Predictive Maintenance for Increasing EV Charging Load in Distribution Power System

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***Abstract*—The increasing number of electric vehicles (EVs) introduces a high intensity charging load to the power system. The distribution systems are not well prepared to cope with this high variance load. To handle such EV charging load, utility companies need a predictive maintenance approach for the distribution transformers. We propose a deep reinforcement learning (RL) based policy to timely replace the distribution transformers by similar or higher capacity ones under a budgetary constraint of selecting at most one transformer for replacement per time step. Our policy outperforms the myopic policies which replace transformers based on load, age, and failure in terms of both economic cost and power outage.**

I. Introduction

Electric vehicles (EVs) use the energy stored in a battery instead of burning fuel. Thus, it needs to be plugged into an electric outlet rather than refueling at a gas station. Advancements in battery and EV technology is rapidly accelerating the electrification of transportation. Automobile manufacturers are introducing new popular EV models, which indicates that EVs will become mainstream in the near future. In fact, the number of EVs on the road by the end of 2020 is expected to be 10 million, up from just a million in 2015 [1]. Bloomberg New Energy Finance (BNEF) predicts the annual passenger EV sales to reach 10 million in 2025, 28 million in 2030, and 56 million by 2040 in its 2019 report [2].

The automobile industry is excelling towards fast and convenient charging of EVs at home [3]. Because of the convenience and low cost, most EV drivers do more than 80% of their charging at home [4]. This recent trend requires the electricity distribution system to be capable of handling high demand peak loads. It is known that EV charging consumes more electricity than any other load in a household. Thus, the capacity of the user end distribution transformers, the major equipment of the distribution network, to accommodate EV charging needs to be assessed. While distribution system maintenance and upgrade is a critical task for the electricity utility companies, EV inclusion makes it more important and challenging. Hence, predictive maintenance for the distribution transformers has become an essential topic for the utility companies nowadays.

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A. Related Work

Majority of the EV charging research focuses on the smart charging method, which aims to optimize the start time and the charging rate for each time interval [5], [6]. The article [7] provides detailed predictions for EV load, which quantifies consumer energy usage and driving patterns. Several works propose a demand-side management approach for mitigating the impact of EV charging on distribution transformers, e.g., [8]. [9] presents an assessment of the transformer residual life. In [10], a method is provided for ranking a number of transformers for replacement based on age and load. However, none of the existing works uses the predicted future EV load in selecting the transformers for replacement. Agent-based modeling has been used for simulating complex systems including home energy management [11], transportation systems [12], and climate change [13]. In this work, it lets us simulate the future impact of EV penetration to the distribution power system.

B. Contributions

We consider the existing load and future EV charging load for estimating aging and failure probabilities for the transformers. In particular, we provide daily aging and failure probability calculations for small 25 kVA distribution transformers. Our contributions can be summarized as follows:

- A realistic simulation tool is developed for transformer aging, failure and fuse blow events considering increasing EV load, as well as regular household loads;
- A Markov Decision Process (MDP) formulation is presented to optimize the transformer replacement policy;
- A deep reinforcement learning (RL) algorithm based on the MDP formulation is provided to learn an effective and practical predictive maintenance policy for transformer replacement considering realistic physical (e.g., budgetary, human resources) constraints;
- The performance of the deep RL policy is evaluated by comparing with straightforward myopic policies.

The remainder of the paper is organized as follows. Section II gives background information about the impact of EV charging on distribution transformers. Section III formulates the MDP problem. Then, a deep RL algorithm based on the MDP formulation is provided in Section IV. Simulation results for a distribution transformer network are presented in Section V, and the paper is concluded in Section VI.

