Resilient analysis of power grids
An OpenCossan Case Study

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Summary and Key Findings

Key Findings

A power grid optimization framework has been implemented in OpenCossan. The toolbox presents the following main features:

1. **Optimal allocation of distributed generators has been investigated and proved effective.**
2. **Robust-Design-Optimization** provides reliable solution which accounts for inherent uncertainties in the operation and environment.
3. **Multi-energy system** modelling and optimization outperform 'classical' analysis where energy networks are treated 'separately' or 'independently';

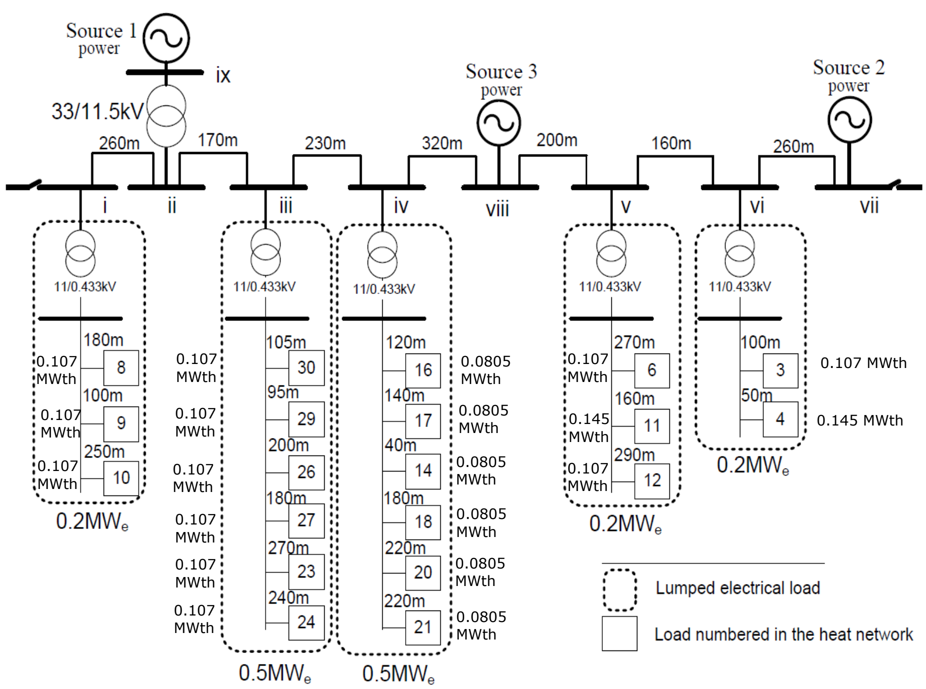

Figure 1: The Barry island power grid and heat network [1], modified from X. Liu et al 2016.

1 Problem Description

This work presents a framework for stochastic analysis, simulation and optimization of networked infrastructures. We investigate the framework with the goal of optimally invest on distributed energy sources. Distributed energy sources (e.g. wind turbines and storage systems) can be integrated within the grids and their performance is modelled. The effect of variable weather conditions and operations on the overall system cost and reliability is assessed taking into account relevant sources of uncertainty. A Monte Carlo Optimal Load Flow simulator is employed and statistical indicators of the system cost and reliability are computed. The frameworks has been tested on 2 examples. First, we compute an optimal investment on solar generators to be allocated on a 14 nodes power grid [2]. Finally, we assess a combined investment on electric-heat power generators on an electric grid coupled to an heat district network in the Barry island in Fig. 1 [1]. Storages (ST), wind turbines (WT), Photo-Voltaic panels (PV) and Heat pumps are the considered technologies. Generators' sizes and positions are analyzed to reveal the sensitivity of the cost and reliability of the grid and an optimal investment problem is tackled by using a genetic algorithm fro multi-objective optimization.

Cite [2] and [1]

2 Analysis

In [1], a Robust Design Optimization is defined. Design variable is a matrix **x** of allocated technologies within the grid. The combinatiorial space of **x** is explored using a genetic algorithm and the fitness of each candidate solution is evaluated using a Monte Carlo simulator which allows propagating the relevant sources of uncertainty to a reliability index (the Energy-not-supplied ENS) and to the expected global cost of the investment (C_{glb}).

