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EXECUTIVE SUMMARY

Reliability management of the transmission network has traditionally been associated to the N-1 rule that is applied in system operation and anticipated in system development analyses. However, the N-1 formulation conceals the obvious fact that the reliability of the whole power system depends on the reliability of the grid infrastructure. Ensuring the good reliability of the transmission assets comes at a cost, which motivated the introduction of asset management in the GARPUR project.

Besides, most of the national electricity supply systems in Europe have been built at the same time few decades ago. Consequently, these assets should arrive to their theoretical end of life simultaneously, which means that an unusually large amount of asset management activities is looming ahead.

If this expected peak of asset management activities is not properly anticipated, the TSOs will experience bottlenecks. Among them are the lack of personnel resources and adequate competence, budget allocation, time and access to spare parts, and the possibility to correctly operate the network during the outages for maintenance.

In this context it is vital that the TSOs get prepared and know how to prioritize the already limited maintenance resources in order to overcome this stressed period for asset management.

The present report compiles the results of the research carried out within the work-package 5 of the GARPUR project, which aimed at upgrading reliability management in the context of asset management activities. The proposed methods are based on the reliability management approaches and criteria developed in WP2 (detailed in the public report D2.2) and on the socio-economic impact assessment approach developed in WP3 (detailed in the public report D3.2).

In order to present the results of the work, both in a synthetic way, and with sufficient technical details, we have organized this document in two levels:

- Firstly, the main body of the report. It starts by discussing in Chapter 2 the needs expressed by TSO in the context of reliability assessment of both maintenance policies (over long-term horizons of about 20 years) and outage schedules (over mid-term horizons from a few months to a couple of years). Then, chapters 3 and 4 describe the modelling choices and algorithmic schemes proposed for handling uncertainties and assessing decisions in these two contexts. They are followed by three chapters further elaborating on important modelling aspects, such as maintenance activities, component ageing and failure rate models, and the generation of scenarios representing uncertainties. Where relevant, we also indicate directions for further work needed for real-life implementation.

- Secondly, 4 appendices provide more technical details of the main algorithms and computational models that have been developed, as well as some first results of simulation tests on the IEEE RTS96 benchmark.

The two methods developed for mid-term and long-term reliability assessment under uncertainty share the following features:

- They both rely on a Monte-Carlo simulation approach, where the uncertainties on external factors are sampled in the form of yearly trajectories at the hourly time-step. In the long-term context, this is complemented by a set of macro-scenarios chosen by the human expert, so as to represent uncertainties about future technical, economic, and regulatory conditions.

- They both represent the shorter-term processes of system operation by a pair of proxies modelling day-ahead operation planning followed by real-time operation. In our first implementations, these 2 proxies are both using a Security Constrained OPF model, explicitly taking into account the short-term reliability criterion when computing day-ahead and real-time decisions along a scenario. In addition, for the long-term maintenance policy assessment problem, the mid-term process of outage scheduling is also represented in the form of proxy, which heuristically determines for a given target year how the outages of transmission assets could be scheduled while taking into account the shorter-term system operation processes.
- They enable to assess probabilistic reliability indicators representative of the level of reliability resulting from the combination long-term, mid-term, short-term and real-time decisions simulated for each time-step. Eventually, these probabilistic indicators can be tested against a probabilistic criterion to determine whether these long-term and mid-term decisions are acceptable. Both methods take into account the (weather dependent and maintenance dependent) probabilities of contingencies together with an OPF based estimation of the amount of energy not served, to compute the expected level of criticality for that time-step.

From a computational point of view, the number of calculations to carry out is tremendous. Nevertheless, these computations may in principle be carried out with a very high-level of parallelism, and take advantage of state-of-the-art optimization and simulation tools. In order to overcome the computational burden, one major avenue for upgrading the proposed methods concerns the proxies used for modelling the shorter-term system operation. Machine learning approaches can be exploited at this level in order to significantly speed up the computations. Some first results about such an approach are presented in appendix A.2. These approaches deserve further development, and will eventually be used in order to represent how the system would be operated according to the new probabilistic RMACs developed in GARPUR.

A second very important direction for future work concerns the presentation of the results of a reliability assessment study, over a long-term or a mid-term horizon, in a suitable way to help experts derive good maintenance policies and outage schedules. The needs for such ‘graphical user interfaces’ and ‘information summarization’ techniques are also discussed in the report. This is a prerequisite for testing the proposed methods in near real-life conditions, and so to tune the model parameters and eventually gain enough confidence to develop the software packages needed for operational use.

We draw the attention of the reader to the fact that the focus of the work in WP5 was on the development of reliability assessment approaches, which is already challenging given the framework incorporates several layers of uncertainties. Let us notice that the question of optimization has been addressed in the context of WP2 and is reported in D2.2.

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1 TERMS AND DEFINITIONS

Asset management: Systematic and coordinated activities and practices through which an organization optimally manages its physical assets and their associated performance, risks and expenditures over their lifecycles for the purpose of achieving its organizational strategic plan [BSI, 2004].

CAPEX: CAPital EXpenditures

Credible scenarios: A scenario whose probability of occurrence is (arbitrarily) deemed sufficiently high to be considered.

Macro-scenarios: These scenarios are expressed at the yearly resolution, and specify macro-assumptions about the demand growth and trends in the evolution of the generation subsystem, as well as possibly climatic and economic conditions that need to be taken into account (e.g. global warming effects, fuel prices, etc.). They also incorporate information about the various network expansion projects that are already envisaged. In our framework, such long-term scenarios are used for the maintenance policy assessment. See chapter 7 for further details.

Micro-scenarios: These scenarios describe the network states in terms of demand, generation, and network component availabilities, for all the time steps of a sufficiently short time-horizon. In our framework, we assume this time-horizon to be of one year. Notice that the micro-scenarios contain both the actual realizations as well as their day-ahead forecasts. In the reliability assessment methodologies, many micro-scenarios will be processed during the Monte-Carlo simulations.

Monte-Carlo simulation: A family of simulation methods suited to problems where the input variables are largely random. From the distributions of the probabilistic input variables, many draws are sampled and then processed to compute the likely outcomes over a large space of possible situations.

N-1 criterion: The N-1 criterion is a principle according to which the system should be able to withstand at all times a credible contingency – i.e., unexpected failure or outage of a system component (such as a line, transformer, or generator) – in such a way that the system is capable of accommodating the new operational situation without violating operational security limits. (The definition is partly based on ENTSO-E documents [ENTSO-E, 2004] and [ENTSO-E, 2013].)

OPEX: OPerational EXpenditures

OPF: Optimal Power Flow

Outage: An outage is the state of a power system component (e.g. a line, a generator, a transformer...) when it is not available to properly perform its intended function due to some event associated with that component (e.g. a component failure; the tripping of some of its protections; a component disconnection switching decided by the operator). An outage is defined by a four-tuple composed of the concerned component identifier, a starting time, a duration, and the description of the event that caused the outage. It is important to distinguish between two main types of outages, namely *forced outages* which occur independently of the TSO's will and are due to some threat, and *scheduled outages*, which are those that are decided by the TSO for asset management activities. [GARPUR, 2015]

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Proxy: In our framework, a proxy is a method that enables to quickly determine a realistic behaviour of the TSO for the shorter-term decision making stages. Normally such shorter-term decisions are made based on the low-level information that will be revealed in the future. However, from a longer-term perspective, as in mid-term outage scheduling or for the asset maintenance policies, dealing with such level of accuracy is not tractable and arguably realistic. Consequently, an approximated method is suitable.

SCOPF: Security Constrained Optimal Power Flow

VOLL: Value Of Lost Load. VoLL is defined as a measure of the cost of unserved energy (the energy that would have been supplied if there had been no outage) for consumers. It is generally normalised in €/kWh[GARPUR, 2016b].

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2 HIGH LEVEL DESCRIPTION OF THE PROPOSAL

This chapter describes the main features of the mathematical methodology that has been developed in GARPUR work-package 5 and explains how it could be valuable to the TSOs in their operational practices.

2.1 Expression of the needs of the TSOs regarding asset management

The world of the power system is going to experience major changes in the coming years.

The TSOs will have to cope with the continuous increase of renewable energies in the power mix, the emergence of storage, electrical cars, DC grids, and the long anticipated components' replacement wave. These well-known and expected challenges require a paradigm change regarding both the network asset management and system operation in the coming years to explicitly account for more uncertainty.

Most of the national electricity supply systems in Europe have been built at the same time and pace, something that also indicates correlated component replacement periods. Historically (looking back 30-40 years), TSOs had a relatively constant activity level with rather risk-adverse and age-based replacement and investment policies. However, in order to manage this replacement wave, business as usual might not be sufficient. TSOs will therefore have to rethink how to manage their resources to overcome the expected amount of asset management activities looming ahead.

If this expected peak of asset management activities is not properly anticipated, the TSOs will experience bottlenecks. Among them are the lack of personnel resources and adequate competence, budget allocation, time and access to spare parts, and the possibility to correctly operate the network during the outages for maintenance. We see a trend that, due to market reasons, capacity expansion projects tend to be prioritized when it comes to the allocation of financial and of human resources, making the life of asset managers even more difficult.

If the TSOs are not able to properly carry out their maintenance policies, the infrastructure would at some point become significantly degraded. Assets in bad conditions mean higher probabilities of contingencies, thus increasing the likelihood of occurrence of insecure operating conditions. Doing less maintenance and perhaps saving money in the short-term will be repaid harder in the upcoming years through unexpected and high system costs, but also high maintenance costs once bigger maintenance efforts will be sorely required.

Certain maintenance works require that the concerned assets are taken out of operation. Some TSOs already report difficulties in planning an increasing number of outages and complying at any time with their operational policies, currently based on the “N-1” criterion. Often the desires of the asset managers and those of the people in the control room are contradictory. The traditional approach applied today by the TSOs consists in widely relying on the expertise of the outage planner to schedule the maintenance outages at a moment of the year when they shouldn’t disturb the future operation. Now, the rise of renewable energies in the power system makes this expertise increasingly challenged.

In the future, more adequate analysis and decision support tools will be needed for better planning in order to limit the impact of outages on system reliability and to limit the constraints on the capacities allocated to the market. Probabilistic methods are expected to be helpful to support this expertise and eventually help drafting an outage schedule which wouldn’t hinder too much the future operation, both from the point of view of system reliability and of the capacities offered to the market.

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In this context, the TSOs expect help from GARPUR to investigate different areas of asset and system management:

- How to make sure the maintenance policies are sufficient to manage the expected peak of asset management activities, and avoid the workforce/outage management bottlenecks?
- How to optimize the –strategic and expensive- investments in asset management activities without jeopardizing future operation and despite large uncertainties on the modelling of the condition of the components and their remaining lifetime?
- Is it worth investigating in live work technologies, and/or in asset condition monitoring devices and more advanced asset management systems/platforms/analysis tools?
- How to revisit the maintenance outage scheduling process if the operating conditions become largely conditioned by uncertain factors such as the renewable in-feeds?

2.2 Main features of the proposed approach

To support the TSOs with the above-mentioned challenges, we have decided in GARPUR WP5 to tackle the following two sub-problems below which will be treated separately in the remainder of this report:

- **The maintenance policy assessment**: Over a horizon of (say) 20 years, simulate the impact of given maintenance policies to determine the resulting costs of maintenance and operation, as well as the impact on system reliability and component health-status over the years. This methodology can be adapted to investigate whether it would be valuable to invest in live work technologies, condition monitoring devices and more advanced asset management systems/platforms/analysis tools.
- **The outage scheduling assessment**: Over a horizon of (say) 1 year, simulate the impact of given outage schedules to determine the resulting costs of maintenance and operation, as well as the impact on system reliability.

In both cases, we aim to compute indicators on:

- The reliability (energy not supplied in MWh, or converted into pseudo-monetary units by accounting for the criticality of the interruption of supply),
- The future operational costs, e.g. generation redispatching or losses.

Once these indicators have been computed and are available to the asset manager, two questions arise:

- Does the proposed maintenance policy/outage schedule enable to obtain good power system performance over the long-term?
- Assuming it is, are there opportunities to minimize the socio-economic costs while keeping good performances?

Being overly stringent on the expectations on reliability would either lead to an infeasible problem or to unacceptable costs. Let’s imagine the TSOs were compelled to respect the N-1 rule for all outages and no matter the renewable generation, the only solution would be to massively build new transmission infrastructures. The cost wouldn’t be worth the benefit. Consequently, we made propositions on possible probabilistic criterion that seem fitter to evaluate these strategic decisions from a perspective of a few months or several years ahead of time (cf. Sections 2.3.2 and 2.4.2).

In the next subsections, we explain some of the core choices we adopted when designing both methodologies.

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2.2.1 A methodology for assessment to support the asset manager

In this work-package and for the two sub-problems exposed above, we worked on the specifications of assessment methods. These methods would then be implemented into a new software tool to support the asset manager.

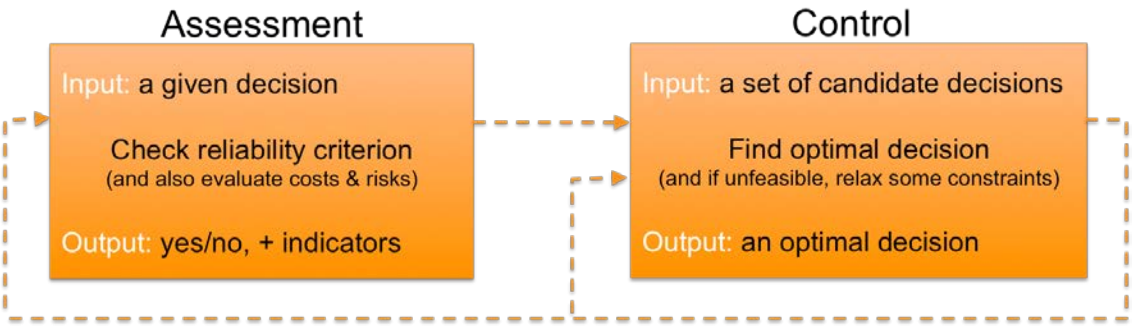

Figure 2-1: Interplay between assessment and control [GARPUR, 2016a].

We assume the TSO planner drafts a tentative schedule/policy and provides it as input to the methodologies developed hereafter. The methodologies will then evaluate both the expected reliability and operational costs, for a large range of credible scenarios and over the full time horizon under consideration, while ensuring the practical requirements hold, for instance crew limitations.

The output of the computation should then inform on whether the schedule/policy seems reasonably robust to enable a safe operation in the future, and at the same time provide indicators on the troublesome geographical areas and time-steps that will help the planner improve its draft. Such indicator could point problematic time-steps, geographical areas, workforce/budget bottlenecks, or drifts in the expected future operational costs. Based on his own knowledge and experience, the planner will then be able to adjust its tentative plan accordingly and can iterate with the tool to validate the proposed modifications.

Working on an assessment methodology rather than optimization was deemed more relevant from the TSO perspective for two main reasons:

- The output of an optimizer can be significantly different from the habits. The validation stage of such optimizer would have been problematic and could have hindered the acceptance of such method by the TSOs. In our strategy of assessment and empirical refinements, the human keeps the control and can start with a familiar tentative schedule, which facilitates the validation and acceptance.
- A planner intuitively performs small adjustments based on some expertise that is hardly possible to incorporate in the mathematical formulation. For instance, it can be a feeling that there might be some delay with a third party, logistic optimization, etc. An optimization module would have missed such input, and therefore its output would not have satisfied the asset manager.

2.2.2 Taking into account the spatio-temporal variations of exogenous factors and the actual criticality of service interruptions

Let's start this section by introducing the notions of exogenous and endogenous variables. *Exogenous* variables are determined by someone else than the TSO, and the TSO will have to adapt its behaviour accordingly. They are opposed to *endogenous variables*, which correspond to variables under the control

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of the TSO. In this section 2.2.2 we discuss the exogenous factors, while section 2.2.3 will tackle the endogenous decisions.

Table 2-1: Exogenous vs endogenous variables

Exogenous variables	Endogenous variables
Weather, Load, Renewable energy, Market Output, Forced outage rates, Criticality of supply interruption, …	Generation redispatching, Cancelling maintenance activity, Load-shedding, Switching circuit-breakers, Changing the tap of a transformer, Available human resources, …

Among the well-known shortcomings of the current practices of the TSOs, no matter the time-frame, is the fact that the modelling of exogenous factors is not taken into account in a probabilistic manner. At best, these considerations are in the heads of the operators and influence them, although it is hardly possible to measure anything quantitatively. Let's also point out that these exogenous variables vary across the year and depend on the geographical area.

The traditional approach for the TSOs to make sure the network should be sufficiently robust basically consists in stressing the average forecast and verifying that the network should withstand any single contingency. Now, should the TSOs operate the network in a context of much higher uncertainties, such worst-case approach would no longer be manageable or would lead to costs that the community is not willing to bear. Therefore, there is a need to go away from the current worst-case approach and transition toward a strategy where the credible scenarios are smartly sampled and the socio-economic consequences more accurately taken into account.

The methodology we developed for assessment considers a wide range of credible scenarios and will compute reliability/cost indicators that explicitly depend on the probabilistic distributions for the uncertain exogenous variables listed above.

2.2.3 A methodology that considers the future actions of the TSO once new information is available

It is suspected that in the coming years, the periods of high renewable infeed will lead the TSO to rely more and more on flexible responses and corrective control. One can already observe in the European grid that the number of phase-shifters or HVDCs is increasing, both kinds of devices offering control on the power flows to potentially mitigate the consequences of any disturbance. Demand-side management and storage are also in the air and would offer flexible levers to the TSOs to react in case of a disturbance.

We believe that in order to be relevant, the future reliability assessment methods need to be probabilistic and to account for the flexibility margins that are available to the TSOs precisely to deal with the unpredictability and volatility of renewable energy production.

To give a concrete example, let's imagine we are assessing the reliability of the power system during the outage for maintenance of a critical transformer. Among the load/generation samples in the Monte-Carlo process, we observe violations of the permitted line flows for some of the samples. If we stopped here without a closer look, we should conclude that there is a risk of having energy not supplied and extrapolate interruption costs. Now, it is possible that if a human operator was manually investigating the problematic snapshots, he would realize that several of these cases are actually not dangerous. For instance, corrective actions on the topology could resolve the threatening contingencies, or generation redispatching could

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easily alleviate the identified overloads. As illustrated in Figure 2-2, modelling the future actions of the TSO should enable to make the distinction between the threats which may be real problems from those which should be manageable without too much trouble.

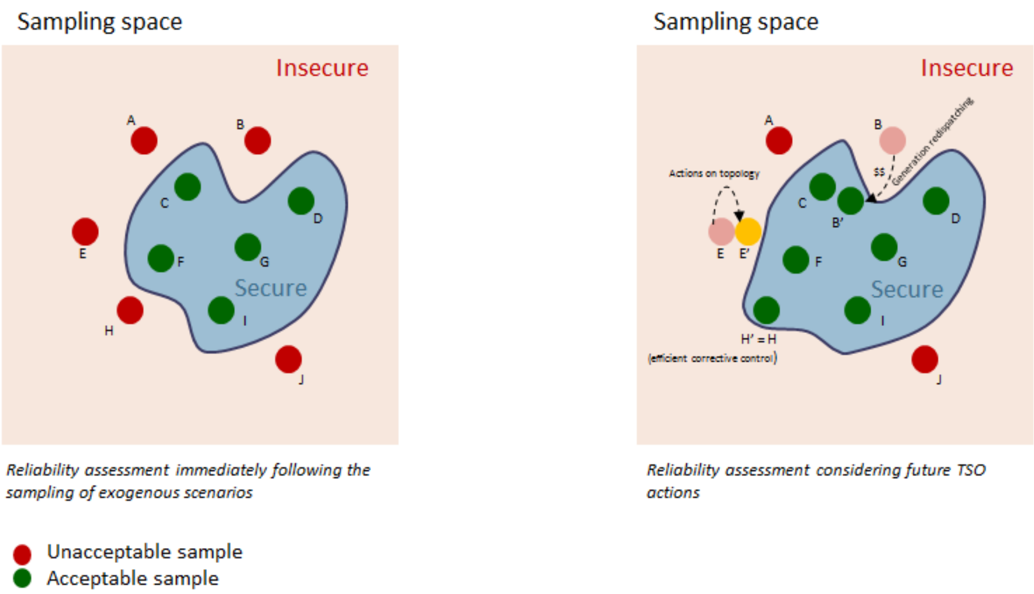

Figure 2-2: Considering the future behaviour of the TSO for a better risk evaluation

In this example, a reliability assessment performed immediately after the sampling stage evaluates that 5 out of 10 samples are insecure. If the same 10 samples were processed to account for future mitigation measures of the TSOs, the risk assessment would be evaluated more accurately.

One of the key elements proposed in our approach is that we model this future behavior of the TSO as time progresses and new information is unveiled. To reuse the vocabulary introduced in the previous section, we now intend to take into account in our modelling framework the endogenous decision variables such as tap-changing, topology switching, or generation redispatching. This superior level of modelling enables to better understand when and where the system is at risk and to capture the expected future reliability and operational costs more accurately.

This future behavior of the TSO can be simulated for example through security constrained optimal power flows (SCOPF) algorithms. Obviously, such modelling is complex and the output of any algorithm may be quite different from what a human operator would do in practice. Fortunately, what is expected here is to get sufficiently representative indicators in terms of costs and reliability. These modules that emulate the future responses of the TSOs against disturbances are called **proxies**. They are further described in section 3.3.1. The name stems from the fact that they are simplified models that *approximate* the expected future behavior of the TSO. These proxies are depicted in Figure 2-3.

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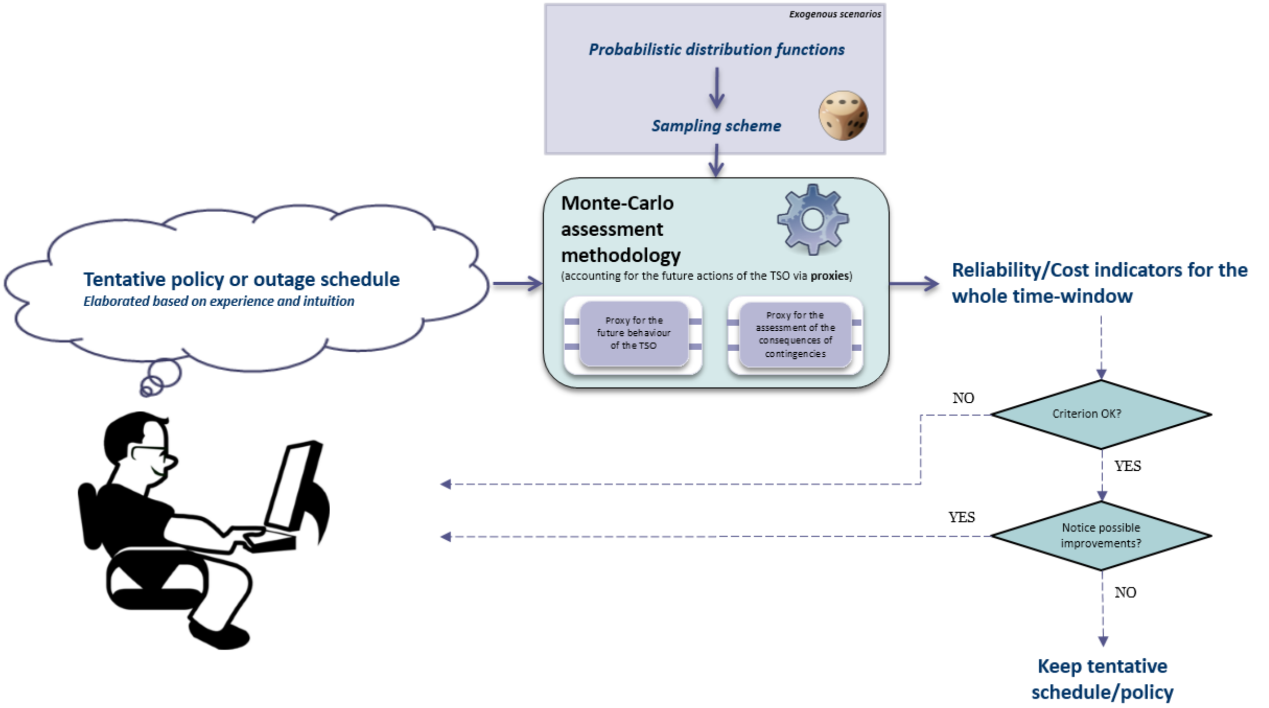

Figure 2-3: Schematic representation of the proposed probabilistic assessment methods

Choice of the operational policy followed by the TSO in the short-term

In the course of task 5.3 of the GARPUR project, which gave birth to the present report, we needed to assume an operational behavior of the TSO that could be implemented in these proxies. For the proof-of-concept, we have decided in the simulations presented in appendix to assume that the TSO would abide by to the classical N-1 rule, which is familiar to the TSOs.

Despite this assumption of a TSO observing a deterministic approach in the short-term without for instance taking into account the probabilities of contingencies, the developed methodology remains consistent with the ambitions of GARPUR and the aim of properly operating the network in a context of growing uncertainties. Indeed, the methodology:

- Considers a large variety of possible scenarios when assessing the expected costs of non-supplied energy and future operational costs (and not just a few worst-cases). The point here is to be aware that the difficult situations in real-time operation often come from the realization of several unfavorable conditions simultaneously. The framework also permits to incorporate high-impact low-probability events,
- Explicitly models the effect of corrective control, and to a larger extent, the multi-stage aspects of the decision-making processes of the TSO. Several months or years ahead of time, there is no way to predict exactly what is going to happen in operation, but one can manage to ensure that the long-term decisions of the TSO are going in the right direction and, with a reasonable level of confidence, that the TSO will have at his disposal enough flexibility to manage operation in the future,
- Delivers as output indicators not only on the expected reliability but also on the expected future operational costs. The reliability criteria that are proposed leave some freedom to sometime bypass the strict respect of the N-1 rule if the risks on the reliability of the system is sufficiently low and/or the gain on operational costs are significant,

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- Make an evaluation over the full time-windows instead of some specific time-steps.

Hopefully, proving the soundness of the method with proxies of the familiar N-1 for the short-term time-frames should facilitate the migration stage from current practices toward probabilistic approaches.

We insist that the ambition in GARPUR is also to push the TSO to adopt a different approach from the N-1 in the short-term decision-making processes. So ultimately, the devised methodology should be revised once a probabilistic substitute to the N-1 is ready. The algorithms that have been developed to emulate the behavior of a TSO following the N-1 rule for the needs of the present report can be easily unplugged and replaced by new ones representative of a different behavior of the TSO. This is left for future work.

2.2.4 Consistency with the previous academic work

The GARPUR project has been constructed under the following logic:

- First define guiding principles proposed in the academic work packages (WP 2 and 3),
- Then adapt these concepts to make them compliant with the real-life requirements (WP 4,5,6),
- Eventually perform pilot tests for validation (WP 7 and 8).

For an in-depth understanding of the aforementioned academic work, we refer the interested reader to deliverables D2.2 [GARPUR, 2016a] and D3.2 [GARPUR, 2016b]. In Table 2-2 below, we synthesize the interpretation of some key academic concepts in the derived implementation for our two asset management sub-problems.

Table 2-2: Interpretation of the academic principles for asset management

Academic concept	Translation in this document on asset management
Model of multi-stage decision making under uncertainties	These aspects are addressed through the exogenous scenarios sampled for the Monte-Carlo simulation as well as through the proxies to emulate the future TSO actions based on the information level available to the knowledge of the TSO. We highlight that in our specifications for the definition of the scenarios, we also requested to receive the information on the range of forecasts errors. So, for each relevant time-horizon, the TSO will be submitted an information state. The corresponding proxy will take decisions based on this information available to him. Then, once in real time, the realized state will be different from the forecast. In periods of high RES production, when forecast errors are high, one expects to witness the TSO either spend more money to react to the forecast errors, or to experience load-shedding.
Reliability assessment vs reliability control (cf. Figure 2-1)	In this document, we have described methodologies to assess given outage schedules/policies. The output indicates whether the tentative outage schedule/policy is acceptable (cf. sections 2.3.2 and 2.4.2) and computes the value of the socio-economic function for the whole time horizon. In this framework, the reliability control is left to the operator who will iterate with the assessment methodology to improve step-by-step this proposal. Beyond GARPUR, algorithms for optimization could be proposed.

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Objective function	Maintenance policy assessment sub-problem The objective function agglomerates the various costs of purchase, workforce including third parties, logistic, and also the future OPEX (mainly expected generation redispatching costs) as well as the interruption costs (accounting for the value of lost load). Outage scheduling sub-problem The objective function agglomerates the future OPEX (mainly expected generation redispatching costs) as well as the interruption costs (accounting for the value of lost load). The impact of scheduled outages on the reduction of cross-border capacities should also be taken into account here. When manually comparing 2 different possible schedules, the outage planner should also take into account the costs for extraordinary actions such as live work, and the costs when contracting with some generators or industrial consumers.
Discarding principle	This principle states that it is impossible for the TSO to analyze the entire scope of possible events that may happen. Consequently, the scenario space studied by the TSO should be built in such a way that meaningful threats should not be missed. In work-package 2, it is proposed to consider a threshold (ΔE) on the disregarded risk that would be acceptable. Although the theoretical principle is sound, in practice it does not seem realistic to pretend to be able to compute a value for the risk that is disregarded. Now, sensitivity analyses can be formed to tune: - The contingencies list, based in particular on expected weather conditions. Besides, should there be assets in very bad condition in the infrastructure, some additional N-K contingencies including such assets could be considered. - The sampling of scenarios
Reliability target and acceptability constraints	The reliability target should tune the risk-averseness level of the TSO regarding the tolerated (small) proportion of time-steps and scenarios where the operational criterion is not met during the simulation horizon. The point here is to make sure that the decisions of the asset manager will enable, with a given level of confidence, his colleague in the control room to correctly operate the system in the future. In addition to the formulation in work-package 2, we propose to incorporate additional constraints to the mathematical formulation to address the question of fairness between the different users of the grid. This question of fairness is political and will have to be addressed by the adequate regulatory body. For the technical side of the question, such constraint could take the form of "*The reliability level for a region R should be above x% of the national reliability level, with a confidence level of y%*".

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2.3 Sub-problem 1: Long-term maintenance budgeting

2.3.1 Maintenance policy assessment

The devised maintenance policy assessment method is a Monte-Carlo simulation that takes as input a tentative policy given by the planner for the inspection, maintenance, and replacement of the assets. Such policy can be time-based, condition-based, wait-for-failure, or a mix. Then, the methodology evaluates both the reliability and expected operational costs over a long-period of time, say 20 years. Such a long duration is required to observe the degradation due to time of the physical infrastructures. Otherwise, the output would be predictable and suggest to save money and carry no maintenance at all. For this probabilistic evaluation, there are some core modelling features:

- Need to model the degradation process due to ageing as well as the benefit brought by the various maintenance activities, and to link the expected health state of the assets with their failure rates. This model should be refined as much as possible to account for the accelerated ageing due to the sustained stress or the hostility of the surrounding environment (e.g. pollution). The component health statuses at the end of the simulation will be observed to make sure the grid is not going to collapse a few years beyond the simulated horizon.
- Need to account for crew limitations. We also take into account that forced outages need to be fixed by the same people, who consequently will have less time to work on the planned duties.
- Need to model the outage scheduling process, and distribute the outages for maintenance realistically over the year. A greedy algorithm has been designed for that purpose (*outage scheduling proxy*).
- Need to model a wide range of credible futures. We propose to consider a few macro-scenarios representative of several possible trajectories for the upcoming 20 years, in a similar fashion than for system development analyses. We also consider micro-scenarios to reflect the intra-year variations.

We recall that we decided, on purpose, to ***use the N-1 criterion for the shorter-term decision making processes*** in the context of the proposed computational model, because this is the current way of exploiting the system and thus eases interaction with asset management experts.

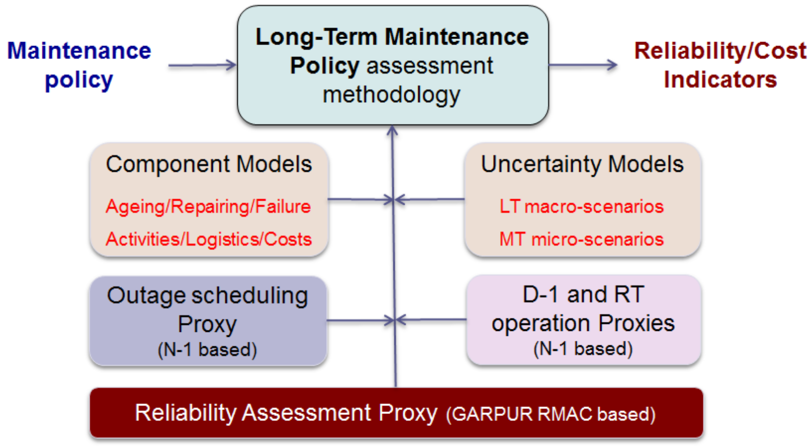

Figure 2-4: Schematic representation of the maintenance policy assessment proposal

2.3.2 On the notion of acceptable maintenance policy

Interestingly, the question of defining an acceptable maintenance policy can be seen from two different points of view:

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- Given a determined budget, what is the best reliability that can be achieved?
- Given a reliability target, how can the TSO optimize the budget?

Intuitively, the core expectations from a good maintenance/replacement policy concern the health status of the infrastructure and the respect of the allocated budgets. Therefore, the following output should be examined:

- Make sure that, for each year, the CAPEX for the policy remain in line with the yearly allocated budget,
- Make sure the workforce allocation is smoothened over the year, in order to guarantee a constant level of activity for the team, cope with possible peak of activities, and maintain an adequate level of skill for the crews,
- In the same spirit and especially in the case of condition-based maintenance policies, make sure there shouldn't be a sudden and unanticipated peak of maintenance requests. Also make sure the amount of forced outages due to insufficient maintenance remains manageable,
- Make sure the health statuses of the assets at the end of the simulation are acceptable. In other words, check that the CAPEX were not tuned to maximize the benefits for the evaluation period while the expenses (both OPEX/CAPEX) would skyrocket in the subsequent years.

In addition, we propose to monitor additional indicators that concern the (future) operation of the network, and thus make explicit the relation that exists between the physical infrastructures and the operation of the transmission system. This obvious dependency is concealed today in the N-1 formulation, although everyone is aware that a well maintained park of assets will limit the risk of contingencies and thus contribute to the good performance of the power systems. The corresponding criteria can be:

- Make sure that for each year the overall amount of non-supplied energy is below some threshold, with a given level of confidence. Possibly, instead of non-supplied energy, a derivative form that would account for the criticality of interruption of service could be employed,
- Make sure that for each year the amount of non-supplied energy is below some threshold at the local level. Moving to a risk-based approach should foster the TSOs to spend more efforts on the most critical parts of their grid, which means some other parts would have to compensate. Likely, the public authorities will also request different reliability levels for different assets in the system
- Make sure the short-term operational policies should be enforced most of the time with a good level of confidence. A monthly resolution may be adequate,
- Make sure the operational expenditures remain under control.

2.3.3 Towards maintenance policy optimization

Manually testing variants of the current policies

In this framework, we should observe that increasing the maintenance efforts should reduce the future operational costs as well as improve the overall reliability – at least, as long as the needs in terms of outages remain reasonable. The TSO will try to adjust manually and step-by-step the tentative policy to make sure it is viable on the long-term while keeping the maintenance costs at an acceptable level.

In particular, the TSO will also pay attention on the budget and workforce to make sure the needs for these resources are smoothened over the years. This TSO will also have the opportunity to test some variations of the regular policies to see whether it is reasonable to reduce the maintenance costs or to rebalance the efforts between the more critical assets and those which are deemed less priority. Similarly, budget shifts between policies for different classes of assets could be tested. This would be consistent with the principles of RCM (Reliability-Centred Maintenance) which are already well-accepted by the TSOs, but which remain difficult to evaluate by other means than empirically. Notice here that the evaluation of

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inspection/maintenance/replacement policies is very sensitive to the models used to evaluate the degradation process of the assets, and that such models are very hard to build.

Detecting and correcting possible bottlenecks

Prior to optimizing the existing policies, one should make sure the expected trajectories for the upcoming decades do not lead to a state where the TSO is no longer capable to operate its system correctly. We refer the reader to subsection 2.3.3.

Asset management policies vs structural changes

A trend reported by some TSOs is that it is increasingly harder to build new assets because of public acceptance. This fact pushed forward the idea that instead of building a network robust to contingencies (N-1 or a different list), the efforts should be put on reducing the probability of failure of the assets, which could be achieved by performing efficient asset management policies. However, sometimes one may find himself in a situation where the best option lies in structural changes.

In order to quantify whether a new system development project could alleviate the difficulties encountered in the asset management processes, the TSO can launch the evaluation of the same maintenance policy for two sets of macro-scenarios. The first set would be the regular one, while the second is a variant of this first set where the proposed structural changes have been embedded.

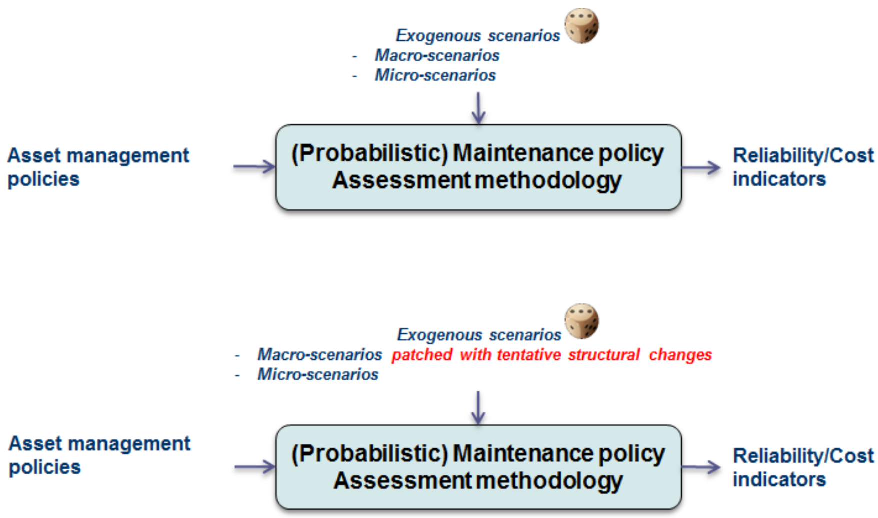

Figure 2-5: Testing structural changes instead of variations of the policies

Investing in live work technologies

The outages requested for the needs of asset management activities will lead to increased operational costs. Investigating whether it is meaningful to invest in live work technologies or similar means to reduce the outage duration can easily be implemented in our framework. To do so, one should reduce/nullify the duration of outages for some maintenance activities while increasing the associated costs.

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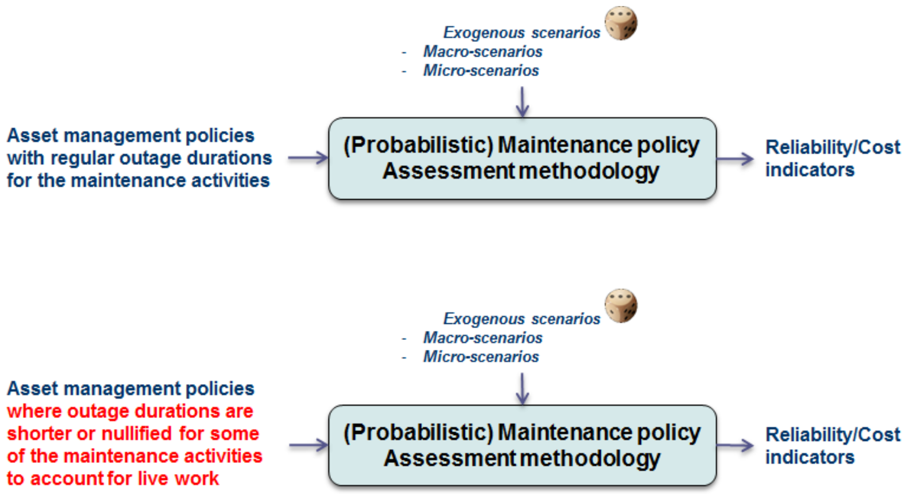

Figure 2-6: Assessing the benefits of higher recourse to live work

Investing in asset condition monitoring

The main drawback with time-based maintenance is that it can result in unnecessary activities if at the scheduled time of maintenance the asset happens to be in good health. In order to avoid such waste, the solution might be to rely more on the monitoring of the asset and react only when signals of degradation are received. At this point, the questions of the frequency of inspection and of the quality (undetected flaws) arise.

