

Fraud Patterns Detection



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Fraud in Distribution Grid

Distribution Grid Losses = Energy IN - Energy OUT

Energy IN: Energy entering the distribution network, from embedded generators or upstream, same level or downstream networks.

Energy OUT: Consumed and properly accounted energy.

Distribution Grid Losses = Technical Losses + Non-technical Losses

Technical Losses (TL): Variable losses (load related), fixed losses (not related to load) and network service (uncontracted consumptions of network equipment).

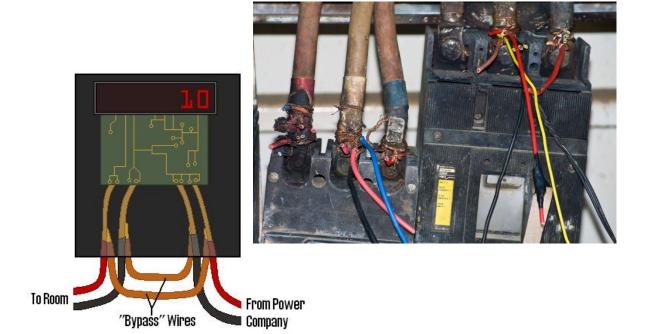
Non-technical Losses (NTL): Network equipment issues, network information issues and energy data processing issues.

Mainly theft and fraud

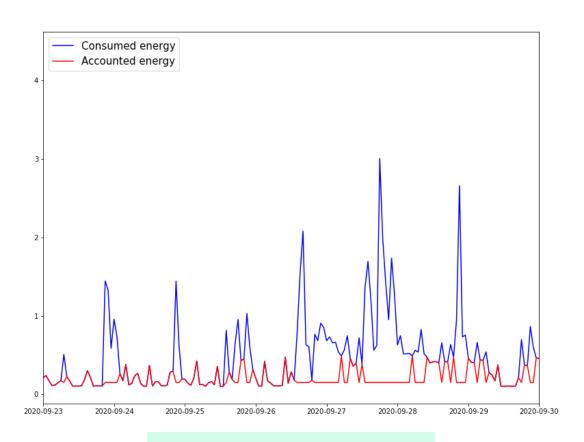
BD40PEM



Fraud in Distribution Grid







False Data Injection





How to detect this type of fraud?

- Upward trend due to SM deployment.
- Many different possibilities.
- Changes in consumption are recorded in the SM, but are more difficult to detect by the operator.
- Possible approaches:
 - Short-pattern clustering.
 - Clustering of all SMs.
- Problem: subtle changes are difficult to detect.

Types	Modification
FDI1	$\widetilde{x_t} \leftarrow \alpha \cdot x_t \text{ where } 0 < \alpha < 1$
I DII	α : same for all reports
	$\widetilde{x_t} \leftarrow f\left(x_t\right)$
EDIA	$f(x_t) = \begin{cases} x_t & \text{if } x_t \le c \\ \widetilde{c} & \text{if } x_t > c \end{cases}$
FDI2	c if $x_t > c$
	c: cut-off point
	$c_{min} < \widetilde{c} < c$: randomly defined
FDI3	$\widetilde{x}_t \leftarrow \max\left(x_t - c, 0\right)$
11013	c: fixed value in kWh
FDI4	$\widetilde{x_t} \leftarrow f(t) \cdot x_t$
	$f(t) = \begin{cases} 0 & \text{if } t_i < t < t_f \\ 1 & \text{otherwise} \end{cases}$
	f(t) = 1 otherwise
	$t_f - t_f$: randomly defined each day $\widetilde{x_t} \leftarrow \alpha_t \cdot x_t$ where $0 < \alpha_t < 1$
FDI5	
LDIS	α_t : randomly defined for each report
	$\widetilde{x_t} \leftarrow \alpha_t \cdot \overline{x_t}$ where $0 < \alpha_t < 1$
FDI6	\bar{x} : average consumption of previous month
	α_t : randomly defined for each report

FDI examples [2]

Correlation between SM consumption and NTL curve can help with this.



