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Description	

Efficient Temporal and Spatial Data Recovery Scheme for Stochastic and Incomplete Feedback Data of Cyber-physical Systems

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***Abstract*—Feedback loss can severely degrade the overall system performance, in addition, it can affect the control and computation of the Cyber-physical Systems (CPS). CPS hold enormous potential for a wide range of emerging applications including stochastic and time-critical traffic patterns. Stochastic data has a randomness in its nature which make a great challenge to maintain the real-time control whenever the data is lost. In this paper, we propose a data recovery scheme, called the Efficient Temporal and Spatial Data Recovery (ETSDR) scheme for stochastic incomplete feedback of CPS. In this scheme, we identify the temporal model based on the traffic patterns and consider the spatial effect of the nearest neighbor. Numerical results reveal that the proposed ETSDR outperforms both the weighted prediction (WP) and the exponentially weighted moving average (EWMA) algorithm regardless of the increment percentage of missing data in terms of the root mean square error, the mean absolute error, and the integral of absolute error.**

***Keywords*-cyber-physical system; data recovery scheme; stochastic data; temporal correlation; spatial correlation; auto regressive integrated moving average**

I. Introduction

Cyber-physical systems (CPS) are a new generation of communication, control and computation that has received a great deal of attention recently [1]. CPS enable the virtual world to interact with the physical world in order to monitor and control the intended parameter in real-time basis. In CPS, technologies such as communication, control, computation, cognition and sensing converge to create new technologies for smarter society. The area of CPS represent the intersection of several systems trends, such as real-time embedded system, distributed systems, control system and networked wireless system.

To facilitate communications between the cyber and the physical world, wireless sensor and actuator network (WSAN) is an essential ingredient of CPS. This is because, the traditional wireless sensor network (WSN) is limited in its ability to monitor the physical world [2]. However, CPS achieve this requirement by facilitating the system to sense, interact and change the physical world in real-time by using feedback control loop. In a typical application of CPS, sensor nodes collect information from the physical world as a source of CPS inputs. Upon receiving input, a controller makes a decision and actuators perform action in the physical world through the closed-loop feedback. Thus, the proper timing and accuracy of feedback data is very important for interaction between cyber and physical world. Fig. 1 shows the general control view of cyber-physical system.

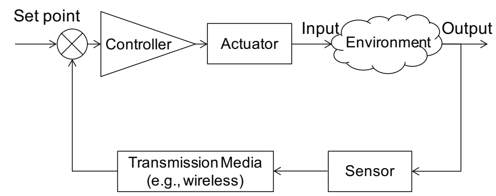

Figure 1. General control view of cyber-physical system.

Since, CPS exploit the physical information collected by WSANs; it also inherit the wireless contention problem of WASN. This makes the challenging issue to control in real-time. Wireless channels have many adverse properties like path loss, fading, adjacent channel interference, node/link failure, etc. Besides these, wireless signals can be easily affected by noise, physical obstacles, node movement, environmental change and so on [3]. Because of this unpredictable and dynamic nature, the sensing data loss is a common phenomenon, which make hamper in controlling decision. Since, the applicability of CPS is found in numerous time-critical applications including smart house to smart grid, data loss makes the system unstable. Emerging applications of CPS include medical devices and systems, aerospace systems, transportation vehicles and intelligent highways, defense systems, robotic systems, process control, factory automation, building and environmental control, smart spaces, intelligent home and so on [4]. In all of these applications, CPS has to monitor and control the state of physical phenomenon in real-time. In particular, for time-critical applications, feedback data must present on time to make decision. In many cases, re-transmission cannot provide appropriate solution because of the unpredictable network behavior, which can cause high delay.

To maintain uninterrupted control, we always need to ensure the presence of feedback data. To do this, we propose a data recovery scheme that can handle insufficient feedback control information. In our paper [5], we proposed a highly

