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Research Paper

Fuzzy logic index for subsurface utility engineering

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ABSTRACT

Conflict with subsurface utilities during project implementation is a growing concern for many municipalities as it increases time and budget. Subsurface utilities refer to buried infrastructures such as water, gas, and electric lines, which vary in material, size, and configuration. Many existing subsurface utility studies proposed to assist in decision-making use traditional computer or paper log methods, exhausting time and affecting accuracy. In this study, a fuzzy logic model is used to develop a complexity number named Fuzzy Logic Index for Subsurface Utility Engineering (FLI-SUE) to determine the appropriate investigation level of subsurface utilities for engineering project implementation. This complexity number does not have units, and its value spans between 0 and 100. The higher the FLI-SUE number, the higher the investigation level of subsurface utilities. FLI-SUE number may assist planners, operators, engineers and decision-makers in determining the most appropriate response to the subsurface utility conflicts in projects construction. A set of input parameters presented in the literature were considered in the current fuzzy logic model.

1. Introduction

Subsurface Utility Engineering (SUE) entails a thorough evaluation and supervision of different underground utilities, each possessing distinct characteristics that impact the complexity of engineering ventures. Minimal spending on SUE studies may save up to 50% of the total project budget in some transportation projects [1]. The SUE procedure is affected by several significant elements, such as Density of Utilities (DOU), Type of Utilities (TOU), Material of Utilities (MOU), and Diameter. For instance, the density of utilities, or the amount of underground infrastructure in a specific area, contributes to project intricacy, particularly in urban environments where higher density heightens the risk of conflicts during excavation. Various types of utilities, such as water, gas, telecommunications, and electrical lines, present specific challenges; for example, high-voltage electric cables necessitate special attention to safety, while water pipelines require measures to prevent contamination. The materials utilized in these utilities, whether they are rigid (like cast iron), flexible (like PVC), or brittle (like clay), also impact handling methods, with each type necessitating individualized approaches to prevent breakage or damage. Larger-diameter utilities, such as major pipelines, further complicate matters due to the increased difficulty of relocating them in a safe manner [2,3]. The Federal Highway Administration (FHWA) defined the subsurface utility engineering (SUE) as a practice in which many States utilize consultants for identifying the quality of subsurface utility information used in highway planning, including acquiring and managing information used in highway project development [4]. This definition, however, may be extended to encompass all projects containing subsurface utilities, such as water distribution networks, wastewater collection and pumping systems, and underground electricity facilities. The interest in subsurface utility studies has increased in the last decades as it contributes to saving time and budget for engineering projects. For instance, in some transportation projects, SUE studies may save $7-$15 for every $1 spent [1].

In 1997, Jeffrey J. Lew introduced SUE as an innovative method to mitigate construction challenges related to inaccurately located underground utilities [1]. He showed that SUE may enhance early project development stages by minimizing utility conflicts and construction delays. His research advocated for integrating SUE in design phases, underlining its role in risk reduction and project efficiency. However, there were no assessments for SUE's limitations across different project types and locations. On the other hand, Hesham Osman and Tamer E. El-Diraby, 2005, studied the impact of SUE on infrastructure projects for the Association of Ontario Sewer & Watermain Contractors [5]. Analyzing nine projects, they showed that the benefits behind SUE studies varied by project and depended on factors like urban density and underground utility complexity. Despite their outstanding outcomes, the generalizability of their study was limited. Later on, Sinha et al. developed 2007 an SUE manual during the study conducted for the Pennsylvania Department of Transportation (PennDOT) [6], analyzing ten SUE projects to develop a decision matrix for implementation at various project stages. They found a correlation between SUE benefits and the complexity of underground utilities, independent of project cost. Key outcomes of their study included the recommendation for using higher quality levels (A and B) defined by the Federal Highway Association (FHWA) in complex settings for risk mitigation. However, their manual focuses on PennDOT's specific practices, which may not directly translate to other regions or other types of projects. Additionally, the evolving nature of underground infrastructure and technology might limit the long-term applicability of the findings. Sunil Sinha et al.'s 2008 study has also demonstrated SUE's effectiveness in reducing costs and risks associated with underground utilities by analyzing 22 projects that include SUE and 8 projects that do not include SUE [7]. They found significant savings, with an average benefit-cost ratio of 13.66 for SUE projects, underscoring its value in avoiding utility relocations and damages.

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Nomenclature

ADT	Annual Daily Traffic (Estimated Volume of Traffic)
AOU	Age of Utilities
ATU	Access to Utilities
DOU	Density of Utilities
DOI	Degree of Importance
EBI	Estimated Business Impact
EEI	Estimated Environmental Impact
ESI	Estimated Safety Impact
ERC	Estimated Relocation Cost
EXD	Excavation Depth
$FLI-SUE$	Fuzzy Logic Index for Subsurface Utility Engineering
f	Fuzzy inference function
g	Fuzzy aggregation function
PAD	Project Area Description
POU	Pattern of Utilities
PTS	Project Time Sensitivity
MOU	Material of Utilities
QL_k	Quality Levels, k is A, B, C, and D.
QUR	Quality of Utility Record
SUE	Subsurface Utility Engineering
TOP	Type of Project
TOU	Type of Utilities

Greek Symbols

ω	Weight factor of parameters in the fuzzy model.
$\sum$	Summation symbol used in aggregating weighted group contributions.
i	Index for parameter groups (i = 1 to 4).
G	Denotes parameter groups (e.g., DOI for Group 1).

