POWOP: Weather-based Power Outage Prediction

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Abstract. The worldwide energy-crisis, in particular current gas shortages, pose a critical risk for the energy-intensive process industry. Rising costs for gas lead to an intensified usage of power (e.g. for heating) in industry and private households that network operators are not prepared for. Weather-dependent energy-sources (e.g. windparks, solar panels) lead to additional fluctuations within the power grid, especially in autumn and winter seasons with potential storms and less sun hours. In worst case a simultaneous and prolonged loss of gas supply and electricity will lead to network bottlenecks, or complete network shutdowns - blackouts. For manufacturers, power outages thereby lead to severe consequences (i.e. waste, broken machines, additional costs), with only limited options to prevent them. Within this paper we highlight the implementation of POWOP, a weather-based service for *POWer Outage Prediction* that increases the resilience within the German process industry by an early forecast for the next 7 days including possible action recommendations. Our publicly available web-application was evaluated for 15 locations of paper manufacturers in the German region Bavaria and will be demonstrated within a screencast.

Keywords: Energy-driven crisis, Outage prediction, Weather, Process industry, Scenario Pattern, Service, Demo

1 Introduction

Hardly any topic is currently discussed as much as the worldwide energy crisis, in particular the restricted gas supply [1]. Widespread power outages as potential consequence pose a critical issue, specifically in the energy-intensive process industry, e.g. glass and paper production or chemical industry. Minimal fluctuations in the power grid below 49.8 and over 50.2 Hertz can already lead to serious effects due to uncontrolled shutdowns of frequency sensitive machines [2]. Ultimately this means that within automated processes chemical reactions are interrupted spontaneously, tons of waste are produced and machine parts can break resulting in high repair costs and personnel expenses for manufacturers [2, 3, 4]. In case of gas shortages and a related increase in costs, industry as well as private households will switch to alternative methods such as power in order to heat, for their energy supply of machines etc. As distribution network operators and their networks are not prepared for such a setting, this will lead to network bottlenecks, voltage drops due to load shortages as well as network shutdowns [5, 6, 7]. What contributes to this situation and causes additional fluctuations within the grid, is the increased usage of weather-dependent energy-sources to generate power [8] in order to balance the occurring gas shortage. Wind turbines and solar panels can thereby increase instability within power grids [9, 10] as they produce power inconsistently based on current weather conditions (e.g. storms, sun hours). One example for this can be seen within the German region Bavaria, as they increasingly depend on installed solar systems that do not produce enough energy in the winter season [11]. Worst case will be a simultaneous and prolonged loss of electricity and gas supply - a blackout. Although such power outages and grid fluctuations pose a well known issue and current threat, there are not many measures to prevent them. For manufacturers these include the acquisition of expensive proprietary power plants or speculative measures like an implicit gut feeling based on expertise [12, 13]. Network operators on the other hand focus on dispatch and re-dispatch measures to balance occurring fluctuations in the grid [2, 11]. In order to enable early preventive actions to outages and fluctuations based on weather changes especially in the upcoming autumn and winter season, a prediction of potential events is needed.

Authors of previous research already address weather-related outage prediction focusing on predictive analytic methods for outages caused by extratropical storms[14], logistic regression or decision trees [15], graph neural networks [16] and regression trees [17]. Orsato et al. developed a tool for anticipating energy disruptions based on climate changes [18]. In contrast, the authors of [19, 20] focus on simulated storm data, while calling out for contextual crisis descriptions of outage events. In addition to missing context, these papers do not focus on presenting their predictions within a demonstration of an intuitive service that also gives action recommendations for the actual user. Based on this gap, we formerly developed AISOP [2] – a model for AI-based scenario planning in the prediction and description of crisis situations. AISOP addresses crisis events (e.g. outages) within four steps: (1) Learning, (2) anticipating, (3) monitoring and (4) responding to a crisis. Initially, semantically enhanced Scenario Patterns are filled based on historical data describing crisis scenarios [2]. The description includes contextual information of a crisis, reason, impact and location, involved actors, measures, resources involved within these measures, the data source and interlinked historical events [2]. By using predictive analytic methods onto historical datasets, a forecasting model is generated and applied on current data to make a prediction. The predicted outage events are mapped onto the Scenario Pattern structure and given as result to the user [2].