In the methodology developed in this document for the assessment of the policies, the maintenance activities triggered by inspections are modelled. A coefficient reflective of the ratio of undetected flaws could be introduced. Then, sensitive analysis could be performed to quantify the benefit in investing in a technology that would bring a better insight of the real health state of the components.

2.4 Sub-problem 2: Mid-term outage scheduling

2.4.1 Outage schedule assessment

In this second sub-problem, the system planner proposes a tentative schedule for the outages of the transmission assets over a pre-defined time horizon (typically one year ahead of time), and the methodology proposes a probabilistic evaluation of this particular outage schedule both in terms of reliability and expected future operational costs.

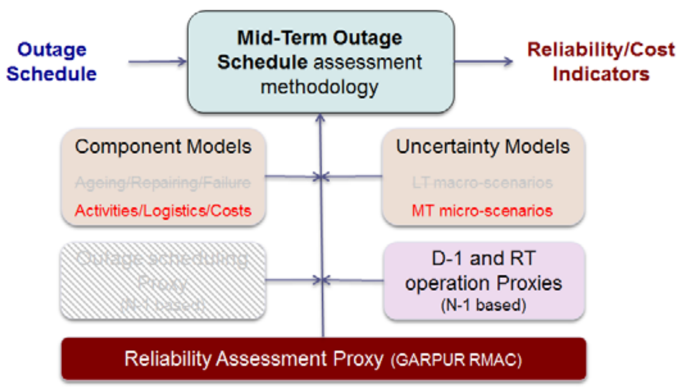

Figure 2-7: Schematic representation of the outage schedule assessment proposal

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Such indicators could be reflective of the proportion of time the short-term reliability criterion (e.g. N-1 criterion) is not fulfilled, or the expected amount and location of energy not supplied. As for the maintenance policy assessment problem, we rely on a Monte-Carlo simulation. The set of outages to schedule encompasses those from the maintenance policies as well as those resulting from system development decisions.

In this framework, the schedule of interruption of the main power plants is given as an input. The future operating conditions (load, renewable energy, failure rates,..) for each time-step are uncertain. The sampling for the Monte-Carlo simulation is based on micro-scenarios. It is expected that in the future, because of the large proportion of renewable in the energy mix, the outage schedule should be quite often disrupted due to system security reasons.

Working with a standard worst-case approach as today would no longer permit to build an outage schedule because we should observe too many infeasibilities. Consequently, the probabilistic assessment enables to grasp whether the odds that the different outages will not jeopardize the security in operation are satisfactory.

We recall that we decided, on purpose, to ***use the N-1 criterion for the shorter-term decision making processes*** in the proposed computational model, because this is the current way of exploiting the system and thus eases interaction with asset management experts.

Because this outage scheduling problem is evaluated on a time-window shorter than the one for the policies, we propose to simplify the problem and neglect the degradation process of the assets along time.

2.4.2 On the notion of acceptable outage schedule

Contrary to the previous problem, here the workforce allocation and the different budgets should have already been settled upstream.

The current practices of the TSO rely a lot on expert knowledge and assess just a few configurations for the notoriously most difficult outages of the tentative schedule. As an improvement, we propose to sketch a reliability criterion where the whole time-window and a large variety of scenarios are considered in an automatic process.

In this context, a reliability criterion to evaluate an outage schedule could request that for each time-step, a large proportion of the credible scenarios respect the operational criterion (N-1 or other). A relaxed form could be to request that for a large proportion of the time-steps, a large proportion of scenarios respect the operational criterion. Indeed, we may find ourselves in configurations where respecting the operational criterion during some outages is either infeasible or would lead to unacceptable operational costs. Assuming the operational policy is the N-1, such formulation explicitly tolerates that the schedule may not be robust anytime, for any scenario, against all N-1.

In addition, several constraints on the expected energy not served could also be incorporated, both at the global level (i.e. the responsibility area of the TSO) as well as on the local level, to ensure the different customers are treated in a fair manner. The mere computation of an expected energy not served could be enhanced by considering the associated criticality of energy not served.

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One of the specificity of outage scheduling lies in the fact that this schedule can be revised at a later stage, depending on whatever new information is available to the knowledge of the TSO, such as for example an update in the outage schedule of the generation units. Rescheduling at the last moment involves logistic and management inconveniences, maybe also financial penalties, but might prove necessary. Indicators on the flexibility of the schedule would be appreciated to make sure rescheduling looks feasible, in particular for the assets that are critical to the system.

2.4.3 Towards outage schedule optimization

Increasing the odds of successful operation during the outages
The very purpose of this methodology is to rework the tentative schedule, or alternatively to anticipate extraordinary actions (see below) to ensure good odds of successful operation once in real time.

The outage schedule assessment (probabilistic) methodology should detect whether some moments in the schedule should be overly difficult to manage once in real-time operation, either because they induce high risk on the end-users or because they may induce high operational costs in the future. In particular, the framework allows to account for the criticality of interruption of supply depending on the kind of customer, location, and time of the year, thus enabling to better understand the actual risk on the system.

Extraordinary actions (live work, helicopter assistance…)
In case the set of outages to schedule does not permit to respect the reliability criterion, or in order to increase the cross-border capacities, the TSO might sometime consider resorting to exceptional actions such as live work to diminish or nullify the duration of the outage. Such actions have a cost and the associated resources are limited.

Increasing the cross-border capacities and reducing the operational costs
Making sure the reliability of the electrical power system should be at the desired level is one thing, but in GARPUR we also ambition to involve the different costs at stake when taking any decision. Consequently, and under the condition that reliability aspects remain satisfied, a schedule could be reworked to diminish the expected generation redispatching costs or to optimize the losses. Another feature of interest for the TSOs is to design the outage schedule in order to make the cross-border capacities available when they are the most needed.

Testing new schedules and justifying arbitrations
The TSOs may not be fond of experimenting new configurations for the outage schedules, meaning for instance that a TSO who usually undertake the maintenance of some asset at a particular period of the year may be reluctant to move it to another period, simply because it is not the custom and it doesn't have any feedback on how well it would work.

A probabilistic assessment tool would give confidence to the planner to test something different. It can also be particularly interesting in case of recent structural changes, for instance after a new asset has been installed and put in operation, or after one has been decommissioned. Some new schedules could also be proposed for instance for resources optimization.

Besides, sometimes there can be opposite needs between system operation who wants a grid element to be in operation while maintenance wants to be allowed to have this asset on outage to work on it. The probabilistic assessment could bring evidence to help solving such conflict and possibly to find another more suitable time-slot.

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2.5 Further work

The question of future work will be addressed in GARPUR D9.2 "A tentative roadmap to evolve the current N-1 practices". We can already propose some suggestions regarding the maintenance policies and outage schedule assessment problems tackled within this report.

Improving the proxies to properly take into account the flexible means available to the TSOs
In their current form, the proxies that we developed to emulate the future behaviour of the TSOs are able to simulate generation redispatching and pre-defined corrective actions. As much as possible, we would like to incorporate the topological actions that may be undertaken by the TSOs, although this is a known computational hurdle because it involves integer variables.

If in the future we observe significant changes in the way the network is operated, the proxies should evolve to adequately represent these behaviours. Among the actions likely to gain popularity in the coming years, we can underline the following that could be worth being modelled in the proxies:

- The response of HVDCs following a contingencies,
- Demand-side management,
- The flexibility brought by storage facilities if such devices were to be installed in the future.

Fastening the proxies
At this point, one should notice that the different proxies are based on notoriously slow computation methods. Even though parallelized computing can alleviate the burden, several hours or even days are likely to be required for the assessment of a real-size grid. Fastening the proxies, or proposing methods to quickly discard a large portion of the scenarios, is likely to be needed when moving toward an industrialization stage.

Definition of the probabilistic scenarios
Obviously, a probabilistic assessment method is conditioned by the quality of the input data. Improving the modelling of exogenous factors and taking into account the different correlations is among the top topics for future research. The socio-economic aspects related to the criticality of electricity supply to society also appear among the requirements that need to be better understood.

Degradation models, benefit of maintenance activities, and link with the failure rates
In the same manner, the output of the maintenance policy assessment depends a lot on the degradation models. Understanding the influence of sustained stress, the external environment, etc, on the ageing of the electrical components for individual assets or families of assets remains a challenge.

Multi-TSO issue
For outages near the borders, communication already exists to keep the neighbouring TSOs informed and potentially coordinate the outages. As much as possible, the outages should be scheduled in such a way as hinder as little as possible the cross-border capacities when they are the most needed.

Validation
The whole methodology will have to be validated prior to (hopefully) be implemented by the TSOs. The validation process of a probabilistic methodology is expected to take time and to rely to a large extent to the human expertise. Determining if the decision (policy/schedule) that was taken was meaningful given the information available at this moment can be difficult, because a posteriori a single realization occurred, which maybe was not very likely at the moment the decision was taken.

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3 MAINTENANCE POLICY ASSESSMENT PROPOSAL

Figure 3-1 describes the overall principle of the long-term maintenance policy assessment approach proposed in WP5.

Over a horizon of (say) 20 years, the goal is to simulate the impact of a priori fixed maintenance policies (given as input to the methodology) on mid-term outage scheduling and short-term operation, so as to determine the resulting costs of maintenance and operation, as well as the impact on system reliability and component health-status over the years.

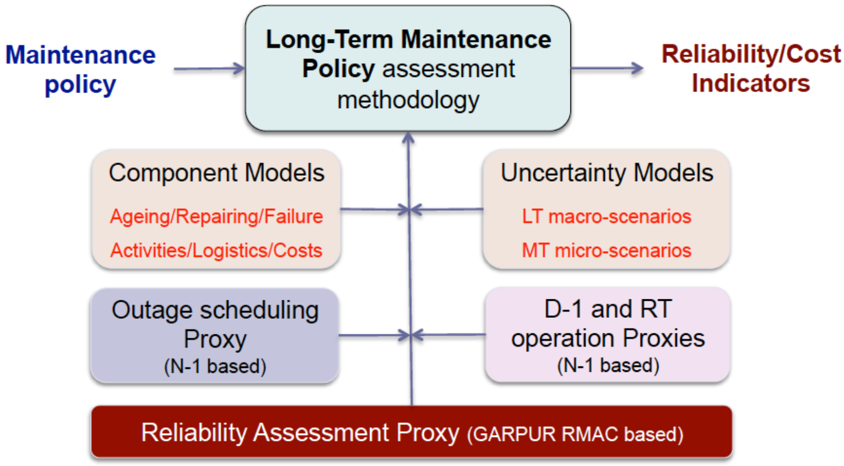

Figure 3-1: Schematic representation of the overall maintenance policy assessment proposal

In the rest of this chapter, we explain the main ingredients of this approach, as highlighted in Figure 3-1, and to this end we start by describing more precisely the inputs and outputs of the assessment methodology (highlighted in the upper half of Figure 3-1), and then discuss the different 'proxies' highlighted in its lower part. We then summarize the whole procedure and discuss various possibilities for enhancing it, e.g. in terms of accuracy and computational speed.

3.1 Inputs

3.1.1 Maintenance policies

The main input to the policy assessment software is a maintenance policy chosen by the expert to be assessed over a horizon of several years (in our presentation, we arbitrarily set this horizon to 20 years, so as to fix ideas, but in real life conditions the horizon could itself also be specified by the user).

The maintenance policy is composed of two parts that are specified for each year Y of the assessment horizon:

1. **A list of maintenance activities to be carried out in year Y**: each individual activity is described by a tuple [activity type, concerned grid component, expected outage duration, cost, man-power requirements, …], where the activity type may be 'repair', 'replace', 'inspect and conditionally repair' etc. (see Chapter 5, for details about the practical definition of maintenance activities).

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Notice that some of these activities may require component outages to be carried out, while others may not (then the outage duration is specified as being equal to zero). Also, the precise moment where the activity should be carried out does not have to be specified as an input; a suitable moment for carrying out each activity can indeed be determined automatically by the 'outage scheduling proxy' (see Section 3.3.2).

2. **A set of manpower constraints for year Y**: they express, for every zone of the network the total amount of human resources that can be devoted to maintenance activities on the components belonging to that zone during a given set of sub-periods covering a particular year (e.g. as a tuple in the following form [Year 1, Zone A, 15MM in Spring, 10 MM in Summer, 15 MM in Fall, 12 MM in Winter]).

   Notice that manpower constraints are automatically enforced by the 'outage scheduling proxy', when the precise timing of each activity to be carried out for a given year is computed. Besides, if desired, the overall problem could also consider uncertainties on the resources.

3.1.2 Component ageing and maintenance models

We assume that each network component is described by a model expressing the impact of ageing and maintenance activities on its internal health-status. In addition, the initial internal health-status at the beginning of the assessment horizon is given for each component. The model is then used in order to update the health-status after each year, given the scheduled activities for that component for that year and or any other inspection triggered or corrective maintenance activities carried out for it.

Furthermore, for each component we also assume that a model is available allowing one to compute the failure rate of that component at any moment as a function of its health-status and as a function of any other relevant information, such as for example instantaneous weather conditions.

We refer the reader to Chapter 6 of this document for a more detailed discussion about the component ageing and maintenance models we propose to use.

3.1.3 Uncertainty model

The uncertainty model is composed of two different parts used in combination, namely a list of macro-scenarios, and a generative model of micro-scenarios:

1. **Macro-scenarios description**: they are expressed at the yearly resolution, and specify macro-assumptions about the demand growth and trends in the evolution of the generation subsystem, as well as possibly climatic and economic conditions that need to be taken into account (e.g. global warming effects, fuel prices, etc.), and they also incorporate information about the various network expansion projects that are already envisaged.

   Notice that in order to carry out an assessment study, at least one such macro-scenario needs to be specified by the user over the full horizon of the study. Also, in order to well reflect uncertainties over long-term horizons such as those considered in the context of maintenance policy assessment, one would naturally organize the set of macro-scenarios in the form of a 'scenario-tree', so as to reflect the fact that macro-uncertainty increases gradually over time.

2. **Micro-scenario generative model**: this model is used, in combination with a macro-scenario specification, and with data about the component health-status and failure rates as well as their

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planned outages, in order to generate multiple Monte-Carlo samples at the hourly time step, for a particular year of the assessment horizon. Each micro-scenario is described at the nodal and component level, in terms of demand, generation, and network component availabilities, and contains both the actual realizations as well as their day-ahead forecasts. Notice that planned outages (resulting from network component maintenance or replacements scheduled for a particular period of time, as well as scheduled generation maintenance activities) are considered as inputs to the micro-scenario generative model, while the forced outages, due to random component (both network and generation) failures and their resulting corrective maintenance, as well as inspection triggered network maintenance activities are both computed for each micro-scenario by the generative model itself.

Notice that the micro-scenario generative model is called multiple times within the policy assessment software, in order to first determine outage schedules (by using the outage scheduling proxy) and then to assess the various indicators of costs and reliability resulting from simulating the system operation (by using the short-term system operation proxies). More details about the generative model of micro-scenarios are given in Chapter 7 of this document. In Section 3.3 we describe how the information contained in a micro-scenario is exploited by the different proxies used for mimicking outage scheduling and system operation.

3.2 Outputs

The objective of a policy assessment study is to evaluate the impact of the given policy (i.e. its given maintenance, inspection and replacement activities) on the system performance over the study horizon, as well as on the overall health-status of its network components in particular at the end of the assessment horizon. Therefore, for each micro-scenario and each particular hour of each year, a large number of detailed indicators are computed and then aggregated and visualised in a proper fashion to allow the user of the software to determine how good the policy is and possibly identify some changes that he would like to implement on it in order to define the input of a subsequent assessment study. For example, if he finds out that planned outages for a given year lead to very high costs in operation or too low reliability levels, he may try to postpone or anticipate some of the activities planned for that year to a later or an earlier year, or he may wish to increase planned maintenance activities if he observes that there are too many corrective or inspection triggered maintenance activities that could be carried out in a more comfortable way if they were done as preventive maintenance activities at an earlier stage.

In the next two subsections we briefly indicate what kind of indicators can be calculated, and how they could be aggregated and visualized. In the last subsection, we sketch how the graphical representation of such information could look like.

3.2.1 Cost indicators calculation and visualisation

The following quantities will be computed over the set of years, macro-scenarios and micro-scenarios by the combined applications of the outage scheduling proxy, the day-ahead proxy, and the real-time operation proxy (see Section 3.3):

1. **Maintenance costs, activities and manpower requirements**: these quantities will be aggregated at the monthly (or possibly weekly) time-step, and over network zones and component families.

   Notice that for those costs that are stochastic (i.e. related to corrective maintenance and inspection triggered repairs), these quantities will be described by relevant statistics over the used set of micro-scenarios (such as sample mean and standard deviation).

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2. **Day-ahead operation planning costs and decisions**: these quantities depend on the day-ahead forecasts, which are possibly variable from one micro-scenario to another. We therefore propose to compute their sample means and standard deviations integrated over the daily, weekly and monthly time-intervals, and possibly aggregate the types of triggered control actions in various ways in terms of spatial distribution and classes of decisions.

3. **Real-time operation costs and decisions**: these quantities are highly-stochastic and are refreshed for each micro-scenario at the hourly time-step based on the corresponding real-time conditions and while taking into account the day-ahead decisions; we propose to integrate them as well at the daily, weekly and monthly time steps before presenting their mean and standard deviations to the user. In addition to the computation of costs and decisions, also the fact that the N-1 security target could be reached or was infeasible shall be reported. For the cases when enforcing the N-1 is impossible, we propose to also display separately the amount of load shedding that was deemed necessary to comply with the N-1 security criterion in real-time conditions, as an indicator of the "distance" between the N-1 target and what was achieved.

Obviously, the amount of information (even if already compacted by the various averaging and integration schemes suggested above) will still be overwhelming to be useful for policy assessment and refinement by the expert. Therefore, some post-processing tools should be used in order to facilitate the analysis of this information. The precise design of such data visualization and data mining tools may benefit from existing tools already in use at the TSO under consideration, but falls out of the scope of the present document (see also the discussions about acceptability criteria and policy optimization in Sections 2.3.2 and 2.3.3 of this document).

3.2.2 Reliability indicators calculation and visualisation

In addition to the above quantities that mimic the impact of the maintenance policy on the mid-term outage scheduling and short-term operation activities that would be carried out by the TSO, we also compute other relevant quantities in order to evaluate the resulting impact on system reliability in operation as well as on the components' health-statuses. To reflect this information we propose to compute the following indicators:

1. **Component health-statuses and failure rates**: for each component and after each year of the study horizon, we can determine its expected component health-status resulting from the deterministically planned maintenance activities as well as from the stochastically induced corrective and/or inspection triggered activities (and possibly the environmental conditions postulated in the macro-scenarios), and from this we can also determine average and/or weather dependent failure rates (by using the component models provided as input to the assessment software). These quantities can then be aggregated over relevant component classes and system zones, and their temporal evolution would be displayed to the analyst.

2. **Workforce requirements:** for each year and each zone corresponding to maintenance centres, we can determine whether the requirements in terms of workforce are coherent with the available crews. If not, the TSO should consider reworking its policies or hiring new staff.

3. **System reliability in operation**: for any specific hour of any micro-scenario, the assessment software uses the reliability assessment proxy (see section 3.3.1.3 in order to determine expected service interruption volumes and costs for that hour (they depend on the decisions already computed by the real-time operation proxy, and indirectly on D-1 and outage scheduling

decisions), by screening a list of contingencies and corrective control failure modes and computing the resulting amount of load shed in every bus of the system. These elementary quantities can be aggregated at the system and/or zone level to estimate expected amounts of energy not served and corresponding costs of service interruptions. These system indicators can then be integrated at daily, weekly, monthly and yearly time-steps and displayed to the analyst along with the other indicators presented above, using the same post-processing tool that we do not discuss in this document.

3.2.3 Graphical presentation of outputs

Figure 3-2 and Figure 3-3 illustrate some possible representations of outputs computed by the policy assessment method. The first figure suggest how the temporal evolution of global cost indicators could be shown, while the second figure suggests how one could represent the spatial variation of indicators related to components ageing.

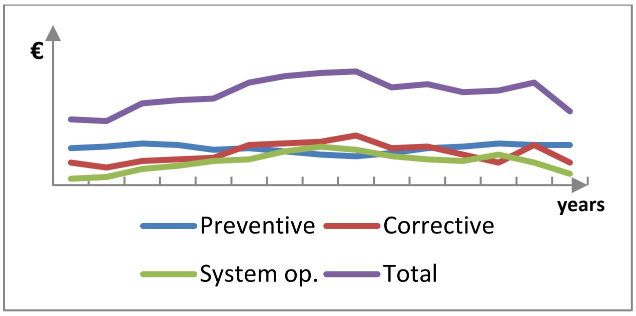

Figure 3-2: Cost of maintenance activities and system operation as a function of time.

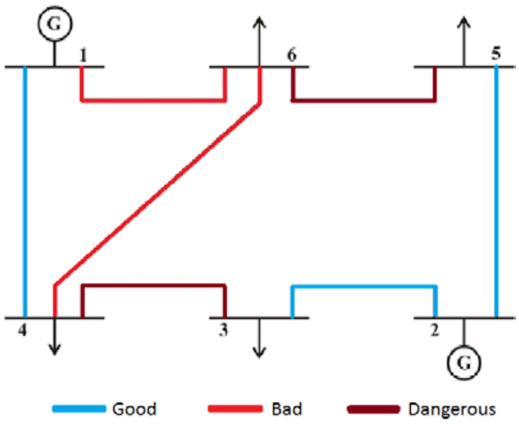

Figure 3-3: Condition of different transmission grid components for year *y*.

3.3 Short-term and mid-term proxies

In this section we describe 'in words only' how the different proxies are used in the context of maintenance policy assessment. We also discuss in the present section the overall computational requirements resulting from our choice of proxies.

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

3.3.1 The three short-term proxies

Figure 3-4 below illustrates how the three short-term proxies are used for each daily simulation of each micro-scenario. The figure also shows the information flow between the uncertainty model and from one proxy to the other, as well as the type of calculations involved at each step.

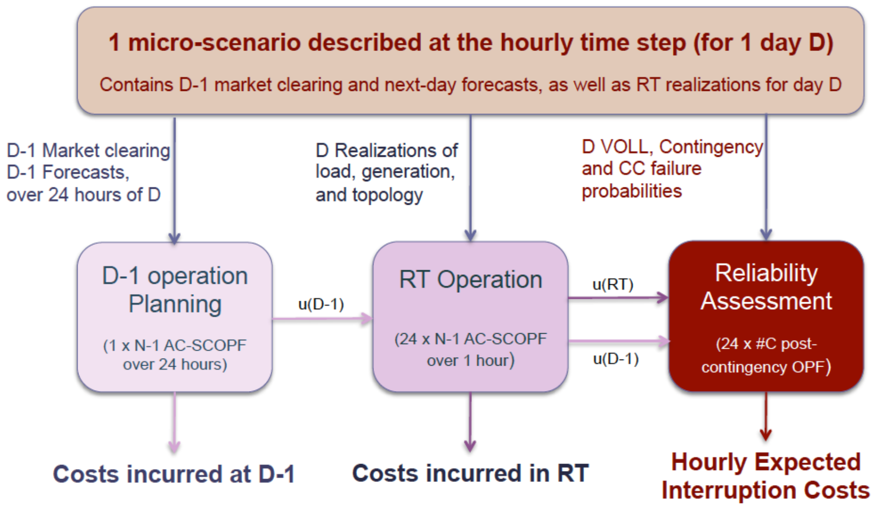

Figure 3-4: Outline of the principle of the intervention of the three short-term proxies. In this figure, CC stands for *Corrective Control*, #C for the *number of contingencies*

3.3.1.1 Simulation of D-1 operation planning under N-1

We assume that the market clearing is simulated exogenously by the micro-scenario generative model and is therefore provided as an input to the D-1 operation planning proxy. This latter information is combined with the outcome of the previous day operation decisions in order to provide a set of thermal and hydro generators for each hour of the next day that may be rescheduled, and/or re-committed in order to cope with expected network congestions given the D-1 forecast of demand and renewable generation. The micro-scenario also furnishes any relevant cost functions and constraints that are needed to simulate day-ahead operation planning, the latter being simulated in the form of an N-1 Security Constrained Multi-period OPF over the 24 hours of the next day. The output of this computation is a set of generators started up (and their planned output) for each hour of the next day, as well as possibly some network topology manoeuvres as deemed necessary to ensure that the system would be N-1 secure[1] in the context of the forecasted load and renewable generation time-series assumed by the micro-scenario generator as being the most likely forecast for the next day. In principle any available existing AC-SCOPF software could be used to carry out this computation; in our test scenarios we used however a DC network model and did not incorporate topology changes as decisions. Depending on the degree of faithfulness sought in these simulations, they need either to be carried out in sequence for the different days of a Monte-Carlo year (so as to model coupling constraints among control variables used in different days) or could be carried out in parallel (by neglecting the coupling among successive days).

[1] We recall that for the needs of this report, it is assumed that the TSO follows the N-1 rule as the short-term operational policy. The methodology can be updated with a different (probabilistic) operational policy.

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One important issue to cope with when designing the D-1 proxy concerns the proper handling of infeasible cases: indeed when screening various micro-scenarios combined with various outage schedules it is not unlikely that some encountered days will consist of situations where the available control means are insufficient to enable the compliance with the N-1 criterion over the full day. If this occurs, we mark the infeasible cases and compute the minimum amount of load shedding necessary in order to restore feasibility as an indicator of the severity of the infeasibility. Such information allows one to detect any violations of the N-1 security criterion (and, to the extent possible, avoid them in the context of the outage scheduling proxy).

3.3.1.2 Simulation of RT operation under N-1

While the day-ahead operation planning is a joint optimization over the 24-hour period, based on the forecast, the simulation of real-time operation is modelled in our proxy as a sequence of 24 successive security constrained optimizations of real-time (preventive and corrective control) decisions, which are based on the output of the D-1 proxy, on the one hand, and on the simulated realization of demand and renewable generation (instead of the forecast). Again, any available AC-SCOPF tool could be used at this stage, while in our tests we used a DC-SCOPF. Since the decisions at different time steps are possibly coupled (by temporal constraints on the control variables), these simulations for a particular day need in principle to be carried out in sequence, but they can be done in parallel for different micro-scenarios.

3.3.1.3 Assessing the reliability while using the GARPUR RMAC

Once both the D-1 proxy and the RT-operation proxy have been applied, we have a complete picture of the real-time situation that would be incurred for every hour of every micro-scenario, under the assumption of planning and operating the system under the N-1 criterion. The last stage is then to assess all these situations in order to determine the ‘actual’ reliability risk that would be incurred in these conditions. Therefore the last stage of our computations consists in computing the reliability level for all these situations by using a proxy of the GARPUR RMAC, taking into account a set of contingencies (typically beyond N-1), their probabilities, as well as probabilities of failure of corrective control decisions and value of lost load. This leads to large number of contingency response simulations, which can in principle be carried out all in parallel, as a post-processing step of the whole procedure. If necessary, this step can therefore take advantage of massive parallelization and comply with rather detailed models, e.g. taking into account system dynamics and stability considerations.

3.3.2 Outage scheduling proxy under N-1

Figure 3-5 below explains the nature of the outage scheduling proxy used within the policy assessment approach. For each year of the long-term study horizon, this proxy is used in order to automatically determine at which moments the various activities defined by the maintenance policy for that year should be scheduled. The detailed algorithm is presented in appendix A.1. The main idea behind this algorithm is to mimic in a reasonable way the considerations currently used by outage scheduling engineers (according to the current N-1 based practice) when they define outage-scheduling plans.

Notice that the outage scheduling proxy uses as input a set of micro-scenarios and a list of maintenance activities, and its calculations are based on the two first short-term proxies already explained in Sections 3.3.1.1 and 3.3.1.2.

This outage scheduling proxy is used for each macro-scenario and each year, in order to plan the maintenance activities while taking into account the macro-assumptions for that particular year as input (so that, as a matter of fact, the outage schedule will depend on these latter assumptions). Therefore, the

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micro-scenario generative model is first used in order to generate a set of Monte-Carlo years for that particular period and macro-assumption, and based on this sample, the proxy will determine automatically at what moment the different maintenance activities shall be scheduled, while enforcing the manpower constraints specified at the input of the policy assessment study for that year.

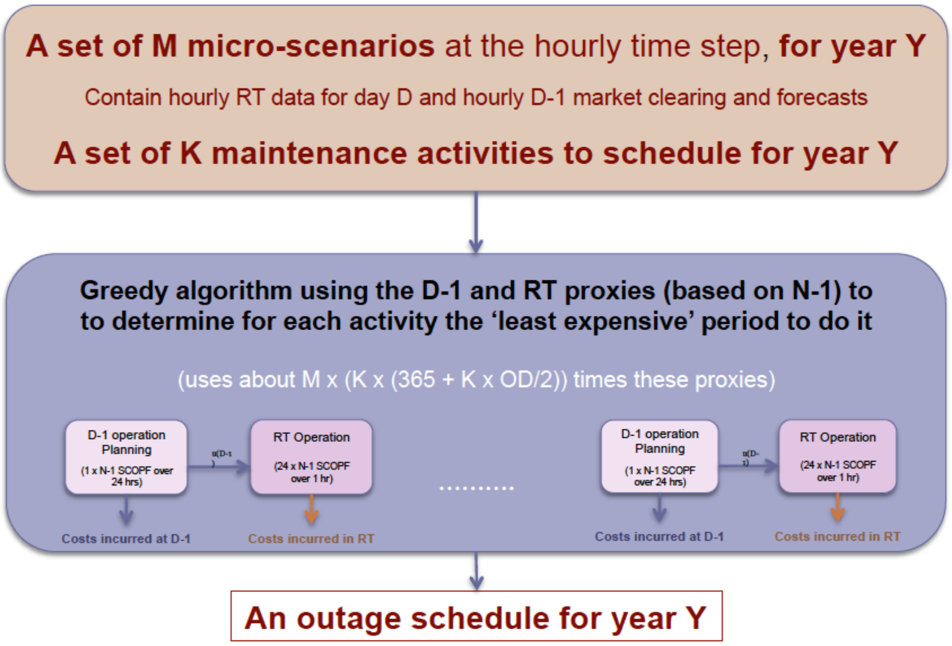

Figure 3-5: Principle of the outage scheduling proxy used within policy assessment

The description of the greedy algorithm can be found in Appendix A.1.

Appendix A.1 provides a working paper describing the proposed algorithm and giving some ideas of computational burden and parallelization opportunities. The implementation of this method is currently under development and planned to be published in the coming months. We notice that with the reliability assessment simulations of Section 3.3.1.3 the computations of the outage scheduling proxy are the most constraining ones in terms of scalability and computational resources of the whole policy assessment framework, so that their feasibility for realistic systems is of paramount importance.

We also notice that this outage scheduling proxy may be exploited independently of the maintenance policy assessment software, for example in the context of actual (real-life) maintenance scheduling activities, or, as another example, in the context of system expansion studies which also need to take into account the 'maintainability' in the mid-term. It is therefore an important result *per se* of the work carried out within WP5.

3.4 Overall description of the policy assessment algorithm

Figure 3-6 shows the overall logic of the policy assessment algorithm, while highlighting the opportunities for parallel computations.

We first notice that the second box from the top (named 'Compute the outage schedule') actually uses the proxy of Section 3.3.2 to determine for a particular year and macro-scenario assumption the appropriate moments where the corresponding maintenance activities (repair, inspect, replace) should be planned so

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as to comply with the manpower constraints and minimize N-1 security criterion violations and operating costs.

We also notice that the computations related to the determination of the 'Interruption costs' (compounded with the DA and RT decision computations in the fifth box from the top) could actually be done as a separate step after the end of all the other computations, while taking advantage of even larger parallelization opportunities (in principle all its computations for different contingencies, different control failures modes, hours, micro-scenarios could be done in parallel, given a sufficiently large high-performance computing infrastructure).

Finally, we would like to stress that the set of micro-scenarios used in box 2 (for computing the outage schedule) should in principle be different from the set used in order to carry out the subsequent steps, so as to avoid any over-fitting problem, and also because the set of micro-scenarios for the subsequent steps, should be generated by using as an input the already decided outage schedule, so as to properly reflect the possible moments where inspection triggered outages may actually occur.

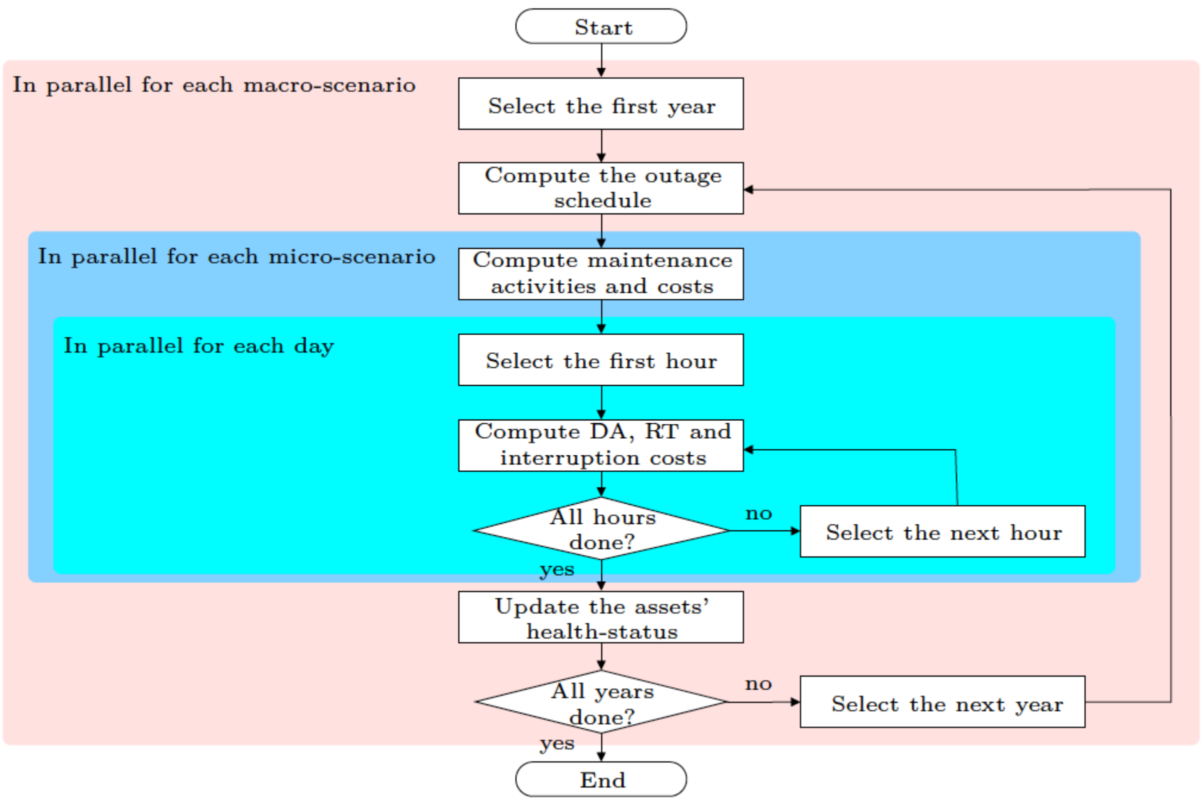

Figure 3-6: Overall description of the policy assessment algorithm

3.4.1 More detailed description of the policy assessment algorithm

In the present section we recapitulate and present a more detailed description of the proposed policy assessment algorithm. First we clarify some notations to be used in the description of the algorithm.

The maintenance policy that we want to assess is provided as an input to the assessment. In what follows, we assume that this maintenance policy is represented as follows:

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1. A vector of activity-sets, denoted by u_{act}, where each element $u_{act}[y]$ is the set of **preventive** maintenance activities to be performed during year y. These activities can be of two types:
   a) **Maintenance** activities having a direct impact on the component's condition (e.g., repairing, replacement).
   b) **Inspection** activities, conditionally triggering a preventive maintenance activity from the observation of the component's condition.

2. A vector of manpower constraints, denoted by u_{cstr}, where each element $u_{cstr}[y]$ is a set of manpower constrains applicable to year y (e.g., number of crews available per geographical zone, per month). The purpose of these constraints is to serve as an input to the outage scheduling decision-making process, as detailed further below in this chapter.

These two decisions should be consistent, i.e., restrictions expressed in $u_{cstr}[y]$ should allow for the execution of all the activities included in $u_{act}[y]$ (even those that may be triggered by inspection). Checking for such consistency constitutes the first step in assessing a policy.

Note that **corrective** (post-failure) maintenance activities are not included in the decision vector u_{act}, since they are unknown at the moment of defining this vector. Nonetheless, constraints expressed in u_{cstr} should obviously leave enough room for covering the needs of corrective maintenance.

We aim at assessing a maintenance policy by (i) its cost, and (ii) the expected condition of grid components at the end of the horizon. The former is computed as the sum of the three terms below:

1. The expected cost of preventive maintenance.
2. The expected cost of corrective maintenance.
3. The expected cost of system operation (including interruption costs) in the short-term window.

In order to compute the above indicators (cost and expected final condition), we need the following input parameters, functions and models:

1. A budgeting horizon, denoted H_{bdg} (say 20 years).

2. A set of **macro-scenarios** defined over H_{bdg} at the yearly basis. These macro-scenarios should provide all the information about exogenous factors necessary to assess long-term decisions, e.g., economic growth, committed grid expansion decisions, etc. Each macro-scenario should have associated a weight so as to represent its relative importance within the set (and the sum of all weights should be equal to one). We denote the set of macro-scenarios by S, and the weight of macro-scenario $\xi \in S$ by π_{ξ}.

3. A generative model allowing us to draw a set of **micro-scenarios**, according to their probabilities, defined over each year in H_{bdg} at the hourly basis. This model should receive at least the following inputs: (i) a macro-scenario realization for one year, (ii) the condition of grid components at the beginning of the year. The resulting micro-scenarios should provide all the information about exogenous factors necessary to take and/or assess the consequences of mid- and short-term decisions, including at least: generator outages, market clearing outcome, weather conditions, contingency probabilities, value of lost load, and **forced component outages**, and **any relevant information needed to determine the outcomes of possible component inspection activities**. Each micro-scenario should also include the day-ahead forecasts needed to determine day-ahead decisions.

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We denote the micro-scenario generative model by $Z_y = g(x_y, \xi_y)$, where x_y is the vector of component's conditions at the beginning of year y, ξ_y is the assumption of macro-scenario $\xi \in S$ along year y. The output, Z_y, is the resulting set of micro-scenarios (we leave implicit the size of this sample). We denote the probability of micro-scenario $\zeta \in Z_y$ by π_ζ.

Given a micro-scenario $\zeta \in Z_y$, and the subset of maintenance and inspection activities scheduled over its time-horizon, we can derive the inspection triggered preventive maintenance activities and hence derive the full set of scenario specific scheduled preventive maintenance activities that we denote by $A^y_{pm}(\zeta)$. Similarly, we can derive the scenario specific set of corrective maintenance activities triggered by forced outages, and that we denote by $A^y_{cm}(\zeta)$.

4. An ageing/repairing model, describing how the health-condition of grid components deteriorates/improves over time and as result of performed maintenance. This model should allow us to compute the expected condition of each asset **at the beginning of each next year**, which is used as input to the micro-scenario generative model. We denote this model by $x_{y+1} = f(x_y, A^y_{pm} \cup A^y_{cm})$, where x_y is the vector of component conditions at the beginning of year y, and $A^y_{pm} \cup A^y_{cm}$ is the set of preventive and corrective maintenance activities being carried out during that year (notice that to simplify our notations, we skipped here the dependence of these sets on the micro-scenarios).

