Electricity Load Forecast using Data Streams Techniques

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Abstract. Sensors distributed all around electrical-power distribution networks produce streams of data at high-speed. From a data mining perspective, this sensor network problem is characterized by a large number of variables (sensors), producing a continuous flow of data, in a dynamic non-stationary environment. In this work we analize the most relevant data mining problems and issues: online learning and change detection. We propose an architecture based on an online clustering algorithm where each cluster (group of sensors with high correlation) contains a neural-network based predictive model. The goal is to maintain in real-time a clustering model and a predictive model able to incorporate new information at the speed data arrives, detecting changes and adapting the decision models to the most recent information. We present preliminary results illustrating the advantages of the proposed architecture.

Keywords: Electricity demand forecast, online clustering, incremental neural networks.

1 Motivation

Electricity distribution companies usually set their management operators on SCADA/DMS products (Supervisory Control and Data Acquisition / Distribution Management Systems). One of their important tasks is to forecast the electrical load (electricity demand) for a given sub-network of consumers. Load forecast is a relevant auxiliary tool for operational management of an electricity distribution network, since it enables the identification of critical points in load evolution, allowing necessary corrections within available time. In SCADA/DMS systems, the load forecast functionality has to estimate, on a hourly basis, and for a near future, certain types of measures which are representative of system's load: active power, reactive power and current intensity. In the context of load forecast, near future is usually defined in the range of next hours to the limit of seven days, for what is called *short-term* load forecast.

Traditionally, real knowledge extraction problems faced a barrier on the relative scarcity of data. Nowadays, not rarely the amount of available data is so huge that traditional systems, based on memory and several reading of same information, cannot operate efficiently. Moreover, on current real applications, data are being produced in a continuous flow, at high speed, producing examples over time [4]. In this context, faster answers are usually required, keeping an anytime model of the data, enabling better decisions.

Given its practical application and strong financial implications, electricity load forecast has been targeted by innumerous works, mainly relying on the non-linearity and generalizing capacities of neural networks, which combine a cyclic factor and an auto-regressive one to achieve good results [5]. Nevertheless, static iteration-based training, usually applied to estimate the best weights for network connections, is not adequate for the high speed production of data usually encountered. Moreover, a predictive system may be developed to serve a set of thousands of load sensors, but the load demand values tend to follow a restrict number of profiles, considerably smaller than the total of registered sensors. This way, clustering of sensors greatly allows the reduction of necessary predictive models. However, most work in data stream clustering has been concentrated on example clustering and less on variable clustering [8].

2 General Description

The main objective of this work is to present an incremental system to predict in real time the electricity load demand, in huge sensor networks. The system must predict the value of each individual sensor with a given temporal horizon, that is, if at moment t_i we receive an observation of all network sensors, the system must execute a prediction for the value of each variable (sensor) for the moment t_i+k. In this scenario, each variable is a time series and each new example included in the system is the value of one observation of all time series for a given moment.

Given the high dimensionality of the problem, a scheme that would generate a predictive model for each variable is not possible. Our approach is to first cluster the sensors using an online data stream clustering algorithm, and then associate to each cluster a neural network trained incrementally with the centroid of the cluster.

The system applies a divisive strategy, with the leaves representing the sensor clusters, which may aggregate in case of changes in the correlation structure. Anytime a cluster is divided, the offspring leaves inherit the parent's predictive model, starting to train a different copy.

The neural networks are trained continuously with data from the corresponding variables, assuming a model for each group since it is expectable that clustered variables should behave with high correlation. Nevertheless, the system makes predictions for all variables, independently, in real time. Overall, the system predicts all variables in real time, with incremental training of neural networks and continuous monitoring of the clustering structure.

3 Incremental Clustering of Data Streams

The clustering strategy used in this system is the ODAC (Online Divisive-Agglomerative Clustering), a variable clustering algorithm that creates a hierarchical structure of clusters in a divisive way [8]. The leaves are the resulting clusters, with a set of variables in each leaf. The union of the leaves is the complete set. The intersection of leaves is the empty set.

The system includes an incremental dissimilarity measure based on the correlation between time-series. The similarity measure is calculated with sufficient statistics gathered continuously over time. There are to main operations in the hierarchical structure of clusters: *expansion* that splits one cluster into two new clusters, and *aggregation* that aggregates two clusters into one. Both operators are based on the diameters of the clusters, and supported by confidence levels given by the Hoeffding bounds [6]. The main characteristic of the system is the monitoring of those diameters.

