Noname manuscript No.
(will be inserted by the editor)

Peer-to-peer Aggregation for Dynamic Adjustments in Power Demand

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Received: date / Accepted: date

Abstract Energy demand-side management becomes a well-established approach in the Smart Power Grid. Aggregation of consumption information is a critical operation performed by most demand-side energy management mechanisms as it provides information about the required adjustment of power demand. However, a centralized demand-side energy management approach controlled exclusively by utility companies is not always scalable, robust and aligned to the privacy requirements of consumers. A large amount of end-user consumption information is aggregated continuously in centralized approaches. This paper introduces an alternative demand-side energy management scheme: ALMA, the *Adaptive Load Management by Aggregation*. In ALMA, consumers adjust their demand by selecting between different incentivized demand-options based on aggregate consumption information provided by peer-to-peer aggregation mechanisms. The feasibility of dynamic adjustment in power demand is

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evaluated and confirmed analytically using data from the current reality and practice of Smart Power Grids.

Keywords demand-side · energy management · demand adjustment · aggregation · Smart Power Grid

1 Introduction

The increasing scale and decentralization of the Smart Power Grid results in an information gap: Consumers do not have collective and summarized information about the availability and consumption of energy resources in the system. Global system objectives need to be met such as matching supply/demand, the minimization of power peaks and the maximization in the use of renewable energy resources [Brandstätt et al, 2011]. Traditionally, these objectives have been managed from the production-side. This approach is often not cost-effective as it involves expensive and time-consuming actions that are handled by system operators. Such actions include the activation of operating reserves, the installation of new power plants and other infrastructure [Joskow and Tirole, 2007]. Demand-side energy management by adjusting energy consumption based on aggregate information is an alternative approach. Decentralized peer-to-peer aggregation of consumption information becomes the means to acquire such collective and summarized information based on which adjustments can be performed.

This paper studies the feasibility of dynamic adjustments in power demand using peer-to-peer aggregation. More specifically, this paper introduces ALMA, *Adaptive Load Management by Aggregation.* ALMA is a demand-side energy management scheme in which consumers dynamically select between a number of predefined demand options that represent comfort and economy levels of their energy consumption. Their selections are made based on price or other incentives provided by utilities. Peer-to-peer aggregation makes the aggregate power demand locally available to consumers in order to trigger the required adjustments of energy consumption.

ALMA relies on behavioral flexibility that consumers can offer based on incentives provided by their utilities. Consumers and more specifically software agents control home devices and configure a level of comfort and economy in the local energy consumption. Under extreme cases in which the Smart Power Grid is stretched by high load, consumers sacrifice a degree of comfort on a voluntary basis to obtain an economic or other revenue from their utilities. Agents require awareness of the total energy consumption in the system to adapt their local energy consumption accordingly. This awareness is achieved via aggregation that consumers perform in a decentralized fashion and without the involvement of utilities. ALMA is based on the peer-to-peer aggregation as it allows multiple utilities and consumers to coexist in an aggregation overlay network and exchange information about the dynamically adaptive energy consumption. The feasibility of ALMA is validated by analytical results computed using data from the an operational Smart Power Grid: the Olympic Peninsula Smart Grid Demonstration Project [Hammerstrom, 2007].

This paper is outlined as follows: Section 2 discusses the concept of demand-side energy management in the Smart Power Grid and illustrates the research focus of this paper. Section 3 outlines and reviews peer-to-peer aggregation mechanisms. Section 4 introduces the demand-side energy management scheme studied in this paper: ALMA, Adaptive Load Management by Aggregation. Section 5 illustrates the Olympic Peninsula Smart Grid Demonstration Project. Data collected during this project are used in the validation approach illustrated in Section 6. Section 7 illustrates the analytical results collected using this data and Section 8 interprets the findings of this analysis. Section 10 discusses and outlines future work in ALMA. Finally, Section 11 concludes this paper.

2 Decentralized Demand-side Energy Management

Demand-side energy management usually concerns (i) load-shifting of energy consumption at different time points and/or (ii) load-adjustment by increasing or decreasing overall energy consumption [Stadler et al, 2009, Strengers, 2008, Ashok, 2006]. Although demand-side energy management is not a recently introduced idea [Schweppe et al, 1989], nowadays it becomes a critical operation of the Smart Power Grid because of the broad adoption of microgeneration using renewable energy resources and enabling control technologies in households such as smart sensors.

Demand-side energy management is orchestrated in practice by power utility companies via demand-response programs. An outline and review of existing demand-response programs is illustrated by Albadi and El-Saadany [2008] and Cappers et al [2010]. These programs include the installation of smart sensors, controllers and thermostats at the households of consumers to extract almost real-time information about the energy consumption. In theory, these devices provide two levels of control: (i) *local* control by the consumer and (ii) *global* control by the utility. Local control concerns changes of consumption behavior via some awareness about the energy consumption and the price the consumer pays. Furthermore, local control provides interfaces to certain households devices, such as heating, ventilation and cooling (HVAC) systems, for the configuration of their operation. In contrast, global (centralized) control may be directly applied by the utility companies via, for example, frequency signals to which household devices respond [Stadler et al, 2009] or indirectly via price incentives in order consumers to change their consumption behavior [Hammerstrom et al, 2010].

Local control cannot always address system objectives, such as minimization of unexpected power peaks, as consumers are unaware of system information. In contrast, global control requires continuous aggregation of all local information in a centralized management entity belonging to the utility companies. This approach raises scalability, fault-tolerance and privacy issues.