II. Background

A. Distribution Transformer Overload by EV Charging

The existing residential distribution grid is not designed for serving emerging EV loads. While a typical home in the US consumes 1.2 kW power on average, an EV adds another 6.6-17 kW load to the transformer, effectively more than doubling the peak residential demand [8]. Consequently, distribution grid transformers that were installed before EV penetration might become overloaded and fail to support additional EV load. Our research focuses on the impact of EV on distribution end transformers that provides electricity directly to the customers. These transformers are smaller in size and rating, and thus less tolerant to loading variation due to EVs. We do not consider the growth of regular loads in this research because it is usually the result of new property developments or new businesses, which require the installation of separate distribution transformers [14].

B. Transformer Aging and Failure

Transformer aging is the result of high temperature, moisture content, and other impurities in the insulation. Transformer insulation oil is maintained to minimize contamination, leaving the insulation temperature as the main reason for aging. Thus, the highest (hottest-spot) temperature (HST) of the transformer is a sufficient parameter for aging estimation [15]. The ambient temperature and electrical load are two major factors responsible for the HST of a transformer [16]. With the inclusion of high-intensity EV load, distribution transformers are now more susceptible to expedited aging and subsequent failure.

1) Hottest Spot Temperature Model: If a transformer operating at full load capacity has Θ_f rise over the ambient temperature, then the top oil temperature rise will be

$$\Theta_o = \Theta_f \left(\frac{L^2 R + 1}{R + 1} \right)^n,$$

where $L = \frac{\text{actual load}}{\text{capacity}}$, $R = \frac{\text{full load loss}}{\text{no load loss}}$, and $n = 0.8$ for ONAN transformer, which is the most common type of distribution transformer. The transient temperature rise of the top oil above ambient after N hours is:

$$\Theta_o(N) = \Theta_o(1 - e^{-N/\tau}) + \Theta_i e^{-N/\tau},$$

where τ is the oil thermal time constant for rated load, and Θ_i is the initial top oil temperature rise over ambient. Only the first value of Θ_i needs estimation as the calculated top oil temperature rise can be used as Θ_i for the next time step. The HST rise over top oil temperature rise is

$$\Theta_g(N) = \Theta_{gf} L^{2q}$$

where Θ_{gf} is HST rise over top oil temperature for full load and $q = 0.8$ for ONAN transformer. Finally, with ambient temperature $\Theta_a(N)$, the HST of a transformer is

$$\Theta_H(N) = \Theta_a(N) + \Theta_o(N) + \Theta_g(N)$$

2) Aging due to HST : Experimental evidence shows that the cumulative effect of HST over time in transformer aging complies with the Arrhenius reaction rate theory [17]. Fig. 1 shows the relation between per unit transformer insulation life and winding HST, and demonstrates that HST is the key variable for aging. This curve applies to both power and distribution transformers as they typically have similar insulation materials. It sets 110 °C as a reference temperature above which aging is expedited. Per unit life is defined as:

$$\text{Per unit life} = 9.8 \times 10^{-18} e^{\frac{15000}{\Theta_H + 273}}$$

where Θ_H in °C is the winding HST.

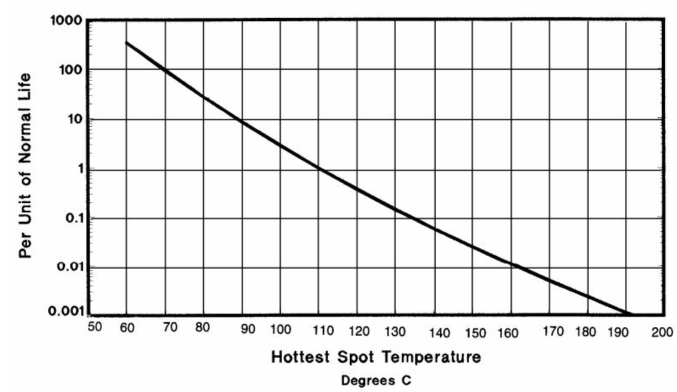

Fig. 1. Per unit transformer insulation life [15]

Fig. 1 is instrumental in calculating the aging acceleration factor, F that has a value more than 1 for $\Theta_H > 110°C$ and less than 1 when $\Theta_H < 110°C$. The equation for the aging acceleration factor is as follows:

$$F = e^{\left(\frac{15000}{383} - \frac{15000}{\Theta_H + 273} \right)}.$$

The days of life lost on a day can be determined by adding the equivalent aging for each hour of the day. Hence, the age of the transformer at the end of ith day is

$$A_i = A_{i-1} + \sum_{j=1}^{24} F_j, \tag{1}$$

where A_{i-1} is the effective age of the transformer at the beginning of the day. F_j is the aging acceleration factor for the transformer at jth hour of the day.

