# Deep Learning Approach for Fault Identification of Contact Reliability for Electrical Test Connectors in Testing Environments

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**Abstract.** Electrical connectors are widely used in modern day technology and products and they play a key role in manufacturing facilities. Specifically in testing equipment in production lines, the contact reliability of electrical test connectors is crucial for obtaining correct measurements of a wide variety of signals coming from the unit under test (UUT) or from the test equipment (TE). Because modern production environments submit testing connectors to constant cycles of contact, which includes several grades of physical and electrical stress, the reliability of any given connector becomes a very important factor in production quality and continuity. Failure of contact may result in unreliable testing results, product failure or even physical damage to product or even testing equipment. Damage to connector terminals due to wearing may induce different degrees of contact failure of contact, which may result in unreliable testing results, product failure or even physical damage. As global modern production quality requirements become more prominent, test processes are expected to be increasingly reliable in modern day industry. In this paper, we provide an approach to identify failure of contact reliability in testing connectors using Deep Learning.

**Keywords:** Deep Learning, Testing Equipment, Electrical Connectors, Industry 4.0.

## 1 Introduction

To this day, there are several well established testing procedures to qualify an electrical connector´s reliability like contact resistance measurement, low current impedance measurement, high resistance metrics, among others. These methods are part of the ANSI C119 Standard Test Methods [3] and are widely used internationally. Lately, novel methods for contact reliability are being published that aim to specific measurement parameters like the HAST test for electrical connectors [2] which presents a degradation model of the electrical contact considering temperature and humidity factors, or the accelerated Life Testing for Marine Cables and Connectors [4] that provides a delamination predictive model of such connectors. On more production-related grounds, systematic approaches have been proposed for connector reliability [1][8] which offers a quantitative solution and offers insight on analysis of material, electrothermal, structure and contact characteristics of a given connector.

On the other hand, there are several industry-grade instruments designed specifically for connector reliability testing that aim to measure both continuity and isolation of the connector under test (CUT) [5]. In the case of isolation, a high resistance is expected to be measured between non-contact terminals (typically: 1M□-1T□ depending on settings), for continuity of contact, a value of low resistance is expected to be measured end-to-end connector wise (typically: <10□ depending on settings). This type of equipment uses current and current-sense matrix to test electrical characteristics of the connector but are susceptible to noise, wiring capacitances and thermoelectric EMFs, which need to be attended beforehand.

Connector Testing Programs are test sequences and procedures that aim to determine the connector reliability based on several factors like mechanical stability, durability cycling, mechanical shock response, among others [6]. These particular sequences are used in several steps of modern industry environments which include: design verification, quality assessment, performance analysis and reliability assessment. Typical generic test plans are divided among several testing groups, each group will evaluate a set of characteristics from the connector, this is shown in Fig. 1.

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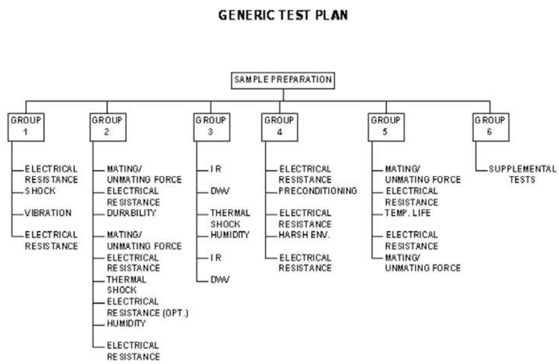


**Fig. 1.** Generic test plan group order and their hierarchy as defined by [6].

Each of the groups shown in Fig. 1. Evaluates a different aspect of the connector reliability and provides a complete performance assessment, which follows the following general criteria:

- First group comprises mechanical tests and the overall initial testing phase.
- Second group adds thermal and corrosion metrics as well as physical forces involved in connecting cycles.
- Third group is an environmental performance testing aimed to measure connector´s construction reliability.
- Fourth group involves preconditioning conditions like corrosion or wearing.
- The Fifth group comprises the same analysis as the Second group but with extreme temperature rating.
- Finally, the Sixth group will have application specific tests.

Considering all of the above, we can infer that the testing scenario for connector reliability is well established, well defined and supported by precision equipment up to this day. Now, by using the resulting data from a well-modelled connector and the measurements of a well-defined connector´s test plan we can define the correct parameters of any given test connector during its normal operation. Furthermore, we can use this information to create a structured data frame that contains all the expected behaviors during connection cycles of a given electrical connector and use them as a reference database.

