

Expert System for Instrumentation Fault Diagnosis in Ethyl Chloride Separation Process

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ABSTRACT

The ethyl chloride separation process in the petrochemical industry relies heavily on the reliability of instrumentation equipment, as failures can lead to significant operational and economic losses. Conventional fault diagnosis remains subjective and time-consuming due to its dependence on expert availability. This study aims to develop a prototype expert system with a knowledge base encompassing 9 process units, 130 symptoms, and 128 possible instrumentation faults. The system employs a forward chaining inference method combined with a hybrid approach of Certainty Factor (CF) and Bayesian Inference to manage data uncertainty. The system was implemented in Python and validated through internal logic consistency analysis and sensitivity analysis. Logic consistency testing demonstrated that the system accurately validated individual rules with an actual CF score of 0.9000. In the ambiguity handling test case, the system correctly prioritized diagnoses based on the highest rule weight (CF = 0.9000) and highest Bayesian probability (0.088785). Sensitivity analysis confirmed that variations in user belief weight (CF_{User}) proportionally shifted the primary diagnosis, for instance, the symptom 'decreasing heating ΔT ' yielded 'Fouling' as the primary diagnosis with a posterior probability of 0.3027 and CF of 0.8900, while increased weight on temperature instability symptoms shifted the diagnosis to 'unstable reboiler steam supply'. The hybrid CF-Bayesian approach proved effective in supporting knowledge-based decision-making, even when operating with limited historical data.

Keywords: Bayesian Inference, Certainty Factor, Expert System, Forward Chaining, Instrumentation Fault Diagnosis

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1. Introduction

The ethyl chloride separation process, which employs a distillation column, holds a central role in the petrochemical industry as the primary separation unit for producing high-purity products [1]. Operational efficiency and final product quality are highly dependent on the performance of this unit [2]. Complex dynamics characterize the distillation

process for ethyl chloride separation and require strict control of critical variables such as temperature, pressure, flow rate, and level. Consequently, this unit relies on the performance of instrumentation equipment and automatic control systems, where instruments such as control valves, transmitters, and sensors serve as vital links between physical process conditions and digital control systems [3].

Instrumentation fault diagnosis in the ethyl chloride separation process is highly complex due to the interactive nature of process variables. In a distillation column, variables such as temperature, pressure, level, and flow rate directly influence one another. For example, failure of an outlet control valve can increase column pressure, causing inaccurate level sensor readings due to fluid density changes, which subsequently trigger incorrect control responses on feed flow rate. This disturbance propagation creates multiple overlapping symptoms, where a single fault can trigger anomalies at several measurement points, while different faults may produce similar symptom patterns [4]. As a result, operators struggle to distinguish root causes from secondary symptoms, particularly during transient conditions or when the system operates near operational limits. To make this coupling concrete, consider a single root-cause fault: when the overhead outlet control valve fails, column pressure rises, which alters the vapor-liquid equilibrium and shifts the boiling point of the mixture; this distorts temperature-based composition inference and, because fluid density changes with pressure, causes the level transmitter to misread. The control system, acting on these erroneous measurements, then issues incorrect corrective actions on the feed flow rate, further amplifying the deviation. This many-to-many relationship between faults and symptoms, where one fault propagates across multiple measurement points and distinct faults may generate nearly identical symptom patterns is precisely what makes a structured, knowledge-based diagnostic aid essential for readers and operators outside the instrumentation domain to appreciate.

Instrumentation failures in the petrochemical industry cause serious impacts, including process fluctuations, increased costs, product quality degradation, and unplanned shutdowns [5]. This issue is critical given that equipment trips and shutdowns are a leading cause of unplanned shutdowns in petrochemical plants [6], with global economic losses from downtime reaching \$1.4 trillion, and the fact that over 80% of accidents in petrochemical units are attributed to human

error in handling abnormal situations [7]. At the component level, instrument and final-control elements are among the most failure-prone assets in continuous service; field reliability studies report control-valve failure rates on the order of 0.1–0.6 failures per valve-year, making them a recurring trigger of process upsets. Industry standards such as API RP 576 emphasize systematic inspection and diagnosis of pressure-relieving and instrumentation devices precisely because undetected faults escalate rapidly into safety and economic losses. Conventional troubleshooting that relies on expert knowledge is inherently subjective and not always available, creating risks of diagnostic errors and delays [8]. Therefore, an expert system capable of consistently and rapidly replicating expert knowledge through a structured knowledge base is needed to analyze symptoms and provide diagnoses, as it has proven effective in complex processes across various domains [9].

In industrial process environments, incoming data is often uncertain or ambiguous, making it necessary for expert systems to employ robust inference methodologies [10]. The Certainty Factor (CF) and Bayesian Inference approaches are particularly important: CF enables the system to measure the degree of certainty for each possible fault based on expert rules [11], while Bayesian Inference updates fault probabilities based on emerging new evidence [10]. The combination of these two methods can provide the most likely correct diagnostic recommendation, thereby improving overall system reliability.

Previous studies have notable limitations: simple rule-based approaches cannot handle overlapping symptom uncertainty, while machine learning methods require extensive historical data that is rarely available in high-uptime plants. Although the combination of Certainty Factor and Bayesian Inference has been applied in the medical domain and other sectors [9], its application for instrumentation fault diagnosis in ethyl chloride separation has never been conducted. Most existing studies also do not validate robustness through sensitivity analysis, creating a

need for a diagnostic system that can work with limited data, handle uncertainty explicitly, and is specific to the characteristics of the ethyl chloride separation process [12].