III. Problem Formulation

We propose an MDP framework for the utility company to make a maintenance schedule for a fleet of M distribution transformers. The mth transformer of the fleet with current age A_t^m and load L_t^m, accumulates additional age ΔA_t^m through serving load for time step t. Meanwhile, ΔL_t^m load is added to the transformer through the introduction of new EVs in the households it serves. We define the system state as a collection of age and load of all the transformers, as shown in Fig. 2, which satisfies the Markov property,

$$S_{t+1} = (A_t^1 + \Delta A_t^1, L_t^1 + \Delta L_t^1, \ldots, A_t^N + \Delta A_t^N, L_t^N + \Delta L_t^N).$$

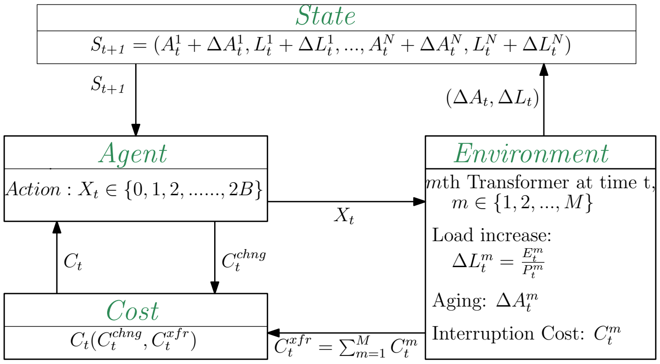

Fig. 2. Proposed MDP Model.

Utility Company is the MDP agent, whose action X_t to change an old transformer by the same capacity one (replace) or a double-sized one (upgrade) changes the system state. Each transformer m causes the breakdown cost C_t^m to the utility if it fails through the combination of replacement cost, corresponding outage, and customer dissatisfaction. The MDP agent's goal is to select the most cost-enduring transformer for replacement or upgrade. It has a constraint of changing at most one transformer at a time step. The upgradation cost, $C_t^{chng} = C_t^{upg}$, is higher than the replacement cost, $C_t^{chng} = C_t^{rep}$. The goal of the MDP agent is to minimize the following discounted cumulative cost in T time steps:

$$C_T = \sum_{t=0}^{T} a_g^t [C_t^{chng} + \sum_{m=1}^{M} C_t^m], \tag{2}$$

where a_g is the discount factor for future decisions.

A. State, S_t

The load and age of every transformer forms the state space. So, for the M transformers in the network, the input state space has $2M$ variables. The existing electrical load for the mth transformer at time t is D_t^m, and the transformer's capacity P_t^m indicates the rated power or kVA capacity. Loading L_t^m is the ratio of kVA load and rated capacity. The additional load due to EV inclusion is ΔL_t^m. The effective age of the transformer is calculated using Eq. (1). ΔA_t^m is the aging accumulated by the transformer on tth time step. Fig. 2 shows the state of mth transformer at time step t. M such tuples of $(A_t^m + \Delta A_t^m, L_t^m + \Delta L_t^m)$ constitutes the input state space.

B. Action, X_t

The under loaded and young transformers make bad candidates for the change. Thus selecting a pool of overloaded and over aged transformers is meaningful in the context of replacing or upgrading. Furthermore, if the load increment due to EV inclusion makes the load higher than the transformer's capacity, then it is more reasonable to upgrade it. Thus, creating a pool of B number of candidate transformers for replacement or upgrade makes the action space smaller than the input state without making a significant compromise. In the case of no overloaded or over aged transformer in the fleet, the best action might be to do no replacement or upgrade. Thus, the action space $X_t \in \{0, 1, 2, \ldots, 2B\}$, contains $2B+1$ actions: replacing or upgrading any of the B transformers or doing nothing.

