A CIM-Based Framework for Utility Big Data Analytics

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Overview

- Opportunities & Challenges
- Patterns & Methodologies
- Practices & Applications

What is Big Data Analytics?

- Big data analytics is a new generation of technology that can be leveraged to extract business values from large volumes of and a wide variety of data.

- Based on analysis of big data, discoveries can be made to promote efficiency, optimize operation, and save cost, etc.

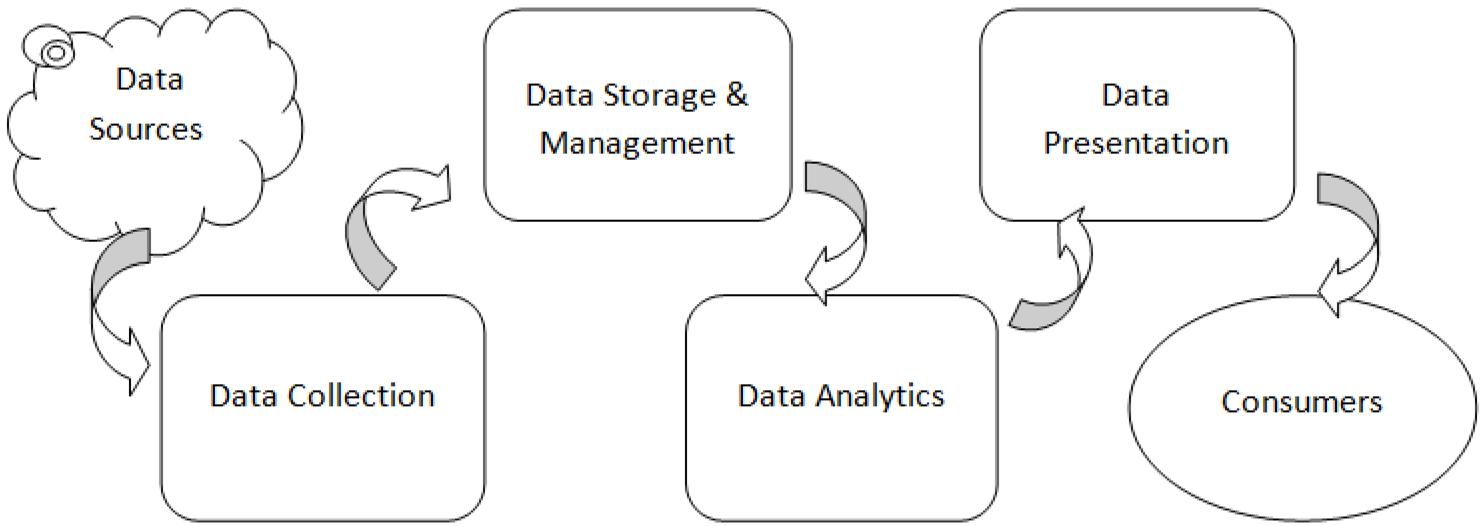
Big Data Analytics for Utilities

- As smart grid deployments created exponentially more data for utilities, the electric utility industry is now seeking new analytics tools and techniques to address their emerging big data issues.

- According to recently conducted surveys:
  - Companies in the utility industries have the highest expectations for generating returns on their big data investments than firms in any other industries. (http://www.tcs.com/big-data-study/Pages/default.aspx

  - It is predicted that global expenditure on utility data analytics will grow from $700 million in 2012 to $3.8 billion in 2020. (http://www.greentechmedia.com/research/report/the-soft-grid-2013)

Gap Analysis



- While tremendous progress has been made in big data collection and management, relying on big data to make decisions is still an industrial effort in its infancy.
- The traditional manual methods of data analysis, such as spreadsheets, ad-hoc queries, and database reporting, have proved insufficient to help analysts capture the patterns and insights from large and complex data sets.

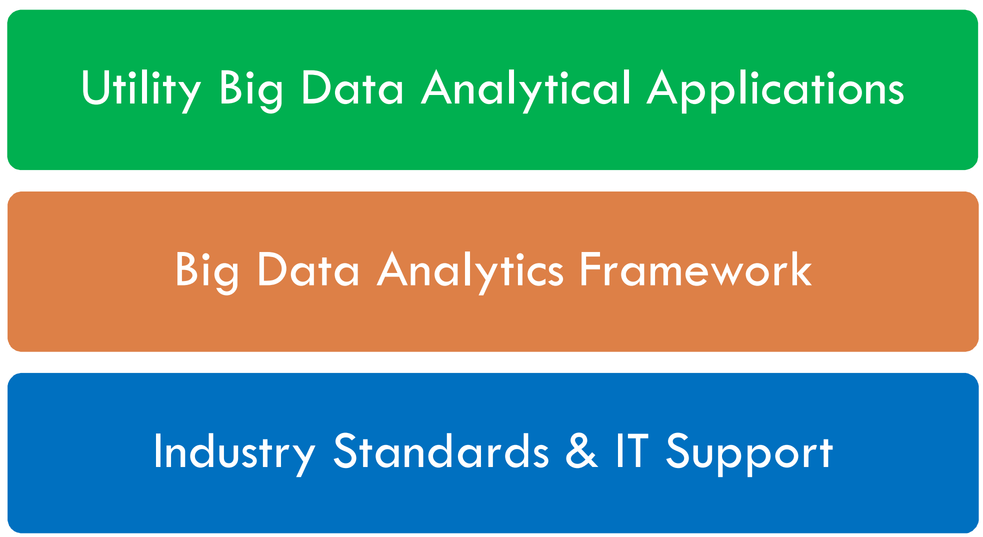
Biggest Challenges

- How to make disparate and incompatible datasets usable, interoperable, and valuable across the enterprise?

- The cost of building and maintaining a specific business-driven big data application is tremendously high due to the common obstacles. Each application must address many of those common issues, if not all.

Objective of the Project

- Developing a software framework to address key utility big data issues and foster development of utility big data analytical applications.



