Optimal extraction and conditioning of historical information to support the operational decisions in a Smart Grid context

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Abstract: - This article presents a proposal for the architectural components that enable the organized and collaborative request, transport, and effective utilization of large volumes of historical information without compromising the performance of the information systems and the supporting technological platform. The architecture and some variants, successfully implemented in semantic interoperability projects within the Smart Grid context, are discussed, with a focus on the use and adoption of the Common Information Model (CIM) as defined in the IEC 61968 and IEC 61970 standards.

Key-Words: - Optimal extraction, Common Information Model, Semantic Interoperability, Smart Grid.

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1 Introduction

Traditionally, the information systems used for the operation of an electric utility consider the handling of large amounts of information related to the operating status of the Electric Power System (EPS), including substations, feeders, transformers, switches, sectionalizers, and reclosers, among others.

This information is measured in the field by monitoring, protection, control, and automation devices and is collected by monitoring and control systems, such as SCADA systems. The information includes digital values (states, alarms, locks) and analog values (voltage, current, real power, reactive power, power factor, imbalance, temperature, humidity, amount of dissolved gases, events intensity, operation counters, among other values).

These values are generated in real-time in the EPS and are almost always stored in large databases that contain the memory of what happened every day. As a whole, this database includes knowledge of the behavior of the EPS under different operating conditions that occurred over a considerably long time, sometimes 10 years or more.

In this sense, recovering historical information, processing it, and using it in an agile and effective way for its analysis allow operators and those responsible for the operation of the EPS to capitalize on historical knowledge to improve current and future operations, prevent adverse situations in the event of failures and contingencies, improve the response to maneuvers required for maintenance and clearance, and, therefore, improve the productivity, efficiency, safety, reliability, and quality indexes associated with the operation of the EPS.

When an electric utility has enough historical information collected directly from the devices installed in the EPS, it has the ability to elevate the level of support and sustenance for each operational decision in:

- Normal or steady-state operation, to meet objectives such as productivity and efficiency.
- Emergency situations, to expedite recovery and enhance security, reliability, and quality.
- Unusual situations or cases, such as disturbances due to natural events, failures, unforeseen demand peaks, or specific maintenance requirements.

2 Problem Formulation

Once the volume of data becomes considerably high, and different operational actors use it in the electrical utility, a typical problem arises associated with the extraction's performance and its ease of use. It is common for an increasing number of users to require access to this data for their daily processes. However, the architecture of legacy systems does not adequately consider the utility's operational evolution.

2.1 Smart Grid Context

In this regard, the Smart Grid and its strategies for adopting increasingly advanced analytical functions introduce a new stress factor on technological platforms. The evolution of the traditional grid is particularly guided by data, communications, and the ability to make new and better decisions with the support of information and inherent knowledge. If this knowledge cannot be retrieved efficiently, it remains stagnant in information warehouses, resulting in a wasted capacity within the utilities.

One of the most crucial functions of the Smart Grid is effective information management to support operational decision-making. Therefore, there is a clear need for more effective and efficient strategies to manage information in a unified manner. [1] [2]

2.2 Data Quality

Another serious issue that information users face is the consistency and quality of the data, which stems from various factors such as the acquisition processes themselves, sensors, device configurations in the field, communication interruptions, data channel speed, and equipment, among others. The raw data stored may not always be of sufficient quality to be used correctly in high-impact analytical functions. For example, power flow calculations for feeder reconfiguration maneuvers, the substation's design and sizing, and the configuration of protection devices, are highly sensitive to data accuracy.

Data quality is often assumed to be a part of the acquisition and storage system that contains the data, leading end-users to believe that the data always has the correct value and appropriate quality. However, this assumption is not necessarily true, and the responsibility for validation is left to the user.

2.3 Components Architecture

Traditionally, the extraction, conditioning, and use of historical EPS information in the information systems of an electric utility are carried out directly by querying the databases that contain the records (raw data) as shown in Fig.1. How the data will be used is delegated to the system or user making the request, without analyzing the end-use for each extraction or analytical function.

In this traditional architecture, strategies are not implemented to prevent the saturation of the technological platform. Optimization strategies are also lacking for handling multiple massive queries to serve all concurrent users efficiently and provide consistent responses as quickly as possible.

