Tagung Zukünftige Stromnetze | Future Power Grids Conference 2025

Conference Papers

https://doi.org/10.52825/zukunftsnetz.v2i.2595

Published: 11 Jun. 2025

Intelligent Prediction of Alarm Response Time in Modular and Data-Centric Transmission Grid Operation

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Abstract. This paper presents the theory and implementation of techniques to predict the time available for the Control Center personnel of transmission and distribution system operators to respond to an alarming event related to a grid asset. The described techniques include trendline, linear regression, value-at-risk and k-means classification-based prediction and are implemented to support decision-making even with poor quality SCADA data. These techniques have already been deployed in a modular transmission control center alarming and logging system and can be applied for a variety of assets in power systems as well as in other utilities and process industries.

Keywords: Modular Grid Operation, Alarming, SCADA, Response Time Prediction

1. Introduction

The primary objective of grid operation is to maintain system security and reliability, ensuring the continuation of normal operation during and after large disturbances in the grid, while also minimizing operating cost. In order to accomplish these objectives, a typical transmission system operator (TSO) employs separate tools for outage management, power flow calculations, voltage management, congestion management, frequency control and market operations, with often opaque dataflows between applications. These tools are based on the information supplied through the Supervisory Control and Data Acquisition (SCADA) systems, which monitor and display measurements from the system in real time. Operators also have the means to directly control the assets in the transmission network, which include switching of transmission lines and transformers, as well as controlling and regulating transformers and other series and shunt devices [1].

Real-time operation of the network involves round-the-clock monitoring and management of complex processes, in which dynamic events must be addressed. These dynamic events include monitoring measurement deviations and generating alarms. Alarms are a special class of dynamic events used to alert operators to situations that can negatively affect the normal operation of the system. These situations demand that measures be taken to prevent malfunction in the grid and ensure safety of the assets and personnel.

As the frequency of extreme weather events increases and assets in the grid age, the corresponding risk of their malfunction also rises [2]. The other challenge facing system operation is complexity. As the number of relatively volatile renewable distributed energy resources (DER) increase, the grid must expand to seamlessly integrate them and ensure reliable supply of electricity to consumers. Many of these DERs connect to the low and medium voltage networks but require the transmission grid to transport electricity to consumers over large distances, necessitating a corresponding increase in the number of substations and transformers. Consequently, it is reasonable to expect that alarm events will become more frequent, which will need to be actively managed to ensure secure and reliable grid operations.

In addition to these challenges, the grid operators are increasingly faced with a shortage of skilled control center operators who can rely on their experience and intuition to undertake countermeasures to respond to an alarming event. Typically, the operators have a number of means at their disposal to respond to each alarm and must select the most appropriate rectifying measure based on the following factors:

- severity of the issue,
- cost of the response,
- speed of the response and complexity of the approval process,
- benefit of the measure and
- any negative consequences of the measure on grid security.

When an event occurs that requires intervention by the operators, the overriding concern of the operator is to consider actions that can have the desired effect considering the time available to implement them, with the available time to respond usually being the limiting factor. Depending on the available time, the operator selects the measure which fulfills the criteria of lowest cost and highest effectiveness.

This paper introduces several methods to predict the time available to operators in the control center to respond to an alarm event. The innovations of this paper are the following: 1. Multiple approaches are employed to robustly predict the available response time after an alarm has occurred, even with poor quality data; 2. The integration of these approaches in the control center of a Transmission System Operator (TSO) to aid the decision-making process for the use-case example of an overheating transformer. This paper is organized as follows: Chapter 2 introduces alarms as a use case for the implementation of these approaches. Chapter 3 describes the modeling approaches in detail. Chapters 4 and 5 describe the integration of the method in the control center and the outlook is discussed in Section 6.

2. Alarm as a use case

The traditional systems (SCADA, EMS etc.) used in today's system operation do not provide any estimates of the time available to the operator to analyze the issue, decide an appropriate response and trigger the necessary actions. This decision-making (depicted in

Figure **1**) is left to the individual judgement of the operator, who rely on their experience and ad-hoc assessment of the validity and priority of the alarm [3].

