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RELIABILITY-AWARE AND EXPLAINABLE ANOMALY DETECTION IN GAS CONSUMPTION MONITORING USING Z-NUMBERS

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A B S T R A C T

Gas distribution companies face a practical problem that many anomaly detection methods do not fully address: detecting an abnormal reading is not enough if the reliability of the result is unclear. A sharp change in consumption may be related to a technical fault, an unusual consumption event, a metering problem, or a normal seasonal fluctuation. In such cases, the same statistical alert may require very different operational responses. This paper proposes a two-level anomaly detection framework based on Z-numbers, where each uncertain assessment is considered together with its reliability component. At the first level, lightweight methods, including Z-score filtering, moving average deviation, Isolation Forest, and PCA-based clustering, are applied to large-scale gas consumption time-series data to identify candidate anomalies. At the second level, each candidate is represented as a Z-number consisting of two components: a fuzzy linguistic assessment that describes the degree of abnormality, and a reliability measure that reflects confidence in that assessment based on data stability and methodological consistency. The output of the system is not limited to a binary anomaly label. Instead, observations are assigned to five risk classes, ranging from normal to absolutely anomalous, while the reliability component is presented together with each classification. The proposed system is implemented as a modular Python-based application supported by PostgreSQL and an operator-facing dashboard that presents risk distributions, detection results by method, and individual consumption profiles. The study shows that including reliability as part of anomaly assessment makes the output easier to interpret and more useful for operational decision-making in gas consumption monitoring.

Keywords: gas consumption; anomaly detection; uncertainty; Z-numbers; soft computing; explainable analytics.

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1. Introduction

Natural gas is a key part of modern energy infrastructure and requires continuous and safe supply across industrial and residential sectors. For gas distribution companies, monitoring consumption matters for economic reasons, but also for technical safety, loss control, and preventing unauthorized usage. Therefore, timely detection of abnormal patterns in gas consumption data remains a practical challenge [1].

Real-world gas consumption data are characterized by a high degree of uncertainty, mainly due to seasonal variability, heterogeneity in consumer behaviour and measurement inaccuracies. In these conditions, it becomes increasingly difficult to discern whether abrupt shifts in consumption indicators are caused by technical failures, risky events or benign fluctuations. Therefore, gas distribution operators need to know both whether an anomaly exists and whether the detection itself can be trusted.

Most of the existing approaches detect anomalies based on statistical or algorithmic techniques, but the interpretability and reliability assessment of the obtained results are often neglected. This increases the uncertainty and risk for decision makers, which is an important limitation for systems used in real-world and safety-critical domains, such as gas consumption monitoring [2].

In this paper, we propose a two-level system that works directly on operational data from a gas distribution company. At the first level, the system performs fast filtering on large-scale datasets. At the second level, it applies a deeper evaluation mechanism with explicit consideration of uncertainty and reliability factors. The main goal of this work is to provide a systematic framework for the detection of gas consumption anomalies and for their interpretable and reliability-aware assessment to support informed decision-making.

The paper is organized as follows. In section 1, we introduce the problem of anomaly detection in gas consumption systems and motivate the need for reliability-aware and explainable analysis under uncertainty. In section 2, the existing statistical, machine-learning based, soft-computing and Z-information based approaches are reviewed and the research gap addressed in this study is identified. In section 3 the problem setting, research objectives, and the proposed two-level analytical principle for anomaly screening and reliability assessment are described. Section 4 describes the system-oriented architecture of the proposed approach

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including data integration, preprocessing, Level-1 filtering and Level-2 Z-number-based evaluation mechanisms. The implementation of the proposed framework, including software modularization, database design, process modeling with UML, and decision-support visualization, is presented in section 5. Finally, the conclusion summarizes the main findings and outlines directions for future research.

2. Literature review

Anomaly detection in gas consumption data lies at the intersection of general anomaly detection and decision-making domains and has been analyzed in a number of methodological contexts. The existing literature has mainly evolved around statistical models, machine learning techniques and soft computing based approaches.

This section reviews these directions systematically and points out the current research gap:

• *Statistical-based methods.* Early anomaly detection research was mainly dominated by statistical methods. These techniques are predominantly based on the distributional properties of time series, deviations from mean values and analysis of variance. Techniques like Z-score, moving averages, exponential smoothing, and ARIMA-type models are included in this category. The methods are computationally efficient and relatively simple to implement but often produce a high rate of false positives when applied to energy and gas consumption data with seasonal variability and non-stationary behavior [3]. Statistical methods are mainly used for basic monitoring and alert systems. That said, in general they do not adequately model structural changes and inherent uncertainty in consumption behaviour, nor do they give reliable information on the severity of risk of detected anomalies.

• *Machine-learning-based approaches.* Machine learning and deep learning methods have been widely used in anomaly detection research in the last decade [4–9]. Models such as isolation forest, one-class support vector machines (SVMs), autoencoders and recurrent neural networks have shown good ability to identify abnormal patterns in unlabeled data [10].

These approaches are successful in modeling complex nonlinear relationships that exist in real-world time-series data in the context of energy and gas consumption. However, most of the machine-learning-based models are black-box systems with limited interpretability. In particular, they do not typically provide transparent explanations about the root causes, severity levels and reliability of the detected anomalies. This lack of interpretability considerably restricts their practical use in operational decision-making processes within real gas distribution companies. Therefore, explainability and decision reliability issues are widely recognized as the main limitations of machine learning-based anomaly detection approaches.

