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Deep Learning for Pipeline Damage Detection: an Overview of the Concepts and a Survey of the State-of-the-Art

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***Abstract*— Pipelines have been extensively implemented to transfer oil as well as gas products at wide distances as they are safe, and suitable. However, numerous sorts of damages may happen to the pipeline, for instance erosion, cracks, and dent. Hence, if these faults are not properly refit will result in the pipeline demolitions having leak or segregation which leads to tremendously environment risks. Deep learning methods aid operators to recognize the earliest phases of threats to the pipeline, supplying them time and information in order to handle the problem efficiently. This paper illustrates fundamental implications of deep learning comprising convolutional neural networks. Furthermore the usages of deep learning approaches for hampering pipeline detriment through the earliest diagnosis of threats are introduced.**

Keywords: Deep learning; convolutional neural network; damage detection

I. INTRODUCTION

The most significant challenge facing the industry today is an aging pipeline infrastructure which can result in leaks and disconnections, leading to economic as well as environmental disasters. Identifying leaks in early stage is essential to prevent serious problems. In order to improve levels of security, dependability and usefulness of operation, novel approaches for pipeline observation have been generated worldwide [1]. Distributed temperature monitoring approaches utilizing optical fibers have been considered as an effective method to identify and localize leakages throughout pipelines [2]. In [3] acoustic impact monitoring method is suggested to detect leakage along gas pipelines. In [4], artificial neural network technique is used to approximate the leak position in pipe networks. Rapid and precise leak identification and location, presents major challenges for recent techniques in the area of damage identification in pipe networks [5-9]. Leakage identification techniques still require to be improved in order to have great precision in specifying leak position.

Recently, different types of artificial intelligence approaches, like artificial neural network are generally implemented in the engineering area. Artificial neural networks have been noticed as one of the useful approaches in recent years as they are widely used in an extensive sort of usages in several fields [10-18]. They are the most competent and operative tools. Artificial neural networks have learning skill and model-free features. Neural networks are made of interrelated groups of artificial neurons that have information which is obtainable by computations linked to them. Mostly, neural networks can adapt themselves to structural alterations while the training phase. Neural networks have been utilized in modeling complicated connections among inputs and outputs or acquiring patterns for the data [19-20]. Artificial neural networks have various noteworthy properties like universal function estimation abilities, as well as match of multiple non-linear variables concerning with unknown interactions [21-24]. Due to these properties, most of the researchers consider the application of artificial neural networks for automatically recognizing the incidence of leakages in oil pipelines, substituting the human operator that observes the online trends from the sonic sensors. Supervised machine learning is identified as an effective implement for leakage recognition. That technology is considered as a part of artificial intelligence which contains the ability to initiate forecast with very little human intermediation.

Currently, pattern recognition as well as machine-learning approaches have been successfully applied for certain structures [25]. In [26] machine learning approaches used for detecting the oil spills on the sea surface utilizing satellite radar images. In [27] machine learning technique is utilized for classifying oil spills. They used decision tree approach to classify oil spills which is a tree-like model. The decision tree is similar to an inverted tree as it contains roots at the top whereas it grows downwards. In [28] feature-based classifiers are used for differentiating structural harm from surroundings troubles in an aluminum plate. In [29] support vector machines are used for pattern recognition in order to identify leaks in pipelines. In spite of the fact that some researches have been represented desirable results for leakage identification, however, there is an absence of realizing of how an effective system can be constructed.

This paper presents the application of deep learning methods combined with classification methods for preventing pipeline damage through the earliest detection of threats. The remaining of the article is organized as follows. In Section 2, different types of damages of the pipeline system are demonstrated and explained. Deep learning methods for damage detection are given in Section 3. Section 4 concludes the work.

II. Typical Damages Related to the Different Threat of the Pipeline System

In this section typical damages related to different threats are introduced.

A. *Metal loss*

Metal loss deficiencies happen in a case that the wall of the pipe becomes thin because of the internal or external corrosion. Metal loss damage in pipeline is shown in Figure 1.

Figure 1. Metal loss in pipeline

B. *Dent*

A dent in pipe networks is a permanent plastic metamorphosis of the circular cross-section in regard to the pipe, see Figure 2. A dent causes a localized stress and also a local diminution in the pipe diameter.

Figure 2. Dent in pipeline

C. *Crack*

A crack can be created due to a stress-induced dissociation of the metal. Crack damage in a pipeline is shown in Figure 3.

Figure 3. Crack in pipeline

D. *Gouge*

A gouge can be caused because of the removal of metal from the pipe wall via mechanical processes. Gouge damage in a pipeline is shown in Figure 4.