To address these gaps, the primary objective of this study is to develop and implement an expert system prototype using a Forward Chaining inference method combined with Certainty Factor and Bayesian Inference. The system is designed to diagnose specific faults in instrumentation equipment across all units of the ethyl chloride separation process. The significant contributions of this study include: (1) a comprehensive knowledge base covering 9 process units with 130 symptoms and 128 possible faults, (2) a hybrid inference mechanism capable of handling ambiguity and uncertainty without requiring extensive historical data, (3) robustness validation through logic consistency and sensitivity analyses, and (4) a framework that can be adapted for knowledge-based diagnostic systems in other process industries.

2. Materials and Methods

This study employs a computational experimental approach based on an expert system to diagnose instrumentation equipment faults in the ethyl chloride separation process. The system was developed using the forward chaining method combined with Certainty Factor (CF) and Bayesian Inference to handle uncertainty in the diagnostic process [13]. System validation was conducted through logic consistency analysis and sensitivity analysis to ensure model robustness [14], [15].

2.1 Research Variables

Research variables were classified into three categories based on their role in the inference system. Input variables consist of 130 operational symptoms (S_i) indicating deviations from normal conditions across 9 process units [15], and user belief levels (CF_{User}) ranging from 0–1 inputted via a GUI slider.

Output variables include a diagnostic ranking based on a combination of CF scores and Posterior Probability ($P^*(F)$) from softmax normalization [16]. System constant parameters include CF_{Expert} representing expert certainty regarding causal symptom-fault relationships, and conditional probability $P(S_i|F)$ for Bayesian calculations. Intermediate variables include Combined CF ($CF_{i \rightarrow F}$) as the product of $CF_{Expert} \times CF_{User}$ and Log-Odds Posterior scores before normalization. The system covers 128 possible instrumentation faults (F) such as fouling, stuck valves, sensor drift, and leakage [16].

2.2 Experimental Equipment and Environment

The system was implemented using Python 3.11 with the Tkinter library for the graphical interface, math for mathematical operations (logarithm, exponential, softmax), data classes for structuring inference rule data, date time for timestamp recording of diagnoses, and matplotlib for historical data visualization. Python was selected for its flexibility in managing rule-based systems and ease of creating interactive GUIs.

2.3 Research Stages

Problem Formulation and System Identification

The initial stage began with an analysis of the Process Flow Diagram (PFD) of Unit 2000 – Product Separation Section, adapted from reference [17]. Major equipment was identified, including V-2010 (Two-Phase Separator), T-2010 (Ethyl Chloride Column), E-2010A/B (Overhead Condenser), E-2020A/B (Bottoms Reboiler), E-2030 (Product Afterheater), and V-2020 (Overhead Receiver). From this analysis, critical instrumentation points were mapped, including temperature sensors, pressure transmitters, level indicators, flow meters, and control valves, along with crucial operational parameters serving as process performance indicators.