• *Soft-computing and fuzzy-based techniques.* Soft-computing and fuzzy-based approaches work well in uncertain and imprecise environments as they can model reasoning processes similar to human cognition. Fuzzy logic-based models allow consumption levels to be represented in terms of linguistic labels such as "low", "normal" and "high", and have been widely used to model the gradual change of the anomaly behavior in the energy consumption data [11].

In most classical fuzzy-based models however, reliability of the evaluation is not taken into account. Membership functions only show the degree of membership of a value to a linguistic concept, but they do not give any information about the source credibility or trustworthiness of the assessment. Thus, the same fuzzy values can be obtained from reliable data or from noisy and uncertain measurements, which is a known limitation of classical fuzzy representations [12].

This limitation is very important for sensor-based systems like gas consumption monitoring, where the measurement uncertainty may cause false anomaly detection and risk-prone decisions. Thus, fuzzy-based approaches have limited applicability in real industrial systems in terms of interpretability and reliability [2].

Recent studies showed that models based on Z-numbers can effectively overcome this restriction by simultaneously representing uncertain values with their corresponding reliability levels. Z-numbers are successfully applied in regret-based decision models, valuation of non-formalized and qualitative factors, and risk analysis based on soft computing [13–18]. The studies show the ability of Z-numbers to extend classical fuzzy representations by directly incorporating reliability information, yielding decision-support outcomes that are more interpretable and useful in practice.

Reliability oriented and Z-information approaches.

To jointly address uncertainty and reliability, Zadeh (2011) suggested the concept of Z-information which is an effort to overcome a fundamental limitation of classical fuzzy models. Z-information represents uncertain estimates together with their reliability components, thereby increasing the semantic depth of decision-making.

Aliev and co-authors formalized mathematical operations and comparison mechanisms of Z-information and proposed Z-distance based approaches. These techniques have been applied in decision support and risk assessment problems [14]. In the previous works of the author, it has been shown that the Z-information based methods can be used to support not only the anomaly detection but also interpretable evaluation of their severity and reliability [19, 20]. These works introduced Z-anomaly classes and reliability-aware decision mechanisms.

Most reviewed approaches fall into one of two groups: fast methods that give little explanation, or detailed models where the reliability of the output is still unclear. Neither group directly addresses what a gas distribution operator needs in practice, which is not just a flag, but a basis for deciding what to do with it.

This paper takes a different approach. Rather than choosing between speed and interpretability, we combine lightweight screening methods with Z-number-based evaluation so that each detected anomaly comes with an explicit reliability measure. In practice, a gas operator receiving a binary anomaly flag still has to decide whether immediate inspection is needed or whether the case can remain under monitoring, and the flag itself gives no guidance on that. The proposed framework is designed around this operational problem.

3. Problem formulation and research objectives

Gas consumption data collected in the information systems of gas distribution companies include different groups of consumers (residential, commercial and industrial) and have a heterogeneous structure both in terms of consumption behavior and quality of measurement. The normal consumption profiles differ between consumer groups and what is normal behaviour in one group can be considered as anomalous behaviour in another. Therefore, anomaly detection in gas consumption data should not be based on a single universal criterion, but should be performed taking into account the consumer type and contextual characteristics.

Formally, let $X=\{x_{ij}^{g}\}$, where x_{ij}^{g} denotes the gas consumption value of the i-th subscriber belonging to the g-th consumer group with respect to the j-th feature. The objective is to identify abnormal consumption patterns relative to the established normal behavior of each consumer group and to assess the degree to which these patterns are suspicious and operationally risky from a decision-making perspective.

Most of the current approaches for anomaly detection focus mainly on the detection of deviations of consumption values from normal ranges. Such deviations can come from sensor errors, temporary technical interventions, seasonal patterns, or short-term changes in consumer behaviour.

Thus, anomaly detection alone is not sufficient to make a reliable and responsible operational decision. It is more important for gas distribution companies to estimate the degree of reliability and operational risk of a detected anomaly.

In this paper, anomalies are evaluated not only in terms of their presence but also in terms of the degree of suspiciousness and reliability of the anomalies. Therefore, the main aim is not only to answer the binary question of whether an anomaly exists, but to answer the question: how reliably anomalous is the detected behavior and how significant is its associated operational risk?

To satisfy these requirements, a two-level systematic approach is suggested. At the first level (Level-1) the large-scale consumption data are processed by computationally efficient techniques for fast detection of potential anomalous cases among different consumer groups. At the second level (Level-2), a detailed analysis of the selected candidate consumption values is conducted by employing a Z-number-driven reliability and suspiciousness evaluation mechanism.

This allows for explainable, reliability-aware and operation-oriented assessment of detected anomalies without sacrificing computational efficiency.

Research objectives. The main objectives of this study are as follows:

to develop a systematic approach to identify anomalies in gas consumption data of different consumer groups, taking into account their contexts;

- to design a two-level analytical framework suitable for large-scale consumption data;

- to enable anomaly evaluation not only in terms of detection but also with regards to levels of suspiciousness and reliability;

- to adapt the Z-number-based anomaly interpretation mechanism to real-world gas distribution systems;

- to present the obtained results to operators and experts using dashboard-based decision support tools.

In line with these objectives, the next section presents the general architecture of the proposed system and then, the main functional components of the system are presented.

