Avoiding Data Traffic on Smart Grid Communication System

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Outline

Overview

Smart Grid = paradigm shift from centralized to distributed

- New communication infrastructure
  - Home Area Networks (HANs)
  - Business Area Networks (BANs)
  - Neighborhood Area Networks (NANs)
  - Data centers
  - Substation automation integration systems

Advanced Metering Infrastructure (AMI)

Is responsible for communication between a smart utility meter (HAN or BAN) and an utility company

What can AMI lead?

- Million of user's homes
  - a lot of smart utility meters sending data
- Data traffic (energy consumption) may generate bottleneck in
  - HAN
  - BAN
  - NAN

Alert

Collapse of communication infrastructure is imminent.

Data Reduction I

Approach based on prediction by Simple Linear Regression

- It computes a data model (represents the readings)
- Coefficients of a linear function are obtained by Simple Linear Regression, which are named α and β
- And sends function coefficients to utility datacenter instead of smart meter readings (raw data)
- Data reduction as done in WSN

Disadvantage

The noise (error) caused by this approach (Figure 1) can be problem.

Data Reduction II

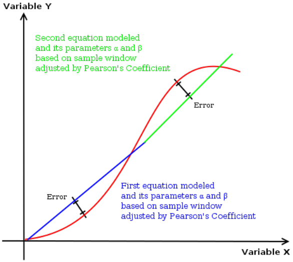

Figure 1 : Energy consumption prediction based on linear regression.

Adaptive Simple Linear Regression (ASLR)

In order to improve the prediction, two mechanisms have been deployed to tune the samples window (amount of readings) to be modeled. We have named our approach of ASLR.

Two mechanisms

How Does Our Adaptive Approach works?

Our approach adjusts the samples window in two ways.

- First is based on prediction error
  - The prediction error is compared against a threshold to check whether the coefficients are better than the previous
  - Ok = coefficients are updated before sending
  - Not Ok = the last set of coefficients is sent to the data center
- Second is based on Pearson's coefficient
  - The comparison with the threshold is to check whether the data to be modeled are temporally correlated
  - Ok = coefficients are updated
  - Not Ok = the last set of coefficients is sent

Scenario

- 140 energy consumption readings (downloaded from http://pvoutput.org)
- It represents 24 hours of measurement
- Our implementations consist on:
  - a monitoring system without data reduction mechanism gathering energy consumption (Raw Data);
  - a monitoring system using data reduction approach not adaptive (Fixed Window);
  - a monitoring system using data reduction approach with samples window size adaptive based on prediction error (Based on Error);
  - a monitoring system using data reduction approach with samples window size adaptive based on correlation coefficient (Based on Pearson).

Noise Added

Avoiding Data Traffic

Our approach can reduce about 90% of the packets sent over the network avoiding the data traffic.

- Achieved with a very low error (Table 1)
  - Home energy consumption reported by monitoring system (Raw Data) is 22.7520
  - Error added by our approach is 0.23% or 0.036%, respectively (Fixed Window and ASLR)

Table 1 : Effects of Noise Added by Our Approach

Mechanism	Watts
Raw Data	22.7520
Fixed Window	22.6988
ASLR	22.7602

Prediction Results I

Figure 2 shows the prediction results from our approach.

- 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)

Benefit of being Adaptive

ALSR is enabled to support data reduction with low noise and adjusting the error according to the samples window.

Prediction Results II

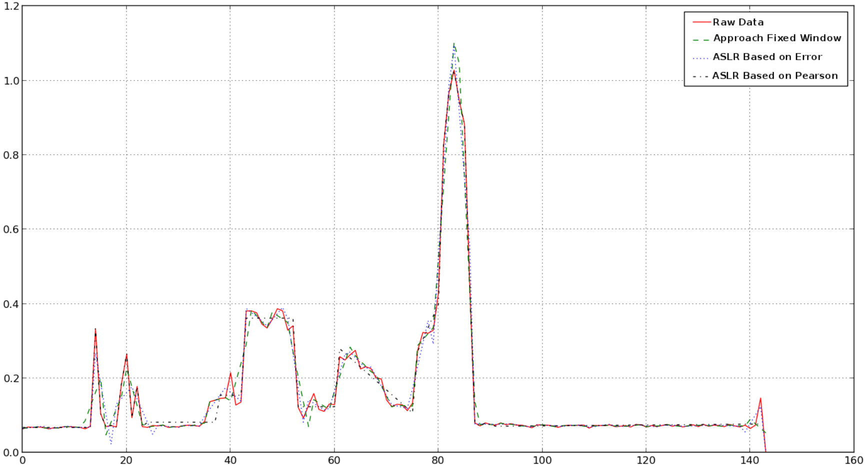

Figure 2 : Prediction Results from ASLR

Discussion

- 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
- 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

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Thank's ;-)

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