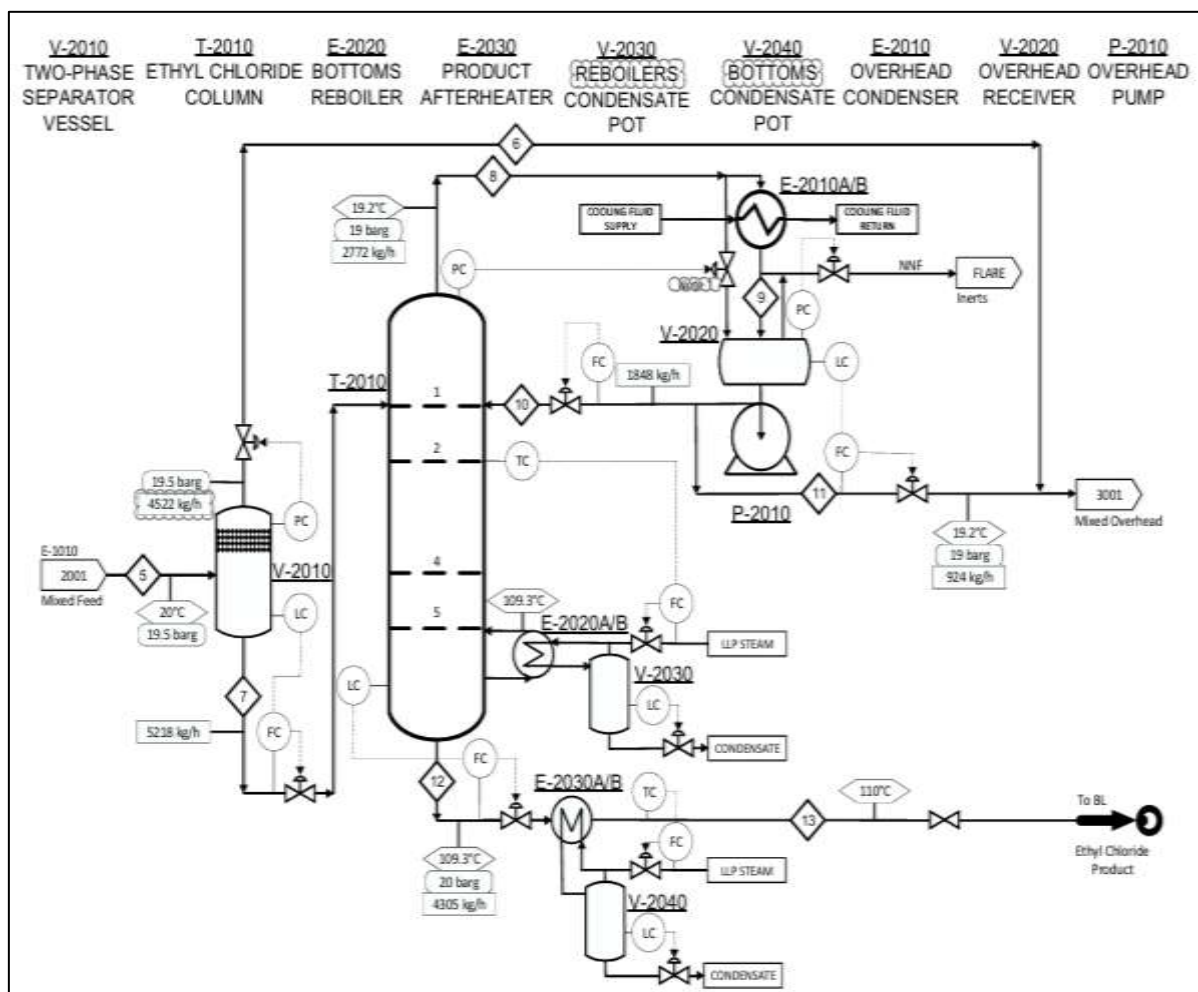


Figure 1. Process Flow Diagram (PFD) Unit 2000 – Product Separation Section [17]

Based on the PFD shown in Figure 1, the separation process utilizes a two-phase separator (V-2010), a distillation column (T-2010), a condenser (E-2010A/B), a reboiler (E-2020A/B), and an afterheater (E-2030). From this analysis, 130 operational symptoms and 128 possible instrumentation faults were identified.

Knowledge Base Development

The knowledge base employs IF-THEN production rules with two quantitative parameters: CF_{Expert} (0–1) indicating expert certainty regarding causal relationships between symptoms and faults, and $P(Si|F)$ representing the conditional probability of symptom occurrence given a fault. Due to limited access to historical data and industry experts for formal consultation, parameter values were established through systematic knowledge synthesis from three validated sources: industry

technical standards, equipment manufacturer troubleshooting manuals, and peer-reviewed scientific literature on fault diagnosis [6]. CF_{Expert} assignment follows causal strength classification (0.90–1.00 for very strong relationships, 0.70–0.89 for strong, 0.50–0.69 for moderate), while $P(Si|F)$ was estimated from literature empirical statistics or conservatively set assuming $P(Si|F) \approx CF_{Expert} \pm 0.1$ when data was unavailable. The knowledge base was enriched with generic rules from ISA-TR5.9 standards and inter-unit disturbance propagation rules, with internal validation to ensure logical consistency [18].

Forward Chaining Inference Mechanism

Inference employs a Forward Chaining approach, reasoning from data toward conclusions (data-driven reasoning) [19]. This method was selected because it aligns with field diagnostic processes, where operators begin

with observed symptoms and the system traces matching rules to identify possible underlying causes (faults). The Forward Chaining workflow in the system is as follows:

1. Initial Fact Input

Users select observed symptoms via the GUI and assign certainty levels (CF_{User}) for each symptom using a slider (range 0–1). Symptoms with $CF_{User} > 0$ become initial facts for the inference process [10].

2. Rule Matching

The inference engine performs pattern matching to find all rules in the knowledge base whose IF conditions (symptoms) match the inputted facts [19], producing a set of activated (fired) rules.

3. Evaluation and Calculation

Individual CF scores for each rule are calculated by Eq. (1).

$$CF_{i \rightarrow F} = CF_{Expert} \times CF_{User} \quad (1)$$

When multiple symptoms point to the same fault, CF scores are combined using serial combination rules calculated by Eq. (2).

$$CF_{Total} = CF_1 + CF_2(1 - CF_1) \quad (2)$$

4. Bayesian Inference Calculation

In parallel, the system calculates probabilistic scores using a log-odds approach for computational efficiency by Eq. (3) [10],

$$L_F = \log \frac{P(F)}{1-P(F)} + \sum_i CF_{User}(S_i) \log \frac{P(S_i|F)}{\beta} \quad (3)$$

where $P(F)$ is the prior fault probability and β is the normalization base factor.

5. Normalization and Ranking

Bayesian log-odds scores are normalized using the softmax function to obtain relative posterior probabilities calculated by Eq. (4).

$$P^*(F) = \frac{e^{L_F}}{\sum_j e^{L_j}} \quad (4)$$

The system then ranks all fault candidates based on a combination of CF scores and posterior probabilities, producing a diagnostic ranking from most to least likely.

6. Conclusion and Recommendation:

The fault with the highest score is presented as the primary diagnosis. The system also generates a reasoning path explaining which symptoms contributed most significantly, along with tiered action recommendations (Immediate, Inspection, Prevention) contextual to the fault type [15], [19].