4. System architecture

The proposed system is an explainable, system-oriented, two-level architecture for the detection of anomalies in time series of gas consumption (fig. 1). The architecture works in two steps. The first step runs fast statistical and machine learning filters across all data to find suspicious cases. The second step applies Z-number evaluation only to those cases, assessing both how abnormal the reading is and how much confidence can be placed in that assessment.

As a result, anomalies are not treated as binary outcomes (anomalous/non-anomalous) but are instead characterized by severity and confidence parameters, making the results directly applicable to operational decision-making. This design accounts for the limitations of classical anomaly detection methods in terms of interpretability and reliability [13–16, 19–21].

The system consists of the following functional modules:

- Data sources;
- ETL (Extract, Transform, Load) – a data integration process that includes extracting data from heterogeneous sources, transforming them into a consistent analytical structure, and loading them into a unified storage system for subsequent analysis;

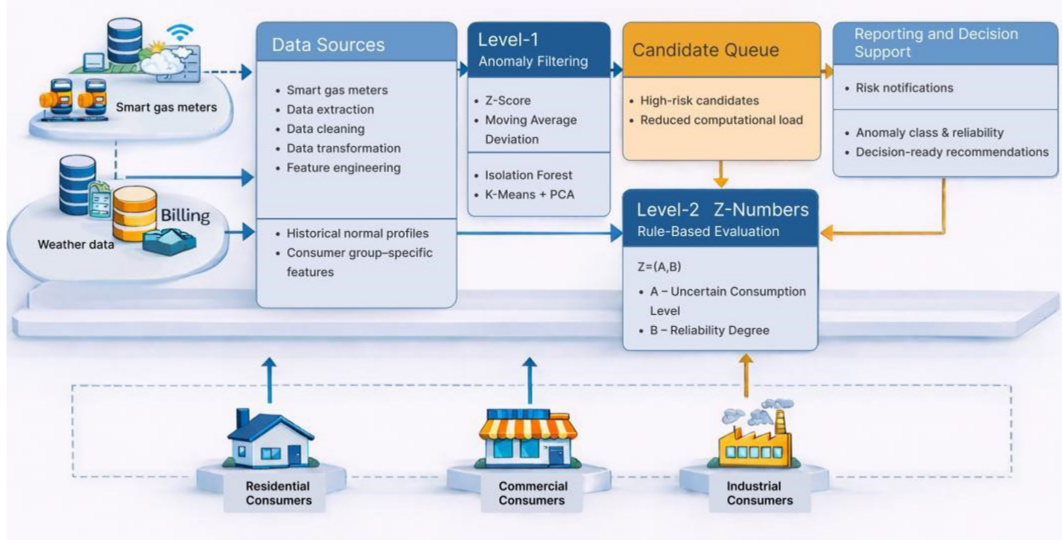

Fig. 1. Two-level anomaly detection in gas consumption

- Feature store – a structured repository to manage and store analytical features created from raw consumption data;
- Level-1 filtering;
- Anomaly candidate buffer;
- Level-2 Z-number-based evaluation;
- Reporting and decision support.

The time series of gas and energy consumption is characterized by strong seasonality, non-stationarity and uncertainty of measurements, therefore synchronization of heterogeneous data sources along the time axis and preservation of data quality indicators are critical components of the architecture [1, 3]. The integration logic is methodologically consistent with the "rapid primary screening + deep Z-analysis" principle proposed in author's previous works [18, 20]. The practical advantages of this two-level modular architecture for the energy consumption monitoring systems have been demonstrated in previous studies [18, 22].

The overall architecture of the proposed two-level system and the flow of information among its main functional blocks are shown in figure 1. In the following we describe the role of these blocks:

- Data sources and integration logic. The system integrates heterogeneous data sources such as:
- Smart gas meters with hourly or daily measurements, derived consumption differences and cumulative readings;
- Billing systems (with billing cycles, invoice records, tariff structures and logs of correction);
- Meteorological data (such as temperature and seasonal indicators) necessary in the precise modelling of the seasonal structure of gas consumption [3].

The strong seasonality, non-stationarity and uncertainty of measurements of gas and energy consumption time series make synchronization of heterogeneous data sources along the time axis and preservation of data quality indicators critical components of the architecture [1, 3].

This logic of integration is methodologically consistent with the principle of "rapid primary screening + deep Z-analysis" proposed in the author's previous works [18, 22]. Recent research has reported that successful monitoring of gas infrastructure and reliability assessment of gas transportation systems require integrated data environments that incorporate technical diagnostics, operational monitoring, and risk evaluation mechanisms [23–25].

• ETL & Feature Store: Data Preparation and Feature Management. The ETL & Feature Store layer serves as the data preparation stage of the system. No anomaly detection algorithms are executed at this level; instead, the objective is to standardize heterogeneous data and construct a consistent feature repository for downstream analysis:

- *Data extraction.* Smart meter and billing data may be collected at different temporal resolutions (e.g., hourly vs. monthly). Accordingly, extraction requires harmonization by a common subscriber identifier, time index, and consumer group label (residential, commercial, industrial).

- *Data cleaning.* Treatment of missing values, spurious jumps, wrong meter readings and duplicated records. Consistent with classical anomaly detection definitions [1, 2], the goal is not to suppress anomalies, but to reduce measurement artefacts that can distort analytical results.

- *Data transformation.* This step includes temporal alignment (e.g., hourly to daily aggregation or projection to billing periods), aggregation (daily or weekly), and normalization/standardization to ensure stable operation of Level-1 methods [3].