However, their study's reliance on historical data without considering the dynamic nature of construction sites and underground utilities might not capture the full spectrum of SUE's benefits and challenges. Yeun J. Jung, in 2009, developed a decision-support tool called the SUE utility impact rating form to help decide which projects should include SUE and to determine the appropriate levels of SUE investigation [8]. Several case studies were conducted to verify the utility impact rating form, demonstrating its usefulness in recommending the appropriate levels of SUE investigation. Actually, based on evaluating the complexity of utilities at the construction site, this form was a valuable tool for project owners and designers, enabling them to make informed decisions on incorporating SUE into their projects for safer and more efficient construction conditions. However, this form was not automated, demanding more time and resources for data entry and processing. In fact, the use of traditional paper or computer log methods may lead to delays and inconsistencies in its application, ultimately reducing its effectiveness. In real applications, SUE may offer a comparison of various alternatives that apparently seem similar in terms of cost and effectiveness. This may typically be determined only through an in-depth SUE analysis. For instance, in 2021, the Richland County Transportation Department in South Carolina analyzed subsurface utility potential conflicts in the Percival Road Sidewalk Project (as a part of the first author's employment), aimed at constructing a 5-foot-wide sidewalk. The county encountered significant utility conflicts, particularly with an existing 10-inch water main discovered through a level B/C SUE investigation. A report presented by DESA, Inc. suggested two design alternatives: offsetting drainage using closed flumes or eliminating curbing to provide a minimum 3-foot buffer. Both alternatives were evaluated across several criteria, leading to the recommendation of using a combination of both strategies along different project segments. A detailed computerized model at that time might provide a deep alternative analysis, suggesting additional solutions. Although SUE has proven effective in mitigating utility conflicts, existing methods often rely on manual processes and simplified models that fail to address the complexities of diverse project environments. To bridge this gap, this study introduces the Fuzzy Logic Index for Subsurface Utility Engineering (FLI-SUE), a decision-support tool that integrates multiple project-specific parameters to provide a more adaptive and precise evaluation of subsurface conditions. This approach enhances the reliability of SUE decision-making and addresses the limitations of traditional models. Nevertheless, it is essential to recognize that individual projects may selectively involve some or all of the research parameters based on their unique characteristics. These diverse characteristics are captured in the current fuzzy model, which adjusts the complexity score according to each project's unique utility parameters, offering a more accurate and adaptive assessment to support effective decision-making in complex projects.

2. Research parameters

A set of sixteen parameters was used in the current study, classified into four groups based on their degree of importance (DOI). Grouping criteria may be different based on each project environment. Classification of parameters is not standardized since they are different in their nature and threshold classification. The flexibility of fuzzy logic, which has been used in the current study, to deal with semantic quantification, may help to overcome such cutoff points. This is a merit in comparison to the traditional log methods. In addition, some parameters are close in nature to any other group. For instance, the estimated business impact (EBI), estimated environmental impact (EEI), and estimated safety impact (ESI) could potentially overlap in certain scenarios depending on the project's nature. Therefore, in projects involving commercial activities, the EBI should be emphasized by assigning it a heavier weight in the model equations. On the other hand, in areas where environmental considerations are crucial, more focus should be placed on the EEI. Meanwhile, for projects with a higher risk of accidents, the ESI tends to take on a greater importance. In such a way, the distinct aspects each parameter aims to capture should be set up carefully to ensure a distinct assessment. The parameters under consideration may be listed as follows:

2.1 Density of utilities (DOU)

This term denotes the quantity of underground utilities anticipated in a project. It may be considered low when there is only one conflicting utility, medium when there are two conflicting utilities, or high when there are more than three utilities in conflict.

2.2 Type of utilities (TOU)

Different utility types may be encountered during a specific project, including, but not limited to, municipal, energy-related, and communication utilities. Type of utility may be considered critical when it encompasses fiber-optic cable, gas lines, oil pipelines, petroleum infrastructure, and high-voltage power lines, less critical when it includes water, forced sewer main, and stormwater utilities, and sub-critical when it encompasses telephone, electric, and television cable, or gravity sewer utilities.

2.3 Pattern of utilities (POU)

This term pertains to the arrangement of buried utilities that one can anticipate encountering during the project. This arrangement may be considered simple when it comprises one utility running in parallel and/or one utility crossing, medium when it encompasses two utilities running in parallel and/or two utilities crossing, or complex when it involves more than two utilities running in parallel and/or crossing.

2.4 Material of utilities (MOU)

This term pertains to the materials used in buried utilities that one can anticipate encountering during the project. These may be considered rigid when they comprise materials like concrete, cast iron, and ductile iron, flexible when they encompass materials such as PVC and HDPE, or brittle when they include materials such as clay.

2.5 Access to utilities (ATU)

This term denotes the level of challenge or convenience in reaching buried utilities that might be encountered during the project. This may be considered as easy as open land areas, medium when it covers areas with a few light structures, or restricted when it encompasses locations with features like bridge piers or other large structures that impede access.