Hybrid CF-Bayesian Integration Mechanism

This system implements a hybrid approach that integrates Certainty Factor (CF) and Bayesian Inference in parallel, rather than sequentially. When users input symptoms with a CF_{User} certainty level, the system simultaneously runs two inference pathways: the CF pathway, which calculates evidence strength ($CF_{i \rightarrow F} = CF_{Expert} \times CF_{User}$) and accumulates evidence using serial combination (Eq. 2), and the Bayesian pathway, which uses CF_{User} as evidential weights in the log-odds posterior calculation (Eq. 3) normalized via softmax (Eq. 4). CF_{User} functions as a universal modulator that consistently influences evidence weights in both methods, ensuring that symptom observation uncertainty is accounted for across both inference frameworks. Rather than mathematically aggregating CF scores and Bayesian probabilities due to their differing semantic interpretations, the system employs a dual-ranking strategy that ranks fault candidates in parallel based on CF_{Total} and $P^*(F)$, then compares both rankings to detect consistency. This parallel approach was chosen to avoid information loss, leverage the complementarity of both methods (CF for heuristic rules, Bayesian for statistical uncertainty), and enable mutual validation to increase confidence in the final diagnosis. To clarify the integration of the two inference methods, the parallel fusion mechanism of the hybrid CF-Bayesian system is illustrated in Figure 2.

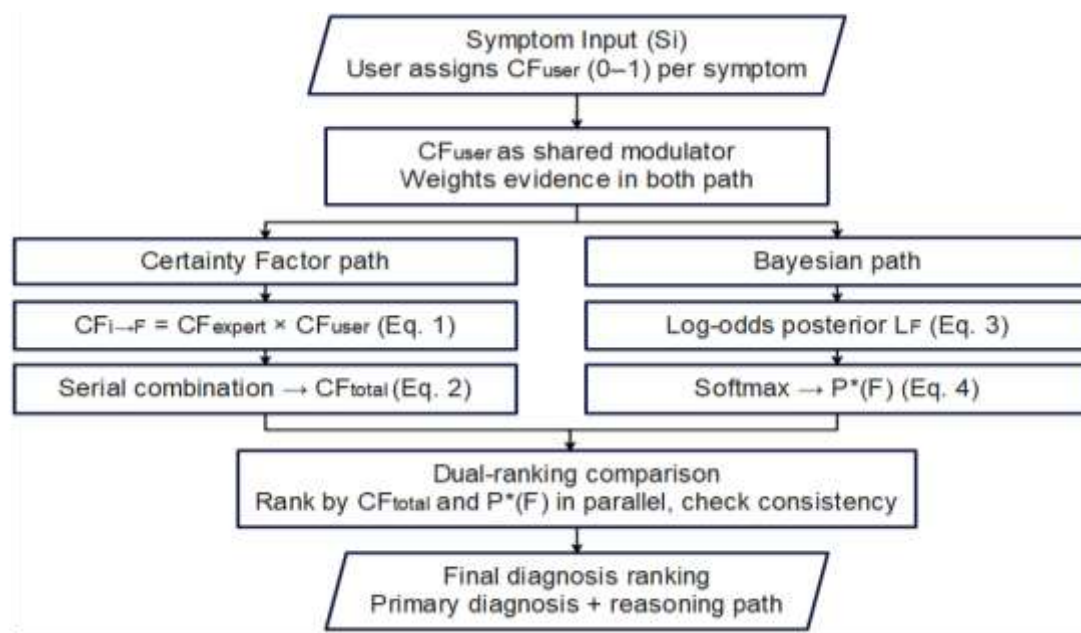


Figure 2. Parallel fusion mechanism of the hybrid CF-Bayesian inference

Application Feature and Interface Development

The system includes a graphical user interface (GUI) built with Tkinter that enables users to select observed symptoms organized per process unit and adjust their certainty levels (CF_{User}) using intuitive sliders, allowing operators to express varying degrees of confidence in each observation without requiring any programming knowledge. Once symptoms are submitted, the diagnostic results are displayed in a ranked tabular format that lists candidate faults alongside their CF scores and Bayesian probabilities, and this table can be exported to .xlsx files for documentation, reporting, and further offline analysis. To support traceability and longitudinal monitoring, each diagnostic session is automatically recorded to a `diagnosis_history.csv` file encompassing timestamps, input symptoms, assigned certainty levels, and diagnostic results, thereby building a cumulative dataset that can be mined for fault trend analysis over time. In addition, the system incorporates a visualization module developed using the matplotlib library, which displays the fault frequency per process unit and the distribution of fault types derived from the accumulated historical data, providing operators and

engineers with an at-a-glance overview of recurring problem areas and supporting data-driven maintenance prioritization [20].

Validation and Results Analysis

Validation was conducted through three complementary, operationally defined procedures. First, logic consistency verification was performed via extreme case testing, confirming that each rule produces an output mathematically consistent with its defined weight ($CF_{Actual} = CF_{User} \times CF_{Expert}$, Eq. 1). Second, sensitivity analysis systematically varied CF_{User} weights over fixed symptom combinations to verify that diagnostic shifts are proportional, monotonic, and traceable. Third, face validation was applied by qualitatively comparing the system's outputs for representative test cases against fault symptom relationships documented in industry standard troubleshooting guides and peer-reviewed technical case studies, in order to confirm the engineering plausibility of the conclusions. Each test was documented with a complete reasoning trace recording the contributing symptoms, intermediate values ($CF_{i \rightarrow F}$, L_F), and the full candidate ranking, ensuring transparency and reproducibility.

