Resilience Modeling of Cyber-Physical Systems: A Comparative Study of Statistical vs. AI Methods

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Abstract: Quantifying resilience in complex systems is crucial for resilience engineering and real-time decision-making in the face of disturbances. The resilience curve, an emerging method, offers a promising approach to quantify resilience and visualize system behavior post-disturbance. This curve is based on real-time data from embedded IoT sensors, providing insights into system performance and aiding in timely responses to disruptions. However, a significant gap exists in formulating a standard method to visualize the resilience curve due to the inherent noise in real-world data. Since employing each method can result in different values for resilience KPIs, especially for performance loss, highly cited methods in the literature will be utilized for this case study and eventually compared. The case study is conducted using open-source maintenance data from water pumps in a small area far from a major town, which experienced 7 failures during the study period. According to the results, the SVM works better than Polyfit and traditional methods (Line Plot and Rolling Average) in representing the behavior of the system in the presence of noise and complex systems. The findings of this study contribute to the advancement of resilience engineering in emerging cyber-physical systems, providing valuable insights for improving system robustness and responsiveness in the face of unforeseen events.

Keywords: Resilience Curve, Cyber-Physical Resilience, Complex Systems Resilience, Resilience Quantification, Resilience Modelling

1. Introduction

Traditionally, risk management has been the primary tool for safeguarding complex systems and critical infrastructures (Pesch-Cronin and Marion, 2016). This approach focuses on identifying and mitigating potential threats to ensure continued functionality. However, in an increasingly interconnected and dynamic world, unexpected events and cascading failures pose a significant challenge. Here, resilience – the ability to absorb disturbances, adapt, and recover – becomes crucial (Aghazadeh Ardebili *et al.*, 2023). By incorporating resilience alongside risk management, we can move beyond simply preventing disruptions to ensuring these systems can bounce back effectively, minimizing downtime and societal impact. This shift is crucial for safeguarding the vital services that underpin modern society (Liu and Song, 2020). Quantifying the resilience of complex systems, like critical infrastructure networks, is essential for ensuring their continued functionality in the face of disruptions. In this respect, resilience curves can play a key role. These curves act as powerful tools for quantifying a system's resilience by charting its performance over time before, during, and after a disruptive event (Fang *et al.*, 2016; Liu and Song, 2020). By analyzing the shape of the curve, we can gain valuable insights into the system's ability to withstand stress, adapt to changing conditions, and ultimately return to an acceptable level of operation. This information is crucial for informing mitigation strategies, resource allocation, and prioritizing investments to bolster the overall resilience of these vital systems.

A resilience curve is built from real-time data produced by embedded IoT sensors, it then provides insights into system performance and supports timely responses to disruptions. However, formulating a standard method to visualize the resilience curve is problematic because of the inherent noise in real-world data. In particular, Several Statistical and AI Methods for fitting polylines are especially available to smooth noisy data. Still, although these methods are well-studied in signal processing, and the application of different methods are formulated based on use case scenarios, they are relatively unexplored in resilience engineering. The study presented here aims to answer the following research questions (RQs):

RQ on Accuracy and Generalizability: How well do AI-based methods for resilience curve estimation compare to traditional statistical methods in terms of accuracy and capturing the true system behavior under stress?

RQ on Data Dependency: Can AI models provide interpretable insights into the factors influencing system resilience, something statistical methods might struggle with, in complex systems?

To answer the questions, a preliminary comprehensive state-of-the-art review of methodologies for constructing Resilience curves (R-Curves) was conducted. However, a significant gap in drawing R-curves of complex and noisy datasets is identified in the domain of resilience engineering; therefore, a systematic literature review is conducted (detailed in Section 3) with the aim to select the best tools for fitting the polyline curve, apply to a case study, and compare the results to answer the research questions. Afterward, Section 4 introduces a case study with real-world industrial pump maintenance data and presents findings from Exploratory Data Analysis (EDA). Section 5 discusses results from both statistical and AI-based methods. Finally, Section 6 acknowledges the limitations of the study and outlines future research avenues.

