

## ELECTROMECHANICAL IMPEDANCE BASED PART IDENTIFICATION VIA LINEAR PROJECTION

Sourabh Sangle<sup>1,\*</sup>, and Pablo Tarazaga<sup>1</sup>

<sup>1</sup> Fusion of Analysis, Simulation, and Testing (FAST) Lab, Department of Mechanical Engineering, Texas A&M University, College Station, TX 77843

### ABSTRACT

*The geographical separation between various supply chain participants creates challenges in ensuring the integrity of the parts under circulation. These supply chains have to regularly deal with counterfeiting, a significant problem with an estimated value equivalent to at least the tenth-largest global economy. Industries are constantly upgrading their anti-counterfeiting methods to tackle this ever-increasing issue. Traditionally, a physical or cyber-physical part identifier is used to assert the integrity and identity of parts moving through the supply chain. For this work, we propose the use of electromechanical impedance measurements to generate a robust, unique part identifier linked to physical attributes. Electromechanical impedance measurements have been employed as a basis for non-destructive evaluation techniques in damage detection and health monitoring. We propose using these high-frequency measurements recorded through bonded piezoceramic transducers to help uniquely identify parts.*

*For this study, identical piezoceramic transducers (cut from the same wafer to minimize variations) were mounted on identically manufactured specimens. The only distinction between these specimens was the physical variation introduced during manufacturing and instrumentation. Multiple measurements for each specimen were recorded. A unique part identification methodology based on linear projection was created using these measurements. Lastly, a leave-one-out study was performed to uniquely identify the left-out specimen. This was used to validate the part identification methodology. This paper introduces the use of electromechanical impedance measurements (widely adopted for damage detection) as a unique part identifier, with a basic experimental implementation of the proposed mechanism on identically manufactured parts. The paper also highlights some challenges and future work needed to make this methodology robust and adaptable.*

**Keywords:** Active materials, Implementation, Impedance, Unique part identification, linear summation

### 1. INTRODUCTION

Counterfeiting is a serious issue that affects supply chains all over the globe. Counterfeiting is at least a \$ 1.5 trillion industry, making it indirectly the tenth largest economy in terms of total GDP [1]. In order to tackle this inevitable issue, supply chains require a mechanism or a methodology to assert the identity and ensure the integrity of a part moving through it. The current methods for identification involve the use of a variety of techniques, ranging from physical markings to chemical markings when exposed to an external stimulus [2]. With the advancements in globalization, the geographical separation between the participants of a supply chain has created challenges in part authentication using traditional identifiers. One way to tackle this challenge is to digitally link the part-specific information to the part itself. Although this digital or cyber-information is invaluable for part legitimacy, linking it to the part is not straightforward and has challenges of its own.

To establish the connection between part information to its physical instance, researchers recommend the use of identifiers that are extrinsic as well as intrinsic. These include but are not limited to serial tags, bar codes, QR codes, or state-of-the-art radio frequency-based identifiers (RFIDs). Identifiers enable distributors and customers, to identify if the part at hand is the same or different than the originally supplied by the original equipment manufacturer (OEM), i.e. authentic part. An appropriate identifier provides the stakeholders and customers with information about the whereabouts, as a point-by-point time-stamp for its movement through the supply chain, while assisting in detecting any foul play. Despite their extensive use, these identifiers have shortcomings that need to be addressed. Through studies, researchers have provided an overview of issues faced by identifiers [3]. The traditional technologies when compared to RFIDs lack certain functionalities and properties required for adequate identification. The type of identifier to be used depends on the requirements of the supply chain. Unlike its extrinsic counterparts, an intrinsic identifier is less vulnerable and more connected to the unclonable inherent characteristics of a part. This type of

\*Corresponding author: sangle96@tamu.edu

identifier generates a unique identity of a particular part instance by exploiting the inherent randomness introduced during manufacturing or fabrication [4]. These unclonable function-based identifiers are versatile and possess lower vulnerability [5].

Electromechanical impedance (EMI) measurements are intrinsic to a part and can be uniquely associated with a part. These measurements have shown promise to create physically unclonable functions [6], and thus can be used as a basis for a robust identification system. Over the decades, EMI measurements have been widely used to detect defects across a large domain of applications, such as, aerospace structures, composite structures, wind turbines, and space structures [7–11]. EMI measurements-based damage detection, first introduced by Park et al. [12], use piezoceramic materials - particularly, lead zirconate titanate, to function as an collated sensor and actuator [13, 14]. EMI-based structural health monitoring (SHM) is a highly sensitive, non-intrusive, real-time, and versatile solution to monitor simple and complex structures. EMI measurements have been successfully adapted for not only post-process evaluation but also in-process monitoring of additively manufactured parts [15–17].

