EPFSTO-ARIMA: Electric Power Forced Stochastic Optimization Predicting Based on ARIMA

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Abstract. With the advance of new technology and management reforms, data sharing has unleashed the full potential for social production during the past decade, especially for enterprise survival. Data poisoning attack is a typical attack faced by data sharing, EPSTO-ARIMA (Electric Power Stochastic Optimization Predicting Based on Autoregressive Integrated Moving Average model) would increase prediction error by generating adversarial shared data, which leads to the failure of the prediction. In response to the EPSTO-ARIMA attack, this paper proposes EPFSTO-ARIMA (Electric Power Forced Stochastic Optimization Predicting Based on Autoregressive Integrated Moving Average model) combined with data sanitization and data grouping. The model was validated by seven sets of data from three datasets. Experimental results indicate that EPFSTO-ARIMA can remedy the flaws of excessive accuracy error caused by the EPSTO-ARIMA. For publicly dataset "Column2", the proposed EPFSTO-ARIMA achieves 30.44% lower prediction error than EPSTO-ARIMA, respectively. Simultaneously, the terrific results in other datasets have also been ascertained the viability and generalization ability of our proposed EPFSTO-ARIMA.

Keywords: Stochastic sampling · Stochastic optimization · Adversarial examples · Inference attack · Data poisoning · Electric power forced stochastic optimization predicting

1 Introduction

Data, as the source of all walks of life and an essential element for critical infrastructures, has been extremely successful used in the last decade, especially in

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energy. Among data value extraction, data sharing technology plays a pivotal role in the whole life cycle of data. The maximization of data value has been achieved by data sharing in multi-field applications. As a promising application of data sharing, electricity data prediction, the amount of electricity used by different consumers can be predicted, which can assist the government in optimizing the planning of electricity infrastructure construction. In a nutshell, data prediction can help countries and enterprises put the resource to good use, improve social planning, optimize social management, and defend against cyber-attacks.

With the continuous evolution of LSTM (Long Short-Term Memory) [1], Bi-LSTM (Bi-directional Long Short-Term Memory) [2], ARIMA (Autoregressive Integrated Moving Average model) [3,4], the capability of data prediction has made great progress and gradually become maturity. However, existing studies have shown that data poisoning is widely concerned [5] in machine learning and data poisoning attacks have gradually eroded the power sector [6,7].

EPSTO-ARIMA (Electric Power Stochastic Optimization Predicting Based on Autoregressive Integrated Moving Average model) was proposed to increase error of prediction by using the concept of dropout and stochastic sampling to generate adversarial samples. The prediction error of EPSTO-ARIMA is higher than ARIMA. Motivated by this, this paper proposed a new prediction model, called EPFSTO-ARIMA (Electric Power Forced Stochastic Optimization Predicting Based on Autoregressive Integrated Moving Average model), which can deal with excessive accuracy error caused by EPSTO-ARIMA with data sanitization and data grouping.

Our main contributions in this paper include:

1) Reduce the prediction error caused by EPSTO-ARIMA. Data sanitization and data grouping are used to defend EPSTO-ARIMA attack.
2) Ensure the availability of data. The EPFSTO-ARIMA prediction results are in line with the original law of the data.
3) Explore data discipline. Utilizing EPFSTO-ARIMA, the influence of data inference prediction results is discussed according to data grouping.
4) The results of EPFSTO-ARIMA have an enlightening influence on the defense of poisoning attack and contribute to the defense of time series data poisoning research.

This paper proceeds as follows. The second section reviews adversarial examples, data poisoning attack defense in literature. The third section describes our response method. The fourth section presents the experimental conditions of models and measures indicators of models, describes and discusses the experimental results. The fifth section makes conclusions and describes future work.

2 Related Work

2.1 Data Poisoning and Adversarial Examples

The concept of adversarial example was proposed in [8], namely adding small perturbations to the original training data. Adversarial examples have been extensively studied [9,10]. The process of model training of adversarial examples is

called data poisoning, adversarial examples are difficult to be perceived but become malicious for the trained model to incur erroneous results. To name a few, Papernot et al. [11] found that the adversarial examples generated by one model can cheat another model.

2.2 ARIMA

ARIMA is one of the most important and widely used models in time series data prediction, which has used in energy [3], transportation [4]. Besides these, ARIMA can be used in combination with other models [12]. But the topic of predicting angle of attack defense is rarely considered.