By using AISOP [2] as basis, we implemented POWOP as a service for *POWer Outage Prediction* that enables decision makers to anticipate outages early, to receive contextual information about the crisis event and recommendations to react accordingly. An exemplary application and demonstration of the service will be explained within a screencast. POWOP was implemented as a web application and will be provided as publicly available open source code, in order to increase manufacturer's resilience within the upcoming seasons.

2 POWOP Service Implementation

By enhancing the presented PoC within [2], we implemented an intuitive user service for manufacturers within the energy-intensive process industry. Our service architecture consists of 3 levels (cf. Fig. 1): A **Data Repository** for data allocation, a logic level for generating **Scenario Patterns** & state-of-the-art **Machine Learning** application and a **User Interface** for presenting the results to the user.

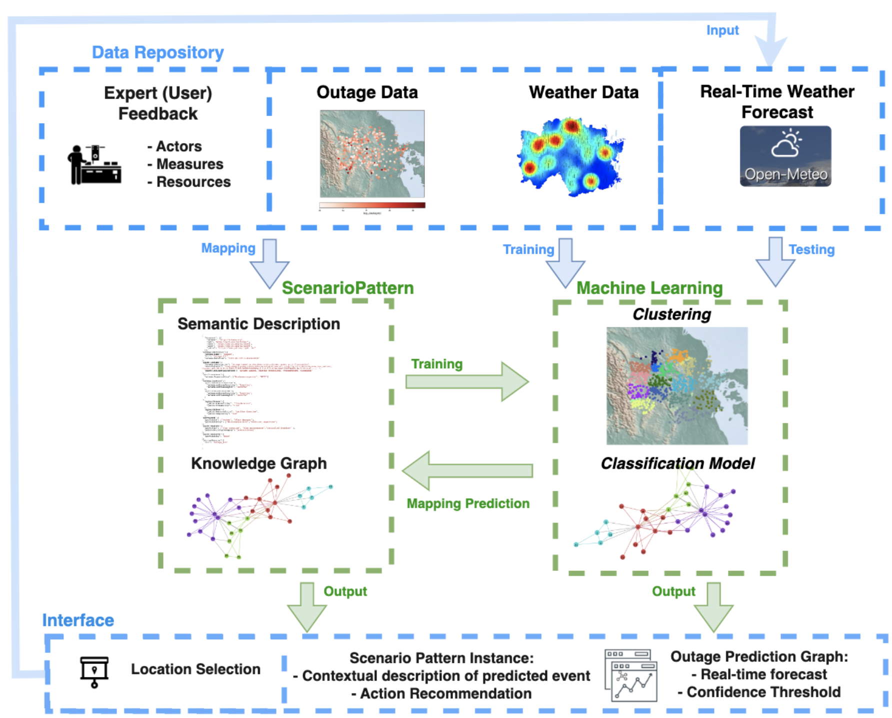

Fig. 1: Technical architecture of POWOP

2.1 Data Repository

The **Data Repository** collects three datasets from different sources to train and test our framework: The *Outage dataset* contains location-specific information on power outages (e.g. date, time, duration, city, reason, planned/unplanned occurrence) collected from the German Federal Network Agency[6], while the *Weather dataset* includes weather characteristics (e.g. windspeed, wingust, temperature, rain, thunder) obtained from the NCEI database[7][2]. Both datasets collect information for the period 2012-2020. In addition to these datasets *User input* on actors that react onto an outage event, measures that should be taken and resources to be used were collected.

