

Original Research Paper

Evaluation of Customer Behaviour Irregularities in Cameroon Electricity Network using Support Vector Machine

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Abstract: Non-Technical Losses (NTLs) in the Cameroonians electricity network are approximately 30 to 40% of production and are estimated at several billion CFA francs per year for National Electricity Company (ENEO); Hence the importance of finding effective solutions to fight against these losses. The purpose of this work was to develop a tool for the fraud detection for Cameroon National Electricity Company (ENEO) using support vector machines which consisted in data preprocessing base on the load profile, development of a model for classification, parameter optimization and detection of customers irregularities and prediction.

Keywords: Fraud Detection, Support Vector Machine, Load Profile, Irregularities, Prediction

Introduction

In Cameroon, the Cameroon National Electricity Company (ENEO) is the only electricity company with nearly one million subscribers. To this figure, it is now necessary to add people and groups who clandestinely connect to the low voltage network or who defraud by illegally handling the meters. The number of these clients of a different kind remains uncertain and difficult to define in an urban and peri-urban. They are characterized by anarchy and spontaneous habitat, a place of preference for wild and clandestine electrical connections. The losses are amount to several billions of CFA francs each year and represent a real technical and economic headache for ENEO distribution department. According to information gathered from the Inter-employer grouping of Cameroon, (GICAM): "The demand of electric power of the companies grows of 8% each year while the supply progresses barely of 2%. Since 2003, the difficulties of supplying electricity have caused losses estimated at more than 60 billion FCFA for ENEO, more than one point of the annual growth rate of the country". For this proposal, Cameroon's economic program for 2020 is to increase energy production from 1337 MW currently to 3000 MW. The objective is not only to fill the national deficit but also to export electricity. In order to absorb energy deficit, Cameroon is engaged in several projects such as:

- The Dibamba Power Developer Company, responsible for the production of electricity from a

thermal power plant with a capacity of 86 Megawatts

- Construction of the reservoir dam of Lom Pangar in the Department of Lom and Djerem with a production capacity of 30 Megawatts
- Construction of Memve'ele Hydroelectric Generating Station on the Ntem in the Southern Region with a capacity of 201 Megawatts
- Construction of the Mekin Hydroelectric Dam with a production capacity of 15 Megawatts
- Construction of a gas-fired power plant in Kribi in the Ocean department, with a capacity of 216 Megawatts extensible to 300 Megawatts
- The commissioning of the emergency thermal program through the installation of thermal power stations in the cities of Bamenda, Ebolowa, Mbalmayo and Yaoundé. These plants operate with light fuel oil and have a total capacity of 100 MW, i.e., 20 MW in Bamenda, 10 MW in Mbalmayo, 10 MW in Ebolowa and 60 MW in Yaoundé (Ahala)

The research question of this study is, how can we improve the supply, availability and quality of electricity in Cameroon by reducing non-technical losses in the Cameroon distribution network? And the Objective of the research to provide to the national electricity companies a reliable tool based on the use of Support Vector Machines (SVM) for the search non-technical losses in the distribution network, in order to eradicate fraud Distribution. Customer consumption patterns are extracted using data mining

techniques. Based on the assumption that load profiles contain abnormalities when a fraud activity occurs, SVM classifies load profiles of customers for detection of fraud suspects. This research concentrates only on scenarios where abnormal changes appear in load profiles, indicating fraudulent activities due to the unavailability of a clear database at ENEO CAMREOON for the others factors contributing to NTL activities.

Methodology

Support Vector Machine

Support Vector Machines are often translated as Large Marge separator (SVM) which is a class of learning algorithms defined for discrimination, that is to say provide variable initially binary (Nagi *et al.*, 2008a). They are based on the search for the optimal hyper plane margin, when possible, class or correctly separates the data while being far away as possible from all observations. The principle is to find a classifier, or a discrimination function, the generalization ability (quality forecast) is the largest possible (Nagi *et al.*, 2008b). That is to say, to bring the issue of discrimination in the linear, the search for an optimal hyper plane and two ideas or tricks achieve this objective (Nagi *et al.*, 2010a; 2010b):

- Define the hyper plane as a solution of a problem of constrained optimization, whose objective function is not expressed only by using scalar products between vectors
- A research nonlinear dividing surface is obtained by the introduction of a kernel function in the scalar product

As in any learning situation, a variable Y is considered to predict but to simplify this basic introduction, we supposed it dichotomous with values $\{-1, 1\}$:

$$\text{Let } X = X^1, \dots, X^p \quad (1)$$

Explanatory or predictor variables and $\phi(x)$ a model for Y function where:

$$x = \{x^1, \dots, x^p\} \in R^p \quad (2)$$

Generally we can simply consider the variable $\{X\}$ with values in a set.

We notice:

$$z = \{(x_1, y_1), \dots, (x_n, y_n)\} \quad (3)$$

A statistical sample size of n and law with unknown.

