J. Electrical Systems 20-3 (2024): 6972-6982

[1]Nur Sofia Idayu Didik Aprianto

[1]Nurfarhana Mustafa

[1]Mohd Faizal Jamlos

[2]Toshihide Kitazawa

[1]Mohamad Shaiful Abdul Karim*

Computational Extraction of Dielectric Properties from Transmission and/or Reflection Coefficients: A Survey

Journal of Electrical Systems

Abstract: - This survey examines the computational methodologies for extracting dielectric properties from transmission and/or reflection coefficients. The overview of conventional measuring techniques – free space measurement, transmission line, resonant methods – and the conversion of the scattering parameters method to dielectric properties such as analytical, numerical analysis, and machine learning techniques, are being explored briefly. Each method has advantages and disadvantages, such as the practicality of the sample size, high-frequency applications, and measurement conditions. The Nicholson-Ross-Weir, National Institute of Standards and Technology, and non-iterative methods provide a straightforward computational extraction technique of dielectric properties. Electromagnetic field analysis and root-finding algorithms improve computational accuracy and stability. Large datasets with varying degrees of complexity can be handled by artificial neural networks, deep neural networks, and neuro-fuzzy networks from machine learning models. This survey provides a computational framework through these various approaches while offering insights into their practicality and effectiveness in characterizing material properties.

Keywords: Computational methodologies, Dielectric properties, Scattering parameters, Material characterization

I. Introduction

Characterization of material is important as it is known for its ability to identify the properties of the raw material, to observe the quality of the material during processing and manufacturing, and even to evaluate the performance of the materials in various applications. In the biology field where material characterization is used to study the properties of biological matters. For instance, one of the material characterization approaches, which is Raman spectroscopy is used to study the biological information of the material [1,2]. Likewise, mechanical characterization is crucial to obtain information about mechanical properties [3-5] such as strength, stiffness, and ductility[6]. The development of material characterization in microwave engineering can be further seen where many techniques are available for the measurement of the dielectric properties of the material [7]**.** Permittivity, permeability, and loss tangent are considered important material characterization properties that being used electrical engineering [8]The dielectric characteristics of materials, which control how electric fields enter and spread through various media, are at the centre of this interaction [9-11]. Accurately describing these characteristics has practical applications in developing electronic devices, improving communication networks, and even in medicine for diagnostic methods like magnetic resonance imaging. The knowledge held within these dielectric properties can provide significant insight into how the materials interact with electromagnetic fields. Properties like dielectric constant and loss tangent are crucial in understanding the ability of a material's capacity to store and dissipate electromagnetic energy upon exposure to microwaves.

Researchers and engineers have developed several measuring techniques to determine these properties with high accuracy and precision. Traditional methods such as free space measurement (FSM) [12-15], transmission lines [16,17], and resonant techniques [7,16,18,19] have been utilized for material characterization, and each method provides insight into the dielectric behaviour of materials under various circumstances. While FSM is known for its non-contact nature, making it ideal for heterogeneous samples and applicable across a wide frequency range[20] transmission line methods have the advantage of their high accuracy and sensitivity in the microwave frequency

[1] Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah, 26600 Pekan, Pahang, Malaysia
[2] Ritsumeikan University, 525-8577 Shiga, Japan
*Corresponding author:mshaiful@umpsa.edu.my

domain [21]**.**Resonant methods, however, bring their high precision to the table while operating at discrete frequencies [21].

Since choosing the right measuring technique based on the necessity of the experiment is essential, the conversion of the raw data - transmission and/or reflection coefficient - obtained from the measurement result plays a huge role in translating the data into a meaningful data–dielectric constant or loss tangent. For example, study from Hasar et al. [22] utilize amplitude-only scattering parameters (S-parameters) in determining complex permittivity of thin material and Lin et al. [23] utilizes all scattering parameters to validate the extracting method they proposed. Thus, a few approaches come in handy; analytical, numerical, and machine learning, to extract meaningful data from the measurement values obtained from the measuring technique. This paper surveys the range of techniques available for extracting dielectric properties, focusing on their methodological nuances, application contexts, and the challenges to overcome.

II. MEASUREMENT TECHNIQUE

Characterization techniques give a detailed understanding of the behaviour of properties or the composition of the materials from their dielectric properties, such as permittivity, loss tangent, and permeability. The most common methods to measure the dielectric properties that are widely used are free space measurement (FSM), transmission line, and resonant methods. These distinct techniques contribute a different approach to measuring the transmission and reflection coefficients to assess the dielectric properties of the materials.