Taking this into account, this paper presents a new method for part identification using EMI measurements via linear projection. Any EMI measurement of a part or structure recorded using the same experimental setup and constrained to the same boundary conditions should be representative of the identity of the part or structure itself. Thus, all else remaining equal, multiple EMI measurements recorded over time can assist to authenticate the identity of the part. For this study, multiple measurements for identically manufactured parts are recorded. These measurements are then processed to establish a linear projection-based binary search method. This further allows the development of an intrinsic identifier for a part under consideration. Using this identifier, one can understand if a new recorded measurement is associated with the intended part or is associated with a counterfeit/tampered part.

The remainder of this paper is organized as follows - Section 2 briefly discusses the fundamentals and applications of electromechanical impedance. Section 3 discusses the methodology and experimental aspect of this study. The proposed linear summation-based identification method is discussed in Section 4. The use and capabilities of the proposed method are demonstrated in Section 4.1. Finally, the concluding remarks and directions for future research are presented in Section 5.

## 2. ELECTROMECHANICAL IMPEDANCE

Owing to its sensitivity and ease of implementation, EMI-based SHM has proven to be a versatile, effective health monitoring technique. This particular technique uses augmented piezoelectric ceramics or piezoceramics to actuate, and simultaneously measure the dynamic response of the host structure. Any structural modification will alter a part's mechanical properties - mass, stiffness, etc. Piezoelectric materials exhibit an electromechanical coupling behavior, that directly relates the mechanical impedance of the host structure  $Z_{st}$  to the electrical impedance  $Z(\omega)$  of the attached piezoelectric sensor. The electrical impedance of the piezoelectric wafer as a function of

the mechanical impedance [13], is expressed as,

$$Z(\omega) = \left[ i\omega \frac{bl}{h} \left( \frac{d_{13}^2}{s_{11}^E} \left( \frac{\tan kl}{kl} \left( \frac{Z_{pzt}}{Z_{pzt} + Z_{st}} \right) - 1 \right) + \epsilon_{33}^\sigma \right) \right]^{-1}, \quad (1)$$

where  $\omega$  is the frequency of excitation,  $Z_{pzt} = -ibhl \left( s_{11}^E \omega \frac{\tan kl}{kl} \right)^{-1}$  is the piezoelectric transducer short-circuit impedance,  $k = \omega \sqrt{\rho s_{11}^E}$  is the wave number  $\epsilon_{11}$  is the 1-direction component of the strain tensor of the coupled piezoceramic wafer,  $s_{11}^E$  is the complex mechanical compliance measured at zero electric field,  $\epsilon_{33}^\sigma$  is the complex permittivity measured at zero stress,  $\rho$  is the density of the piezoelectric material, and  $b, h$  and  $l$  are the piezoelectric patch width, thickness, and length, respectively.

As measuring the electrical impedance is straightforward, any changes in the host structure can be identified based on the recorded electrical measurements. Thus, changes in the host structure can be easily detected. This non-invasive health monitoring technique has been implemented across various domains. An EMI measurement is directly related to a part and is affected by changes to physical characteristics - the basis of EMI-based SHM. The piezo wafers are either attached to the surface (direct measurement) or embedded in the structure during fabrication (indirect measurement).

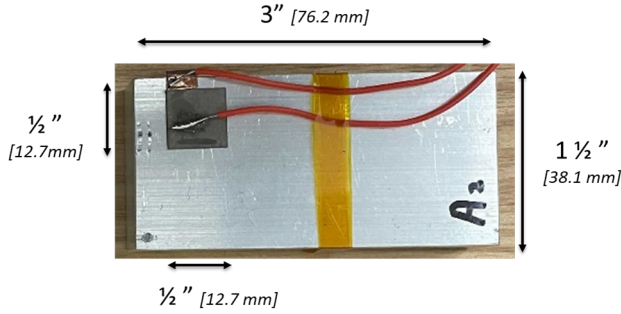
Manufacturing tolerances, deviations in operating conditions, human factors, and/or ambient conditions also affect the EMI measurement. Factors such as ambient temperature have a global effect on EMI measurement. To tackle such situations, several researchers have investigated and developed techniques to compensate for the effects of temperature [18]. Although, these factors are often referred to as deficiencies in the health monitoring domains, the work herein uses these as an advantage. This work aims to leverage these sensitivities as a way of creating part identifiers. At very high frequencies, the sensitivity of the EMI measurement due to manufacturing tolerances, etc can be leveraged to develop a unique part identifier.

