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Theory of Information in Construction – Implementation in Critical Infrastructures exposed to Extreme events

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Abstract

The Theory of Information in Construction based on the hypothesis that failures in critical infrastructures (C.I.) are the result of loss of control in the information system of the CI as a result of information overflow of the system. The theory is established on four phases: (I) Statistical analyses: Probability Density Function of incoming events (PDF), Cumulative Distribution Function (CDF), Power function expressing the magnitude of events, and Scatter analysis; (II) Information Constraint (IC) expressing the capacity if the system, (III) Control circuits (feed-back loops), and (IV) Artificial Intelligence, Machine learning, Artificial Neural Network. The hypothesis of the theory is that failures, deficiencies, accidents and cascading failures are the result of an overflow of information in the system beyond the system's Information Constraint (IC). A similar hypothesis also refers to the performance of critical infrastructures, exposed to extreme abnormal events, caused by extreme events such as climate change, terrorism and seismic events. The events put the critical infrastructures in an extreme situation causing high risk to the continuity of performance of the CI, affecting vital services to civil society. This paper proposes a novel method for multi-hazard risk assessment of overhead transmission lines (OTL) grid. The main objective is to estimate the annual risk using failure rates estimated from historical failure data and modify them by reanalysis data and a dynamic Bayesian scheme. For this purpose, a comprehensive database of power grid supply failures is gathered. ANN is implemented to predict the incoming events, assess the risk and propose preventive activities.

Keywords: Construction Defects, Critical Infrastructures, Quality Control, Resilience, Risk Management and Assessment, Artificial Intelligence, Machine learning.

1. Introduction

Energy supply continuity management is vital to support, prevent, respond to, manage and recover from fallouts of an incidents or a disruptive undesired event. It assists in maintaining uninterrupted availability of all resources required for the continuous provision of essential services.

Extreme events such as climatic hazards, geo-hazards, potential terrorist attacks, rocket impact, explosion, and other man-made threats may lead to loss of Power Transmission Grid functionality and consequentially, interruption or operational disruption of vital services, and cause severe loss to critical facilities operations. Such events may develop cascading and rippling effects in other critical facilities, and consequentially might cause environmental contamination, injuries, fatalities, and systemic failure at the state level. Therefore, it is critical to understand, assess and manage risks associated with power disruptions to enhance its reliability and ensure uninterrupted power supply and the continuous performance of critical operational services.

The complexity of electricity networks makes it vulnerable to extreme events consequences. As compared to random failures in another infrastructures, extreme events or terrorist attacks specifically targeting Power Transmission Grid can result in high impact failure and be followed by serious consequences.

Energy continuity planning is that part of operational risk management that establishes which are the correct reactions and the cost-effective measures to be taken when a disruptive event occurs, to avoid energy supply interruptions and which strategies take place for proactive avoidance of such events and to maintain the performance of critical Infrastructures robust and operational during emergency times.

The present research focuses on the development of AI based analytical tools for the assessment and mitigation of the vulnerability of Overhead Power Transmission Grids under extreme events.

2. **Literature review**

The hypothesis of the theory is that failures, deficiencies, accidents and progressive failures are the result of the flow of information in the system beyond the possible capacity (its Information Constraint). A similar hypothesis also applies for the continuous perfoamce of Critical Infrastructures that are exposed to unusual events, according to (N. Yonat, S. Isaak and I. M. Shohet , 2022)[7] additionally, Global climate change the cause of extreme variation in phenomena such as extreme temperature regime, extreme precipitation patterns, and storms all of which cause critical infrastructures face extreme service conditions and in high risk of the continuous performance of the infrastructures and civil society in general and the citizens in particular.

Climate change creates unusual events, manifested in extreme winds, heat and cold waves.

Fractals were found in all research subjects. Fractals in PDF that is, the same curves repeat at every scale and in every part of the sample. Fractals Fourier Transform of the sample show the same frequency occurrences in each segment on the frequency axis, the failure curves also show a repeat occurrence, and in the spatio-temporal curve in each axis.

According to the research of Yonat Niv and Shohet Igal M.” Complex Infrastructure Systems Analysis and Management, a Case-Study” (2023)[8], The behavior of the number of faults, on the grid axis, it behaves in the form of a fractal, So the main function consists of a series of functions distributed in the same way and vice versa.

According to the research of (Heron and Reason 1997)[1] for knowledge sharing we see a direction of developing integrated systems engineering experience and machine learning.

Failure rates in assessing the risks of the transmission lines - In the literature there are two main approaches to reliability depending on the weather**.**

1. Using a **Markov chain** model with two or more states (Billinton et al. 2002)[5]. However, this method is not suitable for large real-time systems (Panteli and Mancarella, 2015)[3].

