Inferring Energy Consumption Patterns in Public Buildings

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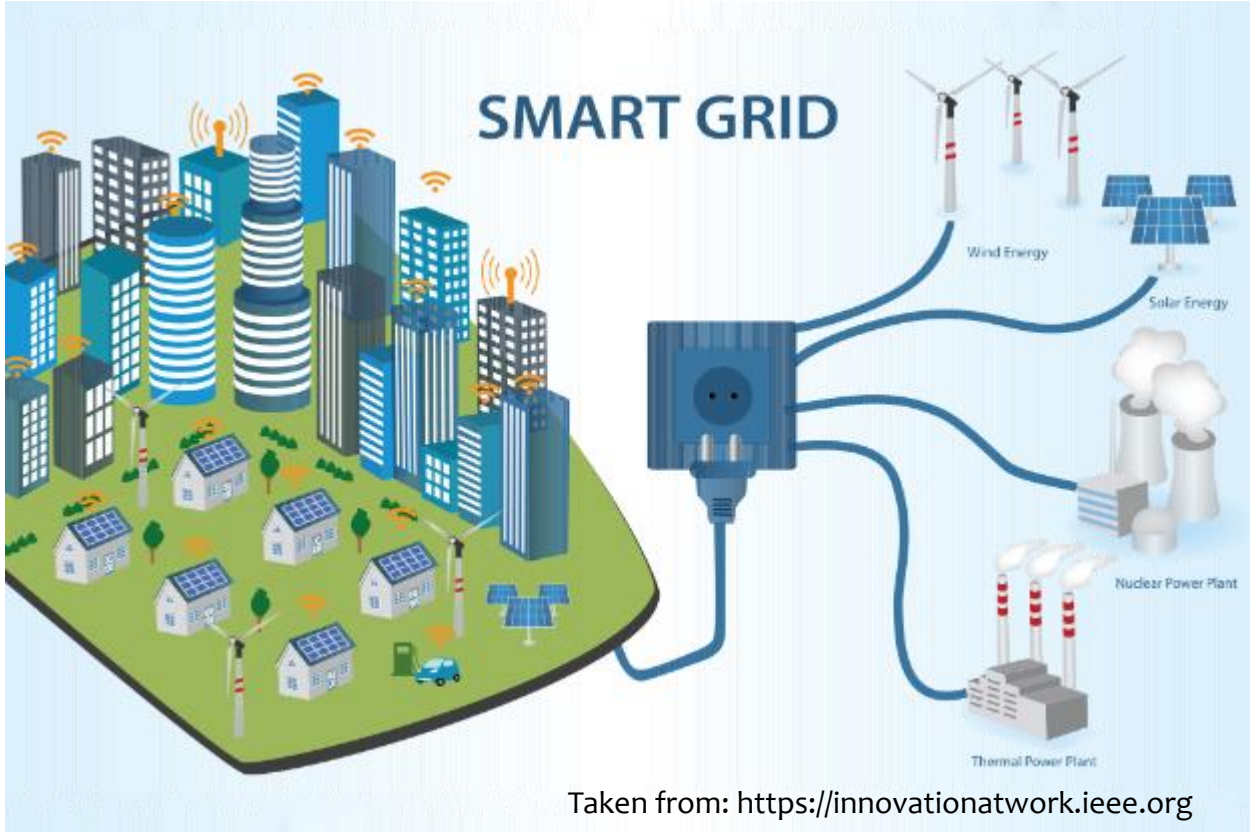
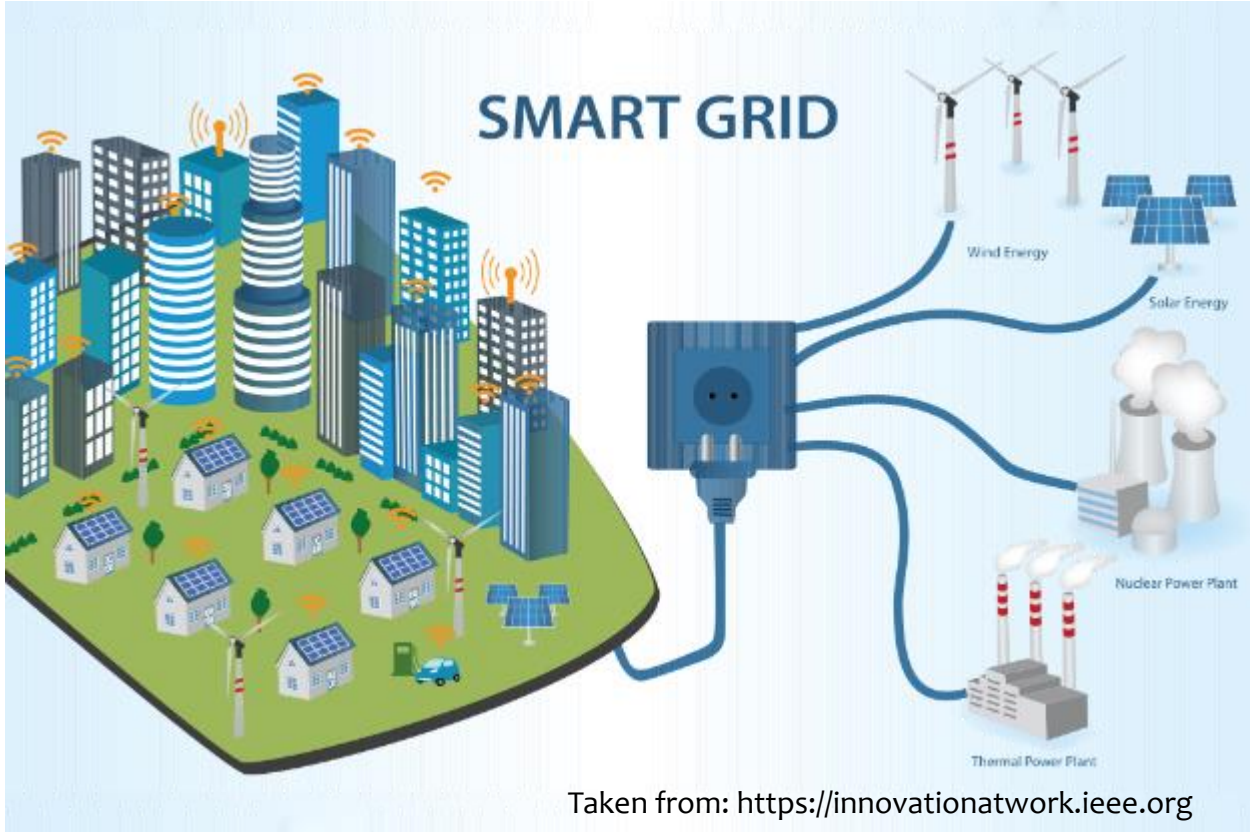
Smart Grid (I)



