Uncertainties in Managing Atmospheric Icing on Power Lines

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Icing affects the infrastructure dramatically, especially in the cold region. Therefore, applying effective ice disaster management (IDM) to provide a systematic approach to dealing with atmospheric icing on power lines is essential. It includes preparedness, response, recovery, learning, risk assessment, and prevention. Integral to this management is the accurate prediction and modeling of icing, which is inherently complex and fraught with uncertainties. However, a significant gap exists in our understanding of these uncertainties, particularly due to climate change causing more complexity in uncertainties. This article tried to bridge this gap by providing a comprehensive overview of the uncertainties associated with atmospheric icing on power lines. By highlighting these uncertainties, it emphasizes the need for their precise consideration in icing management efforts. Furthermore, a range of methods for assessing and quantifying these uncertainties is proposed. Using these methods, decision-makers and researchers can gain valuable insights into the uncertainties inherent in atmospheric icing and make informed choices when devising mitigation strategies.

Keywords: Atmospheric Icing, Disaster Management, Power Line, Risk Assessment, Uncertainty.

1. **Introduction**

Atmospheric icing on power lines holds immense importance due to its potential to severely impact power infrastructure, public safety, economies, and the environment. For instance, in 1998 a large region in eastern Canada and the northeastern United States, an ice storm caused widespread power outages, damage to infrastructure, and loss of lives (Rountree 2005).

This phenomenon demands a comprehensive understanding and effective management strategies to mitigate its adverse effects, particularly in the Arctic region, a frontier with a scattered population and vulnerable power lines. Operation and maintenance of power lines in this harsh and remote area are very high. Moreover, extreme weather, such as atmospheric icing and freezing rain, can greatly affect power transmission lines in the Arctic regions. Such accidents may lead to disaster in a big area. It can cause lines loaded and lead transmission lines to break, the collapse of towers, flashovers, and other serious problems, which make dramatic economic losses (Hong, Tianzheng, and Min 2016). For example, weather-related power transmission lines in the United States are estimated at around 40 billion USD annually (Abdelmalak, Thapa, and Benidris 2021).

To reduce the consequences of such a disaster, it is essential to develop effective ice disaster management (IDM) in the early phase of design and then update it as the influence factors such as the population, industrial activity in the area, and equipment age. Disaster management generally has different steps, including Risk Assessment, Prevention, Preparedness, Response, recovery, and Learning (Christer 2017). Rød et al. developed a framework for risk and resilience assessment to enhance the performance and safety of infrastructures in the Arctic. Figure 1 presents the parallel and interlinked infrastructure risk and resilience management framework (Rød 2020).

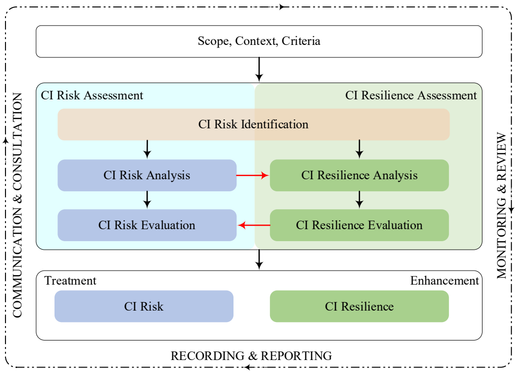

Figure 1. Framework for Risk and resilience assessment (Rød 2020)

Such studies and frameworks rely significantly on data such as weather-related parameters, repair data, failure data, human behavior, frequency of icing, and other relevant information in the specific region, which was gathered over some decades (Seleznev, Vlasenko, and Prokhorova 2023; Panahi, Afenyo, and Ng 2022). These data help to create a suitable model and predict the disaster to make an effective risk assessment, prevention, and preparedness. Nevertheless, these data are associated with different types of uncertainties. These uncertainties include ontological, epistemic, aleatoric, and stochastic uncertainty. For example, climate change leads us to face significant variations in the pattern of natural disasters and weather-related parameters (Sun et al. 2022) that lead us to different uncertainties. Contribution of climate change, societies face a new complex environment that needs different strategies, particularly related to different uncertainties.