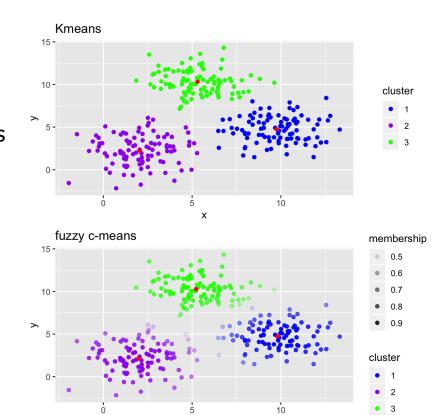


Clustering

Division of the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups. Unsupervised learning.

Features used: Mean, Median, Std, Max, Min, Mean P1 (0-8h), Mean P2 (8-16h), Mean P3 (16-24h), number of times the consumption crosses the average, steep rise, steep descent, peaks average.

Algorithms used: K-Means and Fuzzy C-Means with Euclidean Distance.



K-Means vs. Fuzzy C-Means. [3]

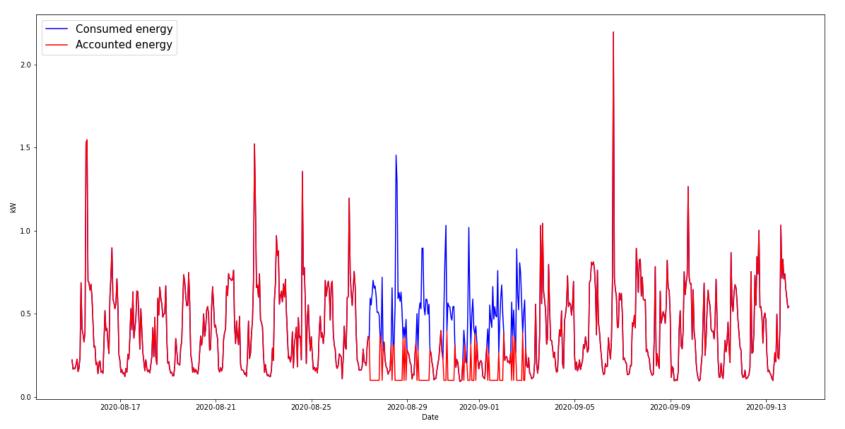
Why is Fuzzy C-Means interesting?





FDI 2* – Examples

A. LGZ003XXX648



$$f(x_t) = \begin{cases} x_t & if & x_t \le TH \\ c & if & x_t > TH \end{cases}$$

$$TH = 0.4 \text{ kW}$$

$$C = 0.1 \text{ kW}$$

Period of fraud:

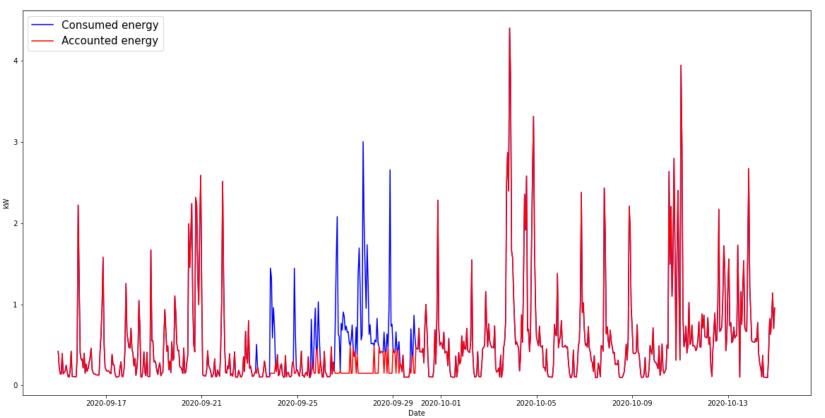
27/08/2020 - 02/09/2020





FDI 2* – Examples

B. SAG01XXX64



$$f(x_t) = \begin{cases} x_t & if & x_t \le TH \\ c & if & x_t > TH \end{cases}$$