Efficient Spatial Data Recovery (ESDR) scheme that deals with deterministic traffic pattern of CPS. This scheme is very efficient for deterministic traffic pattern like temperature, humidity, moisture which is highly correlated with space. In our proposed ESDR scheme, we utilized spatial correlation of neighboring sensors by using the Pearson correlation coefficient (PCC). But, as mentioned already, the applications of CPS are numerous, thus in many applications the data traffic is stochastic. To handle the stochastic data properly we need to consider their nature which contains randomness. The random and non-stationary nature of stochastic traffic pattern makes it more challenging to recover. In many cases, neighbor sensors maintain non-linear relationship between them. The aim of this paper, is to propose an Efficient Temporal and Spatial Data Recovery (ETSDR) scheme for stochastic data traffic of CPS by considering the nature of stochastic data. The proposed scheme consists of two phases. In the first phase, which is offline, we identify the temporal model for stochastic data and determine the spatial effects of neighbors. The stochastic data series is normally highly auto-correlated and outliers have a different correlation structure then the deterministic data series. Auto Regressive Integrated Moving Average (ARIMA) model is a very powerful model to identify the auto-correlated nature or trend of stochastic data. We utilize this model to identify the nature of the stochastic data. In addition to determine the outliers, spatial effect of neighbor is analyzed. In the next phase, which is on line, we use that temporal model and spatial effect to recover missing data. At the same time, we check whether the identified model keeps fitted with recent data or not.

The rest of the paper is organized as follows. Section II summarizes some state-of-the-art research works those are related to this paper. In Section III, the proposed model based recovery scheme is presented. We describe the experimental scenario and the evaluation parameters in Section IV. Simulation results and discussions are presented in Section V. Section VI concludes with conclusion and future works.

II. Related Work

Data recovery is a part of most research and there exist several methods to handle this. Although there exists several methods, but the recovery of data loss for CPS still poses an open problem because of its unique requirement. The whole recovery process for CPS must be held in real-time and invisible to the outside world. Moreover, the applications of CPS are numerous which involves different data patterns. In the existing literature, there is no direction of data recovery based on traffic patterns. Thus, recovery process without considering the pattern can not provide a solution for all. To recover data accurately, we first need to understand the nature of the data and their relationship with others.

Missing data is a well-studied subject in statistics. Maximum likelihood (ML), multiple imputation (MI) and expectation maximization (EM) are widely used methods for missing data imputation. ML [6] calculates the likelihood function for given set of data, which is a hypothetical probability that uses past event with known outcome. Then, by using iterative steps, ML makes the likelihood function maximum. EM [7] also uses iterative steps to maximize the likelihood function but in EM, model depends on unobserved or latent variables. Based on mean and covariance matrix of multivariate normal distribution, expectation (E) step initializes the expected values for latent variables. Maximization (M) step plugs the expected values into the log-likelihood function and maximizes the log-likelihood function by repeating the E and M steps. However initialization step directly impacts the performance of EM based imputation. On the other hand, in MI [8], missing data are filled by m different times to generate m complete data sets. Generated m data sets are analyzed by standard procedure and then combined for inference. But these well known techniques for missing data imputation are not suitable for WSNs, due to their high space and/or time complexities.

Xia, et al. [9] first propose a solution for CPS over WSANs to cope with packet loss. They illustrate three prediction algorithms and provide a comparison between them. Their first algorithm based on the assumption that, the state of the physical system does not change during the last sampling period. So, previous sample is used to replace the missing value. The second algorithm computes a moving average of the previous m samples to restore the lost data. Thus it treats every previous measurement equally. In third algorithm weighted average of all previous samples is taken to replace the missing one. Simulation result shows that third algorithm works well compared with others. All of their procedures are bound for specific situation where current data depends on the previous data or the combination of previous data but not for all conditions.

Choi, et al. [10] exploit an exponentially weighted moving average (EWMA) based value estimation algorithm to reduce the impact of packet loss. When some packets are randomly dropped in wireless network environment, the EWMA algorithm filters an abrupt increase or decrease by exponentially smoothing commands or data based on the past value profile. This method only suits, when the data series is an exponentially weighted combination of past data sets. But in real-life there is no guarantee that data will always maintain this combination. Moreover, none of the existing data recovery scheme includes model identification before recover the data. We believe that successful identification of data model can ensure accurate and timely recovery.

In the literature, there exists some model based data aggregation scheme. In [11], authors proposed an ARIMA based data aggregation method to reduce the energy consumption and number of communication. In their scheme, both sensor node and aggregator have the same model for data generation. Sensor node checks whether the data predicted from the model and measure data is same or not. If the real value and predicted value is within the threshold, then the sensor node will not transmit the data to the aggregator. Otherwise, sensor will send the new data to the aggregator.