Regarding an ice disaster, for example, the effect of climate change on the probability and consequence of icing needs to be addressed as ontological or epistemic uncertainty. However, the available studies mostly focus on the uncertainty associated with the ice accretion model, which will provide the data for risk assessment as one step of IDM. They mostly deal with aleatoric uncertainty, where the probability and severity of a phenomenon are known, while climate change is prone to different types of uncertainties, not only aleatoric. Hence, uncertainties associated with the IDM process must be better studied. Furthermore, the other issue is regarded as limited to assessing the uncertainties. Hence this paper aims to review and propose a holistic view of the different sources of uncertainties with may affect IDM related to atmospheric icing in the Arctic.

This paper analyzed the relevant research on a different part of the disaster management cycle regarding ice disasters. It investigated gaps in uncertainties analysis in each step of IDM. Then considering the uncertainty concept introduced a framework to define and describe a holistic approach to uncertainty analysis.

The rest of the paper is organized as follows. Section 2 discusses different challenges of icing in power lines. In section three, uncertainties in power line icing are considered. Section 4 includes management of the uncertainties, and finally, section 5 concludes the paper.

2. Atmospheric icing and power line components

Mechanical design of electrical power systems in the complex arctic operational condition is challenging. For an effective design, all climatic loads on overhead power-line conductors induced by atmospheric icing, wind, or ice shedding must be addressed early in the design phase. After that, an effective de-icing or anti-icing approach must also be considered (Lifu He, Luo, and Zhou 2021). Considering the unacceptable consequences of failure in the power line system, and to have the safe operation of power grids and prevent huge economic losses, ice accretion rate, ice type, and its mechanical characteristics on specific locations of transmission lines must be predicted effectively (J. Liu, Xue, et al. 2019).

Different types of icing do not have the same effect on the power line distribution. Table 1 shows a simple risk rating for atmospheric icing on different power line components developed using expert judgment. The score for the criticality of each power line component is a number between 1-10. The score for the criticality of Snow, Glaze, Rime, Frost, and Sleet are 10, 9, 8, 3, and 1, respectively. For example, the risk rating for the impact of snow on the transmission pole will be 100. Figure 3 shows different parts of power the power line used in Table 1.

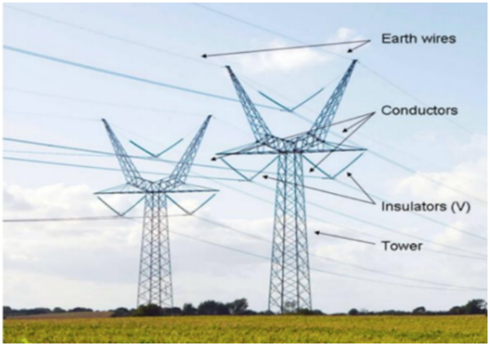

Figure 3. Over Head Power Line Components (Sørensen, Holbøll, and Mikkelsen 2010)

According to the findings presented in Table 1, various components of power lines exhibit distinct structures that offer differing resistance to icing conditions. It is important to note that most power line components are highly susceptible to different forms of atmospheric icing, as indicated by the red section. Consequently, many uncertainties arise due to the potential occurrence of diverse scenarios. Each type of component has the potential to create unique circumstances that can trigger a chain of events, ultimately resulting in a catastrophic outcome. In simpler terms, this complexity creates a highly uncertain environment. Also, many parameters play a role in the intensity of ice accretion, such as the liquid water flux in the cloud, temperature, wind speed, stability, depth of cloud, height above the cloud base, and distance from the coastline (Farzaneh 2008). Figure 4 shows the interdependence of these parameters, as this figure shows that ice accretion is a complex phenomenon involving different factors. A more accurate ice accretion model must be used to estimate the associated risk with a different type of icing.