The objective is to build an estimation $\hat{\phi}$ of ϕ function of X in $\{-1, 1\}$ so that the probability $P(\phi(X) \neq Y)$ is supposed to be minimum.

The problem is like the search for a boundary decision in space F with value in X .

Conventionally, a compromise must be found between the complexities of the border, which can also be expressed as its ability to spray a cloud of points. So the model fit capacity and widespread anticipation of the qualities of the model (Fourie and Calmeyer, 2004).

This is equivalent to solve a problem of classification or separation as follows in Fig. 1.

This case is defined by using the scalar product of H a hyper plane by its equation:

$$f(x) = \langle w, x \rangle + b \quad (4)$$

where, w is orthogonal vector to the plane, x point to predict. This is well positioned if and only if:

$$yf(x) > 0 \quad (5)$$

A plan $(w; b)$ is a separator if:

$$y_i f(x_i) \geq 1 \quad \forall i \in \{1, \dots, n\} \quad (6)$$

and the distance from a point x to the plane $(w; b)$ is define by:

$$d(x) = \frac{|\langle w, x \rangle + b|}{\|w\|} = \frac{|f(x)|}{\|w\|} \quad (7)$$

Search the maximum margin separator plane involved in solving the quadratic problem constrained below:

$$\min_w \frac{1}{2} \|w\|^2 \text{ avec } \forall i, y_i (\langle w, x \rangle + b) \geq 1 \quad (8)$$

The dual problem is achieved by introducing Lagrange multipliers α^* and the solution is provided by a point $(w^*; b^*; \alpha^*)$ of the Lagrangian:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|_2^2 - \sum_{i=1}^n \alpha_i [y_i (\langle w, x \rangle + b) - 1] \quad (9)$$

The cancellation condition of partial derivatives of the Lagrangian allows writing:

$$w^* = \sum_{i=1}^n \alpha_i^* y_i x_i \text{ et } \sum_{i=1}^n \alpha_i^* y_i = 0 \quad (10)$$

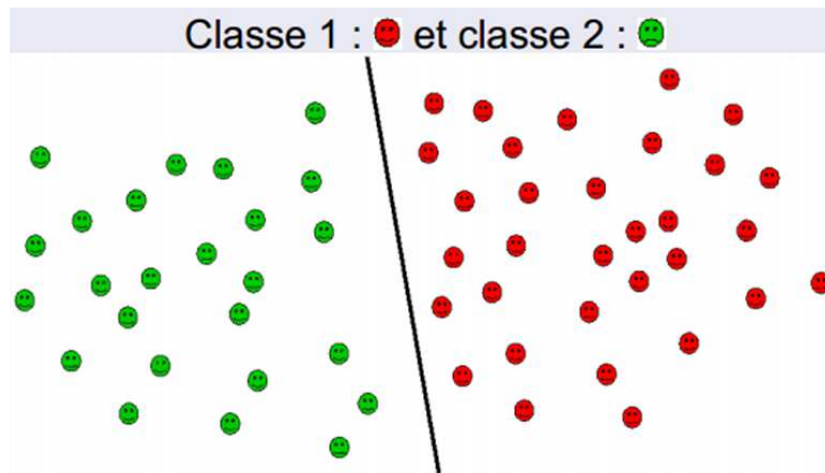


Fig. 1. Example of classification

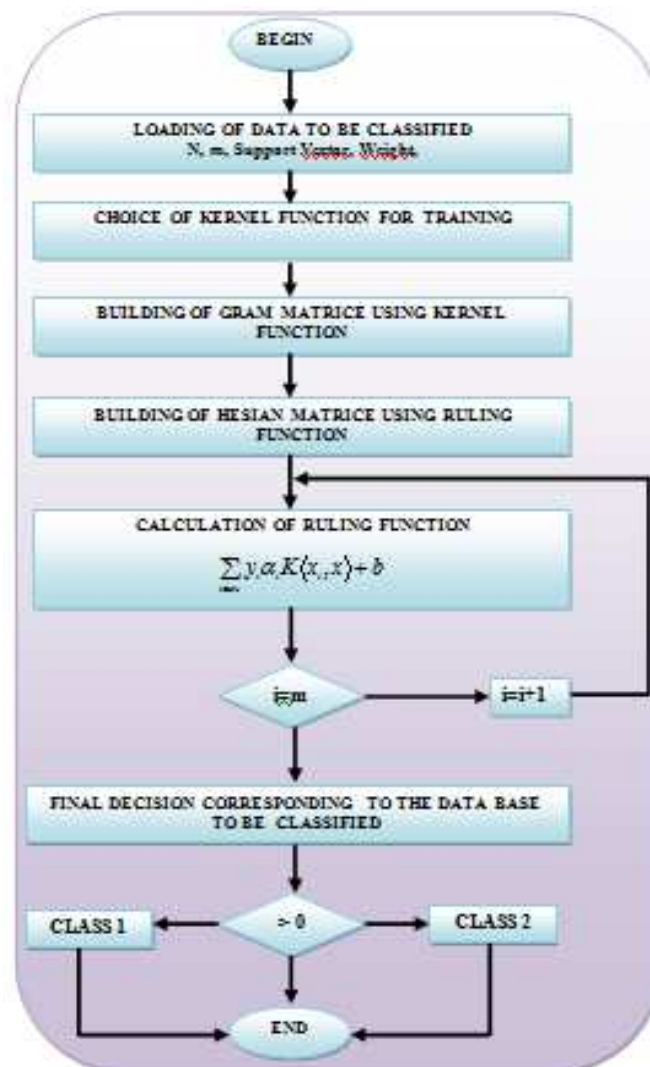


Fig. 2. Flowchart of the proposed framework for detection of NTL activities

These equality constraints allow us to express the following dual formula:

