Computation and Information Hierarchy for a Future Grid

Future Grid Initiative White Paper

Power Systems Engineering Research Center

Empowering Minds to Engineer
the Future Electric Energy System

Computation and Information Hierarchy for a Future Grid

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Executive Summary

This white paper focuses on aspects of computation and information hierarchy of a future grid. On computation architecture for smart grids, challenges and opportunities of having cloud computing architecture for the scalable, consistent, and secure operations of smart grids are examined. On information hierarchy, issues on how information should be partitioned in time and space are examined. The temporal characteristics of information hierarchy are investigated in the context of dynamic scheduling with deadline requirements. The spatial characteristics of information hierarchy are investigated by considering spatially distributed location real-time prices. Effects of data quality on location real-time prices and market dynamics are considered.

This white paper proposes a set of research topics on the computation and information hierarchy for a future grid:

1. ***Cloud architecture for future grid:*** Cloud computing offers a scalable and unified platform to meet computation and information processing needs of a future grid. However, significant advance is necessary to make cloud computing suitable for secure and robust operations, capable of supporting large scale integrations of stochastic generation and a wide range of demand response opportunities. Research is required to quantify fundamental design tradeoffs among scalability, data consistency, security, and trustworthiness for emerging applications of smart grids. Novel cloud architectures are needed for low latency and trustworthy state estimation, real-time dispatch, and market operations. Innovations in highly reliable and efficient distributed storage, computation, and networking are required that take advantage of advances in network coding and cognitive networking technology.

2. ***Information hierarchy for real-time operation under uncertainty:*** The future grid must accommodate high degrees of uncertainties in generation and demand. There is a need to gain fundamental understandings of how information should be partitioned in time and space; how it should be collected, distributed, compressed, and aggregated. The temporal characteristics of information hierarchy can be investigated in a stochastic optimization framework in the forms of risk limiting energy dispatch and optimal energy management with deadline constraints. To this end, computationally tractable multi-time period robust stochastic optimizations are needed for large systems. The spatial characteristics of information hierarchy can be investigated in the context of hierarchical decision making with distributed incentives. Economic incentive and pricing models are needed to capture interactions among transmission and distribution network operators and consumers.

3. ***Big data analytics:*** Successful operations of a future grid require sophisticated big data analytics that extracts hidden patterns, forecasts and tracks trends, and detects anomalies and cyber-attacks. Impacts of data quality on state estimation, real-time dispatch, and real-time locational marginal prices need to be qualified. Mechanisms to discover and preventing data attacks are needed. Important research topics include (i) structured learning techniques that capture the characteristics that high dimensional data are often reside in some low dimensional manifold; (ii) high dimensional statistical inference for situation awareness; (iii) high dimensional online learning that integrates learning and operation decisions; and (iv) data representation and visualization techniques that summarize actionable information.

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1. Introduction

The electric grid in the United States has evolved over the past century from a series of small independent community-based systems to one of the largest and most complex cyber-physical systems today. The grid consists of tens of thousands of generators and substations, linked by transmission and distribution networks. The system state is estimated continuously using remotely collected data, and power delivery is orchestrated by sophisticated decision and computation processes. The electricity markets are tied intimately to the operation of the grid. Despite practical challenges of serving electricity in real time to a large geographical area, the supply of electricity has been mostly reliable with a few well-publicized exceptions of regional blackouts.

The established conditions that made the electric grid an engineering marvel are being challenged by major changes, chief among these being the global effort of mitigating climate change by reducing carbon emissions. The U.S. government has set a target of reducing the national emissions of greenhouse gases by 80% from the current level by the year 2050. Within the United States, the national goal of achieving energy independence also calls for reducing imported oil significantly. While the tremendous growth in domestically produced shale gas and oil makes it a realistic scenario that the US will likely be a major energy exporting country, the environmental and associated economic impact of extracting such energy sources is uncertain.

Achieving a reduction of fossil fuel at this magnitude requires a combination of integrating renewable energy, developing distributed energy sources and control capabilities, electrification of the transportation, and much improved energy efficiency for buildings and appliances. Transformative and potentially disruptive changes to the current structure of the energy industry may be necessary. Critical technological innovations are required.

