Please fill in the name of the event you are preparing this manuscript for.	SPE Offshore Europe Conference and Exhibition 2021
Please fill in your 6-digit SPE manuscript number.	SPE-205404-MS
Please fill in your manuscript title.	EM-based 2D Corrosion Azimuthal Imaging using Physics Informed Machine Learning (PIML)

Please fill in your author name(s) and company affiliation.

Given Name	Middle Name	Surname	Company
Guang An		Ooi	King Abdullah University of Science and Technology
Mehmet	Burak	Özakin	King Abdullah University of Science and Technology
Tarek	Mahmoud	Mostafa	King Abdullah University of Science and Technology
Hakan		Bagci	King Abdullah University of Science and Technology
Shehab		Ahmed	King Abdullah University of Science and Technology
Mohamed		Larbi Zeghlache	Saudi Aramco

This template is provided to give authors a basic shell for preparing your manuscript for submittal to an SPE meeting or event. Styles have been included (Head1, Head2, Para, FigCaption, etc) to give you an idea of how your finalized paper will look before it is published by SPE. All manuscripts submitted to SPE will be extracted from this template and tagged into an XML format; SPE's standardized styles and fonts will be used when laying out the final manuscript. Links will be added to your manuscript for references, tables, and equations. Figures and tables should be placed directly after the first paragraph they are mentioned in. The technical content of your paper WILL NOT be changed. Please start your manuscript below.

Abstract

In the wake of today's industrial revolution, many advanced technologies and techniques are developed to address the complex challenges in well integrity evaluation. One of the most prominent innovations is the integration of physics-based data science for robust downhole measurements. This paper introduces a promising breakthrough in electromagnetism-based corrosion imaging using physics informed machine learning (PIML), tested and validated on the cross-sections of real metal casings/tubing with defects of various sizes, locations, and spacing.

Unlike existing electromagnetism-based inspection tools, where only circumferential average metal thickness is measured, this research investigates the artificial intelligence (AI)-assisted interpretation of a unique arrangement of electromagnetic (EM) sensors. This facilitates the development of a novel solution for through-tubing corrosion imaging that enhances defect detection with pixel-level accuracy. The developed framework incorporates a finite-difference time-domain (FDTD)-based EM forward solver and an artificial neural network (ANN), namely the long short-term memory recurrent neural network (LSTM-RNN). The ANN is trained using the results generated from the FDTD solver, which simulates sensor readings for different scenarios of defects.

The integration of the array EM-sensor responses and an ANN enabled generalizable and accurate measurements of metal loss percentage across various experimental defects. It also enabled the precise predictions of the defects' aperture sizes, numbers, and locations in 360-degree coverage. Results were plotted in customized 2D heat-maps for any desired cross-section of the test casings. Further analysis of different techniques demonstrated that the LSTM-RNN could show higher precision and robustness compared to regular dense NNs, especially in the case of multiple defects. The LSTM-RNN is validated using additional data from simulated and experimental data. The results show reliable predictions even with limited training data. The model accurately predicted defects of larger and smaller sizes that were intentionally excluded from the training data to demonstrate generalizability. This highlights a major advance toward corrosion imaging behind tubing.

This novel technique paves the way for the use of similar concepts on other sensors in multiple barriers imaging. Further work includes improvement to the sensor package and ANNs by adding a third dimension to the imaging capabilities to produce 3D images of defects on casings.

Introduction

There has been a natural transition in technology development for corrosion inspection using electromagnetic (EM) sensors. The early tools used relatively straightforward hardware and software algorithms to infer total cumulative metal thickness at a given depth. The latest time-domain (Larbi Zeghlache et al. 2020) and frequency-domain tools (Larbi Zeghlache et al. 2021) use advanced techniques to discriminate response and estimate individual metal thickness from each barrier at a given depth. However, these new technologies still produce a circumferential average of metal thickness from each barrier. In the literature, there are multiple publications highlighting the benefits of technology upgrade from total cumulative thickness to individual thicknesses of each concentric pipe. This major improvement has enabled a more proactive well integrity management system (WIMS), by providing defect locations in terms of which pipe is affected. In addition, it enabled profiling of metal loss along different barriers, especially for the case of external electrochemical corrosion at shallow depths.