Utilities have to process information from millions of consumers and their devices in almost real-time. This increases the costs of utilities that have to make investments to expensive storage, computation and communication facilities, e.g., data centers. Furthermore, centralization results in single points of failure that can be prevented by additional investments in computer facilities for redundancy. Finally, data centralization and management by utility companies raises several privacy issues. Such detailed energy consumption data can be used to extract information about the lifestyle and activities of consumers as discussed by Lisovich et al [2010] and AlAbdulkarim and Lukszo [2010]. Therefore, an important question is if detailed consumers' data should be stored and managed at the supply-side. Note that the actual interest of the utilities is mainly in the aggregated energy consumption for the purpose of demand-side energy management and not a detailed real-time information about local consumption of individual consumers.

A demand-side energy management system is *decentralized* if it enables consumers to play an active role in the Smart Power Grid by interacting with each other in a peer-to-peer fashion to control their aggregate energy consumption and production. Minimum interventions are introduced from supply-side. Utility companies do not have anymore detailed energy consumption data but only aggregated data. However, utility companies are able to feed consumers with the aforementioned system objectives via high-level policies, incentives, and pricing schemes.

A demand-side energy management system is *autonomous* if it introduces a minimum involvement, participation and interaction of human consumer actors in demand-response programs of an energy management system. Software agent technologies [Scerri et al, 2002, Kok et al, 2005, Kailas et al, 2012] installed in sources of household consumption and production are the technical means to make autonomous control possible.

Decentralization and automation transform the problem of demand-side energy management to a large-scale agent-based coordination problem. Agents representing consumers and controlling their consumption devices may interact with each other in a peer-to-peer fashion and without centralized mediation to collectively coordinate their energy consumption and meet certain objectives of the electrical power grid. For example the minimization of power peaks, referred to as 'peak shaving', the matching of consumption patterns to the availability of renewable resources, or the shifting of energy consumption at different time points are problems that can be modeled using agent-based coordination.

A decentralized aggregation of information about demand is a viable approach to make such demand adjustments possible as consumers can make local selections that have a global impact in aggregate demand. The remainder of this paper illustrates existing peer-to-peer aggregation techniques that can be used by agents controlling households devices of consumers to aggregate demand information. Furthermore, an analytical study is illustrated about the feasibility of dynamic adjustments in power demand. This analytical study is grounded to the current reality and practice of the Smart Power Grid. It provides conclusions about the potential of adjusting aggregate demand in case consumers perform different local demand selections based on information made available by peer-to-peer aggregation mechanisms.

3 Peer-to-peer Aggregation

Peer-to-peer aggregation is a decentralized dissemination, routing, collection and computation of information in large-scale networks. Peer-to-peer interactions between autonomous agents is the main principle behind peer-to-peer aggregation. The purpose of peer-to-peer aggregation is to provide summarized information about the network to each individual node without employing a centralized computational entity or authority. Information summarization is usually performed by computing aggregation functions, e.g., SUMMATION, AVERAGE, MAXIMUM, COUNT and STANDARD DEVIATION. In other words, given the numerical values $S = \{s_1, ..., s_n\}$ distributed in n nodes of a network, aggregation is defined as the computation of $f(S)$ in (i) every node in the network (ii) or individual nodes that perform aggregation queries.

These numerical values are related to the application that uses aggregation and may correspond to the bandwidth of the node in application-level multicasting [Tan et al, 2005] or the power demand in demand-side energy management studied in this paper.

This section classifies peer-to-peer aggregation methodologies in three types: (i) gossip-based aggregation, (ii) aggregation based on efficient information storage and (iii) tree-based aggregation. Note that aggregation mechanisms usually combine principles and concepts from each of these types as shown in the rest of this section.

Gossip-based aggregation is an actual peer-to-peer information routing mechanism that disseminates information in a network in an epidemic fashion. For example, Jelasity et al [2005] introduces an aggregation framework for the computation of the AVERAGE aggregation function. Nodes periodically gossip their numerical values in a pairwise fashion over a dynamic unstructured overlay network. After each exchange, the average is computed that becomes the new exchanging value in the next gossip performed. This process repeats for all nodes and results in an incremental variance reduction of the distributed values that converge to AVERAGE. COUNT can be also computed by applying the 'inverse birthday paradox' [Massoulié et al, 2006]. Then computation of SUMMATION is possible as the product of COUNT and AVERAGE.

Several other methodologies aim to efficiently store the distributed values or a sample of them locally in every node of the network. Usually information is stored in a compressed form using probabilistic data structures. Then, computation of several aggregation functions is locally possible. The distributed values are usually exchanged using gossiping or other routing mechanisms. In this class of aggregation methodologies belongs various synopsis diffusion mechanisms [Haridasan and van Renesse, 2008, Kempe et al, 2003, Kashyap et al, 2006, Nath et al, 2008, Nabeel Ahmed, David Hadaller, 2006] that employ several data structures [Aggarwal and Yu, 2007] to efficiently store information.

Finally, tree-based aggregation [Fei et al, 2001, Ogston and Jarvis, 2010] benefits from the graph property of path uniqueness. Information is aggregated in a bottom-up fashion and aggregation results are broadcasted in a top-down fashion. In this way, counting a value twice is prevented and information is routed efficiently. Nevertheless, tree topologies require maintenance as they are sensitive to single node failures. A removal of a node close to the root disconnects the topology and the routing information paths for aggregation are disrupted. Continuous topology building and maintenance are required. Overlay networks self-organized in tree topologies are introduced in related work [Fei and Yang, 2007, Yang and Fei, 2007, Frey and Murphy, 2008, Pournaras et al, 2010] to capture the problem of fault-tolerance.

Table 1 summarizes the aggregation mechanisms discussed in this section.

Table 1: An overview of peer-to-peer aggregation mechanisms.