The existing power grid is large and complex and its functionalities may have to be expanded significantly due to the need of greater integration of renewable sources, demand-side participations, and the prolific use of web-based information technology for personal energy management.

The current grid has limited observability in space and time, but this situation is being changed by the deployment of Phasor Measurement Units (PMUs) for transmission networks and advanced meter infrastructure (AMI) for distribution networks. Smart sensors are being integrated in buildings and infrastructures, smart devices capable of communicating wirelessly are part of the new generation of appliances.

A back-of-the-envelope calculation by Birman, Ganesh, and van Renesse [1] serves to illuminate the potential need of a new computation and information architecture. It is estimated that a fully deployed PMU infrastructure may have the aggregate data transmission rate of approximately 15 Gbytes/second, beyond the full capacity of a state of the art optical network link.

The proliferation of mobile personal devices makes it convenient for consumers to participate actively in *personal energy management*, creating new dynamic interactions between generations and consumption. For example, mobile apps have already been developed for home energy management that interacts with internet services such as weather forecasting. Such apps can easily incorporate personal lifestyle preferences, real-time pricing signals, traffic information for scheduling the charging of electric vehicles, and consumption profile of local communities. Much of the computation and storage needs that serve the consumer are in a public infrastructure and will likely be in the "cloud" in the future.

While it is not easy to foresee changes in today's mostly centralized energy management paradigm, it is not unreasonable to draw an analogy with the evolutionary path of the computer industry, from centralized mainframe computing for large organizations to personal computing for individuals; from computing at offices and homes to mobile and embedded computing; from high performance parallel computing to cloud computing. Essential characteristics of this evolution are the personalization and localization of computing and the ubiquitous presence of networking. It may be argued that these same characteristics will have impacts on the development of a future grid.

Today's grid is based on a private computation and networking infrastructure. The scalability of such an approach in an era of big data is called into question. It has been argued in [1] that building a private network exclusively used for the future grid may not be an economically viable option; leveraging existing public investments in computation and networking infrastructure such as cloud computing and future internet technologies will be inevitable.

This paper addresses several issues on the computation and information hierarchy of a future grid. On computation architecture for smart grids, challenges and opportunities of having cloud computing architecture for the scalable, consistent, and secure operations of smart grids are examined. On information hierarchy, issues on how information should be partitioned in time and space are examined. The temporal characteristics of information hierarchy are investigated in the context of dynamic scheduling with deadline requirements. The spatial characteristics of information hierarchy are investigated by considering spatially distributed location real-time prices. On big data analytics, effects of data quality on location real-time prices and market dynamics are also considered. Mechanisms of detecting and preventing malicious data attack are considered.

2. Cloud Architecture for a Future Smart Grid

We discuss in this section merits of developing a cloud computing architecture for computation and operation needs of a future grid. It may be argued that cloud computing has the greatest potential to be the information and computation foundation for a future grid [1], [2], and the cloud is a unifying architecture not only for independent generators, ISOs/RTOs, and distribution utilities but also for consumers and communities that are part of the greater social network.

A limiting factor for efficient and reliable operation of today's power grid is the lack of computation power. To this end, cloud computing provides a scalable and economic solution. The current SCADA systems and control centers relies on the architecture of high performance computing (HPC). Such architecture is limited by the so-called checkpoint barrier [3]. In particular, because computation nodes for HPC may fail, check points are needed to ensure continual execution during failures. As the number of computation nodes increases for larger and more complex SCADA operations, the number of required check points increases dramatically, which becomes a fundamental barrier to large scale computation.

The cloud architectures, in contrasts, are supported by multiple data centers, each having a large number of simple and inexpensive servers. Despite that nodes and storage may fail, the redundancy and distributed nature of the cloud make the cloud architecture more reliable for smart grid operations and with greater computation speed and elasticity. A particularly relevant development is the recent advances in applying information theoretic and coding techniques [4]-[6] that mitigate disk failures and other anomalies to improve operation reliability and efficiency.

There have been growing activities on the use of cloud architecture for smart grid applications (see, e.g., [1], [7], [8]). Although the economy of scale favors a cloud architecture, cloud computing was not and has not been designed for power grid operations. Here we outline a few important challenges that must be addressed should cloud architecture become the computation and information backbone for smart grids.

