# HUGO - HIGHLIGHTING UNSEEN GRID OPTIONS: COMBINING DEEP REINFORCEMENT LEARNING WITH A HEURISTIC TARGET TOPOLOGY APPROACH

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#### ABSTRACT

With the growth of Renewable Energy (RE) generation, the operation of power grids has become increasingly complex. One solution is automated grid operation, where Deep Reinforcement Learning (DRL) has repeatedly shown significant potential in Learning to Run a Power Network (L2RPN) challenges. However, only individual actions at the substation level have been subjected to topology optimization by most existing DRL algorithms. In contrast, we propose a more holistic approach in this paper by proposing specific Target Topologies (TTs) as actions. These topologies are selected based on their robustness. As part of this paper, we present a search algorithm to find the TTs and upgrade our previously developed DRL agent CurriculumAgent (CAgent) to a novel topology agent. We compare the upgrade to the previous CAgent agent and can increase their scores significantly by 10%. Further, we achieve a 25% better median survival with our TTs included. Later analysis shows that almost all TTs are close to the base topology, explaining their robustness.

**Keywords** Topology Optimization · Electricity Grids · Deep Reinforcement Learning · Learning to Run a Power Network · Proximal Policy Optimization

## 1 Introduction

As the fight against climate change intensifies, power generation has changed dramatically in recent years. Increasing amounts of RE are being produced, resulting in more variable inputs to the grid. In addition, consumers are not only demanding more electricity through heat pumps and electric cars, but are also starting to generate electricity with their own photovoltaic systems. This poses new challenges for the Transmission System Operators (TSO) as they have to become flexible with their current electricity grid to handle the volatility. One promising approach that is increasingly discussed in the research community is bus switching at the substation level to change the grid's topology. As mentioned in [1], intelligent switching in critical areas of the grid allows overloads to be diverted to stabilize the grid to some extent. To solve this problem, researchers propose applying deep learning methods, particularly in DRL, which could significantly reduce computational costs. Such approaches were first tested in the L2RPN challenge [2] by the French

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**Figure 1:** Simplified example of a topology action based on [2]. With the injections of the generators and the high demand of the load sinks, the grid has an overload in the right line (red) in time step t. To reach the stable state in t + 1, splitting the bottom-right substation by assigning two different buses is essential. This can be achieved by executing the substation action (top-right) on substation No. 4. Alternatively, one can describe the desired outcome in the form of a TT (bottom-right box). Note that the bue dots represent the  $bus_{one}$  and the red ones  $bus_{two}$  while the dotted lines in the TT representation separate substations.



TSO RTE. <sup>5</sup> Through their continuous development, the challenges, and the realistic representation of electricity grids, L2RPN has become the leading benchmark for DRL based grid simulations in the community and is used by various researchers.

## 1.1 Main Contributions

Previously, researchers often considered actions that change bus configurations at the substation level to change the grid topology. These actions affect only one substation but can affect multiple buses on that substation. We refer to these actions as substation actions. The problem is that these actions are often considered in isolation. While they may be beneficial for the next step, they may lead to unstable or suboptimal topologies in the long run. In reality, grid operations do not consider independent substation actions. Instead, they consider changing a combination of substations over multiple steps. However, these holistic topology approaches are rarely addressed in DRL research for grid optimization. This may be caused by the design of the L2RPN Grid2Op environment[3], which allows only one substation to be changed per time step, or by the expensive computations to calculate the combinations.

In our work, we propose to take a different approach. Instead of considering actions that switch only one single substation, we are looking at the overall topology of the electric grid, i.e., the configuration of all buses at all substations. The idea is that there are certain TTs that are more robust than other topologies. If our current topology state is not resilient enough, then we try to reach a close TTs instead. The advantage is that since we can reach the Target Topology (TT) from almost any topology configuration, we do not need to learn specific combinations of substation actions. This is especially helpfull in more complex grids, as the TTs may lead to sequential execution of multiple substation actions. In Figure 1, we visualized the different approaches of the substation action and the TT using a simple example. As a contribution of this work, we propose a search algorithm to find adequate TTs. With the algorithm, we identify TTs that prove to be robust against instability, given an existing set of substation actions. In addition, we extend our previously published CAgent approach [4] to a Topology Agent by adding a greedy search component with TTs. We test our agent on the validation grid of WCCI 2022 L2RPN challenge to ensure that our approach is beneficial for grid optimization.