## 3. METHODOLOGY AND EXPERIMENTAL SETUP

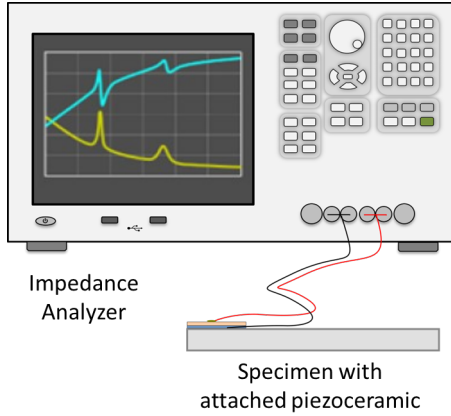
To investigate the use of EMI measurements to create intrinsic part identifiers, multiple high-frequency measurements of a control specimen are recorded. A linear summation-based technique to compare subsequent measurements is then developed using these measurements. An experiment was designed to apply the identification method. Three aluminum beams, each with dimensions 7.6 mm x 38.1 mm x 19.05 mm, were machined from a larger aluminum block. Monolithic piezoelectric patches of dimensions 12.7 mm x 12.7 mm x 0.2 mm, cut from the same wafer, were bonded to the surface of the beams using cyanoacrylate, as shown in Figure 1a. A single larger block of aluminum and a larger piezoelectric wafer were chosen to minimize variations due material properties of each specimen. The piezoelectric transducer was attached about 2 mm from the larger edge and 6 mm from the shorter edge. This configuration was kept consistent for all the specimens.

EMI measurements were recorded using a Keysight E4990A analyzer and later imported into a computer for post-processing.

The measurements were recorded over a frequency range of 940 Hz to 100 kHz. All the specimens were subject to "free-free" boundary conditions and an incremental sine sweep was applied through the analyzer. For each specimen, multiple EMI measurements were recorded. Figure 1b shows a schematic for the experimental setup used for this study.



(a) Aluminum specimen with attached piezoceramic



(b) Schematics for recording EMI measurement using Keysight 4990A analyzer

FIGURE 1: SPECIMEN USED AND SCHEMATICS FOR EXPERIMENTAL SETUP

#### 4. UNIQUE PART IDENTIFICATION USING EMI MEASUREMENTS

As stated, EMI measurements serve as physically unclonable functions capable of differentiating parts from one another. Thus, each individual part has a unique EMI measurement intrinsic and uniquely associated with it. When recorded multiple times, every subsequent EMI measurement of a part should be the exact same. However, factors mentioned earlier, such as ambient conditions, etc, play a role in introducing minor, at times aggregate, variations in the EMI measurements. Because EMI is very sensitive to changes in ambient conditions, every EMI measurement recorded for the same specimen will possess deviations. It can be hypothesized that a particular EMI measurement has two components; a true measurement  $\mathbf{Z}_0$ , at baseline setting of the boundary conditions, ambient conditions, etc, and a variation-dependent measurement  $\mathbf{Z}_\epsilon$ . Mathematically, all the measurements recorded for a particular part, follow a distribution

with a mean and variance. For each individual measurement, a combination of the true and variation-dependent components can be expressed statistically as,

$$\mathbf{Z}_n = \mathbf{Z}_0 + \mathbf{Z}_{n\epsilon} \sim \mathcal{N}(\mu_Z, \sigma_Z^2), \quad (2)$$

where  $\mathbf{Z}_n$  is the  $n^{th}$  EMI measurement,  $\mathbf{Z}_0$  is the true EMI measurement for that particular part instance, and  $\mathbf{Z}_{n\epsilon}$  is the variation, resultant of the aforementioned factors, while  $\mu_Z$  and  $\sigma_Z^2$  are the mean and variance of the said distribution.