$$w(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j \langle x_i, y_j \rangle \quad (11)$$

$$\text{avec } \sum_i y_i \alpha_i = 0 \quad \forall i \in \{1, \dots, n\}, \quad 0 \leq \alpha_i \quad (12)$$

Implementation

Organization of the Method

The research methodology framework proposed in order to develop our intelligent fraud detection system for detection, identification and prediction of NTLs activities is shown in Fig. 2.

Data Acquisition

Electricity customer consumption data was obtained from Cameroon National electricity Company (ENEO) Billing system. The data base consisted of 62 000 customers for a period of 12 months (From January to December 2014) as is shown in Fig. 3 for the central region commercial unit.

But others factors contributing to NTL activities which we did not use in this work due to the unavailability of a clear database at ENEO CAMREOON such as:

- Unauthorized line tapping; tampering with meters so that meters record lower rates of consumption
- Unauthorized line diversions; stealing by bypassing meters or otherwise making illegal connections
- Inadequacies and inaccuracies of meter reading

- Inaccurate customer electricity billing
- Poor revenue collection techniques
- Arranging billing irregularities with the help of internal employees, such as making out lower bills and adjusting decimal point position on bills
- Non-payment of electricity bills
- Losses due to faulty meters and equipment
- Loss or damage of equipment/hardware that is, protective equipment, cables, conductors, switchgear etc
- Inaccurate estimation of non-metered supplies that is public lightning, agricultural consumption, rail traction etc
- In efficiency of business and technology management systems

Although some electrical power loss is inevitable, steps can be taken to ensure that it is minimized. Several measures have been applied to this end, including those based on technology and those that rely on human effort and ingenuity. Among the factors contributing to NTL activities, NTLs based on the components identified are listed in Table 1.

In the majority of factors contributing to NTL activities as indicated in Table 1, electricity customers intentionally avoid paying their bills or are involved in pilferage, theft and unauthorized use. Therefore, the intention of the present study is to focus on detecting and identifying NTL activities in the distribution network where deviations in customer behavior exist. That why, in this research, the approach is a method of data mining using support vector's machine in orders to extract patterns of customer behavior from historical consumption data base in a load profile.

Table 1. Among factors of NTLs

Components	Power utilities	Electricity customers
Meter	Inadequacies and inaccuracies in meter reading.	Unauthorized line tapping and diversion.
	Losses due to faulty meters and equipment.	Stealing by bypassing meters or otherwise making illegal connections.
	Inadequate or faulty metering.	Tampering with meters to ensure meters record lower rates of consumption.
	Loss and damage of equipment/hardware, that is, protective equipment, cables, conductors, switchgear etc.	Faulty meters not reported
Bills	Inaccurate customer electricity billing.	Non-payment of electricity bills.
	Inefficiency of business and Technology management system.	Arranging billing irregularities with the help of internal employees.
	Arranging billing irregularities with the help of internal employees.	Arranging false readings by bribing meter readers.
	Poor revenue collection techniques.	Inaccurate estimation of non-metered supplies, that is, public lighting, agricultural consumption, rail traction etc.
	Making out lower bills, adjusting the decimal point position on bills.	Ignoring to pay bills