C. Cost, C_t

The transformer being loaded will face aging and will be more susceptible to failure. Transformer failure is the most costly event for the utility, and hence modeling it requires the most attention. We use Weibull hazard function to generate aging-related failure events. Weibull distribution has wide acceptability for predicting electrical breakdown in solid insulation [18]. The probability of transformer failure during the ith day is

$$\begin{aligned}
\mathsf{P}(i) &= \frac{\mathsf{P}(i \geq A_i) - \mathsf{P}(i \geq A_i + 1)}{\mathsf{P}(i \geq A_i)} \\
&= \frac{(1 - F(A_i)) - (1 - F(A_i + 1))}{1 - F(A_i)} \\
&= \frac{e^{-(\frac{A_i}{\alpha})^\beta} - e^{-(\frac{A_i+1}{\alpha})^\beta}}{e^{-(\frac{A_i}{\alpha})^\beta}} \\
&= 1 - e^{[(\frac{A_i}{\alpha})^\beta - (\frac{A_i+1}{\alpha})^\beta]}
\end{aligned}$$

Here, scale parameter, α=10690 days (29.29 years) and the shape parameter, β= 5.01 of Weibull distribution are obtained from the [9] for the new group of transformer therein. Transformer effective age on ith day A_i is taken from Eq. (1).

Overloading a transformer will expedite its aging and subsequently cause failure. Failure of the transformer means emergency service work, replacement of the transformer, and unexpected outages, all of which cause the utility company's cost. Apart from failure, we introduce another cost due to fuse replacement. If the load on the transformer is more than 1.8 times its rated load, then a protective fuse blows to save the transformer [19]. Fuse replacement requires less service work, outage, and subsequently less cost compared to a failure event. The monetary value C_t^m of these events vary for different utility companies, but will be significantly higher than the scheduled change cost of the transformer C_t^{chng}. Although the failure and fuse blow events are generated daily, the agent is not bound to take action every day. Instead, it is more pragmatic for the utility to have a weekly or biweekly policy depending on the network's size. In that case, the breakdown cost C_t^m of the transformer will incorporate all the observed daily costs for the duration of the utility's decision time step.

D. Next State, S_{t+1}

Each transformer's age for the next state is the sum of its current age and estimated age to be accumulated at the next time step. Furthermore, the agent's decision to change the mth transformer changes its age to zero. If the transformer is replaced, then the capacity of the transformer will remain the same, $P_{t+1}^m = P_t^m$. However, if the transformer is upgraded, its capacity will be twice, $P_{t+1}^m = 2P_t^m$.

IV. Solution Approach

A. Reinforcement Learning

The solution lies in minimizing the expected cost $\mathsf{E}[C_T]$, where C_T is given in Eq. (2), by selecting the appropriate action X_t. Central to this problem is the following Bellman equation, after ith iteration at time t, the agent's value function is

$$V^i(S_t) = \min\Bigg\{ \underbrace{\mathsf{E}\left[\sum_{m=1}^{M} C_t^m + a_g V^{i-1}(S_{t+1})\right]}_{\text{No replacement or upgrade, } X_t=0}, \underbrace{\mathsf{E}\left[C_t^{rep} + \sum_{m=1}^{M} C_t^m + a_g V^{i-1}(S_{t+1})\right]}_{\text{Replacing } m\text{th transformer, } X_t=m}, \underbrace{\mathsf{E}\left[C_t^{upg} + \sum_{m=1}^{M} C_t^m + a_g V^{i-1}(S_{t+1})\right]}_{\text{Upgrading } m\text{th transformer, } X_t=2m} \Bigg\}.$$

Since closed form solution is not tractable, the RL algorithm looks for the best action through simulations by assessing the expected cost $\mathsf{E}[C_t]$ for each of the $2B+1$ possible actions. C_t^m is the immediate cost caused by the mth transformer by serving load during time t. Since the agent's action changes the next state of the transformer, the future discounted cost through the value function of next state, $V^{i-1}(S_{t+1})$ depends on the action of the agent.

