Anticipating Energy-driven Crises in Process Industry by AI-based Scenario Planning

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Abstract

Power outages and fluctuations represent serious crisis situations in energy-intensive process industry like glass and paper production, where substances such as oil, gas, wood fibers or chemicals are processed. Power disruptions can interrupt chemical reactions and produce tons of waste as well as damage of machine parts. But, despite of the obvious criticality, handling of outages in manufacturing focuses on commissioning of expensive proprietary power plants to protect against power outages and implicit gut feeling in anticipating potential disruptions. With AISOP, we introduce a model for AI-based scenario planning for predicting crisis situations. AISOP uses conceptual, well-defined scenario patterns to capture entities of crisis situations. Data streams are mapped onto these patterns for determining historic crisis scenarios and predicting future crisis scenarios by using inductive knowledge and machine learning. The model was exemplified within a proof of concept for energy-driven disruption prediction. We were able to evaluate the proposed approach by means of a set of data streams on weather and outages in Germany in terms of performance in predicting potential outages for manufacturers of paper industry with promising results.

1. Introduction

The manufacturing industry fears power outages "like the devil fears holy water" [1, 2, 3]. When manufacturing sensitive products by highly automated processes, restarting production lines takes a long time and results in high costs. This is especially critical in energy-intensive process industry, e.g., glass and paper production, where substances such as oil, gas, wood fibers, chemicals or beverages are processed. Power failures can interrupt chemical reactions and produce tons of waste as well as damage of machine parts [2, 4]. It take months, to shut down and raise a glass melting tank; immediate energy stops inducing a quick shutdown would render the tank completely unusable. Also short-term, regionally limited power disruptions represent crisis situations for industrial plants. Due to the reduction of nuclear power plants and the reliance on renewable energy sources with partially strong weather dependency, e.g., wind turbines, solar panels, there are strong fluctuations in the grid [5, 6]. The European power grid is designed to cope with fluctuations between 49.8 and 50.2 hertz, but in case of larger fluctuations, i.e., below 49.8 or above 50.2 hertz for a few tenths of a second, frequency-sensitive machines like in paper industry switch off automatically. In fully automated production processes, consequences of these uncontrolled shutdowns of production lines are serious. The film of water and pulp on a paper machine tears, scrap has been removed completely before starting again causing unplanned downtime, destruction of parts, need for spare parts, additional manpower and loss of production.

However, despite of the criticality of these energy-driven crises for process industry, handling of outages in manufacturing focuses on commissioning of expensive proprietary power plants to protect against power outages and implicit gut feeling in anticipating potential disruptions [3, 7]. On network operator side, dispatch

and redispatch measures more respectively curtailment are used as an intervention to adjust the power input of power plants with the aim of avoiding or eliminating regional overloads or fluctuations in the transmission system. Power network operators started to consolidate redispatch measures via central platforms[1] but these are still in their infancies. In research, related work on anticipating energy-driven disruptions in process industry focuses on linear programming models for estimation of energy disruptions from earth quakes [8], organizational learning approaches for adaption to climate changes [9] as well as knowledge management in energy data spaces [10]. In addition to that, there is related work focusing on the energy industry itself, considering probabilistic risk assessment for preventing safety related disruptions [11, 12], anticipation of power generation and outages [13, 14] as well as outage management approaches [15].

Objective of our research is the anticipation of such energy-driven crises in process industry by AI-based scenario planning for improving resilience in manufacturing. Focusing on responsibility and decision space of manufacturers, anticipation of aforementioned outages enables proactive adjustments of production planning and controlled shutdowns of production lines with rescheduling of maintenance times or planned downtimes.

In this work, we propose AISOP - a model for AI-based scenario planning for predicting crisis situations. AISOP uses conceptual, well-defined scenario patterns to capture entities of crisis situations in history and future, e.g., location and dates of outages, effects like downtimes. Data streams are mapped onto scenario patterns for determining historic crisis scenarios and predicting future crisis scenarios by using inductive knowledge and machine learning. Following the concept of linked data, scenario patterns are operationalized in JSON-LD leading to a knowledge graph of crisis scenarios. A special feature of the model is the applicability of semantically enhanced scenario patterns for explanation of predictive analytics to decision makers (Explainable AI [16]). The model was exemplified within a proof of concept for energy-driven disruption prediction in process industry. We were able to evaluate the proposed approach by means of a set of data streams on weather and outages in Germany in terms of performance in predicting potential outages for manufacturers of paper industry in Bavaria (N=7) with promising results.

