Project no.:

608540

Project acronym:

GARPUR

Project full title:

Generally Accepted Reliability Principle with Uncertainty modelling and through probabilistic Risk assessment

Collaborative project

FP7-ENERGY-2013-1

Start date of project: 2013-09-01

Duration: 4 years

D6.2
How to upgrade reliability management for short-term decision making

Due delivery date: 2016-08-31

Actual delivery date: 2016-10-10

Organisation name of lead beneficiary for this deliverable:

NTNU Norwegian University of Science and Technology

Project co-funded by the European Commission within the Seventh Framework Programme (2007-2013)		
Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential , only for members of the consortium (including the Commission Services)	

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Deliverable number:	D6.2
Deliverable short title:	How to upgrade reliability management for short-term decision making
Deliverable title Annex 1:	How to upgrade reliability management for ST decision making
Work package:	WP6 System operation
Lead participant:	NTNU

Revision Control			
Date	**Revision**	**Author(s)**	**Comments**

Quality Assurance, status of deliverable		
Action	**Performed by**	**Date**
Verified (WP leader)	Íris Baldursdóttir (Landsnet)	2016-10-10
Reviewed (Sc. Advisor)	Louis Wehenkel (ULg)	2016-10-16
Approved (EB)	EB approval by e-mail	2016-11-17
Approved (Coordinator)	Oddbjørn Gjerde (SINTEF)	2016-11-29

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EXECUTIVE SUMMARY

Reliability management aims at ensuring that electricity is delivered in an efficient way to end consumers. It encompasses both the definition of a reliability criterion, and the methods that are used by transmission system operators (TSOs) to enforce the reliability criterion in an optimal manner from the viewpoint of socioeconomic impact.

The present report is concerned with reliability management in short-term operation planning (week-ahead to intraday) and real-time operations. Today, the reliability management approaches used by TSOs in these contexts are based on the N-1 criterion, whereby the supply of electricity must remain unaffected by the loss of any one of its single components (and, in some cases, by the simultaneous loss of two critical components). Power systems have seen many changes in the past decades, which have pushed operating conditions towards the operating limits and have increased uncertainties that TSOs have to face. These changes call for probabilistic methods that can support TSOs by capturing the probabilities of threats and their quantitative consequences in an adequate way. The N-1 criterion has indeed been widely recognized as insufficient to cope with these changes.

The GARPUR proposal is based on the general notion of the reliability management approach and criterion (RMAC) developed in Work Package 2 of the GARPUR project. The formulation of the RMAC considers a socio-economic surplus indicator that is developed in Work Package 3 of the GARPUR project. This RMAC aims at supporting the decision-making process of TSOs under uncertainty. The framework is based on (i) a reliability criterion that explicitly considers scenarios of the uncertain exogenous parameters (such as load, RES production and occurrence of contingencies) and their probability and (ii) methods to enforce this reliability criterion. In particular, the reliability target of the GARPUR RMAC states that the probability that the system performance is acceptable must be higher than a pre-defined tolerance level.

The implementation of an RMAC in a particular context is based on (i) a discarding principle that allows discarding scenarios of the uncertain exogenous parameters to make the reliability management problem tractable, (ii) a set of constraints defining the notion of an acceptable system state, (iii) a maximum tolerance level on the probability of not achieving an acceptable system state, (iii) an indicator of socioeconomic performance, and (iv) the formulation of an optimization problem aiming at finding decisions that are optimal with respect to their socio-economic impact, while being compliant with the reliability target and the discarding principle. In this approach, the expected costs of service interruptions carried by end-users of the system are integrated into the socioeconomic performance indicator and used in the discarding principle.

Reliability management is composed of two complementary tasks, namely “reliability assessment” and “reliability control”. The former essentially aims at determining whether in given circumstances the imposed reliability target is indeed satisfied. The latter aims at choosing decisions to optimize the socioeconomic performance while complying with the imposed reliability criterion.

This document presents proposals to adapt, and progressively implement in practice, the general probabilistic RMAC and corresponding socio-economic surplus indicator developed in Work Packages 2 and 3 of the GARPUR project, in the specific contexts of real-time operation and short-term operational planning. We mostly focus on the development of methods for reliability assessment, but we also provide guidelines on how to use these methods to support power system operators in their reliability control tasks.

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In real-time operations, the RMAC considers the random occurrence of contingencies by using appropriate threat-based models of their probability of occurrence. In addition, special attention is given to the possible failure of corrective actions. Neglecting this aspect would favour too optimistically the use of corrective actions instead of preventive actions. In short-term operational planning, the RMAC considers uncertainty in the load, production, exchanges and probabilities of the contingencies over the considered look-ahead horizon. Appropriate models are proposed for these exogenous parameters.

The proposals made in this document are designed to be implementable within the next few years, during which new required tools must be developed and validated and new required data must be collected. These needs for additional data and tools required for such a migration are analysed as well in this document.

The first-step implementations of the proposed real-time and short-term reliability assessment methods are illustrated in small examples.

1 INTRODUCTION

1.1 Reliability management for real-time and short-term decision making

The state of the art on reliability assessment was reviewed at the start of the GARPUR project [GARPUR, 2015a], which was followed by a review of current practices at TSOs, as well as the motivations for improving reliability assessment [GARPUR, 2015b]. These reviews formed the basis for the formulation of new reliability management approaches and criteria that are described in [GARPUR, 2016c]. The general problem that is addressed in this document is how the proposed methods may be integrated into present day operation, accounting for the procedures and data/model availability described in [GARPUR, 2015]. The following subsections briefly elaborate on the general problem and today's practices.

1.1.1 General problem

Power system reliability management for real-time (RT) and short-term (ST) decision-making aims to guarantee that the bulk power system can provide electricity as it is demanded, at an acceptable quality. Power systems reliability covers two notions:

i) Adequacy: Ensure the system can meet the aggregated power and energy requirements of customers;
ii) Security: Ensure the system can withstand disturbances without interruption to customers, and maintaining operation of the interconnected system.

Power system reliability is managed by taking actions in different time horizons (i.e. long-term planning, operational planning, real-time operation) to satisfy a commonly defined reliability criterion.

Reliability management within a TSO environment entails two main components: reliability assessment and reliability control.

Reliability assessment evaluates the reliability level of a power system, either retrospectively (by reporting observed annual number of interruptions, average interruption duration, annual interrupted energy), or prospectively (by predicting the resilience of the system in anticipation of credible threats).

On the other hand, reliability control determines what actions, if any, are required to ensure that the system will satisfy the reliability criterion. Such actions may be preventive and/or corrective control of the power system. The TSO's ability to control reliability depends on the accuracy of their reliability assessment. Improvement of reliability assessment methods will result in better decision-making and measures of its effectiveness (in terms of reliability level and socio-economic impact).

1.1.2 Today's practices

Currently, reliability management is mainly based on the N-1 criterion defined as the requirement on elements remaining in operation to accommode the new operational situation without violating Operational Security Limits [ENTSO-E 2013b] (such limits might not be fully harmonized within a synchronized electricity network). Until now, the N-1 reliability criterion has provided a satisfactory level of security of supply, due to its transparency and simplicity. The N-1 criterion is quite a generic concept, so each TSO has relaxed/tightened the criterion to adapt to their local characteristics and operational philosophy [GARPUR, 2015b]. The following variations are commonly observed:

- Strict application of N-1 criterion, this mainly results in a highly overdesigned system that is mostly operated under maximum potential;

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- Stricter criterion during specific operational high risk scenarios by applying N-1-1 or N-2 contingencies (e.g. extreme weather conditions) or for some critical elements of the networks;
- Relaxed criterion by tolerating an N-1 unsecured operation for low impact contingencies while facing limited options during specific periods (e.g. night, planned outages..);
- Ad-hoc criteria usually for identified specific unlikely scenarios that could result in substantial consequences (covered by specific operational procedure or automated Special Protection Schemes).
- Systematic N-1 tolerance on limited voltage levels and users (essentially sacrifice quality of supply to customers) if the costs to satisfy the reliability exceeds the foreseen benefits;

To a certain extent, the most basic and commonly applied N-1 criterion is characterized by the following features:

- Contingency impact is managed considering a binary logic (satisfactory, not satisfactory);
- Contingencies are assessed on similar likelihood level (equal probability of occurrence);
- High impact low probability events are not assessed;
- Financial impact (cost of an outage and/or mitigation) is not considered.

To date, application of the N-1 criterion has resulted in a sufficiently reliable power system [GARPUR, 2015b]. However, the increasing complexity, volatility and connectedness of power systems triggered by the ongoing paradigm shift in power system structure[1] will make it difficult for current procedures to sustain a similar level of reliability. Current procedures, common to European TSOs, are detailed in previous GARPUR deliverable D6.1 [GARPUR, 2015]. Increased uncertainty in power production, load and import/export creates difficulties in predicting power system behaviour. It is increasingly difficult for TSOs to determine robust control measures that protect the system against this uncertainty. Sources of uncertainty affecting the reliability of a bulk power system can be categorised as following:

- Generation Mainly due to the increasing penetration of non-dispatchable RES or small-scale distributed generation such as combined heat and power plants. Such unpredictable types of generation result in uncertainties of the energy flows in the system.
- Load: Net load patterns are more and more difficult to predict mainly due to distributed generation sources that are aggregated in an approximate fashion. A TSO neither has the ability to forecast nor monitors accurately the outputs of the distributed generation, and therefore has very limited observability on real time conditions.
- System vulnerability: New threats (e.g. cybersecurity) are not being duly considered while on the other hand vulnerability to existing threats such as weather conditions is increasing (bulk offshore wind capacity, solar eclipses, higher cross-border connections capacity)
- Market: volatility in energy flow, risk of generation inadequacy due to inadequate market design or investment signals.

1.2 GARPUR reliability management approach and criterion (RMAC)

This document aims at finding out how to integrate the GARPUR short-term reliability management approach developed in Work Package 2 [GARPUR, 2016c] in practical system operation activities of the

[1] From traditional systems delivering energy from large centralized generation to passive consumers, to a system with decentralized generation to active consumers.

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transmission system operators (TSO) as detailed in [GARPUR, 2015]. Adopting the terminology of Work Package 2, the proposal is referred to as a Reliability Management Approach and Criterion (RMAC).

The proposals for incorporating the probabilistic RMAC of GARPUR into real-time operations and short-term operational planning were separated by Work Package 2 into a real-time RMAC (RT-RMAC) and a short-term RMAC (ST-RMAC) implementation [GARPUR, 2016e]. They are designed to consider explicitly uncertain exogenous parameters. There are two fundamental differences between the real-time and short-term contexts. The first one is that the range of actions available to the system operator is more limited in real-time. The second is that some exogenous parameters that are uncertain in the short-term become apparent in the real-time.

The uncertain factors that we have considered for the real-time context are [GARPUR, 2016c], [Karangelos, 2016]:

- The occurrence of contingencies: the RT-RMAC exploits the fact that contingencies occur with a certain probability that depends on real-time conditions.
- The post-contingency system response: the RT-RMAC is aware of the probability that the reaction of the system to a contingency may not be as expected, due to system protection failures, for example. Possible failures of corrective control provides additional uncertainty of system response.

For short-term operational planning, the following additional uncertain parameters are considered:

- The probability of occurrence of contingencies: the ST-RMAC considers the fact that the contingency probabilities themselves, as they would be exploited in real-time, may be uncertain in ST decision making since they depend on other uncertain factors, such as weather conditions, that are not yet known.
- The net power injection: the future nodal loads, productions and exchanges are not fully known but can only be forecasted. Errors of these forecast models should be anticipated for.

Both the ST-RMAC and the RT-RMAC are designed around the same cornerstones [GARPUR, 2016c]:

- A reliability target that is to be fulfilled.
- A discarding principle that allows discarding part of the scenarios for the uncertain exogenous parameters in a controlled way, in order to make the RMAC process tractable.
- The residual risk that measures the cumulative risk contribution of all discarded scenarios, and must remain under the discarding threshold as per the discarding principle.
- A measure of risk that is defined as the expected interruption costs.
- A measure of socioeconomic performance that is to be maximized under the constraints that the reliability target and the discarding principle must be fulfilled. This measure was developed in Work Package 3 of the GARPUR project and is described in detail in [GARPUR, 2016a].

In the present document, the first-step implementation of the proposals of [GARPUR, 2016c] and [GARPUR, 2016a] for the measure of socioeconomic performance is proposed to be the sum of expected interruption costs and TSO costs. Note that risk is included in the socioeconomic surplus.

The proposed ST-RMAC and RT-RMAC were designed in a consistent way so that the ST-RMAC is concerned with ensuring the feasibility of the RT-RMAC for scenarios of the ST uncertain parameters that have not been discarded by the discarding principle.

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1.3 Scope of this report

This document presents first-step implementations of the short-term and real-time reliability management approach and criteria (RMAC) developed in the GARPUR project WP2. These first-step implementations have been designed to require as few changes as possible with today's tools and data. Nevertheless, they provide TSOs with a comprehensive and generic approach to support decision-making under uncertainty. The first-step implementations are therefore aimed at answering the following question: "what changes, in terms of tools and data, can be made in the near future to capture risk and uncertainty in reliability management?" The proposals of this document are meant to be implementable within a few years.

As described above, reliability management has two main components: assessment and control. The first-step implementations address the assessment problem, which will enable TSOs to gain insights into the new paradigm formulated in the GARPUR RMAC. In a second step, adequate control algorithms (see e.g. [GARPUR, 2016c] for their formulations) can be adopted based on the experience obtained by running the proposed reliability assessment methods. The practical integration in TSO processes of these control algorithms are not addressed in this document and left as future work once enough insights have been gained from the use of the assessment methods.

1.4 Report structure

Chapter 3 gives a high-level overview of the first-step implementation for the real-time and short-term RMAC and of the required probabilistic models that are needed. Chapters 4, 5 and 6 present in detail the first-step implementations of the probabilistic models, the real-time RMAC and the short-term RMAC, respectively. Chapter 7 concludes and proposes some directions of future work beyond the first-step implementations proposed in this document. The appendices provide material on the formulation of ideal implementations and some additional considerations around some parts of the RMAC concepts.

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2 ACRONYMS, SYMBOLS AND DEFINITIONS

2.1 Acronyms

RMAC	Reliability management approach and criterion
RT	Real-time
ST	Short-term
VoLL	Value of lost load
RES	Renewable energy sources

2.2 Symbols

π_c	Probability of contingency *c*
$\mathcal{N}$	Set of all contingencies
$\mathcal{N}_c$	Set of non-discarded contingencies
Ξ	Set of scenarios
Ξ_c	Set of non-discarded scenarios
$\xi_{1,\dots,T}$	A unique scenario, i.e. a sequence of realisations of exogenous random variables ξ_t, spanning the time horizon [1,T].
π_ξ	Probability of scenario ξ
ΔE_{RT}	Discarding threshold for the real-time RMAC
ε_{RT}	Tolerance level of the reliability target for the real-time RMAC
ΔE_{ST}	Discarding threshold for the short-time RMAC
ε_{ST}	Tolerance level of the reliability target for the short-time RMAC (operational planning)
$x_0, x_c, x_{c.b}$	Pre-contingency, post-contingency, and post-contingency post-corrective actions system states
X_a	Set of acceptability constraints
λ_i	Failure rate of component i (failures per year)
$MTBF_i$	Mean time between failures of component i (years)
$Q_i(\Delta t)$	Probability that component i fails in the time interval [0,t] (where Δt is ommitted, Q_i covers to a single operational period)
J_c	Set of components failing in contingency c
K_c	Set of components not failing in contingency c
$\emptyset$	Used in lieu of ‚c‘ to denote the pseudo-contingency of no component failures
π_r	Probability of a certain system response
π_b	Probability of a certain corrective control behaviour
π_c^*	Combined probability of a contingency and the expected post-contingency behaviour
u_0	Initial preventive actions
LL_c	Lost load immediately following contingency c
LOL_c	Lost load immediately following contingency c, expressed as a percentage
d_c	Service outage duration following contingency c
L_t	Expected system load in operational period t
$ENS_{c,t}$	Energy Not Served due to contingency c, in operational period t (where the contingency occurs when t = 1)
T_c	Number of operational periods required to repair all components failing due to contingency c
π_R	Accumulative probability of any discarded contingency occurring (residual

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	probability)
$S_{c,t}$	Socio-economic surplus in operational period t due to contingency c
S_c	Aggregated socio-economic surplus due to contingency c
$C_{int,max}$	Estimate of the worst-case interruption cost

2.3 Definitions

Consequence Consequence is the outcome of an event. Note: There can be different types of consequences: technical (like interruption), economic or environmental consequences, consequences on personnel/ consumers safety, etc. See GARPUR Deliverable D1.1 [GARPUR, 2015a].

Contingency A contingency is the unexpected failure or outage of a system component, such as a generator, transmission line, circuit breaker, switch, or other electrical element. A contingency may also include multiple components, which are related by situations leading to simultaneous component outages [ENTSO-E, 2004].

Corrective operation In the real-time context, corrective operation concerns the application of post-contingency actions, in the aftermath of specific contingencies [GARPUR, 2016c].

Operational planning Operational planning is the group of reliability management activities linked to system optimization occurring ahead of real-time operation, within the short-term and mid-term horizons.

Outage An outage is the state of a component or system when it is not available to properly perform its intended function due to some event directly associated with that component or system [IEEE, 1997].

Preventive operation In the real-time context, preventive operation concerns the potential application of pre-contingency actions to achieve security and improve the ability to withstand the possible effects of potential contingencies. In the short-term context, preventive operation concerns the application of actions that apply to any realisation of the short-term uncertainty [GARPUR, 2016c].

Real-time horizon The real-time horizon (system operation) in GARPUR focuses on the observed system state, i.e., it covers monitoring, control of the power system, and actions based on observed system state. Control covers corrective actions and activating manual preventive (planned) actions.

Reliability management Power system reliability management means to take a sequence of decisions under uncertainty. It aims at meeting a reliability criterion, while minimising the socio-economic costs of doing so [GARPUR, 2015a].

Residual probability The aggregate probability of all discarded and/or not explicitly modelled events in a reliability assessment.

Residual risk The aggregate risk of all discarded and/or not explicitly modelled events, as defined [GARPUR, 2016c].

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Short-term horizon The short-term horizon in GARPUR covers planning for secure operation of forecasted power system states, for which the power system components cannot be changed through maintenance works and/or system development projects.

Socio-Economic Surplus The sum of surplus or utility of all stakeholders, including external costs and benefits (e.g. environmental costs) as defined in [GARPUR, 2016a].

Threat The ability of a system to perform a required function may deteriorate as a result of any event classified as a threat. Indeed, a threat can be defined as any indication, circumstance, or event with the potential to disrupt or destroy a system, or any element thereof. Threats are phenomena that exist and evolve outside of the system [Hofmann, 2011].

Trajectory A sequence of events affecting the state of the transmission system, such as contingencies, system response, and corrective control, over multiple operational periods.

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3 A SHORT DESCRIPTION OF THE PROPOSED UPGRADE OF RELIABILITY MANAGEMENT FOR REAL-TIME AND SHORT-TERM DECISION MAKING

3.1 Ideal formulation

The concept of the GARPUR reliability management and criterion (RMAC) and its formulation for long-term, mid-term, short-term and real-time decision-making were developed within WP2 of the GARPUR project and are detailed in [GARPUR, 2016c]. To make the present report self-contained, we recall in Appendix 9.1 the general ingredients of an RMAC, and in Appendix 9.2 and Appendix 9.3, the corresponding “ideal” RT-RMAC and ST-RMAC versions. The analysis of these latter “ideal” versions made it possible to identify the extent of data and tool requirements for their application, and to determine practical feasibility issues with this ideal methodology that need to be overcome. By identifying these issues, and attempting to address them using presently available tools and data, we arrived at the first-step implementation proposed in this document. The main practical feasibility issues that we have identified for the implementation of the ideal versions are summarized below:

i) **Computation time -** A number of calculations in the ideal algorithm are not tractable using present day methods, or are not possible to compute within a practical timeframe for real-time operation;

ii) **RMAC meta-parameters** – Setting a tolerance level (ε_{RT}) or acceptable level of residual risk (ΔE_{OP} and ΔE_{RT}) is not presently possible for TSOs[2], as it would depend on sustained experience with the proposed method.

iii) **Insufficient data –** There may be insufficient data to calculate the total socio-economic surplus, or TSOs may not have confidence in existing data. Similarly, data on uncertain parameters (e.g. load forecast errors for building scenarios, or weather data for building variable failure rate models) may not be presently collected by TSOs. Data related to the reliability of system protection and on corrective control failure may also be lacking.

iv) **Insufficient tools –** There are presently no generally accepted tools for estimating component outage durations, or for service outage durations. Ideal modelling of corrective control requires a model of the operator‘s decision making process, for which no adequate models presently exist.

v) **Response and control complexity** – Considering a large number of system response and corrective control trajectories and short-term scenarios is not presently tractable, especially considering the overlapping of contingencies (i.e. additional contingencies occurring during the restoration process of the initial contingency). It is also not presently tractable to model each contingency as a stochastic dynamic simulation with control. Similarly, for short-term operational planning, the control problem is a stochastic dynamic control problem that considers all short-term scenarios and is not presently tractable.

Additionally simplifications to the ideal algorithm are required to ensure that the proposed first-step method is:

- Understandable by operators (i.e. not a black box model);
- Captures the main operational threats;
- Matches TSO processes (i.e. can be integrated into existing TSO workflows);

[2] Note that the current practices are equivalent to setting a tolerance level of zero for the set of operating constraints used today by system operators. However, we refer here to the non-trivial cases of setting a nonzero value for the tolerance level.

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- Outputs are produced quickly enough for their intended use;

Given these feasibility issues and specifications for simplicity, first-step implementations of the RT-RMAC and ST-RMAC are proposed in the present report. These first-step implementations are summarized in Sections 3.3 and 3.4 and described in detail in Chapters 5 and 6. In both the RT-RMAC and the ST-RMAC, exogenous parameters must be modelled. An overview of these models is given in Section 3.2, and they are described in detail in Chapter 4.

3.2 Models of the short-term and real-time exogenous uncertainty

3.2.1 Models of the short-term exogenous uncertainty

In recent years, significantly high level of uncertainties have been introduced to modern power systems. Starting from load uncertainties to renewable energy sources (RES), i.e., wind and solar penetration, these uncertainties have non-ignorable impacts on the balance and stability of power systems. Load stochasticity is still considered as one of the major uncertainties in the current power system. Apart from that, accurate quantification of the uncertainty introduced from RES energy is expected not only by the generation companies but also by the transmission system operators (TSOs).

It is well known that power generation from RES like wind and solar is characterized as being variable and uncertain. Wind power generation is dependent on wind speed while solar power generation is dependent on solar irradiation or insolation. For both the sources, variability refers to the unintentional tendency for generated power to change—perhaps rapidly—from one moment to the next, whereas uncertainty refers to the wide range of unknown future values of wind speed and solar insolation. The stochasticity of system load as well as power generation from RES poses special challenges to power system operation and planning. Increasing penetration levels of wind and solar exacerbate the uncertainty and variability that must be addressed in coming years, and can be extremely relevant to a number of power system operation and management procedures. At the same time, as RES is increasingly integrated into power systems, it is challenging for TSOs to ensure the reliability of power grids under uncertain circumstances and to maintain the maximum utilization of renewable energy.

Appropriate stochastic modelling of uncertainties is required to deal with the existence of uncertainty either in observations of the data (spatial) or in the characteristics that drive the evolution of the data (temporal). It is critical that multivariate dependencies in the forecast uncertainty, including the case of temporal, spatial and spatio-temporal load and weather trajectories, should be accounted for. Specifically, for capturing spatio-temporal interdependencies and determining the requirements for RT-RMAC and ST-RMAC, the GARPUR methodology proposes a multivariate uncertainty modelling approach considering load, wind and solar generation uncertainty together based on the vine copula theory. As copula methods allow for the modelling of the marginal distributions and of the multivariate dependence structure, as embodied by the copula, to be decoupled, they are well suited for GARPUR methodology. Copulas are joint cumulative distribution functions that describe dependencies among variables independent of their marginals. Having described the dependencies using a copula, a transformation function can be applied to each variable to transform the marginal distribution into the desired marginal. It is important to remark that copulas are invariant to monotonic transformations of the variables. This is a great advantage in simulation as the variables may belong to different probability distributions (for instance, system load, wind and solar power). A Gaussian copula is proposed in the first stage, and then d-vine copula is proposed for the modelling of multivariate distribution. Section 4 can be referred to for an extended description on uncertainty modelling.

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3.2.2 Models of the real-time exogenous uncertainty

In the context of real-time system operation, the main sources of uncertainty are the occurrence of unplanned component outages, sudden loss of generation, or significant load interruptions, and the subsequent uncertainty of the physical system response and corrective control following an outage. The probability of a contingency occurring in an operational period can be estimated by using a failure rate model based on historical component outage records, and possibly also based on modelling of exogenous threats (e.g. wind or lightning) and component vulnerabilities (e.g. whether the component is in a damaged or degraded state) as in [Perkin et al., 2016].

In special cases where the continuous uncertainty space presents a potentially substantial risk in the context of real-time system operation, such as large changes in wind power production. Such events can be modelled as discrete events with some probability, similar to how we model contingencies. As a result, the continuous uncertainty modelling described in the previous subsection is not necessary for the real-time assessment of reliability.

In addition to the uncertainty related to contingencies, the uncertainty related to system responses (e.g. failure of system protection schemes) and corrective control behaviour (e.g. human or technical failures in controlling components when attempting to stabilize or restore the system) must also be considered. As a first-step, we suggest that such uncertainty should be included using expert estimates, but in the future should result from cascading outage models and conditional on contingencies and/or control actions.

3.2.3 Scenario selection

In short-term operational planning, a scenario is a sequence of realisations of random exogenous variables with given granularity, typically hourly or half-hourly, over a designated operational planning horizon. The following exogenous variables are considered in the present document:

- Weather conditions;
- Failure rates of components;
- Load and RES forecast error.

Some of the short-term exogenous variables take value in a continuous uncertainty space. Defining scenarios entails discretizing the continuous uncertainty space, which can done by sampling a large number of scenarios.

In each stage of the planning horizon, the risk corresponding to each scenario is the product of the scenario probability and the sum, over a predefined contingency list, of the probability weighted impact of each contingency in terms of service interruption cost. However, due to the expected huge number of generated scenarios, risk assessment over all the scenarios would lead to enormous computational burden. Thus, a further approximation of those continuous distributions must be used in order to make the short-term risk assessment tractable. Therefore, some small subset of scenarios has to be selected before a short-term risk assessment in order to comply with computational constraints.

In the first-step implementation, it is suggested to decrease the number of scenarios that were generated to discretize the continuous uncertainty space by a two-stage method. In the first stage, the scenarios are iteratively clustered only based on mutual distance and their probability of occurrence using the scenario-tree generation method in [Rüdiger et al., 2006]. The first stage terminates when the distance between remaining scenarios is above a certain threshold, indicating that the remaining scenarios are too dissimilar to be clustered. During the scenarios clustering, the probabilities of pending scenarios are adjusted to ensure that their sum is still equal to one. The first stage results in a number of representative “scenario clusters”. At the end of the first stage, the number of remaining scenario clusters may still be

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too large to be assessed. In a second stage, the discarding principle of the ST-RMAC is applied, where a number of scenario clusters are discarded under the condition that their cumulative risk is tolerably low, i.e. under a pre-specified discarding threshold. The cumulative risk is denoted short-term residual risk and is conservatively estimated by associating an estimate of the worst-case risk over the planning horizon to the discarded scenarios.

The proposed first-step implementation of scenario selection algorithm, see Algorithms **4** and **5** in Section 4.4.1, has the following inputs and outputs.
Inputs of the scenario selection algorithm are:

- Model of the short-term exogenous uncertainty (including for those belonging to a continuous uncertainty space),
- Maximum distance between scenarios that characterizes similar scenarios
- Short-term discarding threshold
- Estimate of the worst-case risk over the planning horizon

Outputs of the algorithm are:

- Set of non-discarded scenarios.
- Set of discarded scenarios.
- Residual risk.

After convergence of the scenario selection algorithm, a set of non-discarded contingencies is determined for each operational period of the subset of scenarios.

3.2.4 Contingency selection

As it was mentioned above, the short-term risk assessment is being done by a sequential real-time risk assessment over all possible contingencies in each time instant of planning horizon, which is infeasible due to combinatorial dependence between the total number of contingencies and the number of components of the transmission network. Thus, some subset of non-discarded contingencies from a set of all possible contingencies has to be selected. Let us consider that the initial set of contingencies is defined by generating all the conceivable combinations of outages. This set is enough exhaustive to reflect all possible contingencies that are likely to occur even at very low probability. In the first-step implementation, the probability of contingency occurrence is assumed to be a function of weather conditions. If insufficient data is available to develop threat-based model, these weather conditions can be classified in a first step in categories such as normal and adverse weather and export knowledge used to determine how failure rates change in these categories. Thus, the initial set of contingencies can be adapted in ad-hoc fashion either according to the expected behaviour in future operational periods, where the same set of contingencies can be considered for the periods with similar values of exogenous parameters, or simply adapted after integration of new network elements (Transformers, Lines, Cables…). In the first-step implementation, the contingencies are adapted according to their probability of occurrence independently from their impact. The contingencies are sorted in descending order according to their probability of occurrence. Then, the smallest subset of the most probable contingencies having cumulative probability greater than or equal to a given threshold is selected and the remaining contingencies are discarded. If the cumulative probability of all contingencies in the contingency set were lower than the threshold, than it would be necessary to add other contingencies into the set to fulfil the discarding principle in RT-RMAC, see Section 9.1.2. The probability threshold is related to the acceptable real-time risk threshold and the potential impact of all discarded contingencies, where it is considered pessimistically that every discarded contingency would cause the system blackout.

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The proposed first-step implementation of contingency selection algorithm, see Algorithm **6** in Section 4.4.2, has the following inputs and outputs.
Inputs of the algorithm are:

- initial set of non-discarded contingencies,
- set of scenarios,
- acceptable real-time risk threshold,
- estimation of the worst-case costs of energy not served corresponding to each operational period of all scenarios.

Outputs of the algorithm are:

- sets of non-discarded contingencies for each operational period of each scenario.

3.3 First-step implementation for reliability management in real-time

3.3.1 Reliability criterion

The present day N-1 criterion, as discussed above, can be stated generally as a question of:

Will the system state be N-1 secure?

The N-1 criterion requires the TSO to use a mathematical model of the power system to check if all N-1 contingencies result in a secure system. If the system state is secure after all contingencies, the system is defined as 'N-1 secure'. Loosely, a system state is 'secure' if it does not result in the disconnection of a consumer and is within the current and voltage limits defined in the network codes; however, this varies between TSOs. This process can be described minimally as:

1. Given the present system state;
2. Select all N-1 contingencies;
3. Use a mathematical model to check that the post-contingency system is 'secure', for each contingency;
4. If all contingencies result in a secure system, define the system as 'N-1 secure'.

Therefore, the present day approach to reliability results in a deterministic 'yes/no' answer on system security.

The proposed GARPUR RMAC asks:

Is there a high probability that the system state will be acceptable?

Firstly, we replace the notion of 'secure' with 'acceptable'. A system state is defined as acceptable if it follows a set of rules that we call 'acceptability constraints', as discussed in Section 9.4. These rules consist of not only those related to security and technical constraints defined by regulations, but also may contain broader economic, social and environmental constraints.