System	Aggregation Function	Aggregation Values	Routing Requirements	Storage Requirements
Nabeel Ahmed, David Hadaller [2006]	SUMMATION, COUNT, AVERAGE[1], STANDARD DEVIATION[2]	dynamic	flooding, gossiping or random walks	counting sketches [Flajolet and Nigel Martin, 1985]
Haridasan and van Renesse [2008]	distribution of aggregation values	static	gossiping	synopsis diffusion
Jelasity et al [2005]	AVERAGE, COUNT[3], SUMMATION[1]	static, recomputations	gossiping	hash maps for COUNT
Kashyap et al [2006]	algorithm variations for MINIMUM, MAXIMUM, SUMMATION, AVERAGE, RANK	static	group formation and gossiping	synopsis diffusion
Kempe et al [2003]	algorithm variations for SUMMATION, AVERAGE and quantiles	static	gossiping	synopsis diffusion
Nath et al [2008]	SUMMATION, COUNT	static	ring/tree topologies, flooding	synopsis diffusion
Ogston and Jarvis [2010]	SUMMATION[4] queries	dynamic	tree topology	parent and children

[1] It is derived by the AVERAGE and COUNT aggregates.
[2] It is derived by the SUMMATION and its squares.
[3] It is computed using the 'inverse birthday paradox' [Massoulié et al, 2006].
[4] Others aggregates could be potentially computed.

The choice of a peer-to-peer mechanism may be subject to one or more of the following aspects:

- **Aggregation functions**: Current practice in peer-to-peer aggregation shows that aggregation mechanisms are usually designed to compute specific aggregation functions. More generic computational capabilities are challenging to introduce as aggregation functions have different mathematical properties [Calvo et al, 2002] and therefore, their computational requirements may vary significantly. A single peer-to-peer routing mechanism cannot easily meet computational requirements of different aggregation functions. For example, there is no straightforward way to compute SUMMATION in gossip-based aggregation [Jelasity et al, 2005]. Duplicate-sensitive aggregation functions (SUMMATION) are harder to compute in unstructured overlay networks than duplicate-insensitive (MAXIMUM) aggregation functions.
- **Inaccuracies**: The computation of aggregation functions may be prone to various inaccuracies. Aggregation inaccuracy is defined in this paper as the deviation of the computed aggregates from their actual values. Aggregation inaccuracies originate from duplicate values, outdated values (values that have changed) or values that are not counted at all. Loss of information, failures in nodes and performance trade-offs to make aggregation cost-effective are some sources of inaccuracies [Kennedy et al, 2009]. In gossip-based aggregation, inaccuracies originated from outdated values are captured by recomputations. Inaccuracies in aggregation based on efficient information storage concern duplicate values that can be detected using probabilistic data structures such as sketches [Aggarwal and Yu, 2007] or bloom filters [Brodera and Mitzenmacher, 2004, Bloom, 1970]. Tree topologies need to handle inaccuracies related to node failures that disrupt the aggregation paths. Therefore, a self-organized and robust tree topology provides more accurate aggregation at the cost of higher communication and computational overhead originated by the self-organization process.
- **Dynamic information**: Peer-to-peer aggregation is challenging to perform if the distributed values received as an input in aggregation functions change over time. Adaptation of aggregates to capture these changes requires recomputations that come with extra communication and computational cost [Jelasity et al, 2005]. Alternatively and in case the changes are frequent and introduce a prohibitive adaptation cost, approximation techniques can be employed to estimate a distribution of aggregates over time [Nabeel Ahmed, David Hadaller, 2006, Haridasan and van Renesse, 2008].
- **Performance**: The design of a peer-to-peer aggregation mechanism influences the communication, computational and storage cost. Most aggregation mechanisms introduce performance trade-offs. For example, if the distributed numerical values changes frequently, nodes need to exchange updates and therefore additional communication is required to guarantee a high level of accuracy in the computed aggregates [Nabeel Ahmed, David

Hadaller, 2006, Haridasan and van Renesse, 2008]. Similarly, if various aggregations functions are required for computation, a tree topology can be used at a cost of maintenance required to guarantee that nodes remain connected [Fei et al, 2001, Ogston and Jarvis, 2010].

Peer-to-peer aggregation provides the means to information access in large-scale decentralized networks and their applications. The rest of this paper shows how peer-to-peer aggregation can be used as a building block for a decentralized demand-side energy management in the Smart Power Grid.

4 Adaptive Load Management by Aggregation

Consumers need to adapt their consumption behavior and reduce or even increase their energy consumption as a response to (i) failures in the power supply or (ii) micro-generation that exceeds current demand. In these cases, one option is that consumers need to sacrifice either a level of *comfort* or *economy* for a period of time as a contribution to meet the available power supply and prevent system blackouts. The adjustments required concern not only the reduction of energy consumption but also the increase that is needed to meet the varying availability of renewable energy resources. Note that Paulus and Borggrefe [2011] estimate an accumulation of positive and negative balancing power of 33% and 41% in demand by 2030 in Germany, due to the integration of wind generation.

The problem of controlling the actual energy consumption of consumers using peer-to-peer aggregation is challenging and is influenced by various socio-technical and economic factors. The scope of this section focuses on the following three aspects:

1. Potential incentives of consumers to influence their energy consumption by sacrificing a level of comfort or economy.
2. Peer-to-peer aggregation as the means for a level of reduction or increase in energy consumption.
3. Feasibility of the first two aspects in an operational Smart Power Grid.

Households consumers can manage in real-time their comfort and economy related to their energy consumption by installing home automation technologies such as the ones reviewed by Kailas et al [2012]. Some load management examples include the following:

- Adjustment of temperature setpoints in thermostatically controlled devices [Lu et al, 2005], e.g., water heaters, refrigerators or HVAC systems.
- Turning on/off consumption sources [Clement-Nyns et al, 2010], e.g., the charging of electrical vehicles.
- Adjustment of dimmers that control consumption sources such as lighting [Alahmad et al, 2011].
- Hibernating monitors and personal computers [Ponciano and Brasileiro, 2010].

Note that, demand-side energy management can also be applied in various domains of industrial consumers as illustrated by Paulus and Borggrefe [2011], Ashok [2006] and Middelberg et al [2009].