2.6 Age of utilities (AOU)

This term can provide insights into both the material used for utilities and their overall physical condition. Utilities that are 10 years old or less may be considered new, utilities that are older than 10 years but no more than 25 years may be considered medium in age, and utilities that have been in place for more than 25 years may be considered old.

2.7 Estimated total utility relocation cost (ERC)

In situations where utility relocation expenses are anticipated to be elevated for the project, obtaining more precise underground data becomes crucial to mitigate the potential for heightened project costs or delays in the project schedule. ERC may be considered as low when it is 2% or less of the total project cost, medium when it exceeds 2% but does not surpass 5% of the total project cost, or high when it exceeds 5% of the total project cost. The above classification of cost includes design and construction expenses.

2.8 Estimated volume of traffic, or annual daily traffic (ADT)

This refers to the expected average daily traffic (ADT) volume per lane. It may be considered as low when traffic volumes are 1500 ADT per lane or less, moderate when traffic volumes exceed 1500 ADT but not exceeding 6000 ADT per lane, or high when traffic volumes surpass 6000 ADT per lane.

2.9 Project time sensitivity (PTS)

This deals with the timetable of the projects. Precise utility information can mitigate avoidable project delays stemming from inaccurate design. Projects without strict time constraints have low time sensitivity, projects reflecting some leeway in the schedule have medium time sensitivity, and projects with very tight schedules and no possibility of time extensions have high time sensitivity.

2.10 Project area description (PAD)

This pertains to the project's location or land characteristics. This may be rural when the project lies in sparsely populated areas with ample open land, suburban for lands with a moderate number of businesses and residences, and urban for lands encompassing areas with a high concentration of businesses and residences.

2.11 Type of project (TOP)

The nature and type of a project often determine the need for SUE. Surface projects like pavement resurfacing usually do not require SUE, unlike those with underground work. Project complexity based on TOP is categorized as simple for non-excavation tasks, moderate for shallow digs like guide rail or low-depth pipe installations, and complicated for deep excavation projects, such as full-depth constructions, deep-depth pipe replacement, or bridge foundations.

2.12 Quality of utility record (QUR)

This reflects the reliability of the available underground utility records. Accurate records significantly reduce the risk of unexpected underground utilities during construction. This quality is categorized into three levels: good (highly accurate records), fair (moderately reliable records), and poor (inaccurate or unreliable information). With poor-quality records, securing reliable underground information is crucial.

2.13 Excavation depth (EXD)

This includes temporary construction easements and may influence the need for SUE quality levels A or B. The accurate positioning of underground utilities is essential for reducing costs and time spent on projects, offering significant benefits. Excavation depths are classified into three categories: Low (up to 18 inches), Medium (over 18 inches but under 24 inches), and High (24 inches or more)

2.14 Estimated business impact (EBI)

This refers to the financial losses that local businesses incur from accidental damage to hidden underground utilities, which affect income and property. In areas with many businesses, reliable information about underground utilities is crucial. Considerations include user impact, business access, and service interruption. EBI is classified into Low (minimal impact), Moderate (some impact), and High (significant impact).

2.15 Estimated environmental impact (EEI)

Assessing potential environmental hazards from accidental utility damage, like gas explosions, oil spills, or flooding, is crucial. In areas with high environmental risk, accurate underground information is vital. Environmental impacts are categorized as Low (minimal environmental consequences), Moderate (possible environmental effects), and High (significant environmental repercussions.)

2.16 Estimated safety impact (ESI)

This concerns the risk to people from unintended utility damage. In areas with high populations, reliable underground data is essential to reduce this risk. Safety impacts are rated as Low (minor risk to safety), Moderate (some safety risk), and High (high safety risk). These are the most important parameters to be considered in an integrated SUE research. Other parameters, such as the existence of religious venues, cemeteries, historic or sensitive buildings, and other impact factors, may also be included based on the model application and project nature.

3. SUE quality levels

The Federal Highway Association (FHWA) uses quality levels (QLs) to categorize the risk and detail required for highway project information, highlighting utility data accuracy in project plans. These classifications facilitate risk management and guarantee the precision of project specifications. Utility information falls into four categories. QL-D depends on unreliable records and verbal data collection to be used for general planning projects. QL-C integrates visible utility surveys with already existing records, but is prone to omissions, making it suitable for projects with less complexity. QL-B uses surface geophysics to accurately map most utilities and reduce design conflicts and relocation costs. QL-A is the most precise, involving non-destructive exposure to fully map and characterize underground utilities for detailed engineering and construction planning. The FHWA website comprehensively overviews these quality levels [4, 9, 10].

4. Research methodology

This study utilizes a systematic fuzzy logic method to create a Fuzzy Logic Index for Subsurface Utility Engineering (FLI-SUE) that measures the intricacy of subsurface utility engineering needs using project-specific factors. Fuzzy logic has the power of dealing with semantic quantification, which is suitable for dealing with uncertain applications, as is the case in subsurface utilities. Fuzzy logic has been widely applied in various engineering studies, such as optimizing safety stock levels in supply chains [11], intelligent control of MIMO systems [12], and speed regulation of induction motors [13]. The process may involve selecting parameters and gathering data, developing a fuzzy logic model, developing a mathematical formulation, determining the degree of importance for parameter groups, and calculating the FLI-SUE number.