2.3 Dropout

In 2012, Hinton [13] proposed dropout, which can effectively prevent over-fitting in the training of complex feedforward neural network.

By randomly deleting some neurons on the network, dropout reduces the complex co-adaptive relationship between neurons. Through research, Jagielski et al. [5] found that dropping some contaminated data in training samples will increase the error of some models. Drawing on the above ideas, EPSTO-ARIMA was proposed to implement data poisoning.

2.4 Data Poisoning Attack Defense

In general, robustness improvement [14] and data sanitization [15] are used to defend against data poisoning. In this paper, we use data grouping based on data sanitization to counter data poisoning to improve the loss of prediction.

3 Our Approach

By referring to adversarial examples rapid generation method in [16] and the automatic modulation classification based on deep learning in [17], reversing use of the concept of data protection based on disturbance [18], following the intuition discussed in [19] for sub-Nyquist sampling and the working principle of Dropout [13], this paper proposed EPFSTO-ARIMA, which can realize data disturbance as presented in the later sections. The algorithm of EPFSTO-ARIMA is shown in Table 1 and Fig. 1.

We consider data poisoning and prediction scenario as shown in Fig. 1. In Part 1, the input of the original data is illustrated. In Part 2, data were grouped, stochastic sampling and optimized (Dropout) to generate and publish adversarial examples. In Part 3, adversarial examples and original data were used to train predictive models. In Part 4, the test data are used to verify the trained models and get the predicted results.

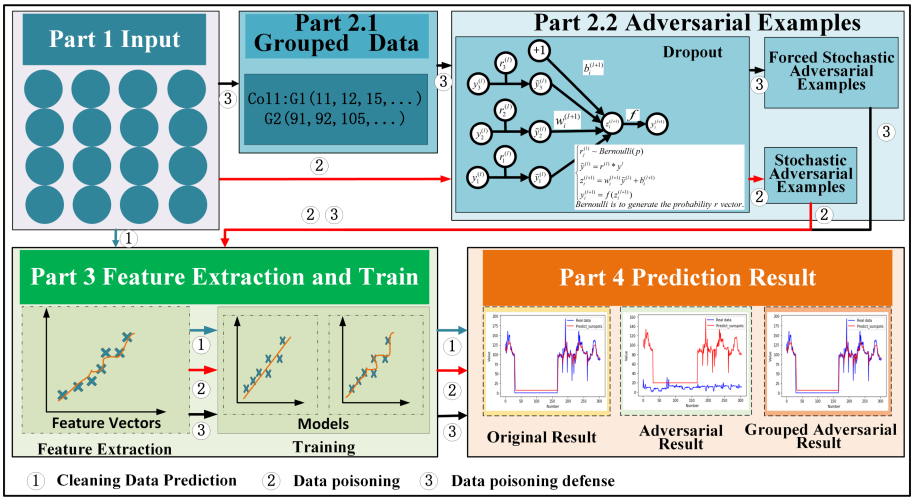

Fig. 1. Generation of adversarial examples vs. prediction.

3.1 Similarity Calculation

We utilize the idea of DTW (Dynamic Time Warping), a commonly used similarity calculation algorithm to calculate the similarity distance between each data and the average. According to similarity, the data is grouped to realize the implementation of the forced stochastic optimization prediction.

Suppose two standard reference templates $R = \{R(1), ...R(m), ...R(M)\}$ and $T = \{T(1), ...T(n), ...T(N)\}$, among them, R is an M-dimensional vector, T is an N-dimensional vector. The distance between R and T is shown as

$$D = \min_{c}\left(\sum_{n=1}^{N}[d(x_{i(n)}, y_{j(n)}) \bullet W_n] / \sum_{n=1}^{N} W_n\right) \tag{1}$$

where W_n is a weighting function, which is affected by the similarity distance of the previous data or the weight of the data. In this paper, we calculate the similarity distance between the average and the data.

From Eq. 1, we can calculate the similarity as

$$S_i = 1/(1 + D_i) \tag{2}$$

where D_i represents the similarity distance between the average value and the data, and it is default value is positive. Otherwise, its absolute value is taken. S_i represents the similarity. The larger the S, the higher the similarity.