2. Preliminary review of related studies

This study focuses on the possibility of constructing resilience curves in the context of complex systems (Salomon *et al.*, 2020). A case study concerning industrial water pump maintenance was considered as a valuable example of such a system. Indeed, industrial pump systems are critical components within various industries, and their resilience directly impacts production efficiency and safety (Tabandeh *et al.*, 2024). In addition, real-life data from pump stations are collected with sensors and are naturally very noisy.

In today's world of interconnectedness and unforeseen disruptions, complex systems like water networks face ever-increasing challenges. Thus, the concept of resilience plays an important role. Resilience refers to a system's ability to absorb disturbances, adapt to changing conditions, and ultimately return to an acceptable level of operation. Quantifying resilience is crucial, and this is where resilience curves come in (Simonovic and Arunkumar, 2016a). These curves act as a powerful tool by charting a system's performance over time: before, during, and after a disruptive event (Venkateswaran V *et al.*, 2021). By analyzing the shape of the curve, we can gain valuable insights into the system's ability to withstand stress and bounce back effectively (Li and Mostafavi, 2024). This information is essential for prioritizing investments, implementing mitigation strategies (HAN *et al.*, 2021), and ensuring the continued functionality of these vital systems (Jiang *et al.*, 2023). Figure 1 shows an example of a resilience curve. As the sample curve shows, it is easy to interpret the curve if it is smooth and without noise. Key points like t_R and y_m are readily identified in such curves.

In Figure 2 the area above the resilience curve is highlighted. This area is a resilience measure that shows Loss of Functionality. The calculation of this area is crucial because it provides a resilience KPI that can be used to measure the system's performance. This underscores the importance of selecting an appropriate tool for curve construction.

There are established statistical methods for constructing resilience curves. One common technique is hysteretic loop analysis, which compares the system's performance before and after a disruption (Fraedrich *et al.*, 2016). Another approach utilizes the area over the curve (AOC) method, where the area below the curve on the performance graph represents the system's resilience loss during the disruption (Jiang *et al.*, 2023; Lan *et al.*, 2024; Li and Mostafavi, 2024; Liao and Ji, 2020; Simonovic and Arunkumar, 2016b; Venkateswaran V *et al.*, 2021; Wang *et al.*, 2023). Additionally, time-to-recovery metrics measure the duration it takes for the system to return to normal operation. Statistical models like the Weibull distribution can also be used to estimate the probability of failure and recovery times (Sartori *et al.*, 2009).

The rise of Artificial Intelligence (AI) has opened new avenues for analyzing complex systems. AI-based methods offer several potential advantages for Polynomial curve fitting (Levy, 1959) and eventually for constructing resilience curves. Unlike traditional methods, novel techniques for Polynomial curve fitting (Motulsky and Ransnas, 1987) can effectively handle large, complex (Yang *et al.*, 2009) and real-life noisy datasets (Arora and Khot, 2002) with higher accuracy (Li and Li, 2020). However, no study explores the possibility of constructing resilience curves with noisy data without losing information on the behavior of the system.

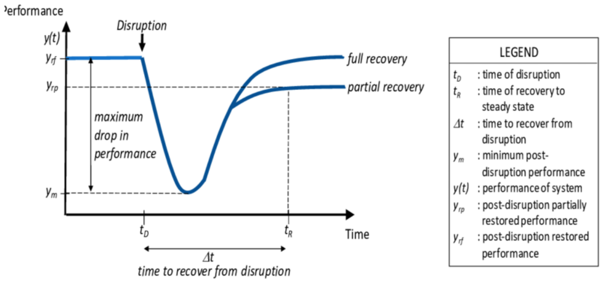

Figure 1 Sample resilience curve (performance-time)(Madni *et al.*, 2020)