In an ideal scenario, the mean  $\mu_Z$  of these measurements should be equal to the true measurement  $\mathbf{Z}_0$ , with a smaller standard deviation  $\sigma_Z$ . Let us assume, one records multiple measurements of a Part  $P_1$  and generates the statistical distribution. By projecting an unknown EMI measurement  $\mathbf{Z}_{unknown}$  onto the statistical distribution  $\mathcal{N}_{P_1}$ , one can deduce the association of the measurement to the part  $P_1$ . This particular method asserts the identity of any part by observing if the recorded measurement is within the tolerance limit of acceptance for the prescribed part. Here, the  $\mathbf{Z}_{n\epsilon}$  for  $P_1$ , is smaller than the difference between  $\mathbf{Z}_{unknown}$  and  $\mathbf{Z}_n$  measurement of  $P_1$ . Figure 2a shows the real part of impedance for a part under investigation projected against the statistical distribution of two candidates. Although this method is straightforward, it has some challenges of its own. Firstly, to get a better idea of the distribution, a number of measurements are required. Secondly, when dealing with identically manufactured parts, their corresponding EMI measurements tend to be closer to each other. In such a situation, differentiating between these parts on basis of the statistical distribution of EMI measurements is challenging, as demonstrated in Figure 2b.

To create a simple but effective unique part identification methodology, the authors propose modifying the representation of an EMI measurement of a part, based on insights from vector algebra and model approximation. The unique part identity of any given part or structure is spanned by the vectors  $\mathbf{Z}_i$  - the individual EMI measurements of the same part. Linear Summation (LinSum) hypothesizes using all the available EMI measurements of the part under study to appropriately represent a new measurement of the same part. This linear combination of EMI measurements can be written as,

$$\mathbf{Z}_u = A_1 \mathbf{Z}_1 + A_2 \mathbf{Z}_2 + \dots + A_n \mathbf{Z}_n = \sum_{i=1}^N A_i \mathbf{Z}_i \quad \mathbf{Z}_i \in \mathbb{C}^{M \times 1}, A_i \in \mathbb{C}^1, \quad (3)$$

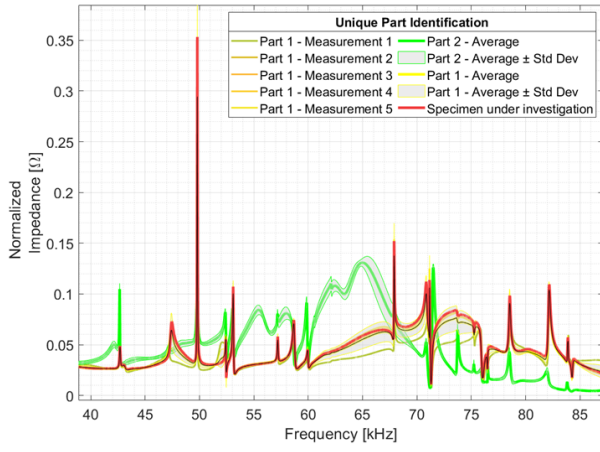
where  $\mathbf{Z}_i$ , are independent EMI measurements recorded for a given part instance at  $M$  frequency points,  $A_i$  are their associated weights and  $\mathbf{Z}_u$  is the impedance measurement under investigation.

To solve for the weights, a least-square problem is solved as,

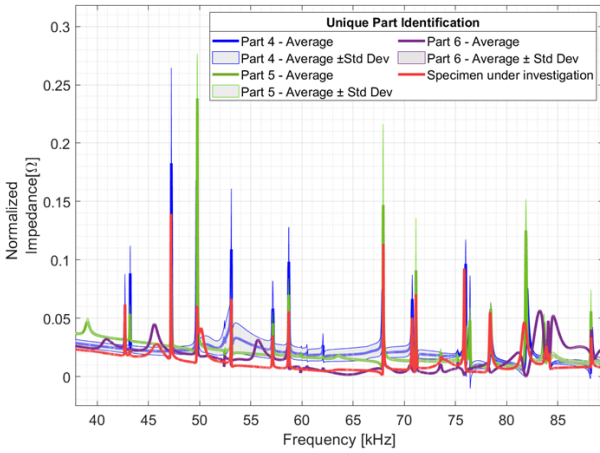
$$\mathbf{A} = \left[ (\mathbf{R}_Z^T \mathbf{R}_Z)^{-1} \mathbf{R}_Z^T \right] \mathbf{Z}_u, \quad (4)$$

where  $\mathbf{Z}_i$ 's form the columns of  $\mathbf{R}_Z$ , and the associated weights  $A_i$  are the elements of  $\mathbf{A}$ . Once the weights corresponding to an EMI measurement under investigation ( $\mathbf{Z}_u$ ) are obtained, they are processed to generate a decision metric  $\bar{K}_u$ . Various functions can be used to calculate the decision metric. The function can