RL provides a very suitable framework to iteratively obtain the value function. The action-value function for our problem is:

$$Q(S_t, X_t) = \mathsf{E}[C_t + a_g \min_{X_t} Q(A_t + \Delta A_t, L_t + \Delta L_t) \mid X_t]$$

where $A_t(A_t^1, \dots, A_t^M)$ is a function of the current age of all the transformers in the fleet. Similarly, $C_t, \Delta A_t, L_t, \Delta L_t$ are respectively functions of cost, accumulated age, current load, and load increase of all the transformers.

B. Deep RL

The age and load are continuous, and create an infinite number of possible states. Thus, we require a neural network-based deep RL algorithm. The Advantage Actor-Critic (A2C) algorithm, which is a policy gradient-based algorithm [20], is suitable for continuous state space. A2C employs two neural networks, actor network and critic network. The actor network, also known as the policy network, outputs probability for each action value through a softmax function. It aims to find the gradient of expected return $J(\pi_\theta)$ of the policy π_θ with respect to the weights θ of the neural network by the following equation:

$$\nabla_\theta J(\pi_\theta) = \mathsf{E}_{a\sim\pi_\theta}[\nabla_\theta \log(\pi_\theta(X_t|S_t)) A(S_t; X_t)] \quad (3)$$

where the advantage function is given by

$$A(S_t; X_t) = a_g V^{\pi_\theta(S_{t+1};\psi)} - V^{\pi_\theta(S_t;\psi)}. \quad (4)$$

Here, $V^{\pi_\theta(S_t;\psi)}$ is the output of critic network for weight matrix ψ. It is also known as the value network to learn the value function for each state-action pair. A pseudocode for the A2C algorithm is given in Algorithm 1.

Algorithm 1 A2C algorithm for distribution transformer replacement schedule

Input: discount factor a_g, learning rate l_r, EV inclusion rate p, and number of episodes e
Initialize Actor network with random weights θ and critic network with random weights ψ
for episode $= 1, 2, ..., e$ **do**
  Initialize transformer state $S_0 = (A_0, L_0)$
  for t $= 1, 2, ..., 50$ **do**
    for d $= 1, 2, ..., 365$ **do**
      Generate EV inclusion from a binomial distribution with probability p
      Add EV charging load to L_t
      Calculate aging of each transformer due to loading from Eq. (1).
      Calculate cumulative operation cost of all transformer as explained in Section III-B.
    end for
    Select action X_t from Eq. (3).
    Execute action X_t and observe cost C_t
    Store transitions (S_t, X_t, C_t, S_{t+1}).
    Update actor network θ via Eq. (4).
    Update critic network ψ through back propagation.
  end for
end for

V. Simulation Results

A. Simulation setup

We utilize the 200 households load profile and predicted EV recharging profile data from [7], which includes households, variable in size, and number of occupants. In the distribution network, there will be three different neighborhoods with different degrees of EV penetration rate. We think of EV penetration as the replacement of current conventional passenger vehicles by EVs. For example, 50% EV penetration means replacing 174 petrol cars by EVs in our proposed neighborhood of 200 households with 348 vehicles. These replacements will come one at a time, and we use binomial distribution for a single EV inclusion in each neighborhood for each day. That means we are looking for one success (1 EV inclusion) in 1 trial (per day) in each of the three neighborhoods with the rate of 100% EV penetration respectively in 25, 50, and 100 years for low, medium, and high EV penetration neighborhood.

Each neighborhood consists of 25 transformers, and each of the transformers serve eight homes. The maximum demand is well below the 25 kVA rating without the EV loads. AC level 2 charging is nowadays very popular [21] and is used as the EV charger in our model. Assumptions for the transformer's characteristics are summarized in Table I.