2.1 Consistency, availability, and reliability

The information and computation infrastructure for a future grid need to be available, responsive, fault tolerant, and resilience to attacks. Data essential for operational decisions need to be consistent in the sense that the asynchronous arrival of information and updates at data centers should not lead to inconsistent decisions. This last property is especially important because the power grid covers a large geographical area, and distributed data collection and storage lead to discrepancies. Thus making decision policies robust to data inconsistency is crucial.

Data consistency and real-time guarantees are known to be at odds in distributed systems. What makes today's cloud architecture scalable is the notion of *weak consistency*, which does not enforce all data at different servers have the same level of accuracy and freshness. The outcome of a search at one location may actually be somewhat different from that obtained at a different location. Nonetheless, for many applications, "pretty good answers" are considered good enough, and weak consistency is deemed adequate. For real-time operation of the grid, however, weak consistency, especially one without quantifiable measure, is insufficient; a much stronger guarantee for consistency is necessary.

It is essential to characterize fundamental tradeoffs among consistency, time criticality, and scalability. To this end, Brewer conjectured in [9] that that *consistency, availability, and partition tolerance (CAP)* cannot be satisfied simultaneously. By consistency it means that distributed processors should have access to the same data at the same time. Availability in a distributed system means that every request receives a valid response. Partition tolerance means that the system continues to function despite arbitrary message loss. Gilbert and Lynch later introduced a formal model and established a set of impossibility results [10]. The models considered in [10] are specific asynchronous models for read-write operations uncommon in grid operations.

The strict notion of CAP is not useful in practical power system; the power grid cannot operate with arbitrary partitions, nor will SCADA systems across wide areas can be perfectly synchronized. While CAP properties represent exceedingly strong theoretical requirements, they have natural practical interpretations in specific applications. It is more relevant to obtain a practically significant measure of CAP. To this end, it is useful to introduce tolerance levels in the three CAP attributes, replacing strict CAP by a deterministic or a probabilistic counterpart.

For example, we may be willing to scale back strict consistency by the probabilistic consistency. Specifically, we may want to require the system achieve consistency with probability ($1-\varepsilon$). We may replace anytime availability to a more realistic measure of availability with high probability, requiring that data outage probability be lower than ε. Instead of considering arbitrary partition of the network, we may consider a weaker notion of reliability similar to that of N-1 contingency requirements.

Characterizing fundamental tradeoffs among consistency, availability, and reliability is a critical step toward addressing architectural issues for a future grid. Once the strict notion of CAP is replaced by the more practical measures of consistency, availability, and reliability, the Brewer conjecture focusing on the achievability of three extreme CAP objectives simultaneously should be replaced by the characterization of the set of achievable objectives that are ε–deviate from the extreme CAP points, as illustrated in Figure 1.

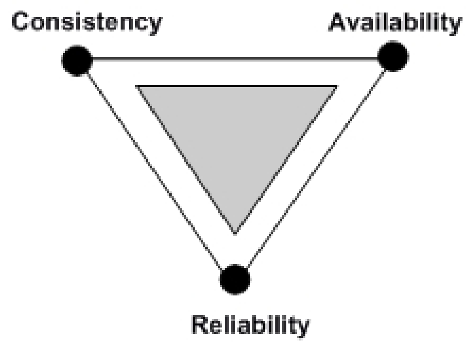

Figure 1. An illustration of the set (shaded area) of practically achievable conflicting objectives on consistency, availability, and reliability.

2.2 Reliability, security, and trustworthiness

Today's cloud technology does not provide the level of reliability necessary for real-time operations. Data inconsistency and other anomalies due to data center and network outages may have detrimental effects on the reliability of the future grid. The increasing reliance on cyber-infrastructure to manage complex grids comes also with the risk of cyber-attacks by adversaries around the globe. If the future grid is to be managed by a combination of public and private cloud platforms, the risk of attacks will only increase.

Existing cloud computing platforms have weak security and privacy guarantees, which makes them vulnerable to internal and external attacks. The notion of "trustworthiness" goes beyond security. Because data are replicated in the cloud, and it is impractical to refresh them at an arbitrarily fast rate, it is possible that outdated data are used in critical decisions.

