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Solving Bernoulli Bandit Problems for Weather-relative Overhead Distribution Line Failures Forecasting

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***Abstract*—In this paper, an evaluation approach for analyzing the impact of weather events on line outage status in the distribution system is explored. By representing weather condition in a tabular form, the possible weather condition scenarios are reduced. Our failure forecasting problem is formulated as an online sequential decision-making problem. Each failure forecaster in the problem attempts to solve multiple independent Bernoulli Bandit problems. There are two learning frameworks based on maximum likelihood and maximum a posteriori used for designing a desired failure forecaster, which can online adjust model parameters using the reported outage data in order to mitigate the impact of unknown inherent uncertainties on model accuracy. A dataset with 10,000 artificial points is used to verify the effectiveness of two proposed algorithms. The results obtained by different action selection strategies are compared.**

***Index Terms*--Bernoulli Bandit, power distribution lines, maximum likelihood, maximum a posteriori, outage status prediction**

I. Introduction

Extreme weather events are threatening the security and reliability of power distribution systems with tremendous economic losses. An report from Department of Energy [1] points out that between 2003 and 2012, roughly 679 weather-relative power outages occurred in the U.S., each of which affected at least 50,000 customers and caused billion-scale outage cost. Meanwhile, with the randomness of weather-relative failure events, it is difficult to prevent completely. Therefore, a good method to estimate the power outages is imperative for helping utilities better understand the impact of weather on outages and facilitate the response to severe weather events.

In order to estimate the number of outages, the failure rate model (FRM) has been widely studied for damage assessment of power equipment, which statistically constructs an relationship between outage occurrence and weather conditions. A special class of nonlinear models, called generalized linear models (GLMs) is a technique to fit so-called fragility curve [2]–[5]. These models tend to assume that the outage times follow a Poisson distribution, whose parameter is dependent on weather conditions. Granular weather data was explored in GLMs including lightning stroke current [4], sky cover [5] and etc.

Instead of modeling outage times, some researchers shifted their attention to outage status, assuming that each distribution line has individual failure model. In [6], a Logistic regression based prediction method is proposed to determine the potential outage of power grid components in response to an imminent hurricane. In [7], the support vector machine (SVM) algorithm is utilized to build a binary classification model for predicting the outage levels based on the weather condition. Since most of the days the outage status is labeled as "in service", there exists a serious imbalance in the outage data. In [8], an oversampling method is introduced to manage the severe imbalance between the two outage levels.

The methods [2]–[8] can be online implemented according its past knowledge. However, in reality, the past knowledge is probably not a sufficient evidence to support the current decision. Firstly, most of weather conditions are rare especially for the extreme weather events, which lacks enough outage data. Secondly, the distribution of outage data is not always homogeneous. The inherent uncertainties of weather forecasting and individual difference (e.g., vegetation environment, aging, and etc.) could change the belief in historical outage data. Therefore, it is necessary to design an online failure forecasting algorithm which can utilize the real-time reported outage data to improve the model.

This paper is mainly focused on online outage status prediction for overhead distribution lines which are the most vulnerable components in distribution systems [9]. The wind gust speed and lightning stroke current [10] were used as inputs for our model. First, a tabular weather representation method is proposed to reduce possible weather condition scenarios. Then, the online failure forecasting problem is reformulated as multiple independent Bernoulli bandit problems. Finally, two learning frameworks based on maximum likelihood and maximum a posteriori are used to design failure forecaster in the problems. Unlike existing failure forecasting techniques, the proposed methods can online learn model as reported outage data arrives with low computational complexity.

II. Problem Formulation

In this work, the distribution line failures forecasting problem is defined as an online sequential decision-making problem as shown in Fig. 1. That is, for each round $t \in [T]$, the

Shengyi Wang conducted this research during his internship at MERL.

failure forecaster(to be designed) of each line first observes a forecasted weather condition $x_t \in \mathbb{R}^{+n}$, then makes a forecast about the outage status $\hat{y}_t \in \{0,1\}$, and finally receives the reported outage status $y_t \in \{0,1\}$. When $y_t(\hat{y}_t) = 1$, the line is on outage, otherwise the line is in service. The above defined problem induces multiple triplet tuples $(x_t, \hat{y}_t, y_t)$ for entire time horizon, which constitutes a trajectory $x_1, \hat{y}_1, y_1, x_2, \hat{y}_2, y_2, \ldots, x_{T-1}, \hat{y}_{T-1}, y_{T-1}, x_T, \hat{y}_T, y_T$.