4.1 Parameter selection and data collection

Selecting research parameters and collecting data on each parameter is a crucial step in SUE studies. The research parameters are usually selected based on experts, engineers, technicians, and operators' input, depending on the project's nature and characteristics. Once the research parameters are selected, data is collected regarding each parameter and its impact on the whole project. There are numerous field methods used to collect subsurface utilities data. For instance, Ristic et. al. in 2017 conducted a study that aimed to examine the benefits of using a mobile system for detecting and assessing district heating networks. Unmanned aerial vehicles with thermal imaging detect pipeline routes and possible leaks, while ground penetrating radar technology verifies data and extracts information. Neural networks were also used to extract data, including pipe depth, spacing, and diameter [14]. Leaks and blockage detection in liquid pipelines was also a subject of interest for many researchers who suggested methods of collecting defect data from one location on the pipeline [15–18]. In the current study, the parameters were selected according to established practices in subsurface utility engineering, taking into consideration various factors that influence the complexities of the field. Sixteen key parameters were meticulously identified, each playing a significant role in shaping the overall landscape. These parameters were categorized into three distinct levels (low, medium, or high) based on their commonly observed values. A crafted membership function was then assigned to each parameter, capturing its unique impact on the comprehensive model being developed. For instance, the Density of Utilities (DOU) was classified based on the abundance of utilities within a specific area, enabling a deeper understanding of the crowded infrastructural network beneath the surface. On the other hand, the Type of Utilities (TOU) was classified based on the associated risk, shedding light on the potential hazards and vulnerabilities prevalent in the subsurface utility infrastructure. Other parameters with their assigned data, which are explained in the Research Parameters section, were summarized in Table 1. The Table 1 aims to accurately show the capturing of the various conditions that may be encountered in SUE projects. It reflects a strong commitment to achieving excellence and maintaining accuracy in understanding this complex field. The approach is driven by continuous efforts to enhance knowledge and ensure a thorough understanding of the research problem.

4.2 Fuzzy logic model development

The FLI-SUE number is calculated using a fuzzy inference system (FIS), which is built by adopting the following components: membership functions, fuzzy rules, and defuzzification. There are two FIS's in the MATLAB software: Mamdani and Sugeno. Such predictive approaches with multi-input and single-output regression structures have also been implemented in other applications, such as aerodynamic modeling using neural networks [19]. The key difference lies in the output type, where Mamdani-type systems yield fuzzy sets as outputs requiring defuzzification, whereas Sugeno-type systems

Table 1. Parametric data used in the fuzzy inference system.

No.	Parameter	Low	Medium	High
1	Density of Utilities (DOU)	1 utility	2 utilities	3 or more utilities
2	Type of Utilities (TOU)	Sub-Critical: Telephone, electric, or television cables	Less Critical: Water lines, stormwater utilities, forced sewer main	Critical: Fiber-optic cables, gas lines, high-voltage power lines
3	Material of Utilities (MOU)	Rigid: Concrete, cast iron, ductile iron	Flexible: PVC, HDPE	Brittle: Clay
4	Access to Utilities (ATU)	Easy: Open land areas	Medium: Areas with light structures	Restricted: Areas with bridge piers, large structures
5	Age of Utilities (AOU)	0-10 years	11-25 years	Over 25 years
6	Estimated Total Utility Relocation Cost (ERC)	$\leq$ 2% of total project cost	$>$ 2% and $\leq$ 5% of total project cost	$>$ 5% of total project cost
7	Annual Daily Traffic (ADT)	$\leq$ 1,500 vehicles per lane	$>$ 1,500 and $\leq$ 6,000 vehicles per lane	$>$ 6,000 vehicles per lane
8	Project Time Sensitivity (PTS)	Flexible schedule	Some schedule flexibility	Strict, no time extensions
9	Project Area Description (PAD)	Rural: Sparsely populated, open land	Suburban: Moderate population, structures	Urban: Dense population, complex utility layout
10	Type of Project (TOP)	Simple: Pavement resurfacing, no excavation	Moderate: Shallow excavation (e.g., guide rails)	Complicated: Deep excavation (e.g., large pipe replacement)
11	Quality of Utility Record (QUR)	Good: Highly accurate records	Fair: Moderately reliable records	Poor: Inaccurate or unreliable records
12	Excavation Depth (EXD)	$\leq$ 18 inches	$>$ 18 inches and $\leq$ 24 inches	$>$ 24 inches
13	Estimated Business Impact (EBI)	Minimal impact on business operations	Some disruption to access or operations	Significant impact, prolonged disruption
14	Estimated Environmental Impact (EEI)	Minimal risk (e.g., minor water or soil disturbance)	Manageable risks (e.g., limited pollution)	Significant risk (e.g., gas leaks, oil spills)
15	Estimated Safety Impact (ESI)	Minimal safety concerns	Some safety risk requiring monitoring	High risk to public or worker safety
16	Pattern of Utilities (POU)	Simple: One utility in parallel or crossing	Medium: Two utilities in parallel or crossing	Complex: More than two utilities in parallel or crossing

produce either linear functions or constant values as outputs. As the current study deals with the SUE study that includes semantic representation requiring defuzzification, the current model used the Mamdani-type FIS. Each parameter is represented by a membership function to describe its degree of influence within the model. For instance, the Type of Utilities (TOU) parameter includes membership functions for sub-critical, less critical, and critical, each covering specific ranges. Membership functions for continuous variables, like Annual Daily Traffic (ADT), are designed using trapezoidal or triangular functions to cover a smooth range of possible values. The model employs a set of 80 fuzzy inference rules to define relationships between parameters and determine the Degree of Importance (DOI) for each parameter group. For example: Rule 1: If TOU is critical and ERC is high, then the DOI for Group 1 (G1) is high. These rules capture expert knowledge about the interdependencies between parameters, enabling the system to calculate the relative importance of each parameter group. After evaluating all fuzzy rules, the fuzzy outputs are defuzzified to yield a single crisp value for each Degree of Importance (DOI). In the defuzzification process, a weighted average of the membership function values is calculated to produce a clear and interpretable output for each group's DOI. The fuzzy model components will be discussed in detail in the following sections.

