Application of Bayesian Networks in distribution system risk management

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Abstract-- **There is an increasing trend towards using the concept of risk assessment as an important tool in distribution system asset management. In an ongoing R&D project (RISK DSAM), the main objective is to investigate how information about risk exposure can improve maintenance and reinvestment decisions in an electrical distribution company. As the popularity of Bayesian Networks (BN) is increasing, the capacity of this methodology is being explored in the project. The paper presents the BN framework and the link to risk based asset management of electrical distribution systems. Examples are included to illustrate the concept as well as a case study evaluating the risk of failure of an overhead line and its dependence of risk influencing factors such as maintenance intensity and environment.**

Index Terms-- **Decision-making, Power distribution maintenance, Power distribution reliability, Risk analysis.**

I. DISTRIBUTION SYSTEM ASSET MANAGEMENT

THERE is an increasing trend towards using the concept of risk assessment as an important tool in distribution system asset management. Asset management is defined in [1] as "Systematic and coordinated activities and practices through which an organization optimally manages its assets, and their associated performance, risks and expenditures over their lifecycle for the purpose of achieving its organizational strategic plan". Over the lifecycle, the distribution system assets and the overall distribution system are subjected to a variety of threats and uncertainties. Risk management is a suitable framework for addressing these challenges.

Risk is defined as a combination of the frequency or probability, of occurrence and the consequence of a specified hazardous event [2]. Risk analysis attempts to answer three fundamental questions [3]:

1. What can go wrong?
2. How likely is it to happen?
3. What are the consequences?

The answer to the first question are the risk scenarios (S), describing the considered threats or hazards, while the answer to the second question is a probability statement regarding the different scenarios (p).

The answer to the third question is a qualitative or quantitative description or evaluation of the consequences (C) of the different scenarios related to individuals, professionals, populations, property or the environment.

Each risk scenario might hence be described by three parameters: <S,p,C> and the total risk picture is given by listing all risk scenarios with their associated probabilities and consequences.

Risk scenarios can include threats or hazards, events and trends. Adverse weather, ageing overhead lines, overloading of components and lack of maintenance, are all examples of risk scenarios that might lead to faults in the system. Hence, understanding component failure mechanisms and how possible barriers (technology, maintenance, protection etc) influence the risk, are of great importance in asset management decision making.

In an ongoing R&D project (RISK DSAM[1]), the main objective is to investigate how information about risk exposure can improve maintenance and reinvestment decisions in a power distribution company. A risk management concept (flowchart) is developed to support the overall working process, and Bayesian Networks are explored in the project as a generic decision support methodology.

The risk management concept and the application of BN are described in the following sections. The paper also includes some small examples and case studies that illustrate the possible application of BN to provide risk relevant parameters.

II. THE RISK DSAM RISK MANAGEMENT CONCEPT

A generic flowchart for risk based distribution system management is given in Fig.1. The concept is largely based on combining distribution system planning concepts used by utilities for years and general risk management concepts described in standards like [1], [2] and[16].

The flowchart consists of four main activities:

1. Risk Study Planning
2. Risk Scenario Identification
3. Risk Modeling, Analysis and Decision Making
4. Risk Communication

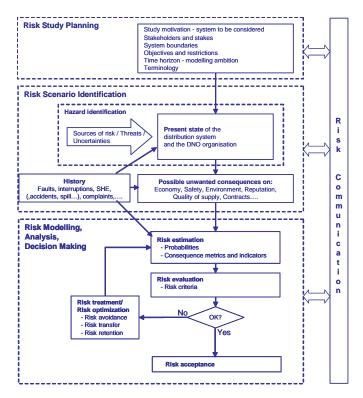The content of each activity is briefly described below. For further details see [4].

Fig. 1. A risk based distribution system management approach

A. Risk Study Planning

This is largely a project planning activity identifying the motivation for the study, identifying the system to be studied, stakeholders involved, objectives and restrictions, and to decide on modeling ambition needed to fulfill the overall goal of the study in a cost effective way.