Based on the author's experience, there are information systems with more than 10 years of historical data stored for a few hundred or thousands of devices in the field at EPS, resulting in millions of records. These systems can be easily affected if the architecture of their components does not account for the situations described. For instance, with a single direct query to the database management system, the system can "fail" if the query is executed without restrictions. For example:

*Select * from HISTORICAL_TABLE*

Under controlled conditions, it is straightforward to carry out the necessary validations to avoid overloading the technological platform. It is essential to have data backup measures and the capability to easily restore data, and physical or virtual processing servers.

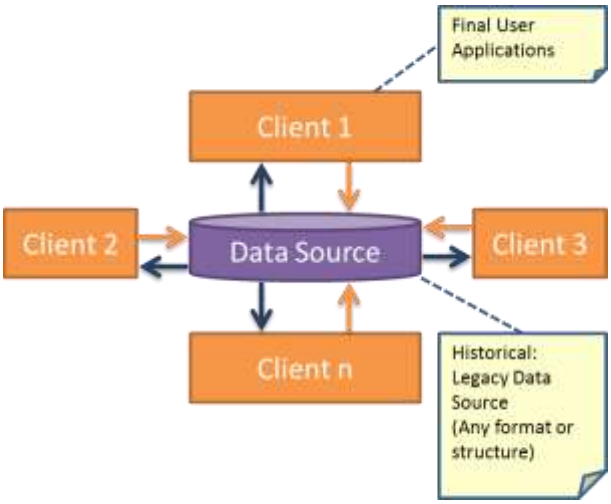

Fig. 1. Traditional components architecture for historical information extraction.

3 Problem Solution

The proposed solution is based on an **Optimal Extractor**, whose modular architecture, as shown in Fig.2, is easily adaptable to any specific situation because it includes several modules, and each one addresses one or a group of situations. The main features of the solution are described below.

3.1 Users Concurrency

When an electric utility begins to accumulate reliable historical information from the EPS, a large number of users and needs naturally arise for its proper management. This management enables the improvement of the utility's business processes, encompassing planning, construction, operation, maintenance, optimization, reconfiguration, and eventual replacement and disposal.

The most critical data utilization occurs in the field of operation. Adequate analytical management of historical information, along with timely response times, allows EPS operators to make better operational decisions with an approach that optimizes both technical and commercial processes.

For an EPS operator to use the required information correctly, it must appear on their screen as quickly as possible, with maximum response times of 10 seconds for simple queries and 50 seconds for complex queries. This speed is essential because, once the operator obtains the necessary information, they have only a few minutes to apply it effectively in response to failures during normal and emergency operations.

It's worth noting that, in most cases, an EPS operator primarily requires straightforward queries to enhance their decision-making capabilities. Typically, they need answers to simple questions such as:

- What was the maximum demand for this circuit yesterday and last week?
- At what time does peak demand typically occur on circuits 1 and 2?
- What is the typical maximum current for circuit X?
- What is the hourly profile for circuit Y during summer holidays?
- How does the voltage behave when demand decreases during winter holidays?

Occasionally, an operator responsible for EPS operation requires slightly more complex queries to make operational improvements focusing on reducing technical losses, enhancing reliability, or improving power quality, among other goals. In these cases, the questions may include:

- Which circuits in a substation have had the greatest current imbalance in the last week and the last month?
- What are the daily profiles for reactive power and power factor at circuit X?
- What is the maximum capacity of circuit Y to receive an energy transfer during the maximum daily demand in the last month?
- Among circuits 1, 2, and 3, which can most effectively receive half the power of circuit Z on a permanent basis? [3]

On the other hand, for an EPS analyst, particularly in planning and construction roles, information queries tend to be more comprehensive and complex. For instance, they may need to identify the Maximum Demand Peak (MDP) of a circuit in a year and track its evolution over the past 5 years. Similarly, they may need to identify Coincident Peak Demand (CPD) for a wide region or a set of circuits for a specific period [4]. These types of queries, of great interest to this user, consume significant resources on the technological platform because the amount of data required can range from thousands to millions, depending on the period and the number of circuits. Notably, the user often requires only 1 to 100 significant data points, but the data retrieval process can be computationally complex and time-consuming.