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Table 1. Risk rating for different components of lines and atmospheric icing

Components of power line	Criticality	Type of atmospheric icing and their criticality				
		Snow	Glaze	Rime	Frost	Sleet
		10	9	8	3	1
Transmission pole	10	100	90	80	30	10
Conductor	10	100	90	80	30	10
Insulator	10	100	90	80	30	10
Cross arm	10	100	90	80	30	10
Jumper	9	90	81	72	27	9
Earth wire	7	70	63	56	21	7
Spacer	6	60	54	48	18	6
Vibration Damper	6	60	54	48	18	6
Corona Ring	5	50	45	40	15	5
Power line marker	4	40	36	32	12	4

In general, there are three main types of ice prediction models: physical models, statistical models, and intelligent prediction models. Physical models have some limitations because the required factors should be obtained in real conditions, which is not always available. (Ma et al. 2022).

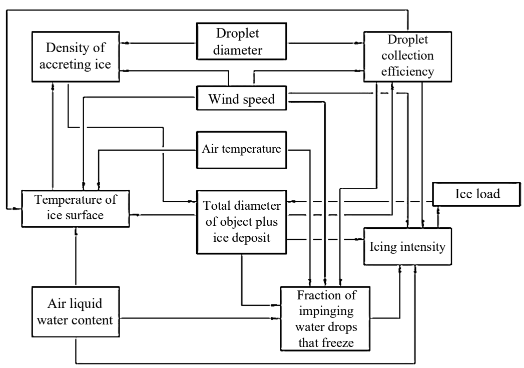

Figure 4. Interdependence of various factors of the icing process caused by water droplets (ISO-12494)

The statistical models rely on a large amount of historical data, which is the most critical part. For example, the ice accretion on the wire in a power line can be calculated by (Zhao, An, and Zhao 2019):

$$\delta_1 - \frac{E{g_1}^2 l^2}{24\delta_1^2} = \delta_2 - \frac{E{g_2}^2 l^2}{24\delta_2^2} \quad (1)$$

where the ambient temperature is t, the conductor load ratio is g_1, and the lowest point stress is δ_1; when the conductor load ratio becomes g_2, the lowest point stress is δ_2, l is the horizontal span.

Intelligent prediction models, such as machine learning models, numerical weather prediction models, artificial neural networks, and decision trees, use different data types (such as temperature, humidity, and wind speed) to predict ice accumulation. These models can be trained on historical weather data and other environmental factors to predict the likelihood of icing conditions. Artificial neural networks (Luo et al. 2012) can model the complex relationships between environmental factors and icing situations. Using real-time weather data, these models can predict icing conditions (Zheng and Liu 2014). Compared to neural networks, support vector machine models (Xiao-min et al. 2016) require fewer samples but have some practical issues that must be addressed (Ma et al. 2022). Different variations of support vector machine models have been developed, such as the least squares support vector machine (X. Huang et al. 2014), wavelet support vector machine (L. Zhang, Zhou, and Jiao 2004), and weighted support vector machine regression (Xu et al. 2015).

However, all these models require meteorological and geographic data, which can take a long time to gather and cover large areas, resulting in less accurate predictions. To improve the accuracy and reliability of predictions, gathering more comprehensive data over longer periods and across wider regions is necessary.

A reliable atmospheric icing model is crucial for IDM, especially in predicting power line failure due to ice accumulation and planning preventative measures such as de-icing or structural reinforcement (Ma et al. 2022). However, as mentioned earlier, it is important to consider all sources of uncertainties associated with each model when selecting a specific one to use.

