

# Data Warehouse Applied to SCADA Historical Data in Electrical Power Systems

WESIN ALVES, ALDEBARO KLAUTAU  
Post-Graduate Program in Electrical Engineering (PPGEE)  
Federal University of Para (UFPA)  
Augusto Correa st., nº 01  
BRAZIL  
wesinec@gmail.com

*Abstract:* - Supervisory control and data acquisition (SCADA) systems are critical for protection and safety operations in modern energy systems. A current challenge is understanding the system behavior through the large volume of data generated by SCADA in which it involves measurements of thousands of heterogeneous physical variables of power systems stored in various tables in a database. In this scenario, the Online Analysis Process (OLAP) in a Data Warehouse (DW) stands out as the most appropriate tool for understanding the electrical system behavior using such complex database. The main contribution of this article is the elaboration of a multidimensional modeling of a DW applied to a SCADA in order to better understanding behavior system and provide easy access to the information stored in its database. Pentaho Suite tools were used to develop proposed approach and experiments with real data from a Brazilian energy company were carried out to illustrate the proposed approach.

*Key-Words:* - Data Warehouse, OLAP, massive datasets, multidimensional modeling, SCADA, electric power system

## 1 Introduction

Growing supply of data in Electrical Power Systems catches the attention of researchers worldwide [1, 2]. This growth occurs through intelligent electronic devices such as the Supervisory Control and Data Acquisition system that uses sensors to collect data remotely periodically or not in a computerized system [3]. Although SCADA system is not exclusive in the energy industry, it has as main characteristic to concentrate information about physical measurements for storage, visualization and processing, that is, it plays a fundamental role in the control and operation of electric infrastructure of a region, state or country [4-6].

Implementation of a SCADA system can range from a simpler design to more complex data collection and analysis applications and large industrial process controls. SCADA is able to store equipment states, analogical and digital variable values, triggered alarms, exceeding operational limits in its historical database, and thus, it generates a solid knowledge base for process behavior analysis [7]. It is not surprise a large volume of data be generated by the SCADA every moment throughout all day, mainly about primary system status [8].

However, large volume of data does not imply large quality of information. SCADA system can generate thousand of tables in historical database to keep data from field, beyond a huge number of messages and alarms when an incident occurs, and this make difficult the task of system behavior analysis by a specialist. Due to the need of understanding and the large volume of information generated by a SCADA [9], OLAP technique in a DW stands out as the most suitable tool to act in this scenario [10-12], since the need to understand system behavior is essential for the proper planning, operation and control of electrical power systems.

OLAP techniques and Data Warehouse systems have been used to data analysis in several areas [13-20], because they create a data structure which can to sum, to aggregate, to average and to get any other calculated metrics from a large volume of data. In the electrical systems area, for example, a hybrid methodology for building DWs is proposed, integrating financial, operational and non-operational data of the public energy transmission company in Serbia [21], but authors just focus on describing the methodology.

Although there are new technologies like Smart Grids and Big Data Analysis, a considerable portion

of companies still uses and will keep using his SCADA system legacy. Thus, this work designs and implements a Data Warehouse application using data from SCADA's historical database. The DW is used in order to circumvent factors that make it difficult to analyze, to allow easy access to information and transforming the data into useful knowledge for operators. Three tools of the Pentaho suite were used for the DW application's development: Pentaho Data Integration (PDI), Schema Workbench, and Pentaho Server [22].

Contributions of this paper also includes multidimensional modeling for a Data Warehouse applied to a SCADA and components creation in the PDI tool to perform data extraction from data source and loading into the Data Warehouse. In addition, it was created OLAP cubes in the Schema Workbench tool and defined set of metrics. Furthermore, publication of analysis cubes in the Pentaho Server tool to facilitate access to information about electrical system was performed.

## 2 SCADA's historical database

According [23], historical database is an important component in a typical SCADA architecture, and it is used to store all data collected by the system. Quantity of data stored by historical database is huge, because it stores thousands of alarms, occurrences, statuses of digital variables, and nominal values of analog variables in various equipments at numerous substations.

Historical database of SCADA systems, such as that implemented by some companies, stores data in two types of entities: reference tables and dynamic tables. The former stores electrical system configurations, that is, unit of measurement, type of equipment, facilities, identifier, etc. The latter stores measured values and time series of analog and digital signals collected in field.