To continue the natural progression of EM technology in corrosion evaluation, from a single data point measurement per depth (Z-axis), to a multiple data points along the depth of investigation (X-axis), to the current work on adding the third component along the azimuth (Y axis) in order to produce an image of the corrosion profile in a concentric pipe configuration. Figure 1 illustrates the transition from simplified multiple casing corrosion measurement with (a) Total thickness for all pipes within the depth of investigation (b) Individual thicknesses for each pipe size (c) Thickness imaging in concentric pipes.

Figure 1: Evolution of downhole multiple casing corrosion evaluation

For the inner pipe corrosion evaluation, multiple technologies can be used depending on the objective and downhole conditions. Mechanical multi-finger calipers, for example, provide high definition inner wall image for scale buildup and inner wall corrosion imaging. For outer surface imaging of the inner barrier, ultrasonic technology is used to provide azimuthal image of thickness, hence, outer surface corrosion imaging is derived. For Figure-1c, the most challenging task is to provide thickness image of the casing(s) behind the inner barrier. In this publication, multiple barriers imaging refers to wall thickness imaging. The wall surface imaging is an additional challenge that will require a much more advanced sensors and algorithms.

The eddy current method is a widespread method for multiple-casing thickness inspection (Yanxiang et al. 2018, Donderici et al. 2021, Rourke et al. 2014, Yu et al. 2019). Common practices include the induction of eddy currents in casings with EM fields generated by transmitters, and the resulting decay curves are recorded and analyzed (Yanxiang et al. 2018). By the nature of their vertical arrangements of transmitters and receivers, such methods emphasize on average thickness (Martin et al. 2017a). Hence, the presence of collars creates a large impact on the voltages induced on the receivers (Jawed et al. 2020), and much work has been done for the automated removal of such signals (Fouda et al. 2020) to alleviate the need for human inspections.

Another major limitation of current EM solutions for multiple casing corrosion is the fact that metal loss is averaged over the circumference of the casing(s). Based on experimental data and field experience, a metal loss of 20% is the threshold for a potential major well integrity defect; however, it can be misleading if this 20% corrosion is related to a generalized corrosion with minimal penetration. In this case, well integrity is not jeopardized compared to the case where the 20% corrosion is concentrated in one or more spots, leading to a potential leak. To illustrate this case, Figure-2 shows how current EM technologies can give the same value for different scenarios.

The examples in Figure 2 demonstrate the need for multiple casings corrosion imaging in order to differentiate between such cases. Defects mapping and orientation can be critical in well integrity evaluation. In fact, through tubing corrosion imaging is the missing piece of the puzzle to complement cement evaluation and leak detection solutions. There are ongoing research and development efforts to address the same challenge from the cement evaluation side (Li et al. 2021).

Figure 2: Examples of 20% corrosion occurrence in double casing

A variety of cost functions are developed to calculate average pipe thickness from the received signals. However, such functions do not extract the inherent semantics represented by the relative positions of the receivers. Additionally, a consistent method to transform the output of these cost functions to casing On the other hand, (Zhang 2018a) shows a means to estimate the azimuthal location of defects using a circumferential arrangement of receivers. Each receiver signal is analyzed and thickness is estimated for their individual quadrants.

An intelligent method to localize and measure defects is therefore required to provide detailed information on casing cross sections. In this study, metal loss detection is viewed as a task of information extraction from receiver readings and its mapping to cross section images. The voltages induced on the receivers are affected by the shapes, sizes, locations, and number of defects, as well as the electromagnetic properties of the wellbore casing (San Martin et al. 2017). Other factors include thermal and environmental noise, apparatus orientation, vibrations, etc. (Yu et al. 2019). The presence of such factors, which are often difficult to measure and quantify, highlights the difficulty in the interpretation of sensor readings. The inner diameters of casings and minimum well restrictions prove to be another limit on the number of sensors that can be integrated in the design of inspection tools. Therefore, a suitable way to extract the inherent semantics represented by the arrangement of receiver readings is required to accurately predict the properties of concentric casings and potential defects.