B. Risk Scenario Identification

To perform risk management, a core activity is to identify the sources of risk, threats and uncertainties that might have harmful consequences. These hazards, when present, influence the distribution system and unwanted events with potential unwanted consequences. The hazard identification is supported by the historic track record and experience of the distribution system operator (DNO) as indicated in Fig.1.

To evaluate the consequence of this unwanted event, it is necessary to identify the impact for all relevant stakeholders.

The consequences might be classified in several ways. In the presented concept the following consequence categories are used:

- Economy: Economic impact for the stakeholders involved
- Safety: Occupational and public safety
- Environment: Pollution, leakage etc.
- Reputation: Branding and goodwill effects
- Quality of supply: Interruptions, voltage quality impact
- Contracts: Violation of contracts, regulations etc.

C. Risk Modeling, Analysis and Decision Making

This main activity comprises:

- The Risk Assessment i.e the overall process of risk analysis and risk evaluation
- The Risk Treatment i.e. the process of selection and implementation of measures to modify risk
- The Risk Acceptance i.e. the decision to accept the estimated risk being within the acceptable risk level for each risk criterion.

D. Risk Communication

Risk communication is a parallel activity supporting the other three activities and serves the purpose of exchanging or sharing of information about risk between decision-makers and other stakeholders.

III. BAYESIAN NETWORKS SUPPORTING THE RISK MANAGEMENT CONCEPT

Bayesian Networks constitute a modeling framework which has found applications in domains like, e.g., software reliability, fault finding systems, and general reliability modeling [5],[7],[9],[10],[11],[12],[13],[15]. As reliability modeling is an important part of the risk management concept, it is of interest to test the usefulness of BNs in distribution system risk management. BNs are more flexible than the traditional Fault Tree concept both in terms of modeling features and in the calculations scheme. BNs can model more complicated relationships between variables and do not require Boolean variables, but can support several variable types. BNs offer among others a compact presentation of the interactions in a stochastic system by visualizing system state variables and their dependencies.

More specifically, the qualitative part of a BN consists of a, a directed acyclic graph where the nodes mirror the random variables, and the edges of the graph represents the conditional dependence between variables. In a risk management context the sources of risk, the consequences, and the threats, all are random variables which might to some degree be dependent of each other.

Bayesian Networks can be used to model and give decision support for large parts of distribution system asset management given in Fig.1. An example is given in Fig. 2:
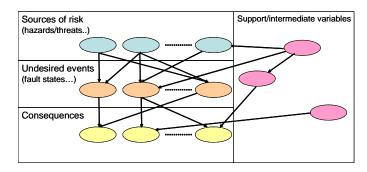

Fig. 2. Risk analysis modeled as a Bayesian Network

The oval shapes in the figure represent state variables and the arrows the causal relationships. The layers in the graph structure the variables in four main classes: 1) sources of risk variables used to describe hazards and threats for a component, group of components or a system; 2) unwanted events variables; 3) consequence variables describing possible unwanted effects of the risk scenarios; and 4) intermediate or support variables not directly fitting into the three other classes.

Bayesian Networks are further described in the following section.

IV. BAYESIAN NETWORKS

Bayesian Networks (BN) originated in the field of Artificial Intelligence, where it was used as a robust and efficient framework for reasoning with uncertain knowledge. BN constitute a modeling framework which is particularly easy to use in interaction with domain experts. A BN consists of two main parts:

- A qualitative part – a directed acyclic graph
- A quantitative part – a set of conditional probability functions

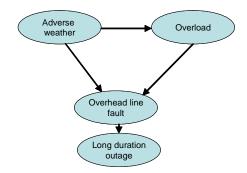Fig.3 gives an example of a small BN:

Fig. 3. Risk of overhead line outage. Example of a Bayesian Belief Network

The BN model in Fig. 3 consists of four nodes which are explained below:

1. {Adverse weather} – a state variable giving the probability of adverse weather in the overhead line surroundings (snow, strong wind etc.)
2. {Overload} – a state variable giving the probability of current overload with respect to the ampacity of the overhead line.
3. {Overhead line fault} – a state variable giving the probability of an overhead line fault.
4. {Long duration outage} – a state variable giving the probability of a long duration outage resulting from the overhead line fault.