5. An outage scheduling proxy, modelling the mid-term outage scheduling **decision-making** process. The outage scheduling proxy consists in a function which receives: (i) a set of micro-scenarios defined over one year, (ii) a maintenance sub-policy for that year (including the sub-vectors of activities and man power constraints for that year) and (iii) a set of outages defined exogenously and required by the new system development projects. The function returns the corresponding outage scheduling decision.

   The outage-scheduling proxy is denoted by $u^y_{sch} = \hat{u}_{sch}(Z_y, u_{act}[y], u_{cstr}[y])$, where Z_y is a set of micro-scenarios defined over year y, $u_{act}[y]$ is the set of maintenance activities to be scheduled during year y, and $u_{cstr}[y]$ is the set of man power constraints applicable to the same year. The output, u^y_{sch}, is the outage scheduling decision vector, where each element $u^y_{sch}[a]$ represents the starting and ending days of activity $a \in u_{act}[y]$. Note that both preventive maintenance <u>and</u> inspection activities are scheduled here. In the case of activities that do not require a component outage, the starting and ending days should be the same.

6. A cost function returning the cost of carrying out the **preventive** maintenance activities considered in the decision vector u_{act}. The cost function is denoted by $c_{pm}(A^y_{pm})$, where A^y_{pm} is the set of preventive maintenance activities carried out during year y.

7. Another cost function returning the cost of carrying out the **corrective** maintenance activities that, as mentioned above, are not considered in the decision vector u_{act}. The cost function is denoted by $c_{cm}(A^y_{cm})$, where A^y_{cm} is a set of corrective maintenance activities carried out during year y.

8. Three proxies of short-term operation:

   8.1 A **day-ahead decision-making** proxy, modelling the day-ahead decision-making process as per the N-1 reliability criterion. This proxy receives a micro-scenario forecast for one day at the

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hourly resolution and the outage schedule; it returns the corresponding hourly day-ahead plan, denoted by u_{OP}, together with its expected cost, denoted by c_{OP}.

8.2 A **real-time decision-making** proxy, modelling the real-time decision-making process as per the N-1 criterion. This proxy receives a micro-scenario realization for one hour, the outage schedule and the day-ahead plan; and returns the corresponding real-time operational decisions, denoted by u_{RT}, together with their expected cost, denoted by c_{RT}.

8.3 A **real-time assessment** proxy, modelling the assessment of real-time operational decisions as per the probabilistic RMAC described in GARPUR D2.2. This proxy receives a micro-scenario realization for one hour, the outage schedule, day-ahead plan, real-time operational decisions, and an assumption on the combined realization of a set of contingencies and corrective control failure modes; and returns the corresponding cost of service interruptions, denoted by r_{RT}.

Algorithm 3.1 below describes how to use the above parameters for determining the three terms of the maintenance policy assessment, as well as the expected final condition of grid components.

Algorithm 3.1: Expected costs of preventive maintenance, corrective maintenance, short-term operation, and expected final condition of grid components.

Input: Maintenance policy decisions u_{act} and u_{cstr}, horizon H_{bdg}, set of macro-scenarios S, micro-scenario generative model g, ageing/repairing model f, outage scheduling proxy $\hat{u}_{sch}$, short-term operation proxies $(\hat{u}_{OP}, \hat{c}_{OP})$, $(\hat{u}_{RT}, \hat{c}_{RT})$ and $\hat{r}_{RT}$, cost functions c_{pm} and c_{cm}, vector of initial component conditions x_0. **Outputs:** Expected cost of preventive maintenance C_{PM}, corrective maintenance C_{CM} and short-term operation C_{OP}.	
1	**For each** macro-scenario $\xi \in S$ **in parallel**:
2	**For each** year $y \in H_{amb}$ **in sequence**:
3	Generate a first set of micro-scenarios, and compute the outage scheduling decision using the outage scheduling proxy (together with the DA and RT proxies): $$Z'_y = g(x_y, \xi_y), \qquad u^y_{sch} = \hat{u}_{sch}(Z'_y, u_{act}[y], u_{cstr}[y])$$
4	Generate a new independent set of micro-scenarios to avoid over-fitting: $$Z_y = g(x_y, \xi_y)$$
5	**For each** micro-scenario $\zeta \in Z_y$ **in parallel**:
6	Compute $A^y_{pm}(\zeta)$ and $A^y_{cm}(\zeta)$, the sets of preventive and corrective maintenance activities being carried out in ζ.
7	Compute the cost of preventive maintenance: $$C^{\zeta}_{PM} = c_{pm}\left(A^y_{pm}(\zeta)\right)$$
8	Compute the cost of corrective maintenance: $$C^{\zeta}_{CM} = c_{cm}\left(A^y_{cm}(\zeta)\right)$$
9	Initialize the cost of short-term operation: $$C^{\zeta}_{OP} = 0$$
10	**For each** day d in year y **in parallel**:
11	Compute the day-ahead operational plan, and its direct cost using the ST proxy: $$u_{OP} = \hat{u}_{OP}(\zeta_d, u_{sch}), c_{OP} = \hat{c}_{OP}(\zeta_d, u_{sch})$$

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Add this cost to the cost of short-term operation: $$C_{OP}^{\zeta} \leftarrow C_{OP}^{\zeta} + c_{OP}$$
For each hour h in day d **in sequence**:
Compute the real-time decisions, and their cost, using the RT proxies: $$u_{RT} = \hat{u}_{RT}(\zeta_h, u_{sch}, u_{OP}), c_{RT} = \hat{c}_{RT}(\zeta_h, u_{sch}, u_{OP}),$$ $$r_{RT} = \hat{r}_{RT}(\zeta_h, u_{sch}, u_{OP}, u_{RT})$$
Add these costs to the cost of short-term operation: $$C_{OP}^{\zeta} \leftarrow C_{OP}^{\zeta} + c_{RT} + r_{RT}$$
End for (hour)
End for (day)
Update the vector of component conditions according to the activities performed in this micro-scenario: $$x_{y+1}^{\zeta} = f\left(x_y, A_{pm}^{y}(\zeta) \cup A_{cm}^{y}(\zeta)\right)$$
End for (micro-scenario)
Compute the expected costs for year y under macro-scenario ξ: $$C_{PM}^{\xi,y} = \frac{1}{\lvert Z_y \rvert} \sum_{\zeta \in Z_y} C_{PM}^{\zeta}, C_{CM}^{\xi,y} = \frac{1}{\lvert Z_y \rvert} \sum_{\zeta \in Z_y} C_{CM}^{\zeta}, C_{OP}^{\xi,y} = \frac{1}{\lvert Z_y \rvert} \sum_{\zeta \in Z_y} C_{OP}^{\zeta}$$
Compute the vector of expected component conditions for the next year: $$x_{y+1} = \frac{1}{\lvert Z_y \rvert} \sum_{\zeta \in Z_y} x_{y+1}^{\zeta}$$
End for (year)
Compute the total expected costs for macro-scenario ξ: $$C_{PM}^{\xi} = \sum_{y \in H_{bgt}} C_{PM}^{\xi,y}, C_{CM}^{\xi} = \sum_{y \in H_{bgt}} C_{CM}^{\xi,y}, C_{OP}^{\xi} = \sum_{y \in H_{bgt}} C_{OP}^{\xi,y}$$
End for (macro-scenario)
Compute the expected costs for the budget: $$C_{PM} = \sum_{\xi \in S} \pi_{\xi} C_{PM}^{\xi}, C_{CM} = \sum_{\xi \in S} \pi_{\xi} C_{CM}^{\xi}, C_{OP} = \sum_{\xi \in S} \pi_{\xi} C_{OP}^{\xi}$$

3.5 Discussion and possible refinements

The proposed approach for long-term maintenance policy assessment uses standard ideas from Monte-Carlo simulations in order to model the impact of uncertainties on the outcome of a maintenance policy. These standard ideas are combined with a certain number of models used as inputs (maintenance activities and their impact on components health-status; failure rates and logistics requirements; uncertainty models of exogenous quantities (in the form of explicitly described - trees of - macro-scenarios and automatically generated sets of micro-scenarios), as well as the definitions and the computational implementations of a set of proxies used to mimic mid-term and short-term activities in an appropriate way, by trading of the degree of fit to the reality with the computational requirements.

Given this standard framework, several bottlenecks and opportunities for improvement can be identified. In this section we will briefly identify and discuss these bottlenecks and opportunities that are left to further work beyond the current stage of the GARPUR project.

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3.5.1 Quality and convergence of Monte-Carlo estimates

Like for any Monte-Carlo approach the quality of the quantities that it can compute depend on the assumptions of the generative model used in order to sample the scenarios and then on the number of scenarios used overall, the larger being the better. Since we are at an early stage in this research, we need to plan for a systematic validation of the proposed approach, which however will not be possible to be fully carried out within the duration of the GARPUR project.

For a given generative model, we will have to assess the variance of the main indicators that will be used by the engineers at the output of the proposed assessment software, so as to estimate the number of micro-scenarios needed to estimate these quantities with sufficient accuracy. We plan to carry out these studies with standard test systems used in the literature. If the results of these studies point to difficulties when using the standard Monte-Carlo approach, we will have to investigate how variance reduction techniques (e.g. importance sampling and control variates) as well as machine learning approaches could be exploited in order to reduce the number of needed micro-scenarios and/or speed up their assessment. These possibilities will however be fully justifiable only once some prototype studies have been carried out with the current implementation and in collaboration with experts in maintenance planning, so that the analysis is indeed focused on the relevant quantities they need for their decision-making. This calls for further collaboration among method designers and method users, beyond GARPUR.

An even more difficult question concerns the certification of the quality of the generative model used in order to sample micro-scenarios. Any model being approximate, the fundamental question is to assess how these approximations affect the decisions finally taken based on the model used. Knowledge produced in the context of other EU research projects and/or published in the literature may be useful, and cross-validation studies will be required to assess the sensitivity of the outputs of the computational tool to its assumptions, and also to see how the method would have performed by using actual observations from the past. This is in itself a step that needs to be foreseen, probably at the level of each individual TSO, in order to enable his engineers to gain confidence in the method proposed. We see this as a major topic of future collaboration between some of the partners of the GARPUR project.

3.5.2 Assumptions about mid-term and short-term TSO activities simulated

In the proposed approach, we have on purpose assumed that the mid-term and the short-term activities of reliability management would still be carried out on the basis of the current N-1 criterion.

Since GARPUR aims at providing the methods and tools to move away from this way of managing reliability, the modular nature of the proposed assessment framework allows to substitute the current N-1 based proxies by any other 'optimization based formulation' reflecting possible future decision making practice at the TSO side, and in particular those proposed in WP2 of the project and adapted in WP6 to the context of system operation. Also, the mid-term outage scheduling proxy, that is itself an outcome of the GARPUR research in WP5, will certainly be able to benefit from further research both inside and beyond GARPUR (see also Appendix A.1 of this document, as well as the GARPUR deliverable D2.2 [GARPUR, 2016a] issued in parallel).

However, we think that before trying to incorporate such further enhancements, the current proposal should first be implemented and tested sufficiently well, and also confronted to the scientific and industrial community outside of the GARPUR consortium, in particular thanks to the on-going dissemination efforts of WP10.

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3.5.3 Accurately assessing component and system reliability

In order to carry out meaningful maintenance policy assessment studies, let alone their optimization, one needs to have sufficient confidence in the component ageing, repairing, and failure models used in these studies, so as to be able to believe that the impact of any maintenance activity on their performances is reasonably well taken into account.

In this respect, it turns out from our investigations within the GARPUR project that overall the knowledge about power systems’ component ageing and repairing models remains very hard to calibrate. Further work definitely needs to be carried out, including the leveraging of physical models from first principles, field experiments, the possible use of condition monitoring devices, and data pooling among TSOs and DSOs about past performances of their components. This certainly calls for more collaboration in the future years, among TSOs, DSOs and suppliers of network equipment.

3.5.4 Adjusting the temporal horizon for maintenance policy assessment

In our work we have considered an indicative period of 20 years to carry out the maintenance policy assessment. This is well adapted in many cases, and corresponds also to a horizon of system expansion studies and over which macro-scenarios could be specified in a sensible way. Nevertheless, this duration should not be understood as an intrinsic limitation of the proposed approach; both shorter horizons as well as longer horizons could be used for specific studies involving components ageing at a faster or a slower speed. In particular, in order to assess the maintenance policies of components that are still young at the current moment, or that have a very long life-time, the approach proposed can be extended by increasing the duration of the study horizon in an appropriate way. Actually, if while carrying out a study with a 20 years horizon the expert sees that some of the components health conditions are experiencing only little change over that horizon, he naturally would like to carry out a further study over a longer horizon, so as to collect some additional signals for assessing the maintenance policy.

3.5.5 Towards policy ranking and more automatic policy optimization

While in our work we have on purpose set the focus on the development of a computational methodology for the assessment of a tentative maintenance policy, the end-goal is to help engineers to optimize these policies.

A first step in this endeavour would be to be able to test and then rank several different policies in terms of their impact on some of the most important indicators found out to be useful for their assessment. While a trivial way to do this would be to use the proposed method several times to assess separately each proposed policy, we believe that it should be possible to evolve the method itself in order to facilitate such rankings, e.g. by making sure that the same set of micro-scenario assumptions is used and/or by assessing ‘gradients’ of the relevant indicators with respect to appropriately chosen search directions over the space of maintenance policies. Further research along this line may be carried out as a sequel to the GARPUR project.

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4 OUTAGE SCHEDULE ASSESSMENT PROPOSAL

Figure 4-1 describes the overall principle of the mid-term outage schedule assessment approach proposed in WP5, while highlighting the main modelling differences with the policy assessment problem presented in the previous chapter. In the present case, we consider a mid-term horizon, of (say) 1 year, and the idea is to simulate the impact of given outage schedules so as to determine the resulting costs of operation, as well as the impact on system reliability over that year. Notice that ageing and repairing models are not needed at this stage, on the one hand, while uncertainty models are not requiring the consideration of several macro-scenarios. Furthermore, since in this assessment approach the outage schedule is given as an input, the corresponding proxy (used in the policy assessment methodology of the previous chapter) becomes irrelevant.

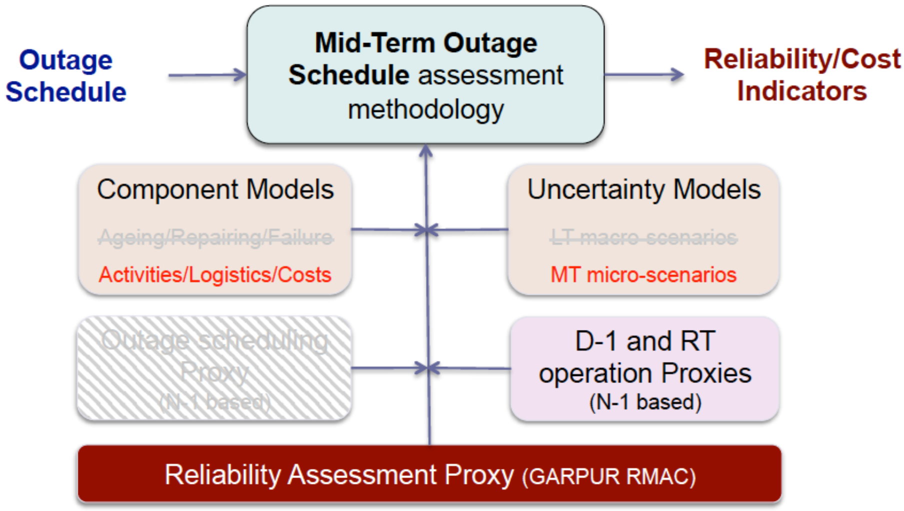

Figure 4-1: Schematic representation of the overall outage schedule assessment proposal

In the rest of this chapter, we explain the main ingredients of this approach, as highlighted in Figure 4-1, and describe more precisely the inputs and outputs of the assessment methodology. Since many of the considerations are rather close to those of the previous chapter, we will stress in our presentation the main modelling differences with respect to what has already been presented in Chapter 3.

4.1 Inputs

4.1.1 Maintenance schedules

The main input to the outage schedule assessment software is a maintenance schedule chosen by the expert to be assessed over a mid-term horizon of several months (in our presentation, we arbitrarily set this horizon to 1 year, so as to fix ideas, but in real life conditions the horizon could itself also be specified by the user).

The maintenance schedule is composed of two parts that are specified by the user over the assessment horizon:

1. **A list of scheduled maintenance activities**: each individual activity is described by a tuple [activity type, concerned grid component, start day, outage duration, cost, man-power requirements,…],

where the activity type may be 'repair', 'replace', 'inspect and conditionally repair' etc. (see Chapter 4, for more details about the notion of 'maintenance activity').

Notice that some of these activities may require component outages to be carried out, while others may not (then the outage duration is specified as being equal to zero). In contrast with the maintenance policy assessment case, here the precise moments where the activities should be carried out is already specified as an input to the study. A further simplification at this stage could be to actually model only those activities that indeed lead to deterministically planned outages, thereby neglecting the effect of corrective and inspection triggered outages; however, for the sake of generality we do not impose this simplification, and we rather leave this choice to the user of the software.

We also stress to the reader that in this assessment method of a given outage schedule, the potential coordination between the outages of transmission assets with the maintenance of specific generation units or industrial customers is embedded in this list provided as input.

2. **A set of manpower constraints**: they express, for every zone of the network the total amount of human resources that can be devoted to maintenance activities on the components belonging to that zone. These constraints may be defined over any suitable set of sub-periods covering the study horizon, e.g. at the daily, weekly or monthly resolutions.

   Notice that these manpower constraints are only used in order to display the result of the study, but otherwise do not intervene in the assessment procedure. They may thus be used by the engineer to check *a posteriori* that his plan (combined with the corrective and inspection triggered maintenance activities) seems indeed feasible for a large enough proportion of the possible future situations.

4.1.2 Uncertainty model

In the context of mid-term outage scheduling the macro-assumption is supposed to be deterministic, so that there is no need to consider multiple macro-scenarios. Therefore, the set (or tree) of macro-scenarios is replaced here by a fixed dataset describing a certain number of fixed input parameters to the study, such as the available generators (and their already known maintenance periods), and such as the failure models of the network components (which are assumed to be unaffected by the studied maintenance plan, and where also ageing is neglected, given the shorter time-horizon of the study).

On the other hand, the main objective being to assess the feasibility of the maintenance plan with respect to uncertainties in the operating conditions, the latter uncertainty is modelled in details in the form of a representative sample of micro-scenarios. The sample of micro-scenarios is assumed to be generated by using the same kind of generative model than the one used in the context of long-term policy assessment. This allows one, in particular, to take into account the activities described in the maintenance plan so as to generate micro-scenarios that also realistically model (stochastic) inspection triggered and corrective outages that could occur during the study period, in addition to the planned outages specified in the maintenance plan. Again, let us however notice that this degree of sophistication may be deemed useless in some practical studies, so that one could use instead a set of micro-scenarios that would be obtained in a way completely independent of the considered maintenance plan.

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4.2 Outputs

The main focus of outage scheduling being to place the outages in such a way that the activities can be carried out given the crew limitations, while the impact on system operation is acceptable according to the reliability criterion used, the output computed shall focus on the impact on operating costs on the one hand, and on system reliability on the other hand. In addition, if corrective maintenance and inspection triggered maintenance activities are modelled in the simulation, proper information about the occurrence of these activities (integrated over the sample of micro-scenarios), should of course be displayed as well.

Below we will focus on the presentation of the operating costs and resulting reliability levels, in such a way that they could be usefully exploited by the software user in order to detect possibilities for improving the schedule, e.g. by changing the starting times of some of the activities, or by requesting exceptional actions such as live work.

4.2.1 Cost indicators calculation and visualisation

There are three types of costs: costs of maintenance activities costs of day-ahead operation planning decisions, and costs of real-time operation decisions. The two latter are computed for each micro-scenario respectively for each activity, day and hour. Their sample averages and standard deviations can then be displayed side-by-side, along a time axis, and suitably integrated over days, weeks, or months, so as to identify periods of higher and lower cost.

Besides, the costs of maintenance activities encompass costs related to logistic, third-parties contracting, contracting with generators or industrial customers, and any extra cost related to the procedure of carry out the operation, such as helicopter assistance or live work. These costs of maintenance activities are not computed by the proposed assessment methodology. In practice, the outage planner will be interested in comparing two slightly different schedules for the same set of outages to plan. Consequently, what is of interest here for the outage planner is not determine the overall costs of maintenance activities, but just the difference that exist between those two alternatives. Classically, the questions at stake are *should I request live work for the maintenance of such line* or *should I postpone such outage although it means extra costs due to contracting with some generation unit*?

In order to better appraise the actual impact of the maintenance plan, we propose to compute these costs twice, once for a base case (where, e.g., all micro-scenarios are assessed without any outages at all) and once for the given plan, so that the difference between these two hypotheses could be computed and then displayed on the same graphic in order to actually highlight the impact of the maintenance plan on these costs terms. Notice that we expect the standard deviations of these differences to be smaller than those of the absolute values of the corresponding indicator, thereby allowing a more precise assessment of the proposed outage schedule, for a same number of micro-scenarios.

Notice that the operating (day-ahead and real-time) cost terms are computed by using the short-term N-1 based proxies briefly discussed in section 3.3.

4.2.2 Reliability indicators calculation and visualisation

Similarly to what has been proposed for policy assessment in Chapter 2, once the day-ahead and real-time operating decisions have been computed for each micro-scenario and each hour of each day, a post-processing stage can be applied to the resulting operating scenarios, in order to compute for each hour the reliability level of the system, while taking into account locations and VOLL in the computation of expected

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interruption costs. This can be done by using the 'reliability assessment proxy based on the GARPUR RMAC', already described in section 3.3.1.3 .

In a similar style to what is proposed for the cost indicators, we propose to run the reliability assessment proxy twice over all micro-scenarios, i.e. once for a base case (e.g. without any planned maintenance activities, or for a base outage schedule that we want to improve) and once while imposing the given plan. We can thus display not only the absolute level of reliability for the two runs (in the form of their sample average and standard deviation) but also the sample average and standard deviations of their differences. The same variance reduction effect as for the assessment of operating costs is also anticipated in the context of reliability estimation.

4.3 Possible uses of the outage schedule assessment algorithm

The proposed assessment software is envisioned as a basic brick that could be used by maintenance planners in order to define and update their outage schedules over the year. In the present section we discuss various different use-cases that may be of interest.

1. **Re-assessment of a fully defined maintenance plan**: this is basic use case that was considered in order to define the requirements of the software; it consists of evaluating the different cost terms, based on the most recent information about the exogenous factors (such as generators planned outages, unforeseen market conditions, recent failures of some network components) that may change over time and hence ask for re-assessing a plan that was previously designed.

2. **Drafting a new plan from scratch**: in this use case, the maintenance engineer starts with a list of maintenance activities that he needs to schedule for the next period (say Year +1), without yet knowing what are the best periods to place the corresponding outages. In this context, the maintenance scheduling proxy, developed for long-term maintenance policy assessment in Chapter 2, could be used in order to provide a first guess of an appropriate scheduling of the activities, and this latter schedule could then be evaluated by using the detailed outage schedule assessment software of the present chapter. Alternatively, the outage schedule assessment software could be used in interaction with the maintenance planner's ideas, in order to compare various alternative schedules, in order to detect potential directions for improvement.

3. **Improving maintenance-scheduling proxies**: the software could be used in off-line mode in order to compare different versions of the outage scheduling proxy of Chapter 3, and so help us in designing a more efficient and/or a more accurate one, that could then be substituted to the existing version used in the context of long-term studies.

4. **Learning faster short-term operation proxies**: the datasets generated while running the software could be exploited by machine learning algorithms in order to learn automatically some input-output functions that well approximate the decision making processes in short-term operation that we need to simulate when carrying out mid-term and long-term studies.

5. **Learning simple outage scheduling rules**: in order to speed up the iterative process of schedule optimization, one could use off-line the proposed tool, together with a clever sampling of outage schedules, in order to figure out simple rules that would allow one to quickly identify proposing schedules for a given system.

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Notice that depending on the considered use-case, one may use the proposed software with different sets of micro-scenarios and while using more or less simplified versions of the shorter-term proxies. We leave the investigation of these further possibilities to subsequent R&D efforts.

4.4 Discussion and possible refinements

The considerations that we have presented in Chapter 3 mostly hold as well in the context of the present chapter, with the main two following modifications:

1. The simulation of micro-scenarios is easier to validate in the mid-term context of outage scheduling than in the long-term context of maintenance policy assessment.
2. Outage scheduling does not need to rely on valid component ageing and repairing models, and therefore would be easier to automatize in practice.

We stress that WP2 has worked in parallel with WP5 on the design of outage schedule optimization methods; we refer the interested reader to D2.2 [GARPUR, 2016a] for a presentation of the main ideas concerning this optimization problem and the proposed algorithms.

On the other hand, Appendix A.2 of the present document provides further details about the proposed outage schedule assessment method and some preliminary results of using it in the context of some academic test systems. It also presents some already convincing first results of the idea of coupling machine learning (using a nearest neighbour approach in the context of day-ahead operation planning) with the scenario simulation approach, so as to speed significantly up the overall methodology.

Finally, let us acknowledge the fact that the market behaviour has been considered as exogenous to the whole design of the maintenance schedule assessment software, since it is in our approach modelled as part of the micro-scenario generative model. Nevertheless, in practice outage-schedules may in some systems more or less strongly influence transmission capacities given to the market clearing mechanism, and hence have an influence on its performance. This can be taken into account in the proposed approach by exploiting the fact that the micro-scenario generation software (see Chapter 7 of this document) takes indeed as input the outages that are scheduled (once there schedules are determined), and hence can in principle take these latter into account in order to determine the market clearing for each micro-scenario. Indeed, in principle in the context of D-2 operation planning the TSO provides so-called network capacities to the market operator, and the latter takes this information into account when determining the market clearing. Thus, to take into account the impact of outages on the market performance, the micro-scenario generative model would have to take into account the information about network capacities, when determining in a given micro-scenario how the market outcome would play out. On the other hand, the determination of network capacities in D-2 operation being endogenous to the TSO, one would have to complement the outage schedule assessment by another 'proxy' used to compute these capacities according, in faithful enough way, with actual TSOs' practice. Finally, in order to assess the impact on the market surplus, the micro-scenario generator would thus need to also return the corresponding economic indicators, which could then be displayed in combination of the other cost terms, and used by maintenance planners to avoid placing the outages at moments where their impact would be deemed unacceptable in this respect.

Along a similar idea to what has been explained in Chapter 3, we would like to stress that the outage schedule assessment method, currently presented to assess a single outage schedule, could as well be upgraded to rank various candidate schedules (by exploiting the idea that when using a same set of exogenous scenarios to assess several outage schedules in terms of the differences in the implied

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indicators, there will be a 'free-of-charge' variance reduction effect). Similarly, there is the possibility to assess the 'gradient' of these cost functions along sensible directions of search in the space of outage schedules. We leave the exploration of these promising directions of further research to work outside of the scope of the GARPUR project.

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5 MODELING THE MAINTENANCE ACTIVITIES

The focus of this chapter is to elaborate on how to describe maintenance policies in a form that can be given as input to the maintenance policy assessment problem, as described in Figure 3-1. Notice that in the remainder of this chapter, we abusively incorporate the inspection and renewal activities within the term "maintenance".

Subsequently, the evolution of the assets condition (which is maintenance-dependent) and thus their failure rates will be modeled, which will enable to evaluate the risks of energy not supplied. The benefit of maintenance activities on the condition of the asset is addressed in chapter 6.

First, we describe what a maintenance policy is from the perspective of a TSO, with the different kind of possible asset management activities and the corresponding triggers. Then we show how to translate such description into a format that can be given as input to the maintenance policy assessment methodology.

5.1 Description of maintenance policies in a TSO language

5.1.1 Organization of maintenance activities

Figure 5-1 depicts a way in which maintenance activities can be implemented by the TSO. In this figure, several kinds of asset management activities are represented.

Corrective maintenance: has to be applied after the equipment has failed. The corrective maintenance can be immediate or deferred depending on the criticality of the equipment regarding the whole system.

Preventive maintenance: such activities are undertaken while the component is still working, in order to avoid future failures. The aim is to maintain the equipment condition at a given (acceptable) level or even to extend its lifetime (if possible).

Several options can be considered by the TSO:

- **Predetermined activities;** the operation of repair or replacement is realized at regular intervals or from a certain age without any inspection or diagnosis being done beforehand.
- **Condition-based activities;** the operation is performed when a specific condition is satisfied, this condition being detected following an inspection and diagnosis activity (notice that in our simulations, the likely outcome of an inspection will be based on the 'simulated' health-condition, and incorporate the fact that inspections may miss some hidden failures, with a suitably chosen probability of 'non-detection').
- **No action**; no operation is performed on the equipment; the TSO reckons it is best to wait until the equipment fails.

Figure 5-1 also displays a *transition criterion*. This criterion corresponds to the condition when the equipment should no longer be maintained but instead should be replaced by a new one. Such condition can be related to the physical age of the equipment, or more subtly could be a virtual age that would take into account the influence of the environment (e.g. pollution level), criticality of the asset with regards to the whole power system, sustained stress,…

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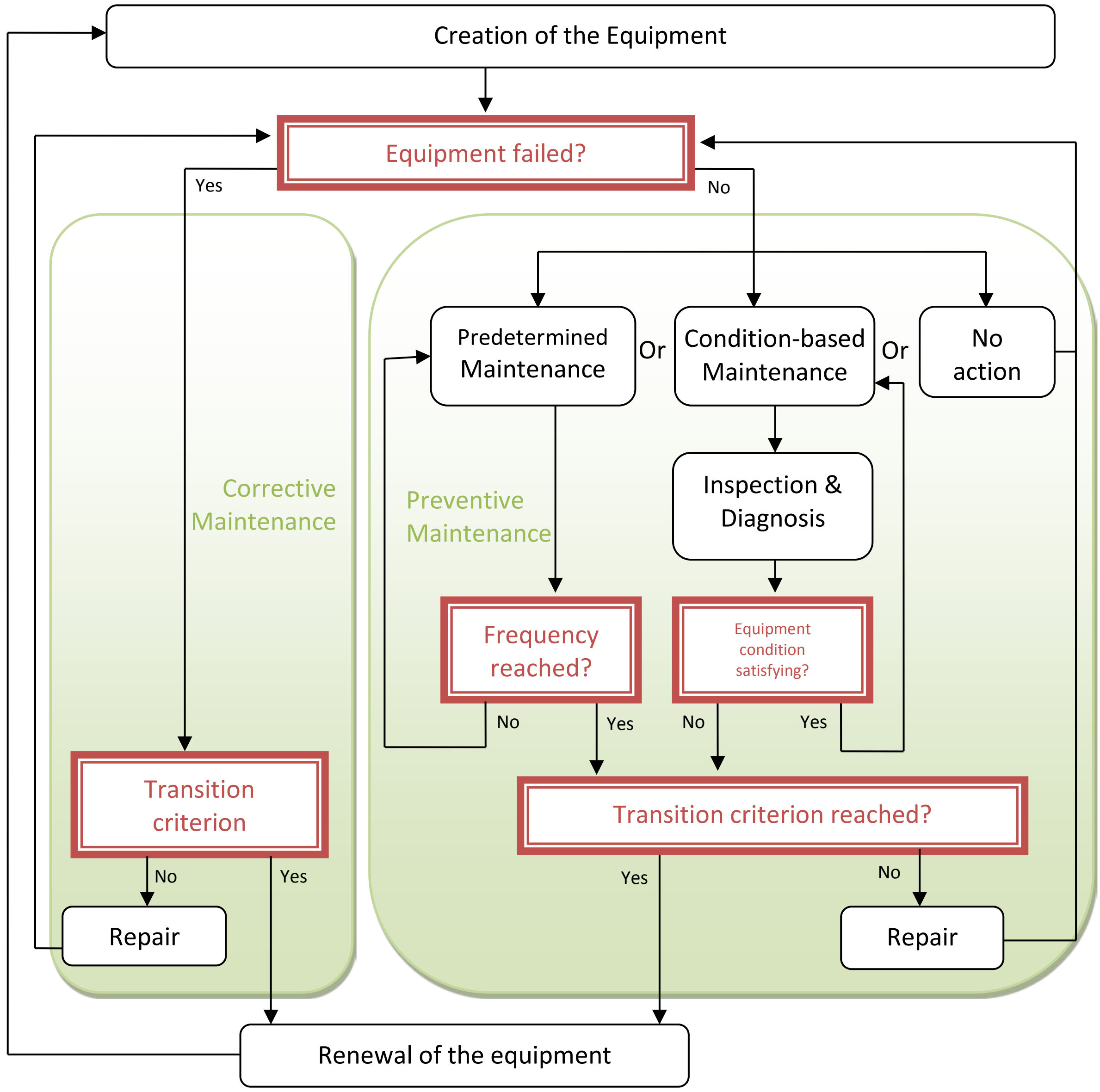

Figure 5-1: Organization of maintenance activities

5.1.2 Realistic description of maintenance activities for overhead lines and cables

Obviously, the parameters for each activity, e.g. cost, duration, crew requirements, as well as the triggers for asset management activities are TSO specifics. Similarly, the level of accuracy of the modeling can also be tuned depending on the specificities the TSO wants to model.

5.1.2.1 Corrective maintenance

In the following paragraphs we refer to the left side of Figure 5-1.

Overhead lines

There are two major kinds of failures for overhead lines: those related to the conductors and their accessories, and those related to towers. As the failures of towers are quite rare compared to the failures of conductors, they can be neglected in the first place.

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The following table gives classical human resources and financial costs related to corrective maintenance for overhead lines:

Table 5-1: Corrective maintenance activity for overhead lines

Corrective maintenance	Activity	Number of operators	External Cost	Duration	Outage needed
Overhead lines	Repair	4	25k€ /km	1d /km	Yes

Notes: The cost for overhead lines is different in repair than in renewal (see §4.3) because the repair for overhead lines consists of replacing just the piece of conductor which failed, not the whole section of the line. In that case, the section of line where the repair took place is considered to be As Bad As Old. In the table the "external costs" refer to all costs (material, logistics, third-parties intervention) except for the work performed by the crews belonging to the TSO.

Underground cables

There are two major kinds of failures for underground cables: those related to the cables and their accessories, and those related to the extremities of the cable. Both of these failures can be agglomerated into one failure mode, represented by the cables.

The following table gives classical human resources and financial costs related to corrective maintenance for underground cables:

Table 5-2: Corrective maintenance activity for cables

Corrective maintenance	Activity	Number of operators	External Cost	Duration	Outage needed
Underground cables	Repair	4	1000k€ /km	15d /km	Yes

One specific constraint that has to be taken into account is related to underground cables located in urban areas: lots of urban cables are located near roads. Therefore, operations are usually delayed because TSOs need specific authorization to open roads. To model this fact, we can assume a delay of one week per operation when a failure occurs.

Notes: The cost for underground cables is the same in repair and in renewal, because the repair operation consists in replacing the whole section of cable. In that case, the section of cable is considered to be As Good As New.

5.1.2.2 Preventive maintenance

In the following paragraphs we refer to the right side of Figure 5-1.

Overhead lines

In order to model the different maintenance activities performed on overhead lines, we suggest to consider 3 sets of activities:

- **Regular maintenance**; contains the different inspection activities and a general repair activity that may be triggered following the outcome of the inspection and diagnosis. We recall that a possible model to represent the degradation process of the assets is given in chapter 6, and that an inspection activity should reveal this condition state to the TSO who may subsequently decide to undertake a repair in case the equipment is in a bad state.

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- **Painting;** each tower is regularly painted.
- **Vegetation trimming;** A main cycle exists which is interval based. The frequency depends on the proximity of the trees to the line and of a vegetation growth rate. In addition, there are ground inspections which can trigger additional tree trimming activities.

The following table gives classical human resources and financial costs related to those preventive maintenance activities for overhead lines:

Table 5-3: Preventive maintenance operations for overhead lines

Preventive maintenance	Activity	Frequency (each X years)	Number of operators	External Cost	Duration	Outage needed
Regular Maintenance	Mounted inspection	6	4	-	1d /km	Yes
	Ground inspection	6	3	-	0,25d /km	No
	Helicopter inspection	3	2	1k€ /km	0,01d /km	No
	Repair	-	4	50k€ /km	1d /km	Yes
Painting	Painting	10	1	4k€ /km	1d /km	Yes
Trimming	Ground inspection	1	1	-	0,25d /km	No
	Trimming	-	1	3k€ /km	0,15d /km	No
	Main cycle	8-15	Depending on the amount of trees to be cut	3-5 k€ /km	Depending on the amount of trees to be cut	No

Notes: the different kinds of inspections activities differ in terms of speed of realization, and also in terms of the probability of missing some situations that would need to launch maintenance/repairing operations; obviously the degree of faithfulness of the modeling of the outcomes of inspection activities depends on the degree of detail covered by the model of the health-condition of the considered component/sub-component.

Underground cables

For underground cables, we propose to assume a simple mechanism similar to the regular maintenance for overhead lines. We consider frequency-based inspections which can trigger a repair activity if the cable is detected to be in a bad state.

The following table gives classical human resources and financial costs related to those preventive maintenance for underground cables:

Table 5-4: Preventive maintenance operation for cables

Preventive maintenance	Activity	Frequency (each X years)	Number of operators	External Cost	Duration	Outage needed
Regular maintenance	Inspection	3	3	-	2d /km	Yes
	Repair	-	4	1000k€ /km	15d /km	Yes

Notes: some TSOs own sea-cables (AC and HVDC cables). The maintenance activities can be summarized as for the underground cables, the parameters to compute costs can be also simplified to match the model proposed above. Of course the costs (especially with inspection and repairs which involve surveys by boat) will be substantially higher.

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5.1.2.3 Renewal

Overhead lines
For overhead lines, the transition criterion to transfer the line from the maintenance policies to the renewal policy can be the physical age of the line, i.e. the age since the line was installed or lastly renewed.

The following table gives classical human resources and financial costs related to renewal policy for overhead lines:

Table 5-5: Renewal operation for overhead lines

Renewal policy	Transition criteria	Activity	Number of operators	External Cost	Duration	Outage needed
Overhead lines	Age = 65 years old	Replacement	0	250k€ /km	4d /km	Yes

Notes: here we assume renewal operations are performed by TSOs subcontractors. Consequently, in this case, the number of operators is set to 0.

Underground cables
Similar to overhead lines.

Table 5-6: Renewal operations for underground cables

Renewal policy	Transition criteria	Activity	Number of operators	External Cost	Duration	Outage needed
Underground cables	Age = 65 years old	Replacement	0	1000k€ /km	15d /km	Yes

5.1.3 Possible enhancement of the description of the asset management activities

The tables above describing possible models of maintenance activities can be declined in many forms, all TSO-specifics. However we can introduce two variants of interest for the asset manager:

Live work and other exceptional measures: for a set of overhead lines, one could propose to recourse to live work, night work, or any exceptional mean to reduce the outage duration. In such case, the costs for the activity would be higher, but the duration would be shortened or the outage for maintenance would no longer be needed.

Asset condition monitoring devices: installing such devices would have a purchase cost and theoretically maintenance costs as for any family of equipment. They could be included in our maintenance model as an inspection activity with no cost and a very high frequency.

5.2 Conversion into a format readable by the policy assessment problem

The maintenance policy assessment methodology requires a list of all activities to be undertaken per year for a period of time of an order of magnitude of 20 years. Our aim in this section is to translate the description of the activities and triggers from section 5.1 into such list.

Let’s call $u_{act}[y]$ the set of activities to be carried out during year y, we seek the vector U_{act_policy} where

$$U_{act\_policy} = [u_{act}[0], u_{act}[1], \ldots, u_{act}[y_{max}]]$$

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The **timed-based activities** are easy to handle and can be anticipated over the full time-horizon from the beginning. Of course in real-life some disrupting events will occur and modify the theoretical plans, however this scheme is expected to be sufficiently reasonable and enables tractability. At this point, we can fill U_{act_policy} with the time-based activities.

