

Introduction

- **Expansion planning problems** refer to the monetary and unit investment regarding energy production or storage.
- Stochasticity is inherent: generation output of renewables, load demand, climate change, **frequency and duration of outages**, etc.
- Outage modeling has remarkable impacts on designing systems, for example, **microgrids**.
- In most of current studies, a single statistical distribution is used for outage modeling, like a **Poisson process**.
- We attempted to relax this assumption by proposing an **alternative outage model**.
- The scheme is based on the premise that outages are classified into **two categories**: regular and severe.
- A **reinforcement learning** approach is applied to solve the expansion planning problem.
- The objective is to derive the **optimal storage expansion plans** for a specific microgrid in a predetermined time horizon.

Nomenclature

S	State set
A	Action set
f	Transition function
R	Reward function
S^{tf}	Timing feature of the state set
S^{ef}	External feature of the state set
S^{if}	Internal feature of the state set
K	Number of decision periods
SU	Set for available storage units
SC	Set for characteristics of storage units
SL	Set of available storage capacity levels
G	Set of facilities in the microgrid
δ	Indicator function for lost demand
C_p	Critical load factor
$P_{annuity}$	Annual investment payment for storage units, \$
y	Number of years in the decision period, yrs
D	Load demand, kWh
T	Grid outage duration, hrs
$CAIDI$	Average interruption duration, hrs/interruption
$VOLL$	Value of lost load, \$/kWh

Methodology

MDPs and Reinforcement Learning

The problem is solved using a variant of Q-learning algorithm.

The MDP formulation is provided [1]:

$$S = S^{tf} \times S^{ef} \times S^{if}$$

where:

$$s^{tf} \in S^{tf} = \{1, 2, \dots, K\}$$

$$\vec{s}^{ef} = (s_{i,j}^{ef}, \forall i \in SU, j \in SC) \in S^{ef}$$

$$\vec{s}^{if} = (s_i^{if}, \forall i \in SU) \in S^{if}, \forall i \in SU, s^{tf} \in S^{tf}$$

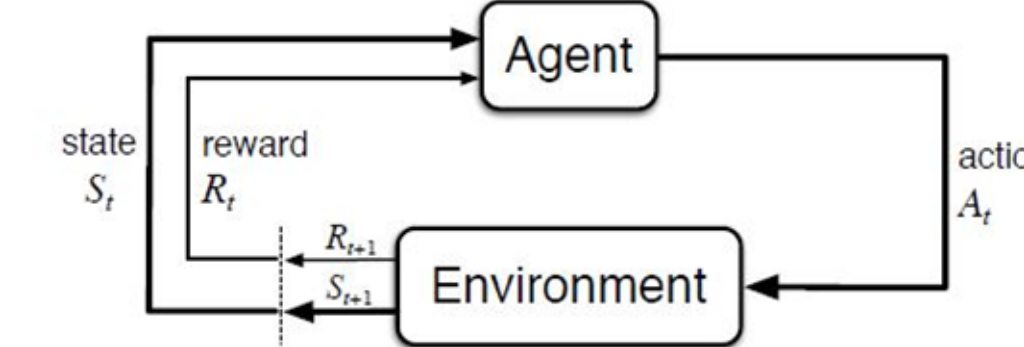
$$\vec{a} = (a_{i,l}, \forall i \in SU, l \in SL) \in A$$

s.t.

$$a_{i,l} \in \{0, 1\}, \forall i \in SU, j \in SL$$

$$\sum_{i \in SU, l \in SL} a_{i,l} \in \{0, 1\}$$

$$r_k(\vec{s}, \vec{a}) = - \sum_{i \in SU} \sum_{l \in SL} (K - k + 1) y a_{i,l} P_{annuity}^i - \sum_{g \in G} VOLL^g \sum_{j \in N_k} \sum_{i \in O_{jk}} \delta(t_{ijk}, g) C_p^g D(t_{ijk}, g)$$



Two outage modeling approaches: Single Poisson Process vs. Superposed Poisson Process

Year	2012	2013	2014	2015	2016	2017
CAIDI (hrs/int)	22.55	1.65	1.42	1.95	1.46	1.70

Table 1 CAIDI data provided by NY State for PSEG-L, years 2012-2017 [2]

- **Single Poisson Process:** $\{N(t), t \in [0, +\infty)\}$ with rate λ . The number of outages at any time τ follows Poisson distribution with a rate $\lambda\tau$.
- **Superposed Poisson Process:** $\{N'(t) = N_1(t) + N_2(t)\}$ with rate $\lambda = \lambda_1 + \lambda_2$ where $\{N_1(t), t \in [0, +\infty)\}$ with rate λ_1 is a Poisson process for the regular outage events, $\{N_2(t), t \in [0, +\infty)\}$ with rate λ_2 is a Poisson process for the severe outage events. Let $\Pr\{Z_n = i\} = \frac{\lambda_i}{\lambda}$ where Z_n is the type of the n^{th} event, $i \in \{1, 2\}$.