4.3 Mathematical formulation

The FLI-SUE number calculates a complexity score for SUE requirements by incorporating key parameters, each weighted according to its impact [20]. It then combines parameters across four groups, each has a group weight that reflects its influence on the model output. The general formula for calculating the FLI-SUE score is as Eq. 1.

$$FLI-SUE = f(TOU, ERC, ESI, ADT, \ldots, POU) \tag{1}$$

where: f represents the fuzzy inference function that processes each weighted parameter according to fuzzy rules and membership functions. Each parameter (TOU, ERC, ESI, ADT,..., POU) may be multiplied by a specific weight, ω_i, which represents its relative importance, as shown in the following sub-section.

4.4 Degree of importance (DOI) calculation

The sixteen parameters are divided into four parameter groups, each assigned a Degree of Importance (DOI) based on the weighted contributions of the parameters within that group. This may be different as per each project's nature and environment. The groups used in the current study are as follows: Group 1 (G1), which includes Type of Utility (TOU), Estimated Total Utility Relocation Cost (ERC), Estimated Safety Impact (ESI), and Annual Daily Traffic (ADT). Group 2 (G2), includes Density of Utilities (DOU), Age of Utilities (AOU), Estimated Environmental Impact (EEI), and Project Time Sensitivity (PTS). Group 3 (G3), includes Access to Utilities (ATU), Quality of Utility Record (QUR), Excavation Depth (EXD), and Estimated Business Impact (EBI). Group 4 (G4), includes Type of Project (TOP), Project Area Description (PAD), Pattern of Utilities (POU), and Material of Utilities (MOU). Each DOI is calculated using the weighted values and fuzzy rules established for the parameters in each single group, represented mathematically as in Eq. 2.

$$DOI_{G_i} = g(_1.TOU, _2.ERC, _3.ESI, _4.ADT, \ldots) \tag{2}$$

where g is the fuzzy aggregation function that processes the weighted parameters in each single group and ω_i is the specific weight of each pertinent parameter, which represents its relative importance. The current model employs the centroid method for defuzzification, which computes the center of mass of the fuzzy output set to obtain a crisp value. This method ensures a balanced output by considering the entire range of the aggregated membership function. For aggregation functions, the combination of membership degrees follows a structured approach. Within each fuzzy rule, the minimum operator was used to determine the firing strength, ensuring that the weakest contributing parameter dictates the rule's activation level. Whilst across multiple rules, the weighted average method is applied to combine outputs from all activated rules, ensuring a smooth transition between different inference conditions. This structured aggregation and defuzzification process enhances the model's interpretability and ensures a robust computation of the FLI-SUE number.

4.5 FLI-SUE number calculation

The final FLI-SUE score is calculated by aggregating the DOI's from all four parameter groups. Each DOI is processed by a unique weight, WG_i, to reflect its relative importance in the final index. The formula for FLI-SUE number may be aggregated in a form similar to the following formula, Eq. 3.

$$FLI-SUE = \sum_{i=1}^{4} W_{G_t}.DOI_{D_i} \tag{3}$$

where W_{G_t} is the assigned weight for each parameter group's DOI. Each DOI represents the crisp value obtained from defuzzification for its respective group. This weighted aggregation allows for nuanced control over each parameter group's contribution to the final FLI-SUE score, providing an accurate representation of SUE complexity.

5. Fuzzy inference system

The essential components of the fuzzy inference process include the following three key stages: specifying membership functions, defining operations for fuzzy sets, and establishing inference rules [21]. As mentioned previously, this study uses the Mamdani-type fuzzy inference system, which represents process states with linguistic variables serving as model inputs. In the current FIS model, the fuzzifier executes a mapping operation that converts the input data into linguistic variables, and the extent of this data serves as the foundation for establishing the fuzzy sets, as shown in Figs. 1 and 2. It links real-world parameters and the fuzzy system, converting the output set into a precise, non-fuzzy representation. The fuzzy inference engine employs the established rules to generate fuzzy outputs based on the given inputs. Fuzzy memberships are then "defuzzified"to reproduce a conventional type of index [22].

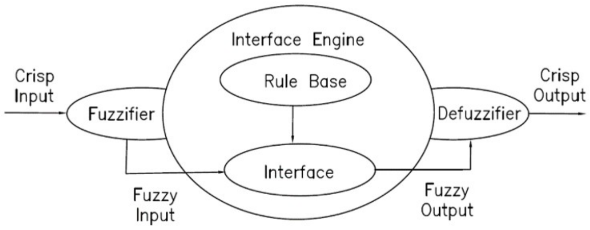


Figure 1. General FIS structure..