The tricky activities are the **condition-based activities** and the **corrective activities,** which are unknown at the beginning because they depend on unforeseeable future events. Fortunately, their amount can be grossly predicted based on the condition-state of the assets and on the amount of maintenance undertaken.

To determine these maintenance activities, one has to proceed year-by-year. At the beginning of each year, the actual health-states of the assets are computed (cf. chapter 6). Therefore, we can deduce which of the inspection activities will trigger condition-based operations. Concerning the faster 'degradation processes', like for example the growth of trees, they could be modeled at a faster time-scale, e.g. based on the simulated meteorological conditions which may differ from one micro-scenario to another, and by using a monthly time step to model this variability.

In the same manner, from the above-mentioned health-states it is possible to infer failure rates for the assets over the year. Ideally, these failure rates should also vary throughout the year to account for the spatio-temporal variations of the failure rates due in particular to the weather conditions, which are season-dependent. So, for each micro-scenario, it is possible to draw a list of asset failures that will request corrective maintenance, with their costs and needs in terms of human resources.

At this point, for the current year we have all the time-based, condition-based, and corrective maintenance. It is then possible to refresh the health-states of the assets accordingly and to move to the next year.

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6 COMPONENT AGEING, MAINTENANCE AND FAILURE MODELS

In the present Chapter we outline the main features of the component ageing and repairing models that have been proposed in Task 5.2, and then further adapted in Task 5.3 to the needs of the maintenance policy assessment approach proposed in Chapter 3.

We start by summarizing the main ideas of the generic modelling framework in Section 6.1, and then outline in Section 6.2 its application to the rather complex case of overhead lines, on which we decided to focus our practical work in T5.3. Appendix A.3 gives a more detailed report on the current status of this on-going modelling work.

6.1 Generic grey-box modelling approach

Without aiming at modelling the detailed physics of the ageing processes, the model is based on the decomposition of a full network component, such as a line, a transformer, or a cable, into a set of subcomponents (conductors, towers, corridors…) that make sense from the physical point of view (and hence also in terms of maintenance activities, and in terms of modelling the impact of subcomponent health-status on the failure rate of the overall component). We therefore call this a 'grey-box' approach.

The overall model is thus built up in four stages, namely: i.) a natural ageing model of the health condition of each subcomponent, ii.) a model of the impact of maintenance activities on subcomponent health condition, iii.) a model of subcomponent failure rate as a function of its health condition and its operating condition and iv.) a proposal for compounding these subcomponent failure models into an overall failure and repair model of full network components. In Section 6.2 we illustrate these steps in the case of overhead transmission lines.

6.1.1 Hybrid discrete-continuous ageing model of subcomponents

We propose to model the health condition of a subcomponent by a combination of continuous and discrete state-variables, which together well represent the 'effective age' of the component.

For the sake of notational simplicity, we assume in this chapter (without limitation) that there is only one variable of each type, i.e. that the health-state is represented by a pair $(\boldsymbol{x}, \boldsymbol{r})$, where $\boldsymbol{x}$ is a positive real number, equal to zero for a new subcomponent and increasing over time to reflect the degradation of the subcomponent (e.g. $\boldsymbol{x}$ could denote the corrosion level of a tower), and where the integer valued index $\boldsymbol{r}$ represents the current regime in which the component degradation process may be (say, from ($\boldsymbol{r}$=1) when the component is new, to ($\boldsymbol{r}$=K), when the component is old), where K is the number of regimes deemed necessary in order to model with sufficient accuracy the different phases of the ageing process. Furthermore, the model takes into account the impact of exogenous processes (to account for the component usage attributes, and those of its natural environmental conditions, which indeed impact the speed of ageing). We denote this latter information abstractly by the variable $\boldsymbol{s}$ in what follows. Finally, the dynamics of the ageing process are modelled as a stochastic process, so as to also take into account the fact that many of the physical details will have to be neglected in practice.

The proposed dynamic model of the *continuous part* of the health state is as follows:

$$\boldsymbol{x}(t+\delta) = \boldsymbol{x}(t) + \boldsymbol{k}(\boldsymbol{x}(t), \boldsymbol{r}(t), \boldsymbol{s}[t, \dots, t+\delta]).\,\delta + \boldsymbol{\xi}$$

where: δ is the elapsed time between state transition modeled,

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$\boldsymbol{k}$ is the expected ageing rate function; typically this rate is increasing when the degradation regime $\boldsymbol{r}$ is increasing,

$\boldsymbol{\xi}$ is a zero mean random variable which variance may be tuned in order to model the non-explained phenomena given the details described in the state and environment variables.

The dynamics of the *discrete part* of the health state is described by a left-right semi-Markov model assuming that the transition time $T(\boldsymbol{r})$ from a particular regime $\boldsymbol{r}$ to the regime $\boldsymbol{r}+1$ has a probability distribution that is possibly dependent also on the value of the continuous state variable and on the exogenous process. The terminal state ($\boldsymbol{r}$=K) of this model is an absorbing state, meaning that once the subcomponent is in this regime, it will remain there forever, unless some renewal activity is carried out.

To derive such a model for a particular subcomponent of a given network component, we use a combined physical-statistical approach, which consists in determining the form of the model based on physical principles, and then in using statistical techniques to estimate the values of the parameters of these models based on available data.

For the needs expressed in Chapter 3, we will consider that the time step δ is equal to one year, and that the actual component usage is neglected in the modeling of the exogenous factors impacting the ageing process, so that only the local natural environment (i.e. the physical location, and its assumed climatic and weather conditions) is taken into account in the variable $\boldsymbol{s}$.

6.1.2 Modelling the impact of maintenance activities of subcomponents

The impact of maintenance activities on the health-condition is expressed separately for the continuous and the discrete part of the health-condition state-vector, as follows:

1. $\boldsymbol{x}[t \text{ after } A] = \boldsymbol{x}[t \text{ before } A]\big(1-\boldsymbol{b}(A)\big)+\boldsymbol{\xi}(A)$, where the factor $\boldsymbol{b}(A)$ represents the expected benefit of the maintenance action A and $\boldsymbol{\xi}(A)$ expresses any variance around it.
2. A (typically) right-left probability transition matrix on the value of $\boldsymbol{r}(t)$, so as to model the possible impact of the activity on the ageing regime of the subcomponent.

   Notice that, if the activity does not lead to a change of the discrete state, it may however lead to an extension of the amount of time the subcomponent may still reside in its current state. This may be modeled by increasing the expected value of the transition time $T(\boldsymbol{r})$ for the current state.

The function $\boldsymbol{b}(A)$, the transition matrix, and the impact on transition time distributions need to be determined on the basis of available data and/or on the basis of expert judgment.

6.1.3 From subcomponent health state to full component failure rate

To enable the use of our ageing models, we also need to infer from the health condition of subcomponents the failure rates of full network components, such as lines, transformer and cables. By failure of such a component, we mean a situation where the component will trip and then be unavailable for a certain period of time, and possibly need some corrective maintenance to become functional again.

In principle, each network component may move towards different 'failure states' depending on the actual failures of its different subcomponents, and hence leading to corrective maintenance and repair times which may be variable from each failure state to another. While we do not insist on this level of detail in

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our models[2], we however want to distinguish at least among outages triggered by protection equipment (distance and overload protections) which can be cleared in real-time by the operator with out any need for corrective maintenance, and those that are related to an 'actual subcomponent failure' that would need some corrective maintenance activity to be carried out before putting the component back into operation. Indeed, making this distinction is paramount for the assessment of maintenance policies, and to take into account their impact on component failure and forced outage rates.

Thus, in order to model these component-wise failure rates, we need to distinguish among those forced outages that are indeed related to a sudden subcomponent failure (possibly triggered by environmental conditions) and that indeed need corrective maintenance before the component can be put back in operation, and those that are merely due to the triggering of overload and/or short-circuit protections and that can be handled by quickly putting the component back into operation via mere switching operations, once the external fault has been cleared.

Hence, a simple model to express overall component failure rate is to express it as the sum of its various subcomponent failure rates, by taking into account only those subcomponents which individual failure would in itself cause the outage of the whole component (in the case of more complex situations, a more complex graph could be designed to relate the causal mechanisms of individual subcomponent failures to full or partial component outages, but the development of such models is beyond the scope of the present document). To be accurate enough, on top of these subcomponent induced failures, a fully exogenous failure mechanism independent of the component health condition should be modelled as well; this can be done by simply adding a 'dummy' subcomponent with a constant age and which failures would hence be purely explained by the environmental condition.

Subcomponent failure rates are time varying and typically depend on both the health-condition of the subcomponent and on the external environmental conditions at the concerned instant. We propose therefore a model in the form:

$$\lambda(\boldsymbol{x},\boldsymbol{r},\boldsymbol{w}) = k_{FR}(\boldsymbol{x},\boldsymbol{r}) \cdot \lambda(\boldsymbol{w}),$$

where $\boldsymbol{w}$ denotes the current external environmental (e.g. weather) conditions, and where $k_{FR}(\boldsymbol{x},\boldsymbol{r})$ is positive factor allowing one to express how the failure rate λ increases as a function of the degradation process modeled by the pair $(\boldsymbol{x},\boldsymbol{r})$.

In particular, this model allows one to discretize the weather conditions according to the current practice at ENTSO-E (normal, bad, very bad) and take this into account in the definition of the function $\lambda(\boldsymbol{w})$. If we consider the overall failure rate of the network component, we will assume that its failure rate is the sum of the individual subcomponent failure rates (including the dummy component modeling the purely exogenously driven outages).

The next section briefly explains how this generic modeling framework could be applied to the case of overhead lines.

[2] In our work, we also did not try to model the impact of the degradation state of a subcomponent on the durations and on the budget of its preventive, inspection induced or corrective maintenance activities (e.g. to take into account the fact that tree trimming may cost more and take longer, if we carry it out at a later stage).

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6.2 Illustrative application to overhead lines

In principle the above kind of model is sufficiently generic in order to be applied to any kind of network component. In T5.3 we have focused our investigations on the application of this type of model to the case of overhead lines, so as to highlight the features of the model and the way its parameters may be estimated from available data, in a both useful and already rather complex case. The details of this study are provided in the Appendix A.3. In the rest of this section we merely outline its main ideas.

The subcomponents that we have considered for the modelling of overhead lines are the following ones: towers, conductors, earth-wires, insulator strings, anti-vibration elements, and vegetation in the vicinity of the lines (we use the term corridor to denote this latter ‘subcomponent’ in the rest of this chapter). These individual subcomponents of a whole set of lines are further grouped according to their technology and also according to their environmental conditions (by using the notion of environmental zone). Inside each combination (technology, zone) the structure and the parameters of the subcomponent model may then be chosen and tuned by pooling the available data about all the corresponding subcomponents. Notice that a particular line may traverse several environmental zones, so that some of its subcomponents may degrade at faster rates then some others.

6.2.1 Example: overhead line towers’ corrosion and maintenance model

For example, considering towers of overhead lines, the proposed model concerns their corrosion only and is composed of the following elements (where we also illustrate indicative values of the different parameters; notice however that these values are to be estimated from actual data):

- $\boldsymbol{k}(\boldsymbol{x}(t), \boldsymbol{r}(t), \boldsymbol{s}[t, \dots, t+\delta]) = \boldsymbol{k_r}(\boldsymbol{r}) \cdot \boldsymbol{k_s}(\boldsymbol{s})$
- Three possible corrosion zones to model in a discrete way the impact of the environment $\boldsymbol{s}$: low, moderate, or severe environment, corresponding to scaling the corrosion rate $\boldsymbol{k}$ respectively by $\boldsymbol{k_s} = 0.5$, 1, and 2.
- One single continuous state variable $\boldsymbol{x}$: percentage of corrosion (between 0 and 100%)
- Four possible corrosion regimes ($\boldsymbol{r} = 1, 2, 3, \text{or } 4$): 1 = good ($\boldsymbol{T}(1)$ = 30 years), 2 = poor ($\boldsymbol{T}(2)$ = 10 years), 3 = bad ($\boldsymbol{T}(3)$ = 5 years), 4 = destroyed (once 100% corrosion is reached, i.e. typically after 40-45 years, in moderate environment and assuming no maintenance).
- Corrosion rates increasing exponentially when $\boldsymbol{r}$ increases: e.g. $\boldsymbol{k_r}(\boldsymbol{r}) = 0.2$%/year in the good regime, $\boldsymbol{k_r}(\boldsymbol{r}) = 4$%/year in the poor regime, and $\boldsymbol{k_r}(\boldsymbol{r}) = 15$%/year in the bad regime.
- Two different maintenance activities: “basic cleaning and painting”, “extended cleaning and 2x painting”, where only the second one has a beneficial impact on the corrosion rate, while the first one only extends the amount of time the component may remain in its current corrosion regime.

The state diagram of Figure 6-1 illustrates the discrete corrosion regimes of towers. In this diagram, the solid arrows indicate the left-right transitions corresponding to natural ageing, whereas the dashed arrows indicate the impact of possible maintenance activities on the corrosion regime. For example, when being in regime $\boldsymbol{r}$ = 3 (bad), only “extended cleaning and 2x painting” would be carried out and this would bring the tower back to state 2, whereas in state 2, the same action would bring the tower back to regime 1, while the “basic cleaning and painting” action would only increase the expected value of $T(\boldsymbol{r})$**.**

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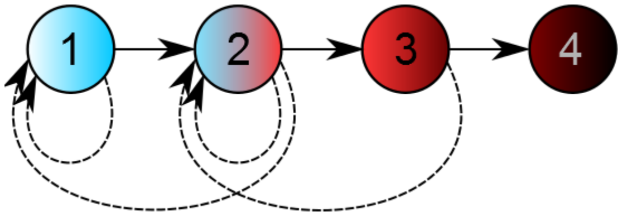

Figure 6-1: State transition diagram of corrosion regimes of towers (with maintenance shown)

Figure 6-2, on the other hand illustrates the continuous exponential evolution of the corrosion rate of a tower, where the different slopes (denoted as "phases" on the graphic) actually correspond to the different corrosion regimes of Figure 6-1. On this figure, we did not represent the impact of maintenance activities. If a maintenance activity was carried out at some moment, it would only affect the shape of this curve for the future time instants, typically by changing the rate and/or by increasing the expected remaining time the component can stay in its current regime.

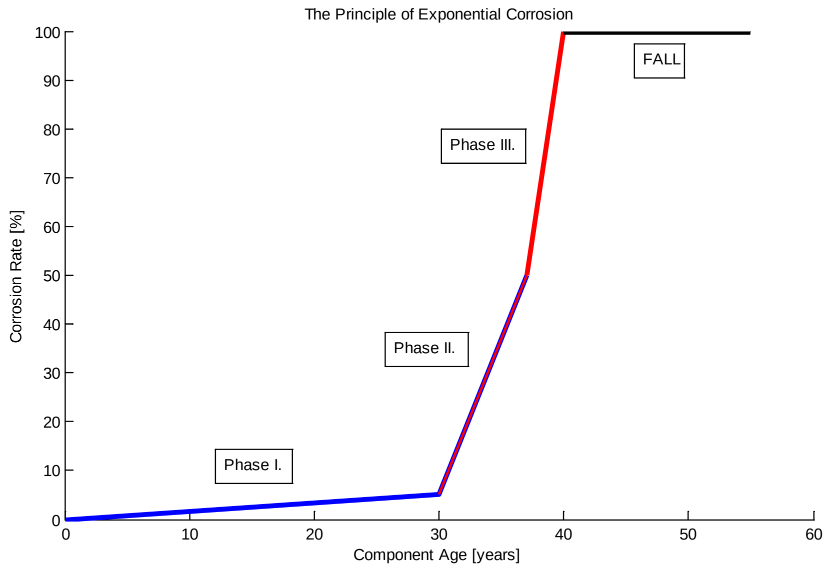

Figure 6-2: Typical exponential evolution of a tower corrosion level (no maintenance shown)

6.2.2 Towards a failure model of a full overhead line

Similar ageing and repairing models can be developed for the other types of overhead line subcomponents, where however the number of discrete states and the definition of zones may be adapted to the physics of the corresponding ageing process (see Appendix A.3).

Once these individual models are obtained for all the subcomponents of a particular line, the next step is to combine them in order to determine failure modes and compute instantaneous failure rates of the whole line. To fix ideas, let us consider a 100km long EHV line, its first part (say 30km) being located in a tower-corrosion-zone 3 (severe) and the rest in a tower-corrosion-zone 1 (mild). Let use also assume that the first 60 km are in free-land (no trees) whereas the other 40km are in a forest-zone (tree trimming needed from time to time in the corridor). Neglecting all the other types of subcomponents, and assuming 2 towers per km, we thus have about 60 towers in corrosion-zone 3 and about 120 in corrosion-zone 1, as well as a corridor of 40km. All these need to be taken into account to model the line failures.

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To simplify, we will furthermore assume that all the towers of a same zone are maintained at the same time, so that we can represent their set of states by a single pair $(\boldsymbol{x}, \boldsymbol{r})$ (thereby also assuming that our model actually represents the state of the ensemble of towers of the zone of concern). Thus, we finally end-up with four different failure modes for the whole line:

1. Failure mode 1: due to a tower failure in corrosion-zone 3 (failure rate: $\lambda_1(x_1, r_1, w)$)
2. Failure mode 2: due to a tower failure in corrosion-zone 1 (failure rate: $\lambda_2(x_2, r_2, w)$)
3. Failure mode 3: due to tree-growth in the forest-zone (failure rate: $\lambda_3(x_3, r_3, w)$)
4. Failure mode 4: all other threats (lightning, birds, trucks…) (failure rate $\lambda_4(w)$)

We notice that the failure rates due to all modes depend in some (mode-specific) fashion on current weather conditions, and the first 3 of them depend also on the assumed subcomponent states and on the number of concerned towers or on the length of the concerned corridor. Assuming that these 4 failure processes are independent (given the current weather conditions) and that they all would lead to the outage of the line, the forced-outage rate of the full line is obtained as the sum of these four rates. Indeed, naturally a line that is longer, or that has a more complex design with more subcomponents, would have a higher failure rate. Nevertheless, upon a forced outage occurrence, its duration and the needed corrective maintenance activity would actually depend on the particular failure mode.

6.3 Further work

In the present chapter we have presented and illustrated an approach for the modelling of component ageing, repairing, and forced outage failure rates, which could be suitable in the context of asset management studies. The corresponding models have been presented in an abstract and generic way, so as to draw the attention on the important aspects to be taken into account when developing such models for real-life studies.

Appendix A.3 provides a more detailed presentation of these ideas and some first studies based on real data.

Nevertheless, we fully acknowledge the fact that a suitable ‘component modelling’ in the context of asset management simulation studies is a very hard problem that deserves further research beyond the GARPUR project, so as to come up with actual models and parameter fitting approaches that make sense given the available data in the TSO’s environment.

In the current state of affairs, these models will have to be chosen and tuned based on expert knowledge.

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7 UNCERTAINTY MODELLING

The present chapter outlines the main features of the uncertainty models that have been investigated in Task 5.2, and then further specified in Task 5.3 to fit the needs of the maintenance policy and outage schedule assessment approaches as proposed in Chapter 3 and Chapter 4 of the present report.

We start by briefly discussing the two different notions of uncertainty -namely macro- and micro-uncertainties- that need to be taken into account in the assessment of maintenance policies and/or outage schedules. Then we explain the main features of the generative model of micro-scenarios that we propose in order to automatically generate the required input about uncertainties needed in the proposed algorithms.

Appendix A.4 gives a more detailed report about this still on-going work.

7.1 Long-term uncertainties in the form of macro-scenarios

Since maintenance policy assessment studies are carried out over long-term horizons, of say 20 years, additional uncertainties need to be taken into account with respect to mid-term and short-term studies. The additional factors that should be taken into account in long-term studies concern, on the one hand, possible ‘policy decisions’ and, on the other hand, possible long-term changes in economic, climatic and technological terms. Both are essentially outside of the decision-making power of the TSO’s experts responsible for asset management.

We propose to model these factors at the yearly time step. They concern the following items:

1. Assumptions about the future generation mix installed in the system, and fuel costs.
2. Assumptions about the future load mix accessing the system.
3. Assumptions about available technologies available in the future to manage the power system (FACTs, communications, sensors, etc).
4. Assumptions about possible climatic changes.
5. Assumptions about changes in future market rules.
6. Assumptions about changes in future environmental impact management policies.
7. Assumptions about changes in the future grid structure.

The specification of these assumptions for a particular assessment study will be based on expert judgement. A number of alternative assumptions may be considered for the different years considered in a particular study, and we will call these latter “macro-scenarios”. If deemed relevant, a set of such macro-scenarios may be explicitly organized in the form of a “macro-scenario tree”, which would allow one to explicitly express the gradual increase of macro-uncertainties along the years of the study time horizon.

7.2 Mid-term uncertainties in the form of yearly micro-scenarios

In addition to the macro-uncertainties, we need to model the uncertainties about the precise operating conditions that could be encountered at every hour of the study horizon, so as to enable the computation of the different indicators as explained in Chapter 3 and Chapter 4 of the present report.

In particular for the outage schedule assessment studies, while there are essentially no macro-uncertainties, we still need to screen a representative sample of operating situations for any particular study. In the same fashion, for a multi-year study used to assess a maintenance policy, we need to combine

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the specified set (or tree) of macro-scenarios with a representative sample, for each year of the study horizon, of situations that could actually be encountered in operation for that year.

We propose to model these factors at the hourly time step. They concern the following items:

A. **Information needed to model day-ahead operation planning**:
   - Assumptions about the day-ahead market-clearing outcome for the 24 hours of the next day.
   - Assumptions about the day-ahead load and renewable generation forecasts, for each hour of the next day and at the nodal resolution.
   - Assumptions about the network component outages as forecasted in the day-ahead context, for the next day.
   - Assumptions about cost-functions and available control means needed to simulate day-ahead operation planning.

B. **Information needed to model intraday real-time operation**:
   - Assumptions about real-time outputs, in terms of available thermal and hydro generation that can be dispatched, actual load, actual renewable generation, and actual network topology, for each hour.
   - Assumptions about the cost-functions and available control means needed to simulate intra-day real-time operation, for each hour.

C. **Information needed to assess reliability level:**
   - Assumptions about contingency probabilities, corrective control failure probabilities and node-wise value of lost load, for each hour.

A particular sequence for a certain number of days (typically a full year of 365 days) of all these assumptions is called a micro-scenario. In order to obtain meaningful results, the assessment methodologies of Chapter 3 and Chapter 4 will need a representative set of such micro-scenarios (possibly in the order of hundreds or thousands), for each year of the study horizon. We will call such a representative set of (yearly) micro-scenarios for a given year and expressed at the hourly time-step “a sample of micro-scenarios”.

In particular, in the context of long-term (multi-year) studies, the corresponding samples of micro-scenarios will have to be consistent with the various assumptions specified in the macro-scenarios, and they should also take into account in a correct fashion the fact that maintenance policies have an influence on the assets’ health-conditions, and hence on their forced outage rates. So in these studies, we will need to dispose of a representative set of micro-scenarios for each year and each macro-scenario over the long-term horizon (of say 20 years), that can be automatically adapted to the maintenance policy that is assessed.

On the other hand, in the context of mid-term studies, typically the only need is to dispose of a single sufficiently large sample of realistic micro-scenarios over the study horizon (say the next year).

7.3 Generative model for micro-scenarios

In order to produce on demand with the required flexibility the needed samples of micro-scenarios, we decided to go for the development of a generative model that can be used both for the needs of mid-term and long-terms studies. In essence, such a generative model of micro-scenarios would be a software tool that can be called upon request with a certain number of input parameters, and that will generate efficiently a sample (of specified size) of micro-scenarios described by the relevant output-variables. By this, we mean that the generative model will use a probabilistic model from which it will sample a specified number of (say yearly) micro-scenarios independently.

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Below we briefly describe the sets of input parameters that should ideally be taken into account and the sets of output variables that should ideally be computed for each hour along each micro-scenario. A full documentation of the actually proposed tool is described in Appendix A.4.

7.3.1 Input parameters to the micro-scenario generator

The inputs are the following ones:

- Explicitly specified on-line at the moment of the call of the software:
  - all the parameters describing the macro-scenario on top of which the sample of micro-scenarios has to be generated,
  - all the parameters of network components health-state needed to sample their forced outages, their inspection-triggered maintenances, and to compute the contingency and corrective control failure probabilities,
  - random seed and number N of micro-scenarios to return.
- Implicitly defined by a set of off-line chosen configuration parameters:
  - all fixed data relevant about the concerned power system,
  - specification of the parameters of the exogenous random processes of weather, demand and renewable generation, according to which the micro-scenarios would be sampled.

7.3.2 Output quantities computed by the micro-scenario generator

They correspond to the micro-uncertainties discussed in Section 7.2 and that have to be provided in the form of (typically hourly) time series for each micro-scenario:

- Day-ahead market-clearing outcome for each day, for the 24 hours of the next day.
- Day-ahead load and renewable generation forecasts, for each hour of the next day and at the nodal resolution.
- Network component outages as forecasted in the day-ahead context, for the next day.
- Cost-functions and available control means needed to simulate day-ahead operation planning.
- Real-time state-estimator outputs, in terms of actual dispatchable generation, load, renewable generation, and network component outages, for each hour.
- Cost-functions and available control means needed to simulate intra-day real-time operation, for each hour.
- Individual contingency probabilities, corrective control failure probabilities and node-wise value of lost load, needed to post-assess the level of reliability resulting from operation planning and real-time control decisions, for each hour.

Notice that in order to correctly model the occurrence of forced outages, and contingency probabilities, failure bunching should be properly taken into account.

Adverse weather effects are generally short in duration and significantly increase the failure rates of individual components in the system. More importantly, as adverse weather are local phenomena, during these short phenomena the probability of overlapping failures of several geographically/electrically close components cannot be neglected, what is known as *bunching effect*. If ignored, reliability indices can be over-estimated and hence provide a wrong image of the current state of system. The different models to account for this effect are therefore enhanced by a common weather environment.

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7.4 Discussion and possible refinements

While the current chapter is written to cover the specific needs and tools for uncertainty models in the context of the asset management tasks covered by WP5, our envisaged methods share many commonalities with similar ones envisaged in other WPs of GARPUR, e.g. on the one hand for long-term system expansion studies and on the other hand for short-term operation planning contexts. While we already have taken advantage of the two-fold contexts of asset management (namely long-term maintenance policy on the one hand, and mid-term outage schedule assessment on the other hand) in order to specify a common micro-scenario generation tool, we believe that further work could be carried out to fully coordinate the various uncertainty models used in the different GARPUR contexts. Such work should also build on the vast literature and industrial expertise available on this topic.

While the currently proposed uncertainty model is designed as a 'pure Monte-Carlo approach' based on *a priori* defined probabilistic models, we believe that future versions of the proposed tools could take advantage of various 'variance reduction techniques', some of them needing additional features of the generative models. For example, in order to reduce computational burdens or increase estimation accuracy, it would be of interest to be able to focus micro-scenario sampling on those regions where the indicators that one wants to estimate have the highest variance. Similarly, rather than using a fixed hourly time step, one could think of methods which are able to use variable time steps in order to represent in a more compact way the temporal variability of the conditions that are to be studied. We leave all these possibilities for further research, beyond the scope of the current work in GARPUR WP5.

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8 CONCLUSIONS

The present report has presented the main outcomes of the research carried out in the context of the design of probabilistic methods to support the future asset management activities of TSOs. In addition to a discussion on the practical needs and overall approach presented in Chapter 2, the main body presents algorithms to assess maintenance policies and outage schedules, from the viewpoint of their impact on power system reliability. We also have discussed in details the type of models that are needed to feed such algorithms, so as to represent in a realistic fashion current asset maintenance and inspection activities, component ageing, repairing and failure modes, and exogenous uncertainties that need to be taken into account, both for mid-term and long-term studies. The appendices document with more technical details and some first simulation results the proposed methods and ideas, while positioning the corresponding work with respect to the scientific literature. In the main body, we have also highlighted the main limitations of the current version of these methods and the most important directions of future research and development.

In spite of the very high complexity of the studied problems, and the still early stage of our developments, we believe that significant enough progress has been made to encourage TSOs to study and possibly adapt the proposed methods.

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APPENDICES

NB: the appendices collect more detailed information about the models and algorithms discussed in the main body of this document.

APPENDIX A.1 OUTAGE SCHEDULING PROXY

APPENDIX A.2 OUTAGE SCHEDULE ASSESSMENT

APPENDIX A.3 COMPONENT MODELS

APPENDIX A.4 UNCERTAINTY MODELLING

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APPENDIX A.1 OUTAGE SCHEDULING PROXY

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Abstract: This working paper presents an approximate model for the outage scheduling of power transmission system assets, to be used in long-term studies such as maintenance policy assessment or system development. A greedy algorithm is proposed which relies on Monte-Carlo simulations with proxies of the short-term system operation, to estimate the impact of outages over operability. It is implemented in the Julia programming language, and then used to solve a small case of outage scheduling defined over the IEEE RTS-96. Results indicate that problematic situations, such as outages of neighbouring branches being scheduled on the same period, are successfully spotted by the algorithm and thus excluded from the solution.

Nomenclature

Abbreviations

TSO	Transmission system operator.
ST	Short-term.
DA	Day-ahead.
RT	Real-time.
SCOPF	Security-constrained optimal power flow.
RES	Renewable energy source.

Symbols

D	Number of days in the scheduling horizon.
$\mathcal{I}$	Set of outage requests.
od	Vector of outage durations.
oc	Vector of outage crews required per day.
ac	Vector of daily available crews.
$\mathcal{S}$	Set of input scenarios.
C_{OP}	Daily outage operational costs.
$\overline{C}_{OP}$	Expected daily outage operational costs.
C_{OUT}	Indicator of the outage total cost.
C_{SCH}	Expected daily outage scheduling cost.

A.1.1 Introduction

A.1.1.1 Motivation

This paper presents ongoing work towards an automatic tool for the outage scheduling of power transmission system assets, to be used as a *proxy* in long-term studies such as maintenance policy assessment or system development studies. The term proxy is used in this paper to refer to any computational model whose purpose is to serve as a building block in another, much larger

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model. Typically, a proxy has specific requirements in terms of accuracy and tractability which are dictated by the scope of the larger model that exploits it.

The purpose of outage scheduling is to accomodate the outages requested by a higher-level maintenance policy in time, so as to minimize the impact on system operation and potentially satisfy given reliability criteria. Current TSO practice typically relies on expert opinion and the simulation of a few selected scenarios for the near future, to generate a schedule that satisfies logistic constraints and avoids most known problems [1]. However, this is insufficient for long-term analyses such as maintenance policy assessment and expansion planning studies, which usually require anticipating peaks of asset management over a horizon of several years. Whereas outage scheduling is not the main focus of these studies, it still needs to be modelled in an accurate yet tractable way, that is to say, a proxy of outage scheduling is needed.

This paper proposes a proxy of outage scheduling in the form of a greedy algorithm that accomodates outages according to their impact on operational costs. The algorithm relies on Monte-Carlo simulations to estimate the costs incurred by the TSO in order to maintain reliability under different outage configurations. The simulation is carried out by using proxies of the TSO behaviour in the ST.

A.1.1.2 Brief literature review

In the literature, outage scheduling is often presented as an extension of the SCOPF for ST operation to the mid-term horizon. This results in a multilevel, multistage, stochastic mixed-integer program. In this preliminary version of the paper we discuss three available solution approaches. Nonetheless, this review will be expanded in future versions.

In [2], the authors use cross-entropy coupled with *ad-hoc* sampling techniques to approach the solution of the outage scheduling problem in a tractable way. The methodology is tested on a PJM 5-bus network and proves to yield cheaper results than other heuristics, however scalability is an issue due to the huge number of candidate schedules that the cross-entropy algorithm needs to assess.

In another work, Bruno *et al.* [3] propose an outage scheduling tool especially tailored for the Italian transmission system. The tool combines, in an iterative fashion, the exact solution of the (inner) ST operational planning problem with an approximate solution of the (outer) outage scheduling problem, the latter approached by tabu search. The tool is tested on the 380-220 kV Italian transmission system with a prototypical maintenance plan, requiring about 350 tabu search iterations to reach a near-optimal solution.

A comparison of four heuristics to solve the ST outage scheduling problem over a horizon of one day is performed in [4]. The heuristics are based on pseudo-costs, which presumably reflect the cost of starting a given outage at different hours in the day, computed from the solution of a SCOPF without outage scheduling constraints. The outage is scheduled based on such pseudo-costs and the feasibility of the resulting schedule is checked by solving another SCOPF with the updated topology. The four heuristics are able to provide near-optimal solutions with an up to tenfold reduction in computing time.

A.1.1.3 Novelty of the proposed approach

The proposed framework gathers two exceptional features of previous approaches, namely, the use of proxies to encapsulate the ST context (see [2] and [3]), and of pseudo-costs to speed-up

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decisions (see [4]). However, our approach is different from previous ones in two relevant aspects regarding scalability and quality of the solution, as discussed below:

A.1.1.3.1 Greedy algorithm for improved scalability

One of the main issues with stochastic optimization methods, such as cross-entropy and tabu search, is the limited scalability of the solution approach due to the large amount of computations required. In this paper we propose a greedy algorithm whose time complexity is quadratic on the number of outage requests. In comparison, typical tabu search implementations require a quadratic amount of time only for the initialization step, and then a linear amount of time for every iteration [5].

A.1.1.3.2 Progressive update of pseudo-costs

In [4], the pseudo-costs that support the outage scheduling decision are computed in a single run of the ST SCOPF. Whereas this may suit the purpose of scheduling a limited set of outages within one day, it is clearly insufficient when it comes to scheduling several outages over a horizon of a few months to one year. In the proposed algorithm, once an outage is scheduled the pseudo-costs associated to the remaining ones are updated, in order to reflect the new operating conditions. This is key to spot issues with the simultanously scheduling of more than one outage over the same period of time.

The remainder of the paper is organized as follows. Section A.1.2 lists the inputs of the proposed model and discusses the underlying assumptions. The proposed greedy algorithm for outage scheduling is presented and illustrated in Section A.1.3. Section A.1.4 describes the implementation of the algorithm and presents a preliminary test for the proof of concept. Finally, Section A.1.5 concludes and outlines directions for future work.

A.1.2 Model assumptions

The proposed model receives four inputs, namely (i) a list of outages to be scheduled over a given horizon, (ii) a set of manpower constraints valid for that horizon, (iii) a set of scenarios defined over the horizon, and (iv) two proxies of the ST system operation.

A.1.2.1 List of outage requests

A set of outages to be performed over the scheduling horizon, specifying the affected grid component, the duration of the outage in days, and the amount of daily maintenance crews needed to carry out the task. Notice that by assuming that both the outage duration and the required crews can be provided as inputs, we explicitly acknowledge that these are independent of the scheduling decision, i.e., of the particular moment in time where the outage is finally scheduled.

A.1.2.2 Manpower constraints

A set of constraints expressing the allocation of maintenance crews by the TSO. They are given in terms of the number of crews that are available for each area of the system in different days of the scheduling horizon. It is worth noting that, in real-life, the crews that perform scheduled maintenance and forced corrective maintenance are typically the same, whereas here we assume

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that some of these crews can be exclusively allocated to scheduled maintenance. Ideally, an *a posteriori* assessment of the resulting schedule should be performed in order to check its ability to cope with the hazards of corrective maintenance under a set of credible scenarios.

A.1.2.3 Nota bene: additional constraints

In practice, it may be useful to a priori impose some further constraints on the outage schedules. For example, it may be desirable to impose some constraints so as to coordinate the outages of some components with already 'scheduled' external events (such as for example the planned outages of some generators). While we do not discuss in this document such additional constraints, they could be easily incorporated by our algorithm and, as a matter of fact, they would possibly allow one to reduce significantly its search space and hence its computational burden.

A.1.2.4 Set of scenarios

The future operating conditions are captured by a set of meaningful scenarios, providing all the necessary information about exogenous uncertainties that are outside the control of the TSO, but will condition TSO behaviour along the scheduling horizon. At each point in time, part of the scenario is revealed to the TSO and thus becomes the so-called *informational state* at that point. Note that in DA operation planning, the informational state contains forecasts of uncertainties such as RES generation and load, whose actual realization only becomes part of the informational state in RT. This distinction is needed to adequately model TSO decisions at different contexts, and grasp situations where high forecast errors lead to increasing operational costs.

Scenarios are obtained from a generative model that produces random samples of the relevant uncertainties with an hourly resolution. Note that the outage schedule of generators and transmission elements is an input to this model. The relevant uncertainties are described below.

A.1.2.4.1 Market clearing outcome

It is given in terms of the scheduling decision, including startup decision, on/off status and real power output, for each dispatchable generator as determined by the market operator and communicated to the TSO in DA.

A.1.2.4.2 Load and RES realization

It includes real power demand and RES generation for each bus in the system as realized in RT.

A.1.2.4.3 Load and RES forecast

It includes the forecast of real power demand and RES generation for each bus in the system, as determined by the TSO in DA.

A.1.2.4.4 Hydro-power capacity

It includes the capacity offered to the system by each hydro-power plant.

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A.1.2.4.5 Forced branch and generator outages

It includes the forced outages of transmission elements and generating units, stating the affected component and the outage duration[1].

A.1.2.5 Short-term proxies

The TSO decisions that determine operational costs, namely DA operational planning and RT operation, are modelled by two proxies. Note that this represents an additional layer of abstraction, where the assessment of outage schedules becomes the master problem requiring accurate yet tractable models of the inner processes.

We assume that in the ST, the TSO follows a certain reliability criterion such as $N-1$, and choses the necessary control actions that minimize the operational costs based on the informational state, as described below:

A.1.2.5.1 DA operational planning proxy

It computes decisions to be commited in DA so as to prepare the RT operation for the next day, together with the cost of these decisions. Available control actions are, e.g., generator startup/shutdown and generator rescheduling. The proxy also computes provisional RT decisions for every hour in the next day, in anticipation of the forecast conditions. The informational state includes the outcome of the market clearing, the load and RES *forecast*, the hydro-power capacity, and the generator and branch outages, all these specified on an hourly-basis for the entire next day.

A.1.2.5.2 RT operation proxy

It computes decisions to be applied in RT preventive mode, prior to the realization of any contingency, together with their cost. Available control actions are, e.g., generator rescheduling, and load- and generation-shedding. The proxy also computes decisions to be applied in RT corrective mode in case of every contingency considered in the reliability criterion. The informational state includes the DA decisions computed by the DA proxy, the load and RES *realization*, the hydro-power capacity, and the generator and branch outages, all these given for the specific hour under consideration.

In a similar way as for the scenario generative model, we have implemented provisional versions of these proxies for testing purposes based on DC SCOPF.

A.1.3 Proposed greedy algorithm for outage scheduling

The proposed algorithm receives the three inputs described above, and returns the outage schedule in terms of the starting day of each outage. It is conceived as a ‘while’ loop that runs until there are no more outages left to schedule. At each iteration the most constraining outage is identified, scheduled at the least harmful period, and then removed from the list of remaining outages to schedule at the subsequent iterations. The first few steps in the loop compute the expected operational costs that would be incurred by having each outage i at each day d, assuming that previous scheduled outages are already commited, that we denote by $\overline{C}_{OP}(i,d)$. This is done by

[1]Note that in the DA informational state, forced outages are given on a daily resolution.