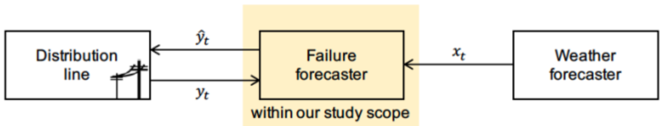


Fig. 1. Illustration of the online distribution line failures forecasting problem

III. Methodology

In this section, a tabular weather representation method is first proposed to reduce possible weather condition scenarios. Then the original problem is converted into multiple independent Bernoulli bandit problems. Finally, two learning frameworks are used to design the failure forecaster in the problem.

A. Tabular Weather Representation Method

In this paper, wind gust speed x_t^w and lightning stroke current x_t^l are used to represent the weather condition, i.e. $x_t = (x_t^w, x_t^l)$, which are effective to model line failures[11]. In order to reduce scenarios of the weather condition x_t, a tabular weather representation method is proposed, as shown in Fig. 2. According to historical data in the weather station, it is easy to obtain the information such as the minimum/maximum wind gust speed $\underline{x}^w / \overline{x}^w$ and the minimum/maximum lightning current $\underline{x}^l / \overline{x}^l$. Then a table with n_w rows and n_l columns is constructed. For cell ij (the i-th row and the j-th column, $1 \le i \le n_w$, $1 \le j \le n_l$), it is denoted by a set $x^{ij} = [\underline{x}^w + \frac{\overline{x}^w - \underline{x}^w}{n_w}(i-1), \underline{x}^w + \frac{\overline{x}^w - \underline{x}^w}{n_w} i) \times [\underline{x}^l + \frac{\overline{x}^l - \underline{x}^l}{n_l}(j-1), \underline{x}^l + \frac{\overline{x}^l - \underline{x}^l}{n_l} j)$. If the weather condition $x_t \in x^{ij}$, x_t can be represented by x^{ij}. When n_w and n_l are large enough, this representation is accurate enough because with certain range the difference of the weather condition is minimal.

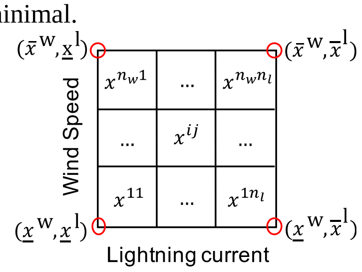


Fig. 2. Illustration of the tabular weather representation method

B. Problem Reformulation

A weather representor equipped with tabular weather representation method is integrated into the problem and substitute the feedback signal y_t with a binary reward $r_t \in \{0,1\}$ which is assumed to be Bernoulli distributed, as shown in Fig. 3. Then the problem can be converted into multiple independent Bernoulli bandit problems. Specifically speaking, for each round $t \in [T]$, the weather representor of each line first represents x_t as x^{ij}, then the agent defined as the failure forecaster (to be designed) observes a state x^{ij} and chooses a two-valued action $\hat{y}_t$, and finally receives the reward r_t based the action he chooses. Note that the action is chosen irrespective of the state, i.e., each state solves an independent Bernoulli bandit problem. The reward r_t is designed as $1 - |\hat{y}_t - y_t|$, which reflects prediction correctness, i.e., $r_t = +1$ with the correct prediction and $r_t = 0$ with the wrong prediction. Next two learning framework is used to design the failure forecaster in the problem.

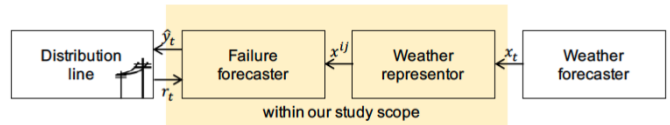


Fig. 3. Illustration of the converted online distribution line failures forecasting Problem