- *Feature engineering.* The Feature Store stores features for consumption level indicators, rate of change and variability metrics, seasonal features, temperature adjusted indicators as well as historical baseline profiles at subscriber and group levels. This structure supports the unified input to statistical filters and nonlinear machine-learning models [2, 3].

• Level-1: Fast anomaly filtering and candidate selection. Level-1 is designed for operational monitoring of large-scale datasets, and is also a candidate generation layer. The goal is to obtain high sensitivity in the recognition of potential suspicious cases which are then subjected to more precise and explainable analysis at Level-2 [1, 2, 22].

The following methods are employed in combination:

- *Z-score filtering.* A classical statistical technique that measures deviations from the mean, widely used in initial monitoring [3]. The normalized score is computed as $z_{ij} = \dfrac{x_{ij} - \mu_j}{\sigma_j}$, ensuring comparability across consumption indicators [22]. Here: x_{ij} denotes the observed value of the j-th consumption-related feature for the i-th subscriber. In the context of gas consumption analysis, this value may represent daily or hourly gas usage, aggregated billing-period consumption, or a derived consumption indicator. μ_j represents the mean (expected) value of the j-th feature, computed over a reference period or across a homogeneous consumer group. This parameter characterizes the normal consumption behavior with respect to the selected feature. σ_j denotes the standard deviation of the j-th feature, reflecting the variability of consumption behavior within the reference dataset or consumer group.

- *Moving average deviation.* Short-term deviations with moving averages are calculated using local trends as a reference, a common method in time-series analysis [3].

- *Isolation Forest.* A scalable unsupervised method for anomaly detection in unlabeled and multidimensional data [10, 22].

- *PCA + K-means.* Principal Component Analysis helps in reducing dimensionality and supports compact visualization while K-means clustering identifies outliers based on the distance from cluster centroids [2, 26]. The mathematical formalization of this combination for energy consumption screening has been done in prior work [22].

The joint use of these methods corresponds to a hybrid screening strategy, where statistical filters provide fast rule-based detection and machine-learning models capture nonlinear structures [1, 2, 6, 27]. After standardization, PCA-based candidate selection can be formalized as follows [22]:

$$\begin{gathered} Z = X'W, \quad Z = [z_1, z_2] \in R^n, \\ T_1 = quantile_{0.95}(PCA1), \quad T_2 = quantile_{0.5}(PCA2), \\ Anomaly_i = (z_{ij} > T_1) \vee (z_{i2} > T_2). \end{gathered} \tag{1}$$

This pipeline is summarized in figure 2.

• Anomaly candidate buffer: scalability and control. Suspicious observations identified at Level-1 are placed into an anomaly candidate buffer, whose main functions are:

- reducing computational load, as Z-number-based

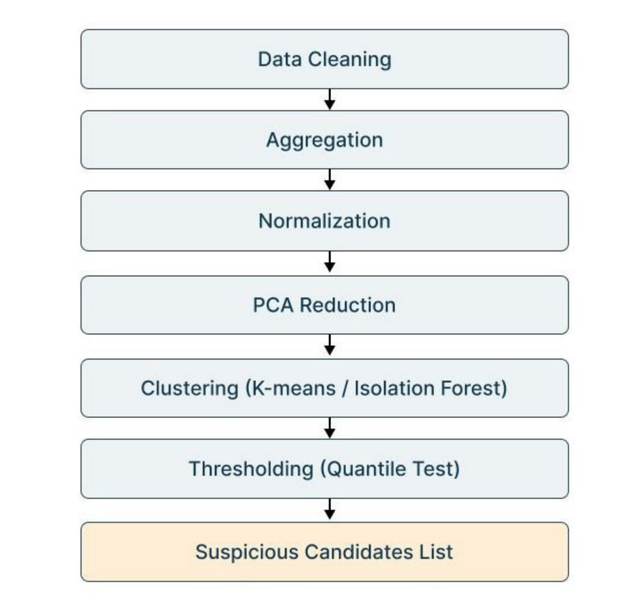

Fig. 2. Preprocessing and initial filtering pipeline

evaluation is more expensive and applied only to selected cases [22];

- prioritization based on risk scores, consumer group criticality, and temporal persistence;

- maintaining an audit trail for operator review and traceability.

This mechanism ensures that the architecture remains system-oriented and practical to deploy, not just theoretically sound [2, 22].

• ***Level-2: Z-number-based explainable assessment (severity + confidence).*** Level-2 constitutes the core scientific contribution of the proposed system. Each selected candidate event is modeled using the Z-number formalism [13–16], defined as $Z = (\tilde{A}, \tilde{B})$, where $\tilde{A}$ represents the fuzzy linguistic assessment of consumption severity and B˜denotes the reliability (confidence) of that assessment.

Classical fuzzy models encode only the degree of membership to linguistic terms and do not explicitly represent the reliability of the underlying information. The Z-information concept unifies uncertainty and reliability in a single formal framework, which makes the decision-making process more meaningful in practice [13–16].