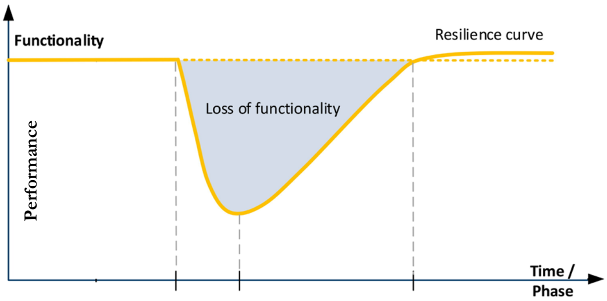

Figure 2 Functionality Loss as a Resilience KPI (R-KPI)

Additionally, the computational cost (Elmousalami, 2020) and data requirements (Roh *et al.*, 2021) of AI methods need further investigation. Nevertheless, these aspects have not been studied in the domain of resilience engineering. In order to contribute to filling these gaps, a systematic review (Section 3) is conducted to identify suitable methods of curve fitting from complex datasets in other domains (mathematics, physics, etc.), that could be used for the construction of resilience curves. This article is a preliminary investigation that shows a promising way to address the issue, but it also calls for potential future avenues of research.

3. Method and Tools

3.1 Suitable Methods Identification

This section aims to identify methodologies that show potential to be used for constructing resilience curves for complex systems. We will explore two approaches: established statistical methods and emerging AI-based techniques. The data utilized for curve construction will be described, followed by a comprehensive explanation of the implementation process for each method.

In order to identify methods and tools used by researchers and practitioners to fit piecewise linear curves (polylines) to data, in the resilience engineering domain, a systematic literature review was carried out. The review process, including screening criteria and results, is outlined in **Error! Reference source not found.**. Before excluding studies from non-engineering fields like medicine, biology, astronomy, and psychology, the initial search yielded over 78,000 articles. The first screening highlighted a significant gap in the body of knowledge regarding resilience quantification through curve fitting. In fact, only 41 articles, representing a small fraction (less than 0.1%) of the retrieved studies, focused on the engineering domain. This suggests a need for further research on methods for fitting polylines to represent and analyze resilience data.

After thoroughly reviewing the selected articles, three methods emerged as the most utilized and cited approaches for assessing the resilience of systems. A critical gap exists in the literature regarding resilience curve construction methods. While over 41% of the reviewed articles (17 documents) utilize resilience curves, the majority of them do not disclose their curve-fitting methods. In these articles, Simple Line Plot and Rolling Average are the two most common methods for constructing resilience curves, which are used in literature. Because of the small number of papers after the screening, the final step of the systematic literature review employed 3 snowballing techniques (last step in **Error! Reference source not found.** under outline of the steps) to identify the most effective methods for constructing resilience curves. This technique leverages keywords from the 17 reviewed articles, along with forward and backward snowballing through references and citations.

After snowballing, we identified documents that implemented AI-based and statistical/numerical methods for polyline curve fitting, mostly utilizing six different methods (see Figure 3 under the Documents column in the last step). In the AI-based methods category, 540 documents employed Support Vector Machine (SVM), while in the statistical/numerical methods category, Polyfit was selected in 378 documents. The forthcoming subsections will provide detailed explanations of these highly cited methods.

3.2 Theoretical Foundations for the Selected Methods

The systematic literature review yielded two AI based and statistically grounded methods for resilience curve construction that are suitable for real-time applications with noisy data. These methods are Support Vector Machine (SVM), an AI-based technique, and Polynomial Regression (Polyfit), which is rooted in statistical methodologies.