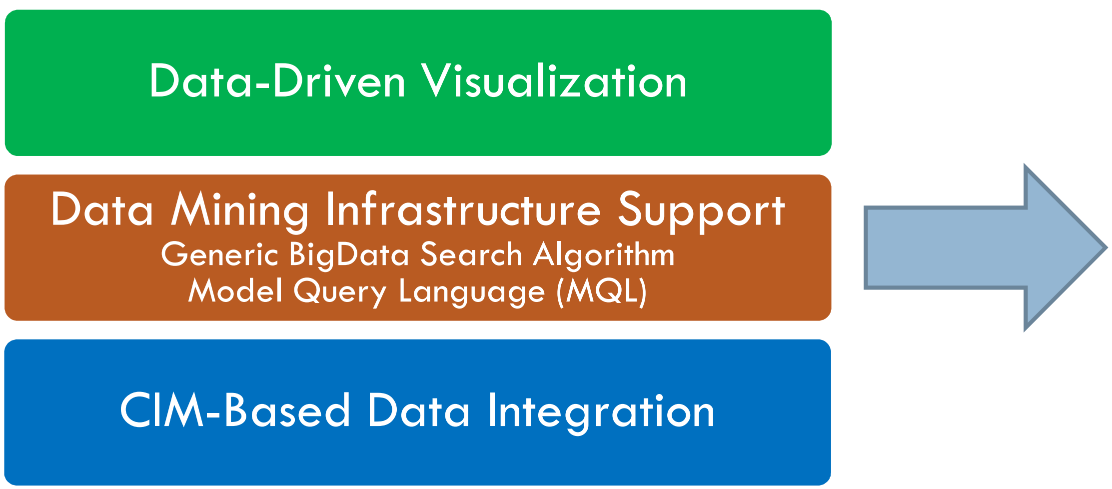
About the Project

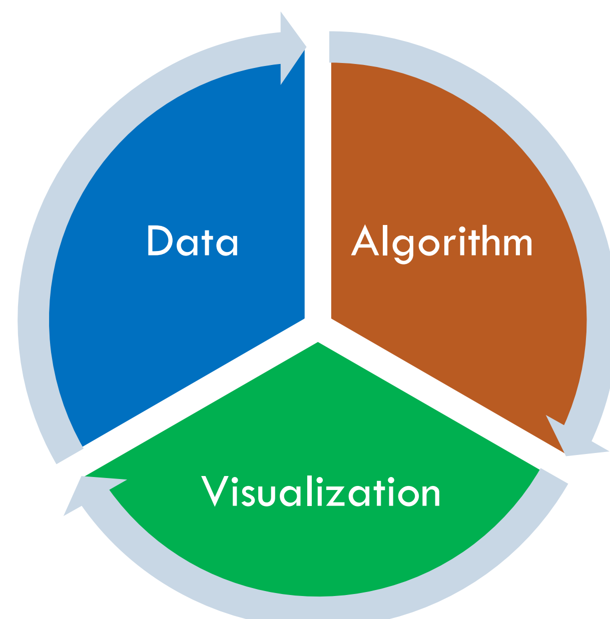
- Funded by US Department of Energy (DOE) under the awarded SBIR Grant (Award No. DE-SC0006347)

- The research results were leveraged by
  - BC Hydro
  - Albert Electrical System Operator (AESO)
  - PJM Interconnect LLC

Layered Architecture of CIM-based Big Data Analytics Framework

- Designed to address the common issues in three BIG areas of big data analytics: Data, Algorithm, and Visualization.
- Providing core data mining infrastructure support from which business-driven utility big data applications can be rapidly developed.





Common Information Model (CIM)

- Common Information Model (CIM) is a standard specification designed for promoting information exchange and fostering collaborations among various utility enterprise applications.

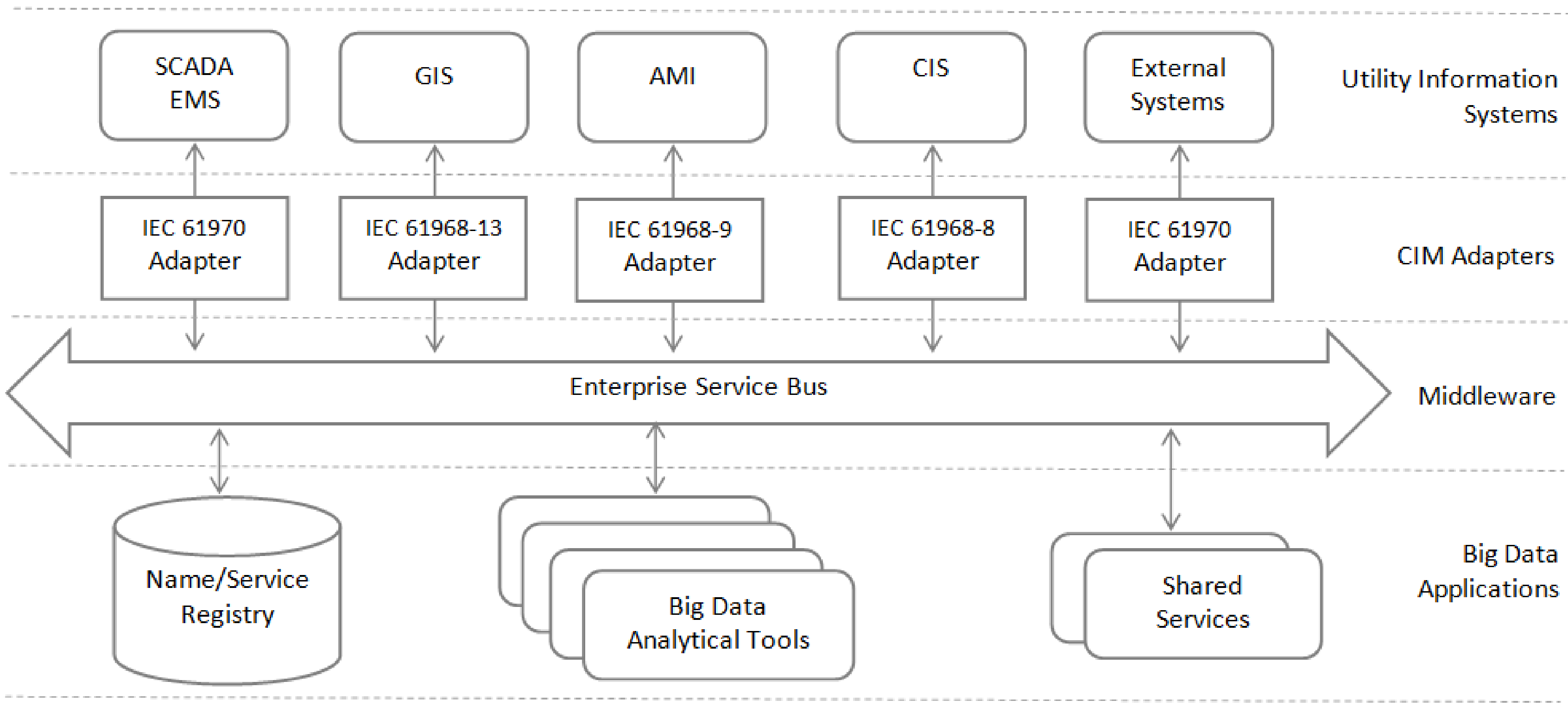
- Because CIM describes all aspects of power system, it provides a standard-based semantic foundation for Big Data Analytics in the utility industry.

