An Informatics Approach to Demand Response Optimization in Smart Grids

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Abstract

Power utilities are increasingly rolling out "smart" grids with the ability to track consumer power usage in near real-time using smart meters that enable bi-directional communication. However, the true value of smart grids is unlocked only when the veritable explosion of data that will become available is ingested, processed, analyzed and translated into meaningful decisions. These include the ability to forecast electricity demand, respond to peak load events, and improve sustainable use of energy by consumers, and are made possible by energy informatics. *Information and software system techniques for a smarter power grid include pattern mining and machine learning over complex events and integrated semantic information, distributed stream processing for low latency response, Cloud platforms for scalable operations and privacy policies to mitigate information leakage in an information rich environment. Such an informatics approach is being used in the DoE sponsored Los Angeles Smart Grid Demonstration Project, and the resulting software architecture will lead to an agile and adaptive Los Angeles Smart Grid.*

1. Introduction

Energy security and environmental sustainability have led to a global, concerted push towards careful and efficient use of energy assets. Partly reflecting this mindset and partly as a consequence of advancing technology, electric power grids are being upgraded with smart meters installed at consumers, and other Grid sensors to better monitor the utility infrastructure. *Smart meters* or *Advanced Metering Infrastructure (AMIs)* allow bi-directional, real-time communication between the utility and the consumer. Besides permitting the utility to measure consumer power consumption in near realtime, the AMIs act as a communication gateway for the utility to interact with the home or building power control system and appliances [1].

AMIs are being rapidly rolled out across the globe. For example, AMI penetration has been increasing from 1% of US in 2006, to 5% in 2008, and 25% planned or installed by 2010 [2]. Europe, Italy and Sweden are approaching 100 percent deployment of smart meters for consumers. While the common notion is that the smart meters make the utility grid smart, it is no different from claiming that attaching a modem to a computer creates the WWW. The real value of smart grids will come from leveraging this ability for bi-directional communication between utilities and consumers to provide value added services by the utility and third parties to consumers, and optimizing the operation of the power grid with their active participation.

The smart grid can be a truly revolutionary advance, akin to the disruptive impact of the WWW, if we treat it not as an advance in power systems or electrical engineering, but as **the arrival of a massively interconnected information processing system**. To this end, informatics tools and techniques have a critical role to play in translating the ability to collect fine grained power usage data into a decision support system for utilities to manage their energy capacities, provide better quality of service, lower electricity costs, and build an ecosystem of information rich applications and services that make energy monitoring and conservation a seamless extension of existing Web technology.

The *Los Angeles Smart Grid Demonstration Project* is an opportunity to explore the informatics challenges and possibilities that exist when building a smart grid for the largest municipal utility in the United States. Funded by the Department of Energy in 2010, this five year project is conducting exploratory research into information systems, electrical vehicles, cyber-security and consumer behavior as part of a smart grid eco-system to identify, deploy and demonstrate effective tools and technology that will make the Los Angeles power grid a smart grid.

The focus of this article is on the informatics approach we are taking to manage data and build smart grid applications to intelligently manage the increasing demand for power and respond by optimizing power consumption within the city. These contribute to a scalable, secure software architecture for demand-response optimization in the Los Angeles Smart Grid that can adapt to the dynamic nature of the eco-system and control the complexity introduced by the data deluge from AMIs and other information sources. Our contributions are:

1) Examining a real-world smart grid project to characterize the challenges posed for informatics researchers by the emerging application domain,
2) Exploring opportunities for research into topics such as stream processing, semantic complex event processing and Cloud computing systems, and
3) Proposing a software architecture that combines these technologies to address demand response optimization in smart grids.

The rest of this article is organized as follows. In Section 2, we introduce the project and present the USC campus as a micro grid for testing our approach. In Section 3, we describe the goals of demand response optimization which we plan to achieve. In Section 4, we identify the characteristics of the problem space that make it challenging. In Section 5, we discuss various informatics techniques that come together to form a solution space to address the identified problems, and highlight research issues in each. Finally, we present our conclusions in Section 6.

2. Background

2.1. The Los Angeles Power Grid

The City of Los Angeles is served by the Department of Water and Power (LA DWP) for its electric utility needs. DWP is the *largest* among the 2000 public utilities in the United States [3], serving 4 Million residents across 465 square miles. This translates to 1.4 Million electrical and 0.7 Million water consumer accounts. The utility is vertically integrated, i.e., it controls and operates its own power generation, transmission and distribution systems. While self-contained and insulated from the energy market volatility, DWP does occasionally purchase and sell power on the spot market.

Table 1: Percentage Contribution from Difference Power Sources to the Installed and Planned Power Capacity for the Los Angeles Department of Water and Power Utility

Power Source	**% of Installed Capacity *(2009)***	**% of Planned Capacity *(2020 target)***
Coal	39%	0%
Natural Gas	31%	60%
Nuclear	9%	
Large Hydro	7%	
Renewables	14%	40%

DWP has an annual sales of 23 Million MWh at a mean price of ¢13/KWh, with a peak demand of 6100 MW (Sep, 2010) as against an installed capacity of 7100 MW [4]. These constitute 1% of the total US consumers [5] and 0.7% of the total US capacity of 1TW [6].