2. Crisis and Resilience in Process Industry

Crisis can be defined as the "perception of an unpredictable event that threatens important expectancies of stakeholders and can seriously impact an organization's performance and generate negative outcomes" [17, p. 2]. Decision makers are confronted with uncertainty, competing goals, changing conditions and time stress [18]. Behavioral economics can be used to explain that intuitive decisions can be biased by heuristics, resulting in sub optimal decisions being made "in the heat of the moment" [19, 20]. Systematic crisis management is characterized by four successive phases: mitigation, preparedness, response and recovery [21]. Identification of the crisis type is defined as elementary in a first step. The objective is to assess the organization's ability to control the event (personal control) and the extent of the organization's culpability for the event (crisis responsibility). Crises take many forms. Several crisis taxonomies have been proposed in literature; according to [22] energy-driven crises in process industry are characterized as predictable but hardly influencable, as industrial accidents (cf. [23]) as well as accidental crises respective technical error accidents (cf. [24]).

3. AI-based Scenario Planning

Theories of crisis handling define variables, assumptions and relationships that should be considered when selecting crisis response strategies, e.g., crisis management with scenario planning processes [25]. Their work combines crisis management with scenario planning processes to provide a mechanism for designing, evaluating and managing future crises, especially in a strategic context. Florez et al. [26] propose an approach to define realistic scenarios based on historical data. Also storytelling is applied to design scenarios, more precisely "storifying" real life events based on a computational model [27, 28]. De Nicola et al. [29] present a framework to support the creative design of emergency management scenarios, i.e., the process of imagining situations and describing them through models and stories. They support the task of gathering knowledge about emergency management situations by the automatic generation of conceptual models linked to fragments of emergency scenarios with the objective of defining use case scenarios for analysis and simulation.

We present **AISOP**, a model for AI-based scenario planning for predicting crisis situations based on the Resilience Analysis Grid (RAG) [30] as well as

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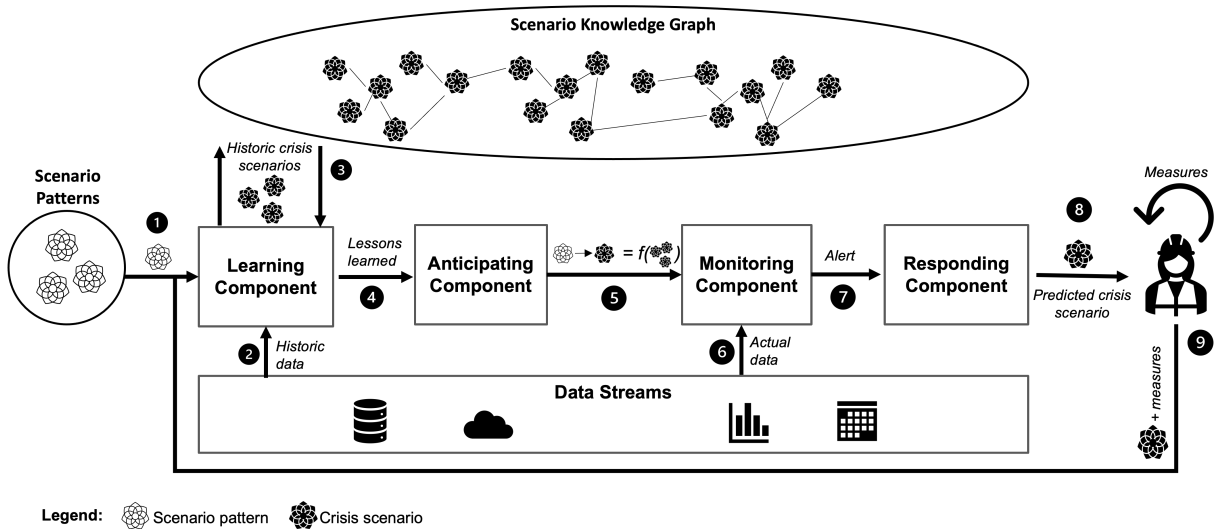[1]https://www.dare-plattform.de/, https://www.openkonsequenz.de