Secondly, a dynamic contingency list is used instead of the N-1 contingency list. This dynamic contingency list is built using contingency probabilities and risk estimates, as described in Section 3.2. Enough contingencies are chosen to ensure that the residual risk of discarded contingencies is tolerably low. The process of the first implementation of the GARPUR RMAC is simply:

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1. Given the present system state[3];
2. Calculate contingency probabilities (See section 4.3 for more detail);
3. Create a dynamic contingency list, based on the contingency probabilities (See section 4.4);
4. Use a mathematical model to check that the post-contingency system is 'acceptable', for each contingency (See section 5.1);
5. Sum up the probabilities of contingencies that result in an acceptable system state.

The reliability of the system is described as a percentage value. The criteria itself is that this probability is 'high'. In other words, "*Is the probability of an acceptable system state greater than* $1-\varepsilon$*?*", where ε is the tolerance level of the reliability target (e.g. 0.1%).

It is not yet established as to what a good target value of ε would be. Therefore, we recommend initially only estimating the probability of an acceptable system state, without checking it against some reliability target (ε). It will be possible to suggest a good reliability target after TSOs have some experience with the measure, how it varies over the year, and how sensitive it is to data and operational decisions.

3.3.2 Reliability assessment

In addition to the reliability criterion, a new reliability management approach is also proposed. Beyond achieving some reliability target, the aim of power system reliability management is:

Determine which control actions result in maximum social welfare.

Although assessment is not concerned with the optimization of control actions, the measure of social welfare can quantify consequences following a contingency, given some pre-determined control actions. To achieve this, a framework for socio-economic impact assessment has been proposed in [GARPUR, 2016a]. This framework estimates the socio-economic surplus for both the total system, as well as its individual stakeholders (consumers, TSOs, market participants). This measure can be used by the TSO to compare the outcomes of possible decisions, allowing them to take the actions which maximise expected social welfare. The calculation of total socio-economic surplus is a combination of the following:

- Value of supplied load
- Cost of unsupplied load
- Cost of TSOs
- Cost of generators
- Cost of environmental impacts

The calculation of these values requires a mathematical model of the power system that describes the response of the system to a contingency, the corrective control of the TSO, and the resulting service outages over time. Modern TSOs already possess in-house tools to predict the response of the system to a contingency (required for N-1 contingency analysis) and some also include an estimate of corrective control in such models. These models can also be used to estimate the location and quantity of unsupplied energy, immediately following a contingency. Heuristic methods can be used to estimate the duration of these service outages, such as in [Henneaux and Kirschen, 2016] or [Rios et al., 1999]. This estimate can then be used to calculate socio-economic impact of a given contingency.

[3] To keep the real-time algorithm tractable in the first-step implementation, we assume there are no uncertainties in the system state (e.g. load injections), and that the only source of uncertainty is the occurence of contingencies and the subsequent system and operator response.

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It is impractical to assess all contingencies for a power system, given the large computational burden of including highly unlikely outcomes. Therefore, to limit the number of contingencies we dynamically divide the set of contingencies into 'non-discarded' and 'discarded' contingencies (See section 4.4). Non-discarded contingencies are those which have relatively high probability and will be modelled using the method described above. Discarded contingencies are relatively low probability, and comprise most contingencies (e.g.N-3 faults or worse). For simplicity, the discarded contingencies are assumed to result in a total system blackout (i.e. are HILP events), to ensure such contingencies are treated with a risk aversion. The socio-economic surplus is then calculated as the probability-weighted sum of the consequences of each contingency.

The contingency probabilities can be adjusted to reflect modelling assumptions, such as the probability of cascading faults, corrective control failure, and overlapping faults (a second contingency occurring before the service outages of a prior fault have been restored. The proposed reliability management approach is covered in technical detail in Section 5. The suggested reliability management approach and criterion is a simplified version of what GARPUR [GARPUR, 2016c] suggests should eventually be implemented.

3.3.3 Support to RT decision making

The reliability management approach and criterion above can be used to support the real-time decision making process. Simply, by changing the underlying assumptions and performing sensitivity tests, the operator can assess how the expected reliability level and/or social welfare are affected. Ideally, a computational tool would automate this process and identify the optimal control actions given the present system state [GARPUR, 2016c][Karangelos, 2016]. Such a tool is identified in the development roadmap. In the short-term however, trial-and-error is a suitable way for operators to compare a handful of candidate decisions, or to see how important certain assumptions/inputs are to the outcome. In different steps of the reliability management approach the operators can adjust some inputs or assumptions to the algorithm based on their experience. Operators may then choose those decisions that turn out to yield the largest social welfare, while also ensuring that the probability of an acceptable system state is high enough (i.e. achieve the reliability criterion).
Some possible inputs that the operators may provide are:

- Information related to the reliability of the system response model, or the probability of failure of corrective actions;
- Based on real-time information they may include certain discarded contingencies to the non-discarded contingency list;
- Changes to the initial system state in the model, to simulate preventive control actions;
- Modifications to the corrective control rules in the model to affect the outcome for either all contingencies or specific contingencies. Therefore, control room operators may use the tool to anticipate the benefit or consequence of possible actions they are considering.

If the outputs are highly sensitive to particular inputs, this will highlight aspects of the system that may require further operator scrutiny in the short-term, and improved modelling and data collection in the long-term.

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3.4 First-step implementation for reliability management in short-term operational planning

3.4.1 Short-term reliability assessment

During short-term operation planning, the following activities are coordinated to prepare the system for real-time operations for a specific time horizon (for example, a whole day in day-ahead operational planning): forecasting, determination of network capacities to send to the market, outage planning, reserve management, voltage control, control of component loading and system protection [GARPUR, 2015]. Preparing the system for real-time operations means that the decisions taken during the short-term operation planning must ensure that the real-time RMAC can be met. In essence, the problem addressed in ST operational planning is to find a risk-based trade-off between actions that can be taken now and actions that can be taken during real-time operation, while optimizing in expectation the overall socio-economic impact of the combination of operation planning and real-time decisions [GARPUR, 2016c].

Short-term operation planning faces a larger level of uncertainty than real-time operations. This is because, first, the number of uncertain parameters increases and, second, the uncertainty of each uncertain parameter increases. In intraday and day-ahead operational planning, the uncertain parameters are mainly the net power injections and weather-dependent parameters such as the failure rates and thermal limits of components. Before the market is cleared, additional uncertain parameters include the commitment decisions of power plants. The short-term reliability assessment process is fed by scenarios, with associated probabilities, for these uncertain parameters. A scenario is a sequence of realisations of these uncertain parameters for all time periods of the considered time horizon (such as 24 hours of the following day).

The reliability assessment process in short-term operational planning is concerned with:

- simulating what decisions would be taken in real-time operations by the real-time operator in each hour of each scenario;
- assessing the socio-economic impact and reliability level resulting from these real-time decisions in each hour of each scenario;
- aggregating the results of the real-time assessments over all scenarios to present meaningful indicators to the operator that supervises the short-term reliability assessment.

Doing so therefore requires:

1) a list of ST scenarios with realisations of the ST exogenous uncertainties for all time periods of the considered time horizons;
2) a model of the real-time decision-making process to determine what real-time decisions would be taken in the different scenarios of the ST exogenous uncertainties, together with the corresponding socio-economic impact indicators;
3) a model of the real-time reliability assessment process to evaluate the reliability level given the real-time decisions;
4) procedures to aggregate the outputs of all real-time assessments into meaningful indicators for the ST operator.

The ST scenarios are assumed to include a contingency list for all hours of each scenario, as explained in Section 3.2. Points 2) and 3) define a model of real-time operations.

The list of assessed scenarios is finite. As described in Section 3.2, it is generated such that the residual risk of discarded ST exogenous uncertainties (the non-assessed ST exogenous uncertainties) is tolerably low, as was done for contingency discarding in the RT-RMAC presented in Section 3.3.

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In the GARPUR approach, two dimensions are presented to the operators: probabilities of events (scenarios, contingencies, corrective action failures) and the socioeconomic surplus. These two dimensions are key contributions of GARPUR and allow computing indicators that can be used to trade off risk of service interruptions and cost of actions.

3.4.1.1 Model of the RT operations

As explained above, the model of RT operations includes a model of the real-time decision-making process and a model of the real-time reliability assessment process to evaluate the effect of these decisions. The first-step implementation of the real-time decision-making process proposed in this section is based on N-1 where the real-time operator secures the system against a contingency list, but does not account for the failure of corrective actions, unexpected system response or for the probabilities of contingencies. Given these actions, the real-time reliability assessment process is performed as proposed in Section 5.1. In particular, this assessment considers the possible failure of corrective actions and their probability, possible unexpected system response behaviours and their probability and the contingency probabilities.

Given a contingency list, realisations of the net power injections and a list of acceptability constraints, the model of the real-time decision-making process will determine the real-time actions to take to enforce all pre- and post-contingency acceptability constraints for all contingencies in the contingency list. Due to the need of automation to simulate this decision-making process in all scenarios, it is proposed to use an optimal power flow (OPF) routine for this purpose. The real-time operator can take both preventive and corrective actions. The former are used to secure the system against a set of contingencies before they occur whereas the latter determine whether post-contingency corrective actions would be available to secure the system should a contingency occur. Our proposal does not assume that robust tools are available today to determine jointly real-time preventive and corrective actions in an automated way. Such tools scalable to the pan-European system have however been investigated in the European project "PEGASE" [PEGASE, 2009], [PEGASE, 2012a], the results of which could be used by TSOs who want to implement such tools. Therefore, our first-step implementation only considers corrective actions and does not consider the possibility of using real-time preventive actions in an automatic way. However, the person performing the short-term risk assessment can apply manual preventive actions in a specific scenario or a set of scenarios. The outputs of this step are:

- Output 1: the real-time corrective actions
- Output 2: the cost of the real-time corrective actions (automatically chosen by the OPF).
- Output 3: the cost of the real-time preventive actions (manually applied).

Once the real-time corrective actions have been determined, the model of the RT operations will assess the real-time risk following the procedure detailed in Section 3.3. The outputs of this assessment include for each hour of the considered time horizon and in each scenario:

- Output 3: The probability that the system state will be acceptable in this hour of this scenario.
- Output 4: An indicator of whether the real-time reliability criterion is fulfilled, i.e. that there is a high probability that the system state will be acceptable.
- Output 5: A measure of risk, defined as the expected cost of interruptions
- Output 6: A measure of the socioeconomic surplus, defined as the expected value of supplied load minus the expected cost of interruptions (risk) and cost of TSO actions.

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3.4.1.2 Reliability criterion in ST

Given the outputs of all runs of the model of the RT operations, the reliability target in ST can be defined as

Is the RT RMAC fulfilled in all hours of all scenarios?

Given the definition of the RT RMAC in Section 3.3, this can be re-formulated as *"for each hour, in each scenario, is there a high probability that the system state is acceptable?*" Note that the probability of the scenarios of the ST exogenous parameters is not considered in this definition. In certain cases, it may happen that the cost of enforcing the RT RMAC in all scenarios of the ST exogenous parameters irrespective of these scenarios' probability may be unacceptably high. Therefore, the RMAC in ST presented above is accompanied by one measure of the violation of the RT RMAC across all scenarios:

What is the probability of not fulfilling the RT RMAC in each hour?

This measure aggregates, for each hour, Output 4 of the model of the RT operations presented in Section 3.4.1.1 across all scenarios by weighing them with the corresponding scenario probabilities.

All the probabilistic indicators above may identify which scenarios and contingencies are the most problematic and what acceptability constraints are most likely to be violated.

3.4.1.3 ST risk assessment

The ST reliability assessment procedure aggregates Output 5 of the model of the RT operations by computing for each hour the average socioeconomic surplus in all scenarios. This average socioeconomic surplus can be broken down into different parts such as the expected value of supplied load, the expected cost of energy not supplied and the expected cost of day-ahead preventive actions and real-time corrective actions. Furthermore, it can be opened up to reveal the contribution of each scenario and, in each scenario, the contribution of each contingency to investigate which contingencies significantly impact the expected socioeconomic surplus.

3.4.2 Support to decision making

Following the reliability assessment stage, the decision-maker will undertake the necessary actions to return to an acceptable reliability level in case a violation of the reliability criterion has been detected. In the same manner, and assuming the reliability target is fulfilled, he may be willing to test different configurations to perform some manual optimization, such as reducing the losses.

One of the difficulties that we face with the GARPUR RMAC for the short-term is that we consider many scenarios at the same time. As explained above, the list of assessed scenarios is finite and generated such that the residual risk associated with the non-assessed ST uncertainty is kept tolerably low. The list of assessed scenarios may still contain a large number of scenarios. In their current practices, the TSOs analyse a single or a very few cases, which allow them to intuitively find the actions that can alleviate the risks and manually verify their efficiency. In a stochastic environment, an action "A" may be efficient for some portion of the scenarios, while being useless – or harmful - for the rest of the scenario space. This is the tricky issue with stochastic optimization. Although relevant, it is difficult to implement.

To overcome this hurdle, we investigate in section 6.2 the following issues:

1) How to visualize the risk (contingencies/scenarios) after a stochastic assessment of reliability?
2) How to provide hints to the operator on what could be the most relevant actions to undertake?

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3.4.2.1 Main features expected for the visualization of the risk-assessment

We expect from the risk assessment method to provide as output:

- Indicators to answer whether the reliability target holds for the period of time under consideration, as well as for each time-step. Such indicators could be binary (OK, NOK), could take the form of traffic lights (green/yellow/red), or any discrete index reflective of the stress of the situation. It can be computed from the probability of achieving the acceptability constraints;
- For each time step, a filtered list of the combinations scenario/contingency that are the most likely to endanger operation. It is desirable that the scenarios contain a tag to understand their peculiarities. A tag could be high-load, low RES, high import from such country,…;
- A list of RT actions that may be triggered either preventively or correctively. Displaying their implementation time would also be of interest. OPF methods seem appropriate;
- Indicators of the socio-economic surplus for the whole period of time and for the different areas, encompassing the expected interruption costs as well as the costs due to losses or the above-mentioned actions triggered automatically.

3.4.2.2 Reliability control in a probabilistic framework

In the case some unsecured configurations are spotted, the operator would start by having a look at the screened time-steps/scenarios/contingencies that have been filtered as the most dangerous. Indeed, an automated process would not always apprehend the risk on the security of the system the same way a human expert would do. For instance, the operator may be aware of possible corrective actions ignored by the automated process.

If the reliability level is still deemed too low despite the additional corrective actions proposed by the operator, or if the operational costs can be optimized, the operator should input a set of planned real-time preventive actions to the assessment model and run the assessment again. These actions could for instance concern the topology, the generation redispatching, or the postponement of maintenance activities. The output from the assessment method provide more clues than the current methods based on the N-1, so we trust the operator to be able to propose relevant measures.

Then, by comparing the indicators on the reliability and the different costs at stake, the operator will choose the solution that enables to ensure the reliability criterion while optimizing the socio-economic impact.

3.4.2.3 Relaxation

In some cases, respecting the reliability target might be infeasible or would lead to unacceptable costs. Such circumstances could be met for instance during periods of very high-load, or following a forced outage before it is repaired. In order to take the best possible decisions in such peculiar context, the TSO has to relax the regular parameters of the RMAC (see Section 9.1) to be more relevant during these (hopefully short) exceptional circumstances. Several options can be considered for the relaxation, namely relaxing the reliability target, the acceptability constraints, or accepting a higher residual risk by discarding additional scenarios. The pilot tests conducted in GARPUR work-package 8 should provide some insight on which parameter is more relevant to relax.

3.5 Additional considerations

The reliability target of the GARPUR reliability management approach and criterion (RMAC) consists of requiring that the probability that the power system response to uncertainties will be acceptable is higher than a pre-specified tolerance. This requires defining a set of acceptability constraints. Whereas the tolerance is a global reliability measure, the set of acceptability constraints can address different various

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aspects of the risk from which a TSO will be protected. The definition of the acceptability constraints will extend the existing operational and safety limits by adding thresholds on quantities that are today not captured by the N-1 criterion. An extensive discussion on acceptability constraints is included in Appendix 9.4.

Satisfying a certain reliability target is impacted by various exogenous conditions, like weather conditions, uncertainty related to the volatility of uncontrollable generation sources, peak demand or market behaviour. On the other hand, it is also impacted by several endogenous factors, which reflect the operational conditions of the network and assets availability (level of asynchronous injections, forced outages or planned maintenance). The proposal is to consider these time and space dependencies in the RMAC, by allowing a modification of the tolerance based on time and/or space. This is discussed extensively in Appendix 9.5.

Finally, the RMAC relies on measuring the socioeconomic surplus. A worst-case estimate of the socioeconomic surplus can be used as a conservative and pessimistic estimate of the consequences of discarded events. This issue of obtaining a worst-case estimate and using it in the processes that discard scenarios and contingencies is discussed in Appendix 9.6.

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Seventh Framework Programme under Grant Agreement No 608540.

4 UNCERTAINTY MODELLING IN REAL-TIME AND SHORT-TERM CONTEXTS

With the large number of factors affecting real-time and short-term decision making process, accuracy of the forecasting method and uncertainty modelling is vital. In order to model the uncertainty, it is necessary to know the possible magnitude of under- or over-estimations and their probabilities, so that TSOs are able to identify potential threats to secure operation of their respective control area early and start the necessary actions to prevent such system states. For example, the lack of accuracy of load forecasts can impact a variety of actions during short-term as well as real-time, such as:

- The dispatch plan of generation units may not be optimal, resulting in economic losses.
- Energy trading schedules may miss advantageous purchasing or selling options.
- Maintenance scheduling may suffer missed opportunities for preventive maintenance.
- System security may misidentify system stability on prospective generation plans.
- Greater forecast uncertainty requires an increased allocation of reserve generation.
- Exacerbate consequences of unplanned outages.

Within the GARPUR RMAC, it is important to introduce the notion of exogenous variables that are modelled explicitly in a reliability management task. Exogenous variables are determined external to the TSO, and the TSO will have to adapt its behaviour accordingly. In this report, the following exogenous variables are modelled in the real-time and short-term decision-making process: load uncertainty, RES (wind and solar power) uncertainty, and failure rate of components (generators, lines and cables). It is intended to analyse forecast error time series, and understand it as a stochastic value. The same procedure is followed for modelling wind and solar power as stochastic variables, which may have several possible future realizations. Failure rate modelling and fault probabilities are required to model the random occurrence of contingencies within an RMAC. How these are calculated is outlined in the final part of this section on uncertainty modelling.

In general, approaches for uncertainty modelling include non-probabilistic approaches and probabilistic approaches. For non-probabilistic approaches, interval analysis, fuzzy theory, possibility theory and evidence theory are most widely used. Probabilistic approach is being considered as the most rigorous approach to uncertainty analysis in engineering design due to its consistency with the theory of decision analysis. This is only true if we have a way of quantifying the probability measure implied by the uncertain parameters. The fundamental characterization of probability is the probability density function (PDF). In probability theory, a PDF, or density of a continuous random variable, is a function that describes the relative likelihood for this random variable to take on a given value. The probability for the random variable to fall within a particular region is given by the integral of this variables density over the region. The two main probabilistic approaches that are widely used are analytical methods and the stochastic methods (or the Monte-Carlo (MC) simulation methods). The analytical method requires a number of simplification methods in order to reach an analytical formulation of the problem, namely, linearization of the model, assuming inputs as independent, and normally distributed. Analytical methods are preferred in load flow studies [Schilling et al., 1990] but it has some drawbacks too. For example, assumption of independence of the nodal loads is quite unrealistic. In stochastic methods, the Monte-Carlo (MC) simulation method is the general designation for stochastic simulations using random numbers [Rubinstein, 1981]. Compared to the analytical methods, stochastic methods offer significant advantages, since the basic computational part is deterministic and there is no need to simplify the mathematical models to ensure applicability of the method. A snapshot represents the system in one particular instant in time. In snapshot approach, the sampling of system inputs provides different snapshots of system operation with all required information that corresponds to different points in time. The snapshot approach is recommended for GARPUR methodology.

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4.1 Load and RES power uncertainty

It is well known that load and RES stochastic variations are the main sources of uncertainty in operational framework of power systems. Accurate load and RES forecasting in short-term horizon is very important because they determine scheduling of generation units for next day or maybe few hours ahead, market clearing, and many other operational tasks. Any error in forecast results in suboptimal commitment of generation unit in day-ahead market and is corrected by TSOs in intraday and/or by balancing markets. Although the load forecasting errors are much smaller than those associated with renewable energy sources (RES), in terms of mean absolute percentage error (MAPE), the absolute value of load forecasting error in terms of Megawatts is typically large. To address this, a common method is to model the load uncertainty as normal distribution or truncated normal distribution as suggested in [Khuntia et al., 2016]. For the first implementation of the GARPUR methodology, we propose that load forecast errors are assumed to follow the normal distribution.

In general, the active power is considered as a random variable; the reactive power can be omitted from the uncertainty analysis, since in most cases the load power factor can be considered to be constant, while the generated reactive power is either regulated for voltage control, or supplied under a constant power factor. In such cases, the reactive power is obtained from the active power based on a deterministic functional relationship. Another advantage of exclusion of reactive power is the reduction of the problem dimension. In cases when this is not valid, reactive power can be introduced as a random variable and the approach presented remains valid. If needed, the load reactive power samples can be obtained from the active power samples based on a constant load power factor obtained from historical data.

Uncertainty and variability can be seen as the two fundamental characteristics associated to renewable energy sources (RES), specially wind and solar/photo-voltaic (PV) generation, when compared to conventional power generation. The output power of both wind farm and PV plants are vulnerable to sudden weather changes, and it can vary from decent value to even zero. This can significantly impact the normal operation; hence failing to consider RES forecast and its associated uncertainty can translate in a poor decision making, negatively affecting the cost and reliability of the system. There are different timescales involved in the forecasting process: from the evaluation of few seconds-ahead wind variations in order to enhance the efficiency of a wind turbine pitch control strategy, to 20-30 year-ahead resource estimation to be used in planning studies. In such cases, high wind power penetration will have significant impacts on power system operation economics, stability, security, and reliability due to fast fluctuation and unpredictable characteristics of wind speed.

Uncertainty in wind generating sources can be divided as:

- Wind speed distribution
- Uncertain power curve

The uncertainties of wind generating sources are mainly from two aspects: the intermittent and volatile wind speed and the uncertain power curve. Wind speed, as an essential measurement for wind power generation, is influenced by many factors such as the weather conditions, the land terrain, and the height above the ground surface. The power curve of a wind turbine is a graph that indicates the mathematical mapping from different wind speeds to the electrical power output of wind turbines.

On the other hand, the often smaller and more recent deployment of solar-PV with respect to wind generation, along with the fact that most of PV installations have a small capacity and are usually connected to the distribution network (DSO) explain the lower degree of attention drawn by solar forecasting with respect to wind forecasting. PV generation forecasting accuracy is mainly influenced by

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the variability in meteorological conditions and to a minor extent to the uncertainties related to the different modelling steps needed to predict power generation from meteorological forecasts [Pelland et al., 2013]. Solar generation presents a high sensitivity to changes in solar irradiation, making the variability (probability of ramp events or sudden changes in production) an additional component of a comprehensive solar forecast.

Even though measurement errors are commonly assumed to follow a Gaussian distribution, this assumption does not always hold for wind forecast errors. A comparison of the distributions of day-ahead and hour-ahead forecast in several countries is presented in refs. [Hodge et al., 2012]. It was found that regardless of the country, forecasted period or installed capacity considered, forecast errors distribution showed relatively heavy tails (high kurtosis) and hence could be only poorly represented by a normal distribution. Hour-ahead (operational) forecast errors presented a much higher kurtosis than those derived from day-ahead forecast. In ref. [Bludszuweit et al., 2008], the forecast errors are modelled as a Beta distribution. From the literature, it can be seen that the distribution of the forecast errors over a large geographical area is mainly influenced by the installed capacity and the geographical distribution of wind generators over the power system. Despite the fact that there is not a universally accepted distribution to describe wind forecast errors, it is important to realize that the use of a normal distribution can lead to significant errors and that a higher degree of flexibility is generally required in order to match the different kurtosis found at different time horizons. This brings additional challenges when it comes to deriving confidence intervals for a prediction, requiring the use of non-parametric approaches. A review of different approaches to deal with the non-Gaussian distribution of errors and the nonlinearities in the process can be found in ref. [Giebel et al., 2012]. Confidence intervals for solar forecasting are also generally assumed to be normal, even though it does not generally reflect the reality. The joint distribution of solar and wind forecasting errors was analysed in ref. [Zhang et al., 2013], even though little correlation was found as this is very site specific.

Wind power forecast essentially depends on the weather conditions such as wind speed and direction, which can be derived using mesoscale meteorological models. However, it is clear that at least a detailed dataset including nodal or area forecast and actual wind generation along with detailed information for some representative wind farms should be accessible, regardless of the methodology to be followed. For the uncertainty modelling, it is assumed that historical data is available at nodal points. Data refers to system load, wind speed and solar radiations at the nodal level.

4.2 Joint probability distribution and scenario generation

It is important to capture the inherent dependence between load, wind and solar generation (here on referred as RES) scenarios, as well as additional exogenous variables that may affect component failure rates. This section discusses how the correlation of wind and solar generation and load scenarios could be handled by similar mathematical approaches. In order to explore and exploit the impacts of wind power uncertainty on the power grid whilst considering load uncertainties, a numerical simulation technique like MC-approach is generally applied. However, this creates a heavy computational burden due to the necessarily large sample size. Scenario generation is an important part of uncertainty modelling. It helps in approximating distributions when the number of outcomes are infinite but can perform poorly when using only a few outcomes. In order to simulate scenarios for two or more variables jointly, their correlation structure must be taken into account. For e.g., if the studied time-series is Gaussian, then Cholesky decomposition is enough to generate a correlated simulation, otherwise a copula approach is necessary.

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The integration of RES in a bulk power system will increase in coming years, and call for the importance of modelling the joint probability distribution. For most of the analysis, it can be recommended that the system dispatch has been set to follow the system net load, which corresponds to perfect forecast, i.e. zero forecast error. When the forecast in the system is not perfect, an increase in the variability of the system power flows should be expected, due to the engagement of units possibly other than expected to support the imbalances. In case of availability of real data and techniques described in previous section, the forecast error may be sampled and incorporated in the analysis. Further, the joint distribution is discussed later in this section.

Study [Giebel et al., 2012] reveals that electrical load has more in common with wind generation as compared to conventional generation. In today's conditions, wind and solar generation can be combined together due to their massive integration into the grid. Thus, electrical load and power generation from RES (wind and solar) cannot be considered as independent statistical variables. This calls for correlation studies among the three entities. On a positive aspect, once correlation studies are performed, uncertainty studies become easy. In case it is desired to generate scenarios for load and RES together, the problem definition leads to a multivariate uncertainty analysis problem and a MC-approach is proposed as solution, based on the theory of copulas or in other words, splitting of the modelling procedure in two basic components, i.e. the modelling of the one-dimensional marginal distributions and the modelling of the multi-dimensional stochastic dependence structure.

For the uncertainty modelling, it is important to model the time-dependency of load stochasticity. The usual convention is use normal distribution or truncated normal distribution in recent studies [Khuntia et al., 2016]. For the ease of modelling, the time dependency can be excluded by performing the calculation for groups of hours with similar statistical characteristics, as performed in [Caramanis et al., 1982]. The joint distribution incorporates the one-dimensional marginal distributions of load and wind and these latter are the most easy to assess through data analysis or expert judgement. But, in reality, the one-dimensional marginal distributions are not sufficient to calculate the joint distribution. They are sufficient if load and power generated from RES are independent random variables, but in reality they are not independent. Obtaining the joint distribution given the marginals is however a non-trivial problem, since there exist an infinite number of joint distributions with the same marginals, corresponding to an infinite number of stochastic dependence structures between the random variables load and wind.

The arbitrary assumption of independence produces a systematic tendency to disregard the effect of the dependence structure. The modelling of stochastic dependence has been a cornerstone in the research on multivariate uncertainty analysis. One of the promising approaches is the use of vine copula models, which is also recommended for our proposed study.

The modelling framework can be divided into two major tasks:

- Modelling the one-dimensional marginal distributions called marginals.
- Modelling the stochastic dependence.

It is important to capture these two aspects. For example, if the marginal distributions remain the same, the joint probability distribution can change due to changes in the dependence.

4.2.1 Modelling the one-dimensional marginal distributions

The one-dimension marginal distributions capture the stochastic behaviour of the individual exogenous parameters. The marginal cumulative density function (CDF) of a random variable X is defined as

$$CDF_X(x) = P(X \leq x).$$

An important property of CDFs is that the cumulative distribution function of X applied to X itself yields a uniformly distributed random variable. Mathematically, it can be written as [Kurowicka and Cooke, 2006]:

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$$For\ x\epsilon[0,1]: P(CDF_X(X) \le x) = P\left(X \le CDF_X^{-1}(x)\right) = CDF_X[CDF_X^{-1}(x)] = x$$

This forms the base of MC-sampling method. Using the equation above, sampling a random variable X with CDF CDF_X can be done by first sampling a random realization y from a uniform random variable Y in $[0,1]$, and then applying the transformation $x = CDF_X^{-1}(y)$. In these cases, the samples x follow the distribution CDF_X [Kurowicka, 2011].

This can be extended for sampling from real measured data by using the empirical CDF. Figure 1 shows an example of an empirical marginal CDF for the forecast error of one single load.

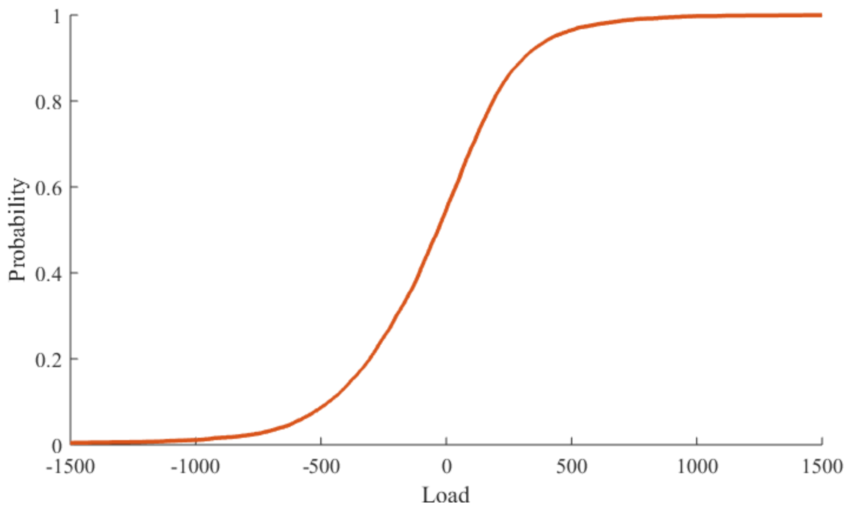

Figure 1: Empirical marginal CDF of forecast error of a single load.

The sampling method above can be applied for sampling any single random variable whose CDF is known. When several random variables that are correlated are to be sampled, the above is not enough since it does not capture any measure of the dependence between the random variables. However, the marginal CDFs are still important as will be seen in the next section.