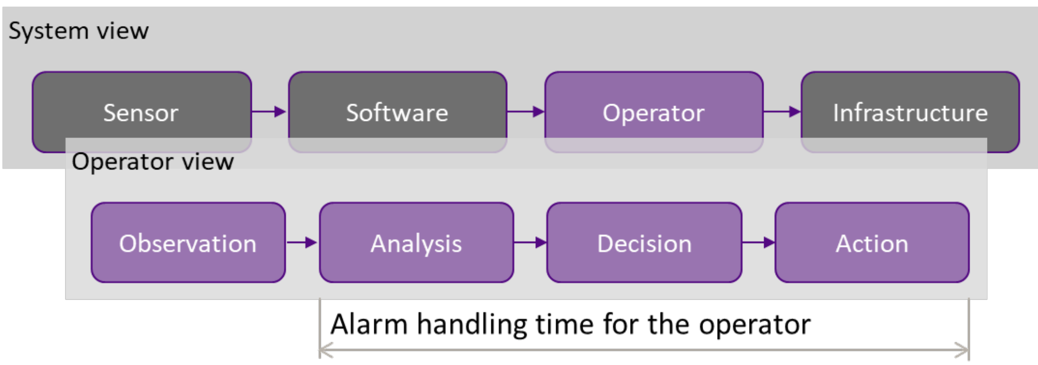

Figure 1. *Stages of operator's response to an alarming event*

Some EMS systems provide relatively undifferentiated guidance based on the alarm class-based rules (see Figure **2**). These policies define reference values derived either from evaluations of previous alarms, underlying issues or on the basis of technical/causal considerations. Operators use these predictions to process the alarms based on the priority of their class. However, efforts to provide real-time intelligent decision-making support to the operators have so far not resulted in implemented solutions.

		Continued Operation			
		Not permitted	≤ 12 hours	≤ 1 week	unlimited
Reaction / Information	Immediate	C1	C1		
	≤ 2 hours			C2	C2
	≤ 10 hours			C2	C2
	≤ 48 hours			C3	C2
	unlimited				C2

Figure 2. *Example of a Priority Matrix according to alarm classes in a standard EMS*

3. Prediction model

Conventional approaches to time series forecasting include variations on the moving average technique, with SARIMA being a popular choice [4]. Popular machine learning algorithms include neural networks and long-short-term memory (LSTM) networks, which require large and consistent measurement data sets to take into account complex patterns, seasonality and dependencies. These characteristics offer two challenges to prediction of alarming response times. The real-time measurements available from the power system assets are generally of an inferior quality and not suitable for generating reliable forecasts using the conventional approaches. The prediction of the alarm response time is short-term in nature, where most measurements prior to the alarming thresholds offer no prediction value to the operators. This makes the conventional approaches over-dimensioned for this purpose, utilizing scarce computational and storage resources.

The concepts described in this chapter utilize multiple methods to aid the operators in the selection of the mitigating measures when an alarm is triggered, depending on the quality of the available measurement data immediately prior to the triggering of the alarm. Only the observations from the preceding 30 minutes are incorporated in the prediction calculation. This approach is adapted due to the lack of meaningful information derived from observations that extend further into the past, as well as to conserve system resources. The steps from the triggering of an alarm to the recommendation of a response time is illustrated in Figure **3**.

