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A Deep Learning-Based Utilization Improvement Framework for Abdullah Hashim Industrial Gases & Equipment Co. Ltd Transportation Network

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Abstract: Transportation disruption causes economic loss in supply chains in the gas industry while population growth increases, which calls for a comprehensive review of the operations by management. Hence, the gas company should study and evaluate the situation and make the right decision by taking corrective action to minimize the negative impact of disruption. This paper aims to develop a deep learning-based model to improve the efficiency of the constrained transportation network of an industrial gas company in conjunction with historical data. The framework was demonstrated using an example case of the gas industry in Jeddah, Saudi Arabia. The findings revealed the usefulness of the Wilde Neural Network model in classifying the trip cost with an accuracy of 100% and a short duration of training of 2.84 seconds.

Keywords: Machine Learning, Deep Learning, Transportation Network, Disruption

I. INTRODUCTION

A well-behaved transportation system influences the economy, safety, and quality of life. However, transportation demands are increasing due to trends in population growth, emerging technologies, and the increased globalization of the economy, which has kept pushing the system to its limits. The rate of increasing the number of vehicles is at points even more than the overall population increase rate, which leads to more congested and dangerous roadways [1].

Transportation disruptions reduce the operating income and the return on sales and assets and increase the production cost and level of inventory [2, 3]. A transportation disruption refers to a disruption in the transit of goods from one node to another, like the supplier to the manufacturer [4]. The impact of transportation disruption might cause missed delivery deadlines, plant shutdowns, and lost sales.

A. Problem Statement

Internationally competitive business environments require a well-executed supply chain, a network that smoothly acquires raw materials from suppliers and generates finished goods [5]. Abdullah Hashim Industrial Gases & Equipment Co. Ltd. (AHG) transportation network was a demonstrated framework in this paper. The company had suffered from increased transportation costs due to transportation disruption, especially when it was frequent and occurred suddenly. The company had some constraints regarding the transportation: a limited number of drivers and trucks, limited drivers who can drive all types of trucks, and short delivery times for some customers with frequent trips across various cities. Furthermore, there were planned round trips across the branches of the company.

B. Research Motivation

Many studies have been done on international freight transportation, supply chain, and logistics management. Furthermore, minimizing transportation disruption increases revenues and sales and reduces production costs and inventory levels. Besides, meeting the promised due dates would positively impact customer relations. The deep learning approach makes this research applicable to companies of similar nature and under similar constraints.

C. Research Objectives

This paper aimed to develop a deep learning-based model to improve the efficiency of the constrained transportation network in conjunction with the historical data to classify the trip costs. The learning model is applied to the same transportation network while the sales are kept in view. Some secondary objectives are to analyze the impact of transportation disruption and minimize the impact of disruption on the total cost to an acceptable level. Consequently, maintain customers' satisfaction and profit subject to the production, supply, demand, delivery, and time constraints using machine learning.

II. LITERATURE REVIEW

A. Transportation Disruption

A 2019 study [6] have studied a lean, two-stage supplier-manufacturing coordinated system where a sudden disruption interrupts the transportation network, creating delivery delays and product quantity losses. They developed a model to generate a recovery plan after a sudden disruption by proposing three heuristic solutions based on the delivery delay and fractional quantity loss. They also conducted several numerical experiments to validate the methods. The results revealed that the proposed heuristics could generate an accurate recovery plan.

A 2018 study [7] have formulated the public transport problem as a supervised sequence classification task, where the sequences were made of geographic coordinates, time, and line and direction of travel as the label. They presented and compared two-driven approaches to that problem: (i) a heuristic algorithm and (ii) a deep learning approach using RNN models. Approach validated with a separate data set of hundreds of real user journeys. The experimental results were auspicious (up to 92.68% on the top 3 predictions), and they were willing to deploy the solution in a production environment.

Natural disasters, labor disputes, and infrastructural failures can cause transportation delays [8]. In addition, delays in delivery to the consumer are a typical result of transportation problems, and some researchers have dealt with the delivery delay after the interruption by recovery models. [9, 10, 11]. However, transportation disruptions can quickly disrupt an entire supply chain [12, 13], leading to late deliveries, shutdowns, lost sales, and a ruined reputation [14].