4.2.2 Modelling the stochastic dependence

For modelling RES, the dependence between the prime movers (wind speed and solar irradiation) and output power (wind and solar power) is important to study. In case of wind power, the wind turbine generator behaves differently in different geographic locations (i.e., wind speed plays an important factor). In general, the wind resources present significant correlation. The same also applies for solar power (i.e., solar irradiation varies with location change). In particular, the power output of stochastic generators situated in a small geographic area show similar fluctuations due to their mutual dependence on the same prime mover, which is not the case for stochastic generators situated in remote areas. With increased penetration of RES into primary grid, it is vital to model the complex interdependencies introduced by the RES in the power system along with system load.

The dependence between exogenous parameters can be captured by different measures of dependence. For general multivariate random variables, Spearman's rank coefficient can be used [Embrechts et al., 2001] to study the non-linear, monotonic relationship between two random variables. Spearman's rank coefficient $\rho_r(X,Y)$ between two random variables X and Y is defined as

$$\rho_r(X,Y) = \rho\big(CDF_X(X), CDF_Y(Y)\big),$$

Where $\rho(U,V)$ is the Pearson correlation coefficient between $U = CDF_X(X)$ and $V = CDF_Y(Y)$ defined as

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$$\rho(U,V) = \frac{E(UV) - E(U)E(V)}{\sigma(U)\sigma(V)} = \frac{E[(U-\mu(U))(V-\mu(V))]}{\sigma(U)\sigma(V)} = \frac{Cov(U,V)}{\sigma(U)\sigma(V)}.$$

From the property of the cumulative distribution function stated above, the variables $U = CDF_X(X)$ and $V = CDF_Y(Y)$ are uniformly distributed. U and V can be interpreted as "ranks" of X and Y. Spearman's rank coefficient can also be estimated from observation points of X and Y as

$$\rho_{rXY} \left(= \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \right)$$

where x_i, y_i are ranks of X_i, Y_i in the data sets X, Y, n is the number of observation points and $\bar{x}$ and $\bar{y}$ are the empirical expected values-

Spearman's rank coefficient helps in defining the dependence structure based on rank with specific functions, called copula functions. Using copula functions, it is possible to simulate two random variables that are correlated according to rank correlation by first simulating a copula and later transforming the obtained ranks into respective marginals. Copula is a multivariate probability distribution for which the marginal probability distribution of each variable is uniform [Nelson, 2006]. Copulas are used to describe the dependence between random variables. By definition, for two random variables X and Y with CDF CDF_X, CDF_Y are joint by copula C if their joint distribution can be written as:

$$CDF_{XY}(x,y) = C(CDF_X(x), CDF_Y(y))$$

Recall that the variables $U = CDF_X(X)$ and $V = CDF_Y(Y)$ are uniformly distributed. The function C is therefore defined on uniformly random variables, and the cumulative distribution functions can be used to map the uniformly random variables to X and Y. Using copula functions to model the exogenous parameters between ρ_{rXY} between X and Y can be done by:

1. Computing the rank coefficient ρ_{rXY} between X and Y
2. Fit a copula function $C_{XY|\rho_{rXY}}$ that can be used to sample from uniformly random variables U and V such that the rank coefficient between U and V is as close as possible to ρ_{rXY}.

More detail about these two steps for modelling load and RES production can be found in [Papaefthymiou and Kurowicka, 2009] and [Louie, 2014].

After these two steps, the copula function and the cumulative distribution functions can be used to produce samples of X and Y as follows:

1. Drawing samples U_i and V_i by sampling the copula function $C_{XY|\rho_{rXY}}$.
2. For each sample, apply the inverse cumulative distribution function to obtain samples $X_i = CDF_X^{-1}(U_i)$ and $Y_i = CDF_X^{-1}(V_i)$ of X and Y. The fact that the inverse cumulative distribution function yields samples of X and Y from samples of the uniformly distributed random variables U and V follows directly from the property of the CDFs that was presented above.

Algorithm **1** describes the steps to sample two random variables using copula.

Algorithm 1: Sampling of two correlated random variables using copula

Inputs: Two uniform independent random variables U_{r1}, U_{r2} (say load and wind power), correlation coefficient, copula function.
Outputs: Sampled distributions

1 Sample two uniform random variables U_{r1}, U_{r2}, and obtain the realizations u_{r1}, U_{r2}.
2 $u_1 = u_{r1}$: presents sampling of the rank distribution U_1
3 Calculate copula function $C_{12|u_1,\rho_{r12}}$, i.e., the conditional distribution of U_2 for rank correlation ρ_{r12} and given u_1.
4 Sample the rank distribution U_2: $u_2 = C^{-1}_{12|u_1,\rho_{r12}}(u_{r2})$, using the inverse copula function. Outcome can be either 0 or constant, depending on the value of independent sample u_{r2}
5 Transform the rank distributions according to the marginals: $x_1 = CDF_1^{-1}(u_1)$ and $x_2 = CDF_2^{-1}(u_2)$
6 **End**

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Note that for a given rank coefficient, different copula functions can be used as described in [Louie, 2014]. A particular instance of the above algorithm is the use of a Gaussian copula. When using Gaussian copula, the overall method in Algorithm **1** is called the joint normal transform [Papaefthymiou and Kurowicka, 2009]. The mean of the Gaussian copula is zero and the covariance matrix is

$$\mathrm{R} = \begin{pmatrix} 1 & \sigma \\ \sigma & 1 \end{pmatrix}.$$

A property of the Gaussian copula is that the covariance σ can be computed from the rank correlation of X and Y as follows:

$$\sigma = 2sin\left(\frac{\pi}{6}\rho_r(X,Y)\right).$$

Note that σ is not the covariance between X and Y but the covariance used in the Gaussian copula. The equation above links this covariance with the rank coefficient of X and Y.

The above procedure describes the joint normal transform for two random variables. The procedure can be generalized to *n* random variables by applying the above to all pairs of random variables. The resulting Gaussian copula will be *n*-dimensional. Algorithm **2** describes how to sample n correlated random variables using the joint normal transform method:

Algorithm 2: Sampling of n correlated random variables using joint normal transform method

Inputs: n correlated random variables
Outputs: Sampled distributions
1 Compute the rank correlation (ρ_r) of any two of n random variables to form the rank correlation matrix (R_r).
2 Convert the rank correlation matrix (R_r) to product moment correlation matrix (R) using the relationship between the covariance of the Gaussian copula and the rank correlations, see above.
3 Formulate the joint distribution function from joint normal transform using R.
4 Sample the distribution function in step 3 directly and obtain n-dimensional standard normal vector $\bar{N} = (n_1, n_2, \dots, n_n)$.
5 Transform $\bar{N}$ to one-dimensional standard normal CDF $\bar{U} = (u_1, u_2, \dots, u_n)$ and each component follows uniform distribution on the interval [0, 1].
6 Transform the rank distributions according to the marginals: $x_1 = CDF_1^{-1}(u_1)$, $x_2 = CDF_2^{-1}(u_2)$, …, $x_n = CDF_n^{-1}(u_n)$.
7 **End**

The application of joint normal transform using the above algorithm can be used for any system with following data availability:

- Marginal distributions: The system load distribution, wind speed distributions and solar power generation at each generation node of the system.
- Dependence structure: The product moment correlation matrix (R) is calculated from rank correlation matrix (R_r), between all pairs of exogenous parameters.

The above algorithm works well when all required data is available. Because available data is needed to calculate the correlation and then later use copula to model the stochastic dependency. In reality, not all required data is available. The reason can be anything from bad measurement devices to confidential information or just 'stochasticity'. In case of data unavailability, mutual correlations between the stochastic inputs is not possible and hence the joint normal transform is not recommended. To tackle this issue, a vine copula model offers suitable solution [Kurowicka, 2011]. In addition, some shortcomings of multidimensional copula functions and the Gaussian copula favour the use of vine copula models, which is preferred as discussed previously. The shortcomings can be listed as [Bedford and Cooke, 2002]:

- Practical infeasibility: The Gaussian copula has the limitation in modelling the data if there are different dependency structures between pairs of variables. For example, modelling of wind generation along with load distribution and solar radiation.
- Dimensionality issues: The choice of adequate copulas is limited when the dimension of problem increases.

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Vine copula models decompose a multivariate copula into a set of bivariate copulas and every bivariate copula function can be imagined as a branch of a graph connecting two consecutive marginal distributions or their conditional bivariate distributions. By definition [Kurowicka, 2011], a vine copula on n variables is a nested set of trees T_j where the edges of the j^{th} tree become the nodes of the $(j+1)^{st}$ tree for $j = 1, \dots, n$. A regular vine on n variables is defined as a vine in which two edges in tree j are joined by an edge in tree $j+1$ only if these edges share a common node. Each edge in the regular vine may be associated with a conditional rank correlation and a copula, and each node with a marginal distribution. All assignments of rank correlations to edges of a vine are consistent and each one of these correlations may be realized by a copula. Based on the bivariate and conditional bivariate distributions, the joint distribution can be constructed. Recent studies have attracted the use of vine copulas and can be found in refs. [Bessa, 2016, Sun et al., 2016].

A regular vine can be either d – vine where each node in T_j has a degree of at most 2 or c (canonical) c – vine in which each tree T_j has a unique node of degree $n - i$. Figure 2 shows the d-vine on four uniform variables labelled X_1, X_2, X_3, X_4.

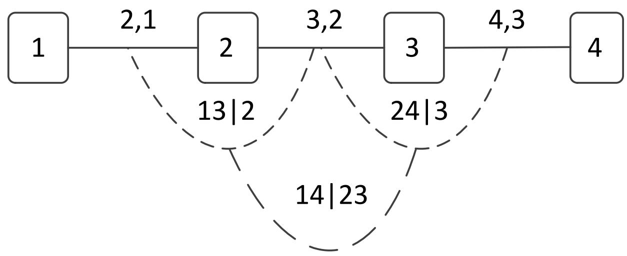

Figure 2: d-vine on four variables

Distributions specified by conditional rank correlation on a d-vine can be sampled, and an algorithm to do it is presented in **Algorithm 3**, which can be expanded from 4 to n variables. The algorithm involves sampling four independent uniform $(0,1)$ variables U_1, U_2, U_3, U_4. The conditional correlation between variables (i, j) given k is given as $\rho_{r_{ij|k}}$. The CDF for X_j given U_i under the conditional copula with correlation $r_{ij|k}$ is given as $CDF_{\rho_{rij|k;U_i}}(X_j)$.

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Algorithm 3: Sampling of 4 uniform random variables using d-vine

Inputs: Four uniform random variables $\{X_1, X_2, X_3, X_4\}$, conditional rank correlations and corresponding CDFs
Outputs: Sampled distributions

$x_1 = u_1$.
$x_2 = CDF^{-1}_{\rho_{r12;x_1}}(u_2)$.
$x_3 = CDF^{-1}_{\rho_{r23;x_2}}(CDF^{-1}_{\rho_{r13|2;CDF_{\rho_{r12;x_2}}(X_1)}}(u_3))$.
$x_4 = CDF^{-1}_{\rho_{r34;x_3}}(CDF^{-1}_{\rho_{r24|3;CDF_{\rho_{r23;x_3}}(X_2)}}(CDF^{-1}_{\rho_{r14|23;CDF_{\rho_{r13|2;CDF_{23;x_2}(x_3)}}(CDF_{\rho_{r12;x_2}}(x_1))}}(u_4)))$
End

The above algorithm can be well adapted to sample n-dimensional distribution. It can be concluded that for uncertainty modelling, it is recommended to devise a multivariate problem taking load, wind speed and solar irradiation together, such as in the method proposed in [e-Highway2050, 2015]. The solution follows MC-sampling approach with two basic components: modelling of one-dimensional marginal distributions and modelling of the multi-dimensional stochastic dependence structure. The multivariate normal distribution is measured by product moment correlation, followed by creation of correlation rank matrix. Finally, scenario generation is performed by the use of copula functions. In short, simulation of bivariate relationships between dependent random variables can be performed using the marginal distributions, the rank correlation and the respective copula functions.

In the GARPUR proposal, we need to generate sequences of realisations of the exogenous parameters (for example, realisations of nodal loads and RES production for each hour of a day). It is important to capture the temporal correlation when generating sequences of realisations. Both the spatial and temporal correlations can be captured by the copula models. The proposed method is therefore adequate for generating such sequences.

Along with the specifications for uncertainty modelling, data requirements for realization of above discussed methodology is important. It can be recalled that data availability is a deciding factor, whether to go for dependency modelling using the joint normal transform or select available features from inadequate data and use dependency modelling using vine copula models.

The selection of an adequate method is restricted by the data availability and the daily grid operation processes. A number of factors influence the uncertainty in load and RES forecasting. First, weather data at the nodal scale is limited, which decreases the accuracy of forecasts for both nodal load and RES production. Second, switching operations in underlying grids could lead to unexpected deviations from the point forecast at certain grid nodes. Third, maintenance activities in wind and solar farms may not be reported, which would lead to an overestimation of the forecast. The latter two factors can only be observed and, thus, incorporated in the uncertainty estimation when real data becomes available.

4.3 Failure rates and fault probabilities

The previous section describes the continuous uncertainty related to power system operation. Power systems are also exposed to discrete uncertainty, such as the sudden loss of components, generators or large end-users. This section describes the probabilistic modelling of discrete contingencies based on threats and vulnerabilities, as well as the probabilities associated with the modelled consequences of the post-contingency system.

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4.3.1 Failure rates

Failure rates are used to describe the reliability of individual components or subsystems. They are commonly used, along with repair rates, in the study of system reliability [Billinton and Allan, 1996], [Endrenyi, 1978]. Failure rates are generally calculated as the inverse of the long-run statistic of mean time between failures (MTBF):

$$\lambda_i = \frac{1}{MTBF_i}$$

Constant failure rates are useful for studying the long-term reliability of the system, determining the contribution of particular components to risk, or planning maintenance. They however are insensitive to the presence of lightning storms, hurricanes, bird migration habits, or other possible short-term threats to the power system. Similarly the failure rate doesn‘t consider the possibility that the vulnerability of a component or subsystem may vary over time due to maintenance activities or damage that doesn‘t result in a fault.

As noted by [Vefsnmo et al., 2015], the short-term probability of a component failure depends upon threats and vulnerabilities. Some examples of threat-based failure rates applied to a real-world power system can be found in [Machado et al., 2014] and [Murray and Bell, 2014]. Alternatively, some research has proposed state-based failure rates [Billinton and Singh, 2006], which correlate faults to the general ‚state‘ of the exogenous system using Markov models. A framework for determining the appropriate complexity of threat-based failure rate models can be found in [Perkin et al., 2016].
To model any threat as part of a failure rate, it requires historical data related to one or more variables that explain the threat. For example, modelling the threat of lightning strikes requires historical weather data. This data requirement may present a significant barrier to TSOs in adopting variable failure rate models. Additionally, variable failure rate models need to be TSO and component specific, given that threats depend upon local phenomenon, and vulnerabilities depend on the technical design of components.
Although the probabilistic methods in this report can be implemented with constant failure rates, the results will not reflect the short-term and real-time risk of the power system in a meaningful way.

4.3.2 Failure probability

The failure rate of a component can be used to calculate the probability of it failing during a given period of time (conditional on it being operational at the beginning of the period) by using the exponential distribution:

$$Q_i(\Delta t) = 1 - e^{-\lambda_i \Delta t}$$

Where $Q_i(t)$ is the probability that component i fails at some point in the time interval $[0, t]$, over which the failure rate is assumed to be quasi-static. The length of the time interval should be the same as the operational period covered by the risk assessment methodology (i.e. 15 minutes).
The calculation of probability is the same, regardless of the failure rate model used.

4.3.3 Contingency probability

A contingency is an unplanned forced outage/failure of one or more components. Contingencies are defined to be mutually-exclusive events over a single operational period. This means that the probability of a contingency in which one component fails is equal to the probability of that failing multiplied by the probability of all other components not failing. The sum of all contingency probabilities should therefore equal one.

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The common-cause failures of components, such as a double line failure due to a severe storm, are captured by the failure rates. Both lines experiencing the storm would have increased failure rates, and as a result the probability of the contingency describing the failure of both components will also increase.

The probability of a contingency occurring, which involves the failure of a set of components, $j \in J_c$, is then calculated as:

$$\pi_c = \prod_{j \in J_c} Q_j \cdot \prod_{k \in K_c} (1 - Q_k)$$

Where the contingency, c, describes the failure of components j and survival of components k, such that each component is exclusively in either set J_c or K_c (i.e. K_c is the complement of J_c). For an N-1 contingency, this is the probability of a single component failing, multiplied by the probability of all other components surviving. It should be noted that this probability refers only to the occurrence of forced outages, and not the probability of cascading or sympathetic outages. Such outages are considered to be part of the system response to the initial contingency, which is addressed in the 'outage probability' section below.

The probability of no fault occurring, is simply the same equation as above, except with all components in set $K_\emptyset$:

$$\pi_\emptyset = \prod_{k \in K_\emptyset} (1 - Q_k)$$

Finally, the probability of no faults occurring following a contingency is calculated using the same equation, but excluding the failed components (i.e. only components in the set K_c, not J_c):

$$\pi_{\{\emptyset|c\}} = \prod_{k \in K_c} (1 - Q_k)$$

The values of π_c and $\pi_{\{\emptyset|c\}}$ are calculated for all contingencies in the non-discarded contingency list, $\mathcal{N}_c$. The list of non-discarded contingencies is determined by using a contingency discarding procedure (see Section 4.4).

4.3.4 Outcome probability

Each contingency in a risk assessment is modelled in order to estimate its consequences. The consequence modelling proposed in this report is determinstic, as we determine the loss of energy over time by assuming a certain system response (π_r), corrective control behaviour (π_b), and a lack of overlapping contingencies (additional forced outages before the failed components are restored).

To account for this asssumption, we suggest an expert guided estimate of the probability of system response reliability and corrective control reliability. This could be supported by a cascading failure model to generate contingency specific parameters for system response reliability. Similarly, the reliability of corrective control may be modelled as a function of the number and type of actions taken [Karangelos, 2016]. If a set of components that fail in contingency c take T_c operational periods to restore to an operable state, the probability of no overlapping contingencies is:

$$\mathbb{P}\{no\ overlapping\ contingencies\} = \prod_{t=1}^{T_c-1} \pi_{\{\emptyset|c\},t}$$

Where $\pi_{\{\emptyset|c\},t}$ is the probability of no fault during operational period t, after the occurrence of contingency c. Noting that one operational period is subtracted from T as the first operating period is the

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zeroth operational period, which is covered by the initial contingency. Under the assumption that the probability of no fault is constant, this can be simplified to:

$$\mathbb{P}\{no\ overlapping\ contingencies\} = \pi_{\{\emptyset|c\}}^{T_c-1}$$

4.3.5 Trajectory probability

The three processes described above that affect the outcome of some initiating contingency can be described as a trajectory; one of many possible paths that the system could take. In the case where only a single outcome is considered per contingency, the trajectory probability is calculated as:

$$\pi_c^* = \pi_c \pi_r \pi_b \pi_{\{\emptyset|c\}}^{T_c-1}$$

Where π_r, π_b, and $\pi_{\{\emptyset|c\}}$ are the probability of the modelled system response, system behaviour, and of no additional contingencies, respectively. The difference between the contingency and trajectory probabilities ($\pi_c - \pi_c^*$) describes the probability of an unmodelled outcome. This probability is therefore discarded, and is assumed to result in the worst-case scenario. Modelling additional trajectories per contingency would reduce the probability discarded.

4.4 Contingency and scenario selection

The short-term risk assessment process (see Section 6.1) evaluates scenarios of the short-term exogenous parameters. The evaluation of each scenario is a sequential simulation of real-time risk assessment (see Section 5.1) for each time step of the short-term operation-planning horizon, given the realisations of that scenario. Each real-time risk assessment evaluates the system response to a predefined contingency list. The short-term scenarios can be generated by generating sequences of realisations as described in Section 4.2. Because the resulting number of scenarios can be large, there is a need to discard in a controlled manner part of the scenarios before performing the short-term risk assessment. Predefining a contingency list that contains a subset of all possible contingencies is also necessary for tractability reasons. This section describes controlled procedures for scenario and contingency discarding.

A short-term scenario, denoted $\xi_{[1,\dots,T]}$, is defined as a sequence of future realisations of exogenous parameters ξ_t at time instants $t = 1, \dots, T$. The following exogenous parameters in ST operational planning are considered:

- Weather conditions;
- Failure rates of components;
- Load and RES forecast error.

As some of these exogenous parameters are continuous random variables (threat-based models for failure rates may take the form of continuous function of weather states), an endless number of scenarios can be generated. Thus, the problem of ST risk assessment is one of infinite dimensions. Some approximation of those continuous distributions must be made in order to render the problem tractable.

Generally, it is assumed that scenarios are generated based on Monte Carlo sampling, which uses models of development of exogenous parameters introduced in [GARPUR, 2016b], to provide a discrete approximation of the continuous probabilistic distributions of those exogenous parameters. However, this approach requires a very large number of generated scenarios, which would render resulting risk assessment difficult to solve in practice. Therefore, another approximation of that huge set of generated scenarios has to be done. A promising approach to obtain sufficiently accurate approximation with significantly smaller number of scenarios is the scenario tree generation, proposed in [Rüdiger et al., 2006], that is adapted and followed by a controlled discarding procedure. The number of contingencies in

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the predefined list is another aspect significantly affecting computational demands when the real-time risk assessments are performed. Therefore, in order to ensure feasibility of ST risk assessment, some small subsets of scenarios and contingencies have to be selected in the first-step implementation of the ST-RMAC.

The scheme describing general principle of scenario and contingency selection is shown in Figure 3.

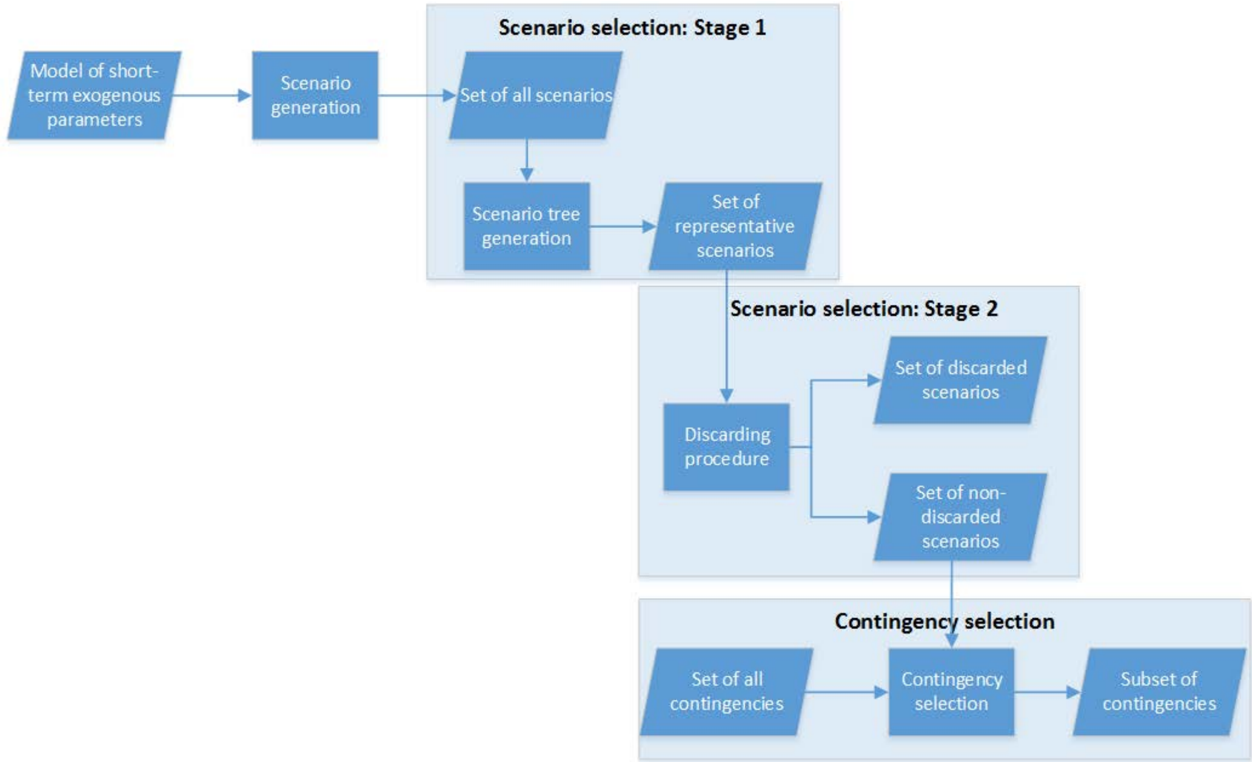

Figure 3: General principle of scenario and contingency selection.

The following two subsections will describe proposals of the first-step implementations of the scenario selection and contingency selection algorithms.

4.4.1 Scenario selection

The aim of the scenario selection is to find some smaller subset from a large set of possible scenarios, which will retain as much information as possible about probable future development of exogenous parameters. The large set of possible scenarios can be obtained by generating a large number of scenarios from the uncertainty models of the ST exogenous parameters described in Sections 4.2 and 4.3.

Let an initial set of scenarios $\xi_{[1,\dots,T]}^{(i)} \in \Xi_0,\ i = 1, \dots, N_0,$ with a given probability of scenario $\pi^{(\mathrm{i})}$ be generated by sampling the uncertainty models of the ST exogenous parameters presented in Sections 4.2 and 4.3. The initial probability $\pi^{(\mathrm{i})}, i = 1, \dots, N_0$, depends on the used sampling probability density function. If the sampling probability density function is the same as the probability density function of the sampled exogenous variable, then the initial probability of each scenario is $\pi^{(\mathrm{i})} = \frac{1}{\mathrm{N}_0}$, otherwise its value will depend on the selected sampling density function, nevertheless the sum of all N_0 probabilities is always equal to 1.

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Seventh Framework Programme under Grant Agreement No 608540.

In the first-step implementation, it is suggested to decrease the number of scenarios that were generated to discretize the continuous uncertainty space by a two-stage method.
In the first stage, the scenarios Ξ_0 are iteratively clustered only based on mutual distance and their probability of occurrence using the scenario-tree generation method in [Rüdiger et al., 2006]. The resulting tree has one common root node representing the same initial state of all considered scenarios. This represents the fact that the current state is given. The first stage terminates when the distance between remaining scenarios is above a pre-specified threshold d_{max}, indicating that the remaining scenarios are too dissimilar to be clustered. During the scenarios clustering, the probabilities of pending scenarios are adjusted to ensure that their sum is still equal to one. The first stage results in a number of representative "scenario clusters". At the end of the first stage, the number of remaining scenario clusters may still be too large to be assessed.
In a second stage, the discarding principle of the ST-RMAC is applied, where a number of scenario clusters are discarded under the condition that their cumulative risk is tolerably low, i.e. under a pre-specified discarding threshold. The cumulative risk is denoted short-term residual risk and is conservatively estimated by associating an estimate of the worst-case risk over the planning horizon to the discarded scenarios.

The next subsection describe the two stages in more detail.

4.4.1.1 Stage 1: scenario tree generation by clustering

To measure the mutual distance between two scenarios $\xi^{(i)}_{[1,\ldots,T]}$ and $\xi^{(j)}_{[1,\ldots,T]}$ the following metric is defined:

$$d\left(\xi^{(i)}_{[1,\ldots,T]}, \xi^{(j)}_{[1,\ldots,T]}\right) = \sqrt{\sum_{t=1}^{T}\left(\xi^{(i)}_t - \xi^{(j)}_t\right)^2}.$$

Another important aspect, which is taken into account, is a scenario probability. When two scenarios $\xi^{(i)}_{[1,\ldots,T]}$ and $\xi^{(j)}_{[1,\ldots,T]}$ are close, it is preferred to remove the scenario that has smaller probability from the probabilities $\pi^{(i)}$ and $\pi^{(j)}$.

The above rationale is done iteratively by removing at each step the scenario $\xi^{(i^*)}_{1,\ldots,T}$ having the smallest mutual distance weighted by its probability of occurrence $\pi^{(i^*)}$, i.e. the scenario such that

$$\pi^{(i^*)} \min_{i \neq i^*} d\left(\xi^{(i)}_{1,\ldots,T}, \xi^{(i^*)}_{1,\ldots,T}\right) = \min_{i=1,\ldots,N_0} \pi^{(i)} \min_{i \neq j} d\left(\xi^{(i)}_{1,\ldots,T}, \xi^{(j)}_{1,\ldots,T}\right),$$

where N_0 is the number of scenarios. This is done while ensuring that the distance from $\xi^{(i^*)}_{1,\ldots,T}$ to its nearest scenario is not above a pre-specified threshold d_{max}. This threshold specifies the distance between scenarios above which two scenarios are considered to be dissimilar and, therefore, cannot be clustered. Altogether, the scenario $\xi^{(i^*)}_{1,\ldots,T}$ is found as

$$\begin{aligned} i^* = \operatorname*{argmin}_{i=1,\ldots,N_0} \pi^{(i)} \min_{i \neq j} d\left(\xi^{(i)}_{1,\ldots,T}, \xi^{(j)}_{1,\ldots,T}\right) \\ s.t. \quad \min_{i \neq j} d\left(\xi^{(i)}_{1,\ldots,T}, \xi^{(j)}_{1,\ldots,T}\right) \le d_{max}. \end{aligned}$$

Simultaneously, the probability of the nearest scenario $\xi^{(\bar{\imath})}_{1,\ldots,T}$ is be increased by the probability $\pi^{(i^*)}$, i.e.

$$\pi^{(\bar{\imath})} = \pi^{(\bar{\imath})} + \pi^{(i^*)},$$

in order to keep the sum of probabilities of remaining scenarios equal to 1.

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The basic steps of scenario tree generation are summarized in Algorithm **4**. Note that the while loop continues until there is no more pair of scenarios with a distance less than d_{max}. At the end of stage one, a set $\widehat{\Xi_0}$ of representative scenarios, or scenario clusters, is obtained.

Algorithm 4: Scenario tree generation

Inputs: Initial set of scenarios $\xi_{[1,\dots,T]}^{(i)} \in \Xi_0, i = 1, \dots, N_0$, probability of scenarios $\pi^{(i)}$, $i = 1, \dots, N_0$, maximum distance threshold d_{max}

Outputs: Set of scenario clusters $\widehat{\Xi_0}$.

1 Calculate $N_0 \times N_0$ distance matrix between all the scenarios $\xi_{[1,\dots,T]}^{(i)} \in \Xi_0, i = 1, \dots, N_0$.

2 **While** 1 do

3 Select scenario to be deleted $\xi_{1,\dots,T}^{(i^*)} = \left[\xi_1^{(i^*)} \dots \xi_T^{(i^*)}\right] \in \Xi_0$ satisfying

$$\pi^{(i^*)} \min_{i \neq i^*} d\left(\xi_{1,\dots,T}^{(i)}, \xi_{1,\dots,T}^{(i^*)}\right) = \min_{i=1,\dots,N_0} \pi^{(i)} \min_{i \neq j} d\left(\xi_{1,\dots,T}^{(i)}, \xi_{1,\dots,T}^{(j)}\right)$$

and $\min_{i^* \neq j} d\left(\xi_{1,\dots,T}^{(i^*)}, \xi_{1,\dots,T}^{(j)}\right) \leq d_{max}$

4 If no solution, STOP.

Change probability of scenario $\xi_{1,\dots,T}^{(\bar{\imath})}$ the nearest to $\xi_{1,\dots,T}^{(i^*)}$ satisfying

$$d\left(\xi_{1,\dots,T}^{(\bar{\imath})}, \xi_{1,\dots,T}^{(i^*)}\right) = \min_{j \neq i^*} d\left(\xi_{1,\dots,T}^{(j)}, \xi_{1,\dots,T}^{(i^*)}\right),$$

such that

$$\pi^{(\bar{\imath})} = \pi^{(\bar{\imath})} + \pi^{(i^*)}.$$

6 **End**

4.4.1.2 *Stage 2: short-term discarding principle*

In stage 2 of the algorithm, part of the set $\widehat{\Xi_0}$ of representative scenarios is discarded.