In a hierarchical structure of clusters, created from a divisive point of view, and considering that the data streams are produced by a stable concept, the intra-cluster dissimilarity should decrease with each split, therefore diminishing the diameter of each cluster. For each cluster, the system chooses two variables that define the diameter of that cluster (those that are less correlated). If a given heuristic condition is met on this diameter, the system splits the cluster in two, assigning each of those variables to one of the two new clusters. Afterwards, the remaining variables are assigned to the cluster that has the closest pivot (first assigned variables). The newly created leaves start new statistics, assuming that only the future information will be useful to decide if the cluster should be split. This characteristic increases the system's ability to react to changes in the concept as, later on, a test is executed so that if the diameter of the leaves approaches the diameter of the parent node, then the previous split may have ceased to represent the current structure of data. When this happens, the system aggregates the leaves, restarting the sufficient statistics for that group.

The ODAC algorithm presents the needed characteristics for adaptive learning systems, namely the ones related with incremental clustering [2]. Moreover, it is one of the first systems clearly proposed to hierarchical clustering of variables over data streams. An important characteristic of this method is that each split of a leaf with n variables reduces the global number of dissimilarities to compute, by at least $n-1$. The temporal complexity of each iteration of the clustering system

is constant given the number of examples, even decreasing whenever a split occurs. This way, it is able to process high speed data streams. Figure 1 presents the resulting hierarchy of the clustering procedure.

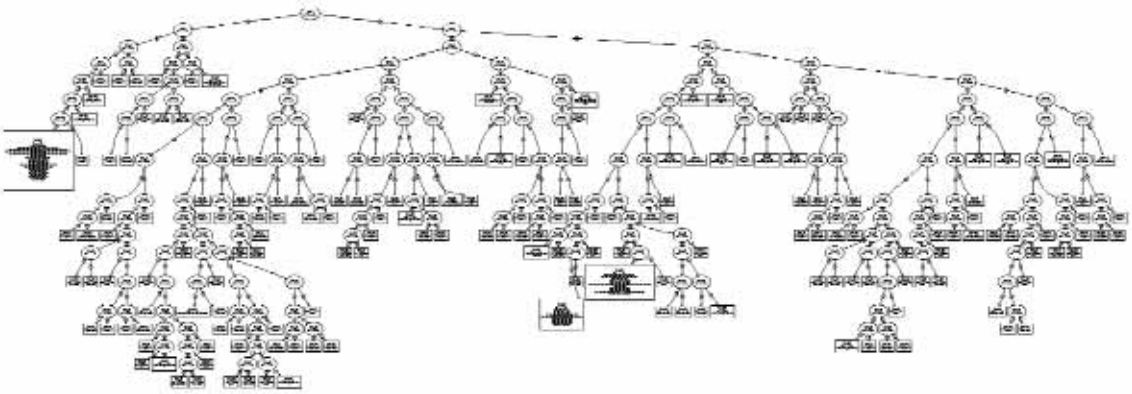

Fig. 1. ODAC clustering hierarchy in the Portuguese Electrical Network (2500 sensors in one year data).

4 Incremental Learning of Neural Networks

A neural network model is associated with each group defined in the clustering structure, in order to perform predictions on the corresponding variables. On a first approach, we focus on predicting the next hour load. At each moment t_i, the system executes two actions: one is to predict the moment t_{i+k}; the other is to back-propagate in the model the error, obtained by comparing the current real value with the prediction made at time t_{i-k}. The error is back-propagated through the network only once, allowing the ability to cope with high speed streams. Although the system builds the learning model with the centroid of the group, the prediction is made for each variable independently. Every time a cluster is split, the offspring clusters inherit the parent's model, starting to fit a different copy separately. This way, a specification of the model is enabled, following the specification of the clustering structure. When an aggregation occurs, due to changes in the clustering structure, the new leaf starts a new predictive model. From the user's point of view, there is now need to predict variables which do not behave accordingly to what is expected. Therefore, our system will only start learning a neural network if and when the corresponding cluster presents good intra-cluster correlation. This heuristic supports the notion that the majority of variables in a group present positive correlation with each other. For groups where no predictive model was created, the prediction is to consider the last known value of the corresponding stream.

The chosen predictive model was the feed-forward neural networks, with 10 inputs, 4 hidden neurons (tanh-activated) and a linear output. The input vector for predicting time series t at time k is k minus $\{1, 2, 3, 4\}$ hours and k minus $\{7, 14\}$ days. As usual [5], we consider also 4 cyclic variables, for hourly and weekly periods (*sin* and *cos*). The initial learning algorithm was the *iRprop*, reducing the system's sensitivity to parameters [7]. To introduce predictive ability in ODAC it was necessary to consider buffering the data, so that neural networks could use historical values of each variable to predict. Figure 2 presents a general description of the procedure executed at each new example.