Consumers require incentives to accept the idea that automation technologies control their energy consumption [Strbac, 2008, Faruqui and George, 2005, Hopper et al, 2006]. Environmental concerns are not always adequate to guarantee a high level of participation and engagement [Hammerstrom, 2007, Sundramoorthy et al, 2011]. Incentives should be provided mainly by utilities via demand/response programs [Albadi and El-Saadany, 2008, Cappers et al, 2010]. However, energy policies may enforce a minimum level of engagement such as the policies of the UK government that require that all British households are equipped with smart meters by 2020 [Sundramoorthy et al, 2011]. An incentive may concern a benefit of lower pricing or other economic revenue offered as a result of allowing a sacrifice of a comfort or economy level for a predefined period of time that is negotiated between the consumers and their utilities. A number of existing contract and pricing schemes are illustrated by Palensky and Dietrich [2011].

Consumer participation should be on a voluntary basis, meaning that the comfort of consumers is a non-negotiable right [Strengers, 2008]. In practice, consumers may have the option to overwrite the adjustments performed by the automated technologies. The concept of adjustable autonomy [Scerri et al, 2002] is highly applicable in this domain and such an option has been an adopted practice by both consumers and utility companies in the Olympic Peninsula Smart Grid Demonstration Project [Hammerstrom, 2007] and the statewide pricing pilot experiment of California [Faruqui and George, 2005]. Similarly, the Dehems[5] system is a pilot project that tests and evaluates the user participation and engagement in realistic innovation platforms referred to as 'living labs'. These platforms bring together and involve end-users, researchers, industrialists and policy makers to examine a wide range of influencing factors such as (i) policies, (ii) behavioral context, and (iii) design concerns for the persuasive feedback and home technologies [Richardson, 2008, Sundramoorthy et al, 2011].

Consumers require information and awareness about the current energy consumption and available supply capacity to adapt their energy consumption. Aggregation can provide this information and awareness and, therefore, it is a crucial and core operation required by load management mechanisms. This section introduces a decentralized demand-side management scheme based on peer-to-peer aggregation: ALMA, *Adaptive Load Management by Aggregation*. The concept of ALMA is the following: On the one hand, utilities disseminate the available supply capacity to consumers without the need to aggregate their individual energy demand in a centralized fashion. On the other hand, software agents installed in household devices of consumers disseminate and collect information in a peer-to-peer fashion about their current demand. Based on

[5] Accessible at: `http://www.dehems.eu/` (last accessed: May 2012)

the aggregate demand in the network, agents adapt their local demand to meet the available supply capacity.

Figure 1 illustrates an overview of ALMA. Adaptation of local demand is performed based on the dynamic selection between a number of predefined demand options. The options actually represent incremental levels of comfort and economy that the user may experience when a certain possible state (demand) is selected. However, note that all demand options are technically possible and approved by consumers. Decision-making expresses their preference level between comfort and economy and selections can be performed (i) manually by the consumers themselves via a user interface or (ii) by an agent strategy that consumers approve and reconfigure. For example, consumers have the option to configure their agents to select demand options that correspond to 80% comfort during the day. Moreover, a consumer may desire an economical consumption that should not exceed a certain number of hours during a day. The definition of demand options and the actual decision-making scheme between these options should be incentivized and negotiated by utilities with consumers via a demand/response program.

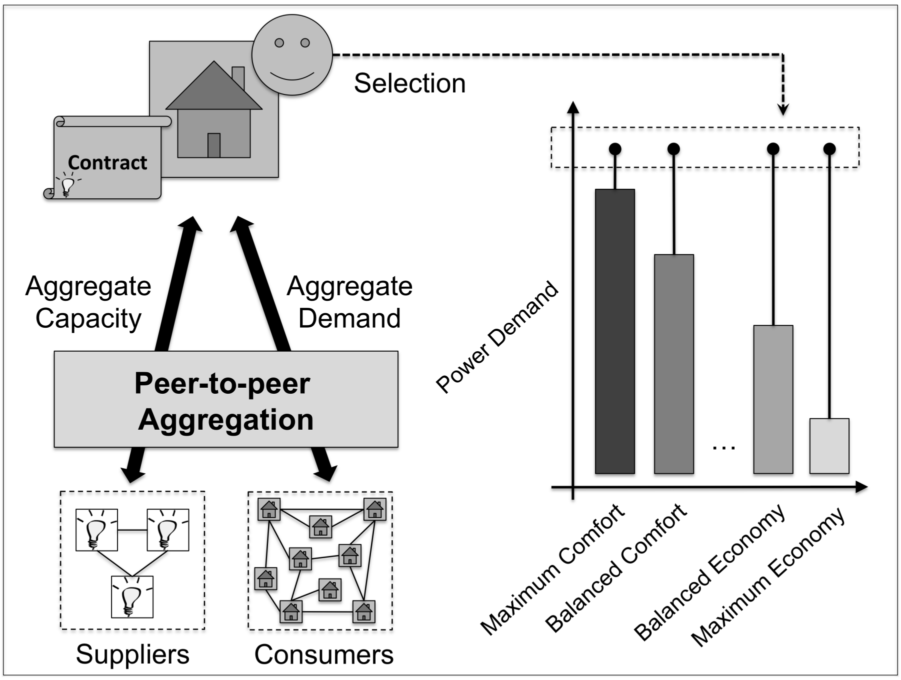

Fig. 1: Demand-side energy management using ALMA. Consumers select between different demand options representing levels of comfort and economy in their energy consumption. The selections are based on the aggregate demand and capacity in the Smart Power Grid.

This paper evaluates the feasibility of ALMA in the current reality and practice of Smart Power Grids. More specifically, this section follows an analytical approach to validate the following hypothesis:

Hypothesis Adjustments of aggregate energy consumption can be achieved with demand options of local energy consumption, representing a wide range of comfort and economy levels, that can be pre-defined and dynamically selected by incentivized consumers.