DWP's generation facilities are spread across state lines, with supplies coming from Arizona, Nevada, Oregon and Utah, besides California. DWP has historically relied upon coal for *base load* generation – the minimum power consumed by the consumers across all times of the day and year. Coal forms 40% of DWP's total power capacity and 80% of its base load [7], followed by Natural Gas (31% capacity), Nuclear (9%), Large-Hydro (7%), and Renewables (14%) [8]. The primary sources of Renewables are currently Wind, Small Hydro and Bio Gas, with the share of Geothermal and Solar expected to increase over this decade. The City of Los Angeles has passed regulations that set targets of 20 percent renewables by 2010, and 35 percent by 2020. The goal of reducing its carbon emissions to 35% of 1990 levels by 2020 will be achieved through elimination of coal based power generation and increasing the share of renewables to up to 40% of capacity.

Optimal use of energy will be essential to meet DWP's carbon goal and to control the infrastructure outlay for setting up new power generating sources. For example, many of DWP's generating stations in the Los Angeles basin were built in the 1960's and are nearing the end of their life despite renovations. The state of California has also restricted import of power from other states that contribute to greenhouse gases beyond prescribed limits. These factors mean that DWP has to find efficient ways to use available capacity through consumer-side load reduction. There are two goals to this: one, is to *reduce per capita power usage* overall, and the second, is to reduce the peak power capacity required by *shifting power usage* to off peak hours. The former leads to lower carbon emissions while the latter reduces the extent of unused, spare capacity by shaping power usage to be close to the average load at all times of the day and year. For example, the base load and peak load on a typical day in Los Angeles DWP varies between 2000MW at ∼4AM to 4800MW at ∼4PM. According to current forecasts, DWP will be unable to meet its peak load 50% of the time by 2020 without further expansion or load curtailment [4]. DWP is planning to meet **500MW of peak load reduction through Demand Response (DR)** programs to control and shift load during peak hours.

2.2. The Los Angeles Smart Grid Demonstration Project

The increasing global concern on the environment and efficient use of energy is causing countries to invest in improved power infrastructure and research into optimal use of energy. Within the U.S., the Department of Energy (DoE) has embarked on a major funding exercise, as part of the American Recovery and Reinvestment Act (ARRA) economic stimulus, to improve energy conservation in buildings, identify new energy sources, make the electric grid smarter, and so on.

Of the $680 Million awarded by the DoE for Smart Grid Regional and Energy Storage Demonstration Projects so far, the LA DWP has been awarded $60 Million [9], making it the *third largest of its kind* that has been funded so far (after projects in Washington and Ohio). Combined with a matching grant by the DWP, this $120 Million project spread over 5 years started in April 2010 as a collaboration between LA DWP, University of Southern California (USC), University of California-Los Angeles (UCLA), NASA Jet Propulsion Lab (JPL), and the USC Information Sciences Institute (ISI).

The goal of the Los Angeles Smart Grid Demonstration Project is to test and evaluate innovative Smart Grid technology over the next 5 years, and demonstrate it on a regional electric grid. There are four activity areas to the project, all of which are supported by the large-scale installation of Advanced Metering Infrastructure (AMI), also known as Smart Meters, at DWP consumers [10]. First, is to use USC campus, UCLA campus and DWP labs as testbeds to research and demonstrate **demand response optimization** to actively curtail and shape power usage. Second, is to conduct sociological and **behavioral studies** on consumers to determine factors that are most effective for improved energy use. Third, is to enable next generation **cyber security** technologies that will make the smart grid robust to external threats and internal consumer actions. Lastly, is to analyze and demonstrate the integration of **electric vehicles** into the power grid. Of these, the demand response optimization is the most relevant to computer science and informatics researchers from whom it has received limited attention, and will be central to this article.

During the initial part of the project from 2010 – 2012, the goal is to conduct research into these four activity areas and experiment on campus and DWP testbed micro-grids. Concurrently, smart meter installation at 50,000 consumers will roll out in the DWP service area. The algorithms, techniques, software tools and architecture that prove suitable from the research will graduate onto the demonstration phase of the project from 2013 – 14 where they will be scaled on actual DWP customer service area in Los Angeles to evaluate their competence. At the end of the project, the experience gained and the smart grid technology generated will be shared with DoE with the intent of replicating the success onto other utilities and regions.

2.3. Demand Response Optimization

Briefly, demand response or DR deals with curtailing the peak load on a utility by offering incentives to consumers to reduce energy consumption when a peak load or loss of reliability situation is encountered [1]. The advantage of this are twofold: (1) it reduces the maximum power generation capacity required by a utility to avoid blackouts or brownouts, and (2) it avoids starting and stopping power generating units by shaping the power usage to remain relatively constant over time. Demand response is typically done either using *a priori* commitment by consumers to reduce load during a power shortage, or using a variable rate market model that increases prices during a shortage. In the former model, the utilities may have direct control to turn off the consumer's equipment or send a signal to the consumer to reduce consumption in return for consumer incentives. The latter model may use static, time of use (TOU) rate slabs, or dynamic, real time pricing. The bi-directional communication enabled by smart meters allows these dynamic DR techniques to be applied to get finer control over energy use.

One of the goals of demand response optimization in the Los Angeles Smart Grid project is to be able to *reduce the electricity demand by 500MW – about 8% of peak load – within 30mins and sustain it for a period of 4hrs*.

2.4. USC Campus as a Micro-grid

The University of Southern California (USC) campus is serving as a micro-grid testbed for the Los Angeles Smart Grid project to experiment and evaluate demand response and other smart grid technologies. USC encompasses many of the features that make up a diverse city like Los Angeles, which make it suitable as a micro-grid. It is the *largest private customer* for the DWP, with an annual consumption of 148GWh at an average load of 21MW (2010) at the University Park campus that forms the testbed. The campus is diverse, both in terms of demographics and buildings. With 33,000 students – 8000 international – and 13,000 faculty and staff spread over 300 acres containing class rooms, residence halls, administrative offices, labs, hospitals, restaurants, public transit, electric vehicles, and even a gas station, it forms a *city within a city*. The 100+ major buildings are between 2 and 90 years old with equally varied electrical, heating and cooling facilities. Two power vaults route power from DWP and a co-generation chiller is available for energy storage.

