

FUZZY DELPHI METHOD FOR IDENTIFYING KEY PARAMETERS IN THE OPTIMIZATION OF INTELLIGENT CONTROL SYSTEMS FOR OIL REFINING PROCESSES

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Abstract. Oil refining involves a series of intricate, nonlinear, and highly dynamic processes that require accurate control to maintain product quality, ensure operational safety, and achieve energy efficiency. As global energy demand grows and refineries aim for improved performance, the demand for intelligent control systems capable of managing uncertainties, external disturbances, and complex multi-variable interactions has increased considerably. Control artificial intelligence-based approaches, like fuzzy logic systems, neural network models, and hybrid intelligent frameworks are increasingly investigated to enhance refinery efficiency and adaptability. A major challenge in developing and optimizing such intelligent control systems is determining the critical parameters that most strongly affect system behaviour. Conventional parameter selection methods frequently rely on deterministic assumptions or limited experimental calibration, which may fail to capture the operational uncertainties characteristic of real refinery conditions. Moreover, this selection process often depends on expert insights typically expressed in qualitative or subjective terms, which traditional quantitative approaches are not well equipped to interpret. The Fuzzy Delphi Method (FDM) presents a powerful means of addressing this issue by merging expert consensus techniques with fuzzy set theory. FDM supports the integration of diverse expert opinions while accounting for ambiguity and uncertainty, making it particularly suitable for identifying parameters within complex industrial systems where both qualitative judgment and quantitative assessment are important. Despite these strengths, the use of FDM for optimizing intelligent control systems in oil refining has not yet been sufficiently investigated. Accordingly, this study employs the fuzzy Delphi technique to systematically determine the key parameters that influence the optimization of intelligent control systems in oil refining processes. By combining expert knowledge through fuzzy evaluation, the proposed methodology establishes a structured and trustworthy foundation for developing more resilient, efficient, and adaptable control strategies.

Keywords: oil refining processes, intelligent control systems, fuzzy Delphi method, expert-based evaluation

METODA FUZZY DELPHI DO IDENTYFIKACJI KLUCZOWYCH PARAMETRÓW W OPTYMALIZACJI INTELIGENTNYCH SYSTEMÓW STEROWANIA W PROCESACH RAFINACJI ROPY NAFTOWEJ

Streszczenie. Rafinacja ropy naftowej obejmuje szereg skomplikowanych, nieliniowych i wysoce dynamicznych procesów, które wymagają precyzyjnego sterowania w celu utrzymania jakości produktów, zapewnienia bezpieczeństwa eksploatacji oraz osiągnięcia efektywności energetycznej. Wraz ze wzrostem globalnego zapotrzebowania na energię i dążeniem rafinerii do poprawy wydajności znacznie wzrosło zapotrzebowanie na inteligentne systemy sterowania zdolne do radzenia sobie z niepewnością, zakłóceniami zewnętrznymi oraz złożonymi interakcjami wielozmiennymi. Coraz częściej bada się podejścia oparte na sztucznej inteligencji, takie jak systemy logiki rozmytej, modele sieci neuronowych oraz hybrydowe struktury inteligentne, mające na celu zwiększenie wydajności i zdolności adaptacyjnych rafinerii. Głównym wyzwaniem przy opracowywaniu i optymalizacji takich inteligentnych systemów sterowania jest określenie kluczowych parametrów, które mają największy wpływ na zachowanie systemu. Tradycyjne metody doboru parametrów często opierają się na założeniach deterministycznych lub ograniczonej kalibracji eksperymentalnej, co może nie uwzględniać niepewności operacyjnych charakterystycznych dla rzeczywistych warunków panujących w rafinerii. Ponadto proces ten często opiera się na spostrzeżeniach ekspertów, wyrażanych zazwyczaj w kategoriach jakościowych lub subiektywnych, których tradycyjne podejścia ilościowe nie są w stanie właściwie zinterpretować. Metoda Fuzzy Delphi (FDM) stanowi skuteczne narzędzie do rozwiązania tego problemu poprzez połączenie technik osiągania konsensusu eksperckiego z teorią zbiorów rozmytych. FDM umożliwia integrację różnorodnych opinii ekspertów przy jednoczesnym uwzględnieniu niejednoznaczności i niepewności, dzięki czemu nadaje się szczególnie do identyfikacji parametrów w złożonych systemach przemysłowych, w których istotne znaczenie mają zarówno oceny jakościowe, jak i ilościowe. Pomimo tych zalet zastosowanie metody FDM do optymalizacji inteligentnych systemów sterowania w rafinacji ropy naftowej nie zostało dotychczas wystarczająco zbadane. W związku z tym w niniejszym badaniu wykorzystano technikę Fuzzy Delphi w celu systematycznego określenia kluczowych parametrów wpływających na optymalizację inteligentnych systemów sterowania w procesach rafinacji ropy naftowej. Dzięki połączeniu wiedzy eksperckiej poprzez ocenę rozmytą proponowana metodologia tworzy uporządkowaną i wiarygodną podstawę do opracowywania bardziej odpornych, wydajnych i elastycznych strategii sterowania.

