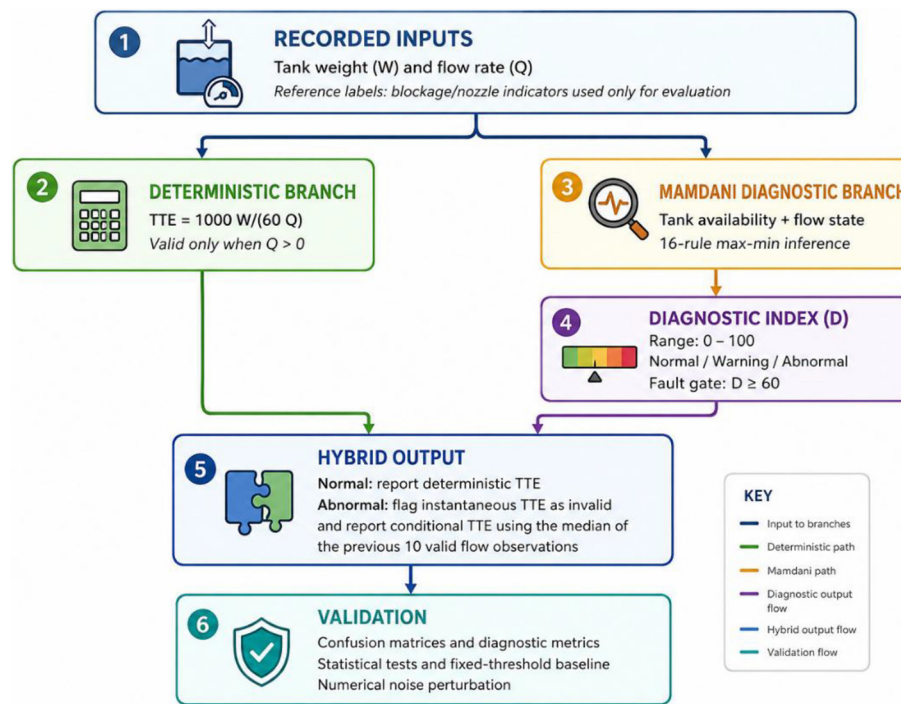


Figure 4. Analysis framework separating reference labels, deterministic TTE, fuzzy consistency gating and quantitative validation

Analytical procedures

The analysis consists of distribution and class-specific descriptive analysis, fuzzy-inference evaluation, quantitative fault-detection validation, deterministic and fault-gated TTE assessment, baseline comparison, and temporal analysis. Diagnostic validation uses confusion matrices, accuracy, precision, sensitivity/recall, specificity, F1-score and false-alarm rate, with sensitivity also reported separately for blockage and nozzle-error labels. A transparent fixed-threshold comparator defines a fault when $Q < 1.0$ g/s and $W > 0.10$ kg. Non-parametric Kruskal-Wallis and Mann-Whitney U tests are used because the fault groups contain a point mass at zero flow. Rank-biserial correlation is used as an effect-size measure. Temporal analysis uses one-minute timestamps; the maximum ACF lag is $L_{\max} = \text{floor}(10 \log_{10} N) = 26$ min for $N = 500$, and tank weight is first-differenced before ACF interpretation to remove the deterministic depletion trend. The complete analytical workflow is summarised in Figure 4.

A supplemental numerical stress test adds independent zero-mean Gaussian perturbations to W and Q at 1%, 3% and 5% of full scale (20 kg and 6.6 g/s), with 100 Monte Carlo repetitions at each level. This analysis evaluates numerical sensitivity only and is not treated as a substitute

for a controlled physical sensor-noise experiment because the sensor noise spectrum, accuracy and calibration uncertainty are not available.

RESULTS

Distribution of tank weight, flow rate and flow-weight relationship

Tank weight is distributed broadly across the measured operating range rather than being concentrated within the 10–15 kg region. Across all 500 observations, the median weight is close to 10 kg and the three class-wise weight distributions overlap substantially. The flow distribution is strongly class dependent: all 454 normal observations have $Q \geq 3.651557$ g/s, whereas all 30 blockage and 16 nozzle-error observations have $Q = 0$. The corresponding tank-weight and flow-rate distributions are presented in Figure 5.

The scatter plot in Figure 6 further shows that, under normal operating conditions, flow rate remained relatively stable even when tank weight changed. In fault conditions, however, the flow rate dropped sharply despite the presence of remaining material. The class encoding is explicit: `supply_tube_blockage = 1` denotes blockage, `nozzle_error = 1` denotes nozzle error, and both labels equal to 0 denote normal

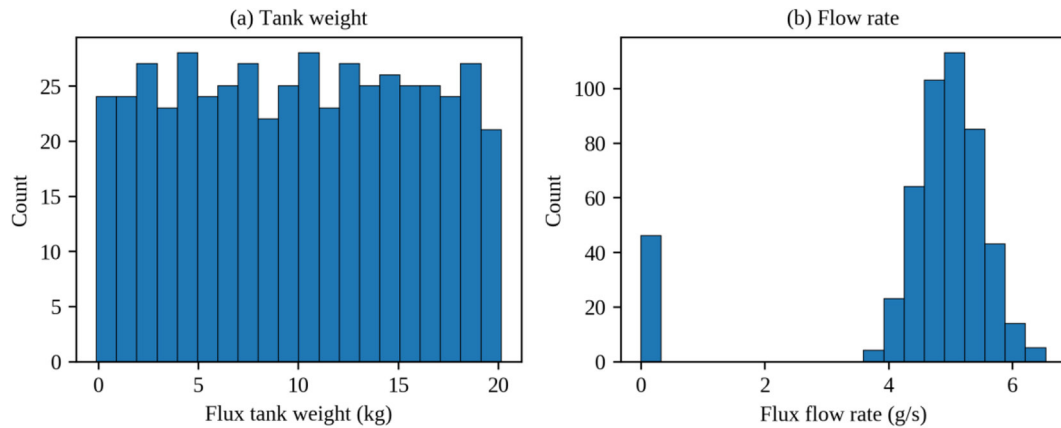


Figure 5. Distributions of recorded tank weight and flow rate across all 500 observations

operation. The observed trends indicate that flow rate alone cannot be treated as a direct indicator of material depletion without considering the operating state.

