OPTIMIZING TECHNOLOGY-BASED DECISION-SUPPORT FOR MANAGEMENT OF INFRASTRUCTURES UNDER RISK: THE CASE OF POWER GRIDS

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Technological developments allow for gathering and processing an increasing amount of data in real time. The integration of these tools into risk assessment allows for the development of dynamic risk assessment and data-driven decision support. The latter is of special interest for systems that are remotely monitored and controlled by operator, such as power grids. Generally, grid operators have little access to environmental information to support decisions on interventions and preventive maintenance. Recent initiatives aim at integrating machine learning and other techniques into dynamic risk assessment of power grids. The performances of these initiatives depend on the quantity and quality of data one can gather and process, the available technology, and the cost-benefit ratio of which these initiatives are synonym. In addition, the development of these solutions must be completed by the list of decisions to which the operators may be subject, as well as the information required in order to make the correct decisions for the system's needs. This paper presents a framework for optimizing decision-support of power grids operators using data-driven solutions, focusing on risks associated to vegetation. We analyse the possible scenarios concerning power grids under risk by surrounding vegetation, and the deriving decisions the operators can make under those scenarios. We further analyse and discuss the information required by the operators for decision making. This information is finally integrated into a data-collection and processing framework.

Keywords: Dynamic Risk Analysis, Decision Support, Power Grid Management, Vegetation Hazard, Preventive Maintenance

1. Introduction

The advent of machine learning, big data, internet of things and other technological solutions, enabled by the increasing access to powerful machines, allows for gathering and processing data in real time. The integration of these tools into risk assessment, in turn, allows for the development of dynamic risk assessment and data-driven decision support. The latter is of special interest for a diversity of applications. Indeed, systems that are remotely monitored and controlled by operators can highly benefit from technological solutions for increasing operators' situation awareness and keeping them in the loop. As such, data-driven and risk-based decision support can thus be particularly beneficial for management of power grids.

Risk management is a main concern for decision makers in power grid related companies. To provide end-users with a reliable and continuous energy flow, they need to ensure the functioning of the grid at all times. Yet, the power grids are exposed to a plurality of hazards such as hurricane, earthquakes, ice storms, floods, etc. Those hazards can have severe consequences (DeCorla-Souza, 2013; Kenward and Raja, 2014). In addition, the vulnerability to these hazards can increase depending on the terrain on which the power poles are installed, the remoteness of the power grid and its size, among other factors.

One of the main hazards related to power grids operations is vegetation. Vegetation can affect a power grid in case a branch or an entire tree falls directly on a power line, or in case it grows under a line, making contact and creating an outage. In some cases, the consequences of these events can be relatively low, with only a few power customers affected. However, consequences can also be particularly severe, such as wildfires (Kumagai et al., 2004) or large blackouts (Alhelou et al., 2019, Sforna and Delfanti, 2006). Vegetation was the number one cause of outage in Norway in 2018 (Eggum, 2019) and is a main

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contributing factor for outages in power grids in general (Hansen, 2018, 2017, 2016).

Vegetation management is typically performed through growth assessments and clear-cutting operations. This can be a costly and challenging task. For instance, internal information reported by an European power grid company shows that a simple visual inspection made by an operator in a helicopter can already have an approximate cost of 40€ per kilometre. The locations and frequency of clear-cutting operations are, in addition, decided based on limited data. Yet, several data sources are available and can be leveraged for risk-informed decisions, such as satellite images, generalized use of point clouds, open-access vegetation-related databases, etc.

The use of these data sources in power grid management is suggested in (Pacevicius et al., 2018). In order to develop an effective decision-support, the data use and technology development can be shaped considering the type and format of the data that is required by the operators for risk-informed decisions.

This paper presents a framework for a risk-based decision-support for operators managing power grids under vegetation hazard. The decision-support is data-based, and benefits from current technological developments. The framework includes the assessment of vulnerable areas and the possible consequences in case of vegetation hazards. The combination of vulnerability and consequence levels results in a risk-ranking of areas that should be visited for clear-cutting. Further development and application of the framework can result in cost-effective and efficient preventive maintenance, reducing outages and other consequences.