The USC Facilities and Management Services (FMS) maintains a relatively "smart" electrical and equipment infrastructure. It has the ability to measure energy usage by building at 1 minute interval, with the possibility of zone or room level measurement for a third of the buildings and the ability to indirectly calculate equipment consumption levels. The FMS Control Center aggregates data across all buildings using a proprietary software system, and can centrally control or override Heating/Ventilation/Air Conditioning (HVAC) equipment that consume up to 50% of the total campus power. However, many of these features are used only semi-automatically when severe conditions like overheating or cost budgeting is required. An automated and intelligent system that can perform demand response optimization at the level of an expert or better is lacking.

These features make the USC campus a ready, instrumented smart grid environment for conducting controlled and calibrated Demand Response experiments end-to-end. Besides the available data collection and control facilities, there is also the flexibility of trying emerging smart grid sensors and instruments from third party vendors on the campus for fine grained and richer sources of data and points of control. The goal is to eventually scale out the successful models that work at the campus scale to a city scale. So any technology and software tools that are built need to be scalable to the city size.

3. GOALS FOR DEMAND RESPONSE OPTIMIZATION

In a smart grid environment, demand response (DR) optimization is a two-step process consisting of *peak demand forecasting* and *selecting an effective response* to it. Both these tasks can greatly benefit from the availability of accurate and realtime information on the actual energy use and supplementary factors that affect energy use. Hence, the software platform that collects, manages and analyzes the information also plays a vital role.

3.1. Demand Forecasting

The goal of demand forecasting is to accurately predict the occurrence of a **peak load** – a situation where the demand for power approaches or goes beyond the current power generation capacity of the utility. *Long term* demand forecast, on the order of days, with coarse accuracy is useful to plan and purchase power supply by utilities, schedule equipment maintenance, and provide early warning to consumers of potential load curtailment or advance pricing information. *Short term* forecast, on the order of minutes and hours, is useful to initiate load curtailment response. The more lead time provided to initiate and apply the response, the better are the chances of an effective curtailment of the peak load since additional capacity can be brought online from slow start power generators. The forecast goal is to determine the *quantity of curtailment*, in Mega Watts, necessary and the *time* by which this has to be met.

Traditionally electricity demand has been cyclical, with diurnal load patterns observed across a 24 hour period, and seasonal patterns seen across a calendar year. However, *technology and environmental changes are starting to impact these observed trends*, making usually reliable forecast models suspect. The growing popularity of electric vehicles (EVs) is expected to skew the load profile. California will have 10% of the 1 Million estimated EVs in the US by 2015. A large fraction of EVs starting to charge simultaneously during a narrow time window in the evening can cause a load spike. This time window may also be a function of traffic patterns. However, the ability to defer charging of EVs to later at night means they can be used pro-actively for load shaping. The ability of smart grid utilities to set variable pricing can also render historical consumer usage data to become less relevant as they react to these pricing changes. Increasing co-generation by consumers using solar panels or wind turbines can reduce the load on the grid, but these are intermittent due to natural causes such as cloud cover and wind speed. As more buildings start deploying automated power management systems, also known as building area networks (BANs), that dynamically adapt to price signals and energy use targets, the base load of buildings and base load on the utility itself may vary.

Consequently, the spread of information required to perform an accurate forecast expands way beyond factors that have conventionally had major impact, namely, weather conditions (particularly heat waves, in Los Angeles) and failure of power generation sources. In this new future, information that may prove crucial for greater forecast accuracy include environmental observation such as cloud cover and wind speed, realtime traffic patterns, schedule of large events and conventions, equipment duty cycle schedule provided by building area networks, and data from call centers, Facebook feeds and Twitter feeds of the utility. This squarely poses an *information integration challenge*.

3.2. Response Design and Selection

Once a peak load has been predicted, actions must be initiated to reduce consumer power consumption by the predicted shortfall before the estimated time of occurrence of the peak. Increasing the power production is not considered as a viable response for DR optimization.

Different response strategies will be required based on the quanta of load to be shed and the available time. Part of this is informed by consumer behavior studies that determine incentives that work best for different demographics, and for different consumer categories such as residential, commercial and industry. Within the DWP power grid, over 50% of power consumption is by *commercial* and *industrial consumers*, while the rest is by *residential consumers*, each with different priorities. Businesses may not wish to lose customers by reducing ambient temperature, but some may, sign up for load curtailment by promoting themselves as a "green" establishment. Industries may respond to early warning on pricing by changing equipment duty cycles for the next day but may not respond to load curtailment signals with short lead times. The ratio of power usage that can be curtailed by a consumer will also vary, as will the speed at which this reduction will happen. Peer pressure, pricing, value added services, environmental consciousness, and celebrity endorsement (given it is Los Angeles) may all form incentives.

The manner in which information is communicated to the consumer to encourage curtailment is also key. While some consumers may sign up for direct control of appliances and equipment by the utility, others may configure their home or building area networks to automatically respond on their behalf, while yet others may manually turn off appliances when they get an SMS or notification on their smart phone app. Educating the consumers about load curtailment benefits will also be necessary. Typically, the first x% of load curtailment is expected to be easier than next the x%. Given this, a graceful degradation of response should be planned.