The contributions can be summarized as follows:

- We provide the retrained CAgent[4] on the WCCI 2022 environemnt with a substation action set of 2030 actions.
- In light of the concept of Target Topologies (TTs), we present our novel search algorithm to find TTs based on existing substation actions.
- We improve our previous CAgent to a Topology Agent ( $TopoAgent_{85-95\%}$ ) agent by adding a greedy component that iterates through TTs and selects the best TT.
- We can show significant increase by more than 10% in the L2RPN score performance.

<sup>&</sup>lt;sup>5</sup>L2RPN challenges: https://l2rpn.chalearn.org/ (last accessed 05/04/2024).

- In addition, we can show that the  $TopoAgent_{85-95\%}$  has a 25% higher median survival time then the previous CAgent agent.
- All extensions will be published upon acceptance as part of the CAgent Github Repo.

The rest of the paper is structured as follows. First, we present the related work in Section 2, followed by a description of the environment and the CAgent in Section 3. We then propose our new TT approach in detail, with the topology search and the topology agent in Section 4. We evaluate the topology agent on the benchmark scenarios in Section 5, followed by a discussion of the results in Section 6. Finally, we conclude in Section 7.

## 2 Related Work

After the pioneering breakthrough of DRL in various Atari games in 2015 [5, 6], DRL has demonstrated exceptional performance in several research areas [7, 8, 9]. As a result, there has been a growing interest in adopting DRL approaches in the field of grid control. This is particularly evident in the context of the L2RPN challenge [10, 11, 12, 13], which had a wide response in the energy and Machine Learning (ML) community. With their Grid2Op environment[3] they introduced a realistic benchmark, which allows researchers to validate their grid control approaches on multiple simulation environments following the GYM framework of OpenAI[14]. While there have been some purely rule-based agents, e.g. [15], the challenges have primarily been won by combining DRL with rule-based elements. In this regard, the first effective DRL approach to grid control has been introduced by the winners of the 2019 challenge [16]. Their approach was based on a Dueling Deep Q Network (DDQN) and combined an imitation learning strategy with guided exploration. Following a more complex L2RPN challenge of 2020 [10], [17] proposed a DRL approach that combines a planning algorithm with an evolutionary strategy. The available actions provided by the policy were searched by the planning algorithm, which was then optimized using the evolutionary algorithm. Gaussian white noise was added to ensure adequate exploration of the policies[17]. The second best performance of the robustness track has been achieved by [18], which is the basis of the curriculum agent and further described in Section 3.2. A similar approach also combining a DRL algorithm with a heuristic was presented by [19]. Another approach worth mentioning was proposed by [20], who introduced a Monte Carlo tree search approach to finding appropriate actions, similar to AlphaZero's [21]. With their agent, they were able to win the L2RPN WCCI Challenge of 2022. Moreover, in their [21] paper, they evaluated the effect of topology optimization with substation actions and showed that inclusion can reduce redispatching costs by up to 60%. This highlights the potential of substation actions and is the reason we chose their action set for this paper.

Another group of approaches is hierarchical agents such as the one presented by [22]. The authors introduce a multiagent DRL framework based on Soft Actor-Critic Discrete (SACD) and Proximal Policy Optimization (PPO). The approach optimizes power grid topologies through three levels. The highest level is rule-based that activates interventions only in critical conditions of the grid. The mid-level identifies and prioritizes actions for specific substations needing intervention. At the low level, substation-specific agents decide on bus configurations by applying DRL to make localized decisions independently. Two related approaches [23, 24]also break down the decision process into three very similar stages. In particular, [23] additionally used a Graph Neural Network (GNN) to learn representations of the power system and its topology at different granularities before the multi-stage decision making. In contrast, [25] also followed a hierarchical approach but focused on fairness, i.e., distributing the long-term benefits among power plants fairly. They introduced a hierarchical optimization function and a reward system focusing on equitable supply-side gains.

Finally, we would like to highlight the work of the winners of the L2RPN WCCI 2020 challenge [26], who present an approach with a similar focus on topologies as ours. Unlike other participants, they were among the first researchers to focus on whole topologies instead of isolated actions. Their approach, based on a Semi Markov Afterstate Actor Critic (SMAAC) algorithm, applies a GNN to the observation space to transform the grid into an afterstate representation to summarize actions. Based on their initial findings, we take up their idea and propose a more holistic approach. We also provide a detailed analysis of the effect of TTs.