Taken from: https://innovationatwork.ieee.org

A new paradigm that combines electric networks and communication networks to obtain an unified system with higher capabilities than the old energy networks

Smart Grid (II)



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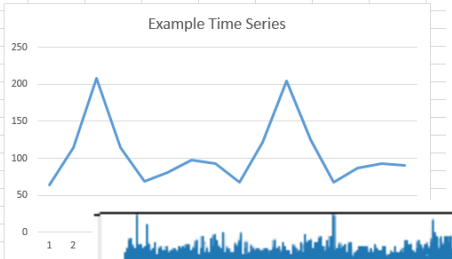
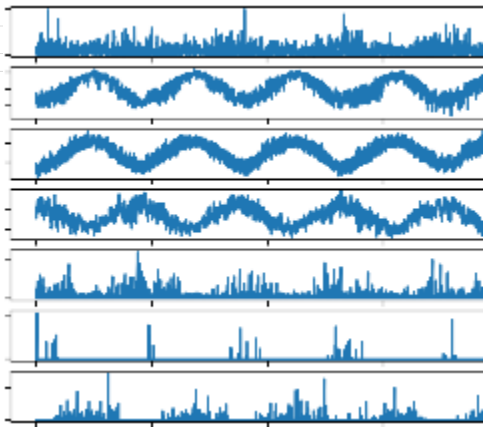
Users & providers: consumption monitoring to detect unusual readings because of