Data recording scheme can be synchronous or asynchronous, it is used to record analog and digital signals, respectively. Due to large amount of data collected by sensors in the field, the system allows partitioning of this data in several tables according to partitioning policy, which is done according to the period of storage that can be daily, weekly or monthly.

Historical database also can have two main dynamic tables: analog point and digital point. Analog point stores voltage, current, active power, reactive power of phases A, B and C. Digital point

stores status of circuit breakers, trip relays, fuses, switches, etc [24].

Typical relationship between the entities present in the historical database of a SCADA is shown in class diagram of Fig. 1. The <<reference>> stereotype defines the reference tables responsible for storing configuration parameters. The <<dynamic>> stereotype defines dynamic tables responsible for storing measured values of field [25].

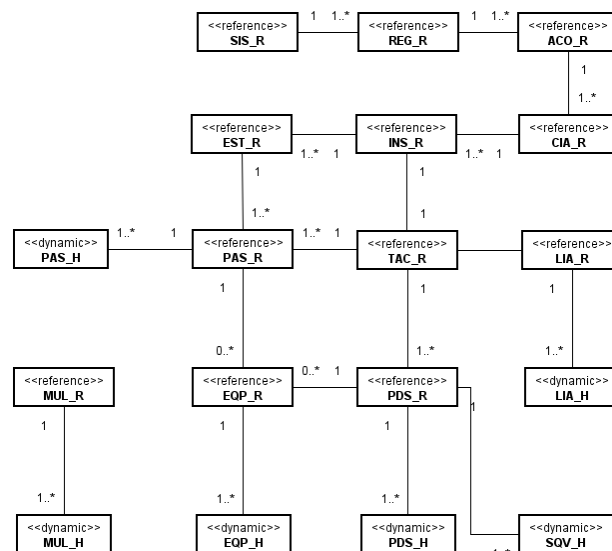


Fig. 1 Typical class diagram of SCADA system.

Recording and partitioning scheme can be observed in the class diagram of Fig. 2, which shows in detail the relationship between reference tables named as PAS\_R and PDS\_R and dynamic tables named as PAS\_H and PDS\_H, respectively. Note that the multiplicity between reference and dynamics tables is 1 for many, that is, for each variable set in PAS\_R there is one or more measures stored in PAS\_H, for example.

Depending on partitioning policy, the reference table can be related to multiple dynamic tables as shown in Fig. 2. If the adopted partitioning policy is a daily policy, each dynamic table will have its name set to default PDS\_H\_yyyy\_mm\_dd, for example, representing scan year, month and day.

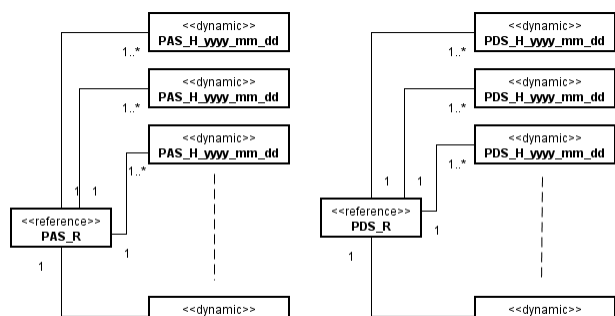


Fig. 2 Class diagram of analogical a digital point with partitioning scheme

### 3 DW Implementation

The purpose of a DW is to reveal patterns, trends, facts and sequences hidden in the large volume of data generated by a system, and thus, to achieve better results in decision making [8,14,16,26].

There are several suites for the DW development; some of them have commercial and other open source licenses. The Pentaho suite, for example, is one of the most popular in the market because it has both commercial and community versions, such that community version is similar to the commercial version.

For this advantage, Pentaho suite tools were selected to develop DW applied to data extracted from a SCADA. Details of each package in this suite are outside paper's scope. However, a comparative analysis of several open source suites considering integration criteria, information delivery and data analysis can be seen in [27].

The methodology used to implement the proposed DW was based in [20] and can be divided in four steps: definition of DW architecture; multidimensional modeling process; ETL process; and Analysis process. SCADA system developed in Brazil by CEPEL (Centro de Pesquisas de Energia Elétrica), known as SAGE [28], was used as data source, whose data were collected during the period from August 2013 to July 2014.