Although failure and fuse blow events are generated daily, the agent takes action once in a year. All the costs assumed for the simulation are in USD, based on market research for the US. Scheduled replacement by a 25 kVA transformer causes 1000$, and upgradation to a 50 kVA costs 2000$. Transformer failure causes 24 hours of outage and replacement cost, 2000$ for 25 kVA or 3000$ for 50 kVA. Failure related replacement

Rated Capacity	25 kVA
Voltage Level	480/208 V
Phase	1
Cooling	ONAN
Ratio of losses, R	3.2
Full load top-oil rise, Θ_f	50 °C
Time constant, τ	3.5 h
HST rise over top oil, Θ_{gf}	30 °C

Table I: Transformer characteristics.

Policy	Cumulative cost	Reduction	Outage	Reduction
Failure based	159408 $	0 %	20862 kWh	0 %
Myopic (Load priority)	99889 $	37.3 %	10767 kWh	48.4 %
Myopic (Age priority)	112719 $	29.3 %	7844 kWh	62.4 %
Deep RL based	72294 $	54.6 %	6243 kWh	70.1 %

Table II: Cumulative maintenance and outage cost for 75 transformers over a 50-year timeline.

costs are higher as they require emergency service and get no salvage value for the failed transformer. Fuse blow costs 500$ and 6 hours of outage. Failure and fuse blow events cause unexpected outages that cost the utility in terms of unserved electricity and customer dissatisfaction. The cost for outage is taken as 1.3 $/kWh for transformer failure, and 1.5 $/kWh for fuse blows reflecting the value of service assessed in [22]. We will ignore outage costs due to scheduled replacement or upgrade as the customers will be notified beforehand, and work will require a shorter time.

We assume discount factor, $a_g = 0.99$ for the RL network to put emphasis on future cost. Both actor and critic networks have 3 hidden layers with 48, 320, and 48 neurons. Learning rate 3×10^{-4} worked best for the experiments.

B. Results

We compare four policies. Failure based policy only replaces a transformer by the same capacity once it fails. This policy does not do upgrades, thus fails to cope with the EV inclusion, and results in excessive fuse blow and transformer failure events, as evident in Fig. 3. Consequently, cumulative outage and cost are the most for this policy.

The myopic policies upgrade or replace the transformer yearly, based on some predetermined thresholds on load (e.g., 170%) and age (e.g., 7000 days). The myopic policy that prioritizes load over age performs well to reduce the number of fuse blows, but the number of transformer failure is high. The other myopic policy that prioritizes age over load performs well to reduce the number of transformer failure, however it fails to control fuse blows. For the simulations, we selected the threshold pair that minimized the total cost for a 50-year timeline.

The proposed deep RL based policy also takes action yearly based on the value function. It achieves the least cost and power outage compared to the failure based policy and myopic policies. Results shown in Fig. 3 and Table II indicate that the deep RL algorithm finds the best balance between age and load for making transformer replacement and upgrade decisions by considering the future expected EV penetration. In Table II, we take the cost and outage of failure based policy as a unit to compare the benefit of maintenance policies. Deep RL based policy reduces 54.6% cost with respect to the failure based policy, compared to the 37.3% and 29.3% cost reduction by the load priority and age priority myopic policies, respectively. Deep RL based policy performs even better in reducing outage by avoiding 70.1% of the outage caused by the failure based policy. The age priority myopic policy reduces outage by 62.4%, whereas the load priority one reduces by about 48.4%. While both myopic policies are effective in reducing the cost and power outage with respect to the straightforward failure based policy, the proposed deep RL based policy clearly achieves the best performance.