4. CHARACTERIZATION OF THE PROBLEM

Several of the focus areas identified above resemble those seen in *eScience* [11]. For example, meso-scale meteorology projects such as LEAD [12] that are scoped under geo-informatics runs compute and data intensive weather forecast simulations on cyber-infrastructure by integrating data from NASA, NOAA and USGS. Bio-informatics projects that deal with genomics data from next generation sequencing machine run compute intensive machine learning algorithms in the Cloud [13], and use Semantic Web technologies for workflow composition and data retrieval [14]. However, a unique combination of features in the smart grid domain, and more generally in energy informatics, pose additional challenges of interest to the informatics researcher.

4.1. Dynamic Environment

The demand response optimization problem operates upon an environment that includes the City of Los Angeles and its residents, and the energy consumers and suppliers for DWP. The problem space is affected by the dynamic nature of information present within this environment. For example, as people migrate or relocate within the city, prior forecast models will need to adapt. Similarly, as energy technology evolves, equipment such as EVs or solar panels can cause the traditional electricity consumption and generation patterns to change. Some of these, like electrical technology, may evolve over months and years, while others like traffic patterns (that determines when people reach home and turn on electrical appliances) and weather may change on a daily basis, e.g., if there is a construction or accident on arterial highways, or if a heat wave strikes.

This means that both the *algorithms* used for data analysis, mining and decision making, as well as the *information sources* used by them will need to change and adapt over time. The ability of the system to continuously learn and rapidly incorporate new information sources and predictors will be essential for a sustainable software architecture. Given that the outcome of these informatics tools will make it into a production system serving millions, changing the architectural components is a big decision. In contrast, the current customer information system used within DWP has been in operation for the past 37 years with plans currently afoot to migrate to a contemporary software stack.

4.2. Complex Information System

The smart grid system will introduce a novel set of problems for both utilities and consumers: one of data and information overload. While earlier, the power usage information was available to utilities once a month (or every other month in the case of DWP) and consumers received monthly bills with static rate slabs, smart grids allow measurement of power usage with frequency on the order of minutes, and setting dynamic pricing for consumers. In addition, integration of diverse sources of information such as weather, traffic, event schedules and even social network data will mean that *utility managers* and *energy consumers* will need guidance on using this information meaningfully to make informed decisions. Else, we run the risk of the data being ignored, obviating many of the advantages of the smart grid.

Incorporating semantics into the information model will be necessary for utility managers to interpret the available data and define policies for detecting loads and responses. Both information and policies should be presented using semantics common to the power utility domain and tied in with existing domain knowledge bases. The information system should be intelligent enough to filter out noise and present only information and actions that are relevant to the current conditions.

On the consumer end, it is important to use familiar forms of communication to address the diversity in the population. A combination of visual and textual cues will be necessary for customers to understand not just the current bill, but also take action to respond to peak load events to assist with demand response optimization or to reduce their monthly power usage and costs. For e.g., there are 7 distinct languages that are spoken by 1% or more of the Los Angeles population [15], and this will require investigation into natural language and multi-lingual processing.

4.3. Distributed Information Sources, Computational Resources

The smart grid moves away from a centralized notion of energy management to a distributed one that empowers the consumers to make intelligent energy use decisions. Besides the energy production and consumption itself being distributed, the information sources and its analysis will also operate in a distributed environment. The AMIs that act as sensors are spatially distributed across households and commercial establishments, and data has to be streamed to the utility. Part of the computation and analysis may take place at the consumer end within their home area network (HAN) or building area network (BAN), while the rest may be done within the utility. Even the utility may offload the processing to commercial Clouds that operate at distributed data centers. In addition to meter data, weather forecast and traffic information need to be continuously elicited from online Web services. Additional information from distributed sources, which may range from social network feeds to ambient light sensors in smart phones, may be relevant for the demand response algorithms and data analysis to operate with accuracy.

According to some estimates, smart grid networks can collectively eclipse the size of the Internet [16]. In such a scenario, scalability becomes a watch word. Algorithms and architectures that are effective for 1000's of consumers and smart meters may not scale to the millions present in the LA DWP operational area. Specifically, scalable infrastructure such as Clouds and clusters may be essential for timely forecast predictions and triggering responses. Additionally, the quality of information ingested, processed and archived may be prohibitively large and it may not be possible to centrally store and manage all the data that is collected.

4.4. Shared Data

Smart grids provide an unprecedented ability to observe the fine grained electricity use patterns in daily life. Given the intrinsic role that electricity plays in our daily lives, monitoring its use also provides a window into a consumer's activities. Several types of unintended, private information leakage have been identified previously [17]. Besides the data from AMI, information integrated from other public or self-reported private sources, such as social networks or