3.2 Data Stochastic Sampling and Data Optimization

We utilize the idea of data sampling, Bayesian theory, and optimizing (Dropout) to generate adversarial examples. Sampling data are stochastic selected from the

Table 1. Algorithm of EPFSTO-ARIMA.

Algorithm 1:EPFSTO-ARIMA
Input:
1) Datasets;
2) The preprocessed data;
3) The start time(T_1).
Initialize:
1) i=0;
2) ARIMA model.
Generate adversarial examples:
1) Calculate the DP with Eq. 4;
2) Calculate the similarity with Eq. 1, Eq. 2;
3) Grouped data according Eq. 13;
4) Stochastic sampling with Eq. 3, Eq. 5 and Eq. 13;
5) Data optimize with Eq. 4 and the Dropout algorithm [13].
Verify data and determine parameters:
1) Determine d,p,q;
2) Determine G with Eq. 13.
Import and train models:
1) Import ARIMA(p,d,q);
2) Import EPSTO-ARIMA(p,d,q,DP);
3) Import EPFSTO-ARIMA(p,d,q,G,DP);
4) Train ARIMA(p,d,q) with original data;
5) Train EPSTO-ARIMA(p,d,q,DP) with adversarial examples;
6) Train EPFSTO-ARIMA(p,d,q,G,DP) with adversarial examples.
Predict:
1) Compute y_{DP} use Eq. 6, Eq. 7, Eq. 8, Eq. 9, Eq. 10;
2) Compute RMSE use Eq. 12;
3) Record the end time(T_2) and compute $TIME = T_2 - T_1$.
Output:
1) Output P_{DP} use Eq. 11;
2) Output RMSE;
3) Output TIME.

data sets according to the poisoning ratio. Each data point has the same probability of being selected, and the selected data is the optimized data (poisoned data), which can be expressed as

$$y^k = \{x_{1+ki}\}, 0 \leq i \leq [(n-1)/k] \tag{3}$$

$$DP = n_o/n_t \tag{4}$$

$$P\left(\bigcap_{i=1}^{n} S_i\right) = \prod_{i=1}^{n} P(S_i) \tag{5}$$

where y^k refers to the sampling data, k represents the sampling interval, DP represents the proportion of optimized data to total data, also known as the data poisoning ratio, n_o refers to the poisoned data, n_t refers to the total data, S_i is the $i-th$ data sampling, $P(S_i)$ is the generation probability of S_i and $P\left(\bigcap_{i=1}^{n} S_i\right)$ is the probability that independent events S_i occur simultaneously.

3.3 EPFSTO-ARIMA

The data are grouped according to their similarity, and each group is stochastically optimized in proportion. Suppose we divide the data into two groups of G_1 and G_2. When performing data optimization with the optimized ratio DP, the forced stochastic optimization includes two steps: i) optimizing DP in G_1 or G_2; ii) optimizing DP in the specific group according to actual needs. Compared with the stochastic optimization, the forced stochastic optimization is specific and can optimize data according to actual needs. We use adversarial examples and original data to train the models.

When original data was used, the predicted results can be expressed as

$$y_t = \theta_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \tag{6}$$

When using adversarial examples, the predicted results can be expressed as

$$y_{DP1} = u + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \tag{7}$$

$$y_{DP2} = u + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \tag{8}$$

$$y_{DP3} = u + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q} \tag{9}$$

$$y_{DPn} = u + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \tag{10}$$

where y_{DP} denotes the value of prediction results under DP parameters, u is estimated constant term, θ is an autoregressive coefficient, ϕ is moving average coefficient.

To exclude extreme values from the prediction process, each parameter is calculated n times, a maximum value and a minimum value are removed, respectively. Then the average value is calculated, which conduces to measure the effect of the model. The predicted value equals

$$P_{DP} = (\sum_{m=1}^{n} y_{DPn} - y_{DP\max} - y_{DP\min})/(n-2) \tag{11}$$

where P_{DP} denotes the mean value of prediction results, $\sum_{m=1}^{n} y_{DPn}$ is the sum of all prediction results under DP parameters. Variables $y_{DP\max}$ and $y_{DP\min}$ indicate the maximum value and the minimum value of the prediction results, respectively. Lastly, $n-2$ represents the number of prediction results involved in the final calculation.