This paper is structured as follows: Section 2 presents an overview on power grids operations, followed by a discussion on data driven solutions for power grids management in Section 3. Section 4 presents the framework for decision-support. Finally, concluding thoughts are presented in Section 5.

2. Power grids operation

Power grids are managed by either Transmission System Operators (TSO) or Distribution System Operators (DSO). These are the operational and regulatory bodies that share the responsibility of properly installing, managing and maintaining the power grids. Despite the long experience these operators have in the field, they continue to face major disturbances all over the world, with sometimes particularly damageable consequences (Alhelou et al., 2019). This is particularly true with exceptional meteorological events. For instance, hurricanes Irene (2011) and Sandy (2012) resulted in 6,69 million and 8,66 million people without power respectively (United States Department of Energy, 2013). More recently, over 6 million people lost power in 2017 due to hurricane Irma (NERC, 2018).

The challenges concerning power grid management are not restricted to abovementioned large impact hazards. Power grids' intrinsic characteristics also pose daily challenges. For instance, the network dimension implies a challenging configuration of large and complex systems leading to dynamics hardly forecastable. This favours the occurrence of unpredictable cascading events, which can have large consequences if occurring on a favourable terrain. In addition, the broad geographical distribution of the power grid mathematically increases the exposure of the infrastructures to external threats. This can make the surveillance, control and management of the grid particularly complicated, especially in remote areas.

Power grids' intrinsic features impose notable difficulties concerning execution of management related tasks, such as maintenance operations and resource optimization. For example, the size of the power grid directly impacts the way inspection and maintenance tasks are scheduled and executed. Those can be time consuming (some inspections tasks are planned on a 10-year basis calendar) and risky, especially in mountainous regions such as in Norway.

The importance of power grids and the nature of the threats to which they are exposed call thus for continuous application and improvement of proper risk management methods. State-of-the-art methods suggest the use of Dynamic Risk Analyses (DRA) for fulfilling this task, which enable a better exploitation of information over time for an improved understanding of the true risk level (Villa et al., 2016).

The potential benefits of using DRA for power grids management are strengthened given the increasing technology for collecting and processing environmental and meteorological data, as well as information concerning users, grids' physical conditions, and others. Next section provides an overview of the available data and its potential use, as well as the related challenges.

3. Overview of potential data driven solutions for power grid management

Data-driven dynamic risk management methods enable to consider changes in key variables as new information is made available. Static approaches, on the other hand, make use of pre-defined plans for scheduling inspection and maintenance tasks. DRA approaches are data driven methods relying on a capacity to consider both (1) real-time data updates for variables already at scope and (2) real-time variable updating, as previously identified hazards may change in terms of potential impact and/or new hazards may emerge. Variable updating implies both integrating new variables if those have been proven to contribute to the risk depiction and/or ignore variables which have become irrelevant for the analysis in process. Proper data management (selection, collection, process and update) is thus a cornerstone for the existence of DRA. The implementation of DRA methods is strongly empowered by the general proliferation of interconnected IT-based technologies, commonly referred to as the "internet of things".

In the field of power grids, the broader use of interconnected devices and the capacity to access more data sources has led to the emergence and extension of "smart grid" configurations, principally over the two last decades. Furthermore, power grids have gained in connectivity since the implementation of the first SCADA (Supervisory Control And Data Acquisition) systems, and management of large-scale infrastructures has been improved over the years thanks to the integration of new technologies.

3.1 Possible data sources

The first cluster of data sources to consider for the evaluation of vegetation-related outages in the power grids is common to all type of outages and composed of the systems enabling to observe the power flow variations. Based on sudden interruptions in the power delivery, operators will be informed of the occurrence of an outage and start to investigate its causes, consequences and location. Depending on those results, they are able to look for an alternative solution in order to return as quickly as possible to initial service levels via rerouting of the power delivery. SCADA systems support those type of operations and are integrated into the management of power grids since multiple decades already. The granularity level of the data that is nowadays accessible has however strongly increased since the implementation of the first SCADA devices, moving from on overview on region level, towards the possibility of obtaining an understanding of local substation and finally the ability to observe power variations on individual building level thanks to the generalized implementation of Advanced Metering Systems (AMS), also called "Smart Meters".