2. Simulations using **Monte Carlo** is another relevant approach (Panteli and Mancarella, 2017)[2].

failure rate, the most basic parameter in reliability assessment, calculated primarily by calculating the **mean value** based on several years of statistics similar to the first article published on reliability assessment Billinton and Bollinger (1968)[6].Since then, several researchers have noted that extreme weather events are the main cause of transmission line failures. This article (Solheim and Kjolle, 2016)[4] presents a method for calculating the risk assessment in overhead transmission lines based on past failure rates annual failure rates, and updated using Bayesian update. Finally, a sample scenario based on Monte Carlo simulation for the transmission lines was carried out to simulate the occurrence of failure events, and then, the annual exceedance probabilities of the loss.

2.1. Summary review main failure factors:

The major root causses of failures in overhaed power grids are:

- Extreme weather such as wind, snow and cold loads
- Oil pipelines
- Emergency shutdown of a hazardous liquid pipeline
- Man-made damages

2.2. Summary of literature review by topics:

Figure 1 delineates the topics classification of the literature on failures in Overhead Power Supply lines.

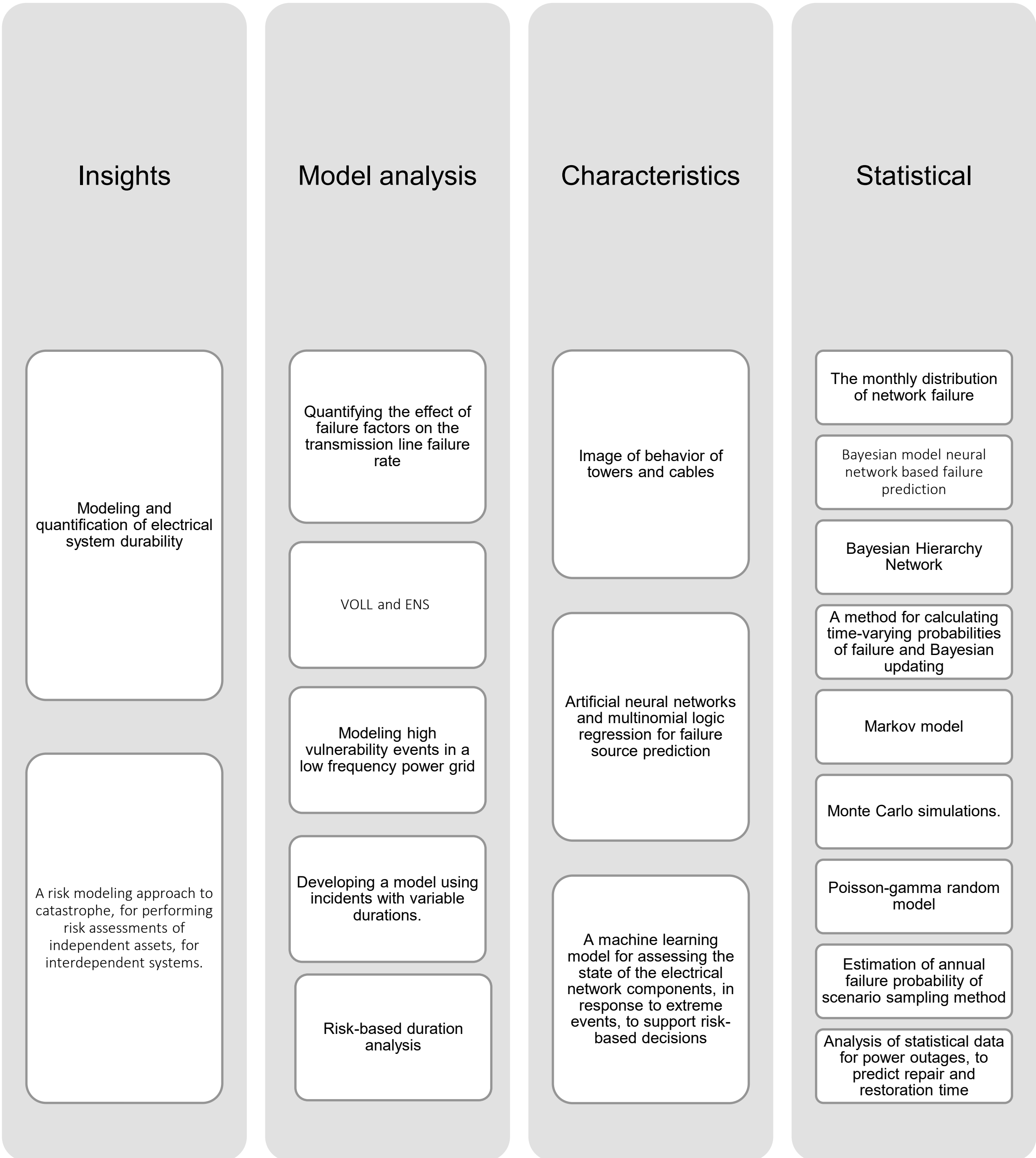

Figure 1 - Topics classification of the literature review

3. Methodology

3.1. The research framework

The research method steams from the Theory of Information and combines statistical features of the failure events with learning tools: AI, ML.

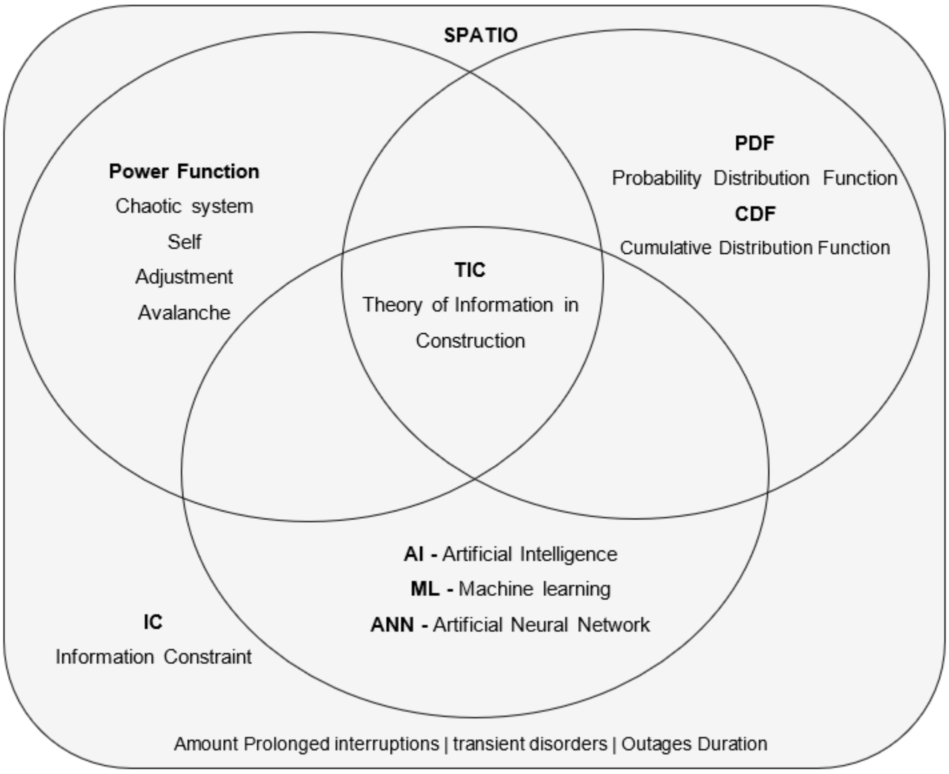

Figure 2 - research framework

3.2. The research method

<u>The research followed five phases:</u>