CIM for Big Data Integration

CIM is designed/targeted to address various Big Data Integration Issues:

- Naming and Object Identification: Master Resource ID (MRID)
- Heterogeneous Modeling Practices: Operation vs. Planning, Node/Breaker (ConnectivityNode) vs. Bus/Branch (TopologicalNode)
- Data Grouping: Profile
- Data Correlation: Profile Dependency
- Data Composition: Frame
- Data Validation: Object Constraint Language (OCL)
- Data Ownership: Model Authority Set (MAS)
- Foreign Data: Extension
- Variations & Changes: Project

CIM-based Utility Big Data Integration



Data Mining for Business Intelligence (BI)

- Data Mining is the process of identifying new **patterns and insights** in data.

- Insight derived from data mining can provide tremendous economic value and critical decision supporting for cost-saving advantages and operation strategies.

- As the volume of data collected and stored in utility databases grows, there is a growing need to identify important patterns and trends and act upon the findings.

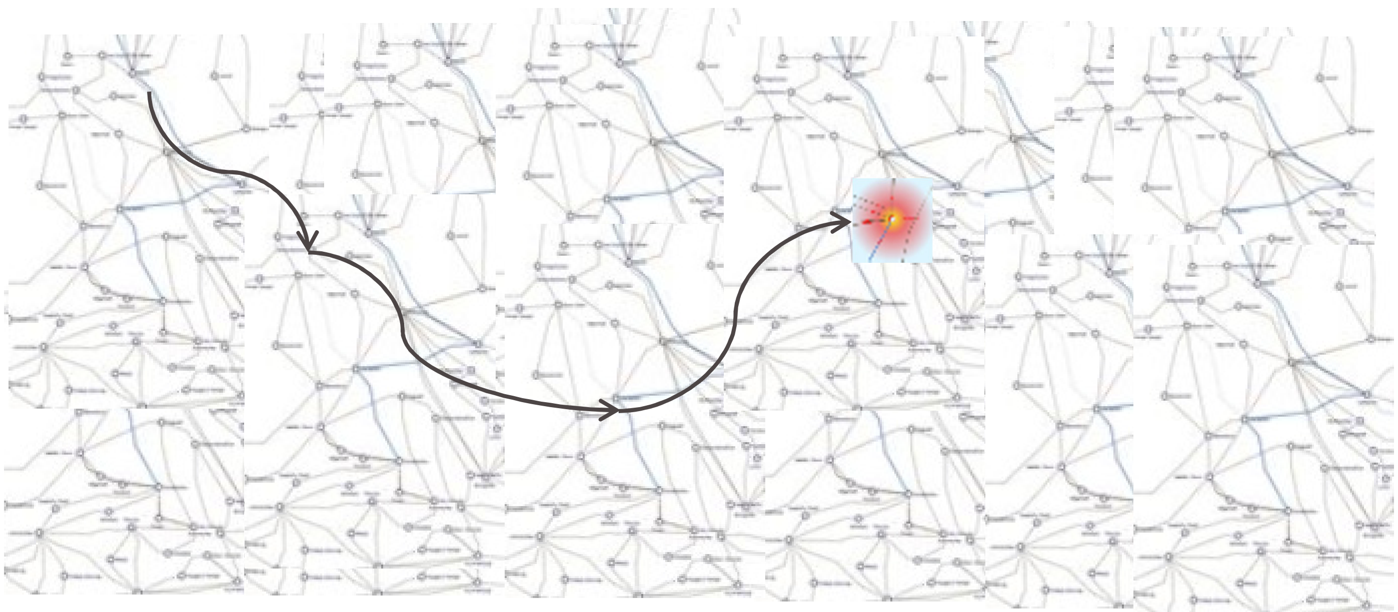
User-Centered Data Mining

- Focusing on providing end-users a capability to build their own analytical applications through **declarative programming** and **plug-in**.

- Providing core data mining infrastructure support from which business-driven analytical applications can be rapidly developed and seamlessly integrated.
  - ✓ Generic BigData Search Algorithm
  - ✓ Model Query Language (MQL)
  - ✓ Report Design

Generic Big Data Search Algorithm

- Designed to support CIM data structures
- Driven by CIM meta-data: CIM Profiles
- Leveraging Google BigTable data management techniques for information cataloging and indexing



Model Query Language (MQL)

Model Query Language is a declarative functional language, specifically designed to query, transform, and manipulate CIM-based data models.

