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Avoiding Data Traffic on Smart Grid Communication System

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Abstract: Smart Grid is a recent area where the key feature is shift the present power system approach. But, the challenges of upgrade this present power system are several, such as: how to add reliable links between customers' home and data centers to enable smart meter sending power consumption data? and how to avoid big data and bottleneck on backbone to transmission of millions of these customers' devices? On the other hand, smart meter can be treated as a sensor network device. Thus, we can use the same data reduction mechanisms that have been studied in wireless sensor network to decrease its traffic. This paper proposes a data reduction approach based on prediction by simple linear regression to avoid flow of readings between smart meter and smart grid system. Our approach models the data gathered by smart meter and turns them into coefficients, which are sent to smart grid system instead of raw data. The prediction mechanism is performed by destination device using these coefficients for data recovering. Although the approximation performed by linear regression increases the prediction error in some instances, we have implemented an adaptive mechanism (Adaptive Simple Linear Regression - ASLR) that checks if the error or lack of relationship between the modeled samples is harmful to our data reduction approach. Thereby, two ways have been deployed to tune the samples window (amount of readings) for improve own approach. One mechanism adjusts samples window based on prediction error and another one adjusts samples window based on Pearson's coefficient.

Keywords: Data Reduction, Smart Grid Communication, Smart Meter.

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1. Introduction

The present power grid is centralized, increasing the cost to the operator of the distribution network. Thus, the introduction of distributed energy resources enables power distribution network more flexible and dynamic [1]. But, this new approach requires upgrading of present power system to support new technologies or adopting of existing technologies. Currently, efforts have been made to standard these technologies and ensure the smart grid operation, such as the NIST Framework. A general smart grid communication infrastructure have been defined for smart grid and includes Home Area Networks (HANs), Business Area Networks (BANs), Neighborhood Area Networks (NANs), data centers, and substation automation integration systems [2]. The Advanced Metering Infrastructure (AMI) is responsible for communication between a smart utility meter (HAN or BAN) and an utility company [2]. The smart meter is an device that takes energy consumption readings from user's home (HAN) and sends its data to utility company. However, this communication infrastructure (NAN) also needs data communication protocols suitable to that new scenario. Routing mechanisms and large bandwidth must be essentials for a reliable communication system [1], which has to support data traffic from thousands or millions of consumers and their smart meters.

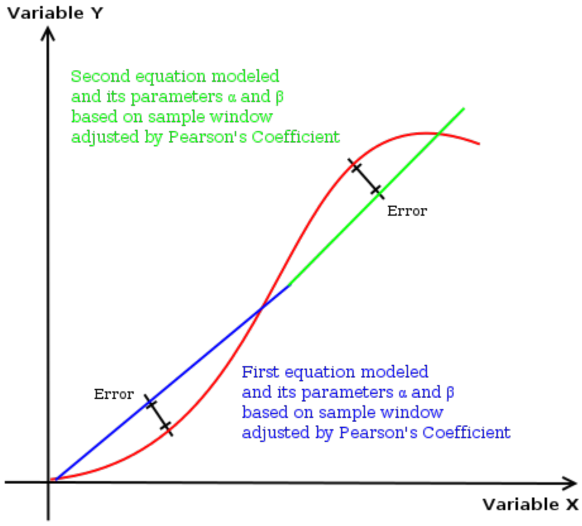
An alternative way of communication infrastructure [3] is recommended between consumers and utility, and even within utility system. Wireless links can be used to backup. Anyway, that data traffic (smart meter readings) may generate bottleneck in HAN, BAN and NAN networks. Then, this paper proposes a data reduction approach based on prediction by Simple Linear Regression to compute a data model (represents the readings). It sends function coefficients to utility datacenter instead of it sends smart meter readings (raw data). We have named this approach of Adaptive Simple Linear Regression (ASLR). The idea is reduces readings communication from smart meter to datacenter as applied in Wireless Sensor Network (WSN). Each smart meter gathers energy consumption readings and then computes function coefficients that represents that data. This data model is sent to the utility server and then a prediction mechanism is used by utility system to get readings that were not purposely sent it.

In order to improve the prediction, two mechanisms have been deployed to tune the samples window (amount of readings) to be modeled. These samples are readings which are modeled in a linear regression function for recovering data instead of sending it to the datacenter. One these mechanisms adjusts samples window based on prediction error. For data modeling, the prediction error is compared against a threshold to check whether the coefficients are better than the previous. In affirmative case, the coefficients are updated before sending. In negative case, the last set of coefficients is sent to the data center. On the other hand, another mechanism adjusts samples window based on Pearson's coefficient. The comparison with the threshold is to check whether the data to be modeled are temporally correlated. In the affirmative, the coefficients are updated. In the negative, the last set of coefficients is sent.