Phase I - Locating data base for research on non-delivery minute data on the website of the Israel Electricity Company [9].

Phase II - Data cleansing and establishment of a database encompassing about 69.3 thousand faults in the electricity network over a period of the years 2017-2022.

Phase III - Statistical analyses of the data, including: adjustment Probability Distribution Function (PDF), adjustment Cumulative Distribution Function (CDF), Power Function (PF), Scatter Analysis, Correlation and Regression analyses.

Phase IV - Data network construction in the method Artificial Neural Network (ANN): district (4) → sub stat (192) → line (3,648) → Prolonged interruptions (40,653) & transient disorders (28,672).

Phase V - Adjusting and building the predictive Machine Learning model employing Artificial Intelligence tools.

Using methods of: Linear regression, supervised learning, support vector machine, logistic regression, ensemble methods, reinforcement learning, naïve bayes etc. When the final run of the method will be done according to the statistical analyses of the data.

4. Findings

The model is developed as a network receiving incoming given events, the events are learned and characterized by Probability Distribution Functions (PDF) as a means for precise prediction of the **magnitude** and **location** of future events. The frequency of events that will take place in the coming year (planning horizon) and their **effect** on the power grid (and finding the high impact lines), If no preventive actions will be taken is derived from the PDF and Power Function. The model investigates the **relationship** between transient faults and prolonged outages in order to find the root-causes of the prolonged power supply interruption.