B. Artificial Intelligence

Machine learning is a form of Artificial Intelligence (AI) and a data-driven solution that learns the latent patterns of historical data to model the behavior of a system and respond accordingly. Machine learning solutions have a higher return on investment than conventional solutions. These solutions aim to reduce congestion, diminish human errors, and improve productivity and efficiency [1].

Deep learning is a new machine learning approach that is still limited in transportation systems [15]. Many methods like *k*-nearest neighbor (*k*NN) predict the class of its *k* nearest neighbors, where the neighborhood relations are induced by a measure of distance between data points. It depends on the distance function, model size, and feature complexity [16].

The support vector machine (SVM) method can be used for classification purposes, regression, or clustering problems [17]. It allows a kernel function to boost the input features up to higher dimensions via the trial-and-error process based on the pattern of historical data. The artificial neural network (ANN) family algorithm can handle complex relationships in multivariate data [18].

III. METHODOLOGY

In this paper, a supervised machine learning method was applied to the training data obtained from the historical records of the transportation system and the sales data of the company by using the deep learning algorithms in the MATLAB® program to train and validate a binary classification model that determines the class of the total cost of trips.

A. Data Collection

The data set was acquired from the logistics and supply chain manager. AHG company provided specific information about dispatched or arrived shipments between branches for the last three years due to the sensitivity of the total costs on business. The data set consisted of six input features or predictors: Years, Months, Sales, No. of Trips, Destination, and Trip Cost. Also, a single output variable (response) was the Class of total trip cost as either Low, Moderate, or High.

B. Classification Learner App

The Classification Learner App automatically trains different classification models on the data, including decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naïve Bayes, kernel approximation, ensemble, and neural network classifications. One of the helpful validation techniques in this application is the Cross-Validation scheme, which evaluates different combinations of feature selection, and dimensionality reduction and protects against overfitting. The application partitions the data set into k folds; and estimates the accuracy of each fold after dividing the data set into two portions: training and testing data sets. In this paper, the k value is considered five-fold; the training data set represented 80% of the data and the remaining for testing the final model.

Then, all classification models were trained and evaluated based on their accuracy using the confusion matrix. According to evaluation, preprocessing of features is applied by ranking their importance scores based on the Chi2 algorithm, which supports categorical and continuous features. Furthermore, the process of training was repeated to achieve the proper model. Hyperparameter optimization enhanced the accuracy of trained models with tools like principal component analysis (PCA) and optimization models. After that, the final model was tested using the testing data set and evaluated before being used to predict new data. Fig.1 represents the flow chart of the methodology used in this research.