Słowa kluczowe: procesy rafinacji ropy naftowej, inteligentne systemy sterowania, metoda Fuzzy Delphi, ocena oparta na wiedzy ekspertów

Introduction

Oil refining is one of the most technologically advanced and economically vital branches of the global energy sector. Refinery operations consist of multiple interconnected, nonlinear, and dynamic processes such as distillation, cracking, reforming, and hydro treating that require highly accurate control to maintain product quality, ensure safe operation, meet environmental standards, and optimize costs. As these processes become more complex, and as regulatory pressures and market volatility increase, there is a rising need for advanced control and optimization methods capable of functioning effectively under uncertainty and varying operating conditions. Traditional control methodologies, such as proportional–integral–derivative (PID) controllers and model-based approaches, often struggle with the nonlinear behaviours, delays, and disturbances typical of refinery processes. Consequently, there has been a noticeable shift toward smart control approaches that incorporate artificial intelligence methods, including fuzzy logic systems, neural computing models, evolutionary computation methods, hybrid intelligent methods. These approaches provide better adaptability, improved fault tolerance, and enhanced modelling capabilities

for complex, hard-to-quantify process interactions. However, a fundamental challenge remains determining and selecting the most influential parameters that shape the performance of intelligent control systems used in refinery environments. The effectiveness of such systems depends heavily on appropriate parameter identification; poor parameter selection can result in reduced efficiency, increased energy consumption, operational instability, or elevated safety risks. Conventional parameter identification methods often rely on deterministic assumptions or limited empirical tuning, which may fail to represent the uncertainties present in real refinery operations. In addition, expert knowledge crucial in industrial decision-making is generally expressed in subjective, linguistic, or imprecise terms that cannot be easily processed by traditional quantitative techniques. The Fuzzy Delphi Method (FDM) offers a robust solution by combining expert consensus processes with the flexibility of fuzzy set theory. This method enables systematic collection, aggregation, and assessment of expert judgments while accounting for ambiguity, uncertainty, and differences in confidence levels. Using fuzzy linguistic scales, FDM provides a more accurate portrayal of expert evaluations and reduces inconsistencies commonly encountered in standard Delphi



procedures. As such, FDM is particularly well suited for identifying key parameters in complex industrial systems like oil refineries, where expert insight is essential and uncertainty is inherent. Although FDM has been successfully applied in various engineering and decision-making contexts, its use in optimizing intelligent control systems within oil refining remains limited. Existing research tends to focus on developing specific intelligent controllers or refining process units, while systematic identification of the critical parameters affecting overall control system performance has received comparatively little attention. Therefore, this study employs utilizing the fuzzy Delphi technique to recognize, assess, and rank the key parameters that have the greatest impact on optimizing intelligent control systems in oil refining. By integrating expert knowledge through fuzzy-based evaluation and consensus-building procedures, the proposed methodology provides a structured and reliable foundation for determining essential parameters. This contributes to enhancing the precision, robustness, and adaptability of intelligent control strategies, while also guiding future development efforts and reducing risks associated with implementation. The findings of this research offer valuable guidance for researchers, automation engineers, and refinery decision-makers working to improve the efficiency, stability, and flexibility of intelligent control systems. Furthermore, the results pave the way for future studies involving multi-criteria analysis, advanced system modelling, and the use of AI-driven optimization techniques, ultimately supporting the development of next-generation refinery automation technologies. The organization of article is structured as follows. Section 1 provides an overview of the pertinent literature. Section 2 outlines fundamental concepts of fuzzy numbers and fuzzy Delphi employed in the analysis. Section 3 introduces the fuzzy Delphi based methodology developed for identifying key parameters of oil refining processes. Finally, study's results and contributions are encapsulated in the conclusion.

1. Literature review

Modern refinery operations are driven by interconnected, nonlinear, multi-variable processes e.g. distillation, cracking, hydro treating, etc. that challenge conventional control methods. Recent surveys and reviews highlight a clear shift from classical PID and simple model-based controllers to intelligent techniques for control, including fuzzy logic [28], neural computing models, model-based predictive control, and hybrid AI architectures [3] because these approaches better handle nonlinearity, disturbances, and process interactions in refinery units. These intelligent methods have been applied to tasks including soft sensing, multivariable control, fault diagnosis, and process optimization [4]. Accurate identification and selection of control parameters (e.g., tuning gains, model coefficients, relevant input/output variables, and thresholds for fault detection) are critical for controller performance and operational safety [5]. Classical identification procedures and purely data-driven tuning often fail to capture the epistemic uncertainty present in industrial settings and may produce models that lack robustness under changing operating regimes. Recent work therefore emphasizes hybrid approaches that combine data-driven model identification with adaptive or online parameter estimation to reduce uncertainty and improve controller reliability [2]. The Delphi method is well established for eliciting expert consensus on complex, uncertain topics [6]. The Fuzzy Delphi Method (FDM) augments standard Delphi by representing expert linguistic judgments as fuzzy numbers, which allows aggregation under vagueness and reduces loss of information from qualitative responses [7]. Practical guides and methodological reviews show FDM's strengths in improving consistency across rounds, accommodating imprecise opinions, and producing ranked lists of factors or parameters for subsequent analysis [20]. FDM has been successfully combined with other multi-criteria techniques such as AHP [8], TOPSIS [19], ANFIS [16], ANN [11], DEMATEL [13] in diverse engineering applications including input selection for predictive models,