A. Free Space Measurement

One of the techniques required to determine material properties without any contact with the materials is called the free space method (FSM). The FSM technique offers such a strong candidate in terms of giving non-invasive and contactless approaches for material characterization, which is beneficial for heterogeneous samples [16] and provides simple preparation and ability to measure at both high and low frequencies [17] However, this kind of effectiveness is limited by the sample size. This method is applicable primarily to large, flat, solid materials, which makes it inadequate to cater to small or varying samples since the diffraction from the material edges can result in significant challenges that affect the accuracy of the measurements.

The measurement setup is simple as it typically requires connecting the antennas to the ports of a vector network analyzer (VNA) and with the sample holder in between where the material to be characterized is being placed. The waves travel through free space and interact with the material, creating reflection, transmission, and absorption conditions. Significant data can be obtained from the material's dielectric properties, such as permittivity and loss tangent. This method offers versatile and efficient capabilities for observing the dielectric properties of the material and giving reliable results even when facing changes. It also has the ability to measure S-parameters expeditiously once calibrated, which are used to calculate the dielectric properties of the materials. Even though the attractiveness of the method is because of the simplicity of the preparation since it is a relatively straightforward setup – involving a transmitting antenna, the sample test, and the receiving antenna – it can be quite complex at the same time in terms of the placement of the sample holder, which is crucial to minimize the error coming from the multiple reflections, mismatches, and diffraction. On the other hand, the sample also needs to be large enough, based on the application intended, to avoid the diffraction effect from the edges, which can cause errors in the measurement of reflection and transmission coefficients, which are essential for extracting dielectric properties. Numerous studies have been held using the FSM method, which undergoes material characterization with various kinds of material and enhances/optimizes the current traditional FSM method.

Bourreau et al. [24] introduce a quasi-optical free space measurement setup for material characterization on dielectric materials, which consists of Gaussian optics lens antennas, known as Gaussian beam horn, and a thru-reflect-line calibration to measure four S-parameters of planar dielectric slabs without time-domain gating. Utilization of Gaussian Beam Horns is believed to have the ability to maintain wavefront shape as it propagates through space where it can maintain the consistency of the wavefront itself [25] Meanwhile, Kim et al. [26] performed an FSM for extracting complex permittivity of low-loss material without the prior knowledge of the sample thickness, unlike the conventional FSM, which only requires scattering measurement data with one polarization that simplifies the process and make it more suitable for measuring materials at high frequency.

It can be concluded that FSM is highly suitable for applications where non-contact measurements are crucial, and the samples are large and homogeneous. It is less effective for small or irregularly shaped samples due to edge diffraction issues. Enhancements such as the use of Gaussian Beam Horns, as discussed by Bourreau et al. improve wavefront consistency, making FSM more reliable. Furthermore, innovations like those by Kim et al., which simplify the process for high-frequency measurements, enhance FSM's applicability in advanced research contexts.

B. Transmission line

Coaxial or waveguide is usually a common method in performing material characterization to obtain the dielectric properties. The method requires putting the sample or material inside the enclosed transmission line, and measurement of both reflection and transmission coefficient will be conducted. Waveguide is known for its high accuracy and sensitivity in measuring the dielectric properties of material, permittivity, and permeability at microwave frequencies because it directly measures electromagnetic wave interactions with the material and limits external interference, ensuring the reliability of the measurement result[18][21]However, one of the main drawbacks is that the demanding sample preparation for this method is difficult since it needs to cover the entire cross-section of the transmission line, which causes high time consumption to ensure the sample size is accurately the same as the transmission line dimension. This complexity makes it less approachable if the application is for quick processing testing scenarios. The method's limitations in sample preparation can be reduced by controlling the size and shape of the sample beforehand, where the material is fabricated to specific dimensions.