To address the concurrency situation, a commonly used alternative is an Enterprise Service Bus (ESB). An ESB, in addition to having a highly efficient queue manager, allows for the implementation of intermediary services to prioritize queries based on the type of query and the user's request. [5]

When an ESB is used, the functions of the **Optimal Extractor** are accessible to any application or client system that requires historical data, without the necessity of understanding the internal data structure of the source systems (Fig.2).

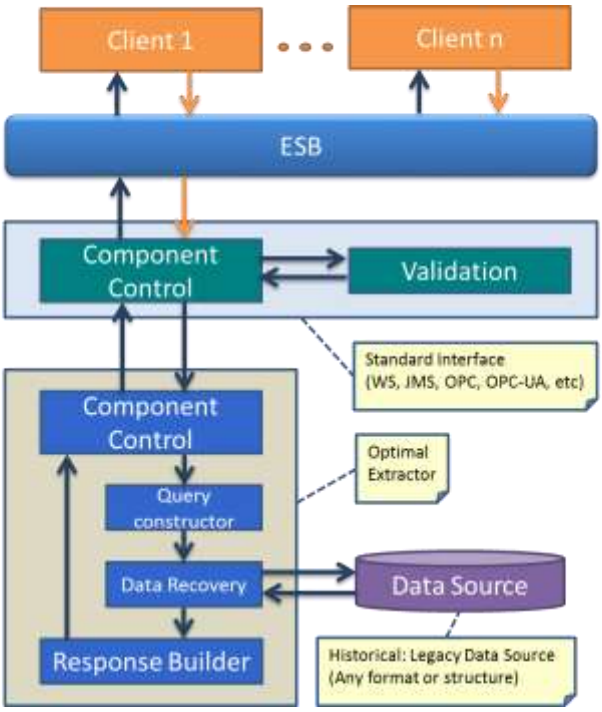

Fig. 2. Proposed components architecture for historical information extraction for syntactic interoperability.

However, if an ESB is not available, the **Component Control** module must handle the sequencing and prioritization of multiple simultaneous queries. It can even break down queries into smaller parts to free up machine time across the entire technological infrastructure, as described in Section 3.5.

3.2 Data Quality Verification

The historical data stored retains the quality with which it was acquired at the moment in real-time; however, multiple factors can affect its quality and precision. A viable option to ensure a response with highly reliable data is to integrate a **Validation** module. This module is responsible for analyzing the data request in a query and applying specific validation, verification, and completeness algorithms. In case it detects inconsistencies, it performs an estimate of the corresponding replacement data and informs the requester about the actions taken in the response calculation.

Within this **Validation** module, the quality of raw data can be verified in several ways. For example:

- Integrity: Counting the number of records available for a data series in a defined period.
- Consistency: Validating a data set according to the electrical or physical laws that model it.
- Accuracy: Comparing a data set with external measurements, redundant measurements, or manual measurements taken during the same period or by integrating measured values at different points in the ESP.
- Behavior: Comparing the profile of a data set with the typical profile of that measurement.
- Validity: Cross-comparing measured values with similar measurements, geographically close measurements, or calculated values.
- AI: Additionally, considering the data complexity, it is feasible to train Artificial Intelligence (AI) algorithms to perform much more comprehensive validations. For example, this can include identifying and applying typical profiles, autonomous autoregression, predictive models, correlation with exogenous variables, comparison with nearby data points (case-based reasoning), and automatic clustering algorithms, among others.

3.3 Handling Large Data Sets

If the database does not impose query restrictions, a request can yield a substantial amount of data as a response. This situation could lead to the saturation or collapse of the technological platform, causing delays in all other concurrently running processes.

To address this issue, the **Component Control** module, working in conjunction with the **Response Builder** module, can adopt a strategy to prioritize, segment, or break down queries into smaller parts. This approach allows for the handling of multiple responses so that the user who requested the data ultimately receives a complete response. In this sense, the data is processed in manageable packages by the technological platform. Consequently, all other concurrent users are served, and the waiting time is distributed among them. As a result, high-priority users receive their answers within the required timeframe, while users with large data volume requests (typically not of high priority) receive their responses only slightly later than if the query were executed directly (in any case, the processing time will be considerably longer than for simple queries).