## **3** Environment and agent structure

## 3.1 Grid2Op Environment

The Grid2Op package is the current state-of-the-art environment for DRL development related to electric grid operations and was developed by RTE France in the context of the L2RPN challenges. Grid2Op includes multiple synthetic power grids, such as the IEEE14 or IEEE118 grids with a pandapower or ligthsimtogrid backend, ensuring realistic load flow caluclations. To ensure that the environments follow a Markov Decision Process (MDP), they are modeled according to the OpenAI's Gym framework [14] and are described in more detail in [2, 11, 27]. In this paper, we use the

L2RPN WCCI 2022 environment, which is composed of the IEEE118 grid with an energy mix of 2050, i.e., the share of fossil fuels for electricity generation is less than 3% and the RE are drastically increased [27]. As seen in Figure 2, the grid has a total of 118 substations, 91 load sinks and 62 generators, as well as the seven battery storages, all connected by a total of 186 lines. As such, the observation space of the grid has the size 4295 and contains various information about the power grid, such as active and reactive power flows, voltage magnitudes and angles of the lines and substation buses. Moreover, the injections of the generators and storages, load demand, time variables, maintenance, cooldown periods and topology configurations are reported. The most important variable for this paper is the line capacity, which we denote as  $\rho_{l,t} \in \mathbb{R}^+$  for line l of all lines  $l \in \mathcal{L}$  as well as the maximum capacity over all lines as  $\rho_{max,t} = \max_{l=1,\dots,L} (\rho_{l,t})$ . Besides observation, Grid2Op provides a simulation method with obs.simulate() that can

predict the state of the next step based on the current action, albeit with some margin of error. From this method we can derive the impact of the action one the maximum simulated line capacity  $\hat{\rho}_{max,t+1} = \max_{l=1,\dots,L} (\hat{\rho}_{l,t+1})$  with  $\hat{\rho}_{l,t+1}$  being

the simulated line capacity of line l.

With respect to the action space, multiple action types are available, however, similar to [4], we are only interested in the substation actions and the line action, as we want to analyze the effect of topology changes on the robustness of the grid. For the latter, the environment has a total of 186 line actions (discrete), where the action  $a^{(line)} \in \mathcal{A}^{(line)}$  can set the status of a line and thus connect or disconnect two substations. More complex is the substation action  $a^{(bus)}$  with a total of 72957 substation actions (discrete). From the set of all possible bus configurations on all substations  $a^{(bus)} \in \mathcal{A}^{(bus)}$ . As shown in Figure 1, the elements of a substation can be connected to either  $bus_{one}$  or  $bus_{two}$ . By using different bus configurations, it is possible to control the power flow in a substation. However, the number of available bus permutations can become quite large with more elements at a substation and their optimization complex [12]. Note that there are some restrictions on taking actions on previously modified lines and substations, as there are cooldown periods that limit interaction on the same element. There is also an adversarial agent [28] that can disconnect lines quasi-randomly. This can cause additional cooldowns.

There are two ways to complete an episode in the environment. The first is a successful termination when all 2016 time steps (one week à five-minute steps) of a chronic are completed. The second is earlier truncation due to grid failure. A major cause is the forced disconnection of lines, leading to a cascading failure. It is induced by the Grid2Op rule that a line is disconnected if  $\rho_{max,t}$  stays above 100% for three consecutive time steps. An immediate game over can also be reached if a generator or a load is disconnected and/or a general islanding occurs in the grid. Finally, an episode may fail if the underlying power flow solver cannot converge in the load flow optimization. This can sometimes happen when the grid is far from its original topology.

As the evaluation metric of this paper, we use the same score as the L2RPN challenge [13] of the 2022 updated scoring method.<sup>6</sup> The scoring is based on the survival of a Do-Nothing Agent (DoNothing), i.e. an agent that does not take any action in the environment. With the DoNothing score set to 0, we evaluate an agent based on its survival. The agent gets a negative score up to -100 if it performs worse than the DoNothing. If outperforms the DoNothing, the score becomes positive, with 80 corresponding to a completion of the episode. To achieve the maximum score of 100, the agent must also optimize the cost of energy loss and the cost of operation. For testing, we were able to obtain the test scenarios of the original WCCI 2022 challenge, thanks to the courtesy of RTE France.

## 3.2 The CurriculumAgent

As part of this work, we are retraining and extending the CurriculumAgent (CAgent) described in detail in [4]. The CAgent is a *Teacher-Tutor-Junior-Senior* framework first introduced by [18] in the 2020 L2RPN challenge. The framework is now shortly described, however for more information we refer to [4].

Due to the high number of substation actions, there is a need to reduce the actions set to a suitable subset. For this the *Teacher* runs with a brute-force approach through a various scenarios of the environment and simulates with the Grid2Op method obs.simulate() the effect of all substation actions. The most frequent actions that were selected are then combined in an action subset. Next to this general approach, the *Teacher* can be modified to search specific, e.g., actions against adversarial agents[18] or actions that fulfill the N-1 criterion [4].

