# A METHOD FOR THE QUANTITATIVE ASSESEMENT OF RELIABILITY OF SMART GRIDS

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## ABSTRACT

*This paper describes a method for the quantitative assessment of reliability of Smart Grids that evaluates the combined behaviour of the distribution grid, the telecom infrastructure and the control functions. It is based on a method that has already been used successfully for large and complex telecommunication networks. We expanded this method to allow the inclusion of distribution grid components and energy flow calculations. This method aims to be a valuable tool during the design and planning phases of Smart Grids: i.e. for comparing the expected reliability of design alternatives and for identifying risk areas, weaknesses and their impact on the reliability.*

## INTRODUCTION

To achieve reliability levels that are at least equal to current standards, the IT components, telecom infrastructure and control of Smart Grids must have a non-negative impact on the reliability of the energy supply. This is non-trivial as the reliability of IT and telecom components are usually lower than the reliability of distribution grids (i.e. in the Netherlands).

Two intuitive reasonings are often heard: adding ICT components with a mediocre reliability can only *lower* the reliability of the total system (which is not acceptable). On the other hand, smart control schemes utilizing ICT may be able to prevent failures or reduce their impact significantly better than traditional grids and hence may *improve* the reliability, for instance by automatically rerouting energy flows, switching off low-priority energy consumption etc. The truth must be somewhere in the middle and the outcome depends on the details of the design.

Typical control schemes in Smart Grids include *feedback control* and this makes it non-trivial to assess the impact of failures on the stability and hence the reliability of the complete system. Because of this feedback nature, it is not possible to calculate the reliability of the energy grid and the ICT layer separately and combine the values in some way or another. This paper proposes a method that follows a holistic approach that treats the Smart Grid as a whole, not as the sum of its parts.

## PERFORMANCE INDICATORS

“Availability” or “Security of supply” is an important key performance indicator (KPI) of Smart Grids. It is a measure for the ability of the system to transport energy to its customers without interruptions and is usually defined as a time fraction (such as 99.999%). Other related performance indicators are the number of outages per time unit (i.e. year) and the (average) duration of outages. Combined with data regarding numbers of customers we can calculate KPI’s such as SAIDI or SAIFI.

Apart from “availability”, SAIDI, SAIFI, etc. there are other performance indicators that may be important ([1]):

- Demand and Supply balancing: the percentage of time that the demand and supply deviate from each other.
- Avoidance of peaks as a measure of the effectiveness of demand management.
- Efficiency of delivery, being the ratio of the consumption of locally generated energy and the total consumption of energy.
- Environmental impact, being an indicator to what level “green” energy sources are used.
- Service offering, for example the probability that an electric vehicle is charged in time.
- Service fairness: an indicator to which extend all distributed energy generators have been granted the right to deliver power to the grid.

In this paper, we will concentrate on ’availability’, but we expect that the same methodology can also be used to quantify other performance indicators. This would make it possible to make full comparisons of design alternatives.

## PROBABILITY RISK ASSESSMENT

“Probability Risk Assessment” is the common name for the evaluation of risks associated with a complex engineered technological entity in a systematic and comprehensive way [2], [3]. Calculation of the expected availability of a system can be performed in different ways:

- *Analytically*. When failure causes are statistically independent and the system is relatively simple, logical operators can be used to combine failures of individual systems, elements, and components into the failure of a service and calculate the probabilities.
- By *simulation*. When failure causes are not statistically independent or failures have non-trivial and interdependent causes, then analytical methods may not be possible and simulation may prove an alternative. Simulation is often costly in terms of time, computational and software resources.

The method proposed here combines these principles and uses: (1) Analytical calculations by means of Fault Tree Analysis, (2) Partial State Space evaluation and (3) Simulation of semi-stationary fault scenarios.

## BASIC PRINCIPLE AND ASSUMPTIONS

The fundamental assumption underlying the proposed method is that the operating state of a Smart Grid is determined by a finite number of external factors such as spontaneous hardware failures, damaged cables, flooding etc. Those are the "root causes" that may cause one or more elements of the system to malfunction. The system can then be seen as always operating in one of a discrete number of failure states, each state being a certain combination of root causes.

A large class of external influences are formed by the spontaneous failures of individual elements, like switches, transformers, cables, routers etc., but there may be others that have impact on groups of elements, like flooding or fire in a distribution station.

Note that failures of elements due to overload are not considered as "root causes": their failure is probably the results of a chain of events that have a different root cause.

For the sake of simplicity, we will assume here that all external influences are bi-modal: true or false. Later this assumption can be broadened to allow multi-model effects, such as the outside temperature or the amount of wind and sunlight (continuous quantities, like temperature, can always be discretized).

Assume there are *N* external influences. Particular state *j* of the system will be written here as vector:

$$S_j = (s_{1,j}, s_{2,j}, \dots, s_{N,j})$$

with $s_{i,j}$ representing the state of external influence *i* in system state *j*.

The total state space is the (finite) set of all possible states and will be written as *S*. The number of elements in the set can be very large: with *N* bi-modal external influences, the number of states is equal to $2^N$.