A natural approach to reliability and consistency is introducing redundancy in the cloud system. A naive solution is to duplicate storage units so that, in events of disk failures, essential data are not lost. Such a solution, however, is flawed because duplicating data necessarily increases data traffic and the chance of data inconsistency.

A more promising approach is to introduce redundancy in a more intelligently. The idea of coded storage [11] and more recent development of network coding techniques for distributed storage [5], [6] provide possibilities of achieving tradeoffs among reliability, efficiency, and security. As an application of error control techniques in communications to data center storage, sophisticated error detection and correction techniques are being developed by taking into account the need of frequent updates, possibilities of disk failure, and potentially malicious actions [12]. These ideas open new avenues toward cloud architecture suitable for real-time and secure operations in a future grid.

2.3. Estimation and control in the cloud

The "state" of the power grid is defined by the voltage phasors at all buses. The state variable captures the operating condition of the grid and contains sufficient statistics for operational decisions. Prior to the advent of PMU technology, state variables cannot be measured directly, and states have been estimated from data collected by the SCADA system. State estimation is implemented in all control centers based largely on the original ideas of Schweppe [13]. The deployment of PMUs greatly enhances the quality and resolution of state estimates [14]–[16]. With faster and synchronized sampling, state estimation will play a greater role in real time operation and control of the future grid.

What happens when state estimation is executed on a cloud platform? What are the impacts of conflicting, bad, or missing samples on state estimation and operations using state estimates as input of operational decisions? How trustworthy are state estimates on a cloud system? Works on estimation and control with intermittent packet drops are particularly relevant (see [17], [18] and their included references). Information theory and coding techniques have also been considered in dealing with imperfections introduced when data sensor data are communicated to the control center [19].

Classical state estimation incorporates practical bad data detection as a way to eliminate outliers or mistakes in data collection [20]–[22]. These techniques, however, are not effective in dealing with complex situations arising in a cloud platform and the possibilities of external or internal (Byzantine) attacks. There have been recent efforts in characterizing effects of bad or malicious data on state estimation and on real-time location marginal price (LMP) (see [23]–[25]).

3. Information Hierarchy in Time

To achieve large scale integration from wind and solar sources that are stochastic and time varying, existing modus operandi based on day-ahead planning and worst case contingencies may have to be changed. Because uncertainty increases with planning horizon, day ahead forecast of generation levels from renewable sources can at best be used to characterize the ensemble behavior. If a high percentage of renewable generation is integrated into a future grid, operation decisions have to be made with a shorter time horizon such that they can be made more adaptive to changing operating conditions. To this end, it is necessary to view randomness in supply and demand not as minor perturbations from some deterministic norm but as fundamental characteristics of energy management in a future grid.

Information hierarchy in time addresses the problem of what kind of information is required and by what time decisions have to be made. The information structure for real-time decisions can be modeled as a nested sequence of observed events—an information filtration. Conditioned on the sequential arrivals of information, the control center takes actions based on cost/profit considerations, constraints, contingencies, and operation deadlines. The general framework for these types of problems is a multistage decision process.

We present below two types of scheduling problems that are particularly relevant; one follows a robust formulation by considering worst case scenarios, the other a stochastic formulation with average performance measure. In both cases, the decision problems involve explicitly deadline constraints.

3.1. Real-time scheduling with deadlines

Deadline scheduling is a classical and fundamental problem where jobs arrive at a control center with different processing needs and deadlines of completion. Such problems arise naturally in home energy management where a controller schedules loads with different characteristics, some with firm deadlines of completion and others with deadlines on the starting time.

For example, a residential consumer may require that an electric vehicle be charged by 7 AM or that a washer/dryer be started no later than 8 PM. Yet other jobs may have deadlines that are not firm, deadlines that may be specified in a probabilistic setting in terms of average time of completion or the probability of completion.

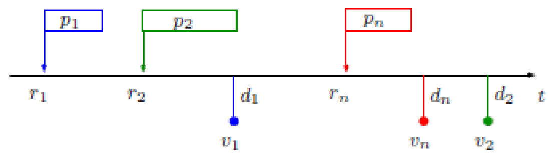

Figure 2. Arrivals of jobs with deadlines

In a generic form, a job $J = (r, p, d, v)$ is defined by a quadruple: the arrival time r, the required processing time p, the deadline d, and v the utility of completing the job. Figure 2 illustrates a particular scenario of the arrivals of jobs with deadlines. The problem of deadline scheduling is to determine, at any time, which jobs are to be served subject to certain processing capacity constraints.

