Applying IT to Solve Societal Grand Challenges: Residential Energy Monitoring Services as the First Pillar

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Abstract— **Society 2.0 is the next stage in the evolution of the Information Society, enabling seamless content and service interaction in support of our environment, to ease our work and life balance, and to enrich our lives. Abundant sustainable resources such as energy, water, and food, together with smart buildings, spaces and transportation are all aspects of the Society 2.0 vision. The domain of residential energy monitoring services and their supporting IT ecosystems provides a rich and challenging environment to push the limits of our current IT service models, designs, and implementation strategies. As part of HP Labs' ongoing research into environmental sustainability we have designed and deployed a Home Energy Intelligence Service for remote monitoring and assessment of residential energy consumption patterns, overlaid by a set of energy-related advisory services. Our solution consists of a residential sensing layer, an energy cloud service that contains a number of back-end components, and a user dashboard experience. These enable our research team to explore issues around holistic and fine grained sensing, differentiated analytics, scaling of IT services, and the surfacing of insights and incentives to enable homeowners to manage and reduce their energy consumption through behavioral change.**

Keywords-component; energy; sustainability, residential; HAN; smart meter; smart grid

I. Motivation and Context

A. *Society 2.0 IT Service Challenges:*

As forces such as population growth, urbanization and constrained natural resource exploitation impact global society, our engineered environments must evolve to meet these challenges [1, 2]. IT technologies, including sensors, information management, automation, man-machine interaction, analytics and visualization, real-time decision making, collaboration tools, security management, sustainable IT infrastructure, and service delivery models (cloud services) will all become components within the toolset used to create Society 2.0 [3]. In a world where IT becomes critical, embedded and ubiquitous, the key research problems and challenges revolve around:

- Preparing all services for unprecedented scale (i.e. sensors, users, data, processing, network traffic, etc.).
- Massive improvements in the availability of low-cost high-bandwidth networks, worldwide.
- Enabling a wide spectrum of physical devices and objects to become networked, and to sense, report and be dynamically controlled.
- Challenges around security, privacy and accessibility become increasingly complex.
- Creation, composition, integration, automation and delivery of sophisticated services, at all levels.
- User-centered design, behavioral analysis, and acceptance of new technologies.
- Enablement of information management and business intelligence services in the cloud.
- Balancing commercial competitiveness against the openness of technologies.
- Leveraging of multi-disciplinary knowledge and experience from companies, universities, and governments.
- An understanding of how to engage in government programs, as many broad sustainability initiatives are being funded by government agencies [4].

B. *Residential Energy Monitoring Environment:*

The residential energy monitoring domain provides a rich environment to explore all of the challenges mentioned above and is of growing interest and concern to countries around the world.

In North America, every residence is destined to become a consumption and (optional) generation end point on the emerging Smart Grid; a collective opportunity encompassing 129 million households, 249 million computing and access devices, and an installed base of more than 1 billion energy consuming appliances. Demand response and consumer energy efficiency have also been highlighted as priorities in the emerging Smart Grid standardization efforts. The initial rollout of smart metering technology, coupled with the introduction of dynamic pricing tariffs, almost ensures that a second wave of in-home energy-aware products will follow; the majority of which we envision being adapted to incorporate intelligent energy-aware attributes. Hence, in the foreseeable future, we expect products to emerge with appropriate hooks to enable their participation as peers within a negotiated supply-demand matched energy-balanced ecosystem. Such a system has the potential to generate vast quantities of mineable data which, if managed and analyzed appropriately, would be of great benefit to consumers, device manufacturers, utility providers, and the public sector; collectively contributing to a reduction in the nation's carbon footprint.