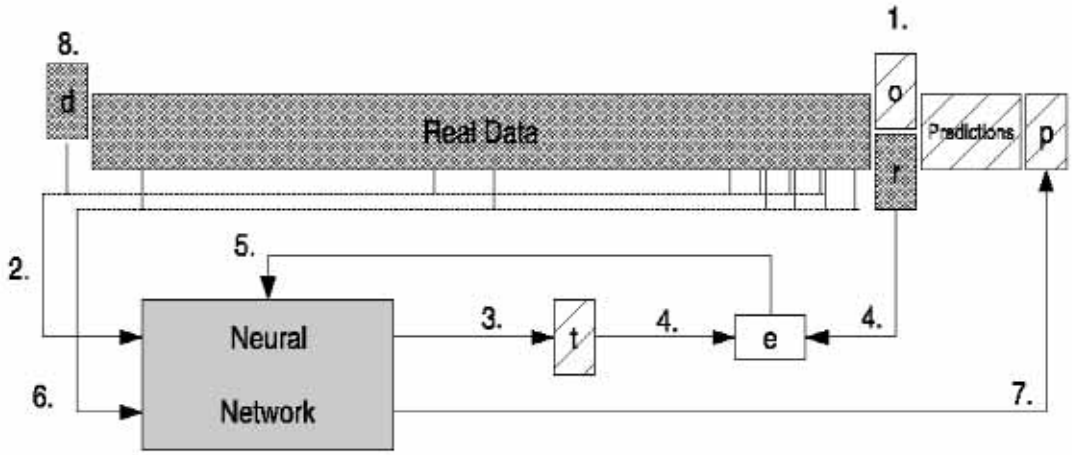

Fig. 2. Buffered Online Predictions: 1. new real data arrives (r) at time stamp i, substituting previously made prediction (o); 2. define the input vector to predict time stamp i; 3. execute prediction (t) for time stamp i; 4. compute error using predicted (t) and real (r) values; 5. back-propagate the error one single time; 6. define input vector to predict time stamp i plus one hour; 7. execute prediction of next hour (p); 8. discard oldest real data (d).

5 Experimental Evaluation

The system's modularity allows the predictive models to be, not only dynamic and easily modified, but also heterogeneous over all clusters. However, for a first evaluation of the system, we will consider homogeneous models for the prediction of the next hour electricity load.

5.1 Predictive Capacity

There are two priority concepts the system should respond. On one side, considering the expected high correlation between series of the same cluster, the system should be able to fit a neural network that represents the cluster, using the centroid of the series included in the corresponding group. On the other side, we should expect that incremental training of neural networks should produce better results when compared with models trained with historical data and no adaptation to current data. The following experiments try to answer this two questions, resulting as expected. The quality measure usually considered in electricity load forecast is the MAPE *(Mean Absolute Percentage Error)* defined as

$$MAPE - \sum_{i=1}^{n} \frac{|(\hat{y}_i - y_i)/y_i|}{n} \quad (1)$$

where y_i is the real value of variable y at time i and $\hat{y}_i$ is the corresponding predicted value. Preliminary results on electrical power demand current data supported some of the motivations for our work. Fitted models resulted in predictions with MAPE evaluation values under 10%. We should stress that neither the clustering system's definitions nor the learning algorithm parameters were exhaustively fit. Nevertheless, Figure 3 presents an example of predictions made by a neural network for one example stream included in a cluster with hundreds of different streams, with intra-cluster correlation < 0.2, capturing the ability to train the network with the centroid of the cluster. Unfortunately, not all clusters' centroids are the best to predict the corresponding streams.

We are also interested on inspecting the advantages of online learning, comparing online training results with the predictions made by batch models. In Figure 4 we can compare the evolution of

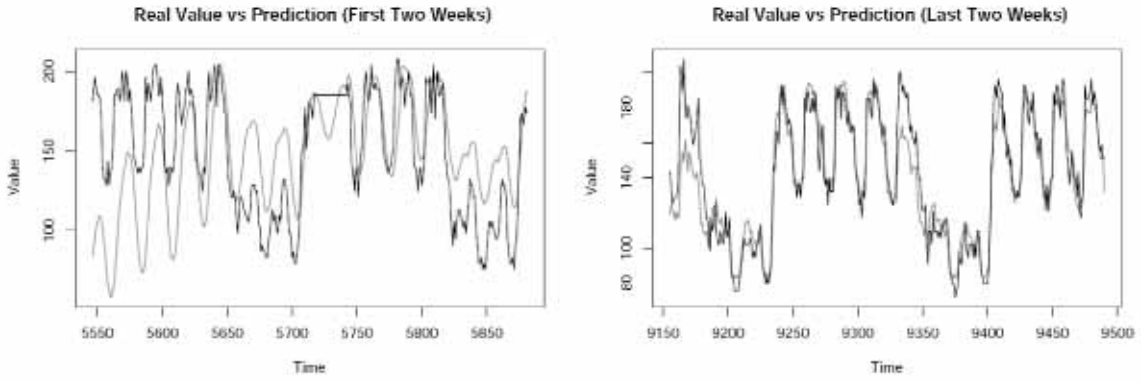

Fig. 3. Predictions for one stream belonging to a cluster with large dimension. Pictures show the plots of real values and predictions for the first two weeks after training and the last two weeks. We can see that, although the first training didn't model the stream as expected due to cluster's dimension, the online training continuously reduces the error, fitting the model to the stream, as seen in the last two weeks.

