# Semantic Information Modeling for Emerging Applications in Smart Grid

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*Abstract*—**Smart Grid modernizes power grid by integrating digital and information technologies. Millions of smart meters, intelligent appliances and communication infrastructures are under deployment allowing advanced IT applications to be developed to protect and optimize power grid operations. Demand response (DR) is one such emerging application to optimize electricity demand by curtailing/shifting power load when peak load occurs. Existing DR approaches are mostly based on static plans such as pricing policies and load shedding schedules. However, improvements to power management applications rely on data emanated from existing and new information sources with the grow of Smart Grid information space. In particular, dynamic DR algorithms may depend on information from smart meters that report interval-based power consumption measurement, HVAC systems that monitor buildings heat and humidity, and even weather forecast services. In order for emerging Smart Grid applications to take advantage of the diverse data influx, extensible information integration is required. In this paper, we develop an integrated Smart Grid information model using Semantic Web techniques and present case studies of using semantic information for dynamic DR. We show the semantic model facilitates information integration and knowledge representation for developing the next generation Smart Grid applications.**

*Index Terms*—**Smart Grid, demand response, Semantic Web, information integration, complex event processing.**

## I. Introduction

*Smart Grid* refers to the modernization of the electric power grid through the integration of digital and information technologies. Smart Grids use instruments and sensors for advanced monitoring capabilities in realtime that can lead to more efficient and reliable management of electrical power systems and optimizing the operations of its interconnected elements – from the central and distributed generations, through the transmission and distribution network, to end-use consumer equipments. Examples of these instrumentation include *phasor measurement units* that can sense grid instability within seconds, *smart meters* installed at consumer locations for realtime bi-directional communication, and programmable *smart appliances* that can report their usage and status.

The improved information collection ability from Smart Grids is leading to novel software applications and tools that can transform the way power consumption is managed at the macro and micro scales to meet the increasing demand for electricity. These include more agile coordination of generation and transmission by the utility, intelligent charging and discharging of electric vehicles from and *to* the power grid, and third party service providers who help manage home energy use using realtime pricing. One cornerstone use is *Demand Response optimization (DR)*, which deals with curtailing/shifting power consumption during periods of peak electricity load. The advantages of DR are twofold: (1) it reduces the maximum power generation capacity required by a utility to prevent blackouts or brownouts, and (2) it avoids starting and stopping power generating units by shaping the power usage to remain relatively constant over time.

Existing DR programs by utilities are typically static, based on time of use pricing or pre-determined load curtailment schedules. However, information available in a Smart Grid allows novel, dynamic DR techniques to be attempted for finer control over power use. This information goes beyond details about the power system available from the utility and incorporates *indirect influencers* of power usage based on consumer activities, natural phenomena, and infrastructure behavior. For example, the current weather, scheduling of a convention, age of a building, or a public holiday can all affect power usage in a city or a micro-grid. Dynamic DR algorithms can locate patterns among a large class of historical and realtime information to predict power usage and identify curtailment opportunities. In order for DR programs and other emerging Smart Grid applications to take advantage of the diverse data influx, a holistic view of information across multiple domains is required.

The goal of this work is to develop an integrated Smart Grid information model using Semantic Web technologies to support these next generation of Smart Grid applications. The model needs to be extensible to meet the organic and rapid growth of information sources in the Smart Grid domain, while also easily interpretable to manage the diversity of information and consuming applications. In particular, the semantic model forms the knowledge base for performing dynamic DR. Our contributions in this paper are as follows:

1) **Information cataloging for DR.** We identify and classify information required for supporting dynamic DR and other emerging applications in the Smart Grid domain.
2) **Semantic Smart Grid Information Model.** We develop an extensible semantic model based on OWL that integrates existing ontologies with newly developed ones to a concept space to support applications and users in the Smart Grid.
3) **Use Case Study of Semantic Model.** We present a case study of applying this semantic model in a campus micro-

grid environment, which highlights the extensibility, versatility and easy of use of the model.