- Most of the today's data query language, such as SQL, OCL, SPARQL, and XPATH, are either inappropriate for CIM models or too complicated for end users.

- MQL targets an object-oriented data model, such as CIM. It uses a simple syntax, similar to algebraic expression, to describe various kinds of data operations, including navigation, filtering, and transformation, etc.

```
ACLineSegment/[BaseVoltage->nominalVoltage]>=220 &&
[EquipmentContainer->Region->name]==“EAST”
```

- MQL was designed to work with Generic BigData Search Algorithm to performs the **user-declared** data operations.

Key Features of MQL

- **Declarative**: Users declare what need to be done rather than programming how to do it.
- **Recursive**: Making a complicated task easy to achieve.
- **Expressive**: Like an arithmetic expression, MQL is easy to construct.
- **Resourceful**: MQL supports
  - bi-directional dataset-to-dataset, object-to-object navigation
  - filtering, grouping, sorting, union, etc.
  - function and operator, built-in or user-defined
  - alias designed to facilitate the reuse of declarations
  - formatting & reporting

Visual Data Mining

- Visualization offers a powerful means of analysis that can help to uncover patterns and trends hidden in unknown data.

- Visual data mining focuses on the combination of visual and non-visual techniques as well as integrating the user in the exploration process.

Common Shortcomings of the Existing Power Grid Visualization Tools

- **Requiring the visual displays to be pre-designed**, thus hindering user's ability to discover. Most importantly, for a large grid, it is very labor-intensive and costly to build and maintain these pre-designed visual displays.

- **Focusing on displaying the data** rather than providing users with the interactive ability to facilitate information exploration.

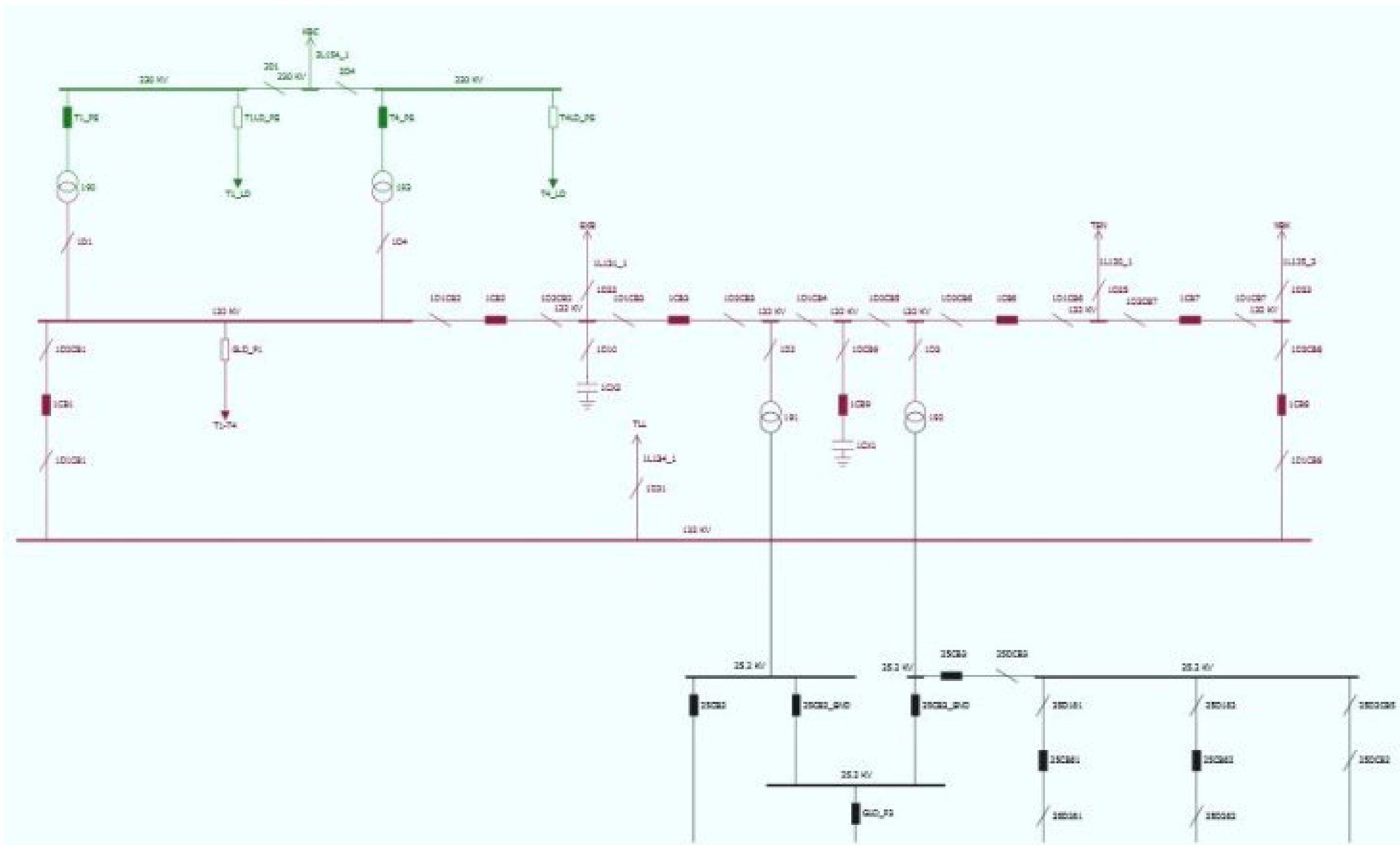
- Designed as a function of a monolithic system and built with proprietary technologies, thus **not interoperable with other utility information infrastructure.**