(a) Normalized Real part of impedance for specimen under investigation along with statistical distribution for two candidate parts



(b) Normalized Real part of impedance for specimen under investigation along with statistical distribution for identically manufactured parts

FIGURE 2: USING  $\mu_Z$  AND  $\sigma_Z$  OF EMI MEASUREMENTS TO IDENTIFY SPECIMENS

be changed according to the needs of the user. For this study, an absolute average of the weights was used as the decision metric. A decision metric threshold,  $\bar{K}_e$ , is set based on the known EMI measurements of the candidate,  $Z_i$ 's. For  $Z_u$ , only when  $\bar{K}_u < \bar{K}_e$ , then  $Z_u$  corresponds to the candidate  $Z_i$ 's are associated with. For practical purposes, the identification is not performed for only a single candidate, but for a set of candidates. For LinSum, these candidates define the stages of the identification method. For any  $Z_u$ , the LinSum method in its basic form performs a multi-stage binary classification to establish its identity and associates it with one of the available candidates. Figure 3 shows a summary flowchart of the LinSum method used for part identification in this work.

#### 4.1 Linear Summation for identical parts

A counterfeit in simplest terms is an imitation of the original, intended to infiltrate and deceive the supply chain participants. Here the authors present the worst identification scenario of differ-

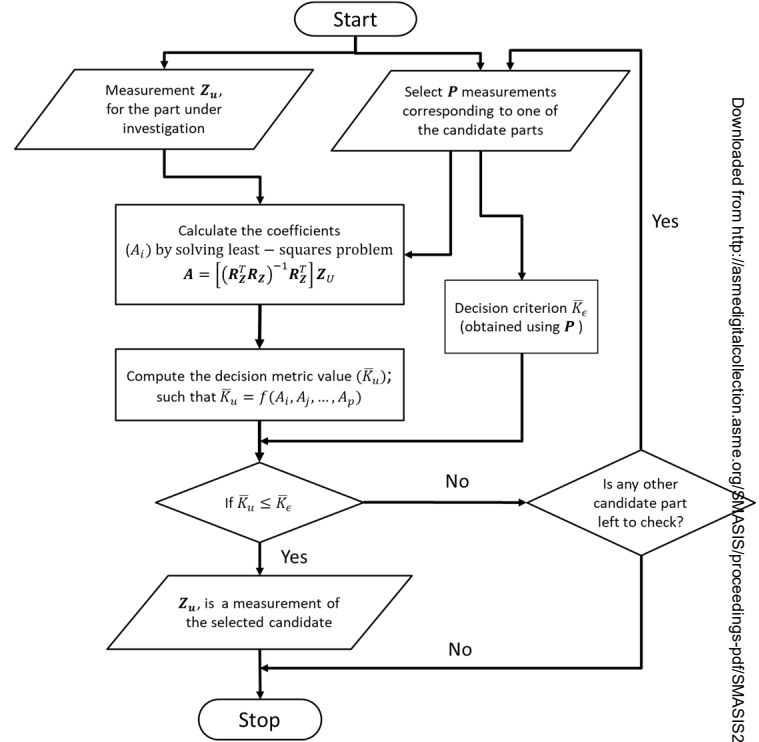


FIGURE 3: LINSUM PROCESS USED FOR PART IDENTIFICATION SYSTEM

entiating between identically manufactured parts. Differentiating between two identically manufactured originals is cumbersome and not an easy task for any unique part identification system (UPIS). Thus, if any UPIS can differentiate between parts identically manufactured by the original supplier, it should be able to differentiate between non-identical parts.

In this work, the authors showcase a problem wherein a replica posing as the original part was manufactured. Multiple EMI measurements for the six identically manufactured specimens (within machining tolerances and human error) were recorded using the setup mentioned in Section 3. Figure 4 shows the one high-frequency EMI measurement for the each of the six specimen. Out of all available EMI measurements corresponding to every specimen, all but one were chosen to form the basis of each identification stage for LinSum. LinSum method was applied to uniquely identify the remaining EMI measurements and their corresponding identity.