Operators also use different methods to acquire information regarding vegetation. The most common approaches consist in visual inspection such as foot patrols, helicopters, and drones (Nguyen et al, 2018). Maintenance reports summarize the main conclusions of these inspections. Additionally, Light Detection And Ranging (LiDAR)-based point clouds are frequently used to get precise distance measurement between power grid infrastructures and foreign objects such as vegetation. This technique is however relatively costly, limiting its use in practice.

A benchmark of the technologies and existing solutions for supporting vegetation-related risk analysis was explored by (Pacevicius et al., 2018). The most relevant results for this paper can be summarized as follows:

- Satellite images: the multiplication of image providers has considerably increased over the last years, leading to both a strong increase of performances (higher resolution images for different bands can be obtained more frequently) and a strong decrease in costs (down to a few dozens of euros/square kilometre, depending on technology and resolution).
- Weather: meteorological models have gained in accuracy over the last decades, enabling to make local estimations of the wind exposition, exposition to precipitations and temperature variations.
- Topography: Digital Terrain Models (DTM), more and more accessible, enable to obtain a description of the raw surface on which power grids are installed, enabling to estimate the role of the terrain orientation (i.e., slope) in the stability of trees.
- Referencing of species: some national registries report the mostly present species per area, enabling to better estimate the average stability of that part of the forest in the area.

Combining the different data sources mentioned, with the grid topology, the database of supplied customers and related levels of importance (e.g., individual housing, hospital, data centre, aluminium factory, etc.), there is here a strong potential to affine the estimation of both the probability and the consequences of a outages caused by vegetation.

3.2 Related challenges

In spite of recent improvements, the implementation of smart grid technologies and infrastructures still face many remaining challenges (Pacevicius et al., 2018). These can be illustrated by data gathering: several advances have been done on the hardware side, while merging and processing data from different data sources is still challenging. Indeed, many sensors have been developed and installed into the infrastructure, leading to the possibility to acquire a large quantity of data. Intra-disciplinary and highly specialized research studies have also enabled progresses in a plurality of fields (e.g., weather forecasts, physics of electricity, computer vision, satellite data analysis). Yet, those advances have mostly been done in silos. The added value of merging inter-disciplinary knowledge remains difficult to be acquired because of a lack of method and recommendations enabling these combinations. This is partially explained due to the challenges of processing heterogeneous data sets (Pacevicius et al., 2018) and due to the complexity resulting from the combination of fields of expertise.

An additional challenge for effective use of data, results from the methods used for its collection. For example, the processing of the information gathered during inspections remains often slow, local and complicated. This is mainly due to the use of outdated and paper-based methods in the

treatment of maintenance reports. In cases more advanced methods for data collection are used, such as using tablets for filling maintenance reports, a lack of proper procedure hinders the use of the data in an automatic and efficient way. Once saved, digital maintenance reports remain usually exploited by other operators in a manual way, similarly to paper-based reports. Transmission of the information may thus, in the best-case scenario, be facilitated from one device to another (e.g., one tablet to another), but its exploitation remains mostly manual and rarely efficiently automated. This illustrates the gap between the ever-increasing data availability and the techniques enabling to exploit them.
Making a proper use of the generated data in order to be aware of real-time of situation evolution (and hence, make risk informed decisions) is thus a challenging task. Automating transmission and processing of data to provide high quality information to decisionmakers requires:

- a good business/ scenario understanding in order to know which information is looked for,
- the implementation of hardware enabling the acquisition of good quality and relevant quantities of data,
- the existence of field-specific expertise to pre-process acquired data,
- the understanding of inter-disciplinary dependencies,
- the knowledge to merge resulting information, and
- the capacity to know which type of decision can be taken in the different identified scenarios.