Generative adversarial networks (GANs) (Goodfellow et al. 2014) aim to create artificial images that are indistinguishable from real ones. With the success of such neural networks, the synthesis of images from text has received increasing attention and work. In a typical GAN, there exists two separate models: the generator and the discriminator. Using random noise, the generator synthesizes fake images, and the discriminator attempts to differentiate the fake images from real ones. The goal of the training process is to achieve a successful differentiation rate of 0.5, i.e. making the fake images indistinguishable from real ones. In text-to-image synthesis (Reed et al. 2016), description text embedding is compressed into vectors with a fully connected layer and concatenated with random noise. The generator in this case then uses the resulting vector to generate fake images. The discriminator views the [image, text] pairs and learns to

differentiate between such matching and mismatching pairs. Hence, the correct extraction of the semantics represented by the test embedding is essential in the successful generation of realistic images. In Attentional Generative Adversarial Network (AttnGAN), an attention mechanism is proposed to emphasize on the relationship between different words and individual regions in the image (Xu et al. 2018). A Siamese mechanism and visual-semantic embedding strategy (Yin et al. 2019) is developed to address the challenge of extracting consistent semantics from the diverse linguistic expressions. Despite the aforementioned advances, this field of study still faces significant challenges such as the generation of high-resolution images and the inclusion of multiple objects (Frolov et al. 2021).

In the case of wellbore casings, the correct, systematic assessment of defects is paramount in ensuring the continued operation and safety of a well. As compared to conventional image generation where the interpretation of linguistic semantics and the similarity of the generated objects to reality are given priority, the defects require detailed rendering in terms of shape, size, and depth. Another important dissimilarity between the two categories is that well logging data contains noise and other disturbances that are often difficult to identify and remove (Rourke et al. 2014). In this paper, the values of the pixels of each cross section image are used to represent their likelihood of being casing or air elements. The semantics extracted from receiver values are mapped to each pixel value through the neural network models investigated. A series of fully connected neural networks as well as a long short-term memory recurrent neural network (LSTM-RNN) (Schmidhuber and Hochreiter 1997, Hertz 2018) are tested. The use of LSTM-RNN enables successful extraction of the sequential relation of receiver data in addition to their individual values. The deployment of neural networks in casing defect detection creates an automated and more reliable inspection algorithm as compared to human interpretation or hard-coded rules and formulae. It also provides a faster and more dynamic approach than inversion from measurements and pre-loaded look-up libraries (Assous et al. 2021).

Methodology

The workflow developed, which incorporates a finite-difference time-domain (FDTD) forward solver (Kunz and Luebbers 1993), a series of LSTM-RNN, and a physical experiment setup, is described in the following sections. Due to the limited availability of measurement data, the forward model is developed to simulate scenarios of metal loss and the corresponding voltages on the receivers. Scenarios of metal losses of various numbers, sizes, shapes, and azimuthal locations are simulated using the forward model in order to create a complete and diverse dataset for the training of the neural networks. In this study, the input to the neural networks is the receiver readings, and the output is in the form of cross sectional profiles with 100 x 100 pixels. The validity of the simulations is verified with data from physical experiments. The neural networks, trained on only simulated data, are able to perform accurate predictions on casing metal loss properties using receiver data from both simulated and experimental scenarios. As a proof of concept, this study focuses on a single pipe configuration.

Forward Model

Electromagnetic wellbore integrity tools operate in the low-frequency range (Martin et al. 2017b, Castaneda et al. 2014, Brill et al. 2011). In this case, Maxwell's equation-based forward solvers can be used to simulate possible defect scenarios. To this end, the finite-difference time-domain (FDTD) method is used since it is one of the most popular and extensively studied methods in EM problems (Taflove and Hagness 2005). Especially in the case of low-frequency electromagnetic induction problems, the quasi-static finite-difference time-domain (QS-FDTD) method is more suitable for this purpose (Özakin and Aksoy 2016). Fundamentally, the QS-FDTD method is based on the upscaling of the dielectric permittivity ϵ , which directly increases the numerical time step as $\Delta t^{QS} = \sqrt{\alpha} \Delta t$, which significantly decreases the total computational time. In this work, a Maxwell equation-based, three-dimensional QS-FDTD method is used to generate training data for machine learning.

Figure 3: (a) Cross section of problem space with wellbore integrity inspection tool (yellow and blue cells referred to metallic pipe and background, respectively). (b) Discretized 3D problem space (red and green cells referred to metallic pipe and rectangular hole regions, respectively).

The wellbore integrity inspection tool in this study uses a design different configuration from conventional logging devices (Yanxiang et al. 2018, Fouda et al. 2020, Zhao et al. 2020). The tool consists of a transmitter and several receivers arranged perpendicularly to each other. The transmitter is located at the center of the tool and all receivers are located equidistant from the transmitter, as illustrated in Figure 3 (a).