First, the scenarios in $\widehat{\Xi_0}$ are sorted by ascending order of probabilities. Then, the *m* scenarios with lowest probabilities such that a worst-case estimate of their cumulative risk is under a pre-defined short-term discarding threshold ΔE_{ST}. Algorithm **5** describes the procedure. The algorithm takes as input a worst-case estimate of the risk over the planning horizon, which can for example be taken as the expected costs of energy not served in case of the total system blackout throughout the planning horizon.

Algorithm 5: Short-term discarding principle

Inputs: Set $\widehat{\Xi_0}$ of scenario clusters, short-term discarding threshold ΔE_{ST}, worst-case estimate of the risk over the planning horizon $C_{int,max}^{T}$

Outputs: Set of non-discarded scenario Ξ_C.

1 Sort the scenarios in $\widehat{\Xi_0}$ by descending order of probabilities.

2 Find maximum number m such $\sum_{i=1}^{m} \pi^{(i)} C_{int,max}^{T} \leq \Delta E_{ST}$.

3 Let $\Xi_c = \widehat{\Xi_0} \setminus \left\{\xi_{[1,\dots,T]}^{(i)}\right\}_{i=1,\dots,m}$

4.4.2 Contingency selection

An initial set of contingencies is defined by generating all the conceivable combinations of outages $\mathcal{N}$. Such set reflects all possible contingencies that are likely to occur even at very low probability. Subsequently, the initial set of contingencies can be adapted in ad-hoc fashion either depending on a set of operational periods $t = 1, \dots, T$, where the same set of contingencies can be considered in the periods with similar values of exogenous parameters, or simply adapted after integration of new network elements (Transformers, Lines, Cables…). In the first-step implementation, the probability of contingency occurrence π_c is assumed to be a function of weather conditions. If insufficient data is available to develop threat-based model, these weather conditions can be classified in a first step in categories such as normal and adverse weather and export knowledge used to determine how failure rates change in these categories.

The idea of contingency selection is to discard all the contingencies with the cumulative probability below a certain threshold independently from their impact. Thus, for each operational period t and scenario $\xi_{[1,\dots,T]}^{(i)}$ from the set of scenarios Ξ_c, $\xi_{[1,\dots,T]}^{(i)} \in \Xi_c$, starting from the initial set of generated contingencies $\mathcal{N}$ and considering values of the scenario exogenous parameters such as weather conditions, loads and renewable energy injection levels, the contingencies are discarded based on their probability of occurrence resulting in subsets of non-discarded contingencies $\mathcal{N}_c\left(\xi_t^{(i)}\right)$. The following relation holds between probabilities of non-discarded and discarded contingencies

$$1 - \pi_\emptyset(t,i) - \sum_{c \in \mathcal{N}_c\left(\xi_t^{(i)}\right)} \pi_c(t,i) = \sum_{c \in \mathcal{N} \setminus \mathcal{N}_c\left(\xi_t^{(i)}\right)} \pi_c(t,i),$$

where $\pi_\emptyset(t,i)$ is probability that no contingency occurs, see Section 4.3.3. The right hand side of the relation represents cumulative probability of discarded contingencies.

The GARPUR methodology introduces a risk threshold ΔE_{RT} to guide the discarding process. The latter considers the risk contributions (expected interruption costs) of all discarded contingencies. Since these risk contributions are not known at this stage, it is proposed to approximate them pessimistically by the cost of the worst-case event represented by a total system blackout, see Section 9.6. Considering that every discarded contingency would cause the system blackout the cumulative probability of discarded contingencies should meet the following relation

$$\sum_{c \in \mathcal{N} \setminus \mathcal{N}_c\left(\xi_t^{(i)}\right)} \pi_c(t,i) \leq \frac{\Delta E_{RT}}{C_{int,max}(t,i)},$$

where $C_{int,max}(t,i)$ represents the expected costs of energy not served in case of the total system blackout in terms of occurrence of the i-th scenario and in the t-th operational period.

Combining the two inequalities above, the rule for contingency discarding can be written in terms of the non-discarded contingencies as

$$1 - \pi_\emptyset(t,i) - \frac{\Delta E_{RT}}{C_{int,max}(t,i)} \leq \sum_{c \in \mathcal{N}_c\left(\xi_t^{(i)}\right)} \pi_c(t,i).$$

Contingency discarding can therefore be performed by sorting contingencies in descending order according to their probability of occurrence $\pi_c(t,i)$. Then, the first m contingencies having cumulative probability of occurrence greater or equal than the value on the left-hand side of the relation are selected.

Algorithm **6** illustrates the steps of contingency discarding.

Algorithm 6: Contingency selection

Inputs: Set of all contingencies $\mathcal{N}$, Set of scenarios Ξ_c, residual risk threshold ΔE_{RT}, the worst-case costs of energy not served $C_{int,max}(t,i)$

Outputs: Contingency lists $\mathcal{N}_c(\xi_t^{(i)})$.

For each Scenario $\xi_{1,\dots,T}^{(i)} = [\xi_1^{(i)} \dots \xi_T^{(i)}]$ in Ξ_c do

  For *each time step*, $t \in (1,\dots\dots,T)$ **do**

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For each $\xi_t^{(i)}$, sort all the contingencies according to their probability in descending order.

Find minimal number m such that $1 - \pi_\emptyset(t,i) - \frac{\Delta E_{RT}}{C_{int,max}(t,i)} \leq \sum_{c=1}^{m} \pi_c(t,i)$.

Discard remaining contingencies: $\mathcal{N}_c\left(\xi_t^{(i)}\right) := \mathcal{N} \backslash \{c_{m+1}, \dots, c_n\}$.

End

End

Figure 4 illustrates the contingency selection principle. In the illustrated example, it is shown that, the cumulative sum of probability of contingency occurrence is from the contingency c_m above the given threshold and that the contingencies $c_{m+1}, \dots, c_n$ can be discarded.

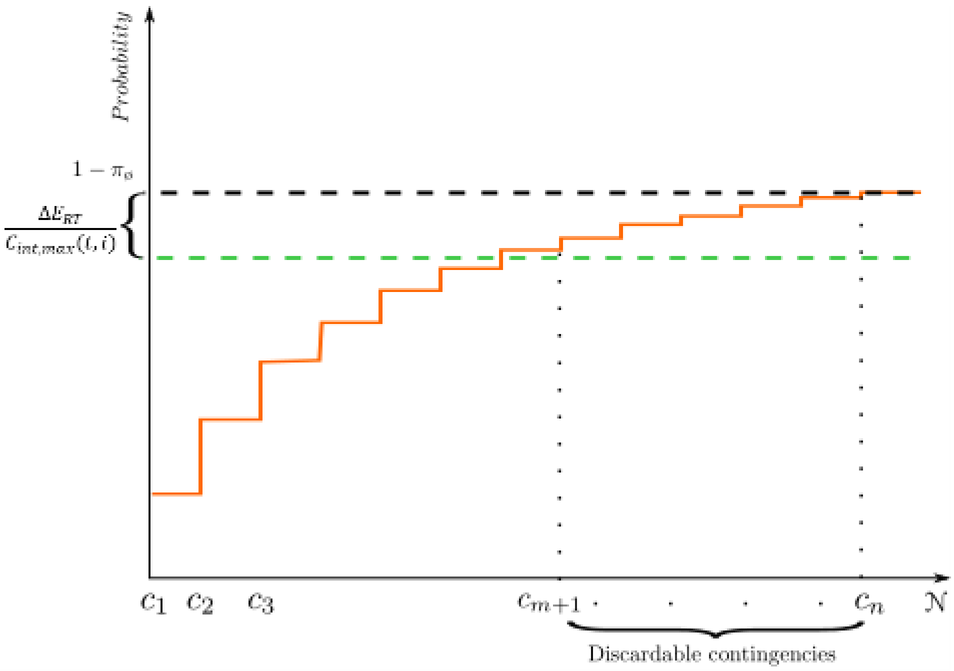

Figure 4: Contingency discarding principle. Contingency discarding for *t*-th operational period of one specific scenario.

In practice, TSOs may want to start by defining an initial set $\mathcal{N}_c\left(\xi_t^{(i)}\right)$ of non-discarded contingencies according to their internal practices. The derivation above can then be used to tune this initial set to add contingencies to be assessed or to discard more contingencies. Compare to today's practices, this offers the benefit of considering contingency probabilities in the determination of the contingency list.

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5 UPGRADE OF RELIABILITY ASSESSMENT FOR REAL-TIME DECISION MAKING

The following two sections outline the proposed implementation of the GARPUR real-time RMAC, and how the method can be used to support decision making in real-time, respectively.

5.1 Real-time reliability assessment

Real-time reliability assessment covers the present operational period, calculated online, to provide reliability diagnostics to the control room operators. Additionally real-time reliability assessments may be applied to analyse past events or to anticipate possible future operational scenarios. Typically, an online reliability assessment will allow the operator to determine whether any preventive actions are immediately required in order to secure the system over the coming hour(s). They also provide an estimate of the consequences of contingencies, such that the operator can also plan corrective control actions. Essentially, they interpret the present state of the system and the exogenous world into one or more metrics that alert the operator to threats to the system.

This section outlines a first-step approach to implementing probabilistic real-time reliability assessments. The proposed method is a simplified version of the ideal method (See Sections 9.2 and 9.3), but is an improvement upon present day reliability assessments (based on the N-1 criterion) and should be easy to implement. Some short-term improvements to the first-step method are also discussed in this section. A migration plan will be published at the end of the GARPUR project that states the long-term improvements in models and data collection/quality required to implement the ideal probabilistic reliability assessment.

This section begins with a small description of the main assumptions of the proposed method, followed by an algorithmic description of the first-step implementation, a line-by-line explanation of the algorithm, and finally an example application of the method on an IEEE test system.

5.1.1 General Assumptions

A number of assumptions are made to simplify the method, such that it can be applied with present day models and data available to most TSOs. These assumptions are shown for transparency of the method, noting that the assumptions are no worse than current practice.

Uncertainty: we assume that the net power injections and contingency probabilities are known in real-time, such that there are no forecast errors (of load, generation or environmental parameters) to consider in the reliability assessment. The only probabilistic parameters are the contingency occurrences. In cases where extreme changes in power injections are credible in real-time (e.g. wind gusts disconnecting several wind farms), such events can be defined as discrete events with adequate probabilities.

Contingencies: We assume that a contingency list is calculated offline, prior to the real-time reliability assessment, using a method such as those described in Section 4.4. These methods replace the static N-1 contingency list with a dynamic contingency list based on probabilities or estimated risk. Note that TSOs may simply use their existing contingency lists as input to this method prior to implementing contingency discarding tools (see Section 4.4).

Operational period: An operational period is assumed to be 15 minutes, given that most TSOs can apply initial corrective controls within this timeframe. Similarly, given that the first-step method assumes that power injections are known (i.e. no forecast errors), the operational period must be as short as possible to reduce the error introduced by this assumption.

System response model: We assume that the modern TSO already possesses a system response model that is capable of estimating the loss of load immediately following a contingency. Such a model could be as simple as an AC load flow combined with some heuristic load-shedding model, such as described in [Henneaux and Kirschen, 2016].

Time: In the following sections, time is abstracted into 'operational periods', where $t = 0$ defines the initial state of the system, $t = 1$ defines the state of the system after 15 minutes (within which time the contingency and corrective actions have occurred), and so on. Therefore a service outage duration of 4 refers to an hour-long outage.

5.1.2 First-step implementation

The proposed first-step implementation is described by Algorithm 7 below. The method loops over the contingencies described in a contingency list, estimating the system response to the contingency and using heuristic models to estimate the outcome of the system response. The outcome is described by a loss of load, which lasts for some service outage duration, and results in some energy not served (ENS) over time. This can then be used to calculate the expected socioeconomic surplus (as defined in Appendix 9.1.1 and in more detail in [GARPUR, 2016] and [GARPUR, 2016a]) of the post-contingency system, and used to check the reliability target

Algorithm 7: Real-time reliability assessment

Inputs: initial system state, failure rates, response parameters (π_r, π_b), acceptability constraints, value of lost load curves, value of supplied load, system response model, planned preventive actions, contingency list, component repair times;

Outputs: expected ENS; Risk; socio-economic surplus; reliability indicator;

Given the contingency list, $\mathcal{N}_c$, and component failure rates, calculate the probability of all non-discarded contingencies π_c, the no fault probability $\pi_\emptyset$, and the conditional no fault probabilities $\pi_{\{\emptyset|c\}}$.

Adjust input system state for the planned preventive actions $x_0 = f_0(x_0, u_0)$;

for $each\ contingency, c \in \mathcal{N}_c$ **do**

 Apply system response model to determine the disturbed system state, x_c, and initial loss of load LL_c

 Using a heuristic model, estimate the duration of the service outage, $d_c = f_d(LL_c)$

 Using a heuristic model, estimate the ENS over the service outage duration, $ENS_{c,t} = f_{ENS}(LL_c, d_c)$

 Using the response parameters, $\{\pi_r, \pi_b\}$, and the contingency repair time, T_c, calculate the outcome trajectory probability: $\pi_c^* = \pi_c \pi_r \pi_b \pi_{\{\emptyset|c\}}^{(T_c - \Delta t)}$

 Calculate the service interruption costs and cost of control

 Calculate compliance with the acceptability constraints: $\mathbb{P}(x_c, x_{c,b} \in X_a | c) = \pi_c^* . \mathbf{1}(x_c, x_{c,b} \in X_a)$;

End

Calculate the residual probability: $\pi_R = 1 - (\pi_\emptyset + \sum_c \pi_c^*)$

Calculate the total expected ENS: $\mathbb{E}(ENS) = \pi_R ENS_{max} + \pi_\emptyset ENS_\emptyset + \sum_c (\pi_c^* ENS_c)$

Calculate the Risk and expected socio-economic surplus

Calculate compliance with reliabilitytarget, $\mathbb{P}(x_c, x_{c,b} \in X_a) = \mathbb{P}(x_c, x_{c,b} \in X_a | \emptyset) + \sum_c \mathbb{P}(x_c, x_{c,b} \in X_a | c)$

Each line of the algorithm is explained clearly in the following section, along with some extensions to the method that may be possible in the near future. To assist with interpretation of the above algorithm, Figure 5 shows the evolution of the system state over time, highlighting their notation. Additionally, the blue areas highlight in which periods of time that further cascading of faults are considered in RT, when load is lost and when any components may be in a failed state. Additionally, when aggregating consequences over time for different system trajectories, they must be considered over a consistent assessment period. Therefore the figure also shows a final state occurring at some time, T, which is equivalent to the planned system state at that point in time.

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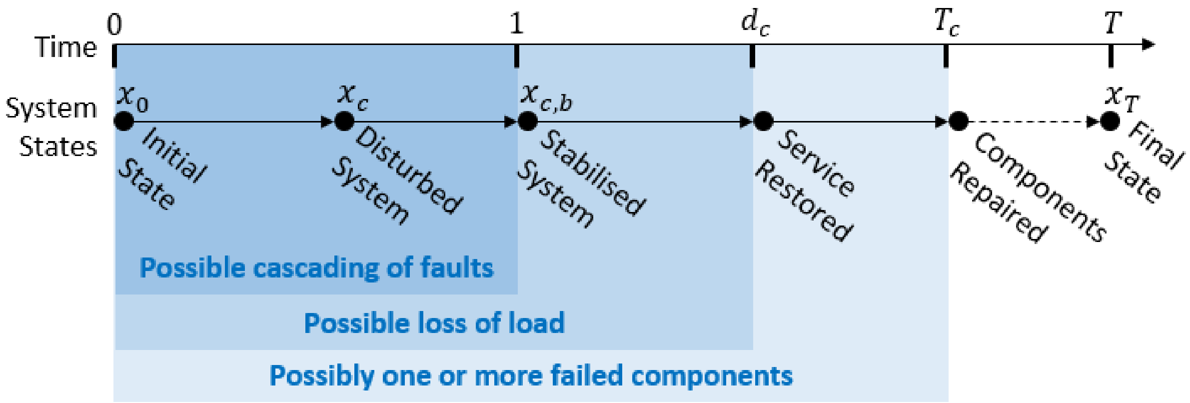

Figure 5: Visualisation of the system states over the course of the assessment period (T)

5.1.3 Detailed description of implementation

Each of the following subsections relate to a specific line of the real-time algorithm above, elaborating on each line such that appropriate models can be identified or new tools can be built in-house by TSOs.

5.1.3.1 Probabilities

Contingency probabilities are calculated using the equations and approach described in Sections 4.3.2 and 4.3.3, assuming that failure rates are available as input, as well as a set of non-discarded contingencies. The set of non-discarded contingencies is determined using the approach described in Section 4.4.2.

5.1.3.2 Apply preventive actions

The initial system state may be modified in order to simulate any preventive actions that may be taken during the period. This includes actions such as topological changes (switching actions), changing voltage set points or tap changer positions, and generator redispatch among others (see [GARPUR, 2015] for a discussion on TSO processes).

5.1.3.3 Loop over contingencies

Lines 4-9 are applied to each contingency in the non-discarded contingency set, $\mathcal{N}_c$, where the system response to each contingency is simulated in a deterministic way, assuming perfect system response and without modelling corrective control failure. The failure of system protection and of corrective controls is accounted for by modifying the contingency probabilities (Line 7) as an alternative to TSOs implementing probabilistic tools to model additional trajectories of system response or corrective control failure in real-time. Note that this loop can be parallelized, allowing for computation speed to scale efficiently.

5.1.3.4 System response model

We assume that TSOs have some system response tool that they use to perform N-1 reliability assessments at present. We assume that such software is capable of assessing the lost load due to the occurrence of a contingency. This software generally consists of an AC power-flow model, with some heuristic load shedding process that estimates the automatic loss of load. Simply, the model must provide the following function:

$$system\ response\ model: (x_0, c) \mapsto (x_c, LL_c)$$

An important near-future improvement is the probabilistic modelling of faults cascading following a contingency. If a probabilistic cascading tool is implemented, each individual cascading trajectory can be modelled explicitly, rather than only modelling one possible outcome and using modifying the contingency probability using the probability of a system response failure (π_r).

5.1.3.5 *Service outage duration*

In reality, service outage duration is a function of the dynamic response of the system to the initial contingency and the corrective control actions that follow. TSOs do not presently have software that is capable of determining the service outage duration. Therefore a heuristic approach to estimating outage duration should be used. As suggested by [Henneaux and Kirschen, 2016] a reasonable first-step is to use a heuristic linear model, where service outage durations are a function of initial lost load ($LL_c \mapsto d_c$). Their heuristic model is:

$$d_c = \alpha_1 . LOL_{c,0} + \alpha_0$$

Where d_c is measured in units of hours, and $LOL_{c,0}$ is the initial lost load (LL_c) expressed as a percentage. The parameters α_1 and α_0 are determined through linear regression, and can be interpreted as the restoration rate (% of load recovered per hour) and minimum restoration time (in hours), respectively. Europe-wide values for α_1 and α_0 were determined by [Henneaux and Kirschen, 2016] as 0.1419 and 0.6482, respectively, by assessing a number of major outages at different TSOs in Europe. TSOs should consider developing their own system-specific models of service restoration and outage duration prediction, but the above parameters may be a reasonable assumption in lieu of adequate data.

5.1.3.6 *Estimate energy not served over time*

Ideally, the energy not served over time is a function of the control actions taken to restore an outage, the time required to implement them, as well as changes in energy demand. However, this is not presently possible as discussed in the previous subsection. Therefore the heuristic model in Line 5 can be inverted to find the lost load in any operational period:

$$LOL_{c,t} = \frac{LOL_{c,0}}{d_c}(d_c - t)$$

Note that the term $\frac{LOL_{c,0}}{d_c}$ is equivalent to a restoration rate (i.e. percent of system load restored per hour). The energy not served is then estimated as:

$$ENS_{c,t} = \frac{1}{2}\left(LOL_{c,t-1} + LOL_{c,t}\right). L_t . \Delta t$$

Which is the geometric mean of the lost load over the operational period, $t \in [1, d_c]$, where L_t is the expected load at time t, and Δt is the length of an operational period in hours. Note that the discrete approach shown here can quite easily be replaced with a continuous formulation. The total ENS for a particular contingency can be simply estimated as:

$$ENS_c = \sum_t ENS_{c,t}$$

5.1.3.7 *Contingency probability adjustment*

Given that we do not model system protection failure, corrective control failure or overlapping contingencies (i.e. N-1-1 events), we must adjust the contingency probabilities. That is, we model the 'perfect' outcome following a contingency, and therefore we must consider the probability of imperfect

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outcomes. As discussed in Section 4.3.4, we define π_r and π_b which are the probability of the expected system response and expected corrective control behaviour, respectively. These values must be based on expert estimates, given a lack of available data. We also define a value T_c which is the component outage duration, which is independent of the service outage duration, d_c. This can be taken to be the maximum value of mean time to repair (MTTR) of the individual failed components. Given these values and the probability of no further faults following the initial contingency, we can calculate the adjusted probability as discussed in Section 4.3.5 as:

$$\pi_c^* = \pi_c \pi_r \pi_b \pi_{\{\emptyset|c\}}^{(T_c-1)}$$

Where the new contingency probability is less than the original probability ($\pi_c^* < \pi_c$) and the difference is considered to be part of the residual risk (i.e. we assume that any non-modelled system response, control or additional outages result in the worst-case scenario). Note that the use of π_c instead of π_c^* implies that system protection and corrective control is 100% reliable, and that all faults have 0% probability after the contingency.
The suggested simplifications can be resolved by making the probability of system protection failure or corrective control failure a function of the contingency, by applying probabilistic cascading fault models, for example. Similarly, the effect of exogenous variables on these parameters may be considered.

5.1.3.8 Calculate cost of service loss and control

Ideally, the consequences of a contingency would be quantified using the socio-economic surplus formulation detailed in [GARPUR, 2016a]. In the first-step implementation however, we propose that the only consequences to be calculated for specific contingencies are:

- Service interruption costs
- Costs of corrective actions

The service interruption costs can be calculated as:

$$C_{int,c} = \sum_{a \in A} v_a(t).ENS_{c,t,a}$$

Where $C_{int,c}$ is the interruption cost due to contingency c, and $v_a(t)$ is the value of lost load at economic node a at time t in units of Euros per megawatt-hour. An economic node is a group of consumers of the same type (e.g. residential) at the same location (e.g. connected to the same substation, or region of the transmission network). The division of consumers into economic nodes depends heavily on both economic data available to TSOs as well as information on DSO connectivity. In cases where a particular consumer may be connected (via a DSO) to one or more TSO substations, the interruption costs can only be estimated at a regional level.

Given that the corrective actions may not be explicitly modelled in the first-step implementation, depending on TSO models, their costs may not be possible to include in the consequence formulation. If corrective control is modelled with enough resolution to determine a set of actions, u_c, in response to contingency c, then the they may be included with some TSO-defined cost model $C_{cc}(u_c)$. Note that although there is no direct cost of most common actions, a cost may be derived from the reduction in the components life due to its activation (e.g. the cost of activing a switch may be assumed as the cost of the switch divided by the expected number of operations in the switch's lifetime).

5.1.3.9 Assess acceptability

As discussed in Section 9.1, the reliability target is defined by a set of acceptability constraints (X_a) on the post-contingency system trajectory. Given that we do not model corrective control in the first-step

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implementation, the system state is not considered after the first time step. It is assumed that if the system state is acceptable at $t = 1$ then it will be acceptable for the remaining operational periods, $1 < t \leq d_c$. Where we assume the system state at t=1 is the post-disturbance and post control system state ($x_1 = x_{c,b}$). Therefore we assess acceptability by calculating:

$$\mathbb{P}\left(x_c, x_{c,b} \in X_a \middle| c\right) = \pi_c^*. \mathbf{1}\{x_c, x_{c,b} \in X_a\}$$

Where $\mathbf{1}\{x_c, x_{c,b} \in X_a\}$ is equal to one if the post-contingency system states are within the bounds of the acceptability constraints, and zero otherwise. The resulting value of $\mathbb{P}\left(x_c, x_{c,b} \in X_a \middle| c\right)$ is therefore equal to π_c^* or 0.

5.1.3.10 End of the loop

Lines 4 to 9 are repeated until the set of non-discarded contingencies, $\mathcal{N}_c$, is depleted. At this point the results can be displayed for each individual contingency. The remaining lines of the algorithm relate to aggregation of the results into general reliability and economic indicators.

5.1.3.11 Residual probability

The residual probability is the probability that a discarded contingency occurs, as well as the probability that an assessed contingency is followed by system protection failure, corrective control errors, or additional overlapping contingencies. In other words, it is the probability that any non-modelled, unplanned event occurs. This is calculated as:

$$\pi_R = 1 - \pi_\emptyset - \sum_c \pi_c^*$$

This value itself is important as it defines the total coverage of the risk assessment methodology. The value $1 - \pi_R$ also gives an upper limit for the probability of achieving the acceptability constraint, for the given set of non-discarded contingencies.

5.1.3.12 Aggregate ENS indicator

Physical indicators for individual contingencies, such as ENS, can be aggregated into a single index for the system by applying the following equations:

$$\mathbb{E}(ENS) = \pi_R ENS_{max} + \pi_\emptyset ENS_\emptyset + \sum_c \pi_c^* \, ENS_c$$

Where $ENS_{max}$is the worst-case scenario consequences in terms of energy not served. The worst-case scenario for ENS can be easily estimated by assuming a lost load equivalent to a total system blackout and applying the heuristic model for service outage duration. The estimate of worst-case economic impacts is discussed in Section 9.6.

5.1.3.13 Calculate risk and expected socio-economic surplus

The first-step implementation of risk only considers the combined cost of preventive actions and expected cost of interruptions and corrective control. The risk (R) is calculated similarly to the aggregate ENS indicator:

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$$R = \pi_r C_{int,max} + \pi_{\emptyset} C_{int,\emptyset} + \sum_c \pi_c^* C_{int,c}$$

Where risk is measured in Euros, $C_{int,max}$ is the worst-case interruption cost, $C_{int,\emptyset}$ is the cost of outages and control in the case of no contingencies (equal to zero in most cases) and the final term is the probability-weighted costs associated with each assessed contingency.

The expected socio-economic surplus (S) is then calculated as:

$$S = V \sum_{t \in [0,T]} L_t - R - C_0(u_0) - \sum_c \pi_c C_{cor}(u_c)$$

Where V is the value of served load in Euros per megawatt-hour, as in [GARPUR, 2016a], L_t is the system load at time t in some assessment period $t \in [0, T]$, $C_0(u_0)$ is the cost of preventive controls, and the final term is the expected cost of corrective control over the contingency set. Note that the contingency probability of (π_c) is used instead of trajectory probability (π_c^*), given that corrective controls respond to the initial disturbance. In cases where corrective control isn't explicitly modelled, the cost of corrective control should be set to zero.

The measure of risk can be used as a general severity indicator for different contingencies, whilst the surplus function can be used as an objective function in the optimisation of preventive or corrective controls. A first-step proposal on how this function can be used to tune preventive or corrective controls is discussed in Section 5.2.

It is important to note that the socio-economic surplus must be evaluated over the same period of time T for all contingencies, regardless of their disconnection time (d_c) or repair time (T_c). That is, consequences and benefits need to be aggregated over the same period of time to be comparable.

5.1.3.14 Reliability target

The reliability target requires the aggregation of the calculation made on Line 9, such that:

$$\mathbb{P}(x_c, x_{c,b} \in X_a) = \mathbb{P}(x_c, x_{c,b} \in X_a | \emptyset) + \sum_c \mathbb{P}(x_c, x_{c,b} \in X_a | c)$$

Where $\mathbb{P}(x_0, x_{c,b} \in X_a)$ is the total probability that the system will comply with the acceptability constraints for the given operational period. Note that the discarded trajectories are assumed to result in unacceptable system states. Note that $\mathbb{P}(x_c, x_{c,b} \in X_a | \emptyset)$ refers to the probability that the no-fault case results in an acceptable system state, which may not necessarily be guaranteed due to large changes in load or RES power generation.

Given some tolerance level, ε, the reliability of the system can be assessed by checking that:

$$\mathbb{P}(x_c, x_{c,b} \in X_a) \geq 1 - \varepsilon$$

It may be necessary that this value is variable with time (more risk accepted in the winter than in the summer) or spatially. A discussion on the rationing of risk by using a variable tolerance level is in Section 9.5. Given that a reasonable value of ε is not presently known by TSOs, we suggest that the left part of

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the inequality is calculated over an extended period of time and in response to various stimuli, to develop an understanding of what a reasonable value may be.

5.1.4 RT risk indicators

The indicators presented above for estimating risk, socio-economic surplus, and the probability of acceptable system states are considered over the set of all possible system trajectories, including those that are not explicitly modelled or are discarded from assessment. It should be noted here that the accuracy of the estimation by these indicators depends on both the probability as well as the potential consequence of those events that are not explicitly modelled and/or are discarded from assessment. In particular, decreasing the number of events that are discarded and/or not explicitly modelled should increase the accuracy of such estimations. For example, consider the increase in accuracy by assessing all single contingencies (as in the N-1 contingency list) on top of the "no-outage" system state. The former case provides much more accurate estimates of risk, expected socio-economic surplus and probability of acceptable system states. Notice also that in the RMAC framework proposed in WP2 [GARPUR, 2016c], the so-called "discarding principle" serves to guarantee the accuracy level of the combined socio-economic surplus and risk indicators.

5.1.5 Case-study

The following section gives an example application of the above first-step implementation for the RT-RMAC. The case-study is applied to the IEEE RTS 24-bus system, by applying the algorithm described in Section 4.1 in combination with Matpower [Zimmerman et al., 2011]. Only failure of overhead lines and generators are considered in this case-study for simplicity, however the method can easily be extended to include all grid components and other contingencies. The IEEE RTS 24-bus system consists of four zones, as shown in Figure 6. All topological, load and generation data, and component reliability data (failure rates and repair times) is taken from the original publication [Wong et al., 1999]. Data related to value of lost load is sourced from [Bjørk et al., 2012], and the value of supplied load from [GARPUR, 2016]. The values used for probability of expected system response and expected corrective control behaviour are assumed.