The creation of a home Energy Intelligence Service (EIS) for remote monitoring and assessment of residential energy consumption patterns, overlaid by a suite of energy-related advisory services, is a significant business opportunity. At the heart of an EIS service is an energy-orientated cloud service, enabling customers who deploy an energy information aggregator within their homes, to have open access to, and control over, their customized residential energy profile from any web-enabled device. Additionally, the service's collection of energy information from, potentially, millions of households creates an opportunity for "Energy Intelligence" brokers to provide 3rd parties (device manufacturers, utilities, and governments) with a platform to analyze and deliver targeted services based on energy-oriented analytics, performed against a massive energy intelligence repository.

II. HP Labs Home Energy Monitoring Research Proof of Concept

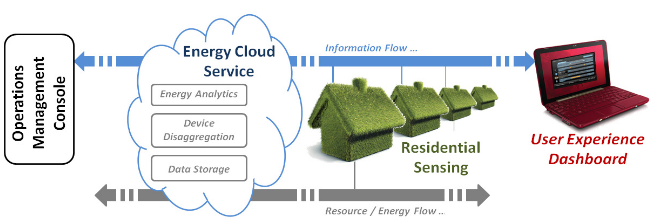

Figure 1. *Architecture and main system components of the HP Labs home energy monitoring solution; our prototype residential Energy Intelligence Service (EIS).*

The HP Labs prototype contains several distributed elements, as shown in Figure 1, where sensed data from real homes is retained by our energy cloud service. This enables our research team to explore issues around fine grained sensing, energy analytics, and the surfacing of actionable insights, which we present to the homeowners in the form of hints and tips to better manage their energy consumption related activities and behaviors. Over the last year we have designed and deployed these components throughout seven real test homes in the San Francisco bay area. The main system components are described in the following sub-sections.

A. Residential Sensing:

Each residence is instrumented with a heterogeneous network of wireless sensor nodes, as shown in Figure 2. We monitor whole home consumption, emulating data from a smart meter, and also monitor individual or clustered devices, emulating the information stream we expect to receive from future Smart Grid enabled products. These measurements combine to provide the measurement stack as shown in Figure 3, comprised of measurements from actual nodes (hard sensors) plus values derived using data analytics (via disaggregation) from aggregate measurements (soft sensors). We can also subtract out the unmonitored portion of household energy consumption, which is often due to items that would be difficult to instrument without access to the homes' internal wiring infrastructure (switched lighting circuits for the most part).

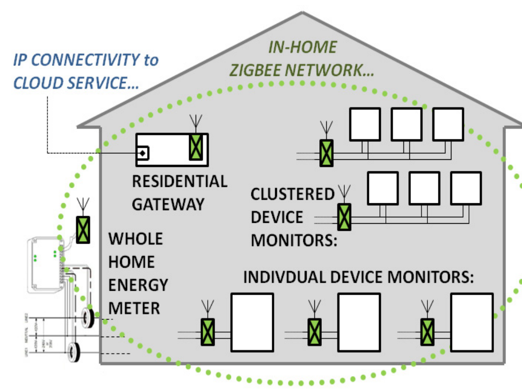

Figure 2. *Residential Sensing Topology.*

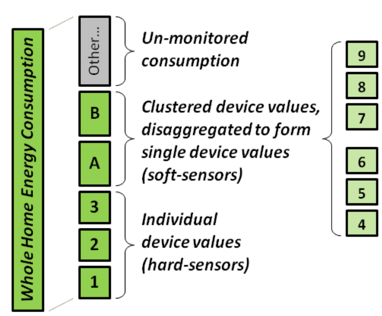

Figure 3. *Energy Measurement Stack.*

Our initial deployments utilized commercially available Zigbee networking products incorporating Hall-effect sensing to measure alternating current at each node (a reasonable proxy for power consumption). An HP Labs custom sensor node design now provides true AC power monitoring, incorporating real and apparent power values, voltage, current, frequency and other parameters on a per node basis; greatly enhancing the available information within each installation. To cope with this increased data set, we created a custom software gateway, residing on a HP NetBook equipped with a USB dongle acting as the Zigbee network coordinator. This application collects and periodically uploads blocks of energy measurement data to our energy cloud service.

