STEFAN HOSEIN

WEB APPLICATION FOR POWER GRID FAULT MANAGEMENT

INTRODUCTION

- Smart power grids have been introduced in many developed countries and facilitate more efficient and economical utilization of generated power.
- The components of such a grid are usually remotely monitored and selected components are controlled either manually or through advanced software programs.
- However, many countries still rely on an Automated Meter Reading (AMR) network. AMR meters periodically report electrical energy consumption information to a centralized location and can also (since they contain batteries) transmit indications of power outage as well as power restoration.
- We make use of these meters to create a web application that examines and detects faults (blackouts, brownouts and surges) in an electrical grid. This application complements any existing sensor networks and software so that no new equipment needs to be implemented.

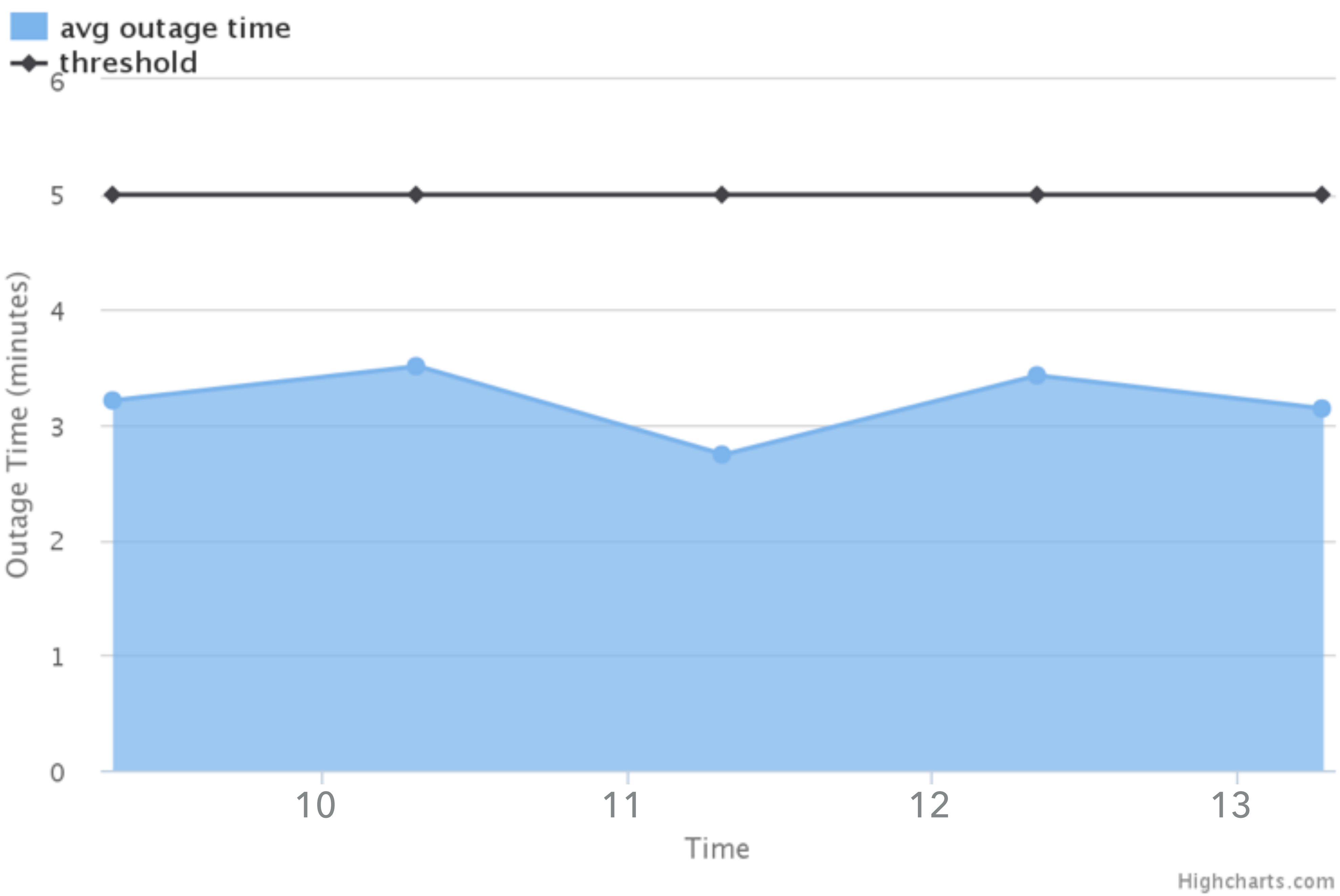
OBJECTIVES

- Open Source
- Tackle blackouts, brownouts and power surges
- Network Monitoring
- Fault detection and isolation
- Central Communication Unit (CCU) Monitoring