The application of transmission line measurement, which is being used to characterize the material and measure the transmission and reflection coefficient, has been established very well. This approach aligns with the studies from Karim et al. [19], where they proposed a method to determine the complex permittivity of the two-layered medium by making use of the waveguide focusing on transmission parameters instead of complex reflection parameters. This method is advantageous for high-loss layers, as it allows accurate measurements without the need for precise machining of the sample material. The fabrication of materials such as epoxy resin-barium titanite, which is considered a low-loss material, after undergoing a characterization using a waveguide technique at a G-band frequency range, which complements the advantage of the utilization of the waveguide [20,27], gives an accurate measurement of material electrical characteristics. Another recent study from [21] utilizes the coaxial line method to reconstruct the dielectric properties of dispersive and non-dispersive materials with low and high losses, which requires only transmission measurement from amplitude-only parameters excluding the phase measurement.

C. Resonant

The resonant method is known for its higher accuracy and sensitivity, although it is constrained to single and discrete frequencies [25]. The principle behind the resonant technique is that it relies on the observation of the resonant frequencies and quality factors of materials to determine the dielectric properties depending on the desired experiment objectives. The characterization technique that utilizes the resonant cavity method can be seen in multiple works of researchers [22,28,29] where usually the sample will be filled in the cavity resonator and the resonant frequency will be measured, and the quality factor will be calculated to determine the dielectric properties of the material and analyze the precision and sensitivity of the measurement. Other forms of resonators can be expressed in microstrip-line resonators and circular resonators, which serve the same purposes. Rashidin et al. [30] utilized a modified ring resonator and microstrip line technique to measure the permittivity and loss tangent of dielectric materials. The application of a rectangular resonator can be viewed in [28] works, where it is claimed to be more convenient, and the sample preparation is much easier for the liquid sample since the hole is designed on top of the cavity to insert the sample.

This method is highly appropriate for applications where high accuracy and sensitivity are vital since precise dielectric characterization of material is important in scientific research. The limitation mentioned to be only at discrete frequencies can be catered for in cases where detailed frequency-specific measurements are required.

Factors such as size, frequency range, the level of vitality in accuracy, and the preparation technicality should be specified beforehand to go into specific applications. A thorough understanding of these methods allows us to select appropriate techniques for specific research or industrial applications to achieve reliable and accurate dielectric property measurements. The advancement of each technique should be further explored or invented to enhance its applicability and make it more valuable in material characterization.

III. Computational Methods for Dielectric Property Extraction

Determining the dielectric properties of numerous materials can be challenging due to their distinctive behaviour when interacting with electromagnetic fields. The necessity of measuring and analyzing the dielectric properties is crucial as this extraction method can convert the raw measurement data – specifically, the transmission and/or reflection coefficient – into meaningful physical properties, such as permittivity, permeability, and loss tangent. In this work, three extraction methods; analytical analysis, numerical analysis, and machine learning methods, will be discussed. Each of these distinctive methods offers different insights to address the challenges in accurately determining dielectric properties under various conditions.

A. Analytical Analysis

Employing mathematical formulations and equations derived from theoretical principles in determining the dielectric properties. Some of the approaches utilized explicit formulas, closed-form solutions, and analytical methods to clarify the behaviour of the dielectric properties. A few analytical approaches will be discussed in this section to demonstrate the precision of these methods offered in characterizing dielectric materials.

1) Nicholson-Ross-Weir

The Nicholson-Ross-Weir (NRW) method is widely known for its analytical approaches to extracting the complex permittivity and permeability of materials from transmission and reflection coefficients, which are famously measured in the waveguide or coaxial transmission line configuration. In calculating the measured S-parameters, this method provides explicit formulas to calculate the complex permittivity and permeability, thus providing a straightforward and effective analysis of dielectric properties.

Rothwell et al. [31] and Chan et al. [32] employed the closed-form expressions of the NRW method for characterizing the electromagnetic properties of the materials where the condition of the material associated as lossless material is assumed. Then, the extracted parameters – real and imaginary parts of permittivity and permeability – are obtained from the measured value of magnitude and phase of S-parameters. Utilizing this method could reduce the common source of the error. However, the utilization of this method that uses mathematical expression and formulas can be too complex for materials with certain characteristics since the calculation is based particularly on assumptions of the material's behaviour in electromagnetic fields, and an in-depth understanding of electromagnetic theory is crucial. Albeit the expressions are only valid when the material is lossless in [31] works, it is still possible to use the expressions to show an understanding of the behaviour of the low-loss material. The NRW mathematical model can be further analyzed in [31] for various types of measurement techniques.