B. *Energy Cloud Service:*

This provides a suite of back-end services as shown in Figure 4. These incorporate data storage, data aggregation, data modeling and service endpoints for both incoming sensor data uploads and for the aggregate information required by the user interface presentations. Over time, we create and store a rich set of energy-related activity profiles for each home; modeling each residence as a zonal hierarchy, with hourly consumption and production figures being calculated along with corresponding baseline and average consumption patterns for each sensor instantiation.

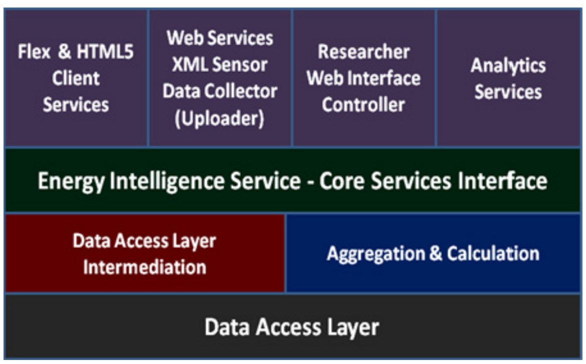

Figure 4. *The energy cloud service's core application layered architecture*

1) *Data Model:*

A primary goal was to design a data model that would provide the flexibility for heterogeneous resource types and home configurations, support enhanced sensor types and the use of virtual sensors, and enable two-way interaction with the user regarding usage patterns and events.

The energy cloud service runs on top of a rich hierarchical, but not overly complex, model to represent home installations, the sensing equipment within them and the spatial organisation of those sensors, as depicted in Figure 5. An installation model can accommodate multiple, diverse energy resources (electricity, gas, solar, etc), each arranged into a number of zones that contain sensors. These zones often map directly onto the physical layout of the home, where a zone represents a room, but are not restricted to such, and can be created to match whatever logical view of the home a user desires.

In addition, the model supports "virtual" sensors, from which usage is not measured by a physical sensor reading. Instead, virtual sensor values are a result of calculations within the application, or are provided by an external source. The implemented example of this is to provide usage figures for the unmeasured portion of a home's energy consumption, utilising a whole-home sensor to provide the total home usage, from which the total usage of all the individual sensor nodes is subtracted. This type of virtual sensor is commonly known as an "Everything Else" sensor.

The energy cloud service is capable of integrating data from multiple diverse sources, with the ability to handle varying intervals between readings from different power installations and different units of power (both within a single power installation, such as Amp and Watt readings for electricity, and across different types of energy resources with varying units, for example where gas, water, and electricity all utilise different measurement units).

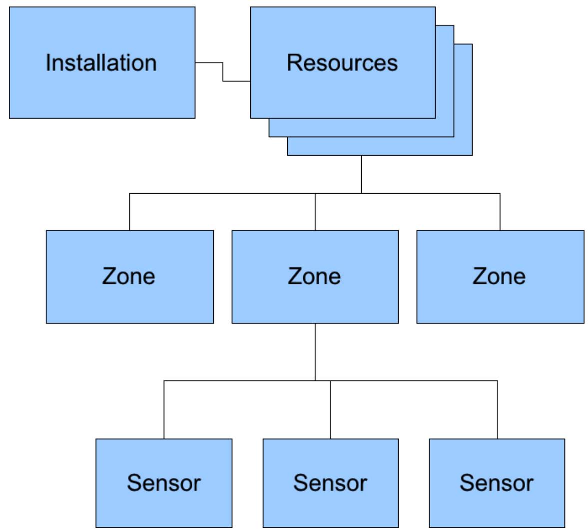

Figure 5. *The energy cloud service's data model hierarchy*

2) *Data Collection & Storage:*

The primary route for data collection is via a web service endpoint, exposed by the energy cloud service to allow client devices, typically the residential gateway within each home, to directly connect to the service and upload sets of sensor readings. This feature allows each client to independently determine the frequency of data collection. Multiple resources can provide data within the same set of readings, or they can be segregated by the client. The back-end system allows for the automatic detection of new sensors within the data provided by a client, and will store readings and usage aggregates for those new sensors automatically. Newly discovered sensors are corralled within a special zone that is excluded from the normal user views and whole-home aggregations. Once those sensors are identified and placed into their correct resource type and zone, the system will then ensure that all aggregations since each sensor was first discovered are updated to reflect the new sensor's selected placement.