Case Study

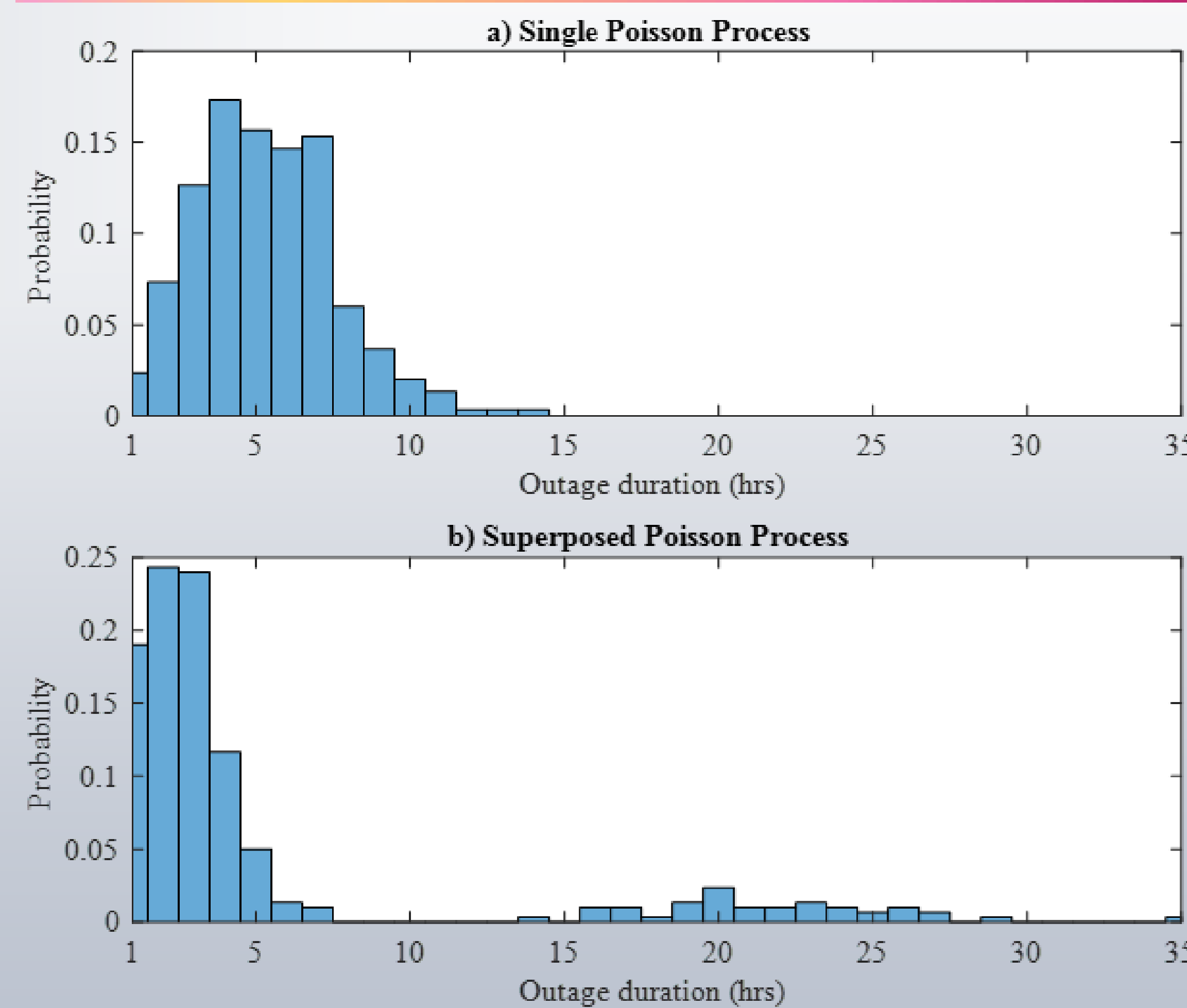


Fig. 1 Distribution of outage duration using two different probabilistic modelling approaches

Major difference!

- Mean duration is the same
- Distribution is not!

A case study for a microgrid in Westhampton, NY is conducted [3].