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$out.\backslash day$	1	2	$\dots$	D		
1	$\overline{C}_{OP}^{(1,1)}$	$\overline{C}_{OP}^{(1,2)}$	$\dots$	$\overline{C}_{OP}^{(1,D)}$	$\xrightarrow{avg.\times od}$	$C_{OUT}^{(1)}$
2	$\overline{C}_{OP}^{(2,1)}$	$\overline{C}_{OP}^{(2,2)}$	$\dots$	$\overline{C}_{OP}^{(2,D)}$	$\longrightarrow$	$C_{OUT}^{(2)}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
$\lvert\mathcal{I}\rvert$	$\overline{C}_{OP}^{(\lvert\mathcal{I}\rvert,1)}$	$\overline{C}_{OP}^{(\lvert\mathcal{I}\rvert,2)}$	$\dots$	$\overline{C}_{OP}^{(\lvert\mathcal{I}\rvert,D)}$	$\longrightarrow$	$C_{OUT}^{(\lvert\mathcal{I}\rvert)}$

(a)

$out.\backslash day$	1	2	$\dots$	D
i_0	$\overline{C}_{OP}^{(i_0,1)}$	$\overline{C}_{OP}^{(i_0,2)}$	$\dots$	$\overline{C}_{OP}^{(i_0,D)}$

$\xrightarrow[\text{of length } od[i_0]]{\text{intg. over periods}}$

1	2	$\dots$	$D - od[i_0]$
$C_{SCH}^{(i_0,1)}$	$C_{SCH}^{(i_0,2)}$	$\dots$	$C_{SCH}^{(i_0,D-od[i_0])}$

(b)

$out.\backslash day$	1 $\dots$ $d_0 - 1$	d_0	$\dots$	$d_0 + od[i_0]$	$d_0 + od[i_0] + 1$ $\dots$ D
1		$\overline{C}_{OP}^{(1,d_0)}$	$\dots$	$\overline{C}_{OP}^{(1,d_0+od[i_0])}$	
$\vdots$		$\vdots$	$\ddots$	$\vdots$	
$i_0 - 1$		$\overline{C}_{OP}^{(i_0-1,d_0)}$	$\dots$	$\overline{C}_{OP}^{(i_0-1,d_0+od[i_0])}$	
i_0					
$i_0 + 1$		$\overline{C}_{OP}^{(i_0+1,d_0)}$	$\dots$	$\overline{C}_{OP}^{(i_0+1,d_0+od[i_0])}$	
$\vdots$		$\vdots$	$\ddots$	$\vdots$	
$\lvert\mathcal{I}\rvert$		$\overline{C}_{OP}^{(\lvert\mathcal{I}\rvert,d_0)}$	$\dots$	$\overline{C}_{OP}^{(\lvert\mathcal{I}\rvert,d_0+od[i_0])}$	

(c)

Figure A.1.1: Illustration of the main steps in the proposed algorithm: (a) Expected daily operational costs of each outage, denoted by $\overline{C}_{OP}$, are computed by means of Monte-Carlo simulations with the ST proxies. An indicator of the outage total cost, denoted by C_{OUT}, is then computed by averaging $\overline{C}_{OP}$ over days and multiplying the result by the corresponding outage duration. (b) The outage with the highest C_{OUT} will be scheduled next, say i_0. To do so, the cost of starting the outage at each day, denoted by C_{SCH}, is computed by integrating $\overline{C}_{OP}$ over succesive periods of length equal to the outage duration. (c) The outage is scheduled to start on the day where C_{SCH} is the lowest, say d_0. Afterwards, the daily operational costs of remaining outages on the days between d_0 and $d_0 + od[i_0]$ are recomputed, so as to acknowledge for the last outage scheduled.

running Monte-Carlo simulations over the set of scenarios using the ST proxies. Note that in the first iteration all days are considered, whereas subsequent iterations only consider days where an outage has just been scheduled, as for the others the cost will not change.

Then, for each outage i, the $\overline{C}_{OP}(i, d)$ are averaged over days and multiplied by the outage duration to compute $C_{OUT}(i)$, as an indicator of how 'difficult' the outage is. The outage with the highest C_{OUT} is scheduled next, say i_0. This is done in two steps: first, a set of days where the outage could be started is obtained by checking manpower constraints on the one hand, and the requirement that the outage must be finished before the end of the horizon, on the other hand. Note that the algorithm exits with an exception if no such days are available. Second, the expected operational costs that would result from starting outage i_0 at each available day d, that we denote by $C_{SCH}(i_0, d)$, is computed by integrating $\overline{C}_{OP}(i_0, d)$ over succesive periods of length equal to the outage duration. The outage is scheduled to start on the day where C_{SCH} is the lowest. Before moving to the next iteration, the available manpower is updated to reflect the

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Input: Number of days in the scheduling horizon D; set of outage requests $\mathcal{I}$; vector of outage durations od; vector of outage crews required per day oc; vector of daily available crews ac; set of input scenarios $\mathcal{S}$; ST proxies.

Output: Vector of outage starting days sch.

procedure OutageScheduling
  Set sch equal to an empty vector.
  Set $d_0 = 1, d_1 = D$
  while $\mathcal{I} \neq \{\}$ **do**
    for $i \in \mathcal{I}$ **do**
      for $d \in \{d_0, \ldots, d_1\}$ **do**
        for $\xi \in \mathcal{S}$ **do**
          Set $C_{OP}(i, d, \xi)$ equal to the daily operational costs that would be incurred should outage i be scheduled on day d under scenario ξ, considering that the current schedule sch is already committed. ▷ By using the ST proxies.
        end for
        Set $\overline{C}_{OP}(i, d) = \frac{1}{|\mathcal{S}|} \sum_{\xi \in \mathcal{S}} C_{OP}(i, d, \xi)$, where $|\mathcal{S}|$ is the number of elements in $\mathcal{S}$.
      end for
      Set $C_{OUT}(i) = \frac{od[i]}{D} \sum_{d=1}^{D} \overline{C}_{OP}(i, d)$
    end for
    Set $i_0 = \arg\max_{i \in \mathcal{I}} \{C_{OUT}(i)\}$
    Set $\mathcal{D} = \{d \in \{1, \ldots, D - od[i_0]\} : \forall d' = d, \ldots, d + od[i_0], ac[d'] \geq oc[i_0]\}$
    if $\mathcal{D} = \{\}$ **then**
      return "Outage i_0 could not be scheduled due to insufficient crews available."
    end if
    for $d \in \mathcal{D}$ **do**
      Set $C_{SCH}(i_0, d) = \sum_{d'=d}^{d+od[i_0]} \overline{C}_{OP}(i_0, d')$
    end for
    Set $sch[i_0] = \arg\min_{d \in \mathcal{D}} \{C_{SCH}(i_0, d)\}$
    Remove i_0 from $\mathcal{I}$.
    Set $d_0 = sch[i_0], d_1 = sch[i_0] + od[i_0]$
    for $d \in \{d_0, \ldots, d_1\}$ **do**
      Set $ac[d] \leftarrow ac[d] - oc[i_0]$
    end for
  end while
  return sch
end procedure

Figure A.1.2: Proposed outage scheduling algorithm.

crews just commited.

The most relevant steps are illustrated in Fig. A.1.1. Notice that manpower constraints are bypassed for sake of clarity. In addition, Fig. A.1.2 presents the full algorithm in tabular form. The remainder of this section discusses the computational burden of the proposed algorithm as well as opportunities for parallelization.

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A.1.3.1 Computational burden

The proposed algorithm is dominated by the computation of $\overline{C}_{OP}$ using Monte-Carlo simulations with the ST proxies. Note that one day of simulation requires one call to the DA proxy plus 24 calls to the RT proxy. We can compute how many days we need to simulate in different iterations as follows. In the first iteration, we simulate as many days as combinations of outage in the list, day in the horizon, and scenario. This number, that we denote by ND_1, can be computed as follows:

$$ND_1 = |\mathcal{I}| \cdot D \cdot |\mathcal{S}|, \tag{A.1.1}$$

where $|\mathcal{I}|$ is the number of outages, D is the number of days, and $|\mathcal{S}|$ is the number of scenarios.

In further iterations, we simulate as many days as combinations of remaining outage in the list, day in which the last outage was scheduled, and scenario. This number, that we denote by $ND_{\{2,\ldots\}}$, can be approximated as follows:

$$\begin{aligned} ND_{\{2,\ldots\}} &\approx \sum_{i=1}^{|\mathcal{I}|-1} i \cdot \overline{od} \cdot |\mathcal{S}| \\ &= \frac{(|\mathcal{I}|-1) \cdot (|\mathcal{I}|-2)}{2} \cdot \overline{od} \cdot |\mathcal{S}|, \end{aligned} \tag{A.1.2}$$

where $\overline{od}$ is the average outage duration.

From Eqns. (A.1.1) and (A.1.2), the total number of days simulated in the entire algorithm, that we denote by ND, can be approximated as follows:

$$ND \approx \left(|\mathcal{I}| \cdot D + \frac{(|\mathcal{I}|-1) \cdot (|\mathcal{I}|-2)}{2} \cdot \overline{od} \right) \cdot |\mathcal{S}| \tag{A.1.3}$$

Note that that the time complexity of the proposed algorithm is thus quadratic on the number of outages to be scheduled.

A.1.3.2 Parallelization opportunities

The algorithm can be trivially parallelized over different scenarios for the Monte-Carlo simulation. Additional parallelization opportunities can be found within the ST proxies, e.g., over different days in the DA proxy and different hours in the RT proxy. However, these could be limited by the presence of time-coupling constraints in the respective SCOPF formulations, which may call for a specific decomposition scheme. This problem and the investigation of such schemes are left for future works.

A.1.4 Implementation and tests

We have implemented the proposed outage scheduling algorithm in the Julia programming language [6]. We have also implemented in Julia a provisional scenario generative model and ST proxies for testing purposes. The scenario generative model is based on the copper plate market and standard assumptions about load and RES realization and forecast [10]. The short-term proxies are based on the well-known SCOPF. To solve optimization problems, we have used the Julia package for mathematical programming, JuMP [7], and the CPLEX optimizer [8]. To compute

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Table A.1.1: List of outage requests.

Branch outage	Connecting buses	Duration (days)
16	10 and 11	7
17	10 and 12	10
18	11 and 13	7

Table A.1.2: Resulting outage schedule.

Branch outage	Starting day	Ending day
16	47	53
17	83	92
18	84	90

outage schedules of generating units, we have implemented the methodology developed within the e-Highway2050 project [11].

The program spreads into multiple tasks when running Monte-Carlo simulations. In such case, every scenario is treated by a separate task, whereas different days and hours are processed sequentially within each task. The remainder of this section presents a preliminary case study and a note on computing times.

A.1.4.1 Case study

For the proof of concept, the proposed implementation is used to schedule a small set of three outages defined over the single-area IEEE RTS-96 [9]. The test system consists of 24 buses connected through 38 branches, with 33 generating units connected over 10 generator buses, and 17 loads.

The outage requests are selected so as to have neigbouring branches affected, as presented in Table A.1.1. Indeed, note that the three affected branches form a path from bus 12 to bus 13. Therefore, scheduling one of the outages may significantly increase the operational costs for the others during the same period of time, and we should see that in our method.

For sake of simplicity we chose to ignore manpower constraints in this case study. Furthermore, in order to speed up computations we consider a scheduling horizon of half a year, i.e., 182 days, and only 4 scenarios as input. Additionally, we use an optimality gap of 5% in the SCOPF solutions.

Table A.1.2 presents the schedule returned by the algorithm, while Fig. A.1.3 shows detailed results from the first two (out of three) iterations. Note that the vertical axes are in a logarithmic scale. Specifically, Figs. A.1.3(a), A.1.3(b) and A.1.3(c) show the daily operational costs of each outage in the list taken individually as computed during the first iteration. We can see that none of these outages has a distinctive impact on system operation, and possibly the three are handled in a similar way by the ST proxies. The outage of branch 17 gets scheduled first probably due to its longer duration.

Figure A.1.3(d) shows the expected scheduling cost of the outage of branch 17, computed by integrating the expected operational costs over the appropriate intervals. We see that there is a global minimum at day 83, where the outage thus gets started. Figures A.1.3(e) and A.1.3(f) show updated daily operational costs after scheduling the outage of branch 17 on days 83 to 92. On the one hand, we observe a notorious increase in the cost of the outage of branch 16, thus confirming

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Table A.1.3: Computing times of the proposed implementation in the case study (hh:mm:ss).

iteration \outage	branch 16	branch 17	branch 18	total
1	06:54:36	06:13:30	03:24:08	16:32:14
2	00:10:09	–	00:09:15	00:19:24
3	–	–	00:08:38	00:08:38
				17:00:16

that scheduling the simultaneous outage of both branches would not be a smart choice. On the other hand, we only observe a minor increase in the cost of the outage of branch 18, which allows it to be scheduled within the same period as the outage of branch 17 (see Table A.1.2).

Note that for some days the cost *decreases* rather than increasing, after scheduling the outage of branch 17. This is due to the DC model that we employed in our tests, where changes in the admittance matrix following the outage of one particular branch may allow for a redistribution of flows which ends up being beneficial for the system. Indeed, we have observed that for some hours during the concerned days, the N-1 DC SCOPF is unfeasible with branch 17 in operation and becomes feasible after removing it, which in our model leads to much higher costs in the former case.

A.1.4.2 Performance evaluation

For the previous case study, the proposed implementation was run on the CECI's NIC4 cluster[2] with four tasks, each one treating a different scenario on a dedicated computing node. In addition, we allow CPLEX to do multithreading within each task by assigning 8 CPUs per task. We used Julia version 0.4.5, JuMP version 0.13.1 and CPLEX Optimization Studio version 12.6.3.

Computing times are reported in Table A.1.3. Note that the first iteration accounts for about 97% of the total time, since here the simulation is run for the entire horizon rather than just a few days in the following iterations. One could consider saving the daily operational costs computed during the first iteration into a database, for further runs of the algorithm with some of the same scenarios and outages. This would help reducing the large time spent in the first iteration.

Additional detail on the computing times of the DA and RT proxies is given in Fig. A.1.4. Figures A.1.4(a) and A.1.4(b) show the distribution of DA computing times, split among outages and scenarios, respectively. Figures A.1.4(c) and A.1.4(d) show the same for the RT proxy. Note that the distribution of these times among outages and scenarios is quite homogeneous in RT, whereas in DA there is one outage, that of branch 18, which takes significantly less time than the two others.

The average computing times of the DA and RT proxies are about 95.32 and 0.27 seconds, respectively. This means that one day in the simulation is processed in about 101.8 seconds in average (by calling once the DA proxy and 24 times the RT proxy). Using Eqn. (A.1.3) in Section A.1.3, we can estimate the total CPU time required by the algorithm in about 62 hours and 40 minutes. As we only require about a quarter of that time using four computing nodes (i.e., about 17 hours, as reported in Table A.1.3), we can conclude that the proposed Julia implementation has little parallelization overhead.

[2] The hardware and software configuration of NIC4 can be found at `http://www.ceci-hpc.be/clusters.html#nic4`.

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A.1.5 Conclusion and future work

This paper presents a computational model and software for outage scheduling of transmission system assets. The model is characterized by the use of Monte-Carlo simulations with proxies of the ST system operation, into a greedy algorithm that tries to minimize the operational costs and impact on reliability of each scheduled outage. The proposed model is used to schedule a set of three outages defined over the IEEE RTS-96, and is able to determine that scheduling two of them on the same period would not be a smart choice, due to the affected branches being close to each other.

Future work will consider larger and more comprehensive case studies using both academic and real-life systems. Also, alternative scheduling mechanisms and ideas for improving performance will be investigated.

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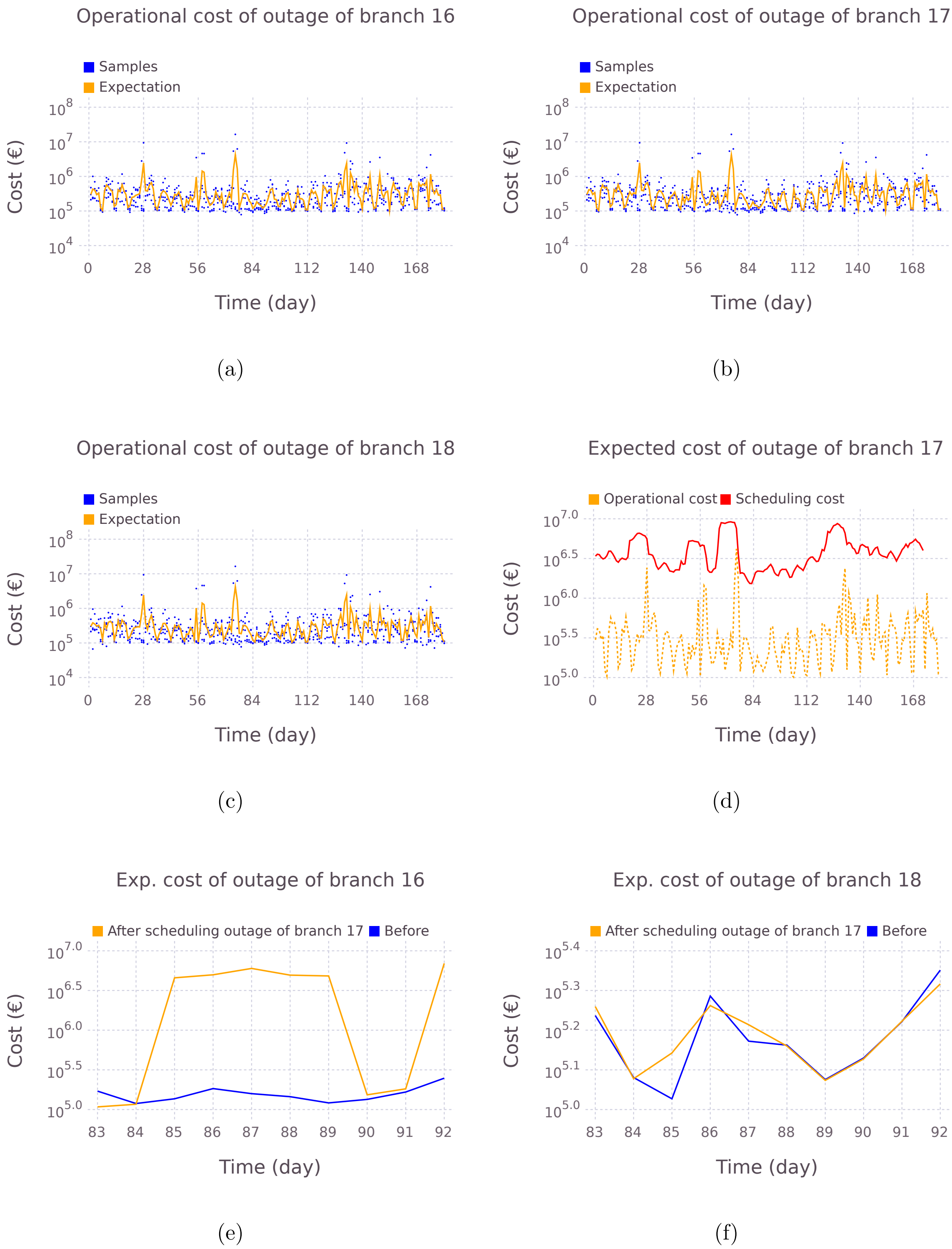

Figure A.1.3: Results of the first two iterations: (a, b and c) Daily outage operational costs computed during the first iteration, when no outage has been scheduled yet. (d) Expected operational and scheduling costs of the first outage to be scheduled, i.e., branch 17. The scheduling cost, in solid red, is computed by integrating the operational cost, in dotted orange, over succesive periods of length equal to the outage duration. (e and f) Expected daily outage operational costs computed during the second iteration, after scheduling the outage of branch 17 on days 83 to 92.

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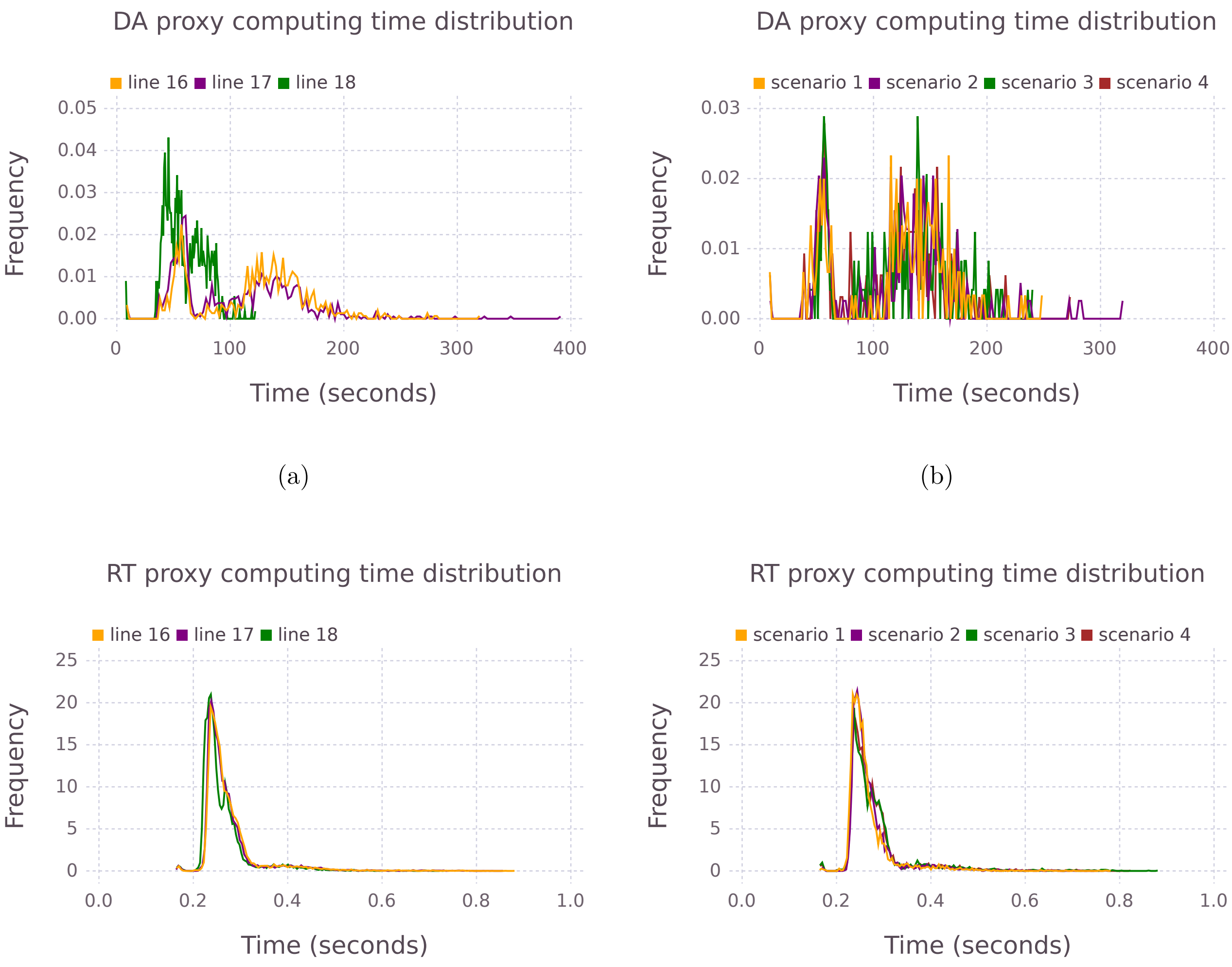

(a) (b)

(c) (d)

Figure A.1.4: Distribution of computing times of the ST proxies: (a) DA times for different outages; (b) DA times for different scenarios; (c) RT times for different outages; (d) RT times for different scenarios.

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APPENDIX A.2 OUTAGE SCHEDULE ASSESSMENT

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Abstract: This working paper presents a general framework for assessing, over a mid-term horizon from a few months to a few years, the impact of an outage schedule on reliability management in short-term operation planning and real-time operation. To deal with the computational complexity of the problem, we introduce the idea of automatically building a proxy for short-term reliability management by exploiting machine learning methods. Some first simulation results based on the IEEE-RTS96 benchmark are presented.

A.2.1 Introduction

Outage scheduling is a task performed as an integral part of the asset management procedure, conducted by transmission system operators (TSOs) in order to keep the power grid in operation by routinely maintaining the assets under their management. Maintaining an asset improves its working condition and resiliency, which reduces the risk of failures. However, scheduling of the required outages for maintenance jobs is a complex task since it must take into account constrained resources (working crews, hours, and budget), increased vulnerability of the grid to contingencies during outages, and the impact of the necessary scheduled outages on short term operations and system security. Outage schedules, which are often planned several months into the future, must also be robust with respect to the uncertainties arising from operating in a changing environment.

In this work we present a general framework for assessing the impact of a given outage schedule, defined over a mid-term time-horizon of several months to a few years, on system reliability while operating the system during this period. When evaluating outage schedules in the mid-term time-horizon, one must take into account the shorter time-horizons decisions that will take place during this time interval. The shorter time-horizons decisions include the short-term (day-ahead) operational planning decisions and real-time control decisions. On the other hand, the component aging mechanisms and resulting impact on failure rates can be neglected in the mid-term context.

The complex dependence between the multiple time-horizons and the high uncertainty in the context of mid-term planning makes the corresponding assessment problem challenging. To deal with the complexity of the outage schedule assessment problem we introduce a novel concept – learning a proxy for approximating short-term decision making, relieving the dependence of mid-term outcome assessment on exact short-term decision making simulations. Thus, allowing for a tractable assessment method.

When planning for future outages to enable maintenance, a certain reliability criterion is attempted to be satisfied at all future times. In present day, the common practice among TSOs is to consider the deterministic N-1 reliability criterion. Probabilistic criteria are also being investigated [1, 2]. In order to make the system N-1 compliant months in advance, the asset management operator must assess whether each of the possible future scenarios (taking into account the short-term day-ahead planing decisions and real-time operation decisions) are N-1 secure. Since taking into account all possible realizations of future events is impractical, they must be approximated using sampled paths of future scenarios. For this reason, devising a good sampling scheme which gives a rich, informational representation of possible future occurrences is important, as well as

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

reiterating the decision process as new information becomes available.

A.2.1.1 Literature Review

Much work has been done in the asset management and outage scheduling literature [3–7]. We review several works that deal with approaches for optimizing outage scheduling, and as such devise outage schedule assessment methods. Current state-of-the-art in transmission asset management offers three main approaches: time-based preventive maintenance, condition-based preventive maintenance, and reliability-centered preventive maintenance. The trade-off, that usually comes into play in the objective function, is between increasing the transmission equipment reliability via maintenance, and minimizing the effect of transmission equipment maintenance outage on socio-economic welfare while satisfying operating constraints.

In [4], these two aspects of the trade-off are being considered simultaneously. The authors use a linearized Weibull probability to calculate the probability of asset failure in future scenarios. Their method is based on a two-stage optimization formulation. The first stage involves a midterm asset maintenance scheduler that explicitly considers the analytic term of the probability of asset failure scenarios, and the solver iterates on all of these possible scenarios. For this stage, a coarse division to time blocks is done, where each time block is assigned with its designated asset maintenance actions. The second stage introduces a short-term maintenance scheduler with the $N-1$ reliability criterion that schedules the output of the mid-term maintenance scheduler in the short run for each of the time blocks, with fine constraints such as security limits. The mid-term and short-term stages are completely decoupled schemes to make the problem computationally tractable.

In a different work, Yong Jiang et. al [5] focus on cumulative risk reduction as the objective of asset maintenance optimization. They define two important terms: severity and risk. Severity is defined to be a quantity describing the bad effect of four possible outcomes of contingencies assessed using power-flow simulations: overloads, cascading overloads, low voltage, and voltage collapse. The risk is then defined to be the product of the probability of a contingency happening and its severity. Each maintenance action has its added contribution to risk reduction, which is initially negative during the actual maintenance (due to the forced outage), and positive afterwards (due to its reduction in probability of future contingencies). The paper also addresses the asset life model, with functional description of Weibull and Markov models, and their appropriate parameter estimation description. Despite its broad system perspective and important contribution, this work necessitates strong assumptions such as an additive structure of the risk function, and the knowledge of generation and load profiles a year-ahead for each hour. In addition, the hourly year-long trajectories used for optimization introduce high variance to the optimization algorithm.

Other works focus on maintenance outage scheduling of pre-determined maintenance actions, without considering the possible outcomes of asset failures and their condition.

In general, considering all factors relevant for the assessment of an outage schedule quickly renders the problem intractable. The primary contributors to the complex structure of mid-term planning of maintenance outages are generation unit commitment (UC), economic dispatch (ED), resource allocation and utilization, and transmission security.

To overcome these technical barriers, a coordination strategy between the different optimization tasks is proposed in [7]. Optimal coordination of midterm planning is proposed, accounting for the unavailability of generators and transmission lines during planned outages. The authors formulate an analytical cost objective in a setting that imposes coupling between available network topology and daily unit commitment, solved using decomposition methods. The optimization is deterministic, tested for a period of 168 hours – eliminating the need of scenario sampling consid-

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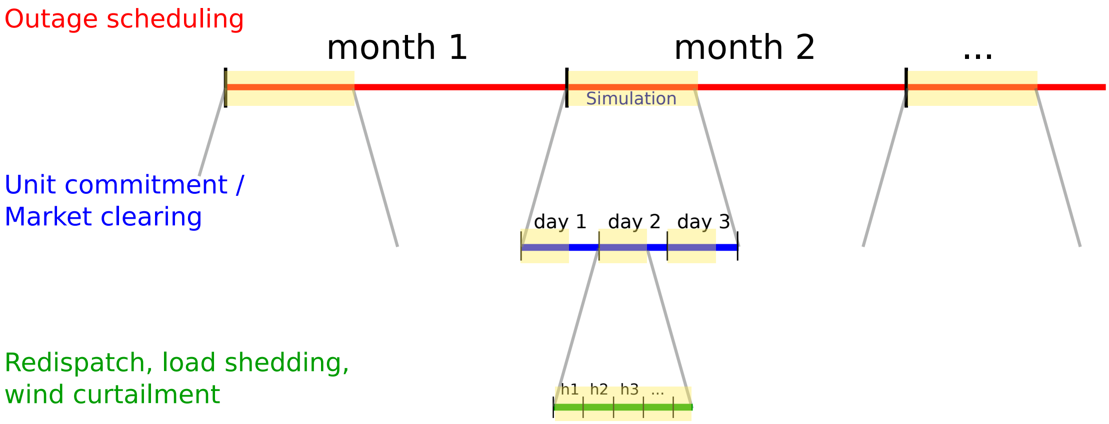

Figure A.2.1: The *hierarchical window scenario sampling* is a scenario generation approach, combining both sequential trajectory simulation and snapshot sampling. In each level of the hierarchy, a snapshot of future grid and environment conditions is sampled, and sequential simulation is performed from that point on, for a limited time window.

erations, and evaluation of real-time decisions under a constantly changing stochastic environment of load and renewable generation.

A.2.1.2 Novelty of the Framework

In this work we introduce a new scenario approximation approach. A visualization of it can be found in Fig. A.2.1. This approach combines both sequential trajectory simulation and snapshot sampling, while accounting for the coordination problem between a hierarchy of three decision layers, namely mid-term, short-term and real-time. The coordination transpires in an information sharing scheme, which we formulate in detail throughout the paper.

In addition, we introduce a novel concept of learning the short-term decision making outcomes using a 'proxy' – a black-box allowing for mimicking decision making in TSOs. For that purpose we utilize a well-known machine learning algorithm and extend it to encompass the notion of confidence. We thus enable a critical reduction in computation time, which turns the table and deems large-scale network simulation-based assessment with multiple time-horizon coordination tractable.

A.2.2 Problem Formulation

We formalize the mid-term outage schedule assessment task in Eq. (A.2.1), in which a planned outage schedule u_m, is being assessed. The evaluation spans over a time horizon of T hours. The outage schedule variable undergoing evaluation in Eq. (A.2.1) u_m is composed of a sequence of planned outage actions with certain moments of activation chosen in the corresponding horizon. Consider the outage schedule $u_m \in \mathcal{U}_m = \{0,1\}^{n^l \times T_M}$ to be a binary matrix, where $T_M (= \frac{T}{24 \cdot 30})$ are monthly time indices and n^l is the number of transmission lines in the system each entry, $u_m(i_m, i_l)$, mentions whether transmission line i_l is maintained during month i_m or not. While being maintained, a transmission line is being taken offline.

The resulting formulation is therefore the following evaluation problem:

Assess outage schedule u_m by evaluating:

$$\textbf{Expected operational costs} \qquad \mathbb{E}_Z\left[C(Z_{\boldsymbol{u}_m,\theta}, u_m, u_p^*, u_{\mathrm{RT}}^*)\right] \tag{A.2.1a}$$

$$\textbf{Expected real-time reliability} \qquad \mathbb{E}_Z\left[r(Z_{\boldsymbol{u},\theta})\right] \tag{A.2.1b}$$

$$\textbf{Expected overall load shed} \qquad \mathbb{E}_Z\left[\mathrm{LS}(Z_{\boldsymbol{u},\theta})\right] \tag{A.2.1c}$$

such that

$$u_p^* = \underset{u_p \in \mathcal{U}_p(u_m)}{\arg\min}\ C_p(y_m, u_m, u_p) \tag{A.2.1d}$$

$$s.t \quad u_{\mathrm{RT}}^* = \underset{u_{\mathrm{RT}} \in \mathcal{U}_{\mathrm{RT}}(u_p)}{\arg\min}\ C_{\mathrm{RT}}(y_{\mathrm{RT}}, u_p, u_{\mathrm{RT}}) \tag{A.2.1e}$$

The operational costs in Eq. (A.2.1a) are associated with the uncertain future conditions of the grid, denoted by $Z_{\boldsymbol{u},\theta}$ and under the shorter time decision policy (i.e., short-term operation planning and real-time) θ (e.g., $N-1$ security criterion). The reliability and cost of a power-system are defined in real-time. A real-time decision depends on the decisions taken in the short-term planning, which in turns depends on decision taken in the mid-term. Therefore

$$\mathbb{E}_Z\left\{C(Z_{\boldsymbol{u}_m,\theta}, u_m, u_p^*, u_{\mathrm{RT}}^*)\right\} = \sum_{t=1}^{T} \mathbb{E}_{s_t \in Z}\left\{C_{\mathrm{RT}}(S_t, u_m, u_p^*, u_{\mathrm{RT}}^*)\right\} \tag{A.2.2}$$

is the expected cost of real-time operational decisions summed over the evaluation horizon, where the expectation is over the distribution of a stochastic scenario $Z_{\boldsymbol{u}_m,\theta}$ that is composed of a series of states S_t, as explained in § A.2.3.1.

When assessing decisions in the mid-term time-horizon, one must take into account the shorter time decisions that take place during these time intervals. The shorter time-horizons decisions include the short-term (day-ahead) operational planning decision $u_p \in \mathcal{U}_p(u_m)$ and real-time balancing market control $u_{\mathrm{RT}} \in \mathcal{U}_{\mathrm{RT}}(u_p)$ decision. Each of the sets of possible shorter time decisions $\mathcal{U}_p(u_m)$, $\mathcal{U}_{\mathrm{RT}}(u_p)$ is defined by decisions that were taken one level higher in the hierarchy.

A real-time operational decision u_{RT}^* is defined to be vectors of redispatch values for each redispatchable generator, wind curtailment values for each wind generator, and load shedding values for each bus. The cost $C_{\mathrm{RT}}(S_t, u_m, u_p^*, u_{\mathrm{RT}}^*)$, associated with such an action is the cost of deviation from the market clearing outcome u_p^*, given current grid topology that is dictated by outage schedule u_m.

The constraints in Eqs. (A.2.1d)-(A.2.1e) describe the connection between the different time-horizon decisions, with short-term operational planning cost C_p and real-time control cost C_{RT}, where an optimal solution in one time-horizon must take into account how it will effect the future shorter time-horizon decisions. The informational states y_m and y_{RT} appearing as arguments in C_p, C_{RT} are revealed to the decision makers in these time-horizons, on which we expand in § A.2.3.2.

To assess the level of reliability, we perform a test that is independent of the TSO's operation policy θ being simulated. We treat the notion of reliability as a unified standard to be assessed and enforced in power system operation, that enables equitable comparison between different maintenance strategies. Our choice of reliability assessment in this work is to employ the common $N-1$ criterion used in the industry, in order to evaluate the system ability to withstand any contingency of a single asset. To calculate the reliability of the system, it is examined using a sequence of line contingencies from the $N-1$ contingency list, denoted as $\mathcal{N}_{-1}(S_t)$. Each

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contingency is an attempt to take out a single given the current topology as determined by state S_t and check if the system retains safe operation. Hence, the real-time reliability $r(S_t) \in [0,1]$ expresses the portion of contingencies under which the system can still safely operate. The reliability is calculated for a given state of the grid, and is dependent of current topology, dictated by u_m. In practice, preserving the system in safe operation means being able to obtain a feasible solution to the AC power flow equations. We define $\mathbb{I}_{[\mathrm{PF}(c,S_t)]}$ to be 1 if a power flow solution is found under contingency $c \in \mathcal{N}_{-1}$, and 0 otherwise. As a result:

$$r(S_t) = \frac{1}{|\mathcal{N}_{-1}|} \sum_{c \in \mathcal{N}_{-1}} \mathbb{I}_{[\mathrm{PF}(c,S_t)]}. \tag{A.2.3}$$

Based on that definition, we also define $r(Z_{\boldsymbol{u},\theta})$ to be corresponding sequence of values for $Z_{\boldsymbol{u},\theta} = (S_0, \ldots, S_T)$.

In a similar fashion, $\mathrm{LS}(S_t)$ is the total load that was shed during state S_t (as determined by the real-time decision u^*_{RT}), and $\sum\limits_{S_t \in Z_{\boldsymbol{u},\theta}} \mathrm{LS}(S_t)$ is the overall load shed during scenario $Z_{\boldsymbol{u},\theta}$.

A.2.3 Probabilistic Model Components and Definitions

In this section we present the definitions and probabilistic mathematical model used in this chapter. We define a state-space representation in terms of the states of the world in which the power system, the decision maker, and their exogenous environment can be in and their evolution in time (see Fig. A.2.3). This is a generic model that can be adapted for the study of any transmission system by adjusting the definitions of the states, actions and transitions, as will be defined later.

A.2.3.1 State-Space

We use a *state* notation $S_t \in \mathcal{S}$ to represent all the information about the grid and its external environment at some time point t, needed to make informed decisions [8]. It includes the relevant information of all three time horizons, namely mid-term, short-term and real-time. Denote n^l_t, n^b, n^g_d, n^g_w to be the number of transmission lines, number of buses, number of dispatchable generators, and number of wind generators in the network respectively. The topology top_t changes with time and certain lines become unavailable when under maintenance, hence the time index in the variable n^l_t which will be used from now on. The state S_t is defined as the following tuple:

$$S_t = (J_t, W_{d.a}, D_{d.a}, W_t, D_t, top_t)$$

where

- $J_t \in \mathbb{R}^2$ is the seasonal weather factor, determining the intensity of demand and wind generation. This variable changes monthly, with values drawn around a mean profile that corresponds to typical European seasonal trends.
- $W_{d.a} \in \mathbb{R}_+^{n^g_w \times T_{d.a}}$ is the day-ahead wind generation forecast. The n^g_d dispatchable generators are fully controlled by the short-term and real-time decision makers, and therefore are deterministic (determined by the commitment plan u_p and dispatch u_p) and are not a part of the state. $T_{d.a}$ is the day-ahead planning horizon, taken to be 24 in our simulations.
  To avoid confusion, all variables with subscript $d.a$ do not include a time index subscript, rather they stay fixed for time periods of length $T_{d.a}$, and are updated each $T_{d.a}$ time-steps.

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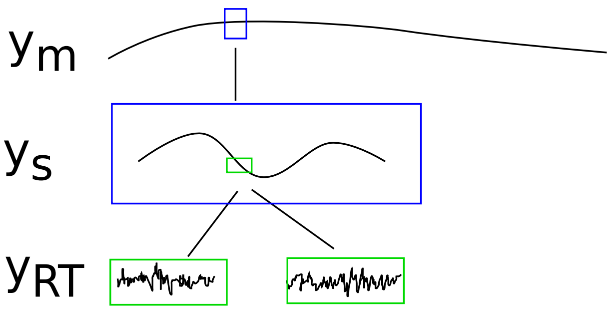

Figure A.2.2: Hierarchical division of state S_t to its three levels of informational states.

- $D_{d.a} \in \mathbb{R}_+^{n^b \times T_{d.a}}$ is the day-ahead load forecast.
- $W_t \in \mathbb{R}_+^{n^g_w}$ is the realized wind generation at time-step t. It stays fixed for the actual duration of the time period (1 hour in our simulations).
- $D_t \in \mathbb{R}_+^{n^b}$ is the realized load at time-step t.
- $top_t \in \{0,1\}^{n^l}$ is the network topology at time-step t. A transmission line normally up (1), and goes down (0) for the duration of a planned outage.