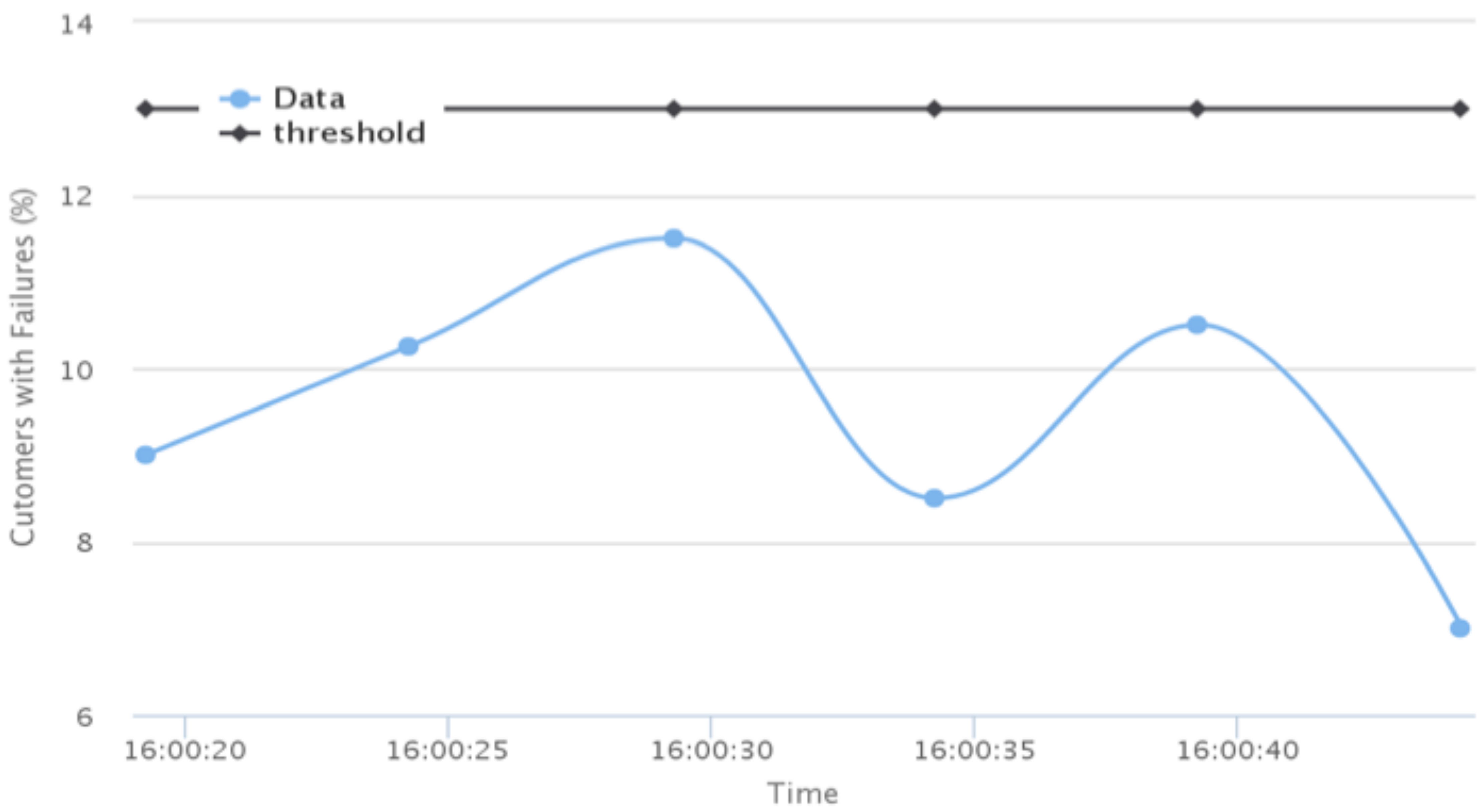
PSEUDOCODE FOR DETERMINING FAULTY COMPONENT

$S \leftarrow$ the set of meters
$L \leftarrow 1$ ▷ level counter
$F \leftarrow 0$ ▷ denotes the faulty component
while $F == 0$ **do** ▷ For each leaf k, A_k is ancestor list, if $k \in S$ reports PON then $x_k = 1$ else $x_k = 0$
    for all $k \in S$ **do**
        if $x_k == 1$ **then**
            if $F == 0$ **then**
                $F \leftarrow A_k(L)$
            else
                if $F \neq A_k(L)$ **then**
                    $L \leftarrow L + 1$
                    $F \leftarrow 0$
                    exit
                end if
            end if
        end if
    end for
end while