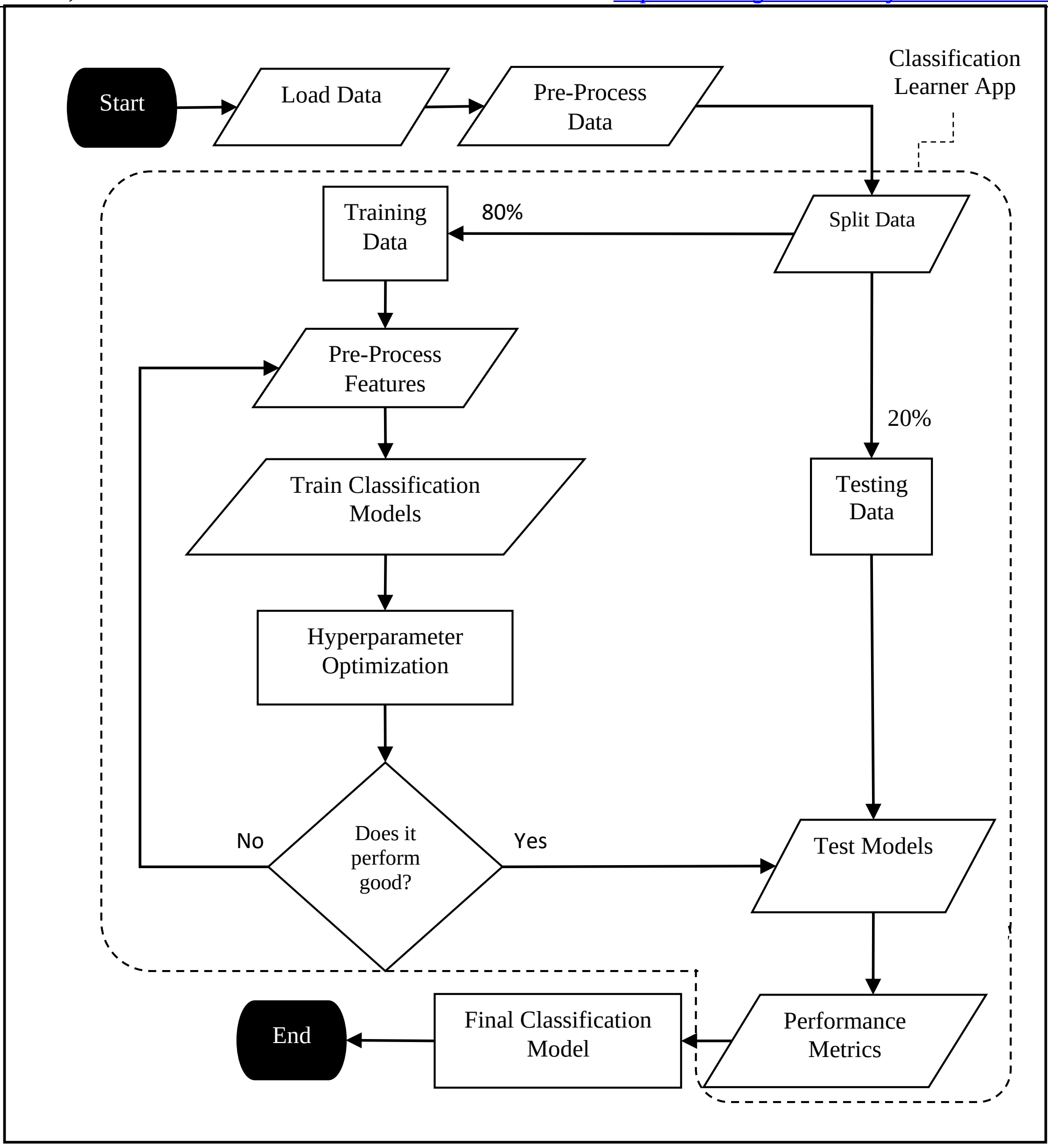

Figure 1: Flow chart for the methodology.

IV. RESULTS AND DISCUSSION

The training results of all twenty classification models with all the features (year, month, sales, number of trips, destination, and total cost) are represented in Fig.2, where the trained models were ordered in descending order of duration of training in seconds.

Thus, the best model with the lowest training duration of 3.80 seconds was the Cubic SVM, where the accuracy was 100%. Furthermore, Fig. 3 and Fig. 4 shows the ability of the Cubic SVM model to classify the classes of costs when plotting destination versus both trip cost and the number of trips, respectively, as the classes of the trip cost were separated in this model.

The confusion matrix of the Cubic SVM model is represented in Fig. 5, which helps identify the areas where the classifier performed poorly. Here it showed that the model predicted all the classes correctly.