Figure 1: AI-based scenario planning for predicting crisis situations (AISOP)

the Functional Resonance Accident Model (FRAM) [31, 32]. Focusing on preparedness and response in crisis management [21], AISOP defines components for four abilities that make up a resilient system [33]: **learning, anticipating, monitoring** and **responding** (cf. Fig. 1). On the one hand, AISOP operates on semantically enhanced scenario patterns that describe the conceptual structure of crisis situations in terms of context, actors, resources, effects, reason, source, measures and history. Thus, scenario patterns enable a kind of highlighting of relevant information sources (priority areas [30]) within or in expectation of crises. On the other hand, AISOP uses streams of historic data that are mapped on scenario patterns for deriving historic crisis scenarios emerging to a scenario knowledge graph. Both, the later as well as scenario patterns are processed under consideration of actual data for predicting potential crisis scenarios in future (cf. Fig. 1).

The **learning component** takes care for generating crisis scenarios out of historic data according to scenario patterns. Historic crisis scenarios are arranged into a knowledge graph and provided as lessons learned to the **anticipating component** that applies predictive analytics to determine a model to forecast potential crisis situations in the future (cf. Fig. 1). The ability to monitor refers to actual conditions. Based on the scenario pattern that serves as a marker template, the **monitoring component** enables an observation of what is happening in the surrounding environment of manufacturers by applying the model to actual data streams. In case of a detected potential crisis that could impact the power supply and lead to outages, slots of

the scenario pattern are filled with derived data and an alert is given. The **responding component** assures fast and effective responses by users according to the predicted crisis scenario (cf. Fig. 1). By showing the scenario as a graph with additional evidence-based explanations like time horizon and probability as well as potential measures applied in historic scenarios, users are supported in decision-making. Last, the predicted crisis scenario including applied measures if any is forwarded to the learning component to be integrated into the scenario knowledge graph (cf. Fig. 1).

3.1. Scenario Patterns

Scenario patterns represent the core concept of AISOP. They demonstrate a conceptual representation of historical or future crisis situations. Related work on scenario patterns stems from requirements engineering [34, 35, 36], cognition [37, 38, 39], software engineering [40, 41], knowledge representation [42] and crisis communication [43]. According to the state of the art and especially the work by Leite et al. [44], Hoekstra et al. [42], Rolland et al. [34], Tsai et al. [41] and Xie et al. [43], our scenario pattern model is composed of the entities *Identifier, Context, Source, Location, Reason, Effect, Actors, Measures, Resources,* and *History* (cf. Tab. 1).

Each scenario pattern has an **Identifier**, that includes unique information of the scenario such as a specific title [44], ID and timestamp (cf. Tab. 1). The **Context** Entity elaborates on further background information of the scenario [44, 34] by providing a description, data the scenario is based on and further influencing factors

(cf. Tab. 1). [43] identify the information source as an important facet in order to describe the origin and reliability of crisis information. So, the **Source** entity includes information regarding the organization acting as the source for data and information with respect to the scenario (cf. Tab. 1). Furthermore, [43] introduce the importance of dividing between a local crisis, and a crisis that can have a general impact and that is not bound to one specific location. We adopted this division to our specific context within the attributes of the **Location** entity (cf. Tab. 1). According to [34, 41, 40, 35, 43], scenarios are described by cause and effect relationships, that include pre- and post-conditions leading to or resulting from the scenario. The entities **Reason** and **Effect** therefore include these attributes (cf. Tab. 1). In order to measure the likeliness of the scenario, the attribute probability was added while the attribute complexity was introduced to measure the impact of the effect. We also integrated **Actors** that can take certain **Measures** to react on a scenario [42, 38, 44]. Actors are described by their specific role and their acquired skill set that is needed to take certain measures (cf. Tab. 1). Measures are based on expert feedback and include action steps, that can be categorized as precautionary or sudden. **Resources** include equipment such as instruments, tools and aids used to do action steps (cf. Tab. 1). Lastly, as [34] point out, information about scenarios evolve over time. Therefore, the **History** entity was included in order to capture information on historical scenarios by referencing to their ID.