4 Experiments and Results

4.1 Experimental Data and Parameter Description

The data sets used in this paper include ElectricityLoadDiagrams20112014 [20], Individual household electric power consumption [21] and the Solar power [22]. The Column2, Column257, Column277 and Column314 are selected from ElectricityLoadDiagrams20112014.

The parameters used in the experiments are shown in Table 2, the experimental environment is shown in Table 3. In EPSTO-ARIMA and EPFSTO-ARIMA experiments, DP values are the same. In addition, G refers to the grouping of data based on similarity calculation. The data is divided into two groups, as shown in Table 4.

Table 2. Experiments parameters.

Model	Column2,257,277,314	Household	Solar
Parameters	(p,d,q) or (p,d,q,DP) or (p,d,G,DP)		
ARIMA	(9,0,8)	(9,0,2)	(9,0,8)
EPSTO -ARIMA	(9,0,8,DP)	(9,0,2,DP)	(9,0,0,DP) (6,0,0,DP)
EPFSTO -ARIMA	(1,0,0,2,DP) (3,0,5,2,DP)	(1,0,3,2,DP) (1,0,2,2,DP)	(2,0,9,2,DP) (2,0,2,2,DP)
DP	0.001,0.002,0.003,0.004,0.005,0.006,0.007,0.008 0.009,0.01,0.02,0.03,0.04,0.05,0.06,0.07,0.08,0.09,0.1		

Table 3. Experimental environment.

Environment	Parameter
Operating system	Windows 10, 64bit
Processor	Intel(R) Core (TM) i7-9700 CPU @ 3.00 GHz
Internal storage	8.00 GB
Pycharm	Professional Edition 11.0.3
Tensorflow	2.3.0

4.2 Adopted Metrics

We measure the prediction effect of EPFSTO-ARIMA in terms of RMSE (Root Mean Squared Error). RMSE defines the deviation between the predicted value and the real value, which can be calculated as

Table 4. Grouping of data.

Item	Column2	Column257	Column277	Column314	Household	Solar
G_1	[0,0.053]	[0,0.0094]	[0,0.0006]	[0,0.00001]	[0,0.002066]	[0,0.1427]
G_2	(0.053,1]	(0.0094,1]	(0.0006,1]	(0.00001,1]	(0.002066,1]	(0.1427,1]

$$RMSE\left(X,P\right)=\sqrt{\left(1/m\right)\sum_{i=1}^{m}\left(p\left(x_i\right)-y_i\right)^2} \tag{12}$$

where $p\left(x_i\right)$ and y_i denote the predicted and the real values, respectively.

4.3 Experiments Results

In this section, ARIMA, EPSTO-ARIMA and EPFSTO-ARIMA experiments are carried out. In the experiments, we first check whether the data are flat and stable. After the ACF (Auto Correlation Function) test, the method of censoring and PACF (Partial Auto Correlation Function) diagram with the method of tailing, the value of d, p and q is determined. The value of G can be determined by

$$\begin{aligned}
&S_{(i,j)}=1/(1+D_{(i,j)})\\
&=1/(1+\min_{c}(\sum_{i=1}^{n}[d(y_i,V)\cdot W_n]/\sum_{i=1}^{n}W_n))\\
&=1/\left(1+d(y_i,V)+\min\left\{\begin{array}{l}D(i-1,j)\\D(i,j-1)\\D(i-1,j-1)\end{array}\right\}\right)\\
&=1/\left(1+d(y_i,(\sum_{i=1}^{n}y_i)/n)+\min\left\{\begin{array}{l}D(i-1,j)\\D(i,j-1)\\D(i-1,j-1)\end{array}\right\}\right)
\end{aligned} \tag{13}$$

where V represents the average of the data, y_i represents the value of the $i-th$ data.

The results presented in this section are optimal solutions under the following two constraints. RMSE and TIME both take the minimum values. The models use the same environment to make prediction. From the Table 5, we can observe:

1) For EPFSTO-ARIMA, we perform forced optimization on the data according to Table 4. The RMSE is lower than that of EPSTO-ARIMA, but higher than that of ARIMA.
2) Take Column2 as an example. The RMSE of EPFSTO-ARIMA is 30.44% lower than that of EPSTO-ARIMA and 12.22% higher than that of ARIMA. For the rest of the clients, similar results can be obtained.