In modern industry standards, like industry 4.0, Artificial Intelligence (AI) is rapidly gaining notoriety in numerous applications like autonomous driving and assembly, battery lifespan and degradation analysis, renewable energy optimization, steelworks forecasting, semiconductor anomaly detection, among others [7].

Alongside several artificial intelligence models, Deep Learning (DL) stands as a reliable and successful approach for several problems that involve visual and nonvisual problems in wide areas like: engineering, medical, transportation, security and many others[9][11][12]. The Convolution Neural Network (CNN) that comprises the base of the algorithm, allows the extraction of relevant data known as *characteristics* without losing significant information during the deep process of the scheme: Convolution-Rectification-Max pooling-Padding[10]. Finally, the fully connected section (FC) of the DL algorithm consists of a multilayer perceptron (MLP) and a hierarchical statistical output (SoftMax) that provides a very precise classification output [14].

One of the key factors in Deep Learning success is its innate ability to identify data structures that are: high order, unknown and non-linear. Which might be difficult or impossible for the human eye to perceive [10][13].

If we use data from several electrical connector models and their corresponding test plan results with varying degrees of reliability, then we can train a DL modern to correctly identify any deviation from acceptable electrical connector reliability.

## Model Description and Limitations

In order to create the DL model needed to identify the correct data structure and how this data will be used to define characteristics to be convoluted by the CNN and processed by the several following layers, it is crucial to select the relevant data that has relevant information on the connector performance during operation, this data will be known in the rest of this document as *reliability vector* and will be used as the *input vector* for the DL model. In many cases it will contain consecutive measurements like sliding coefficient during contact process or contact pressure; but also can have parametric values like coefficients that are defined by connector´s modeling.

Once we select the relevant data to be fed into the CNN, we need to define the DL configuration that will be used, that is the number of layers to be used (deepness) and the amount of neurons for the MLP and the number of desired outputs for the connector´s contact reliability; in this case will be using only two possible outcomes: *reliable and non-reliable contact*.

Because electrical connectors can be used in a wide variety of applications, the signals across these connectors can have several orders of magnitude of current, voltage, power, electromagnetic fields and frequency that can severely affect both the modeling and testing schemes needed to understand and measure contact reliability. For this reason the scope of this work is limited to low power, direct current (DC) and low transmission length applications of electrical contact.

### 2.1 Contact Reliability Vector Description

The data considered in modern modeling of connectors is vast and varying, because it must consider all possible factors from design to manufacture of the aforementioned product; however, for the scope of this work, we will focus on the operating cycle of the connector and because of this, the selected vector to train the DL solution will be the one that is relevant for the electrical connection performance. For this matter this work will not consider any modeling of degradation due to extreme temperatures, wear due to oxidation, delamination or any other environmental stress; as this data is considered to be reflected in either physical or electrical characteristics of the connection during operation.

#### Contact Pressure

The first parameter of the vector is the *Contact Pressure*, which is defined as the pressure force exercised over the connector and its corresponding counter force[8]. This value is obtained by (1) in the following manner:

$$F = \frac{3EI_z\delta}{L^3} \tag{1}$$

where $E$ is the elastic modulus of the base material, $I_z$ is the inertial moment of the reed, $L$ is the connectors length and δ is the reed deflection coefficient of the connector's material.

#### Contact Bounce

One of the most common phenomena in electrical contact is the contact bounce. This can be defined as the mechanical sway and posterior oscillation that occurs upon initial switch closure or physical contact between two moving connectors. This phenomena has been widely analyzed, simulated and modeled by several authors [15-17] and while a mathematical modeling of contact bounce is difficult to obtain due to the complexity of the mechanical-electrical perturbations involved in it, the measurements and waveforms are well known and might hold hidden structured data showing contact behavior. Because of this, the generated time series data from electrical contact bounce will be constructed by taking a single value of the contact force during bounce. A graphical approach of bouncing effect can be seen in Fig. 2.

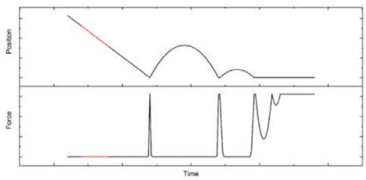


**Fig. 2.** General diagram of switch bounce as defined by [16].

**Conductivity and Isolation**

As mentioned in the previous section, these parameters are expected to be constant during the entire slide of the contact cycle. Therefore, any significant variation in the measurements during the operation cycle might indicate a poor reliability on contact.