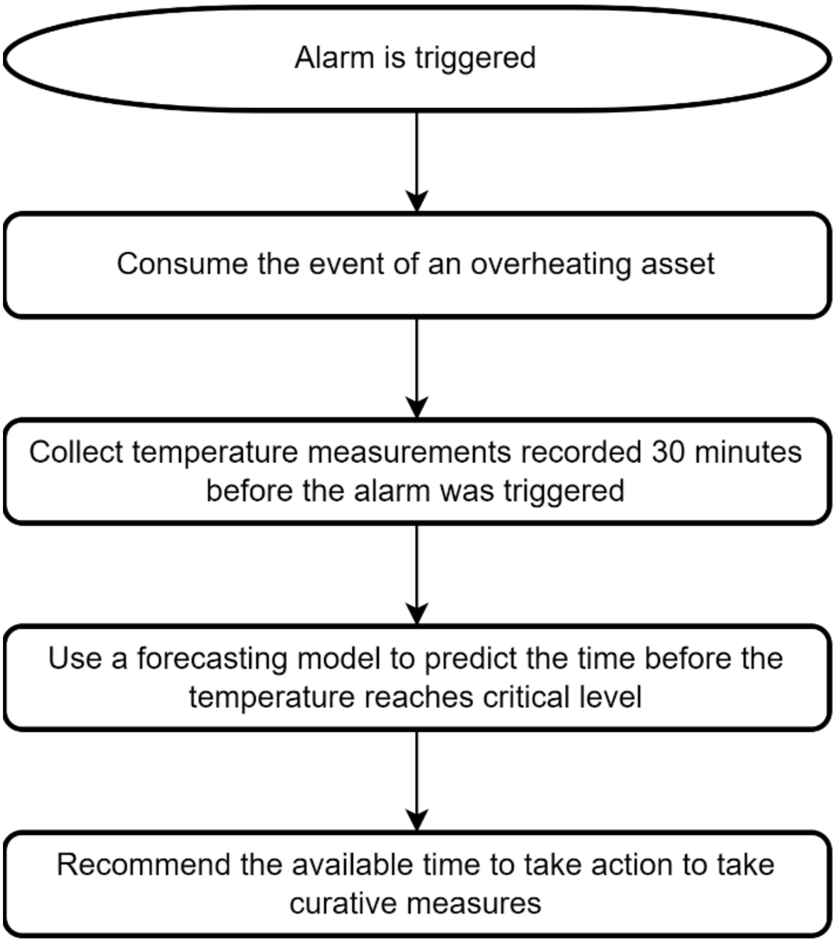

Figure 3. *Alarm response time prediction steps*

Once the calculated time t_r to reachcritical value is calculated using each method, the standardized recommended response time (RRT) in the lookup Table **1** is selected based on whichever range the calculated time lies inside. The time ranges are set wide to avoid overfitting the recommended values to the calculated value and allow for uncertainty due to limited data points. The RRT corresponding to the calculated value thus overestimates the time to reach critical value and thereby errs on the side of caution.

Table 1. *Recommended Response Time*[1]

t_r	**RRT**
> 60 min	40 min
40 - 60 min	30 min
20 - 40 min	10 min
0 - 10 min	React immediately

The methods discussed in the following subchapters are listed in **Table 2**. Normative response time is modeled for alarm types, asset groups, or individual assets to ensure that response time is always recommended as a fail-over strategy.

[1] The standardized RRT slots can be set smaller if large data sets with high quality measurements are available

Table 2. *Prediction techniques for calculating response time*

Prediction technique	**Method of use**
Trend analysis	The gradients between multiple observations are extrapolated to calculate t_r
Linear Regression	Linear regression is applied on multiple arrays created from observations to calculate t_r
Value-at-risk (VaR)	Gradients with the highest level of confidence are used for prediction of t_r
K-means	K-means is used to cluster and classify gradients from historical observations. Membership of present gradients in clusters is used to calculate t_r

3.1 Trend and Linear Regression

3.1.1 Trend-based prediction

The trend forecast is the basic approach available even when only a handful of observations are available. It uses the available time series measurements $x(\mathrm{t}) = \{x_t\ , t = 1, 2, \ldots, T\}$ of discreet observable signals to extrapolate the available time until the critical value x_c is reached. When the alarm is triggered, measurements recorded during the preceding 30 minutes are selected as a data set D with end time t_n and beginning time t_a . Multiple start-end value pairs from this data set are used to calculate the response times.

The first value pair D_1 has as its last value $x_{\mathrm{n}1}$ at which the alarm was triggered, corresponding to the time t_{n1}= t_n. If the measurement value x_a at time t_a is higher than the end value x_n, immediately succeeding elements of the data set D are checked successively until a smaller value is observed, which is then used as the first value x_{a1}, with a corresponding time t_{a1}:

$$x_{n1} = x_n \tag{1}$$

$$x_{a1} = \min\{x_i | i \ = \ a, a + 1, a + 2, \ldots, n\ and\ x_i < \ x_n\}\ for\ x_i\ in\ D \tag{2}$$