The investigated problem space includes the inspection tool and a metallic cylindrical pipe with metal losses on the pipe at various azimuthal locations. The length of the metallic pipe is set to 0.5 m, and its inner and outer diameter are equal to 61.025 mm and 73.025 mm, respectively. In the FDTD method, non-uniform discrete grids are used for the numerical modeling of the problem in three-dimensional Cartesian coordinates as shown in Figure 3 (b). The 3-D grid size is selected as $1.0 \text{ mm} \times 1.0 \text{ mm} \times 5.0 \text{ mm}$. Therefore, a total of $100 \times 100 \times 100$ grid points are used in the numerical problem space. Also, the first-order absorbing boundary condition is used at the outer boundaries (Taflove and Hagness 2005). The operating frequency of the transmitter is chosen as 100 kHz because a single barrier inner loss scenario is investigated. Additionally, the electrical conductivity of the materials in the problem space are selected as 0.1 S/m and $5.7 \times 10^6 \text{ S/m}$ for the background and metal pipe, respectively. The amplitudes of the induced voltages on the receivers are obtained by the maximum value of the frequency-domain response of the time-domain signal calculated from the forward solver. Instead of solving separately for each scenario of the metal loss position at different angles on the pipe, circular observation points have been defined on the same cross-section of receivers with the purpose of decreasing the total number of the forward solver simulations for the training of the NNs.

Data Generation, Preprocessing, and Representation

This section details the dataset generation scheme using the proposed FDTD forward solver. In this work, the metal losses simulated are configured to be either complete losses (holes), inner partial losses, or combinations of both. For any simulated scenario, a random number of individual metal losses are formed on the casing, with the first metal loss having 100% chance of appearance, the second 75%, the third 50%, and so on. In addition, random values of width and length in the range of $[1 \text{ mm}, 60 \text{ mm}]$, and penetration in the range of $[1 \text{ mm}, 6 \text{ mm}]$ are assigned for each defect. The losses are also assigned random azimuthal locations around the circumference of the casing cross section. The overlapping of multiple losses is also allowed in order to form more complex defects with varying depths. To ensure suitable discretization and ease of calculation, the thickness of the casings is set to 6 mm, and the resolutions of the x- and y-meshes are set to 6 mm.

A batch of 700 simulations are run in parallel using a cluster of Skylake, Cascadelake, and AMD CPUs with 2.6 GHz, 2.5 GHz, and 2.0 GHz clock speeds respectively, assigning 1 GB of memory for each simulation. The average completion time for one such batch is approximately eight hours. A total of 80000 different scenarios are simulated and compiled into our dataset, 60% of which are used to train the neural network, 20% for validation, and 20% for testing. Some examples of the cross sections simulated are shown in Figure 4.

Figure 4: Cross sectional profiles of simulated metal loss cases. Four values of S^d of the layer are shown.

The method through which data is acquired is visualized in Figure 5. The values of the voltages induced on receivers affixed on a plate are recorded as $S = s_1, s_2, \dots, s_N$, where N is the number of sensors on the plate. A set of reference values S^r is taken at a known section of the casing where no metal loss occurs.

For each layer of measurements, S , the differences between the reference values and S are taken as in (1) to generate the difference matrix S^d .

$$S^d = S^r - S \quad (1)$$

Each S^d is used for the prediction of the casing cross section at the level measured. Here, S^d is used instead of S because the presence of defects are reflected in the change of induced voltages, and the base values of the sensors are redundant as long as the power supplied to the transmitter is kept constant and no changes to acquisition parameters such as electromagnetic properties of the pipe, pipe nominal thickness and eccentricity.

The training dataset is augmented by artificial data created by injecting zero-mean Gaussian noise to duplicates of receiver values calculated by the forward solver. The addition of such data not only provides robustness for the neural network models (Huang et al. 2019, Schlüter and Grill 2015), but also prevents overfitting and memorization (Feng et al. 2019). To further enrich the training data, the simulated sensor array is rotated about the longitudinal axis in steps of one degree and the corresponding readings are recorded and used in the training process. The revolution of sensors in this way ensures better resolution for each scenario. After verification with the experimental setup, experimental data is also incorporated and is found to enhance the performance of the neural networks. In addition, several models are trained using datasets with various levels of noise. The injection of noise results in models of different parameters,

Figure 5: Data acquisition and input to LSTM-RNN.

and the overall results obtained by averaging the predictions made by such models are found to be more consistent and robust when tested with perturbed receiver values.

Neural Network

The LSTM network (Hochreiter and Schmidhuber 1997) consists of N individual cells in parallel as shown in Figure 5. The memorial nature of such cells is represented by the input memory c^{t-1} and output memory c^t . Each cell in the network is able to throttle the amount of memory to retain using a single layer neural network into which the memory state c^{t-1} and the output h^{t-1} from the previous cell, as well as the current input x^t , are fed.