**Contact Voltage Drop**

The voltage drop upon contact should be negligible ($V_d \to \epsilon$) as the connectors impedance is close to 0 ohms; The equivalent circuit of a low power, DC short transmission line neglects any significant capacitance and inductance [18] and can be calculated by applying Ohm's law:

$$V_d = V_i - I_c R_d \quad (2)$$

where $V_i$ is the input voltage, $V_d$ is the voltage drop on the connector, $I_l$ is the test current delivered to the contact circuit and $R_d$ is the known testing resistance of the test circuit. In this document we will consider that maximum voltage drop is $V_d \to 1mV$.

**Stress relaxation**

After metal collides in the contact event, occurs a phenomena known as *metal relaxation* which can be modeled by considering the initial restoring force of every spring, the maximum allowable contact resistance and the minimum contact force [1]. This can be represented as a percentage given by:

$$D = t^k e^{(A-B/T)} \quad (3)$$

where D is the number of relaxation percentage, t is time, k,A, and B are material-related coefficients, and T is absolute temperature.

Finally, each different element of the *input vector* has a limit in which the values can sway; however, to maintain the data symmetry necessary for correct classification, normalized data will be used on the entirety of the vector. Table 1 shows the 6th order *input vector* that will be used as input for the proposed AI Model.

**Table 1.** Modeling and testing data for the input vector.

| Data | Description | Type of data | Min | Max |
|---|---|---|---|---|
| Stress Relaxation | Stress Coefficient after Contact Force | Scalar value | 0 | 1 |
| Contact voltage Drop | Voltage drop after contact | Scalar value | 0 | 0.001v |
| Conductivity | Resistance after contact | Time series | 0 | 10□ |
| Isolation | Isolation from other terminals | Time series | 1M□ | - |
| Contact Bounce | Electrical Waveform upon contact | Time series | 0 | 1 |
| Contact Pressure | Force applied from connector | Time series | 0 | 1 |

### 2.2 Two Dimensional Convolutional Neural Network Model

Once all the behavior information on the connector is obtained as an input vector, the well-known 2D-CNN methodology shown in [4] can be used to identify any significant deviations for the contact reliability. In this case, a high-order vector is constructed from modeling and testing data to train the network to recognize patterns and characteristics of the connector and then to classify them as compliant or not.

For Deep Learning to be used in this approach, we need to reconfigure the input vector as a tensor by slicing the data as defined by [20]. In this case, each slice is no other than the time series representation of the *n* parameters shown in Table 1, but fed into the CNN in a matrix format of *m* by *l* size, as shown in Fig. 3 and the proposed IA model is represented in Fig. 4.

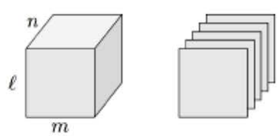


**Fig. 3.** Tensor representation of *input vector*

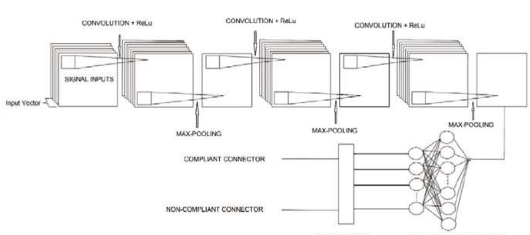


**Fig. 4.** Deep Learning Model for Electrical Connector Reliability Compliance

## Simulation Data Generation and Model Configuration

### 3.1 Simulation algorithms

Simulation of the *input vector* requires that compliant values and non-compliant values are considered in a wide spectrum between physical boundaries (metal stress, electrical properties, etc); for each element of the input vector a different behavior is considered to create a reliable simulation vector field.

In order to use this data in the DL model, two sets of simulations should be built: Complaint Data and Non-Compliant data.

For creating the Complaint Data modeling vector, it was considered to simulate a normal environment that involves: manufacturing processes, material defects and unknown physical events during the contact cycle, the sway of the values of each element of the *input vector* is considered to be unknown but normal distribution in nature because physical limits exist that *push* the values to a certain limit. Because of this, the simulation function chosen for this work will be the Gaussian Distribution and will simulate 10,000 normalized samples.

The probability distribution of one sample of the 10,000 randomly selected values whose boundaries are normalized is shown in Fig 5.