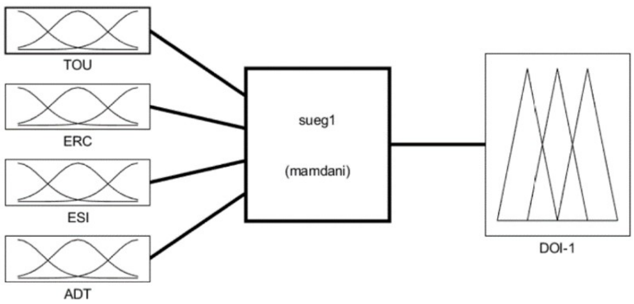
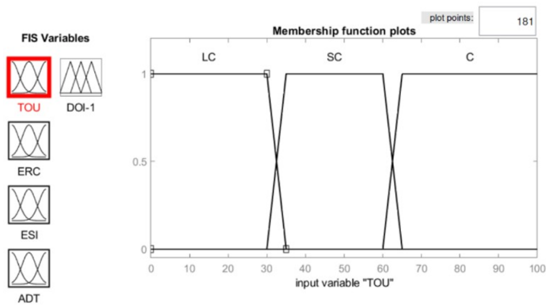
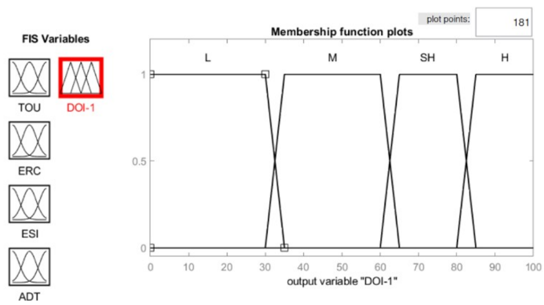


Figure 2. Current model FIS structure for group-1 parameters.



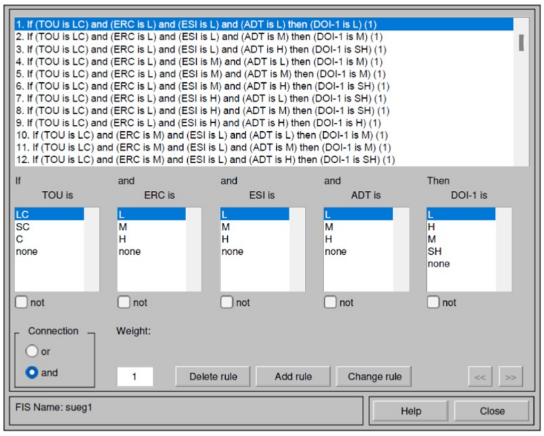
(a) type of utilities (TOU), as an input



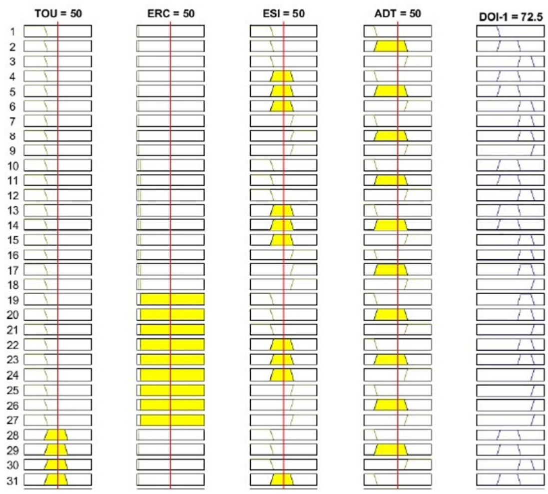
(b) Degree of importance of fuzzy Group I (DOI-1), as an output

Figure 3. Sample membership functions for TOU and DOI-1.

The defuzzifier translates fuzzy output variables into real-world variables suitable for controlling real-world applications. More clearly, input parameters are first mapped into fuzzy sets using pre-defined membership functions as shown in Fig. 3. These membership functions categorize input values into linguistic terms. On the application of fuzzy inference rules, the resulting fuzzy output is defuzzified to generate a single crisp value for the FLI-SUE score. This transformation ensures a quantitative representation of qualitative assessments, enhancing decision-making accuracy in SUE. The defuzzification process essentially reverses the fuzzification process [23]. The fuzzy inference system (FIS) provides a structured approach to dealing with uncertainty in decision-making [24]. In the context of SUE, this system is specifically adapted into the FLI-SUE model, which integrates key project parameters to determine the required level of utility investigation. By applying fuzzification, rule-based inference, and defuzzification, the model calculates a numerical index that quantifies the complexity of subsurface conditions, offering an adaptive and more precise decision-making tool. The proposed index number is unitless and falls within the range of 0 to 100. A greater FLI-SUE number corresponds to a higher level of subsurface utility investigation. Sixteen input parameters were used in the FIS model using MATLAB software version 7.11.0 (R2010b) to provide one output indicator (FLI-SUE) describing the suggested level of SUE. As mentioned in the research methodology, the sixteen inputs were divided into four groups based on their correlated details to simplify setting up governing rules and improve model control. Each parametric group was investigated for its degree of impact (DOI) on the crisp output (FLISUE number). For example, as noticed in Fig. 4a, the DOI of Group I (G-1) is low (L) as the ERC, ESI, and ADT are low (L), and the TOU is less critical (LC). The key stages of the fuzzy inference system are discussed in the following subsections.