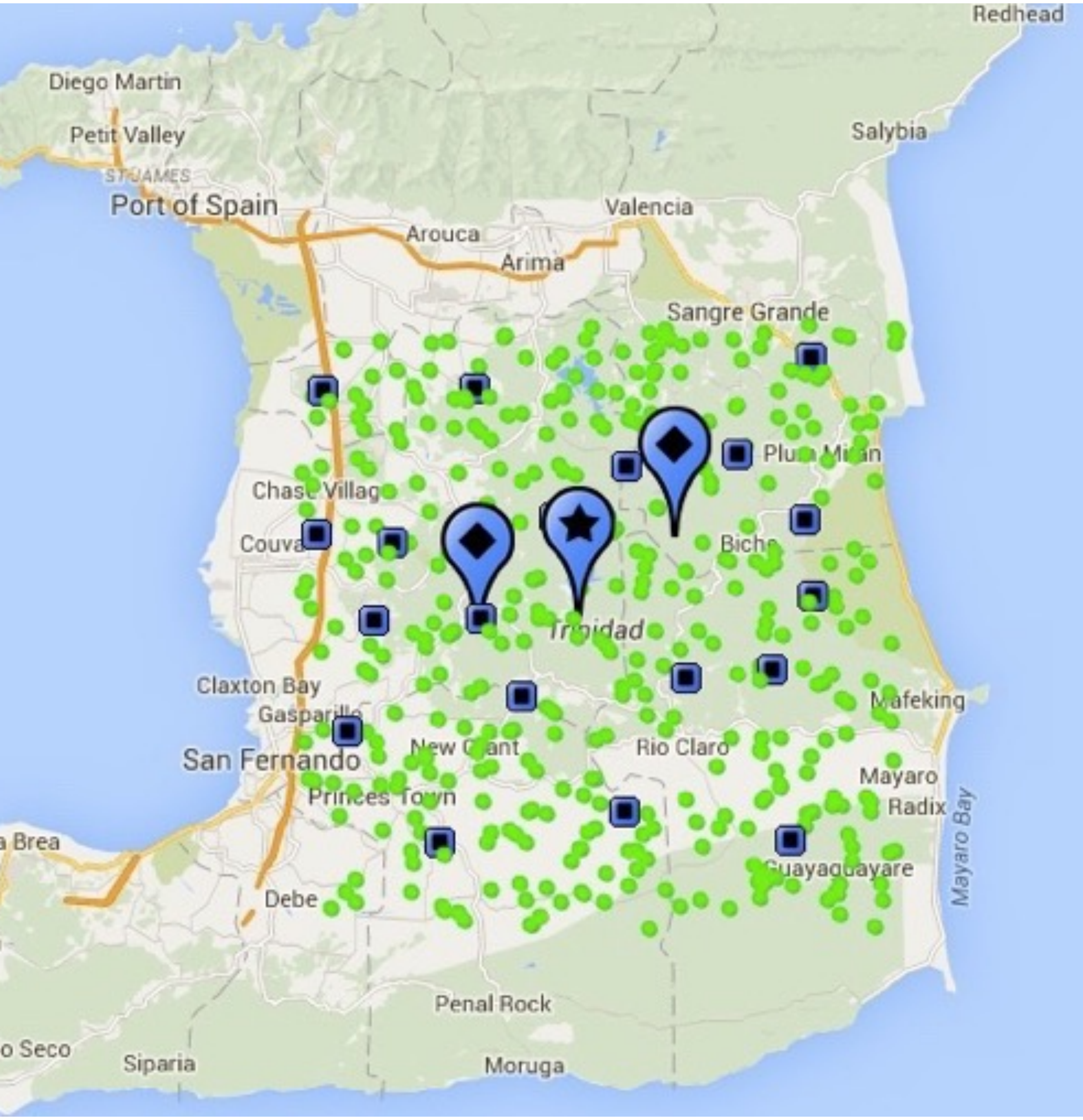
NETWORK MONITORING – AVERAGE USER OUTAGE (PER HOUR)