There exists three gates in the LSTM cell: the forget gate, the update gate, and the output gate, as shown in Figure 6 (Olah 2015).

Figure 6: The components of a single LSTM cell unit

The forget gate can be formulated as in (2).

$$\Gamma_f^t = \sigma(W_f[h^{<t-1>}, x^{<t>}] + b_f) \quad (2)$$

where σ is a sigmoid activation function, W_f and b_f are the weight matrix and bias vector of the forget gate respectively, and $[a^{<t-1>}, x^{<t>}]$ represents the concatenation of the output from the previous cell and

the current input. This concatenated matrix undergoes element-wise multiplication with W_f . Similarly, the update and output gates can be formulated as in (3) and (4) respectively.

$$\Gamma_o^t = \sigma(W_o[h^{<t-1>}, x^{<t>}] + b_o) \quad (3)$$

$$\Gamma_u^t = \sigma(W_u[h^{<t-1>}, x^{<t>}] + b_u) \quad (4)$$

Additionally, a candidate value $\tilde{c}^t$ is computed as in (5).

$$\tilde{c}^t = \tanh(W_c[h^{<t-1>}, x^{<t>}] + b_c) \quad (5)$$

Finally, the memory and output of the cell is calculated as (6) and (7).

$$c^t = \Gamma_u^t * \tilde{c}^t + \Gamma_f^t * c^{t-1} \quad (6)$$

$$h^t = \Gamma_o^t * c^t \quad (7)$$

At the final cell of the neural network, a softmax layer is used to predict the values y^T of the pixels in the cross sectional profile, where the values of each pixel represent its likelihood to being a casing or empty space element. When connected in series, as shown in Figure 5, it is easy to see that information from any individual sensor can be memorized by simply setting its forget gate coefficient to one. For every pixel in the prediction task, the LSTM-RNN corrects its weight matrices and biases such that the best fit for the training dataset is found. Such values are updated in the backpropagation step of the training process and optimized using the adaptive moment (ADAM) algorithm (Zhang 2018b).

Experimental Setup

An experiment setup as shown in Figure 7 has been developed to validate simulated results and provide additional data for the training and testing of the neural networks. Transmitter coils, surrounded by receivers in coaxial and equidistant arrangements, are used to generate the required magnetic flux and measure the induced voltages. To ensure uniformity, the transmitters and receivers are affixed on a container such that the normal distances between the inner surface of the casing and the receivers are equivalent. The setup is axially aligned with the casing and deployed for testing. During measurements, the transmitter emits an alternating electromagnetic signal with a specific frequency through a compensation circuit. The receivers are located close to the inner surface of the casing to maximize the detected signals. With tuning circuits, voltages induced on the receiver coils are detected. The recorded voltages are then processed and used as input to the neural networks. In this work, air-cored coils have been chosen as receivers instead of ferrite-cored coils due to their linear behavior and ease of adjustment.

Figure 7: Transmitter and receiver placements of the proposed setup. (a) 3D view. (b) Top view.

Evaluation and Results

In this section, the performances of the neural networks are compared and evaluated. The outputs of the neural networks are arranged in images of 100 x 100 pixels, as shown in Figure 8 (a). The white and pale blue pixels represent casing elements that are predicted with high confidence, while the faded pixels in proximity to the suspected metal loss location are indications of less certainty. A threshold can be applied where all pixels above an arbitrary value are regarded as casings while the rest are classified as air/empty, as shown in Figure 8 (b).

Figure 8: Cross section images predicted by the LSTM-RNN using receiver values from a 25 mm-wide complete metal loss at 135°. (a) Original values. (b) Filtered values.

By the pictorial nature of the outputs, three kinds of metrics are used to evaluate the accuracy of each prediction: angle error δ_θ , size error δ_σ , and mean absolute error (MAE). The azimuthal angle of a metal loss θ on the cross section image is calculated as in (8);

$$\theta = \tan^{-1} \frac{y}{x} \quad (8)$$

where x and y represent the coordinates of the center of the metal loss. The size of a predicted metal loss is found as in (9);

$$\sigma = \sum p_h \quad (9)$$

where p_h is the value of pixels that are predicted as metal loss elements. Hence, the angle error and size error can be calculated as in (10) and (11);