This hypothesis is validated within the context of a well studied and state of the art demonstration project that involves real customers, utilities and other stakeholders under realistic settings that shape and underpin the future Smart Power Grids: *The Olympic Peninsula Smart Grid Demonstration Project* [Hammerstrom, 2007]. The next section provides an overview of this project and the validation approach followed. The analytical results computed using the actual data of the Olympic Peninsula project confirm the above hypothesis.

5 The Olympic Peninsula Smart Grid Demonstration Project

The Olympic Peninsula Project, illustrated in the report of Hammerstrom [2007], is a Smart Power Grid demonstration project funded by the U.S. Department of Energy and led by the Pacific Northwest National Laboratory (PNNL). A wide range of stakeholders[6] are involved such as regional utility companies, balancing authorities etc. Within this project, consumers play an active role in managing the Smart Power Grid by adjusting their individual energy use based on price signals. These signals are exchanged between consumers and utility companies, forming a two-way bidding market. Interactions are supported by novel communication technologies such as the Internet-Scale Control System (iCS) [Ambrosio et al, 2011]. The advantages of the approach followed is (i) improvement of reliability in the Smart Power Grid, (ii) reductions of consumers' bills, (iii) minimization of the future infrastructure investments and (iv) higher integration of renewable energy resources. The results collected in the period between March 2006 and March 2007 show that a 15% peak reduction can be achieved during a year and consumers can lower their energy bills by 10%. Furthermore, $70 billions can be saved in a 20 year period by avoiding infrastructure changes in generation, transmission and distribution systems that are required to meet the increasing demand.

Three types of controllable assets are involved in the project: (i) Two backup diesel generators, (ii) five water-pumping stations and (iii) 112 households. For illustration purposes, this section focuses on the controllable assets

[6] Some of the stakeholders involved are the Bonneville Power Administration, PacifiCorp, Portland General Electric, the City of Port Angeles and Clallam County Public Utility District #1. Industrial collaborators include Invensys Controls, Whirlpool Corporation and IBM Thomas J. Watson Research Center.

of households. Engineering details about the control of generators and water-pumping stations are provided in the project report [Hammerstrom, 2007]. Despite the fact that the households are regionally distributed and connected to different feeders[7], the project positions consumers within a single virtual feeder under the control of a dashboard software platform managed by grid operators. The capacity of this virtual feeder is varied at different periods during the project year to evaluate the consumer behavior under different capacity constraints.

Three types of contracts are assigned to consumers: (i) FIXED, (ii) TIME OF USE and (iii) REAL TIME PRICING. The FIXED contract does not involve changes in the electricity prices regardless of the amount and times of consumption. This group is the most inflexible to react to price incentives. The TIME OF USE contract involves three electricity price schemes, the 'off-peak', 'on-peak' and 'critical peak'. The price of electricity increases for each scheme respectively. This group has the option to configure home automation software to match certain comfort and economy settings in each price scheme. Finally, the REAL TIME PRICING contract varies the electricity price every five minutes. This contract type is the most flexible as it provides to consumers the option to continuously adjust their level of comfort and economy and, therefore, achieve the highest bill savings. Finally, there is a fourth group of consumers, the CONTROL group that is used for the evaluation of the demand/response program. Consumption information is collected from this group as well, however, the difference is that consumers do not have any contract within the context of the project.

Load-control modules are installed in HVAC systems, water heaters and cloth dryers of consumers. These modules communicate wirelessly with a home gateway from which communication with a centralized PNNL shadow market is performed every five minutes. This communication is two-way and concerns a bidding price and a clearing price for this period of five minutes. The bidding price represents the current demand based on history information about the clearing prices and the preference of consumer about the level of comfort and economy. The clearing price for a certain five-minutes period of time is the marginal[8] price at which the aggregate load curve and demand curve intersect. The exact computation of both bidding and clearing prices is out of the scope of this paper and is illustrated in detail by Hammerstrom [2007].

Consumers adjust their power demand by making selections about (i) the *occupancy mode* and (ii) the *heating/cooling mode*. These modes are referred to in this this paper as *consumption modes*. An occupancy mode represents a temperature configuration related with a certain state of a consumer, e.g., away, sleep etc. Eight possible occupancy modes can be pre-programmed by consumers. Technically, an occupancy mode is configured by a temperature

[7] Feeders are circuits of the distribution system that connect substations with end-consumers. They run along streets or underground and power the distribution transformers at or near the consumer premises.

[8] In the context of the Olympic Peninsula Project, the marginal price is the change in the total price as a result of a unit change in demand.

setpoint. However, consumers with a real time pricing contract additionally select for each of their controllable devices a temperature range between a number of pre-defined temperature ranges. Each range is defined by a maximum and minimum temperature in relation to the configured temperature setpoint. Within this range, energy saving can be achieved. For examples, consumers of HVAC systems with a real time pricing contract select between five temperature ranges that represent incremental levels of comfort and economy as illustrated in Table 3.4 of the project report [Hammerstrom, 2007]. Note that the actual temperature ranges are system parameters and cannot be modified by consumers. Finally, the heating/cooling mode concerns the selection between three operational modes of HVAC systems: heating, cooling and automatic. Note that each occupancy mode concerns temperature configurations for both heating and cooling.