Fuzzy inference structure for abnormal operating conditions

The fuzzy inference structure was formulated to convert the observed mismatch between tank weight and flow rate into interpretable fault information. The complete membership functions, 16-rule base, inference operators and centroid defuzzification are given in Tables 3–5, while Figures 2 and 3 show the membership functions and diagnostic surface. The direct Mamdani outputs range from $D = 14.08$ – 50.00 for normal samples, $D = 69.78$ – 85.92 for blockage samples and $D = 85.09$ – 85.92 for nozzle-error samples. The key

result of this formulation is that the diagnostic interpretation is not based on a fixed flow threshold alone. Instead, it considers the combined meaning of tank weight and flow rate. However, because every labelled fault in the available dataset has exactly zero recorded flow, a simple fixed-threshold rule also separates the classes perfectly. The present dataset therefore demonstrates reproducible fuzzy implementation and graded output behaviour but does not establish superiority over threshold diagnosis under partial or overlapping fault conditions.

Effect of blockage and nozzle error on flow stability and TTE prediction

Figure 7 shows the flow-rate distributions separately for normal, supply-tube-blockage and nozzle-error conditions. Normal operation has

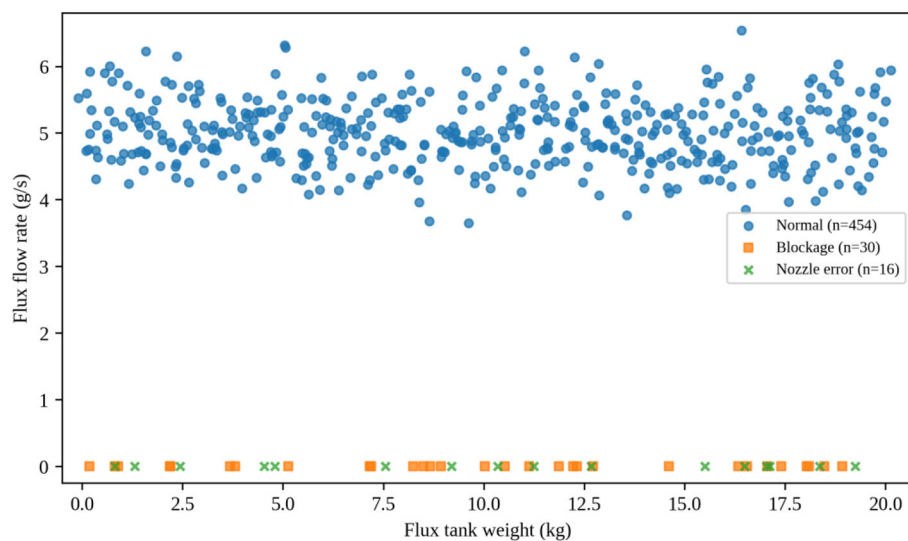


Figure 6. Recorded flow rate versus tank weight using explicit normal, blockage and nozzle-error reference classes

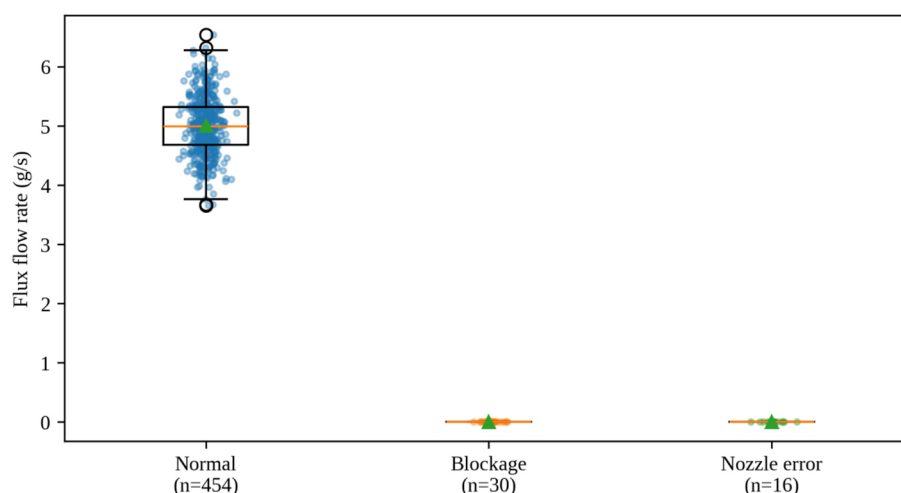


Figure 7. Flow-rate distributions by operating class; blockage and nozzle-error observations are both located at $Q = 0$

mean flow 5.004 ± 0.492 g/s and median 4.990 g/s, whereas both fault classes have $Q = 0$ for every labelled observation. Thus, the available record represents complete recorded flow interruption rather than graded partial blockage or nozzle restriction. The corresponding class-wise descriptive statistics for tank weight and flow rate are summarised in Table 6. The flow-rate Kruskal-Wallis test is significant ($H = 125.151$, $p = 6.66 \times 10^{-28}$). Pairwise Mann-Whitney

comparisons show complete separation of normal flow from blockage ($U = 13,620$, $p = 4.35 \times 10^{-20}$, rank-biserial effect size = 1.00) and from nozzle error ($U = 7.264$, $p = 1.32 \times 10^{-12}$, rank-biserial effect size = 1.00). Blockage and nozzle-error flow distributions are indistinguishable because both consist entirely of zero-flow values. Tank weight does not provide comparable class separation and overlaps across the three operating classes.