With the action subset, the a rule-based *Tutor* is used to generate experiences for imitation learning. In its interaction with the environment, the greedy agent is only activated if the  $\rho_{max,t}$  is above the threshold of  $\rho_{tutor} = 0.9$ , else  $a_{DoNothing}$  is returned instead. Within the greedy search, the agent selects the best action based on the lowest  $\hat{\rho}_{max,t+1}$  by simulating the actions with obs.simulate(). If there is no immediate danger, i.e.  $\rho_{max,t} < 0.8$ , the *Tutor* checks if for a topology reversal, i.e., if a modified substation can be reverted to its original state. Besides reversion, the *Tutor* also checks if it is possible to reconnect any disconnected lines.

The next component is the Junior agent, which is a simple feed-forward network that is trained on the experience of the

<sup>&</sup>lt;sup>6</sup>For a detailed description see https://grid2op.readthedocs.io/en/latest/utils.html#grid2op.utils. ScoreL2RPN2022 (last accessed 20/04/2024).

Figure 2: Visualization of the WCCI 2022 L2RPN environment based on the IEEE118 grid. Grid2Op's internal plotting method was used to create the Figure.



Tutor as an imitation learner. The model weights are later used to initialize the DRL algorithm (warm start). Given that the Junior is a supervised learning model, it is further ideal for hyperparameter search and the scaling of the experience. For our paper we used the Bayesian Optimization Hyperband (BOHB) algorithm [29] for the hyperparameter search. The last component of the CAgent is the DRL agent called Senior. It requires a modified DRL environment that encapsulates the Grid2Op environment. The agent is trained using PPO[30] and its hyperparameters are chosen by Population Based Training (PBT)[31]. After the DRL algorithm reaches convergence, the model is transferred to a MyAgent method, which we call for simplicity Senior Agent (Senior<sub>95%</sub>). The model is combined with heuristic strategies, automatic line reconnection, topology reversion at  $\rho_{max,t} < 0.8$  if possible and  $a_{DoNothing}$  for every remaining action as long as  $\rho_{max,t} < 0.95$ . If  $\rho_{max,t} > 0.95$ , we do not take the direct action of the DRL agent but instead look at the policies (action probabilities), sort them by probability and iterate with the obs.simulate() through the substation actions until the action is below  $\rho_{senior}$ . With all these measures, the CAgent shows a strong performance [4] and is therefore a strong benchmark as  $Senior_{95\%}$  in our work.

## 4 The Topology Approach

#### 4.1 Target Topologies as an alternative to substation actions

We pointed out that researchers often consider substation actions only. However, it is already known that the power grid is quite stable in its base topology, i.e., when all substation buses are set to one, as is the case in Figure 2. For this reason, [4] revert their agents back to the base topology when the grid is stable and were able to reach a better performance. In this work, we investigate the hypothesis that not only the base topology but also other specific topologies increase the stability of the power grid. Consequently, we want to evaluate the impact of these Target Topologies (TTs) on the survival of the power system. This can be useful when the base topology is unavailable, e.g., when certain lines are disconnected. To find these TTs, we propose a search algorithm, described in pseudocode in Algorithm 1, based on counting the number of visits from an agent in a given topology. We expect better performance for topologies with a higher count since the agents actively try to reach the topologies with their substation actions.

For the search algorithm, an agent agent interacts with the desired Grid2Op environment env, which in our case is the greedy *Tutor* agent. As one can see in Algorithm 1, we first initialize both an empty topology list  $\Psi$  and an empty experience list  $\Theta$ . Next, we iterate through a certain number of chronics of env to ensure enough diversified topologies. For each chronic of length T with time steps  $t = 0, \ldots, T$  we must first reset the environment and save both the current observation  $obs_{t=0}$  and the topology  $\psi_{t=0}$  of the state. Afterwards, we iterate through the chronic with our agent and check whether its action is a Do-Nothing action  $a_{DoNothing}$ , a substation or line action. For the first case we have to check whether the topology  $\psi_t$  is already part of our topology list  $\psi_t \in \Psi$ . If it is, it should already have an ID and a counter in  $\Psi$ , thus we increment the counter by one. If  $\psi_t \notin \Psi$ , we call the set\_id( $\psi_t$ ) method to get a new ID and