#### 4.2 Results & Discussions

For this work, the LinSum method was applied for each of the 6 identically manufactured specimens. For the multi-staged LinSum, each stage is associated with a particular specimen (e.g., Specimen A, Specimen B, etc). Each stage comprised leave-one-out-tests equal to the number of total EMI measurements associated with the specimen to be identified in the stage. A total of  $N$  measurements, divided among the 6 specimens were recorded. Ideally, for every stage, each of the  $P$  leave-one-out-tests using  $P - 1$  measurements of a particular specimen should produce 1 positive decision for the left-out measurement for that specimen

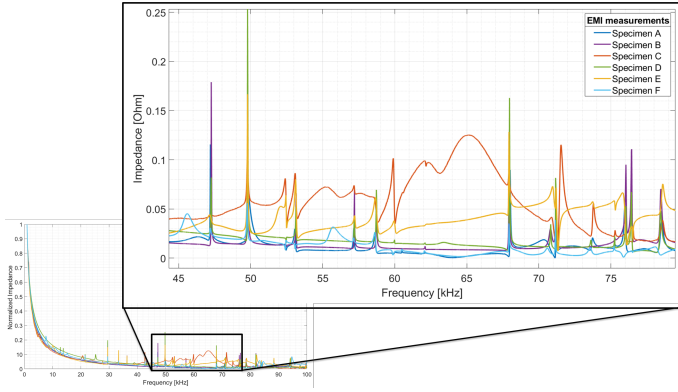


FIGURE 4: EMI MEASUREMENTS FOR IDENTICAL SPECIMENS

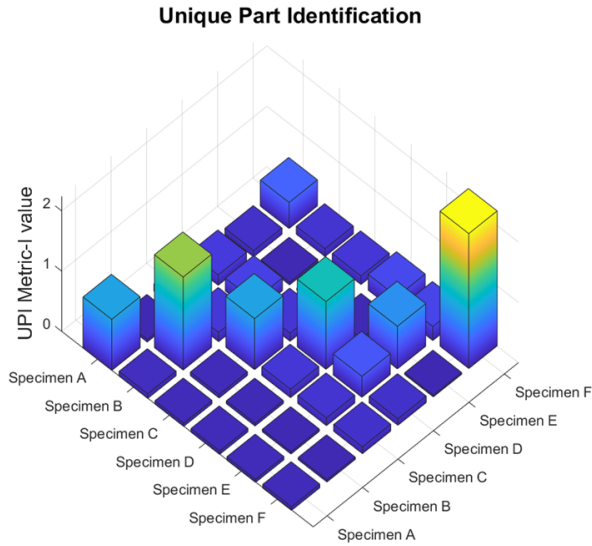


FIGURE 5: CLASSIFICATION OF SPECIMENS USING LINSUM APPROACH

and  $N - P$  negative decisions for measurements associated with the remaining specimens. The experimental case study used 33 EMI measurements distributed among 6 specimens. A representative classification of 6 EMI measurements using the LinSum is presented in Figure 5. As observed, the LinSum method effectively differentiated between true and false parts for each stage of the part identification. Despite this, with the current threshold, the method did not recognize the identity of 2 EMI measurements. It is noted that although undesirable, this particular result of false rejection is favorable over false acceptance for the anti-counterfeiting application. Falsely rejecting a good or real part would lead to a second scan which is still less expensive than falsely accepting a bad or fake part in circulation that could yield to catastrophic results if intended.

As the LinSum method basically forms a classification model, its effectiveness is evaluated using the standard  $F_1$ -test and Matthews Correlation Coefficient (MCC)-test. The  $F_1$ -score and the  $MCC$ -value are calculated as,

$$F_1 = \frac{2TP}{2TP + FP + FN}, \quad (5a)$$

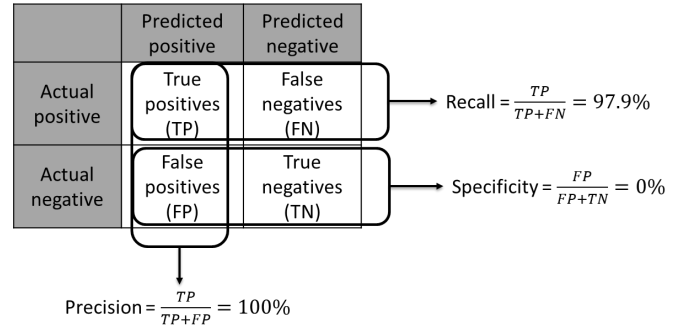


FIGURE 6: A GENERIC 2X2 CONFUSION MATRIX COMPARING ACTUAL AND PREDICTED LABELS

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{((TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN))^{1/2}}, \quad (5b)$$