Numerical assumptions

- The microgrid consists of 2 hospitals, 5 schools and 300 residential facilities
- 4 storage options existing in SU : lithium-ion, lead-acid battery, vanadium redox battery and flywheel storage
- Options to install at one of three predetermined levels (300, 1000, 3000 kWh)
- The considered stochastic component is the price of the storage unit, modeled by a DTMC

Results

Discrepancies in both timing and level of investments

- The experiment is implemented twice with identical parameters, except the outage model
- Storage unit prices are declining for both scenarios
- Optimal policies differ significantly
- 7000 kWh total storage capacity in Single PP, 4000 kWh in Superposed PP
- First investment happens one period earlier in Single PP scenario

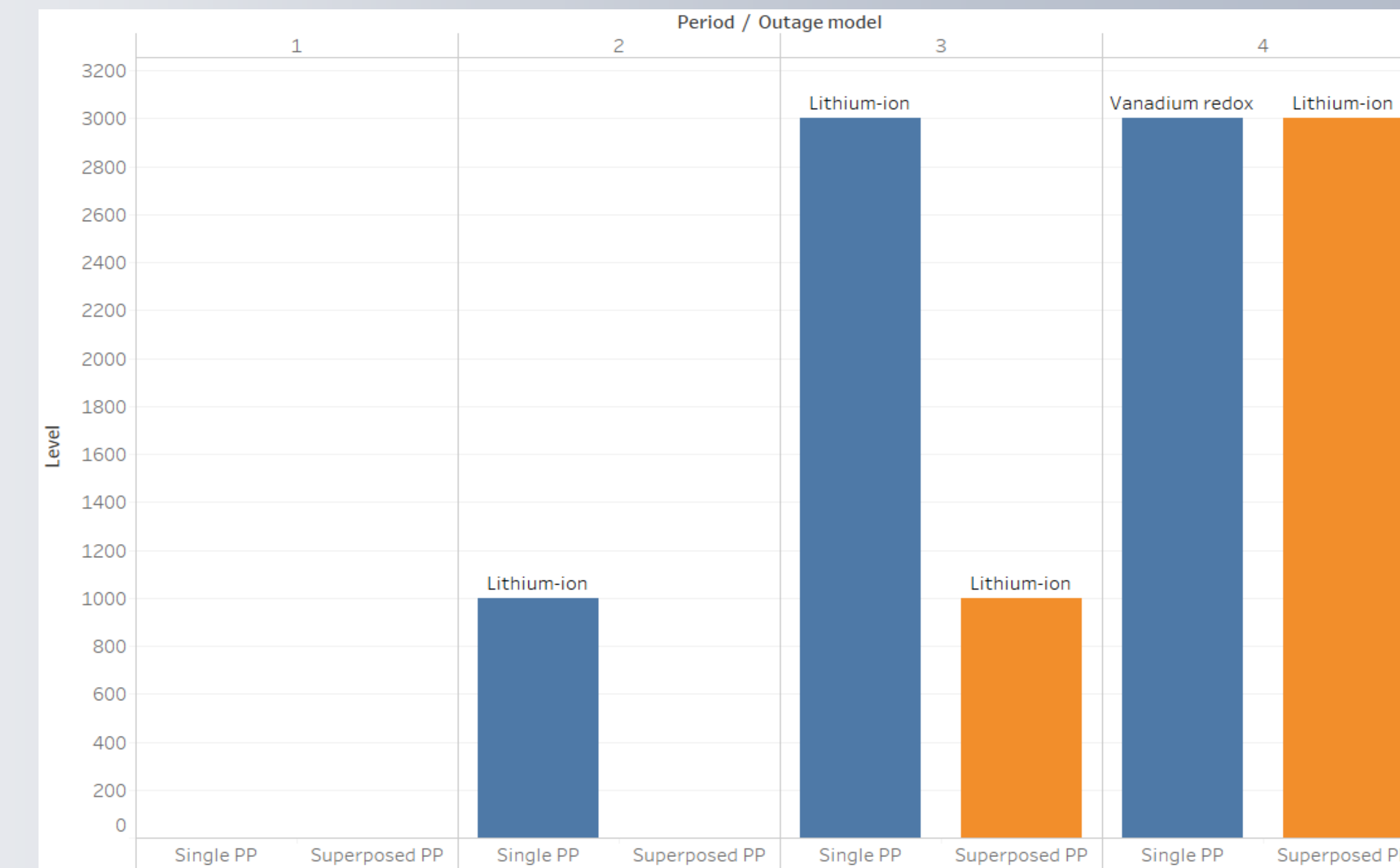


Fig. 2 Optimal policies for both outage models

Conclusions

- In the superposed PP scenario, the vast majority of outages are not long-lasting and can be handled with a moderate amount of storage capacity.
- This could be the underlying reason behind the research findings presented here (timing and level differences).
- The focus of this study is to highlight the importance of analytical and accurate outage modeling, specifically tailored for microgrid applications.
- An open research question is how to derive ways to optimally mitigate the impacts of catastrophic events.

References

1. S. Tsianikas, N. Yousefi, J. Zhou, M. Rodgers, and D. Coit. (2020), A sequential resource investment planning framework using reinforcement learning and simulation-based optimization: A case study on microgrid storage expansion. Available: <https://arxiv.org/abs/2001.03507>
2. D. o. P. Service, "Electric Reliability Performance Report," 2018
3. S. Tsianikas, N. Yousefi, J. Zhou, and D. Coit. (2020), The impact of analytical outage modeling on expansion planning problems in the area of power systems. Submitted in IISE 2020.