Given the unavailability of historical operational data for empirical validation, system

testing focused on internal logic validation and model robustness analysis through three approaches: extreme case testing with single-symptom input ($CF_{User} = 1.0$) to verify output consistency with the knowledge base, where actual $CF = CF_{User} \times CF_{Expert}$ According to Eq. (1); overlap case testing to verify the handling of symptoms with multiple fault associations based on rule weights and conditional probabilities, and sensitivity analysis by systematically varying CF_{User} weights to observe diagnostic shifts that are proportional, logical, not overly sensitive to minor changes yet responsive to significant ones, with CF scores and posterior probabilities changing monotonically [16], [21].

Although no formal expert validation or cross-checking with real case data was conducted due to limited access, diagnostic re-

sults for test cases were qualitatively compared against knowledge documented in industry standard troubleshooting guides and technical literature case studies [6], [22] to ensure the reasonableness of the conclusion (face validation). Each test result was documented with a reasoning trace recording contributing symptoms, intermediate values ($CF_{i \rightarrow F}$, L_F), and the complete fault candidate ranking for calculation transparency.

Flowchart

The research stages are documented in a systematic flowchart in Figure 3, illustrating the workflow from problem identification to system validation, including iteration paths for rule calibration and weight value refinement in the event of inconsistencies. This iterative structure allows detected logical conflicts to be fed back into knowledge base refinement before finalization.

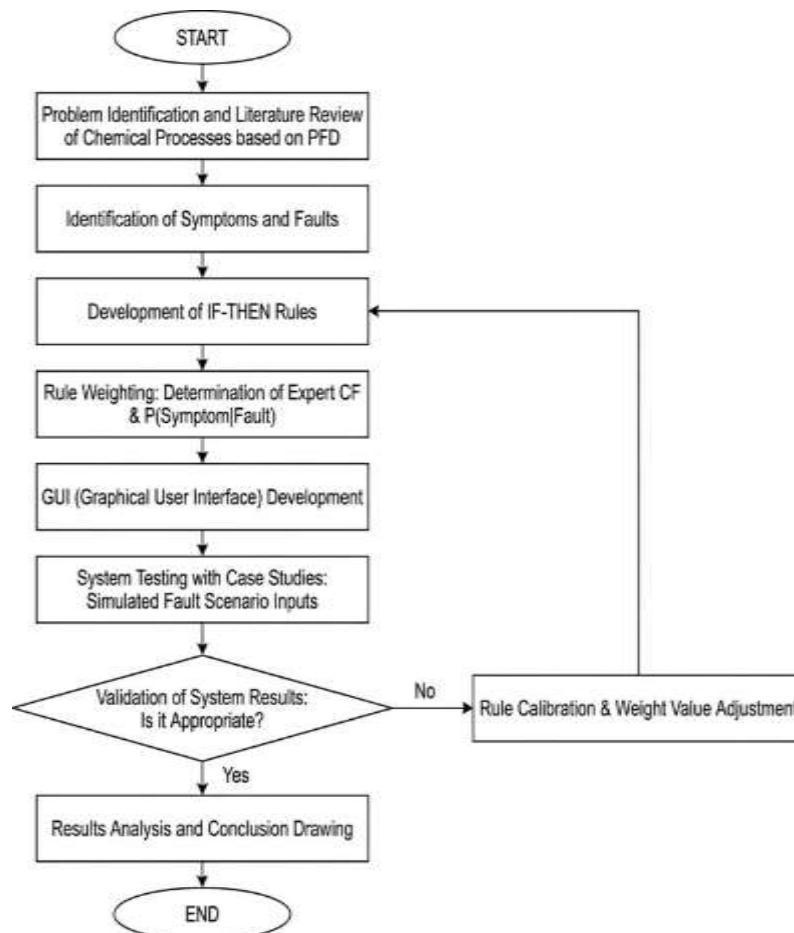


Figure 3. Expert System Research Flowchart

3. Results

The expert system for instrumentation fault diagnosis in the ethyl chloride separation process was successfully implemented and validated using the hybrid Certainty Factor (CF) and Bayesian Inference approach. The developed system encompasses a comprehensive knowledge base with 130 symptoms and 128 possible faults distributed across 9 process units. Given the unavailability of historical operational data for empirical validation, system evaluation focused on internal logic validation and model robustness through logic consistency and sensitivity analyses. Test results demonstrate that the system is capable of executing inference rules consistently, handling ambiguity with logical prioritization, and responding to evidence weight changes proportionally.

This study adopted a proof-of-concept approach focused on developing and internally validating the hybrid CF-Bayesian expert system inference mechanism for ethyl chloride separation instrumentation diagnosis. Due to limited access to historical operational data and industry experts for formal consultation, system evaluation was focused on internal logic consistency verification, model sensitivity analysis, and mathematical validation of inference calculations [6], [16], [21],

with CF weights and conditional probabilities established based on the literature. Although the absence of empirical plant data limits objective accuracy measurement under real operational conditions and no user acceptance testing (UAT) with field operators has been conducted, this study provides a methodological contribution in the form of a hybrid inference framework that can be adapted and calibrated once plant data becomes available. Test results demonstrate that the system is capable of executing inference rules consistently, handling ambiguity with logical prioritization, and responding to input changes proportionally, fundamental characteristics required for a reliable diagnostic system before it can be empirically validated in real-time applications.