3. Uncertainty and Atmospheric Icing on Power Line

Uncertainty refers to insufficient information or knowledge regarding a particular event, circumstance, or hypothesis (Aven 2010). In the presence of uncertainty, when there is a lack of data, inadequate models, or unexpected events, making precise predictions may be impossible. Such situations make prevention a challenging process. In broad classification, uncertainties can be classified into two main categories: objective and subjective. Objective uncertainty corresponds to the "variability" that emerges from the stochastic characteristic of an environment, non-homogeneity of the materials, time drifts, space variations, or other kinds of differences among components or individuals. And subjective uncertainty is the uncertainty that comes from scientific ignorance, uncertainty in measurement, the impossibility of confirmation or observation, censorship, or other knowledge deficiency (Campos, Neves, and de Souza 2007). Both uncertainties may be incorporated in IDM in the power line. For example, the effect of climate change on the ice accretion on the power line can be considered objective uncertainty, and missing data regarding the failure or repair data of the power line can be considered subjective uncertainty.

These uncertainties may affect the severity and the probability of any accident and the effectiveness of any activities that need to be implemented to reduce the risk of such accidents. Managing uncertainty most of the time needs a mixture of quantitative and qualitative methodologies. Risk analysis and its developed methods and tools are a way to capture such uncertainties. Risk is the effect of uncertainty on objectives (ISO31000 2018), which can be formalized by (Aven 2010):

$$Risk = (A\,C\,U) \quad (2)$$

where A represents the events (initiating events, scenarios), C is the consequences of A, and U is the uncertainty about A and C (will A occur and what will the consequences C be). According to this definition, the uncertainties can be related to A, C, or both. For example, event A can be considered the ice accretion event of more than 20cm on the power line in northern Norway. Examples of C are the blackout time in hours in the area or economic loss due to such a blackout. Under this condition, four situations can arise: known-knowns, known-unknowns, unknown-knowns, and unknown unknowns. Figure 5 depicts the possible uncertainties and their associated defined risks.

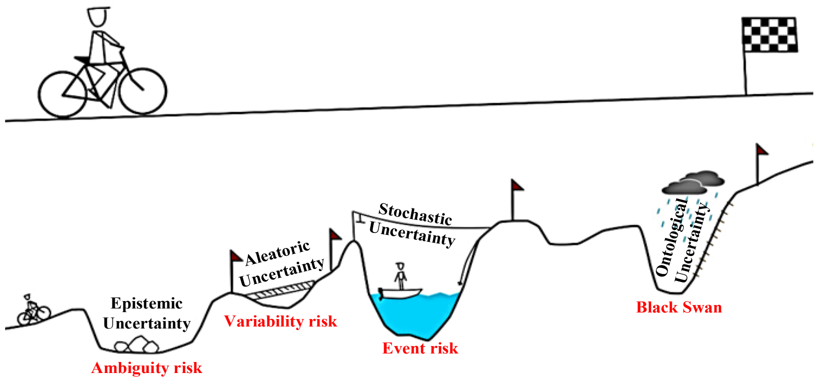

Figure 5. Different types of uncertainties and their representative risk type

Known-known is the case when the probability of A and C, as the consequences of A, are known. This uncertainty is called aleatoric uncertainty. Aleatory uncertainties or inherent uncertainties arise from the randomness and variability of natural phenomena, such as the atmospheric conditions that lead to icing on power lines. Aleatoric uncertainty cannot be eliminated or controlled.

These uncertainties provide a risk for the object of our disaster management, which can be considered variability risks. Some examples of this kind of uncertainty are changes in atmospheric temperature and humidity, wind speed and direction, size and shape of ice crystals on the power lines, rate of ice accumulation, frequency and severity of freezing rain as well as the timing and duration of conditions giving rise to icing on power lines. Here, quantitative risk analysis is used to assess this type of uncertainty.

Known-unknown is when the probability of A is known; however, C, as the consequence of A, is unknown. This can be due to incomplete knowledge, understanding, or information about a system or phenomenon, leading to reducible or epistemic uncertainty. Knowledge gaps or uncertainties in our understanding cause epistemological uncertainties. It is also known as systematic uncertainty; associated risk can be called ambiguity risks. This uncertainty can be addressed through improved knowledge and information. Ambiguity risks can be managed through better knowledge and understanding of icing and its effects.