VI. Conclusion

This work aims to guide electrical utility companies for predictive maintenance of the distribution transformers. We have analyzed distribution transformer failure events in light of high EV load inclusion. A reinforcement learning (RL) algorithm was presented to decide on replacing or upgrading a transformer at each time step considering the future EV penetration in addition to the maintenance cost and instantaneous risk of failure. The proposed algorithm was compared with a straightforward policy that replaces failed transformers, and two myopic policies which replace or upgrade a transformer based on current age and load. Experiments exhibit the superior performance of our deep RL algorithm for total cost and power outage reduction. The results indicate that the deep RL algorithm better controls the priority decision between load and age of a transformer by considering the future expected EV penetration. The proposed method is flexible enough to be implemented for various utility companies.

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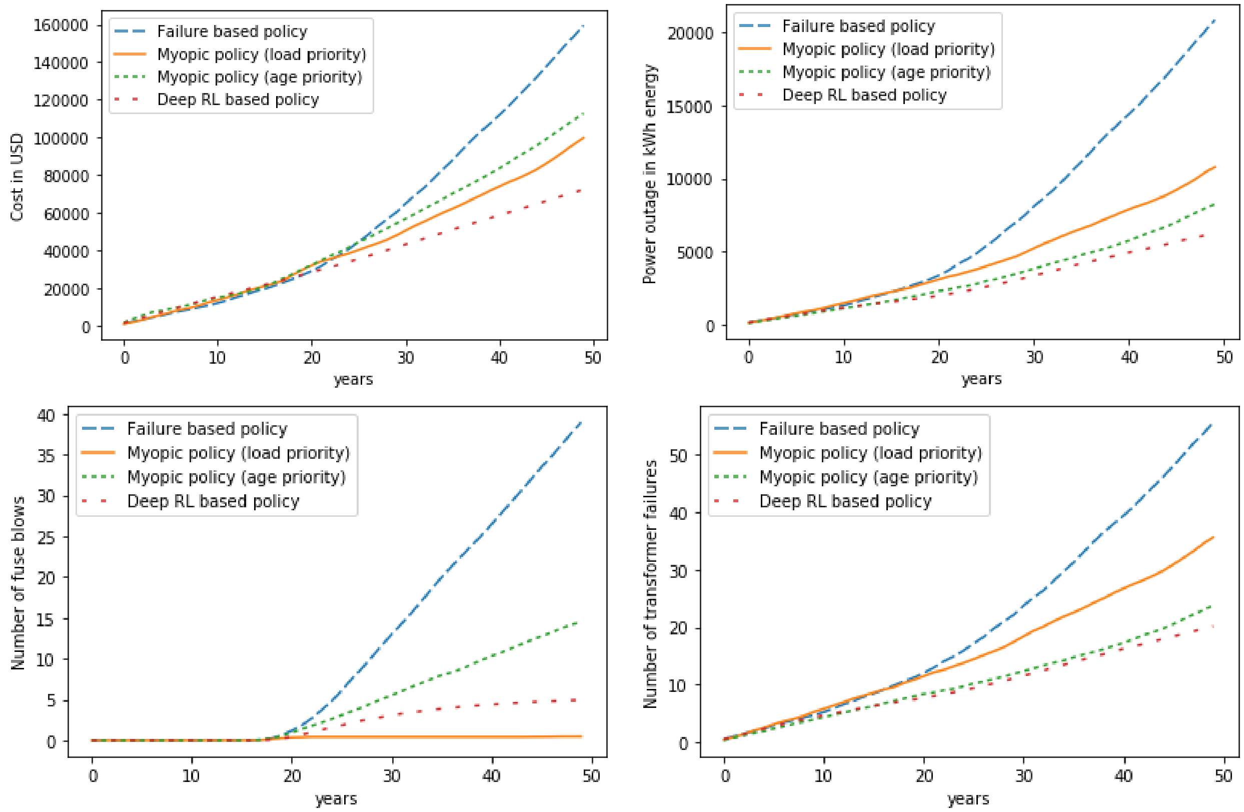

Fig. 3. Comparison between the straightforward failure based policy, two myopic policies, and the proposed deep RL based policy in terms of cumulative cost (top left), power outage (top right), fuse blows (bottom left), and transformer failure (bottom right). 75 transformer distribution system is simulated for a 50-year timeline.

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