The rest of the paper is organized as follows. Section II illustrates applications from the Smart Grid domain that motivate the need for and aspects of a semantic information model. Section III summarizes knowledge concepts that are relevant to these applications. Section IV describes the integrated Smart Grid information model, including existing and novel Semantic Web ontologies, and relationships that we introduce. Section V shows the semantic model being used in a complex event processing framework used for dynamic DR. Related work is described in Section VI. Finally, we discuss future work and present our conclusions in Section VII.

## II. Background and Motivation

### A. Grid Information Integration

Improvements to power information systems rely on data from existing and new information sources within and outside the power grid. Smart Grids, when viewed from the consumer perspective, consists of three basic components: smart devices, two-way communication networks and advanced IT applications. Numerous sensors, smart appliances and smart meters are under deployment to monitor power use activities. Emerging Smart Grid applications not only process data from smart devices, but also need to leverage information from other relevant domains - weather, traffic, social networks, and so on [27].

An extensible information integration framework is required to meet the organic growth of Smart Grid information space. Smart devices and IT applications are developed by various software and hardware vendors and utilities. Information from different sources is heterogeneous in terms of data structures, semantics, software and hardware platforms used [28]. To enable communication between data sources and applications as well as between applications, information needs to be interpreted in a common way. Traditional power grid information integration adopts a one-to-one architecture, in which applications and data sources from a narrow domain were tightly coupled in a closed architecture that limits extensibility and reuse. This approach is not scalable in Smart Grid information space which is broad and will change often as applications adapt. When data from several parties are involved for exchange, and when new data sources need to be included for legacy applications, one-to-one integration will not be sustainable.

Model based information integration offers the benefits of extensibility and reusability of applications over a dynamic information environment. In particular, Semantic Web [10] provides a domain-specific ontology language for building common information models shared across domain and application boundaries. Ontologies that can be developed in a modular manner capture knowledge in individual domains and provide data exchange standards at a semantic level. Ontology models are integrated in a loosely coupled architecture by explicitly describing relations between concepts from different domains.

### B. Dynamic Demand Response

Existing DR approaches are mostly based on static plans. Consumption curtailment/shift decisions rely on peak demand predictions. Traditionally, power demand was only monitored in a coarse-grained manner spatially and temporally. Conventional meters which record aggregated power usage of customers were read on a monthly basis. Statistic and mathematic models were built based on such meter data to predict power consumption in long-term ignoring intermediate influencers. Based on these predictions, existing DR is typically done by static planning (1) using *a priori* commitment by consumers to directly control end-use equipments for load shedding during pre-scheduled hours, or (2) setting prices that vary by season or time of the day, offering incentives to consumers for proactively tailoring energy consumption.

In Smart Grid, traditional DR approaches can be complemented by data driven dynamic DR algorithms that locate patterns among a large class of realtime information to predict usage and curtail/shift peak consumption. Smart meters and sensors can monitor power consumption to equipment level in the interval of minutes. Finer consumption prediction can be made by combining realtime load measurement with observations of energy use influencers. Consider in a campus micro-grid, for example, consumption change in a classroom can be predicted by using meter reading, equipment operation status and class schedules. Based on realtime consumption predictions, consumption curtailment/shift strategies can be applied adaptively in multi-stages, which can help reduce the system's latency. In addition, opportunistic curtailment can be applied to increase the curtailment output. For example, when it was observed the temperature in a lobby did not decrease to the HVAC setpoint within a time window, we can reset the setpoint or turn off the corresponding HVAC unit to prevent power wastage.

An integrated semantic information model for Smart Grid can facilitate the development of dynamic DR applications. Firstly, this allows rapid inclusion (or deprecation) of information from multiple domains, loosely coupled through related concepts. Secondly, it allows users to represent load prediction and curtailment domain knowledge at high level. Information patterns used for realtime load prediction and opportunistic curtailment need to specify fine-grained constraints on type of equipments, spaces or customers. This requires the underlying information model to capture the various domain concepts and their semantic relations.

Complex Event Processing (CEP) [18] combined with Semantic Web technology is a promising solution to dynamic demand response. CEP deals with detecting event patterns in realtime from among a cloud of information represented as events. CEP has been successfully applied in many application domains ranging from supply chain management [25], [26] to financial services [15], [19]. The requirement of timely response to power use activities in dynamic DR makes CEP an attractive approach. In Section V, we present a complex event processing framework based on the semantic Smart Grid information model for dynamic DR.