- Natural factors
- Technical problems
- Security attacks

Our approach

T_t	C_t (p=8)	S_t (p=4)	N_t	Y_t
100	1	0.6	1.06	63.6
101	1.2	1	0.94	113.928
102	1.4	1.4	1.04	207.9168
103	1.2	1	0.93	114.948
104	1	0.6	1.1	68.64
105	0.8	1	0.96	80.64
106	0.6	1.4	1.09	97.0536
107	0.8	1	1.09	93.304
108	1	0.6	1.04	67.392
109	1.2	1	0.93	121.644
110	1.4	1.4	0.95	204.82
111	1.2	1	0.94	125.208
112	1	0.6	1.01	67.872
113	0.8	1	0.96	86.784
114	0.6	1.4	0.97	92.8872
115	0.8	1	0.98	90.16





Identify consumption patterns in buildings

- Applying clustering techniques
- Applying predictive techniques

Validation:

- Data set from university buildings (UVIGO & UPC)

AtlantTIC
Universidade Vigo

Data sets

University	Num. buildings	Period	Samples/building
UVIGO	7	2013-2018	36,673
UPC	74	2011-2018	55,762

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Date	Event
25-03-2018 - 01-04-2018	Easter
01-05-2018	Labour Day
21-05-2018	Heatwave
25-07-2018	Feast of St. James
12-10-2018	National public holiday in Spain
01-11-2018	All Saints' Day

Clustering

Infer energy consumption patters for different types of buildings (administrative, labs, etc.)

- UPC database (more buildings)
- Hierarchy-based clustering: Silhouette coefficient 0.29 (very poor)
- K-means + DTW and K-shape: Silhouette coefficient 0.11 (very poor)

Manual classification of the 74 buildings (classroom, administrative, library and labs) → very similar patterns

Predictive approach

Seasonal behavior → prediction → energy consumption readings

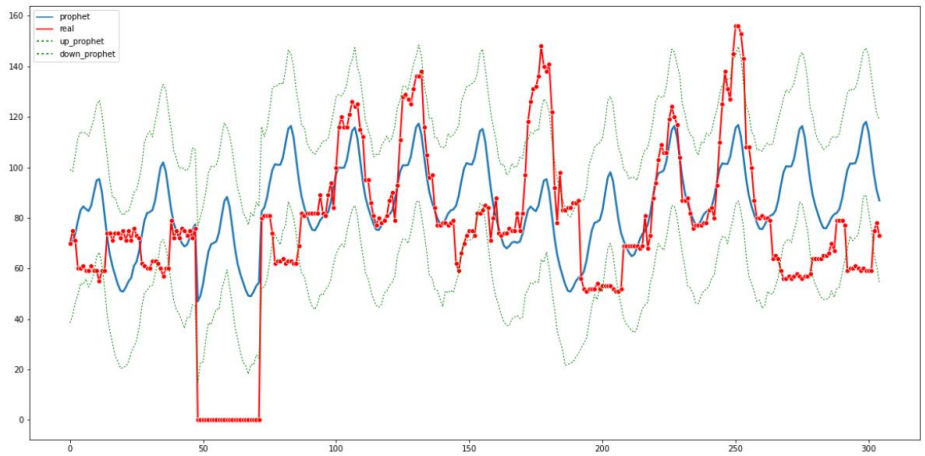
- Influence of already known anomalies (holidays): (i) first fortnight (with one day off) and (ii) second fortnight (no holidays)