Algorithm 1 Search method for TT

```
Set \Psi \leftarrow [] and \Theta \leftarrow [
for chronic in env do
   obs_{t=0} \leftarrow env.reset()
   a_{t=0} \leftarrow a_{DoNothing}
   \psi_{t=0} \leftarrow \psi_{start} \text{ from } obs_{t=0}
   done \leftarrow false
   while not done do
       a_t \leftarrow \texttt{agent.act()} \text{ with } obs_t
      if a_t == a_{DoNothing} then
          if \psi_t in \Psi then
              \Psi(ID_{\psi_t}) + = 1 increase counter
          else
              ID_{\psi_t} \leftarrow \mathtt{set\_id}(\psi_t)
              \Psi(ID_{\psi_t}) \leftarrow [\psi_t, 1]
          end if
       else
          Record obs_t, a_t, ID in \Theta
       end if
       obs_{t+1}, done \leftarrow env.step() with a_t
   end while
end for
Sort \Psi based on counter
return most frequent topologies \Psi_{sub}^*
```

save the new topology in  $\Psi$  with a counter of one. Note that  $a_{DoNothing}$  appears either at the beginning of the chronic or in case the  $\rho_t$  falls below the threshold of  $\rho_{agent}$  again.

In case the action is not  $a_{DoNothing}$ , we record the first observation  $o_t$  where this is the case, the IDs of the end topologies and the actions that led to the specific topologies in our experience list  $\Theta$ . However, it is possible that the agent can have multiple steps where the action is not  $a_{DoNothing}$ . So we have a record of the first observation and all subsequent actions together. While, this recording of  $\Theta$  is not necessary for our paper, it allows for future work on training topology *Junior* and *Senior* agents If enough chronics are run, we can gather the generated data and sort the topologies of  $\Psi$  based on their occurrences. Subsequently, by selecting the most frequent M topologies, we are able to assemble our set of TT  $\Psi^*$  with  $\psi_m^*$  and  $m = 1, \ldots, M$ .

#### 4.2 Topology Agent

With a suitable subset of TTs  $\Psi^*$ , we now extend our CAgent agent to incorporate the topology approach. The underlying idea is to switch to TTs when the network starts to become unstable, but before a real emergency occurs. Therefore, we set the threshold of our topology agent to  $\rho_{topo} = 85\%$  for  $\rho_{max,t}$ . This ensures that the agent reacts faster to imbalances and steers the network to more stable topologies. However, we still keep our DRL trained Senior component with its usual threshold of  $\rho_{senior} = 0.95$ . Thus, in very critical situations, we first try to resolve the situation with single substation actions before returning to topology optimization. The agent also has the line reconnection component, Do-Nothing actions, and topology reversion when the grid is stable. All these methods are combined in the agent.act() method of our  $TopoAgent_{85-95\%}$ , which can be found as pseudo code in the Algorithm 2. A new feature within the method is the action buffer  $B^{act}$ . The buffer allows us to store multiple substation actions and execute them sequentially based on their effect on  $\hat{\rho}_{max,t+1}$ . Through  $B^{act}$  we can reach a TT  $\psi_m$  in multiple steps without breaking the environment rules. Within the method we can see that different components are triggered depending on the  $\rho_{max,t}$  of the observation. For  $\rho_{max,t} > 0.95$  the Senior component is activated, for  $\rho_{max,t} < 0.8$  we test for topology reversion and for the interval of  $0.85\% < \rho_{max,t} < 0.95\%$  the TT component is selected.<sup>7</sup> Note that for all other actions, we select the Do-Nothing action. This is also the case if no suitable substation action or topology could be found. We pass all actions to  $B^{act}$  and automatically check for line reconnections. In the TT component, we iterate through the M different TTs with a simple greedy approach. For each target topology  $\psi_m$ , we first extract from the current topology  $\psi_t$  the combined substation actions required to reach the new topology, denoted as  $a_{topo,m}$ . We then take the combined actions and simulate their effect on the grid. However, since obs.simulate() only allows one

<sup>&</sup>lt;sup>7</sup>We performed an extensive evaluation for different thresholds on the training environment. Our results showed that the interval between  $85\% < \rho_{topo} < 95\%$  gave the best result, even though this creates a gap to the topology reversion.

Algorithm 2

Topology Agents act method

**Require:** Observation with  $\rho_{max,t}$ **Ensure:** No previous action in  $B^{act}$ if  $\rho_{max,t} > 0.95$  then Run Senior for substation action  $B^{act} \leftarrow a_{Senior}$ else if  $\rho_{max,t} > 0.85$  then for all  $m = 1, \dots, M$  do  $\psi_t \leftarrow obs_t$  Get current topology  $\begin{array}{l} a_{topo,m} \leftarrow \psi_m - \psi_t \\ \hat{\rho}_{max,m} \leftarrow \text{Simulate effect of } a_{topo,m} \end{array}$ if Any  $\hat{\rho}_{max,m} < 0.85$  then  $B^{act} \leftarrow a_{topo,m}$ end if end for else if  $\rho_{max,t} < 0.8$  then Search if topology reversion possible  $B^{act} \leftarrow a_{reversion}$ else  $B^{act} \leftarrow a_{DoNothing}$ end if return  $B^{act}$ 

substation change action per time step, we use Grid2Op's Simulator class instead, which supports multiple topology changes at once.<sup>8</sup> If we were able to find a topology that satisfies  $\hat{\rho}_{max,m} < \rho_{topo}$ , we select that topology and pass the combined substation actions to the  $B^{act}$ . The  $TopoAgent_{85-95\%}$  can then execute these consecutive steps to reach the new TT. With the TTs incorporated in the agent format, we are now interested in their effect.