- Construction of $\tilde{A}$. The candidate consumption behavior is modeled using trapezoidal (or other) fuzzy numbers which stand for linguistic terms such as normal, suspicious, and highly suspicious/anomalous, based on the author's Z-anomaly framework [18].
- Construction of $\tilde{B}$. The reliability component is based on data quality indicators such as missing values, measurement instability and billing corrections. Reliability classification and interpretation are treated as a dedicated stage within the Z-number algorithm [13].
- Comparison and selection. Each candidate Z-number is compared with a pre-defined set of expert Z-prototypes.

$$Z = \left\{Z_{\{ns\}}, Z_{\{svs\}}, Z_{\{vss\}}, Z_{\{amc\}}, Z_{\{aavs\}}\right\} \quad (2)$$

and the anomaly class is determined via distance minimization:

$$class_{\{da\}(x_i)} = \arg\min_{\{Z_k \in Z_{da}\}} D\left(Z_{\{x_i\}}, Z_k\right) \quad (3)$$

The arithmetic operations and distance mechanisms of Z-numbers serve as the theoretical foundation at this stage [14]. The distance function for trapezoidal components (Aliev's approach) is defined as follows:

$$D\left(Z_{\{x_i\}}, Z_k\right) = 0.5\left(\sum_{i=1}^{4}\left|a_i^{Z_{\{x_j\}}} - a_i^{Z_k}\right| + \sum_{i=1}^{4}\left|b_j^{Z_{\{x_j\}}} - b_j^{Z_k}\right|\right) \quad (4)$$

When conversion to classical fuzzy numbers is required, the transformation approach by Kang et al. can be applied [22].

The consumption indicator of selected candidates is first translated into a linguistic assessment by means of fuzzy logic, generally in the form of low, normal and high. At the same time, a reliability measure is developed which is based on data quality indicators, contextual consistency and historical stability of the consumption behavior.

These two components jointly form a Z-number representation $Z = (\tilde{A}, \tilde{B})$, where $\tilde{A}$ denotes the fuzzy characterization of consumption severity and $\tilde{B}$ represents the associated reliability level.

At the subsequent stage, each candidate Z-number is compared with a pre-defined set of expert Z-prototypes using distance-based similarity measures. This comparison enables both the anomaly class and its explainable reliability level to be determined, allowing reliability-aware and interpretable decision-making (fig. 3).

• ***Reporting and decision support: operator-oriented outputs.*** The system output is not just an "anomaly score" but an investigation-ready package for the operator, including a risk alert, anomaly class (e.g., normal/suspicious/anomalous), reliability indicator, concise explanation (which filter was triggered at Level-1 and which prototype was most similar at Level-2), and recommended operational actions (inspection, monitoring, technical verification, etc.). Operationally this module addresses the interpretability issues of black-box machine learning models and reduces decision-making risk for human operators [2, 6, 19, 20]. The Level-2 results are passed to the operator-oriented reporting and decision support module, where the risk score, anomaly class and level of reliability are visually presented and suitable intervention options (investigation, technical inspection, notification) are suggested (fig. 4). The panel presented in the figure illustrates the operational-level output of the proposed two-level Z-number-based architecture. The detected anomaly is presented not only in terms of its magnitude but also together with its associated reliability level, thereby enabling explainable and risk-based evaluation for decision-makers.

Methodological insight: Why two levels? In anomaly detection there is a structural trade-off between scalability and operational efficiency on the one hand and explainability of results on the other. Existing approaches either provide fast but weakly interpretable methods, or highly explainable models at a substantial computational cost [1, 2, 6]. The proposed architecture overcomes this trade-off as follows:

• Level-1: scalability and speed by statistical and unsupervised machine learning filters [2, 3, 10, 26];

• Level-2: decision making with Z-numbers and reliability assessment [13-15, 19-21].

Thus, the system allows for operationally relevant, explainable and reliable anomaly assessment in high-responsibility domains, e.g., gas distribution systems.