#### 3.1 DW architecture

DW's architecture proposed provides a system implementation overview and can be seen in Fig. 3 [13]. Starting from the left, data sources are composed of historical and reference base tables. Alarm files generated by the system are also taken into account.

Data warehouse was developed using the Postgre 9.3 DBMS (Database Management System), with

the help of Pentaho Data Integration tool that was responsible for ETL process. OLAP cubes were created using Schema Workbench tool. Front end was developed with help from the Pentaho Server tool.

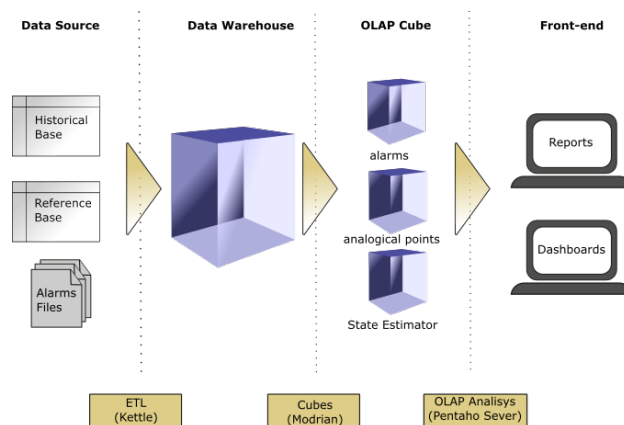


Fig. 3 DW proposed architecture

In the context of SCADA systems, the concern with alarms, outages and quality of state estimator are constant in tasks performed by system operator [23,29-33]. In addition, knowledge about state of the system can be determined by observing the quality of variables collected by the system. Therefore, the set of metrics in DW proposed will consider the following items:

- Alarms
- State estimator
- Analogical point

#### 3.2 Modeling process

Multidimensional modelling applied to SCADA is composed of a fact table and six dimensional tables arranged in the star scheme, as shown in Fig. 4 by a class diagram [25].

The fact table is called analog point and contains value, valest, flag, flagest, resnorm, BH\_VARIACAO, rgalr attributes referring to an analog value measured by the system at moment defined in BH\_DTTHR. Measured and estimated values are stored in the value and valest attributes, respectively. Measurement status of value and valest is stored in the flag and flagest attributes, respectively. These attributes are indicators of the quality of the measurement performed, and can indicate if there were any faults, whether they were assigned manually or if they are correct.

Resnorm attribute stores normalized difference between measured and estimated value.

BH\_variation indicates which mode of recording scheme has been selected, and rgalr indicates what operational limit the measured variable is found.

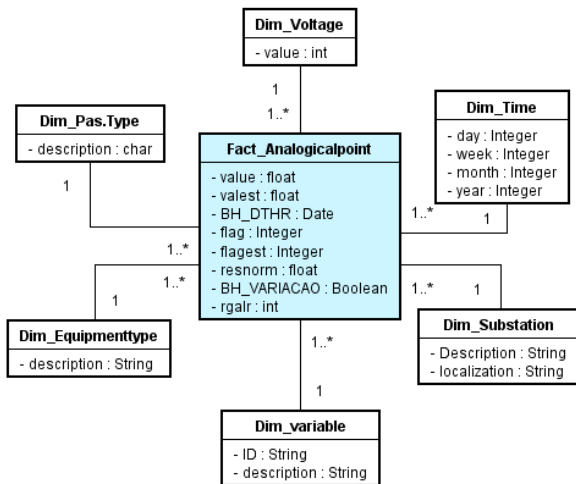


Fig. 4 SCADA multidimensional modelling

Time dimension allows you to filter values stored in the fact table according to desired day, week, month, or year. On the other hand, Substation dimension allows filtering values by a given substation among 97 substations contained in dataset.

Variable dimension allows you to select which variable you want to analyze from number of approximately 12,000 analog variables contained in dataset. Voltage dimension allows you to select measurements for a given voltage level that measurement is related. Dataset has 7 voltage levels ranging from 13.8 kV to 500 kV.

Type of equipment dimension allows you to filter data by type of equipment you want. Dataset has 11 types of equipment such as transmission lines, capacitor bank, transformers, generating unit, etc. Type dimension allows filtering by the type of measurement magnitude like voltage, current, power, etc.