Figure 4. Gouge in pipeline

E. Free span

A free span on a pipeline is a place in which the seabed fouling have been corroded such that the pipeline is not anymore supported on the seabed, see Figure 5.

Figure 5. Free span

F. Buckling

Buckling is defined as an instability which results in structural failure and creates gross deformation of the pipe cross-section, see Figure 6.

Figure 6. Pipeline buckling

G. Coating damage

Coating damage can be happened if a pipe being pulled through an excavation. The pipe coating damage is demonstrated in Figure 7.

Figure 7. Coating damage

Anode damage

Anodes are at risk of damage when the pipeline travels over the stinger on the back of the lay barge. The pipe anode damage is demonstrated in Figure 8.

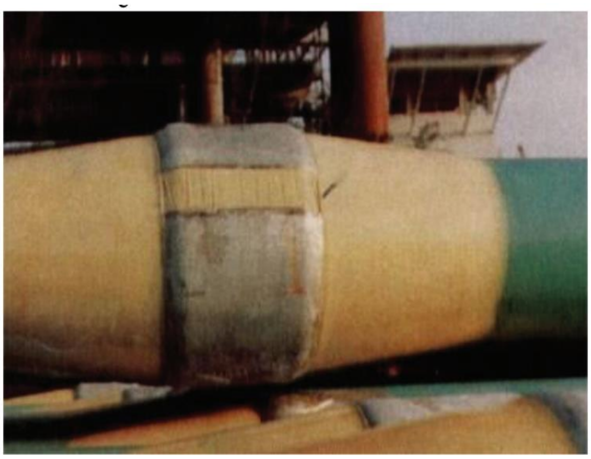

Figure 8. Anode damage

III. NEURAL SYSTEMS

Neural networks are constructed from neurons and synapses. They alter their rates in reply from nearby neurons as well as synapses. Neural networks operate similar to computer as they map inputs to outputs. Neurons, as well as synapses, are silicon members, which mimic their treatment. A neuron gathers the total incoming signals from other neurons, afterward simulate its reply represented by a number. Signals move among the synapses, which contain numerical rates. Neural networks learn once they vary the value of their synapsis.

In this Section effective intelligent techniques for damage detection are presented.

A. Artificial neural networks

In 1940, McCulloch-Pitts suggested the initial artificial neuron model that is later utilized in different feed-forward artificial neural networks like multilayer perceptrons [30]. The artificial neuron carries out a linear conversion via a weighted addition using the scalar weights. According to Figure 9, the activation function is computed by obtaining the addition of the input and its corresponding weight $\tilde{y}_t * \tilde{w}_t$ for every input unit. The bias amount, $\tilde{b}$ can be added to the addition outcome, . Afterward, the new suits into the activation function $f(\tilde{S})$. Finally, the outcome of the activation function is applied for predicting the output neuron J .

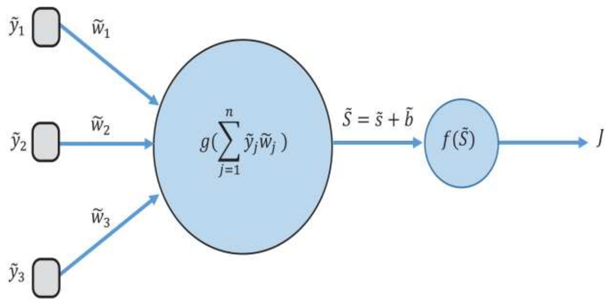

Figure 9. Structure of an artificial neuron

Artificial neural network technique can be used for detection and identification of multiple leaks in a pipeline [31]. The dynamic of the fluid throughout the pipeline (see Figure 10) can be defined as following mathematical model,

$$\frac{\partial S}{\partial t} + hC\frac{\partial F}{\partial w} + \psi|S|S = 0, \qquad (1)$$
$$v^2\frac{\partial S}{\partial w} + hC\frac{\partial F}{\partial t} = 0$$

such that F is taken to be the pressure head, S is taken to be the flow, w is taken to be the length coordinate, t is taken to be the time coordinate, h is considered as the acceleration of the gravity, C is considered as the cross-section area, v is taken to be the speed of sound, and $\psi = \frac{u}{2KC}$. K is considered as the pipeline diameter, and u is the Darcy-Weissbach friction coefficient.