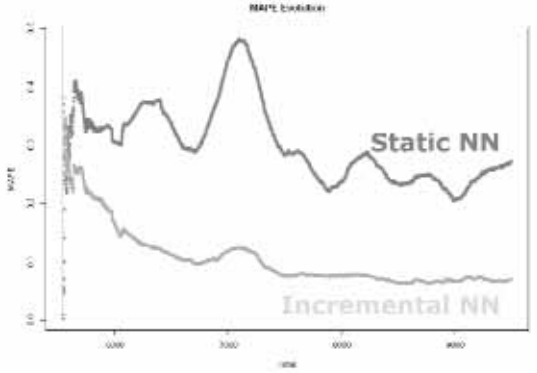

Fig. 4. MAPE evolution for the stream. The improvement achieved by incremental learning is clear, maintaining an error descent through time.

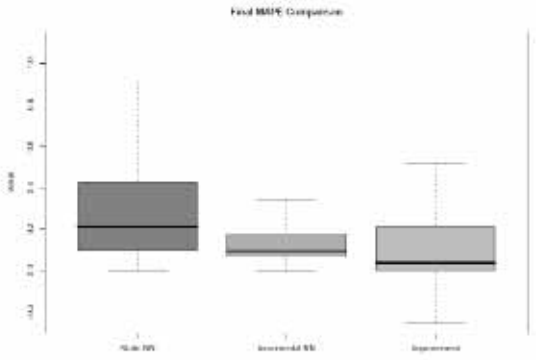

Fig. 5. Final MAPE comparison. Incremental learning of neural networks for non-null variables resulted in improvements of around 5% MAPE.

the MAPE error in the following weeks, comparing predictions made by static neural networks and incremental neural networks. The graph shows the consistency and advantages of using incremental learning. On the last week, the overall improvement achieved by online training was around 5% and is sketched on Figure 5 for all non-null variables, where positive improvement represents a decrease on the MAPE.

From this results, not only the ability to learn a model with the centroid of the group is confirmed, but also the continuously applied incremental learning is shown to favor no only the model fitting but, more important, the model adaptation to dynamic behaviors.

5.2 Comparison with another predictive strategy

To assess the quality of prediction, comparing with another predictive system, we have conducted experiments where, for a given year, the quality of the system in each month is compared with Wavelets on two precise variables, chosen as relevant predictable streams (by an expert) but expressing either low or high error. These variables are shown on Figures 6 and 7. Moreover, the

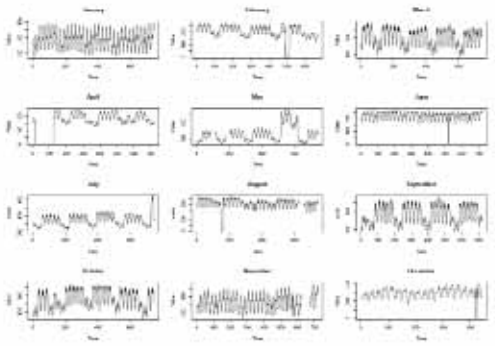

Fig. 6. Selected variables each month (low err).

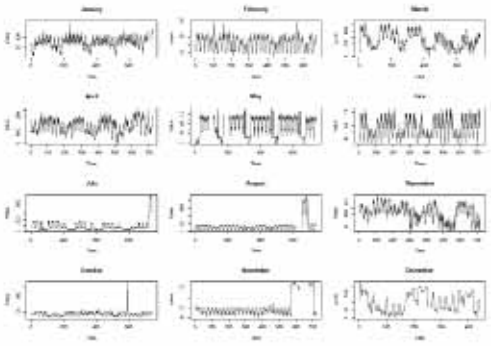

Fig. 7. Selected variables each month (high err).