Deadline problems can be formulated in a deterministic or a stochastic setting. The latter often requires knowledge of joint probability distributions of arrival time, job sizes, processing time, and deadlines. Such prior knowledge, however, may be difficult to have in practice. An alternative is the framework of *competitive scheduling* based on a deterministic formulation. In such a setting, all variables are modeled as deterministic quantities, and the performance of any online scheduling algorithm can be compared with the optimal offline algorithm.

The *competitive ratio* $C(\pi)$ of an online policy π is defined as the ratio of the reward accrued by the online policy π over that by the optimal offline policy for the worst possible job arrival scenarios. The optimal online policy is then defined as the one that achieves the supremum of competitive ratio among all online policies. Scheduling under deadlines are well known challenging problems with many new applications. It was shown by Karp [26] that optimal off scheduling for problem of deadline scheduling is NP-complete. Thus no polynomial time solution is known to exist. On the other hand, simple online scheduling algorithms that achieve the best competitive ratio do exist. For example, the earliest deadline first (EDF) algorithm works on the job with the earliest deadline, and it switches to a newly arrived job if the new arrival has an earlier deadline. It is known that such a simple scheduling algorithm is optimal when the traffic load is light. See in particular the seminal work of Liu and Layland [27], the work of Mok [28], Locke [29], recent applications in scheduling jobs for cloud systems [30] and the large scale EV charging [31]

As an application, consider the problem of charging electric vehicles (EVs) at a parking lot or a garage. The customers arrive with different charging needs and required deadlines for completion. Suppose that the chargers are powered by a mixed of (inexpensive and locally generated) renewable source and expensive electricity purchased from the grid. Given varying level of available renewable sources, an operator wishes to have a scheduling policy that maximizes its operating profit by optimizing its charging schedule.

The energy management system for the large scale charging of EVs faces multiple challenges. The service provider has to deal with uncertainties associate with the arrivals of jobs (demand) as well uncertainties associated with the varying price of electricity. Given a fixed pricing scheme, the service provider optimizes its profit by exploiting flexibilities associated with specified deadlines.

The problem of pricing EV charging services is nontrivial. For instance, it is reasonable to charge a consumer a higher price when a submitted job has a tight deadline. Therefore, a service differentiated pricing may be appropriate, which makes jobs with tight deadlines higher priority and more profitable. On the other hand, a consumer may respond to pricing schemes by either reducing consumption or turn to competing service providers. A main challenge is to optimize jointly deadline scheduling and pricing in a competitive market.

3.2. Multistage decision and risk-limiting dispatch

The objective of unit commitment and economic dispatch in the electric power system is to schedule generators and reserves to meet the demand in the presence of uncertainties and random contingencies. The decision process in the current power system is a two-stage optimization involving day ahead planning and real-time adjustments. The decisions at the two stages are only loosely coupled. When there is a high degree of uncertainty, reliability considerations based on worst case scenarios lead to over provision and inefficiency. When the generation portfolio includes a high percentage of renewable sources, the cost of over-provision of reserve offsets the benefits of renewable integration.

The key idea of risk limiting dispatch articulated by Varaiya, Wu, and Bialek [32] is to exploit the fact that uncertainties associated with random generation decreases as the decision horizon reduces. To take advantage of real-time measurements that help to improve forecast accuracies, risk limiting dispatch reduces the decision horizon by increasing the number of stages in the stochastic optimization. As time gets closer to the scheduled actions, increasingly tighter limits on risks are imposed.