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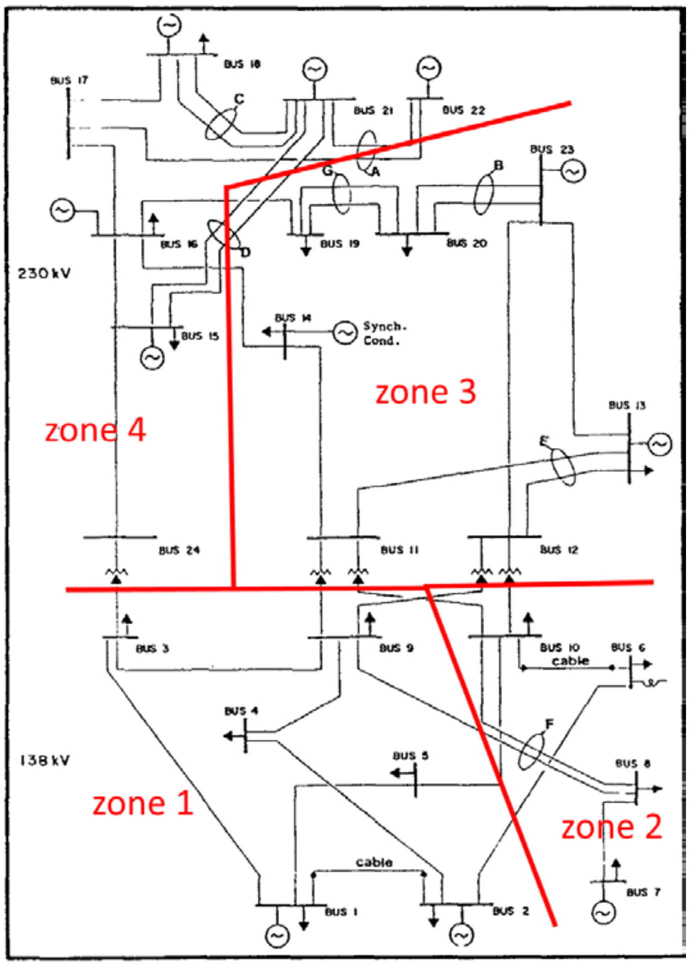

Figure 6: IEEE reliability test system.

The case-study is initialised by simulating a market using a DC unit-commitment OPF algorithm. Other inputs required for the case-study are listed below in Table 1.

Table 1: Real-time case study inputs and assumptions

Inputs	*Value*
Probability of expected system response (π_r)	95%
Probability of expected corr. control behaviour (π_b)	99%
Value of lost load	See Figure 8
Value of supplied load	5000 EUR / MWh
System response model	Single-stage AC-OPF with load shedding
Planned preventive actions	None
Contingency list	N-1 contingencies only
Component repair times	From IEEE test-case
Acceptability constraints	• No lost load • Acceptable component loads • Compliance with voltage limits
Operational period duration	15 minutes (4 periods per hour)
Assessment period (T)	15 hours (60 periods)

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The contingency list is set to be equivalent to the N-1 contingency list in order for an easier comparison with the N-1 criterion. Increasing the set of contingencies considered can be done either by expert opinion or by applying the contingency discarding algorithm outlined in Section 4.4. The example below follows the line numbering of Algorithm 6 presented in this chapter as much as possible.

Lines 1 and 7: Figure 7 shows the resulting probabilities of all the considered contingencies. The calculations here are based on the equations presented in Section 4.3. Where the height of the bar is the initial contingency probability, the black part is the probability of discarded post-contingency events (e.g. unexpected system responses) and the remaining white part is the probability of the modelled and assessed trajectory. The proportion of the discarded probabilities depends, not only on the assumed values of π_r and π_b, but also the contingency durations which are equal to the component repair times in this example.

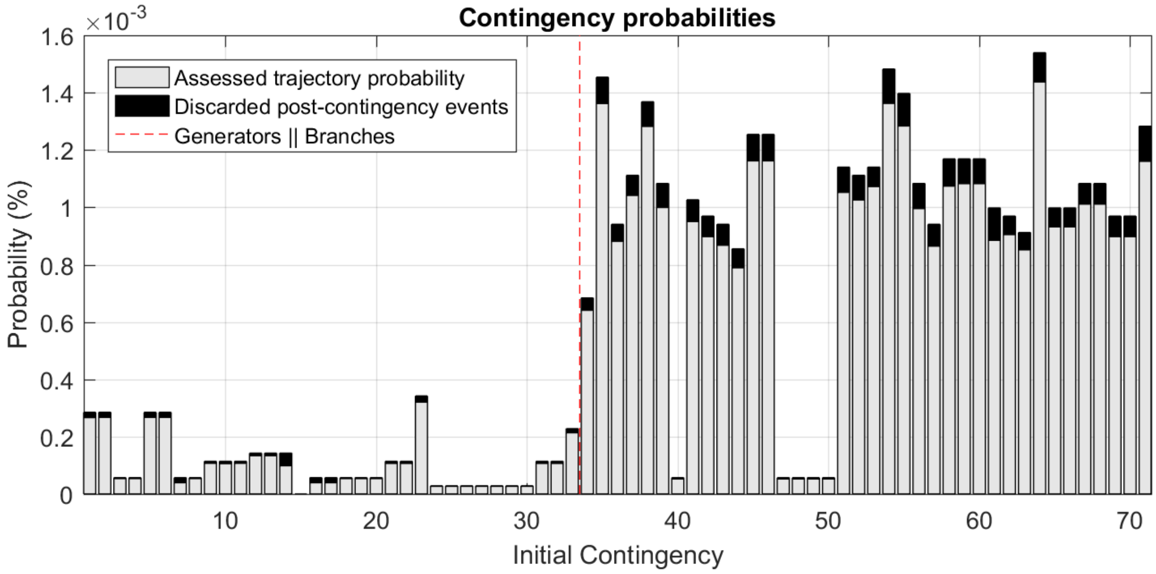

Figure 7: Probabilities associated with each contingency and the assessed post-contingency system behaviour. The first 33 contingencies relate to single generator failures, and the remaining relate to single branch failures.

Line 2: This example does not consider any initial preventive control, however it would trivially implemented by making a manual adjustment to the input system model after completing the market initialisation.

Line 3: The internal loop of the algorithm is computed for the set of 72 considered system trajectories (71 contingencies plus 1 no-fault case). This loop is straightforward to parallelize as each contingency can be assessed independently, and therefore the computation time scales well with the available computational power.

Line 4: The outage of a generator or a transmission line is simulated by altering the case-file to remove the specified component from operation. The altered system model is then run through an AC-OPF algorithm with load shedding to approximate the lost load due to the contingency. No fault cascading is considered in this example, and the only corrective control considered is that of load shedding and generator redispatch. Although this model is simple and does not reflect the decision making in system operation, it is assumed that TSOs have access to more sophisticated tools available for more realistic computations of lost load.

Of all the N-1 contingencies, only the failure of lines L5, L10 or L27 result in lost load. The resulting lost load due to these contingencies is shown in Table 2.

Line 5: The duration of any service outages is calculated using the linear model from [Henneaux and Kirschen, 2016], shown in Section 5.1.3.5 . The maximum outage is implicitly assumed to be 14.8 hours,

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in the case of 100% loss of load, which is equivalent to 60 operational periods in this example. The estimated duration of contingencies that lead to an outage are shown in Table 2.

Line 6: The same duration model is used to convert lost load into energy not served, using the equation in Section 5.1.3.6 , which results in the values shown in Table 2. The ENS is assumed to occur for the users that experience the initial loss of load, and is a function of the expected load over the duration of the outage. The values presented in the table are aggregated over the entire system.

Line 8: Interruption costs are calculated from the VOLL curve, shown in Figure 8, which is a function of the contingency's duration. The VOLL curve is equivalent to the marginal VOLL curve for commercial consumers presented in [GARPUR, 2016], which is based on Norwegian survey data from [Bjørk et al., 2012]. This curve is used to estimate the expected interruption cost in each operational period, and can then be aggregated into an estimate of total expected interruption cost. For example, an outage lasting 1 hour would have a value of 3100 EUR/MWh for unserved energy in the first operational period, and a value of approximately 2000 EUR/MWh in the following three operational periods. Note that Line 7 accounts for the assumption that no further faults occur.

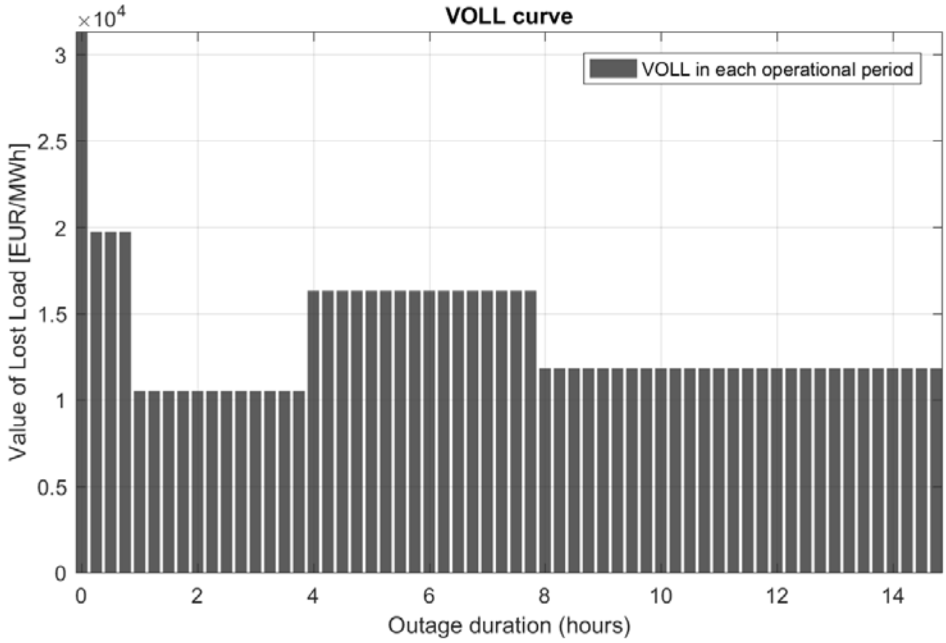

Figure 8: The assumed Value of Lost Load curve for the test system, where each bar represents the value of load lost within the specific operational period (15 minutes) following an outage at time zero.

Line 9: Compliance with the acceptability constraints is measured by checking the initial system state, and the post-contingency and control system state (system response and corrective controls are modelled together) against a set of acceptability criteria. In this case, it is simply the requirement that component load limits are satisfied, and that there is no lost load. As such, the three contingencies listed in Table 2 result in non-compliance, and all other contingencies result in an acceptable system state.

Line 10: This line defines the end of the internal loop, and the remaining lines of the algorithm aim to aggregate the individual contingency simulations into meaningful indicators.

Line 11: The residual probability consists of the pre-discarded contingencies as well as the discarded post-contingency trajectories, for the sake of estimating the consequences in a deterministic way. The residual probability is estimated to be: $\pi_R = 0.003\%$. Figure 9 below provides an accounting of the entire probability space, including some insight into the composition of the residual probability. This figure also shows the contribution of contingencies to the probability of acceptability, where green bars relate to the sets of events that result in acceptable system trajectories. Of the three red bars, the unacceptable states are those that are assessed to result in unacceptable system states, whilst the remaining two relate to

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contingencies or outcomes that have not been modelled, and therefore must be assumed to result in an unacceptable state.

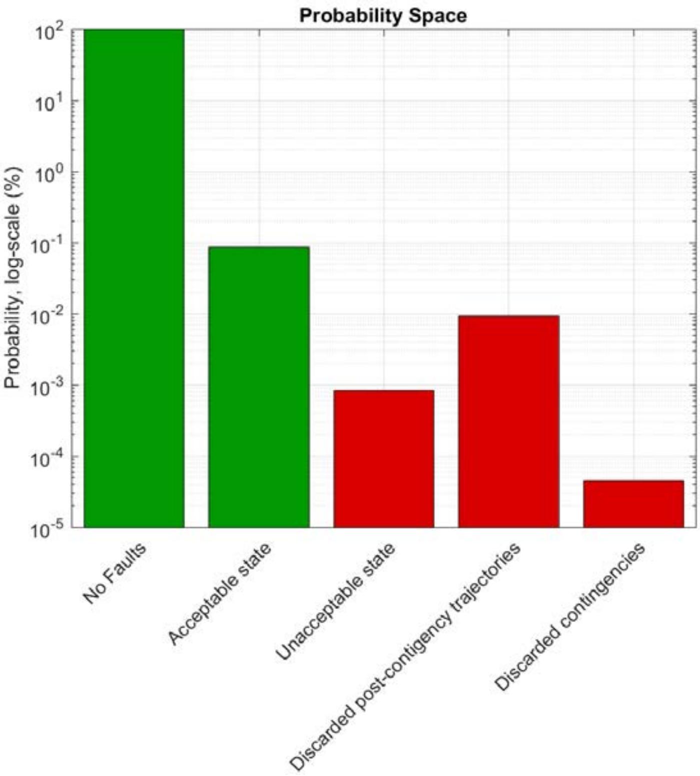

Figure 9: Division of the probability space, where the sum of the five probabilities equals one. Note that a log-scale must be used as the probability of no faults occurring is a few orders of magnitude more likely than the other outcomes.

Line 12: The total expected ENS is calculated as 0.851 MWh. If the discarded trajectories and contingencies are not considered, the total expected ENS is estimated as 0.232 MWh.
Line 13: The Risk is calculated as 12 103 Euros (3294 Euros without considering the residual risk) and the expected surplus is estimated as 504 million Euros (10.6 million Euros per 15 minute operational period). The expected surplus value is quite large, given that it is calculated over the entire assessment period. Therefore, it is more useful to consider the difference between the expected surplus and the surplus of the 'no fault' trajectory. Trivially this difference is equal to the risk for this example, but for detailed surplus formulations, as in [GARPUR, 2016a], this will not be the case.
Line 14: The compliance with the probabilistic reliability target is calculated to be 99.997%. This is easy to discern from Figure 9 as the probability of 'no fault' plus the probability that any assessed fault results in an acceptable trajectory (the green elements of the figure). An alternative formulation of this may be to consider only the set of assessed trajectories, in which case the probability of an acceptable system state would be 99.9991%.

Table 2: Contingency specific outputs, showing the estimated service outage duration, initial loss of load, overall energy not served (ENS) and subsequent interruption cost.

Contingency	Contingency Probability (π_c)	Outcome Probability (π_c^*)	Lost Load (%)	Outage Duration (hours)	ENS (MWh)	Interruption Cost (million Euros)
Line 5 (L5)	0.0014%	0.0013%	0.016%	0.65	77	1.1

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Line 10 (L10)	0.0009%	0.0009%	100%	14.8	20 398	290.1
Line 27 (L27)	0.0012%	0.0011%	1.38%	0.84	4 946	70.3

5.1.6 Considering the effect of weather

We assume that there is 20% probability of having an adverse weather state from hours 17 and 24 in the zones 2 and 3. The adverse weather state is modelled as follows:

- We assume that the adverse weather state occurs in scenario 1 between hours 6 and 10.
- Under the adverse weather state, the failure rates of all generators in zones 2 or 3 increase by a factor of 5.
- Under the adverse weather state, the failure rates of branches whose "from" and "end" buses lie in zones 2 or 3 increase by a factor of 5. The failure rates of branches with only one of the "from" or "end" buses in zones 2 or 3 increase by 2.5.

With bad weather, the probability or consequence of the above contingencies does not change, as the contingencies of L5 and L27 are not within zones 3 or 4 (where the severe weather state was assumed to occur) and L10 is not affected by weather given that it is cable. If the contingency discarding algorithm accounts for the probability of contingencies, then the set of assessed contingencies is likely to vary under the influence of bad weather (not the case in this case study).
The bad weather only affects the overall expected outcome in this case, and is most easy to see when considering the Expected ENS and the Risk parameters. Notably, our estimate of the risk increases due to the increased probability of discarded events occurring, and given the assumption that unassessed system trajectories result in the worst-case scenario. The comparison between the normal and bad weather cases is shown below in Table 3.

Table 3: Effect of bad weather on total risk indicators

Parameter	Base case	Bad weather case
Residual probability	0.003%	0.0095%
Prob. of acceptability	99.997%	99.9968%
Prob. of acceptability (excl. residual prob.)	99.9991%	99.9992%
Expected ENS	0.851 MWh	2.159 MWh
Residual ENS	0.619 MWh	1.934 MWh
Expected ENS (excl. residual prob.)	0.232 MWh	0.225 MWh
Risk	12 104 Euros	30 710 Euros
Residual Risk	8 810 Euros	27 505 Euros
Risk (excl. residual prob.)	3 294 Euros	3 205 Euros

Most importantly, it is worth noting that the expected ENS, Risk and probability of acceptable system trajectories all improve if the residual probability is ignored when weather worsens. This is a result of the increased residual probability (greater chance of multiple line faults due to weather) being discarded. This significant increase in residual risk may only be addressed by assessing more contingencies. This implies that it is insufficient to apply a constant contingency list (i.e. the N-1 contingency list) under changing exogenous conditions, especially if the residual risk is not quantified/considered.

Additionally, the sensitivity of reliability indicators to changing exogenous conditions, and to contingency lists, needs to be assessed further to ensure that the indices respond to threats in a sensible manner. The above case-study, for example, suggests that if the residual risk isn't controlled to a negligible level (e.g. through applying the GARPUR 'discarding principle' in contingency discarding) that the residual probability must be considered as part of, or alongside, the reliability indicators. The sensitivity of indices to modelling choices will be investigated in the pilot tests of the GARPUR methodology in the coming year.

5.2 Support to real-time reliability control

The reliability assessment informs the operator whenever the acceptability criteria are not met. This signals the operator to take some action to improve the system's reliability. Another important use of the assessment is to increase the operator's situational awareness for decision-making. This requires an efficient visualization of the probabilistic results to the operator.

It is therefore important to show which contingencies have resulted in an unacceptable post-contingency state. Note that since the contribution of a contingency to the reliability target is either zero or π_c^*, if an unacceptable contingency is turned into an acceptable state using a corrective action, it would increase the reliability by π_c^*. Therefore, amongst these contingencies the one with the highest π_c^* has a better chance of improving the reliability target.

Due to the lack of fully developed tools that can satisfy operational time constraints, we do not suggest use of an optimization method to find the best possible actions in the first stage. Instead, the proposed assessment method can be used to assess whether a given corrective and/or preventive action can improve the reliability target by manually altering the inputs and observing its effect on risk and surplus.

In real-time, operators have a limited set of control actions that they can use to achieve an acceptable reliability level. To find the optimal actions they can use the reliability assessment approach outlined above and run the algorithm on the list of available actions to find the least costly action that restores the reliability criteria. This procedure is outlined as:

1. Given the present state of the system and a list of non-discarded contingencies;
2. Given a list of available control actions;
3. Manually select a set of candidate control actions, using expert opinion;
4. Run the reliability assessment method over the candidate control actions;
5. Choose the feasible control action that minimizes the expected socio-economic surplus.

The list of contingencies that has caused the violation of the reliability target as well as the acceptability constraints that are violated are amongst the important inputs for the operator. Since $\mathbb{P}(x_0, x_1 \in X_a|c) = \pi_c^*.\mathbf{1}\{x_0, x_1 \in X_a\}$ is either zero or π_c^*, one suggestion is to sort the list of contingencies that does not satisfy the acceptability constraints based on their π_c^* values. The operator may remove some of the contingencies from this list based on their experience; for example if they know that for a certain contingency there is no corrective action that can alleviate the consequences of it. For this aspect, it is useful for the operator to be informed about the cause of the unacceptability of the post-contingency state and also what constraints in X_a were violated.

The time for decision-making in real time is critical and depending on the computational complexity of the assessment algorithm, it might be the case that there is only time to evaluate a few of the available control options. The experienced operators have a good intuition about viable control actions for some of the contingencies. They can use their experience to change the order of the list of the list of available options and prioritize some of them to see if they are feasible.

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6 UPGRADE OF RELIABILITY ASSESSMENT FOR SHORT-TERM DECISION MAKING

6.1 Short-term reliability assessment

6.1.1 Proposal for a first-step implementation

As introduced in Section 3.4.1, the reliability assessment process in short-term operational planning takes as input a list of scenarios with realisations of the ST exogenous parameters for all time periods of the considered time horizon. Given this input, and taking the example of time periods of one hour, the ST reliability assessment does the following:

1) It simulates what decisions would be taken in real-time operations by the real-time operator in each hour of each scenario;
2) It assesses the real-time reliability level resulting from these real-time decisions in each hour period of each scenario;
3) It aggregates the results of the real-time reliability assessments over all scenarios to present meaningful indicators to the operator that supervises the short-term reliability assessment.

The values taken by the short-term exogenous parameters will become apparent during real-time operations. These parameters include, in particular, all parameters that depend on weather. Therefore, data related to the correlation of all uncertain parameters is necessary. Scenarios with realisations of exogenous parameters for all hours of the studied time horizon are generated and given as inputs to the short-term reliability assessment process (See Section 5.1). A probability is assigned to each scenario. The following exogenous parameters are included in the scenarios, for each scenario and each hour:

1. A contingency list;
2. Probability of each contingency in the contingency list;
3. Load and RES forecast errors.

The set of all possible exogenous parameters is denoted Ξ. A scenario of the exogenous parameters is denoted $\xi_{1,\dots,T}$ and is a sequence of realisations of all exogenous parameters in time steps *1* to *T*. As explained in Section 4.4.1, the set of assessed scenarios is a finite subset Ξ_c of Ξ that is generated to keep the residual risk associated with the non-discarded scenarios tolerably low.

Related to contingencies, it is important to observe that, in real-time operations, the random variable is the occurrence of a contingency. In short-term operation planning, the random variables associated to contingencies are the failure rates, which are not perfectly known at the time of the short-term risk assessment since they depend, for example, on weather.

Given short-term decisions and a list of scenarios for the exogenous parameters, the risk assessment problem is to assess whether the real-time RMAC (RT-RMAC) is feasible in all hours of these scenarios and to aggregate the results of the evaluation of real-time operations to present aggregate indicators to the short-term operator. The assessment must consider the possibility of real-time preventive and corrective actions that real-time operators would take. Due to the possibly large number of scenarios, the evaluation of real-time operations in all hours of each scenario must be automated. The short-term reliability assessment procedure therefore performs multiple, coordinated and automated assessments of real-time operations. Since a single scenario contains a sequence of realisations for all studied hours, time coupling constraints must be considered. Furthermore, if the real-time reliability management model includes the possibility to take real-time preventive actions, such actions are still active in the hours following their application, if they have not been reset. An example of this is preventive re-dispatch in hour *t,* which is still active at the start of the next hour *t+1*.

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The short-term reliability assessment procedure is outlined in Algorithm 8.

Algorithm 8: Short-term reliability assessment

Inputs: Finite list of scenarios Ξ_c, base case system configurations for all t in [1,T], RT-RMAC inputs, economic parameters

Outputs: Outputs of the RT-RMAC evaluations;

for each scenario $\xi_{1,\dots,T} = [\xi_1 \dots \xi_T]$ in Ξ_c **do**
    for each time t in {1,…,T} **do**
        Set the system configuration to the base case system state for time t;
        Set all generators, loads and exchanges according to their market schedule;
        if t>1 **then**
            Implement preventive actions taken in RT-RMAC at times t'<t within the current scenario;
        End
        Set the uncertain parameters (e.g. load, RES output, etc.) to their realised values in ξ_t;
        Simulate the frequency control response to the deviations from the market schedule to get a balanced system state;
        Simulate RT-RMAC and store the results (including reliability target and socio-economic surplus);
    End
End
Build aggregate ST indicators from the results of all real-time risk assessments.

The following inputs must be provided to the short-term reliability assessment procedure:
1. Time horizon covered by the short-term risk assessment;
2. Generation and consumption bids to be provided to the market-clearing algorithm, if the short-term risk assessment is performed before the market is cleared;
3. A list of scenarios including realisations of the exogenous parameters listed above for all hours of the studied operating period, as described in Section 0;
4. A model of the system during all time steps included in the considered time horizon: it includes all the information known about the system configuration at the time of the assessment, such as base case topology (considering maintenance execution) and generation and consumption plans (if the reliability assessment is performed after the market is cleared);
5. A model of the RT-RMAC to perform automated real-time reliability management as described in Section 6.1.2;
6. All inputs necessary to evaluate the indicators computed by the RT-RMAC, see Section 5. Note that some of these inputs may depend upon the exogenous parameters;
7. A list of short-term decisions (possibly empty to evaluate the reliability of the system before taking any ST actions).

The output of the short-term reliability assessment is a list of indicators that quantify the risk associated with the inputs and with the list of short-term decisions that is fed to the reliability assessment procedure. The risk in each scenario and hour is quantified by:
- The real-time reliability target that measures the probability that some system states will not fulfil the acceptability constraints for the considered scenario and hour.
- The socio-economic surplus as defined in [GARPUR, 2016].

Seen from the short-term, these two indicators can then be aggregated in or broken down into different hierarchical levels (per scenario, hour or contingency) in each scenario and hour as described in Section 6.1.3. In this aggregation process, the probability of each scenario is considered when the indicators are aggregated across all scenarios.

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The following subsections provide more detail about the model of the real-time operations and the computation of aggregate indicators to assess the short-term risk.

6.1.2 Model of real-time operations

The first-step implementation of the real-time reliability assessment of the GARPUR RT-RMAC is presented in Section 5. From the perspective of short-term operational planning, however, the possibly large number of scenarios require having an automated procedure not only for the RT reliability assessment but also for the reliability control problem of the RT-RMAC. Since the reliability control problem is not addressed in the first-step implementation of the GARPUR RT-RMAC, it is proposed to build an automated model of real-time operations that approximate today's practices to choose the control actions that would be performed in real-time should a scenario realise. Given these real-time control actions, the indicators for the real-time reliability assessment presented in Section 5 are computed considering additional probabilistic information that is not taken into account in the real-time control problem. These real-time indicators are then aggregated in different hierarchical levels once real-time operations have been assessed for all hours of all scenarios (Line 13 in Algorithm 8, see also Section 6.1.3). The model of the RT-RMAC used in short-term operational planning is therefore a two-step procedure in which, first, real-time actions are determined according to today's practices and, second, the real-time reliability assessment is performed following the procedure in Section 5. This is illustrated in Figure 10.

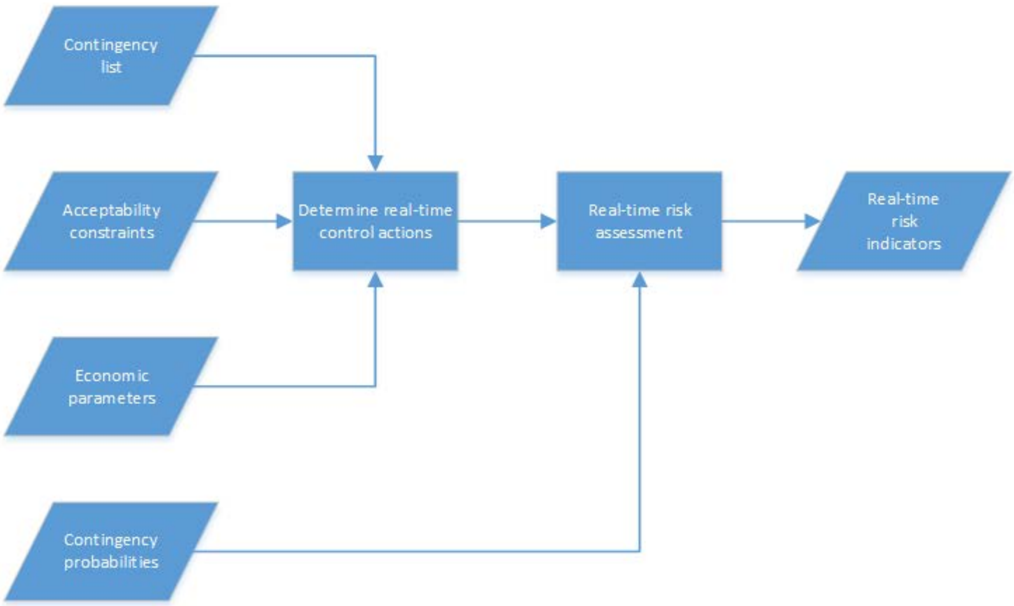

Figure 10: Model of RT-RMAC.

Today's practices for real-time operations place the real-time operator at the centre of the decision-making process. The operator has supporting tools at his disposal, such as contingency analysis tools or lists of proposed actions for certain well-studied contingencies, but has the responsibility to determine actions, either preventive or corrective, if necessary. Actions must be taken to ensure that the operating constraints are fulfilled in all pre- and post-contingency system states for all contingencies in the considered contingency list.

In order to automate this process, a tool must be available to determine real-time preventive and corrective actions given a contingency list and a set of operating constraints. In the GARPUR framework,

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the operating constraints are contained in acceptability constraints as explained in Section 9.4. The automated and simultaneous determination of real-time preventive and corrective actions is a very complex optimization problem. The complexity arises from the number of contingencies that must be considered simultaneously and the types of actions available to TSOs. This so-called Security Constrained Optimal Power Flow Problem has been extensively studied in the literature. In the Euopean context, this problem has been studied extensively in the FP7 PEGASE project [PEGASE, 2012b], and more specifically in [PEGASE, 2009] and [PEGASE, 2012a]. The methods developed in the PEGASE project could serve as a basis for developing automated models of the real-time decision-making process considering both real-time preventive and corrective actions.

For the first-step implementation of the short-term risk assessment, we propose to neglect the possibility of automatically using real-time preventive actions. It should be emphasized that this is an approximation since a real-time operator would also use real-time preventive actions. When neglecting the real-time preventive actions, the only recourse actions become the post-contingency corrective actions. Optimal power flows can be used to determine these automatically in order to fulfil the acceptability constraints in the post-contingency systems. Some TSOs have reported experience with optimal power flows [López et al., 2015]. In order to filter out contingencies that do not need corrective actions, contingency analyses are run first on all contingencies in the contingency list. The post-contingency OPF is only used for the contingencies that do not fulfil the acceptability constraints. This is illustrated in Figure 11.

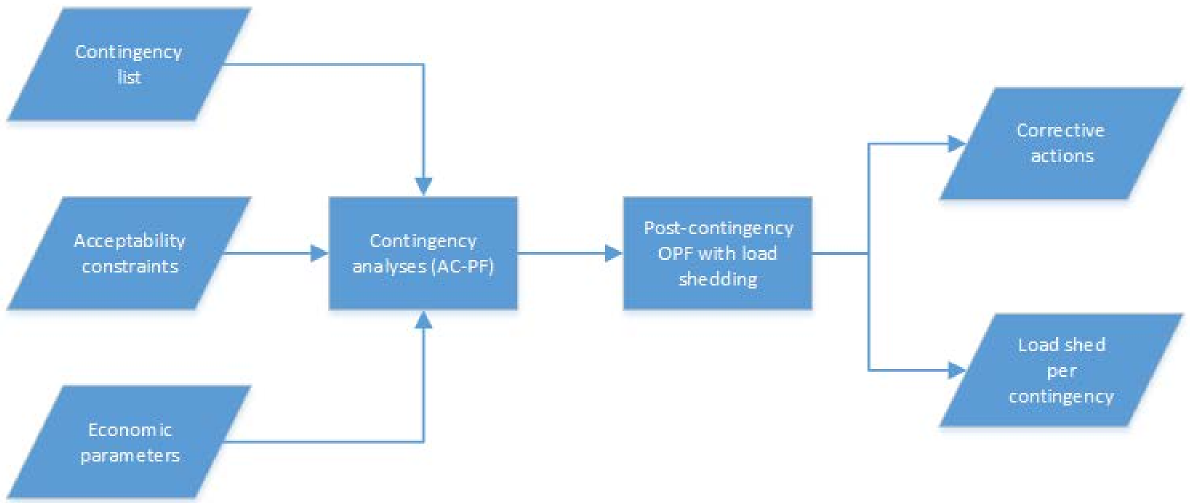

Figure 11: Automated determination of corrective actions.