NAME	activite_terrain	METER_NUMBER	SUPPLY_REF	STATUS	CONSUMPTION_M	CONSUMPTION_M	CONSUMPTION_M_COI
CLIENT1	Etablissement Administratif	8962242	802-07-03-016-00-02	ACTIVE	76187	52642	52492
CLIENT2	Activités commerciales en contair	1301703175	806-02-21-090-00-01	ACTIVE	0	19405	17257
CLIENT3	Boutique	0924100004832	808-03-20-048-00-03	ACTIVE			
CLIENT4		1200506718	804-10-46-654-00-03	ACTIVE	0	23646	11823
CLIENT5		74522585	802-10-01-041-00-02	ACTIVE	19630	21596	21679
CLIENT6	Bureaux	74522594	806-11-20-003-00-01	ACTIVE	0	15248	14386
CLIENT7		1201101751	806-02-14-013-00-023	ACTIVE	23815	17263	23556
CLIENT8	Bureaux	CT200600061753	806-11-24-004-00-01	ACTIVE	24849	15301	17005
CLIENT9	Etablissement Administratif	CT200600061525	802-04-14-206-00-01	ACTIVE	17727	17433	18584
CLIENT10	Bureaux	8983482	806-03-06-347-00-01	ACTIVE	16374	16737	17820
CLIENT11		8973090	808-02-10-133-00-031	ACTIVE	16480	13920	15000
CLIENT12	Maison d'habitation	11013385	804-03-16-096-00-01	SUSPENDED (DELINQUENT ACCOUNT)	188	105	92
CLIENT13	Boulangerie	1402443216	808-02-15-150-00-02	SUSPENDED (DELINQUENT ACCOUNT)	19300	19211	20210
CLIENT14	Poissonnerie	1301644450	803-02-01-001-00-01	ACTIVE	13660	22336	13137
CLIENT15		CT200500015688	803-01-24-101-00-01	ACTIVE	483	425	556
CLIENT16		1200506636	806-14-04-803-98-001	ACTIVE	0	468	515
CLIENT17	Maison d'habitation	0904100282470	806-04-04-003-00-02	SUSPENDED (DELINQUENT ACCOUNT)	16332	19564	15410
CLIENT18	Boulangerie	CT200600061427	802-12-20-068-00-01	SUSPENDED (DELINQUENT ACCOUNT)	16936	15718	18109
CLIENT19		CT200600061438	801-05-19-222-00-01	ACTIVE	17191	14936	16842
CLIENT20	Bureaux	1301640145	802-11-02-167-00-022	SUSPENDED (DELINQUENT ACCOUNT)	13714	12118	11410
CLIENT21		0904100284414	808-11-01-302-00-02	ACTIVE	17902	18034	18419
CLIENT22	Poissonnerie	1301639193	806-08-11-023-00-01	ACTIVE	13106	21389	10666
CLIENT23		1301650982	805-07-02-045-00-04	ACTIVE	15152	12558	11965
CLIENT24	Poissonnerie	1201108366	806-04-04-043-00-01	ACTIVE	13681	9156	11562
CLIENT25		QAT712808	806-11-13-113-00-021	SUSPENDED (DELINQUENT ACCOUNT)	3781	11090	10476
CLIENT26	Etablissement Administratif	200600061816x	802-11-02-137-00-01	ACTIVE	13020	12803	13220
CLIENT27		1402443210	802-11-06-002-00-021	ACTIVE	10907	10519	10654
CLIENT28	AI ITRFS	0804100149830	806-06-05-022-00-01	SUSPENDED (DELINQUENT ACCOUNT)	14900	14904	13745

Fig. 3. Customer consumption data from ENEO

O	P	Q	R	S	T	U	V	W	X	Y	STATUS CLIEN	
0,1612966	0,1114284	0,111111	1	FAUX	0,007233	0,0127257	0,000508	0,007233	0,012726	FAUX	suspect	
FAUX	1	0,889307	0,9470755	0,929142	0,189075	0,5810358	FAUX	0,970111	0,839784	0,80159753	normal	
FAUX	FAUX	FAUX	1	0,0031409	0	0,0660412	0,009216	0,090714	0,086829	0	normal	
FAUX	1	0,5	0,5183118	0,4621078	0,519961	0,4915842	0,4922608	0,452381	0,436903	0,41457329	normal	
0,6293813	0,9289851	0,941634	0,958062	0	1	0,7622676	0,7921365	0,550442	0,426852	0,68530936	normal	
FAUX	1	0,943468	0,8580467	0,8390609	0,756165	0,720947	0,6341159	0,536464	0,852964	0,72488195	normal	
0,9926401	0,3037535	0,965408	1	0,5423194	0,3906	0,1073494	0,2135422	0,210914	0	0,18399748	suspect	
1	0,2618477	0,393583	0,3168922	0	0,107228	0,2596057	0,1545419	0,149671	0,065868	0,08310785	suspect	
0,5027069	0,4458623	0,868407	0,386891	0,6937355	0,997486	1	0,6198763	0,043117	0	0,58758701	normal	
0,7660054	0,3969793	0,641118	0,777277	0	0,602795	0,655771	0,284716	1	0,145176	0,58205591	normal	
1	0,4764826	0,697342	0,591002	0,4744376	0,550102	0,2556237	0,1472393	0	0,145194	0,16564417	suspect	
13	1	0,1354167	0	0,9791667	0,5520833	0,135417	0,3541667	0,125	0,302083	0,302083	0,26041667	normal
14	0,7495872	0,7250963	1	0,6714364	0,8926802	0,629884	0,1703357	0,3403963	0,505228	0	0,00330215	suspect
15	0,1570338	1	0,109506	0,3199746	0,1961105	0,241458	0,2191021	0,1424936	0,220465	0,213922	0	normal
16	0,7286245	0,5130112	1	0,0297398	0	0,241636	0,1189591	0,4237918	0,204461	0,193309	0,13011152	normal
17	FAUX	0,0846906	0,925624	1	0,9087948	0,362106	0,2964169	0,3376764	0,249548	0,706659	0,39847991	normal
18	0,8654672	1	0,787671	0,8295338	0,7699857	0,855807	0,8181354	0,8697608	0,627939	0,827183	FAUX	normal
19	0,9076741	0,8118064	1	0,1575758	0,034632	0,050531	0,082015	0,0212515	0,005274	0,038882	0	normal
20	0,4969555	0,4315704	0,486836	0,4445024	0,3976746	0,345019	0,3474252	1	0,042276	0	0,00878566	suspect