- Three predictive algorithms: (i) Facebook Prophet; (ii) LSTM and (iii) XGBoost

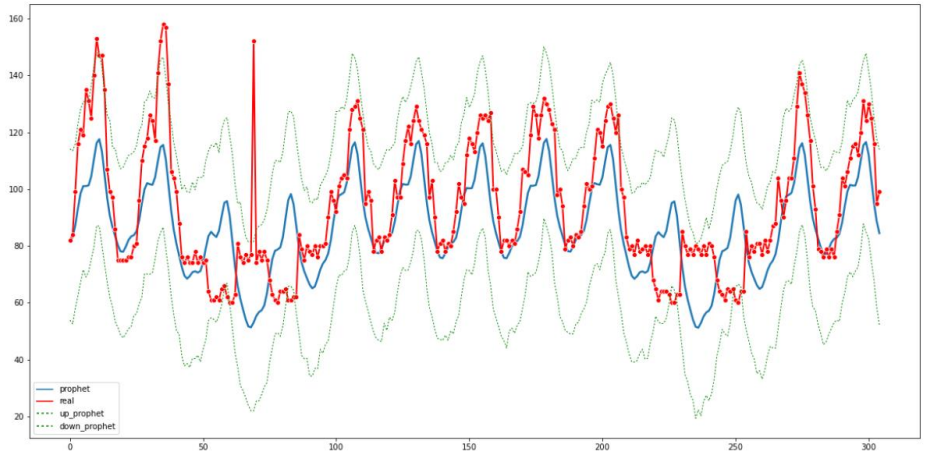
- Validation: (i) MAE, Mean Absolute Error, and (ii) RMSE, Root Mean Square Error.

Facebook Prophet

- It takes into account the holidays effect that are manually included by the users



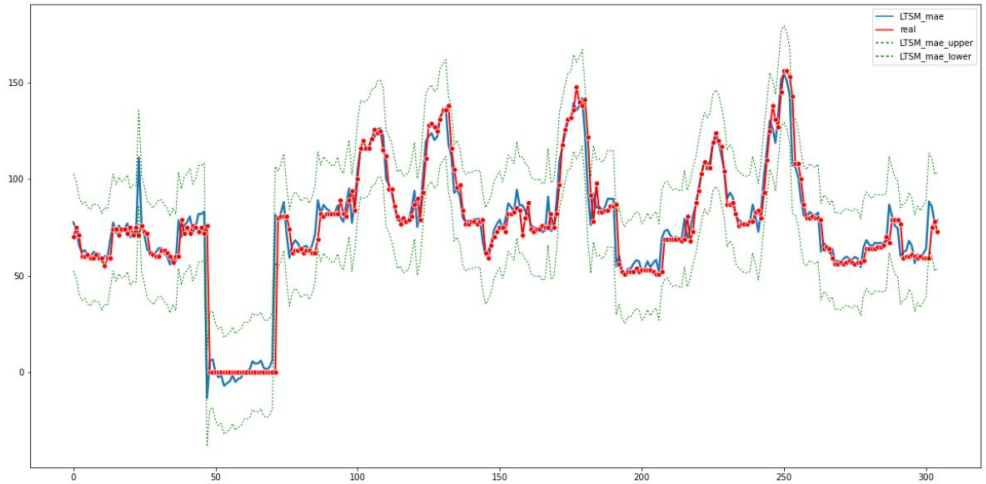
(a) First fortnight



(b) Second fortnight

LSTM prediction

- It needs a training step
- This model does not take specifically into account the holidays, since they are embedded in the training data set.