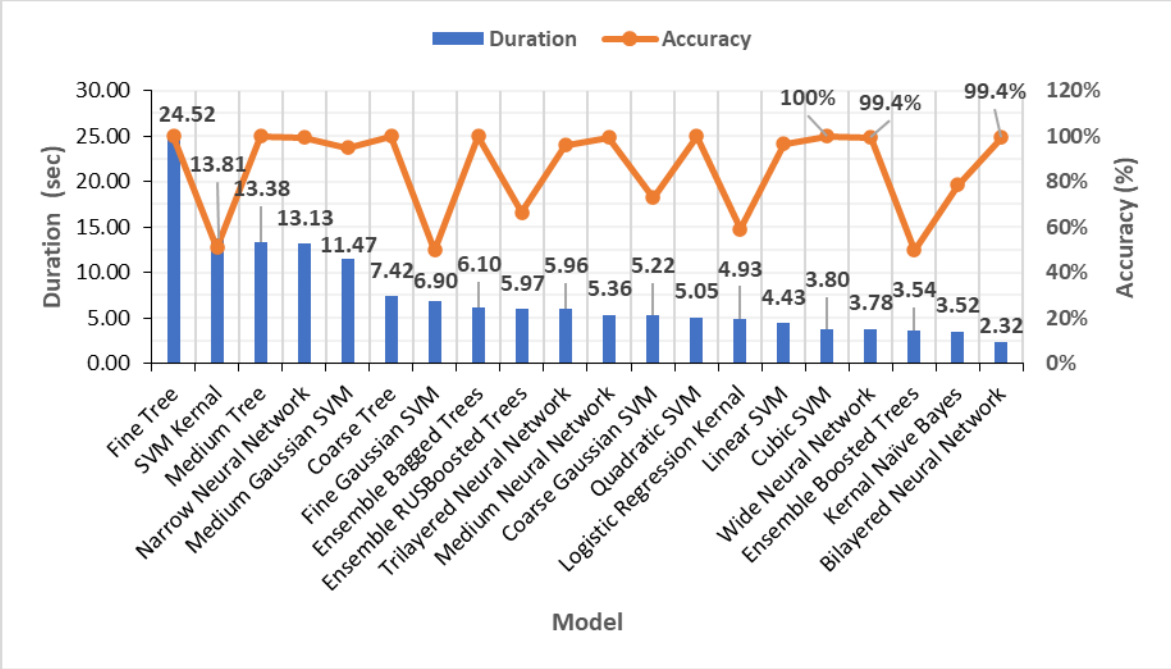

Figure 2: Accuracy and duration in seconds of trained classification models with all six features.

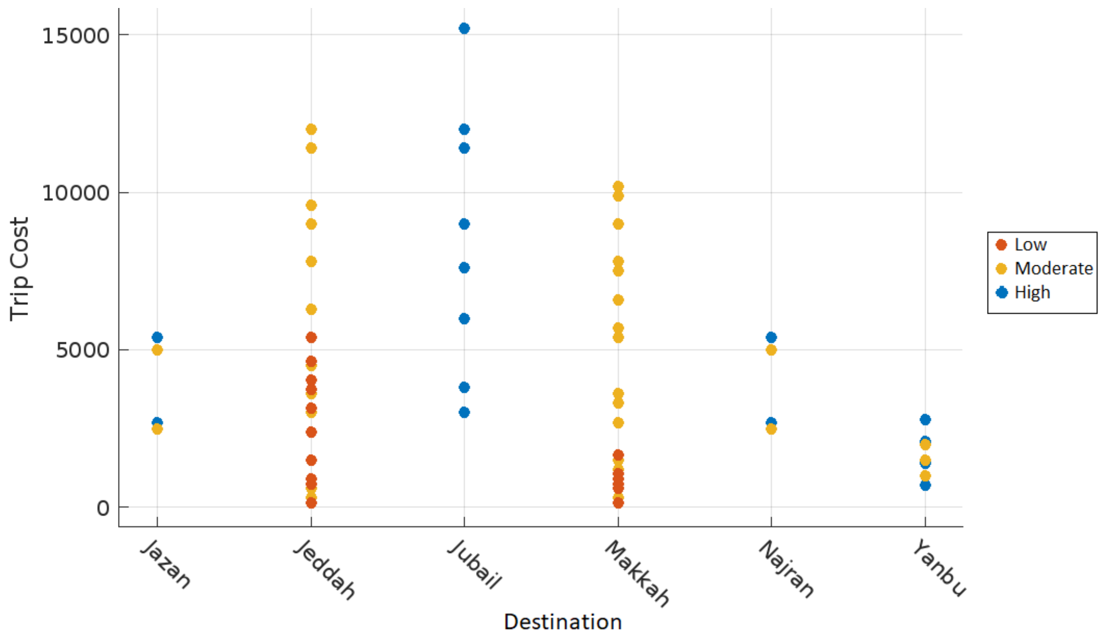

Figure 3: Plot of destination vs. trip cost for predicted classes of Cubic SVM model.