6 Validation Approach

Validation of the hypothesis set in Section 5 is based on analysis of power demand from the Olympic Peninsula Smart Grid Demonstration Project [Hammerstrom, 2007]. The project data[9] used concern the demand bids of the households consumers made every five minutes during the project year. For illustration purposes, assume a function $f(t, j, i, o)$ that computes the power demand using the project data. $f(t, j, i, o)$ is computed based on the following information:

- $t \in [1, 288]$: The five minutes period of a project day during which a bid is sent. The total number of bids during a day is $288 = 60$ minutes $*$ 24 hours / 5 minutes.
- $j \in [1, 365]$: The project day in which the bid t is sent. The total number of projects days are 365.
- $i \in [1, 112]$: The consumer who sends the bid t. The total number of residential consumers is 112.
- $o \in \begin{cases} [0,7] & \text{for occupancy modes} \\ [0,2] & \text{for heating/cooling modes} \\ [0,23] & \text{for their combination} \end{cases}$ $\left\{ \begin{array}{l} \text{The consumption mode selected when the bid } t \text{ is sent. The selection is} \\ \text{made from the 8 occupancy modes, the 3 heating/cooling modes or their} \\ 8 * 3 = 24 \text{ combinations.} \end{array} \right.$

The goal of validation is to show if the power demand aggregated from the total consumers is influenced by alternative selections of consumption modes. An adjustment of the aggregated power demand may come as a result of selecting different consumption modes compared to the actual selections. Technically, aggregation of information about power demand and actual selections of

[9] Available at: `https://svn.pnl.gov/olypen` (last accessed: May 2012)

consumption modes can be performed by one of the peer-to-peer aggregation mechanisms discussed in Section 3. Maximum and minimum adjusted power demand are computed by analyzing the average level of power demand for each selected consumption mode. The analysis performed concerns the computation of the following information:

- D_j^o: The cumulative power demand of the total consumers that select the consumption mode o during the day j of the project.
- N_j^o: The number of samples (bids sent every five minutes) based on which the cumulative power demand D_j^o is computed.
- N_j: The total number of samples (bids sent every five minutes) for the total consumers during the day j of the project.

N_j counts the bids regardless of the selected consumption mode. The cumulative power demand D_j^o during a day j of the project with the consumption mode o selected is computed as follows:

$$D_j^o = \sum_{i=1}^{112} \sum_{t=1}^{288} f(t, j, i, o) \tag{1}$$

Bids with zero power demand are excluded from the data analysis as they bias the computed results. These bids are treated as if they contain no information. Based on D_j^o, N_j^o and N_j, the adjusted cumulative power demand $\hat{D}_j^o$, when consumption mode o is selected during the day j of the project, is computed as follows:

$$\hat{D}_j^o = \frac{D_j^o}{N_j^o} N_j \tag{2}$$

Based on the above, the minimum and maximum adjusted power demand for a day j of the project is computed as follows:

$$\hat{D}_j^{\text{MIN}} = \min_{o=0}^{x} \hat{D}_j^o \tag{3}$$

$$\hat{D}_j^{\text{MAX}} = \max_{o=0}^{x} \hat{D}_j^o \tag{4}$$

For $x = \begin{cases} 7 & \text{for occupancy modes} \\ 2 & \text{for heating/cooling modes} \\ 23 & \text{for their combination} \end{cases}$

The goal of validation is to compare both minimum and maximum adjusted power demand $\hat{D}_j^{\text{MAX}}$, $\hat{D}_j^{\text{MIN}}$ $\forall j \in [1, 365]$ with the actual power demand D_j of the raw data during the project year. This comparison indicates if the actual power demand can be adjusted by making different selections of consumption modes using a dynamic and decentralized peer-to-peer aggregation. Confirmation of the hypothesis is based on this comparison.

7 Analytical Results

Figure 2 compares the actual power demand D_j $\forall j \in [1, 365]$ of the raw data with the minimum $\hat{D}_j^{\mathrm{MIN}}$ and maximum $\hat{D}_j^{\mathrm{MAX}}$ power demand computed. When adjustments are performed via selections of occupancy modes, the minimum and maximum adjusted power demand computed on average during the project year is 6362.5 KW and 23937.2 KW respectively when the actual power demand is 11844.7 KW. In contrast, these adjustments are significantly lower in heating/cooling modes. The minimum and maximum adjusted power demand computed on average during the project year is 7131.6 KW and 12324.9 KW respectively. Finally, the combined occupancy and heating/cooling modes provide the highest adjustments of power demand. The minimum and maximum adjusted power demand computed on average during the project year is 4793.1 KW and 25048.0 KW respectively.

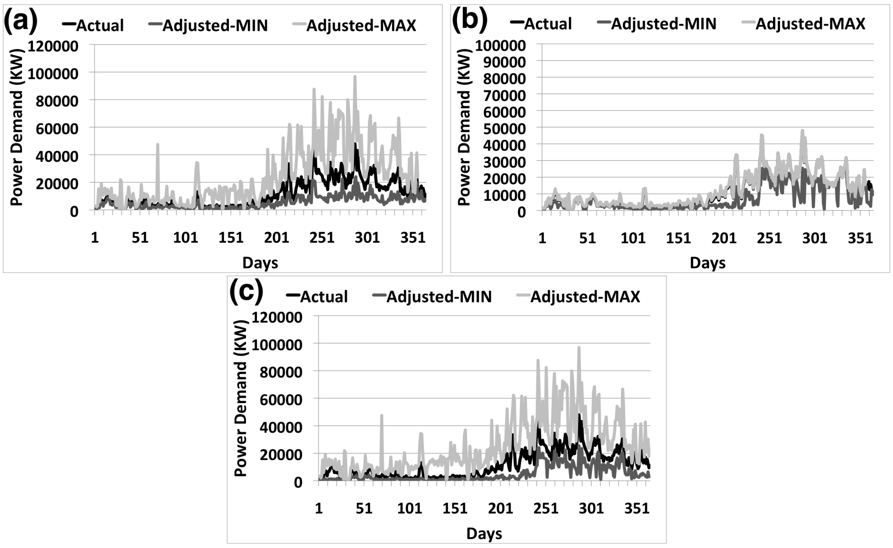

Fig. 2: The actual, minimum adjusted and maximum adjusted power demand during the project year. The adjustments performed concern the selections of (a) occupancy modes, (b) heating/cooling modes and (c) their combination.