3) *Data Aggregation:*

While sensor readings may provide raw data in a variety of units, the user is always presented with a consistent view of the data – that of aggregate usage. For electricity this would be kilo-watt hours (kWh), and for gas, this could be Therms. To enable this, all power readings are converted into a unit of usage (again, for an electricity-based resource this would be a conversion from Amps, or Watts, to kWh) for a given period.

With performance in mind, the system continually calculates hourly aggregate usage figures for each sensor, and stores them. When asked to display usage, it is those aggregate figures which are either used directly (if the granularity desired is hourly), or combined to form new aggregates for longer time periods. This approach of pre-calculating aggregates provides significant performance benefits, with no loss of precision, for the most common usage scenarios, while retaining the flexibility to offer whatever aggregation intervals are desired.

Only aggregates for sensors are stored. If usage figures for a whole home or zone are required, those are generated on-the-fly from the appropriate sensors. This allows the maximum flexibility in allowing sensors to be moved from one zone to another, without requiring the recalculation of parent aggregations. There are situations where recalculation of historical values is required, however: a notable one is where a whole-home or whole-zone smart meter is added to an installation. Once this special sensor is identified as such, the system creates a virtual "Everything Else" sensor to represent the unmeasured load (the difference between the smart meter and the total consumption of the device-level smart plug sensors). At this point, the system must then calculate all historic aggregate usage values for this virtual sensor.

As part of the aggregate usage record that is stored for each hour, a record of the baseline usage during that hour is also saved. As the baseline is a particularly useful measure to help users gain insight into their energy consumption, we ensure that this is easily available for each interval, and that the system provides easy ways to calculate accurate baseline figures for any given period.

One potential challenge for aggregation is to ensure that any gaps in the raw sensor data are dealt with, as outages in home installations or smart plugs are always a possibility. The way the system is designed to collate and present usage aggregates allows for extension of the basic behaviour to include simple smoothing of gaps or more sophisticated data creation based on historical usage analysis.

4) *Energy Analytics:*

The energy analytics module operates at both the individual and aggregate level; detecting and smoothing gaps in the sensor data with historically derived estimates of usage, mining for patterns of energy use, modeling changes in energy demand, and detecting anomalous behaviors. In turn, this generates hints and tips, customized for each residence, which we present as personalized, energy reducing behavioral recommendations via the home user interface. In addition, consumers could be provided with other types of actionable options to help them reduce their consumption; potentially via time-sliced load balancing with anonymized peers. Also, each device's energy profile could be compared against current best-in-class performance data, resulting in a customized ROI calculation for their potential replacement.

Early in the project we realized that surfacing "actionable" insights requires fine grain monitoring of energy usage (on an individual device/appliance level). While nodal sensing, accomplished with smart plugs, provides the breakdown of residential consumption we desire, we also recognized that their mass market adoption would be challenging; primarily due to their expected unit cost and installation/configuration complexities. Energy disaggregation allows an aggregate energy measurement to be separated into its constituents. Hence we developed a prototype disaggregation module, based on factorial hidden Markov model and its extensions, to reduce the number of sensors required to determine the load breakdowns we require. This work is described in more detail in the energy analytics examples section of the paper.

C. *Home User Interface:*

Our goal was to build an "insanely simple" home energy awareness experience which engaged the user, and required minimal steps to achieve and provide actionable and relevant energy usage insights.