Those elements correspond to the building blocks of a system architecture enabling the sustainable development of DRA methods. Recent study by (Pacevicius et al., 2020) stresses the need of the development of feedback loops methods for enabling the consideration and integration of new observations made by the systems and/or the operators. Above all, the architecture must be developed in such a way that efficient information use can be made possible by power-grid operators for improved decision making. It must thus be profitably integrated in their daily tasks, considering their expectations and the challenges they face.

4. Integrating data driven solutions for optimized power grids decision support

Power grids operators make decisions on preventive and corrective maintenance on a daily basis. Today, these decisions are based on limited information. This is especially true because of the latency sometimes resulting from slowly transmitted information in current day-to-day operations, where some asset-related databases are only manually updated after several years (Pacevicius et al., 2018).
When more detailed information is necessary, such as the state of vegetation close to a power line, in-loco data must be acquired. These operations can be highly costly and error prone.
The use of the data and technology described in the previous section can improve the efficiency of decisions on preventive maintenance. The level of vulnerability of a power line and the possible consequences in case of an outage generated by vegetation hazard can provide the operators with priority areas for observation and clear-cutting. Those, in turn, can highly improve resource allocation while avoiding outages and more severe consequences.
This section presents a framework for data-driven decision-support for power grids operators. The scope of the framework is on vegetation hazard and preventive maintenance. The framework can be expanded for other hazards types. The problem statement is described in Section 4.1, followed by an analysis of the operators' decisions in Section 4.2. These are integrated with data-driven technologies in Section 4.3 for the decision-support framework.

4.1 Scenario description: vegetation hazard

Outages due to vegetation are mostly due to branches/trees falling on the infrastructures or due to vegetation growing under/on/in the installations, generally leading to short circuits and/or damaging of infrastructures. Vegetation-related outages represent a cost to the grid operator, in terms on non-delivered power to its different customers. Financially, it also implies having to send teams on the ground to clean the affected area and replace the parts of the power lines that have been damaged during the event. Sending teams solving such situations in not without significance and does sometimes lead to tragical consequences (Line, 2016). In addition, disturbances may lead to reputation loss. Above all, vegetation hazard can lead to wildfires. In case the location and environmental conditions are favourable, these can quickly spread and have severe outcomes.
Several variables can indicate the vulnerability of a power line to vegetation hazard. Some are related to the trees, such as their size, species, health and shape, and their proximity to the power line. Additionally, external parameters such as wind exposition, exposition to precipitations, temperature variations, and topography, are known to affect the stability of trees and should as such be studied for a proper vegetation-related risk analysis.

4.2 Power grids' operation and vegetation hazard

Power grid operators can be sectorized in different groups, depending on their role in the management of the network. Although operators' roles and responsibilities can be changing among different organizations, a common distinction can be described as following:

(1) Control-room operators: those operators oversee real-time management of the power grid and focus on a short-term horizon. They are responsible for restoring the initial service levels as fast as possible after an outage has occurred, among other tasks.

(2) Maintenance operators: They are responsible for the management of inspections & maintenance operations in order to avoid the occurrence of outages and potentially reduce their consequences if those would occur. As such, they work on a short- to middle-term horizon.

(3) Planning operators: They are responsible for future extensions or rerouting of the power lines when new customers integrate the network or when alternatives for existing routes are required.

Although the distinction above may not be the same among all organizations, this paper adopts it for increasing clarity and comprehension in this case study.

Current operations relative to vegetation management are characterized by two main limiting factors:

- Maintenance operator schedule inspections and preventive vegetation cleaning operations on a calendar basis rather than on real needs;
- Control-room operators are aware of an incident only after it has happened.

A risk-based decision support can give grid operators the possibility to optimize the currently applied decision-making. With an indication of vulnerable areas and their risk levels, operators can prioritize crucial operations and send teams for clear-cutting the area where required before any damage is reported, postponing in parallel non-urgent inspection missions. In addition, they will be able to spot areas more likely to be affected by vegetation-related outages when disturbances are observed, increasing thus the probability to gain precious minutes in the power grid restauration.