A Data-Driven Approach

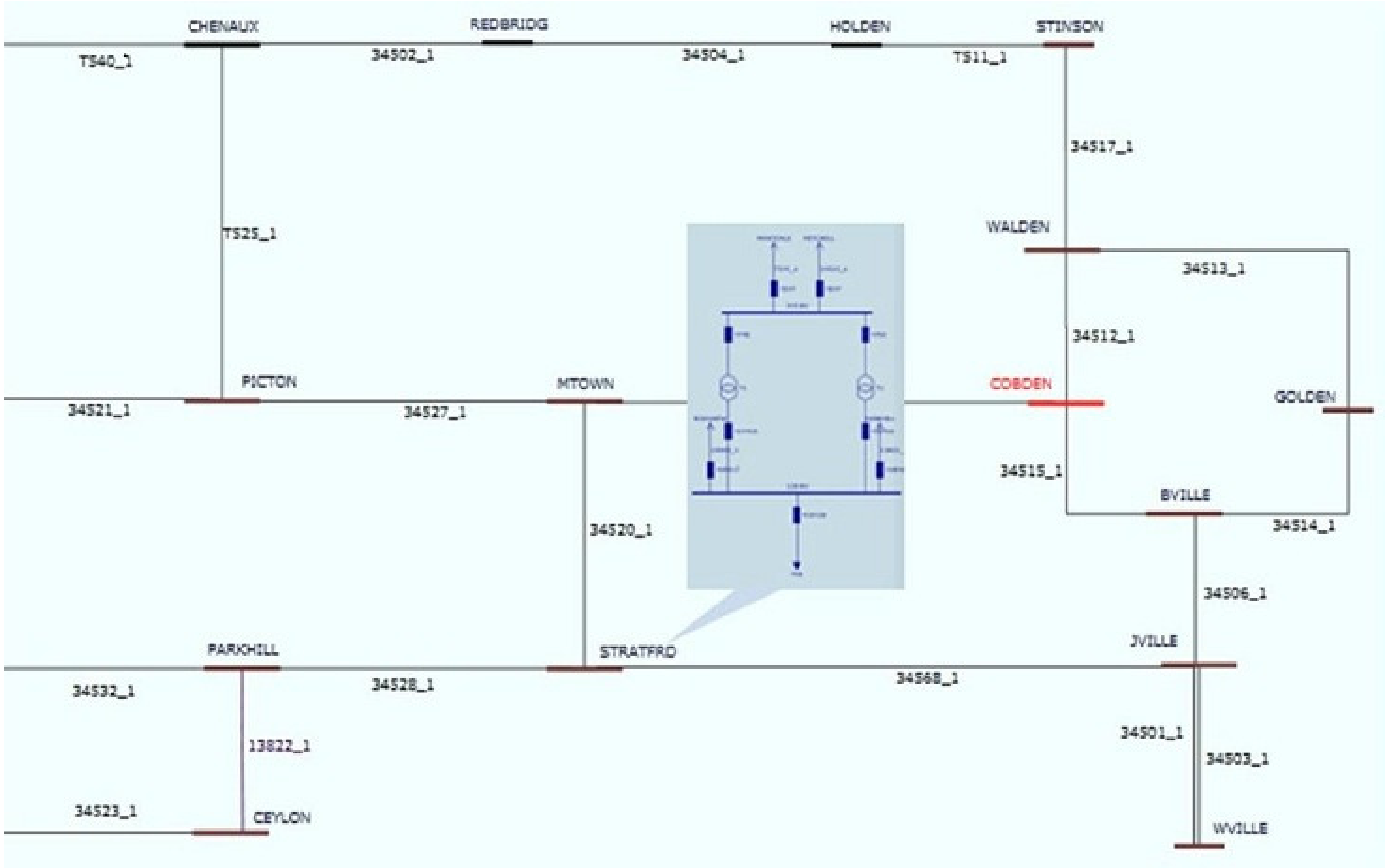
- A data-driven approach relies on developing sophisticated and powerful algorithms for manipulating the data under analysis and transforming it dynamically to create interactive visualizations. **It creates the visualization on-the-fly**, thus completely eliminating or significantly reducing the cost of building visual displays.

- The resulting visual presentations **emphasize what the data is** rather than how the data should be presented in a pre-designed manner, thus, **fostering comprehension and discovery**.

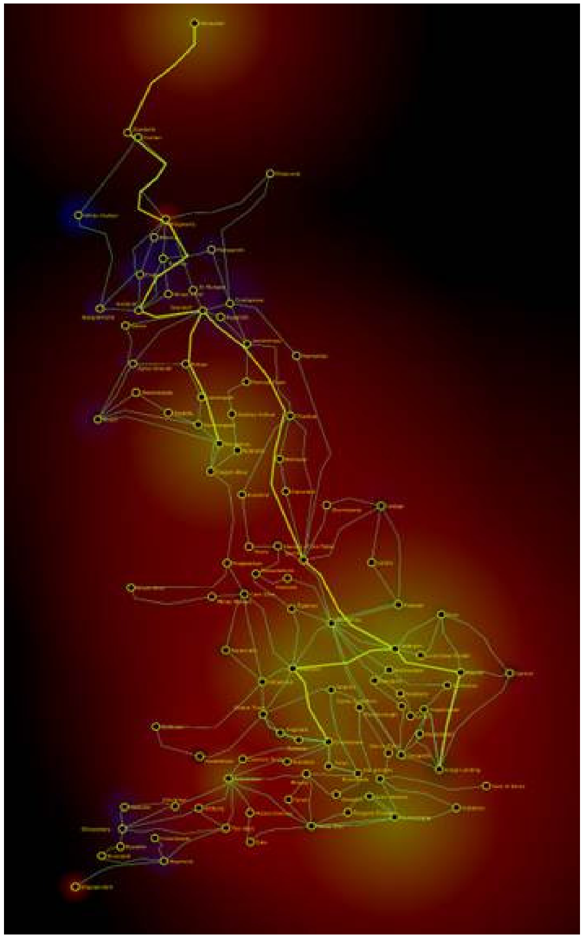
Example 1: Pattern Recognition for Auto Generation of Substation One-Line