3.2.1 *Support Vector Machine (SVM)*

Support Vector Machine is a powerful machine learning algorithm used for both classification and regression tasks. It works by finding the optimal hyperplane that best separates data points belonging to different classes or predicts continuous outcomes(Noble, 2006). SVM is

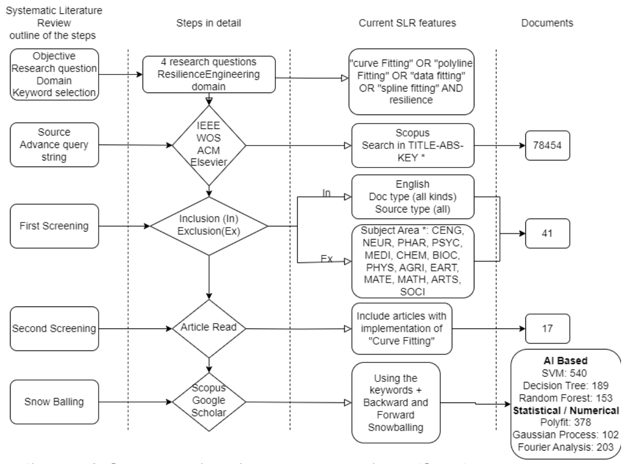

Figure 3 Systematic Literature Review (SLR) process

particularly effective in high-dimensional spaces and is widely used (Pisner and Schnyer, 2020). Polyline Fitting with SVM (Jiang et al., 2021; Luo, 2012) includes the following steps: *Data Preparation* Prepare the dataset comprising input features (independent variables) and target values (dependent variables). *Feature Engineering*Extract relevant features from the dataset to effectively represent the relationship between inputs and outputs. *Model Training* Train the SVM model using the dataset. In polyline fitting, the SVM model is trained to find the optimal line or curve that best fits the data points. *Model Evaluation* Assess the performance of the trained model using appropriate metrics to ensure its effectiveness in fitting the polyline to the data. *Prediction* Utilize the trained SVM model to predict output values for new input data points. *Data Preparation:* Prepare the dataset comprising input features (independent variables) and target values (dependent variables). *Feature Engineering:* Extract relevant features from the dataset to effectively represent the relationship between inputs and outputs. *Model Training:* Train the SVM model using the dataset. In polyline fitting, the SVM model is trained to find the optimal line or curve that best fits the data points. *Model Evaluation:* Assess the performance of the trained model using appropriate metrics to ensure its effectiveness in fitting the polyline to the data. *Prediction:* Utilize the trained SVM model to predict output values for new input data points.

The core mathematical concepts underlying SVM include the objective function, decision function, and kernel trick (Gholami and Fakhari, 2017, p. 27). The objective function of SVM aims to find the optimal hyperplane that maximizes the margin between the classes while minimizing classification errors. It is formulated as:

$$\min_{w,b} \frac{1}{2}\left\|w\right\|^2 + C\sum_{i=1}^{n} \xi_i$$

This equation balances the margin width (controlled by $\|w\|$) and the classification error (controlled by ξ_i) using the regularization parameter C. It ensures that the SVM model finds the best possible decision boundary for the given data. The decision function of SVM computes the output value for a given input vector. $f(x)= w * x + b$

Where w represents the weight vector, b denotes the bias term, and x is the input vector. The decision function determines which side of the hyperplane a data point lies on, thus classifying it into one of the classes. These mathematical formulations and steps outline how SVM can be applied to polyline fitting tasks to construct the resilience curves, providing a robust and effective method for capturing complex relationships in data.

3.2.2 Polynomial Regression (Polyfit)

Polynomial regression is a statistical method used to fit a polynomial curve to a set of data points. It is an extension of linear regression and is particularly useful when the relationship between the independent and dependent variables is nonlinear (Vrdoljak and Mostar, 2013). Polynomial regression works by minimizing the sum of squared errors between the observed and predicted values, similarly to linear regression. The degree of the polynomial determines the complexity of the curve, with higher degrees allowing for more flexible curve fitting. of the Steps of the method (Eubank and Speckman, 1990; Kowsher *et al.*, 2020; Ostertagová, 2012) are: *Data Preparation:* Prepare the dataset consisting of input features (independent variables) and target values (dependent variables). *Feature Engineering:* No specific feature engineering is required for polynomial regression. However, it is essential to ensure that the data is properly cleaned and preprocessed to remove any outliers or missing values. *Model Training:* Train the polynomial regression model using the prepared dataset. The model aims to find the coefficients of the polynomial equation that best fits the data points. The polynomial regression equation takes the form: $y = \beta_0 + \beta_{1x} + \beta_{2x2} + \dots + \beta_{nxn}$

Where y is the dependent variable, x is the independent variable, β_0 , β_{1x} , β_{2x2} , ... β_{nxn} are the coefficients of the polynomial terms, and n is the degree of the polynomial.