## III. Knowledge Space of Smart Grid Applications

Smart Grid applications depend on the availability of relevant information for their effective operation. A variety of information can be leveraged in the context of demand response and these are considered in our semantic information model.

**Real Time Consumption.** Power consumption details, collected from smart meters, will enable us to improve the accuracy of forecast models by correcting errors in the prediction model and improving the model within a short cycle. These also help monitor the response of curtailment strategies that are initiated and actively tune them. Different frequencies of information can be attempted to make tradeoffs against accuracy and cost of information collection. For example, smart meters can collect and report power consumption information as frequently as once per minute, though once per hour is more often used. The Complex Event Processing module can make use of the frequent measurement readings to find out interesting patterns which will help in reducing the consumption at the observed place. For instance power consumption information can be useful either at the individual consumer level or when aggregated over neighborhoods.

**Infrastructure Information.** Besides information about the power grid infrastructure, such as the distribution network, substations and feeders, it is also useful to model information about environment infrastructure at the city and consumer scale since they influence power usage. Information at the level of individual buildings may provide features such as building structures, orientation (for sunlight), and equipment installation. At the macro scale, the layout of the road networks as well as traffic flow can provide pertinent knowledge. For example, traffic information from road networks provide some interesting insights about how the consumption would be affected. When the traffic congestion is higher during the evening the power demand in households would be shifted based on the number of people staying at home.

**Customer Behavior.** Customer behavior provides valuable insight about electricity consumption and helps in understanding power usage patterns. For instance, a customer's billing information over a period of time can be used to predict his/her electricity consumption for the next billing cycle. Similarly customer demographics will help understand how the consumption varies from one demographic to the other as well as find the similarity between them for clustering response strategies. Apart from these information Social Network feeds can be used to understand how a person's action influence other people around him. A person might be motivated to cut down the electricity consumption by reading his friend's cost savings through energy conservation or a person might just be passive. These information will help in finding out groups which actively try to do energy conservation, and may be early adopters of new tools. These feeds, when combined with location details that may be available from mobile phone GPS's, provide us with ”human sensors” to report environmental information.

**Schedule Information.** Scheduling information provides knowledge about a future occurrence ahead of time. These information will enable us to estimate the demand at the particular venue based on the type of event scheduled, as well as on the number of people expected to turn up for the event. Schedule information about individual people as well as facilities are useful. A person planning a vacation from work may indirectly indicate that they may not be at home either, thus predicting lower demand while also eliminating a source of demand reduction during curtailments in that period.

**Natural conditions.** Natural conditions, such as weather and seasonal changes, help in providing a good idea about the electricity consumption pattern in an area during a particular weather condition. For instance, when the outside temperature is around 60'F, the chillers inside the building would be set to higher temperatures thereby causing a slump in electricity consumption. Similarly, an impending serious weather condition, such as a heatwave or a thunder storm, may indicates a different demand pattern from usual. These details may, once again, be at different spatial and temporal scale, and include future events.

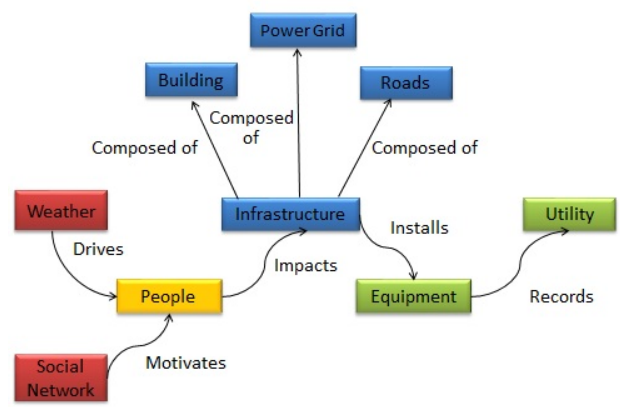


Fig. 1. Interplay between information concept spaces that are interesting to Smart Grid Applications.