The use of data and related technology for decision-support is generally performed as in Figure 1. The available data-driven solutions are assessed based on the possible information they can generate. This information, in turn, is assessed based on its capacity to support operators' possible decisions. Yet, the development of the decision-support can follow a different path, as we suggest here and as is illustrated in Figure 2. The operators' possible decisions are initially defined in view of the system's needs (i.e., vegetation management in the present use-case). The information required for the possible decisions is then further identified. The necessary information for decision making is finally used to shape the development and exploitation of data-driven solutions. Note that the present process is a high-level approach brought forward to illustrate the need of shaping data driven solutions by firstly considering operators' needs. Development of data-driven solutions are however also known to be shaped by hardware and software limitations, as well as by the possibilities to access relevant databases.

Figure 1: Use of data and related technology for decision-support

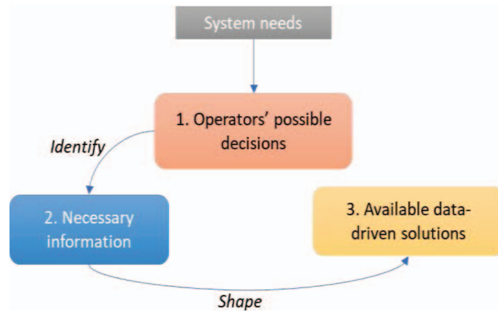

Figure 2: Approach for development of data-driven decision support shaped by operators' needs

The first step into developing an effective decision support is thus to evaluate the operators' possible decisions when managing vegetation hazard. Three possible decisions are considered:

(1) Send a team for observation

In case the information provided by the system has a high level of uncertainty, operators can send observation teams to assess vegetation level and reduce the uncertainty. The system should be designed to accommodate the output of this operation and use it to update the level of vulnerability of the grid.

(2) Send a team to clear-cut the area

The operators should receive enough information to decide when it is necessary to send a team to clear-cut the area, i.e., perform preventive maintenance. This decision can be made considering the risk level provided by the system.

(3) Redirect flow/shut down grid sections

This decision is to be made in extreme situations, in which the operator believes required maintenance may not be done in time and the potential consequences resulting from the reported top events may be too severe.

A next step is to evaluate the necessary information for the operators to make the correct decisions. The decision of sending a team for observation operations is based on the reported exposition level of the grid to the vegetation-related hazards, as well as on the uncertainty degree of this estimation.