The simplified NRW method can be seen further in Sahin et al. [33] works as they implement single-port measurements instead of two-port, which are commonly used in NRW analysis that relies on both transmission and reflection coefficients of the materials. This approach can indirectly obtain two S-parameters of the sample by only utilizing a one-port network analyzer. The result in this work shows good agreement for the value that uses conventional and single-port NRW methods, which validates that it can be effective as a two-port procedure, but this method depends on the calibration process, which can jeopardize the accuracy of the material characterization process.

2) Non-Iterative Method

This method simplifies the determination of dielectric properties by avoiding the iterative processes and utilizing the direct mathematical parameters of the measured parameters to obtain the dielectric properties. The non-iterative method is almost identical to the NRW method, but it does not require iterative refinement to estimate the material's dielectric properties in solving the inversion problem. It is intended to simplify the process by directly calculating the dielectric properties from transmission and reflection coefficients utilizing a set of closed-form equations. Reflection-only measurements have been established quite well among researchers since they require simple and inexpensive instrumentation. However, it is known that extracting the complex permittivity from the reflection coefficient only can be difficult.

Demonstrating the non-iterative extraction method to extract complex permittivity from reflection asymmetric amplitude-only measurements has been discussed by Hasar et al. [34]. Despite its simplicity in instrumentation handling, it requires intensive measurements on the material itself as they need different measurements from the front sides causing the derivation of the formula to become more complex. Apart from that, Yang et al. [35] proposed a non-iterative method to extract the complex permittivity and thickness of the material that can be obtained from the short and match-backed, thus eliminating the requirement for prior thickness knowledge of the material. Nevertheless, the initial derivation of the calculation needs to be optimized, which causes the complexity of the existing method since it is not applicable to low-loss and thick materials at certain frequencies.

There is also an application that uses the transmission and reflection coefficient to find the permittivity of material with arbitrary sample length in wide-band frequencies since low-loss material is rather stable and accurate over a wide range of frequencies without divergence at specific frequencies corresponding to multiples of one-half wavelength in a sample. [36]introduce the non-iterative transmission/reflection method to measure the permittivity of the sample, and this method is a simplification of the well-known NRW method. This paper shows that the instabilities of the NRW method occur when associated with low-loss materials, which leads to divergence in measurement results. They took the initiative to suppress this issue by modifying the technique for evaluating the dielectric property.

3) National Institute of Standards and Technology Iterative

In extracting the dielectric properties of materials, such as permittivity from transmission or/and reflection coefficient, the National Institute of Standards and Technology (NIST) iterative method can be considered. The iterative process is to refine the estimation of the dielectric properties, starting with the initial assumption of the dielectric constant and optimizing these values iteratively to minimize the difference between measured and calculated S-parameters. From the scattering parameters, the relative complex permittivity can be computed by solving the Newton-Raphson iterative approach [37]. This method avoids the discontinuities – that happen in the NRW method – which requires a good initial guess and a long and low-loss sample Besides, the assumption of permeability equal to one can reduce the instability present in the NRW method, but this could be applied to only non-magnetic materials [38].

In Chang et al.[39] work, the NIST iterative employs the mathematical property, which is the matrix determinant that uses all four complete two ports S-parameters measurement. The drawback is that even a small distance movement that could cause phase error can be overcome by this procedure since it is independent of the reference plane position, which does not require placing the sample on the calibration reference plane. The NIST iterative mathematical model has been discussed in [39].

B. Numerical Analysis

The analytical method had the advantage of giving a straightforward analysis of the dielectric properties of the material based on explicit expression. However, it has tendencies where the magnitude of the reflection coefficient is near zero for low-loss material when the thickness of the material is close to multiples of half a wavelength in the sample, which affects the equation to become more unstable and inaccurate for a certain range of the thicknesses [40]. Nonetheless, with the conjunction of numerical methods to help in converging the solution, the accuracy and stability of the computational can be improved. Root-finding algorithms, non-linear regression, and genetic algorithms are a few examples of numerical techniques [41].

1) Root Finding Algorithm

Gagnon et al. [41] have discussed the utilization of both numerical and analytical methods in determining the permittivity and permeability of dielectric materials. The sample is inserted into a waveguide while being exposed to the incident electromagnetic field. It shows in detail how the electric and magnetic fields behave, integrating Maxwell’s equations and boundary conditions. It then proceeds to leverage the determinant of the S-matrix in solving the roots from the equations derived.