$$\delta_\theta = \frac{\tilde{\theta} - \theta}{n} \quad (10)$$

$$\delta_\sigma = \frac{\tilde{\sigma} - \sigma}{\sigma} * 100 \% \quad (11)$$

where $\tilde{\theta}$ is the sum of the predicted metal loss angles, θ is the label metal loss angles, n is the number of holes, $\tilde{\sigma}$ is the sum of the predicted metal loss sizes, and σ is the sum of the label metal loss sizes. Finally, the mean absolute error is calculated as in (12);

$$MAE = \frac{1}{n} \sum_{i=1}^n |\tilde{y}_i - y_i| \quad (12)$$

where n is the total number of casing pixels, $\tilde{y}_i$ is the calculated output for each pixel, and y_i is the labeled value of each pixel. δ_θ and δ_σ provide a measure of the accuracy of the azimuthal angle and size of the metal loss, while the MAE represents the overall performance of the neural networks, and is a better way of measuring the overall performance of a neural network. A good prediction is expected to have low values for all three metrics. For example, the neural networks may perfectly predict the size of a metal loss, but at an incorrect position.

The performances of the neural networks tested are shown in Table 1. The dense neural networks, while showing general improvement as the number of layers increased from one to four, began to exhibit an inability to improve further as more layers are added. This behavior is due to the vanishing gradient problem, where information extracted is lost in deep neural networks as their impact on layer weights decreases to infinitesimal values. The LSTM-RNN, on the other hand, effectively solves the vanishing gradient problem by deciding the amount of memory to keep as an intrinsic feature within each of its cells. Each LSTM cell is able to completely pass memory on to the next cell by setting the forget gate value to one, thus maintaining the significance of information.

Table 1: Performances of tested neural networks

Neural Network	δ_θ (°)	δ_σ (%)	MAE
Dense 1 Layer	1.8144	8.2635	0.0141
Dense 2 Layer	1.5184	6.9155	0.0118
Dense 3 Layer	1.6190	4.2926	0.0113
Dense 4 Layer	1.4284	4.2166	0.0111
Dense 5 Layer	1.4541	6.6225	0.0113
Dense 6 Layer	1.4670	4.3306	0.0114
Dense 7 Layer	1.5184	6.9155	0.0118
Dense 8 Layer	3.1521	5.1663	0.0136
Dense 9 Layer	3.3144	5.4322	0.0143
Dense 10 Layer	3.6157	9.1426	0.0156
LSTM	1.2482	3.6848	0.0097
LSTM-5	1.1637	3.2635	0.0091

Figure 9 and Figure 10 show the predictions made by the four-layer dense NN (which performed the best out of the ten tested dense neural networks) and the LSTM-RNN, respectively. To ensure fairness of comparison, both models are trained with the same dataset with Gaussian noise $\delta \sim (0, 0.032)$ and the outputs of a single neural network are used instead of the averages of five. We observe that while both models predicted the metal loss locations accurately, the dense NN made some errors with sizes in the 45° and 270° cases. On the other hand, the LSTM-RNN predicted such cases without error.

Figure 9: Predictions made by the four-layer dense neural network for 25 mm holes located at 30° , 45° , 135° , and 270° from left to right. (a) Prediction of the neural network. (b) Ground truth. (c) Error pixels.

Figure 10: The predictions made by the LSTM-RNN for 25 mm holes located at 30° , 45° , 135° , and 270° from left to right. (a) Prediction of the neural network. (b) Ground truth. (c) Error pixels.

Figure 11 and Figure 12 show the generalization performances of the two models. In these tests, the scenarios of 10 mm, 20 mm, and 30 mm holes are omitted deliberately from the training dataset, while only 15 mm and 25 mm holes are used in training. The results show that the LSTM-RNN is able to better generalize its predictions on previously un-encountered data.

Figure 11: Performances of the four-layer dense neural network on hole size estimation. (a) Prediction of the neural network. (b) Ground truth. (c) Error pixels. From left to right: 10 mm, 15 mm, 20 mm, 25 mm, 30 mm.

Figure 12: Performances of the LSTM-RNN on hole size estimation. (a) Prediction of the neural network. (b) Ground truth. (c) Error pixels. From left to right: 10 mm, 15 mm, 20 mm, 25 mm, 30 mm.