Figure 6. *The home user interface.*

The user experience was designed to mimic emerging and current HP entertainment experiences in ease of discovery, usage, and family-oriented engagement. The goal was to strike a balance between 1) just enough information displayed in a compelling way for novices, and 2) more detail (easily accessible) for enthusiasts. As shown in Figure 6, the top-level user interface presents zonal regions (akin to virtual rooms), scaled in proportion to total consumption and color shaded in response to usage trends over time. Insights are revealed in relation to the source of the occurrences.

D. *Operations Management Console:*

A second user interface shown in Figure 7, provides a spatial view of energy information, potentially from millions of households. This creates a service opportunity for 3rd parties (e.g. manufacturers, utilities, regional governments) through a targeted platform hosting energy-oriented analytics which are performed against a collective data repository, enabling operational views of energy activity across a specific customer's business function or region.

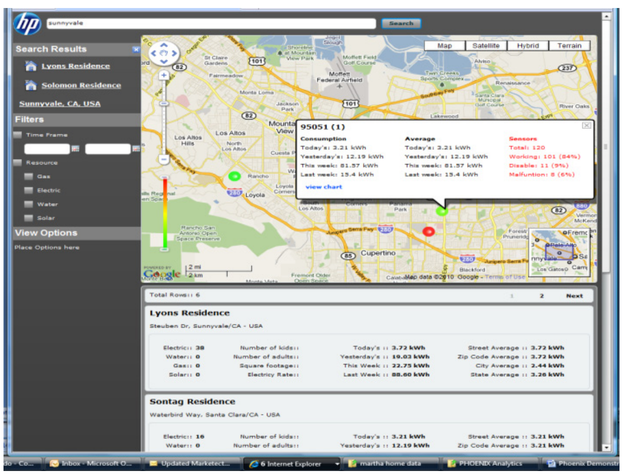

Figure 7. *Operations Management Console.*

III. ENERGY ANALYTICS EXAMPLES

A. *Power Load Disaggregation:*

We propose a methodology for disaggregation of load into its constituents using the aggregate load and contextual information such as time of day, environmental conditions, usage of other resources, etc [8]. The main advantage of our methodology is that it allows aggregate load to be split up into its constituents without requiring each individual device or appliance to be instrumented. This provides visibility into component wise resource consumption. Furthermore, since disaggregated load becomes available, analytic techniques can be applied individually to devices and appliances.

The problem of power load disaggregation can be formally stated as: given the aggregate power consumption for T time periods, $Y = [\, y_1, y_2, \ldots, y_T \,]$ and the number of appliances, M, we want to infer the power load by each of the M appliances, that is,

$$S_1 = < s_{11}, s_{12}, \ldots, s_{1T} >$$
$$S_2 = < s_{21}, s_{22}, \ldots, s_{2T} >$$
$$\ldots$$
$$S_M = < s_{M1}, s_{M2}, \ldots, s_{MT} >$$

where S_i is the time series of the disaggregated load of the *i*th appliance.

Hart [6] first investigated the problem of power load disaggregation in homes. He looked at changes in the aggregate power consumption and related them to on/off events. In order to disambiguate appliances or devices with similar power consumption, he considered additional AC power metrics such as reactive power, power factor, etc. While two-state appliances could be tracked using on/off events, Hart used state machines for multi-state appliances. He focused on two kinds of features for power disaggregation – transient signatures and stable-state signatures [6]. Transient signatures capture electrical events, such as high frequency noise in electrical current or voltage, generated as a result of an appliance turning on or off. Although these features are good candidates for use in disaggregation, sampling data fast enough to capture them requires special instrumentation. For example, Patel et al. use a custom built device to measure at rates up to 100KHz [7]. However, most smart meters deployed in the U.S. have low sampling rates, typically 1Hz or less.