supplier selection, maintenance indicator identification, and accident investigation [1]. There is growing evidence of FDM (and its spherical/extended fuzzy variants) being used specifically in oil, gas, and heavy industry domains to identify key performance indicators, maintenance criteria, and sustainability/operational indicators [18]. Studies integrating fuzzy-Delphi outputs with ranking or decision methods TOPSIS, BWM, AHP, or hybrid AI models show that expert-driven parameters produced by FDM serve as robust inputs for downstream modelling and optimization tasks in industrial settings [21]. Nevertheless, direct applications of FDM for selecting or prioritizing control-system parameters in refinery process control remain sparse [22]. Although intelligent controllers for refinery units and hybrid parameter-selection techniques have been widely studied, the literature lacks systematic, expert-based frameworks tailored to identify the most influential control parameters for AI-based controllers in oil refining. Existing studies either develop controllers without a rigorous expert-driven parameter screening step, or apply FDM to adjacent problems (maintenance indicators, supplier selection, sustainability metrics) rather than control parameter identification [23]. This gap motivate the present work: applying FDM to produce a validated, prioritized set of parameters that can feed into controller design, multi-criteria evaluation, and AI-based optimization for refinery automation [26]. It supports decision-makers in making comprehensive and strategic decisions consistent with organizational objectives and preferences [25]. Sustainability considerations are addressed during the evaluation process.

2. Theoretical framework

The Delphi method is a method of obtaining group knowledge, which has been employed for more than fifty years. Calculations by the Delphi method rely on the view of experts [12]. Consequently, mistakes or disagreements in expert evaluations affect the calculation results. Although traditional Delphi methods rely on experts' cognitive skills and judgments for comparison, a limited number of expert opinions cannot fully capture the complexity of human thinking. The application of fuzzy sets better accommodates linguistic and inherently imprecise human assessments, making them more appropriate for real-world decision-making through the use of fuzzy numbers. Consequently, the level of error is reduced when fuzzy sets are employed [17]. The Delphi technique is survey approach of checking the assessment of an expert group and does not require group members to work together and does not allow group members to meet and exchange ideas on the problem to be solved, that is, the independence of the opinions of group members is ensured [11]. The method provides analysis and selection of solutions by performing several multi-stage cyclic procedures. Members of the group are informed about the problem situation and invited to evaluate possible solutions based on a few indicators. Each member of the group anonymously and independently gives evaluations and justifications of decisions or offers his options. All ratings and opinions of members of the group are collected centrally and combined into a generalized document. Each member of the group receives a copy of the summary document. Getting to know the opinions of other participants, he can change his opinion about possible solutions to the problem. These steps are repeated as many times as necessary to reach an agreed solution [14]. The Delphi method is the most effective when developing solutions to complex, poorly understood, unique problems that are initially characterized by high uncertainty and require the involvement of specialists of a different profile. This requires considerable time and clear organization of the procedure for its implementation. The traditional problem of the Delphi technique is the definition of rounds of the Delphi technique. Studies have shown that one round can be used for the selection criteria of the fuzzy Delphi method [24]. The fuzzy Delphi methodology is extension of the classic Delphi method, a multi-criteria decision-making

method that involves considering both existing criteria and additional criteria proposed by experts in the survey [10].

The definition of an expert in the Delphi method depends on the specific context and field of application. Expertise is generally characterized by experience, specialized skills, or in-depth knowledge in a particular domain. However, selected experts are not required to possess formal status or standardized academic credentials. Expertise is typically determined by four key criteria. The first is substantive knowledge and practical engagement with the research problem. The second is the expert's ability and willingness to participate in the study. The third is the availability of adequate time to complete the Delphi process, and the fourth is effective communication between the researchers and the experts. In general, an expert may be any individual with relevant knowledge, and in some cases, Delphi panels are designed to encompass a broad range of interests and disciplinary perspectives. However, since expert opinion is required, purposive sampling may be necessary. Although the selected experts are multidisciplinary, there are some difficulties in identifying and justifying their selection. In fact, there are currently no external criteria in the literature regarding the selection of Delphi experts. However, choosing the most appropriate group of experts and defending this choice becomes a critical task for every researcher. This method employs linguistic terms to capture expert opinions. While expert knowledge and cognitive abilities are utilized in the decision-making process, quantitatively representing expert judgments cannot fully reflect human reasoning [15]. The application of fuzzy sets better aligns with the linguistic and inherently uncertain nature of human perceptions, making fuzzy numbers more suitable for real-world decision-making. The linguistic terms representing varying levels of criterion importance are defined using a seven-point Likert scale. If the opinion of any expert is expressed by a triangular fuzzy number the simplest way calculating the fuzzy mean

of the expert asses, is $\left(\sum l_i / n, \sum m_i / n, \sum u_i / n \right)$. The

expression of linguistic terms related to the importance of criteria by triangular fuzzy numbers with a seven-point scale is as follows.