One aspect investigated is the comparison of the consumption modes with regards to the contribution in the adjustment of power demand. In the case of occupancy modes '1', '2', the highest decrease of power demand by 1888.3 KW and 3236.6 KW on average per day respectively is observed. The selections of occupancy modes '4' and '5' have the highest increase of power demand, 3999.0 KW and 6982.2 KW on average per day respectively. However, note that no conclusions can be reached about the effect of certain occupancy modes as their semantic is only known to consumers who define it by choosing their temperature configurations. In contrast to the occupancy modes, the heating/cooling modes have a clearer impact on the adjustment of power demand. The selection of cooling has the highest decrease of power demand that reaches 3920.5 KW on average per day, whereas, the highest increase of power demand is computed by the selections of heating modes with 195.2 KW on average per day. The potential of a decrease in power demand using cooling instead of heating is expected given the fact of extreme cold winter conditions in the Olympic Peninsula [Hammerstrom, 2007]. Finally, the combination of occupancy mode '1' with cooling and occupancy mode '2' with heating results in the highest decrease of power demand by 3422.5 KW and 2658.5 KW on average per day respectively. The highest increase of power demand is 6162.5 KW and 7314.5 KW on average per day respectively for the combination of occupancy mode '4' with heating and the occupancy mode '5' with heating.

The influence of the contract type assigned to each consumer is investigated as well. The actual, minimum adjusted and maximum adjusted power demand of different consumers' groups are aggregated respectively. Table 2 and Table 3 illustrate the minimum adjusted and maximum adjusted power demand respectively, relative to the actual one. The results for each group of consumers and consumption mode are shown.

Table 2: The minimum adjustments of power demand relative to the actual one based on selections of occupancy modes, heating/cooling modes and their combination. The results concern the CONTROL group and the consumers with FIXED, TIME OF USE and REAL TIME PRICING contract.

	Occupancy Modes	Heating/Cooling Modes	Combined
CONTROL	47.3%	13.0%	51.9%
FIXED	61.1%	19.7%	63.2%
TIME OF USE	50.2%	26.6%	62.7%
REAL TIME PRICING	33.6%	30.9%	48.4%

Table 3: The maximum adjustments of power demand relative to the actual one based on selections of occupancy modes, heating/cooling modes and their combination. The results concern the CONTROL group and the consumers with FIXED, TIME OF USE and REAL TIME PRICING contract.

	Occupancy Modes	Heating/Cooling Modes	Combined
CONTROL	43.0%	7.6%	46.2%
FIXED	51.7%	16.7%	57.1%
TIME OF USE	48.3%	17.1%	54.7%
REAL TIME PRICING	33.8%	10.4%	39.0%

For the occupancy modes, the consumers with the REAL TIME PRICING contract have the lowest minimum and maximum adjustments of power demand of 33.6% and 33.8% respectively, relative to the actual power demand.

The low adjustment potential of the REAL TIME PRICING group compared to the other groups of consumers is explained by the fact that this is the group that achieves the highest adjustments of power demand within the Olympic Peninsula Project [Hammerstrom, 2007]. The highest minimum and maximum adjustments are 61.1% and 51.7% respectively, relative to the actual power demand. These highest adjustments correspond to the consumers with a FIXED contract.

For the heating/cooling modes, the highest minimum adjustment of power demand is 30.9% relative to the actual power demand for the consumers with a REAL TIME PRICING contract. The highest maximum adjustment of power demand is 17.1% relative to the actual power demand for the consumers with a TIME OF USE contract. Moreover, the lowest minimum and maximum adjustment of power demand is 13.0% and 7.6% respectively, relative to the actual power demand. These lowest adjustments correspond to the consumers of the CONTROL group.

Note that, although the consumers with REAL TIME PRICING contracts have the lowest minimum adjustment of power demand based on selections of occupancy modes, the opposite holds for selections of heating/cooling modes. Consumers with REAL TIME PRICING contracts have for each occupancy mode two temperature ranges, one for heating and one for cooling. A switch from a heating to a cooling mode is an actual utilization of an extended temperature range that is larger than switching between different occupancy modes. These switches are observed within the transition period autumn-winter during which the total power demand gradually increases and consumers may select both heating and cooling modes during the day.

Finally, the results concerning the combination of occupancy and heating/cooling modes are similar to the results of occupancy modes. The difference is that the adjustments are higher. The consumers with REAL TIME PRICING contract have the lowest minimum and maximum adjustments of power demand by 48.4% and 39.0% respectively, relative to the actual power demand. The highest minimum and maximum adjustments are 63.2% and 57.1% respectively, relative to the actual power demand. These highest adjustments correspond to the consumers with a FIXED contract.

8 Interpretation of Results

The analytical results computed using data from the Olympic Peninsula Smart Grid Demonstration Project confirm the hypothesis set in this paper:

Hypothesis Adjustments of aggregate energy consumption can be achieved with possible demand options of local energy consumption, representing a wide range of comfort and economy levels, that can be pre-defined and dynamically selected by incentivized consumers.

In all of the demand options studied i.e., the occupancy modes, the heating/cooling modes and their combination, a significant level of adjustments in the aggregate energy consumption is possible. The higher the number of consumption modes that consumers configure, the higher the potential for adjustments in the energy consumption is. The combination of occupancy and heating/cooling modes results in the highest adjustments of energy consumption compared to each ones individually.

Moreover, the analytical results show that a significant degree of adjustment in energy consumption is unexploited by the group of consumers with a FIXED and TIME OF USE contracts. The group of consumers with a REAL TIME PRICING contract is better incentivized within the Olympic Peninsula Project, however, further adjustments can be achieved even in this group. Finally, various temporal and regional factors, such as the weather conditions, influence adjustments of energy consumption. For example, higher adjustment is observed during transition periods in which consumers behave more unpredictable and vary their energy consumption significantly during their day, e.g., from autumn to winter.