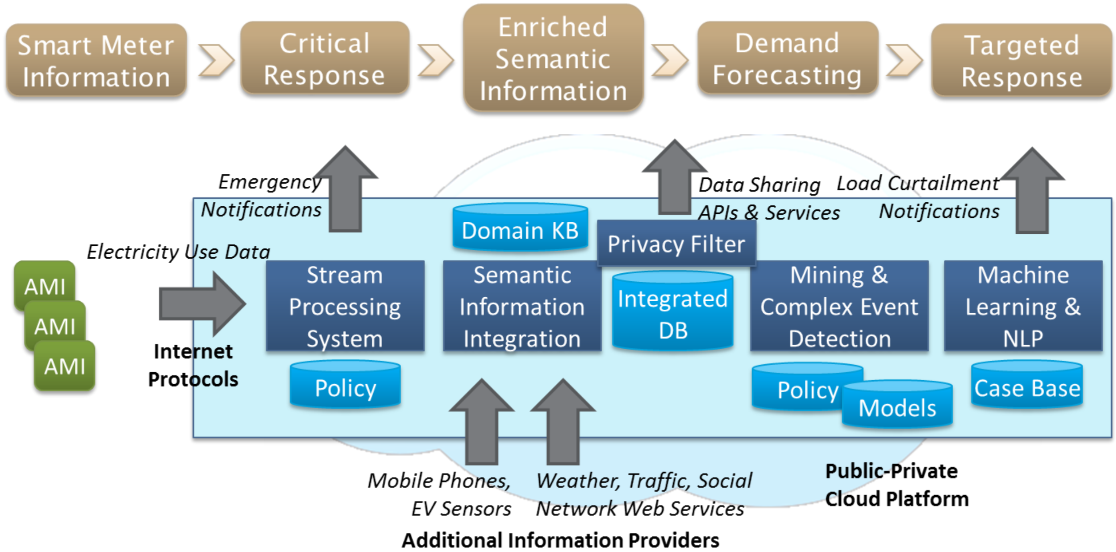

Figure 1: Software Architecture for Demand Response Optimization in the Los Angeles Smart Grid project

GPS location from smart phones, used for DR optimization may cause additional private data to be exposed.

Regulatory compliance on privacy [18] that may affect the type of data collected, stored and integrated must be reconciled with the need to share data with the consumers, their agents or third parties, both to ensure transparency (e.g. on pricing by a public utility) and to provide value added online services [19], [20]. This will require drawing of privacy boundaries around smart grid data, ensuring an audit trail of data made available through Web services, and understanding evolving notions of privacy by consumers in an increasingly open world.

5. ANALYSIS OF INFORMATICS APPROACHES FOR A DR SOFTWARE ARCHITECTURE

Much of the smarts in the smart grid will come from the ability to meaningfully translate the availability of data into knowledge and subsequent action to improve the efficiency of the power grid [21]. The solution space for the smart grid demand response optimization problems we have characterized above lies solidly in informatics. Different aspects of information processing – information integration, data mining, complex event processing, and machine learning – contribute to a software architecture that can effectively address these issues. In addition, distributed and internet technologies such as Semantic Web, Cloud computing, Web services and social networks form essential platforms to build the solution on top of. Security and data privacy cut across these to play a crucial role.

Figure 1 shows a model software architecture for demand response optimization for the Los Angeles Smart Grid project that incorporates several of these features. The top of the figure shows the major tasks to be performed for DR while the central section shows the interplay between technology. The primary tasks are to ingest real time information arriving from 2 Million smart meters, detect critical anomalies with very low latency to take response, proceed with non-critical task of annotating smart meter data with other information sources, updating the demand forecast using latest information, and responding to peak load or other events that are detected by interacting with consumers. This entire process implicitly includes a feedback since any response taken will impact the consumer energy usage, which is measured by subsequent readings of the smart meters.

The technologies that will enable these tasks include **scalable stream processing** systems that accept meter readings streaming over internet or other communication protocols and detect/react to emergency situations based on defined policies, **semantic information integration** that uses domain ontologies to integrate and enhance AMI data with diverse information that are pulled from online services, **data mining and complex event processing** systems that use prediction models based on higher order policies to fore-

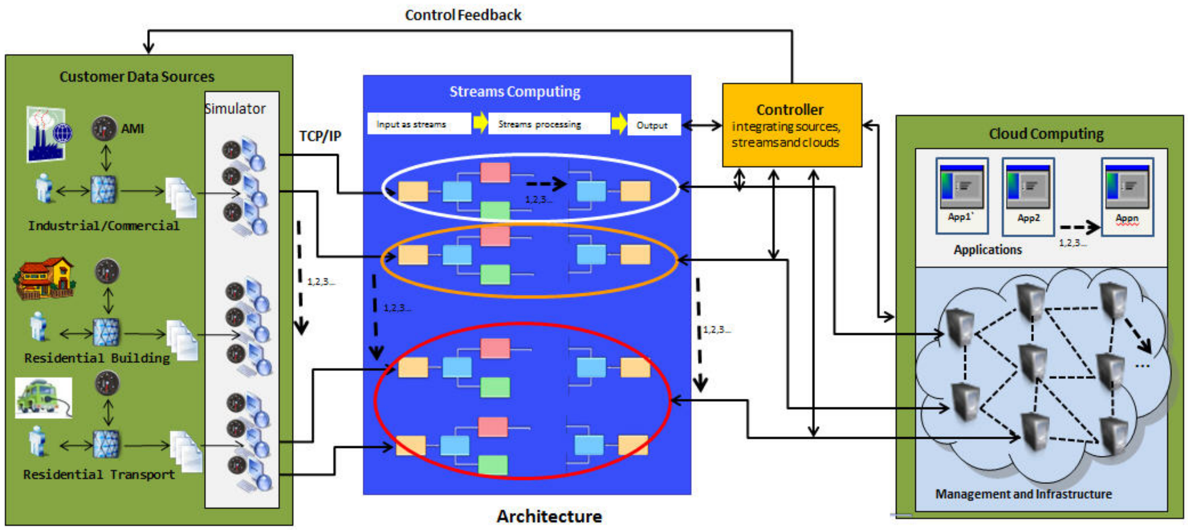

Figure 2: Design for adaptive rate control feedback from stream processing system to AMIs to optimize bandwidth into Cloud platform

cast a supply-demand mismatch, **machine learning** algorithms that use knowledge from prior customer response to determine the most effective technique for load curtailment, and lastly **natural language and multi-lingual** methods that will translate the selected response into an actionable form that is propagated to consumers and their agents. All of these tools will run on scalable platforms that combine public and private **Cloud infrastructure**, and allow information sharing over Web service APIs while enforcing **data privacy** rules.