As shown in Figure 1, it is interesting to see how each of these information sources are related or influence other information sources. It can also be seen that electrical equipments are installed on various infrastructures and people make a direct impact on how these equipments are used which would ultimately determine the total consumption at a place at any point in time.

## IV. Semantic Smart Grid Information Model

We propose to use Semantic Web ontologies to model Smart Grid information, providing an integrated information view for DR applications.

### A. Model Architecture

Smart Grid being diverse in nature involves a wide range of concepts from various domains. It is not possible to build one single model from scratch which encapsulates all the relevant concepts. Hence, our approach to finding a solution is to identify well defined and understood ontologies in the candidate domains and integrate these by just fill in the gaps. This modular and extensible strategy leverages the features provided by Semantic Web technologies, allows us to build on top of domain expertise, provides familiar conceptual terms for users, and potentially helps us leverage existing tools for knowledge sharing and reuse.

Depending on the level of knowledge representation present in these domain, we may have access to (1) complete ontologies that capture all concepts that are required by the smart grid applications, (2) partially complete ontologies with some concepts or relationships missing, (3) absence of an ontology but existence of well defined metadata schemas, or (4) just a glossary of terms without a well defined structure or semantics. Each of these require a different level of intervention on our part. This includes identifying common or related concepts across domains and introducing relationships between them, introducing new, relevant concepts that are missing from a domain ontology, mapping existing metadata schemas to an ontology framework, or construct a new domain ontology from the domain dictionary.

Our Smart Grid information model is represented using Web Ontology Language(OWL), one of the standards known for knowledge representation. We have retained the namespaces of all the component ontologies we have reused, and for the ontologies and concepts we have introduced we have maintained our own namespace. The ontologies were integrated using Protege [9] and the instances were populated using Jena [6] Semantic Web Framework for Java. The Ontology schema as well as the instance data were stored in MySQL Database using Jena API and querying was performed using SPARQL [11].

### B. Component Ontologies

The various a component ontologies does not exist in isolation. The relationships between concepts from individual ontologies have been carefully established so that they form a single coherent Ontology which can be used as the Smart Grid Information model. Instead of developing the component ontologies from scratch we have reused some of the very well developed and standard ontology for each domain.

**Electrical Equipments Ontology.** The main domain Ontology we are interested in is the one pertaining to Electrical Equipments and Electrical Measurements. These information being the crux of the Smart Grid needs to be captured in the information model. The International Electrotechnical Commission's Common Information Model [1] is a standard that describes the components of a power system at an distribution level and defines information exchange between them. We are interested in the Equipments at the Consumer side and how much consumption the equipment records at each point in time. CIM describes these domain features in a structural form but does not describe their semantics. Hence, we transform the CIM standard to an ontology representation tailored to our needs. The Ontology captures different types of equipments, as well as measurement units used by these equipments. Figure 2 shows the different categories of equipment like *Lighting*, *Refrigeration*, *Sensor*, and so on. Each of the category has subcategories or specialization of equipment,for example $CO_2$ sensor is a type of sensing element which help in detecting the $CO_2$ level in area at a point in time.

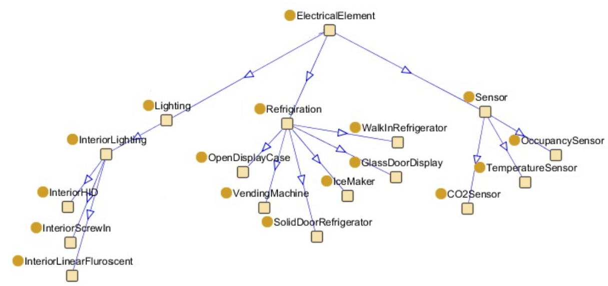


Fig. 2. Electrical Equipments Ontology

**Organization Ontology.** It is essential to classify different classes of organization since the electricity consumption for them would be different. For instance the consumption pattern of an airline is going to be different from that of an educational institution. The presence of these added information will induce some prior knowledge to the forecast models as to what the consumption pattern would be for each category of organization. Along with the organization information it is also essential to capture people involved in the organization as well as their roles within the organization. Information about people and their respective roles are relevant since they also help in understanding the consumption pattern, as also their response to request for curtailing power consumption. For instance, the holidays for an organization or its departments may depend on their type, while the response of its members to demand reduction may depend on who in the organization sends such a request (facility manager, head of organization, immediate supervisor, etc.). These relevant concepts are included in the DBPedia Ontology [2] and we have reused this ontology in our information model to capture the corresponding information.