Table 6. Class-wise descriptive statistics

Class	n	Weight mean $\pm$ SD (kg)	Weight median	Flow mean $\pm$ SD (g/s)	Flow median
Normal	454	9.972 $\pm$ 5.766	9.906	5.004 $\pm$ 0.492	4.990
Blockage	30	10.130 $\pm$ 5.944	10.273	0.000 $\pm$ 0.000	0.000
Nozzle error	16	10.542 $\pm$ 6.391	10.799	0.000 $\pm$ 0.000	0.000

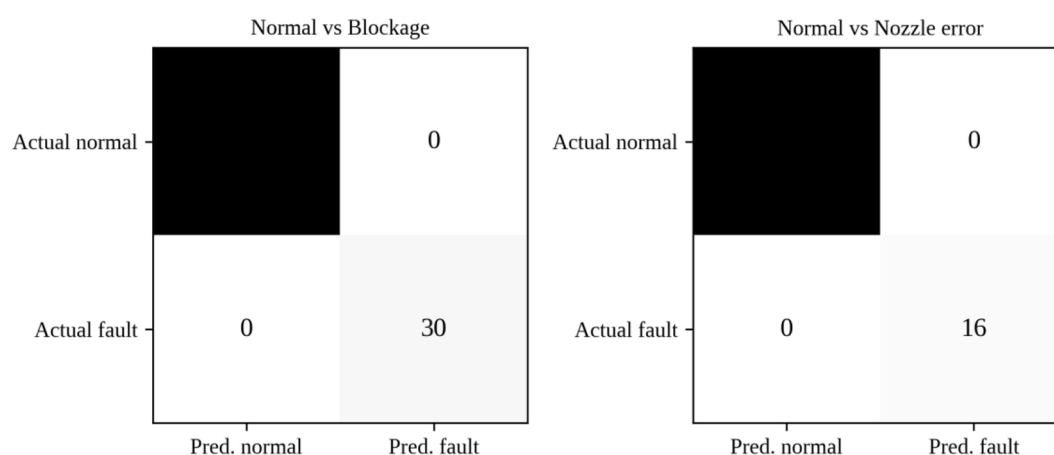


Figure 8. Fault detection - matrices for blockage vs. normal and nozzle-error vs. normal detection

Quantitative fault-detection performance

The classification performance was evaluated against the external reference labels using separate blockage-versus-normal and nozzle-error-versus-normal confusion matrices, as shown in Figure 8. The corresponding sample-level performance measures are summarised in Table 7.

For the combined 500-observation evaluation, the Wilson 95% confidence interval for accuracy is 99.24–100.00%, and the interval for specificity is 99.16–100.00%. Sensitivity confidence intervals are wider for the smaller fault groups, particularly the 16 nozzle-error observations. The FIS identifies every labelled fault on the same one-minute sample in which $Q = 0$ and the reference label is recorded, corresponding to 0-sample (0-min) delay relative to the archived labels; the physical fault-onset time is not independently available.

A fixed-threshold comparator defined by $Q < 1.0$ g/s and $W > 0.10$ kg also produces $TP = 46$, $TN = 454$, $FP = 0$ and $FN = 0$. Therefore, the fuzzy system and the threshold rule are indistinguishable on the unperturbed dataset, and the

results do not support a claim that fuzzy logic is more accurate than a fixed threshold under the available complete-flow-interruption conditions.

Supplemental numerical noise stress test

The numerical stress test evaluates the sensitivity of the fuzzy classifier and the fixed-threshold baseline to Gaussian perturbations applied to tank weight and recorded flow. Figure 9 compares the resulting classification accuracy at 1%, 3% and 5% full-scale disturbance levels, while Table 8 summarises the Monte Carlo results.

The threshold benchmark is slightly more accurate than the fuzzy system under the selected numerical perturbations; at 5% full-scale noise, mean accuracy is 99.12% for the FIS and 99.706% for the threshold rule. This numerical test does not establish physical sensor-noise robustness because the actual sensor noise spectrum, accuracy and calibration uncertainty are not documented.

This behaviour directly affects TTE estimation. A deterministic model may treat a low or zero

Table 7. Fuzzy fault-detection performance on the 500-observation dataset

Evaluation	TP	TN	FP	FN	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1 (%)	FAR (%)
All abnormal vs normal	46	454	0	0	100.0	100.0	100.0	100.0	100.0	0.0
Blockage vs normal	30	454	0	0	100.0	100.0	100.0	100.0	100.0	0.0
Nozzle error vs normal	16	454	0	0	100.0	100.0	100.0	100.0	100.0	0.0

Note: *TP – True Positive; TN – True Negative; FP – False Positive; FN – False Negative; F1 – F1-Score; FAR – False Alarm Rate.