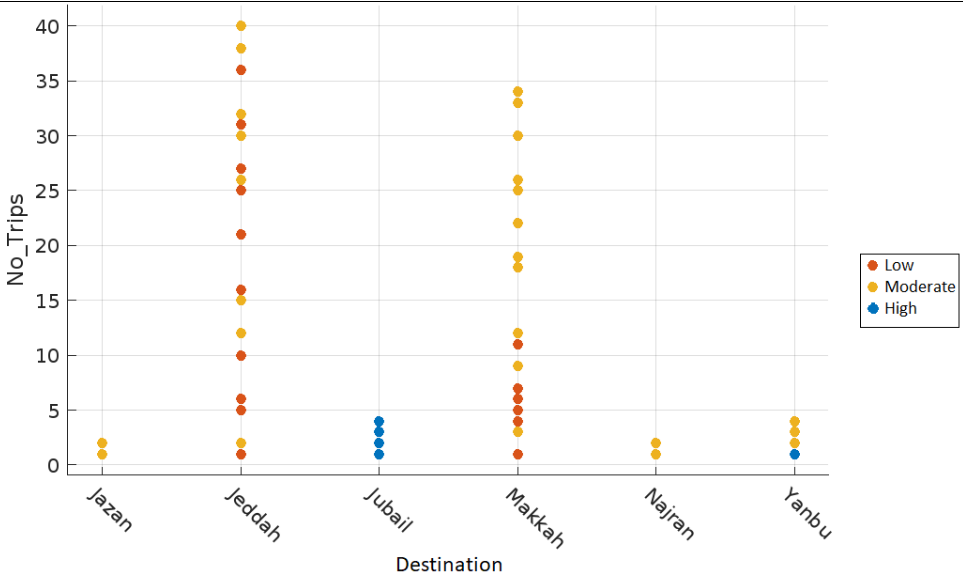

Figure 4: Plot of destination vs. the number of trips for predicted classes of Cubic SVM model.

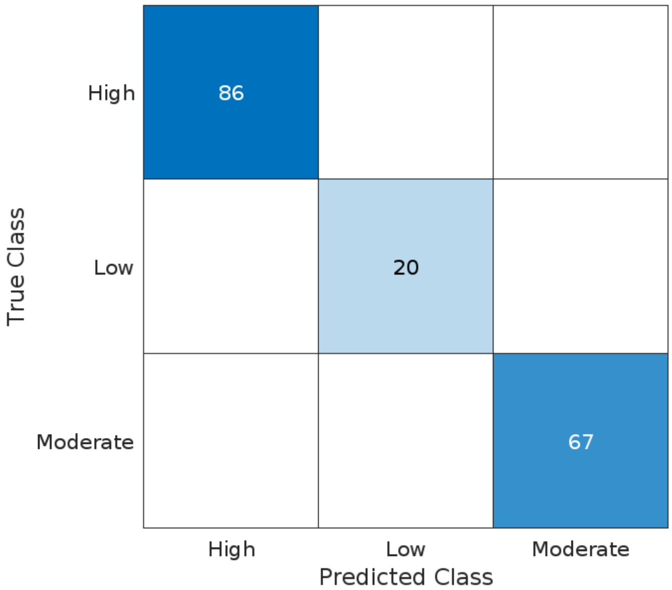

Figure 5: Confusion matrix of Cubic SVM model.

For enhancement of the model, the number of features was reduced using the feature's importance ranking based on Chi^2 scores, as shown in Fig. 6, where it examined whether each feature is independent of the response (Class of trip cost) by using individual Chi^2 tests and then ranked features using the *p*-values of the Chi^2 test statistics, where the scores corresponded to -log(p) [19]. After that, the top four features were selected and trained in the Cubic SVM model.

Thus, the classification model results after enhancement are represented in Fig. 7. Although multiple models have achieved 100% accuracy, the model Wide Neural Network was the fastest in training. In contrast, the Cubic SVM took more time than previous training with 0.8 seconds.