A.2.3.2 Informational State

The state-space representation exhibits a division of the state variables to the different temporal evolution processes (time horizons). We formulate this separation of state variables according to the information that is exposed to the decision maker at a decision time point, and refer to it as the *informational state*. Decision makers at different time-horizons are exposed to different amounts of information about the world, hence the higher the time resolution of decisions the more state variables are realized at the time of the decision. For a general integer k, denoting $S_t^{1:k}$ to be the sub-vector of S_t which includes elements 1 to k, denote $y_m = S_t^1 = J_t$, $y_s = S_t^{1:3} = (J_t, W_{d.a}, D_{d.a})$ and $y_{\mathrm{RT}} = S_t$ to be the informational states of the mid-term, short-term and real-time decision resolutions respectively. Fig. A.2.2 presents a separation of the state to informational states.

A mid-term planner is exposed only to the realization of the y_m part of the state, and can base its mid-term decision u_m on it and on its expectations of the rest of the state in future times. In the case of y_s, on top of being exposed to J_t, a short-term planner is also exposed to the realization of the day-ahead forecast of generation and load. It is also exposed to the higher-level mid-term decision u_m, however it is not modeled as a part of the informational state. Lastly, as for y_{RT}, the real-time planner is exposed to all of the realizations of the components in the state, along with being informed of higher level decisions, i.e., mid-term decision u_m and short-term decision u_p.

A.2.3.3 Shorter Time-horizon Action-Space

Our formulation contains three hierarchical levels of decision making, namely mid-term maintenance, short-term (day-ahead) operational planning, and real-time control. We often refer to the short-term and real-time problems as the *inner problems*. We now present the possible actions in these two inner problems.

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A.2.3.3.1 Short-term Operational Planning Decisions

The optimal short-term operational planning action

$$u_p^* = \underset{u_p \in \mathcal{U}_p(u_m)}{\arg\min} \quad C_p(y_s, u_m, u_p) \tag{A.2.4}$$

as appears in Eq. (A.2.1d) is defined to be the solution of the unit commitment (UC) schedule. As explained in § A.2.2, the overall cost in Eq. (A.2.1) is the sum of all real-time interval costs. Therefore the contribution of the solution for this optimization problem is not in directly calculating the overall cost of Eq. (A.2.1), rather it is being used as a constraint for the lower-level real-time problem, and as a reference for redispatching costs of real-time operation. Notice this day-ahead market problem does not account for the possible developments in the real-time balancing market. This formulation is often referred to as *inefficient market* [9].

This UC problem includes DC OPF, with $N-1$ reliability criterion enforced. It also includes wind curtailment and load shedding decisions. It is a single-stage formulation that comes to estimate the market-clearing process in TSOs nowadays, where multiple-stage unit commitment problems are being solved, usually in a continental scale at a first stage, an in a zonal level at a later stage.

This results in a mixed integer-linear program (MILP) that can be solved efficiently using commercial solvers [10]. The full inner optimization problem is the following:

$$
\begin{aligned}
& u_p^* = \underset{u_p \in \mathcal{U}_p(u_m, y_s)}{\arg\min} \; C_p(u_m, u_p) = \underset{\alpha, \Theta, P_g, t, WC, LS}{\arg\min} \\
& \sum_{t'=t}^{t+Td.a} \Bigg[\sum_{i=1}^{n_d^g} \Big(\alpha_{t'}^i f_P^i(P_{g,t'}^i) + \alpha_{t'}^i (1 - \alpha_{t'-1}^i) SU_i(t_{\text{off}}^i) \Big) \\
& \qquad + \sum_{iw=1}^{n_w^g} WC_{t'}^{iw} \cdot C_{WC} + \sum_{ib=1}^{n^b} LS_{t'}^{ib} \cdot VOLL \Bigg] && \text{(A.2.5a)} \\
& \text{subject to} && \text{(A.2.5b)} \\
& g_{P,t'}^l(\Theta^l, \alpha, P_g) = \; B_{\text{bus}}^l \Theta_{t'}^l + P_{BUS,\text{shift}}^l + D_{d.a,t'} && \text{(A.2.5c)} \\
& \quad + G_{sh} - LS_{t'} - (W_{d.a,t'} - WC_{t'}) - C_g(\alpha_{t'} .* P_g) = 0 \\
& h_{f,t'}^l(\Theta_{t'}^l) = B_f^l \Theta_{t'}^l + P_{f,\text{shift}}^l - F_{max}^l \le 0 && \text{(A.2.5d)} \\
& h_{t,t'}^l(\Theta_{t'}^l) = B_f^l \Theta_{t'}^l - P_{f,\text{shift}}^l - F_{max}^l \le 0 && \text{(A.2.5e)} \\
& \theta_i^{\text{ref}} \le \theta_{i,t'}^l \le \theta_i^{\text{ref}}, \quad i \in \mathcal{I}_{\text{ref}} && \text{(A.2.5f)} \\
& \alpha_{t'}^i p_g^{i,\min} \le p_{g,t'}^i \le \alpha_{t'}^i p_g^{i,\max}, \quad i = 1, \dots, n_d^g && \text{(A.2.5g)} \\
& 0 \le WC_{t'}^{iw} \le W_{d.a,t'}^{iw}, \quad iw = 1, \dots, n_w^g && \text{(A.2.5h)} \\
& 0 \le LS_{t'}^{ib} \le D_{d.a,t'}^{ib}, \quad ib = 1, \dots, n^b && \text{(A.2.5i)} \\
& t_{\text{off}}^i \ge t_{\text{down}}^i, \quad i = 1, \dots, n_d^g && \text{(A.2.5j)} \\
& t_{\text{on}}^i \ge t_{\text{up}}^i, \quad i = 1, \dots, n_d^g && \text{(A.2.5k)} \\
& l = 0, 1, \dots, n_t^l && \text{(A.2.5l)} \\
& t' = t, \dots, t + Td.a && \text{(A.2.5m)}
\end{aligned}
$$

where

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- l is the index of a line that is offline. $l = 0$ means that all lines are connected and online. (lines that are under maintenance are not counted in n_t^l to begin with).
- $\alpha \in \{0,1\}^{n_d^g \times Td.a}$ is the commitment (on/off) status of all dispatchable generators, at all time-steps.
- $\Theta \in [-\pi, \pi]^{n^b \times (n^l+1) \times Td.a}$ are the different voltage angle vectors for the different network layouts, for all time steps.
- $P_g \in \mathbb{R}_+^{n_d^g \times Td.a}, WC \in \mathbb{R}_+^{n_w^g \times Td.a}, LS \in \mathbb{R}_+^{n^b \times Td.a}$ are the dispatchable generation, wind curtailment and load shedding decision vectors, with $f_P, C_{WC}, VOLL$ as their corresponding prices.
- $t^i_{\text{down}}, t^i_{\text{up}}$ are the minimal up and down times for generator i, after it had been off/on for $t^i_{\text{off}}/t^i_{\text{on}}$.
- $SU_i(t^i_{\text{off}})$ is the start-up cost of dispatchable generator i after it had been off for t^i_{off} time-steps.
- $g^l_{P,t'}(\Theta^l, \alpha, P_g)$ is the overall power balance equation for line l being offline.
- $B_{\text{bus}}, P_{BUS,\text{shift}}$ are the nodal real power injection linear relation terms.
- $B_f, P_{f,\text{shift}}$ are the linear relation terms of the branch flows at the *from* ends of each branch (which are the minus of the *to* ends, due to the lossless assumption).
- G_{sh} is the vector of real power consumed by shunt elements.
- C_g is the generator-to-bus connection matrix, $(\alpha_{t'}.*P_g)$ is the dot-product of the two vectors.
- F_{max} are the line flow limits.
- $\mathcal{I}_{\text{ref}}$ is the set of indices of reference buses, with θ_i^{ref} being the reference voltage angle.
- $p_g^{i,\min}, p_g^{i,\max}$ are the minimal and maximal power outputs of generator i.

More information on the DC approximation can be found in [11].
Constraints in Eqs. (A.2.5c)-(A.2.5e) ensure load balance and network topology constraints.
Constraints in Eqs. (A.2.5f)-(A.2.5i) restrict the decision variables to stay within boundary, namely voltage angle limits, generator minimal and maximal power output range, wind curtailment and load shedding limits.
Constraints in Eqs. (A.2.5j)-(A.2.5k) bind the different time steps to follow generator minimal up and down time thermal limits.
Notice that the UC is an optimization program, where the decision is based on the informational state y_s which the decision maker is exposed to when facing a day-ahead planning problem. The informational state y_s contains the wind power and load forecasts $W_{d.a}, D_{d.a}$, which appear in the UC problem formulation. The short-term action-space $\mathcal{U}_p(u_m)$ in Eq. (A.2.4), from which the decision variables (as appearing in their detailed form in the full inner optimization problem) are chosen, is the set of possible short-term operational plans. Mid-term decision u_m dictates which assets are not taking part of the current plan due to maintenance.

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A.2.3.3.2 Real-time Control Decisions

The optimal real-time control action

$$u^*_{\text{RT}} = \underset{u_{\text{RT}} \in \mathcal{U}_{\text{RT}}(u_p)}{\arg\min} \quad C_{\text{RT}}(y_{\text{RT}}, u_p, u_{\text{RT}}) \tag{A.2.6}$$

as appears in Eq. (A.2.1e) is defined to be the solution of a DC optimal power flow problem, with the N - 1 reliability criterion being enforced, and with additional wind curtailment and load shedding decisions, that follows the original unit commitment plan α^* obtained in the day-ahead planning procedure as detailed in the full inner optimization problem, meaning the participating generators in the power flow at time-step t are those who have 1's in their indices in the vector α^*_t. It therefore includes re-dispatch decisions, as well as load shedding, wind curtailment and unit re-commitment if necessary, for each time step t individually. In practice, the real-time optimization problem in Eq. (A.2.6) results in a formulation similar to the operational planning formulation in Eq. (A.2.4) that is presented in detail in Eq. (A.2.5), therefore we use its formulation and solve it $T_{d.a}$ times sequentially, with the following adaptations:

- it is solved for a single time step t, instead of a full day-ahead horizon $T_{d.a}$.
- the on/off commitment schedule is no longer a decision variable, rather it is obtained from u^*_p and set as a constraint for each real-time optimization problem at time-step t.
- wind power and load forecasts $W_{d.a}, D_{d.a}$ for the $T_{d.a}$ time-steps are replaced with their actual realizations W_t, D_t.
- an additional re-dispatch cost is added to the objective: $\sum_{i=1}^{n_d^g} \alpha^{*,i}_{t'} |f^i_P(P^{*,i}_{g,t'}) - f^i_P(P^i_{g,t'})|$, assuming re-dispatch cost is the symmetric difference in prices of the generation declared in the day-ahead plan $P^{*,i}_{g,t'}$, and the actual realized power consumed in real-time $P^i_{g,t'}$.

Having as an input the full realized state $y_{\text{RT}} = S_t$ (either by witnessing it in real time, or by sampling future realizations of it), we solve the real-time control decision problem using the power flow equations and obtain the voltage magnitude and angle at all network nodes. We can then use it to model different related processes, such as aggregated stress effect on equipment failure. However, since this modeling topic requires careful attention and additional research, we currently do not include it.

A.2.3.4 Scenario-Space

The dictionary definition of a scenario is *"a postulated sequence or development of events"*. We use scenarios as a way to examine plausible future developments in the grid system. Using a scenario-based approach provides a way of dealing with uncertainties and the complicated interaction between these uncertainties [12].

A.2.3.4.1 Scenario Definition

A scenario $Z_{\boldsymbol{u}_m,\theta} \in \mathcal{S}^T$ is defined as a sequence of states over the time horizon T that are dependent on actions $u_m \in \mathcal{U}_m$:

$$Z_{\boldsymbol{u}_m,\theta} = (S_0, S_1, \dots, S_T)$$

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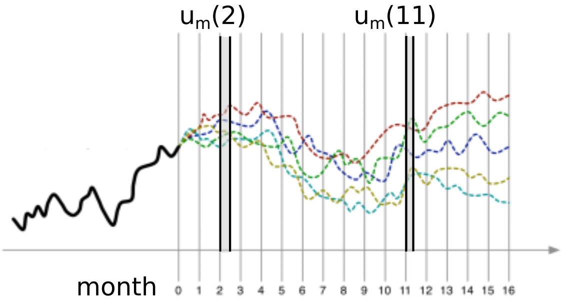

Figure A.2.3: Illustration of sample paths of possible scenarios in the mid-term time horizon. It shows the progression of sampled future scenarios in the mid-term point of view. As time progresses the variance of state S_t grows because of increased uncertainty. Each scenario that is generated as a full continuous sequence can be used to test one possible maintenance schedule. A given mid-term planned schedule is shown with maintenance actions in the second and eleventh months, which affect all the mid-term sample paths.

where θ is the shorter-term policy, namely the short-term and real-time $N-1$ unit-commitment and DC OPF presented in § A.2.3.3. Under the Markovian assumption, possible due to our state and its transition probability definition, the following relation holds:

$$\mathbb{P}\{Z_{\boldsymbol{u},\theta}\} = \mathbb{P}\{S_0\} \cdot \mathbb{P}\{S_1|S_0\} \ldots \mathbb{P}\{S_T|S_{T-1}\}$$

where the state transition probability $\mathbb{P}\{S_{t+1}|S_t\}$ describes the evolution of the stochastic processes in the system. The stochasticity stems from the wind power produced in the wind generators W_t, the load process D_t, and topology of the network top_t, as determined by contingency events (unexpected line failure). In Appendix A.2.9 we provide details on the models used for these three probabilistic processes, along with the data and test-cases they are based on. Figure. A.2.3 shows an illustrative example of the scenario-space and scenario generation.

A.2.4 Short-term proxy for quick decision assessment

As demonstrated in GARPUR T2.3, the method presented here, that involves solving an extensive amount of UC problems to mimic short-term decision making, will not scale well to realistic grids, with thousands of nodes, generators and loads. To enable outage schedule assessment in large networks while accounting for inner decisions such as unit commitment, approximated 'proxy' methods are necessary. In this section we present a novel concept of learning the day-ahead unit commitment outcomes, using a well-known machine learning algorithm – *nearest neighbor classification* [13]. We therefore call it UCNN.

The methodology relies on a simple concept – creating a large and diverse data-set that contains samples of the environment and grid conditions along with their respective UC solution. Then, during assessment of an outage schedule, instead of solving the multiple UC problem instances required to simulate decisions taken, simply choose among the already existing UC solutions. The UC solution chosen to be used is the one with the closest conditions to the current environment and grid conditions.

The essence of this method's advantage lies in the fact that planning and assessment for long horizons in stochastic environments such as ours, requires obtaining multiple samples (UC solutions in our case), which are often very similar to each other. Therefore, instead of repeating

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the expensive process of obtaining these samples (solving MILPs in our case) for environment and grid conditions that often are repetitive within a single scenario and across different scenarios, utilize samples created ex-ante as representatives of sets of similar repetitive conditions. The initial creation of the data-set is a slow process which can either be done offline, or alternatively online by running continuously on a dedicated server for constant expansion of it.

After obtaining the training set, UCNN reduces computation time by several orders of magnitude. Under the simulation environment and updated IEEE-RTS96 network described in Section A.2.6, the calculation of a single $N-1$ secure UC solution spans over 1500 CPU-seconds. A non-$N-1$ secure solution takes 22 seconds. In contrast, obtaining a single UCNN solution (using the train set described in Section A.2.4.2) for both the $N-1$ and non-$N-1$ cases takes only 0.18 seconds, spent on searching for a nearest neighbor of a sample. Without this huge reduction in computation time, the outage scheduling assessment process described in this paper, which accounts for short-term decisions based on multiple UC instances, would have not been possible due to computational intractability.

A.2.4.1 Nearest neighbor classification

Formally, once obtaining the learned short-term proxy, the short-term decisions which were initially obtained as exact solutions of Eq. (A.2.4), $u_p^* = \arg\min_{u_p \in \mathcal{U}_p(u_m)} \quad C_p(y_s, u_m, u_p)$, by solving the complex MILP in Problem (A.2.5), are now obtained as approximate solutions $\hat{u_p^*}$, solving a much less complex problem – finding the closest neighbor to the environment and grid conditions (y_s, u_m) – with computation time that is several orders of magnitude lower.

As explained, for nearest neighbor classification we first need to build a large data-set of pre-solved unit commitment problems, a process which we refer to as *training*. Given the day-ahead forecast and maintenance plan (y_s, u_m), the daily conditions which are the input for the UC problem are 24-h per-bus demand and wind generation forecasts $D_{\text{d.a}}, W_{\text{d.a}}$, and daily network topology $\text{top}_{\text{d.a}}$. Denote x to be a column-stack (single-column vector representation) of a UC daily condition tuple: $x = [D_{\text{d.a}}^{\text{cs}}; W_{\text{d.a}}^{\text{cs}}; \text{top}_{\text{d.a}}] \in \mathcal{X}$, where superscript $\cdot^{\text{cs}}$ stands for column-stack. The training stage involves generating multiple samples $\{x_k\}_{k=1}^N = \mathcal{X}_{\text{train}}$, drawn from the marginal distribution expected to be used during the actual outage schedule assessment, solving each of them using the formulation presented in Problem (A.2.5) and obtaining $u_p^*(x_k)$. In the context of classification in the machine learning literature, the solution $u_p^*(x_k)$ is often referred to as the *label* of sample x_k.

After the training set has been created, while running the assessment procedure, classification is performed for each new sample x to obtain its corresponding label. The label is chosen to be the label of x's nearest neighbor in $\mathcal{X}_{\text{train}}$. In order to find x's nearest neighbor we first need to define an appropriate distance metric. We choose the distance between two UC daily conditions x, x' be the β-weighted L_2-norm of their element-wise difference:

$$d(x, x') = ||x - x'||_\xi = \left[\sum_{i=1}^{\text{length}(x)} \beta_i^2 (x_i - x_i')^2 \right]^{\frac{1}{2}}. \tag{A.2.7}$$

The weights β_i are used for expressing the importance of different entries in correctly choosing the nearest neighbor x'. For instance, in our simulation the β_is multiplying the entries of $\text{top}_{\text{d.a}}$ are chosen to be 100, whereas the rest are set to 1. This choice stems from the relatively higher importance of network's topology than the forecast values of demand and wind generation. In addition, β is used for scaling different units, e.g., for the binary values received for differences in

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$\mathrm{top}_{\mathrm{d.a}}$, compared to the values in [MW] received for differences in $D^{\mathrm{cs}}_{\mathrm{d.a}}$, $W^{\mathrm{cs}}_{\mathrm{d.a}}$. Further research in the field of *metric learning* is anticipated by the authors for optimizing over the choice of β or over different metrics.

The classification of a new sample x will therefore be done by finding

$$x_{\mathrm{NN}} = \arg\min_{x' \in \mathcal{X}\mathrm{train}} d(x, x')$$

and setting

$$\hat{u_p^*}(x) = u_p^*(x_{\mathrm{NN}}).$$

Further explanation on the nearest neighbor classifier can be found in Fig. A.2.4.

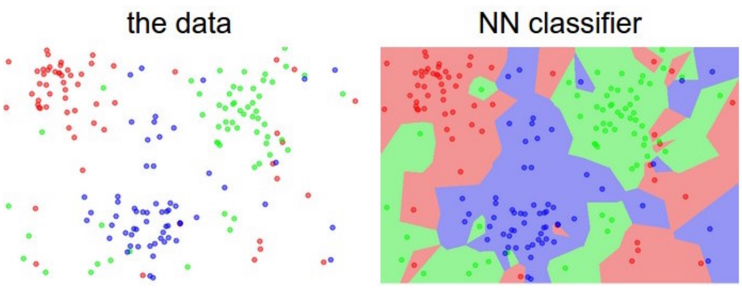

Figure A.2.4: Illustration of the nearest neighbor classifier algorithm[4]. In the first stage on the left, labled data is treated as the train set. The points are samples in the $\mathcal{X}$ space, colored according to their label (specific UC solution). In the second stage on the right, different regions are formed, coloring each new data point x according to its nearest neighbor in the train set.

A.2.4.2 Approximation quality – experimental results

There is no obvious technique for comparing two UC solutions. UC schedules are represented in binary matrices that can be very different in standard metrics, such as Manhattan distance, and yet practically identical in terms of operation, depending on the network test-case and choice of generator representation. To better understand UCNN algorithm, we evaluate the quality of its output, approximate UC solutions, using two criteria – cost and daily reliability level. Particularly, cost is the objective function's value in Problem (A.2.5), at its solution; daily reliability level is the average hourly reliability level $r(S_t)$, as defined in Eq. (A.2.3).

Using the simulation environment and updated IEEE-RTS96 network described in Section A.2.6, we generate a train set of $|\mathcal{X}_{\mathrm{train}}| = 5000$ labeled (solved) UC schedules, with daily demand-wind generation and topology conditions drawn from the marginal distribution expected to be used during the actual outage schedule assessment. We then obtain a labeled test set by generating 1000 additional such UC problems and solving them. In this experiment, $N-1$ is not enforced. Each sample x in the test-set is classified using UCNN, and the resulting approximate solution $\hat{u_p^*}(x)$ is compared to its exact counterpart, $u_p^*(x)$, using the cost and reliability criteria. The results are the following.

A scatter of the costs of exact UC solution vs. UCNN solution is presented in Fig. A.2.5. Very high match is shown. The form of small clusters is received since several profiles of daily mean demand-wind forecasts are used (according to the season of the year). During summer demand is

[4]Drawing taken from lecture notes of Stanford's CS231n class, 2016.

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low and generation production is cheap. The months of this season correspond to the three small clusters of low UC costs. As a result, smaller errors are received compared to when costs are high, which cause the computed correlation coefficient to be extremely high – 0.991. When neglecting these samples (with costs below $0.5 \cdot 10^7$), correlation coefficient is still sufficiently high – 0.97.

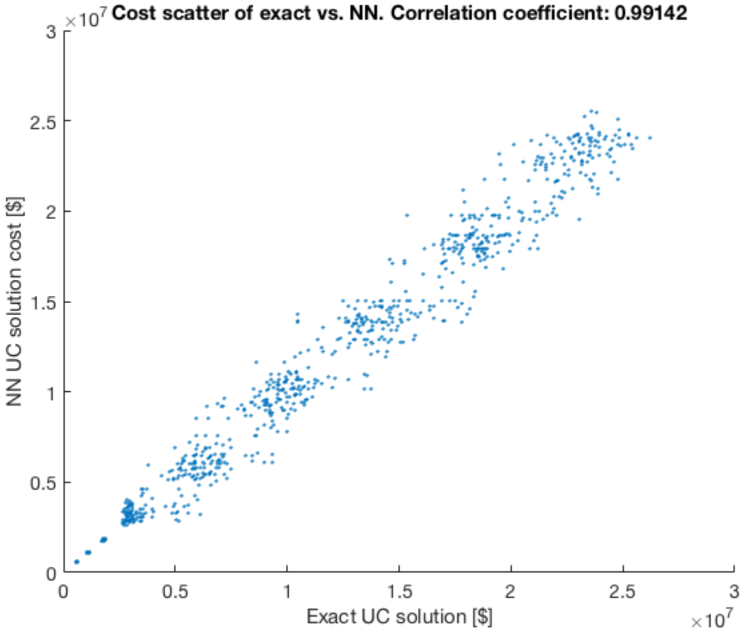

Figure A.2.5: Scatter of unit commitment costs. x-y axis correspond the cost of exact UC solution, and the cost the NN UC solution, respectively. An excellent match is witnessed. The form of small clusters is received since several profiles of daily mean demand-wind forecasts are used (according to the season of the year). Computed correlation coefficient is 0.991.

Testing for reliability again reveals low approximation errors. However, this time it is not sufficiently low as with the case of the cost. Computed correlation coefficient is 0.78. We therefore suggest an improvement for our algorithm – usage of confidence level. Confidence per each sample is determined by the agreement among its K nearest neighbors, i.e., the standard deviation of the K nearest neighbors' reliability values; we choose $K = 10$. The relation between the level of confidence and quality of approximation is presented using a heat-colored scatter plot in Fig. A.2.6. Samples are colored according to the aforementioned standard deviation. High confidence (low standard deviation) is obtained for samples with high correlation. In addition, to show a possible practical usage of this trait, we set 10 increasing thresholds of maximal standard deviations. For each such threshold, we drop all test samples whose standard deviation is above the threshold, i.e., samples with low confidence. At the top of Fig. A.2.7, the corresponding correlation coefficients are presented for the 10 thresholds, and at the bottom the respective remaining test set size.

The experiments demonstrate the strength of the our improvement to UCNN. We are able to capture the notion of confidence of an approximated solution, and utilize it for predicting its quality in terms of approximation error. Two usages of this method can be considered when performing outage schedule assessment: account for the sample with respect to its confidence level (weight it accordingly), or alternatively discard samples below a certain confidence threshold and compute them accurately. This improvement to UCNN is not employed yet in the outage schedule assessment experiments presented in Section A.2.6, as this is beyond the scope of this work.

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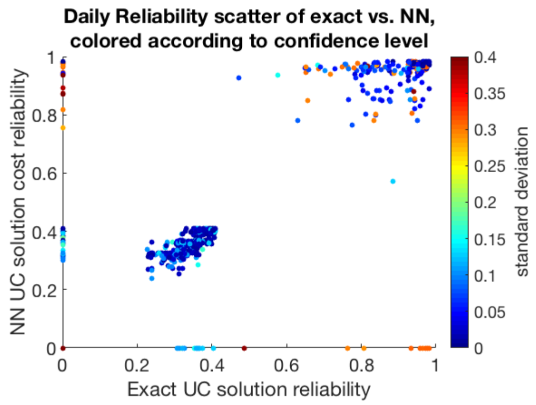

Figure A.2.6: Scatter plots of daily unit commitment reliability levels, calculated for exact UC solutions and their corresponding NN samples. Each sample is colored according to the standard deviation of its $K = 10$ nearest-neighbors' reliability values. High confidence (low standard deviation) is obtained for samples with high correlation.

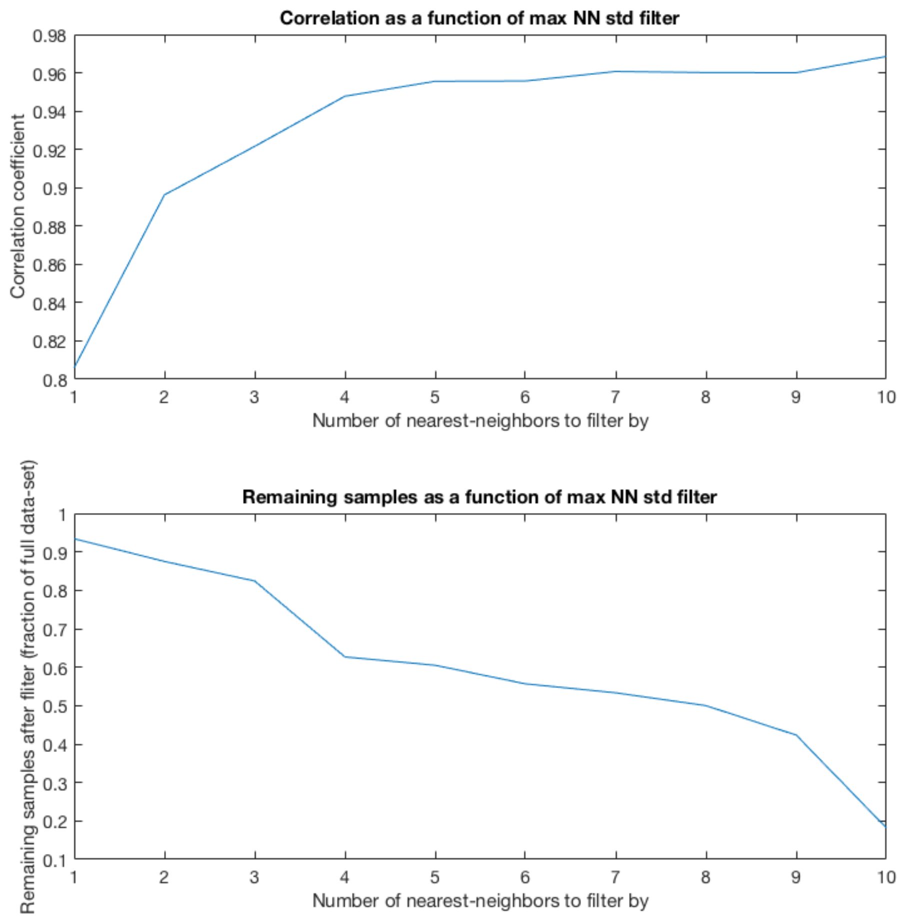

Figure A.2.7: Correlation coefficient values, calculated for exact UC solutions and their corresponding NN samples. High correlation demonstrates high reliability approximation quality. When filtering according to the 10 different levels of standard deviation in the x-axis (above this level of std, NN will not be used and instead an exact calculation will be made), one can see the correlation improving and number of remaining samples shrinking. This suggests that high level of confidence among the NNs imply lower approximation error.

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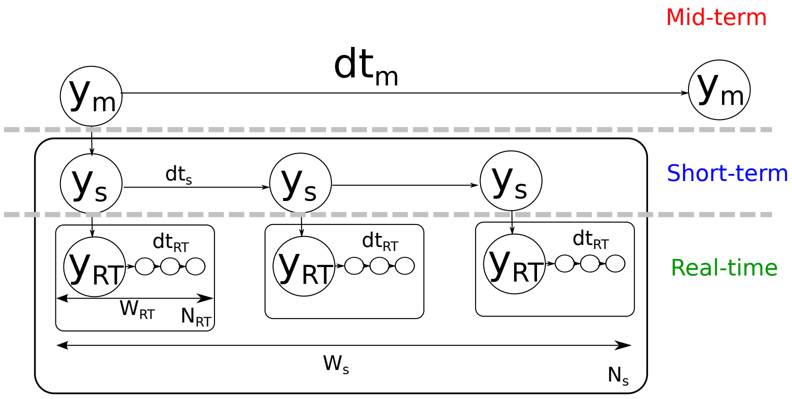

Figure A.2.8: Hierarchical window scenario sampling approach for scenario cost approximation.

A.2.5 Simulation and assessment method

Each scenario $Z_{\boldsymbol{u},\theta}$ has its associated distribution of cost as appears in Eq. (A.2.2), composed of the summation of real-time atomic costs, due to different events such as redispatching, commitment of generators, and loss of load. To evaluate costs such as these, Monte-Carlo simulation is often used in the literature and industry, with two main categories of scenario generation approaches. The first is full-trajectory simulation, where all real-time hourly developments are simulated as a full sequence as being done in [5], while realizing the different uncertainties. For our mid-term problem, which can span over a full year, such an approach will necessitate an intractable number of samples in order to produce a decent evaluation of the scenarios cost, and will incur very high variance of the samples. The second category of approaches is based on snapshot sampling of possible static moments of the state of the world and the system. The main problem with such a methodology is the loss of temporal development information, originating in sequential implications of decisions made.

Therefore in order to deal with the high complexity of assessing cost/implications of maintenance actions via scenario evaluation, we introduce a novel scenario approximation approach. The *hierarchical window scenario sampling* is a hybrid version of the two previous sampling methods, which aims at mitigating the disadvantages of each of them.

As visualized in Fig. A.2.8, the sampling scheme is done by drawing a sequence of snapshots of the system, for each month (associated with y_m), in sequential development of time-ticks t_m(=month). Notice that it is governed by the maintenance schedule u_m. Then, to approximate the cost of each month we draw N_s samples of W_s sequential days (trajectories of y_s at time resolution t_s=day). Notice that the short-term inner optimization problem is solved for each day in each trajectory. In this work we simulate only the days of the planned outage, for all outages scheduled.

Next, for each day (y_s) we simulate the real-time progression by sampling N_{RT} trajectories of length W_{RT} (=24) of the hourly sequential y_{RT}[5]. For each y_{RT} we calculate the real-time cost by solving the real-time OPF problem with its associated sampled (realized) uncertainties.

[5]The choice of the window lengths W_s and W_{RT} controls the level of interpolation between the completely sequential scenario sampling of all T time steps, and the alternative completely static approach of solely sampling snapshots of states, with no temporal relation between them. Essentially, they arbitrate between the bias and variance of the sampling process. Full trajectory sampling has low bias but high variance, while static snapshot sampling lowers the variance, though it introduces bias due to its simplicity and choice of times of snapshots.

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

A.2.6 Experimental Results

We run our experiments on a Sun cluster with Intel(R) Xeon(R) cpus @2.53GHz, containing 300 cores, each with 2GB of memory. All code is written in MATLAB. We use YALMIP [14] to model the full inner optimization problem both in its short-term and real-time versions. It is then solved using CPLEX [10].

In our simulation we consider two test-cases: the IEEE RTS-79 and IEEE RTS-96 networks. For both of them we adopt updated generator parameters from Pandzic et. al [15], namely their capacities, min-output, ramp up/down limits, min up/down times, price curve and start-up costs. Capacities and daily wind generation profiles are based on real historical records from the US as published in [16]. Peak loads and daily demand profile are based on real data, taken from [16]. For more information on the wind generation and load distributions used in our experiments please refer to Appendix A.2.9. Value of lost load cost is set to $VOLL = 1000[\frac{\$}{MWh}]$, taken from [17] and wind-curtailment price is set to $C_{WC} = 100[\frac{\$}{MWh}]$, taken from [18].

We assess Problem (A.2.1) for a time-horizon of $T_M = 12$ months. Several outage schedules are assessed in parallel, where each evaluated month of such a schedule is split to a different server, and is simulated as $W_s = 3$ consecutive days, resulting in 3 unit-commitment solutions of the full inner optimization problem for each such trajectory. For each of those days, we simulate $N_{\text{RT}} = 15$ samples of real-time trajectories of $W_{\text{RT}} = 24$ hours per each sample. Each such trajectory is a realization of the actual wind power W_t and load D_t that occurred in that duration, using which the real-time control decision in Eq. (A.2.6) is calculated and its cost is obtained. In this simulation, Problem Eq. (A.2.5) is solved for the non-$N-1$ case.

A.2.6.1 IEEE RTS-79 network

To validate the competence of our methodology and showcase a possible representation of its outputs, we apply it on two possible outage schedules and compare their full-year assessment results. The first schedule is a blank plan that includes no outages. For the second schedule we randomly generate an arbitrary outage plan, referred to as 'outage plan 1'. A visualization of it can be found in Fig. A.2.9.

In such a comparison, since outages are expected to have negative influence on network operation in terms of cost and reliability, one would expect the blank outage plan to have low overall cost and lost load, along with high success rate, compared to 'outage plan 1'. This claim is indeed supported by the results as summarized in Fig. A.2.10. A monthly average is computed per each of the three following indicators:

1. Daily operational cost – includes redispatch cost, re-commitment cost, and wind curtailment cost.
2. Daily success rate – average hourly reliability level $r(S_t)$, as defined in Eq. (A.2.3).
3. Daily load lost.

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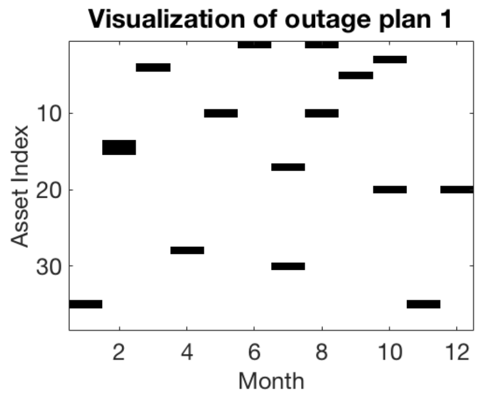

Figure A.2.9: Visualization of 'outage plan 1', which was created in random. A black mark in entry (asset i, month j) indicate an outage is performed on asset i during month j, and it is taken offline for its duration. In this work, assets are transmission lines.

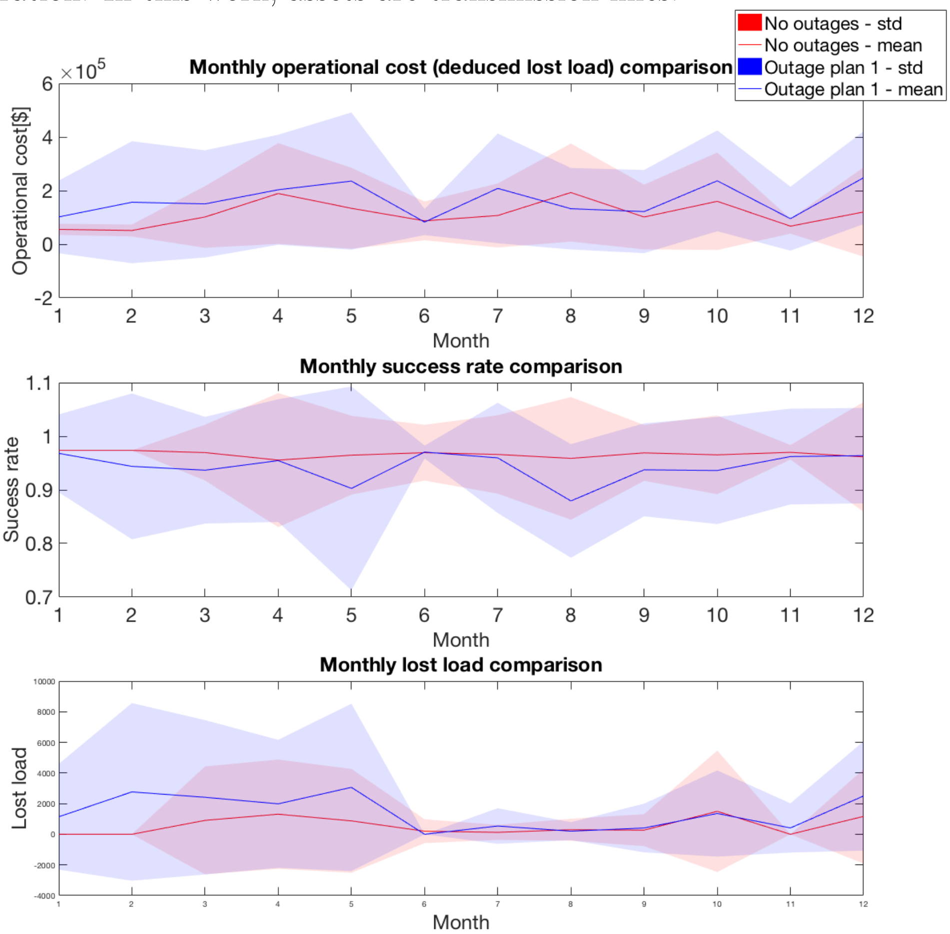

Figure A.2.10: Monthly mean and standard deviation of operational cost (redispatch cost, recommitment cost, wind curtailment cost), success rate average and load shedding. Two outage plans are being assessed – a blank, no-outage schedule, and an arbitrary outage plan which we refer to as 'outage plan 1'.

The results are consistent throughout the whole assessment period. They show an overall higher operational cost, lower success rate, and more load lost in the case of 'outage plan 1', compared to the blank plan, as expected.

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

A.2.6.2 IEEE RTS-96 network

We again randomly generate an arbitrary outage schedule, 'outage plan 2'. A visualization of it can be found in Fig. A.2.11. We compare it to a blank plan that includes no outages and present the results in Fig. A.2.12.

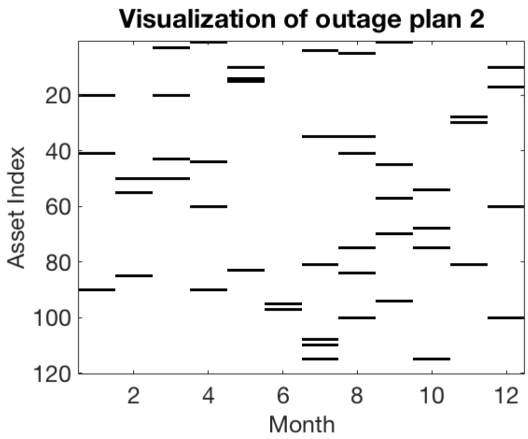

Figure A.2.11: Operational cost (redispatch cost, re-commitment cost, wind curtailment cost), success rate average and load shedding.