C. Failure Forecaster

In the context of Bernoulli bandit problem, it is assumed that r_t follows a Bernoulli distribution, i.e., $r_t \sim Ber(\mu_{\hat{y}_t}^{ij})$ where $\mu_{\hat{y}_t}^{ij} = P_r\left(r_t = 1 | \mu_{\hat{y}_t}^{ij}\right) = P_r(r_t = 1 | \hat{y}_t, x^{ij})$. For the agent to decide which action is best, we must define the value of selecting each action. These values are called the action values or the action value function. The value of selecting an action is defined as the expected reward the agent receives when selecting that action, $q_*^{ij}(y) := E[r_t | \hat{y}_t = y, x^{ij}] = \mu_y^{ij}, \forall y \in \{0,1\}$ where y is the value of $\hat{y}_t$. Given x^{ij},the goal of the agent is to maximize the expected reward $\hat{y}_t^* = \arg\max_y q_*^{ij}(y) = \arg\max_y \mu_y^{ij}$. Unfortunately, μ_y^{ij} isn't known to the agent. Instead, a way is needed to estimate it.

1). Using Maximum Likelihood (ML) Estimation: Let $r^{ij} = \{r_t | x_t \in x^{ij}\}$ denote the set of rewards the agent has in state x^{ij}. The ML estimator of μ_y^{ij} is given by maximizing the log-likelihood of r^{ij} given μ_y^{ij}:

$$\hat{\mu}_y^{ij} = \arg\max_{\mu_y^{ij}} log P_r\left(r^{ij} | \mu_y^{ij}\right) = \frac{\sum_{r \in r^{ij}} r}{|r^{ij}|} \tag{1}$$

where $|r^{ij}|$ is the number of elements in r^{ij}. The ML estimator $\hat{\mu}_y^{ij}$ is a sample average that reflects the accuracy of predicting y in state x^{ij}. Then an ML based online failure forecaster is designed in Algorithm 1.

Algorithm 1 ML-based Online Failure Forecaster

initialize $\hat{\mu}_y^{ij}[0] = 0$ and $r^{ij} = \emptyset$ for $\forall y, \forall i, \forall j$
for $t = 1{:}T$ **do**
  Agent observes a state x_t represented by x^{ij}
  if $\hat{\mu}_0^{ij}[t-1] = \hat{\mu}_1^{ij}[t-1]$ **then**
    Agent uniformly samples an action $\hat{y}_t$
  else
    Agent selects an action $\hat{y}_t = \arg\max_y \hat{\mu}_y^{ij}[t-1]$
  end if
  Agent receives a reward r_t
  Agent updates $r^{ij} \leftarrow r^{ij} \cup \{r_t\}$ and $\hat{\mu}_y^{ij}[t] = \frac{\sum_{r \in r^{ij}} r}{|r^{ij}|}$
end for

In the realm of reinforcement learning, the Algorithm 1 is a greedy action selection method, which exploits current knowledge to maximize immediate reward without spending time exploring apparently inferior actions to see if they might really be better. In order to balance exploration and exploitation, this paper also uses ϵ-greedy method and upper-confidence-bound (UCB) method, whose description are summarized as follows:

- In the ϵ-greedy method, the agent either selects the best action $\arg\max_y \hat{\mu}_y^{ij}[t-1]$ with a probability $1-\epsilon$ or the actions at random with a probability ϵ.
- In the UCB method, the agent selects the action that has the highest estimated action-value function plus the upper-confidence bound exploration term, which considers the inherent uncertainty in the accuracy of his estimate

$$\hat{y}_t = \arg\max_y \hat{\mu}_y^{ij}[t-1] + \mathrm{c}\sqrt{\frac{\ln(t)}{n_y^{ij}[t]}} \quad (2)$$

where $\ln(t)$ is the natural logarithm of t, $n_y^{ij}[t-1]$ is the number of times that action y has been selected prior to time t, and $c > 0$ controls the exploration level.

2). Using Maximum A Posteriori (MAP) Estimation: The μ_y^{ij} is assumed to be modeled as a Beta prior, i.e., $\mu_y^{ij} \sim Beta(\alpha_y^{ij}, \beta_y^{ij})$ where α_y^{ij} and β_y^{ij} are parameters of the prior $p(\mu_y^{ij})$ which we are free to set according to our prior belief about μ_y^{ij}. By varying α_y^{ij} and β_y^{ij}, we can encode a wide range of possible beliefs. The MAP estimator of $\hat{\mu}_y^{ij}$ is given by maximizing the log-posterior of μ_y^{ij} given r^{ij}:

$$\hat{\mu}_y^{ij} = \arg\max_{\mu_y^{ij}} \log p(\mu_y^{ij}|r^{ij}) = \arg\max_{\mu_y^{ij}} log P_r(r^{ij}|\mu_y^{ij}) + \log p(\mu_y^{ij}) = \frac{\sum_{r\in r^{ij}} r + \alpha_y^{ij} - 1}{|r^{ij}| + \beta_y^{ij} - 1 + \alpha_y^{ij} - 1} \quad (3)$$