We will also assume that is possible to calculate (or at least estimate) probability $P_j$ of state *j*. When the elements $s_i$ are all statistically independent, we can calculate $P_j$ from the probabilities of the element states $s_i$:

$$P_j = \prod_{i=1}^{N} P(s_i = s_{i,j})$$

Next we have to define quantity *G* that we want to use to evaluate the performance of the system, for instance the fraction of the time (or probability) that the energy demand of a given customer can be fulfilled. We assume that we can define a function *g(S)* that maps every state *S* to a certain (binary) outcome, i.e. whether the customer demand can be fulfilled or not.

A further assumption is that the outcome *g* in a certain state only depends on the state vector *S* and not on the previous state(s). In other words, the system states are supposed to be memoryless. In order to fulfil this assumption, it may be necessary to model any "memory" effects as external influences (and include them in state vector *S*).

Determining the value of *g(S)* may not be trivial as it may involve evaluating the effects of failure chains, protection mechanisms and corrective actions by control units. For instance, a single damaged cable may cause other elements to be overloaded or switched off by protection mechanisms etc. We will assume here that such a chain of events will always lead to a stationary situation for which the value of *g(S)* can be determined.

With this function *g*, it is now possible to calculate the expected value of the desired quantity *G* as a weighted sum:

$$E(G) = \prod_{j=1}^{2^N} P_j \cdot g(S_j)$$

Calculating this weighted sum may be problematic in practice as the size of set *S* may be very large and calculating g($S_j$) for each state $S_j$ can be time consuming.

## PARTIAL STATE SPACE EVALUATION

The computational complexity of calculating the weighted sum *G* can be reduced significantly by only evaluating a subset *S'* of *S*. Assume *W* to be the set of all possible values of *j* (1...$2^N$). Then let *V* be the subset of all indices of the states in *S'*: *S'* = { $S_j$ } for all $j \in V$. Then *G* can be calculated as follows:

$$E(G) = \sum_{j \in V} P_j \cdot g(S_j) + \varepsilon$$

with ε indicating the approximation error. The maximum error that is made can be calculated by a worst/best case analysis: in the best case, *g* evaluates to *true* (or 1) for all states in *S-S'*, in the worst case it evaluates to *false* (or 0) for those states. Hence:

$$0 \le \varepsilon \le \sum_{j \in (W \setminus V)} P_j$$

The subset *S'* should be chosen wisely: in order to minimize the error, the sum of the probabilities of the excluded states should be smaller than the allowed inaccuracy of the results. At the same time, we want to minimize the number of states in *S'* in order to keep the computation time limited.

The best solution is to sort all elements of *S* according to their probability and choose subset *S'* from the states with the highest probability, up till the desired accuracy is reached. However, this also can be impractical since the number of states in *S* can be too large to handle. Therefore, we apply some heuristic methods to select the states for *S'* .

First step is to select states with an increasing number of failures (or other disruptive effects). The first state is the failure-free state, then all states with exactly one failure, then all states with exactly two failures etc. Since failure probabilities are often roughly in the same order of magnitude, this results in a more-or-less sorted order.

A second refinement is to only consider states that have a certain minimum probability, for example 0.00001 %. This may help to exclude certain states with *N* failures that hardly contribute to reducing the error, while other states with *N*+1 failures may have a higher probability.

While selecting states for subset *S'* in this way, we keep track of the aggregated probability of *S'* and stop when the required accuracy is reached. See the figure below.

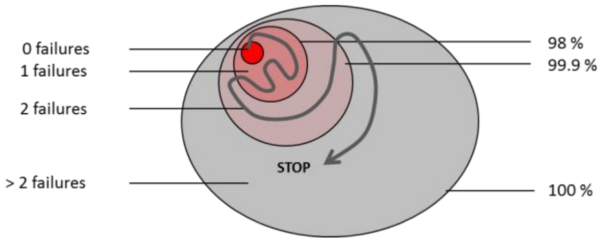


**Figure 1: Partial State Space Evaluation**

## FAULT TREES

A set of Fault Trees is used to map the external influences to the states of system components, like cables, transformers, switches, telecom links, routers, control units etc. A Fault Trees combine binary events by means of the logical operators AND and OR and are often drawn in a tree-like fashion, using symbols to represent the logical operators.

In the simplest case, a single external influence (like cable damage) causes exactly one element to fail (the cable). However, it is also possible that a single influence (such as fire) causes many elements to fail, or that multiple simultaneous external influences are needed for a single element to fail (in case of redundancy).