The arrows in the diagram represent dependencies between nodes – and can be interpreted as causal relationships. Hence the probability of an overhead line fault is dependent of the

two parent states: {Adverse weather} and {Overload}. (The example also indicates a causal relationship or correlation between {Adverse weather} and {Overload} which might be due to the fact that when adverse weather such as snow occurs, the load increases due to increased need for space heating, increasing the probability of line overload.

The parents of any variable X_i is denoted: $pa\{X_i\}$, e.g.:

$pa\{$Overhead line fault$\} = \{$Adverse weather, Overload$\}$

The arrows in the graph represent the assertion that a variable is conditionally independent of its non-descendants given its parents in the graph. Hence, {Long duration outage} is conditionally independent of the variables {Adverse weather} and {Overload} given the variable {Overhead line fault}.

The underlying assumptions of conditional independence encoded in the graph allow us to calculate the joint probability function as in (1):

$$f(x_1.....x_n)= \prod_{i=1}^{n} f(x_i \big| pa(x_i)) \qquad (1)$$

Hence, the conditional probability might be calculated, e.g. the probability of overhead line fault given the parents {Adverse weather, Overload}:

f(Overhead line fault)|(Adverse weather, Overload)

As stated in [5] one of the interesting properties of the BN framework is that it can be extended to represent decisions using so-called influence diagrams. The basis for the representation is utilities, which are quantified measures for preference. That is, a real number is attached to each possible scenario in question. Exploiting the probability updating of the BN framework, it is easy to calculate the expected utility for each decision option in a domain. The example given in Fig. 3 is expanded by introducing redundancy in terms of a second overhead line L2, feeding the load in parallel with the existing line L1. The utility of the expansion is evaluated by the expected costs of energy not supplied (CENS). The expanded BN model is shown in Fig. 4:
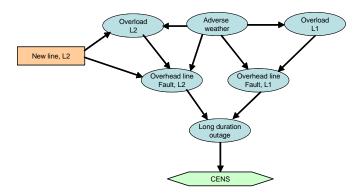

Fig.4. Risk of overhead line outage. Example of a BN including decision node "New Line L2" and utility node "CENS". Existing line is denoted L1.

The model given in Fig. 4 is entered into a BN tool[2] with some sample data. For simplicity, all variables in the example are discrete two-state variables, i.e. yes/no-variable. In general BN allow both discrete multi state variables and to some extent continuous variables as shown in the case study presented later in the paper.

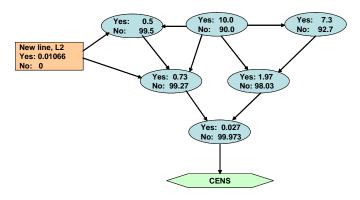The results based on the sample data are shown in Fig.5:

Fig. 5. Risk of overhead line outage. Example of a BN with sample data

The probabilities of the different variables are shown in the colored boxes, e.g. the probability of adverse weather is 10%. As {Adverse weather} has no parents, the probabilities shown for this node are the user input data. The utility of introducing a second overhead line is 0.01066 units compared to not introducing the new line. One unit is equal to 1 mill. NOK per year – the CENS reduction due to the introduction of a new line is approx. 11.000 NOK/year.

V. CASE STUDY

A. Introduction

The study focuses on the calculation of the failure probability for a MV overhead line feeder, to assess the impact of different risk influencing factors, such as vegetation, age of the feeder, wind and maintenance strategy. For this purpose, a risk analysis is carried out using Bayesian Networks. The variables are modeled based on available knowledge of the probability distribution for each random variable from historic fault statistics combined with expert judgment. The case study covers part of the overall concept presented in Fig.1 and illustrates some of the features of the BN method.

B. Modeling

1) The Bayesian Belief Network:

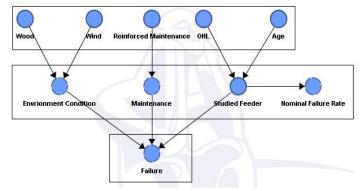The Bayesian Belief Network studied is shown in Fig.6 :

Fig.6. Overhead line model

The top level represents the input variables (sources of risk variables). The mid level gives the intermediate variables of the network and the bottom level gives the output variable (the consequence variable).