3.4 Database Operational Security

Another specific issue in traditional architecture is that the operational stability of the technological platform is not guaranteed. As explained in section 2.3, it is relatively easy to disrupt it through uncontrolled use.

The solution proposed by the **Optimal Extractor**, as shown in Fig.2, involves breaking down queries into smaller parts to manage the machine time of the technological infrastructure. In this regard, the **Component Control** module is responsible for executing the following actions:

- Calculate the amount of data that will be queried in a user request.
- If the data amount exceeds an empirically defined limit (based on the hardware resources of the technology platform and the granularity of stored data), the query will be segmented or divided into sections, and the **Query Constructor** and **Response Builder** modules will be notified.
- Multiple partial queries are generated.
- A waiting period is introduced between queries (the duration is also determined empirically using the same criteria as the data limit).
- Partial responses are consolidated into a single coherent response.

- The **Validation** Module algorithms are executed.
- The final result is delivered to the user who initiated the request.

3.5 Standard Data Access

A significant issue with the traditional architecture depicted in Fig.1 is that each application or client system requires the application of the data access standard to the technological platform. Furthermore, they need to have knowledge of the database's internal structure. The problem becomes more severe when, for specific reasons, the database undergoes changes in technology, data access standards, or internal structure.

To address this problem, the **Optimal Extractor**, as presented in its architecture in Fig.2, incorporates a data abstraction layer. Consequently, if an ESB is used, all clients must adopt a single connectivity standard determined by the ESB, which is typically open and well-known. In cases where an ESB is not available, the proposed architecture provides flexibility by allowing access to the **Component Control** module through one or more standard data interfaces, such as Web Services (WS), Java Message Service (JMS), OLE for Process Control (OPC), OLE for Process Control - Unified Architecture (OPC-UA), and others. If necessary, it can even accommodate communication protocols like DNP, Modbus, or ICCP.

An additional advantage of this architecture is that if the database undergoes changes in technology or internal structure, it will only require modifications to the **Data Recovery** module, without any impact on the data clients. [6] [7]

3.6 Standard Data Model

For Smart Grid applications, it is highly recommended to implement semantic interoperability between applications or systems. To achieve this, a canonical data model based on standards should be used. This model enables the unification and formalization of the meaning of exchanged data. It is particularly advisable to adopt the Common Information Model (CIM) defined primarily in the set of standards IEC 61968 and IEC 61970.

In the architecture proposed in Fig.2, a wrapper should be added on the **Component Control** module side, as well as another on the **Client** side. This addition ensures that all information transported between applications can be read, interpreted correctly, and unified by any current or future application client, as illustrated in Fig.3. Furthermore, the adoption of standards allows for the utilization of various integration patterns, including those defined in the IEC-61968-100 standard.

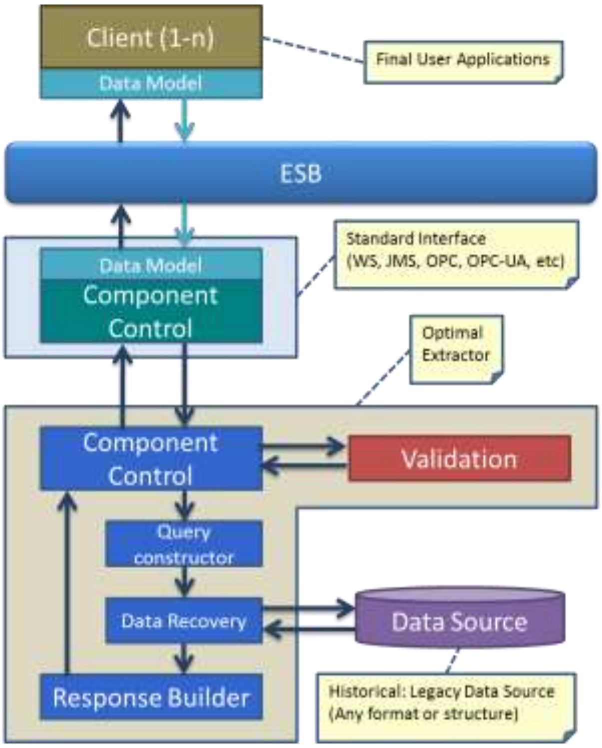

Fig. 3. Proposed components architecture for historical information extraction for semantic interoperability.