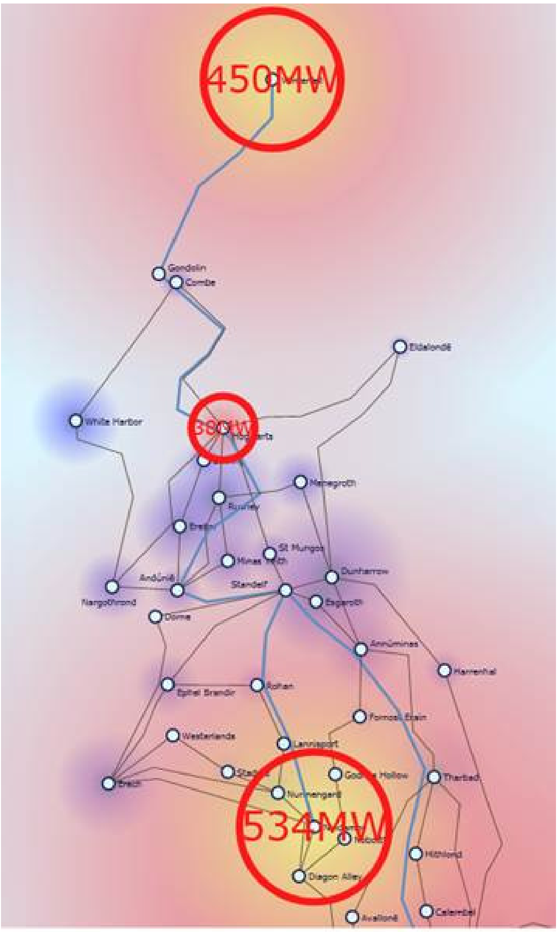


Example 2:Force Directed Layout of Line-Substation Connections

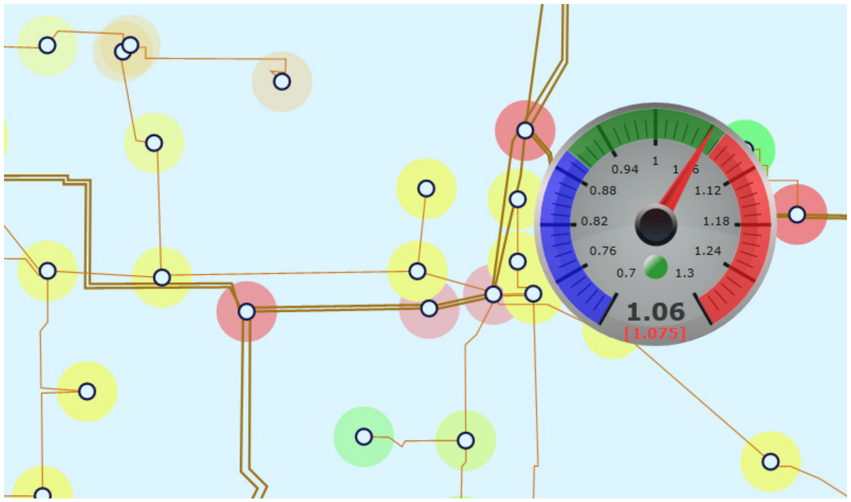


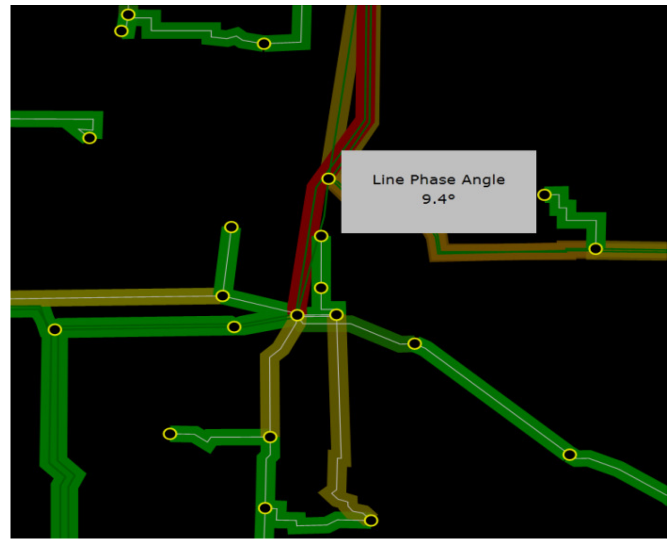
Example 3: Heat Map Representation of Energy Generation & Consumption