III. Proposed Efficient Temporal and Spatial Data Recovery Scheme

In this section, we propose a data recovery scheme called Efficient Temporal and Spatial Data Recovery Scheme (ETSDR) for stochastic traffic pattern of CPS. Before doing this, we classify the pattern and types of CPS data traffic. We classify three traffic patterns for CPS applications: deterministic, stochastic and time-critical. The deterministic traffic pattern always maintains a stable state. On the other hand, any traffic pattern which involves random change and indeterminacy is defined as a stochastic traffic pattern. We concentrate stochastic traffic patterns in this paper. And, these traffic patterns can be transmitted by four different traffic types [12] : fixed, periodic, bursty and arbitrary rate. In this research, we design our scheme to mitigate the problem of periodic traffic type. As mentioned already, the proposed scheme contains two steps: i) Offline temporal model identification and ii) Online recovery of data.

A. *Offline Temporal Model Identification*

The aim of this step is to identify the temporal correlation or pattern of the observed data and build a model based on that available data. The proposed flowchart for off line temporal model identification is shown in Fig. 2. The following assumptions have been considered. First, n observed sensor data is available for model identifications and e observed sensor data is available for model verification. Second, the maximum number of attempts (C) to generate the model is fixed at initialization stage. The parameter C is also used to make the decision that, the model cannot be generated from the available data. In the flowchart, first we analyze the data series trend by modelling it into ARIMA series. Before modelling, we analyze the nature of stochastic data which can be perfectly modelled with ARIMA model.

ARIMA model [13] is a very powerful tool that uses historical data to predict future data values. Any type of stochastic data series can be identified by this model. The ARIMA model, also called Box-Jenkins model, can be divided into three components: auto-regressive (AR), moving-average (MA), and one-step differencing [13].

1) Auto-regressive model of order p : AR model is a simplified version of ARIMA model which describes random time-varying process. The AR model specifies that the output variable depends linearly on its own previous values [13]. The AR model of sensor s data series $d_{s1}, d_{s2}, .., d_{sn}$ with order p is defined as follows $d_{sn} = c + \sum_{i=1}^{p} \varphi_i d_{s(n-1)} + \varepsilon_n$, where p is the order of auto-regressive terms, $\varphi_1, \varphi_2, ..\varphi_p$ are the parameter of the model, c is a constant and ε_n is white noise.

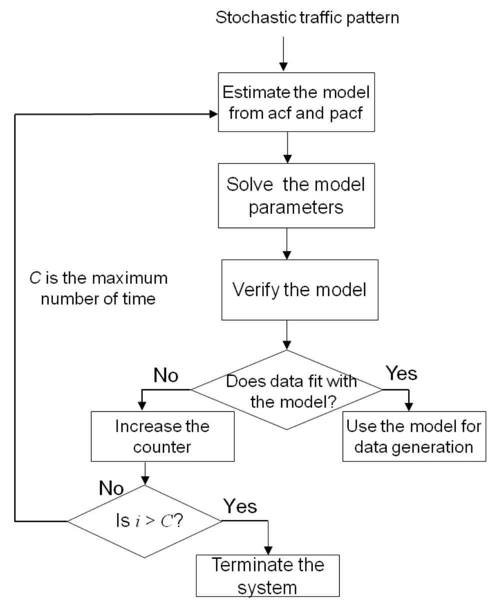

Figure 2. Proposed flowchart for temporal model identification.

2) Moving average model of order q : MA model is a linear regression of the current and previous error of a random series. The MA model of sensor s data series $d_{s1}, d_{s2}, .., d_{sn}$ with order q is defined as follows $d_{sn} = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{n-1}$, where, q is the number of moving average terms, μ is the mean of the series, $\theta_1, \theta_2, ..\theta_q$ are the parameter of the series, and ε_n is the error.

3) Auto Regressive Integrated Moving Average (ARIMA) Model: ARIMA model predicts future values of a sensor s data series by a linear combination of its auto-regressive past values, integrated, and moving average of errors. The model is generally referred to as an ARIMA(p,d,q) model where parameters p, d, and q are non-negative integers that refer to the order of the auto-regressive, integrated, and moving average parts of the model respectively. The ARIMA model is defined as $\theta_p(B)\triangle^d d_{s(t)} = \Theta_q(B)\varepsilon_n$, where, B is the backward shift operator, $\triangle$ is the backward difference, d is the order of differencing and θ_p and Θ_q are the polynomial of order p and q respectively. In addition, $Bd_{sn} = d_{s(n-1)}$ and $\triangle = 1 - B$. ARIMA(p,d,q) model is the product of an AR part AR(p): $\theta_p = 1 - \varphi_1 B - \varphi_2 B^2 - ... - \varphi_p B^p$, an integrating part: $I(d) = \triangle^{-d}$ and a MA part MA(q): $\Theta_q = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$.