where  $TP$  is the number of true positives,  $FP$  is the number of false positives,  $TN$  is the number of true negatives and  $FN$  is the number of false negatives predicted by the model respectively. Figure 6 shows a 2x2 Confusion matrix to help the reader with the nomenclature. The precision of the model is the ratio of  $TP$ s to the sum of  $TP$ s and  $FP$ s, recall is the ratio of  $TP$ s to the sum of  $TP$ s and  $FN$ s, while, specificity is the ratio of  $FP$ s to the sum of  $FP$  and  $TN$ s. The current UPIS model has a precision of 100%, a recall of 97.9%, and a specificity of 0%. The balanced  $F_1$ -score of the UPIS is 98.95% while the  $MCC$ -value is 0.987. A model with a higher  $F_1$ -score and  $MCC$ -value is always preferred. Thus, the proposed LinSum-based UPIS is robust and efficient in uniquely identifying identical parts from each other. This proposed approach would prove better than the classical operator-based approach wherein an operator makes a decision about the part identity. The current UPIS takes into account raw unprocessed EMI measurements for performing the identification. Pre-processed EMI measurements can assist in eliminating false decisions, thus, increasing precision.

## 5. CONCLUSION

In this work, we proposed a new way to utilize high-frequency EMI measurements for unique part identification. The proposed method, LinSum uses available EMI measurements of a part to recognize the identity of an unknown new EMI measurement. The method used for part identification is operator independent and semi-autonomous in terms of decision-making. This identification method had a  $F_1$  score of 98.95% and  $MCC$  value of 0.987, a precision of 100% in identifying 3 identical specimens from one another.

Out of all the false decisions made, the system predicts more  $FN$ s than  $FP$ s which in the context of asserting part identity are preferred. It is suspected that most of the  $FP$ s decisions were associated with EMI measurements affected by ambient conditions, a condition that can be compensated by data-driven models. For future work, a goal would be to develop a more robust UPIS to eliminate the  $FP$ s altogether which can be accomplished through the use of alternative projection techniques, parameter-sensitive studies, and/or appropriate frequency band selection.