Completely insignificant – (0, 0, 0.1),

Highly insignificant – (0, 0.1, 0.3),

Low significant – (0.1, 0.3, 0.5),

Medium significant – (0.3, 0.5, 0.7),

Significant – (0.5, 0.7, 0.9),

Highly significant – (0.7, 0.9, 1),

Completely significant – (0.9, 1, 1).

New attribute determined by expert is expressed by a triangular fuzzy evaluation (l_i, m_i, u_i) . In the subsequent stage, the differences between each expert's individual judgment and the collective opinions of other experts are statistically analysed and communicated back to the experts. This procedure is repeated until the responses converge toward the desired outcome. Finally, following the fuzzy aggregation of expert opinions, the results are fuzzified, and the significant criteria are evaluated using a predefined threshold and retained. Various advanced defuzzification techniques exist, among which one of simplest is calculating mean fuzzy numbers

$\left(\sum l_i / n + \sum m_i / n + \sum u_i / n \right) / 3$. To enhance the accuracy

of results, this method can be extended by involving additional experts and increasing the number of iteration rounds. This approach not only retains the most significant criteria but also establishes a hierarchical structure by identifying their relative priorities. The fuzzy Delphi method integrates the traditional Delphi technique with fuzzy set theory and was first introduced by Kaufman and Gupta in 1988 [12]. The Delphi method itself is an interactive forecasting approach that relies on iterative feedback from a panel of experts over multiple rounds until consensus is achieved. However, in conventional Delphi methods, the quantitative representation of expert judgments does not fully

capture the complexity of human reasoning. Consequently, incorporating fuzzy sets into the Delphi framework enhances decision-making effectiveness and reduces error rates. The compatibility between the fuzzy Delphi method and the traditional Delphi approach was demonstrated by Ishikawa et al. in 1993 through a comparative analysis of the classical Delphi method, the Max–Min fuzzy Delphi method, and the fuzzy Delphi method with fuzzy integration [9]. In the classical Delphi process, expert responses are statistically evaluated in each round, and feedback is provided to guide subsequent questionnaires until satisfactory results are obtained. In contrast, the fuzzy Delphi method employs fuzzy numbers to statistically analyse expert responses in each iteration. Fuzzy statistical analysis is used to assess deviations between individual evaluations and the aggregated expert consensus, and this information is fed back to the experts. This iterative process continues until convergence toward an acceptable solution is achieved, although it typically requires more time to gather expert opinions. The main negative and positive features of the classical Delphi method are the high cost due to the repeated survey, the low recovery rate of the survey, the ease of reaching a consensus in the event of misinterpretation of the expert opinion, and the preservation of anonymity among the experts. The core procedure of the fuzzy Delphi method involves defining an appropriate scale for the defuzzification of linguistic expressions, determining the importance levels of criteria through defuzzification, aggregating expert opinions using fuzzy numbers, and statistically analyzing the deviations between individual judgments and the collective average. The experts' evaluations are then reviewed and adjusted based on feedback from the previous round. Subsequently, the aggregated fuzzy values are defuzzified, a threshold value is selected, and the significance of the criteria is assessed. A triangular fuzzy number is denoted as $\tilde{A} = (a, m, b)$ [27]. It is usually illustrated using a triangular membership function and defined through three principal parameters:

a is the left boundary, b is the peak or most representative value, and c is the right boundary. Corresponding membership function assigns a membership value (μ) to each point within this interval based on these parameters. The graphic depiction of triangular fuzzy number is shown in Figure 1.

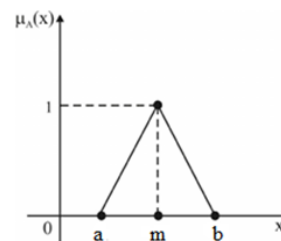


Fig. 1. Triangular fuzzy numbers

Equation (1) illustrates the membership function $\mu_{\tilde{a}}(x)$ corresponding to a triangular fuzzy number membership.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{m-a}, & a < x < m \\ \frac{x-m}{b-m}, & m < x < b \\ 0, & x \geq b \end{cases} \quad (1)$$

Defuzzification is the process of converting fuzzy sets, expressed via linguistic terms that capture uncertainty or imprecision, into precise, crisp values suitable for analysis and decision-making. This step is essential in fuzzy logic systems because it allows practical conclusions to be derived from fuzzy input data. For fuzzy numbers, which represent uncertain or approximate quantities, defuzzification entails selecting a single representative

(crisp) value that best reflects the information conveyed by the fuzzy number. One such defuzzification technique is illustrated in Equation (2).

$$v = \frac{a + m + b}{3} \quad (2)$$

3. Research methodology

The fuzzy Delphi method is implemented through several sequential steps:

Step 1. The qualitative variables are identified, and the necessary information is gathered to develop the initial questionnaire.