Assume a set of Fault Trees $F = \{ f_i(S) \}$, with each $f_i(S)$ being a Fault Tree that maps the state vector *S* to the state of element *i*, then we can define vector $T_j$ as the state of all elements in state *j*: $T_j = \{ t_{i,j} \}$, with $t_{i,j} = f_i(S_j)$

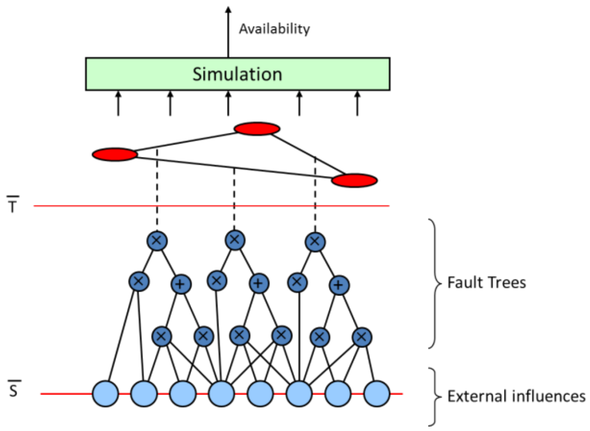


**Figure 2: Fault Trees**

It is not necessary that the elements in vector *T* are “physical” components. Often it is possible and advantageous to define “super elements” or functions that internally consist of multiple elements. For example, the end-to-end data link between a smart meter and a control unit can be defined as “super element”. It is up to the Fault Trees to determine if this link is fully operational in a certain failure state. In general, we will include as much logic as possible in the Fault Trees, leaving only the more complicated evaluations to the simulation function.

Keeping the number of elements in vector *T* as small as possible (reducing the size of the state space) helps to reduce the computation time of the simulations, because multiple vectors $S_j$ may be mapped onto the same vector $T_k$ and the simulation of that state only has to be performed once.

So instead of treating each state $S_j$ in *S'* individually and calculating the weighted sum of evaluation function $g(S_j)$, we define a new function $h(T_k)$ that determines the outcome for each state $T_k$, with the probability of $T_k$ being the sum of the probabilities of all states $S_j$ that map to $T_k$.

## SIMULATION

The function $h(T_k)$ determines the outcome for each value of $T_k$. Since this may involve a lot of complex aspects, like energy balance, cascading failures, protection switching, corrective actions by control units, this generally can only be solved by simulation.

For the purpose of testing the methodology, a simplified model was implemented, based on the following assumptions:

- Electrical cables and components are loss-free
- There is only a single electricity phase
- The voltage is fixed and everywhere the same
- For every junction the first law of Kirchhoff applies ($\Sigma i_k = 0$)

- Shortage or surplus of current is distributed over the links with higher order networks, in proportion to their maximum capacity.
- Every consumer draws current from all sources, in proportion to the total production of those sources.
- No chain reactions of failures
- The main objective of the "smart control" is availability (security of supply).

No Ohm's law has been implemented so far. Obviously, this is far too simple to produce useful results, but it served to validate and demonstrate the viability of the method.

## EXPERIMENTS

The complete method has been implemented in a software tool (Figure 3 shows a screen shot) and tested on a very small scale Smart Grid.

The results of these experiments show that our method is feasible and that implementation in a software tool is possible. Obviously, the computation time depends on the required accuracy. We did not yet perform experiments with a realistic Smart Grid, but earlier experience with realistic telecommunication networks (with complex dynamic routing features) have shown that 5-digit precision is possible within 1 hour of computation on a standard PC.

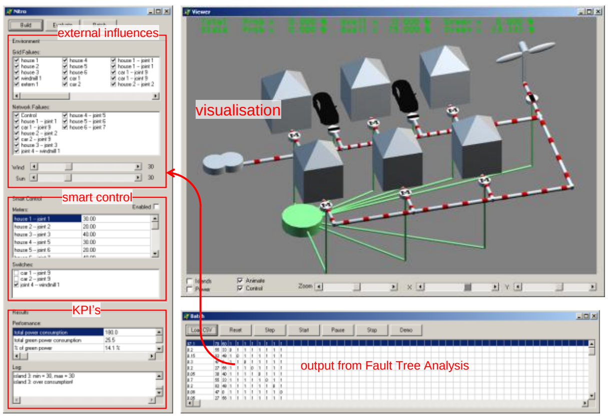


**Figure 3: Screen shot of Proof of Concept tool**

The promising results have already spurred the interest from some DSO's in the Netherlands. Further research however is required before it can be tested in practice, e.g. regarding the energy flow calculations, allowing for more types of electrical and ICT components, improving the input and output handling and validate and possibly improve scalability.

## CONCLUSIONS

The main conclusion that can be drawn after implementing and testing this "proof of concept" tool is that the proposed combination of Fault Tree Analysis, simulation and Partial State Space Evaluation is very promising and can be an important validation tool during the design of smart grids. The tool could be used to:

- Confirm if the target values for "availability" or other target values can be reached, during the design phase of the grid
- Define the performance requirements for the underlying ICT infrastructure and how these should be expressed in terms of a Service Level Agreement.
- Decide on the "best" architecture for energy distribution networks and underlying ICT infrastructures.
- Decide on the best "Smart" control strategy
- Learn basic design rules and best practices by designing simple smart grids and ICT infrastructures.

Improvement to the concept requires both expertise from ICT network architects and design experts combined with experts on (modelling the) energy delivery network. A major task will be to prove scalability is also sufficient to handle realistic smart grids.

## REFERENCES

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