3.2. Algorithm and Example Course

For introducing the proposed approach, we will give an example course of anticipating energy-driven crisis scenarios starting with the generation of historic crisis scenarios and ending with an alert of a potential crisis scenario. The description of the process will be supported by the model view marked with step numbers in Fig. 1. In the example, we apply AISOP on domain-specific data streams on weather and outages in Germany. The outage data is obtained from publicly available data sets of German Federal Network Agency (GFNA)[2] between 2012 and 2020, which contain features such as network operator number, timestamp, duration, type and occasion of the outage and further features regarding power measurement. Weather data is obtained from the NCEI database [3] which is an

integrated database of daily climate summaries from land surface stations across the globe. The data set contains numerous weather-related features such as maximum and minimum temperature, wind speed, wind gust, total daily precipitation, snowfall, dew point, and indication of thunder or rainfall. For the following, imagine a manufacturer in paper industry using a service based on the AISOP model that wants to be pro-actively alerted in case of upcoming, unplanned outages to be able to adjust production planning with respect to controlled shutdowns, maintenance and planned downtimes.

Generating historic crisis scenarios: As a first step, the learning component fills empty scenario patterns (cf. step 1, Fig. 1) with provided data and information by the user (cf. step 2, Fig. 1). Scenario patterns are operationalized in JSON-LD[4], which enables representing semantic relations within a network of linked data. Fig. 2 shows a JSON instantiation of an exemplary pattern, without contextual JSON-LD specific syntax details. We use a semi-automated approach for mapping data features of historical weather and outage data as well as additional user input onto the scenario pattern blueprint. This means, that the user needs to supervise this step, i.e. revise the output, in order to achieve correctness of assigned attributes. Certain attributes, like ID and timestamp of the entity **Identifier** are generated automatically (cf. Fig. 2). The features and data entries (e.g. wind speed, maximum wind speed, wind gust) of the provided input data sets are inserted within the data attribute of the **Context** entity (cf. Fig. 2). Furthermore, attributes within **Effect, Reason** and **Location** entities can be filled by using Natural Language Processing tools in combination with the semantic network Babelnet[5] on the data sets' features, i.e., assigning data features directly to the pattern's attributes (e.g., City) or finding related synonyms in order to assign these features (cf. Fig. 2). Further information regarding **Actors** or **Measures** can be given as input by the user (cf. step 9, Fig. 1). As scenario patterns are now filled with historic crises, step 3 of AISOP includes executing a cypher script to transform semantic relations and linked data within the JSON-LD code (cf. right side of Fig. 2) into a respective instance of a Knowledge Graph (KG) (cf. Fig. 2). The resulting scenario KG is then forwarded as lessons learned to the anticipating component (cf. step 4 in Fig. 1) that applies predictive analytics to determine a forecasting model on energy specific crisis situations (cf. Fig. 1).

Entity	Description	Attributes	Example
Identifier [44]	Identifier of scenario	Title, ID, Timestamp	Title:'Outage', ID:'Outage_987', Timestamp:'2020-09-13T22:23:05+00:00'
Context [44, 34]	Background information and details	ScenarioDescription, Data, InfluentialFactors	ScenarioDescription: 'Outage based on shutdown windturbines' Data: 'wdsp,mxpsd,gust,4.0,7.0,26.66..', InfluentialFactors: 'Autumn Season'
Source [43]	Origin and reliability of the scenario	Organization	Organization: 'German Federal Network Agency','NCEI'
ScenarioLocation [43]	Location of occurence of the scenario	City, Address, Region, Country	City: 'Munich' Region: 'Bavaria' Country: 'Germany'
ImpactLocation [43]	Location influenced by the scenario	City, Address, Region, Country	City: '-' Region: 'Bavaria' Country: 'Germany'
Reason [34, 40, 35, 41]	Conditions leading to and explaining the crisis	Precondition, Probability	Precondition: 'Wind speed', Probability: '0.78'
Effect [34, 35, 43, 41]	Impact of a scenario and resulting conditions	Postcondition, Complexity	Postcondition: 'Machine downtime' Complexity: 'Low'
Actor [44, 38, 42]	People, groups, departments taking action	ActorRole, Skillset	ActorRole: 'Worker', Skillset: 'Maintenance work,..'
Measure [38, 42]	Actions taken to resolve the scenario	Actionstep, Category	Category: 'Precautionary', Actionstep: 'Plan downtime,..'
Resource [44, 38]	Involved aids and tools	Equipment	Equipment: 'None'
History [34]	Related historical scenarios	Identifier.ID	Identifier.ID: 'Outage_913'