Unknown-known is when the probability of A is unknown; however, C as the consequence of A is known. It is a discoverable uncertainty, and it is related to event risks and is called stochastic uncertainty. For example, cascading failures and system-wide blackouts resulting from atmospheric icing events can be considered event risks. A systematic investigation and analysis process can help discover and reduce this uncertainty. Regularly monitoring and analyzing power transmission line performance over time and collecting and analyzing historical data on atmospheric icing events lead to addressing this uncertainty. Moreover, scenario analysis effectively assesses the potential impact of different atmospheric icing events.

Unknown-unknown is when the probability of A and C are unknown; rare and unpredictable events cause ontological uncertainty. It refers to uncertainty about the nature of the world and the relationships between different entities and phenomena. While the impacts of atmospheric icing on power lines are well-documented, there is still much to be learned about the specific impacts on different types of power lines and the effects on the larger power grid and local infrastructure. This lack of understanding can lead to ontological uncertainty about the underlying mechanisms that drive the impacts of atmospheric icing and make it difficult to accurately predict the extent and severity of damage or power outages that may result. For example, in the context of atmospheric icing on power lines, ontological uncertainty might refer to the relationships between environmental factors such as temperature, humidity, wind speed, and precipitation and the likelihood and severity of icing on power lines. Ontological uncertainties or black swans are obvious with potential for unexpected or rare events.

Black swan events could occur and cause severe disruptions to a power grid. Although the occurrence of those events is unpredictable, having such strategies can help mitigate the impact of these events on the power grid infrastructure. Developing comprehensive risk management strategies incorporating scenario and contingency planning can address ontological risks. Table 2 shows some sources of these uncertainties.

Table 2. Some examples of different types of uncertainties on power-line

Uncertainty	Example
Known - Knowns (Aleatoric) Variability Risk	Changes in atmospheric temperature and humidity, wind speed and direction, size, and shape of ice crystals on the power lines, rate of ice accumulation, frequency and severity of freezing rain as well as the timing and duration of conditions (Fu, Farzaneh, and Bouchard 2006; Z. Zhang et al. 2023).
Known Unknowns (Epistemic) Ambiguity Risk	Insufficient data on the specific location and conditions and incomplete knowledge of weather patterns (Zarnani et al. 2012; Z. Zhang et al. 2023).
	Lack of understanding about the complex interactions between the atmosphere, power lines, and icing (Fu, Farzaneh, and Bouchard 2006; Z. Zhang et al. 2023).
	The effectiveness of strategies for mitigating the effects of icing due to the conditions and location of the power lines (Hrabovský et al. 2017; Tao et al. 2022).
	The effect of influence factors includes the duration of the icing, the type of power line, and the local infrastructure (Peng et al. 2022; Z. Zhang et al. 2023).
	Response of human operators and maintenance crews to atmospheric icing events (Bao et al. 2018; Haugen et al. 2018).
	The behavior of power lines under icing conditions depends on the type of power line, its age and condition, and the local infrastructure (Y. Huang, Jiang, and Virk 2021; Fan and Jiang 2018; Z. Zhang et al. 2023).
Unknown Knowns (Stochastic) Event Risk	Difficulty in predicting the exact weather conditions in a particular location. Random temperature, humidity, and wind speed variations affect icing (Chen et al. 2021).
	The size and shape of the ice particles, the velocity and direction of the wind, and the surface characteristics of the power lines (Bretterklieber et al. 2016; Zarnani et al. 2012).
Unknown Unknowns (Ontological) Black Swan	Cyber-attacks on the power grid.
	Extreme weather events include major ice storms or severe winds (Solomon 2023).
	Insufficient knowledge about physical processes, the complex interactions between the atmosphere, power lines, and icing (Solangi 2018).
	Lack of knowledge about how power lines behave and respond to different types and amounts of icing (Rossi et al. 2020; Ling He et al. 2022).
	Lack of understanding of the effectiveness of mitigation measures in different types of icing conditions and on different types of power lines (Rønneberg et al. 2019; Mishra et al. 2020).
	The long-term impacts of atmospheric icing on power lines (Neumayer, Bretterklieber, and Flatscher 2018; X. Liu, Chen, et al. 2019).
	Large geomagnetic storms or solar flares may affect atmospheric icing events (Jasiūnas, Lund, and Mikkola 2021).