Peer-to-peer aggregation is able to compute and aggregate these adjustments in the power demand in a fully decentralized fashion without the need of a centralized aggregator as the Olympic Peninsula Project imposes. Information about demand is made locally available to consumers that have the option to react to a power peak or an excessive micro-generation. This is possible by adapting their comfort and economy levels via dynamic selections between the possible demand options. In contrast to ALMA, the actual selections of comfort and economy levels in the Olympic Peninsula Project are static and pre-defined. The actual adjustments achieved in the project are smaller than the ones computed in this section.

9 Comparison with Related Work

Compared to other related approaches [Stadler et al, 2009, Shaw et al, 2009, Lu et al, 2005, Middelberg et al, 2009, Strengers, 2008, Ashok, 2006, Faruqui and George, 2005] of demand-side energy management, the main advantage of ALMA is its decentralization in the adjustment of energy consumption.

In the work of Stadler et al [2009] about load-shifting, cooling devices, such as refrigerators, are assumed to respond to signals from the power grid. Energy consumption is decreased during peak times or the 'on' states of the controlled devices are shifted to periods with low energy demand. However, the whole process is centrally controlled without any coordination and interactions between the responding devices. For example, it is not clear what happens when devices shift their consumption to another time period resulting in a shift of the peak. This is the 'rebound effect' discussed by Palensky and Dietrich [2011]. Similarly, Lu et al [2005] study and model the flexibility of thermostatically controlled appliances for load-shifting, however, coordination between devices is not addressed.

Centralized coordination approaches can achieve optimal control and load-shifting. For example, Middelberg et al [2009] propose such an approach based on a binary integer programming problem solved with existing methods. The model is applied for the management of a colliery. A similar integer programming model is proposed by Ashok [2006] for the management of steel plants. In contrast to ALMA, these centralized methods are suitable and scalable within closed industrial environments rather than within a large-scale environment of residential consumers.

Adjustments of power demand based on price incentives are usually achieved within a centralized two-way market between consumers and utility companies. Examples of such markets are illustrated by Kok et al [2005], Hammerstrom [2007], Faruqui and George [2005] and Hopper et al [2006]. This centralized approach has a significant impact on scalability and privacy as discussed in Section 2. In contrast, ALMA introduces a decentralized aggregation and adaptation of power demand via interactions between consumers with a minimum intervention of their utilities.

10 Discussion and Future Work

This paper shows that demand-side energy management is a complex socio-technical problem with challenges crossing a wide range of stakeholders in this domain. Consumers are larger in number, more distributed and dynamic compared to producers. Furthermore, consumers evolve to prosumers having the option to produce energy as well and actively participate in energy markets. Using peer-to-peer aggregation for demand-side energy management is a promising approach. A knowledge transfer from the domain of distributed computing to the evolving domain of Smart Power Grid provides new technical insights and the means for large-scale decentralized demand-side energy management.

ALMA is based on peer-to-peer aggregation to adapt energy consumption with minimum interventions from the supply-side. This potentially contributes to the robustness of the Smart Power Grid and prevents system blackouts [Pournaras et al, 2012]. Yet, future work should show the cost-effectiveness of different peer-to-peer aggregation mechanisms in the domain of the Smart Power Grid. Adjustments are achieved by making the aggregate consumption locally available to consumers in order to adapt their selected demand according to economic or other incentives. Selections represent the trade-off between comfort and economy. An analysis of the power demand during the Olympic Peninsula Project [Hammerstrom et al, 2010] shows that adjustments of power demand are technically possible using peer-to-peer aggregation. A further analysis of the semantic that occupancy modes have for each consumer may provide a better understanding of the consumption behavior. Moreover, subject of future work is the exact economic and other incentives that should be designed to meet the maximum possible technical adjustments in power demand. An interesting aspect that needs investigation is the degree to which decentralization itself is an incentive or not for consumers to participate in demand/response programs. The added benefit of user privacy, compared to centralized approaches, can certainly help here.

Finally, note that the introduction of such highly dynamic and decentralized mechanisms in a critical infrastructure such as the Smart Power Grid raises crucial cyber-security issues [Khurana et al, 2010]. Although solutions on security issues are out of the scope of this paper, some challenges that need to be addressed include the integration of existing computer and radio security countermeasures in the Smart Power Grid and the engineering of new cyber-security systems for Internet-scale control systems. Security technologies may require new policies and expertise in the domain of the Smart Power Grid.

11 Conclusions

This paper concludes that the demand-side energy management scheme of ALMA can achieve adjustments in power demand by applying local selections of consumers incentivized by their utilities. The analytical study illustrated in this chapter, grounded to the current reality and practice of Smart Power Grids [Hammerstrom, 2007], shows that adjustments in the aggregated energy consumption are possible. Decentralization by using peer-to-peer aggregation provides a higher scalability, autonomy and fault tolerance. Peer-to-peer aggregation is also the means to provide to consumers a collective and summarized information about the availability and consumption of energy resources in the Smart Power Grid. Utilities do not need aggregate and detailed end-user consumption information for this purpose. Beyond its technical scope, peer-to-peer aggregation motivates alternative business and market structures for demand-side energy management in future Smart Power Grids.

Acknowledgements This research is partially funded by the NLNet foundation, the NWO project "RobuSmart: Increasing the robustness of Smart Grids through distributed energy generation: a complex network approach", grant number 647.000.001 and the European Institute of Technology project: "Smart Grid Value Modelling". The authors would like to thank Donald J. Hammerstrom, Ronald B. Melton and David P. Chassin for providing access to the data of the Olympic Peninsula Smart Grid Demonstration Project. Furthermore, authors are grateful to Mark Yao and Ron Ambrosio for their intuition about the use of this data.

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