Table 1: Description of scenario pattern model with entities, attributes and examples
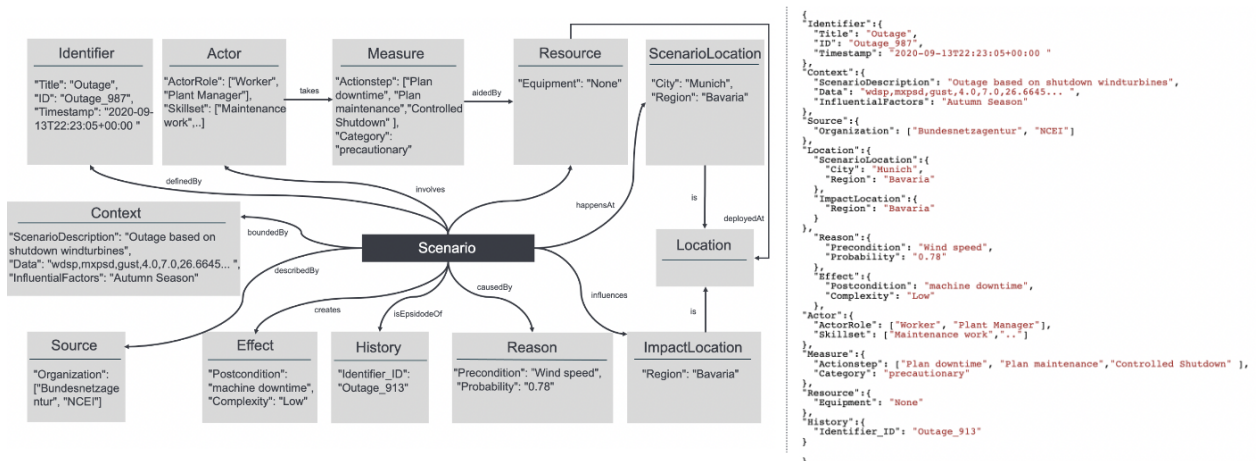

Figure 2: Instance of a crisis scenario pattern represented as conceptual knowledge graph and implemented in JSON (extract)

Observing potential scenarios: The monitoring component monitors actual weather data within a specific region (cf. step 6, Fig. 1). The forecasting model provided by the anticipating component (cf. step 5, Fig. 1) is applied on actual weather data (cf. step 6, Fig. 1) in order to predict future outages. In case of potential outages, the prediction features (e.g., model confidence) and entries are mapped onto the data attribute within the **Context** entity (cf. Fig. 2). All features and data entries of actual weather data and outage data are mapped as stated in the previous section. The timestamp attribute within the **Identifier** entity, the probability attribute within **Reason** as well as **ImpactLocation** are further derived from the outage prediction (cf. Fig. 2). An inductive learning approach is applied onto historical crisis scenario patterns as well as the predicted outages for a specific time frame and region (e.g., Bavaria) (cf. step 5, Fig. 1) in order to explain results to the user. Inductive learning covers inductive knowledge acquisition and prediction based on generalized patterns of input observations, applying numerical or symbolic approaches [45]. Based on the structure of the scenario KG defined by scenario patterns, we apply self-supervised symbolic learning [45] in order to bridge the gap between symbolic knowledge patterns and predictive analytical methods. The application of symbolic learning enables to learn from labels in natural language that explain information within a KG. Considering predicted outages of the forecasting model and attributes of entities of the scenario pattern (e.g., Context entity with weather features such as temperature, wind speed, wind gust etc.) (cf. Fig. 2), rules can be derived. For instance, based on the occurrence of an influential factor for a certain outage reason, we could derive the rule:

`IF` Context.Influence = 'Autumn Season'
`THEN` Reason.Precondition = 'Wind speed';

This rule set is continuously revised and extended based on the inserted information within the scenario KG. Assuming a user inserts a list of feedback on possible actions (Measure.actionSteps = ['plan downtime', 'plan maintenance', 'controlled shutdown']) (cf. Fig. 2) for a crisis scenario, the rule set could grow to:

`IF` Context.Influence = 'Autumn Season'
`THEN` Reason.Precondition = 'Wind speed';
`IF` Reason.Precondition = 'Wind speed'
`THEN` Measure.actionSteps=['plan downtime', 'plan maintenance', 'controlled shutdown'];

Alerting crisis scenario: In case of a predicted potential outage, an alert is triggered and results, including the filled scenario patterns (cf. Fig. 2) and

inductive knowledge based explanations are given as response to the user (cf. step 7, Fig. 1). The user can provide feedback by adding input, e.g., on precautionary action steps in the **Measures** entity (cf. step 8, Fig. 1). The enriched scenario pattern is then forwarded and reinserted as historic scenario pattern into the scenario KG (cf. step 9, Fig. 1). This leads to a refinement of further inductive knowledge rules enabling more precise explanations of the predicted results.

4. Implementation and Evaluation

Based on the proposed model (cf. Fig. 1), we implemented a proof of concept focusing on step 5 and 6 in AISOP, i.e., the observation of the surrounding environment of manufacturers by applying scenario patterns to actual data streams, i.e., weather data in this case. If a potential crisis scenario is detected that could impact the power supply and lead to outages, slots of the scenario pattern are filled with derived data and an alert is given. In order to be able to observe potential crisis scenarios, we combined the semantic representation of scenario patterns with self-supervised symbolic learning and a supervised classification approach. The proof of concept was implemented in Python, JSON and JSON-LD. Having confirmed the location of a manufacturer of the paper industry, slots of the scenario pattern are used as a marker template that is filled rule-based with results of analyzing actual weather data streams with respect to a classification model. A prerequisite for the implementation is the availability of historic data on outages and weather data that can be mapped onto scenario patterns as well as actual weather data to observe.

4.1. Setting

To evaluate our approach, we conducted a run time study with the implemented proof of concept. Goal of this study was to assess the performance in predicting potential outages caused by weather for manufacturers of paper industry in Germany. For that purpose, we applied a publicly available data set on power outages published by German Federal Network Agency [6]. These consist of 1.5 million power outages, that occurred in Germany between 2012-2020. We noticed, that outages occurred very unevenly in time. Furthermore, as shown in Fig. 3, these outages are not evenly distributed over Germany, as some cities show more outages than others. Each outage is identified based on the network

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operator id, date, city, reason, customers affected as well as further outage-resulting features[7]. Tab. 2 lists all the features of the applied data set. Furthermore, only network operators that are still operational are considered for this study and therefore only outages caused through their respective network are included within the analysis. For preprocessing, outages were
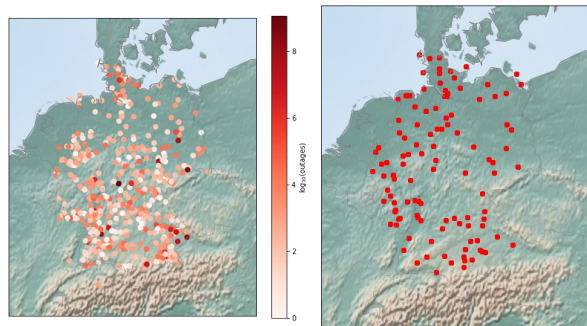

Figure 3: Distribution of outages in Germany 2012-2020 (Source: German Federal Network Agency) (left) and distribution of weather stations across Germany (Source: NCEI database) (right)

grouped based on date and city. Missing dates for each city are filled with 0. After that, since this data set is to be integrated with weather data, outage events that are marked as planned or that are not related to weather events were excluded. Finally, labels for a classification problem are obtained where each row contains date, city and outage-occurred which is a binary variable.