3.1 Expert System Prototype Implementation

The expert system prototype has been successfully implemented using Python with a Tkinter-based graphical interface. Figure 4 displays the system's diagnosis results in a ranked table that presents damage candidates along with CF scores and Bayesian probabilities. Users can input symptoms and confidence levels through interactive sliders, and the system then displays the primary diagnosis along with a reasoning path and action recommendations.

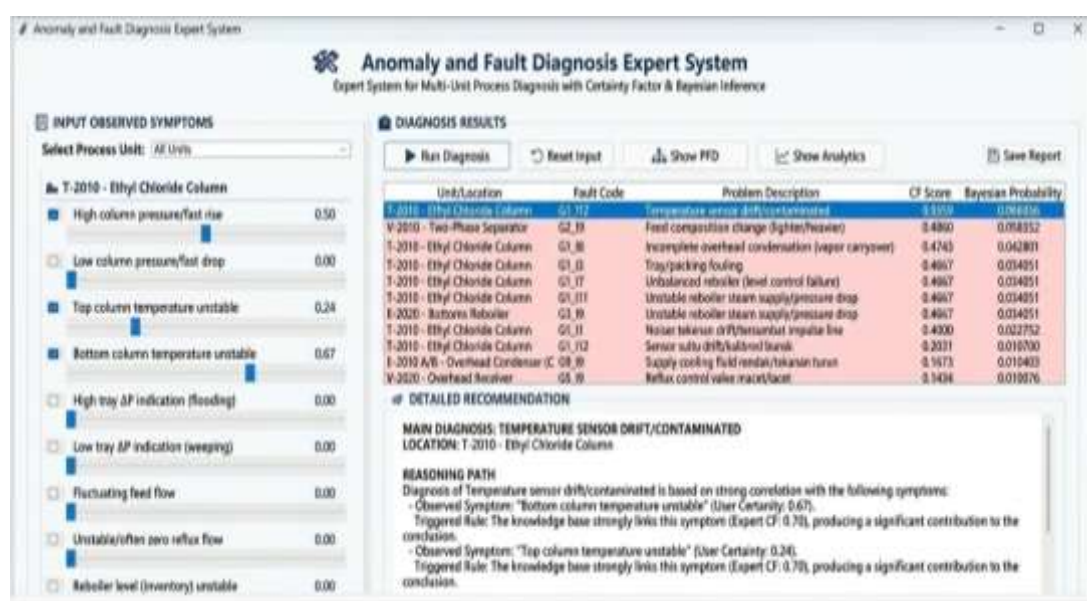


Figure 4. Expert System Prototype Results Display

3.2 Internal Logic Consistency Validation Extreme Case Testing

Extreme case testing was conducted by providing a single maximum-certainty symptom

input ($CF_{User} = 1.0$) to validate individual rules in the knowledge base without interference from other symptoms. Table 1 presents the results of three tested scenarios.

Table 1. Extreme Case Test Results

Scenario	Input Symptom ($CF_{User} = 1.0$)	Expected Diagnosis (Rank #1)	Actual Diagnosis (Rank #1)	Actual CF Score	Actual Bayes Prob.	Result
1	(G1_A2) Low column pressure	(G1_I9) Relief/vent valve open	(G1_I9) Relief/vent valve open	0.9000	0.118012	Valid
2	(G6_A5) Reverse flow	(G6_I4) Check valve failure	(G6_I4) Check valve failure	0.9000	0.131944	Valid
3	(G9_A5) Air ingress	(G9_I6) Inadequate air purging	(G9_I6) Inadequate air purging	0.9000	0.117284	Valid

Across all three scenarios, the system identified the expected diagnosis as the top-ranked result with an actual CF score of 0.9000, consistent with the theoretical calculation $CF_{Actual} = CF_{User} \times CF_{Expert} = 1.0 \times 0.9 = 0.9000$ according to Eq. (1). The correct diagnosis in each scenario consistently received the highest Bayesian probability weight, yielding a Consistency Rate of 100% (3/3 scenarios valid).

Ambiguity Handling Test

To evaluate the system's capability in handling situations where the available evidence does not point to a single conclusion, a scenario was designed using symptom 'G6_A4 High Vibration', which is associated with multiple faults in the knowledge base. This test simulates conditions where a single symptom can be caused by various underlying causes. The test results are presented in Table 2.

Table 2. Ambiguity Handling Test Results for 'High Vibration'

Actual Rank	Fault Description	Rule Weight (CF_{Expert})	Actual Bayes Prob.
1	(G6_I6) Mechanical misalignment	0.9000	0.088785
2	(G6_I3) Worn seal/bearing	0.7000	0.074766
3	(G6_I10) Temperature sensor drift/poor calibration	0.5000	0.056075

The system ranked 'Mechanical misalignment' as the primary diagnosis, corresponding to the highest rule weight ($CF_{Expert} = 0.9000$) in the knowledge base. The ranking order based on CF scores was fully consistent with the ranking order based on Bayesian probabilities, yielding a Consistency Rate of 100% (1/1 case handled with logical ranking).

3.3 Sensitivity Analysis

Sensitivity analysis was conducted to evaluate model stability against variations in user input certainty levels (CF_{User}). Three scenarios were designed by manipulating CF_{User} values across the same symptom combination to observe how the system responds to weight changes [26]. The results are presented in Table 3.