The second value pair D_2 starts with the smallest value in the data set D, and the corresponding time t_{a2} and ends at point x_{n2} and the corresponding t_{n2} the same as the first data set D_1:

$$x_{a1} = \min D \tag{3}$$

$$x_{n2} = x_n \tag{4}$$

The third value pair D_3 starts with the smallest value $x_{\mathrm{a}3}$ with the corresponding t_{a3} and takes the highest value of D as the end value x_{n3} with the corresponding t_{n3}:

$$x_{a3} = \min D \tag{5}$$

$$x_{n3} = \max D \tag{6}$$

The three value pairs provide three different gradients G, with k representing the value pairs 1, 2 and 3,

$$G_k = \frac{x_{n,k} - x_{a,k}}{t_{n,k} - t_{a,k}} \tag{7}$$

The corresponding three response times $t_{r,k}$ are calculated as,

$$t_{r,k} = \frac{x_c - x_{a,k}}{G_k} \tag{8}$$

The calculated response time is used as basis for the selection of a standard recommended response time (RRT) from Table **1**. If the RRTs calculated using the three data sets are different, the operator is provided a choice to select one of these values as final.

3.1.2 Linear regression

The linear regression approach is used when a relatively larger set of observations for the last 30 minutes is available. If the values continuously rise with each subsequent observation, a single array is sufficient, otherwise multiple arrays are built. In the latter case, the first array is built by comparing the last measurement x_n at the alarm timestamp t_n with the preceding values until a positive difference (value is smaller than x_n) is found, beginning with the third-last measurement t_{n-3} to ensure there are always multiple data points to perform the linear regression, as shown in (9). This value is then selected as the end of the first array.

$$x_n > x_{n-3} \tag{9}$$

The starting value of this array is selected by continuing to go further back in time until a value is found with a difference that is no longer positive.

The condition (9) is tested for subsequent values until it becomes true again. This observation is used as the last value of the second array. The array is populated until the condition becomes untrue again. This process is repeated until all values in the last 30 minutes have been allocated to arrays.

Once the arrays have been built, linear regression with curve fitting is performed to create the function y for each array to compute characteristic parameters β_0 and β_1 using (10).

$$y(t) = \beta_0 + \beta_1 . x(t) \tag{10}$$

The calculated fitted regression line is used to forecast the time until the critical value x_c is reached, as depicted in Figure **4** for a transformer temperature.