In the optimal power flow, it may be necessary to use load shedding as a last resort action to enforce the acceptability constraints. The amount of load shedding can then be passed to a model of the service restoration to estimate the duration of the service outages. The energy not supplied could then be monetised and used in the computation of the socioeconomic surplus, as discussed in Appendix 9.1.1.

Since real-time preventive actions are neglected in the first-step implementation, the contingency analyses and determination of the post-contingency corrective actions are completely separable. The procedure is therefore highly parallelisable.

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6.1.3 Short-term indicators

6.1.3.1 Review of real-time indicators

After the model of the real-time operator is run for each hour of scenario, the following outputs will be available for all hours of all scenarios:

1) The list of RT corrective actions as well as their cost.
2) Reliability target: The probability that the system state fulfils the acceptability constraints.
3) The socioeconomic surplus
4) The measure of risk.

In the following, we denote by ξ_t the exogenous parameters at time t, and by $u_0(\xi_t)$ and $u_c(\xi_t)$ the real-time preventive and corrective actions taken at time t. These actions depend on the exogenous parameters.

The real-time probability that the system state is (see Section 5.1.3.7):

$$p_{RT}(u_0(\xi_t), u_c(\xi_t), \xi_t) = \sum_{c \in \mathcal{N}_c} \pi_c^* \mathbf{1}\{x_c \in X_a\}.$$

For the sake of brevity, we will omit the dependence of this probability on the real-time actions and write $p_{RT}(\xi_t)$.

The real-time risk indicator $R_{RT}(u_0(\xi_t), u_c(\xi_t), \xi_t)$ for time t is the expected customer interruption costs attributed to this time t, given the realisation ξ_t of the exogenous parameters at this time, and the real-time preventive and corrective actions u_0 and u_c. For brevity of notations, we will omit the dependence of the real-time risk on real-time actions and write $R_{RT}(\xi_t)$.

Similarly, recall from Section 5.1.3.13 that the real-time socioeconomic surplus $S_{RT}(u_0(\xi_t), u_c(\xi_t), \xi_t)$ is formulated as

$$S_{RT}(\xi_t) = V_{cons}(\xi_t) - C_{actions}(\xi_t) - R_{RT}(\xi_t)$$

where V_{cons} is the valuation of the supplied energy, $C_{actions}$ are the costs of real-time actions and $R_{RT}(\xi_t)$ is the real-time risk. For brevity of notation, we omit the dependence of the real-time surplus on the real-time actions and write $S_{RT}(\xi_t)$.

6.1.3.2 Short-term reliability target

For each time step t, the probabilities of acceptability $p_{RT}(\xi_t)$ can be aggregated across all non-discarded scenarios:

$$p'(t) = \sum_{\xi = \xi_{1,\ldots,T} \in \Xi_c} \pi_\xi p_{RT}(\xi_t) / \mathbb{P}(\Xi_c),$$

where the denominator $\mathbb{P}(\Xi_c)$ is used to condition the probabilities on the occurrence of a non-discarded scenarios. In other words, $p'(t)$ measures the probability of acceptability among non-discarded scenarios only. $\mathbb{P}(\Xi_c)$ is the sum of the probabilities of all non-discarded scenarios.

While this measure offers an overview of the probability of acceptability across all scenarios, it does not link to the real-time reliability target $p_{RT}(\xi_t) > 1 - \epsilon_{RT}$. The following measure is therefore used in the short-term reliability target

$$p(t) = \sum_{\xi = \xi_{1,\ldots,T} \in \Xi_c} \pi_\xi \mathbf{1}\{p_{RT}(\xi_t) > 1 - \epsilon_{RT}\} / \mathbb{P}(\Xi_c).$$

The short-term reliability criterion is then formulated in a similar way as the one for real-time in Section 5.1.3.14 :

$$p(t) > 1 - \epsilon_{ST},$$

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where ϵ_{ST} is the short-term reliability target.

It is advised to start computing and collecting $p(t)$ in a database. Once sufficient insight has been gained on the values taken by $p(t)$, an appropriate short-term reliability target ϵ_{ST} can be set. Setting $\epsilon_{ST} = 0$ leads to a robust problem in which the system operator ensures that the real-time reliability target can be fulfilled in all non-discarded scenarios. Setting $\epsilon_{ST} > 0$ allows some flexibility in short-term operational planning.

Finally, we note that it is possible to include the discarded scenarios in the reliability target by assuming pessimistically that their occurrence results in unacceptable state. In this case, $p(t)$ takes the following form:

$$p(t) = \sum_{\xi=\xi_{1,\dots,T}\in\Xi_c} \pi_\xi \mathbf{1}\{p_{RT}(\xi_t) > 1 - \epsilon_{RT}\},$$

The difference with the first formulation of $p(t)$ given above is that the normalizing factor $\mathbb{P}(\Xi_c)$ is not used. Therefore $p(t)$ measures the probability of fulfilling the real-time reliability target across all (non-discarded and discarded scenarios). The difference between the two formulations of $p(t)$ is similar to the corresponding discussion on including discarded contingencies or not in the real-time reliability target see Section 5.1.4.

We do not make any recommendation at this point as to which formulation of $p(t)$ to use. This issue will be studied in the pilot tests that will be performed in the remainder of the GARPUR project.

6.1.3.3 Short-term risk and socioeconomic surplus.

The short-term risk indicator is built by aggregating the real-time risk indicators for the non-discarded scenarios and assuming conservatively that all *T* time steps in the discarded scenarios would result in a worst-case situation where the customer interruption costs are $C_{int,max}$. Therefore, the short-term risk indicator is

$$R_{ST}(u_{OP}) = \left(1 - \sum_{\xi=\xi_{1,\dots,T}\in\Xi_c} \pi_\xi\right) T \cdot C_{int,max} + \sum_{\xi=\xi_{1,\dots,T}\in\Xi_c} \pi_\xi \sum_{t=1}^{T} R_{RT}(\xi_t),$$

where u_{OP} are short-term preventive actions taken during operational planning (OP) before the realisation of the exogenous parameters. Everything but the parts capturing the worst-case costs depends on the ST preventive actions u_{OP}. This is not shown for the sake of brevity of notation.

The short-term socioeconomic surplus is built similarly by aggregating the difference between the valuations of supplied energy and costs of real-time actions over non-discarded scenarios, and subtracting the cost of short-term actions and the short-term risk:

$$S_{ST}(u_{OP}) = \sum_{\xi=\xi_{1,\dots,T}\in\Xi_c} \pi_\xi \sum_{t=1}^{T} \left(\sum_{c\in\mathcal{N}_c} \pi_c^* V(u_0(\xi_t), u_c(\xi_t)) - C(u_0) - \sum_{c\in\mathcal{N}_c} \pi_c C(u_c) \right) - C(u_{OP}) - R_{ST}(u_{OP}),$$

where $V(u_0(\xi_t), u_c(\xi_t))$ is the valuation of supplied energy after contingency *c*, $C(u_0)$, $C(u_c)$ and $C(u_{OP})$ are the cost of real-time preventive and corrective actions and short-term preventive actions.

6.1.3.4 Remarks about the aggregation of real-time indicators to short-term indicators

Following the above aggregation and disaggregation procedures, a hierarchy of aggregate indicators can therefore be defined. These indicators can be opened up to reveal the underlying, finer indicators. Table 4 presents an overview of the hierarchy of indicators in a top-down approach, from the highest level

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indicators (most aggregation) to the lowest level indicators (most specific) with the examples of how expected cost of energy not served (which is the risk measure) and satisfaction of the acceptability constraints would be reported at the different levels. The fact that aggregate indicators can be opened up is very important to ensure that they are understandable, explainable and helpful to operators.

Table 4: Hierarchy of indicators

<table>
<tr><td>Per-hour indicators (aggregation over all scenarios)
Example 1: Expected cost of energy not served in one specific hour across all scenarios.
Example 2: What is the probability, for a specific hour, that the probability of the post-contingency system state is acceptable?</td><td>Per-scenario indicators (aggregation over all hours)
Example 1: Expected cost of energy not served in one scenario across all hours.
Example 2: What is the probability in a specific scenario that the probability of the post-contingency system state is acceptable?</td></tr>
<tr><td colspan="2">Per-hour and per-scenario indicators (aggregation over all contingencies)
Example 1: Expected cost of energy not served over all contingencies.
Example 2: What is the probability, across all contingencies, that the post-contingency system state is acceptable?</td></tr>
<tr><td colspan="2">Per-contingency indicators (aggregation over all behaviours of corrective actions)
Example 1: Expected cost of energy not served for one contingency.
Example 2: What is the probability that the post-contingency system state is acceptable?</td></tr>
</table>

Going from one level to the higher one can be done in different ways such as counting or averaging. For example, if a threshold indicator (such as whether a system state is acceptable) is aggregated across realisations of a probabilistic parameter, the resulting aggregate indicators can be the probability that the threshold is violated or the number of times it is violated. When the indicator is a value (such as energy not served after a contingency), it can be aggregated into an average, a variance or any other measure that is built upon the distribution of the absolute values. For example, in Table 4, the averaging operator was used.

6.1.4 Case study

This case study shows an illustrative example of post market clearing day-ahead risk assessment, using the method described above. For the sake of the example, we consider the IEEE RTS96 described in Section 5.1.5. We consider the short-term operation planning for all 24 hours of Tuesday on week 30. The loading profile of this day is shown in Figure 12.

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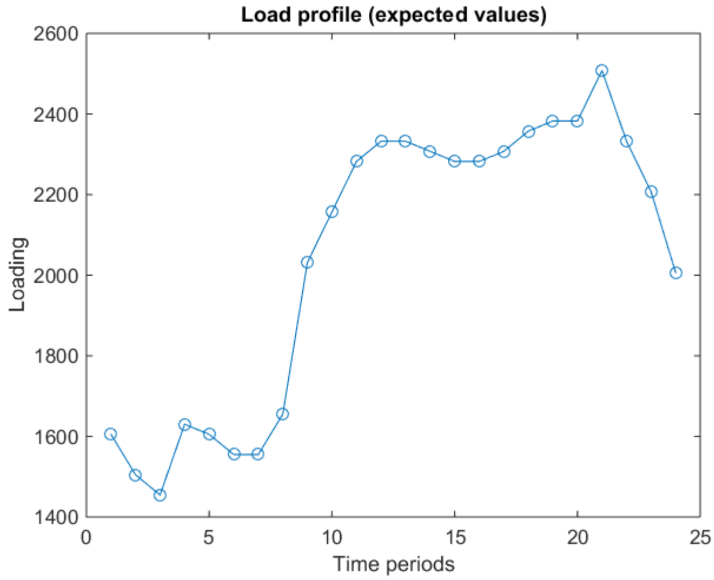

Figure 12: Load profile of Tuesday of week 30.

6.1.4.1 Uncertainty

The uncertain parameters are assumed to be loads only. We do not consider spatial or temporal correlations so the samples for different time periods are drawn independently. We assume that all loads follow a normal distribution with mean equal to their share of the load profile and standard deviation equal to $\sigma(t) = \sqrt{t}\,/2$ percentage points of their mean value. For example, if forecasted values for a load are 10 MW at time 1 and 40 MW at time 4, the standard deviations in MW for this load will be $\sigma(1) = 0.05$ MW and $\sigma(4) = 0.4$.

Five scenarios for the load profile are generated. Each scenario consists of realisations of the loads for all 24 hours.

6.1.4.2 Acceptability constraints

The acceptability constraints are assumed to include limits to line flows and bus voltages that are defined in the original data.

6.1.4.3 Contingencies

Non-discarded contingencies are assumed to be all of the N-1 contingencies as well as the N-0 system. This means that we consider in this example only a very simplistic scenario discarding procedure which discards all N-k contingencies, for k>1. There are 72 N-1 contingencies in total, corresponding to outages of one of the 33 generators or one of the 39 branches.

The hourly contingency probabilities π_c are computed from the failure rates λ_c:

$$\pi_c = 1 - \exp\left(-\frac{\lambda_c}{8766}\right)$$

6.1.4.4 Effect of weather

The effect of weather is considered as described in Section 5.1.6.

6.1.4.5 Market clearing and reserve procurement

The aim of the case study is to perform a day-ahead risk assessment after the market is cleared. To determine the generation plans and the amount of available reserves, the following procedure is used.

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The market is cleared separately for all 24 hours of the considered day. A DC model is used. The reserves are jointly auctioned. Losses are considered by scaling all loads by a common loss factor. By default, the loss factor is set to 1.025, under the approximation that losses will be about 2.5% of total load. A decommitment heuristic is used. This step is performed using the corresponding built-in functions in MATPOWER [Zimmerman et al., 2011]. Note that scenarios are not considered here.

The amount of reserves in the system has a significant impact on the results. In MATPOWER's tool for joint market clearing and reserve procurement, the reserve requirements are set on a zonal level. The reserve requirements are considered as follows. The market is cleared without reserves. Then, we check if there is enough reserve in MW to compensate the loss of the largest generator dispatched by the market. If this is not the case, the total required system reserves are set to the production of this generator and spread among the zones according to their share of the total system load. Then, the joint energy market and reserve procurement problem is solved again.

This procedure does not aim at being fully representative of the way the market is cleared and the reserves are procured in reality. Rather, it aims at providing a base case from which the day-ahead risk assessment is performed.

6.1.4.6 TSO actions

In this case study, we only consider re-dispatch of active power production and load shedding as TSO actions. These actions are the only actions available in the simulation package that is used. This is not meant to represent all possible actions that TSOs can take. The GARPUR method that is presented above is not limited to any particular actions. Real-world pilot testing performed later in the GARPUR project will provide a real-world example of the GARPUR method.

6.1.4.7 Scope of the case study

The case study aims at illustrating the short-term reliability target and the part of the short-term risk associated with the assessed real-time trajectories in the non-discarded scenarios. In particular, the short-term residual risk associated with the discarded scenarios and the part of the real-time risk associated with the non-assessed trajectories are not considered. These residual risks are important but are not the focus of this case study.

6.1.5 Algorithm

The day-ahead risk assessment is performed as per Algorithm 8. The inputs are:

- The five load profile scenarios.
- The list of contingencies (constant throughout the day) and their probabilities (different for some hours and components, as explained above).
- The set of acceptability constraints on voltages and line flows.
- The market clearing results that form the base case of each hour.
- A model of RT-RMAC as presented in Section 6.1.2 consisting of
    - AC power flow for contingency analyses to check whether the acceptability constraints hold in the post-contingency system
    - Post-contingency corrective AC-OPF with generation re-dispatch and load shedding that is used to find the optimal re-dispatch and load shedding actions to enforce the acceptability constraints, for the post-contingency states that fail the contingency analyses.
    - A model to estimate the service outage duration from the amount of load shed, from [Henneaux and Kirschen, 2016].

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- The value of lost load which is assumed to be constant throughout the day and the same at all nodes, equal to 5000 €/MWh. Note that compared to the real-time case study in Section 5.1.5, the variation of the value of lost load as a function of outage duration is not modelled here.
- The costs of generator re-dispatch assumed to be linear functions of the positive or negative re-dispatch with linear coefficient equal to the marginal cost computed at the set point of the generators. These costs are much lower than the value of lost load. Hence, re-dispatch actions are performed in priority in the post-contingency corrective OPF of the model of real-time operations.

6.1.6 Results

6.1.6.1 Contingency analyses without corrective actions

Figure 13 shows the results of the contingency analyses before any application of corrective actions for all hours of the five load profile scenarios. It shows the probability of the system state to be unacceptable, i.e. $p_{RT}(\xi_t)$ as defined in Section 6.1.3.1 . The analyses of all violations reveal that all are violations of the bus voltage constraints. The effect of adverse weather in scenario 1 between hours 17 and 24 is clearly visible. In contrast, Figure 14 shows the same information, but without consideration of the impact of adverse weather on the failure rates. It can be clearly seen that doing so would underestimate the likelihood of the system state to be unacceptable.

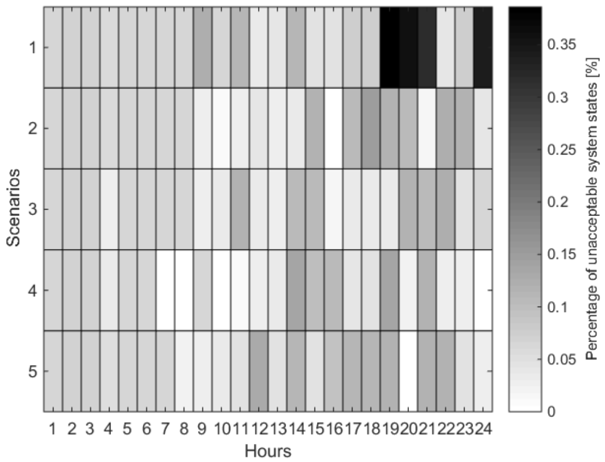

Figure 13: Probability of system state to be unacceptable, with consideration of adverse weather in scenario 1 between hours 17 and 24.

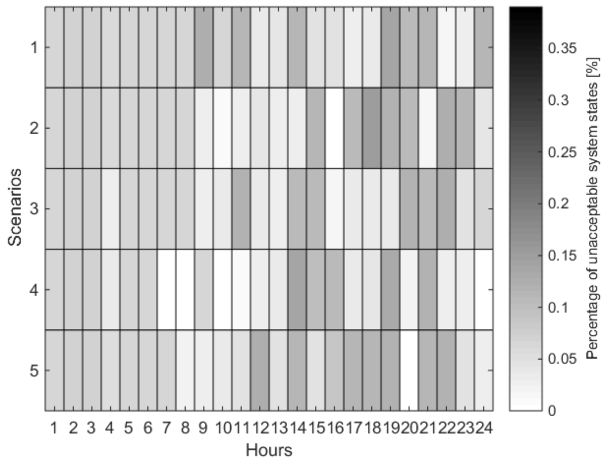

Figure 14: Probability of system state to be unacceptable, without consideration of the impact of adverse weather.

Recall from Section 5.1.3, that the tolerance of the real-time reliability target is $p_{RT}(\xi_t) > 1 - \varepsilon_{RT}$. For the sake of the example, we assume that the system operator sets $\varepsilon_{RT} = 1.3 \cdot 10^{-3}$, i.e. that the real-time reliability target is fulfilled if the percentage of unacceptable state is below 0.13 %. Figure 15 and Figure 16 show the hours in which the real-time reliability target is fulfilled, with and without consideration of adverse weather, respectively. It can be seen that not considering the effect of adverse weather would lead to categorizing hours 20 and 21 in scenario 1 as acceptable, although they are not if the adverse weather is properly considered.

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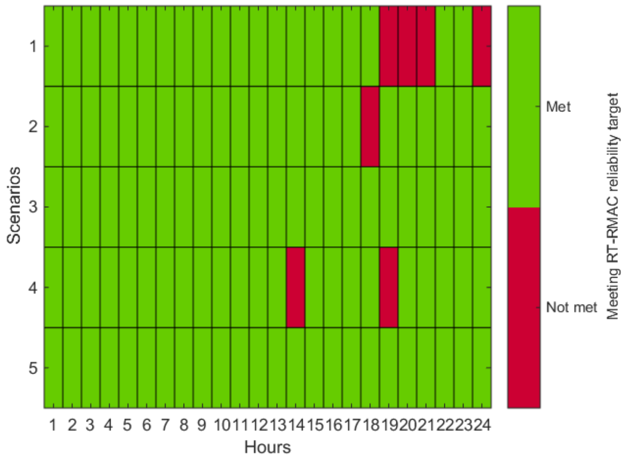

Figure 15: Assessment the real-time reliability criterion with consideration of adverse weather.

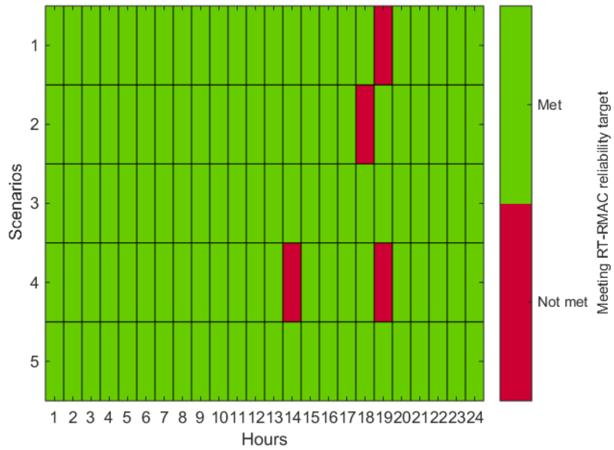

Figure 16: Assessment the real-time reliability criterion without consideration of adverse weather.

Finally, Figure 17 shows a classical N-1 analyses where the contingency probabilities are not considered. Instead, Figure 17 only shows how many contingencies would lead to unacceptable system states. By comparing this figure to the previous ones, in particular to Figure 13, it can be seen how the classical deterministic N-1 results can be misleading when identifying the most likely problematic situations.

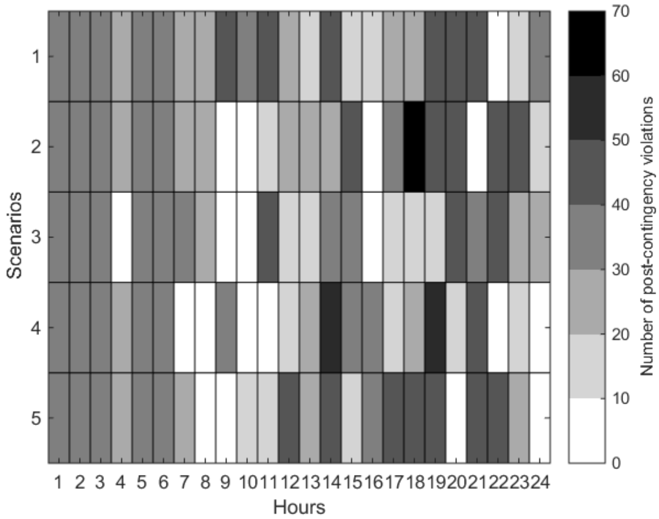

Figure 17: Number of post-contingency violations.

Figure 18 aggregates the results of Figure 13 and Figure 14 per hour over all scenarios. Figure 19 aggregates in a similar way the results of Figure 15 and Figure 16. Once again, the importance of considering the impact of adverse weather on failure rates is clear.

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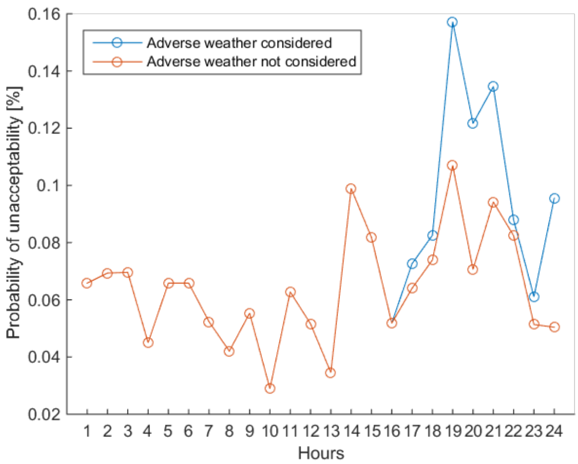

Figure 18: Probability of reaching an unacceptable system state per hour.

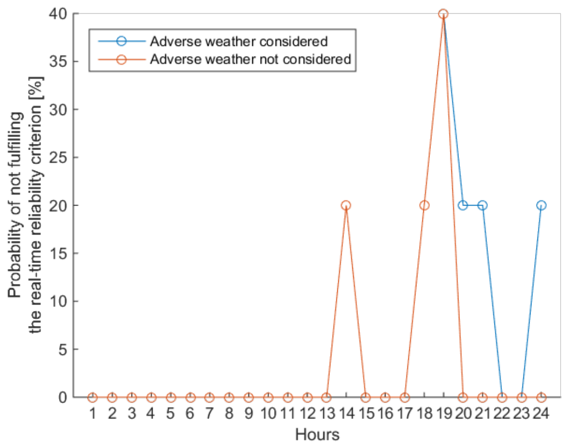

Figure 19: Probability of not fulfilling the real-time reliability target without corrective actions.

Note that the five scenarios have equal probabilities 20%. Therefore, the probability of fulfilling the real-time reliability targets changes in increments of 20%. In reality, the number of scenarios would be much higher and this probability would change in a less abrupt fashion. Figure 20 shows whether the short-term reliability criterion is fulfilled for different values of the reliability targets ranging from 0 to 30%.

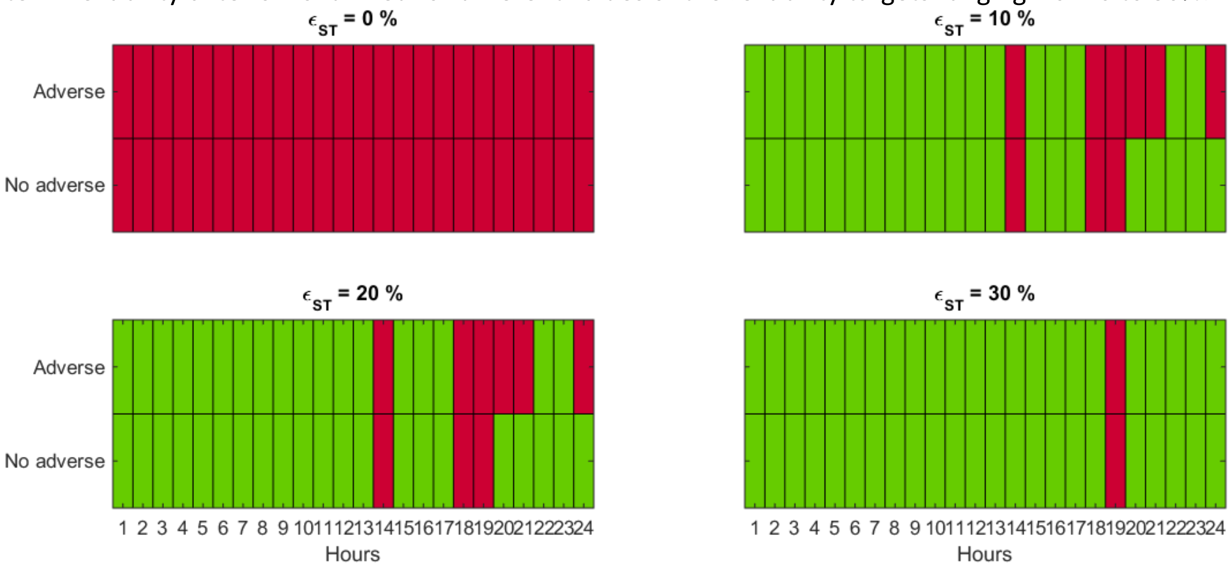

Figure 20: Fulfilment (green) or not (red) of the short-term reliability criterion for different values of the short-term reliability target.

6.1.6.2 Corrective actions

A post-contingency corrective AC-OPF is run to re-dispatch generation to enforce the acceptability constraints for all contingencies leading to violations.

Figure 21 shows the expected cost of corrective re-dispatch actions when considering the impact of adverse weather in scenario 1 between hours 17 and 24. Once again, the effect of the adverse weather can be clearly seen. By comparing Figure 21 with Figure 13, it can be seen that they provide two different probabilistic indicators measuring different dimensions of the risk. For example, hours 12 to 14 in scenario 2 had lower probability of resulting in unacceptable system states than hours 1 to 8 in the same scenario, as seen in Figure 13. However, the expected cost of corrective actions to remedy these

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unacceptable system states is higher for hours 12 to 14 than for hours 1 to 8 in scenario 2, as can be seen in Figure 21. In contrast, hours 14 to 18 in scenario 5 had higher probability of resulting in an unacceptable system state than hours 1 to 7 in this same scenario, but the expected costs of corrective actions to remedy hours 14 to 18 are lower.

Figure 22 shows the effect of not considering the adverse weather when computing the expected cost of re-dispatch actions. Once again, this gives misleading information, as the risk in the problematic hours 17 to 24 in scenario 1 is underestimated.

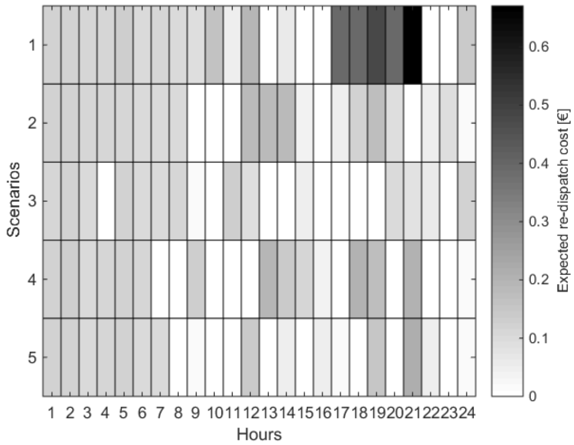

Figure 21: Expected cost of corrective re-dispatch actions, when considering the impact of the adverse weather in scenario 1 between hours 17 and 24.

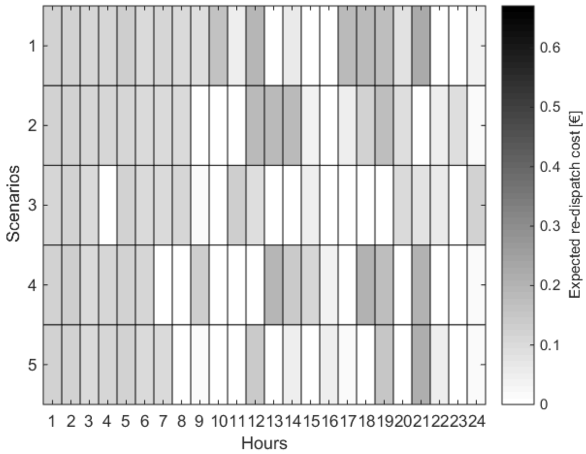

Figure 22: Expected cost of corrective re-dispatch actions, without considering the impact of adverse weather on failure rates.

Figure 23 aggregates Figure 21 and Figure 22 per hour over all scenarios.

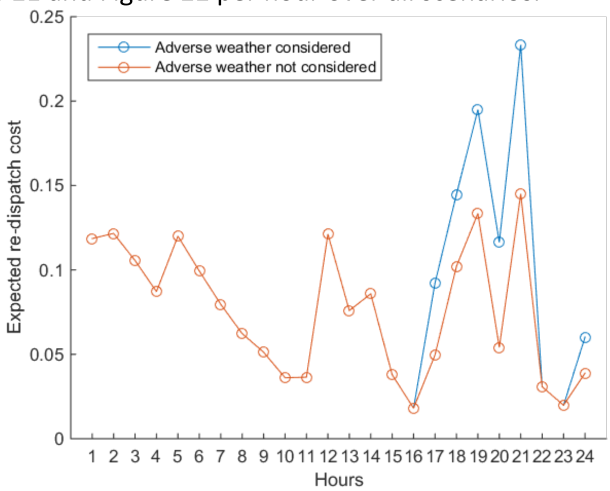

Figure 23: Expected re-dispatch cost per hour.

Note that in all cases, generation re-dispatch alone was sufficient to enforce the acceptability constraints and load shedding was not necessary.

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6.1.6.3 *Opening up the aggregate indicators*

As mentioned in Section 6.1.3, the aggregate indicators can be opened up to investigate in details which contingencies cause violations. The most problematic situation in the results above is hour 21 in scenario 1. Table 5 lists all contingencies with probability of unacceptability larger than 1e-4. Table 6 lists all contingencies with expected cost of corrective actions greater than 1e-2.