The distinction between ML and MAP is that the former is to find a μ_y^{ij} under which the r^{ij} is most likely, and the latter is to find the most likely μ_y^{ij} given r^{ij}. As $|r^{ij}| \to \infty$, it is easy to see the effect of the prior goes to zero, and the MAP estimator is close to the ML estimator. Therefore, the MAP estimator could be interpreted as a regulated version of the ML estimator.

The MAP estimator is particularly useful when dealing with rare events. For example, extreme weather events are rare. The ML estimator tells the agent that $P_r(r_t = 1|\hat{y}_t = 1, r^{ij}) = 0$. The MAP estimator would allow the agent to incorporate its prior knowledge that there is some large probability that taking $\hat{y}_t = 1$ will receiving a positive reward even if he just hasn't seen it yet. The prior knowledge here could be fragility curve which demonstrates a fact that the more severe weather condition the line suffers, the more likely it encounters outage, and thus a heuristic method is proposed to set prior parameters:

$$\alpha_y^{ij} = \begin{cases} n_w + n_l - (i+j+2) & y=0 \\ i+j+2 & y=1 \end{cases} \quad (4)$$

$$\beta_y^{ij} = \begin{cases} i+j+2 & y=0 \\ n_w + n_l - (i+j+2) & y=1 \end{cases} \quad (5)$$

where α_y^{ij} and β_y^{ij} can be interpreted as number of times of $r_t = 1$ and $r_t = 0$ when $\hat{y}_t = y$, respectively. Then a MAP based online failure forecaster is designed in Algorithm 2.

Algorithm 2 MAP-based Online Failure Forecaster

1: initialize $\alpha_y^{ij}[0]$ and $\beta_y^{ij}[0]$ (by (4) and by (5)) for $\forall y, \forall i, \forall j$
2: **for** $t = 1{:}T$ **do**
3: Agent observes a state x_t represented by x^{ij}
4: Agent samples $\hat{\mu}_y^{ij}[t] \sim Beta(\alpha_y^{ij}[t-1], \beta_y^{ij}[t-1])$ for $\forall y$
5: **if** $\hat{\mu}_0^{ij}[t] = \hat{\mu}_1^{ij}[t]$ **then**
5: Agent uniformly samples an action $\hat{y}_t$
6: **else**
7: Agent selects an action $\hat{y}_t = \arg\max_y \hat{\mu}_y^{ij}[t]$
8: **end if**
9: Agent receives a reward r_t
10. Agent updates $(\alpha_y^{ij}[t], \beta_y^{ij}[t] \leftarrow (\alpha_y^{ij}[t-1] + r_t,$ $\beta_y^{ij}[t] + 1 - r_t)$
11: **end for**

In the field of reinforcement learning, the Algorithm 2 is a Thompson sampling (TS) action selection method, which utilizes the prior knowledge to explore the action space. As posterior distribution gradually concentrates, the agent will perform less exploration and more exploitation, which strikes an effective balance.

IV. Data Generation

In this paper, we have taken the overhead distribution lines as an example to demonstrate the proposed algorithms. Two of the most influential weather events, wind W and lightning L are selected as the weather-relative outage causes, where wind gust speed X and natural log of lightning stroke current Z are representative weather data, respectively. A two-valued outage status Y is considered: $Y = 0$ (i.e., in service) and $Y = 1$ (i.e., on outage). The relation among W, L, X, Z and Y can be represented by a Bayesian network as shown in Fig. 4, which depicts a data generation process with the following joint distribution:

$$P_r(W, L, X, Z, Y) = P_r(W)P_r(L)P_r(X|W)P_r(Z|L)P_r(Y|X,Z) \quad (6)$$

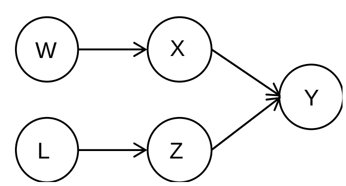


Fig. 4. Illustration of the Bayesian network for data generation

Based on (6), a dataset with n artificial data points can be generated by following the process specified in Fig. 5, where w, l, x, z and y are values of random variables W, L, X, Z and Y, respectively. We define three wind-based weather events $w \in \{1,2,3\}$ in term of wind level, as well as five lightning-based weather events $l \in \{1,2,3,4,5\}$ in term of lightning level. Therefore, a discrete distribution law is used to parameterize $P_r(W)$ and $P_r(L)$. Both wind gust speed $x \geq 0$ and lightning stroke current $l \geq 0$ are assumed to follow a truncated normal distribution. Then, $P_r(X|W) = N(\mu_{X|W}, \sigma_{X|W})$ and $P_r(Z|L) = N(\mu_{Z|L}, \sigma_{Z|L})$, where $\mu_{X|W}, \sigma_{X|W}$ are the mean and standard deviation for $X|W$, and $\mu_{Z|L}, \sigma_{Z|L}$ are the mean and standard deviation for $Z|L$. The outage state $y \in \{0,1\}$ is assumed to follow a Bernoulli distribution with parameter $\mu_{Y|X,Z} = P_r(Y = 1|X, Z)$.

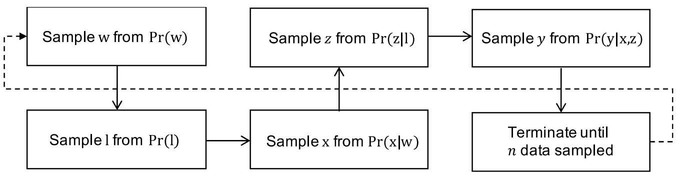


Fig. 5. Illustration of the process to generate dataset of n artificial data points

The parameters of each component in (6) can be customized as statistics of one specific distribution line. Note that the parameter $\mu_{Y|X,Z}$ can be interpreted as the failure probability. Therefore, we directly use a failure rate model [11] induced failure probability to set the parameter $\mu_{Y|X,Z}$:

$$\mu_{Y|X,Z} = 1 - e^{c\times e^{\beta_0+\beta_1 X+\beta_2 Z+\beta_3 XZ}} \quad (7)$$

where $C = -\frac{1}{24}$, $\beta_0 = -3.0832$, $\beta_1 = 0.057$, $\beta_2 = 0.3817$, $\beta_3 = -0.0019$. By changing the value of intersection β_0, the reader can simulate distribution lines with the different robustness to the same weather events. As shown in Fig. 6 and Fig. 7, the failure rate and the failure probability have one to one correspondence of the points, i.e., the higher the failure rate is, the higher the failure probability is. The detailed parameter settings are given in Table I for wind and Table II for lightning. Then a dataset with 10,000 artificial data points is generated to verify the proposed online forecasting algorithm. Their data distribution is shown in Fig. 8. It can be observed that most of points are situated in the area with low wind gust speed and small lightning current while most of outages occurs in the weather event with either high wind gust speed or large lightning current.

TABLE I
PARAMETERS SETTING FOR WIND-RELATIVE DATA GENERATION

	Level 1 [0,35) mph	**Level 2 [35,45) mph**	**Level 3 [45,80] mph**
$p_r(W)$	0.9	0.085	0.015
$\mu_{X\|W}$	17.5	40	62.5
$\sigma_{X\|W}$	2.5	2	1

TABLE II
PARAMETERS SETTING FOR LIGHTNING-RELATIVE DATA GENERATION

	Level 1 0 kA	**Level 2 (0,3.5) kA**	**Level 3 [3.5,6.5) kA**	**Level 4 [6.5,9.5) kA**	**Level 5 [9.5,16] kA**
$p_r(L)$	0.855	0.024	0.063	0.051	0.007
$\mu_{Z\|L}$	0	1.75	5	8	12.75
$\sigma_{Z\|L}$	0.001	0.8	0.5	0.25	0.1

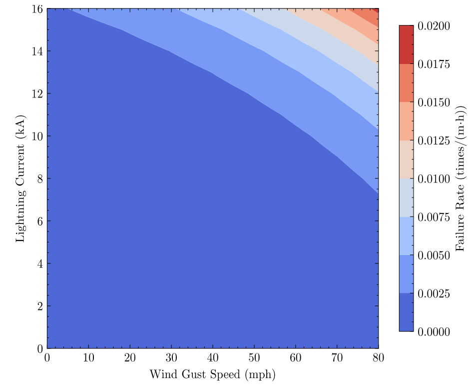


Fig. 6. Illustration of the failure rate model in [11]