2.2 Scenario Patterns

Furthermore, we implemented **Scenario Patterns** within a *semantic description* using JSON-LD as format. Semantic web standards such as the vocabularies schema.org[8], DCMI[9], DCAT[10] and PROV Ontology[11] were applied (cf. Fig. 2). Respectively historical information from the collected datasets were filled into the Scenario Pattern's structure as historical crisis scenarios via a simple mapping of the included data features. By using the JSON-LD format and by registering related events within the history entity [2], the resulting descriptions form a network that can further be transferred into a knowledge graph by using a knowledge graph database such as Neo4j[12] and Cypher script[13].

[6] https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Versorgungssicherheit/Versorgungsunterbrechungen/Auswertung_Strom/start.html
[7] https://www.noaa.gov/
[8] https://schema.org/
[9] http://purl.org/dc/terms/
[10] https://www.w3.org/ns/dcat
[11] https://www.w3.org/TR/2013/REC-prov-o-20130430/
[12] https://neo4j.com/
[13] https://neo4j.com/labs/apoc/4.3/cypher-execution/

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{
  "@context": [{
    "schema": "http://schema.org",
    "dct": "http://purl.org/dc/terms/",
    "dcat": "http://www.w3.org/ns/dcat#",
    "prov": "http://www.w3.org/ns/prov#",
    "pairs": "https://www.pairs-projekt.de/"
  }],
"schema:identifier":{
  "schema:name": "Outage",
  "@id": "Outage_987",
  "schema:DateTime": "2020-09-13T13:38:56+0000"
},
"pairs:Context":{
  "schema:description": "Outage based on shutdown
windturbines; power grid fluctuation",
  "dcat:Dataset":
"temp,dewp,slp,stp,visib,wdsp,mxpsd,gust,max,min,prcp,fog,r
ain_drizzle,snow_ice_pellets,thunder,423,32.9,31.2,1029.7,9
95.5798903987854,6.9,2.7,7.0,26.66451733796205,36.9,32.0,0.
..... ",
  "pairs:InfluentialFactors": "Autumn Season, weather
conditions, Thunderstorm, Windspeed"
},
"dct:Provenance":{
  "schema:Organization": ["Bundesnetzagentur", "NCEI"]
},
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    "schema:addressRegion": "Bavaria"
  },
  "pairs:ImpactLocation":{
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    "schema:addressRegion": "Bavaria"
  }
},
  "pairs:Reason":{
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    "pairs:Probability": "0.78"
  },
  "pairs:Effect":{
    "pairs:Postcondition": "machine downtime",
    "pairs:Complexity": "Low"
  },
"prov:Agent":{
  "prov:Role": ["Worker", "Plant Manager"],
  "prov:Activity": ["Maintenance work","Technical
expertise"]
},
"pairs:Measure":{
  "prov:Plan": ["Plan downtime", "Plan
maintenance","Controlled Shutdown" ],
  "pairs:ActivityCategory": "precautionary"
},
"pairs:Resource":{
  "prov:Entity": "None"
},
"dct:hasVersion":{
  "@id": "Outage_430"
}
```


Fig. 2: JSON-LD Instance of a filled Scenario Pattern

2.3 Machine Learning

Within the **Machine Learning** component, we first prepared our datasets for further use and merged weather and outage data respectively by their date. In doing so, we found a scarcity of occurring outages per city which led to an imbalanced situation [2]. In particular, only 2% of the data could be used effectively. This percentage was further reduced to 1.5 % as more than one outage could occur per city on each day. To cater this issue, we used a K-means *clustering approach* to group nearby cities with similar weather behaviour into one cluster and aggregated their outages, which increased the data quality to work with [2]. In particular, given the set of n cities' coordinates $D = \{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$, with $K = 19$, K-means groups the cities into 19 clusters according to the distance using latitude and longitude. Once the algorithm converges, the data records for each cluster are aggregated and normalized to mitigate bias of high range features. The final dataset contains features such as cluster-id, weather-station-id, date and weather-related features while an outage is used as a binary label [2].