The initial value of the permittivity must be estimated first using algebraic technique before applying the root finding algorithm to ensure the convergences of the algorithm towards actual roots. An accurate initial estimate for permittivity can ensure a precise solution [42].However, it is crucial to quickly and accurately compute this solution [42].The derivation of the iterative solutions, Newton-Raphson iteration, from this paper providing a stability over the measurement spectrum while treating the length’s sample and the length of the air as unknown [41].

2) Extended Spectral Domain and the Mode-Matching (ESDMM) Method

Abdul Karim et al. [43] utilized a hybrid electromagnetic analysis approach in analyzing the resonant characteristic of rectangular waveguide cavity with the sample. This method is a combination of the Extended Spectral Domain and the Mode-Matching (ESDMM) method to effort highly efficient and fast computation of scattering parameter. Then, the unknown material parameters are discovered by solving the inverse problem of the scattering parameters obtained.

It is mentioned that in the homogeneous regions, electromagnetic fields are represented by simple sinusoidal functions, while in the sample-containing regions, more complex eigenfunctions are constructed from mode-matching methods. These functions are then transformed into the spectral domain and related to the aperture fields, with Green's functions derived to facilitate this process. Through Galerkin's procedure, integral equations for aperture fields are formulated and solved, maintaining the continuity of the magnetic fields at the interfaces. Then, by computing the inner product of the aperture field together with the dominant modes in waveguides, the scattering parameters S_{11}, S_{21}, and S_{22} can be calculated.

This analytical derived of this method is detailed explained by Miyagawa et al. [44,45]; then to ensure the converging of the complex permittivity value, the ESDMM comes in handy in extracting the dielectric properties of the sample from S_{21} parameters. The Finite Element Method (FEM) and ESDMM methods show a good agreement between both calculations in Abdul Karim et al. [43] work. It has been proven that the method is numerically efficient.

C. Machine Learning

1) Artificial Neural Network

An Artificial Neural Network (ANN) is a computational model that replicates the nerve cells that work in the human brain. It uses learning algorithms that can adjust independently as receiving new information or input. The model of ANN usually consists of three or more layers that integrate together. The first layer is known as input neurons, where it sends data to deeper layers. The hidden layers, called neural layers, are formed adaptively from the information received through a series of changes. Each of the layers plays a role of input and output for the ANN to understand the complexity of the systems. By weighing the information gathered in the neural layer, the results can then be generated and provided to the next layer as an output. Back propagation is one of the learning rules in which ANN can adjust its output results by taking errors into account during the training level where the information is sent backwards, the weight then being updated. The ANN will learn how to minimize errors and unwanted results. The use of ANN in applications such as dielectric property extraction is becoming more common due to its ability to adapt to complex datasets and minimize errors effectively [46].

In the context of extracting the dielectric properties of the material, the application of ANN can be further analyzed in research implementation. In Bonello J. et al. [47] works, the experiment was conducted to determine the complex permittivity of biological tissue by taking advantage of the use of an open-ended coaxial line integrating with VNA to measure the reflection coefficient (S_{11}), which is then converted to corresponding tissue permittivity which requires calibration technique at the tip of the probe. However, the method proposed utilizes the ANN algorithm, which does not require the intensive calibration technique. A total of 102 tissue samples have undergone the experiment process, and data is being treated for the implementation of the ANN model. While in Álvarez-Botero et al. [48] works, they implement the resonant sensor with the VNA to measure the magnitude of S_{11} and S_{21} and the resonant parameters – f_r (resonant frequency), $|\Gamma|_{fr}$ (magnitude of reflection at f_r), BW (3-dB bandwidth), and the power loss of the input – are extracted. These resonant parameters can be used as training parameters to be implemented in ANN model. The input layer consists of 8 neurons, – the resonant parameters – 10 hidden layers, and an output layer with two neurons – permittivity, permeability, and loss tangent.

In this process, the data is divided into two sets, which are for training and testing purposes. The training set is then divided into two parts, which are for training and validation of the ANN model. The training sets were randomly split into two, and the remaining went into validation sets. The weights within ANN were accustomed to minimizing the loss value during the training process. The loss value must converge to a minimum, and the model will be considered once the loss value does not exceed the set tolerance. Right after the model converged during the training process, the validation data set was used to assess the learning quality and the prediction of the model performance to refine the ANN architecture and parameters. Then, the model will be exported to predict the test data. The input layer consists of the real and imaginary of S_{11}, five hidden layers, and output the real and imaginary part of permittivity distinctively.