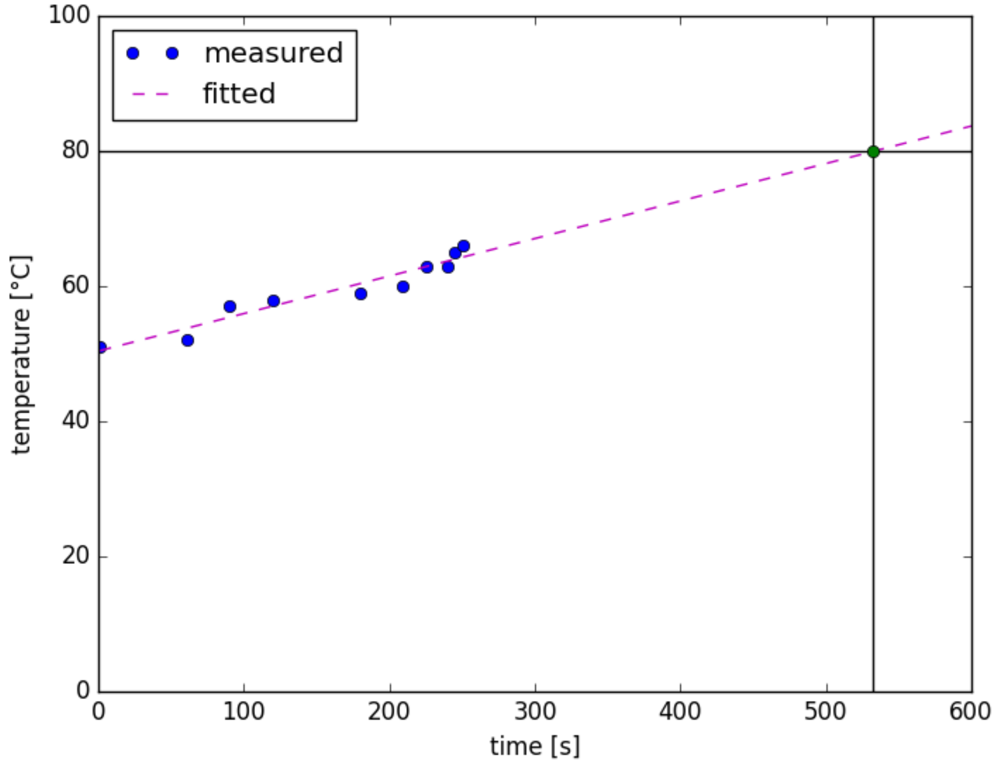

Figure 4. *Temperatures extrapolated by linear regression*

In case of multiple arrays, the arithmetic mean of their times to reaches x_c is used to select the RRT from Table **1**.

3.2 Value at risk (VaR) based prediction

The Value at Risk (VaR) based method is a risk management technique primarily used in the financial sector to estimate the potential loss on an investment over a specific time horizon, providing a quantitative measure of the maximum amount of loss that can be expected with a given level of confidence [5].

The VaR approach is applied to the time series observations and the 90th percentile confidence value is calculated and reported as the RRT. Immediately after an alarm is triggered, all preceding measurements during the last 30 minutes are read and entered into the corresponding tables for the asset and a forecast for the gradient for different time horizons is calculated, with the gradient ordered from highest to the lowest values and the 90th percentile for each time horizon is calculated. The temperature rise for each time horizon is added to the currently measured temperature value to forecast the future temperature at the end of the time horizon and compared with the threshold value. The time horizon in which the forecasted value exceeds the threshold serves as the response time available to the operator.

The algorithm is activated when alarm is triggered at temperature $x_i = x_n$ sampled at time t_n, where i represents the event ID of the measurement and n is the total number of observations. The gradients (°C/min) R for temperature changes between all consecutive measurements x_i- x_{i-1} are calculated, with only the positive gradients used for calculation,

$$R_{i-1} = \begin{cases} \frac{x_i - x_{i-1}}{t_i - t_{i-1}} & x_i - x_{i-1} > 0 \\ 0 & x_i - x_{i-1} < 0 \end{cases} \tag{11}$$

Similarly, gradients R for temperature changes between all measurements x_i- x_{i-2} are calculated as:

$$R_{i-2} = \begin{cases} \frac{x_i - x_{i-2}}{t_i - t_{i-2}} & x_i - x_{i-1} > 0 \\ 0 & x_i - x_{i-1} < 0 \end{cases} \tag{12}$$

This is repeated for all $x_i - x_{i-3}$, $x_i - x_{i-4}$, …$x_i - x_{i-a}$, where a is the index of the first value in the time series, until all combinations (CR) of measurements (${}_nC_2$) are calculated. The calculations for the example case are shown in Table 3.

Table 3. *Calculation of gradients*

Event ID	x (°C)	t	R_{i-1}	R_{i-2}	R_{i-3}	R_{i-4}	R_{i-5}	R_{i-6}	R_{i-7}	R_{i-8}	R_{i-9}
111	51	0:01									
112	52	1:01	0.02								
118	52	1:30	0.00	0.01							
119	54	2:00	0.07	0.03	0.03						
121	56	3:00	0.03	0.04	0.03	0.03					
130	59	3:29	0.10	0.06	0.06	0.05	0.04				
131	61	3:45	0.13	0.11	0.07	0.07	0.05	0.04			
132	65	4:00	0.27	0.19	0.15	0.09	0.09	0.07	0.06		
133	68	4:05	0.60	0.35	0.25	0.18	0.11	0.10	0.09	0.07	
135	70	4:11	0.33	0.45	0.35	0.26	0.20	0.12	0.11	0.09	0.08

The calculated gradients are placed in histograms according to their values with bins of equal sizes as shown in Table **4** for the example use case:

Table 4. *Placement of gradients in bins*

Bin Nr.	Bin lower bound (°C/min)	Bin upper bound (°C/min)	Values	Cumulative
1	0	0.05	12	12
2	0.05	0.1	14	26
…	…	…	…	…
11	0.5	0.55	0	44