4.1. Phase II – statistics

4.1.1. Probability Distribution Function:

Histogram Mean outages duration (minutes) for the years 2017-2021
Distribution: Exponential
Expression: EXPO (48.5)
Square Error: 0.002572
Chi Square Test: Corresponding p-value < 0.005

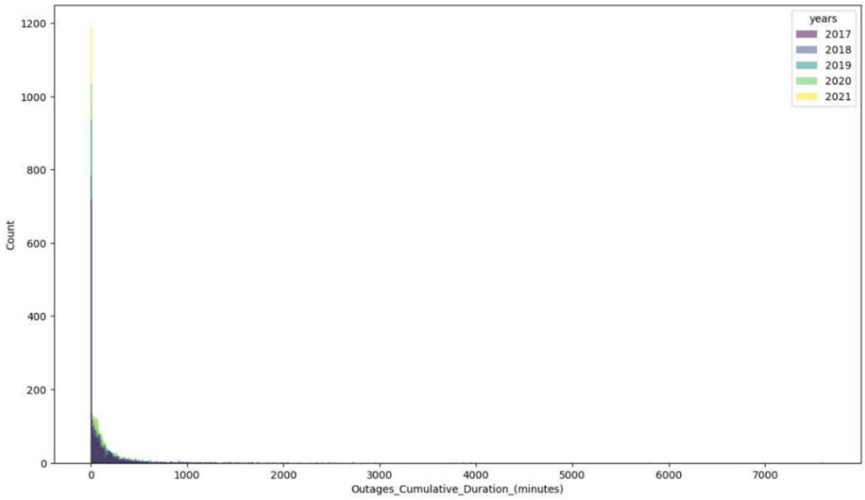

Figure 3 – Histogram of Mean outages duration in minutes

Histogram Amount Prolonged interruptions for the years 2017-2021.
Distribution: Exponential
Expression: 0.999 + EXPO (3.13)
Square Error: 0.000400
Chi Square Test: Corresponding p-value < 0.005
Kolmogorov-Smirnov Test: Corresponding p-value < 0.01

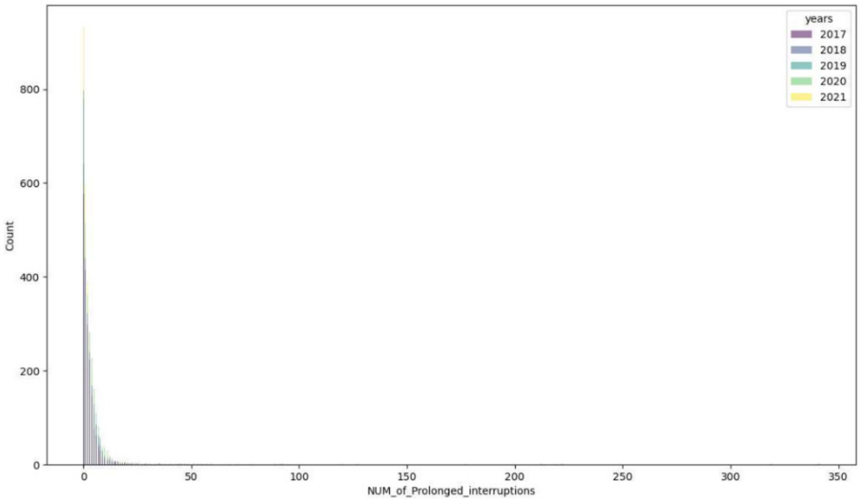

Figure 4 - Histogram of Amount Prolonged interruptions

Histogram Energy not supplied (ENS) for the years 2017-2021.
Distribution: Exponential
Expression: -0.001 + EXPO (7.08)
Square Error: 0.000516
Chi Square Test: Corresponding p-value < 0.005

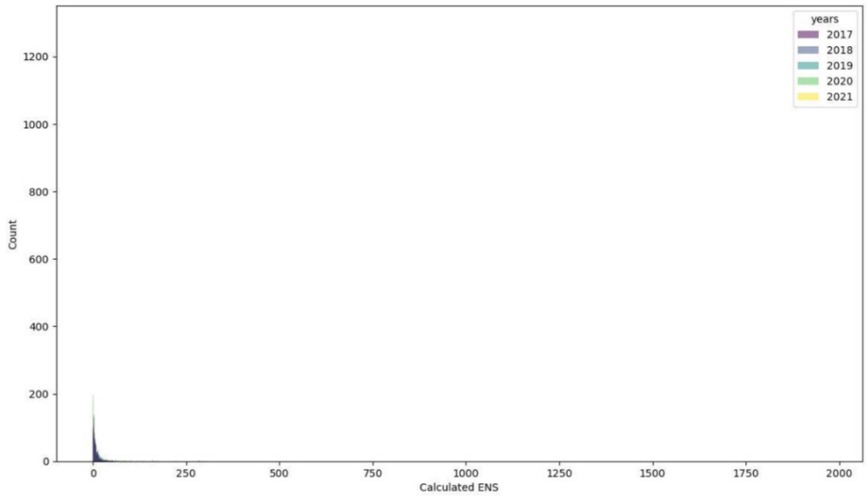

Figure 5 - Histogram of Energy not supplied

Conclusions from the statistical analyses:

- Histograms and fitting an exponential distribution, in confidence tests with α <0.05
- Proof that the data behaves according to the "fractal" theory.
- Proof of the "Pareto" principle when about 10% of faults have the highest impact.

4.1.2. Correlation

The heat map and Correlation matrix shows the significance and correlation of dependence between the variables relativel, the darker the color, the higher the dependence between the variables. And represents the correlation number when the value is 1 the relationship is the strongest between the variables. A high dependency can be seen between NUM_of_Prolonged_interruptions and Calculated_ENS with a value of 0.75. and a high dependency between NUM_of_Prolonged_interruptions and Outages_Cumulative_Duration_(minutes) with a value of 0.65

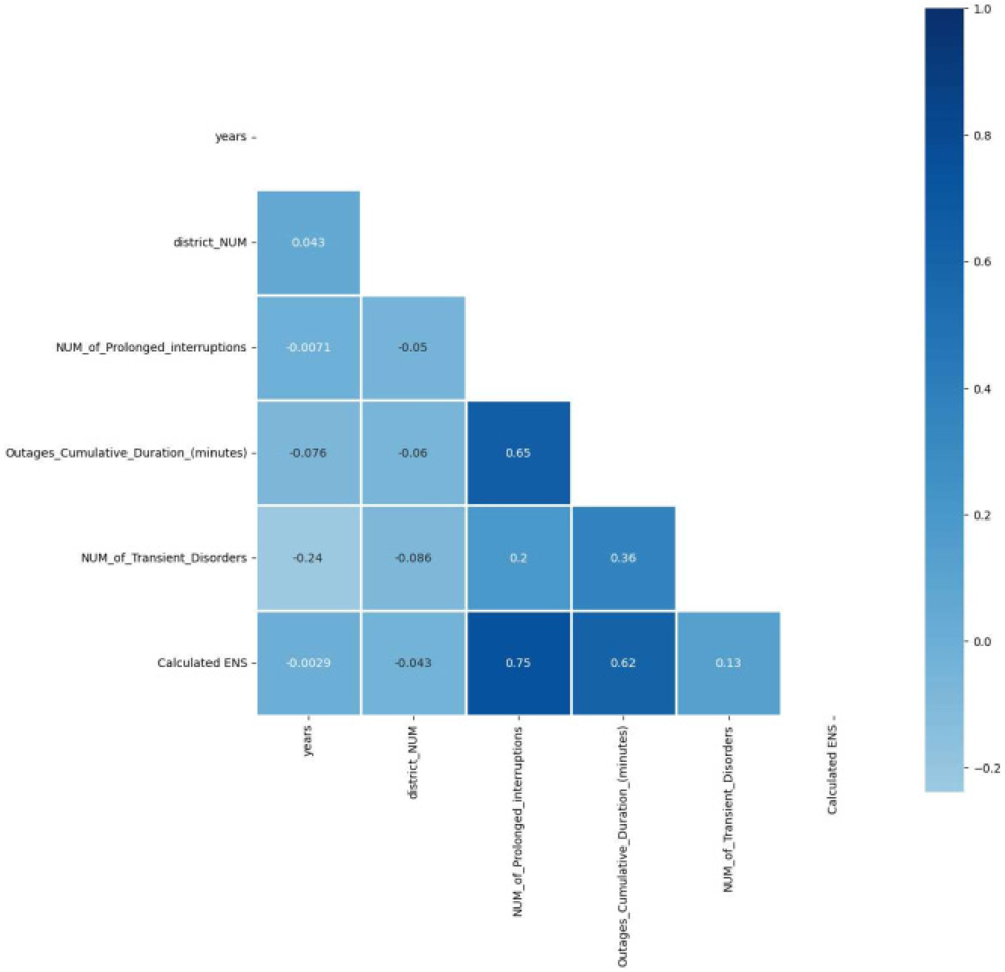

Figure 7 - Heat Map of Correlation

	year	district_NUM	NUM_of_Prolonged_Interruptions	Outages_Cumulative_Duration_(minutes)	NUM_of_Transient_Disorders	Calculated_ENS
year	1.000000	0.042923	-0.007104	-0.076369	-0.238758	-0.001162
district_NUM	0.042923	1.000000	-0.049564	-0.060488	-0.086402	-0.056679
NUM_of_Prolonged_interruptions	-0.007104	-0.049564	1.000000	0.653726	0.201077	0.746802
Outages_Cumulative_Duration_(minutes)	-0.076369	-0.060488	0.653726	1.000000	0.364463	0.636800
NUM_of_Transient_Disorders	-0.238758	-0.086402	0.201077	0.364463	1.000000	0.155384
Calculated_ENS	-0.001162	-0.056679	0.746802	0.636800	0.155384	1.000000

Figure 6 - Correlation matrix

4.1.3. Regression

A regression analysis on the timeline for the fault data shows a direct relationship, because over the years the unreliability of the network has started to decrease.

Graphs of NUM_of_Prolonged_interruptions and Calculated ENS are the same, which proves a direct relationship between them.