To identify the model, we consider the following steps.

Step 1: Calculate ACF and PACF

The Auto-correlation function (ACF) is a set of correlation coefficients between the series and lags of itself over time [13]. The k-order auto-correlation coefficient of a data series $d_{s1}, d_{s2}, .., d_{sn}$ of sensor s is defined as

$$r_k = \frac{\sum_{i=1}^{n-k} (d_{si} - \bar{d_{si}})(d_{s(i+k)} - \bar{d_{si}})}{\sum_{i=1}^{n} (d_{si} - \bar{d_{si}})^2} \tag{1}$$

where, r_k is the k lag sample auto-correlation and $\bar{d_{si}}$ is the average of n observations. The PACF stands for the partial correlation coefficients between the series and lags of itself over time. The k-order partial auto-correlation coefficient of a data series is defined as

$$\phi_{11} = r_1 \tag{2}$$

$$\phi_{22} = (r_2 - {r_1}^2)(1 - {r_1}^2) \tag{3}$$

$$\phi_{kj} = \phi_{(k-1)j} - \phi_{kk}\phi_{(k-1)(k-j)} \tag{4}$$

$$\phi_{kk} = r_k - \sum_{j=1}^{k-1} \phi_{(k-1)} r_{k-j} \Bigg/ 1 - \sum_{j=1}^{k-1} \phi_{(k-1)} r_j \tag{5}$$

Step 2: Estimate the Temporal Model

From the ACF and PACF, the ARMA model that closely fit to the data can be identified. We determined the order of p and q by matching the patterns in the sample ACF and PACF with the theoretical pattern of known model. Table I shows the theoretical properties of ACF and PACF of AR, MA and ARMA series.

Table I
PROPERTIES OF ACF AND PACF

	ACF	PACF
AR(p)	Tails off as exponential or damped sine wave	Cuts off after lag p
MA(q)	Cuts off after lag q	Tails off as exponential decay or damped sine wave
ARMA(p,q)	Tails off after lag $(q-p)$	Tails off after lag $(q-p)$

Step 3: Solve the Parameters of Temporal Model

In this step, we calculate the parameters of the identified model using method of moments and Yule-Walker equations [13].

Step 4: Verify the Temporal Model

To verify the model, we compare the model generated data with the e observed sensor data. If the verification fails, we continue to estimate the model until the maximum counter C is reached. In the case of successful verifications, we use that model to generate the data.

B. Online Data Recovery

To deploy our proposed stochastic data recovery scheme, we propose a flowchart with the recovery scheme for CPS as depicted in Fig. 3. In the flowchart, the proposed ETSDR scheme will compute the model estimated data when there is an input measured data from the sensors. If there is no missing data, then the measured data is used as a feedback data. At the same time the difference between the measured

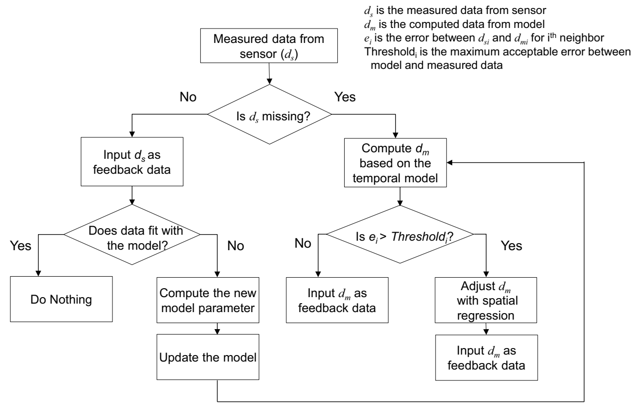

Figure 3. Proposed flowchart for ETSDR scheme.

data and model estimated data is computed and if the difference is greater than error offset, model is updated by computing new parameters. On the other hand, when there is a missing data, the neighbor's model estimated data is compared with neighbor's measured data . If the neighbor's model estimated data cross the threshold, then the spatial effect is considered. To estimate the missing data properly, the model estimated data is adjusted with spatial effect and is used as a feedback data.