### 3.3 ETL process

ETL process was implemented with help of Pentaho Data Integration tool and PostgreSQL DBMS [14]. Data were extracted with PDI and stored on PostgreSQL database according to the model presented previously.

In the transformation of dimension tables, basically two types of PDI components were used:

Input table and Output table. Input table is responsible for connecting to data source, while the Output table connects to DW. Fig. 5 presents this procedure.

The construction of time dimension was different since other components such as Generate rows, Add sequence, Calculator, and Select value were needed beyond Output table.

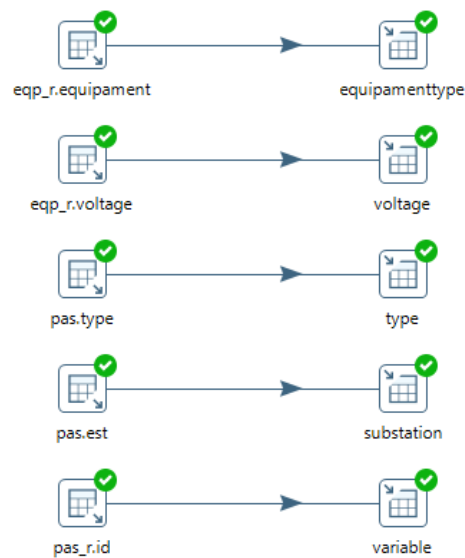


Fig. 5 Components used by dimension table

Generate rows has been configured to generate a thousand rows with starting date value (2013-06-01) arbitrarily; Add sequence was used to generate the dates in sequence from the start date; Calculator was used to extract information about year, month, week, and day for each date; Finally, Select value has configured how these values were stored in corresponding table. Fig. 6 shows transformations used in Time dimension.

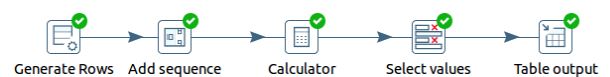


Fig. 6 Components used by Time dimension

In order to automate the process of extracting data to be stored in the fact table, a job was created in PDI. This job has two transformations, two Abort components, and one Table Exists component. Get name table transformation receives the name of historical base table that has analog variables data

by parameter, if parameter is not supplied, the job is aborted. Table exists component evaluates whether the table passed by parameter exists, if so, transformation is called to populate fact table, otherwise, job is cancelled. Fig. 7 illustrates the job created for ETL process.

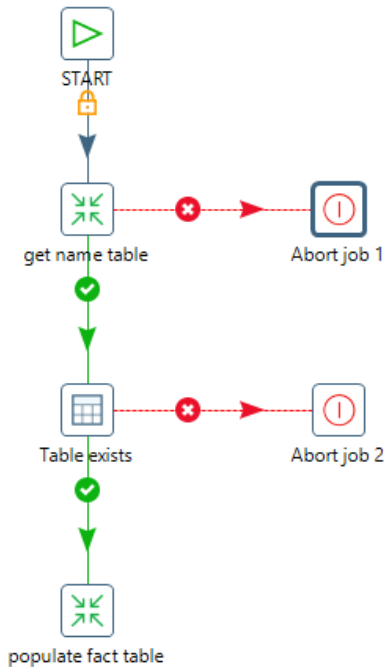


Fig. 7 Job created for ETL process

3.4 Analysis process

The analysis process begins with creation of an OLAP cube schema in Schema Workbench tool. Each schema created must contain at least one cube, where each cube is a set of metrics and dimensions [15]. Metrics are equivalent to measures of interest, total outages for example. Dimensions are attributes that divide metrics into subcategories, for example, total outages by voltage levels.

For analysis of the SCADA system data in question, three cubes were created: analog point cube, alarm cube, and state estimator cube.

The analog point cube is composed of three dimensions: substation, variable and time. It has nine metrics: mean, minimum and maximum of value, valest and resnorm measure by the system.

The alarm cube is also composed of three dimensions: substation, type of equipment and time. Metrics for this cube are formed by total of the following alarms: upper and lower warning, urgency, and emergency limits. The total of variables in normal state is also part of its metrics.