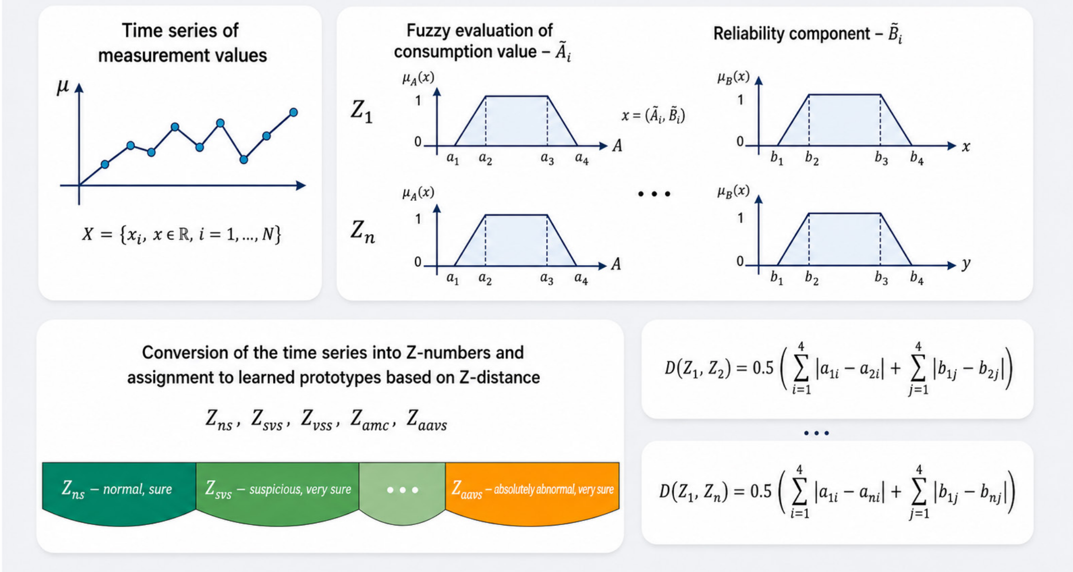

Fig. 3. Z-number-based anomaly assessment and explainable classification

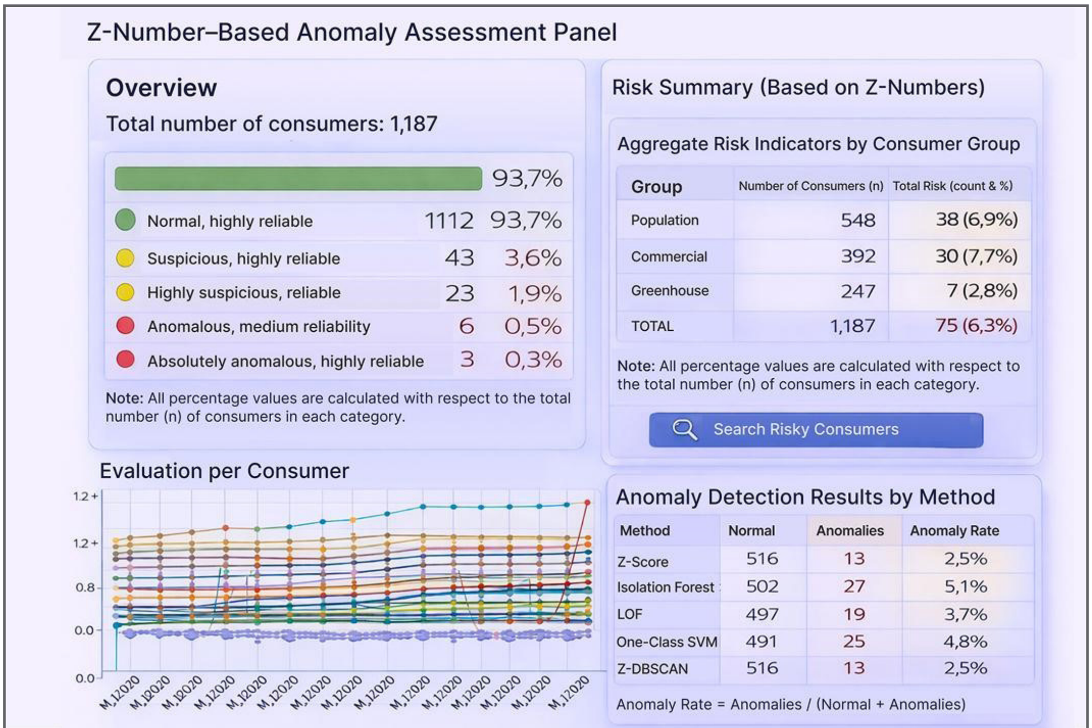

Fig. 4. Operator dashboard mock-up for anomaly investigation.

5. Structure and implementation of the software system for gas consumption anomaly detection

To enable the practical application of the proposed Z-number-based anomaly assessment approach, a modular software system has been developed. The system processes time-series data related to energy consumers, performs multi-stage analytical processing, and ultimately provides reliability-based risk assessment. Unlike most detection tools, the system shows not just whether an anomaly exists, but also how confident that finding is. From a functional perspective, the system architecture is organized as a set of interrelated sequential modules, each implemented using specific technological tools. The overall structure of the software system is illustrated in figure 5.

As illustrated in figure 5, the software system operates according to a sequential and multi-stage processing workflow, starting from data acquisition and progressing toward reliability-based risk assessment of detected anomalies for decision-making purposes:

1. *Collection of consumption data (Input stage).* The main input data are time-series records concerning energy consumers. These data can be extracted from smart gas meters, billing systems, or structured file formats such as CSV and Excel. The first step in any analytical process is the input step, and the quality of the incoming data will directly affect the reliability of the final results. At this stage, Python is selected as the main execution environment. Extensibility and scalability are possible due to Python's flexibility and its large analytical ecosystem.

2. *Data loading and pre-processing*. Subsequently, the input data are transferred to the preprocessing module. The main objective of this module is to convert raw data into a form

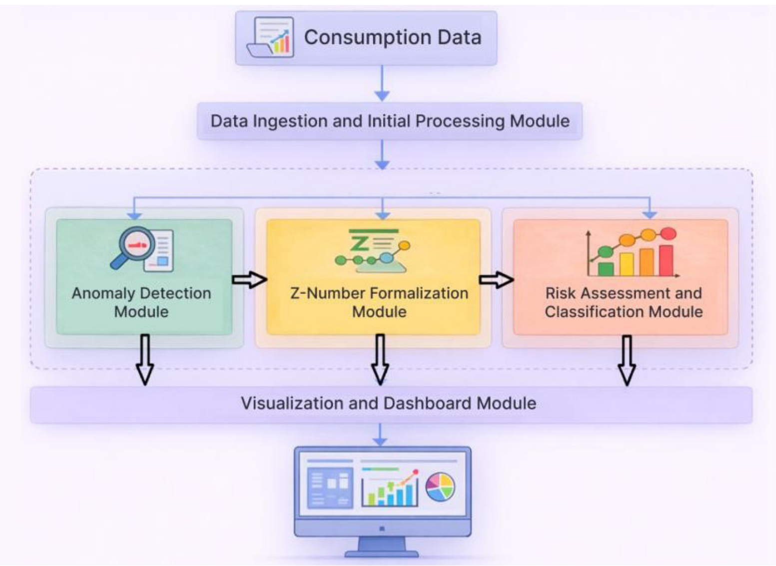

Fig. 5. Structure of the software system

that is suitable for analytical modeling. At this stage, data are structured in a uniform way, missing and inconsistent values are identified and the effect of the technical noise is minimized. The Pandas library is used to manage time-series, and for aggregation (daily, weekly, monthly), filtering and tabular operations. NumPy is used for efficient array-based computations and ensures numerical stability of the data. The above preprocessing step is required to obtain stable, comparable and reliable results from the following analytical modules.