Step 2. Membership functions are defined for each variable. For instance, if the evaluation involves different factors such as social, political, or economic, a triangular membership function is assigned to each one. The three parameters that define each membership function are the minimum value – $\min J$, maximum value – $\max J$, and geometric mean – $\sqrt[n]{\prod mean j}$, where j represents sample size, n represents number of experts.

Step 3. The values obtained in the previous step are incorporated into a revised questionnaire, which is then sent back to the experts for further evaluation.

Step 4. Statistical analyses are conducted to verify whether the defined membership functions are appropriate and consistent.

Step 5. Once the membership functions are validated, fuzzy numbers are assigned to the linguistic terms used in the assessment. For example, if a quality model includes social, economic, health, and educational factors, each factor requires a corresponding membership function triangular, trapezoidal, or another suitable form.

To illustrate the fuzzy Delphi approach for determining and validating the importance of criteria, it is useful to compare it with the traditional Delphi method. One key advantage of the fuzzy Delphi technique is that it enables criteria and their sub-elements to be screened and selected within a single round.

The main stages of applying the fuzzy Delphi method include establishing an appropriate linguistic scale for defuzzification, converting expert linguistic judgments into fuzzy data, defuzzifying the collected information, and selecting the results.

Step 1. Expert opinions are gathered, and their linguistic expressions are expressed in terms of fuzzy numbers. In fuzzy Delphi screening process, an appropriate fuzzy scale must be defined to represent respondents' linguistic assessments. This can be achieved using established fuzzy scale development methods or general fuzzy linguistic scales. Triangular fuzzy numbers are commonly used for 5-point, 7-point, or 9-point importance scales. For a five-point scale, the triangular fuzzy numbers may be defined as illustrated in Figure 2.

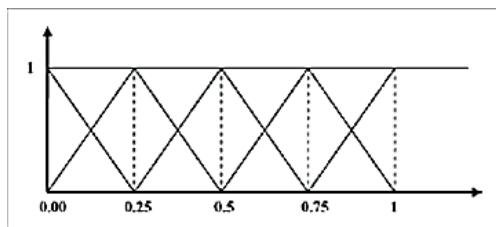


Fig. 2. Triangular fuzzy numbers on a five-point rating scale

Highly significant (0.75,1,1), Significant (0.5,0.75,1), Medium significant (0.25,0.5,0.75), Slightly significant (0,0.25,0.5), Small significant (0,0,0.25).

Step 2. Fuzzy aggregation of opinions. Fuzzy aggregation of expert judgments involves collecting and converting their views into fuzzy values using the selected fuzzy scale. Once the opinions are fuzzified, they must be combined. Various techniques exist for aggregating fuzzy expert assessments. When an expert's evaluation is expressed as triangular fuzzy number, the most

straightforward approach is to compute the fuzzy average of all expert judgments [12]:

$$F_{average} = \frac{\sum l}{n}, \frac{\sum m}{n}, \frac{\sum u}{n} \quad (3)$$

Besides the fuzzy mean, several alternative techniques can be applied to combine expert judgments. These aggregation procedures are largely empirical approaches proposed by different scholars. For example, common method for aggregating triangular fuzzy numbers uses $\min l$, average m , and $\max u$ values of the set [9].

$$F_{aggregation} = \left(\min \{l\}, \left\{ \frac{\sum m}{n} \right\}, \max \{u\} \right) \quad (4)$$

Certain studies recommend using the geometric mean instead of the basic arithmetic mean [9].

$$F_{aggregation} = \left(\min \{l\}, \prod \{m\}, \max \{u\} \right) \quad (5)$$

Some researchers propose determining the upper and lower bounds by applying the geometric mean instead of traditional averaging methods [15]. Ultimately, the selection of an aggregation technique for expert judgments is left to the discretion of the researcher. Employing fuzzy aggregation methods rather than simple fuzzy means makes it possible to better capture the full variability in experts' assessments. An expert is classified

as pessimistic if the value of u_i falls below $\frac{\sum l}{n}$, whereas an optimistic expert is identified if the value of l_i exceeds $\frac{\sum u}{n}$.

To enhance reliability, the evaluations of both pessimistic and optimistic experts may be excluded from the analysis.

Step 3. Defuzzification. Following the fuzzy aggregation of expert evaluations, the resulting values must be converted into crisp numbers. In many fuzzy-based approaches, the researcher transforms the final fuzzy quantities into a single, interpretable value. Typically, aggregated triangular or trapezoidal fuzzy numbers are reduced to a representative crisp value that reflects the central tendency of the fuzzy set. This conversion process is known as defuzzification. Although numerous sophisticated defuzzification methods exist, one of the most straightforward techniques involves taking the average of triangular fuzzy numbers.

$$\text{If } \tilde{f} = (l, m, u) \text{ then } f = \frac{l + m + u}{3} \quad (6)$$

We can also use a more complex method: $f_{average} = (l, m, u)$.

$$x_m^1 = \frac{l + m + u}{3}, x_m^2 = \frac{l + 2m + u}{4}, x_m^3 = \frac{l + 4m + u}{6} \quad (7)$$

To explain the fuzzy Delphi algorithm, it is important to distinguish between its two primary applications: criterion selection and forecasting. Criterion selection purpose is to identify, filter, and validate the most relevant criteria in a decision-making or evaluation process, especially under uncertainty. The fuzzy Delphi method is also used for predicting future events, trends, or values when expert knowledge is uncertain or imprecise. Guidelines for implementing the Delphi technique using fuzzy logic principles have been established. Initially, expert opinions are converted into fuzzy values according to an appropriate fuzzy scale. These fuzzified opinions are then aggregated using fuzzy aggregation methods. In the Delphi method for criteria selection, results are obtained through defuzzification and threshold analysis to assess the suitability of each criterion. In contrast, the Delphi forecasting approach involves repeating the calculation of averages and expert judgments over successive rounds. This iterative process continues until two consecutive averages converge sufficiently, indicating stability in expert consensus.