(a) Listing



(b) Viewer

Figure 4. Fuzzy inference system rules for DOI-1.

5.1 Membership functions

Fuzzy logic operates on the premise that the truthfulness of any statement can exist in varying degrees, implying that any statement can exhibit some level of ambiguity. The concept employs a membership function, which visually indicates the degree of truth for a specific statement of an input value. This function outlines how each point in the input space is associated with a membership value that falls between 0 and 1, detailing how the input relates to the level of truth or falsity of the statement [25]. Numerous studies have been conducted regarding the choice of an appropriate membership function for a specific variable. For instance, Bouchon-Meunier, et. al. [21], focused on the selection of membership functions in a Mamdani-type fuzzy controller. Membership functions for each parameter in the current study may be set up based on the classification of each parameter as explained in the Research Parameters section. Figure 3a shows a sample membership function for one of the sixteen input parameters, TOU. The degree of temership was classified into three categories: less critical, LC with (0-35%) degree of importance, slightly critical, SC (30-65%), and critical, C (60-100%). The other three input parameters in G-1 (ERC, ESI, and ADT) and the output DOI may be categorized in the same manner, as shown in Fig. 3b. For instance, the output parameter, DOI, is classified as low, L (0-35%), medium, M (30-65%), slightly high, SH (60-85%), and high, H (80-100%). It may also be noticed from Fig. 3 that there is an interaction among the borders of the membership function categories. This interaction is a vital component of the fuzzy inference system and aligns more closely with real-world applications, where some categories may not precisely fit into a single membership function category.

5.2 Fuzzy inference rules

In fuzzy logic, the process of connecting inputs to generate outputs relies on experiential knowledge involving parametric analysis and anticipation of events. To contemplate the majority of conceivable input permutations, eighty rules were used in each of the four degrees of impact. Figure 4 shows the governing rules representation for the first DOI with its four input parameters (rules listing is shown in Fig. 4a, and rules viewer is shown in Fig. 4b. It may be noticed from this figure, for instance, that if the type of utilities is less critical and the estimated safety impact is low, then the degree of importance for G-1 is low. Similarly, other degrees of impact were correlated in a fuzzy inference system with suitable governing rules.

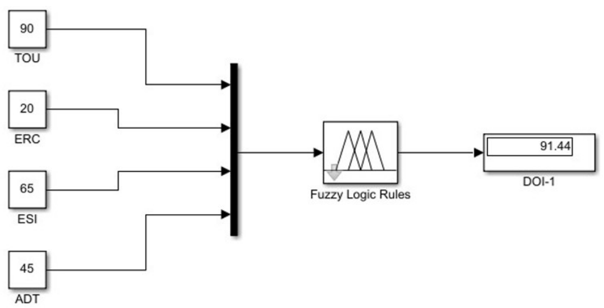


Figure 5. Simulink model of G-1 research parameters.

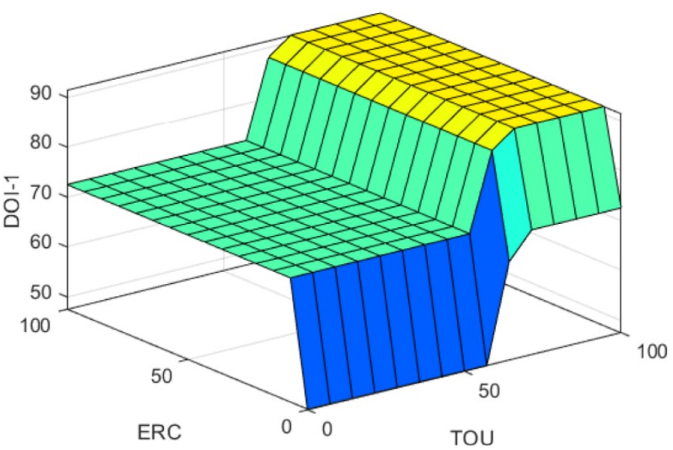


Figure 6. Surface viewer of ERC-TOU-DOI-1 relationship.