As far as we are concerned, most of the spatial correlation measures the linear correlation between the nearest neighbors. If an environment is highly correlated in space, then the spatial information can be used to estimate missing data and the estimation function can achieve a high accuracy. Pearson Correlation Coefficient (PCC) is a common measure of the linear correlation between two random variables i and j. It reflects the degree of association between two variables. But in real-life environment, the neighbor sensors can be correlated non-linearly with their neighbors also. We consider this phenomenon and calculate the spatial effect based on the applications. Fig. 4 describes the proposed ETSDR algorithm, which is used to produce an estimated data from time to time.

IV. NUMERICAL STUDIES

In this section, we conduct the simulation studies to evaluate our proposed ETSDR scheme compared to the WP algorithm [9] and the EWMA algorithm [10]. We create an simulation environment with five sensors and one base station. We generate random series data in MATLAB simulator for one sensor. We add distance based non-linear co-relationship to the generated data and assign to the other four sensors. We estimate the model from the generated data by calculating the ACF and PACF. We identify possible value of p and q and find $p = 2$ and $q = 0$ for our simulation. Then, we solve the parameters using Yule-Walker equations for the identified AR(2) model. In the series, the autocorrelation at lag 1 is $r_1 = 0.807$ and autocorrelation at lag 2 is

Algorithm: Efficient Temporal and Spatial Data Recovery(ETSDR)

```
if d_s = available then
  for each d_s from the sensor s do
    Compute d_ms(t) from the model
      if abs(d_s(t) − d_ms(t)) > error offset then
        Update the model with new parameters
      end if
  end for
else
  for all one hop neighbor j of sensor s do
    if abs(d_j(t) − d_mj(t)) > threshold then
      d_e(t) ⟵ d_s(t) = d_ms(t)+ spatial effect
    else
      d_e(t) ⟵ d_s(t) = d_ms(t)
    end if
  end for
end for
```

Figure 4. Pseudo code for Efficient Temporal and Spatial Data Recovery Algorithm

$r_2 = 0.429$. The equations for the estimators of this series are $1.000\hat{\varphi}_1 + 0.807\hat{\varphi}_2 = 0.807$ and $0.807\hat{\varphi}_1 + 1.000\hat{\varphi}_2 = 0.429$, which has a solution $\hat{\varphi}_1 = 1.321$ and $\hat{\varphi}_2 = -0.637$. Since $c = \mu(1 - \varphi_1 - \varphi_2)$, then it can be estimated $c = 46.590(1 - 1.321 - 0.637) = 14.9$. Thus the estimated model is $d_{sn} = 1.321 \times d_{s(n-1)} - 0.637 \times d_{s(n-2)} + 14.9$. This model is used to generate the data and we set the maximum tolerable error between model and measured data 2.0 which is denoted as error offset.

Based on the generated data, we investigate the performance of our proposed scheme using a MATLAB. In this simulation, we assume that the single sensor produces a missing sensed data when it transmits its packet to the base station. We randomly delete the data according to the percentage of missing data from the original set and recover them using the aforementioned data recovery algorithms. We use the root mean square error (RMSE), mean absolute error (MAE) and integral of absolute error (IAE) to evaluate the performance of the said algorithms.

The RMSE is a frequently used measure of the difference between values estimated by an algorithm and the values actually measured from the real environment. The RMSE of an algorithm estimation with respect to the estimated value, de is defined as the square root of the mean squared error as written as $RMSE = \sqrt{\frac{\sum_{n=1}^{N} (d_s(n) - d_e(n))^2}{N}}$ where d_s is original measured value.

The MAE is another statistical measurement that used to measure how close the estimated values are to the measured values. The MAE is given by $MAE = \frac{1}{N}\sum_{n=1}^{N} |d_e(n) - d_s(n)|$

The MAE measures the average magnitude of the errors in a data set, without considering their direction. In [14], Wilmott, et al. indicate that the MAE is the most natural and unambiguous measure of average error magnitude.

On the other hand, the IAE is a widely used performance metric in control community, which is recorded to measure the performance of the control application. The IAE is calculated as $IAE = \int_0^1 |d_e(t) - d_s(t)|\, dt$

where, t denotes total simulation time. In general, the larger the IAE values imply the worse the performance of the control algorithm.

V. Simulation Result and Discussion

In this section, we present our simulation results and make some discussions on the performance of algorithms. The aim of this simulation is to examine the potential of the proposed algorithm in coping with the data missing for the CPS application. In our simulation, we investigate the impact of increasing percentage of missing data on the data recovery algorithm performance. The percentage of missing data is varied from 10% to 60% in steps of 10%.