For a comprehensive and advanced architecture, it is essential to define a specific profile based on the Canonical Data Model that represents the particular data sets.

If CIM is utilized, established methodologies enable the definition of the CIM Profile for data exchange within a semantic interoperability strategy for the Smart Grid. [8]

In the architecture of Fig.3, the **Data Model** module is responsible for implementing the wrapper that performs the translation between data from the source system and the **Client** requiring the information.

Fig.4 illustrates a portion of the CIM Profile proposed for the implementation of the developed **Optimal Extractor**.

This partial view encompasses the use cases and relationships involved in integrating the CIM Profile associated with analog measurements in the EPS. It takes into account elements such as timestamp for synchronization, maximum and minimum values, unit multiplier, associated equipment type, and its unique identification within the entire context.

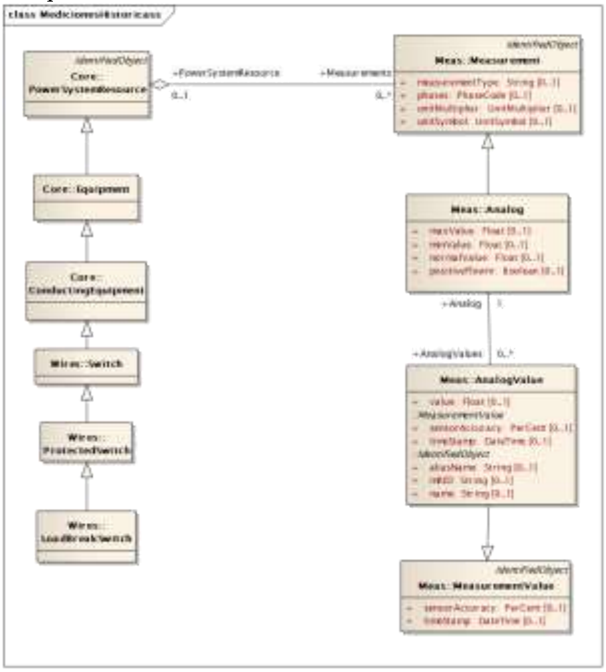

Fig. 4. CIM Profile (partial view) for Smart Grid semantic interoperability strategy.

4 Optimal Extraction and Conditioning

This section describes some of the key optimal conditioning functions for efficient data transfer between the source system and the client in need of the information.

4.1 Raw Data

The following data can be queried for any time range and any variable registered in a steady-state:

- Normal: This option retrieves registered data without applying filters or validations. It is not recommended, as it consumes the most resources on the technology platform. The rules described in sections 3.3 and 3.4 apply
- Discrimination: This option retrieves data while eliminating invalid values. It verifies the consistency of measurement values based on the rules described in section 3.2
- Missing rows: In some cases, specific reasons can prevent certain measurement equipment from collecting data during a period, resulting in gaps in the historical database. This function identifies missing samples for each selected equipment in the queried period. It includes two options: "Only missing rows" and "Raw data with missing rows".

4.2 Statistical Data

The following values can be calculated for any time range, at any of the data groupings by frequency, for any recorded steady-state variable. The rules described in section 3.2 apply.

- Average: This represents the arithmetic mean of the requested values.
- Maximum: This corresponds to the highest value among the requested values. It is useful for identifying extreme values that could be outliers or data entry errors.
- Minimum: This represents the lowest value among the requested values. It is employed to identify extreme values that might be outliers or data entry errors.
- Sum: This is the result of adding up all the requested values. It is useful for aggregating values within a region, such as the real power of substation circuits or a group of substations.
- Standard deviation: This is the square root of the variance of the requested values. It serves as a measure of dispersion and is particularly characteristic.

4.3 Data Grouping by Frequency

The following grouping strategies of the calculated values of section 4.2 allow optimizing the queries, generating and transporting only the data that is really useful to the end-user, depending on the function in which it will be used.