Table 3. Sensitivity Analysis Results

Scenario	Symptom	CF _{User}	Diagnosis Rank #1	CF Score	Bayes Prob.
1	(G3_A5) Decreasing heating ΔT	0.90	(G3_I3) Fouling/scale on upper surface	0.8900	0.302700
	(G3_A1) Reboiler temperature too high/low	0.60			
	(G1_A4) Unstable lower column temperature	0.30			
2	((G3_A5) Decreasing heating ΔT	0.30	(G3_I9) Unstable reboiler steam supply/pressure drop	0.8900	0.254345
	(G3_A1) Reboiler temperature too high/low	0.90			
	(G1_A4) Unstable lower column temperature	0.60			
3	(G3_A5) Decreasing heating ΔT	0.60	(G3_I9) Unstable reboiler steam supply/pressure drop	0.7292	0.132852
	(G3_A1) Reboiler temperature too high/low	0.30			
	(G1_A4) Unstable lower column temperature	0.90			

In Scenario 1, where the highest CF_{User} weight (0.90) was assigned to symptom 'Decreasing heating ΔT ', the system identified 'Fouling' as the primary diagnosis with a posterior probability of 0.3027 and CF of 0.8900. In Scenarios 2 and 3, the redistribution of CF_{User} weights giving dominance to temperature instability symptoms shifted the primary diagnosis to 'Unstable reboiler steam supply/pressure drop'. Across all three scenarios, both CF scores and posterior probabilities changed monotonically in response to weight variations, yielding a Consistency Rate of 100% (3/3 scenarios produced proportional and logical diagnostic shifts).

4. Discussion

4.1 Inference Rule Execution and Logic Consistency

The 100% consistency rate achieved in the extreme case testing confirms that the inference engine executes individual rules precisely without computational errors. The perfect alignment between theoretical and actual CF values (CF_{Actual} = 0.9000) demonstrates that the CF algorithm implementation is mathematically correct, with no bugs in the inference code. This result is fundamental for a rule-based system, as accurate logic execution forms the foundation of diagnostic reliability.

This finding is comparable to previous expert system studies employing CF, with the additional advantage that this system also integrates a Bayesian mechanism to provide a complementary probabilistic perspective.

The consistent alignment between CF-based and Bayesian probability rankings across all extreme case scenarios further reinforces this finding. The fact that both inference pathways independently converged on the same diagnosis under single-symptom conditions confirms that the dual inference architecture functions as intended, where each method validates the output of the other without introducing conflicting conclusions.

4.2 Ambiguity Handling Capability

The ambiguity handling test demonstrated that the system correctly prioritized 'Mechanical misalignment' as the primary diagnosis due to its highest rule weight (CF_{Expert} = 0.9000), while simultaneously presenting 'Worn seal/bearing' (CF_{Expert} = 0.7000) and 'Temperature sensor drift' (CF_{Expert} = 0.5000) as ranked alternatives. The full alignment between CF-based and Bayesian probability rankings confirms that both inference mechanisms respond consistently to the relative evidence strength defined in the knowledge base.

This capability is particularly significant for practical industrial applications, as field symptoms are rarely unambiguous. A single symptom, such as high vibration, can originate from multiple mechanical or instrumentation causes, and the ability to present a prioritized diagnostic ranking rather than a single deterministic output enhances operator situational awareness during troubleshooting. By allowing operators to see both the primary diagnosis and its alternatives alongside their respective confidence scores, the system supports more informed decision-making, especially in transient conditions or when operating near process limits.

4.3 Sensitivity and Robustness of the Hybrid Inference Mechanism

The sensitivity analysis results reveal that the system responds proportionally and logically to changes in CF_{User} weights, which reflects the behavior expected of a robust diagnostic system. In Scenario 1, assigning the highest certainty weight ($CF_{User} = 0.90$) to the symptom 'Decreasing heating ΔT ' correctly produced 'Fouling' as the primary diagnosis (posterior probability 0.3027), which is logically sound as fouling directly causes reduced heat transfer effectiveness in reboiler surfaces [11]. The contribution of this symptom to CF score accumulation can be traced through Eq. (1) and (2): $CF_{i \rightarrow F} = 0.891$, yielding $CF_{Total}(Fouling) = 0.937$.

In Scenarios 2 and 3, redistributing CF_{User} weights to give dominance to temperature instability symptoms caused the primary diagnosis to shift to 'Unstable reboiler steam supply/pressure drop', as this fault has stronger causal associations with multi-location temperature instability patterns in the knowledge base. In Scenario 2, dominance of 'Reboiler temperature too high/low' ($CF_{i \rightarrow F} = 0.63$) combined with other symptoms produced $CF_{Total}(Steam\ supply) = 0.774$, exceeding $CF_{Total}(Fouling) \approx 0.65$, thereby driving the diagnostic shift. The monotonic change of both CF scores and posterior probabilities across all scenarios indicates that the system is neither brittle nor overly sensitive to minor input variations nor insen-

sitive to significant evidence changes, confirming that the CF_{Expert} weights and $P(Si|F)$ values were reasonably calibrated despite the absence of formal industry expert validation.

The practical implication of this proportional sensitivity is that the system assigns greater weight to symptoms with high operator certainty, consistent with real-world troubleshooting processes where experienced operators distinguish primary symptoms (high CF) from secondary symptoms or observational noise (low CF). This behavior ensures that operator judgment is respected without compromising the logical consistency of the knowledge base.