<sup>&</sup>lt;sup>8</sup>See https://grid2op.readthedocs.io/en/latest/simulator.html





# **5** Experiments

## 5.1 Research Design

As described in Section 3.1, we conduct our research on the WCCI 2022 L2RPN environment (Figure 2), where we trained our agents on the publicly available data and used the validation data provided by RTE France. The evaluation set contains a total of 52 scenarios, each consisting of 2016 time steps with a higher RE mix in comparison to today's power grids. Again, similar to [4], we propose to use multiple master seeds to obtain statistically significant results due to the inherent variation between scenarios depending on the environmental seeds. With 20 random master seeds generating the environment seeds, we have a total of 1040 chronics for our evaluation.<sup>9</sup> Regarding the substation action set in this paper, we did not use the *Teacher* method to generate the actions. Instead, we took the 2000 actions of the 2022 challenge winner [20] and added 30 expert actions selected by RTE.

With this research design, we have chosen a total of four agents to compare the effect of the topology optimization. The advanced agents have the same basic set of substation actions as well as the rule-based components of line reconnection and topology reversion.

- 1. The first agent is the DoNothing baseline, which is expected to score 0.0.
- 2. Second, we propose our previous  $Senior_{95\%}$  from [4] as our benchmark.
- 3. Next we have the new  $TopoAgent_{85-95\%}$  with the enhancements of Section 4.2. As TTs, we selected the most frequent 500 topologies that were found with our topology search from Section 4.1 on the WCCI 2022 environment with the 2030 substation actions.
- 4. To properly evaluate the effect of the topology approach, we also introduce the 85%-Senior Agent (Senior<sub>85%</sub>), with a lower threshold of  $\rho_{senior} = 0.85$ . The reason is that the  $TopoAgent_{85-95\%}$  can already start interacting at a  $\rho_{max,t} = 85\%$ . This way, we enable a fair comparison and make sure that the results of the  $TopoAgent_{85-95\%}$  are not induced by the lower threshold.

## 5.2 Experimental Results

**L2RPN Score:** With the research design set, we first look at the L2RPN score of the 20 seeds that can be found in 1. There is a clear increase in the score, as the  $TopoAgent_{85-95\%}$  agent is able to achieve an average score of 41.26. In comparison, the  $Senior_{95\%}$  reached a mean score of 37.13 and the  $Senior_{85\%}$  only reached 31.64. Given that the  $TopoAgent_{85-95\%}$  agent only has the additional TT search, it is a clear indication that the topology search might be beneficial. Further, we see that this increase in performance can not be credited to the earlier execution of  $\rho_{max,t} = 85\%$ , as the  $Senior_{85\%}$  is performing much worse. To ensure significance, we tested the  $H_0$  hypothesis that the  $TopoAgent_{85-95\%}$  is from the same distribution as the other agents with the Welch's t-test. The test results are in Table 2, which all reject the  $H_0$  hypothesis, indicating significance in the better performance of the  $TopoAgent_{85-95\%}$ . This result is not only reflected in the mean, but also by the median values as well. Additionally, looking at the quantiles in Table 1, it becomes clear why multiple seeds are necessary, as a clear variation can be seen between the 25% and 75% quantiles.

**Survival Time:** Although the score is largely tied to the time steps per chronic, it is quite interesting to look directly at the survival of the agents. For this reason, we added the last two columns of the Table1. Here we show the Median Survival Time (MST) over all 1052 episodes, where the  $TopoAgent_{85-95\%}$  was able to reach a median value of 1232 steps out of 2006. The  $Senior_{95\%}$  and  $Senior_{85\%}$  were only able to reach 988 and 766 time steps, and the DoNothing agent only survived 229 steps. As the survival is next to the seeds highly dependent on the chronic, we also conduct the Median Survival Time across Chronic Medians (MSTCM) in the last column, which is the median survival time after we took the median of the results per chronic. As expected, the MSTCM is higher than the MST, since it is not affected as much by outlier performance and instead averages over the chronics first. Nevertheless, we also see a better performance of the  $TopoAgent_{85-95\%}$  (1436 time steps) in comparison to the  $Senior_{95\%}$  (1160) and the  $Senior_{85\%}$  (807). Next to the two metrics, we also visualized the median performance of the agents for all scenarios of the seeds in Figure 3. Here the  $TopoAgent_{85-95\%}$  shows a much better performance with a total of 17 survived scenarios. For comparison, the  $Senior_{95\%}$  reached median completion in 12 and the  $Senior_{85\%}$  in 11 scenarios, while the DoNothing did not survive any. Note that full survival in the median score means that the agent was able to survive at least 50\% of the time. Overall, we argue that optimizing with TTs increases agent survival on the test data.