2. Related Work

Data reduction for energy saving is widely used in Wireless Sensor Networks (WSN), decreasing the transmission of sensor readings on the network. The sensor node avoids sending gathered readings as it can be recovered at the sink node (destination device) by means the raw data history applied to data reduction approach (i.e. prediction). In literature, there are several works on WSN data reduction,

Figure 1. Energy consumption prediction based on linear regression



such as [4,5]. Also, there are few survey [6,7] which describe the characteristics of certain mechanisms. Therefore, perform data reduction by using mechanisms such as aggregation or data fusion becomes unviable. Furthermore, the lossless compression [8] may also be impractical because that requires memory and processing devices which are already constrained computational resources. In our previous works [9] recommend that data modeling should be done by source node and sent to the sink node. That approach enables the sensor node make decisions instantly, regardless of the transmission delay of the model.

3. Approach to avoid smart meter data traffic

Correlation between the data gathered by a sensor node and its neighbors, as well as the correlation between the data gathered by the sensor node itself over a given time, must be explored by efficient protocols to improve energy consumption. Works, such as [9] apply data prediction to reduce traffic from sensor node to the sink. An algorithm is embedded within the sensor node to modeling data from readings. Coefficients of a linear function are obtained by Simple Linear Regression. These coefficients are named α and β, and represent a sequence of samples gathered by the sensor, such as temperature. Thus, the sensor node sends the coefficients to the sink, instead of sending the sequence of samples. When α and β arrive at the sink, them are used by the linear regression function embedded within the sink. Then the readings sequence is predicted by the monitoring system.

We decided to adopt the Simple Linear Regression through prediction, in order to perform data reduction with loss, but obeying a threshold that can be set previously. Smart meter readings prediction using Simple Linear Regression enables to send only coefficients instead of samples of energy consumption. In Figure 1, note that there are losses (error) caused by this mechanism due to the linear approximation, but it meets requirements for recover modeled data. The data reduction by means of linear regression is performed by using least squares for data modeling from readings gathered. A reading identification (r_id) is proposed to record that reading. In this case, each smart meter calculates the coefficients α and β by using the variable, usually the r_id as independent variable. The dependent variable to be predicted is the energy consumption (e_c). Based on previous experiments on WSN, it was observed that a fixed samples window, in some cases, generates a high prediction error. In order to improve this, it is essential to adopt an adaptive mechanism for the previously determined threshold is obeyed. Every time, when the mechanism reaches a threshold, a new data model is generated and the coefficients are sent to the data center utility. This ensures that when establishing a error bound, the mechanism will be more precise.

The first modification of the solution proposed in [9], which was used in a fixed samples window size in the calculation of the coefficients, consists of using an adaptive window of readings (w) and guided by the prediction error. This error ($Error_{predictor}$) is calculated by the sum of difference between the actual sample value ($y_{i_{actual}}$) and the sample value predicted ($y_{i_{predicted}}$). w is established by the mechanism adaptively. The Mean Squared Error (MSE) is analyzed to verify how the mechanism fits the w obeying the $Error_{predictor}$. The prediction mechanism with window readings (w) adaptive, guided by the prediction error, following considerations: i) the initial value of w (w_0) is previously determined according to the application requirements; ii) whenever the mechanism detects that l_{error} was reached, the samples window size returns to its initial value, ie, $w = w_0$; iii) if l_{error} is not reached for each verification, w will be incremented by one, and iv) the MSE maximum for cases where w is greater than l_{error} will be the $w * (l_{error})^2$, ensuring higher accuracy of information sensing, after the recovery of the samples in the utility's datacenter.

Other mechanism can be used in our adaptive approach (ASLR). Here, the sensor node adjust the samples window size based on correlation coefficient. In this case, α and β are computed from samples based on Pearson's Coefficient. This coefficient shows the level of correlation between two variables and its direction (positive or negative). The Value of the coefficient should be in the range $[-1, +1]$. The value of coefficient can be played as follows: if value is $+1$, then there is a perfect positive correlation between the two variables; if value is -1, then there is a perfect negative correlation between two variables. If the value is 0 then there is not correlation or correlation is non-linear. In our case, the better results on performance evaluation from prediction (low error) were got when Pearson's Coefficient ranged between $[0.6 - 1]$.

4. Experimental results

In order to check the performance of our data reduction approach, we realized experiments with the implementation of the solution in a programming tool named Octave. A file containing 140 energy consumption readings (downloaded from http://pvoutput.org) was used, representing 24 hours of measurement. Our implementations consist on: 1) a monitoring system without data reduction mechanism gathering energy consumption (Raw Data); 2) a monitoring system using data reduction approach not adaptive (Fixed Window); 3) a monitoring system using data reduction approach with samples window size adaptive based on prediction error (Based on Error); and a monitoring system using data reduction approach with samples window size adaptive based on correlation coefficient (Based on Pearson). Figure 2 shows the prediction results from our approach. Note that our approach can recover the reduced data in all situations, including the mechanism using fixed and adaptive samples window (Based on error or correlation coefficient). Furthermore, it can be seen that the mechanism of the fixed samples window size is less efficient in terms of quality of the recovered information (i.e. error).