Fig. 4. Data normalization

Customer Filtering, Selection and Extraction

The raw data obtained from Cameroon National electricity Company (ENEO) billing system was filtered for extraction of customer load profiles and features. Hence, data mining techniques using data base querying were applied for:

- Removing repeating customers in monthly data
- Removing customers having no consumption (0 kWh) throughout the entire 12 month period
- Removing customers who are not present within the entire 12 month period that is, removing new customers registered after the first month

Data Normalization

The load data needs to be represented using a normalized scale for the SVM classifier. Therefore, the monthly average kWh consumption feature data is normalized as follows:

$$Nindex = \frac{x_m - \min(x_m)}{\max(x_m) - \min(x_m)}$$

where, x_m represents the current kWh consumption of the customer, $\min(x_m)$ and $\max(x_m)$ represent the minimum and maximum values in the 12 months consumption

feature set as is shown in Fig. 4. Then typical load profiles of customers were then established, with each load profile being represented by the 12 normalized monthly average kWh consumption features.

Feature Adjustment

All 62 000 customers were given a label, where the labels are represented by integer values; (« 1 » for suspects Customer's and « 2 » For normal customer's). Normalized feature values with labels are represented as a LIBSVM feature file, denoted by the matrix W, in the form:

$$W = \begin{pmatrix} 1 & \dots & 1:Nindex(11) & 2:Nindex(12) & \dots & M:Nindex(1M) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 2 & \dots & 1:Nindex(n1) & 1:Nindex(n1) & \dots & 1:Nindex(nM) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 2 & \dots & 1:Nindex(m1) & 1:Nindex(m1) & \dots & 1:Nindex(nM) \end{pmatrix}$$

where, « m » Is total number of customer and « M » Is the total number of months.

Results and Discussion

Results

Graphics Interface

The graphic interface of the fraud detection system here in Fig. 5, (that is, support tool to decision making in the fight against non-technical losses in the

distribution network: Case of ENEO Cameroon) was developed and designed simple for the detection and identification of suspicious customers (customers list to check); the different buttons and their functionality are presented Table 2.

Data Base Selection

To launch the software, a given excel format based file must be selected. To select a data file, users simply click on the button "Import Customer Data", it opens a file browser in the File Browser dialog box, excel file is then selected as indicated in Fig. 6. Loading of customer data base is indicated in Fig. 7.

Implementation of Detection

Once the customer data file is selected, by clicking start, the software will run in trade detection indicated in Fig. 8. It applies all the procedures mentioned in the previous listed.

Table 2. Presentation of buttons and their functionality

Botton	Function
Browser	To choose Data Base
Start	To start classification
Unclassified	To obtain unclassified customer's list
Suspects list	To obtain suspects customer's list
Normal list	To obtain normal customer's list
Help	Provide help for the use of the software
Quit	To exit

