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Analysis of Methods for Predicting H_2 Sensor Responses

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Summary: Hydrogen (H_2) is crucial for replacing fossil fuels and achieving net-zero emissions, but its flammability and explosiveness pose safety challenges. Rapid H_2 leak detection is essential for triggering emergency accidents. However, H_2 sensor response is constrained by material properties and gas flow dynamics, causing response and detection delays. Our current study explores various available algorithms for H_2 sensor response prediction from early responses with a small time window, accelerating leakage detection. Our findings identify the most efficient algorithms for real-time implementation, enhancing H_2 safety systems.

Keywords: H_2 safety,early H_2 leakage detection,stable H_2 value prediction, prediction algorithms

Introduction

(H_2) plays a significant role in clean energy, but its storage and transportation pose several challenges due to leakage and permeation. Leakage occurs through structural defects, while permeation involves the slow diffusion of hydrogen through materials. These risks are heightened in high-pressure storage, increasing the potential for rapid release and ignition. To address risk concerns, sensor systems with advanced predictive algorithms are essential for early hydrogen safety, especially leak detection. The algorithms improve detection speed and accuracy by analyzing transient response signals and estimating stable sensor values. Numerous studies have explored predictive modeling for hydrogen sensor response. Shi et al. applied a CNN-LSTM model to forecast hydrogen concentration for rapid detection [1]. Hübert et al. developed a mathematical approximation algorithm to estimate the sensor t_{90} response time [2]. Osorio-Arrieta et al. utilized the Gauss-Newton method to accelerate the measurement time by fitting transient response curves [3].

Existing literature primarily focuses on predicting sensor response using the entire H_2 sensor response. This study focuses on algorithms that predict H_2 entire sensor response from an early small time window of the sensor response. Our study evaluates various algorithms' mathematical feasibility and practical applicability for sensor response prediction while providing a comprehensive overview of methods used in H_2 sensor analysis.

Hydrogen Sensor Response Behavior

In gas measurement, a sensor reacts to a change in gas concentration, resembling a negative exponential curve as the hydrogen concentration increases [4, 5]. Ideally, the sensor response is stable when it reaches the targeted H_2 gas concentration. However, sensor response can be affected by both extrinsic and intrinsic factors. Extrinsic factors include gas delivery dynamics and data acquisition delays. In contrast, the intrinsic factors related to the sensor's physical properties influence the delay between hydrogen release and initial signal detection [2]. As illustrated in Fig. 1, we aim to predict the stable value of the sensor response (green curve) using a model (red curve).

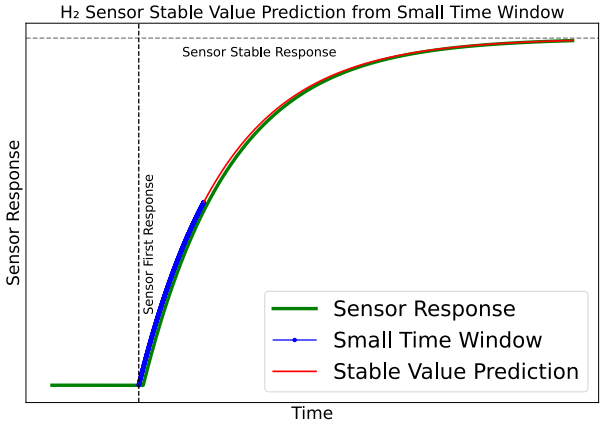

Fig. 1: Hydrogen sensor response with key features: sensor response, a small time window, and the predicted response

We will follow a structured workflow to predict H_2 sensor response from a small time window. First, raw time-series sensor responses will be collected from experiments and real-world use cases. Next, key variables—including the initial response, small time window, and stable sensor response—will be defined. Different prediction models will be selected based on their accuracy

and applied to estimate the stable response using small time data. In this research, we will present various prediction models in the following sections. The models' outputs will be analyzed and evaluated, taking into account uncertainties and potential errors in real-world sensor responses. Finally, we will identify the most effective model for H_2 sensor response prediction.

Classic Approximation (CA)

CA algorithms are based on analytical transfer functions that approximate hydrogen sensors' transient and steady-state response. They help estimate key response characteristics such as time delay and stable values. CA algorithms establish a clear analytical framework, enhancing interoperability and providing valuable insights into sensor dynamics. Different CA models, such as First-Order Plus Dead Time (FOPDT) and Second-Order Plus Dead Time (SOPDT), Exponential and Polynomial Curve Fitting explained in [6] are computationally efficient, requiring minimal processing power, which makes them well-suited for efficient applications.

Statistical Regression (SR)

SR algorithms predict sensor responses based on past sensor readings, making them practical for time-dependent predictions. In [7], various SR algorithms such as Auto-regressive (AR), Auto-regressive Moving Average (ARMA), and Auto-regressive Integrated Moving Average (ARIMA) are discussed, which provide a powerful approach for forecasting sensor values using historical data. These algorithms are particularly well-suited for time-series forecasting and real-time sensor response prediction. By leveraging past sensor readings, they can identify patterns and trends, making them valuable for long-term monitoring and adaptive calibration.

Machine Learning (ML)

ML is also a data-driven algorithm for predicting hydrogen sensor responses, leveraging large datasets for improved accuracy and robustness. It offers advanced, data-driven solutions for predicting hydrogen sensor responses, particularly in complex time-series data analysis. In [7], different ML algorithms such as Support Vector Machines (SVMs), Random Forest Regression (RF), Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) Networks are discussed, which leverage large datasets to improve prediction accuracy and robustness. Unlike traditional classic and statistical algorithms, ML approaches can handle nonlinear sensor behaviors, adapt to environmental variations, and extract hidden patterns from sensor signals. However, ML models require large, high-quality datasets for training and can be computationally intensive, making them less suitable for low-power embedded sensor systems. Despite the limitations, ML-based sensor prediction models significantly enhance early leak detection and adaptive monitoring, making them a powerful tool in hydrogen safety applications.

Discussion

The H_2 sensor response is dynamic and influenced by ambient factors such as temperature, pressure, and humidity, which introduce uncertainties that should be quantified using appropriate error metrics and validation techniques. Our study starts with classical models (FOPDT, SOPDT), which estimate stable responses using a small time window. Furthermore, we will consider ARIMA for accurate prediction by considering uncertainties. Finally, we train the LSTM model to enhance real-time H_2 sensor response predictions in large-scale datasets.

Conclusion

In this study, our objective is to predict the H_2 sensor response using only a small time window from the early H_2 sensor response. Each model has its strengths and limitations—some algorithms excel at capturing specific features, while others offer higher accuracy with lower computational costs. Therefore, we are exploring the most efficient and reliable algorithms for quick H_2 sensor response prediction. In the future, we aim to test hybrid algorithm approaches by integrating CA, SR, and ML models to achieve optimal prediction accuracy.

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