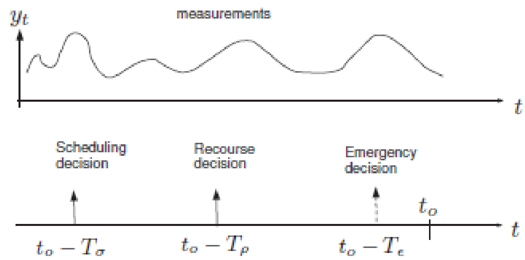

Figure 3. Decision epochs of risk limiting dispatch [32]

Figure 3 illustrates a sequence of decision epochs that influence the actual actions (power generated or consumed) at the decision deadline $t = t_o$. Three types of decisions are made based on available information from time 0 up to time t: the scheduling decision u_σ at $t_o - T_\sigma$; the recourse decision at $t_o - T_\rho$, and the emergency decision (if necessary) taken at time $t_o - T_e$.

The formulation of such decision processes requires an abstraction of information and decision structure, reliability/ security constraints, and constrained optimizations. The underlying optimization in risk limited dispatch is nontrivial, but structured solutions may exist under certain conditions (see [33], [34]).

4. Information Hierarchy in Space

Information hierarchy in space addresses the problem of collecting and disseminating information to a large geographical area and issues related to networking requirements, data resolution, and latency. We discuss in this section the significance of investigating spatial aspects of information hierarchy, focusing on economic aspects of the electricity market for future smart grids. We then outline research topics—the use of distributed incentives and Location Real-Time Pricing (LRTP)—that are rooted in and give a new context for Schweppe's vision of user participation in a deregulated electricity market.

4.1 Impacts of data inconsistency on Location Real-Time Price

The real time location marginal price (RT-LMP) has been the main mechanism to settle day-ahead and real-time markets [35], [36]. If the cloud is to be a backbone for the computation and information management of the smart grid, the issue of data quality has to be addressed. We have already discussed earlier that the current cloud assumes merely weak data consistency. Furthermore, there are always possibilities that adversaries (potentially insiders of the energy industry) can covertly manipulate data to affect real time prices.

The impact of data inconsistency on RT-LMP is not well understood. If demand response is one of the main characteristics of a future grid, one has to consider impacts of data quality on the volatility and stability of the electricity market.

In a recent work [37] has shown that the manipulating data from unprotected meters can result in a significant change of RT-LMP [37]. Indeed, data attacks on one location can change significantly prices far away. Indeed, because the RT-LMP is a solution of a linear program from a linearized incremental optimal power flow, RT-LMPs are computed from vertices of a certain polytope determined by congestion conditions of the network. Inconsistencies or data anomalies can result in the congestion pattern deviating from the reality, causing significantly changed RT-LMP values.

To understand data inconsistency in the smart grid electricity markets, we need to characterize both analytically and through numerical study effects of data inconsistency on LRTP. How much does network latency or using incorrect or outdated data change LRTP? Since the condition of transmission network congestion is estimated through state estimation, does the information network congestion causes significant real-time price changes throughout the network or is it localized? Second, market monitoring algorithms that provide detections, localizations, and warnings for irregular price changes are needed.

4.2 Demand response, hierarchical control, and location real time price

The electric grid covers a large geographic area and the information available and collected for processing has spatial significance. The information flow, however, is not bidirectional; the customers have traditionally been considered as passive loads that can be “shed” in emergencies caused by supply-demand imbalances. Such a “master-slave” relationship is beginning to change and will definitely not be appropriate for a future smart grid.

The technological barriers for obtaining and distributing information have largely been removed, although capacity constraints may still be significant. A customer equipped with dynamic pricing information and the ability to manage their demand over time would benefit from LRTP of the electricity purchased. Indeed, providing LRTP to customers ultimately benefits the network operators because these customers are likely to shift their demand from peak to off-peak periods, and as a result, the installed capacity of the peaking units needed to maintain reliability can be reduced significantly [38].

Full demand-side participation in a future smart grid is, however, likely to require some form of hierarchical control to manage devices on distribution networks [39,40]. It is essential for such a control hierarchy to have a spatial information hierarchy that manages the collection and distribution of information and provides the correct economic incentives to influence customer behavior. While the role of real-time pricing has been studied extensively [38], the spatial aspect of LRTP is less known but this is an essential issue for mitigating the variability of generation from renewable sources that are also spatially distributed on the grid.

The use and impact of distributed incentives on demand-side behavior by customers who wish to minimize their net payments for purchasing electricity from the electric grid and compare the performance of the grid with a system in which all devices are controlled centrally.