The state estimator cube is composed of three dimensions: voltage, type of equipment and time. Metrics of this cube are formed by total of the following states related to the estimator: abnormal, error, excluded by estimator, excluded by outages, excluded by operator, excluded by pre-processing, external system, out of scope, normal, unvalued, constraints and redundancy.

Table 1 summarizes the cubes that were created for data analysis. Fig. 8 illustrates the graphical interface of tool used to create cubes.

Table1 Cubes summary created for OLAP analyses

Cube	# dimensions	# metrics
Analogical point	3	9
Alarms	3	7
State estimator	3	12

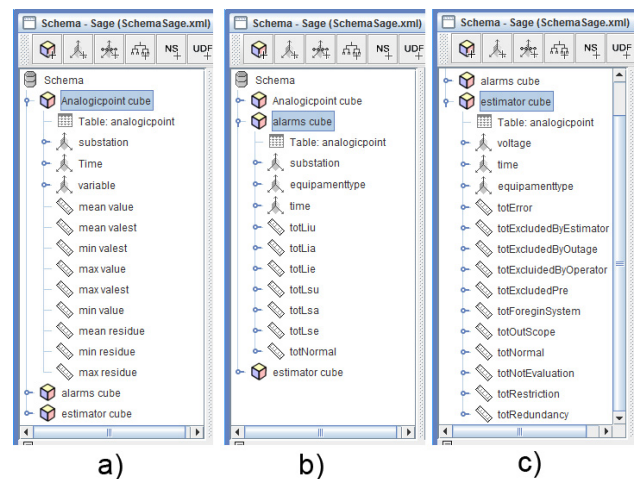


Fig. 8 OLAP cubes in Schema Workbench. a) view of analogicpoint cube. b) view of alarms cube. c) view of estimator cube.

4 Results

After ETL process, the analog point fact table is shown in Fig. 4, received more than 257 million records extracted from data source, generating a total of 39 GB of stored data. The DW system implementation was performed on a Win 10 machine with 8 GB of RAM and Pentium 3.5 GHz processor.

Some of the key analyzes that can be obtained using proposed DW are listed below:

- Daily average of the estimated value by variable.

- Daily average of the measured value by variable.
- Daily mean of normalized residue by variable.
- Total of alarms that exceeded the upper limit of urgency by substation.
- Total of alarms that exceeded the lower limit of urgency by substation.
- Total of alarms exceeding the emergency upper limit by substation.
- Total of alarms exceeded the lower limit of emergency by substation.
- Top 10 substations that exceeded urgency upper limit alarms.
- Top 10 substations that exceeded emergency upper limit alarms.
- Top 10 substations that exceeded urgency lower limit alarms.
- Top 10 substations that exceeded emergency lower limit alarm.
- Top 10 type of equipment that exceeded emergency upper limit alarms.
- Top 10 type of equipment that exceeded urgency upper limit alarms.
- Top 10 type of equipment that exceeded emergency lower limit alarms.
- Top 10 type of equipment that exceeded urgency lower limit alarms.
- Total errors in state estimator by network voltage levels.
- Total errors in state estimator by type of equipment.
- Total of measures excluded by the state estimator by voltage levels.
- Total of measures excluded by the state estimator by type of equipment.
- Top 10 types of equipment with the highest number of outages.

Pentaho Server Community Edition 7.0 tool was used as graphical interface for the Data Warehouse system applied to SCADA, as can be seen in Fig. 9. Note in detail that it is possible to observe the panel to select measures available for the cube. All of these analyzes also have time dimension in their scope, which allows them to be filtered by year, month, week and day. Access to system can be done from any web browser pointed to address of the application, which will request authentication through username and password.

All results obtained through queries to OLAP cubes published in Pentaho Server can be accessed in tabular or graphical format [13]. These queries

can be configured with the options available to system user when navigating each cube.

Query configuration includes selecting one of the published cubes in server, selecting dimensions by which the summary information is obtained for both rows and columns generated by the Jpivot analysis module, and choosing one or more metrics defined for each cube.