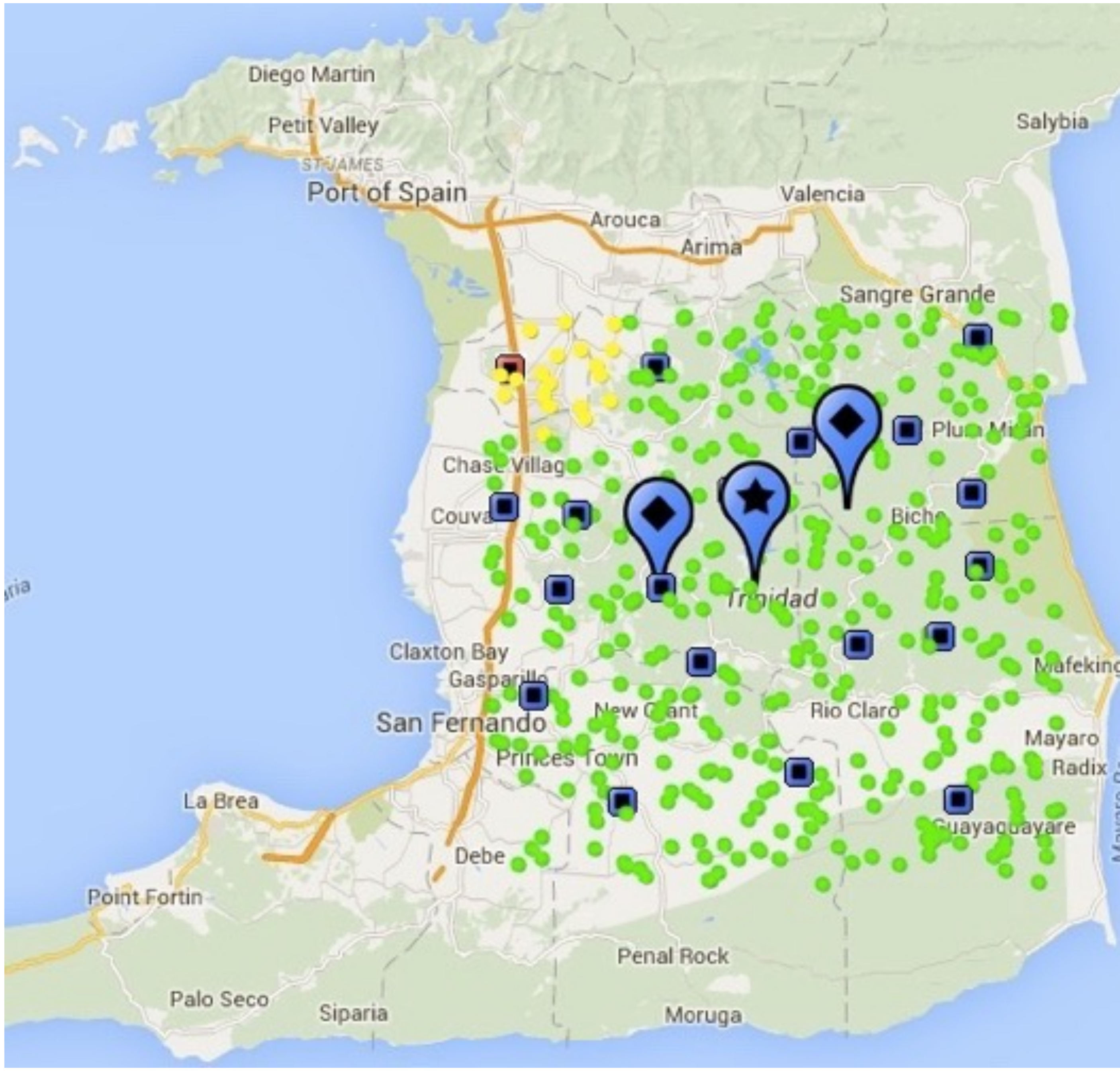


NETWORK MONITORING – HEALTH OF THE NETWORK

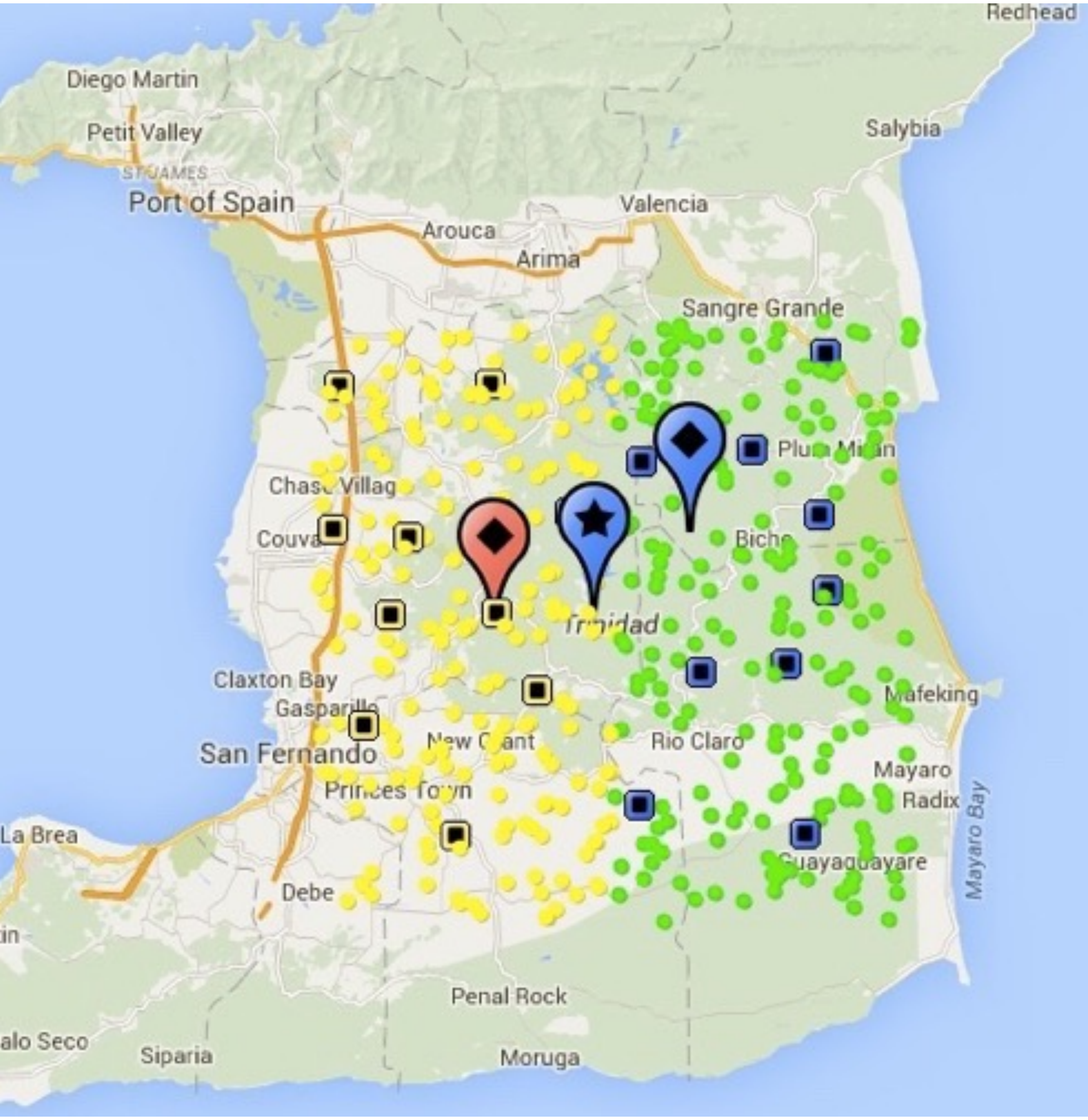


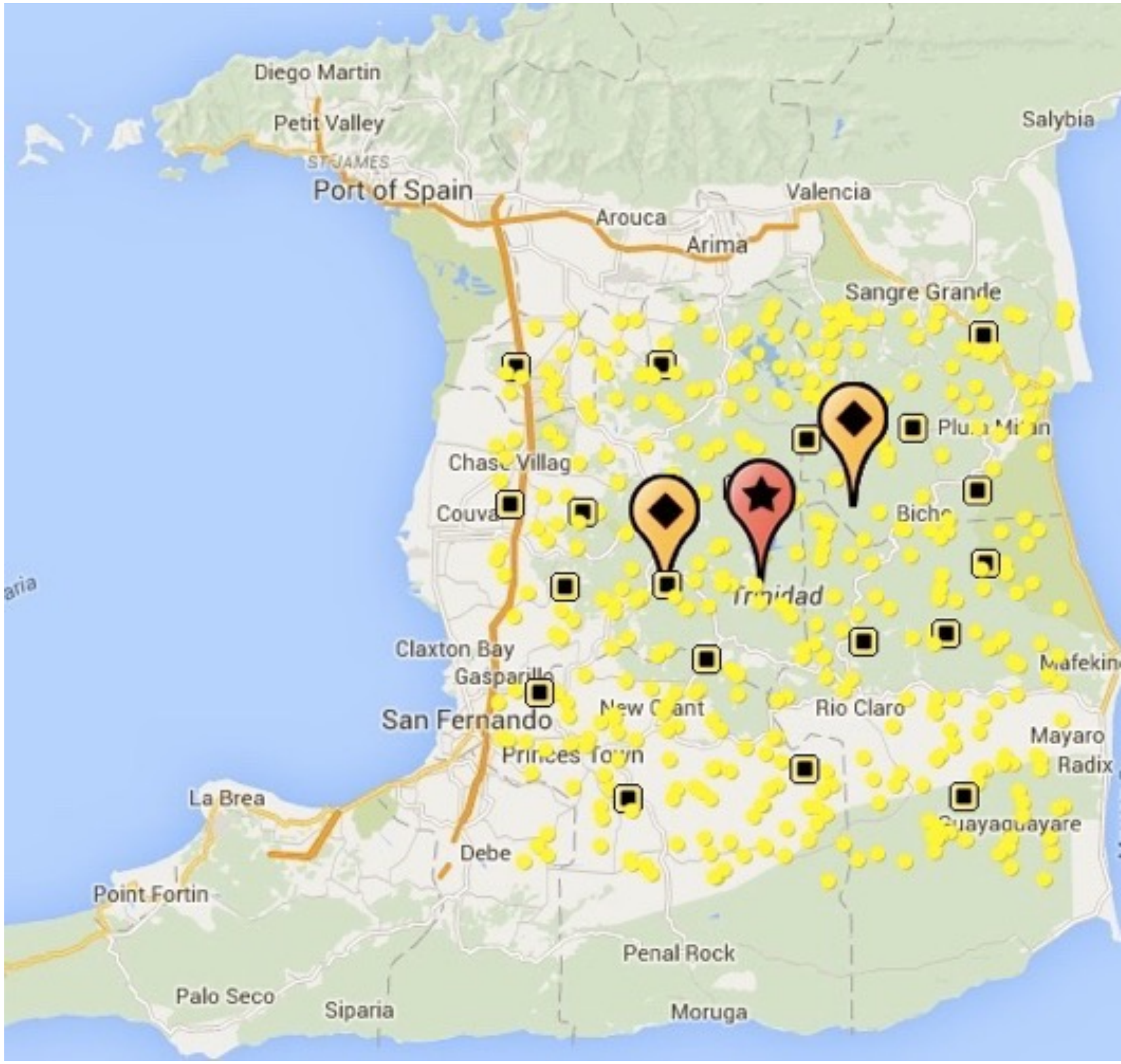
POWER GRID FAULT DETECTION



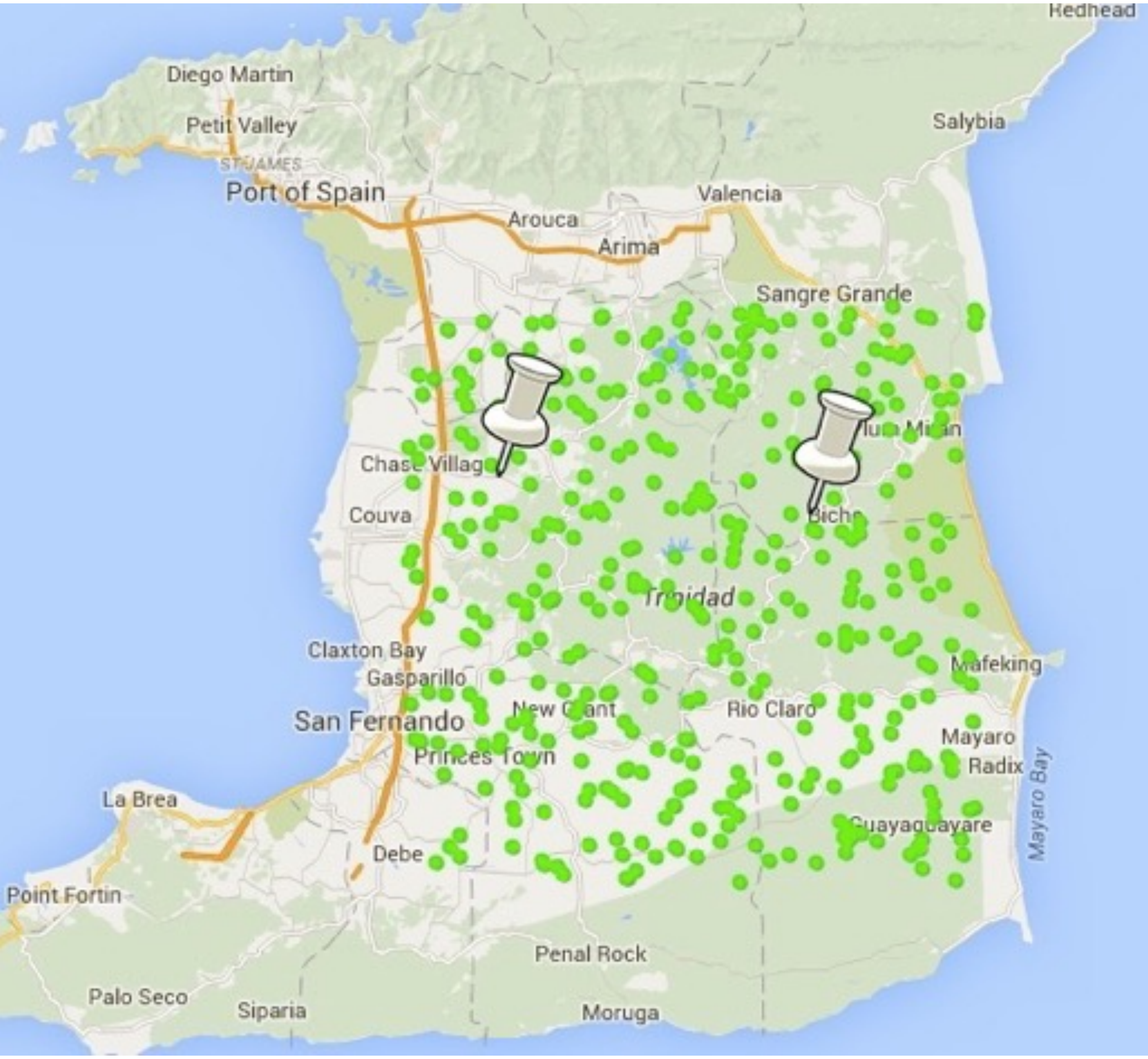


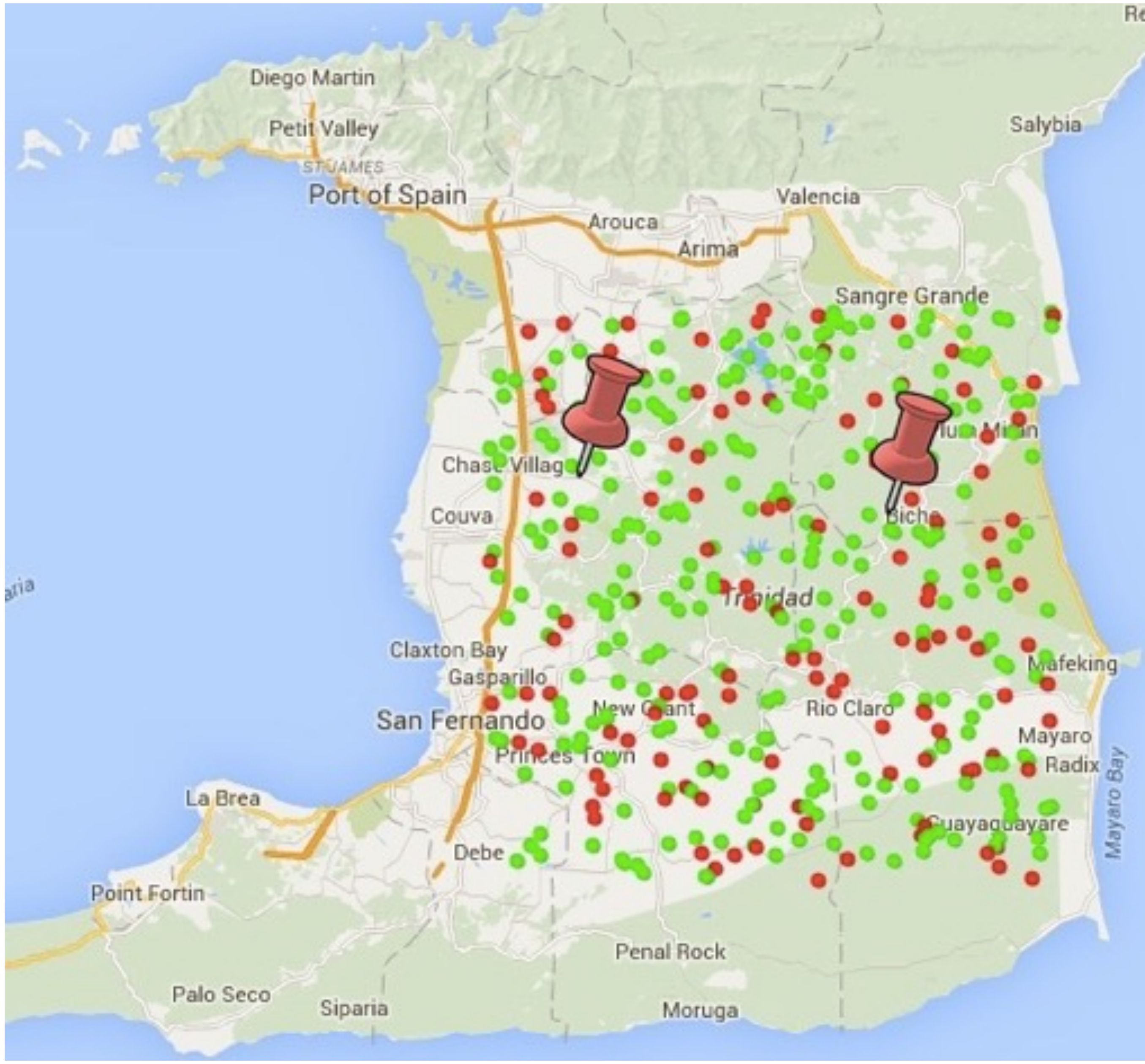
POWER GRID FAULT DETECTION





CCU MONITORING





STEFAN HOSEIN

DEEP LEARNING FOR SHORT-TERM LOAD FORECASTING

INTRODUCTION

- Short-term electricity demand prediction is of great importance to electrical companies since it is required to ensure adequate capacity when needed and, in some cases, it is needed to estimate the supply of raw material (e.g., natural gas) required to produce the required capacity.
- The deregulation of the power industry in many countries has magnified the importance of this need. Research in this area has included the use of shallow neural networks and other machine learning algorithms to solve this problem.
- Recent results in other areas, such as Computer Vision and Speech Recognition, have shown great promise for Deep Neural Networks (DNN). Unfortunately, far less research exists on the application of DNN to short-term load forecasting.