In the next few sub-sections, we discuss the research and engineering challenges for developing and applying these informatics and internet technologies to the DR software architecture.

5.1. Scalable Stream Processing

Stream processing systems perform continuous queries over a moving window of tuples to perform selection, transformation and aggregation operations. Stream processing has its roots in sensor networks and such systems are optimized for low latency operations.

In this project, we use streams processing as the initial entry point for the electricity usage data that is continuously arriving from smart meters. Each AMI acts as a stream that generates a meter reading tuple every N minutes, where N typically ranges from 1min to 60 mins. Besides ingesting the data from AMIs, the stream processing system acts as a first responder to detect potentially calamitous events that require low latency response. These may include a certain neighborhood sharply increasing usage by, say 100%, over the observed average, or a hospital or emergency service consumer dropping power consumption to zero - which can signify an outage. The stream processing system maps simple, clearly specified policies defined by utility managers into continuous queries that are executed, and trigger well defined actions such as notifying a supervisor or maintenance crew. The system also performs simple information aggregation and passes the data to the semantic information integration system.

One of the challenges posed by the smart grid domain to stream processing is scaling. Initial estimates assuming AMI data rate of 1KB per power usage reading, and 1 reading per minute for 2 Million consumers suggests the need to process 3TB of meter data per day. This is both network and compute intensive, and the streaming system has to scale on distributed platforms such as clusters or Clouds to manage these data rates. However, the network costs for the utility to ingest such high data rates can be prohibitive.

One interesting research problem this poses is determining what rates the meter usage data should be provided by each AMI for it to be meaningful for DR optimization and critical response. In other words, can we dynamically throttle the AMI stream rates to optimize for bandwidth usage while ensuring a minimum quality of service for demand response is maintained? Some approaches to this include looking at moving averages or standard deviation of power usage data from a particular AMI and reducing data publish frequency when they are sustained, or comparing the power usage levels against historical levels for that consumer making the frequency proportional to deviation from historic levels.

In a global model, we can consider the difference between available capacity and total aggregate power demand, and make the data frequency inversely proportional to the difference between them. This is intuitive when considering that current power usage curves show excess capacity at night, and meter usage data may be required less often at night for DR optimization. There will, however, be minimum data rate requirements possible configured according to consumer class, to ensure critical situations are detected. Figure 2 shows an initial design for sending adaptive stream rate control feedback to the AMIs using observations within the stream processing system running on a Cloud. The controller logic ensures that minimum stream rate requirements for detecting events is present while optimizing for bandwidth usage between the AMIs and stream processing system in the Cloud.

5.2. Semantic Information Integration

Information integration is at the core of the DR architecture and supports the building of data analysis and mining applications for forecasting and response. Traditionally, monthly meter data has been integrated with customer relationship management and billing systems within the utility's IT infrastructure. However, treating AMIs as just a temporally fine grained form of meter data fails to reap the full benefits of the smart grid.

In particular, as electrical technology advances and consumer software tools that dynamically control home and building area networks become commonplace, demand forecasting will become more challenging as the load curves change. The current forecast models [22] that primarily combine power usage, weather forecast and demographics into mathematical models will give way to data driven mining algorithms that locate patterns among a large class of information attributes to predict power usage. Such an information rich space could incorporate fine grained appliance information from AMIs, evening commute traffic flow to determine expected arrival time of EVs at neighborhoods, location information published through smart phone apps, event schedule information from classrooms and convention centers, and social network and micro-blogging feeds with specific hashtags.

The space of such information sources and types is broad and will change often as algorithms adapt. It can be effectively used and interpreted only if it is grounded in semantically meaningful terms. It is not just the utility managers who will be using this information to define policies, but also data mining and analysis algorithms, third party tools with which the data is shared, transmitted to other utilities and regulators, and possibly even the consumers. This goes beyond just a normalized form for exchanging meter data usage [23], [24] using a power systems domain ontology and suggests integrating ontologies from different domains – weather, traffic, social networks, and so on – and using sematic definition for policies and service APIs using well understood Web standards such as OWL and RDL.

5.3. Semantic Complex Event Processing

Complex event processing deals with computation, transformation and pattern detection over large volumes of partially ordered events and messages [25]. An event represents something that occurs or changes the current state of affairs. In Smart Grid, for example, tuning thermostats or turning on/off heavy-duty electric appliances are both events relevant to DR. CEP has been used successfully in financial services industry to detect stock trading patterns and several vendors such as Oracle, Microsoft, Sybase and StreamBase have CEP products.

CEP is considered as a core component of smart grid software architectures and solutions provided by vendors, including Microsoft [26] and Oracle. They are used for defining standing queries or business rules that detect a combination of attributes present in a set of events and triggering pre-configured business processes. As such, the CEP systems currently proposed for smart grid solutions are closer in form to the critical response of stream processing systems, and intended to supplement IT systems in current utility grids rather than support emerging and future smart grid applications. The fine grained specification of structural properties within events and the consequent actions is too complex for most utility managers in an information rich space. For example, the Oracle's Meter Event and Meter Data Management services [27] that are replacing the current LA DWP customer information system can abstract the diversity of different AMIs and their data representation to easily map to existing billing systems. But defining advanced policies for detecting peak load events requires the specification of numerous complex business rules, and demand forecasting as required for DR optimization is absent.