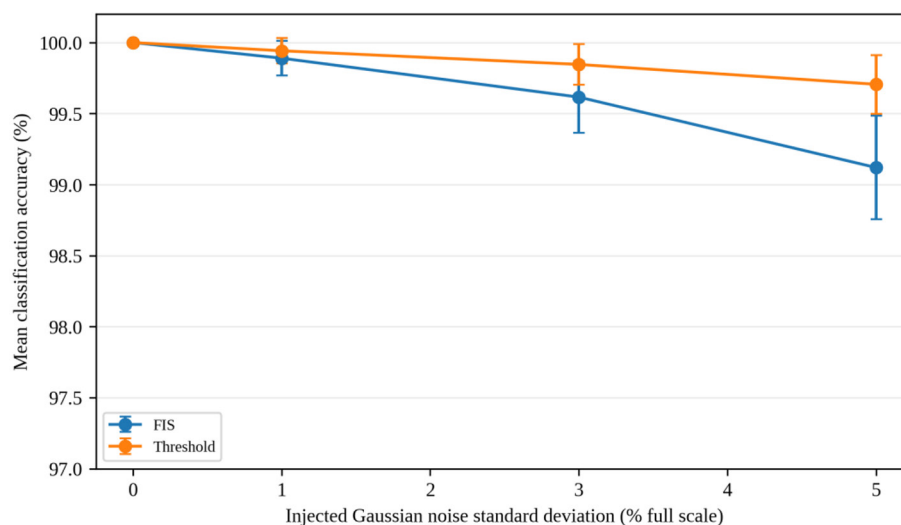


Figure 9. Numerical perturbation stress test comparing fuzzy system with fixed-threshold baseline

Table 8. Monte Carlo perturbation results (100 repetitions per noise level)

Noise (% full scale)	Method	Accuracy mean (%)	Accuracy SD (%)	Sensitivity mean (%)	Specificity mean (%)
0	FIS	100.000	0.000	100.000	100.000
0	Threshold	100.000	0.000	100.000	100.000
1	FIS	99.890	0.121	99.000	99.980
1	Threshold	99.942	0.091	99.370	100.000
3	FIS	99.616	0.252	97.783	99.802
3	Threshold	99.846	0.144	98.326	100.000
5	FIS	99.120	0.364	95.609	99.476
5	Threshold	99.706	0.207	96.804	100.000

flow condition as an indication of very long or undefined TTE, even when the tank still contains material. In the present framework, $Q = 0$ is treated as TTE-invalid when the fuzzy diagnostic index indicates abnormal flow; a conditional recovery horizon can then be calculated using the median of the preceding 10 valid non-fault flow observations.

Figure 10 compares timestamp-based TTE calculations with the empirical within-run depletion horizon. For normal observations, raw-channel deterministic TTE is finite for all 454 samples but exhibits MAE = 215.48 min, RMSE = 248.85 min and MAPE = 86.49%. The fuzzy gate does not alter normal samples and therefore has the

same normal-condition error. At the 46 labelled zero-flow faults, deterministic TTE has 0% finite coverage, whereas the conditional fuzzy-gated recovery horizon is finite for all fault observations. Its combined-fault MAE is 222.43 min, RMSE is 256.89 min and MAPE is 86.74%. The large errors reflect the unresolved recorded-flow scaling and do not demonstrate improved absolute TTE accuracy.

The numerical TTE consistency results for normal operation, combined faults, blockage, and nozzle error are summarised in Table 9.

From $TTE = 16.6667 \text{ W/Q}$, the absolute sensitivity to flow is $|dTTE/dQ| = 16.6667 \text{ W/Q}^2$. For

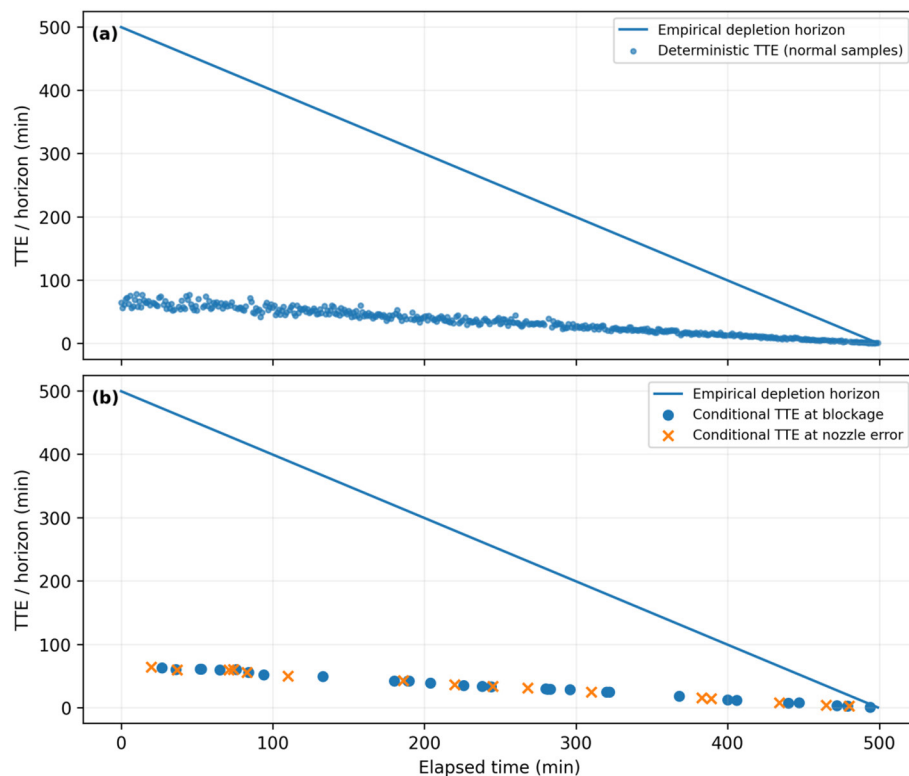

Figure 10. Timestamp-based TTE comparison against the empirical within-run depletion horizon