The 90th-quantile ordinal rank of the measurements is calculated by (13)

$$P_{90} = \frac{90}{100} \cdot (\mathrm{CR}) \tag{13}$$

and the corresponding gradient R_{90} is selected. The response time is calculated as follows:

$$t_r = \frac{x_c - x_i}{\mathrm{R}_{90}} \tag{14}$$

3.3 K-means based prediction

K-means has been shown to perform well when applied in time series forecasting, as shown in [6] and [7]. Historical measurement data is leveraged to derive intelligent estimation of the available response time using k-means clustering. This is performed by identifying the membership of the value change data points from the observations in the 30 minutes preceding the alarm in the clusters already identified from historical measurements of the asset type. The time series data is converted to data points of temperature changes and the corresponding elapsed time between two adjacent observations. This conversion is shown in **Table 5** for the example use-case.

Table 5. *Data points for clustering*

Event ID	111	112	118	119	121	130	131	132	133	135
Measurement (°C)	51	52	52	54	56	59	61	65	68	70
Time stamp	0:01	1:01	1:30	2:00	3:00	3:29	3:45	4:00	4:05	4:11
Time change (s)		60	29	30	60	29	16	15	5	6
Temperature change (°C)		1	0	2	2	3	2	4	3	2

An example of a k-means clustering trained on limited historical data with 5 clusters is shown in Figure **5**, with the quickest gradient indicated by cluster 0.

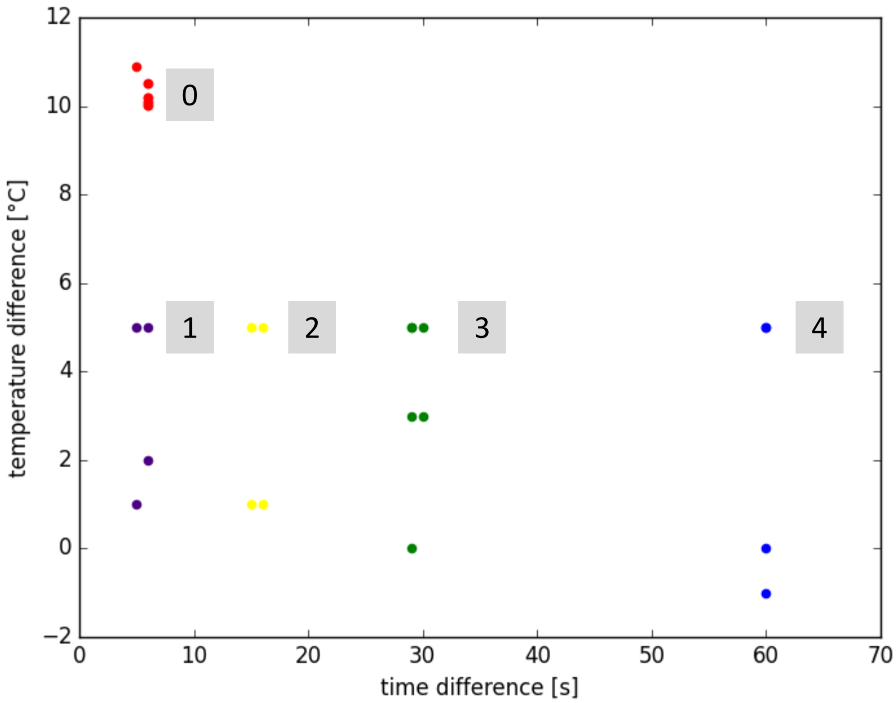

Figure 5. *Clustering of temperature differences with labels*

3.3.1 S-curve

The purpose of assigning weights to each cluster based on a reverse s-curve (illustrated in Figure **6**) is to ensure that slower changes in temperature do not excessively affect the results of the response time calculation. For this purpose, longer gradients are assigned smaller weights and shorter gradients vice versa.