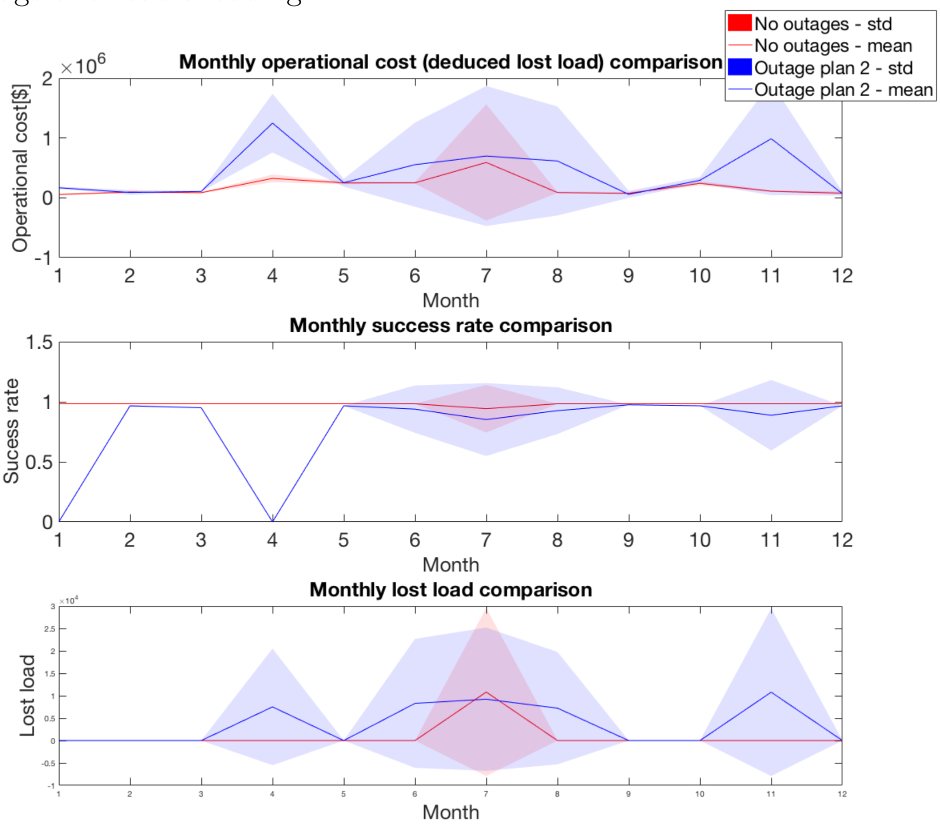

Figure A.2.12: Operational cost (redispatch cost, re-commitment cost, wind curtailment cost), success rate average and load shedding.

As with the case of the IEEE RTS-79 network, the results show an overall higher operational cost, lower success rate, and more load lost in the case of 'outage plan 2', compared to the blank plan.

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A.2.7 Conclusion

The outage scheduling problem requires careful attention, due to the hierarchical structure of several layers of decision making need to be accounted for. This makes the outage scheduling task a very challenging problem for mid-term planners within a TSO. The scenario assessment framework developed in this work enables to evaluate the multiple complex implicit implications an outage schedule inflicts on a power system. We harness the power of distributed computing for the evaluation of these implications and present it along a whole year of assessment.

A major conclusion from the work described here and in a previous paper [19], is that approximated 'proxy' methods that learn and mimic TSO decision are necessary in enabling tractable simulation with such a high level details. In this work we design, investigate and utilize such a proxy. It evidently reduces computation time of short-term inner decision simulation in several orders of magnitude and enables assessment of larger networks, or alternatively higher confidence in terms of sample size.

Our method facilitates the ability to compare different outage schedules, and provides maintenance planners with a tool for validating their proposed outage schedule. In additional planned efforts, we intend to wrap this assessment methodology into an outage schedule optimization scheme, where an optimal outages schedule is searched for, in terms of cost and reliability level.

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A.2.9 Distributions of the Stochastic Processes within the Model

The stochastic processes in the system are the wind power produced in the wind generators W_t and the load process D_t. In this section we provide details on the models used for these two probabilistic processes, along with the data and test-cases they are based on.

A.2.9.1 Wind Power Distribution

The wind generation capacities for buses with wind generators attached are taken from [16], along with their daily mean profile. The wind process mean $\mu_w(t)$ is therefore obtained by the formula

$$\mu_w(t) = \mu_w(t_D) \cdot p_{w,\text{annual}}(t_M)$$

, where $\mu_w(t_D) \in \mathbb{R}_+^{n_w^g}$ is the daily wind mean profile at time-of-day t_D, and $p_{w,\text{annual}}(t_M) \in [0,1]$ is the annual wind profile relative to its peak at month t_M of the year.
Wind generation process W_t is a multivariate, normally distributed random variable

$$W_t \sim \mathcal{N}\left(\mu_w(t), diag((p_{w,\sigma} \cdot \mu_w(t))^2)\right)$$

where $p_{w,\sigma} \in [0,1]$ is a constant (0.15 in most simulations) that multiplies the mean $\mu_w(t)$, to obtain a standard deviation that is a fixed fraction of the mean. $diag(x)$ is a square diagonal matrix, with the elements of x as its diagonal, so different wind generators are assumed uncorrelated. W_t is truncated to stay in the range between 0 and the generator's capacity.

A.2.9.2 Load Distribution

Load D_t is assumed to follow the same normal distribution as the wind, with the same formula containing peak loads and daily profiles for each bus $\mu_d(t_D) \in \mathbb{R}_+^{n^b}$ with values taken from [16]. Fraction of mean for standard deviation is set to be $p_{d,\sigma} = 0.02$.

The research leading to these results has received funding from the European Union
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APPENDIX A.3 Component models

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Organization: NTIS - University of West Bohemia, Pilsen, Czech Republic

Abstract: This working paper presents the models investigated in the GARPUR project for representing power system components' ageing and failure rates in the context of asset management studies. The proposed models decompose a component into subcomponents, for each one of which a model is designed for his health-status by suitably instantiating a generic stochastic model; furthermore these models are adapted to express the effect of maintenance activities and to derive failure modes and rates of whole components. A case study based on real data from the Czech TSO CESP is presented.

A.3.1 Introduction

Modelling of a time development of a system component state requires to analyse all the most relevant ageing and degradation processes and their impact on important elements of the system. Then, obtained results are applied to a suitable mathematic formalism for description of their dynamics. A generic modelling framework for continuous and discrete events dynamics is introduced in this article. Further, the model is specified for the most important subcomponents of overhead lines, especially for towers, conductors, insulators and corridor, together with the most outstanding processes and environmental effects that accompany the ageing. The series of factors such as corrosion, vibration, lightning, fatigue and vegetation growth is considered. Finally, examples of model parameters identification based on statistical analysis of corresponding available data are presented.

A.3.2 Modelling framework

The aim of the model is to describe degradation level or ageing associated with the lifetime consumption of major transmission network components and subcomponents. Degradation usually occurs because of the negative effects of the environment, their wear or fatigue during operation and depends on absolute time, operating time, number of starts or changes of operating mode. The level of degradation is closely associated with the network component reliability or loss of resistance to external influences.

A.3.2.1 Subcomponent level

From the modelling point of view, each component is composed of a set of different devices (called subcomponents). Typically, a TSO operates a huge number of subcomponents of the same type, which allows him to create groups of such subcomponents with the same model and similar age or condition. The ageing, degradation and reliability models are developed and parametrized for these groups. For these groups, there are generally enough historical data available to allow:

- to estimate actual or past failure rates,

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- to compare reliability with other groups of similar subcomponents and detect an equipment design error.

Note that these data contain information only about reliability in current or past equipment condition under current maintenance policy. The data should be fused with expert knowledge and results of accelerated ageing tests for development reliability models that describe reliability under future (worse) component conditions.

A.3.2.2 Degradation and ageing models

The model should contain more than one attribute for sufficient description of various aspects of asset health state (e.g .: kind of tower construction steel and corrosion protective coating). Generally, it is possible to represent these attributes as a set of continuous variables based on physical principles of major degradation phenomena and their effects.However, often very complex dependencies and lack of ability to determine their parameters, e.g. using statistics development signs, makes this task almost impossible to be implemented. Therefore, models with discrete parameters are frequently used instead.

A.3.2.2.1 Hybrid discrete-continuous state model of subcomponents

This section presents the mathematical description of an ageing model structure based on a dynamic state variable theory. Generally, we assume the following multidimensional state variables with mixed type attributes. Let the attributes be described by the continuous state variable $X(t) \in \mathbb{R}^N$, discrete state variable $R(t) \in \mathbb{R}^M$ and exogenous variable $S(t) \in \mathbb{R}^K$ defined as

$$X(t) = [x_1(t), x_2(t), \ldots, x_N(t)]' \ , \tag{A.3.1}$$

$$R(t) = [r_1(t), r_2(t), \ldots, r_M(t)]' \ , \tag{A.3.2}$$

$$S(t) = [s_1(t), s_2(t), \ldots, s_K(t)]' \ . \tag{A.3.3}$$

The dynamic model of the elements of the health state $X(t)$ is given as follows

$$x_i(t+\delta) = x_i(t) + k(X(t), R(t), S(t)) \cdot \delta + \xi(t) \ , \quad i = 1, \ldots, N \ , \tag{A.3.4}$$

where: δ is the elapsed time step,
$k(X(t), R(t), S(t))$ is a rate factor depending generally either on asset health state $X(t)$ and $R(t)$ together with environment state $S(t)$,
$\xi(t)$ is a zero mean random variable, which may be tuned in order to represent the non-modelled phenomena.

For practical reasons, the rate factor $k(X(t), R(t), S(t)))$ will be considered as:

$$k(x, s) = k_x(X(t)), R(t)) \cdot k_{sx}(S(t)) + k_s(S(t)), \tag{A.3.5}$$

where: $k_x(X(t), R(t))$ is a rate factor depending on the health state $X(t)$ and $R(t)$,
$k_{sx}(S(t))$ is a time scale factor for specific environment $S(t)$ related to the state vector $X(t)$,
$k_s(S(t))$ is an additional time scale factor for specific environment state $S(t)$.

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This simplified form scales time axis, which makes possible to recalculate data among different environments and use all observed data to determine the rate factor.

Dynamics of discrete part of the health state is described as a finite state machine or left-right semi-Markov model. The elements of discrete part of health state $R(t)$ have values from a final set given as:

$$r_i \in \{r_i^1, r_i^2, \ldots, r_i^{Q_i}\} \ , \quad i = 1, \ldots, M \ . \tag{A.3.6}$$

Dwell in the state r_i^q is given as a random variable with probability distribution T_i^q generally depending on the all state vectors:

$$r_i^q : \tau \sim T_i^q(X(t), R(t), S(t)) \ , \quad i = 1, \ldots M, \ q = 1, \ldots, Q_i \ . \tag{A.3.7}$$

Similar to continuous states, dwell model can be also simplified by time scale factor $k_s(S(t))$. Dwell in the state x_i^q is given as a product $k_s(S(t)) \cdot \tau$, where τ is a random variable with probability distribution $T_i^q(X(t), R(t))$ depending only on the asset state vectors.

Transition between state nodes is given by a transition probability matrix, which is defined for natural evolution of sequential degradation process without the maintenance by the following simple formula:

$$P(x_i)_{i \in N+1..N+M} = (x_i \xrightarrow{\Pi} x_i \times x_i) : p_{q,w}(x_i) = p(x_i^q | x_i^w) = \langle \begin{array}{l} 1 : \forall_{w=q+1} \\ 0 : \forall_{w \neq q+1} \end{array} \tag{A.3.8}$$

A.3.2.2.2 Model extension for the maintenance repair action application

The maintenance repair action A with an influence to health state can be described as:

$$X(t), R(t) \xrightarrow{repair A} X(t|A), R(t|A) \tag{A.3.9}$$

The impact of maintenance activities on the health-condition is expressed separately for the continuous and the discrete part of the health-condition state-vector, as follows. For continuous variables apply a multiplicative (gradual) formula:

$$x_i(t|A) = x_i(t) \cdot (1 - b(A)) + \xi(A) \ , \quad i = 1, \ldots, N \ , \tag{A.3.10}$$

where $b(A)$ is expected benefit of the maintenance action A depending generally on whole component health state vectors X and R and $\xi(A)$ is a random variable expressing variance about action benefit.
For discrete variables then apply a full probability transition matrix:

$$P_R(r_i)_i = (r_i \xrightarrow{\Omega} r_i \times r_i) : p_{q,w}^R(r_i) = p(r_i^q | r_i^w, A) \ , \quad i = 1, \ldots, M \ . \tag{A.3.11}$$

To derive such a model, we can use physical-statistical approach, which consists in determining the form of the model based on physical principles and in the subsequent statistical calculation of values of the parameters based on long-term observation.

A.3.2.3 Impact of component health state on failure rate

This subsection will focus on impact of subcomponent health state on subcomponent failure rate. Cause of outage can be divided into environment influence and subcomponent damage. In both case, failure rate $\lambda(X(t), R(t), w(t)$ depends on subcomponents health states $X(t)$ and $R(t)$ and

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environment state $w(t)$. However, such general dependence can not be identified with sufficient accuracy only based on data. Therefore we had to find a simplified formula, that is described below.

Environment state describes especially weather condition that is usually considered as discrete for practical reasons, e.g. ENTSO-E classifies weather to tree classes – normal weather, bad weather and extremely bad weather. This makes data available for each class.

It is more complicated to collect data for different subcomponent condition, because European TSOs have the most of subcomponents in perfect or good condition at the moment. Failure rate data of current component should be fused with data of reliability of previous equipment and expert's knowledge. Assuming proportional relation between environment state and failure rate, the general dependence will be simplified for first implementation in following product form:

$$\lambda\left(X(t), R(t), w(t)\right) = k_{FR}\left(X(t), R(t)\right) \cdot \lambda(w(t)), \tag{A.3.12}$$

where $k_{FR}\left(X(t), R(t)\right)$ denotes coefficient of failure rate increase due to degradation and $\lambda(w(t)$ is subcomponent failure rate in good condition and weather $w(t)$. This form allows intuitive model parametrization and setting the same a priori parameters $k_{FR}\left(X(t), R(t)\right)$ for every similar equipment. We will assume that the k_{FR} is monotonously increasing function. If the health state is considered as discrete, then value of $k_{FR}(r_i)$ is assigned for each health state r_i. The following form is used in [1] for approximation $k_{FR}(x_i)$ for continuous health states:

$$k_{FR}(x) = A \cdot e^{B \cdot t} + C, \tag{A.3.13}$$

where A, B, C are parameters that shape the function. Determination of the parameters is based on a priori technical knowledge with reliability data sources support and it will be the subject of further research.

A.3.2.4 Connection between component failure and subcomponent damage

From the grid operation perspective, only the forced outages of the whole components are relevant. Therefore, this subsection proposes a model for the (whole) component failure rates based on the subcomponent failure or damage rates.

At first, we introduce several possible types of failure:

- Caused by other component (FOC) – failure is caused by failure of another component in grid, e.g. line outage caused by failure or malfunction of switch gear.
- With successful automatic reclosing (FAR) – failure is ended by automatic reclosing of switchgears by protection systems. The initial short circuit can be caused by subcomponent damage, however there is a huge amount of events without damage, that are caused usually by environmental factors like lightning.
- Failure without damage (FWoD) – this type of failure has the following scenario: automatic reclosing is unsuccessful, no damages are observed by inspection and the component is put manually back into operation without repair.
- Failure with damage (FWiD) – this type is connected with significant damage of one or more subcomponent. The inspection patrol decides if it is possible to put the component temporally back in operation and repair it in the next few days, or if it is necessary to repair the component immediately.

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These types are disjunctive by definition. The component failure rate h(t) can be split by type:

$$h(t) = h_{FOC}(t) + h_{FAR}(t) + h_{FWoD}(t) + h_{FWiD}(t) \tag{A.3.14}$$

Failure rate $h_{FOC}(t)$ caused by other components is assumed to be a part of their models. Failures without damage are considered as random events and their failure rate depends on environment variables and component states. Failures with successful automatic reclosing are mixtures of events with (FARD) and without (FARN) subcomponent damage. The failure rate can be split again:

$$h(t) = h_{FOC}(t) + h_{FARD}(t) + h_{FARN}(t) + h_{FWoD}(t) + h_{FWiD}(t) \tag{A.3.15}$$

Failure rates $h_{FARD}(t)$ and $h_{FWiD}(t)$ can be computed from rates of subcomponents damages $h_{a,d}(t)$, where $a \in A$ are all subcomponents and $d \in D$ are all possible damages.

To prevent components failures, the same subcomponents may be assembled redundantly. The damage on redundant subcomponent can cause failure, subsequently the failure rates are described by equations:

$$h_{FARD}(t) = \sum_{a\in A} \sum_{dinD} p_{SAR}(d,a) \cdot h_{a,d}(t), \tag{A.3.16}$$

$$h_{FWiD}(t) = \sum_{a\in A} \sum_{dinD} p_{UAR}(d,a) \cdot h_{a,d}(t), \tag{A.3.17}$$

where $p_{SAR}(d,a)$ is the probability of failure with successfully automatic reclose and $p_{UAR}(d,a)$ is the probability of failure with unsuccessfully automatic reclose.

A.3.3 Degradation and ageing models of overhead power lines

In the section, a general model of ageing described in previous section A.3.2 is here specified for individual main overhead line subcomponents and relevant degradation processes.

A.3.3.1 Specification of the subjects and relevant degradation events or processes

EHV overhead lines consist of several various elements (subcomponents) with different factors having an impact on degradation. The following table A.3.1 shows an overview of main overhead line subcomponents and relevant degradation events or processes including a distinction by regularity of their nature (accidental, depending on the weather, gradual) as well as an overview of the corresponding maintenance activities (prevention, inspection and corrective). The next subsections are focused on the bold marked processes.

A.3.3.2 Selection of the significant subcomponents and phenomena for the degradation model

For modelling purposes, only several significant elements of the overhead transmission power lines (OHL) and relevant most important degradation phenomena will be selected, especially with an escalating character that could be reduced by preventative maintenance activities. Then, it makes sense to optimize the maintenance of such subjects with respect to a long-term overall cost.

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subcomp.	degrad. event/process	occurrence	maintenance preventive/inspect/corrective		
conductor	**corrosion Al+Fe**	gradual, hidden	x	deep insp.	replace
	vibration fatigue	gradual, hidden	damper	deep insp.	replace
	lightning strike (+arc)	weather, evident	x	measure.	x
	untwisting	accidental, evident	x	visual insp.	repair / repl.
	sagging	accidental, evident	spacer	visual insp.	repair
earthwire	**corrosion Al+Fe**	gradual, hidden	x	deep insp.	replace
	vibration fatigue	gradual, hidden	damper	deep insp./ measure	replace
	lightning strike (+arc)	weather, evident	x	visual insp.	x
	untwisting	accidental, evident	x	visual insp.	partial repl.
	stealing (missing)	accidental, evident	x		supply
conductor joints, spacers, dampers	corrosion	gradual, evident	x	visual insp.	replace
	grip releasing	accidental, hidden	x	deep insp.	repair / repl.
	deformation	weather, evident	x	visual insp.	replace
	droping out (missing)	accidental, evident	x	visual insp.	supply
insulator string	corrosion of metal parts	gradual, evident	x	visual insp.	partial repl.
	power arc	accidental, evident	x	visual insp.	replace
	fatigue (crack , break)	gradual, evident	x	deep insp.	replace
	gunshot damage	accidental, evident	x	visual insp.	replace
	soiling	gradual, evident	cleaning	visual insp.	clean
tower	**corrosion**	gradual, evident	painting	visual insp.	partial repl.
	deformation	weather, evident	x	visual insp.	repair / repl.
	part droping out (lost)	accidental, evident	x	visual insp.	supply
foundation	corrosion of metal parts	gradual, evident	painting	visual insp.	reconstruction
	geo activity(crack,break)	accidental, evident	x	visual insp.	reconstruction
	grounding damage	accidental, evident	x	deep insp.	replace
corridor	**vegetation encroachment**	gradual, evident	trimming	visual insp.	trim
	unauth. construction	accidental, evident	x	visual insp.	remove
	tree falling, conductor strikes	weather, evident	trimming	x	trim

Table A.3.1: Overview of main overhead line subcomponents and relevant degradation processes

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First, it is necessary to define a set of model attributes, parameters and dependencies in accordance with the above proposed structure. Table A.3.2 shows a summary of selected significant entities and attributes considered in the degradation model.

subcomp.	state attribute	dependencies	model type	data source	model ref.
tower	surface protect state	corrosive zone (z1)	discrete	inspection	[7], [8], [2]
	steel corrosion state	corrosive zone (z1) surf. prot. state (x1)	continuous	inspection	[7], [8], [2]
conductor	steel/Al corrosion state	corrosive zone (z1)	discrete	inspection	[6], [4]
	vibration fatigue state	vibration zone (z2) dumper state (x10)	continuous	inspection	
earthwire	steel/Al corrosion state	corrosive zone (z1)	discrete	inspection	[6], [4]
	vibration fatigue state	vibration zone (z2)	continuous	inspection	
	lightning damage state	lighting act. zone (z3)	discrete	measuring	
insulator string	age/condition state	—	continuous	inspection	[6], [11]
corridor	vegetation growth state	vegetation zone (z4)	discrete	inspection	[10], [5], [3]
antivibration element	dumper ability state	vibration zone (z2)	discrete	inspection	[12]

Table A.3.2: Overview of entities and attributes captured in the degradation model

In the degradation model, we want to capture a health status and progress of entire EHV overhead line system, which consists of many subcomponent instances of few different types with their specific condition attributes. We will consider the aggregate attributes associated with a respective group of elements of the same type, age and located in the same degradation zone (e.g. every towers of relevant part of the overhead transmission line built at the same time inside the same corrosion zone). In the case of description of subcomponents from appreciably different types or materials the aggregate attributes must be subdivided (e.g. insulators made from glass, porcelain or composite having different resistance to a degradation influences).

A.3.3.3 Degradation zone type specification

The degradation zone is an area with the same degradation factors, which corresponds primarily to its geographical location and climate. For the modelling purposes, we can distinguish four types of zones as follows:

- corrosion zones - areas with the same environmental factors of chemical aggressiveness (humidity, temperature, salinity, acidity),
- vibration zones - areas with the same environmental factors of mechanical activity (wind gusts),
- lightning activity zones - areas with the same incidence of lightning,

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- vegetation zones - areas where are the same rates of vegetation growth.

In Table A.3.3, it is shown an example of estimated range of individual zone types and the corresponding rate parameter of the model:

zone type	zone variable	scale factor k_s
corrosive	1 - low	*0.8*
	2 - moderate	*1*
	3 - severe	*1.5*
vibration	1 - mild	*1*
	2 - harsh	*3*
lightning activity	1 - low	*0.4*
	2 - medium	*1*
	3 - high	*1.8*
vegetation	1 - farmland	*0*
	2 - forest	*1*

Table A.3.3: Example of estimated range of individual zone types

A.3.4 Case studies

The section provides two examples of application of the modelling framework on a real data. There are presented identification procedures of parameters used in previously proposed models based on statistical analysis of corresponding available data.

The first example deals with the scale factor of subcomponent ageing model for each line segment passing through different lighting activity areas. There is shown how values listed in section A.3.3.3, Table A.3.3 was determined from data of lighting occurrences.

The second example deals with parameters of the insulator ageing model using a failure data collected during the lifetime. It shows how to determine the dependency between failure rate and age described in section A.3.3.2, Table A.3.2.

A.3.4.1 Lightning zones

For the purpose of this study, we analysed characteristics of real lightning activity measured by radar in the vicinity of transmission line corridors. We used data provided by the Czech TSO CEPS, which contain approximately 291,000 available data records of lighting occurrence position collected during the 5 years period. From which, approximately 74,000 records of lightning ground strikes along the transmission lines within up to 500m of ground distance from a transmission line were selected. For the parallel lines, intensity was counted only one of them. Data were allocated to the individual lines and segments. Subsequently, a lighting intensity related to 1 km line length and 1 year time period was computed for each line in according to two aspects. One in the form of intensity of lightning occurrence along transmission line length in 2 km resolution and one in the form of geographical distribution along transmission line area calculated with resolution of 0.02 x 0.02 degrees.

Thus, prepared data followed to determine the affiliation of each transmission line segment into one of three lighting zones according to the respective lightings intensity.

Range of intensities for each zone was determined based on a statistical evaluation of the data by calculating 20 % and 90 % quantile, respectively, subsequently the scale factor was calculated as the mean value of relative intensities in both outer zones related to the zone 2, which represents the average lightning activity over the entire transmission network, i.e. normal zone. The results are provided in the Table A.3.4.

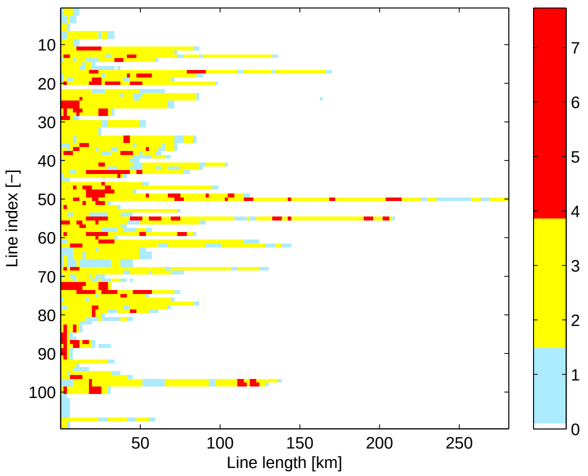
zone number	zone type	scale factor	zone color
1	low	0.4	light blue
2	medium	1	yellow
3	high	1.8	red

Table A.3.4: Example of estimated factor based on lighting zone type.

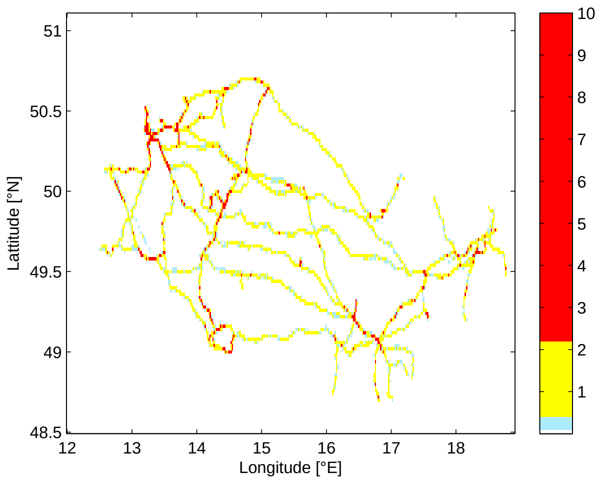
The diagrams in Figure A.3.1 show how the results fit the data in two aspects:

a) The linear distribution of transmission line segments coloured with the appropriate lighting intensity zones in 2 km grid size.

b) The geographic distribution of transmission line segments coloured with the corresponding lighting intensity zones calculated with resolution of 0.02 x 0.02 degrees.



(a) intensity of lightning occurrence along the line length



(b) lightning distribution along the line geo-position

Figure A.3.1: Lighting activity zones

A.3.4.2 Impact of line ageing on failure rate

This section deals with effects of line ageing, especially with rising of failure rate. The analysis is based on TSO CEPS data. The TSO operates 101 HV overhead power lines with total length 5400

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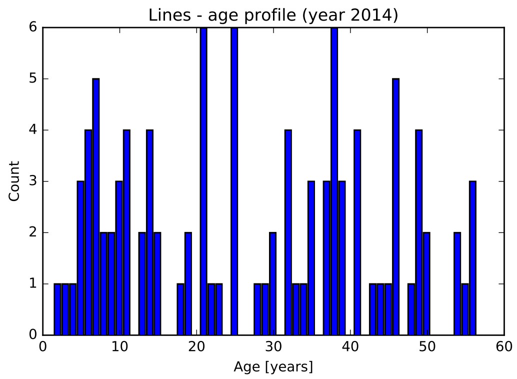
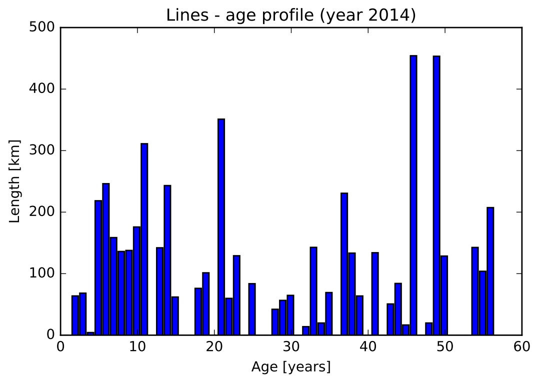
km. The transmission lines have been installed from 1947 and most of them has been renewed since 1996, depending on the life expectancy of the asset and requirements for capacity upgrades. Due to pooling subcomponents renewing, the all important components have the same age on each line. Figure A.3.2 shows age profile of all lines for the year 2014.



(a) Count



(b) Length

Figure A.3.2: Line - age profile

This analysis is based on line failure data from 2006 to 2014, where data contain only 76 records of line failure that were caused by subcomponent damage. Due to sparse data, the lines ware clustered into 5 years intervals.

Failure rates are computed by dividing the number of events by total length belongs to same cluster. The results are approximated by the formula A.3.13:

$$k_{FR}(t) = 0.0072 \cdot e^{0.023 \cdot t} - 0.0025. \tag{A.3.18}$$

Raw results and approximation of failure are plotted in Figure A.3.3. The results show that the failure rate significantly increased, i.e. more than 5 times.

A.3.5 Conclusion

In the present paper we have presented and illustrated an approach for the modelling of component ageing, repairing, and forced outage failure rates, which could be suitable in the context of asset management studies. The corresponding models have been presented in an abstract and generic way, so as to draw the attention on the important aspects to be taken into account when developing such models for real-life studies.

We fully acknowledge the fact that a suitable ‘component modelling’ in the context of asset management simulation studies is a very hard problem that deserves further research, so as to come up with actual models and parameter fitting approaches that make sense given the available data in the TSO’s environment. In the current state of affairs, these models will have to be chosen and tuned based on expert knowledge.

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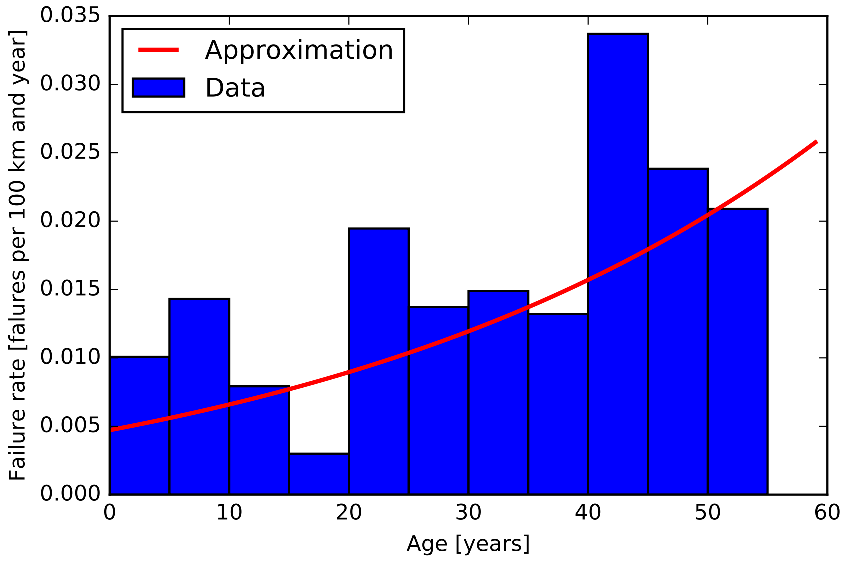

Figure A.3.3: Failure rate as function of line age.

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APPENDIX A.4 UNCERTAINTY MODELLING

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Abstract: This annex is an extension and an elaboration of the proposed case study on the modelling of exogenous uncertainties for asset management studies as described in Chapter 7. The exogenous factors may be considered as continuous time random variables and it is required to fit a model for their evolution over time. The annex aims to find an appropriate stochastic process model which best satisfies the characteristics of exogenous factors, so as to model their uncertainties. Chapter 1 focuses on load modelling, chapter 2 on wind power modelling, chapter 3 on hydro inflow forecasting and optimal hydrothermal scheduling, and chapter 4 focuses on failure rate modelling. The last chapter summarizes and discusses further work.

A.4.1 LOAD MODELLING

A.4.1.1 Proposed methodology

Demand is one of the major uncertainties introduced to the power system network. To study its impact in asset management decision-making processes, it is proposed to generate yearly load time series. A neural-network based load forecast model is designed and calibrated to forecast hourly day-ahead loads given temperature forecasts, holiday information and historical loads for the region the forecast should be valid for [8]. The model is trained on hourly data from 2010 to 2013 and tested on out-of-sample hourly data from 2014[1]. The performance of the model is assessed by calculating the mean average percentage error (MAPE), and it was found to be 1.78%. In this work, load forecast errors are assumed to follow the normal distribution. In addition to the point forecast, standard deviations in each hour are also provided. Load uncertainty is then represented as stochastic scenarios which are generated using the point forecasts and the corresponding standard deviations. Since, all data used in this case study corresponds to only one region, spatial correlation is not accounted for. It is however highly recommended that spatio-temporal correlation should be well addressed in practice.

A.4.1.2 Simulation results

To assess the effectiveness of our proposed forecast methodology, the Neural Network toolbox in MATLAB [11] is used. Hereon, it can be understood that MATLAB is used for all our modelling purposes unless/otherwise stated. The data for neural-network model is divided into two sets: the first data set is used for training purpose of network and second data set is used for testing of forecasting results. The first data set comprises four years (2010-2013) of 24-hourly load and weather data, that are used to train the network and are called the *training* data set. The second data set comprises one year (2014) of 24- hourly load data, and is called the *testing* data set. Figure A.4.**1** represents the zonal load forecast value as well as seven realizations, which are considered in this study.

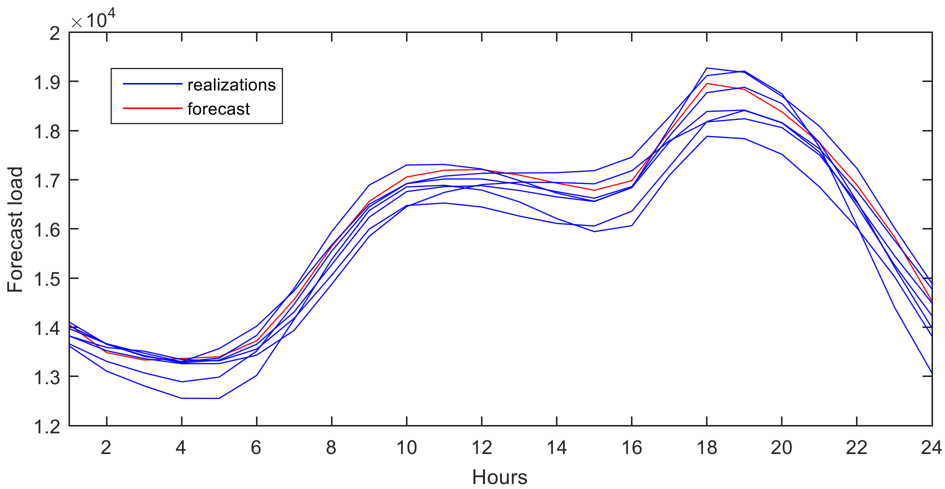

Figure A.4.1: Load realizations and forecast

[1] Data available from www.iso-ne.com/

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

From the TSO point of view, it is important to study the forecast as well as realization from nodal point rather than zonal point of view. The translation is explained with the help of an example. The zonal load realizations are shown in Figure A.4.**2**(a). The translation from zonal to nodal level depends on the correlation factor, and it is chosen based on the total system load and power generation in the system. For instance, in our study, the translation of zonal load data to nodal level is carried out in the following steps:

- Each column of data is normalized so that each column has mean = 1.
- The resultant matrix shown in Figure A.4.**2**(b) is scaled with a factor 0.8. This was needed because the total load was so high compared to production that it might provoke load shedding which is undesirable.
- The matrix in Figure A.4.**2**(b) is truncated to only include the first 24 rows. As compared to the actual realizations that consisted of 8760 (24x365) hours, the daily load profile (24 hours) is selected for our proposed case study.

It is to be stressed again that the above rules of translation is system dependent. For our proposed case study, the IEEE RTS-96 bus system is to be used. So, the translation is dependent on generation and system load of IEEE RTS-96 bus system. The same rule applies when this methodology is changed for another test case system.

8760x7 double

	1	2	3	4	5	6	7
1	1.3622e+...	1.3974e+...	1.3665e+...	1.3826e+...	1.4032e+...	1.4108e+...	1.3825e+...
2	1.3109e+...	1.3666e+...	1.3309e+...	1.3524e+...	1.3660e+...	1.3657e+...	1.3590e+...
3	1.2809e+...	1.3474e+...	1.3073e+...	1.3364e+...	1.3409e+...	1.3424e+...	1.3514e+...
4	1.2556e+...	1.3299e+...	1.2891e+...	1.3261e+...	1.3301e+...	1.3279e+...	1.3344e+...
5	1.2553e+...	1.3372e+...	1.2987e+...	1.3262e+...	1.3567e+...	1.3331e+...	1.3317e+...
6	1.3021e+...	1.3834e+...	1.3517e+...	1.3433e+...	1.4022e+...	1.3654e+...	1.3556e+...
7	1.4159e+...	1.4790e+...	1.4471e+...	1.3939e+...	1.4741e+...	1.4312e+...	1.4183e+...
8	1.5379e+...	1.5945e+...	1.5548e+...	1.4874e+...	1.5673e+...	1.5274e+...	1.5058e+...
9	1.6375e+...	1.6891e+...	1.6450e+...	1.5849e+...	1.6501e+...	1.6240e+...	1.5997e+...
10	1.6855e+...	1.7300e+...	1.6922e+...	1.6456e+...	1.6921e+...	1.6760e+...	1.6477e+...
11	1.6887e+...	1.7311e+...	1.7074e+...	1.6743e+...	1.7016e+...	1.6860e+...	1.6527e+...
12	1.6790e+...	1.7220e+...	1.7131e+...	1.6901e+...	1.7015e+...	1.6879e+...	1.6447e+...
13	1.6550e+...	1.6984e+...	1.7138e+...	1.6951e+...	1.6908e+...	1.6781e+...	1.6261e+...
14	1.6210e+...	1.6728e+...	1.7144e+...	1.6944e+...	1.6756e+...	1.6651e+...	1.6112e+...
15	1.5945e+...	1.6562e+...	1.7185e+...	1.6917e+...	1.6625e+...	1.6558e+...	1.6060e+...
16	1.6066e+...	1.6842e+...	1.7459e+...	1.7183e+...	1.6862e+...	1.6842e+...	1.6362e+...

(a)

24x7 double

	1	2	3	4	5	6	7
1	0.9343	0.9588	0.9366	0.9482	0.9630	0.9685	0.9492
2	0.8992	0.9377	0.9122	0.9275	0.9375	0.9376	0.9331
3	0.8786	0.9245	0.8960	0.9165	0.9202	0.9216	0.9279
4	0.8612	0.9125	0.8835	0.9095	0.9128	0.9116	0.9162
5	0.8611	0.9175	0.8901	0.9095	0.9310	0.9152	0.9143
6	0.8931	0.9492	0.9264	0.9213	0.9623	0.9373	0.9307
7	0.9712	1.0148	0.9918	0.9559	1.0116	0.9826	0.9738
8	1.0549	1.0940	1.0657	1.0201	1.0756	1.0486	1.0339
9	1.1232	1.1589	1.1275	1.0870	1.1324	1.1149	1.0983
10	1.1561	1.1870	1.1599	1.1286	1.1613	1.1506	1.1313
11	1.1583	1.1878	1.1702	1.1483	1.1677	1.1575	1.1347
12	1.1516	1.1815	1.1742	1.1591	1.1677	1.1587	1.1292
13	1.1352	1.1653	1.1747	1.1625	1.1603	1.1520	1.1165
14	1.1118	1.1477	1.1750	1.1621	1.1499	1.1431	1.1062
15	1.0937	1.1363	1.1778	1.1602	1.1409	1.1367	1.1026
16	1.1020	1.1555	1.1967	1.1784	1.1572	1.1562	1.1234

(b)

Figure A.4.2: (a) Zonal load data, (b) Translated nodal level data

The translated load at nodal level is represented in Figure A.4.**3**.