3. *Initial anomaly detection (Level-1 analysis).* The preprocessed data are then passed to the anomaly detection module. The main aim of this step is to automatically identify observations that significantly differ from the normal behaviour by using computationally lightweight but effective techniques. At this stage, the main analytical toolkit used is the Scikit-learn library. In this framework, statistical methods and unsupervised machine learning methods are applied in parallel. The use of multiple methods in parallel enables cross-method comparison, reduces false-positive detections, and supports a more stable initial screening process. The output of this phase is not a final decision but a list of candidate risky observations which are passed to the next stage of analysis.

4. *Formation of Z-number-based representation (Level-2 input).* In the next stage, a Z-number-based representation is constructed for the candidate observations selected at the initial stage. In this phase, consumption levels are described in a fuzzy manner using linguistic terms, while the reliability component is constructed simultaneously by taking into account data stability, temporal variability and cross-method consistency. The module is implemented by means of dedicated functions developed in the Python environment. The proposed approach is designed such that fuzzy mapping and reliability computation are separated into different logical blocks. Additional evaluation criteria can be incorporated in future extensions of the system. The outputs of this phase are the reliability-aware Z-representations which serve as the basis for the following decision-making process.

5. *Classification and risk assessment.* The following step is to classify the observations in the form of Z-numbers according to their risk levels. The classification process depends not only on whether the consumption behavior is anomalous, but also on the confidence level associated with the corresponding decision. The results are categorized into normal, suspicious, highly suspicious, anomalous and absolutely anomalous. This method provides the operator with a risk profile based on reliability rather than a hard binary decision. The results are summarized in absolute numbers and percentage indicators to form an overall risk landscape.

6. *Dashboard module (visualization and decision support).* Finally, all results are displayed to the operator in a visual and interactive way. For this, static visualizations are created with Matplotlib and Seaborn and an interactive dashboard environment is built with Dash or Streamlit. In the visualization stage, the dashboard presents an overview of risk distributions, aggregated risk indicators for consumer groups, anomaly ratios by method and individual consumption behavior profiles. This stage keeps a human in the decision loop, integrating automated analysis with human expertise efficiently.

An open-source relational database management system, PostgreSQL, was selected for the database layer of the software system. PostgreSQL was chosen because it handles concurrent read/write operations reliably, keeps foreign key relationships intact, and runs complex queries across multiple tables without producing inconsistent results. All records, including raw consumption readings, detection outputs, Z-number components, and risk scores, are stored in the order they are generated, so earlier stages can always be checked against later ones.

Foreign keys, indexing mechanisms and logical database views are used to formally maintain the relationships between data generated at different stages of analytics, satisfying the real-time query requirements of dashboard-based decision support modules. In addition, PostgreSQL supports semi-structured data types via the JSON data type, which enables the structured storage of fuzzy and Z-number components and can support later extensions of the system's analytical models.

The proposed software system has been developed with a relational database structure for data storage, management and transfer between analytical stages. This structure is directly integrated with the functional workflow described in the UML Login–Analysis–Decision sequence diagram (fig. 6) and ensures that all data generated throughout the system are stored in a clear sequence across all processing stages.

The database system sequentially stores time-series consumption data, initial anomaly detection results, Z-number-based representations and risk assessment results stage by stage, fully supporting the modular software architecture. Each analytical service (DataService, AnomalyService, ZService, RiskService) stores the output of its respective processing stage in specific database tables, which are the data foundation for the next analytical stages, as shown in the UML Sequence diagram.

The database was designed around four practical needs: keeping records in the order they arrive, being able to trace any result back to the stage that produced it, storing the A and B components of each Z-number separately, and returning query results fast enough for the dashboard to stay responsive.

To do this, a set of logically connected core tables has been defined in the database and its usage follows the workflow shown in the UML Sequence diagram described below.

The login stage is where the user is authenticated and the session is started. The diagram shows that this stage is implemented by the AuthService and SessionService components and its results are stored as user and session records in the system tables. All subsequent analytical processing is done within the context of an active session. This approach allows tracing which user generated certain analytical results, so that each result can be linked to the user who generated it.

At the beginning of the analysis stage, the time-series consumption data related to the consumer are extracted from the database through the DataService (ETL/Preprocess) component as shown in the UML diagram. The Consumers table contains basic consumer information, such as the consumer's unique identifier, region or network code, subscriber type, and other static attributes. This structure is useful for long-term tracking of individual consumption behavior and is the main input for the StartAnalysis invocation shown in the diagram.

Consumption_TimeSeries – Time series data for gas consumption. In the UML Sequence diagram, this table is accessed directly by the FetchTimeSeries operation. The record includes a timestamp, a consumer identifier and the consumption value it relates to. The time-series data organized in a specific structure ensures the efficient execution of the aggregation, trend analysis and anomaly detection phases.