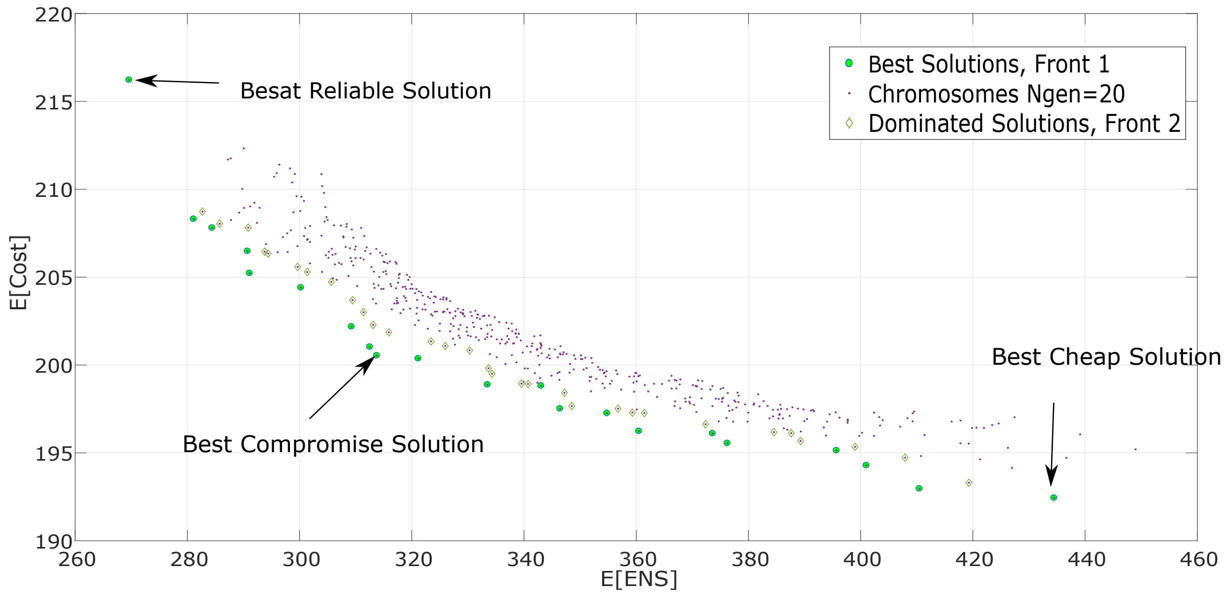

Figure 2: The 3 best chromosomes selected among the best front in the generation of the NSGA-II procedure.

Table 1: Example of low cost investment, high reliability investment and best compromise solution, see Fig. 2. Statistical analysis on the global cost and network reliability performance.

Solution	**Reliable**	**Compromise**	**Cheap**
$\mathbb{E}[ENS]$	290	315	435
$\mathbb{E}[C_{glb}]$	209	202	193
$C_V[ENS]$	1.55	1.46	0.79
$p_{95}[ENS]$	1302	1578	2520
$C_V[C_{glb}]$	0.27	0.29	0.42
$p_{95}[C_{glb}]$	287.1	284.3	301.1

Summary and Key Findings

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After careful analysis, a number of conclusions have been reached:

1. **A novel simulation method** based on a computationally cheap **emulator of the optimal power flow** is presented and used to speed up the computation of the expected energy not supplied by the network.
2. The method **greatly reduces the computational cost** of the time-demanding analysis (up to a 99% reduction).
3. Problems of lack of data are discussed and the efficient simulator, embedded within a generalised uncertainty quantification framework, allows **the effect of lack of data to be quantified**.
4. **Sensitivity analysis ranks sources of imprecision and allows data collection prioritisation** (i.e. parameters that if better specified lead to the highest reduction of the imprecision in the resilience index).

Figure 3: Severe weather conditions (e.g. an ice storm in figure) are triggering power grid failure.

3 Problem Description

Extreme weather conditions have the potential to trigger severe power grid failures, compromising its structure and operations. Fig. 3 shows an example of failure induced by a severe ice storm. The weather conditions drifting towards extremes and the increasing use of renewable energy sources are tightening the interactions between power network states and the external environment. Robust reliability/resilience assessment frameworks have, then, to incorporate weather models and consider interactions between grid states and environmental states, accounting for relevant sources of randomness (i.e. aleatory uncertainty) but also for parameters values imprecision (i.e. epistemic uncertainty). In this work we propose a framework for (imprecise) probabilistic resilience assessment of power networks. The framework has been designed to capture complex coupling between weather conditions and power grid operations, by incorporating weather-influenced failures and repairs of the grid's components. An Artificial Neural Network (ANN) is trained to emulate the total load curtailed given specific lines failures and the load profile, and has been embedded within the framework to increase computational efficiency. For further details refer to [3].