Table 1. Effects of Noise Added by Our Approach

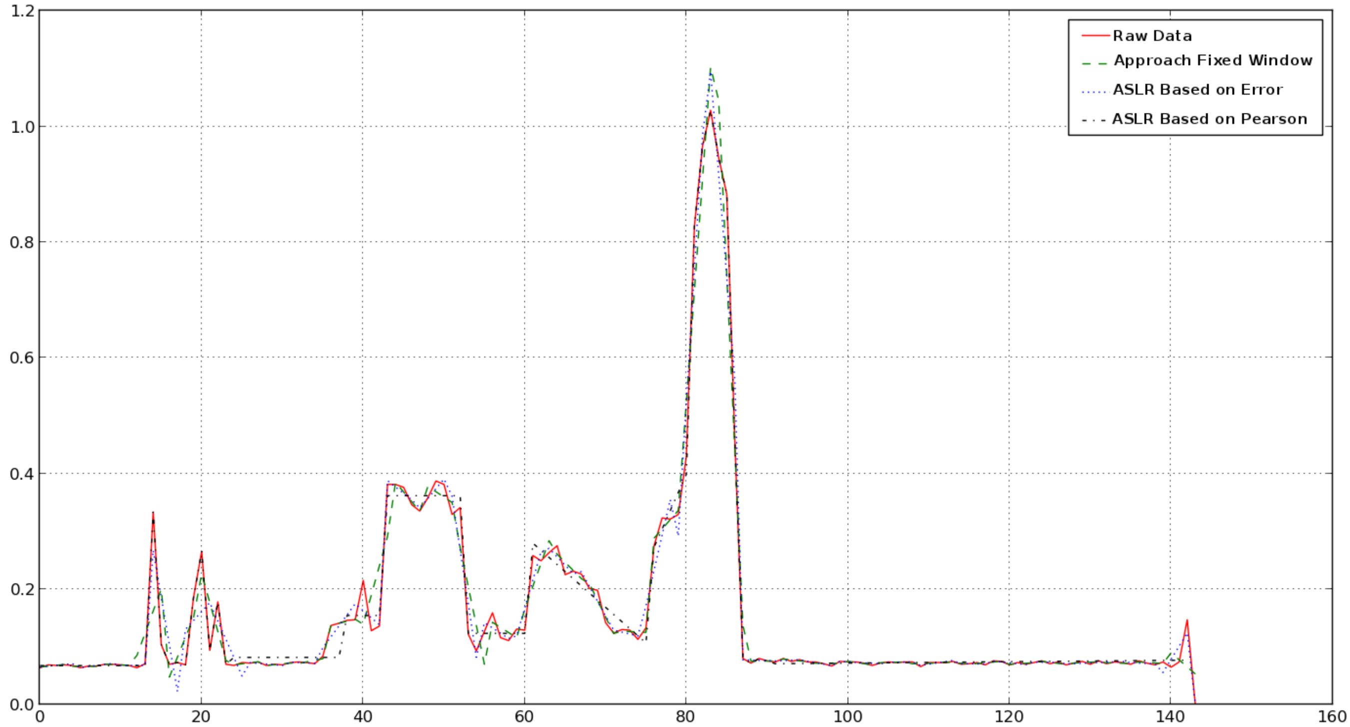
Mechanism	Watts
Raw Data	22.7520
Fixed Window	22.6988
ASLR	22.7602

About bandwidth, our approach can reduce about 90% of the packets sent over the network avoiding the data traffic. These results were achieved with a very low error. Table 1 describes the effects of noise added in the recovery of data in our approach. Note that the home energy consumption reported by monitoring system (Raw Data) is 22.7520 and the error added by our approach is 0.23% or 0.036%, respectively (Fixed Window and ASLR).

5. Discussion and conclusions

The number of smart meter causing traffic towards the network of the smart grid can generate bottlenecks leading to system collapse. Therefore, we propose to use data reduction approach to tackle the problem at source (i.e. smart meter), reducing the amount of packets that will be sent across the network. This reduction should be achieved by techniques such as Simple Linear Regression, which in our experiments obtained a reduction of approximately 90% of the data traffic and added error from 0.23% to 0.036% in monitoring system for energy consumption. However, there are other mechanisms more accurate, like digital signal processing techniques, but we're still experimenting to adjust to the input data from a smart meter, rather than using the same mechanisms adopted in WSN. Additionally, we are developing a platform for monitoring homes or buildings, which will be able to be embedded

Figure 2. Prediction Results from ASLR



in smart meters to allow integration of appliances having sensors at a low cost and with less bandwidth consumption.

Conflicts of Interest

The authors declare no conflict of interest.

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