Several key research challenges emerge when building CEP systems for DR optimization in smart grids that we are currently addressing. First, CEP systems use syntactic patterns that require utility managers to have knowledge of hundreds of event properties and information attributes to specify demand policies and triggers. A semantic CEP system based on the semantic information integration introduced earlier will ease the policy definition [28]. Second, the demand forecast and detection patterns themselves should be automatically generated from high level goals specified by utility managers, rather than requiring them to explicitly define the complex patterns. For example, a high level goal may be to retain a 10% buffer between available power capacity and current demand, which may get mapped to complex patterns in the CEP system that are generated by data mining over the semantically integrated information. Automated data analysis tools that look for interesting causality patterns over diverse information sources for peak load forecasting will help define realtime complex patterns that are executed by the CEP system. Lastly, one interesting area of research is probabilistic matching of complex patterns that can withstand uncertainties in the information sources, caused by less accurate or incomplete information.

5.4. Machine Learning

Machine learning (ML) and data mining are recognized as important tools for data analysis in smart grids. Several authors have investigated the use of ML for load forecasting [29], predicting user comfort levels in home area networks [30], and even for security of smart grids [31]. Our interest in machine learning is in its application to demand response optimization, and particularly for (1) modeling the energy use footprint of buildings at the USC campus that will help determine demand, and (2) for learning the responses that are most effective for load curtailment. We are currently undertaking experiments to learn and test power usage models for different buildings on the USC campus that will use attributes such as the intended use of the building (classroom, office space, residence hall), their capacity and occupancy based on class schedule, and fine grained power usage data from the past 3 years to accurately forecast demand on the USC campus. In subsequent studies, we will be mining large data sets provided by the LA DWP on customer demographics, geographical location, building type and energy usage, to identify power usage patterns that will allow us to create targeted policies for load curtailment responses to different clusters of consumers. Observing the difference between expected and actual response should be part of the learning process by the system to improve subsequent responses. The eventual goal is be to determine the appropriate response and target population that will achieve a load curtailment of X KWh within N minutes.

5.5. Natural Language Processing

Related to effective response for load curtailment is how the information is communicated to the consumers that will elicit the required reduction in electricity usage. The consumer is a key element in the functioning of the Smart Grid. It is important to devise means for better consumer engagement. In particular, effective feedback methods need to be developed to persuade and motivate the consumer towards sustainable energy consumption behavior. Industry experts have also indicated that better communication with the consumers is necessary to meet the challenge of user adoption of the Smart Grid.

Providing the consumer with extensive consumption information may raise awareness but may not necessarily translate into modifying consumer behavior.Different consumers react differently to visual, text or audio feedback. While many consumer-oriented smart energy websites use graphical charts and diagrams to provide monthly usage information, not everyone responds to them once the novelty wears off. One less studied but important aspect of consumer feedback is using text and natural language. In particular, we are investigating the use of reinforcement learning techniques for text generation that will determine what, how and when textual cues should be provided to customers for effective load curtailment .The consumers will find it easier if the information is interpreted for them and they are provided with specific actions to take [32]. Strategies that will be driven by consumer behavior studies will include positive encouragement for energy saved, reminders to turn off appliances, and comparison with peers.

When the information is communicated in form of natural language feedback, the consumers may find it easier to comprehend and interpret, and more convincing than the structured data presented in the form of tables, or graphs. Moreover, in such a setup, the utility companies could also benefit from the ability to communicate actionable items and targeted incentives in a simple language to specific consumer groups.

One advantage of generating textual information is the possibility of using it as input to other systems, such as Text-to-Speech systems. Such a system would allow delivery of feedback in audio format delivered through mobile phones.Text information could also possibly be integrated with Machine Translation systems to generate information in multiple languages and provide consumers the option to indicate their preferred language for receiving feedback. This feature has the potential to increase the coverage of feedback to a much wider populace.

Natural Language generation techniques can be used to automatically generate text information from structured data. The generated messages need to be tailored in content and style according to the user models. Key challenges in this field include: content selection, presentation, and context). The underlying goal in these problems is to present information to the consumer that is personally relevant and actionable. Natural Language feedback can incorporate a variety of information content: actual energy usage, rate of usage, disaggregated usage, comparison with peers, progress towards a goal, carbon footprint based on energy used, etc. Some use case scenarios are given below [32]:

- Usage information:
- Predicted information and advice on how consumption could be reduced.
- Friendly reminders, which could be accompanied with expected energy savings.
- Positive encouragement.
- Explanations about specific aspects of the usage graph, or possible reasons for high bills.
- Strategic advices, for example, on energy-efficient appliances.
- Friendly competitions and peer pressure.

5.6. Scalable Cloud Computing platform

The informatics tools such as stream processing, CEP, data mining and ML used by DR applications can be data and compute intensive. In order to support consumers on the order of millions, and to ensure that new data sources or novel algorithms that are computationally costly can be added and run over time, the DR software architecture will have to be deployed and run on a scalable platform. HPC Clusters have typically been used for parallel and distributed programming. But the growing presence and popularity of commercial Cloud computing presents features that more closely suit the needs of DR applications [33], [34].

Clouds provide a convenient model for growing processing and data storage over time as the number of consumers served by DWP increases and more complex algorithms are incorporated into the DR application pool. This avoids costly capital costs that may otherwise add to the DWP budget immediately. Similar to throttling data rates for stream processing, the computational requirement will also vary based on the mismatch between power capacity and demand. The flexible scale up and down model of Cloud virtual machines (VMs) allows compute resources to be acquired on demand and released when not required, allowing the utility to only pay for the resources used. Cloud VMs also provide redundancy allow additional VMs to be started to perform duplicate computation for mission critical applications. Cloud storage offers implicit replication of data. Cloud data centers are also well suited to handle the millions of open network connections to AMIs with small data exchanges per connection. This workload is similar to Web search workloads for which data centers were originally conceived for. The ability to share data is another feature made easier by Clouds, with the option for external third party software to migrate their application to the Cloud to avoid costly data transfers to client machine [35].