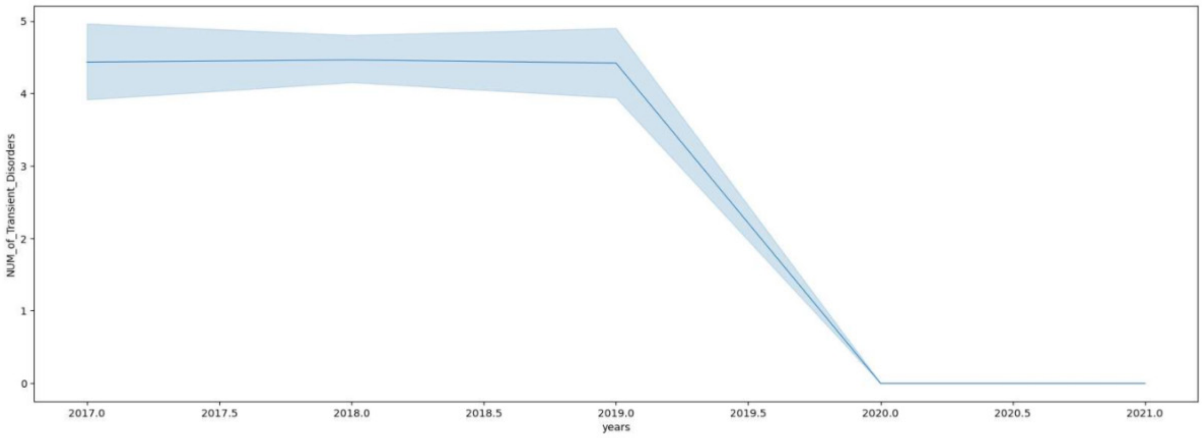

Figure 10 - Regression between NUM of Transient Disorders to Time

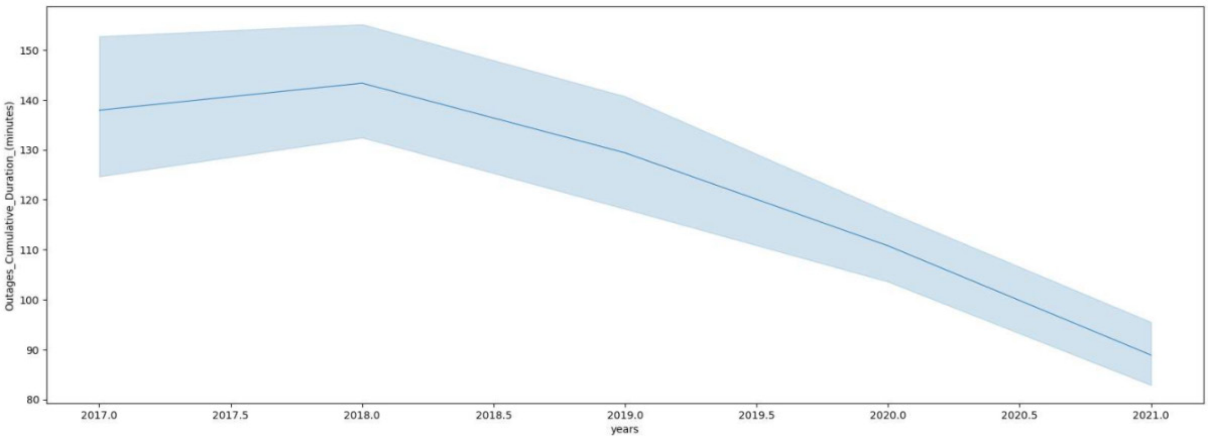

Figure 9 - Regression between Outages Cumulative Duration in minutes to Time

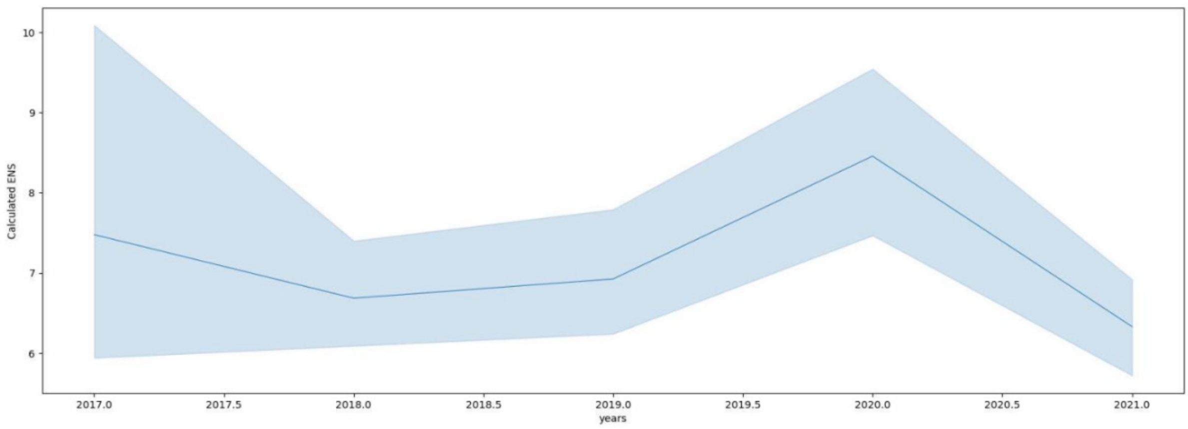

Figure 8 - Regression between ENS to Time

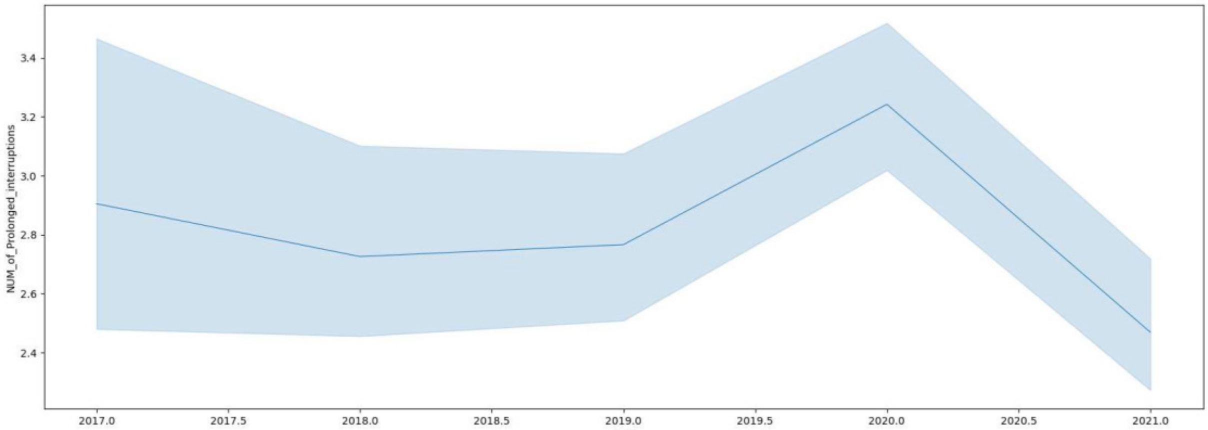

Figure 11 - Regression between NUM of Prolonged interruptions to Time

4.2. ***Phase IV - Artificial Neural Network (ANN)***

Artificial Neural Networks are biologically inspired systems which convert a set of inputs into a set of outputs by a network of neurons, where each neuron produces one output as a function of inputs.

Artificial Neural Networks may be used to identify and classify outstanding failures from recorded data base that caused severe outages at power transmission lines.