Figure 13, Figure 14 and Figure 15 show the predictions made by the LSTM-RNN on three categories of randomly chosen scenarios where multiple holes occur. The error pixels in these cases are more prominent than the easier single-hole cases due to the increased number of defects and the inclusion of inner partial losses. Note that the above scenarios are excluded from the training dataset in order to verify the validity of the model. From Figure 13 and Figure 14, we observe that the predictions made for inner losses are more accurate than those for complete losses in general. However, when both kinds of defects are present, the overall performance is reduced. A particularly severe case is found in the fifth scenario of Figure 15, where the inner loss in the bottom left corner of the casing is predicted with an altered shape.

Figure 13: Predictions made by the LSTM-RNN on multiple-hole scenarios 1, 2, 3, 4, and 5 from the left

Figure 14: Predictions made by the LSTM-RNN on multiple-inner loss scenarios 1, 2, 3, 4, and 5 from the left

Figure 15: Predictions made by the LSTM-RNN on complex metal loss cases 1, 2, 3, 4, and 5 from the left

Figure 16 shows the predictions made by the LSTM-RNN with a 25 mm on a carbon steel casing at various azimuthal locations. The resulting performances on both location and size predictions are shown.

Figure 16: Output and performances of the LSTM-RNN on experiment input data obtained with a 25 mm hole located at 0°, 45°, 90°, 135°, 180°, 225°, 270°, and 315°, respectively.

Conclusion

A machine learning approach is investigated in this study to detect defects present on wellbore casings. The outcomes of this work are summarized as follows:

1. The incorporation of LSTM-RNNs enabled accurate predictions of defects on a wellbore casing by extracting information not only from individual sensors, but also from their sequential and positional relations.
2. Defect simulation data is augmented by the injection of Gaussian noise. With various levels of noise, different models can be trained and used at the same time in order to provide more consistent predictions on experimental data.
3. The resolution and robustness of detection are improved by learning the mappings from available receivers on an inspection tool to individual pixels on the output images.

The future work of this project is to combine convolutional and recurrent neural networks to extract spatio-temporal information from acquired data. An automated physical experiment setup is also required to produce real data to augment the training of the neural networks.

References

- Assous, Said, Whetton, James, and Bacciarelli, Mark. 2021. Magnetic Flux Leakage Data Processing for Casing Inspection: An Inversion Approach. *Proc.*, International Petroleum Technology Conference. <https://doi.org/10.2523/IPTC-21167-MS>.
- Brill, Thilo Michael, Demichel, Cindy, Nichols, Edward Andrew et al. 2011. Electromagnetic Casing Inspection Tool for Corrosion Evaluation. *Proc.*, International Petroleum Technology Conference. <https://doi.org/10.2523/IPTC-14865-MS>.
- Castaneda, Claudio, Higuera, Josue, Portela, Fernando et al. 2014. Corrosion Monitoring With EM Induction Tool in 3 Outer Casing Strings through a 7 Inch Chrome Production Tubing Scenario. *Proc.*, SPE/ICoTA Coiled Tubing and Well Intervention Conference and Exhibition. <https://doi.org/10.2118/168277-MS>.
- Donderici, Burkay, Capoglu, Ilker R, and Fouda, Ahmed Elsayed. 2021. *Adaptive workflows for artifact identification in electromagnetic pipe inspection*, Google Patents (Reprint).
- Feng, Ruicheng, Gu, Jinjin, Qiao, Yu et al. 2019. Suppressing model overfitting for image super-resolution networks. *Proc.*, Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops0-0.
- Fouda, Ahmed Elsayed, Donderici, Burkay, and Capoglu, Ilker R. 2020. *Artifact Identification and Removal Method for Electromagnetic Pipe Inspection*, Google Patents (Reprint).
- Frolov, Stanislav, Hinz, Tobias, Raue, Federico et al. 2021. Adversarial Text-to-Image Synthesis: A Review. *arXiv preprint arXiv:210109983*.
- Goodfellow, Ian J, Pouget-Abadie, Jean, Mirza, Mehdi et al. 2014. Generative adversarial networks. *arXiv preprint arXiv:14062661*.