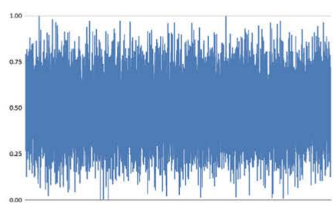


**Fig. 5.** Simulation Sample Probability Distribution for Complaint Connector

For the Non-Complaint Data modeling, the Weibull probability distribution was selected because it is considered to be a Time to Failure distribution.

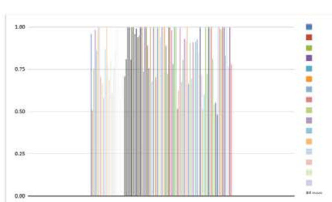


**Fig. 6.** Simulation Sample Probability Distribution for Non-Complaint Connector

High order vectors can have a considerable impact in the computational requirements of training of a DL model, like GPU capacity, memory usage and power consumption but also, model´s accuracy can be affected significatively by the input image size and the depth of the model (number of layers) [10]. Due to these restrictions we will constraint the model to the configuration shown in Table 2.

**Table 2.** DL Model Configuration.

| Parameter | Value |
|---|---|
| Input Vector Size | 25*25*6 |
| Number of DL filters | 6 |
| 1st Layer CNN feature size | 32 |
| 2nd Layer CNN feature size | 64 |
| 3rd Layer CNN feature size | 128 |
| Kernel size | 3 |
| Training epochs | 50 |
| MLP 1st layer size | 128 |
| MLP hidden layer size | 164 |

To simulate the problem at hand as much accurate as possible, the training vector will be constructed by taking randomly a value from the simulation distribution for each element of the *input vector* and then construct a training vector, once the vectors are created, 80% of the created vectors will be used for training the model and 20% for testing it.

## Results

The model proposed in Section 3 of this document was implemented using a computer with AMD Ryzen 5 CPU, NVIDIA 3080 RTX GPU and 56 GB of DDR5 RAM. Initial training results after training and validating the DL model can be shown in Fig. 7 and the Loss function plot can be seen in Fig 8.

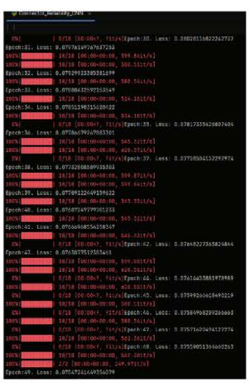

**Fig. 7.** Fault Identification results for simulation environment.

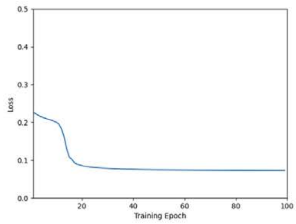


**Fig. 8.** Loss result for fault identification during simulation environment.

After initial results, a MonteCarlo round up of 10 simulations was executed to observe simulation accuracy behavior. Which resulted in a simulation **accuracy average of 0.8**. Which can be appreciated in Fig 9 and their corresponding Loss results can be seen in Fig 10.

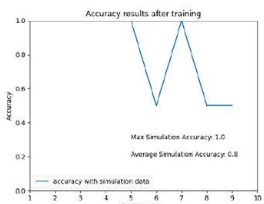


**Fig. 9.** Fault Identification average accuracy after 10 cycles.

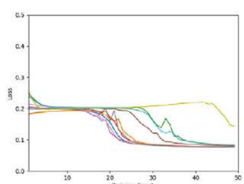


**Fig. 10.** Loss results for fault identification after 10 cycles.

## Conclusions

In this work, an Artificial Intelligence Model based on Deep Learning was proposed for Fault Identification of Contact Trajectory for Electrical Connectors. Several modeling and electrical test parameters were identified and grouped to form a high order input vector eligible for Convolution operations. The simulated data fed into the DL algorithm followed Gaussian distribution for compliant simulation and Weibull distribution for non-compliant simulation. The results were satisfactory (**average accuracy = 0.8**) although maximum accuracy reached 100% a couple of times as seen on Fig 9, these two exceptional results are more likely anecdotal rather than regular. Finally the results of this work demonstrates the successful application of a Deep Learning approach to identify faulty contact trajectory on electrical connectors.

Future work on the subject involves deeper simulation data construction using empirical data, because probability functions were used to build simulation, these results are to be tested under a more complex simulation environment. Additionally, real-time data from real industry measurements would complement the results and provide better insight on field applications of the proposed model.

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