- Hourly: Returns a single data point for each requested hour. It facilitates the creation of daily profiles of EPS electrical behavior
- Daily: Returns a single data point for each requested day. It facilitates the generation of weekly or monthly profiles of EPS electrical behavior
- Weekly: Returns a single data point for each requested week. It facilitates the generation of monthly profiles of EPS electrical behavior
- Monthly: Returns a single data point for each requested month. It facilitates the generation of annual profiles of EPS electrical behavior.
- Annual: Returns a single data point for each requested year. It allows for comparisons of annual EPS electrical behavior and trends
- Period: Returns a single data point for the entire requested time range. This function is used to compare EPS electrical behavior during specific periods of interest

4.4 Power Quality Events

The following values can be requested for any time range, but metering devices must have power quality functions.

- Interruptions: These are instantaneous changes in frequency from the steady state of current, voltage, or both. They have unidirectional polarity and are primarily characterized by their rise and fall times and their maximum value
  - Momentary. Obtains values with a voltage percent less than or equal to 10% and a duration less than or equal to 3,000 ms.
  - Temporary. Obtains values with a voltage percent less than or equal to 10% and a duration greater than or equal to 3,000 ms but less than or equal to 60,000 ms.
  - Sustained. Obtains values with a voltage percent of 0% and a duration greater than or equal to 60,000 ms.
  - All. Retrieves all interruptions when the current flow stops for any reason in the selected time range.

- SAGS: These are decreases in the effective voltage value between 0.9 and 0.1 per unit (P.U.) with durations ranging from 16 ms up to a few seconds
  - Instant. Values with a voltage percent greater than or equal to 10% but less than or equal to 90%, and a duration greater than or equal to 16 ms and less than or equal to 500 ms.
  - Momentary. Values with a voltage percent greater than or equal to 10% but less than or equal to 90%, and a duration greater than 500 ms and less than or equal to 3,000 ms.
  - Temporary. Values with a voltage percent greater than or equal to 10% but less than or equal to 90%, and a duration greater than 3,000 ms and less than or equal to 60,000 ms.
  - All. Retrieves all SAGs records stored for the selected time range.

- SWELL: These are increases in the effective voltage value between 1.1 and 1.8 P.U. with durations ranging from 16 ms up to a few seconds.
  - Instant. Values with a voltage percent greater than or equal to 110% but less than or equal to 180%, and a duration greater than or equal to 16 ms and less than or equal to 500 ms.
  - Momentary. Values with a voltage percent greater than or equal to 110% but less than or equal to 140%, and a duration greater than 500 ms and less than or equal to 3,000 ms.
  - Temporary. Values with a voltage percent greater than or equal to 110% but less than or equal to 120%, and a duration greater than 3,000 ms and less than or equal to 60,000 ms.
  - All. Retrieves all SWELLs records stored in the selected time range.

4.5 Calculated Data

- SCADA Equivalent Value: This is used when real-time data is unavailable, typically from a SCADA system, or when it's necessary to compare the actual SCADA value with an estimated value based on historical data. It is obtained through the following sequence.
  - Calculate the equivalent previous date, such as the day of the previous week that is similar to the current day or the day of the previous month that is similar to the current day
  - Use the current time without minutes.
  - Request the average of historical values for the current time on the equivalent previous date.
- Last Stored Value: For any variable, this request provides the last value that was entered in the historical record along with the corresponding timestamp. It allows for validation of the operational status of the historical record and estimation of the quality of the stored data.

5 Conclusion

The value added by the **Optimal Extractor** to the processes of supporting operational decisions in a Smart Grid context has been highly significant. Specialist users continually discover new ways to leverage the advantage of visualizing the EPS behavior over time.

For example, the **Optimal Extractor** enables the graphical representation or export to Excel of hourly average measurements by phase for each substation circuit in a year. This query generates approximately 8,760 values per electrical parameter (365*24), regardless of the equipment's sampling frequency. In contrast, a standard extraction of raw data with a 10-minute sampling frequency involves transferring approximately 52,560 values for each parameter (365*24*6), and double that if the sampling frequency is 5 minutes (365*24*12). Additionally, it consumes time and hardware resources on the client-side to process all the obtained data.

The integration of technology, optimal data extraction strategies, and the adoption of standards have enabled the execution of high-level functions with exceptional performance, reducing user response waiting times by up to 95%. For instance:

- An EPS operator can generate the graph of the hourly real and reactive power profiles for the last 24 hours in approximately 5 seconds.
- The graph or table displaying the hourly maximum values for voltage or real power measurements of a circuit over a year can be generated in approximately 50 seconds.
- If the above query is requested daily, the response time is less than 20 seconds.