6. Model application results and discussion

The model parameters for each input group are correlated by a Simulink model, as shown in Fig. 5. As shown in Fig. 5, a numerical example for the first group of input parameters (TOU, ERC, ESI, and ADT) was taken into consideration. Each input parameter was given a value representing its degree of importance based on the nature of the project and its application. For instance, if the TOU is critical (C) for the project implementation (say 90% degree of impact), the ERC is low (20% membership function indicator), ESI is moderate (say 65% membership function indicator), and the ADT is moderate (say 45% membership function indicator). The super-imposed degree of impact (DOI) for G-1 is 91.4%, which may be represented by an FLISUE number of 0.914. This number is relatively high in this example, which may indicate that the type of utilities plays a substantial role in deciding the amount of effort required for subsurface utility engineering. The relationship between any two parameters within the same group may also be closely analyzed to redirect the utility investigation effort regarding each correlated parameter. Actually, the current model provides two key types of relationship analysis: (1) the impact of each individual parameter on the DOI, where the contribution of a single factor to the overall index is assessed, and (2) paired parameter interactions, which examine how two parameters together influence the DOI. For example, TOU and ESI exhibit a compounding effect where, when both are high, the DOI significantly increases. This analysis helps prioritize parameters in utility risk management. As mentioned previously, the FIS does not assign equal weight to all parameters; rather, factors with higher risk potential exert greater influence on the final DOI score. For example, while ATU contributes to DOI, it has a lower impact compared to TOU and ESI, which carry more weight due to their direct impact on risk and project complexity. This unequal influence ensures that critical factors drive decision-making, preventing minor influences from overshadowing key project risks. Recognizing these weight differences helps decision-makers focus resources and prioritize high-risk utilities over less critical infrastructure. The 3D surface viewer, shown in Fig. 6, also, provides a deeper insight into parameter relationships by demonstrating non-linear trends and threshold effects in DOI calculation. For instance, as TOU increases, DOI remains relatively stable until TOU exceeds a threshold of approximately 58%, after which DOI rises sharply. This indicates a trigger point where critical utility types have a disproportionate effect on investigation requirements. Similarly, ERC and ADT show an interaction where merely a moderate ERC does not significantly alter DOI, but when paired with high ADT, the DOI escalates due to increased project complexity and disruption risks. These insights help engineers identify crucial risk points in utility assessments. Other input parameters for all other groups may be analyzed similarly. In addition, as previously noticed from the rule viewer shown in Fig. 4b, the DOI is not essentially equally referenced to each individual parameter. For example, if all parameters in G-1 have the same membership function indicator in the medium range (say 50%), the DOI for their inferential group is still in the higher range (72.5%). This is governed by the fuzzy logic inference rules controlling the processing unit, which may definitely be controlled and set up ahead.

7. Model application procedure

The purpose of this section is to provide a systematic approach for the engineering community to effectively utilize the FLI-SUE model in order to make well-informed decisions concerning subsurface utilities. This would ultimately improve project efficiency and reduce the risks associated with utility conflicts. The following procedure may be followed as a general guide to translate this method to a practical field application. These steps are also summarized in the flowchart shown in Fig. 7.

- Identify and gather the project parameters that have an impact on subsurface utility management.
- Assess and prioritize the parameters according to specific site conditions and project requirements through site assessment or stakeholder consultation.
- Categorize the parameters into groups to illustrate their relationships and simplify the model's application.
- Develop membership functions for each parameter based on input from experts and consultants.
- Create rules that reflect practical scenarios and define the relationships between parameters with the assistance of consultants and stakeholders.
- Use MATLAB's Simulink to create a system that calculates the FLI-SUE number, ensuring proper connectivity between inputs and outputs.
- Input site-specific data into the model for each identified parameter and conduct simulations to generate the FLI-SUE score.
- Utilize the FLI-SUE number to guide decision-making in subsurface utility engineering, such as determining necessary levels of investigation and creating relocation plans.

By following these guidelines, the engineering industry can utilize the FLI-SUE framework to improve project outcomes and streamline subsurface utility management.

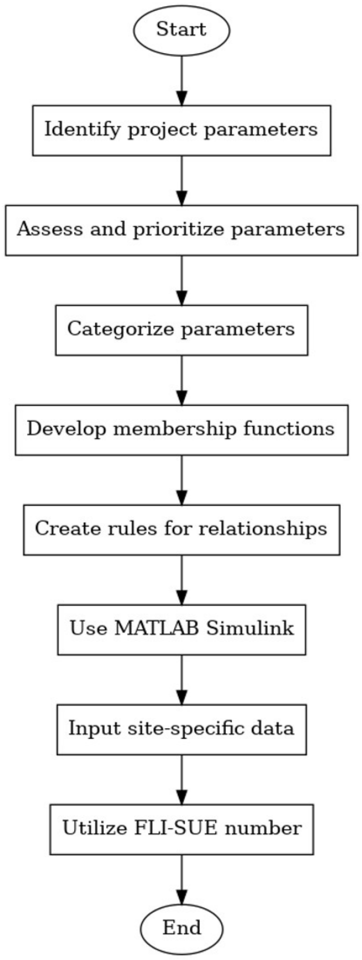


Figure 7. Flowchart summarizing model application procedure

8. Conclusion

The results showed that the application of FLI-SUE gives a more specific description of the level of investigation required for subsurface utilities in conflict with project implementation. The model, incorporating sixteen key parameters relevant to subsurface utility engineering, offers flexibility for future inclusion of other factors such as the existence of religious venues, cemeteries, historic or sensitive buildings. Application of the current model showed that fuzzy logic is an effective replacement for the traditional computer or paper log methods used to investigate subsurface utilities. It offers greater objectivity due to the ability to add controlling details, operates faster with execution times, and provides inclusion of an unlimited amount of information. It also provides better resource allocation and saves time and budget, especially in infrastructure projects. In addition, the current model gives an index number representing the scale of efforts needed for subsurface utility engineering, which shows a more accurate description than the traditional methods, which classify in categories without locating the target effort within each category. Furthermore, the interaction between different degrees of representation membership within each parameter classification provides a more realistic representation, as there is no pure classification for a degree of membership specifying a certain parameter. This provides improved management of uncertainty, given the inherent ambiguity involved in dealing with subsurface utilities. The current model has the potential for further improvement, including, but not limited to, refining parameter classification, sensitivity analysis, and incorporating additional factors to enhance model accuracy and applicability.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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