TH = 0.5 kW

C = 0.15 kW

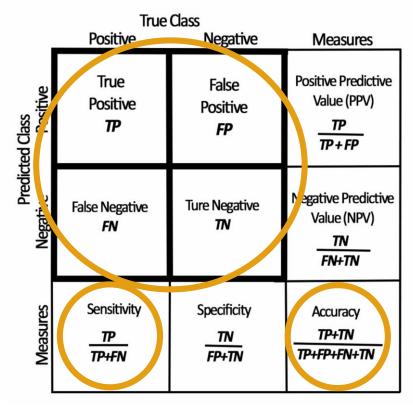
Period of fraud:

23/09/2020 - 30/09/2020

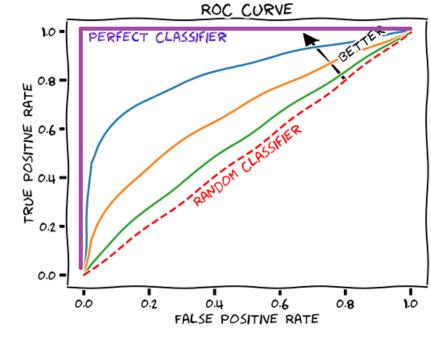




KPIs Used



Binary classification KPIs. [4]



AUC-ROC curve. [5]



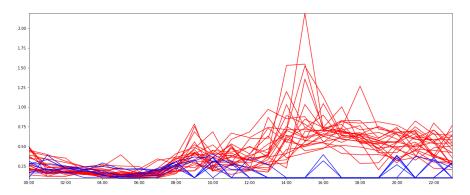


Results - A. LGZ003XXX648

K-Means

		True Class	
		Positive	Negative
d Class	Positive	7	0
Predicted Class	Negative	0	23

$$Accuracy = 1$$

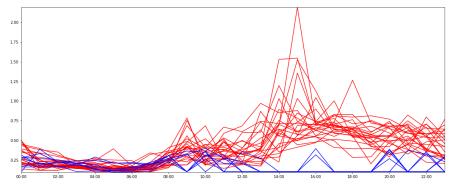


Fuzzy C-Means

		True Class	
		Positive	Negative
d Class	Positive	7	0
Predicted Class	Negative	0	23

Fraud Membership =
$$0.5$$

$$Accuracy = 1$$



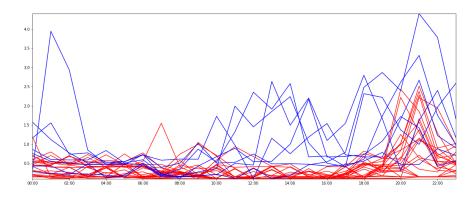


Results - B. SAG01XXX64

K-Means

		True	Class
		Positive	Negative
ed Class	Positive	7	16
Predicted Class	Negative	0	7

Accuracy =
$$0,47$$



OQ: How should we define the fraud membership degree in order to optimize the clustering?

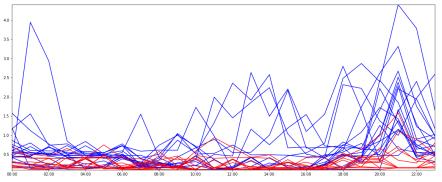


Fuzzy C-Means

		True Class	
		Positive	Negative
ed Class	Positive	7	5
Predicted Class	Negative	0	18

Fraud Membership =
$$0.85$$

Accuracy =
$$0.83$$







Ethical Questions of the Service

- AI ethics is a field of increasing relevance.
- Generally, in technical services, it might not be taken into account.
- Fraud Detection involves people, so social aspects are also part of the service.

OQ: Should geospatial data be included to predict frauds? Location is closely related to wealth and race - danger of malicious feedback loop.

OQ: Why are these frauds happening? Not all of them should be considered the same – energy poverty shouldn't be criminalized.



Thank you for your attention



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