A very representative and valuable query of the **Optimal Extractor** in support of operational decisions for an EPS operator during a failure and reestablishment event is the ability to calculate, on the fly (OLAP), the maximum hourly demand profile for the circuits involved, including the circuit that experienced the fault and those that can support the restoration. This integrated function allows for displaying the graph on screen in less than 3 seconds for each circuit.

Another integrated function that provides significant value for users responsible for EPS operational analysis is the computation of the Coincident Peak Demand (CPD) for all circuits in a geographical region over a year [4]. Manually, this analysis for a geographical region with at least 500 circuits can take from 2 to 3 months. The **Optimal Extractor** calculates the value in approximately 30 seconds, and 2 minutes if data quality algorithms are applied, along with generating the necessary calculation memory to support the results and operational decisions. This specific function enables impressive time savings and eliminates human errors that may occur when manually managing large amounts of data.

Table 1 displays the results obtained by comparing the performance of three architectures.

- ARQ1: Traditional components architecture.
- ARQ2: Proposed components architecture for syntactic interoperability.
- ARQ3: Proposed components architecture for semantic interoperability.

In all the Test Cases, ARQ2 provides the best response time for the end user, with notable improvements compared to ARQ1. Regarding ARQ3, when the data volume is relatively low, the response time for the end user may be greater than ARQ1 due to the metadata required by implementing the CIM Instances. However, in general, this effect does not occur as the data volume increases, and the end user's perception is not affected since the total added time is less than 2 seconds.

The architecture and strategies proposed for the **Optimal Extractor** facilitate the implementation of functions for the Smart Grid within the context of EPS operations. These functions, along with the architecture for semantic interoperability, were successfully implemented in multiple information systems in Mexico, supporting EPS operations.

Future work for advanced Smart Grid applications includes the application of Artificial Intelligence to enhance response times, improve data quality, implement new validations, and enhance the user experience. For example, this could involve incorporating prognostics for demand, voltage drops, or climate-related impacts; all without affecting hardware performance or increasing end-user waiting times.

Table 1. Comparison results using the three architectures described.

Test Case			ARQ1		ARQ2			AQR3		
Case	Grouped by frequency	Period	Float values* transferred	Total time for user [s]	Float values* transferred	Total time for user [s]	Time % (ARQ2/ARQ1)	Float values* transferred	Total time for user [s]	Time % (ARQ3/ARQ1)
Statistical (AVG)	Hourly	1 Hour	420	0.15	35	0.09	60.0%	35	0.28	186.7%
		1 Day	10,080	0.47	840	0.16	34.0%	840	1.52	323.4%
		1 Week	70,560	0.80	5,880	0.14	17.5%	5,880	2.42	302.5%
		1 Month	302,400	6.73	25,200	0.86	12.8%	25,200	5.57	82.8%
		1 Year	3,679,200	71.36	306,600	6.92	9.7%	306,600	15.89	22.3%
	Daily	1 Day	10,080	0.37	35	0.13	35.1%	35	0.32	86.5%
		1 Week	70,560	0.70	245	0.29	41.4%	245	1.33	190.0%
		1 Month	302,400	5.93	1,050	1.36	22.9%	1,050	2.73	46.0%
		1 Year	3,679,200	70.86	12,775	2.62	3.7%	12,775	6.88	9.7%
	Monthly	1 Month	302,400	6.23	35	0.27	4.3%	35	0.43	6.9%
		1 Year	3,679,200	70.06	426	1.92	2.7%	426	3.06	4.4%
	Anualy	1 Year	3,679,200	69.26	35	1.74	2.5%	35	1.89	2.7%
CPD	Anualy	1 Year	18,396,000	^ 86729.55	4	3.90	0.004%	4	4.09	0.005%

* 32 Electrical measurements + Timestamp (date - time) + Circuit ID
^ Includes 86,400 [s] for CPD processing in the client side

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Contribution of individual authors

Alfredo Espinosa-Reza was responsible for the design of the architecture proposed, CIM Profile validation, and testing of the final products.
Marxa Torres-Espindola carried out the development of the components in C#.NET and implementation in many information systems.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.