TRADITIONAL METHODS USED

- Weighted Moving Average (WMA).
- Linear and quadratic Regression (LR, QR).
- Support Vector Regression (SVR)
- Multi-layer Perceptron (MLP)

DEEP METHODS USED

- Deep Neural Network without pre-training (DNN-W).
- Deep Neural Network with pre-training with stacked auto encoders (DNN-SA).
- Recurrent Neural Network (RNN)
- Recurrent Neural Network - Long Short Term Memory (RNN-LSTM)
- Convolutional Neural Network (CNN)
- Convolutional Neural Network - Long Short Term Memory (CNN-LSTM)

MEAN ABSOLUTE PERCENTAGE ERROR

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \widehat{y_t}|}{y_t}$$

where n is the number of data points, t is the particular time step, y_t is the target or actual value and $\widehat{y_t}$ is the predicted value.

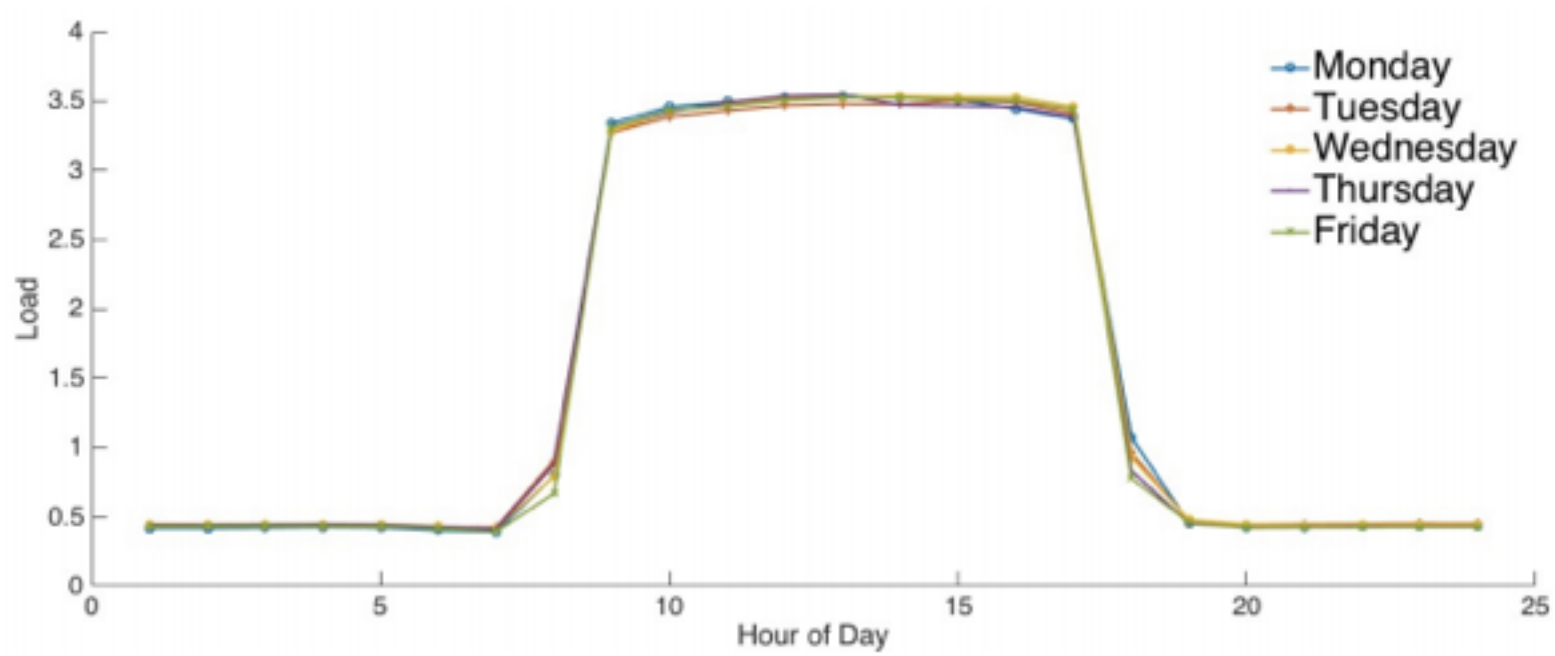
BASELINE ALGORITHMS

Algorithm	MAPE	Runtime (s)
WMA	9.51	100
MLR	24.25	1
MQR	12.91	7
RT	**7.23**	15
SVR	13.65	19