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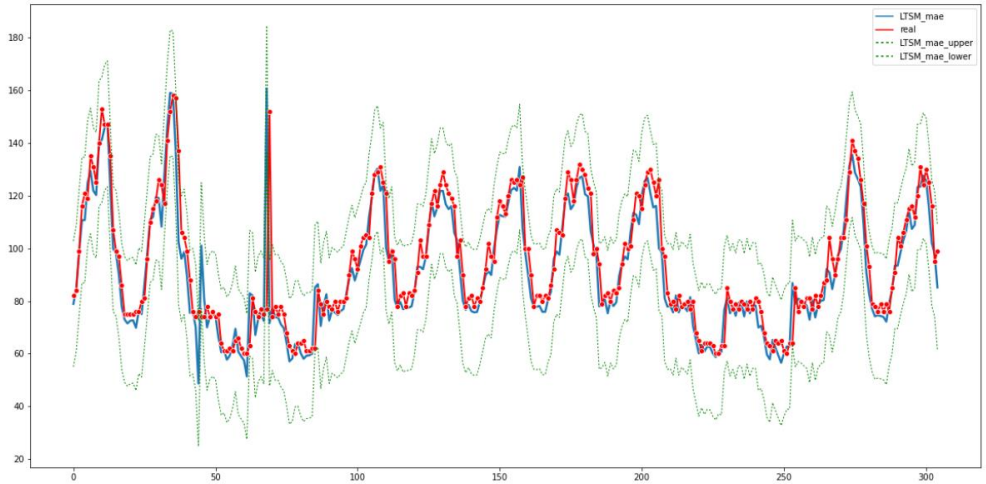
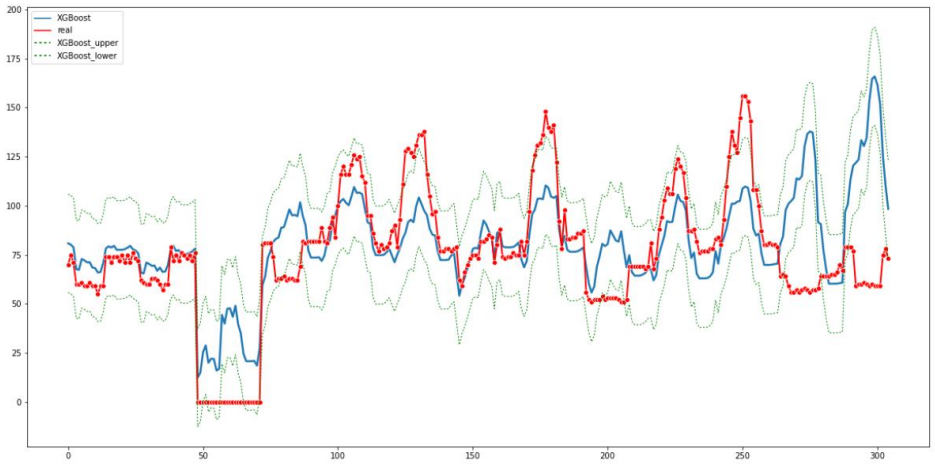


(b) Second fortnight

XGBoost

- It needs a training step to infer the weights for each feature
- The most relevant features are the hour of the day and the day of the year