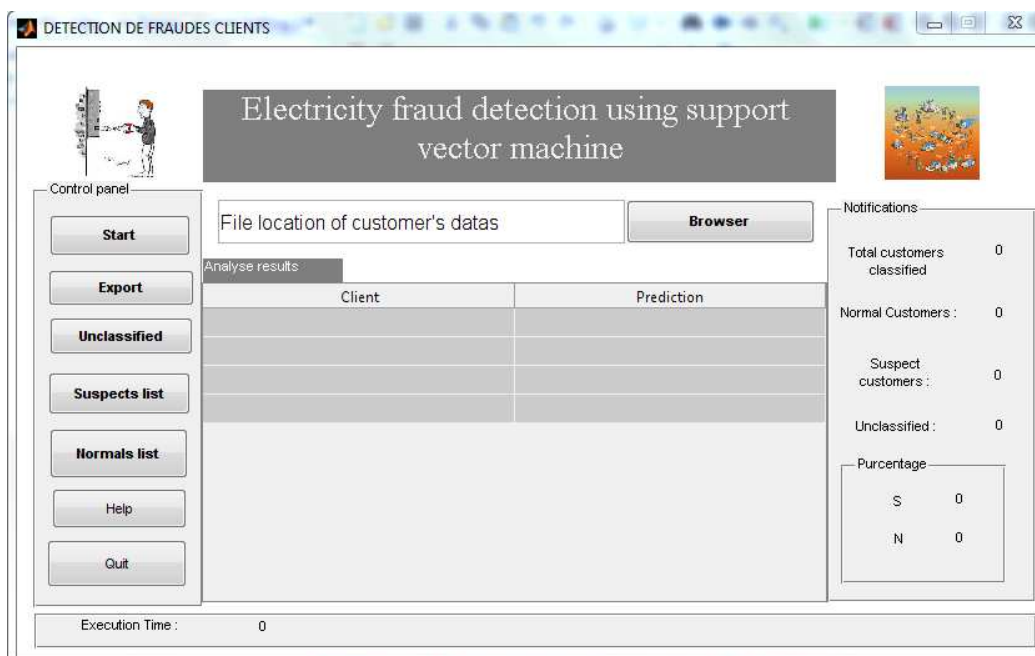


Fig. 5. Principal screen of the software

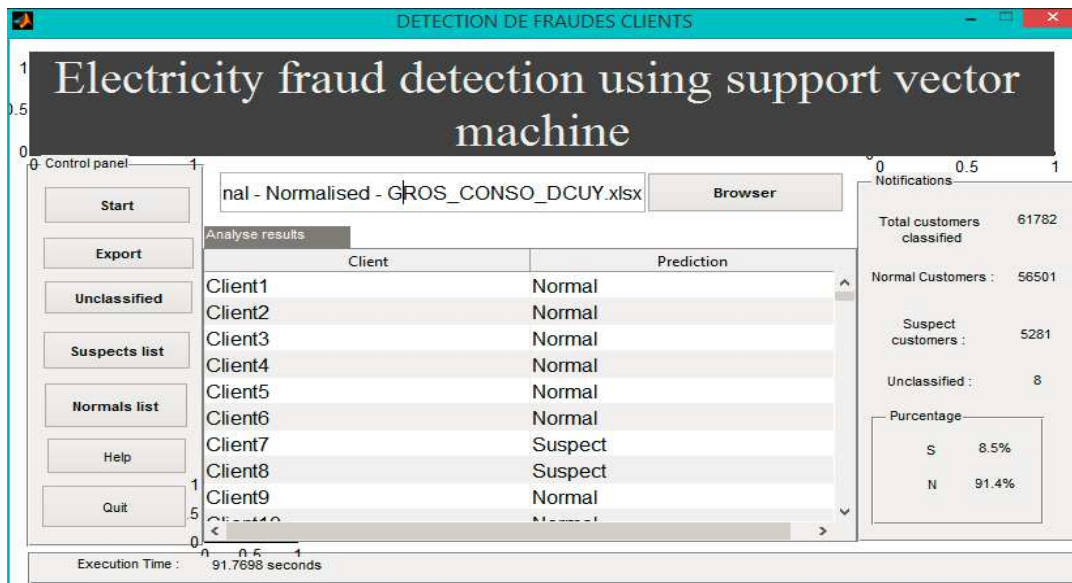


Fig. 9. Display of customers list with the prediction of their behaviors

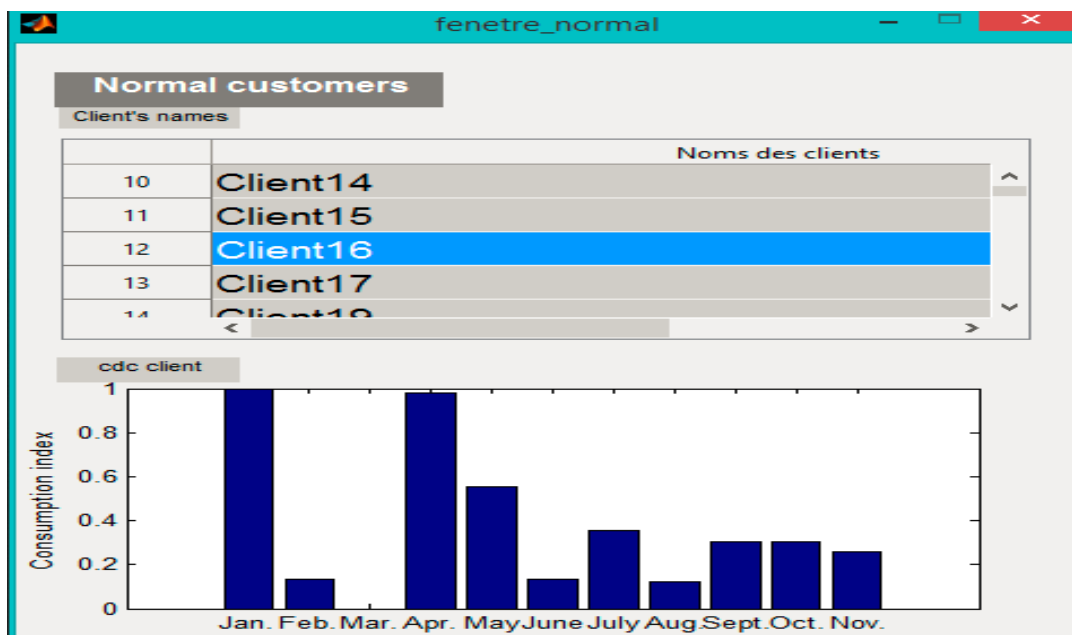


Fig. 10. Curve of suspected customers

Detection is complete once the display of trial appears in the customers list, with their status indicated in Fig. 9.