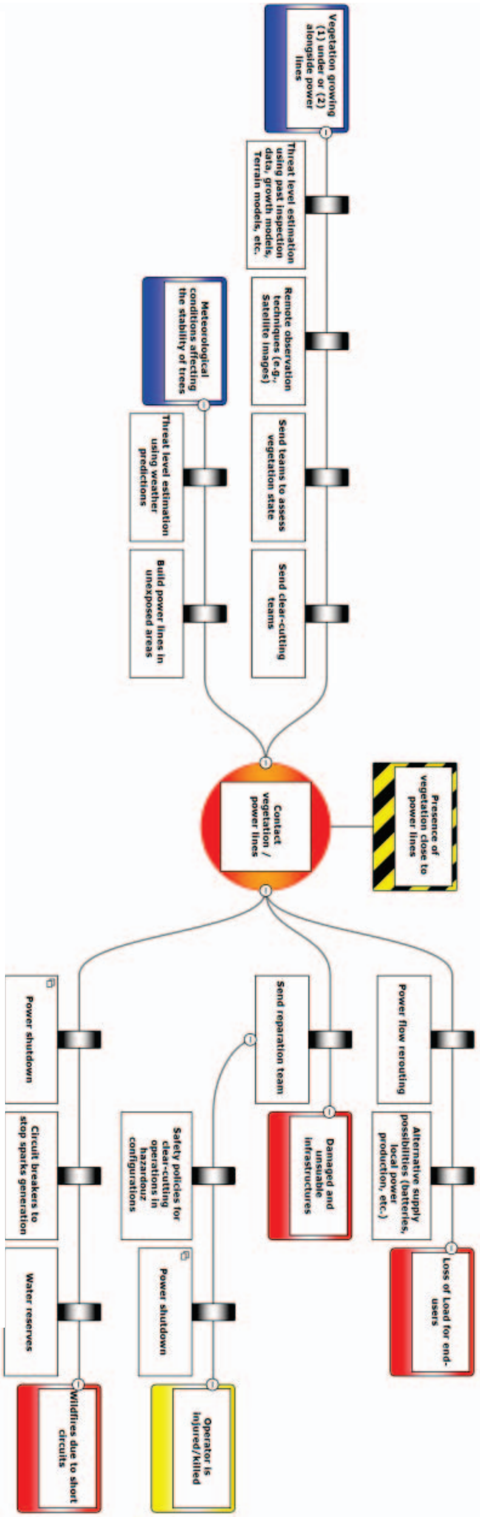

Figure 3: Bowtie diagram describing the most relevant causes & consequences of vegetation coming in contact with power lines

A decision to sending a team for clear-cutting the area can moreover be taken when consequences of potential outages are furthermore added to the present analysis. This is particularly important for resources allocation and actions prioritizing, especially in case two or more vulnerable spots are reported. Finally, the more extreme decision of redirecting power flows and/or shutting down power, relies on the previously mentioned sources of information, plus the overview on the available and missing resources in terms of personnel, material, power budget, time, etc.

A partial bowtie diagram addressing the main causes & consequences relative to the vegetation-related hazard is available in figure 3. It is based on (Pacevicius et al., 2018) and focuses on the most relevant dimensions in the present study. It is however to be mentioned that additional elements (i.e., barriers, threats and consequences) may be added, depending on the case study. The present diagram - as well as the data sources used to exploit it - can furthermore be used to shape the development of technology and data-driven solutions, as further explored in the following section.

4.3 Decision support framework

Risk can be defined in multiple ways, depending on the fields to which it is applied, the methods it is integrated in or the authors it is used by (Aven, 2012). We adopt one of the most common definition, provided by Kaplan and Garrick (Kaplan and Garrick, 1981), in which *risk* is as a triplet of a *scenario* (s) happening, as well as the *probability* (P) and the *consequences* (C) of this scenario occurring. Furthermore, due to its relevance to the present work, we add the variable of *uncertainty*. The risk level to be used by the operators for decision support is thus a function of:

$R=f(s,P,C,u)$

In the scenario of vegetation hazard, the probability refers to the probability that the vegetation under or around the power line affects the grid. The probability will indicate the vulnerability level of the line. This probability is a function of the vegetation specificities, its proximity to the power lines, the environmental conditions and the local shape of the terrain:

P=f(vegetation specificities, distances to the lines, environmental conditions, terrain)

The consequence of the event refers to the possible outcomes in case vegetation affects the line, as described in figure 3. The consequences are estimated based on the impact the realization of the different scenarios have on the involved assets. By converting big/important costumers (hospitals, large industries, etc.) into an equivalent "number of individual households" in terms of importance (e.g. 1 hospital ≈ 500 individual households), one can quantify the impact relative to non-delivered power in terms of "non-supplied end-users". Focusing on wildfire, we can integrate a binary variable characterizing each Are in the direct surrounding of the lines as being prone to wildfire (1) or not (0). Finally, one should also integrate infrastructure costs related to corrective maintenance. In the present case, the consequences can thus be expressed as:

C=f(∑ [non-supplied end-users], ∑ [Are prone to wildfires], infrastructure costs)

The uncertainty, in turn, refers to the uncertainty associated to the generated probabilities and consequences.

The way the different data sources can be combined to obtain the mentioned risk metrics and eventually support power grid operators in the decision they take is illustrated in Figure 44. A relevant use-case based on ongoing work[1] can illustrate the framework as following:

Probability of outage:

- o Using Satellite images and point clouds, one can automatically detect the presence, size and proximity of trees in the surrounding of power lines.
- o Adding topographical data and vegetation categorization, one can assess the importance of relatively static influencing factors.
- o Completing the analyses with weather-related and power flow-related time-series, one can obtain a dynamic estimation of the probability of an outage happening.