Table 9. TTE consistency metrics using the empirical depletion horizon

Condition	Method	Finite coverage	MAE (min)	RMSE (min)	MAPE (%)	MAPE n
Normal	Deterministic (raw Q)	100%	215.477	248.848	86.486	453
Normal	Fuzzy-gated conditional	100%	215.477	248.848	86.486	453
All faults	Deterministic (raw Q)	0%	Undefined	Undefined	Undefined	0
All faults	Fuzzy-gated conditional	100%	222.433	256.894	86.744	46
Blockage	Deterministic (raw Q)	0%	Undefined	Undefined	Undefined	0
Blockage	Fuzzy-gated conditional	100%	219.400	252.704	86.750	30
Nozzle error	Deterministic (raw Q)	0%	Undefined	Undefined	Undefined	0
Nozzle error	Fuzzy-gated conditional	100%	228.120	264.572	86.733	16

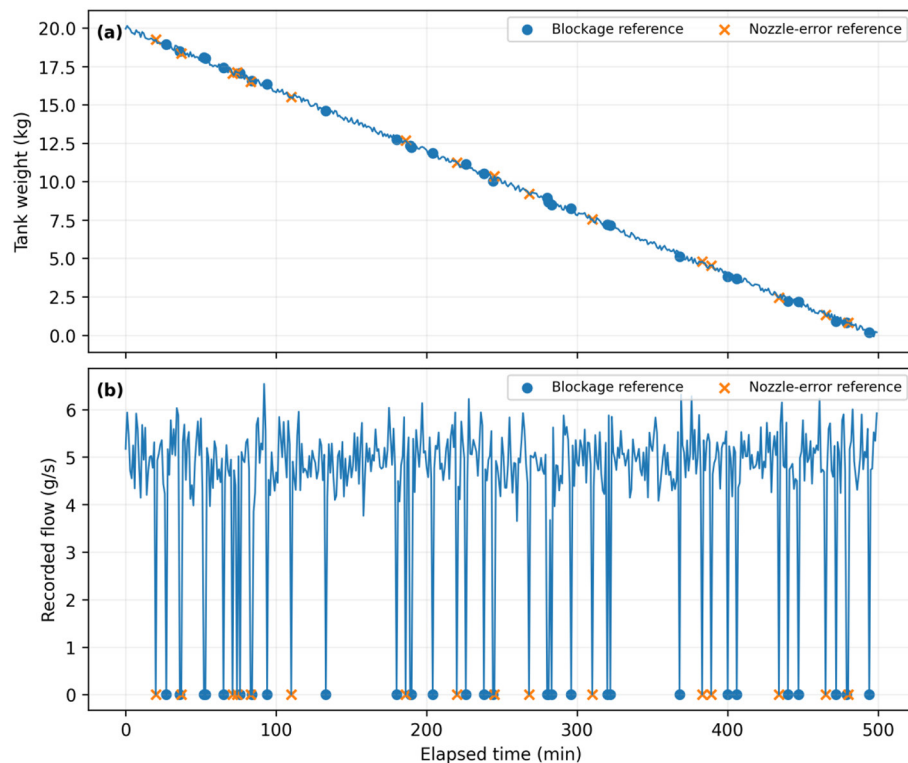
comparable flow uncertainty, absolute TTE variability therefore increases with remaining mass W rather than intrinsically increasing as the tank approaches depletion. The terminology is standardised to tank weight/tank availability and TTE.

Time-series and autocorrelation behaviour of flow rate and tank weight

The complete 499-min acquisition shows an almost linear tank-weight depletion trajectory, while the recorded flow remains approximately 4–6 g/s during normal samples and falls to zero at each labelled fault observation. Reference

blockage and nozzle-error samples are marked explicitly. The blockage labels form 27 contiguous episodes and the nozzle-error labels form 16 episodes; the longest labelled fault interval is 2 min. Because sampling is exactly 60 s, temporal lags are reported directly in minutes. These temporal patterns are shown in Figure 11.

The raw tank-weight series has very high lag-1 autocorrelation because it contains the deterministic depletion trend, so a raw-weight ACF would be dominated by non-stationarity rather than local fault dynamics. After first differencing, the strongest feature is a negative lag-1 correlation ($\rho_{01} = -0.470$), with little persistent


Figure 11. Time-series behaviour of tank weight and recorded flow rate, with labelled blockage and nozzle-error observations

structure at longer lags. The recorded flow ACF is also weak overall; only small coefficients near lags 4–6 min cross the approximate 95% zero-correlation limits. These results do not provide strong evidence of long-memory temporal fault dynamics; the clearest temporal evidence is the directly observed one- to two-minute zero-flow interruptions. The corresponding autocorrelation results are presented in Figure 12.

DISCUSSION

The first result, shown in Figures 5 and 6, can be explained by the different physical meanings of tank weight and flow rate. Tank weight represents material availability, whereas flow rate represents discharge behaviour. Under normal conditions, the two variables provide mutually consistent information for TTE estimation. Under fault conditions, however, this consistency is lost because the discharge path is disrupted while material remains in the tank. The quantitative analysis shows that normal flow is completely separated from the two labelled fault groups in the available dataset, while tank-weight distributions overlap across classes. Unlike conventional

mass-flow models that assume stable discharge behaviour, the fuzzy inference structure interprets the combined condition of tank weight and flow rate. This is the main advantage of the proposed framework. It does not replace the physics-based model; rather, it adds a diagnostic layer that identifies inconsistent process states. This hybrid logic is consistent with the broader direction of combining physics-based and data-driven reasoning for failure prediction [9]. However, a fixed threshold reproduces the same 100% classification on the unperturbed dataset, so the present evidence supports interpretability and TTE-validity gating rather than superior classification accuracy.