ARIMA is optimal for resource consumption in the existing data set. In EPFSTO-ARIMA, we optimize different amounts of data to analyze how they

affect the results. Because EPFSTO-ARIMA has certain randomness, we carry out many experiments for each DP and take the mean value. The results of EPFSTO-ARIMA are shown in Fig. 2.

Table 5. RMSE of EPSTO-ARIMA (EPSTO) and EPFSTO-ARIMA (EPFSTO).

Item	Column2	Column257	Column277	Column314	Household	Solar
ARIMA	6.819	53.240	863.190	14105.370	412.520	0.570
EPSTO	11.000	79.604	1194.183	18190.421	418.333	1.027
EPFSTO	7.652	65.382	946.181	15345.276	414.574	0.588

Table 6. Maximum, minimum and increase rate of EPSTO-ARIMA and EPFSTO-ARIMA RMSE.

Item	Column2	Column257	Column277	Column314	Household	Solar
Min1	7.124	56.36	871.369	13898.56	412.994	0.617
Max1	16.957	113.083	1726.456	24181.739	430.323	1.633
Rate1	138.03%	100.64%	98.13%	73.99%	4.20%	164.67%
Min2	7.597	65.305	931.742	15115.735	412.642	0.583
Max2	7.682	65.562	971.298	16118.49	416.001	0.600
Rate2	1.12%	0.39%	4.25%	6.63%	0.81%	2.92%

For EPFSTO-ARIMA, the data used in the experiment is divided into two groups based on the similarity results, as shown in Table 4. According to DP, optimization is carried out in two groups. From Fig. 2, we can observe that:

1) The RMSE of EPSTO-ARIMA and EPFSTO-ARIMA increase with the increase of DP. However, the increase in EPSTO-ARIMA is more prominent.
2) For EPFSTO-ARIMA, with the continuous increase of DP, RMSE shows a slower upward trend than that of EPSTO-ARIMA. It means that EPFSTO-ARIMA is effective in solving the problem of prediction accuracy degradation as in EPSTO-ARIMA. According to the results, the ratio of the optimized data in the two groups can also be calculated.
3) Take Column2 as an example. In EPSTO-ARIMA, the RMSE increases gradually to about 138.03% with the increase of DP as shown in Table 6 (in Table 6, Min1 and Min2 are the min RMSE of EPSTO-ARIMA and EPFSTO-ARIMA, respectively. Max1 and Max2 are the max RMSE of EPSTO-ARIMA and EPFSTO-ARIMA, respectively. Rate1 and Rate2 are the increase rate of EPSTO-ARIMA and EPFSTO-ARIMA RMSE, respectively.). In EPFSTO-ARIMA, RMSE also increases gradually with the increase of DP, but by only about 1.12%. Other results are shown in Table 6.

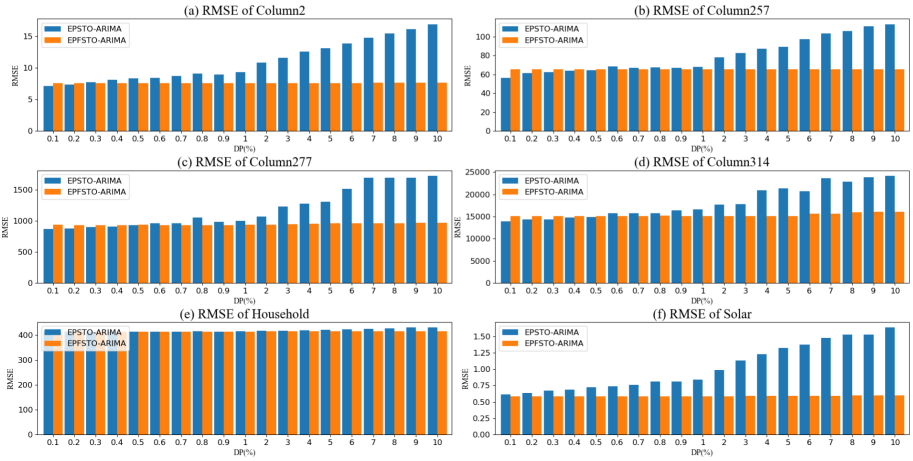

Fig. 2. The RMSE of EPFSTO-ARIMA and EPSTO-ARIMA.