4. Uncertainty Management and Modeling Approaches for IDM

Figure 6 shows the disaster management cycle for atmospheric icing. As this figure showed, based on the risk assessment result, suitable prevention and pre-crises management should be designed, followed by preparedness, monitoring, and early warning and, in the case of disaster by, response and consequence management, learning, and post-crisis evaluation. This circle shows that an accurate and trustable risk assessment is critical for an effective IDM. Hence, all uncertainty needs to be identified then an accurate model needs to be implemented to capture the identified uncertainties. Another loop is considered in the risk assessment, which includes i) data collection, ii) uncertainty detection, and iii) uncertainty modeling using appropriate models. The first part of the methodology is data collection, where all relevant data, such as humidity, wind aspects, the shape of structures, and all other influencing factors, need to be collected. The aim is to collect the data to represent the upcoming condition in the system's life cycle. Hence, all previous accidents and icing phenomena in the area must be investigated in detail. However, by the effect of climate change, the severity and frequency of phenomena may be affected significantly. Then the collected data is assessed to reveal every kind of uncertainty. Such a process can be named uncertainty detection. After that, based on the type of uncertainty, an appropriate approach needs to be selected to address the identified uncertainties, and finally, the risk evaluation should be formed. This risk evaluation later provides the necessary input for IDM.

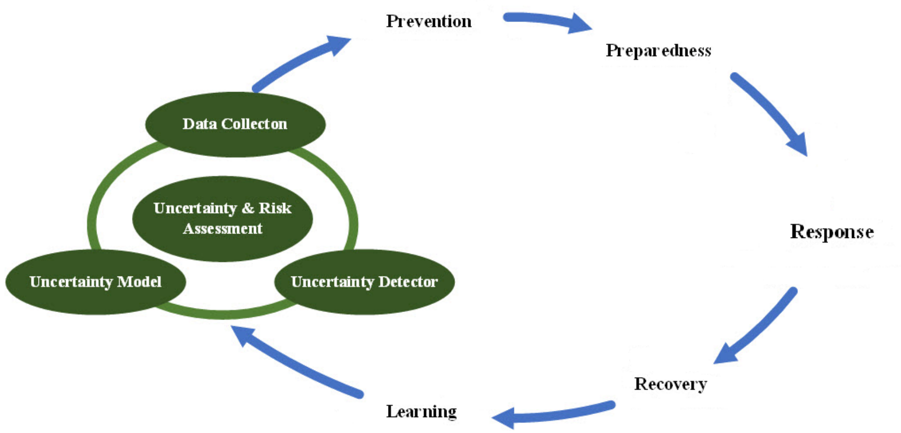

Figure 6. The crisis management cycle(Adapted from (Christer 2017))