**Infrastructure Ontology.** The Smart Grid information model also captures environment concepts including transportation networks, buildings and so on, besides the Power Grid infrastructure. These concepts will improve demand response applications by bringing in context about the type of infrastructure which consumes electricity. For instance, an office building that has 20 floors would consume more electricity than an office building with 5 floors, and likewise the traffic in freeways will help evaluate the shift in demand. The DBPedia ontology integrated in our model covers a broad range of infrastructure specific concepts at the same time provides specialization of various infrastructures like *Office Buildings*, *Hospitals* etc.

**Weather Ontology.** Weather information is one of the crucial part of our Information model which will help in understanding the electricity consumption pattern in a particular geography. We integrated the NNEW Weather Ontology [8] which uses SWEET 2.0 [12], JMBL [7], and WordNet [14] Ontologies in a coherent manner, to provide a rich set of vocabularies to define various weather phenomenon. The SWEET Ontology captures concepts pertaining to earth sciences like *Physical Phenomenon*, *Space*, *Human Activities* etc., where as WordNet provides large set of domain independent lexical database. NNEW Ontology makes an attempt to reuse the concepts mentioned in other ontologies and carefully extend those concepts which are essential to describe weather phenomenon. The NNEW covers various low level domain specific concepts like *ThunderStorm*, *Hurricane*, *Precipitation* as well as high level concepts which are not domain specific like *Phenomenon*. While not all concepts from the domain are required by the Smart Grid applications, we do not modify these ontologies to allow us to use and update them consistently. However, only the relevant parts of the ontology needs to be populated with instances and used in queries and inferencing.

**Spatial Ontology.** Power consumption is linked to specific equipment or infrastructure at a spatial location drawing power from feeders supplying at that location. But the usage is also influenced by people whose locations change or external influences like weather that have regional impact. The fact that a building is part of a city's downtown gives an intuition that the building will experience decrease in demand during evening and during weekends. We also go beyond latitude and longitude; address or zip codes are available some times. We may also have point co-ordinates or regions, these needs to be captured in the ontology so that we can perform inferencing and geo-spatial queries at a later point in time. For example, mobile phones may report the location of a person but also add an error boundary that places them within a broader circle. Just like organizational and infrastructure concepts the spatial concepts are also covered in the DBPedia Ontology, and the fact that some of the basic relationships amongst them are already established makes it a much better choice compared to other isolated ontologies. Figure 3 shows a small snapshot of the DBPedia Ontology. The concepts are shown on the left side while the relationships between different concepts are shown using arrows between concepts. For instance *Person* and means of *Transportation* share a relationship to show how people use different means of transportation to commute. It can also be seen that the ontology relates different infrastructures that are available to how people make use of them.

**Temporal Ontology.** Power consumption happens over time, and demand response applications specifically attempt to learn from past consumption patterns to predict and control future consumption. Scheduling information of infrastructure, electrical equipments as well as of individual people are relevant in understanding how much the electricity demand is going to be. For example, the fact that an air conditioner is scheduled to run everyday for a certain period of time at a

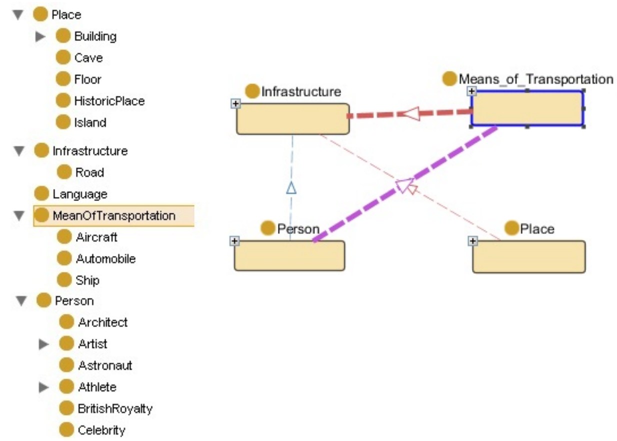


Fig. 3. Infrastructure Ontology

predefined temperature gives a sense how much consumption is going to be for the scheduled period. The W3C calendar Ontology [13] provides the set of vocabularies to capture scheduling and calendering related information. The Ontology is an attempt to integrate ICalendar [5], a widely used format for sending meeting requests, data with other Semantic Web data.