Utilities will however opt for a mix of both public and private Clouds due to data privacy, security and reliability considerations. This will mean that a core set of internal, regulated services may be hosted within the utility's privately hosted Cloud while the public Cloud is used for a different set of public facing services and to off-load applications that exceed the local computational capacity. Another reason for this is that the time to instantiate and start VMs in the Cloud is on the order of minutes and this can lead to lower computational throughput when the computation requirement suddenly surges [36]. The private Cloud hosts captive computational resources that are always available instantly. Also, the network latency to Cloud data centers may exceed permissible levels for some time sensitive applications and the private Cloud may be closed in the network topography. Lastly, regulatory requirements that evolve may impose restriction on where consumer data is hosted and require strict audit trails on data usage. While Clouds are working towards HIPAA compliance, required for medical records, there is no obvious push for such regulation or compliance for utility data.

Several interesting research issues emerge when we use public-private Clouds as an application platform for the DR software architecture. Streaming applications on Cloud platforms will have to be cognizant of network bandwidth costs as they may be non-trivial. Stream throttling discussed earlier becomes more relevant. Scheduling latency sensitive application on Clouds required planned startup of VMs to ensure they are available for instant scale out. Here too, prediction of computational resource needs can be derived from the state of the power system. Trade-off between the cost for performing accurate, but computationally costly forecast against the energy gains (and indirectly costs) for the utility can be considered. Data sharing and privacy issues become even more crucial on public Clouds, and are discussed next.

5.7. Data Privacy and Security

The smart grid will be characterized by a large scale heterogeneous communication network in which the data flows through various media, wired and wireless. There are inherent security concerns with any large scale communication system as it is susceptible to security attacks on the various media through which the data travels. At the same time there exist a number of vulnerabilities in the power grid because most of the current devices were built specifically with the focus on securing the devices from physical tampering and with less focus on securing the communication [37]. Data and cyber security issues in the smart grid domain deal with securing the transportation channel carrying smart meter and other utility and consumer data between different entities in the smart grid. It also aims to prevent disruption of the power grid through introducing unauthorized code or "viruses" [38], or attempts by consumers to modify the power usage data reported to the utility. In addition it is extremely important to integrate with the legacy system in a secure manner in such a way that the vulnerabilities in the existing system do not put the entire smart grid at risk. Moreover, due to the close interaction between the cyber and physical infrastructure, the smart grid possesses a number of unique security concerns.

At the same time the nature and frequency of communication, especially meter readings, is very different in the smart grid as compared to conventional grid. In the traditional system, the only information that is communicated with the utility is the aggregated power usage over a couple of weeks or even months, particularly for billing and maintenance purpose. In the smart grid system, the power usage information for an individual or an area is needed at a much higher frequency (once in fifteen minute to as high as a 30 to 60 times within a minute for power quality measurement) for effective demand response and load management [39]. Data privacy concerns stem from the ability of the utility to observe real-time energy usage and consequently interpret consumer behavior, either just from the usage information or by integrating it with public data available about the consumer or private data shared by them [17], [40]. We envision that along with the optimized demand response system, the smart grid will provide various other applications for the benefit of the end user as well as the utility providers. However these applications will demand even greater flow of information to and from the end user including personally identifiable information which, if not handled carefully, can provide opportunities for violation of individual privacy.

While cyber security of smart grids has understandably gained attention [41] due to the possible consequences of power grid blackouts from attacks, data privacy is a less tractable problem and will become increasingly hard to manage. Information about real-time power usage can be used to detect, say, the breakfast time of a consumer or, in extreme cases, plan burglaries. One of the unique problems for smart grids is to balance the efficiency and service features gained from integrating electricity usage information with other public and private sources, against the possibility of personal data being leaked. For example, one effective response technique in DR optimization may be through peer pressure. Providing information on lower energy consumption by a neighbor or a Facebook friend may lead to lower energy consumption. But this may be information that not all users would be willing to share. One reason for this difficulty is that privacy is a personal choice that people are increasingly willing to sacrifice in return for free services – Web search and social networks are cases in point.

A smart grid software architecture has to be secure and enforce privacy rules required by regulators. While doing so, there must be provisions for sharing data with authorized users, be they the consumers, their authorized agents, other utilities, or regulators. Experiences from eHealthcare [42] systems will be valuable as utilities craft privacy policies and provide information access mechanisms. Given that smart grids are at their inception, any major privacy exposure can cause a trust deficit among the general public that hinders adoption [43]. Data privacy and security also permeate all aspects of the architecture. There may even be restrictions on sharing data between software components of the utility. For example, a customer support representative may have access to billing information that software used by a maintenance crew should not have access to. Moving consumer data between private and public Clouds may require an identification process. Fine grained authorization controls may need to be built on top of storage service provided by public Clouds to before access to this data can be given to third parties.

6. Conclusion

These are early years in the Los Angeles Smart Grid project, but the advantages of taking an informatics approach to building an intelligent and adaptive grid are apparent. We have presented several informatics research issues that emerge from this domain and are actively exploring novel solutions for them. Together, they will go towards making the Los Angeles Smart Grid a reality and provide guidance for hundreds of smart grids that are expanding worldwide.

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