	Wavelets	NNets	NNets-Wav	
	%	%	%	*p-value*
Month				
January	1.69	2.72	**1.03**	**<0.001**
February	2.99	2.79	-0.20	0.196
March	3.63	2.75	**-0.88**	**<0.001**
April	2.05	2.58	**0.53**	**0.002**
May	2.69	2.28	**-0.41**	**<0.001**
June	2.33	2.52	0.29	0.051
July	2.14	2.12	**-0.02**	**0.049**
August	2.59	2.54	-0.05	0.537
September	2.65	2.64	-0.01	0.374
October	2.28	2.36	0.08	0.127
November	2.41	2.14	-0.27	0.085
December	3.56	2.97	**-0.59**	**0.029**

Table 1. MEDAPE for selected variables (low err).

	Wavelets	NNets	NNets-Wav	
	%	%	%	*p-value*
Month				
January	9.04	10.34	**1.30**	**<0.001**
February	8.51	9.82	**1.31**	**0.002**
March	11.52	11.28	-0.24	0.166
April	9.36	12.74	**1.38**	**<0.001**
May	12.89	10.54	**-2.35**	**0.035**
June	6.68	8.10	**1.42**	**<0.001**
July	14.52	10.68	**-3.84**	**<0.001**
August	11.11	12.27	**1.16**	**0.034**
September	10.52	9.81	-0.71	0.656
October	12.45	11.25	**-1.20**	**0.002**
November	8.85	7.71	-1.14	0.356
December	11.76	10.91	**-0.85**	**0.040**

Table 2. MEDAPE for selected variables (high err).

quality measure was changed to MEDAPE *(Median Absolute Corresponding Error)*, the corresponding *median* of the APE measure, to reduce sensibility to extreme values [1]. Results are shown on Table 1, for low error variables, and Table 2, for high error variables. For the difference of the medians, the Wilcoxon [3] test was applied, and the corresponding *p-value* is shown (difference is statistically significant if $p < 0.05$). The relevance of the incremental system using neural networks is exposed, with lower error values on the majority of the studied variables. Moreover, it was noticed an improvement on the performance of the system, compared to the predictions made using Wavelets, after failures or abnormal behavior in the streams.

6 Challenging Problems

The sensor networks created by this setting can easily include thousands of sensors, each one corresponding to a given sub-network and, therefore, being object of predictive analysis. Moreover, given the evolution of hardware components, these sensors act now as fast data generators, producing information in a streaming environment. The data flow usually generated by each sensor can be extremely fast and possibly infinite in size, what corresponds to a known scenario of data stream analysis.

This setting reveals a large sensor network, where thousands of streams produce data continuously over time, representing an interesting scenario for ubiquitous computing. This problem

shares some of the requirements and objectives usually inherent to ubiquitous computing. Sensors are most of the times limited in resources such as memory and computational power, and communication between them is easily narrowed due to distance and hardware limitations. Moreover, given the limited resources and fast production of data, information has to be processed in quasi-real-time, creating a scenario of multi-dimensional streaming analysis.

7 Conclusions and Future Issues

This paper introduces a system that gathers a predictive model for a large number of data variables with an horizon forecasting, incrementally constructing a hierarchy of clusters and fitting a predictive model for each leaf. The main setting of the clustering system is the monitoring of existing clusters' diameters. The main setting of the predictive strategy is the buffered online prediction of each individual variable, based on a neural network trained with clustered variables. The examples are processed as they arrive, using a single scan over the data. The system incrementally computes the dissimilarities between time series, maintaining and updating the sufficient statistics at each new example arrival. Experimental results show that the system is able to fit predictive models using the centroids of the cluster they are associated to. Moreover, applying incremental learning, using the online strategy developed in this work, seems to outperform predictions made with static predictive models.

Future work will focus on the definition of global evaluation strategy and the inspection of other online learning techniques. We believe further work on the learning task will improve the quality of neural network basic accuracy. Moreover, the electrical network spreads out geographically. The topology of the network and the position of the electrical-measuring sensors are known. From the geo-spacial information we can infer constraints in the admissible values of the electrical measures. The geo-spacial information can be used by sensors themselves. Sensors would become smart devices, although with limited computational power, that could detect and communicate with neighbors. Data mining in this context becomes ubiquitous and distributed.

Acknowledgement

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Load Forecast in Power Supply Networks

Load forecast is a relevant auxiliary tool for operational management of an electricity distribution network enabling:

- identification of profiles.
- prediction of picks on the demand.
- identification of **critical points** in load evolution
- necessary corrections **within available time**
- **support** for previously planned interventions
- checking the viability of **charge transfer** scenarios

Load Forecast in SCADA/DMS

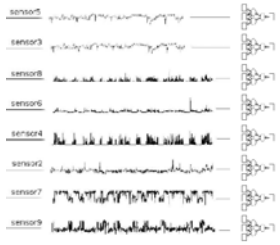
In **SCADA/DMS** (Supervisory Control and Data Acquisition / Distribution Management Systems), the load forecast functionality has to estimate, on a hourly basis, and for a **near future**, certain types of measures which are representative of system's load:

Sensor network (2500 sensors). Each sensor measures:

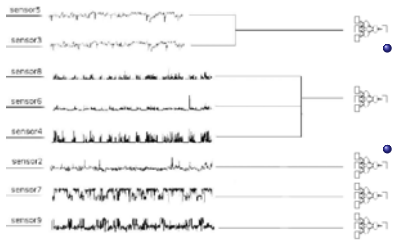
- active power
- reactive power
- current intensity

In the context of load forecast, near future is usually defined in the range of **next hours** to the limite of **seven days**.