### *C. Relating Concepts from Different Domains*

Since the component ontologies pertain to domain specific concepts it is necessary to integrate all these into one single Information model, the *Smart Grid Information Model*. A simple integration of the concepts from various domains will not suffice. It requires establishing concise and meaningful relationships between domains so that we can perform complex query and inferencing. While a structural schema can help us perform queries (even complex ones), semantic inferencing is possible only if adequate relationships across domains exist. i.e. we perform knowledge capture, not just information capture. The inferences will help figure out patterns which are less intuitive and also help in improving the performance of the entire Architecture.

Figure 4 shows some of the inter domain relationships we have established as well as how the key concepts in one domain is related to key concepts in other domain. A place which is part of Spatial Ontology will experience certain weather conditions which is part of Weather ontology and hence we have established a relationship between Place and Weather Phenomenon. This relationship would help to query information about Infrastructure in various places that are experiencing certain weather conditions. Similarly Infrastructure at various places will have many Electrical Equipments installed. It is essential to establish relationship between these concepts even though they are part of two separate domains. These relationships help in understanding the consumption pattern of the particular Infrastructure as well as in understanding the consumption at a higher granularity like the consumption of an area since Infrastructure is related to Places as well.

Similarly, the scheduling information as mentioned before could be related to people, infrastructure or equipments. All these concepts are part of different component ontologies, but we have established relationships corresponding to a person's schedule, a venue's schedule information or an equipment's operating schedule to make sure that we capture the correct relationship as well as provide a platform to make meaningful inferencing.

Apart from the relationships we have identified, deep linking between concepts from different domain can also occur. These linking will be performed as we attempt to capture much more knowledge about different domains. Although we do not have any relationships of this category, we would be able to do this selectively as the need for them arises over time.

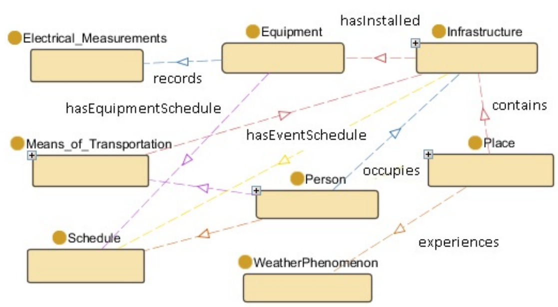


Fig. 4. Integrated Ontology

## V. Case Study - Semantic Complex Event Processing for Dynamic DR

In this section we show how the semantic model can be easily extended and combined with complex event processing to develop dynamic DR algorithms.

Complex event processing deals with detecting event patterns from an event cloud. Continuous data from a wide variety of data sources within Smart Grid can be abstracted as events. These may be from sensors and appliances (*SpaceSetpointChange* event), smart meters (*MeterReport* event), weather phenomena (*WeatherForecast* event) or consumer activity (*ClassSchedule* event). Meaningful combinations of events are formulated as pattern queries over event streams to predict power demand and identify curtailment opportunities in realtime.

### A. Semantic Event Model

The state-of-the-art CEP systems process events as relational data tuples characterized by a time point or a time interval, i.e.,

$$event \quad e ::=< attributes;\ timestamp(s) >$$

Using the above event model, event patterns are normally defined as a group of events with constraints on attributes presented in the data tuples. Event patterns are hence only matched by evaluating syntactically identical attribute values. Defining DR event patterns over plain data tuples can be very tedious and time consuming. For example, if interested in aggregating power consumption from all classrooms on campus, the pattern designer needs to know the details of meters and submeters, their locations, data structures and define patterns using data level pecifications.

We extend the semantic Smart Grid information model to capture Smart Grid events and their relationships with domain concepts and entities, e.g., physical infrastructures and equipments. The semantic Smart Grid event model and domain models prepare the ground for high level pattern specification for dynamic DR.