The first anomaly detection stage triggers the AnomalyService (Level-1) component in the UML diagram. The results are stored in the table Anomaly_Level1 which contains the name of the method used, the anomaly score, the initial label and the timestamp. The structure allows storing the results of the parallel preliminary analyses in a comparative way as shown in the diagram and allows the subsequent computation of the reliability component.

At the next stage, the ZService component constructs the Z-number-based representation. The results of this stage are saved in the table Z_Number_Representation. This table stores the fuzzy consumption component (A) and the related reliability component (B) as separate fields. This structure retains the mathematical essence of the Z-number formalism at the database level, and is a direct input to the AssessRisk invocation shown in the diagram.

The RiskService component is activated at the stage of risk assessment and classification and its results are stored in the Risk_Assessment table, which is illustrated by the UML diagram. The risk class, risk score, reliability level, and final decision are stored in this table. The steps Decision and NotifyHighRisk shown in the diagram are performed on the data stored in this table. Such a structure allows the creation of a historical record of the generated risk profiles and their subsequent use in expert evaluation.

Finally, the dashboard and the notification mechanisms illustrated in the last stage of the UML Sequence diagram use the results stored in the database. Auxiliary database views and aggregation structures are created for risk and anomaly results to enable the visualization and decision support modules to work efficiently, allowing graphs to be generated in real-time and the user interface to responsively support decisions.

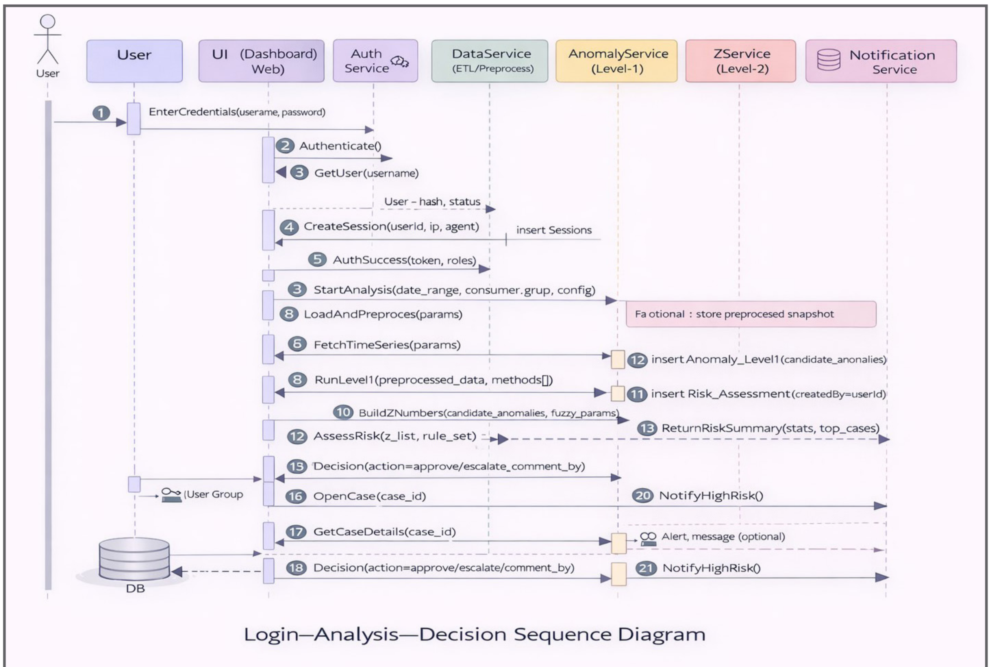

Fig. 6. UML sequence model of the anomaly detection and decision-making process

Conclusions

Gas consumption monitoring produces large volumes of time-series data that are noisy, seasonally variable, and often collected under imperfect metering conditions. For this reason, anomaly detection in such data should not be treated only as a pattern recognition task. In practice, operators also need to judge whether a flagged observation deserves attention or whether it may simply come from measurement noise, data instability, or temporary fluctuations. Classical statistical and machine-learning methods usually stop at producing anomaly labels, while the reliability of these labels is often left unclear.

The two-level architecture proposed in this paper addresses this issue by making reliability part of the anomaly assessment itself. Level-1 processes large-scale gas consumption data efficiently by using statistical filters and unsupervised learning methods to identify candidate anomalous cases. These candidates are then evaluated at Level-2 using Z-numbers, where both the abnormality of the consumption pattern and the confidence in that assessment are considered together. This difference is important in operational settings. A highly unusual reading based on unstable or incomplete data should not be handled in the same way as an anomaly supported by consistent historical measurements.

The Z-number representation also shows a limitation of classical fuzzy models. In a standard fuzzy approach, two observations may receive similar membership values even if one is based on reliable data and the other comes from a noisy or faulty source. By adding the reliability component to the fuzzy assessment, the proposed framework gives operators a clearer picture of the risk behind each detected anomaly.

We implemented the approach as a modular software system supported by PostgreSQL, Python-based analytical modules, and an operator-oriented dashboard. The database structure keeps the results of each analytical stage in a clear sequence, so that the path from raw consumption data to the final risk class can be followed when needed. This is important for practical use in gas distribution environments.

Future work will focus on adding feedback from field inspections and expert review into the reliability component. The framework should also be tested on larger multi-year datasets from different regional networks to see how well it works under different operating conditions.

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