We focused on low frequency stable signatures in our work, and used unsupervised models such as factorial hidden Markov model (FHMM) to disaggregate the power data. In particular, we proposed a variant of FHMM, conditional factorial hidden semi-Markov model (CFHSMM), which performed better than other known unsupervised methods. The models considered were tested on real power data collected from seven homes. Further details on the models and their performance evaluations are presented in Kim et al. [8].

B. *Anomaly Detection:*

Appliances such as refrigerators have a temporally varying power consumption behavior. For example, a refrigerator compressor turns ON/OFF periodically based on the degree of cooling required. This behavior directly impacts the amount of energy consumed by the appliance. A deviation from normal operational behavior may be caused by an anomaly and result in increased energy consumption. Furthermore, certain anomalous behavior may manifest as unique changes in the operational characteristics. Here, we describe a methodology to characterize the operational behavior of an appliance or device which could be used for determining deviance from normal behavior and for detecting anomalies. Characterization of the power consumption of an appliance or device can be broken into the following steps:

1) *Data pre-processing*. Here the raw time-series samples are checked for invalid or out of range values; multiple time series are synchronized, if required; missing

values are filled in and the time intervals between readings made uniform through linear interpolation, etc.

2) *Edge detection*. The difference between sensor readings at time *t* and at time *t–1* is computed. This provides a time series of all the deltas in successive time points in the quantities measured.

3) *Clustering*. The deltas obtained in the previous step are clustered using a suitable clustering algorithm such as k-means. The number of clusters, an input to most clustering algorithms, can be determined using domain information, or through one of many techniques discussed in clustering literature such as silhouette coefficients, evaluating ratio of within clusters and between clusters sum of squares distances, etc.

4) *Filtering the clusters*. This step requires feedback from a domain expert (in this sense the methodology is semi-supervised). The clusters discovered are labeled to link them to a physical event or state. For example, where the appliance analyzed is a refrigerator, the clusters discovered are labeled as noise, compressor ON events, compressor OFF events, positive outliers and negative outliers.

5) *Estimate operational characterization parameters*. The event/state clusters arrived at in the previous step can be used to estimate parameters that characterize the operation of the appliance or device. These parameters can be computed through density estimation using mixture models. For example, for a refrigerator, the compression cycle frequency distribution can be estimated. Similarly, the distribution of ON/OFF times can be estimated.

To exemplify the cloud service features, an example of the device disaggregation is shown in Figure 8. In this case we disaggregate a single energy measurement from a power strip into its constituent parts. Within the home user interface, this single measurement is represented as four individual devices or virtual sensors.

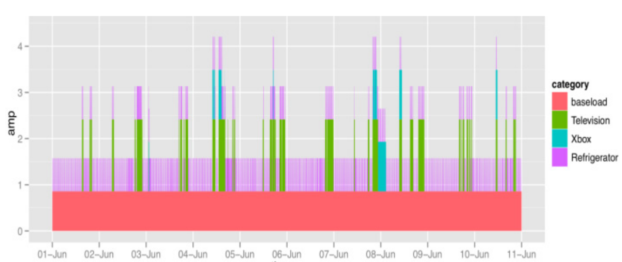

Figure 8 – *Disaggregation results plot of four devices within the home, monitored via a single sensor node*

IV. Current Status

Our demonstrator has an installed base of seven real test homes. Each is instrumented with between 10 and 20 sensor nodes. Each node is sampled every 5 seconds, with locally collected data being uploaded every ten minutes. Over the last 12 months our cloud service has collected over 15 million sensor readings, which we process and present back to each home, with 2 minute granularity, via our home user interface .

With such fine grained sensing we build "activity profiles" for each appliance or device, which often reveal interesting family behavioral patterns that can be helpful in understanding how to shift energy usage to save money or leverage novel utility pricing programs. Figure 9 shows a selection of energy heat-maps, derived from activity profiles in a number of real test cases. Each plot details the relative energy usage, averaged on an hourly basis (x-axis) for each day of the week (y-axis). The upper plot shows laundry room activity, with predominant use on Friday mornings (a direct match to the house cleaner's schedule) and more scattered use in the evenings throughout the week. The middle plot shows home office usage, highlighting a correlation between daytime energy use and when the individual normally works from home on Tuesdays and Thursdays. The lower plot shows usage from a gaming console, with this activity heating up during after-school hours and over the weekends.