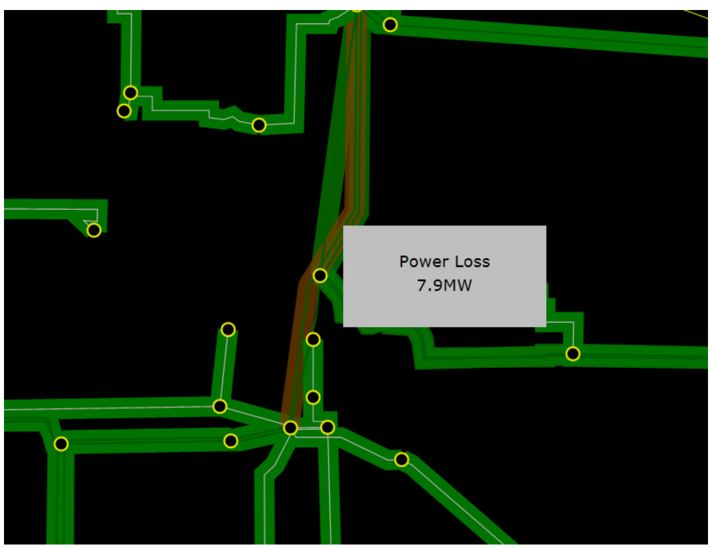


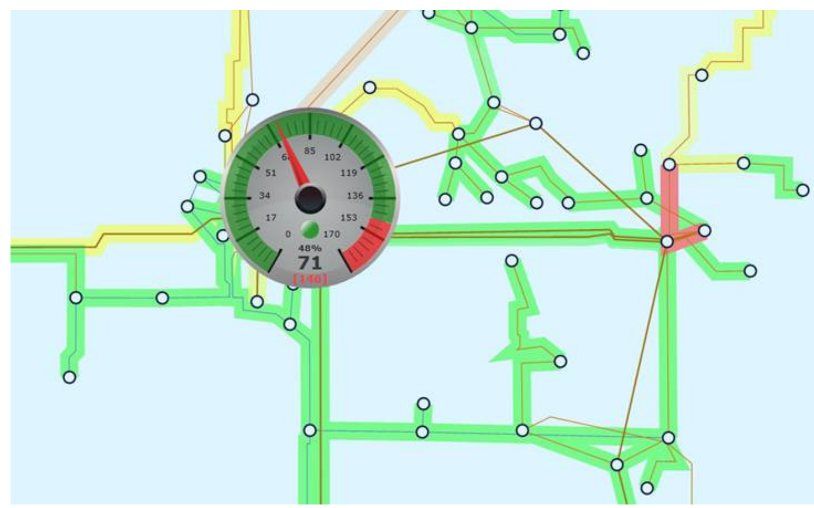


Example 4: Fuzzy Model Based Profiling









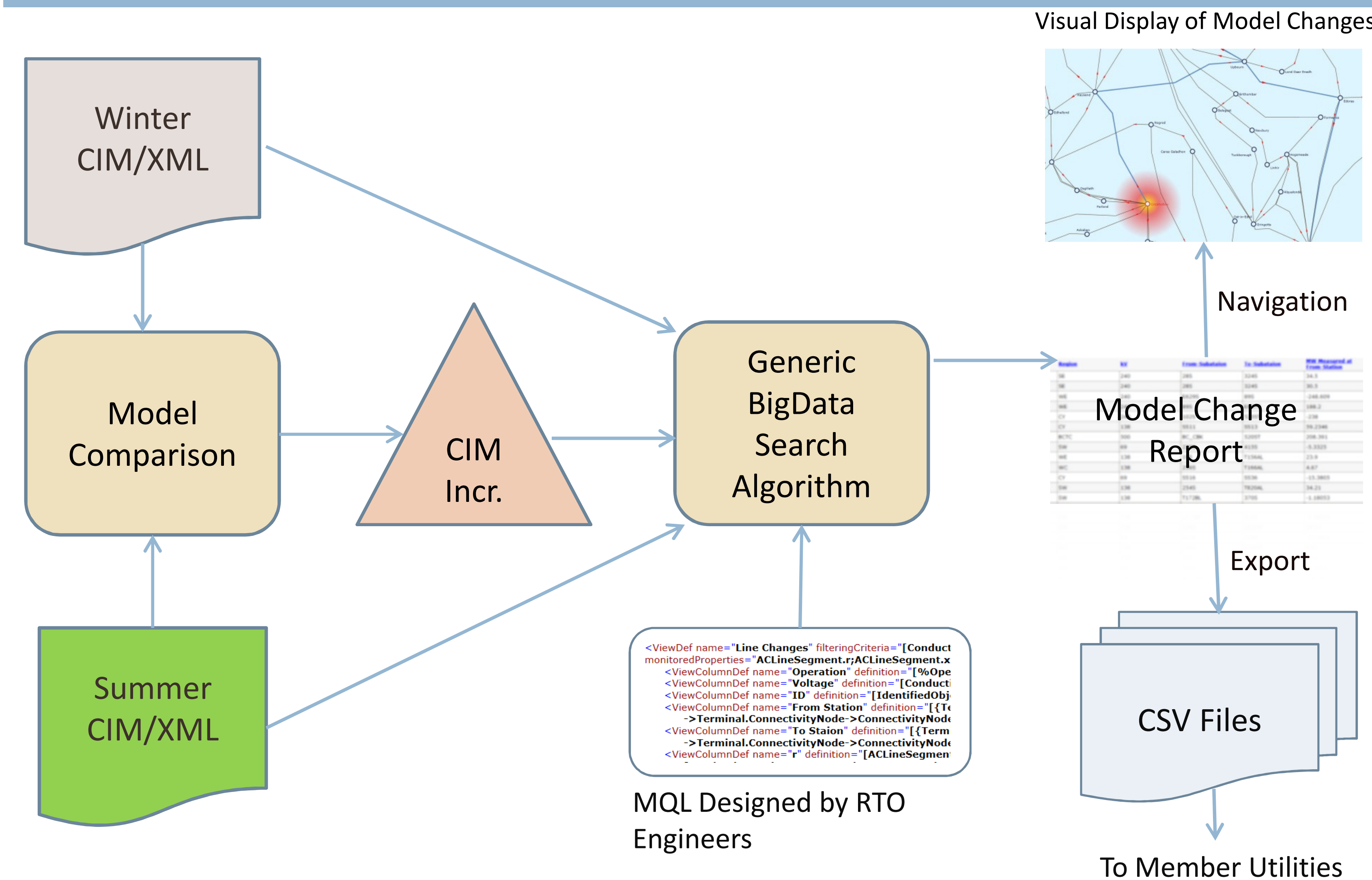
Application 1: Facilitating Model Sharing (Use Case)

Periodically, PJM need report model changes to their members & neighboring RTOs and have them confirm the accuracy of the model changes. This used to be primarily a manual process involving a lot of effort from both data providers and data recipients. The major challenges identified include:

- The model changes are represented in incremental CIM/XML format, which is not human friendly. CIM models grids at fine granularities, not suitable for reporting. Most importantly, many of the member utilities are lack of CIM expertise.

- The in-house developed spreadsheet-based model change reports are difficult and time-consuming to maintain. It is very difficult for member utilities to interpret these data-centric tabular reports.

Application 1: Facilitating Model Sharing (Solution)



Application 1: Facilitating Model Sharing (Proof-of-Concept)

- The model change reporting tool was derived by PJM modeling engineers with minimum engineering effort involved.