<sup>&</sup>lt;sup>9</sup>The master seeds were randomly chosen by np.random.choice() with np.seed of 8888. For each seed with separately copied an validation environment and recomputed its underlying statistics. This ensures that our results do not contain any kind of cherry picking.

Agent	Mean	Sd	Median	Q25	Q75	MST	MSTCM
DoNothing	00.00	0.00	00.00	00.00	00.00	229	383
$Senior_{95\%}$	37.13	4.49	37.21	33.48	39.84	988	1160
$Senior_{85\%}$	31.64	2.45	31.39	29.91	33.41	766	807
$TopoAgent_{85-95\%}$	41.26	3.01	40.41	39.41	43.69	1232	1436

**Table 1:** Summary of the agents' results. All agents were run on the evaluation environment of the WCCI 2022 with 20 different seeds. The performance across the seeds is recorded below. We list the mean and the standard deviation in the first column and the median as well as the 25% and 75% quantile in the second column. Further, we depict Median Survival Time (MST) and the Median Survival Time across Chronic Medians (MSTCM) of each agent.

$H_0$ Hypothesis	p-value		
	2.6e-23 0.001681 2.9e-13		

**Table 2:** Test Results of the Welch's t-test [32] with the hypothesis  $H_0 : \mu_i = \mu_j$  against the alternative hypothesis  $H_1 : \mu_i \neq \mu_j$ . For the normality assumption we tested with D'Agostino test [33] and could not reject the  $H_0$  hypothesis, so non-normality could not be assumed.

**Topology Distribution** Having established that TTs provide a new strategy for topology optimization, we want to take a closer look at the topologies that were most prominent in the validation set. Therefore, similar to Section 4.1, we counted the number of time steps an agent stayed in a topology and sorted them by occurrence. The results are visualized in Figure 4, where we show the Top100 topologies and mark in blue if the topology is part of the 500 TTs. Note that we have excluded the base topology and scaled the y-axis to a logarithmic scale for better visualization. Interestingly, we can observe that  $Senior_{95\%}$  and  $Senior_{85\%}$  have some topologies from the TT set in their Top20 topologies. However, in later topologies there are only marginally some TTs in their topologies. This may indicate that they selected less stable topologies, e.g., topologies that move farther away from the base topology, by using only the substation actions. With Figure 5 we take a closer look at the actual topologies by looking at the Top50 TTs of the  $TopoAgent_{85-95\%}$  agent. The y-axis in this Figure denotes the number of substations where the buses have been changed from the base topology. Because different configurations are possible between buses on the same substation, some substations appear more than once, e.g., substation 48. In general, there are a few interesting things to note. First, we observe that in most cases the TT is only one or two changed substations away from the base topology. This supports our understanding that too much deviation from the base topology leads to more imbalance. Second, we have a few exceptions, with the Top2 TT affecting four substations, and the Top25 and Top42 TTs affecting three substations. In these cases, their stabilizing effect seems to outweigh the deviation from the base topology. A third point to note is that there are some substations that change quite frequently. These are substation 48 with 13 entries in the Top50, followed by substations 58 and 10 with 11 entries, 68 with 8 entries, and 95 with 5 entries. Looking at Figure 2, we can see that these substations are important hubs in the grid, especially substation 48.

**Computation Time:** Lastly, we want to look at the computation time of the agents. Since we have to iterate through 500 TTs, we expect a higher computation with the greedy component of  $TopoAgent_{85-95\%}$ . In Figure 6a we can see the execution time of the four agents on one exemplary seed run. As expected, the DoNothing is the fastest agent, followed by the  $Senior_{95\%}$ . However, in direct comparison, there is only a small increase in execution time for the  $TopoAgent_{85-95\%}$ . More interestingly, we can see that the  $Senior_{85\%}$  takes even longer, which could be explained by the more frequent activation due to the lower  $\rho_{senior} = 0.85$ . In addition to the individual results, we can also see that the winter months seem to require longer execution times for both the  $Senior_{85\%}$  and the  $TopoAgent_{85-95\%}$ . Looking at the Figure 3, we can see that these months are more critical, which explains the longer computation. The exemplary result of the one seed is also supported by the box plot of Figure 6b. Here we can see that the computation over the seeds is quite large for the  $Senior_{85\%}$ . Note that while the  $TopoAgent_{85-95\%}$  generally takes a bit more time, its overall variation in computation time and its maximum value is less than that of the  $Senior_{95\%}$ .