Approach 1



Approach 2



- **similar load profiles** should be **clustered**, and
- **predictive models** should be applied to **each cluster**.

A Streaming Environment

Current SCADA/DMS systems gather a **continuous flow** of data generated at **high-speed** from sensors of an electricity distribution network.
The usual approaches for clustering and prediction use **batch procedures** which cannot cope with this streaming setting.
Our approach is in the **Data Stream** framework, maintaining in **real time** both a clustering model and a predictive model capable of:

- **incorporating** new information at the speed data arrives, and
- **detecting** changes and **adapting** the decision models to the most recent information.

Goals

Develop predictive models for groups of sensors:

- An **incremental** system is used to perform **clustering** of time series over data streams;
- At each cluster (leaf) exists an **online predictive model**;
- The system should cope with:
  - the **high-speed** and **any-time output** of the clustering structure definition and predictions;
  - the ability to **detect and adapt** to changes in the clustering structure;

With this approach, we intend to:

- **reduce or eliminate** the effort applied on configuration and training (usually slow and based on huge amounts of data)
- reach short-term predictive results with **acceptable performance**

Data Pre-Processing

- The electrical network spreads out geographically.
- The topology of the network and the position of the electrical-measuring sensors are known.
- Sensors send information at different time scales.
- Sensors act in adversary conditions: they are proneness to noise, weather conditions, battery conditions,

To reduce the impact of the noise, missing values, and different granularity, data is aggregated and synchronized in time windows of 15 minutes.

Online Divisive-Agglomerative Clustering [Rodrigues, Gama, 2006]

- Incremental system to **monitor clusters' diameters**
- Performs hierarchical clustering of **first-order differences**
- Can **detect changes** in the clustering structure
- Two Operators:
  - Expansion: expand the structure
  - Agglomeration: contract the structure
- Splitting and agglomerative criteria are supported by a confidence level given by the **Hoeffding bounds**.

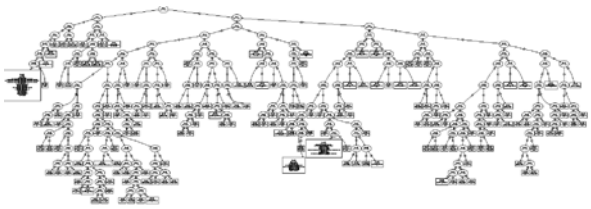
Main Algorithm [Rodrigues, Gama, 2006]

- ForEver
  - Read Next Example
  - For all the clusters
    - Update the sufficient statistics
  - Time to Time
    - Find the two farthest variables
    - Verify Merge Clusters
    - Verify Expand Cluster

Properties of ODAC

- For stationary data the cluster's diameters monotonically decrease.
- **Constant update time/memory consumption** with respect to the number of examples!
- Every time a **split** is reported
  - the **time** to process the next example **decreases**, and
  - the **space** used by the new leaves is **less than** that used by the parent.

A snapshot - 1 year data, 2500 variables



Load Forecast in Data Streams

The goal is to have an **any-time prediction** of the next-hour load value for all sensors.

The strategy is to have **one predictive model at each cluster**, predicting all of its sensors.

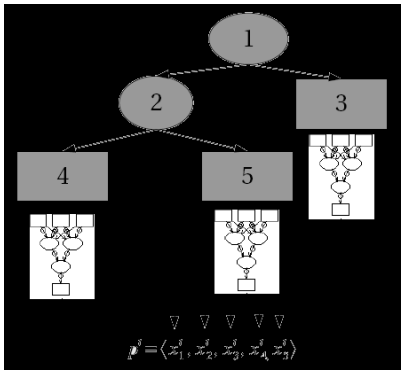
Predictive models are created for clusters which present **good behaviour**, that is, **good intracluster correlation**; for the others, the last known value is used.

iRprop [Igel and Hüsken, 2000] algorithm is used to train the feedforward neural networks, with 10 inputs, 4 *tanh*-activated hidden neurons, and one linear output neuron.

Splitting triggers **inheritance** of the ancestor's predictive model.