3.1. Research design

Optimizing intelligent control systems in oil refining processes requires precise tuning of numerous interrelated parameters that influence product quality, energy efficiency, operational safety, and overall system performance. However, identifying the key parameters is challenging due to the nonlinear, dynamic, and multi-variable nature of refinery operations, combined with uncertainties in process data and variability in expert knowledge. Traditional parameter selection methods often rely on deterministic models or limited experimental data, which may not adequately capture the uncertainty and subjectivity inherent in expert judgments. Therefore, there is a need for a systematic approach that can collect, fuzzify, aggregate, and analyse expert opinions to identify and prioritize the parameters that most significantly affect the optimization of intelligent control systems. This study addresses this gap by applying the Fuzzy Delphi Method (FDM) to provide a structured, reliable, and consensus-driven framework for key parameter identification, supporting the development of robust, adaptive, and efficient control strategies in oil refining processes. Assume that $C = \{C_1, C_2, C_3, C_4, C_5, C_6\}$ is a set of criteria: C_1 is control accuracy – ability to maintain optimal process parameters, C_2 is response speed / real-time capability – how quickly the system reacts to disturbances, C_3 is reliability and stability – consistent functioning under varying operating conditions, C_4 is fault detection and diagnostics – ability to detect and isolate abnormalities, C_5 is scalability and adaptability – suitability for different units of a refinery (distillation, cracking, etc.), C_6 is process safety enhancement – contribution to safer operation and reduced risk.

To achieve consensus on the relative importance of the criteria, each expert assesses them using linguistic terms: Very High (VH), High (H), Medium (M), Low (L), and Very Low (VL). These evaluations are then used to construct a decision matrix. The linguistic assessments of the eight experts (decision-makers) for the criteria are presented in Table 1.

Table 1. Linguistic characterization of criteria

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
C_1	VH	H	M	VH	L	H	H	L
C_2	H	M	M	M	VL	H	L	L
C_3	VH	M	M	VH	M	M	M	M
C_4	H	H	L	H	VL	L	L	H
C_5	H	M	L	H	H	VL	M	L
C_6	H	M	L	M	VH	VL	L	M

3.2. Key parameters

In optimizing intelligent control systems for oil refining processes, several key parameters play a critical role in determining system performance, efficiency, and safety. One fundamental criterion is control accuracy (C_1), which reflects the system's ability to maintain process variables, such as temperature, pressure, and flow rate, within desired limits. High control accuracy ensures that product quality remains consistent while minimizing waste and energy consumption.

Table 2. Expert opinions of criteria

	D_1	D_2	...	D_8	Fuzzy average ΣD	Crisp value	Weight W
C_1	(0,75,1,1)	(0,5, 0,75, 1)	...	(0, 0,25, 0,5)	(0,41,0,78,0,84)	0.63	0.22
C_2	(0,5, 0,75, 1)	(0,25, 0,5, 0,75)					
	...	(0, 0,25, 0,5)	(0,22,0,47,0,72)	0.47	0.15		
C_3	(0,75, 1, 1)	(0,25, 0,5, 0,75)					
	...	(0,25, 0,5, 0,75)	(0,38,0,63,0,81)	0.58	0.18		
C_4	(0,5, 0,75, 1)	(0,5, 0,75, 1)	...	(0,5, 0,75, 1)	(0,25,0,47,0,72)	0.48	0.15
C_5	(0,5, 0,75, 1)	(0,25, 0,5, 0,75)					
	...	(0,25, 0,5, 0,75)	(0,25,0,47,0,72)	0.48	0.15		
C_6	(0,5, 0,75, 1)	(0,25, 0,5, 0,75)					
	...	(0,25, 0,5, 0,75)	(0,25,0,47,0,72)	0.48	0.15		