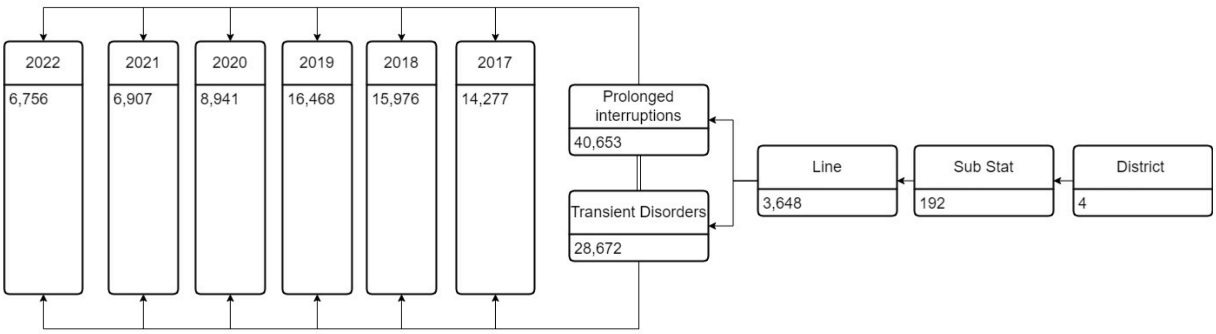

Figure 12 - diagram of model Artificial Neural Network

4.3. ***Phase V – Artificial Intelligence (AI) by Machine Learning (ML)***

The model is based on machine learning and receives input of its faults and characteristics, the model learns from the data and its behavioral patterns, adjusting the model accordingly.
The purpose of the model, is the identification of failure factors prior to a state of collapse in the power grid, analysis of the vulnerability of the electricity network and establishment of risk management tools for proactive prevention of prolonged power supply interruptions events.
The model is based on the “Forecast” technique - A forecast model is a mathematical or statistical representation of a system or process used to predict future outcomes or events. It utilizes historical data and various variables to generate forecasts or predictions about future conditions or trends. These models help in decision-making, resource allocation, risk assessment, and strategic planning.

5. Conclusions

The paper introduces the implementation of Statistical Inference tools based on TIC for prediction prevention of failure events in Overhead Power Grid. The research includes five phases as follows:

- **Phase I -** Locating data base.
- **Phase II** - Data cleansing
- **Phase III** - Statistical analyses.
- **Phase IV -** Artificial Neural Network (ANN)
- **Phase V** - Building the predictive Machine Learning model employing Artificial Intelligence tools.

The statistical tests stood with p-value < 0.01.

The research is innovative and creative due to the use of (ANN) Artificial Neural Networks may be used Prediction and prevention of failures in electricity transmission systems.

The model built as a network receiving incoming given events, the events are learned and characterized as a means for precise prediction of the **magnitude** - **location** - **effect** of future events.

So, in the prediction platforms preventive activity can be performed that saves millions of dollars to maintain the reliability of the electricity grid.

References

[1] J. Heron and P. Reason, "A Participatory Inquiry Paradigm," Qualitative Inquiry, vol. 3, (3), pp. 274, 1997. https://journals.sagepub.com/doi/abs/10.1177/107780049700300302?journalCode=qixa. DOI: 10.1177/107780049700300302.

[2] M. Panteli, C. Pickering, S. Wilkinson, R. Dawson and P. Mancarella, "Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures," *Tpwrs,* vol. 32, *(5),* pp. 3747-3757, Sep 01, 2017. Available: https://ieeexplore.ieee.org/document/7801854. DOI: 10.1109/TPWRS.2016.2641463.

[3] Panteli, Mathaios & Mancarella, Pierluigi. (2015). Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies. Electric Power Systems Research. 127. 10.1016/j.epsr.2015.06.012.

[4] O. R. Solheim, T. Trotscher and G. Kjolle, "Wind dependent failure rates for overhead transmission lines using reanalysis data and a bayesian updating scheme," in Oct 2016, pp. 1-7Available: https://ieeexplore.ieee.org/document/7764104. DOI: 10.1109/PMAPS.2016.7764104.

[5] Peng Wang and R. Billinton, "Reliability cost/worth assessment of distribution systems incorporating time-varying weather conditions and restoration resources," Tpwrd, vol. 17, (1), pp. 260-265, Jan 2002. Available: https://ieeexplore.ieee.org/document/974216. DOI: 10.1109/61.974216

[6] Roy Billinton, Kenneth E. Bollinger 1968 “Transmission System Reliability Evaluation Using Markov Processes”, DOI: 10.1109/TPAS.1968.292051

[7] Yonat, N., Isaak, S., & Shohet, I. M. (2022). Complex Infrastructure Systems Analysis and Management, a Case-Study. Open Engineering Inc. 10.31224/2624

[8] Yonat, N., & Shohet, I. M. (2023). Theory of Faults (ToF). Open Engineering Inc. 10.31224/2389

[9] https://www.iec.co.il/content/info/filespages/dataaminut

[10] Yonat, N., & Shohet, I. M. (2022). “Theory of Information in Construction- TIC”

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