The second and third results, shown in Figures 7 and 10, indicate that blockage and nozzle error cause severe reductions in flow rate and destabilise TTE estimation. In a conventional model, near-zero flow may lead to unrealistic or undefined TTE values. In the proposed framework, this same condition is interpreted as a possible fault when the tank still contains sufficient material. The within-run TTE consistency analysis further shows that the fuzzy gate does not improve normal-condition numerical error; its demonstrated role is to reject invalid zero-flow TTE states and provide a finite conditional recovery horizon.

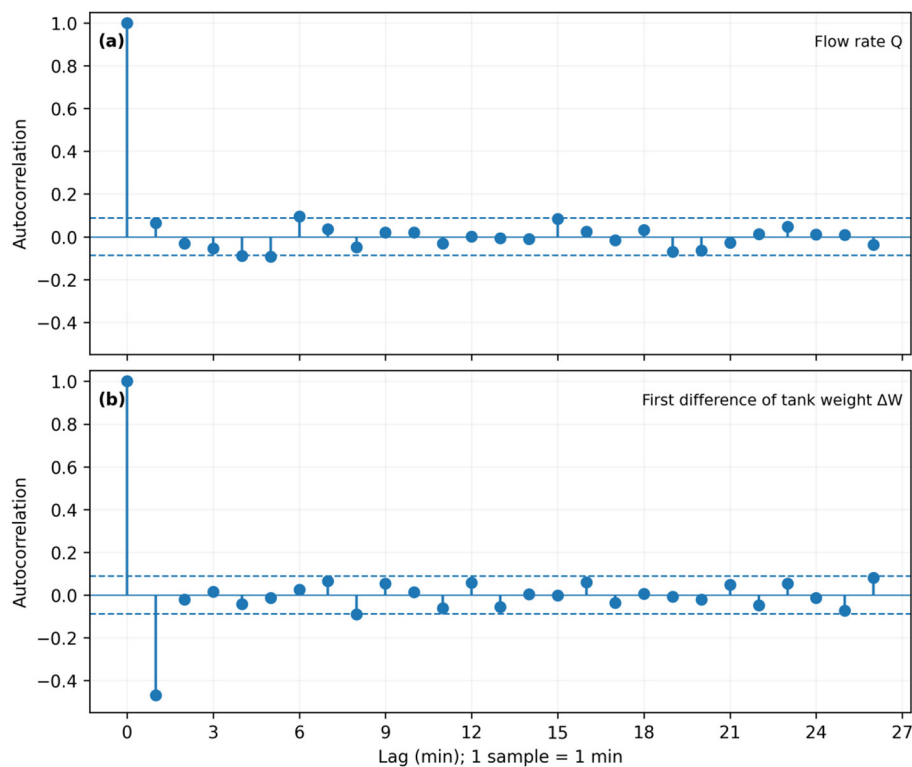


Figure 12. Autocorrelation up to 26 min for recorded flow Q and first-differenced tank weight ΔW ; dashed lines are approximate 95% zero-correlation bounds

The fourth result, shown in Figures 11 and 12, indicates that temporal behaviour provides additional evidence for fault detection. Sudden flow drops are consistent with anomaly behaviour in time-series monitoring [33]. After removal of the deterministic weight trend, the ACF results show limited longer-lag dependence; consequently, temporal autocorrelation is treated as descriptive support rather than an independent classifier.

The results cover the unresolved problem by showing that fault-sensitive fuzzy reasoning can interpret abnormal flow behaviour that deterministic TTE models may misclassify. The framework is particularly useful when a low flow condition occurs together with medium or high tank weight. Nevertheless, because blockage and nozzle error have identical zero-flow signatures and overlapping tank weight in the available record, the two physical fault types cannot be isolated using W and Q alone. Additional discriminating measurements such as local pressure, pressure difference or nozzle-actuation information would be required for fault-type isolation.

Several limitations must be considered before practical application. The present study focuses on two representative faults: supply tube blockage and nozzle error. The model does not yet include gradual mechanical wear, partial degradation, air entrapment or sensor drift as separate diagnostic classes. Sensor model, accuracy, resolution, response time, calibration traceability and physical measurement uncertainty are not documented, and the fault-induction protocol is also unavailable. The supplemental Gaussian perturbation test is numerical only and does not establish physical sensor-noise robustness.

The current dataset also limits independent TTE validation. Although timestamps permit an empirical within-run depletion horizon and calculation of MAE, RMSE and MAPE, the reference is derived from the same continuous experiment and the raw flow channel differs by approximately 7.5 times from the weight-derived depletion rate. Further validation should synchronously record calibrated mass flow, cumulative dispensed flux or independently timed depletion across repeated runs and graded fault severities. Direct PCB quality outcomes, including defect rate, rejection/rework frequency, soldering defects, downtime and yield, are also required before any improvement in PCB production quality can be claimed.