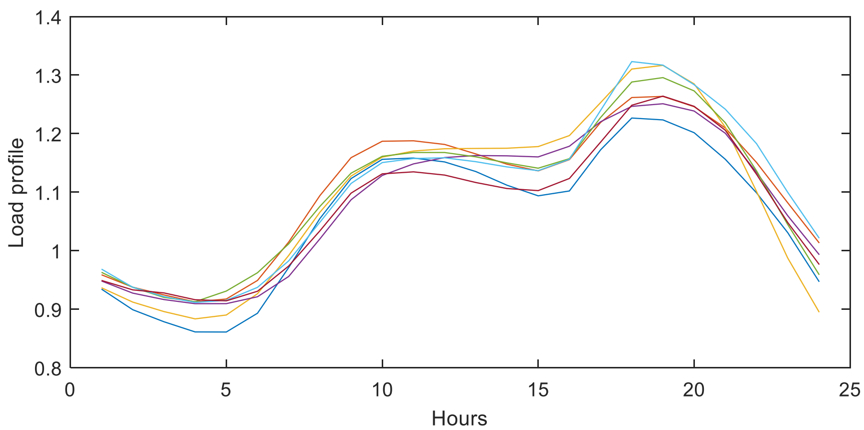

Figure A.4.3: Translated load profile

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

A.4.2 WIND POWER MODELLING

After load, power generation from renewable energy sources like wind and solar introduce uncertainty to the power system. In this chapter, wind power modelling for the proposed case study is discussed. It is to be noted that solar power modelling is not discussed in this chapter, and it is assumed that it follows the same modelling approach. Wind power modelling is based on a meteorological database of historical weather variables. It is based on CorWind, an advanced tool able to simulate consistent and correlated wind power generation patterns developed at DTU Wind Energy Department [14]. The model generates time series of *real power* i.e. estimated available wind power and/or day-ahead power forecast. In the modelling study, time series has been generated based on reanalysis techniques, which aims at reconstructing the state of the atmosphere over large geographical areas at specific grid points. It combines past available observations from different sources as an input for a Numerical Weather Prediction (NWP) model, which is used to generate the most plausible representation of climate. The current database was generated based on the Weather Research and Forecasting (WRF) model, using the initial and boundary conditions provided by the ERA Interim Reanalysis. The current state is regularly updated every 6-12 hours with new observations, which allows propagating the meteorological variables in time. The current database extends back to the year 2010, providing consistent model-assimilated climate variables on an hourly resolution, averaged over elementary 30 square-kilometre grid cells.

A.4.2.1 Proposed methodology

CorWind is based on a deterministic realization (10 years of wind speeds) on top of which is built a stochastic process (forecast error). The main assumption is that the weather conditions in the future will be similar to those observed in the past. The error model implemented in CorWind assumes that the day-ahead wind power forecast can be attributed to the same underlying error source, inherent to the forecast method. Hence, the error term changes based on the appropriate (effective) horizon considering the difference from the last weather update. In addition, it varies with the diameter of the analysed area (smoothing effect). The forecast error term is assumed to follow a multivariate autoregressive moving-average (ARMA) model. Essentially, the value of a given state variable depends on its previous values (AR part) and the previous values of random sources (MA part). A univariate ARMA model used to create the multivariate version can be expressed as:

$$\varepsilon(k) = \alpha\varepsilon(k-1) + Z(k) + \beta Z(k-1) \qquad \text{(A.4.1)}$$

where $\varepsilon(k)$ is the error value at the k-th hour of the forecast, with $\varepsilon(0) = 0$, $Z(k)$ is a random Gaussian variable with standard deviation σ_Z and $Z(0) = 0$ and α, β are the parameters of the ARMA-series.

An advantage of such a modelling approach is that if the model is run for a year using different seeds for the ARMA, then different realizations for that meteorological year can be achieved. The outputs are on an hourly resolution and the forecast can be day-ahead or hour-ahead. In principle it is possible to generate scenarios, although the duration would be limited by the number of meteorological years (in this case 10). For a realistic modelling approach, the parameters for the ARMA model are tuned based on Danish data. They represent errors in wind speed forecasts. Due to the availability of measurements in wind power only, the fitting is done backwards in an iterative manner.

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

A.4.2.2 Simulation results

The wind generation profile is shown in Figure A.4.4, and realizations for a 24-hour period is shown in Figure A.4.5. The figure corresponds to single day for the Danish region, and the data is available from Danish TSO[2].

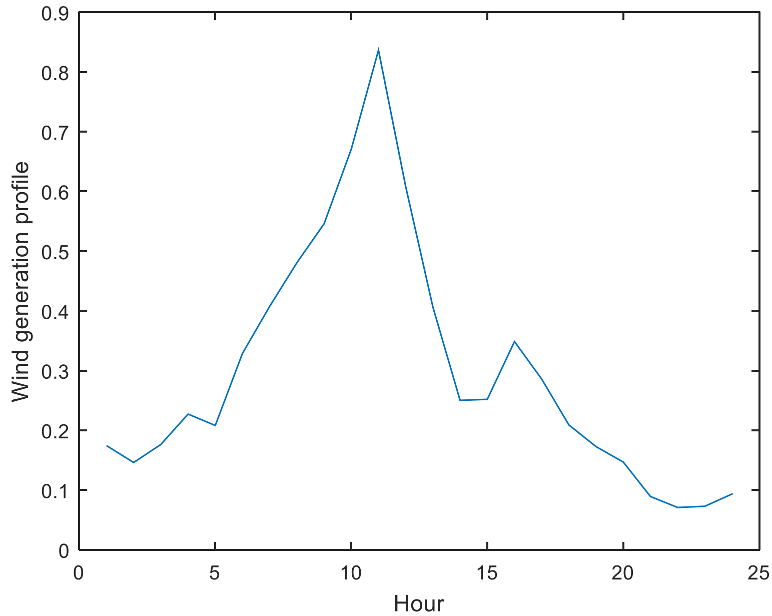

Figure A.4.4: Wind generation profile

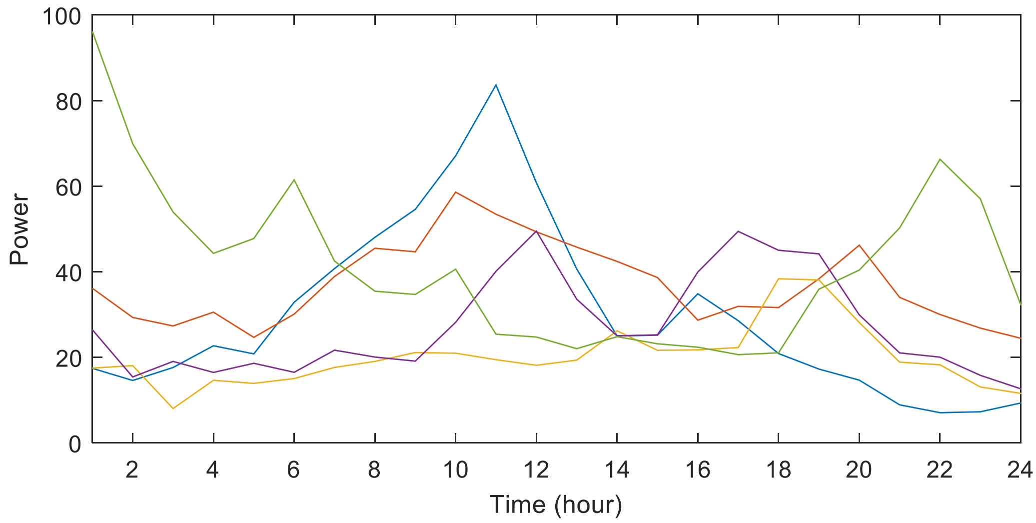

Figure A.4.5: Wind power realizations

[2] Available at www.energinet.dk

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

A.4.3 HYDROLOGICAL MODELLING AND OPTIMAL HYDROTHERMAL SCHEDULING

Hydrothermal modelling is itself a complicated task, and its modelling for reliability evaluation is important at the same time. In this chapter, it is aimed to present a stochastic model for hydro inflow into the reservoir and later an optimal hydrothermal scheduling problem is proposed for the case study.

A.4.3.1 Hydrological inference

Planning of hydrothermal systems involves greater complexity as compared to a pure thermal system. This is because of the considerable uncertainty related to hydrological inflow and the time horizon of its operation. The limited availability of hydroelectric energy in the form of water stored in hydro reservoirs plays an important link between the decisions at a given stage and its future consequences [4]. In other words, if in a given period all hydroelectric power is consumed, and the volume of inflow in subsequent periods are low, it may be necessary to use expensive thermal generation or even can have loss of load in the system by lack of generation resources.

The random behaviour of water inflow is a critical input from operation and system planning aspect, so forecasting models are required to determine the inflow of expected water in the reservoirs. Historical data of monthly inflow are generally known for insufficient periods of time to obtain statistical results describing their future behaviour, so that one commonly uses stochastic models, which allow one to exploit the sample and estimate parameters that characterize its possible evolution probabilistically. The resulting hydro inflow forecasts are used in the optimization models to reproduce the historical data.

For our proposed case study, the hydro inflow is represented in the form of a Markov model. In the general form, the value of a variable x at one period of time is dependent on the value of x in the predecessor period plus a random component, as shown in eq. (A.4.2). So, for a historical record of average flows, the timing of inflows can be modelled as:

$$A_t = \mu_t + \sigma_t X_t \tag{A.4.2}$$

where,

A_t	Flow in time t
μ_t	Periodic median in sub-period t
σ_t	Variance or periodic deviation in sub-period t
X_t	Stationary random variable.

The random variable (X_t) is usually autocorrelated and μ_t and σ_t are parameters that can be estimated based on the frequency distribution of the available sample or historical record. In this study, the hydro inflow is modelled using a linear autoregressive or the modified Markovian model that describes best the stationary variable flow [15]:

$$X_t = \sum_k a_k X_{t-k} + b\varepsilon_t \quad \forall k = 1, \ldots, m \tag{A.4.3}$$

where,

a_k, b	Model parameters
ε_t	Independent random residue
m	Order of the regressive model.

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For monthly flows, good fits are usually obtained through autoregressive first order ($m = 1$), given as:

$$X_t = \rho_1 X_{t-1} + \sqrt{1 - \rho_1^2}\,\varepsilon_t \tag{A.4.4}$$

where,

ρ_1	Delay correlation coefficient '1' of variable X
$\sigma_{X_t, X_{t-k}}$	Covariance estimated sample for X_t and X_{t-k} .

The correlation coefficient k delay is defined as:

$$\rho_k = \frac{\sigma_{X_t, X_{t-k}}}{\sigma_{X_t}\,\sigma_{X_{t-k}}} \tag{A.4.5}$$

Thus, the inflow forecasts model can be described as:

$$A_t = \mu_t + \sigma_t \left(\rho_1 \frac{A_{t-1} - \mu_{t-1}}{\sigma_{t-1}} + \sqrt{1 - \rho_1^2}\,\alpha \right) \tag{A.4.6}$$

where μ, σ, and ρ_1 are estimated from the sample of historical flows. The random residue α can be determined based on a theoretical probability density to which the variable is fitted.

A.4.3.2 Optimal hydrothermal scheduling (OHS)

Computing optimal operational strategies for a hydrothermal-based power system, dominated by hydropower, is a very demanding problem, both theoretically and computationally, since it is stochastic and usually large-scale. One of the greatest advantages of hydrothermal systems is that water has no direct monetary cost, so that the marginal cost of generation is given only by the thermal generation used. Besides, the resources can be stored. However, its storage is conditioned by the physical capacity of the reservoirs of the system. In addition, the stochastic behavior of the water inflow introduce the problem of deciding whether to use the water now or save it for further use, producing a temporal dependence between these decisions. The hydrothermal scheduling task can be divided into three horizons: long-term scheduling (3-5 years or more), mid-term scheduling (1-2 years) and short-term scheduling (few days to 1 week) [10]. The long- and medium-term scheduling problems are stochastic in nature. Thus, the hydrothermal scheduling problem can be described as a dynamic process, which could be resolved as an optimization problem, where the objective is to make an assessment of the hydro availability, in respect to thermal energy that it can replace in a certain time horizon.

In this proposed case study, a system confined in a geographical area that can be covered by a single power balance equation (without internal transmission bottlenecks), and typically owned by a single power company is assumed. The hydro inflow forecast was studied in the previous sub-section A.4.3.1. Our geographical region is a particular region from Norway and it is also usually assumed that the system is not large enough to influence market price, and hydro is the base. To establish the probability distribution for price and inflow, we simplify by considering the stochastic processes for inflow and price as independent of each other and using the marginal

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probability distributions for each. It is reasonable that more water leads to lower prices and the other way round. However, it would be a challenge to include this in the model. Hydro price is set to '0' in our study. The primary aim of hydrothermal scheduling is to schedule the power generation of the hydro and thermal units in the system to meet the load demands for 1 day or a few days while satisfying various constraints on the hydraulic and power system network [17]. In such case, the objective function for an optimal scheduling is to minimize the fuel cost of thermal units for the given short term.

A.4.3.3 Problem formulation for optimal hydrothermal scheduling (OHS) including market modelling

Besides of its dynamic nature, the optimal hydrothermal scheduling problem is nonlinear, stochastic, non-separable and non-convex problem. The different variables and constraints affecting the problem formulation are, namely, power demand balance, loading limits of thermal and hydro generator units, limits of water reserve volume, total outflows and generations, hydropower generation functions, and water balance equations.

A.4.3.3.1 Objective function

In our proposed case study, the objective is to minimize the fuel cost of thermal units, and it is mathematically represented as

$$\min F = \sum_{i=1}^{M} f_i\,(P_{Ti}) \tag{A.4.7}$$

$$f_i(P_{Ti}) = a_i P_{Ti}^2 + b_i P_{Ti} + c_i \tag{A.4.8}$$

where,

f_i	Cost function
P_{Ti}	Power generation of thermal plant at i^{th} interval
M	Total number of intervals.

A.4.3.3.2 Power demand balance

$$P_{T(i)} + \sum_{k=1}^{N} P_{H(k,i)} = P_{D(i)} + P_{Loss(i)} \tag{A.4.9}$$

where,

$P_{H(k,i)}$	Power generation of k^{th} hydro plant at i^{th} interval
$P_{D(i)}$	Power demand
$P_{Loss(i)}$	Power losses
N	Total number of hydro units.

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A.4.3.3.3 Thermal generator loading limits

$$P_T^{min} \leq P_{T(i)} \leq P_T^{max} \qquad (A.4.10)$$

A.4.3.3.4 Hydro generator loading limits

$$P_{H(k)}^{min} \leq P_{H(k,i)} \leq P_{H(k)}^{max} \qquad (A.4.11)$$

A.4.3.3.5 Reservoir capacity limits

- Physical limitation on reservoir storage

$$V_{(k)}^{min} \leq V_{(k,i)} \leq V_{(k)}^{max} \qquad (A.4.12)$$

where,

$V_{(k,i)}$	k^{th} reservoir volume at interval i .

- Initial and final storage volume of each reservoir

$$V_{(k,0)} = V_{(k)}^{initial} \qquad V_{(k,M)} \leq V_{(k)}^{final} \qquad (A.4.13)$$

- Physical limitation on discharge rates

$$Q_{(k)}^{min} \leq Q_{(k,i)} \leq Q_{(k)}^{max} \qquad (A.4.14)$$

where,

$Q_{(k,i)}$	Water discharge rate for k^{th} reservoir.

- Hydro reservoir continuity equation

$$V_{(k,i+1)} = V_{(k,i)} + \sum_{j=\Omega_{(k)}} \left(Q_{(j,i-\tau)} + S_{(j,i-\tau)}\right) - Q_{(k,i)} - S_{(k,i)} + R_{(k,i)} \qquad (A.4.15)$$

where,

$\Omega_{(k)}$	Index set of the upstream reservoirs contributing to the k^{th} reservoir
τ	Time delay for the water in j^{th} upstream reservoir to reach the k^{th} reservoir
S	Spillage
R	Inflow rate.

- Hydro power generation characteristics

$$P_{H(k,i)} = c_{(1,k)}V_{(k,i)}^2 + c_{(2,k)}Q_{(k,i)}^2 + c_{(3,k)}\left(V_{(k,i)}Q_{(k,i)}\right) + c_{(4,k)}V_{(k,i)} + c_{(5,k)}Q_{(k,i)} + c_{(6,k)} \qquad (A.4.16)$$

where,

$c_{(1,k)}, c_{(2,k)}, c_{(3,k)}, c_{(4,k)}, c_{(5,k)}, c_{(6,k)}$	Constant coefficients of the system for the k^{th} reservoir.

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A.4.3.4 Proposed methodology for optimal hydrothermal scheduling (OHS)

The comprehensive learning particle swarm optimization (CLPSO) [9] is adapted in our study to solve the OHS problem. The CLPSO is an advanced version of the well-known particle swarm optimization (PSO) algorithm [6], which tackles the problem when particles get trapped in a local optimum if the search space is complex or if it has a multimodal landscape. In PSO, the population of candidate solutions or particles are evaluated at each iteration q. From one iteration to another, each particle updates its position based on its own exploration, the global best of swarm experience, and its previous velocity vector according to (A.4.17) and (A.4.18),

$$x_i^{q+1} = x_i^q + v_i^{q+1} \tag{A.4.17}$$

$$v_i^{q+1} = \omega v^q + c_1 rand_{i1}\left(b_i^q - x_i^q\right) + c_2 rand_{i2}\left(b_g^q - x_i^q\right) \tag{A.4.18}$$

where,

b_i	Best location found by the particle i in its past life until current generation
b_g	Best global location found by the swarm in its past life until current generation
c_1, c_2	Acceleration constants that pull each particle toward b_i and b_g positions
ω	Inertia weight used to balance the global and local search abilities
$rand_i$	Uniform random numbers in the range [0,1]
i	Number of particles.

In comparison, the CLPSO algorithm uses all particles' best position b_j to update the velocity of any one particle in order to ensure that the diversity of the swarm is preserved and to discourage premature convergence. Thus, in CLPSO, each dimension of a particle learns not only itself, but also from the corresponding dimension of different b_i. In contrast to PSO, where each particle learns from b_i and b_g at the same time, in CLPSO, each dimension of a particle learns from just one exemplar. The CLPSO's learning strategy employs the following velocity update equation,

$$v_i^{q+1} = \omega v^q + c_1 rand_{i1}\left(b_j^q - x_i^q\right) \tag{A.4.19}$$

The OHS optimization problem is described by four main constituents:

- Inputs: Load demand ($P_{D(i)}$), water inflows ($R_{(k,i)}$), limits (P_T^{min}, P_T^{max}, $P_{H(k)}^{min}$, $P_{H(k)}^{max}$, $V_{(k)}^{min}$, $V_{(k)}^{max}$, $Q_{(k)}^{min}$, $Q_{(k)}^{max}$), and power generation functions ($f_i(P_{Ti})$)
- State variable: Storage volumes ($V_{(k,i)}$)
- Dependent variable: Hydro generation ($P_{H(k,i)}$)
- Control variables: Thermal generation (P_{Ti}), spillage values ($S_{(k,i)}$), and water discharge rates ($Q_{(k,i)}$)

Parameter settings for the CLPSO algorithm used in this study are shown in Table A.4.1. The OHS problem can be divided into two sub-problems, namely, the hydro sub-problem, and the thermal sub-problem, as illustrated in Figure A.4.6. The hydro sub-problem is solved by using a

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meta-heuristic algorithm considering the storage in the reservoirs in each stage x_{jt} as optimization variables. In this way, each individual particle has a length of $t_n = (24x4) = 96$.

Table A.4.1: Parameter settings for CLPSO used in OHS

Parameter	Nomenclature	Value	Value in OHS problem
Number of variables	N_{var}	$N_{var} > 0$	96
Population size	m	$m > 2$	20
Learning probability	P_c	[0 0.5]	$P_{ci} = [0\ 0.5]$
Inertia weight	$\omega(q)$	$\omega(k) = \omega_0 \frac{(\omega_0 - \omega_1)k}{\max\ \_gen}$ $k = 1, \ldots, \max\ \_gen$	$\omega_0 = 0.9, \omega_1 = 0.4$
Acceleration constant	c_1	[0 2]	1.49445

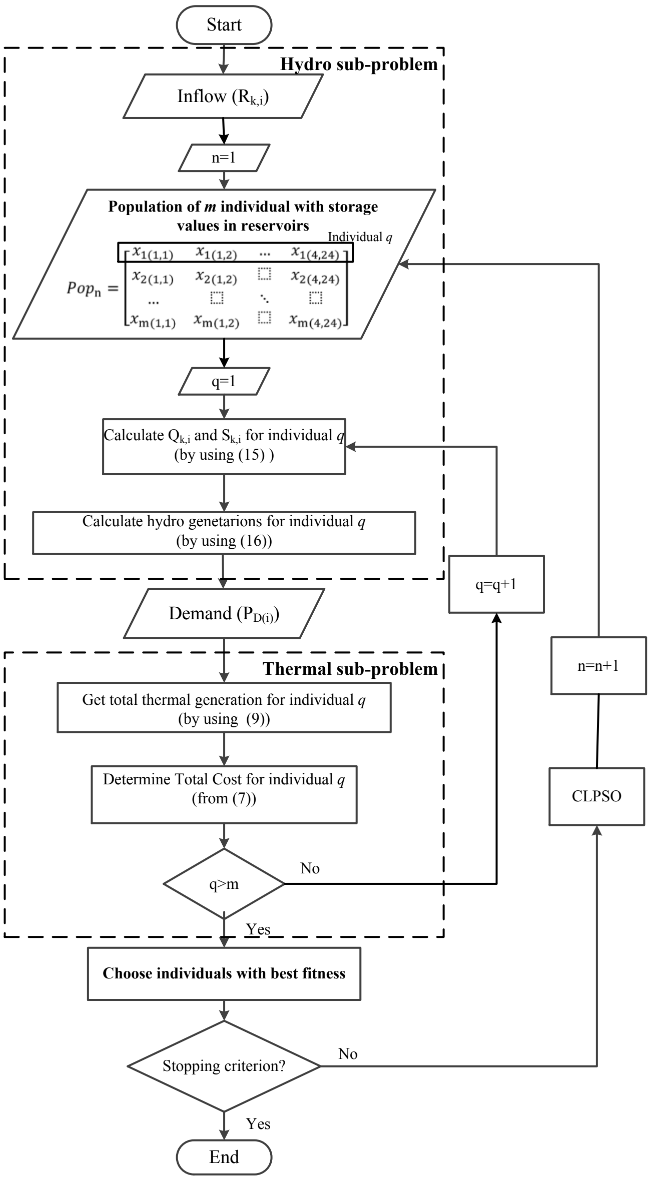

Figure A.4.6: Optimal hydrothermal scheduling using CLPSO

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Selection of a suitable optimization method is entirely dependent on the TSO. The selection of CLPSO in the proposed case study is due to its simplicity and efficiency.

A.4.3.5 Test case under study for OHS

The system presented in ref. [13] is used to test the performance of the OHSO methods. The one-line diagram of the system is shown in Figure A.4.7(a). The system is composed by four cascaded hydro plants and an equivalent thermal plant, which supply a load demand throughout a time horizon of 24h (section A.4.1). The four hydro plants mimics the hydro units in four regions of Norwegian data. The configuration of the hydro system network is shown in Figure A.4.7 (b). In the hydraulic network, the water transport time delay from reservoir j to k is defined in Table A.4.1. Hourly water inflows for each hydro plant are assumed as shown in Table A.4.2. An assumption in this study is system losses are neglected, i.e. $P_{Loss(i)}$ in (A.4.9). The cost of thermal generation is represented by an equivalent function as defined in (8) where the coefficients are referred from ref. [16], and is written as:

$$f_i(P_{Ti}) = 0.5P_{Ti}^2 + 10P_{Ti} + 1000 \qquad \text{(A.4.20)}$$

The hydro generation function for each plant is modelled by using (A.4.16), and the values are shown in Table A.4.3.

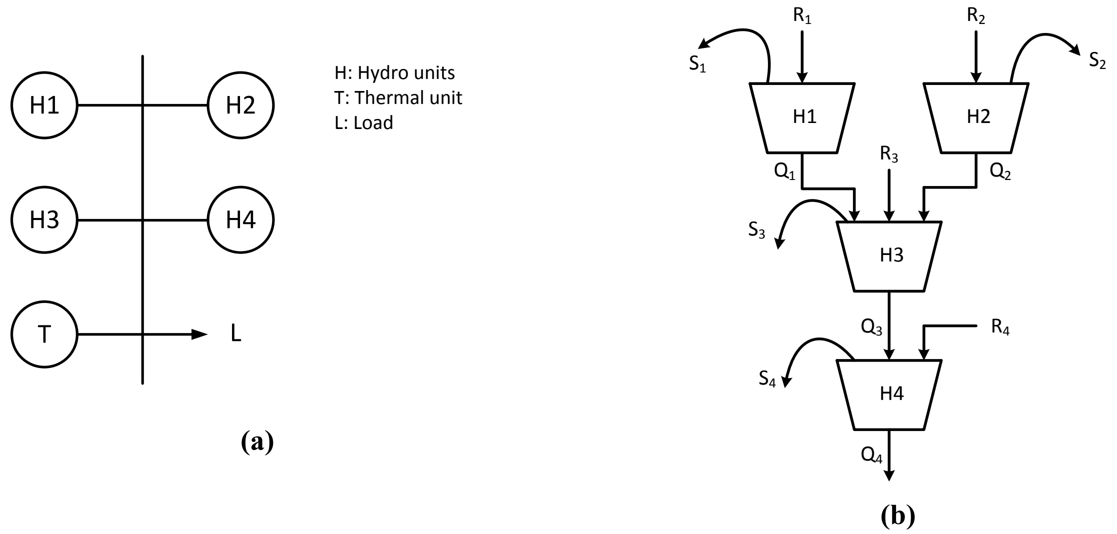

Figure A.4.7: (a) One-line diagram of the studied hydrothermal system, and (b) Hydro system unit

Table A.4.1: Time delay (τ) to immediate downstream plant

	H1 – H3	H2 – H3	H3 – H4
$\tau(h)$	1	2	2

Table A.4.2: Reservoir inflows (10^4 m^3)

Hours	R_1	R_2	R_3	R_4
1-24	10	8	1	0

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Table A.4.3: Hydro plants coefficients [13]

Hydro unit	c_1	c_2	c_3	c_4	c_5	c_6
1	-0.001	-0.1	0.01	0.40	4.0	-30
2	-0.001	-0.1	0.01	0.38	3.5	-30
3	-0.001	-0.1	0.01	0.30	3.0	-30
4	-0.001	-0.1	0.01	0.38	3.8	-30

A.4.3.6 Simulation results

The OHS problem is solved system using MATLAB [11] on a system with the following configuration: Intel(R) Xeon(R) 8GB 3.7GHz. Table A.4.4 shows the cost of generation with the CLPSO algorithm, and Figure A.4.8 shows the storage in four reservoirs.

Table A.4.4: Cost of generation

Hour (i)	Cost (P_{Ti})	Hour (i)	Cost (P_{Ti})
1	143.82	13	132.13
2	144.30	14	166.33
3	126.08	15	132.13
4	142.21	16	166.37
5	152.13	17	161.69
6	137.26	18	145.36
7	117.91	19	160.85
8	129.80	20	132.02
9	138.62	21	181.45
10	170.39	22	113.43
11	171.82	23	153.10
12	166.33	24	151.75

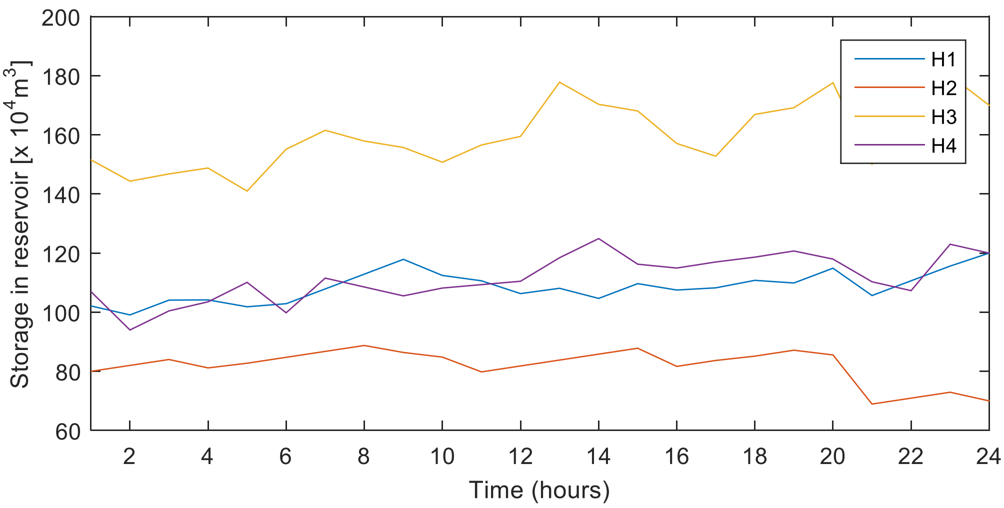

Figure A.4.8: Storage in the reservoir

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A.4.4 FAILURE RATE MODELLING

The section on failure rate modelling investigates the issue of computing meaningful failure rates for power system assets that may be used in the proposed probabilistic framework developed in GARPUR. Proposing models to infer the failure rates of the different grid assets, assuming the maintenance actions are performed correctly and on time is performed in this section. Basically, failures can be explained either because of ageing and insufficient maintenance, or be triggered by any event (most of the time adverse weather conditions) while the asset is healthy. The proposed model would depend among other factors on the asset technology, geographical locations, and would vary during the different periods of the year along with the weather severity. They would be used in particular for the outage-scheduling problem. For the short-term horizon, such models would take into account more accurately the weather forecasts. Failures of assets are tied to outage duration of assets. Outage durations should then become an entry to a subsequent model which will evaluate the energy not supplied in case of a contingency. Regarding scheduled outages, the TSOs are assumed to have a good knowledge of the time needed to perform the action. It is expected that assets with a longer outage duration should be more carefully monitored compared to others.

For instance, a generator unit can be either available or not available in its role of delivering power on demand. When a generator is available for delivering power, it can be operated at its maximum continuous rating or in a derated state due to operational constraints (i.e., operating at less than its rated capacity) or remain idle due to insufficient demand (i.e., reserve shut down state). There are many causes that make a generating unit unavailable to meet the demands imposed on it (e.g., forced outage, planned maintenance, scheduled maintenance, failure to start, etc.). Ref. [12] proposed a probabilistic model to present various uncertainties for setting the operating reserve. These uncertainties include load forecast and wind power generation forecast uncertainty, unplanned outages of conventional generators and wind turbines etc. Capacity outage probability table (COPT) was applied to represent the discrete probability distribution of conventional generation. COPT gives the probability of occurrence for each possible outage capacity level. In power systems, operating reserve margin, percentage reserve, expected energy not supplied (EENS), loss of load probability (LOLP), loss of load frequency (LOLF), loss of load duration (LOLD) are the reliability measures. Uncertainties of generation and transmission line outages are also related to the power system reliability, especially for the EENS, LOLP and LOLF [12].

A.4.4.1 Proposed methodology for failure rate modelling

In the GARPUR project, it is proposed to model the failure rates by improving the clustering of assets, in particular in order to grasp the seasonal aspects which can be very important depending on the geographical locations. Adverse weather effects are generally short in duration and even though they increase the failure rates of individual components in the system they may not have an impact on the overall power system's reliability. However, the probability of overlapping failures of different components cannot be neglected and usually concentrates in short periods of the year, what is known as bunching effect [2].

Monte-Carlo (MC) simulation is proposed as it allows modelling regional features, such as a transmission line being exposed to different weather conditions. A simple model considering two weather states is presented in Figure A.4.9.

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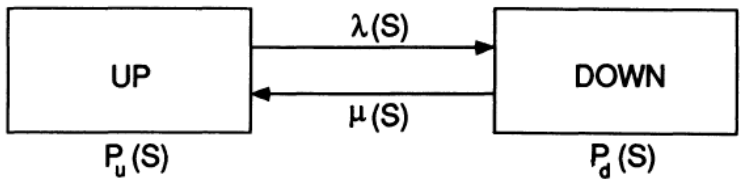

Figure A.4.9: Schematic representation of a two-parallel components system in a Monte Carlo framework [3]

The variable S can have two values: 0 or 1 corresponding to normal and adverse weather conditions respectively. Hence, two different failure rates can be identified i.e. $\lambda\,(0)$, $\lambda(1)$ and two repair rates $\mu(0)$, $\mu(1)$. The failure bunching on multiple components depends on the probability of adverse weather and the failure rates and repair rates in that state, but not specifically on the transition between weather conditions [3]. Knowing the fraction of time that a line spends in adverse weather *U,* and the proportion of failures occurring in adverse weather *F,* both probabilities can be obtained:

$$\lambda(0) = \lambda(1 - F)/(1 - U) \qquad \text{(A.4.21)}$$

$$\lambda(1) = \lambda\, F/U \qquad \text{(A.4.22)}$$

Assuming a total of *N* regions and two possible weather states, there are 2^N combinations. Since the length of a transmission line is generally small compared with the area covered by each weather environment, it is not necessary to divide the system into a great number of regions. In addition, the final choice of regions will also depend on the available data, such as forecast reports. Once the total number of weather regions has been selected and their probabilities computed i.e. from available meteorological records, the procedure can be summarized as:

1. **Sample the regional weather state**

Let $P_1, P_2, \dots, P_{N-1}$ represent the states in which at least one region undergoes adverse weather and P_N the probability of all regions being under normal weather. Then, these values can be organized sequentially on $[0,1]$ and the current weather state of the transmission line can be obtained based on a random number uniformly distributed on the same interval.

2. **Obtain the transmission line forced unavailability and repair time**

The forced unavailability (FU) and repair time for a transmission line can be calculated based on the current weather state of the system. For example in Figure A.4.10, let a transmission line (shown below) cross two regions (a) and (b) on adverse and normal weather conditions respectively and let *R* be the percentage of the line region (a).

Assuming that the mean repair time of the line is negligible compared to its MTTF and that the two regions are adjacent, the total FU can be derived as:

$$FU = FU_a + FU_b - FU_a FU_b \cong FU_a + FU_b \qquad \text{(A.4.23)}$$

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where the forced unavailability for each region is:

$$FU_a = \frac{\lambda(1) \cdot R}{\lambda(1) \cdot R + \mu(1)} \tag{A.4.24}$$

$$FU_b = \frac{\lambda(0) \cdot (1 - R)}{\lambda(0) \cdot (1 - R) + \mu(0)} \tag{A.4.25}$$

Being $r = 1/\mu$ the repair time for a component, the equivalent repair time of the line would be:

$$r = \frac{r(1)\lambda(1) \cdot R + r(0)\lambda(0) \cdot (1 - R)}{\lambda(1) \cdot (R) + \lambda(0) \cdot (1 - R)} \tag{A.4.26}$$

3. Reliability evaluation

Reliability evaluation is performed on the desired test-case system.

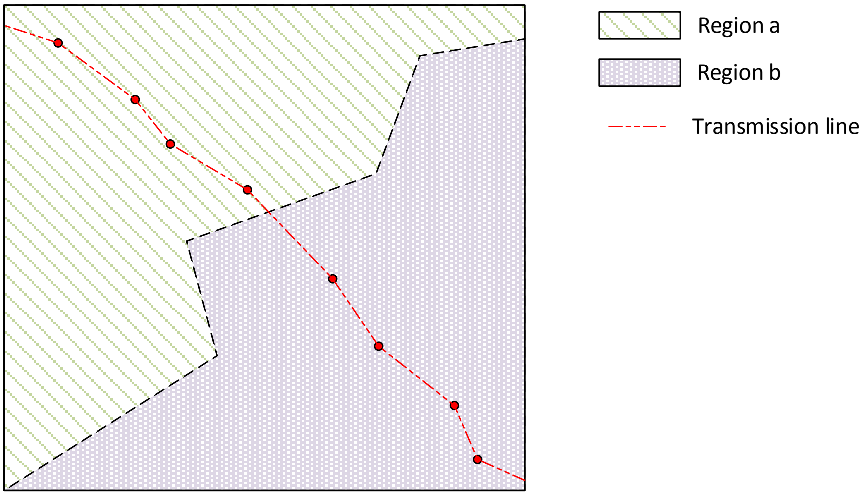

Figure A.4.10: Example of a transmission line exposed to two different weather regions

A.4.4.2 Proposed methodology for contingency analysis

Despite the efficiency of Monte-Carlo (MC) simulation, evaluation of reliability using MC can take considerably long time even for the moderate level of precision. For the contingency analysis in this proposed case study, ref. [7] is considered. The data-set consists of state vectors as nodes represented as Generator (G), Line (L), Bus (B) and Loss of Load (LOL). MC simulation is used to generate training data for the contingency analysis. Non-sequential MC simulation technique is preferred in our study, which neglects chronological histories of components. It randomly samples system state according to its probability of occurrence. This technique, in general, reaches convergence faster than sequential MC though it needs additional computation when calculating frequency and duration (F & D) indices. In our study, components considered are generators, transmission lines and buses[3]. They have only two states of operation, i.e., up/normal or down/failure.

The dataset structure is

$$[G1\ G2 \ldots Gn\ L1\ L2 \ldots Ln\ B1\ B2 \ldots Bn\ LOL] \tag{A.4.27}$$

where LOL refers to loss of load event, which is considered one unless there is zero load supply.

For the training data, preventive and corrective actions are considered while deciding the state. During preventive action, a random number between $\{0,1\}$ is generated for each generating unit, which is compared with the forced outage rate (FOR). If the random number is greater than FOR, it's an up or normal state, equivalent to zero. Otherwise, it is a down or failure state, equivalent to one. During corrective actions, generation rescheduling and load shedding as described in [1] is carried out. And, the optimization problem is modified by adding a weighting factor to the load curtailment vector.

Thus, the new optimization problem is

$$min \sum_{i \in NC} W_i C_i \tag{A.4.28}$$

such that,

$$\begin{gathered} T(S^j) = A(S^j)(PG + C - D) \\ \sum_{i \in NG} PG^i + \sum_{i \in NC} C_i = \sum_{i \in NC} PD_i \\ PG^{min} \leq PG \leq PG^{max} \\ 0 \leq C \leq PD \\ |T(S^j)| \leq T^{max} \end{gathered} \tag{A.4.29}$$

where,

C_i	Load curtailment vector
W_i	Weighting factor for load
NC	Set of load buses
S^j	System state in jth state
$T(S^j)$	Line flow vectors under state S^j
$A(S^j)$	Relation matrix between line flows and power injections under state S^j
PG	Generation output vector
C	Load curtailment vector
PD	Load power vector

In the above formulation, load is considered constant, and convergence of LOL is chosen as stopping rule in sampling process. The contingencies analysis aims at calculating the down time and probability of all possible fault combinations in the system for each time step. It is necessary

[3] https://www.ee.washington.edu/research/pstca/rts/pg_tcarts.htm

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to do these calculations for each time step because factors that influence the reliability of the components will likely change.

A.4.5 FURTHER WORK

The work reported in this appendix is a first attempt to generate micro-scenarios needed to represent exogenous uncertainties in the context of asset management studies. Inspired by the literature, we have proposed models for the generation of day-ahead load-forecasts and the subsequent forecast errors, wind-power generation forecasts and realizations, and hydro-thermal generation scheduling. We have also described a first attempt to model the spatio-temporal variability of outage rates and contingency probabilities.

Further work will aim at building on existing state-of-the-art methods so as to come up with a generative model of micro-scenarios that would be suitable in practice.

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