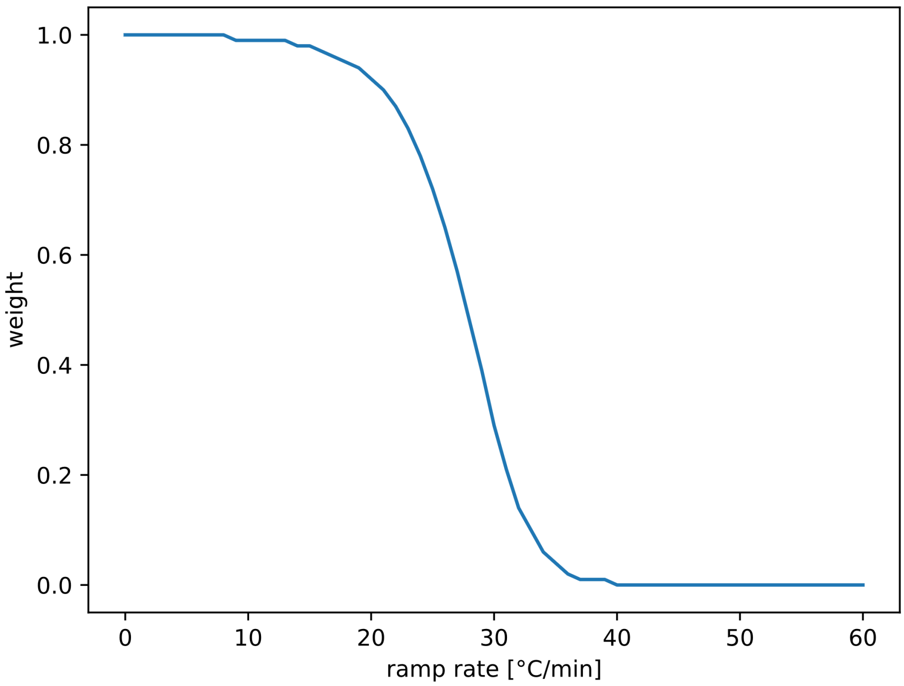

Figure 6. *The weightage is assigned to each data point using a reverse s-curve*

Table **6** shows the use of the reverse s-curve with the 5 clusters. The assigned response time to each cluster is determined by its centroid.

Table 6. *Assignment of weights to data points to calculate the RRT*

Cluster	**Assigned response time**	**Data points**	**S-curve assigned weight**	**Total weight (w_i)**	**Weighted Response time (R_i)**
0	0	120	1.00	0.08	0 .00
1	5	110	1.00	0.07	0.37
2	10	120	0.99	0.08	0.80
3	30	1000	0.29	0.20	5.86
4	60	150	0.00	0.00	0.00

The response time t_r is calculated according to (15) and then used to select the RRT from Table **1**.

$$t_r = \sum_{i=1}^{n} R_i \Big/ \sum_{i=1}^{n} w_i \tag{15}$$

4. Use case implementation

Depending on the RRTs provided, the operator can select one or multiple counter-measures, examples of which are shown in Table **7**.

Table 7. *Example of counter-measures based on the RRT*

RRT	Action
40 min	Switching / Topology changes
30 min	Interrupt loads
10 min	Redispatch
React immediately	Load shedding

5. Implementation as online tool

The described prediction methods have been deployed in the alarming and logging system of a modular control center system of a grid operator as illustrated in Figure **7**. The alarm events are consumed in real-time from the event stream and the calculated RRT is displayed in columns with the corresponding alarm in the dashboard. The operator is able to view the results of each method and select the preferred value for displaying via a drop-down selection menu or overwrite them completely.