CONCLUSIONS

The distribution and scatter analyses show that normal flux monitoring behaviour is characterised by recorded flow above 3.65 g/s, while all 46 labelled blockage and nozzle-error observations have zero recorded flow. The fully specified Mamdani fuzzy inference system uses tank availability and recorded flow as operational inputs, with the fault-status indicators reserved for validation. The complete membership functions, 16-rule base, inference operators, centroid defuzzification, decision surface and worked outputs provide a reproducible diagnostic specification. On the available dataset, the FIS detects all 30 blockage and all 16 nozzle-error observations without false alarms; however, a fixed-threshold detector achieves the same unperturbed classification, so general superiority of fuzzy logic is not established. The deterministic TTE equation is dimensionally defined as $1000\text{ W}/(60\text{ Q})\text{ min}$ and is treated as invalid at zero-flow fault states. An empirical within-run depletion horizon permits MAE, RMSE and MAPE to be calculated, but the large errors and the approximately 7.5-fold discrepancy between raw recorded flow and weight-derived depletion rate show that the flow channel requires traceable calibration before absolute TTE accuracy can be established. Accordingly, the supported contribution is an interpretable flow-fault and TTE-validity gate rather than demonstrated improvement in absolute TTE prediction or PCB production quality. Independent repeated experiments with calibrated sensors, graded partial faults, documented fault induction, physical noise testing and direct PCB-quality outcomes are required for external validation.

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REFERENCES

- Bianchi D., Di Gennaro S., Di Ferdinando M., Acosta Lúa C. Robust control of UAV with disturbances and uncertainty estimation. *Machines*. 2023;11(3). <https://doi.org/10.3390/machines11030352>
- Allmendinger M., Erhard M. Reinforcement learning-based PID controller design for mass flow. 14th International Fluid Power Conference, 2024. <https://doi.org/10.13052/rp-9788770042222c48>
- Hlalele T.S. Geomagnetically induced currents: Review, impact, and mitigation strategies. *Int. J. Eng. Trends Technol.* 2025;73(10). <https://doi.org/10.14445/22315381/IJETT-V73I10P121>
- Srivastava A., Bhanot D., Jasim L.H., Varshney N., Patil V. Advancements in fuzzy logic applications for diagnostic decision support systems in healthcare. *Fuzzy Inf. Eng.* 2025;17(3):284–297. <https://doi.org/10.26599/FIE.2025.9270064>
- Saatchi R. Fuzzy logic concepts, developments and implementation. *Information (Switzerland)*. 2024;15(10). <https://doi.org/10.3390/info15100656>
- Xu Z., Shi S., Er M.J., Hu Z. Fuzzy-model-based robust control of Markov jump nonlinear systems with incomplete transition probabilities and uncertain packet dropouts. *Asian J. Control.* 2023;25(6). <https://doi.org/10.1002/asjc.3188>
- Radhi H.S. Real time machinery safety monitoring by hybrid fuzzy system. *Diyala Journal of Engineering Sciences. Conference Articles*. 2015:557–567.
- Li Y., Liu L. Research on robust adaptive model predictive control based on vehicle state uncertainty. *World Electr. Veh. J.* 2025;16(5). <https://doi.org/10.3390/wevj16050271>
- Li Z., Zhou J., Nassif H., Coit D., Bae J. Fusing physics-inferred information from stochastic model with machine learning approaches for degradation prediction. *Reliab. Eng. Syst. Saf.* 2023; 232:109078. <https://doi.org/10.1016/j.res.2022.109078>
- Du P., Wilhite B., Kravaris C. Model-based fault diagnosis in closed-loop safety-critical chemical reactors: An experimental study. *AIChE J.* 2025;71(9). <https://doi.org/10.1002/aic.18906>
- Dippenaar M.C., van Schoor G., Uren K.R., van Niekerk W.M.K. Fault detection and isolation in transient conditions on a heated two-tank system: A multi-way principal component analysis approach. *Processes*. 2024;12(8). <https://doi.org/10.3390/pr12081620>
- Cioch M., Kulisz M., Kański Ł. Implementing AI collaborative robots in manufacturing – modeling enterprise challenges in Industry 5.0 with fuzzy logic. *Adv. Sci. Technol. Res. J.* 2024;18(7):229–238. <https://doi.org/10.12913/22998624/192833>
- Tahoon A.I., Rusli R., Khan F., Zainal Abidin M. Logic-based probabilistic network model to detect and track faults in a process system. *Process Saf. Prog.* 2020;39(S1). <https://doi.org/10.1002/prs.12110>
- Aboshosha A., Hamad H.A. Employing adaptive fuzzy computing for RCP intelligent control and fault diagnosis. *Nucl. Sci. Tech.* 2023;34(9). <https://doi.org/10.1007/s41365-023-01288-y>
- Wu L., Zhao R., Li Y., Chen Y.H. Optimal design of adaptive robust control for the delta robot with uncertainty: Fuzzy set-based approach. *Appl. Sci.* 2020;10(10). <https://doi.org/10.3390/app10103472>
- Nasir Ahamed N.N. Fuzzy sets and the holographic principle: Uncertainty in black hole physics. *J. Adv. Sci. Technol.* 2024;20(1). <https://doi.org/10.29070/qf8tsq22>
- Maghfiroh H., Wahyunggoro O., Cahyadi A.I. Energy management in hybrid electric and hybrid energy storage system vehicles: A fuzzy logic controller review. *IEEE Access*. 2024;12. <https://doi.org/10.1109/ACCESS.2024.3390436>
- Dominik I., Flaga S. Implementation of type-2 fuzzy controller in Matlab software. *Adv. Sci. Technol. Res. J.* 2023;17(5):374–384. <https://doi.org/10.12913/22998624/171118>
- Martinez-Viol V., Urbano E.M., Delgado-Prieto M., Romeral L. HVAC early fault detection using a fuzzy logic based approach. *Renew. Energy Power Qual. J.* 2020;18. <https://doi.org/10.24084/repqj18.270>
- Dapshima B.A., Pandey A., Srivastava A., Ali J. Fault detection and protection of power transformer using fuzzy logic. *Int. J. Sci. Res. Eng. Manag.* 2023;7(1). <https://doi.org/10.55041/ijserm17525>
- Moshkin V., Kurilo D., Yarushkina N. Integration of fuzzy ontologies and neural networks in the detection of time series anomalies. *Mathematics*. 2023;11(5). <https://doi.org/10.3390/math11051204>
- Karrar A.E. The effect of using data pre-processing by imputations in handling missing values. *Indones. J. Electr. Eng. Inform.* 2022;10(2). <https://doi.org/10.52549/ijeei.v10i2.3730>
- Rodrigues A.K.G., Ospina R., Ferreira M.R.P. Adaptive kernel fuzzy clustering for missing data. *PLoS One*. 2021;16(11). <https://doi.org/10.1371/journal.pone.0259266>
- Bojanowska A.B., Kulisz M. Using fuzzy logic to make decisions based on the data from customer relationship management systems. *Adv. Sci. Technol. Res. J.* 2023;17(5):269–279. <https://doi.org/10.12913/22998624/171117>
- Sun H., Fink O. TARD: Test-time domain adaptation for robust fault detection under evolving operating conditions. *Reliab. Eng. Syst. Saf.* 2026; 271:112135. <https://doi.org/10.1016/j.res.2025.112135>
- Gardiola O., Maulud A.S., Nawaz M., Jamaludin N.F. Fault detection using multiscale recursive principal component analysis for chemical process systems.