The values taken by the input variables are entered by the user depending on the type of overhead line (OHL), its age, its environment and if a reinforced maintenance strategy is carried out or not.

The intermediate random variables depend on the values of the input variables and are the parents of the consequence variable - the failure probability density of the considered feeder in its environment.

2) Random Variables Description:

This section provides a discussion about the variables and the input information used in the case study. The random variables used are characterized in terms of: type (D=Discrete or C=Continuous). The features of variables used in the case study are summarized in Table I.

TABLE I
DESCRIPTION OF THE RANDOM VARIABLES

	Random Variables	Type	Possible Values
Input Var.	Wood	D	Yes, No
	Wind	D	$\leq$ 30km/h >30 km/h
	OHL	D	Family 1, Family 2
	Age	D	Young, $\leq$ 37yrs Old > 37yrs
	Reinforced Maintenance	D	Yes, No
Inter. Var.	Environ. Conditions	C	Index with possible values [0,6]
	Maintenance	C	Index with possible values [0,0.5]
	Studied feeder	D	Discrete table
	Nominal Failure Rate	C	Range [0,1.3] faults/100km/yr
Output Var.	Failure	C	Range [0,10] faults/100km/yr

Further details are given in the following tables:

[2] Netica see.www.norsys.com

a) Input random variables:

The input variables, are set by the user and they are specific to the studied feeder (OHL & age), its location (wooded area & wind) and if a reinforced maintenance strategy is carried out or not.

TABLE II
FEATURES OF THE INPUT RANDOM VARIABLES

Random Variables	Remarks
Wooded area	Wood is set to Yes or No respectively if the feeder's location is in a wooded area or not. Example : 30% of the OHL feeder is in a wooded area : *P(Wood =Yes =30%) P(Wood =No =70%)*
Wind	Depending on the yearly mean wind speed during one hour, if it is lower than 30 km/h or higher than 30 km/h the variable takes the value Inf 30 or Sup 30. Example. Localisation in a windy area – 40% of the length subjected to wind > 30 km/s : *P(Wind=Inf 30) =60% P(Wind=Sup 30) =40%*
OHL	MV Overhead Lines construction : Example: If 55% of the length of the feeder is of family 1 and the rest is of type family 2: *P(OHL=Family1) =55% P(OHL=Family2) =45%*
Age	If the feeder is older than 37 years then the variable is set to Old if not, it is set to Young. Example of a MV feeder where 80% is younger than 37 years: *P(Age = Young) = 80% ⇒ P(Age = Old) = 20%*
Reinforced Maintenance	The variable is set to Yes, if Reinforced Maintenance has been carried out on the feeder else it is set to No. Example : Reinforced maintenance used at 30% length : *P(Rein.Maint = Yes) = 30% P(Rein.Maint = No) = 70%*

b) Intermediate random variables:

The intermediate random variables {Environment Conditions} and {Maintenance} correspond to a numerical coefficient (index) that impacts on the output variable's probability density function.

{System}acts as a reminder of the considered type of OHL and age whereas the {Nominal Failure Rate} gives the probability density function of the considered feeder without any external influence except ageing.

As shown in the Table III, the parameters for the probability density function of the intermediate variables depend on the possible values of the parents nodes:

TABLE III
FEATURES OF THE INTERMEDIATE RANDOM VARIABLES

Random Variables	Parents Node	Conditional probability density function *P(Intermediate R.V./Parents' Node Value)*
System	Age, OHL	Discrete table
Nominal Failure Rate	System	$Normal\ (M_{System}, S_{System})$
Environment	Wood, Wind	$Normal\ (M_{Wood,Wind}, S_{Wood,Wind})$
Maintenance	Maint.	$Normal\ (M_{R.\ Main.}, S_{R.\ Main.})$

The intermediate variables {Environment Conditions} and {Nominal Failure Rate} have been estimated based on experience feedback. For example, to model the "nominal failure rate" the following assumptions have been made:

- a "material" failure rate has been defined as a function of the age of the component, based on recorded data-experience feedback. The failure rate probability density function is modeled by a normal distribution shown in the Fig. 7 below. This 'material' failure rate corresponds to the intrinsic or nominal failure rate excluding external impact.
- two categories of OHL have been considered based on failure rate recordings: Young OHL (< 37 years) and Old OHL (> 37 years) – see Fig.7
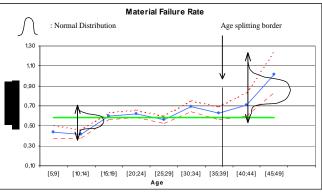

Fig.7. MV feeder material failure rate versus age

The last intermediate random variable "Maintenance" is a continuous variable (see Table III) and is modeled based on expert judgment and experience.

c) Output random variable:

The output of the BN model is a continuous random variable which gives the failure rate probability density function of the OHL. This output variable depends on the values of the variables of its parents nodes. The conditional probability density function is assumed to be normal with the following mean value:

$$Mean_{Failure} = Mean_{System} \times Value\ (Env.Cond.) \times [1 - Value\ (Main.)] \quad (2)$$

- $Mean_{System}$ is a static value which depends on the feeder, each feeder has its own.
- *Value(Env.Cond)* and *Value(Main.)* and are the index values of the random variables {*Environment*} and{*Maintenance}*.

The result is a normal distribution whose mean value depends on normal distributed random variables.

The output random variable reflects the combination of all the risk influencing factors for the MV overhead line feeder: external factors (wind and wood), the intrinsic vulnerability of the components and the effect of reinforced maintenance.

C. Results and Applications

The BN model previously described has been used to study how the failure rate of a MV overhead line feeder may vary, by varying the values of the input variables. Two analyses have been performed. The first analysis has been focused on studying how changes in environmental conditions may affect the failure rate of the component. The second analysis has been focused on changes in the intrinsic characteristics of the line.

1) Influence of the wind and wooded area on the failure rate:

It has been assumed that the feeder under study is a young feeder of type 1 where no reinforced maintenance has been done. Three scenarios regarding the environmental conditions (wood and wind) have been defined:

TABLE IV
SCENARIOS

Scenario	Wood	Wind
1	Yes = 0%	Inf 30 =100%
2	Yes = 50%	Inf 30 =50%
3	Yes = 100%	Inf 30 =0%

For each scenario, the failure rate's probability density has been estimated. An output example from the BN estimation is given in Fig. 8:

Fig. 8. Failure rate probability density Scenario 2

The main results are given in Table V.

TABLE V
RESULTS –FAILURE RATE EXPECTATION VALUES AND VARIANCE

Scenario	Mean	Variance
1	0,587	0.173
2	1.160	0.543
3	1.855	0.216

Being subjected to a more severe environment (scenario 3) compared to a more favorable environment (scenario 1), the risk in terms of failure rate more than triples.
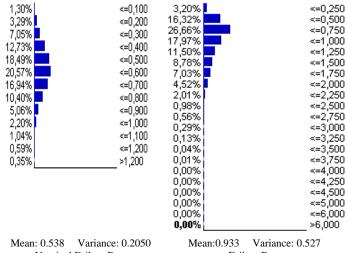
The failure rate expectation value for scenario 2 has the largest uncertainty in terms of variance.

2) Influence of the external factors on the failure rate:

Consider an OHL feeder in a given environment, with partial reinforced maintenance specified as follows:

Wood	Wind	OHL	Age	Reinforced Maintenance
Yes = 50%	Inf 30 = 70%	Family 1 = 50%	Young = 85%	Yes = 40%
No = 50%	Sup 30 = 30%	Family 2 = 50%	Old = 15%	No = 60%

When comparing results for the node {nominal failure rate} in the Bayesian Network given in Fig. 6 with the node {failure}, one can judge the influence of the external factors such as wind, wood, and the maintenance strategy, see Fig. 9:

Mean: 0.538   Variance: 0.2050   Mean:0.933   Variance: 0.527
Nominal Failure Rate   Failure Rate

Fig. 9. Comparison of failure rate densities

The close to doubling of the failure rate from 0.538 faults/100km/year to 0.933 faults/100km/year is the net impact of the external environment and the applied maintenance strategy.