- Hertz, John A. 2018. *Introduction to the theory of neural computation*: CRC Press.
- Hochreiter, Sepp and Schmidhuber, Jürgen. 1997. Long short-term memory. *Neural computation* **9** (8): 1735-1780.
- Huang, Liang, Pan, Weijian, Zhang, You et al. 2019. Data augmentation for deep learning-based radio modulation classification. *IEEE Access* **8**: 1498-1506.
- Jawed, Rehan, Maheshwari, Kishore, Jamali, Jay et al. 2020. Through Tubing Casing Break Detection: An EM Thickness Tool Application. *Proc., SPE Canada Heavy Oil Conference*. <https://doi.org/10.2118/199952-MS>.
- Kunz, Karl S and Luebbers, Raymond J. 1993. *The finite difference time domain method for electromagnetics*: CRC press.
- Larbi Zeghlache, Mohamed, Bazaid, Abdulaziz, Hill, Freeman et al. 2021. Comprehensive Casing Corrosion Inspection Using Multi-frequency Array EM Technology. 2021/205050-MS.
- Larbi Zeghlache, Mohamed, Noui-Mehidi, Mohamed, Rourke, Marvin et al. 2020. Enhanced Time Domain EM Technology for Multiple Casing Corrosion Monitoring. *Proc., Abu Dhabi International Petroleum Exhibition & Conference*. <https://doi.org/10.2118/202725-MS>.
- Li, Jie, Yang, Qinshan, Zhao, Jinsong et al. 2021. A Resonance-Based Through-Tubing Cement Evaluation Technology. Paper presented at the SPWLA, 62nd Annual Logging Symposium.
- Martin, Luis Emilio, Fouda, Ahmed Elsayed, Amineh, Reza Khalaj et al. 2017a. New High-Definition Frequency Tool for Tubing and Multiple Casing Corrosion Detection. *Proc., Abu Dhabi International Petroleum Exhibition & Conference*. <https://doi.org/10.2118/188932-MS>.
- Martin, Luis Emilio San, Fouda, Ahmed Elsayed, Amineh, Reza Khalaj et al. 2017b. New high-definition frequency tool for tubing and multiple casing corrosion detection. *Proc., Abu Dhabi International Petroleum Exhibition & Conference*.
- Olah, Christopher. Understanding LSTM Networks. <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>.
- Özakın, Mehmet Burak and Aksoy, Serkan. 2016. Application of magneto-quasi-static approximation in the finite difference time domain method. *IEEE Transactions on Magnetics* **52** (8): 1-9.
- Reed, Scott, Akata, Zeynep, Yan, Xinchun et al. 2016. Generative adversarial text to image synthesis. *Proc., International Conference on Machine Learning* 1060-1069.
- Rourke, Marvin, Jin, Yingxin, and Dong, Qiuzhao. 2014. Algorithm Development and Case Study for A 1-11/16 Pulsed Eddy Current Casing Inspection Tool. *Proc., SPWLA 55th Annual Logging Symposium*.
- San Martin, Luis Emilio, Amineh, Reza Khalaj, and Donderici, Burkay. 2017. Casing defect determination using stored defect response information.
- Schlüter, Jan and Grill, Thomas. 2015. Exploring Data Augmentation for Improved Singing Voice Detection with Neural Networks. *Proc., ISMIR* 121-126.
- Schmidhuber, Jürgen and Hochreiter, Sepp. 1997. Long short-term memory. *Neural Comput* **9** (8): 1735-1780.
- Taflove, Allen and Hagness, Susan C. 2005. *Computational Electrodynamics: The Finite-Difference Time-Domain Method*.
- Xu, Tao, Zhang, Pengchuan, Huang, Qiuyuan et al. 2018. AttnGAN: Fine-grained text to image generation with attentional generative adversarial networks. *Proc., Proceedings of the IEEE conference on computer vision and pattern recognition* 1316-1324.
- Yanxiang, YU, Boggs, Nicholas, and Zhao, Jinsong. 2018. *Fractal magnetic sensor array using mega matrix decomposition method for downhole application*, Google Patents (Reprint).
- Yin, Guojun, Liu, Bin, Sheng, Lu et al. 2019. Semantics disentangling for text-to-image generation. *Proc., Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* 2327-2336.
- Yu, Yanxiang, Redfield, William, Boggs, Nicholas et al. 2019. An Advanced Technique for Simultaneous in Situ Inspection of Multiple Metallic Tubulars. *Proc., SPE/ICoTA Well Intervention Conference and Exhibition*. <https://doi.org/10.2118/194269-MS>.
- Zhang, Jun. 2018a. *Electromagnetic casing inspection tool with azimuthal sensitivity*, Google Patents (Reprint).
- Zhang, Zijun. 2018b. Improved adam optimizer for deep neural networks. *Proc., 2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)* 1-2.
- Zhao, Jiajun, Yang, Qinshan, and Zhao, Jinsong. 2020. *Method and System of Light-Weight Cement Bond Evaluation by Acoustic Vortex Waves*, Google Patents (Reprint).