Another essential parameter is response speed or real-time capability (C_2), which refers to the system's ability to react quickly to changes in process conditions. In dynamic refining operations, delays in response can lead to suboptimal performance or even safety hazards, making rapid and reliable control actions crucial. Delays in data acquisition, signal processing, decision-making, or actuator response can result in deviations from optimal operating conditions, reduced product quality, increased energy consumption, or even safety hazards. Reliability and stability (C_3) constitute another core factor, as intelligent control systems must operate continuously under varying process conditions without frequent failures or deviations. A stable and dependable control system not only improves operational efficiency but also reduces maintenance costs and downtime. The ability to perform fault detection and diagnostics (C_4) is equally important. Intelligent systems must identify abnormalities or equipment malfunctions promptly and provide diagnostic insights to prevent process disruptions or safety incidents. This capability enhances both the resilience and safety of refinery operations. Scalability and adaptability (C_5) are also key parameters. Refinery processes are often expanded, modified, or integrated with new technologies. Control systems must therefore be flexible enough to adapt to changing process requirements and scalable to handle increased complexity or capacity. Finally, process safety enhancement (C_6) remains a central concern, particularly, in refining operations where high temperatures, pressures, flammable materials, and hazardous chemical reactions are routinely involved. Intelligent control systems must ensure safe operation by monitoring critical variables, preventing dangerous deviations, and supporting compliance with industry safety standards. By prioritizing these key parameters, control accuracy, response speed, reliability and stability, fault detection and diagnostics, scalability and adaptability, and process safety refinery operators can optimize intelligent control systems for both performance and safety, ultimately supporting more efficient, resilient, and adaptive operations.

3.3. Solution of problem

The overall fuzzy weight for each criterion is then determined by aggregating the linguistic evaluations provided by all eight decision-makers. In the fuzzy decision-making questionnaires, expert opinions are represented as triangular fuzzy numbers, as presented in Table 2.

The total weights of the criteria are computed using the formulas outlined below.

$$\begin{aligned}
 D_{ij} &= (1/m) \otimes (D_{ij}^1 \oplus D_{ij}^2 \oplus \dots \oplus D_{ij}^m), \\
 D_{ij} &= (LD_{ij}, MD_{ij}, UD_{ij}), \\
 LD_{ij} &= \left(\sum_{ij}^m LD_{ij}^k \right) / m, \quad MD_{ij} = \left(\sum_{ij}^m MD_{ij}^k \right) / m, \\
 UD_{ij} &= \left(\sum_{ij}^m UD_{ij}^k \right) / m, \\
 BNP_{ij} &= \left[(UD_{ij} - LD_{ij}) + (MD_{ij} - LD_{ij}) \right] / 3 + LD_{ij} \forall i, j
 \end{aligned}
 \tag{8}$$

The outcomes of the calculations, along with the ranking of the criteria based on their relative importance, are presented in Table 3.

Table 3. Ranking criteria based on relative importance

Rank	Criteria	Value
1	C_1	$H(C_1) = 0.63$
2	C_3	$H(C_3) = 0.58$
3	C_2	$H(C_2) = 0.48$
4	C_4	$H(C_4) = 0.46$
5	C_6	$H(C_6) = 0.43$
6	C_5	$H(C_5) = 0.41$

4. Discussion and conclusion

The findings of this study provide valuable insight into the elements that significantly influence the optimization of intelligent control systems in oil refining operations. Because refinery processes exhibit nonlinear behaviours, strong interdependencies among variables, considerable uncertainty, and strict operational requirements, understanding which factors most profoundly affect system performance is crucial for maintaining efficiency, stability, and safety. The fuzzy Delphi evaluation conducted in this work shows that the parameters do not contribute equally to system optimization; instead, their impacts differ notably, emphasizing the complex nature of refining systems and the necessity for customized control strategies. A major finding from the analysis is the well-defined ranking of the evaluated parameters, revealing a clear structure of relative importance. Expert assessments were processed through fuzzy logic to minimize bias, account for uncertainty, and capture nuanced evaluations that conventional precise-scale methods may fail to represent. The ranking demonstrates that some parameters have a much greater influence on control stability, responsiveness, and prediction capability than others. This underscores the need to prioritize these key factors when developing or tuning intelligent control systems. Rather than distributing attention evenly across all inputs, engineers should direct more analytical and computational resources toward the most impactful parameters. The results also reinforce the idea that effective intelligent control systems in oil refining must be grounded in specific process knowledge. The parameters ranked as highly important are closely tied to the nonlinear and dynamic characteristics of refinery units such as distillation columns, hydro processing reactors, and catalytic cracking units. In these systems, even small deviations can propagate rapidly, affecting product quality, energy efficiency, and overall safety. Identifying the parameters that matter most allows engineers to refine measurement precision, introduce more reliable sensing technologies, and design advanced control approaches such as adaptive fuzzy control or model predictive control that focus on the variables with the greatest effect on system behaviour. Another key point from the findings is the link between parameter significance and uncertainty management. Refineries experience frequent disturbances, noisy data, and changing operating conditions, making reliable control a challenge. By incorporating expert judgments expressed through fuzzy linguistic terms, the fuzzy Delphi method proves effective for handling uncertainty and reaching consensus on parameter priorities. This aligns with the broader direction in control engineering, where successful optimization depends not only on sophisticated algorithms but also on the accuracy and dependability of the input parameters used. Although lower-ranked parameters still play a role, their reduced influence suggests that variations in these areas are less likely to cause substantial performance deviations. The results further highlight the importance of multi-expert collaboration in refining system design. Refinery optimization requires input from control engineers, process specialists, safety experts, and plant operators. The fuzzy Delphi method enabled the integration of these varied perspectives, resulting in a more comprehensive evaluation

of parameter importance. Such interdisciplinary cooperation is critical when dealing with complex industrial systems where no single expert possesses complete knowledge of all influencing factors.