By comparing these two lists, we can observe once again that the two indicators (the probability of reaching unacceptable system states and the expected cost of corrective actions as proxy for the socioeconomic surplus) give two different perspectives on reliability and risk, respectively. For example, the failure of lines 19 and 30 are two of the five largest contributions to the probability of reaching an unacceptable state but the violations of the post-contingency acceptability constraints can be remedied with cheap control actions. The only contingencies common to both lists are the failure of lines 11 and 12, which are two parallel lines connecting the three generators at bus 7 to the system. Their failure would severely impair the amount of these generators' production that can be injected to the rest of the system. These generators are the only ones in zone 2 and contribute greatly to both supplying the loads and supporting the voltages in zones 1 and 2.

Table 5: Results of contingency analyses for hour 21 in scenario 1, sorted by probability of unacceptability.

Contingency	Probability of unacceptability	Cost of corrective actions	Expected cost of corrective actions
Line19 (bus11-bus13)	2,27E-04	1,71E+01	3,89E-03
Line11 (bus7-bus8)	1,70E-04	7,76E+02	0,13
Line12 (bus7-bus8)	1,70E-04	7,76E+02	0,13
Line24 (bus14-bus16)	1,29E-04	1,12E+02	0,014
Line30 (bus16-bus19)	1,16E-04	1,34E+01	1,55E-03

Table 6: Results of contingency analyses for hour 21 in scenario 1, sorted by expected cost of corrective actions.

Contingency	Probability of unacceptability	Cost of corrective actions	Expected cost of corrective actions
Gen33 (bus23)	4,54E-05	1,97E+04	0,89
Gen23 (bus18)	1,36E-05	2,75E+04	0,37
Line11 (bus7-bus8)	1,70E-04	7,76E+02	0,13
Line12 (bus7-bus8)	1,70E-04	7,76E+02	0,13
Gen31 (bus23)	2,27E-05	5,51E+03	0,13
Gen32 (bus23)	2,27E-05	5,51E+03	0,13

6.1.6.4 *Overview of the problematic contingencies*

Table 7, Table 8 and Table 9 present the list of top 10 contingencies, according to three different contingency-specific aggregate indicators:

- "Number of unacceptable time steps": The number of time steps in which a contingency results in an unacceptable system state in at least one scenario.
- "Probability of unacceptability": the average probability of a contingency to result in an unacceptable system state, for all scenarios and time steps.

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- "Expected corrective action costs": the expected corrective action costs associated with a contingency, for all scenarios and time steps.

By comparing the three tables, it can be seen that they provide complementary information. Probability of failures of lines are higher than that of generators. Therefore, failures of lines contribute the most to the probability of unacceptability, as shown in Table 8. Failures of generators, however, typically result in higher costs of corrective actions. Therefore, although their probabilities of failure are lower, the two outages with largest expected corrective action costs are failure of generators, as shown in Table 9. Table 7 shows that some contingencies will lead to unacceptable system states in at least one scenario in all time steps (a closer analysis reveals that none of the contingency results in unacceptable system states in all scenarios for all time steps).

Table 7: Top 10 contingencies according to the number of time steps in which the contingencies result in unacceptable system states in at least one scenario.

Contingency	Number of unacceptable time steps	Probability of unacceptability	Expected corrective action costs
Line29 (bus16-bus17)	24	2,86E-03	6,91E-03
Gen31 (bus23)	24	3,53E-04	8,87E-04
Gen32 (bus23)	24	3,53E-04	8,87E-04
Line14 (bus8-bus10)	24	4,05E-03	2,37E-05
Line8 (bus4-bus9)	24	2,77E-03	2,87E-08
Line16 (bus9-bus12)	24	1,86E-04	6,30E-10
Gen21 (bus15)	23	2,85E-04	1,65E-03
Line32 (bus17-bus22)	23	3,33E-03	5,52E-08
Gen25 (bus22)	23	6,83E-05	1,99E-08
Gen26 (bus22)	23	6,83E-05	1,99E-08

Table 8: Top 10 contingencies according to their average probability of resulting in acceptable states, across all scenarios and time steps.

Contingency	Number of unacceptable time steps	Probability of unacceptability	Expected corrective action costs
Line14 (bus8-bus10)	24	4,05E-03	2,37E-05
Line32 (bus17-bus22)	23	3,33E-03	5,52E-08
Line23 (bus13-bus23)	17	3,02E-03	3,76E-08
Line22 (bus12-bus23)	17	3,01E-03	2,54E-08
Line5 (bus2-bus6)	18	2,96E-03	3,16E-09
Line29 (bus16-bus17)	24	2,86E-03	6,91E-03
Line20 (bus11-bus14)	18	2,77E-03	4,02E-08
Line8 (bus4-bus9)	24	2,77E-03	2,87E-08
Line9 (bus5-bus10)	22	2,74E-03	2,52E-08
Line28 (bus15-bus24)	18	2,61E-03	9,21E-04

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Table 9: Top 10 contingencies according to the average cost of corrective actions, across all scenarios and time steps.

Contingency	Number of unacceptable time steps	Probability of unacceptability	Expected corrective action costs
Gen23 (bus18)	20	6,95E-04	3,95E-02
Gen33 (bus23)	18	5,38E-04	2,22E-02
Line29 (bus16-bus17)	24	2,86E-03	6,91E-03
Line11 (bus7-bus8)	20	2,22E-03	4,84E-03
Line12 (bus7-bus8)	20	2,22E-03	4,84E-03
Gen24 (bus21)	18	5,03E-05	2,78E-03
Gen21 (bus15)	23	2,85E-04	1,65E-03
Gen14 (bus13)	11	2,04E-04	1,60E-03
Line25 (bus15-bus16)	20	1,63E-03	1,33E-03
Gen22 (bus16)	16	1,71E-04	1,08E-03

6.1.7 Discussion

The first-step implementation of the GARPUR methodology to perform risk assessment for short-term operational planning has been presented. It was illustrated in the IEEE RTS96 test system. It was shown that it is important to consider not only contingency probabilities but also the effect of weather on these probabilities to obtain an accurate assessment of the risk. Furthermore, the two indicators of reliability and risk were illustrated, namely the probability of reaching an unacceptable system state and the expected cost of corrective actions necessary to enforce the acceptability constraints.

6.2 Support to short-term reliability control

Following the reliability assessment stage, the decision-maker will undertake the necessary actions to return to an acceptable reliability level in case a violation of the reliability target has been detected. In the same manner, and assuming the reliability requirements hold, he may be willing to test different configurations to perform some small optimization, such as reducing the losses.

One of the challenges that we face with the GARPUR RMAC is that we consider many scenarios at the same time [GARPUR, 2016c]. In their current practices, the TSOs analyse a single or a very few cases, which allow them to intuitively find the actions that can alleviate the risks and manually verify their efficiency. In a stochastic environment, an action “A” may be efficient for some portion of the scenarios, while being useless – or harmful - for the rest of the scenario space. Consequently, one has to quickly find a common set of actions to apply that would protect the network against a large share of the threats. To make the link with the mathematical formulation, if initially we find ourselves with a probability of an acceptable state ($P(X_a)$) that is below the reliability target 1-ε, we need to apply a set of actions such that the recomputed probability of an acceptable state becomes sufficiently high.

To the best of our knowledge, in the context of power systems reliability management no optimization method exist yet to propose a good solution over many scenarios and over a period of time, or at least none that scales well (the design of such scalable optimization algorithms is considered in WP2 of the GARPUR project, and we refer the reader to its deliverable D2.2 [GARPUR, 2016c], where the problem is discussed from an algorithmic and mathematical point of view). Some decisions, typically the start-up of

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generation units, are actions with a cost and actions that last for, at least, a few consecutive hours. To add to the overall complexity, managing a transmission system is a multi-stage process where, depending on the future conditions in operation, the TSO will be able to trigger new actions. Solving such problem does not seem tractable without assumptions. Besides, even if some optimization method was proposed, the time to perform any stochastic simulation is limited in the context of short-term operation.

Consequently, we believe that a first step towards short-term reliability control should be to exploit the hints given by the short-term reliability assessment and manually assess a few possible solutions. From the perspective of the TSO in charge of taking decision, two questions arise:

- How to visualize and understand the risk after a stochastic assessment of reliability?
- How to provide hints to the operator on what actions could be undertaken to improve the probability of being in an acceptable state?

6.2.1 Main features expected for the visualization of the risk-assessment

Figure 24 depicts a possible graphical user interface that was proposed in the FP7 project iTesla [iTesla, 2016] for risk visualization in the short-term. A first feature of interest is that the operator is given an overview of the expected reliability for the upcoming several hours. Should the reliability of some parts of the system be jeopardized, this information should also be brought forward. That way, the operator could quickly grasp whether the threat on the system should be temporary or last for a significant duration.

Should the threat be expected to last for long, the TSO should likely undertake actions for these parts of the system for the targeted period of time, especially if the value of lost load is important for the customers that are concerned. Should it last for only a short duration, for instance because of a load peak or intermittent adverse weather conditions, it may not be relevant to trigger unplanned actions.

The information on whether a time-step is deemed safe should precisely be determined according to the GARPUR RMAC. Depending on the probability of achieving an acceptable state, a reliability index, possibly under the form of green/yellow/red traffic lights, could be displayed. Other representations could also be considered, see for instance Figure 14.

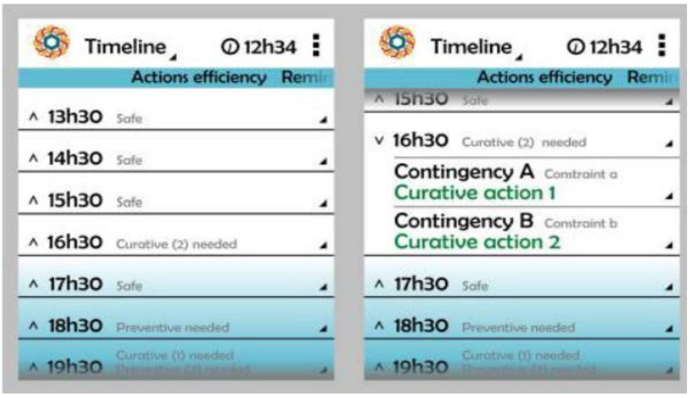

Figure 24: GUI proposed in iTesla for risk visualization in the short-term[4]

[4] http://www.itesla-project.eu/news/presentations-from-the-17-march-2016-workshop-with-energy-regulators-and-ministries-available

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Whenever needed, the threatening combinations of scenarios and contingencies for the different time-steps should be displayed. Once again, the point here is not just to mention an agglomerated value for the reliability assessment, but to point the elements which may be dangerous and where the TSO could apply actions to reinforce the reliability. Obviously, knowing which contingencies can lead to overloads or voltage issues is relevant. In order to limit the amount of information displayed to the operator, some filtering and sorting will however be required.

Still in this spirit of informing the operator of what could happen and have him ready for action, it seems relevant to highlight the remedial actions that may be triggered following a contingency. This leads us to the question of what remedial actions the assessment method is allowed to use. As discussed in the previous section, such list could be proposed a priori by the operator, or it could be automatically determined through OPF. One danger in such approach is that the assessment method may be too optimistic while automatically considering corrective control and assuming it will work in real life as well as in the model. This is one of the reasons that motivated the introduction in GARPUR of the probabilities of failure of corrective control, which can be interpreted as a penalty on corrective control to prevent an abuse of such recourse actions in the risk assessment. See [GARPUR, 2016c] and [Karangelos, 2016] for further detail.

6.2.2 Reliability control in a probabilistic framework

One interesting feature that remains difficult to integrate in this probabilistic assessment process is the activation of preventive control, typically preventive generation redispatching. To the best of our knowledge, there exists no algorithm capable of properly handling the trade-off between preventive and corrective control in a multi-stage stochastic optimization framework, at least not in a tractable way. Moreover, in short-term operational planning the time left before triggering any action is likely way too short for any heavy OPF simulation. However, what could be of interest for the TSO would be to have access to a comparator software where, on the left side there would be an assessment of the reliability for the basecase, while on the right side there would be an assessment of the reliability for the basecase patched with a tentative action from the operator, such as generation redispatching for 6 hours. Such interface could help to perform a risk-based comparison and eventually determine whether the (probabilistic) gain in terms of reliability is worth the redispatching cost.

Before activating any (costly) action, the operator will try to wait as much as possible so that the operating conditions become more accurate. Therefore, it would be helpful if the reliability assessment framework could propose some possible (future) preventive actions, and display an information on the last time to trigger such action.

6.2.3 Relaxation of the RMAC

In some cases, respecting the reliability target might be infeasible or judged too costly. Such circumstances could be met for instance during periods of very high-load, or following contingencies as long as the failed component is out of operation. In order to take the best possible decisions in such peculiar context, the TSO has to relax the regular parameters of the RMAC. Several options can be considered for the relaxation, namely relaxing the reliability target, the acceptability constraints, or accepting a higher residual risk by discarding additional scenarios.

Table 10: Comparison of different relaxation methods of the RMAC

Relaxing the acceptability constraints (Xa)	Depends on the acceptability constraints that have been defined. For instance, one could accept a lower/higher

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	voltage on some buses. If Xa takes the form of an energy not supplied (in MWh), a more permissive threshold could be employed. We recall that the acceptability constraints can be seen as local parameters. By relaxing some of the acceptability constraints, the operator keeps a good understanding of what he is doing for the relaxing and of the risks at stake.
Relaxing the tolerance level (ε)	Relaxing the tolerance level consists in accepting a larger share of scenarios where the acceptability constraints are not respected. A drawback with such relaxation is that sometimes, some of the acceptability constraints may simply be infeasible. This can happen in particular during planned outages or following a contingency. Therefore, in order to comply with a relaxed tolerance, the relaxation may have to be very strong, which may render such target irrelevant.
Relaxing the discarding principle (ΔE)	Relaxing the discarding principles consists in discarding additional scenarios and contingencies from the reliability evaluation. A first issue here is to decide how to discard these additional scenarios/contingencies. Intuitively, the TSO would start by disregarding the least probable events. Indeed, it seems to be the easiest choice to justify in terms of public acceptance. Among the drawbacks, one would notice that in order to determine cleanly the risk that is indeed discarded by removing some scenarios/contingencies from the evaluation, some heavy computations might be required, while in the short-term, time is precious.

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Seventh Framework Programme under Grant Agreement No 608540.

7 CONCLUSIONS

7.1 Summary

This document has proposed first-step implementations of the GARPUR reliability management approach and criterion for real-time operations (RT-RMAC) and short-term operational planning (ST-RMAC). These implementations are formulated around several cornerstones:

(i) a discarding principle that allows discarding some scenarios of the exogenous parameters to make the reliability assessment problem tractable,

(ii) reliability targets for real-time operations and short-term operational planning ensuring that the probability of the system state to be acceptable is larger than a pre-specified level,

(iii) a measure of the socioeconomic surplus.

(iv) Implementations and illustrations of algorithms for short-term and real-time reliability assessment.

The proposed methods require new tools to be developed and data to be collected, but are designed to be implementable within a few years. The approach is generic and can be integrated with TSOs' own tools.

Compared to today's reliability management based on the N-1 criterion, the GARPUR RMAC considers explicitly the uncertainty faced by the system operator, and the resulting risk in the form of interruption costs. This provides TSOs with more granular indicators than the binary N-1 criterion. Furthermore, the consequences of different scenarios of the uncertainty are adequately weighted by their probability of occurrence by using appropriate probabilistic models.

In real-time operations, the random occurrence of contingencies and the possible failure of corrective actions have been considered. This allows capturing properly the consequences of different contingencies, while avoiding overreliance on corrective actions. In short-term operations, load, production, exchanges and the probability of occurrence of contingencies are modelled as uncertain parameters. The resulting short-term risk assessment enables TSOs to have a more comprehensive assessment of reliability in the context of operation planning.

7.2 Recommendations

7.2.1 Data collection

The approach presented in this document relies on models that must be populated by appropriate data. Today, this data may not be recorded at all, or not recorded in a consistent and automated way. Expert knowledge and sensitivity studies will be crucial in the first steps towards the implementation of the proposed RMAC.

7.2.1.1 Failure probability

Threat-based models that capture the variable failure rates depending on exogenous parameters have been presented in this document. Today, constant failure rate models are commonly used. Furthermore, fault statistics may not be comprehensive (for example, the causes of the faults may not recorded). To implement the proposals made in this document, the fault statistic collection should be improved. The threat-based models are system specific in that the failure rates depend on different threats in different systems. Studies must be performed to identify these threats and start recording the necessary data. These studies should rely on improved recording of weather. In addition to better data for the exogenous

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parameters, contingency probabilities depend also on physical parameters such as line lengths, their environmental conditions, and their set of sub-components. These latter should ideally be taken into account to model the health states and failure rates of the power system components. Sufficient data to do this in a suitable way may not be available today either.

7.2.1.2 Failure of corrective actions

The proposal for the RT-RMAC includes the consideration of the probability of failure of corrective actions. Disregarding this aspect would lead to overreliance on corrective actions due to their perceived lower expected costs (since corrective actions are only taken after the occurrence of contingencies, which occur with low probabilities). Today, statistics on the behaviour of corrective actions are mostly non-existent. Data collection efforts should be started to identify the manual and automatic corrective actions in place and their failure modes, and to build an appropriate database. An issue is that corrective actions are activated very rarely (since they are only activated if needed after a contingency). Building a statistically relevant database is therefore a challenge. Expert knowledge and sensitivity analyses of the risk assessment outputs on these probabilities of failure will be crucial.

7.2.1.3 Load and RES production

An important feature of the uncertainty models presented in this document is that they capture the spatiotemporal correlations of load and RES production. To populate these models, data has to be collected to quantify these correlations at the nodal level. Currently, either this data is not collected or it is collected at a larger level (zonal level). An issue is that the grid may not be visible to the transmission system operators beyond the interfaces with the distribution and neighbour transmission grids. Research to create nodal forecast in the absence of visibility beyond these interfaces is ongoing [Cheung, 2014], [Sun et al., 2013].

7.2.1.4 Value of lost load

The value of lost load (VoLL) is used to quantify the economic consequences of interruptions. The expected interruption costs are used as a measure of risk and integrated in the measure of socioeconomic surplus. In practice, the value of lost load depends on several characteristics such as consumer type, location of the consumer, time of interruption, duration of interruption, advance notification of interruption, weather at the time of interruption, urban area vs rural area and previous quality of supply. An accurate estimation of (VoLL) is therefore important to get an accurate picture of the spatiotemporal variations of service interruption costs.

7.2.2 Tool development

The proposals made in this document require tools and models that TSOs may not have today.

7.2.2.1 Threat-based model for contingency probabilities

Contingency probabilities depend on exogenous parameters such as icing, precipitation, wind or lightning. The actual exogenous parameters that explain the most the contingency probabilities depend are system-dependent. Therefore, once sufficient data is collected about failures and their causes, it is recommended to perform studies to develop threat-based models adapted to the power system of interest.

7.2.2.2 AC security-constrained optimal power flows

In the short-term reliability assessment problem, an automated model of decision-making process of the real-time operations is necessary to analyse quickly a large number of scenarios and make a trade-off between short-term preventive actions and real-time actions. Optimal power flows (and security-constrained optimal power flows) are particularly suited for this task. Few TSOs have implementations of

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Seventh Framework Programme under Grant Agreement No 608540.

AC optimal power flows today. The implementation and validation of robust AC-OPFs (and security-constrained optimal power flows) that fulfil the requirements of the TSO is therefore recommended. These tools would also be crucial in studying and implementing solutions for the reliability control problem in the future. We note that some TSOs have reported the adoption of such tools [López et al., 2015].

7.2.2.3 Copula-based models for load and RES forecast errors

It is advocated in Section 4.2 to use Copula-based models, either the joint normal transform or vine copulas, to model the load and RES forecast errors. Recent studies have shown that vine copulas are a promising option [Bessa, 2016, Sun et al., 2016]. Further work is however needed to validate these models and implement them in a real-life environment.

The research leading to these results has received funding from the European Union
Seventh Framework Programme under Grant Agreement No 608540.

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The research leading to these results has received funding from the European Union Seventh Framework Programme under Grant Agreement No 608540.

9 APPENDICES

9.1 Ingredients of the Reliability Management Approach and Criterion (RMAC) proposed in [GARPUR, 2016c]

GARPUR WP2 proposed a probabilistic approach both for assessing the power system reliability as well as for making socio-economically optimal decisions in order to achieve a set reliability target, gathered under the acronym RMAC (reliability management approach and criterion). The probabilistic approach is described in detail in the work of WP2 in [GARPUR, 2016c]. A summary is presented below.

The proposals for real-time operations and short-term operational planning are separated in a real-time RMAC (RT-RMAC) and a short-term RMAC (ST-RMAC) [GARPUR, 2016c]. The proposed RMACs are designed to consider explicitly uncertain exogenous parameters. There are two fundamental differences between the real-time and short-term RMACs. The first one is that the range of actions available to the system operator is more limited in real-time. The second is that some exogenous parameters that are uncertain in the short-term become apparent in the real-time.

The list of uncertain exogenous parameters that are considered in real-time are:

- The occurrence of contingencies: the RT-RMAC considers the fact that contingencies occur with a certain probability.
- The reliability of the post-contingency system response: The RT-RMAC considers the probability that the immediate reaction of the system to a contingency may not be as expected, due to system protection failures, for example.
- The behaviour of post-contingency corrective actions: the RT-RMAC considers that the corrective actions that the operator plans to take should a contingency occur may not work as expected. In its simplest form, the behaviour of a corrective action is a success or a failure.

For short-term operational planning, the following additional uncertainty exogenous parameters are considered:

- The probability of occurrence of contingencies: the ST-RMAC considers the fact that the contingency probabilities themselves may be uncertain in ST since they depend on factors, such as weather conditions, that are not known.
- Thermal limits of components exposed to weather: the limits of transmission lines, for example, vary depending on the weather. Since the weather is not known in ST, the limits are not known either.
- The net power injection: the nodal loads and productions are not known but can only be forecasted. Forecast models are discussed.

Both ST- and RT-RMAC are designed around the same cornerstones:

- A reliability target that is to be fulfilled.
- A discarding principle that allows discarding part of the scenarios for the uncertain exogenous parameters in a controlled way, in order to make the RMAC process tractable.
- The residual risk that measures the cumulative risk contribution of all discarded scenarios, and must remain under the discarding threshold as per the discarding principle.
- A measure of socioeconomic surplus that is to be maximized under the constraints that the reliability criterion and the discarding principle must be fulfilled.
- A measure of risk that is defined as the expected interruption costs.

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The proposed ST-RMAC and RT-RMAC were designed in a consistent way so that the ST-RMAC is concerned with ensuring the feasibility of the RT-RMAC for scenarios of the ST uncertain parameters that have not been discarded by the discarding principle [GARPUR, 2016c].

9.1.1 Socioeconomic surplus

The socioeconomic surplus is the sum of the surpluses of five stakeholder groups: the electricity consumers, the electricity producers, the TSO, the government and the society and environment. The ideal formulation of the socioeconomic surplus is given in [GARPUR, 2016] and [GARPUR, 2016a], to which the reader is referred to get the full formulations.

The expected interruption costs are the probability-weighted sum of the interruption costs in the different short-term and real-time scenarios of the uncertain exogenous parameters. The interruption cost in a particular scenario is the sum over all regions, consumer types and interruption durations of the product of the energy not served (ENS) in MWh and the value of lost load (VoLL). The value of lost load depends on several characteristics such as consumer type, location of the consumer, time of interruption, duration of interruption, advance notification of interruption, weather at the time of interruption, urban area vs rural area and previous quality of supply. Detailed discussions about VoLL are included in [GARPUR, 2016] and [GARPUR, 2016a].

9.1.2 RT-RMAC

The discarding principle of the RT-RMAC states that the reliability target applies to only a subset of all possible contingencies [GARPUR, 2016c]. The discarded contingencies are not considered in the application of the reliability target The discarding principle of the RT-RMAC states that the cumulative risk contribution of the discarded contingencies must remain under a pre-defined threshold. This cumulative risk contribution of the discarded contingencies is called the residual risk. Mathematically, this can be formulated as [Karangelos, 2016]:

$$R_{RT}(\mathcal{N}\backslash\mathcal{N}_c) = \sum_{c\notin\mathcal{N}_c} \pi_c R(c) \leq \Delta E_{RT}, \qquad (1)$$

Where $R_{RT}(\mathcal{N}\backslash\mathcal{N}_c)$ is the real-time residual risk, $\mathcal{N}$ is the set of all possible contingencies, $\mathcal{N}_c$ is the subset of non-discarded contingencies, π_c is the probability of contingency *c*, $R(c)$ denotes the risk (expected service interruption costs) of contingency *c* and ΔE_{RT} is the discarding threshold.

For the non-discarded contingencies, the reliability target of the RT-RMAC states that the probability that the system state fulfils the acceptability constraints must be above a certain threshold called the tolerance. Acceptability constraints are discussed in detail in Section 9.4. The system state may violate acceptability constraints either because a contingency occurs and no corrective actions can bring the system state back into an acceptable state, or because a contingency occurs and the applied contingency actions do not work as expected [Karangelos, 2016]. These possible outcomes occur with certain probabilities (the contingency probability and the probability of failure of corrective actions). These probabilities are the ones considered in the reliability criterion. Mathematically, this can be formulated as:

$$\mathbb{P}\{x_0, x_c, x_{c.b} \in X_a | c \in \mathcal{N}_c\} \geq 1 - \varepsilon_{RT}, \qquad (2)$$

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where $x_0, x_c, x_{c.b}$ are the pre-contingency, the post-contingency and post-contingency post-corrective control system states; c is a contingency and $(1-\varepsilon_{RT})$ is the tolerance level. We propose to further broken down to

$$\mathbb{P}\{x_0, x_c, x_{c.b} \in X_a | c \in \mathcal{N}_c\} = \pi_0 \cdot \mathbf{1}\{x_0 \in X_a\} + \sum_{c \in \mathcal{N}_c} \pi_c \cdot \pi_r \cdot \mathbf{1}\{x_c \in X_a\} \cdot \sum_{b \in B} \pi_b \cdot \mathbf{1}\{x_{c,b} \in X_a\} \geq 1 - \varepsilon_{RT}, \tag{3}$$

where $\mathbf{1}\{x \in X_a\}$ is equal to 1 if the pre-contingency state x is acceptable and 0 otherwise, π_r is the probability of the modelled system response, *B* is the set of possible behaviours of the corrective control actions and π_b is the probability of behaviour *b*.

The tool used to simulate the system response to contingencies may not consider all possible events. For example, protection systems may fail but the tool may not consider their failures. Therefore, out of all possible system trajectories, only some of them are simulated, which is captured by the probability π_r of the modelled system response.

In its simplest form, *B* contains either the success or the failure of a corrective action. The double sum indicates that we sum over all non-discarded contingencies and, for each contingency, we sum over all possible behaviours of the post contingency corrective actions.

Section 3.3 presented in a succinct way a proposal for first-step implementation of the RT-RMAC. Further detail are given in Chapter 5.

9.1.3 ST-RMAC

Short-term operational planning is concerned with enabling secure real-time operations for a time horizon of interest, such as 24 hours of a particular day. The scenarios for short-term uncertain exogenous parameters are sequences of realisations of the exogenous parameters for all times in the considered time horizon.

The discarding principle of the ST-RMAC states that the reliability target applies to only a subset of all possible scenarios of the short-term uncertain exogenous parameters [GARPUR, 2016c]. The scenarios that do not belong to this subset are discarded. The discarding principle of the ST-RMAC states that the cumulative risk contribution of the discarded scenarios must remain under a pre-defined threshold. This cumulative risk contribution of the discarded scenarios is called the short-term residual risk. Mathematically, this can be formulated as:

$$R(\Xi \backslash \Xi_c) = \sum_{\xi = \xi_{1,\dots,T} \notin \Xi_c} \pi_\xi \sum_{t=1}^{T} R(\xi_t) \leq \Delta E_{ST}, \tag{4}$$

where $R(\Xi \backslash \Xi_c)$ is the short-term residual risk, Ξ is the set of all scenarios of short-term uncertain exogenous parameters, Ξ_c is the set of non-discarded scenarios, π_ξ is the probability of scenario $\xi = \xi_{1,\dots,T}$, $R(\xi_t)$ is the risk contribution of a scenario in a particular time t, and ΔE_{ST} is the discarding threshold. A scenario is defined as a sequence $\xi_{1,\dots,T}$ of realisations of the exogenous parameters ξ_t spanning the whole considered time horizon [0,*T*].

The reliability target of the ST-RMAC states that in all non-discarded scenarios, the real-time RT-RMAC must be feasible in all times of the considered time horizon. Put in other words, after realisation of any non-discarded scenario of the short-term uncertain parameters, there should be enough range of actions

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to enforce the reliability criterion of the RT-RMAC considering that some contingencies can be discarded as per the discarding principle of the RT-RMAC. Mathematically, this can be formulated as:

$$\forall\ \xi \in \Xi_c, \forall\ t = 1, \dots, T, \text{ RT-RMAC at time } t \text{ is feasible after realisation of } \xi. \quad (5)$$

This can be re-formulated in the form of a probabilistic target as for the RT-RMAC:

$$\mathbb{P}\{\text{RT-RMAC feasible for } \xi_t, t = 1, \dots T | \xi = \xi_{1,\dots,T} \in \Xi_c\} = 1, \quad (6)$$

which says the for all non-discarded scenarios, the corresponding RT-RMAC must always be feasible. Note that this is equivalent to having short-term reliability target ε_{ST}, with $\varepsilon_{ST} = 0$.

Section 3.4 presented in a succinct way a proposal for first-step implementation of the ST-RMAC. Further detail are given in Chapter 6.

9.1.4 Assessment and control problems for the RMAC

The RMACs as defined above are said to be feasible if it is possible to find real-time or short-term actions such that the reliability target is satisfied. For given actions, evaluating the RMAC feasibility is an assessment problem. Finding the optimal actions is a control problem. The notion of reliability management approach and criterion (RMAC) encompasses both the assessment and control problems.

TSOs can evaluate the socioeconomic surplus to measure the expected costs and benefits in real-time operations and short-term operational planning. Doing this allows TSOs to measure the expected costs and benefits at different stages of their activities and compare with previous data to identify whether they are in a relatively high or low risk state. Furthermore, the socioeconomic surplus can be used to compare different possible sets of actions, which leads to the control problem. In the GARPUR proposals, the actions are compared in terms of socioeconomic surplus. Therefore, the optimal actions are those that maximize the socioeconomic surplus while ensuring feasibility of the RMAC. The full control problem is therefore an optimization problem whose objective function is the socioeconomic surplus and the constraints are the equations above that define RMAC feasibility.

The actions that can be taken by the system operator during real-time operations are grouped into preventive and corrective actions. Real-time preventive actions are actions that TSOs take before the occurrence of any contingency. Corrective actions are actions taken after the occurrence of contingencies. Therefore, real-time preventive actions will affect the outcome of all contingencies whereas corrective actions are contingency-specific. The control problem of real-time RMAC is therefore concerned with choosing a combination of preventive and corrective actions. Because corrective actions are taken after the occurrence of contingencies, their expected cost is the product of the probability of the contingency and the cost of the actions themselves. Therefore, the expected cost of an action is much lower as a corrective action than as a preventive action. This could lead to an excessive reliance on corrective actions. In the GARPUR methodology, this is mitigated by the consideration of the behaviour of corrective actions, recognizing the fact that if a corrective action fails, it can result in large consequences in terms of interruption costs.