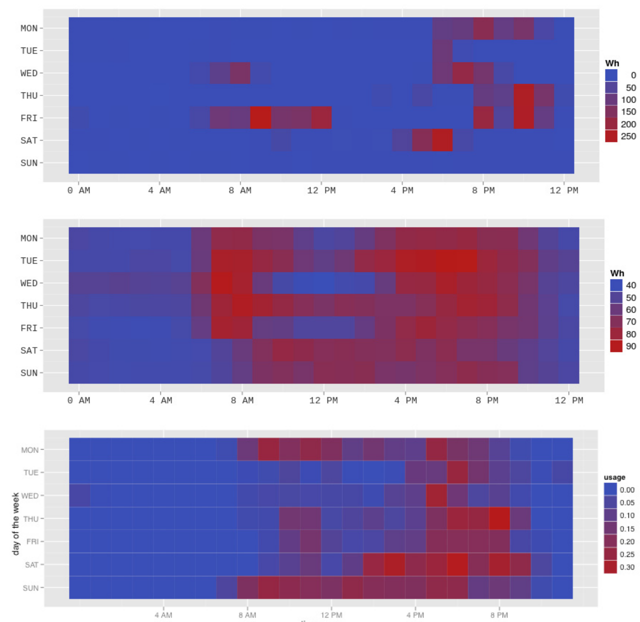

Figure 9. – *A selection of zonal and device heat maps, showing activity profiles in each case: Laundry Room (upper), Home Office (middle), and Gaming Console (lower).*

V. Competitive Approaches

Our initial competitive market analysis study [5] classified three main types of emerging energy-orientated consumer products: basic sensing devices (e.g. TED's Energy Detective), home energy systems and services (e.g. Eaton's Home Heartbeat), and web-based software services (e.g. Microsoft's Hohm). This study also revealed a distinct convergence of consumer and utility centric solutions, toward integrated end-to-end offerings. These findings drove our decision to incorporate both consumer and operations interfaces within our demonstrator, and to leverage existing HP consumer products where possible. Also, most solutions measure a single energy consumption variable; our solution enables much finer grained sensing and insights. No solutions we have seen take a holistic view of multiple resources (gas, solar, water, electric), which we could incorporate via additional sensors due to the Open XML-based data format we've adopted, or which we could import (via 3rd parties) directly into our energy cloud service. We also de-emphasized the graph views prevalent in the majority of solutions today.

VI. CONCLUSION

The IT services required to support residential energy monitoring services and EIS solutions are being explored with a number of emerging ecosystem and partnering dimensions in mind. Our demonstrator proof of concept confirmed the need to prepare services of this type for unprecedented scale (sensors, users, data, processing, network traffic, etc.) and to enable the composition and integration of services from multiple players. Seamless content and service integration is key to EIS solutions especially those that aggregate data from multiple sources and content providers (city utilities, home management systems, etc.). Enabling the creation of value-added services, for example plug-in analytics modules, is also key.

Looking at the energy monitoring space in the context of the Smart Grid rollout uncovered a number of players which could partner to deliver compelling value-added services. These range from incentives for measured reduction in energy usage for neighborhoods, utility and city scale supply-demand side optimization, community-oriented social networking and incentive-driven services, consumer appliance and electronics retail incentive generation directly tied to consumption usage patterns, time-of-use program optimization and program offer generation, differentiated analytics services, etc. Two of the biggest challenges to implementing these programs will be: 1) the integration of services from the multiple players and partners in the value chain and 2) the privacy protection of activity-oriented consumer usage data.

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