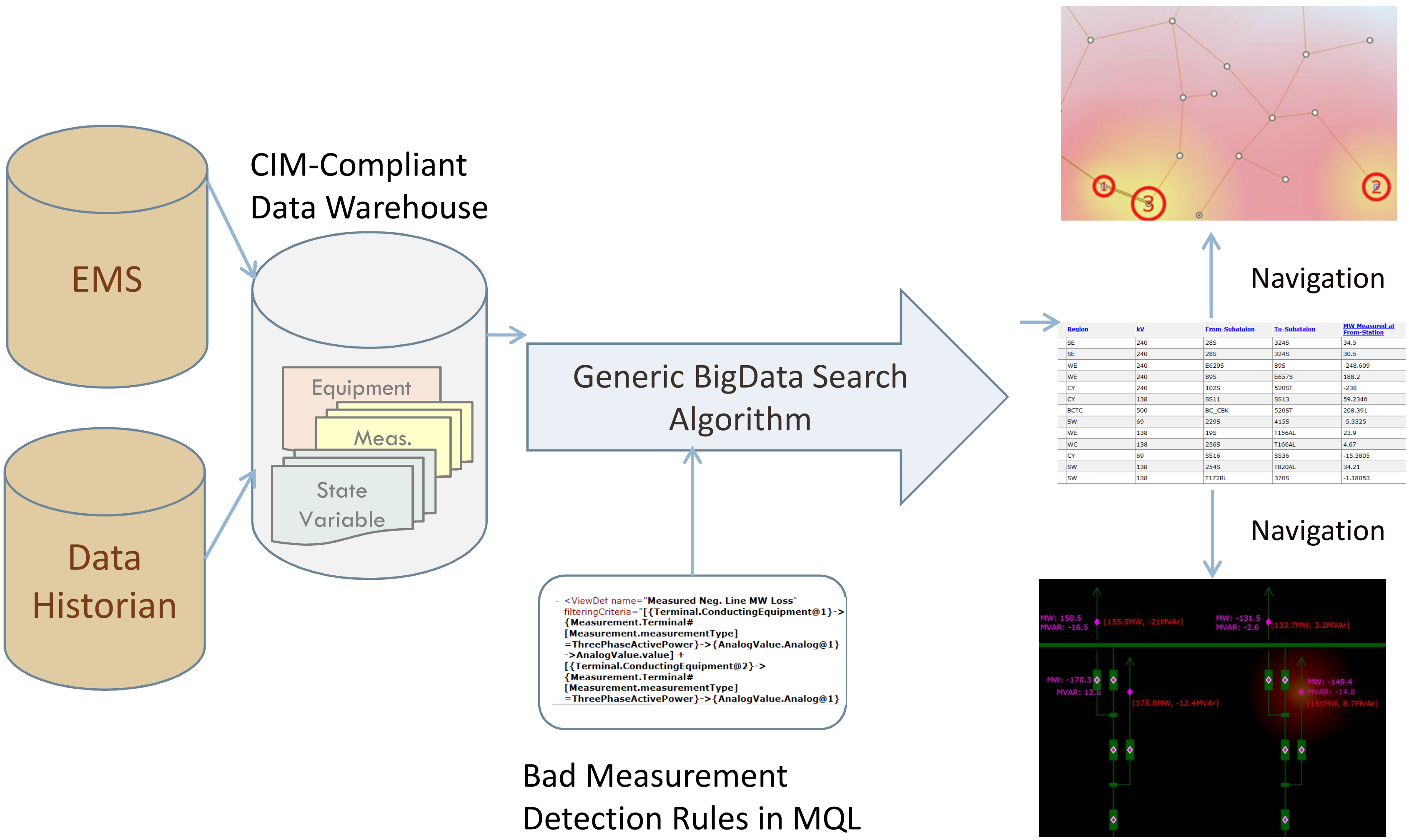
- In comparison with the legacy model change reporting tool, the new model change reporting tool has improved the business practice from the following perspectives:
  - Converting machine-friendly CIM Incremental to human-friendly tabular;
  - Transforming fine-granulated CIM objects to reality-based modeling entities familiar to model engineers;
  - Supporting advanced data presentation including classification, filtering, sorting, and grouping,
  - Visual display of model changes to facilitate interpretation and comprehension.

Application 2: Bad-Measurement Detection (Use Case)

Albert Electrical System Operator (AESO) recently extended their EMS network model to include a selected portion of the neighboring stations. During the project, engineers found that the quality of state estimation was downgraded due to the bad measurements from the external network.

- State estimator marks thousands of "suspect" measurements, most of which are either redundant or caused by noises.
- No indication of the severity and no classification.
- Many of the "suspect" measurements could be just temporary disturbances. The state estimation based solution is based on a single operational snapshot. It does not look at history.
- Tabular displays of "suspect" measurements are neither intuitive nor interactive.

Application 2: Bad-Measurement Detection (Solution)



Region	kV	From-Subataion	To-Subataion	MW Measured at From-Station
SE	240	28S	324S	34.5
SE	240	28S	324S	30.5
WE	240	E629S	89S	-248.609
WE	240	89S	E657S	188.2
CY	240	102S	520ST	-238
CY	138	SS11	SS13	59.2346
BCTC	500	BC_CBK	520ST	208.391
SW	69	229S	415S	-5.3325
WE	138	19S	T156AL	23.9
WC	138	256S	T166AL	4.67
CY	69	SS16	SS36	-15.3805
SW	138	254S	T820AL	34.21
SW	138	T172BL	370S	-1.18053

Application 2: Bad-Measurement Detection (Proof-of-Concept)

- Driven by a set of bad measurement detection rules specified in MQL, the query engine successfully detects a dozen of bad measurements combing the data from both EMS and data historian.
- Reports and visual displays are generated by visual display generator to indicate the location and impact for each of the detected bad measurements.
- After fixing the detected bad measurements either in model or in field, the quality of state estimation has been significantly improved.
- The effort involved in building the application is about two-man week from a consultant of Power Info and one-man week from a supporting engineer of AESO.

Conclusion

- CIM holds the key to Big Data Analytics in the utility industry.