As an example of a query in the proposed DW, the graph of Fig. 10 shows metrics from alarm cube. Most alarms related to the lower limit of urgency (totLiu) have been triggered in transmission lines (LTR), in the same way that load-type equipment (CAR) has triggered more upper limit of urgency alarms (totLsu) than others. The graph also shows total of lower limit of warning (totLia), lower limit of emergency (totLie), upper limit of warning (totLsa) and upper limit of emergency (totLse). Other type of equipments in the graph are: capacitors bank (BCP), static compensator (CRE), static synchronous compensator (CSE), mechanical synchronous compensator (CSI), reactor (REA), transformer (TRF) and generating plant (UGE).

Table 2 shows the numbers of graph shown in Fig. 10, that is, the number of alarms by type of equipment in the system. Numbers show that there was only one alarm that exceeded the lower limit of emergency on a transmission line. Numbers also show that there were 10 alarms that exceeded the upper limit of emergency in load-type equipment.

Next example of query that can be done by proposed approach is observed in Fig. 11 that shows some metrics from estimator cube, that is, measures excluded by outages, measures that are in error according to the estimator and measures excluded by operator manually in the system. Fig. 11 indicates that BCP equipment type has the highest number of measures excluded by outages, following by CAR equipment type. On the other hand, LTR equipment type has the highest rate of errors regard to state estimator, and still TRF equipment type was the only that has presented measures excluded by operator.

Another example can be explored from proposed DW is observed in Fig. 12 that shows daily mean value and estimated of voltage during 90 days from MBTC701VBV variable regard to metrics stored in analogical point cube, where MBTC701VBV is a 500 kV transmission line. Fig. 12 shows that occurred three drops in voltage in this period and that the state estimator had some problems after the lower drop in estimate values (see mean valest).

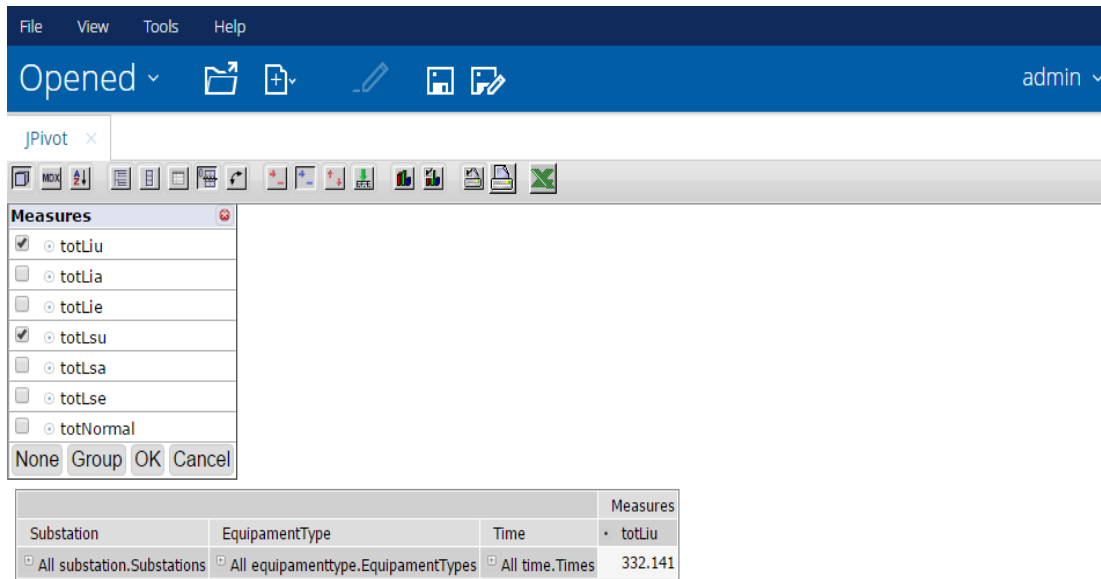


Fig. 9 Graphical interface of Pentaho Server

Table 2 Total of alarms by type of equipment (K = x1000)

	totLiu	totLia	totLie	totLsu	totLsa	totLse
BCP	0	0	0	0	0	0
CAR	2.6K	1.7K	0	183K	3.1K	10
CRE	60	2	0	0	286	0
CSE	0	0	0	0	0	0
CSI	0	0	0	6	0	0
LTR	304K	2 K	1	4.8K	18K	0
REA	0	0	0	0	0	0
TRF	3.4K	42 K	0	1.6K	34K	0
UGE	21K	3.4K	0	8	377	0
Total	332K	49K	1	190K	56K	10