This approach highlighted that the reliance on extensive calibration could be reduced, which is usually compliant with the labour-intensive and time-consuming aspects, especially when numerous data are involved while undergoing an experiment. Other than that, the dependency on a number of datasets in the training process is also important as reducing the number of datasets could also reduce the accuracy of the ANN model; thus, the reliability of a number of data is important in order for the model to converge to the set tolerance and reduce the loss value.

2) Deep Neural Network (DNN)

A deep neural network (DNN) is an architecture that can learn vast amounts of data and imitate the capability of the human brain to operate. DNN is part of the machine learning models and comprises multiple layers of interconnected nodes. It is composed of several layers, commonly several, like two or more layers, which include input, output, and at least one hidden layer in between. It is always often related to dealing with complex, unlabeled, and unstructured data. The contribution of DNN can be further seen in several ways in the extraction of dielectric properties from transmission and/or reflection coefficients.

In Tan et al. [49], the implementation of DNN can be further observed. Utilizing the ridge waveguide as measuring equipment to measure the large size of the sample is much more convenient from an industry point of view. A combination of finite difference time domain (FDTD) simulation and a deep learning algorithm is used to construct the dielectric properties. To predict the dielectric properties, the deep learning process needs to be trained first with 40 samples, in this case, the scattering parameters such as magnitude of S11 and S21, phase of S11 and corresponding dielectric properties, to enable the model to learn the complexity between these variables effectively. The more predictable the data relationship between scattering parameters and dielectric properties, the better the inversion. A clear match-up of one-to-one relationships where each set of scattering parameters maps to a unique set of dielectric properties makes it easier for the model to learn how to map each set of dielectric properties accurately. However, if the mapping process is not one-to-one but rather one-to-many (multivalued), it will face difficulty in inverting the data accurately due to the multiple sets of scattering parameters generating multiple possible sets of dielectric properties, complicating the training process where the network cannot reliably predict a single set of dielectric properties which leads to inaccuracies. Thus, it is important to be well-defined and careful in selecting or preparing the inputs (scattering parameters) and the desired output (dielectric properties) to ensure the training network makes an accurate prediction.

From research conducted by Tan et al. [49], a total of 8000 sets of data were sampled by setting the sweep parameters of the relative dielectric constant and the loss tangent to be used as training data in a deep learning network. The DNN prediction model, which consists of an input layer, four hidden layers, and an output layer, using scattering parameters – magnitude of S_{11} and S_{21}, phase of S_{11} – as inputs and outputting dielectric properties ($\tan \delta$, ε_r). Every hidden layer receives its input from the previous layer, applies an activation function to carry out a non-linear transformation, and subsequently forwards the output to the following layer.

The performance of the network is evaluated using mean squared error (MSE) and the coefficient of determination (R^2). The result shows a low prediction MSE for the relative dielectric constant and loss tangent, which proves the network's accuracy. The performance of the accuracy of DNN is highest over support vector machine (SVM) and back propagation neural network (BPNN) models, evaluated using MSE and R^2. Thus, the deep learning approach demonstrates better generalization capability, achieving lower prediction error rates for dielectric properties. However, in order to achieve this kind of accuracy, the time constraint should be taken into account since collecting a vast number of datasets can be time-consuming, and the computation of storage will also be affected.

3) Neuro-Fuzzy Network

Neuro-Fuzzy is a combination of both neural networks and fuzzy logic in artificial intelligence. A neural network is known for its ability in pattern recognition, and fuzzy logic is good at handling imprecise or incomplete data; thus, it concludes that if both models are combined, they can handle both structured data and unstructured data. Neuro-fuzzy systems can learn and make decisions like any other neural network, and they have an extra advantage in dealing with incomplete data. However, it can be difficult to design and train and finding the right combination of algorithms can be challenging.

In one of the works conducted by [50], he has applied the Neuro-fuzzy network in extracting the dielectric properties from the measured transmission parameter (S_{21}) obtained by FSM method. This method consists of five layers and contains as many neurons which is named as Sugeno type Adaptive Neuro-Fuzzy Inference System (ANFIS).