Weather data is obtained from the NCEI database[8] which is an integrated database of daily climate summaries from land surface stations across the globe. The GHCN-daily data set provided by NCEI contains records from over 100,000 stations in 180 countries. The data set contains numerous weather-related features such as maximum and minimum temperature, wind speed, wind gust, total daily precipitation, snowfall, dew point, and indication of thunder or rainfall. Tab. 2 lists the weather features used in the evaluation. Each record is uniquely identified by the weather station id and the date. For preprocessing, weather stations were filtered based on latitude and longitude to retain weather stations in Germany (cf. Fig. 3).

Next step was to augment outages data with weather data and to handle the imbalance of outages. Since not all weather stations have complete historical data in the NCEI data set, a set of weather stations (N=19) was selected that contains all historical data from 2012

Features of weather data	Features of outages data
Max Wind Speed	Operator ID
Wind Gust	Operator Name
Average Wind Speed	Date
Average Temperature	Time
Max Temperature	Duration
Min Temperature	City
Dew Point	Planned/Unplanned
Visibility	Max Voltage
Rain	Mid Voltage
Snow	Low Voltage
Ice	Reason
Hail	Interrupted active power [MW]
Thunder	Customers Affected
Tornado	-

Table 2: Overview of features of weather data (Source: NCEI) (left) and outages data (Source: German Federal Network Agency) (right)

until 2020. Then, to cater the unbalancedness problem, K-means clustering with $k = 19$ was applied to group cities close to each other with the nearest weather station. For our experiment, south-west part of Germany was selected as it has shown the highest number of outages (cf. Fig. 4). This resulted in increased percentage of dates having outages for each cluster. The final data set contains features such as cluster-id, weather-station-id, date and weather-related features while outage is used as a label to predict potential outages [9]. Finally, data for each cluster was divided into 80% for training, 10% for validation and 10% for testing.

4.2. Results

Outage predictions were modeled as a supervised learning classification problem with power outage as label and weather conditions as feature. We report on results of different models trained on the cluster of cities in the south-west of Germany as shown in Fig 4. For evaluation, accuracy, sensitivity and specificity were used. Tab. 3 shows classification results of different models. XGBoost (XGB) outperforms other models in terms of overall accuracy (0.812) and sensitivity (0.700). In particular, sensitivity is the most important metric since it evaluates out of all outage events, how many the model could identify, which is crucial given the aforementioned scarcity of outage events. In order to analyse which features have the strongest contribution to outage prediction, weights of features that XGB

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[7]Data are imbalanced as most of the dates do not contain details for outages in a particular city. In particular, only 2% of the dates for all cities are assigned to outages. This percentage is reduced to 1.5% if cities have more than 1 outage in a day.

[8]https://www.noaa.gov/

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[9]To handle different ranges for different features, we scale all features to be in the range 0 to 1.

Metrics	LR	SVM	RF	NN	XGB
ACC	0.634	0.759	0.784	0.806	**0.812**
SP	0.950	0.952	0.978	0.868	0.850
SN	0.290	0.270	0.218	0.618	**0.700**

Table 3: Classification results of different models on predicting outages in south-west Germany (ACC = accuracy, SP = specificity, SN = sensitivity, LR = Logistic Regression, RF = Random Forest, NN = Neural Network)
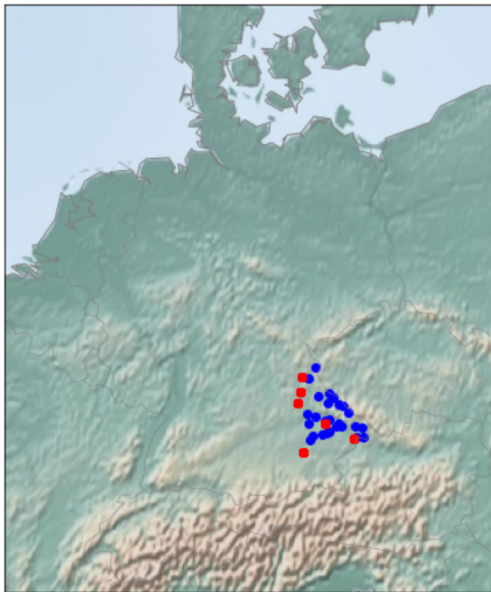