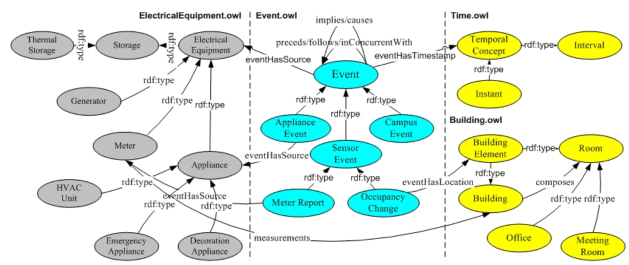


Fig. 5. Semantic Smart Grid Event Model

As shown in Figure 5, we model Smart Grid events using Semantic Web ontology linked with domain concepts and entities captured in the integrated Smart Grid information model. We organize the ontologies in a modular architecture for easier extension. The event ontology captures concepts and relationships between events, such as the time the event occurs and which domain entities it happens to. The notion of an event is classified into domain specific classes corresponding to different types, like *SpaceSetpointChange*, *MeterReport* and so on. The Smart Grid information ontology stack contains the subjective domain ontologies capturing electrical equipments, infrastructure, organization, weather, spatial and time concepts. Relations between concepts in the event ontology and Smart Grid information ontologies are modeled using properties such as *eventHasSource* and *eventHasLocation*, whose domain is an event and value is a domain entity. For example, a *meterReport* that was generated from a meter is a concept defined in the electrical equipment ontology.

### B. Semantic Event Patterns for Dynamic DR

Semantic pattern queries can be defined over the event ontologies for the use of predicting demand and identifying curtailment opportunities in realtime. The benefits of a semantically enhanced event model for complex event processing include,

- Facilitating high level knowledge representation. DR event patterns are defined over an abstract information model instead of raw data streams.
- Improving expressiveness of pattern queries. Not just limited concepts in power grid standards but concepts across multiple domains including physical spaces, weather forecast and campus event schedules can be easily integrated and used for specifying DR patterns.

Complex event queries over semantic events can be expressed using SPARQL triple patterns combined with continuous CEP patterns. Event data are expected to be represented in RDF, i.e., as RDF triples, additionally accompanied with timestamps. The overall structure of a semantic event pattern is:

```
[PREFIX <namespace>]
[Target event streams]
[CEP constraints]
[Semantic constraints]
```

In the following, we explain the various constructs of the semantic event pattern through examples and show its abstraction and expressiveness in modeling dynamic DR applications.

**Example 1. Opportunistic Curtailment.** Consider two event data streams, *SpaceSetpointStream* as setpoint temperature from thermostats and *SpaceTempStream* as space temperature measurements from ambient temperature sensors. This pattern detects in a *Lobby*, the temperature measurement is 5'F higher than the setpoint in 15-minutes time window. The situation specified by this pattern indicates there is power wastage if the HVAC unit is on, which can be curtailed upon detection. The curtailment strategy can be expressed as an intuitive query over the event streams as below,

```
PREFIX bd:<http://cei.usc.edu/Building.owl#>
PREFIX evt:<http://cei.usc.edu/Event.owl#>
PREFIX rdf:<http://www.w3.org/1999/02/22-
rdf-syntax-ns#>

FROM SpaceSetpointStream, SpaceTempStream
SEQUENCE {
     (?stsEvent, ?stmEvent)
     (?stmEvent.reading -
            ?stsEvent.setpoint>5)
     TIME_WINDOW(15min)
}
SPARQL {
     (?stsEvent hasSource ?src) .
     (?stmEvent hasSource ?src) .
     (?src hasLocation ?loc) .
     (?loc rdf:type bd:Lobby)
}
```

Enhanced with semantic information, the CEP framework allows users to specify domain constraints over abstract models. As shown in the *SPARQL* clause, the semantic concept *Lobby* was captured in *Infrastructure* ontology. Events sent from sensors located in a room annotated with type *Lobby* or its subclass type will be filtered and evaluated against the CEP temporal constraints specified in the *SEQUENCE* clause.