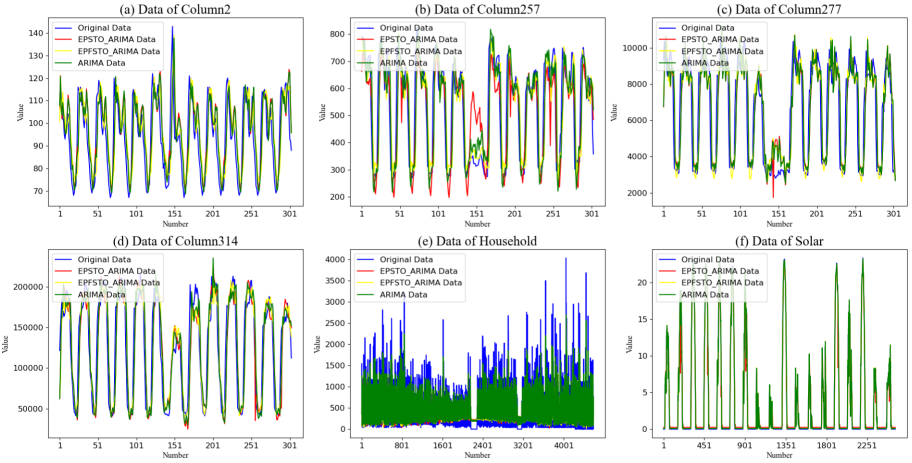

Fig. 3. The original data vs. Prediction data.

Meanwhile, the prediction data of EPFSTO-ARIMA basically conform to the data discipline of the original data as shown in Fig. 3.

In summary,

1) EPFSTO-ARIMA can effectively counter the excessive prediction loss caused by EPSTO-ARIMA.
2) In the aspect of data availability, EPFSTO-ARIMA basically conform to the data discipline of the original data.
3) In addition to the above conclusions, we also found that the time resources used are also saved (as shown in Fig. 4), which will not be discussed in detail in this paper.

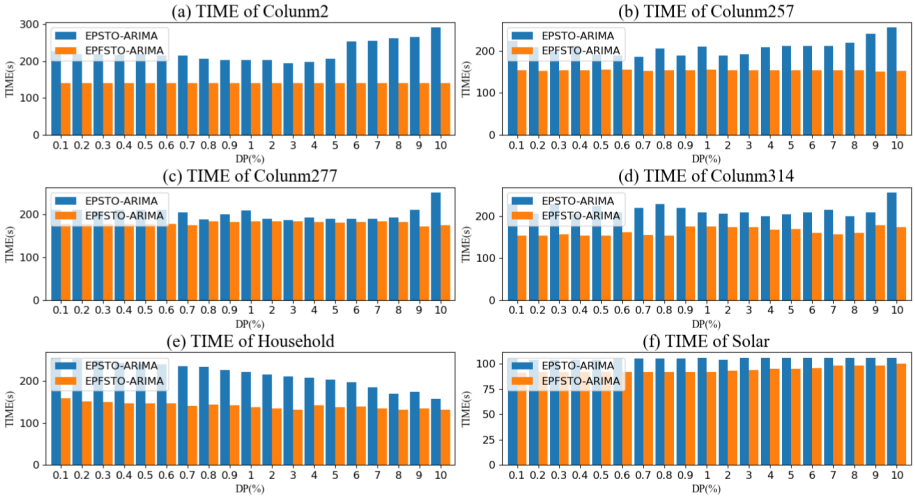

Fig. 4. The TIME of EPFSTO-ARIMA and EPSTO-ARIMA.

5 Conclusions and Future Work

Electricity data prediction is important for the national economy and the lives of people. However, EPSTO-ARIMA will causes serious degradation of electricity prediction service. To deal with the above challenge, we propose EPFSTO-ARIMA, which can reduce prediction error caused by EPSTO-ARIMA. In the meantime, the prediction result can help us to explore the discipline of data. Through experiments, proposed EPFSTO-ARIMA outperforms in reducing prediction error. In the future, the following aspects can be further analyzed:

1) EPFSTO will be tested and demonstrated in other models.
2) EPFSTO will be tested and verified under more detailed data grouping.
3) Exploring the specific effects of EPFSTO-ARIMA on model training time and prediction time.

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