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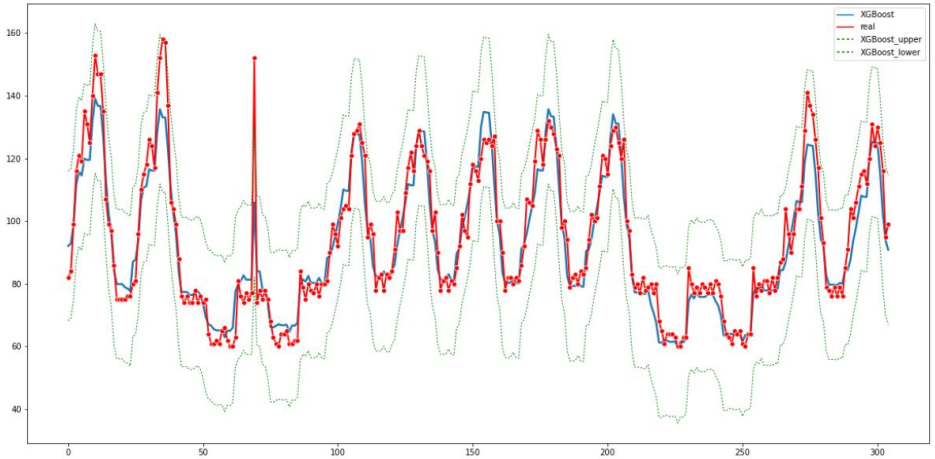
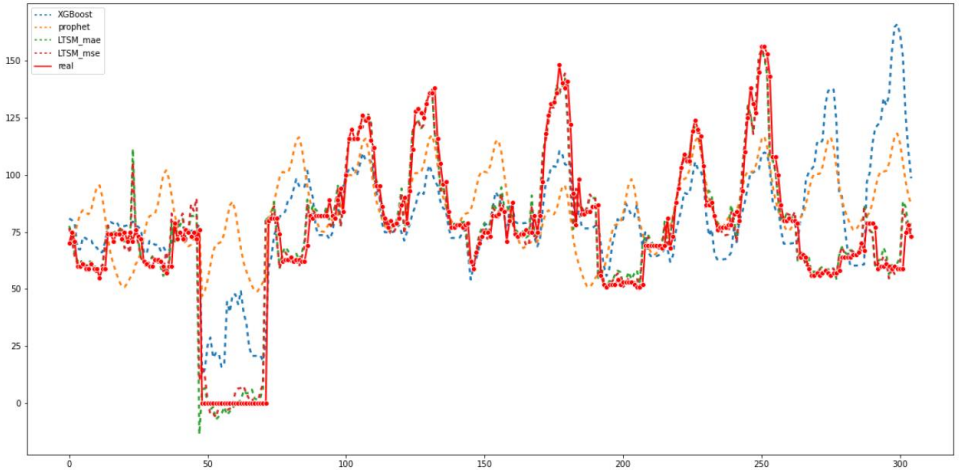


(b) Second fortnight

Comparison

(kW, second fortnight)	MAE	RMSE
Prophet	13.91	17.50
XGBoost	4.78	6.77
LTSM	5.56	9.09

(kW, first fortnight)	MAE	RMSE
Prophet	22.39	29.91
XGBoost	18.90	27.09
LTSM	5.24	9.34



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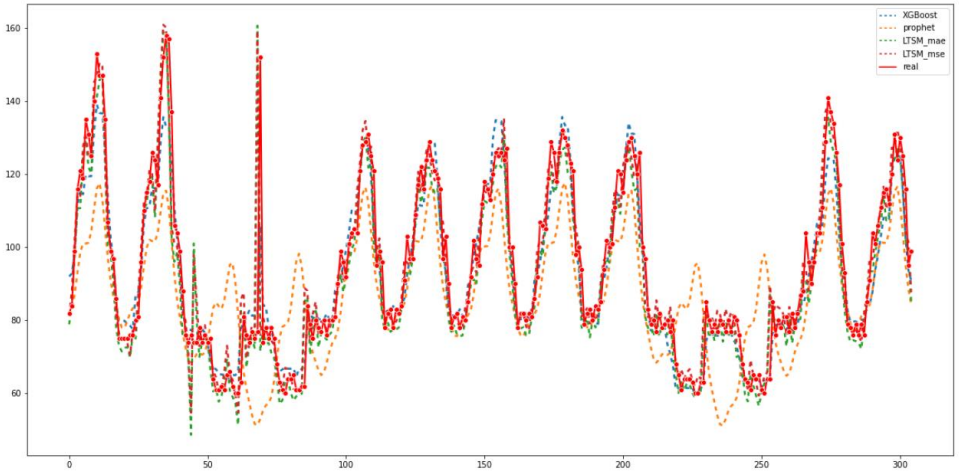

(b) Second fortnight

Conclussions & Future work

- XGBoost algorithm obtains the best performance in the scenario without holidays
- LSTM obtains the best performance when there are holidays
- Facebook Prophet algorithm is not working as desired when there are anomalies, they are not detected and, consequently, the energy pattern is not as accurate as expected

- We re currently working on providing an API that merges different approaches to track faults in the Smart Grid: (i) for obtaining energy patterns and (ii) for anomaly detection.

Thanks for your attention

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