**Example 2. Realtime Prediction.** Consider three event streams, *AirflowStream* as airflow rate measurements from HVAC units, *WeatherForecastStream* as weather forecast from an online weather service and *ClassScheduleStream* from the campus class schedules. This pattern detects in a *Classroom* which has a class scheduled in one hour, the airflow rate is lower than 100 cfm while the outside air temperature reaches the *Heatwave* temperature limit. This pattern indicates the power demand from the classroom will reach its peak in 1 hour. We have the following pattern,

```
PREFIX bd:<http://cei.usc.edu/Building.owl#>
PREFIX wth:<http://cei.usc.edu/Weather.owl#>
PREFIX evt:<http://cei.usc.edu/Event.owl#>
PREFIX rdf:<http://www.w3.org/1999/02/22-
rdf-syntax-ns#>

FROM AirflowStream, WeatherForecastStream,
              ClassScheduleStream
AND {
     (?aflEvent, ?wthEvent, ?clsEvent)
     (?aflEvent.flowRate<100)
     (?clsEvent.nextSchedule<1)
}
SPARQL {
     (?aflEvent hasSource ?src) .
     (?wthEvent hasSource ?src) .
     (?clsEvent hasSource ?src) .
     (?src hasLocation ?loc) .
     (?loc rdf:type bd:Classroom)
     FILTER(?wthEvent.airTemp >
              wth:HeatwaveTemp)
}
```

Semantic CEP system can be easily extended to correlate events from multiple domains such as weather and class schedules captured in the Smart Grid ontology to detect DR situations. The *FILTER* construct in the above *SPARQL* sub-pattern evaluates the outside air temperature against a domain concept *HeatwaveTemp* captured in the weather ontology. Thus, we see how the integrated Smart Grid ontology that combines multiple domain concepts helps us build a novel semantic CEP application that detects patterns for DR optimization. The model allows us to use a higher level language abstraction, operate across domain concepts and provides easy extensibility.

## VI. Related Work

There have been many efforts for Smart Grid information integration using a one-to-one architecture, especially for consumer facing interface applications. These interfaces to energy data provides histogram of energy usage or equipment operations over time. Examples include Google's PowerMeter [3] application and Honeywell's Enterprise Buildings Integrator (EBI) [4]. While this approach is common, they do not facilitate extension to integrate external information sources and applications to cooperate in a plug-and-play manner.

The existing Smart Grid standards designed by different organizations including IEC and NIST for power grid assets including generation systems, delivery networks and electrical appliances have influenced our selection of the domain ontologies. These standards are specified in structural formats such as XML. In particular, IEC has been working on creating a Common Information Model (CIM) to resolve data inconsistency in the power industry. CIM series standards define data exchange specifications for power grid components so that the interoperability between various platforms and applications can be achieved. However, information that was proven to be crucial to Smart Grid applications also include those from domains such as organization, weather and physical spaces. A framework that enable seamless integration of concepts and knowledge from other domains is required.

Semantic Smart Grid information modeling discussed in this paper enhances standards based information integration. Semantic modeling is an active research area that has been studied in many domains including Smart Oilfield [29], eHealthCare [16], [24], biology [17], [23] and transportation [20], [21]. Different from existing Smart Grid standards, the semantic Smart Grid information model allows us to describe data semantics as well as represent domain knowledge using a description language and automate data and knowledge transforms based on reasoning. This enables smart grid participants to focus on making innovative use of information for application design, shielding them from low level data specifications and integration.

## VII. Conclusion and Future Work

In this paper, we present our work on a semantic Smart Grid information model. The semantic model is extensible to meet the growth of the Smart Grid information diversity with the provision to easily integrate new information sources and domain concepts. We also introduce use cases of the information model in a dynamic DR context. We show the semantic model allows information integration across multiple domains, and facilitates knowledge representation in developing dynamic DR algorithms. Future work includes transforming additional Smart Grid standards to Semantic Web ontology representations. We are also on the progress of developing a Semantic Complex Event Processing (SCEP) engine [22], used for dynamic DR. The SCEP system allows domain experts specify realtime consumption prediction and opportunistic curtailment strategies as semantic level queries and evaluates queries over continuous Smart Grid data streams.

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