- Digital Chemical Engineering. 2025;16:100264. <https://doi.org/10.1016/j.dche.2025.100264>
27. Ma S., Wu Y., Hua Z., Gou L. Application of fuzzy inference system in gas turbine engine fault diagnosis against measurement uncertainties. *Chin. J. Mech. Eng. (Engl. Ed.)*. 2025;38(1). <https://doi.org/10.1186/s10033-024-01145-y>
28. Ardianto F., Ermatita, Sofijan A. Photovoltaic fault detection in remote areas using fuzzy-based multiple linear regression (FMLR). *Int. J. Adv. Comput. Sci. Appl.* 2025;16(4). <https://doi.org/10.14569/IJACSA.2025.0160425>
29. Yahya Y., Qian A., Yahya A. Power transformer fault diagnosis using fuzzy reasoning spiking neural P systems. *J. Intell. Learn. Syst. Appl.* 2016;8(4). <https://doi.org/10.4236/jilsa.2016.84007>
30. Zhang C., Zhou Z., Ning P., Zhang P., Lian Z., Ming Z. MBRB: Micro-belief rule Base model based on cautious conjunctive rule for interpretable fault diagnosis. *Eng. Appl. Artif. Intell.* 2024; 135:108598. <https://doi.org/10.1016/j.engappai.2024.108598>
31. Kizito A.E., Ojei E., Okpor M.D. A fuzzy logic-based automobile fault detection system using Mamdani algorithm. *Int. J. Sci. Res. Manag.* 2024;12(3). <https://doi.org/10.18535/ijsrcm/v12i03.ec06>
32. Noorsaman A., Amrializzia D., Zulfikri H., Revitasari R., Isambert A. Machine learning algorithms for failure prediction model and operational reliability of onshore gas transmission pipelines. *Int. J. Technol.* 2023;14(3). <https://doi.org/10.14716/ijtech.v14i3.6287>
33. Pota M., De Pietro G., Esposito M. Real-time anomaly detection on time series of industrial furnaces: A comparison of autoencoder architectures. *Eng. Appl. Artif. Intell.* 2023;124:106597. <https://doi.org/10.1016/j.engappai.2023.106597>
34. Zadeh L.A. Fuzzy sets. *Inf. Control.* 1965;8(3):338–353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
35. Tasevski G., Papazoska E. Model for improvement of fluxing process on selective soldering machines (model 6747). *Balkan Reg. Conf. Eng. Bus. Educ.* 2015;1(1):1–6. <https://doi.org/10.1515/cplbu-2015-0030>
36. Vesely P., Busek D., Krammer O., Dusek K. Analysis of no-clean flux spatter during the soldering process. *J. Mater. Process. Technol.* 2020;275:116289. <https://doi.org/10.1016/j.jmatprotec.2019.116289>
37. Ulger F., Yuksel S.E., Yilmaz A., Gokcen D. Solder joint inspection on printed circuit boards: A survey and a dataset. *IEEE Trans. Instrum. Meas.* 2023;72:2515121. <https://doi.org/10.1109/TIM.2023.3277935>
38. Dominik M., Kesek M. Application of computer simulation to evaluate performance parameters of the selective soldering process. *Appl. Sci.* 2025;15(15):8649. <https://doi.org/10.3390/app15158649>
39. Chang S.Y., Chang C.T. A fuzzy-logic based fault diagnosis strategy for process control loops. *Chem. Eng. Sci.* 2003;58(15):3395–3411. [https://doi.org/10.1016/S0009-2509\(03\)00218-5](https://doi.org/10.1016/S0009-2509(03)00218-5)
40. Cheded L., Doraiswami R. A novel integrated framework for fault diagnosis with application to process safety. *Process Saf. Environ. Prot.* 2021;154:168–188. <https://doi.org/10.1016/j.psep.2021.08.008>
41. Pfab K., Eichler R., Mallandur A., Rothering M. Data of automated optical inspection of surface-mounted technology electronic production. *Data Brief.* 2024;53:110110. <https://doi.org/10.1016/j.dib.2024.110110>