Consequence of Outage:

- o Equivalent number of non-supplied end-users,
- o Quantity of energy not provided,
- o Values of infrastructures,
- o Number of Ares prone to wildfires,

Uncertainty:

- o Based on the uncertainty related to the data sources and the process chosen to combine their output, one can eventually estimate the uncertainty level related to both the probability of outage estimation and the consequence of outage estimation

5. Discussion and Concluding Thoughts

The present paper illustrates the added value of integrating data-driven solutions into decision-support for management of infrastructures under risk. For that it takes the example of power grid management and focuses more especially on the evaluation of the threat originating from the presence of vegetation close to power grid infrastructures. It illustrates how relevant data sources should be manipulated in such a way that decision makers can optimize their judgements and the management of their resources, as well in a pre-event resilience perspective as from a post-event restauration point of view. How the risk reduction actions are executed and the way the resulting information is integrated into the new cycle of risk assessment is however an additional

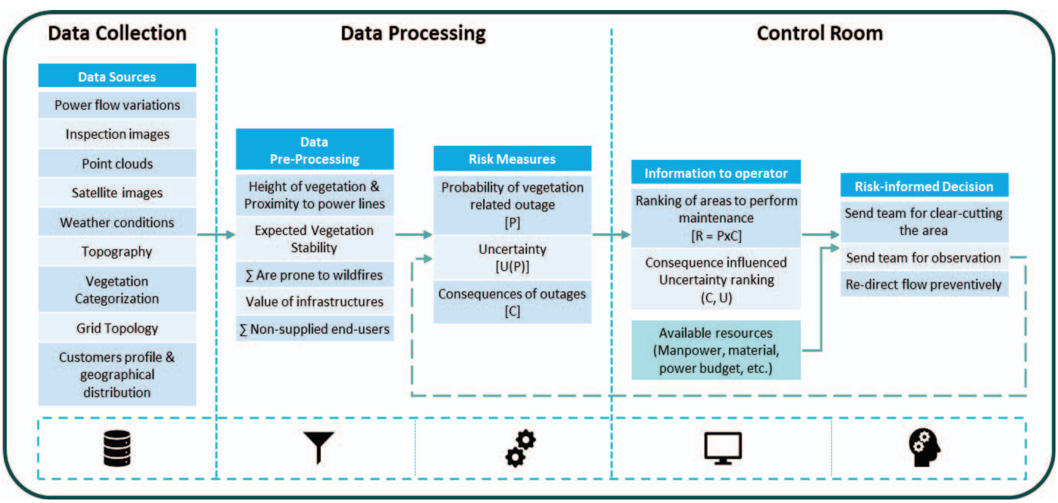

Figure 4: Framework for data-driven decision support for power grid operators for management of vegetation hazards

[1] https://business.esa.int/projects/grideyes

dimension that needs to be correctly executed in order to ensure optimal risk management of the infrastructure over time. While continuing the development of the presented framework and reinforcing the steps already suggested, there is thus a need for further studies in order to assess and quantify the role of human factors on the final true risk level, and evaluate how to reinforce the feedbacks of the operators in the developed system.

A data-driven and efficient decision-support as suggested by the framework can lead to correct decisions by the operators regarding maintenance scheduling and prioritizing. Yet, operators' decision is also influenced by internal factors (e.g. distraction, fatigue) and external and organizational factors (e.g. human-system interface quality, procedures, workplace adequacy). Those must also be considered when developing a system that aims to reduce human error.

With the description done in the present work, we focused on the risk generated by vegetation in power grids. Although vegetation is often the final element in the causal chain, the causes of events including vegetation are often plural and include, for example, wind or snow. Those factors taken independently can also be at the origin of outages, making them similarly items to assess in order to quantify their influence on the final holistic risk image. As such, further work will also need to deepen and highlight the interactions between variables in order to properly quantity the influence of each dimension on the true risk value.

This paper highlights the benefits of interconnected IT-based technologies for the management of infrastructures under risk, supporting that way the generalization of data-driven methods for risk analyses and calling thus also for a generalization of the use of dynamic risk analyses. The extended access to a large number of data sources can however also come with additional complications and lead to potential sources of inefficiency. As such, this paper is also an occasion to recall the need for risk assessment methods to be both model-based and data-driven.

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