Display of Customer Load Profile

Once the software has posted the list of clients with their status, it is possible for us to visualize their load profile. Simply right click on the customer whose profile you want to see indicated in Fig. 10 to 12 respectively suspect, normal and unclassified customers.

Discussion

The training accuracy of the SVC model is estimated by tuning the SVC kernel parameter and the error penalty parameter, C . In this study, the RBF kernel is used, hence, the parameter gamma which controls the width of the Gaussian is to be fine-tuned.

Experimentally, by iterating different parameter combinations for our model we firstly obtained the accuracy of 75, 9% as is shown in Fig. 13.

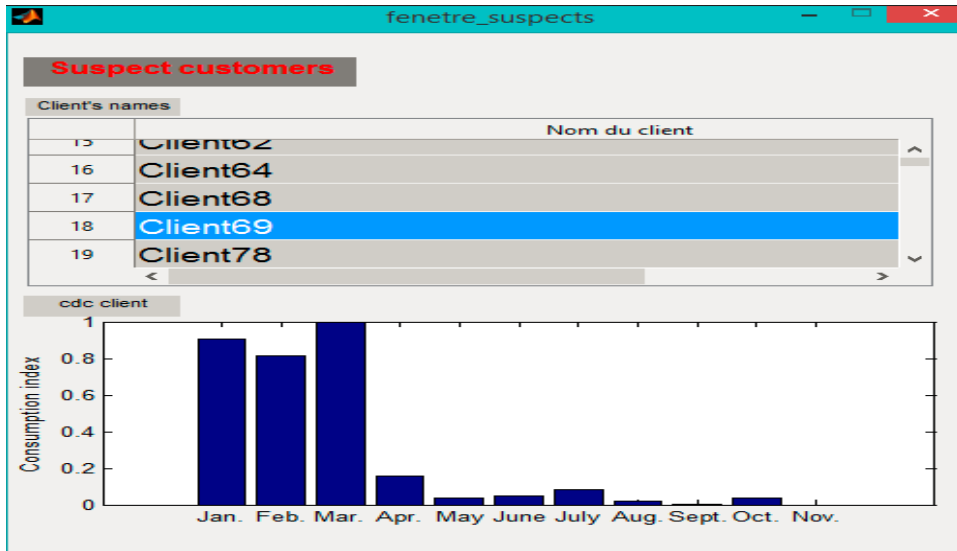


Fig. 11. Curve of normal customers



Fig. 12. Visualization of unclassified customers

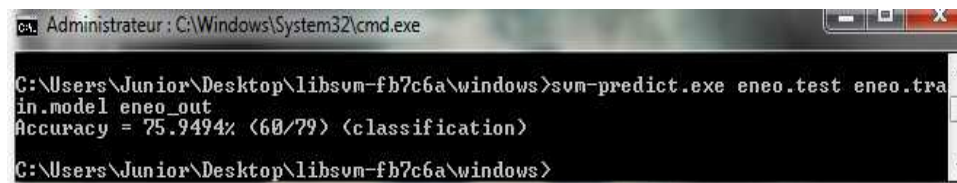


Fig. 13. LIBSVM test phase

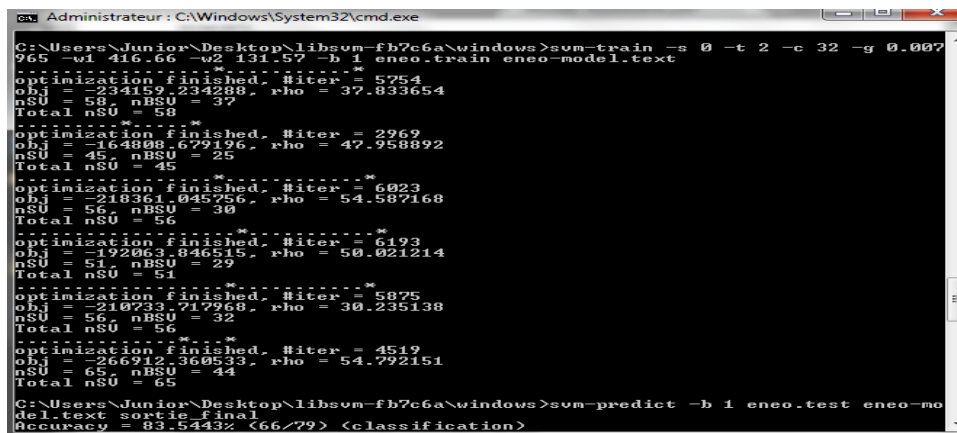


Fig. 14. Training and test after the tuning kernel parameters

Table 3. Result of the literature

Authors	Title	Accuracy
J. Nagi and Al	NTL Detection of Electricity Theft and Abnormalities for Large Power Consumers in TNB Malaysia Conference and Exposition, Seattle, Washington, United States, Mar.15-18, 2009, pp. 1-10	55%
V. Figueiredo and Al	An Electric Energy Consumer Characterization Framework Based on Data Mining Techniques, IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 20, NO. 2, MAY 2005	81% working days 74% for weekend
Breno C and Al	Fraud detection in electric power distribution networks using an ANN-based knowledge-discovery process, International Journal of Artificial Intelligence and Applications (IJAIA), Vol. 4, No. 6, November 2013	87.17%,
J. Nagi and Al	Detection of Abnormalities and Electricity Theft using Genetic Support Vector Machines	81.63%