More specifically, the reason a change in CF value reshapes the output is that CF_{User} enters the evidence calculation as a direct multiplier (Eq. 1) before serial combination (Eq. 2): raising the weight on a symptom raises the combined evidence for every fault that symptom supports, which is why shifting weight away from 'decreasing heating ΔT ' and toward the temperature-instability symptoms moved the dominant evidence mass from 'Fouling' to 'unstable reboiler steam supply'. Critically, both the CF scores and the Bayesian posteriors shifted in the same direction and rank order across all three scenarios, and they changed monotonically rather than abruptly. This demonstrates that the system is neither over-sensitive, over-reacting to minor weight changes that may stem from observational noise, nor under-sensitive to genuine shifts in evidence strength. Because every diagnostic shift is fully traceable to explicit rule strengths and evidence weights rather than to opaque computation, the system satisfies the central requirement of an explainable diagnostic aid.

4.4 Value of the Hybrid CF-Bayesian Approach

The results collectively demonstrate that the hybrid CF-Bayesian approach provides clear added value compared to either method applied in isolation. Certainty Factor provides an intuitive mechanism for combining evidence from multiple symptoms in a manner consistent with expert reasoning patterns,

while Bayesian Inference complements it with a rigorous probabilistic framework for updating beliefs based on conditional probabilities $P(Si|F)$ [10], [11]. The consistent alignment between CF rankings and Bayesian probability rankings across all test scenarios, extreme case, ambiguity handling, and sensitivity analysis indicates that both methods converge on the same conclusions under varied conditions.

Importantly, this integration not only improves diagnostic accuracy but also provides an internal sanity check mechanism. Significant divergence between the two rankings would serve as an automatic indicator of inconsistencies in the knowledge base or conflicting evidence requiring further investigation, thereby enhancing system transparency and explainability. This property is particularly valuable in industrial settings where diagnostic decisions carry operational and safety consequences.

4.5 Limitations and Scope of Validation

This study adopted a proof-of-concept approach focused on developing and validating the internal mechanisms of the hybrid CF-Bayesian expert system. The absence of historical plant operational data limits objective accuracy measurement under real operational conditions, and no user acceptance testing (UAT) with field operators has been conducted. Further sub-Expert weights and $P(Si|F)$ values were established through literature synthesis rather than formal industry expert consultation, which may affect the calibration accuracy of the knowledge base for specific plant configurations.

A direct consequence of this scope is that conventional classification metrics such as accuracy, precision, recall, or RMSE relative to expert decisions could not be reliably computed at this stage, because they require a validated ground-truth reference derived from real operational cases or formally annotated expert judgments, neither of which was available. Reporting such metrics without a validated reference would convey a false sense of empirical rigor. Accordingly, the system was instead evaluated with quan-

titative measures appropriate to its developmental stage: a Consistency Rate of 100% across the extreme-case tests (3/3) and the ambiguity-handling test (1/1), full rank-agreement between the CF and Bayesian pathways, and monotonic, proportional responses across the sensitivity scenarios (3/3). These measures verify the correctness and internal robustness of the inference engine, the prerequisite properties that must hold before any meaningful field-accuracy benchmarking can be performed.

Despite these limitations, the study provides a methodological contribution in the form of a hybrid inference framework that is modular and can be calibrated once plant data becomes available. The qualitative comparison of test case results against industry standard troubleshooting guides and technical literature [6], [22] confirmed the reasonableness of the system's conclusions (face validation), supporting the premise that the knowledge base reflects sound engineering judgment. Future work involving empirical validation with real operational data and formal expert review will be essential to establish the system's practical reliability before deployment in real-time monitoring applications.

5. Conclusion

An expert system for instrumentation fault diagnosis in the ethyl chloride separation process has been successfully developed and validated using the hybrid Certainty Factor (CF) and Bayesian Inference approach. Validation results demonstrate that the system executes inference rules consistently with 100% precision in accordance with theoretical calculations, handles ambiguity by logically prioritizing diagnoses based on rule weights, and responds to evidence weight changes proportionally without producing arbitrary conclusions. The alignment between CF rankings and Bayesian probabilities across all test scenarios confirms the validity of the hybrid inference mechanism. Nevertheless, this study has primary limitations in that validation was conducted solely through simulation without historical operational da-

ta, and rule weights have not been validated by industry experts.

This study provides a methodological contribution by demonstrating that the integration of CF and Bayesian Inference produces a diagnostic system that is consistent, robust, and explainable for domains with limited historical data. The developed framework is modular and can be adapted to other process units through customization of the knowledge base according to specific process characteristics. Future research should focus on validation using historical operational data, collaboration with industry experts for knowledge base refinement, and integration with DCS for real-time monitoring.

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List of Symbols

CF_{Expert} = Certainty Factor value representing the expert's degree of belief in a given rule
 CF_{User} = Certainty Factor value representing the user's degree of belief in a given symptom
 $CF_{i \rightarrow F}$ = Combined Certainty Factor from both expert and user for a single inference rule
 CF_{Total} = Total Certainty Factor after serial combination of multiple rules
 F = Variable representing a fault hypothesis
 Si = Variable representing the i -th symptom
 $P(Si|F)$ = Conditional probability of symptom Si occurring given that fault F is present
 $P(F)$ = Prior probability of fault F
 L_F = Posterior log-odds score for fault hypothesis F
 $P^*(F)$ = Posterior probability of fault F after softmax normalization
 β = Normalization base factor in the log-odds calculation
 e = Euler's number, the base of the natural logarithm (used in the softmax function)