Model Evaluation: Assess the performance of the trained polynomial regression model using appropriate evaluation metrics such as mean squared error (MSE) or Rsquared (R^2) coefficient. This step helps determine how well the polynomial curve fits the data and whether the model is suitable for making predictions. *Prediction:* Utilize the trained polynomial regression model to predict output values for new input data points. The predicted values are obtained by substituting the input values into the polynomial equation obtained during the training phase.

In summary, polynomial regression fits a polynomial curve to the data points by minimizing the sum of squared errors. The degree of the polynomial determines the complexity of the curve, allowing for flexible curve fitting. This method is useful for modeling nonlinear relationships between variables and can be applied in various fields such as economics, engineering, and biology.

4.Case Study

The case study utilizes data collected from 52 sensors embedded in a centrifugal pump (however the data is collected correctly from 49 for 152 days). The dataset comprises two types of data: one related to the driving equipment for the motor and the other related to the driven equipment for the pump. The dataset is an open dataset available in Kaggle data science communities' repositories (More than 20 opensource Exploratory Data Analysis (EDA) is available for the mentioned dataset in Kaggle)[1].

The parameters that the sensors are measuring are Motor and pump, Casing Vibration, Frequency, Speed, Current, Active Power, Apparent Power, Reactive Power, Shaft Power, Phase Current, Coupling Vibration, Phase Voltage, Impeller Speed, Inlet Flow, Discharge Flow, Lube Oil Overhead Reservoir Level, Lube Oil Return Temp, Thrust Bearing Active Temp, Radial Bearing Temp, Thrust Bearing Inactive Temp, Inlet Pressure, Discharge Pressure. (Some parameters are measured in more than one place with different sensors.) different types of the sensors are employed like accelerometers, strain gauges, temperature gauge, pressure gauge etc.

4.1 Exploratory Data Analysis (EDA)

The first step is a comprehensive EDA to identify general patterns in the data, missing data, outliers and features of the data that might be unexpected.

Sensor with null values >5% will be dropped. Moreover, the following sensors follow the same pattern: Sensors: 43/42/41/40/39/38, Sensors: 35/34/33/32/31/30, Sensors: 29/28/27/26/24/23, Sensors: 22/21/20/19/18/17, Sensors: 16/14, Sensors: 12/11/10, Sensors: 09/08/07/05, Sensors: 04/00, Sensors: 01/02/03. Then LGB Feature importance[2] using Python Scikit-learn and Spark along with XBOOST[3] is used to extract the feature importance. The selected feature (that is related with the performance of the system) with the highest importance will be used for the resilience curve construction in the next section. Figure 4 shows SENSOR_06, which is measuring Motor Active Power is of paramount importance because the other sensors that gained higher score, are not directly representing the performance of system; since it is measuring the power, it is the best index for the performance of the system. Therefore, this parameter is selected to construct the Resilience curve.

The light blue line in Figure 4 shows the status of the system over the lifecycle including the number of the

[1] https://www.kaggle.com/datasets/nphantawee/pump-sensor-data/data

[2] https://towardsdatascience.com/ The Mathematics of Decision Trees, Random Forest and Feature Importance in Scikit-learn and Spark/

[3] XGBoost is a boosting algorithm that uses bagging, which trains multiple decision trees and then combines the results. XGBoost Python is one of the most popular machine learning frameworks among data scientists.

times that full failure happened. The first Failure and recovery will be used for the Resilience Curve construction. Since the focus of this article is comparing different methods for construction of the curves, one failure will be used; however, in the real-world resilience quantification, since the resilience is scenario-based approach, all the failures should be assessed differently based on the reason of the failure. Figure 4 shows the time of the failures in the operation lifecycle of the pump. Also, it shows the difference in the noise in different sensors can be different. This highlights the importance of selecting the parameters that we want to use for resilience curve construction. Because less noise will help to have smoother Resilience Curve.