Fig. 5 depicts the RMSE comparison among data recovery algorithms for stochastic traffic patterns. As the percentage of data missing increases, the proposed algorithm always shows better performance that is compared to the existing two algorithms. The reason for this improvement is because, the proposed scheme estimates the data model then uses that model to generate data. On the other hand, other two algorithms always use the same combinations of previous measurement without considering the effect from the neighbors. Both WP and EWMA algorithm use the fix combination of previous measurements only. Thus, they unable to cope with long consecutive missing and frequent changes in the environment.

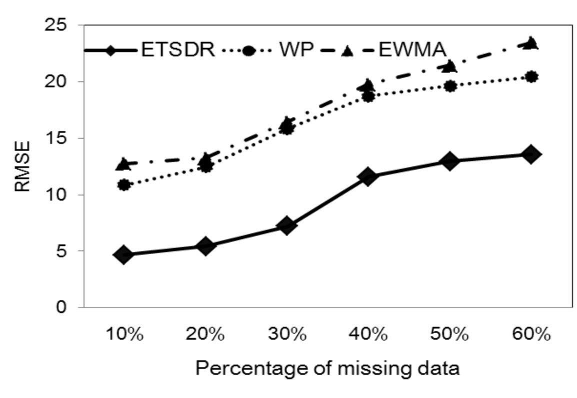

Figure 5. The comparison of RMSE of stochastic data of all the data recovery algorithms as the percentage of missing data changes from 10% to 60%.

The MAE comparison for stochastic data traffic among three data recovery algorithms is shown in Fig. 6. We can see that the proposed scheme outperforms the WP algorithm and the EWMA algorithm. Besides that, the proposed scheme can steadily maintain a small value of MAE regardless of the increment of missing data.

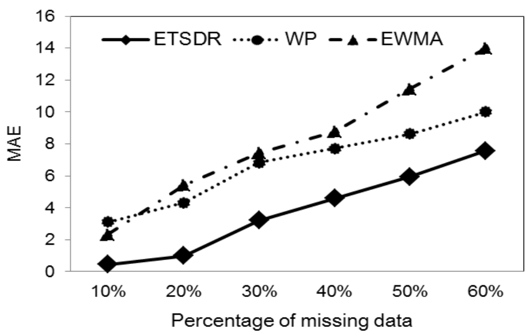

Figure 6. The comparison of MAE of stochastic data of all the data recovery algorithms as the percentage of missing data changes from 10% to 60%.

In Fig. 7, the accumulated IAE comparison for stochastic data traffic of all the data recovery algorithms is plotted. The simulation results demonstrate that the proposed scheme outperforms the WP algorithm and the EWMA algorithm. In the 30% data missing the proposed algorithm's IAE is 0.62668 on the other hand the IAE of WP and EWMA is 1.9211 and 4.02 respectively. At 50% data missing, the proposed scheme's IAE is five times smaller than the EWMA algorithm.

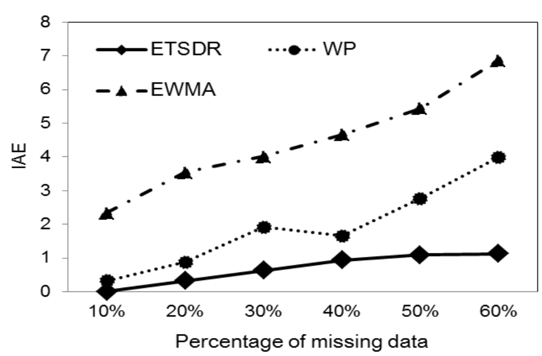

Figure 7. The comparison of IAE of stochastic data of all the data recovery algorithms as the percentage of missing data changes from 10% to 60%.

VI. Concluding Remarks

In this paper, we have proposed ETSDR scheme for stochastic data traffics of CPS. In this research work, we also identified that the stochastic data is more difficult to estimate and thus to handle the stochastic data we incorporate the model from that data pattern. Our simulation results reveal that the proposed ETSDR scheme is very beneficial and outperforms the WP and the EWMA algorithms regardless of the increment of missing data. Moreover, further research is required for examining more time-critical traffic patterns. Besides that, a future work will focus on examining the real-time recovery using the proposed ETSDR scheme.

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