Cite: *A power-flow emulator approach for resilience assessment of repairable power grids subject to weather-induced failures and data deficiency* [3]

4 Analysis

The framework has been applied on a modified version of the IEEE-RTS 24 nodes power grid which counts 24 nodes, 17 loads, 32 generating units, 33 transmission lines, 5 transformer links and a total installed capacity of 3.405 GW.
A parallel computing strategy has been used to solve 15000 independent years; For the selected parameter setting the average number of failure events per each $T_{sim} = 8760$ [h] (1 year) is estimated to be 311, of which 73 normal failures 223 wind-induced failures and 15 lightning-induced failures. The expected load curtailed for each failure event is estimated to be 0.23 [W/failure]. The Expected Energy not Supplied is 147.5 [MWh/yr] with coefficient of variation (CoV) 0.175, and slowly converges after about 2000 simulations.

The probabilistic model describing the uncertainty affecting the grid and weather is extended to include different imprecision levels affecting the parameters of the model. The grid model and ANN surrogates are tested and effect of imprecision quantified in the resilience score as displayed by Fig.5.

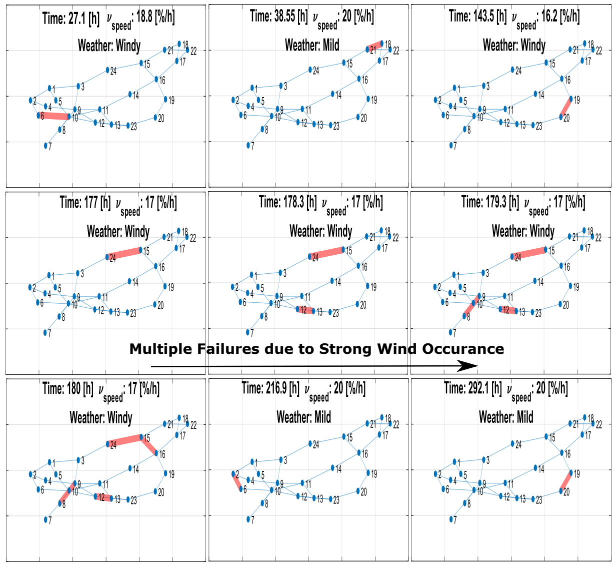

Figure 4: An example of 9 sequential failure events extracted from a simulated year for the grid. Strong Wind occurrence (from hour 177 to hour 180) increase line failure rates and decrease the repair speed, hence, leading to 4 common cause outages.

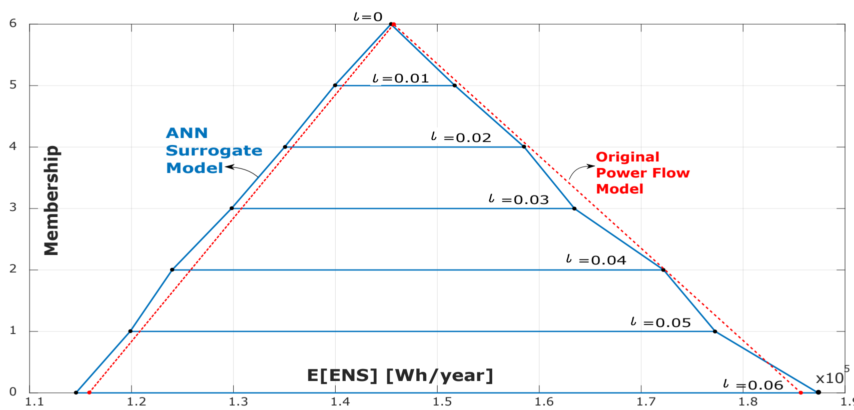

Figure 5: Comparison between Fuzzy Expected Energy Not Supplied ($\mathbb{E}[ENS]$) computed using the original Optimal Power Flow (OPF) model and the Artificial Neural Network surrogate.