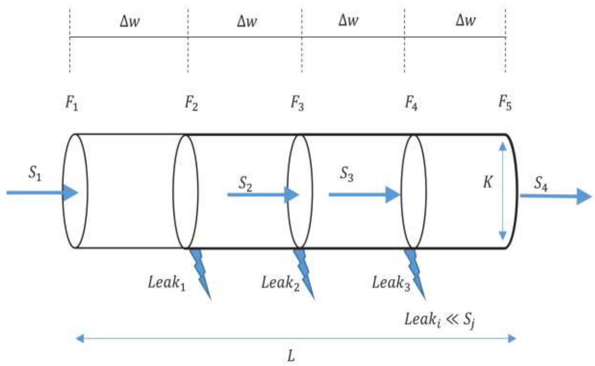

Figure 10. The structure of the pipeline

A detector system can be constructed consists of an artificial neural network which detects the leak and its position in the pipeline. The detection of the leak is mostly based on the performance of the artificial neural network. The artificial neural network utilizes merely the inlet/outlet flow measurements. The detector system recognizes the feasible pipeline operating states which can be used in detection of leak.

B. Recurrent neural networks

Recurrent neural networks have been considered as artificial neural networks models which are established in [32] in order to permit us to work with sequences of data. Recurrent neural network saves the old information of the prior sequences so that transits it to the subsequent sequences. A simple recurrent neural network is shown in Figure 11 which has input a_t , output y_t and also a loop j between them.

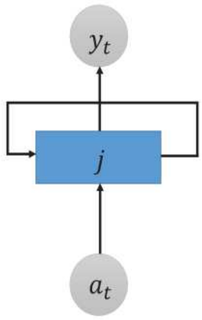

Figure 11. The structure of a simple recurrent neural network

j Loop saves information from a recurrent cell and afterwards crosses it to the subsequent cell in the subsequent recurrent network.

Leak detection systems have been divided into internally and externally based systems. Internally based systems use flow, pressure as well as fluid temperature for monitoring internal parameters of the pipeline, whereas, externally based systems apply local dedicated sensors. However, recurrent neural networks can also be used for nonlinear system identification for fuel oil leak detection [33]. In order to train the network, data can be taken from inlet and outlet flow parameters of the pipeline.

C. Convolutional neural networks

Convolutional neural network contains convolutional and pooling layers [34-38]. Convolutional neural networks combine the feature extraction and feature classification procedures into a sole learning frame. They have the ability for adapting to various input sizes and can also learn to optimize the features while training stage straightly from the raw input.

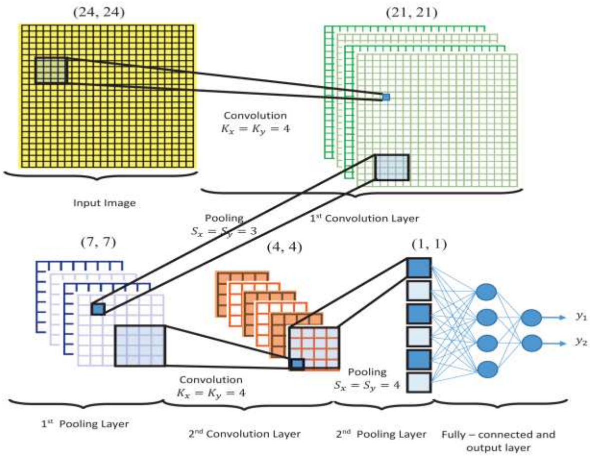

Figure 12. The structure of a simple convolutional neural network

A sample convolutional neural network having two convolution and one fully-connected layers is shown in Figure 12 that categorizes a 24×24-pixel grayscaling image into two classes.

The acoustic signals gathered by an audition device on pipeline systems are mostly used for identifying leakage in buried water pipe networks. Practically, the process is based on a listening tool to gather the sonic signal on the road along the path of pipelines and validates the sonic signal if it is the leakage or not. Nevertheless, the leak signals are constantly corrupting with non-leak sonic sources, which impacts not only the precision of leakage identification but also the time to locate the leakage. Convolutional neural networks can be used for leak identification in water distribution pipelines [39]. The precision of the classification of the convolutional neural network is significantly high.

IV. CONCLUSION

Protecting pipelines from stealing as well as leakage is one of the major objectives of the oil as well as gas companies. Several types of defects can threaten the pipeline such as corrosion, exhaustion cracks, metal loss, gouge, and dent. Thus, if these defects are not correctly fixed can lead to the pipeline destructions having leak or dissociation which causes exceedingly downtime and environment risks. In this paper, different types of damages of the pipeline system are given. Furthermore deep learning methods for damage detection are presented.

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