Such incentives will allow individual customers to make local decisions on the timing and quantity their purchases of electricity. This paradigm of distributed decisions that respond to real-time distributed incentives is potentially of particular significance for the producers of electricity from renewable sources. These sources are becoming an increasingly important component of generation and integrating them into the electric grid has already caused operating and financial challenges in some regions. Some related recent work can be found in [41,42]

5. Big Data Analytics in Real Time

Information processing in a future grid faces big data challenges in multiple fronts. Previous sections discussed computation and storage aspects of dealing with a large amount of wide area data collected in real-time. In this section, we focus on real-time data analytics that addresses algorithmic challenges.

Data analytics in a future grid can be broadly characterized as algorithms that discover hidden patterns from large data sets, track and stochastic processes and random phenomena in the system, and learn acquire consumer behavior model. The data sets include meter measurements from transmission and distribution networks, generation and consumption history data, day ahead and real-time location marginal prices, weather data, and social network data relevant to consumer behavior.

The real-time location marginal price, for example, is a vector process of over 10,000 dimensions and computed at the rate of once every 5 minutes. This means that the available data in each day represent merely 3% of the data dimension. Applying conventional techniques to estimate correlations among LMPs with any reasonable accuracy would have require at least one year of data, assuming (unreasonably) that the underlying process is a stationary. This example is one instance of many challenges in big data analytics in a future grid.

There is an expanding body of literature on data analytics from the machine learning, signal processing, and computer science communities. The developed theory and techniques, however, are inadequate to tackle unique challenges in a future grid in which big data problems have several important characteristics:

- The real-time operation with instantaneous balance of power delivery demands that data analytics provides on-line actionable intelligence.
- Real-time measurements in a power grid are nonstationary, non-Gaussian, and in general cannot be accurately be modeled by traditional time series models.
- Data in power systems often involve multiple time scales: PMU data in sub-second time scale, SCADA data in sub-minute time scale, load forecasts are in hourly and day ahead time scales.
- Big data in a power grid have both the data poor and data rich regimes. Analytics for real-time operation has to cope with very high dimensional data but with limited samples such as the cases of real-time LMP processes and state estimates. In other situations, the amount of data available for processing exceeds computation and storage capacities. The real-time feed of PMU data, for example, provides the level of details and resolutions that make extracting actionable information difficult.

Investments in research and development in key areas of data analytics will help to usher new generations of big data analytics tools for the future grid.

- Structured learning and graphical model techniques that capture the characteristics that high dimensional data are often reside in some low dimensional manifold;
- High dimensional statistical inference for situation awareness. This includes distributed detection of anomalies and attacks, transient detections, change point detections for early warning of catastrophic events, and techniques dealing with a large number of dynamically evolving hypotheses.
- High dimensional online learning algorithms that integrate learning and operation decisions; such techniques need to capture uncertainties and dynamics of the system, capable of reacting emerging events.
- Data representation and visualization techniques that summarizes actionable information.

6. Conclusions

This paper addresses aspects of computation and information hierarchy for a future grid. Our underlying premises are that the future grid needs to integrate a much higher percentage of stochastic (renewable) generations and that the consumers will participate much more actively in demand response programs. Of course, neither of these premises is guaranteed to be realized in the near future. But if they do become reality at some point in the future, significant changes on how information is collected, stored, and processed are necessary.

There are also technological drivers and innovations that make a compelling case for considering alternative paradigms of computation and information processing. Specifically, cloud computing, despite its imperfections and lack of guarantees in privacy, security, and robustness, is likely to be the dominant mode of computation in the future. As cloud overcomes its shortcomings over time and scales up, it is likely to replace the status quo approach.

The prolific use of wireless devices will likely enable a new generation of consumers who find it comfortable, in fact, natural to manage their energy usage. The personalization of energy management may have dramatic impacts on future energy generation, delivery, and consumption.

The topics covered in this white paper are limited in scope and depth. The issues addressed, however, are fundamental and require considerable and sustained research efforts at both the theoretical and applied levels. In many ways, the problems considered here are classic distributed computation and decision theory problems, except that the scale of the problems is much larger, and the underlying physical system is a critical infrastructure that on which new algorithms and techniques cannot be easily tested.

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