Table 4. Data used for the construction of the model

DATA	Learning	Test
Learning	198	54
Test	59	20

To increase this percentage of success, we use the "search grid" to optimize the kernel parameters. The best results were obtained for the optimal parameters $C = 8$, $\gamma = 0.0078$, $w_1 = 416, 66$; $w_2 = 131, 57$ and we obtained the accuracy of 83% as is shown in Fig. 14

This result is in agreement with those obtained in literature as indicated in Table 3.

In order to apply a supervised learning technique, we chose a data base of 331 customers. This data base was used to establish the SVM classification model through training and testing as shown in Table 4.

We selected 61 782 customers data to test our model and we obtained 56 501 normal customers, 5 281 suspect customers and 8 unclassified customers.

Conclusion

NTLs on the Cameroonian transmission and distribution network are about 30-40% of electricity production, causing enormous losses estimated at several billion FCFA per year to the State. Hence the importance of finding effective solutions to these losses. The purpose of this work was to develop a tool for the fraud detection for Cameroon National Electricity Company (ENEO). Firstly we present the context and the problems of our study in the introduction. Secondly, we present the methodology of support vector machines which consisted in data preprocessing, development of a model for classification, parameter optimization and testing and validation of SVM model.

For the implementation of this work we use:

- A database of nearly 62,000 customers for ENEO central region business unit
- In order to apply a supervised learning technique, we chose a data base of 331 customers and this data base was used to establish the SVM classification model through training and testing

- We selected 61 782 customers in the data base to test our model
- Despite the good performance achieved, validating the proposed system required the comparison of results of the SVC protocol with practical cases detected by ENEO

The development prospects are many, including:

- Use of Genetic Algorithms for a "fine tuning" of SVM parameters such as: The penalty coefficient C and γ
- The fraud detection system requires the use of multiple data from different regions for learning and testing. That is to say customer data already classified: Normal or suspect
- The operation and contribution of experience ENEO agents for the development of the final decision algorithm
- To finish, we believe that fraud detection system available offline can be operated at commercial agencies ENEO to create an optimal system of customer management
- In addition, the use of the proposed system will allow ENEO improve its management of NTL and revenue protection

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Author's Contributions

All authors made substantial contributions to this paper.

Lekini Nkodo Claude Bernard: Contributed to research design, literature review, model development and manuscript preparation and revision.

Ndzana Benoît and Oumarou Hamandjoda: Contributed to conceptualization, manuscript review, revision and research supervision.

Ethics

These authors have no ethical issues that may arise after the publication of this manuscript and confirm that this work is original and has not been published elsewhere.

References

- Fourie, J.W. and J.E. Calmeyer, 2004. A statistical method to minimize electrical energy losses in a local electricity distribution network. Proceedings of the 7th IEEE AFRICON Conference, Sept. 15-17, IEEE Xplore Press, pp: 667-673.
DOI: 10.1109/AFRICON.2004.1406768
- Nagi, J., K.S. Yap, S.K. Tiong and S.K. Ahmed, 2008a. Detection of abnormalities and electricity theft using genetic support vector machines. Proceedings of the IEEE Region 10th Conference, Nov. 18-21, IEEE Xplore Press, Hyderabad, India, pp: 1-6.
DOI: 10.1109/TENCON.2008.4766403
- Nagi, J., K.S. Yap, S.K. Tiong, A.M. Mohammad and S.K. Ahmed, 2008b. Non-technical loss analysis for detection of electricity theft using support vector machines. Proceedings of the 2nd IEEE International Power and Energy Conference, Dec. 1-3, IEEE Xplore Press, Johor Bahru, Malaysia, pp: 907-912. DOI: 10.1109/PECON.2008.4762604
- Nagi, J., K.S. Yap, S.K. Tiong, S.K. Ahmed and F. Nagi, 2010b. Improving SVM-based nontechnical loss detection in power utility using the fuzzy inference system. IEEE Trans. Power Delivery, 26: 1284-1285. DOI: 10.1109/TPWRD.2010.2055670
- Nagi, J., K.S. Yap, S.K. Tiong, S.K. Ahmed and M. Mohamad 2010a. Nontechnical loss detection for metered customers in power utility using support vector machines. IEEE Trans. Power Delivery, 25: 1162-1171. DOI: 10.1109/TPWRD.2009.2030890