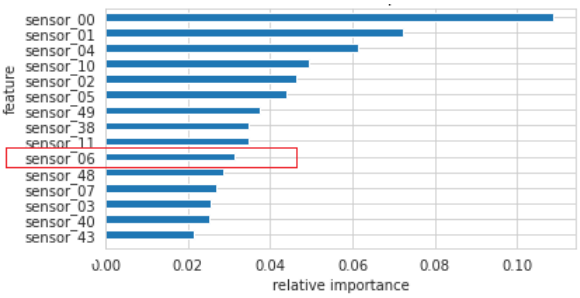

Figure 3 The relative importance of parameters (top 15)

In the next section the resilience curves constructed with different methods with a focus on the 5th failure (because it has more fluctuation after disturbance, therefore it can be a clear sample of irregular behavior of the system) in Figure 6 are shown and discussed.

5.Results and Discussion

If the data exhibits minimal noise and fluctuations, a straightforward traditional approach of depicting the resilience curve is by connecting all data points with a line. However, in the presence of noise and high complexity, a simple line plot can become confusing. In such cases, employing a moving average can offer a clearer representation of the resilience curve. The line plot and a plot generated using rolling averages with a moving window are shown in Figure 5. It is evident from the Figure 5 that the resilience curve appears less smooth with the presence of noise, thereby complicating the interpretation of the system's behavior.

As depicted in Figure 5, the line plot fails to construct a meaningful resilience curve for all the disturbances. Nevertheless, for the initial four disturbances characterized by lower noise levels, the moving average proves to be a suitable method. But the moving average method falters in accurately depicting the behavior of the system during the 5th disturbance demonstrating a longer drop in performance. Furthermore, during the last two failures, the moving average fails to capture the dramatic drop in performance. This shows that traditional statistical methods are not always accurate in capturing the true system behavior.

Figure 6 shows the curves that are fitted by SVM (up) with polynomial kernel of degree 10 and a low regularization parameter (C=1000), and Polyfit (down) with the Degree of Freedom=10. Both methods in Figure 6 work better than traditional methods like Moving Average and Line Plot; especially the AI-based method shows better capacity in representing the behavior of the system after disturbance compared to statistical method. The differences in the two methods can be discussed in terms of accuracy and capturing the true system behavior regarding the resilience KPIs that are shown in Figure 1. These results address RQ1.

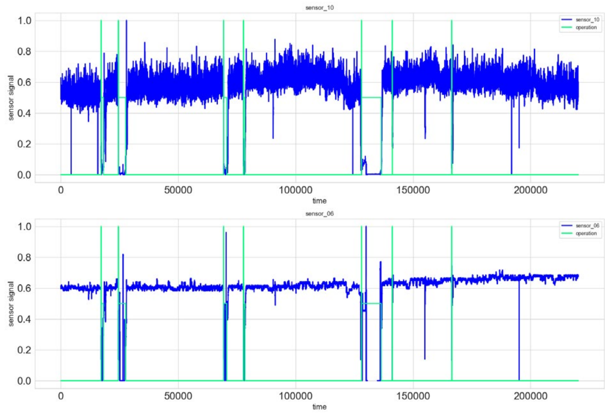

Figure 4 Up: Sensor_10(Motor Phase Current A) Down: The collected data for Sensor_06(Motor Active Power) along with operation status of the system (0 in light blue line means normal operation with no fault). The values are normalized in both axes.

Figure 5 Line plot in orange and moving average plot in blue (The failures are numbered in red and the drop after 2018-08 is an outlier). The values are not normalized.