Aggregation triggers **reset** of the predictive model.

Load Forecast in Data Streams

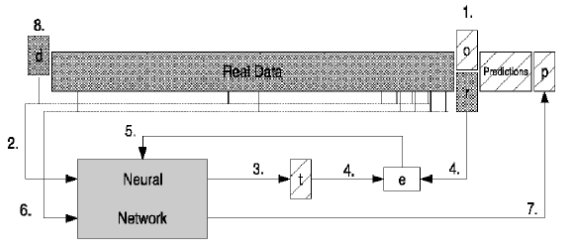


Why Neural-Nets?

- A Function approximation approach
- A 3 layer ANN can approximate any continuous function
- Fast Train and Prediction:
  - Each example is propagated once
  - The Error is back-propagated once
- No overfitting
  - First: Prediction
  - Second: Update the Model
- Smoothly adjust to gradual changes

Buffering the Input Data and the Predictions

Online prediction and training is achieved with **buffered input**.



Validation of the Clustering Approach [Rodrigues, Gama, 2006]

- For **stationary** data, ODAC performs **similar to batch** divisive analysis clustering.
- For **drifting** data, ODAC **detects and adapts** the structure to the new concepts.
- On real physiological data, ODAC resulted in the **same partitions as k-Means**.

Load Forecast of Large Sensor Networks

The system should be able to fit a **predictive model that represents the whole cluster**, training with the cluster's centroid.

Also, it is expectable that **online learning** should produce better adaptation to new examples, comparing to predictive models trained with past examples and no adaptation to current data.

Evaluation is made using the **MAPE** error measure:

$$MAPE = \sum_{i=1}^{n} \frac{|(\hat{y}_i - y_i)/y_i|}{n} \quad (1)$$

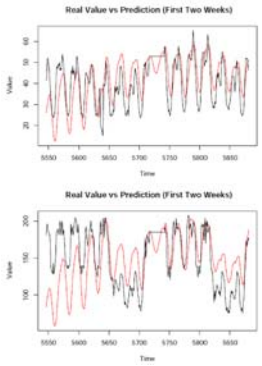
Clusters as Representatives

We have conducted experiments for current intensity measured on **over 2500 sensors** and built the clustering structure with **one year** of real data.

For each cluster which possess good intra-cluster correlation, **the system learns a predictive model using the centroid** of the corresponding time series, for a **recent period** of past data and tests them in the following weeks, for **each variable individually**.

Fitted models resulted in predictions with **MAPE evaluation values under 10%**.

Clusters as Representatives

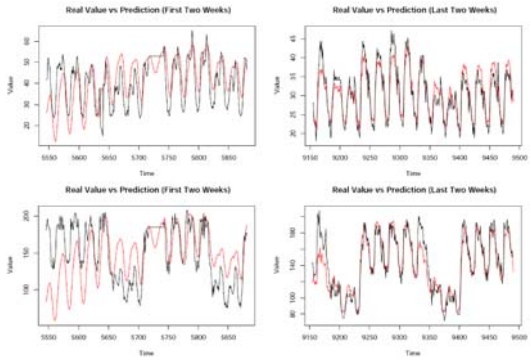


Predictions for sensor variables included in a large cluster.

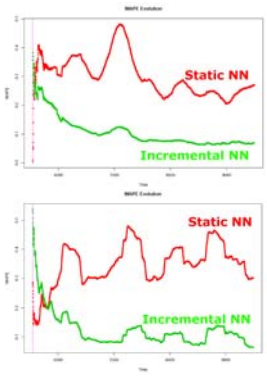
Plots present the first two weeks after initial training.

Due to the batch training, **the network is struggling to fit all the series**.

Online Learning

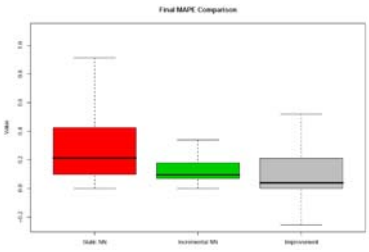


Online Learning



After some time, the incremental learning combines its efficiency with accuracy, diminishing the error **below the static model**.

Online Learning



Considering all non-null variables, after the first week, **the average improvement achieved by online training is about 5%**.

Comparison with Wavelets

The quality of the system in each month is compared with **Wavelets** on two precise variables, chosen as **relevant predictable streams** (by an **expert**) but exhibiting either **low** or **high** error.

The relevance of the incremental system using neural networks is exposed, with **lower error values** on the **majority** of the studied variables.

Moreover, it was noticed an **improvement** on the performance of the system, compared to the predictions made using Wavelets, **after failures or abnormal behavior** in the streams.