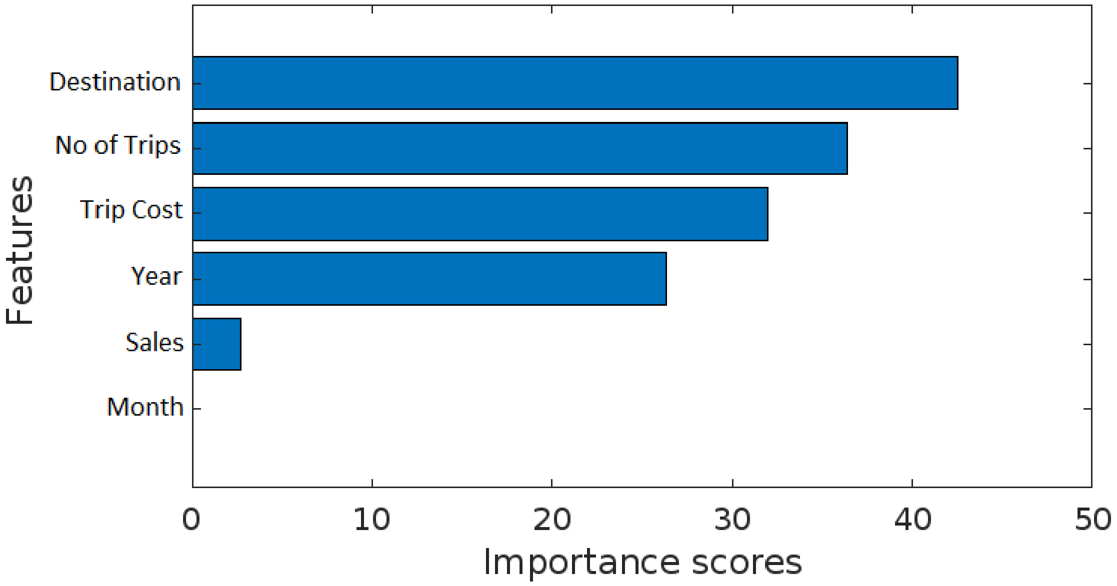

Figure 6: Feature importance scores with Chi^2 algorithm.

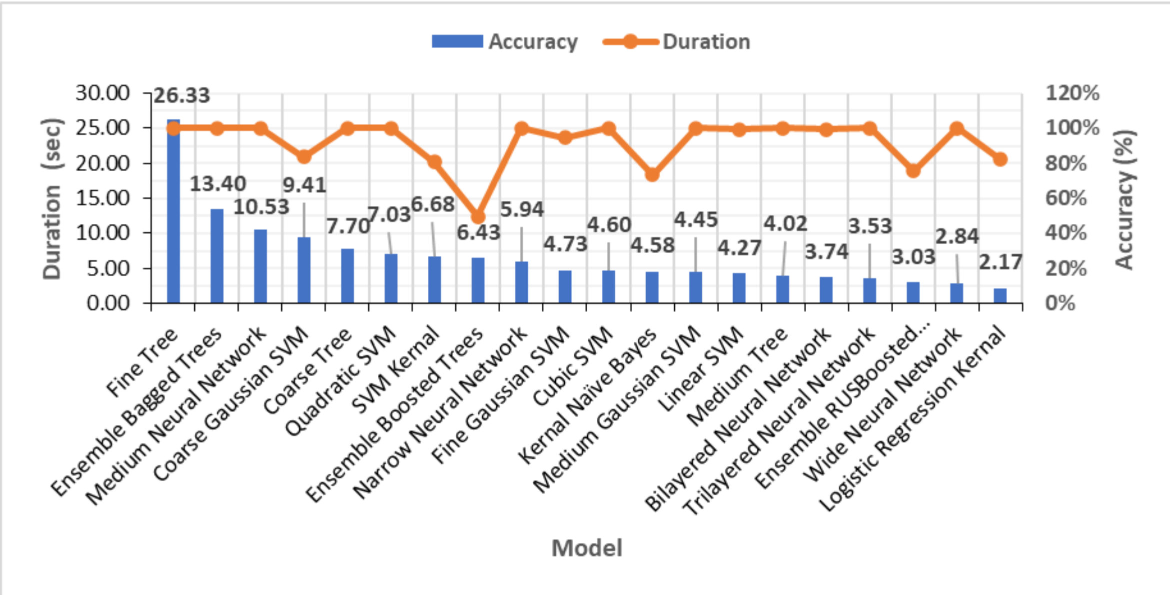

Figure 7: Classification models results after features reduction.

V. CONCLUSION

The primary goal of this study was to develop a deep learning-based model to improve the efficiency of the constrained transportation network. Various models were trained with six input features and one response (Class of trip cost), which led to the Cubic SVM model, which was the fastest in training. However, the features were reduced to four after the features ranking algorithm was applied using Chi2 scores. Then, another model was obtained, which was the Wide Neural Network model.

It is recommended to apply this methodology to a more extensive data set to explore the variations of the models. Furthermore, it could be a good insight into research to have a different approach to such problems in the gas industry in future work.

Conflict of interest: The authors declare that they have no conflict of interest.

Ethical statement: The authors declare that they have followed ethical responsibilities.

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