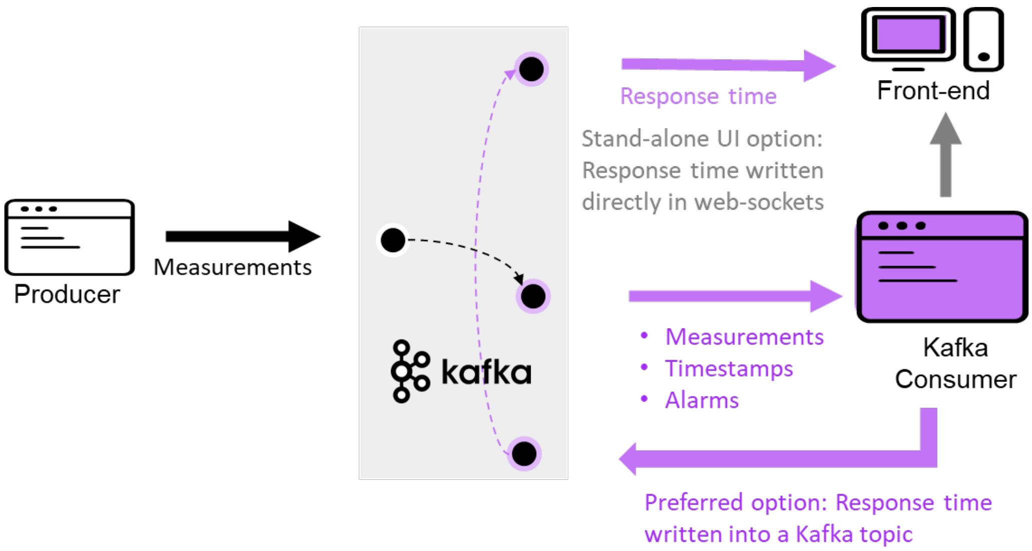

Figure 7. *Integration of RRT functionality in the architecture of a transmission system operator*

6. Outlook

The trend analysis, linear regression and VaR approaches calculate the predicted response time using only the preceding 30 minutes measurements and are thus also useful for assets for which no historical measurements are available. The k-means method leverages historical measurements from previous alarm events and thus provides a more intelligent prediction, which improves as more measurements are recorded. These methods are of different levels of sophistication and their use can be rule-based, depending on the frequency and quality of available observations. In the absence of a rule-based approach, all methods are used to calculate predictions and the interpretation and selection of the results is left to the operator responsible for the alarm, who can select the preferred result to be displayed in the notification window.

The introduced methods help operators in the decision making process of selecting appropriate preventive measures and will be successively incorporated into other system operations processes and extended to change from alarm-based to alert-based predictions, in which the parameters of the asset are continuously monitored and the time to reach an alarm-state is predicted, so that if it is detected that the asset's operation is becoming unstable, an warning flag is triggered in the SCADA monitoring system to bring the potential triggering of an alarm to the operator's attention, so that preventive measures can be taken.

Aside from being useful for monitoring assets controlled by electric utilities and grid operators, use-cases have been identified for gas utilities and process industry, which can use these methods to predict available time to respond to temperature, pressure, fluid/gas flow and level alarms.

More advanced artificial intelligence techniques can provide further improvements in this area. Two such feasible techniques include:

- deep learning models trained on historical alarm data to improve the accuracy of predictions over time and adapting to the specific characteristics of the asset and operational environment, and
- natural language processing to analyse operator logs and incident reports and training using reinforced learning to learn optimal response strategies and implement them automatically.

Both of these techniques are currently under investigation to further enhance situational awareness and decision support for operators.

Data availability statement

The concepts and results presented in this paper are based on proprietary real-time field measurements that cannot be made available to third parties. Simulated data inspired from these measurements is already included in this paper to illustrate the implementation of the concepts. The authors remain available for further information and inquiries.

Author contributions

Hamza Bokhari: Conceptualization, Formal analysis, Investigation, Data curation, Writing-original draft, Writing-review & editing, Methodology, Visualization. Ilja Krybus: Conceptualization, Funding acquisition, Data curation, Writing-review & editing. Maik Scholz: Resources, Validation and Ralf Heisig: Resources, Validation.

Competing interests

The authors declare that they have no competing interests.

References

[1] F. M. Enescu and N. Bizon, "SCADA applications for electric power system," *Reactive Power Control in AC Power Systems: Fundamentals and Current Issues*, pp. 561–609, 2017.
[2] N. Bhusal, M. Abdelmalak, M. Kamruzzaman, and M. Benidris, "Power system resilience: Current practices, challenges, and future directions," *Ieee Access*, vol. 8, pp. 18064–18086, 2020.
[3] M. S. Thomas and J. D. McDonald, *Power system SCADA and smart grids*. CRC press, 2017.
[4] C. Chatfield, *Time-series forecasting*. CRC press, 2000.
[5] D. Duffie and J. Pan, "An overview of value at risk," *Journal of derivatives*, vol. 4, no. 3, pp. 7–49, 1997.

[6] T. W. Liao, "Clustering of time series data—a survey," *Pattern recognition*, vol. 38, no. 11, pp. 1857–1874, 2005.
[7] S. Rani and G. Sikka, "Recent techniques of clustering of time series data: a survey," *International Journal of Computer Applications*, vol. 52, no. 15, 2012.