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## REFERENCES

- [1] Goldstein, Keith. "Council post: The global impact of counterfeiting and solutions to stop it." (2022). URL <https://www.forbes.com/sites/forbesbusinesscouncil/2022/08/02/the-global-impact-of-counterfeiting-and-solutions-to-stop-it/?sh=285a6c151ca2>.
- [2] Heston, Tim. "Intelligent part identification: Keeping track of it all." (2015). URL <https://www.thefabricator.com/thefabricator/article/materialshandling/intelligent-part-identification-keeping-track-of-it-all>.
- [3] Ilie-Zudor, Elisabeth, Kemény, Zsolt, Van Blommestein, Fred, Monostori, László and Van Der Meulen, André. "A survey of applications and requirements of unique identification systems and RFID techniques." *Computers in Industry* Vol. 62 No. 3 (2011): pp. 227–252.
- [4] Gao, Yansong, Al-Sarawi, Said F and Abbott, Derek. "Physical unclonable functions." *Nature Electronics* Vol. 3 No. 2 (2020): pp. 81–91.
- [5] Shamsoshoara, Alireza, Korenda, Ashwija, Afghah, Fateh-meh and Zeadally, Sherali. "A survey on physical unclonable function (PUF)-based security solutions for Internet of Things." *Computer Networks* Vol. 183 (2020): p. 107593.
- [6] Sandborn, Michael, Olea, Carlos, White, Jules, Williams, Chris, Tarazaga, Pablo A., Sturm, Logan, Albakri, Mohammad and Tenney, Charles. "Towards secure cyber-physical information association for parts." *Journal of Manufacturing Systems* Vol. 59 (2021): pp. 27–41. DOI <https://doi.org/10.1016/j.jmsy.2021.01.003>. URL <https://www.sciencedirect.com/science/article/pii/S0278612521000030>.
- [7] Giurgiutiu, Victor, Zagrai, Andrei and Bao, Jing Jing. "Piezoelectric Wafer Embedded Active Sensors for Aging Aircraft Structural Health Monitoring." *Structural Health Monitoring* Vol. 1 No. 1 (2002): pp. 41–61. DOI [10.1177/147592170200100104](https://doi.org/10.1177/147592170200100104). URL <https://doi.org/10.1177/147592170200100104>.
- [8] Taylor, Stuart G, Farinholt, Kevin, Choi, Mijin, Jeong, Hyomi, Jang, Jaekyeong, Park, Gyuhae, Lee, Jung-Ryul and Todd, Michael D. "Incipient crack detection in a composite wind turbine rotor blade." *Journal of Intelligent Material Systems and Structures* Vol. 25 No. 5 (2013): pp. 613–620. DOI [10.1177/1045389x13510788](https://doi.org/10.1177/1045389x13510788). URL <https://doi.org/10.1177/1045389x13510788>.
- [9] Pitchford, Corey, Grisso, Benjamin L. and Inman, Daniel J. "Impedance-based structural health monitoring of wind turbine blades." Kundu, Tribikram (ed.). *SPIE Proceedings*: pp. 508–518. 2007. SPIE. DOI [10.1117/12.715800](https://doi.org/10.1117/12.715800). URL <https://doi.org/10.1117/12.715800>.
- [10] Zagrai, Andrei, Doyle, Derek, Gigineishvili, Vlasi, Brown, Jacob, Gardenier, Hugh and Arritt, Brandon. "Piezoelectric Wafer Active Sensor Structural Health Monitoring of Space Structures." *Journal of Intelligent Material Systems and Structures* Vol. 21 No. 9 (2010): pp. 921–940. DOI [10.1177/1045389x10369850](https://doi.org/10.1177/1045389x10369850). URL <https://doi.org/10.1177/1045389x10369850>.
- [11] Peairs, Daniel M., Tarazaga, Pablo A. and Inman, Daniel J. "Frequency Range Selection for Impedance-Based Structural Health Monitoring." *Journal of Vibration and Acoustics* Vol. 129 No. 6 (2007): pp. 701–709. DOI [10.1115/1.2775506](https://doi.org/10.1115/1.2775506). URL <https://doi.org/10.1115/1.2775506>.
- [12] Park, Gyuhae, Sohn, Hoon, Farrar, Charles R, Inman, Daniel J et al. "Overview of piezoelectric impedance-based health monitoring and path forward." *Shock and vibration digest* Vol. 35 No. 6 (2003): pp. 451–464.
- [13] Liang, C., Sun, F.P. and Rogers, C.A. "Coupled Electro-Mechanical Analysis of Adaptive Material Systems — Determination of the Actuator Power Consumption and System Energy Transfer." *Journal of Intelligent Material Systems and Structures* Vol. 5 No. 1 (1994): pp. 12–20. DOI [10.1177/1045389x9400500102](https://doi.org/10.1177/1045389x9400500102). URL <https://doi.org/10.1177/1045389x9400500102>.
- [14] Giurgiutiu, Victor and Zagrai, Andrei N. "Characterization of Piezoelectric Wafer Active Sensors." *Journal of Intelligent Material Systems and Structures* Vol. 11 No. 12 (2000): pp. 959–976. DOI [10.1106/a1hu-23jd-m5au-engw](https://doi.org/10.1106/a1hu-23jd-m5au-engw). URL <https://doi.org/10.1106/a1hu-23jd-m5au-engw>.
- [15] Albakri, Mohammad I., Sturm, Logan D., Williams, Christopher B. and Tarazaga, Pablo A. "Impedance-based non-destructive evaluation of additively manufactured parts." *Rapid Prototyping Journal* Vol. 23 No. 3 (2017): pp. 589–601. DOI [10.1108/rpj-03-2016-0046](https://doi.org/10.1108/rpj-03-2016-0046). URL <https://doi.org/10.1108/rpj-03-2016-0046>.
- [16] Sturm, Logan D, Albakri, Mohammed I, Tarazaga, Pablo A and Williams, Christopher B. "In situ monitoring of material jetting additive manufacturing process via impedance based measurements." *Additive Manufacturing* Vol. 28 (2019): pp. 456–463.
- [17] Tenney, Charles, Albakri, Mohammad I, Kubalak, Joseph, Sturm, Logan D, Williams, Christopher B and Tarazaga, Pablo A. "Internal porosity detection in additively manufactured parts via electromechanical impedance measurements." *Smart Materials, Adaptive Structures and Intelligent Systems*, Vol. 58257: p. V001T08A009. 2017. American Society of Mechanical Engineers.
- [18] Femi-Oyetoro, James, Sangle, Sourabh, Tarazaga, Pablo and Albakri, Mohammad I. "Temperature Compensation for Electromechanical Impedance Signatures With Data-Driven Modeling." *Smart Materials, Adaptive Structures and Intelligent Systems*, Vol. 86274: p. V001T05A009. 2022. American Society of Mechanical Engineers. URL <https://asmedigitalcollection.asme.org/SMASIS/proceedings/SMASIS2022/86274/V001T05A009/1150766>.