The actions that can be taken during short-time operations are called short-term preventive actions. Recall that the ST-RMAC is concerned with ensuring the feasibility of a sequence of RT-RMAC, covering all times of the considered time horizon (such as the 24 hours of a day). Short-term preventive actions can be applied to specific times (for example, starting up a power plant to be available for a few hours) or to the whole time horizon. They apply to all scenarios of the short-term uncertain exogenous parameters. Note that, in contrast, real-time preventive actions apply only to a particular short-term scenario since the short-term uncertain exogenous parameters become apparent in real-time operations.

The research leading to these results has received funding from the European Union
Seventh Framework Programme under Grant Agreement No 608540.

9.2 Ideal Real-Time RMAC for Reliability Assessment

The set of algorithms below describes an ideal implementation of the RT-RMAC. The algorithm A8 describes the general process (as an alternative to Algorithm **7**), while algorithms A9-A12 describe specific computations required by algorithm A8. Note that the algorithms described in this appendix are not necessarily tractable, and require models that do not necessarily exist (especially not in a form that is generally accepted by TSOs). Given that these algorithms are not presently applicable, they are not elaborated on in detail, but are provided to outline the perceived long-term target method of probabilistic reliability assessment.

Algorithm A9: Ideal real-time risk assessment

Inputs: system state, failure rates, marginal distributions for uncertain parameters, correlation information, response parameters, ΔE_{RT}, X_a, $\varepsilon_{RT,t}$, economic parameters, time step (Δt), list of corrective actions, time required for corrective actions, list of planned preventive actions;
Outputs: Expected socio-economic surplus, reliability indicator; selected corrective actions;

1 Generate a set of non-discarded contingencies, $\mathcal{N}_c$, with probabilities π_c; (*see Algorithm A9: Contingency Discarding*)
2 Generate a set of continuous uncertainty samples, Ξ; (*see Algorithm A10: Uncertainty Modelling)*
3 Estimate a maximum load disconnection duration, d_{max};
4 **for** $each\ uncertainty\ sample, \xi \in \Xi$ **do**
5 Simulate the balancing of load for the base system case using the uncertainty sample, ξ, based on predefined dispatch criteria;
6 **for** $each\ contingency, c \in \mathcal{N}_c$ **do**
7 Simulate the disturbance after the realisation of c and ξ resulting in a set of possible post-disturbance system states, x_b and behaviours, $b \in \mathcal{N}_b$; (*see Algorithm A11: System Response)*
8 Calculate the probability of each disturbed system state, π_b, using the response parameters;
9 $each\ possible\ disturbed\ system\ state, x_{c,b}, given\ b \in \mathcal{N}_b$ **do**
10 Determine whether the disturbed system state, $x_{c,b}$ complies with the acceptability constraints X_a;
11 Estimate a system restoration procedure given the time required for corrective actions, $u_{c,b}$; *(see Algorithm Bessa*, 2016*: System Restoration)*
12 Estimate ENS at each node given the system restoration procedure over time periods $t \in \{0, \dots, \frac{d_{max}}{\Delta t}\}$; (*see Algorithm A12: System Restoration)*
13 Calculate the periodic expected socio-economic surplus $\mathbb{E}(S_t|b, c, \xi, d_{max})$ for each time period in $t \in \{0, \dots, \frac{d_{max}}{\Delta t}\}$;
14 Calculate the expected socio-economic surplus, $\mathbb{E}(S|b, c, \xi, d_{max}) = \sum_t \mathbb{E}(S_t|b, c, \xi, d_{max})$
15 **End**
16 Calculate expected socio-economic surplus $\mathbb{E}(S|c, \xi, d_{max})$, of the combined disturbance of c and ξ, over the maximum load disconnection duration d_{max}, given π_b;
17 Calculate expected probability of compliance with the acceptability criteria for the combined disturbance of c and ξ, over the maximum load disconnection duration d_{max}, $\mathbb{P}(x_b \in X_a|c, \xi, d_{max})$, given π_b;
18 **End**
19 Calculate expected socio-economic surplus of sample ξ over the set of contingencies, $\mathbb{E}(S|\xi, d_{max})$, given π_c;
20 Calculate expected compliance with the acceptability criteria over the set of samples $\mathbb{P}(x_b(c) \in X_a|\xi)$;
21 **End**
22 Calculate the total expected socio economic surplus $\mathbb{E}(S|d_{max})$ over all samples $\xi \in \Xi$, for the period $t \in \{0, d_{max}\}$;
23 Determine if the system meets the reliability criteria $\mathbb{P}(X_a) = \mathbb{P}(x_b(c, \xi) \in X_a)$;

The research leading to these results has received funding from the European Union
Seventh Framework Programme under Grant Agreement No 608540.

Algorithm A10: Contingency discarding

Inputs: System state, failure rates, ΔE_{RT}, time step (Δt), economic inputs

Outputs: Credible contingency list, contingency probabilities

Convert time specific failure rates into probabilities of faults over Δt;
Create a list of n valid single contingencies (all contingencies with non-zero probability);
Using the list of single contingencies, generate a list of all 2^n contingencies, $\mathcal{N}$;
for *each contingency,* $c \in \mathcal{N}$ **do**
  Calculate the probability of c;
  Estimate the consequence of c in terms of socio-economic surplus;
  Multiply the probability and consequence to estimate the risk of c;
End
Sort the list of contingencies in order of decreasing risk;
Select a set of non-discarded contingencies such that the sum of risk of the discarded contingencies is less than ΔE_{RT};
Output the list of non-discarded contingencies and their probabilities;

Algorithm A11: Uncertainty modelling

Inputs: marginal distributions for uncertain parameters, correlation data

Outputs: samples of uncertain parameters ($\xi \in \Xi$) and associated likelihood ratios

Combine correlation data into a single correlation matrix for all uncertain parameters;
Convert the marginal distributions and correlation matrix into a joint probability distribution;
Randomly sample a set of uncertain parameters from the joint distribution, $\xi \in \Xi$, and compute their likelihood ratios;

Algorithm A12: System response simulation

Inputs: System state, corrective actions, a contingency (c), an uncertain parameter sample (ξ), response reliability parameters

Outputs: Post-fault system state

Apply the uncertain parameter sample and contingency to the system state;
Enumerate the possible system protection and automated corrective actions, given the response reliability parameters;
Describe each system protection response as an entry, b, in the list of possible response behaviours, $\mathcal{N}_b$;
for $each\ possible\ system\ response\ behaviour, b \in \mathcal{N}_b$ **do**
  Simulate the system response behaviour (cascading failures, hidden faults, etc.);
  while $the\ system\ is\ not\ secure$
    Simulate the corrective control response of the operator, given the list of available corrective actions;
  End
  Output the resulting disturbed system state as $x_{c,b}$, and the corrective actions as $u_{c,b}$;
End

Algorithm A13: Outage duration estimation

Inputs: disturbed system state ($x_{c,b}$), corrective actions ($u_{c,b}$), time required for corrective actions

Outputs: duration of disconnections, nodal ENS over the duration of consumer disconnections

Calculate the expected time to implement the proposed corrective actions, $u_{c,b}$;
Given the implementation time, estimate the ENS over time at each node, given the system states resulting from the restoration procedure;

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Seventh Framework Programme under Grant Agreement No 608540.

9.3 Ideal Short-Term RMAC for Reliability Assessment

The set of algorithms below describes an ideal implementation of the ST-RMAC. The algorithm A13 describes the general process (as an alternative to Algorithm 8. Note that the algorithms described in this appendix are not necessarily tractable, and require models that do not necessarily exist (especially not in a form that is generally accepted by TSOs). Given that these algorithms are not presently applicable, they are not elaborated on in detail, but are provided to outline the perceived long-term target method of probabilistic reliability assessment.

Algorithm A14: Ideal short-term Risk Assessment

```
Inputs: Joint (spatiotemporal) probability distribution on the space S of all scenarios, base case system configurations for all t in [1,T], RT-RMAC inputs, economic parameters
Outputs: Expected socio-economic surplus, reliability indicators and TSO-specific indicators;
Perform scenario discarding to obtain a finite list of scenarios S_c ⊂ S and their probabilities and residual risk of the discarded scenarios
for each scenario ξ_{1,…,T} = [ξ_1 … ξ_T] in S_c do
    for each time t in {1,…,T} do
        Set the system configuration to the base case system state for time t;
        Set all generators and loads according to their market schedule;
        if t>1 then
            Implement preventive actions taken in RT-RMAC at times t'<t within the current scenario;
        End
        Set the uncertain parameters (e.g. load, RES output, etc.) to their realised values in ξ_t;
        Simulate the frequency control response to the deviations from the market schedule to get a balanced system state;
        Simulate RT-RMAC, get an indicator of RT-RMAC feasibility (δ*_RT in Equation (10)), expected RT cost (W_RT in Equation (12)), as well as preventive and corrective RT decisions (u*_RT in Equation (12));
    End
End
Compute the ST indicators.
for each time t in {1,…,T} do
    Compute the socio-economic surplus of time t.
    Compute the probability of non-feasibility of RT-RMAC in time t
    Compute TSO-specific indicators for time t.
end
Aggregate the socio-economic surplus at all times t into the total socio-economic surplus.
Compute the probability of non-feasibility of RT-RMAC during the whole ST time horizon.
Compute TSO-specific aggregate indicators for the whole ST time horizon.
```

9.4 Acceptability constraints

The reliability target of the GARPUR reliability management approach and criterion consists of ensuring that the power system can perform its required function with a certain level of confidence. It has been formulated as a chance constraint of the following generic form (cf. §3.2.1 for the exact mathematical of the RMAC depending on the considered short-term or real-time horizon):

$$\mathbb{P}\{x \in X_a | \xi \in \Xi_c\} \geq 1 - \varepsilon$$

where X_a denotes the set of system trajectories deemed as “acceptable” over the considered time-horizon, and ε<<1 is fixed a priori.

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In this formulation, ε is a global reliability measure while X_a can address different various aspect of the risk a TSO will be protected from.

By definition, the acceptability constraints deal with equipment security, human safety, and all the different phenomena - local or wide-ranging - that can jeopardize the grid security. The following items are encompassed within these categories:

- load balancing, reserves and security of supply limits,
- current, angular and capacity limits,
- voltage limits,
- short-circuits, voltage drop limits,
- stability and protection limits.

Among the acceptability constraints, we will then retrieve all the classical and pre-existing limits dealing with equipment security, human safety that already describe the real-time domain regarding TSO risk policies.

To implement the ideal RMAC as it is defined we should be able to:

- estimate correctly the future operating states on all the credible situations,
- estimate correctly the consequences of all non-discarded contingencies, and of the remedial actions in charge to reduce those consequences,
- estimate correctly the different components of the socio economic surplus function as it has been defined in the deliverable 3.1,
- master the time complexity of a problem which imposes to let sufficient time to an operator to state it and take the best decisions.

To implement efficiently the GARPUR RMAC it appears necessary to complete this first set of classical acceptability constraints with complementary acceptability constraints, which will simplify and support the human decision-making in a stochastic environment such as the Short-term operational context.
The objective of those complementary acceptability constraints will be to define a frontier between risky and non-risky situation domains considering the necessary simplifications, due to:

- data and model imprecisions,
- time complexity of the considered problem.

Depending on those two factors those complementary acceptability constraints could take a lot of different forms accordingly to the sophistication and the reliability of the system response model of a specific TSO.
For example could be defined as potentially risky, situations where:

- the deviation on a specific network parameter, such as the lost load or the Energy Not Served for example, following a contingency simulation is judged too important and the TSO considers too risky to rely on the estimation of the system response model or on a corrective remedial action,
- a contractual quality service indicator has been reached,
- the deviation of a cost component of the socio economic surplus function is judged too important to appreciate correctly all the induced consequences …

Once the risky situations are defined, different techniques can be used in order to build those constraints, specific studies, use of standard techniques such as decision tree or classification techniques, or more sophisticated ones such machine learning techniques.
The simplest way to formulate those constraints in order to use them in the system response model of a TSO will be as a function of different network parameters of this system response model, such as flows, powers, voltages …, compared to specifics limits.

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Seventh Framework Programme under Grant Agreement No 608540.

As a proof of concept, we can emphasize that a similar approach has been operated by the iTesla project in order to reduce the computational burden of on-line static and dynamic N-1 security assessment analysis [iTesla, 2016].

However, certain conditions should be met concerning the constraints' properties, such as:

- Constraint validity (what are the conditions to be respected to use the constraints),
- Constraint intelligibility by an operator or a security assessment or control tool.

In a transition phase, we do not recommend to automatize fully in a closed non-supervised loop the building of those acceptability constraints, but to rely on predefined set of generic constraints, simple, understandable and persistent in their form and composition. Nevertheless, as the operating conditions evolve it will be necessary to re-assess frequently the limits and sometimes the definition of those constraints by dedicated process that should be human supervised in order to produce sound constraints usable by an operator. The frequency of this process will depend on its capacity to anticipate the future operating conditions and on the precision requested on the real-time risk estimation.

Another question mark concerns the relaxation of those constraints, for example in case the Reliability Target or the RMAC seems out of reach. To relax knowingly a specific constraint one needs not only to assess precisely its effects on the RMAC global indicators, but also how it will affect or disturb the operation process. To answer this question the TSO will need first an adaptation phase in order to gauge accurately the RMAC features.

To illustrate the issues due to the building of those constraints, we have devised the following short-term computation algorithm in charge of predefining on a shorter time horizon when a Short-Term or Real-Time preventive action should be requested upon a deterministic Real-Time corrective action. This problem is particularly difficult to solve in a limited time as it can induce numerous iterations between the assessment and the control problems. Consequently, the use of predefined complementary acceptability constraints in charge of imposing this trade-off can be requested.

9.4.1 Short-term stochastic acceptability constraint computation algorithm

We will suppose here a sequence of several processes in charge of the building and the continuous reassessment of the short-term acceptability constraints.

The first one, set on the longer horizon, will be in charge of building a first approximate set of acceptability constraints. This could be done as it is done today, by the help of specific studies, restricted or not the N-1 rule, or using a more sophisticated algorithm such as the one presented in the second process.

The next ones, following the same logic of implementation, will be set on shorter time horizon (Week/Day/Intra-Day Ahead), where new contextual information is available in order to anticipate potential risky situations. They will be in charge of assessing the performance of the previous set of acceptability constraints, of even enhancing it with new ones under the supervision of an operator.
The purpose of those processes is then the following:

- Allow a better anticipation of risk foreseen situations (assessment, remedial actions …),
- Reduce the computational burden on the shorter-time horizon,
- Produce intelligible acceptability constraints that will further facilitate their management by operators.

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Seventh Framework Programme under Grant Agreement No 608540.

The last one, set on the real-time horizon will just memorized for further analysis the risky real-time situations not respecting the previous acceptability constraints.

The sequence of processes is illustrated in the following figure.

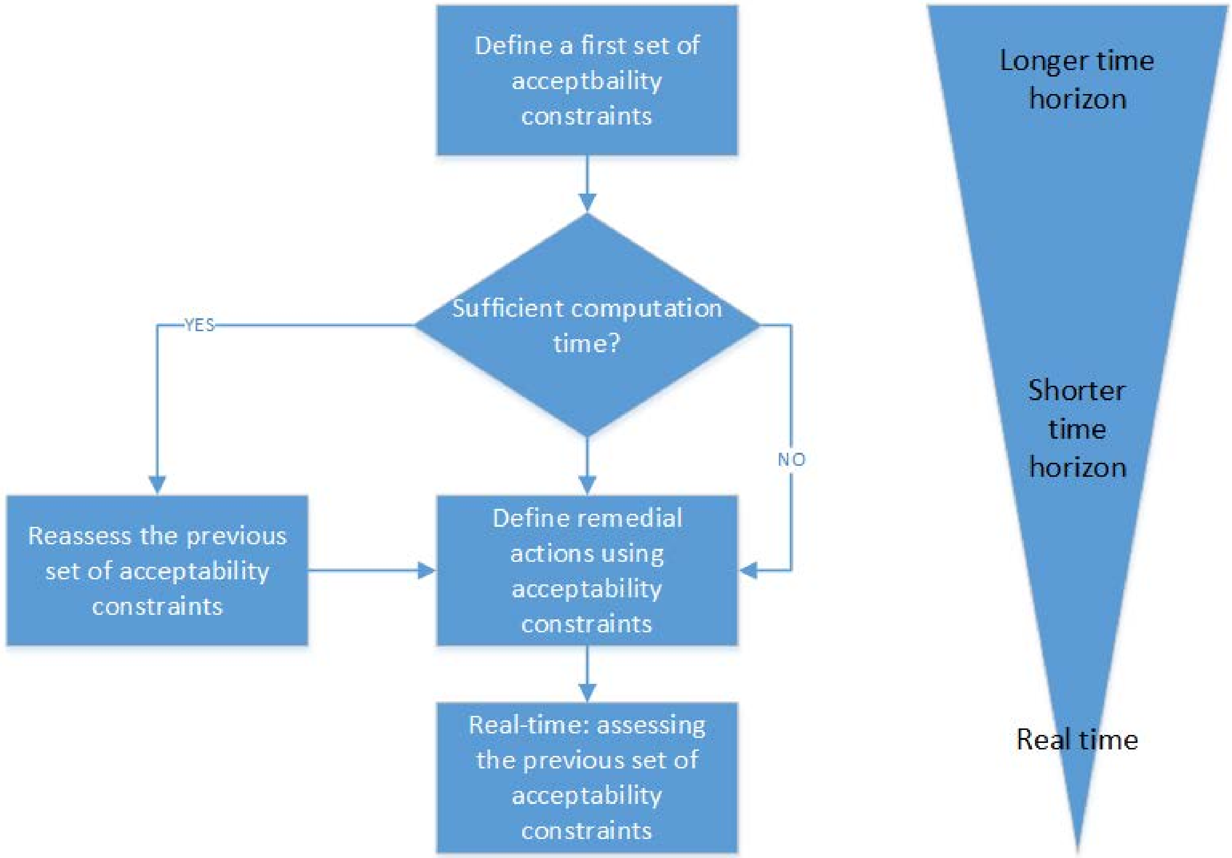

Figure 25: Reassessment of acceptability constraints during time.

Reassessment function of the acceptability constraint

Depending on the time horizon, it is necessary to build for each main relevant scenarios considered (on production availability for example), different sets of associated acceptability constraints. If insufficient time is allocated to perform this reassessment, the operator will have to select the best set of pre-computed acceptability constraints to use considering the forecasted information at his disposal.
Those short-term scenarios will be very important, and the more they will be representative of future conditions the more pertinent will be the final set of acceptability constraints.

Nevertheless, depending on the short-term time horizon, it will not be possible to simulate all the possible non-discarded scenarios. For this reason, it will be then very important to define among them different risk conservative scenarios that could be used to define default conservative sets of acceptability constraints in case the future operating conditions differ slightly from those anticipated scenarios.

The reassessment function can be decomposed as such:

- For a main anticipated scenario, for all the considered contingencies and RES scenarios, determine the situations at risk after the use of possible corrective control actions. Then build an associated acceptability constraint set using decision tree techniques for example.

- To enhance this first set, it will also be necessary to build the preventive actions in order to reach the expected reliability target and to estimate their possible induced consequences on security.
- Then eventually a more complete security assessment can be run to present the results to an operator.

This process can be highly automatized for its most part but it has also to be human supervised to control its soundness, to enhance the set and definition of acceptability constraints, to restart the different functions by adding/suppressing scenarios or contingencies or new possibilities regarding corrective and preventive remedial actions.

The reassessment function is illustrated in the following figure.

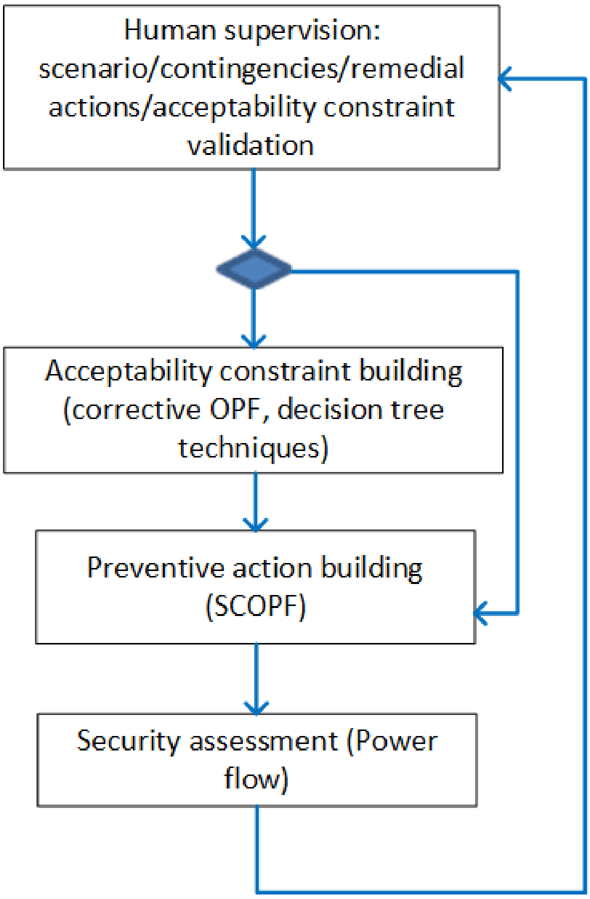

Figure 26: Acceptability constraint Reassessment function.

<u>Limitations and main drawbacks to consider</u>

Rapidly, the increasing number of situations to consider will impose the use of synthetic indicators to present the results to the operator, to help him identify the right problematic scenarios and contingencies to look at more closely in order to reduce rapidly the global residual risk.

Tools will be needed in operation that are not commonly used today, such as SCOPF to implement automatically corrective or preventive remedial actions. The operator will then need to gain confidence in the use of those tools, which implies that the solutions they propose should be understandable and realistic.

9.5 Tolerance level

Satisfying a reliability target with a certain tolerance is impacted by various exogenous conditions, like weather conditions, uncertainty related to the volatility of uncontrollable generation sources, peak demand or market behaviour. On the other hand, it is also impacted by several endogenous factors which reflect the level of stress of the network (equipment loading, level of demand, level of imports, level of non-synchronous power injections) and assets availability (forced outages, planned maintenance).

The proposal is to consider these time and space dependencies in the RMAC, by allowing a modification of the tolerance level based on time and/or space. Time-based modification is straightforward to implement as it is applicable to all the network elements and reflected on a system level. On the other hand, the space dependency is defined based on network elements in a certain location or their significance (critical branch or node) to the overall network adequacy.

9.5.1 Time dependency

Long-term and medium -term perspective

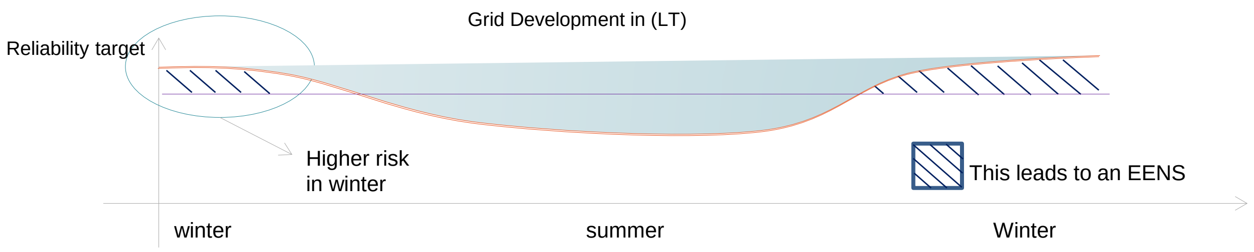

Figure 27: reliability target: yearly average value

During long-term grid development studies, bottlenecks are identified via load flow and contingency analyses for a set of scenarios (growth scenario, peak demand, generation capacity, etc). Each scenario results in a different risk profile (similar to the orange line in Figure 27). Ideally, grid development would be planned to guarantee a certain reliability target even during the highest risk period as shown in Figure 27 (right and left extremities). However, these high risk periods seldom occur, and a grid designed at this level of security of supply will result in an over-engineered grid that would be underused most of the time (blue shaded area in Figure 27), which is subject to high Capital Expenditure (CAPEX).

On the other hand, if the grid were designed to comply with a less inclusive reliability target (higher risk of not always complying with the reliability target with certain confidence margin) this would ultimately result in a limited adequacy level (eventual ENS reflected by the shaded area in Figure 27). This will naturally impact the Operational Expenditure (OPEX) by either the solicitation of costly remedial actions or bearing costs of unsupplied loads and RES curtailment.

An optimal accommodation can be reached by managing cost-efficiently the reliability where the target shall be modified through the year reflecting the stress level of the network with a compromise between CAPEX and OPEX under operational constraints and regulatory framework. In such a case, the result of applying different tolerance levels throughout an operational period (e.g. yearly based) shall result in an average reliability index that is well below the foreseen fixed threshold as depicted by the purple horizontal line in Figure 27.

The research leading to these results has received funding from the European Union
Seventh Framework Programme under Grant Agreement No 608540.

Short-term and real-time perspective

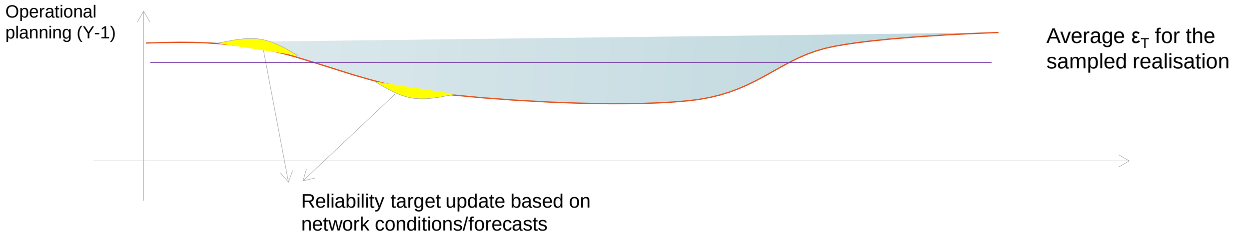

Figure 28: Updating the reliability target in ST and RT condition

In the short-term and real-time, the initial reliability target evolution is subject to adjustments either to take into consideration previous events or subsequent changes as defined below:

Post-event driven adjustments: where the tolerance of the reliability target has not been respected for some time sample, the subsequent tolerance shall be adjusted to maintain the average. For example, in some specific cases and depending on the risk policy of the TSO, some users that have been disrupted would be granted a higher reliability target to avoid further outage.

Pre-event driven adjustments: made close to RT conditions to take into consideration changes in the foreseen operational scenarios, like:

- Forced outages (unavailable nuclear power plants, unavailable critical branches)
- Updated RES forecasting on close RT conditions (high deviation from the original forecasting)
- Update on market directions
- Update on weather conditions (storms, icing, heavy rains…..)

In such perspective, a TSO as a public service provider shall guarantee a minimum level of security of supply meaning that a lower boundary constraint on the tolerance shall be enforced.

9.5.2 Space dependency

Some assets in a grid may be identified as more important than others for maintaining adequate security of supply, and therefore should be subject to higher reliability levels. The categories could be based on the geographical locations or their specific nature and significance to the overall network adequacy. Some examples are provided below:

- Specific voltage levels in the network might require higher reliability target with respect to voltage acceptable ranges either by relaxation or constraining (ex. EHV levels during scenarios of high imports scenarios);
- Pilot nodes with constrained voltage range e.g. nodes with high short circuit power contributions or nodes with high power injections;
- Critical Branches that have high impact e.g. branches that could limit the import capacity or affect the voltage stability;
- Relaxing thermal limits for lines equipped with dynamic line rating;
- Acceptable unserved load below a certain threshold within certain zones;
- Specific customers e.g. Industrial loads during day peak or residential loads during night peak (however this might be redundant in the case VOLL is assessed for the decision making).

Such specific constraints can be tailored either to take into consideration the overall system resilience or specifically to address explicit requirement of some elements.

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As the RMAC does not foresee to enforce a reliability target per each post-incident state (the constraint will be the cumulative states for all the assessed contingencies) it will be difficult to define tolerances for specific elements or zones. In fact, the outcome of each post-incident state is quantified in term of a probability of compliance with the acceptability criteria; therefore, an alternative would consist in acting on the acceptability constraints (Xa) themselves by further relaxing or constraining it for a specific element of the network or within a limited geographical area.

9.6 Worst-case estimation

Detailed models based on micro-economic approaches for quantifying the socio-economic cost of local and well-controlled interruptions are developed in [GARPUR, 2016], [GARPUR, 2016a]. However, it is suggested that due to the high impact of blackouts, the validity of these models is questionable. The alternative approach is to use a macro-economic based approach where the cost of blackout is estimated based on the potentially lost growth domestic product in the control area of a TSO. This approach assumes that an estimation of the duration of blackout is provided based on expert judgments.

The cost of a blackout in the whole control area of a TSO is assumed to be an appropriate estimate of the worst-case event for the socio-economic costs of the service interruption. Therefore, it is also suggested to use this cost, denote by $C_{int,max}$ as an upper bound for the expected interruption costs. This upper bound can be used as a conservative estimate for the risk of high impact, low probability events (HILP events) whose costs cannot be explicitly evaluated.

Relation to the threshold on residual risk ΔE:
The $C_{int,max}$ can be used to find the set of non-discarded contingencies. This is based on the pessimistic approach for defining $\mathcal{N}_c$. Given ΔE, it is suggested to use the following relationship as described in Section 4.4:

$$\sum_{c\in\mathcal{N}_c} \pi_c \geq 1 - \frac{\Delta E}{C_{int,max}}$$

This is done by starting adding the contingencies with the highest probabilities to $\mathcal{N}_c$ until the above condition is meet.

Identifying contingencies that lead to blackout:
For non-discarded contingencies, we must model the trajectory of events following the contingency in order to estimate ENS. Obviously, the system trajectory after a contingency is not deterministic, but we must model it as such. If our model is π_r% accurate, and the contingency probability is π_c%, we will be discarding (1-π_c)% of the probability space for each non-discarded contingency as described in Section 5.1. This discarded probability includes the possibility of the contingency leading to a complete blackout of the system. If we also treat this using the pessimistic assumption (i.e. all discarded events result in a blackout), we therefore cover all HILP events without explicitly modelling them.

Dynamic calculation of worst-case cost:
The micro-economic method that is suggested in [GARPUR, 2016] and [GARPUR, 2016a] formulates the value of lost load depending on several characteristics, such as:

- consumer type
- location of the consumer
- time of interruption
- duration of interruption
- advance notification of interruption
- weather at the time of interruption

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To include the effect of these characteristics, different multipliers are used. For example to include the effect of region and advance notification of interruption

$$c_{INT} = \sum_{i=1}^{I} \sum_{c=1}^{C} u_{ic} V_{ic} \cdot f_{ic}^{m} \cdot f_{ic}^{n}$$

is suggested for the cost of interruptions, where f_{ic}^{m} is the multiplier accounting for the moment of interruption and f_{ic}^{n} the multiplier considering advance notification of interruptions.

A similar approach can be used to model the effect of advance notification in the worst-case cost. The following factors must be included:

- The duration of blackout
- The advance notification
- The weather conditions

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