This study applied the Fuzzy Delphi Method to systematically identify and prioritize key parameters influencing the optimization of intelligent control systems in oil refining processes. The method was selected because it combines the structured consensus-building principles of the traditional Delphi technique with fuzzy set theory, allowing experts to express their judgments under conditions of uncertainty, ambiguity, and imprecision. Through iterative evaluation of candidate parameters by a panel of domain experts, the FDM facilitates the identification of the most significant criteria while reducing the influence of individual subjective judgments. The identified parameters were subsequently assessed according to their relative importance and relevance to the operational requirements of intelligent refining control systems. This approach provides a systematic and reliable basis for establishing a prioritized set of parameters that can support the design, evaluation, and implementation of intelligent control solutions, while also improving their responsiveness, efficiency, reliability, and safety in complex and dynamic refining environments. A panel of experts with relevant knowledge and professional experience in oil refining, process control, automation, artificial intelligence, and industrial operations was considered to evaluate the proposed parameters. The initial parameters were developed based on an extensive review of the relevant literature and the operational characteristics of intelligent control systems. These parameters included technical, operational, economic, reliability, responsiveness, adaptability, and process safety considerations. The experts evaluated the importance of each parameter using predefined linguistic scales, after which the responses were transformed into corresponding fuzzy values.

The collected judgments were then aggregated to determine the collective importance of each parameter. A defuzzification and threshold-based screening procedure was subsequently employed to distinguish the parameters that achieved an acceptable level of expert consensus from those considered less significant. This process reduced the potential influence of individual bias and ensured that the final parameter set reflected the collective knowledge and experience of the expert panel. The resulting prioritized parameters provide a systematic foundation for assessing and optimizing intelligent control systems under the complex, nonlinear, and dynamic conditions characteristic of oil refining processes.

Furthermore, the application of the FDM enables the study to establish a transparent and reproducible decision-making framework. By integrating expert knowledge with a quantitative evaluation procedure, the method helps identify the parameters that should receive greater attention during the development, implementation, and evaluation of intelligent control systems. The resulting framework can therefore support decision-makers in balancing competing objectives, including control performance, response speed, process stability, energy efficiency, system reliability, adaptability, economic performance, and process safety. Ultimately, the FDM results contribute to the development of a more robust parameter structure for intelligent control system optimization and provide a basis for subsequent multi-criteria analysis, modelling, and empirical validation. By integrating expert opinions and accounting for uncertainty through fuzzy linguistic terms, the approach provided a structured and reliable framework for evaluating the relative importance of multiple control criteria. The results indicate a clear ranking of the parameters considered, with identified as the most critical, followed by C_3 , C_2 , C_4 , C_6 , and C_5 being the least significant. This ranking highlights the parameters that should be prioritized during the design, tuning, and optimization of intelligent control systems to achieve enhanced performance, reliability, and operational safety. This hierarchy provides valuable insights into which aspects of intelligent control systems should receive the greatest

attention during system design, calibration, and optimization. For example, the predominance of control accuracy criterion highlights the necessity of focusing on this parameter to ensure overall system effectiveness, while the lower ranking of scalability and adaptability criterion suggests that it may have a limited impact on operational outcomes and can be given secondary consideration.

The results underscore several important considerations for the utilization and evolution of intelligent control systems in oil refining. First, parameters related to control accuracy, response speed, and reliability are often the most influential, reflecting the critical need for precise and timely control in complex refinery operations. Second, features such as fault detection, adaptability, and process safety, while ranked lower in this evaluation, remain essential for robust system performance, particularly in scenarios involving abnormal conditions or process disturbances. Prioritizing the parameters identified through FDM allows engineers and decision-makers to allocate resources efficiently, reduce the risk of system failures, and improve both operational efficiency and safety. Furthermore, the use of the Fuzzy Delphi Method proved to be particularly effective in capturing the nuanced opinions of multiple experts, accounting for uncertainty, and translating qualitative judgments into quantitative assessments. Unlike traditional Delphi methods, the fuzzy approach allows for a more flexible representation of expert opinions through linguistic variables and triangular fuzzy numbers, reducing the impact of individual bias and enhancing the reliability of the consensus achieved. This demonstrates the utility of FDM not only as a tool for parameter identification but also as a framework for structured decision-making in complex industrial systems.

In conclusion, this study confirms that the systematic identification and prioritization of key parameters are essential for optimizing intelligent control systems in oil refining. By applying the Fuzzy Delphi Method, it is possible to derive a clear, expert-driven ranking of critical parameters, providing a reliable foundation for the design and implementation of more efficient, adaptive, and safe control strategies. The findings of this research contribute to the advancement of intelligent control in refinery operations, offering practical guidance for engineers and decision-makers. Future research can build upon this framework by integrating the identified parameters into simulation-based optimization models or combining FDM in conjunction with other MCDM methods, further enhancing the performance and resilience of intelligent control systems in complex industrial environments.

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