## 6 Discussion

After analyzing the experiment results, we were able to show a superior performance of the  $TopoAgent_{85-95\%}$  agent against the previous  $Senior_{95\%}$  and  $Senior_{85\%}$ . This is even more remarkable considering that the  $Senior_{95\%}$  with



**Figure 5:** Display of the most frequently used TTs on the validation data by the  $TopoAgent_{85-95\%}$ . We rank the topologies based on their occurrence and visualize the effected substations changes. Consequently, the y-axis shows the switched substation in comparison to the base topology. The x-axis shows the ranked Top50 TT. The coloring was done to better distinguish the TTs and has no deeper meaning.

its DRL agent is already a very strong benchmark for substation actions, line reconnection, and topology reversion. Nevertheless, both the score and the survival time show a better result of the  $TopoAgent_{85-95\%}$  over the seeds. Furthermore, as we could see in Figure 3, we have some scenarios that were solvable in the median survival time by the  $TopoAgent_{85-95\%}$  agent that the previous agents could not solve. This is noteworthy because we did not use a different set of substation actions. Instead, we used the existing 2030 substation actions to identify suitable TTs with the novel search approach. Furthermore, the performance of the  $Senior_{85\%}$  clearly shows that the pure "early" interaction does not correspond to better survival, on the contrary. Therefore, we see the direct topology optimization approach as a possible avenue that should be pursued further.

Furthermore, we suggest further research in the direction of our topology search. Our experiments indicate that measuring the quality of a topology by the duration an agent stays in it may be beneficial in identifying stable candidates. These topologies seem to create new topology strategies that have not yet been considered, as one could see in Figure 4. In addition, Figure 5 shows that these strategies are all relatively close to the base topology. This ensures that our desired topologies are still robust.

With respect to the computation times we expected a higher cost for the greedy iteration. However, it seems based on Figure 6a,6b that these costs were only marginal as a more stable grid needed less interaction from the *Senior* component in the  $TopoAgent_{85-95\%}$  agent. Therefore, the inclusion of TTs can definitely be recommended.

In terms of future work, we already outlined that we save the experience of the topology search. This is of course quite beneficial for future training of  $Junior_{topo}$  and  $Senior_{topo}$  agents as we can use the experience to train the DRL models. Further, multiple researchers propose a more hierarchical approach [22, 23, 24]. This might be interesting when combining them with a topology optimization approach.



(a) Visualization of the execution time (in s) per action of the four

different agents on an exemplary seed run. The left image shows (b) Boxplot of the computation time for each agent. Each dot the execution time across all chonics over the year. The right image represents the overall computation time (in s) for one respective seed across all chronics.

Figure 6: Execution time for one seed and boxplot of overall computation time across all seeds.

## 7 Conclusion

In this article, we propose a novel addition to the field of topology optimization for power grids. The underlying hypothesis is that certain topologies are more robust than others and should be used for optimization. To this end, we introduce the concept of the Target Topologies (TTs) and provide a search algorithm to identify these more robust topologies. We extend our previously developed CAgent to a topology agent  $TopoAgent_{85-95\%}$ , incorporating the TTs with a greedy component. The impact of the proposed topology agent on the WCCI 2022 L2RPN environment was evaluated in a multi-seed evaluation with 500 TTs. We found that the  $TopoAgent_{85-95\%}$  agent outperformed the benchmark by 10% in score and by as much as 25% in median survival time. Further analysis revealed that the  $TopoAgent_{85-95\%}$  is close to the base topology, which explains the robustness of its performance. Finally, we demonstrate that the incorporation of TTs as a greedy iteration only marginally increases the execution time. Therefore, we encourage other researchers to pursue the concept of TTs further, especially in combination with DRL.

## Acknowledgement

This work was supported by the research group Reinforcement Learning for Cognitive Energy Systems (RL4CES) from the Intelligent Embedded Systems of the University Kassel and the project Graph Neural Networks for Grid Control (GNN4GC) founded by the Federal Ministry for Economic Affairs and Climate Action Germany.

## **Disclosure of Interest**

The authors have no competing interests to declare that are relevant to the content of this article.

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