In order to train our forecasting model, the pre-processed dataset is split into 70% for training, 10% for validation and 20% for testing purposes. The training set is used as input to our *classification model*, for which we use the state-of-the-art gradient boosting algorithm *XGBoost* [21]. However, XGBoost has many hyperparameters that need to be tuned which makes it infeasible to perform a Grid-Search given the large hyperparameter space [21]. Instead, OPTUNA[14] was used as framework to perform automatic hyperparameter optimization.

[14]https://optuna.org/

Furthermore, the forecasting model has been applied on real-time weather information in order to predict outages for the next 7 days. A location selected by a user within the **User Interface** is therefore used as input to the weather API *OpenMeteo*[15], that collects real-time weather information. These features are then passed to the Machine Learning component, normalized and used as input to XGBoost to get the prediction.

Our model was tested on 15 chosen locations of paper manufacturers within Bavaria, Germany. Experimental results showed the effectiveness of our model in capturing both outage and non-outage events, achieving a 81.2% overall accuracy and 70% sensitivity, stating the correct identification of outages specifically [2]. The implementation of the Machine Learning component was realized in Python.

2.4 Graphical User Interface

After the user has selected a *location* for generating prediction results, a regional forecast of power outages for the next 7 days is shown within a *prediction graph* (cf. Fig. 3). The position of each bubble on the graph depends on the predicted day and the probability of the actual occurrence of the predicted event (confidence level). Potential outages are represented by red bubbles, while green bubbles illustrate that there will be no outage on that day. Fig. 3 thereby shows a potential outage for the city Raubling with a probability of 74%. The orange line represents a threshold for the confidence level, meaning that events above are more likely to occur. In case of a predicted outage, a filled *Scenario Pattern Instance* is generated and integrated using Highcharts[16] in order to provide potential decision makers with relevant information about the predicted event (cf. Fig. 4). We used JavaScript for the implementation of the User Interface component. A demonstration of the developed service[17] is presented within a screencast[18].

3 Conclusion

In this paper we described the development of the intuitive service POWOP for weather-based outage prediction within the energy-intensive process industry in Germany. The service allows potential decision makers to predict regional power outages for the next 7 days. As databasis weather information and outage data were collected in order to train a predictive analytics forecasting model. Additionally, contextual insights and action recommendations were derived from these datasets enriched by additional user input and mapped onto semantically

[15] https://open-meteo.com/en

[16] https://www.highcharts.com/

[17] The open source code of the service will be provided in case of acceptance of this paper after the blind review

[18] https://youtu.be/aRw6lNgAqa4

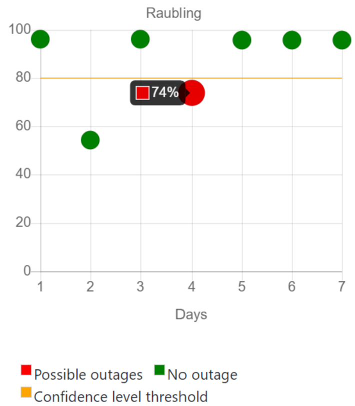

Fig. 3: Outage prediction

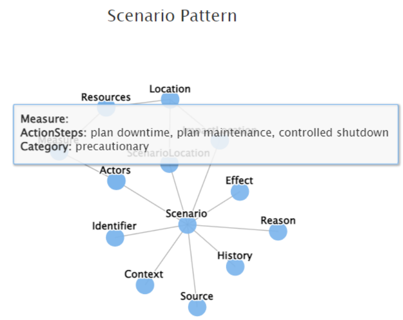

Fig. 4: Scenario Pattern

enhanced Scenario Patterns. Our service was evaluated with values of 81.2% for accuracy and 70% sensitivity for 15 locations of paper manufacturers in Bavaria and demonstrated within a screencast.

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