Static nodes which typically perform fixed operations during the training process; they pass the input without altering the information to the next layer. The adaptive nodes change during the training process for the ANFIS model and learn from data by adjusting its parameters to reduce the error between the actual and predicted outputs. The nodes in each layer can be simply discussed here. Layer 1 is the Fuzzification Layer, which converts input values into fuzzy values using Gaussian functions. Layer 2 is a Rule Layer, which represents fuzzy logic rules; the output is the product of membership grades from layer 1. Next, layer 3 is the Normalization Layer, which normalizes the rule firing levels. Layer 4, known as the Defuzzification Layer, functions to calculate weighted result values; parameters here are called result parameters. Lastly, layer 5 is a summation layer that combines all outputs from layer 4 to get the final system output. The result of the dielectric constant of materials measured using neuro-fuzzy design (NFD) gives a good agreement with the conventional Newton-Raphson method with a small margin of difference, which proves that NFD can estimate the dielectric properties of the material from raw data without an extra procedure such as NRW or Newton Raphson (NR).

IV. FORTHCOMING RESEARCH DIRECTION

The extraction methods that have been discussed show distinctive advantages and also a few drawbacks. Analytical methods like NRW and non-iterative methods are much more likely to give straightforward analysis but can simultaneously be complex and limited by certain assumptions. Waveguide and coaxial transmission line configurations are most used to characterize material using these analytical methods. They are ideal for high-precision measurements, especially the S-parameters value essential for analytical calculations without iterative refinement.

Numerical methods can improve stability and accuracy but require precise initial values and need to be intensively computed. These methods typically utilize waveguide and resonant cavity measurements since the algorithm requires accurate initial permittivity values and precise S-parameter measurements to converge on correct dielectric properties. Thus, these methods come in handy since the numerical extraction method involves complex electromagnetic field analysis and needs a high-precision measurement of resonant characteristics and scattering parameters to solve the inverse problem and determine the dielectric properties of the material.

On the other hand, machine learning offers high accuracy and efficiency in handling large datasets but requires intensive data collection, training, and data quality. Various measurement techniques are often utilized in machine learning techniques, but they still depend on the intended application. For example, they usually employed the open-ended coaxial probe, resonant, and waveguide measurement technique due to the easily gathered hefty number of datasets necessary for training the neural network model. They employed FDTD to train complex data patterns and validate the model. Some leverage the FSM method due to its simplicity but still tend to give imprecise data. However, Neuro-Fuzzy Networks can cater to imprecise data effectively.

Several recommendations can be made to deal with the drawbacks of current extraction methods and improve their effectiveness. For instance, numerical analysis can be integrated with machine learning to improve the accuracy and efficiency of numerical methods. Computational efficiency is increasing instead of going through manual computations, which is complicated and time-consuming, making it more practical for real-time applications. Besides, machine learning requires us to build many comprehensive datasets with diverse materials and conditions to improve the training and accuracy of machine learning models and also express the difficulties in obtaining reliable datasets. Developing hybrid models, combining learning with traditional analytical and numerical methods, can leverage the advantages of each approach, providing more robust and accurate solutions in material characterization.

V. CONCLUSION

Dielectric property extraction from transmission and/or reflection coefficients is still a developing field of research, with each approach offering unique advantages and difficulties. Practical solutions are provided by free space, transmission lines, and resonant methods; the mathematical difficulty required for accuracy is provided by analytical and numerical methods. With the introduction of machine learning models, new opportunities have been created, providing notable improvements in predicting accuracy, and handling complex data. This survey has demonstrated that selecting a method requires striking a balance between the practicality, accuracy, and particularity of the material under test requirements.

Instead of focusing on one particular method for extracting the dielectric properties of a material, combining different techniques – analytical methods, numerical methods, and machine learning – allows one to leverage the strengths of each method and compensate for each challenge coming from it. For example, the numerical method has the advantage of attempting to find the approximate solutions but requires detailed modeling for different models and involves iterative processes. By combining machine learning methods, the complex patterns and correlations in the data that may be difficult to obtain or time-consuming through numerical or analytical methods can be identified. To push the boundaries of material characterization in electromagnetic fields, the future of dielectric property extraction points toward an integrated approach that combines the advantages of traditional analysis with computational models.

Acknowledgment

The authors would like to thank Universiti Malaysia Pahang Al-Sultan Abdullah for laboratory facilities as well as additional financial support under Internal Research grant RDU240319 and PGRS230355, and the Ministry of Higher Education for providing financial support under Fundamental Research Grant Scheme (FRGS) No. FRGS/1/2021/STG07/UMP/02/3 (University reference RDU210123).

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