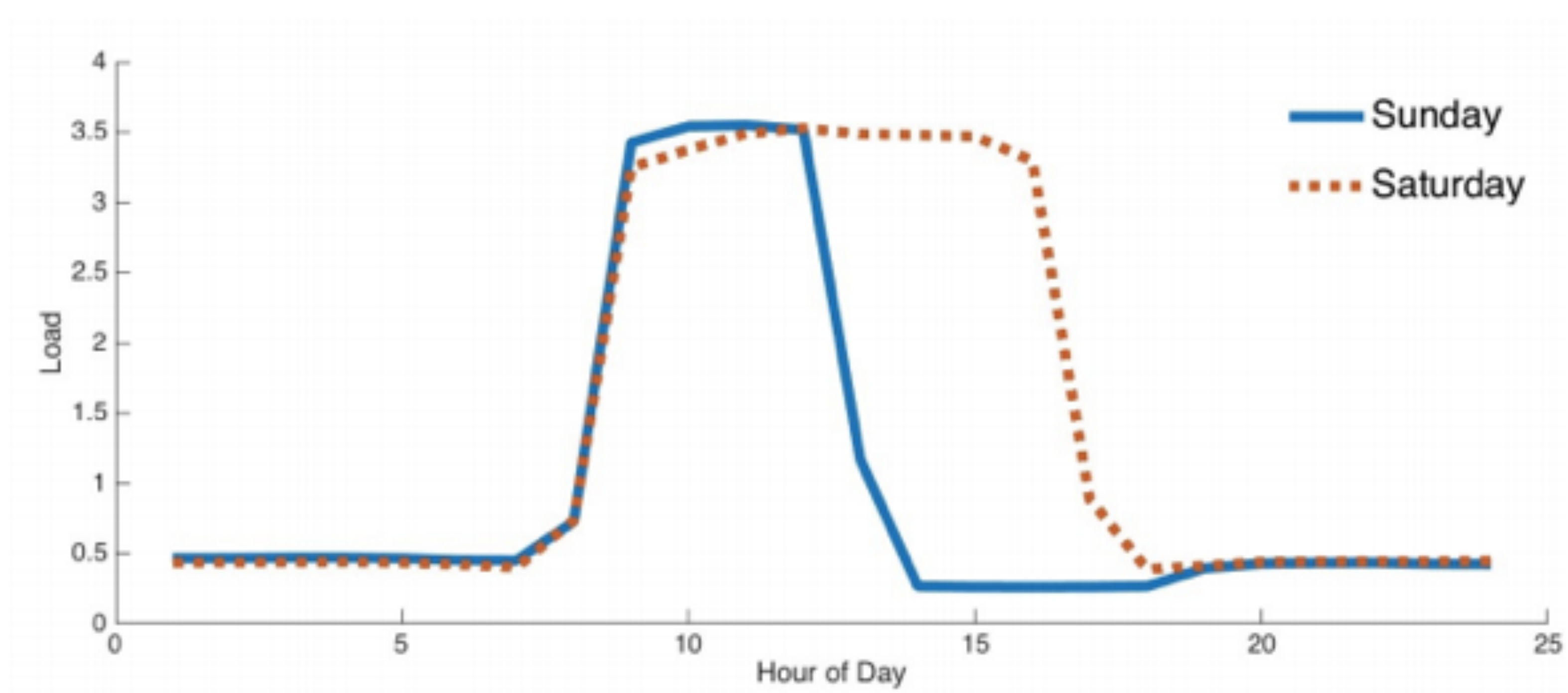
DEEP NEURAL NETWORK ALGORITHMS

Algorithm	200 Epocs		400 Epocs	
	MAPE	Runtime (s)	MAPE	Runtime (s)
MLP	5.62	14	4.55	25
DNN-W_3	**2.64**	30	2.50	56
DNN-W_4	5.71	37	5.48	72
DNN-W_5	4.40	38	5.98	69
DNN-SA_3	2.82	23	2.01	25
DNN-SA_4	2.89	29	2.37	42
DNN-SA_5	2.92	37	1.84	49
RNN	5.23	174	5.13	359
RNN-LSTM	5.33	880	5.26	1528
CNN-LSTM	10.81	1029	6.43	1912
CNN	3.15	799	**1.67**	1188

ELECTRICAL PROFILES



(a) Weekday Electrical Usage



DAILY MAPE VALUES

Algorithm	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
WMA	5.71	10.05	8.87	10.24	10.74	10.37	10.67
MLR	65.46	27.61	12.55	11.39	9.01	9.38	35.59
MQR	1.17	11.92	9.88	14.24	14.11	17.11	13.24
RT	7.45	5.99	7.63	7.37	5.98	7.26	8.87
SVR	20.70	12.96	10.73	11.53	11.63	10.90	17.40
MLP	5.18	4.62	4.43	4.27	4.31	4.70	4.34
DNN-W_3	2.95	1.88	2.12	2.49	2.54	2.46	3.12
DNN-W_4	6.67	5.45	5.25	4.88	4.61	5.65	5.83
DNN-W_5	7.23	5.53	5.56	6.14	6.13	5.81	5.48
DNN-SA_3	2.29	1.84	1.76	1.97	1.87	2.03	2.35
DNN-SA_4	2.67	2.19	2.00	2.14	2.27	2.55	2.82
DNN-SA_5	2.28	1.47	1.63	1.93	1.60	1.76	2.22
RNN	5.38	5.30	4.41	5.14	5.11	5.35	5.45
RNN-LSTM	4.25	4.34	4.96	4.55	5.64	6.97	6.13
CNN-LSTM	7.79	6.86	6.04	6.05	5.65	6.44	6.21
CNN	1.86	1.62	1.46	1.68	1.59	1.59	1.89

WEEKDAY AND WEEKEND MAPE

Algorithm	Weekday		Weekend	
	MAPE	Runtime (s)	MAPE	Runtime (s)
RT	7.62	11	5.70	7
WMA	9.78	104	8.11	116
DNN-SA_5	**2.63**	38	**4.66**	25
CNN	3.54	857	6.82	360