As illustrated, the BN model used in the case study allows for detailed studies of impact of various parameters on the risk in terms of failure rates which in term will be important input to asset management decisions.

VI. ADVANTAGES/DRAWBACKS OF BN IN DISTRIBUTION SYSTEM ASSET MANAGEMENT

BNs have a great potential for application in asset management of distribution systems. The main advantage of this methodology is that it allows its users to describe all elements of the 'risk' picture like in well as they can imagine it. As illustrated in the examples in this paper, BNs can be used at an aggregated decision level as the example shown in Fig. 4 or at a very detailed level as shown in the case study. The method has the power of combining statistical data and expert judgments in deriving the estimates of system condition and performances, but also to simulate what can happen to a system in the future.

The method allows for the definition of the most critical factors for the problem at hand, and models how the combination of these influencing factors leads to various (unwanted) events and consequences.

The information provided by BNs can be used in decision making for distribution system asset management both as a

low level tool in the overall risk management concept or at a high level including decisions and costs/utilities directly in the BN model.

Scenario analysis is a very popular decision support tool in many organizations. Using BN, scenarios with probabilities can be defined by varying for example the input probabilities of critical risk factors for a system under study.

BNs can also be used in maintenance strategy making for groups of components. For example, when developing a maintenance strategy for coastal overhead lines, 'standardized' BNs can be constructed to account for the risk factors common to this type of components: salt pollution, wind, age of the overhead line, etc.

In addition, the BN approach can be used to improve the analysis of how combinations of different undesirable events (e.g. poor asset condition/asset ageing, severe weather events, fire, human error, geographical factors, etc), can contribute to unwanted consequences on the economics, environment, safety, security, quality of supply or on the reputation of a company.

Some if not all of these criteria are inherently uncertain, being influenced by risk factors that often cannot be controlled by the decision maker. BN is an important tool here because it offers means for handling this uncertainty. Future work will focus on applications of the BN approach together with other decision support techniques such as those in the category of Multi-Criteria Decision Aid (MCDA).

There are however several drawbacks concerning the use of BN in practice, by asset managers. Building BNs using statistical data or expert opinion can be both difficult and time consuming [5]. A BN model building comprises several steps: 1) decide what to model; 2) define variables; 3) define probabilities and the conditional relationships between the model components; 4) verify the model. This is typically an exercise that may require the intervention of a BN expert that guides the model building, asks relevant questions, and explains the assumptions that are encoded in the model to asset managers.

Particularly difficult when building up BNs is to decide what probability data to use. In the example in section V probability density functions have been used which implied:

- a choice of the probability distributions fitted to each physical phenomena: Normal, Weibull.
- Include probability information from expert judgment by choosing the appropriate probability distributions even if the information is not complete.

VII. CONCLUSION

This paper discusses the use of BN as a relevant tool for risk assessment in distribution systems asset management. The method gives decision makers a good visualization of relationships between risk influencing factors, system states and risk consequences (variables in the graph) as well as offering statistical estimation of the variables included. Hence, in general it contributes to estimation of the answers of the three fundamental questions of the risk analysis:

1. What can go wrong?
2. How likely is it to happen?
3. What are the consequences?

The examples and case study included, illustrates the relevance of the method in distribution system asset management when risk is involved.

VIII. ACKNOWLEDGMENT

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X. BIOGRAPHIES

Kjell Sand was born in Bodø, Norway, on October 24, 1952. He graduated as Electrical Engineer (M.Sc), 1976 from Norwegian University of Science and Technology (NTNU, former NTH) and received his Ph.D degree from NTNU in 1987.He has been with SINTEF Energy Research since 1978 working mainly with power system planning and analysis, quality of supply (reliability, voltage quality) , monopoly regulation and benchmarking. Sand holds a position as associate professor at the Department of Electric Power Engineering, NTNU.

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