There are three main differences between the results. Statistical methods struggle to accurately represent the behavior of complex systems with noisy data. In contrast, Support Vector Machines (SVMs) offer a powerful AI approach that provides interpretable insights into the measurable factors influencing system resilience. This advantage is particularly pronounced in complex systems, where statistical and traditional methods may encounter difficulties: the results of the comparison answer RQ2.

For noisy data, SVMs excel at pinpointing the start of a disturbance, and the system's return to stability with greater precision. This enhanced accuracy translates to more precise calculations of recovery time after disruptions. Furthermore, SVMs demonstrate superior stability compared to methods like Polyfit, especially when system performance stabilizes at either the minimum performance level or post-recovery. Additionally, SVMs offer a more efficient representation of functionality loss (Figure 2) compared to traditional statistical methods.

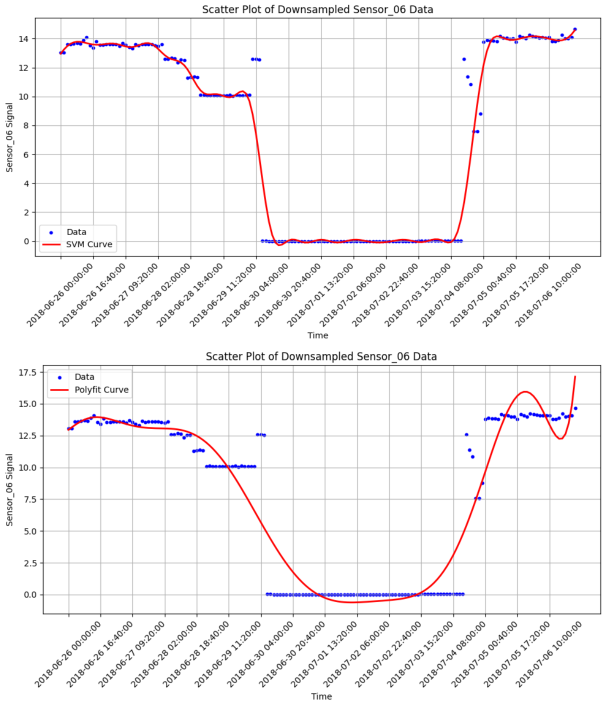

Figure 6 Resilience Curve of Sensor_10. Up: Fitted by SVM, Down: Fitted by Polyfit

6.Limitations

Two key limitations of this study emerged during the case study analysis. Firstly, the possibility of exploring a hybrid solution, combining statistical and AI-based methods, was not investigated. Secondly, the potential of the employed methods to be integrated with AI based real-time anomaly detection services was not explored.

7.Conclusion and Future Studies

The results show that traditional methods struggle with noisy data in complex systems. The Polyfit and Support Vector Machines (SVMs) showed better results than traditional methods (Line Plot and Rolling Average); in particular, the AI-based approach provides clearer insights into behavior of the system after disturbance, especially valuable for Critical Infrastructures. SVMs offer improved precision in noisy data, leading to more accurate calculations of 3 Resilience-KPIs: Recovery Time, Minimum Performance Level, and Functionality Loss.

In future studies, the authors aim to delve into the efficacy of AI-based methods in managing the inherent noise and uncertainty within complex system data, particularly concerning the estimation of resilience curves. This exploration seeks to assess the ability to navigate the intricacies of complex data sets. Additionally, a key focus will be on understanding how AI methods tackle the challenge of identifying and integrating early warning signals indicative of potential system collapse, a task that traditional methods may overlook due to their inherent limitations.

Another area of interest for future research involves the development of hybrid approaches that capitalize on the respective strengths of both traditional and AI-based methods. These hybrid solutions aim to create resilience curves that are not only robust but also highly informative. This combination seeks to enhance the accuracy and reliability of resilience curve estimations. This exploration into hybrid methodologies represents a promising avenue for advancing the field of resilience analysis and fostering more comprehensive insights into complex systems.

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