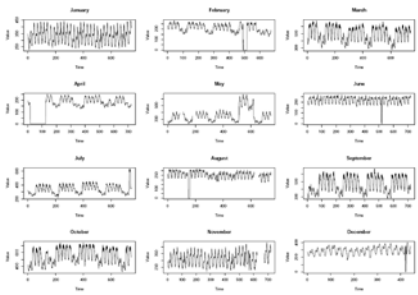


Figure: Selected variables each month (low err).

	Wavelets	NNets	NNets-Wav	
	%	%	%	*p-value*
Month				
January	1.69	2.72	**1.03**	**<0.001**
February	2.99	2.79	-0.20	0.196
March	3.63	2.75	**-0.88**	**<0.001**
April	2.05	2.58	**0.53**	**0.002**
May	2.69	2.28	**-0.41**	**<0.001**
June	2.33	2.52	0.29	0.051
July	2.14	2.12	**-0.02**	**0.049**
August	2.59	2.54	-0.05	0.537
September	2.65	2.64	-0.01	0.374
October	2.28	2.36	0.08	0.127
November	2.41	2.14	-0.27	0.085
December	3.56	2.97	**-0.59**	**0.029**

Table: MEDAPE for selected variables (low err).

Values for the median of the APE, for each sensor in their corresponding month, for predictions using **Wavelets** and our approach **(RETINAE)**.

Difference is presented between Wavelets approach and our approach, with *p-value* from Wilcoxon test.

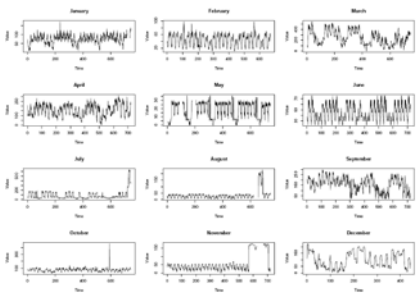


Figure: Selected variables each month (high err).

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	Wavelets %	NNets %	NNets-Wav %	*p-value*
Month				
January	9.04	10.34	**1.30**	<**0.001**
February	8.51	9.82	**1.31**	**0.002**
March	11.52	11.28	-0.24	0.166
April	9.36	12.74	**1.38**	<**0.001**
May	12.89	10.54	**-2.35**	**0.035**
June	6.68	8.10	**1.42**	<**0.001**
July	14.52	10.68	**-3.84**	<**0.001**
August	11.11	12.27	**1.16**	**0.034**
September	10.52	9.81	-0.71	0.656
October	12.45	11.25	**-1.20**	**0.002**
November	8.85	7.71	-1.14	0.356
December	11.76	10.91	**-0.85**	**0.040**

Table: MEDAPE for selected variables (high err).

Values for the median of the APE, for each sensor in their corresponding month, for predictions using **Wavelets** and our approach **(RETINAE)**.

Difference is presented between Wavelets approach and our approach, with *p-value* from Wilcoxon test.

Conclusions

System gathers a predictive model for a **large number** of data variables:

- Incrementally constructs a **hierarchy of clusters** fitting **one predictive model for each leaf**.
- The system has the ability to **cope with high speed** production of examples.
- The rate of predictions can be as fast as the rate of incoming examples, considering the usual rates higher than one minute.
- The system is **capable of dealing with changes** in the clustering structure.

Discussion

Experimental results show that the system is **able to fit predictive models using the centroids of the cluster** they are associated to.

Moreover, applying incremental learning, using the online strategy developed in this work, seems to **outperform predictions made with static predictive models**.

Comparing our system's predictions with other predictive strategies indicates **competitive performance** for the problem of load forecast.

Open Issues

Current work is concentrated on:

- improve predictions by **combining** them with the **last known value** (e.g. Kalman Filters);
- compare with **other predictive strategies** (e.g. Wavelets);
- **application** to all **three dimensions** of the electricity load;
- **testing** the system on the **24-hour forecast** and **1-week forecast** problems;
- treating **missing data** and **special events**;

Thanks for your attention!

More information:

ODAC P. P. Rodrigues, J. Gama and J. P. Pedroso. *ODAC: Hierarchical Clustering of Time Series Data Streams*. In *Proceedings of the Sixth SIAM International Conference on Data Mining*, pages 499-503. Bethesda, Maryland, USA. April 2006.

OnlineNN P. P. Rodrigues and J. Gama. *Online Prediction of Clustered Streams*. In *Proceedings of the Fourth International Workshop on Knowledge Discovery from Data Streams*, pages 23-32. ECML/PKDD, Berlin, Germany. September 2006.

iRprop Christian Igel and Michael Hüsken. *Improving the Rprop learning algorithm*. In *Proceedings of the Second International ICSC Symposium on Neural Computation*, pages 115–121, Berlin, 2000.