Figure 7 shows the relationship between different types of uncertainties. The aim is to change unknown quantities to known quantities using appropriate tools. Statistical methods like Monte Carlo simulation can be used with aleatoric uncertainties (Rezaei et al. 2017; Pohya, Wicke, and Kilian 2022). This process involves generating multiple scenarios that account for the variability of input variables and quantifying the range of potential outcomes and the probability of each outcome occurring. In the presence of epistemic uncertainty, Bayesian inference, exploring and experimenting, prototyping, and benchmarking seeks expert input that can be used to turn the unknown probability into a known quantity (Nagel 2019; Acar et al. 2021). Here, using sensitivity analysis, variables with the greatest impact on the model outcome can be identified. This method prioritizes areas where additional research or data collection may be needed to reduce uncertainty and Bayesian inference to incorporate prior knowledge and update the model as new data becomes available. Discoverable uncertainties or stochastic uncertainties arise when the potential for new knowledge or data becomes available over time (Aven 2010; Doyle et al. 2019). Hence, there is a need for a model that accounts for the inherent randomness and variability in the data. Here the aim is to understand the nature of the phenomena or the relationships between different entities and phenomena. For example, using the Bayesian neural networks process, the consequence of phenomena can be estimated. One way is adding additional parameters to a model that capture the data distribution or using Bayesian neural networks to estimate the uncertainty in the model parameters (Ebrahimi et al. 2019).

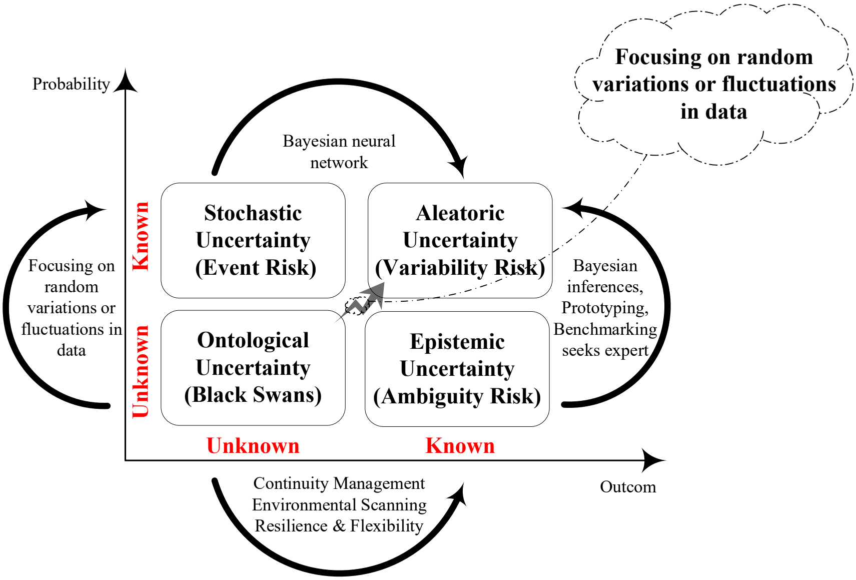

Figure 7: Uncertainties modeling in IDM(Adapted from(Amoroso, Moncada-Paternò-Castello, and Vezzani 2017))

Different methods can be used to handle ontological uncertainty depending on the available data, the circumstances, the knowledge required, and other at-hand information. As Figure 7 shows, there are three different ways to convert unknown to known. It means using probabilistic modeling techniques that explicitly model the uncertainty in the data. For example, scenario analysis can identify the impact of extreme events on the power distribution system. By developing multiple scenarios, it can consider different levels of severity and likelihood for the Black Swan events (Lyon and Popov 2022). Epistemic uncertainty can also be handled by developing effective continuity management, environmental scanning, resilience, and flexibility (Settembre-Blundo et al. 2021).

5. Conclusion

Atmospheric icing on power lines can severely impact power grid infrastructure and cause significant economic and social losses. Managing such risks requires a comprehensive understanding of the uncertainties associated with atmospheric icing and their potential consequences. These uncertainties include aleatory, epistemological, stochastic, and ontological uncertainties. Each type of uncertainty requires a unique approach to management, ranging from quantitative risk analysis to improved knowledge and information, regular monitoring and analysis, and contingency planning. This paper has developed a review of the different approaches that can be used to model different types of uncertainty. Using an effective approach to uncertainty modeling provides a more comprehensive understanding of the hazards associated with atmospheric icing and makes better-informed decisions about mitigation management.

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