Summary and Key Findings

Key Findings

A reinforcement-learning toolbox. Key findings are as follows:

1. **Operations and maintenance of grids is framed as a Sequential Decision Problem**;
2. **Prognostics and health management capability** support maintenance decision-making;
3. Q-learning with neural networks **tackle high dimensional and continuous problems**;
4. A grid with prognostics and health management is considered as test case study;
5. **Comparison with BellmanâĂŹs optimal policy** highlights the effectiveness of the method;

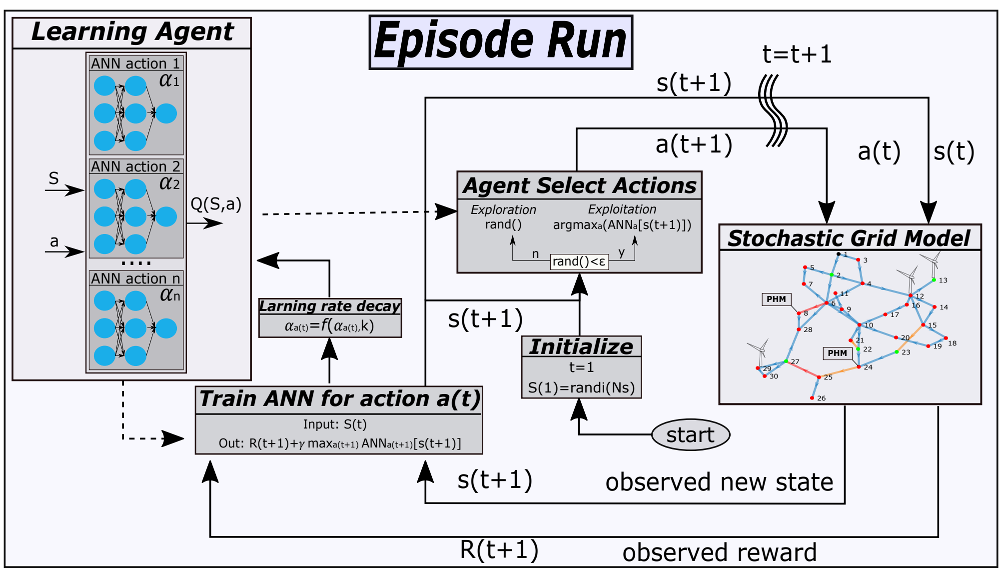

Figure 6: The proposed Reinforcement Learning method [4]

5 Problem Description

We develop a Reinforcement Learning framework for the optimal management of the operation and maintenance of power grids equipped with prognostics and health management capabilities. Reinforcement learning exploits the information about the health state of the grid components. Optimal actions are identified maximizing the expected profit, considering the aleatory uncertainties in the environment. To extend the applicability of the proposed approach to realistic problems with large and continuous state spaces, we use Artificial Neural Networks (ANN) tools to replace the tabular representation of the state-action value function. The non-tabular Reinforcement Learning algorithm adopting an ANN ensemble is designed and tested on the scaled-down power grid case study, which includes renewable energy sources, controllable generators, maintenance delays and prognostics and health management devices. Figure 6 depicts the framework architecture. The point of strengths and weaknesses of the method are identified by comparison to the reference solution (BellmanâĂŹs optimally). Results show good approximation capability of Q-learning with ANN, and that the proposed framework outperforms expert-based solutions to grid operation and maintenance management.

Cite [4] A reinforcement learning framework for optimal operation and maintenance of power grids, Applied Energy 2019, https://doi.org/10.1016/j.apenergy.2019.03.027

6 Analysis

A method which combines Q-learning algorithm and an ensemble of Artificial Neural Networks is developed to identify optimal operations and maintenance (O&M) policies. An analytic (Bellman's) solution is provided for scaled-down power grid, which includes Prognostic Health Management devices, renewable generators and degrading components, giving evidence that Reinforcement Learning can really exploit the information gathered from Prognostic Health Management devices, which helps to select optimal O&M actions on the system components. The proposed strategy provides accurate solutions comparable to the true optimal. Although inevitable approximation errors have been observed and computational time is an open issue, it provides useful direction for the system operator. In fact, he/she can now discern whether a costly repairing action is likely to lead to a long-term economic gain or is more convenient to delay the maintenance.

References

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