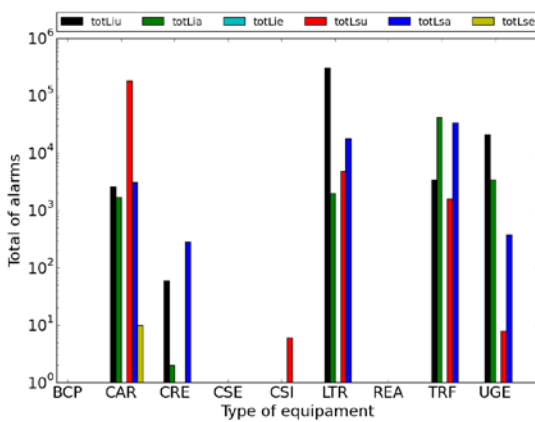


Fig. 10 Total of alarms by type of equipment

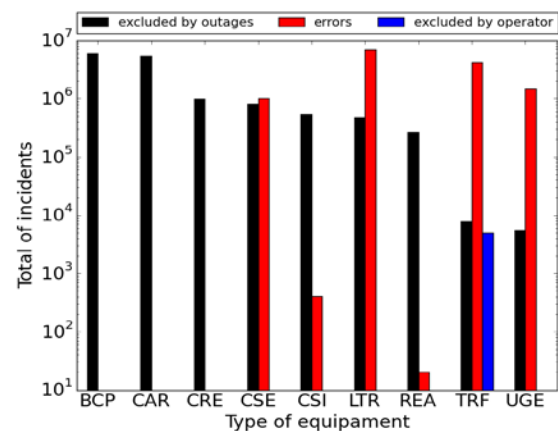
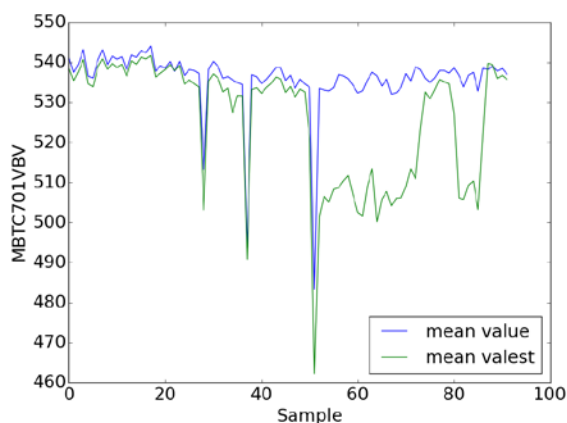


Fig. 11 Total of incidents by type of equipment

Therefore, through the graphical interface of Pentaho Server tool, a wide variety of information about behavior of electrical system will be available to end users who have access to the system. OLAP cubes exploration makes information access much easier and intuitive when compared to partitioning scheme done in relational base of SCADA system used as example in this experiment.



**Fig. 12** Daily average value and estimated from MBTC701VBV variable

The use of this DW system will allow operators and managers of electrical companies to find answers to questions such as which type of alarms was most frequently triggered in a particular substation, or which substation has the highest number of outages, or how many errors that estimator of the variable  $x$  committed throughout the year, etc.

## 5 Conclusion

The implementation of DW in a SCADA allows a greater understanding of system behavior, providing an efficient tool for audits as well as a support for decision making by companies in the electric sector. Errors evaluation in state estimator, alarms validation in substations, verifying occurrence of faults, extracting data for load forecasting, managerial reports and ease of access to information are some advantages of implementing proposed approach.

In this paper, data model of the proposed DW was presented using a class diagrams and ETL process was detailed step by step. Also, total of alarms by type of equipment, total of incidents by

type of equipment, daily mean value and estimated from a voltage variable was presented as example of its use. In additional, graphical interface of the system were presented too. Pentaho Suite tool was used to implement the proposed DW.

Results have showed that LTR and CAR are equipment types that have triggered more alarms in the system. In the same way, BCP equipment type has had highest rate of measures excluded by outages. Moreover, at least three days have presented perturbations in a 500 kV line transmission.

The proposed DW has limited to extracting information only from the SCADA system, but with this technology it is possible to integrate multiple sources of information such as climate, fires, qualimetry and PMU (Phasor Measurement Unit) databases. This integration is a suggestion for future work.

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