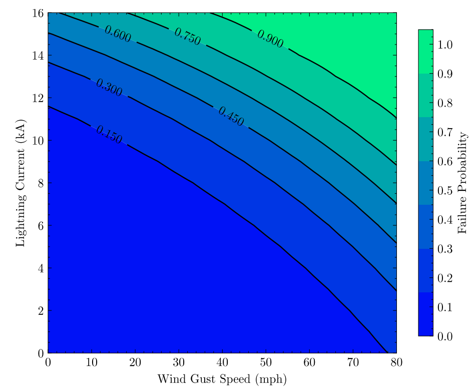


Fig. 7. Illustration of the failure probability given in (7)

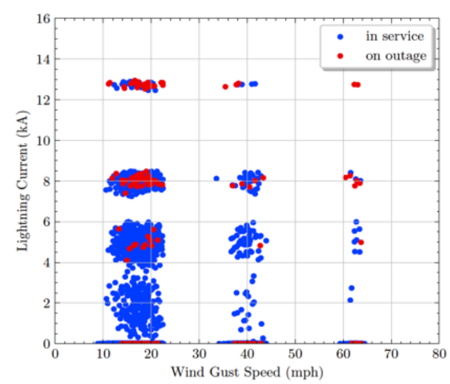


Fig. 8. Illustration of the data distribution of artificial data points

V. SIMULATION RESULTS

To evaluate performance of the proposed algorithms, the following two classification metrics are employed:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{F1} = \frac{2TP^2}{TP^2 + TP(FP + FN)}$$

where TP is the *true positive* indicator, i.e., is the algorithm predicts "on outage" and the actual status is indeed "on outage", TN is the *true negative* indicator, i.e., is the algorithm predicts "in service" and the actual status is indeed "in service", FP is the *false positive* indicator, i.e., is the algorithm predicts "on outage" but the actual status is "in service", and FN is the *false negative* indicator, i.e., is the algorithm predicts "in service" but the actual status is "on outage".

As shown in Fig. 9, five action selection strategies are compared where "mle" is a base method to directly model outage status using maximum likelihood estimation, "greedy", "ϵ-greedy", and "ucb" are action selection strategies based on Algorithm 1, and "ts" is based on Algorithm 2. As the time step goes, each action selection strategy can converge, and "ts" can perform the best with the highest average accuracy and F1-score after a period of learning. The other action selection strategies are not as good as "ts", because their exploration is unguided.

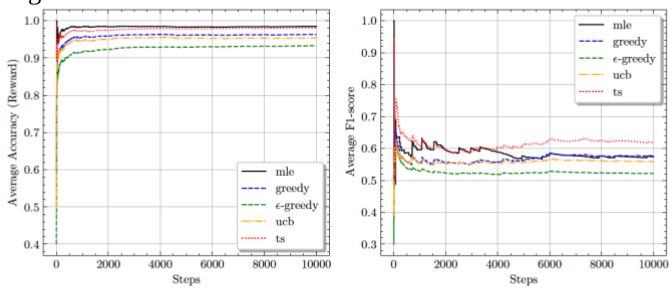


Fig. 9. Illustration of evaluation results using average accuracy and average F1-score

In addition, the parameters in the Bernoulli distribution for "ts" are also visualized in Fig. 10 and Fig. 11. Three representative weather block is selected: high occurrence weather events, medium occurrence weather events, low occurrence weather events. It can be observed that in the some weather blocks as the learning depth for a agent is increasing, the distribution of the parameters will concentrate around some point, which demonstrate the process of the revision of data distribution through the feedback reward signal. This is also a reason why "ts" can perform better by constantly learning to find the most possible optimal parameters.