Figure 4: City clusters (blue) and weather stations (red)

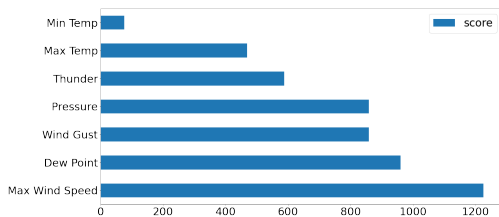converged to are plotted in Fig. 5^{10}. We see that

Figure 5: Feature importance in weather data for predicting outages

maximum wind speed, dew point, wind gust along thunder indicators and temperature features had the most contribution to the outage prediction. This is aligned with several studies [46, 47] that show how storms pose a challenge to power distribution operators in many countries in Europe.

For evaluation, locations of paper industry within the city cluster (cf. Fig. 4) were selected as published by the German Paper Industry Association[11]. For those paper manufacturers in south-west Germany $(N=7)^{12}$, we were able to predict outages in 2020 with the aforementioned accuracy of 0.812. In case of a predicted outage for the location of the paper manufacturer, relevant data were mapped onto the scenario pattern structure, as specified in (cf. Tab. 1). Features of both data sets as listed in (cf. Tab. 2) and their respective data entries for the date of the potential outage with affected region were filled into the scenario pattern ($Context.Data$). Furthermore, the date was inserted as $Identifier.Timestamp$ into the pattern. The *City* feature within the data set of German Federal Network Agency (cf. Tab. 2) was mapped onto $ScenarioLocation.City$ similar to the *Reason* feature that fills the slot $Reason.Precondition$. As the applied classification model also captures the level of confidence regarding its prediction, this value is mapped onto $Reason.Probability$. The feature of *affected customers* (cf. Tab. 2) was mapped onto $Effect.Postconditions$ in the scenario pattern. The $History$ entity is automatically generated in each newly generated scenario pattern for linking it with historic crisis scenarios caused by outages at the same location ($Identifier.ID$). In summary, completely filled scenario patterns with explanatory information on the predicted outages potentially affecting the manufacturers (N=7) were generated. In a next step, an alert would be given for presenting the predicted scenarios to manufacturers for supporting decisions on the pro-active initiation of measures in production planning.

5. Conclusion

We considered energy-driven crises in process industry. Despite of the criticality of power outages and fluctuations for energy-intensive process industry and serious consequences of uncontrolled shutdowns of production lines, handling of outages in manufacturing focuses on commissioning of expensive proprietary power plants to protect against power outages and

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[10]Feature importance score is calculated for a single decision tree in XGBoost by the amount that each attribute split point improves the performance measure, weighted by the number of observations the node is responsible for.

[11]https://www.papierindustrie.de/
[12]Cities: Raubling, Trostberg, Augsburg, Schrobenhausen, Fürth, Teisnach, Plattling

implicit gut feeling in anticipating potential disruptions. Putting the emphasis on responsibility and decision space of manufacturers, we introduced AISOP, a model for AI-based scenario planning for predicting crisis situations. AISOP uses conceptual, well-defined scenario patterns to capture entities of crisis situations in history and future, e.g., location and dates of outages, effects like downtimes. Data streams, e.g., historic outages, weather data, are mapped onto scenario patterns for determining historic crisis scenarios and predicting future crisis scenarios by using inductive knowledge and machine learning. The model was exemplified within a proof of concept for energy-driven disruption prediction in process industry. We were able to evaluate the proposed approach by means of a set of data streams on outages in Germany in terms of performance in predicting potential outages for manufacturers of paper industry with promising results.

6. Acknowledgement

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