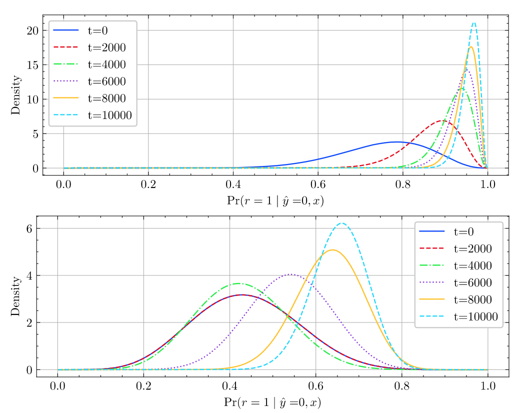
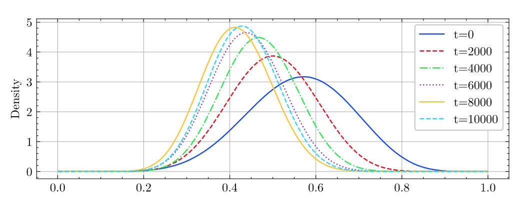


Fig. 10. Illustration of the parameters in Bernoulli distribution (The first figure is from high occurrence weather events and the second figure is from medium occurrence weather events.)



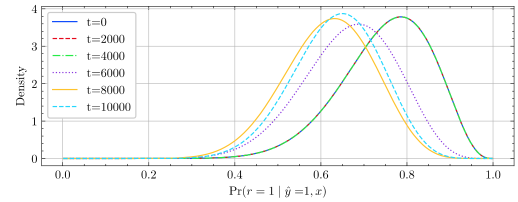


Fig. 11. Illustration of the parameters in Bernoulli distribution (The first figure is from medium occurrence weather events and the second figure is from low occurrence weather events.)

VI. Conclusion

In this paper, two online failure forecasting algorithms are designed to evaluate the impact of the weather conditions on outages in the distribution system. The proposed prediction methods not only can online predict outage status with the light computational complexity, but also online update its knowledge for the next decision-making task utilizing the reported outage data. The results showed that the proposed algorithms are effective for the positive and negative samples, i.e., the binary outage status. The Thompson sampling action selection strategy based on Algorithm 2 is the best compared with other strategies. And its embedded prior knowledge can help the exploration for the better learning performance.

References

[1] W. House, "Economic benefits of increasing electric grid resilience to weather outages," *Washington, DC: Executive Office of the President*, 2013.

[2] R. Z. Fanucchi, M. Bessani, M. H. M. Camillo, J. B. A. London, and C. D. Maciel, "Failure rate prediction under adverse weather conditions in an electric distribution system using negative binomial regression," in *2016 17th International Conference on Harmonics and Quality of Power (ICHQP)*. IEEE, 2016, pp. 478–483.

[3] S. Yang, W. Zhou, S. Zhu, L. Wang, L. Ye, X. Xia, and H. Li, "Failure probability estimation of overhead transmission lines considering the spatial and temporal variation in severe weather," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 1, pp. 131–138, 2019.

[4] M. Panteli and P. Mancarella, "Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events," *IEEE Systems Journal*, vol. 11, no. 3, pp. 1733–1742, 2015.

[5] E. Kabir, S. D. Guikema, and S. M. Quiring, "Predicting thunderstorminduced power outages to support utility restoration," *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4370–4381, 2019.

[6] R. Eskandarpour and A. Khodaei, "Machine learning based power grid outage prediction in response to extreme events," *IEEE Transactions on Power Systems*, vol. 32, no. 4, pp. 3315–3316, 2016.

[7] ——, "Leveraging accuracy-uncertainty tradeoff in svm to achieve highly accurate outage predictions," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 1139–1141, 2017.

[8] Y. Zhang, A. Mazza, E. Bompard, E. Roggero, and G. Galofaro, "Discussion about the weather impact on the daily outages in urban distribution system," in *2019 54th International Universities Power Engineering Conference (UPEC)*. IEEE, 2019, pp. 1–4.

[9] R. E. Brown and J. R. Ochoa, "Distribution system reliability: default data and model validation," *IEEE Transactions on Power Systems*, vol. 13, no. 2, pp. 704–709, 1998.

[10] P. Kankanala, S. Das, and A. Pahwa, "Adaboost+: An ensemble learning approach for estimating weather-related outages in distribution systems," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 359–367, 2014.

[11] Y. Zhou, A. Pahwa, and S.-S. Yang, "Modeling weather-related failures of overhead distribution lines," *IEEE Transactions on power systems*,vol. 21, no. 4, pp. 1683–1690, 2006.