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ABSTRACT

In modern environments, more and more "smart appliances" exist. Those devices are equipped with sensors to measure their internal state and environmental variables, with processing power, and also with networking capabilities. To make these appliances aware of their own electricity expenditure we propose the concept of virtual electricity sensors. Instead of adding dedicated hardware sensors, we use the device integrated sensors in conjunction with an energy model to estimate the actual power draw based on the current device state. First results indicate that this approach leads to an accuracy of up to 98% for various smart appliances. Our approach leads to cost-efficient fine grained electricity metering for future smart appliances.

1. INTRODUCTION

According to recent studies, the electricity consumption of consumer electronics has grown by +18% over the last decade (cf. Residential Energy Consumption Survey 2009). With the rise of the Internet of things, we expect this growth to continue. While traditional electricity consumption monitoring systems could supervise these loads, their application is often not beneficial from a financial point of view. The cost for these metering systems often outweighs the potential savings [1]. Thus, we present an alternative approach which significantly reduces the cost of electricity metering by replacing hardware circuitry with software components.
So-called "smart appliances" are equipped with a variety of different sensors. The core idea of our work is to infer the electricity consumption of smart appliances solely from sensor data which is available by accessing the sensors already installed. This methodology leads to three main advantages:

1. A reduction of costs as no dedicated current sensors are required for monitoring the electricity consumption.
2. A reduction of complexity as the total number of sensors in an environment decreases.
3. The capability to implement novel feedback and interaction services on systems aware of their own consumption.

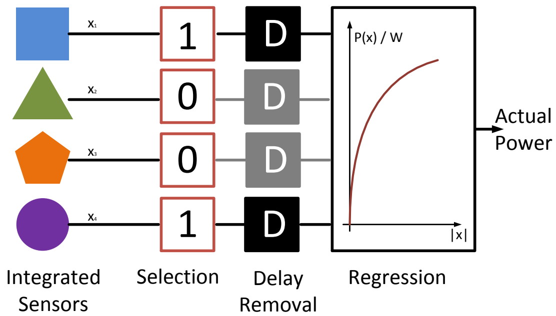
2. RELATED WORKS

Related works exist in two areas: First, our approach competes with load disaggregation methods and distributed electricity sensors in the area of smart homes. In this area a lot of effort has led to higher accuracies[2] and better scalability [3]. However, using this technology, it is impossible to influence the monitored environment. On the other hand, distributed electricity meters have a rather poor scalability of one sensor per appliance. Second, our work adopts techniques for system modeling from the field of energy efficient computing. In order to make computing machinery more energy efficient, models are used to determine the electricity consumption of different subtasks. E.g. Kansal [4] uses energy models to optimize the utilization of servers in data centers which leads to huge electricity savings. Zhang [5] enhances the battery life of smart phones by making the owner aware of energy consuming apps. What both approaches have in common is that manually fine-tuned models are used to express the power consumption based on the current system load.

3. VIRTUAL ELECTRICITY SENSORS

As illustrated in Figure 1, energy models consist of three major steps. First, the sensors with data relating to power consumption are selected from all available sensors for further processing. The selection of relevant sensors is either made manually by domain experts or automatically by calculating a correlation coefficient between the sensor data stream and the appliance's electricity consumption. Second, the omnipresent time-lag between each sensor data stream and the power consumption data stream is compensated for. Finding appropriate factors for the delay compensation is rather challenging if events indicated by the sensor data and their impact on the electricity consumption do not follow one another promptly. Finally, a regression algorithm is used to calculate the actual power consumption based on the selected and shifted sensor readings.
In order to adopt this rather general model to particular appliances, we developed a non-parametric training algorithm for energy models. This algorithm factors in time series of sensor data as well as the corresponding time series of power recordings for the appliances obtained from an externally connected power meter. Based on this input data, our algorithm selects relevant sensors, compensates for the time lag and inputs the data into an appropriate regression model. To do so, our training algorithm parametrizes the energy model with appropriate, non-zero default values and calculates the resulting accuracy on a subset of the training

Figure 1: Overview of components for the energy model.



data. Based on that, our algorithm varies model parameters in order to maximize the resulting model accuracy. We use the mean squared error between the predicted instantaneous power draw and the measured power draw as fitness function for this optimization.

4. EVALUATION

In order to test the real world applicability of virtual electricity sensors, it is important to consider three important properties:

1. *Accuracy* of predictions.
2. *Adaptability* to different appliances.
3. *Consumption overhead* due to additional calculations.

To determine the *accuracy* of virtual electricity sensors we compare the predicted power demand with the actual power demand obtained from an external power meter. The *accuracy* should be as high as possible in each individual prediction step and over a long period of time the difference between the predicted and measured energies should be as low as possible. As shown in Table 1, our virtual electricity sensors already achieve good *accuracy*.

The property of *adaptability* states how well virtual electricity sensors generalize for arbitrary appliances without requiring manual fine-tuning during the fitting of the model parameters. Currently, we test for this property by applying energy models to different appliances and testing the *accuracy* of the resulting energy model (cf. Table 1). However, a more systematic approach would be desirable to quantify this property. Last but not least, the *consumption overhead* of the virtual electricity sensors themselves should be as low as possible. By running the calculations on embedded processors, the energy demand for those calculations should be as low as possible. Furthermore, embedded systems are often carefully optimized for low resource demand and thus low prices. The hardware requirements should not change due to the inclusion of virtual electricity sensors.

5. APPLICATION SCENARIO

Virtual electricity sensors can be applied in a wide spectrum of environments. The technology is useful in residential homes to estimate the electricity consumption of multimedia appliances. However, we expect this technology to have an even greater impact on office- and industrial environments with a multitude of different networked appliances. In this field, virtual electricity sensors offer deep insights into causes of high electricity consumption whilst requiring nearly no financial investment.

Table 1: Results of the Regression Algorithm with energy models for different networked appliances

Machine	Regressor	e_{tabs}	Class
Dell 1	ERFR	2.067 %	3
Lenovo 1	ERFR	0.683 %	3
Lenovo 2	KNNR	2.685 %	3
Macbook	LassoR	0.162 %	3
Gaming PC	LassoR	3.400 %	3
Philips Hue	KNNR	4.539%	2
Fan	RFR	1.322%	1
Canon Printer	ERFR	3.757%	1..2
Vending Machine	DTR	10.8%	1

6. CONCLUSION AND OUTLOOK

Our concept of virtual sensors for measuring the electricity demand of networked appliances has great potential to simplify the task of electricity metering with a high level of detail in a cost-efficient manner. Our current implementation is capable of determining the power draw of office appliances with an accuracy of up to 98% without adding additional hardware sensors. Furthermore, we have developed a non-parametric algorithm to train energy models for virtual sensors and showed its applicability for six different classes of office appliances. In the future, we plan to apply the technique of virtual electricity sensors to a much broader spectrum of electrical appliances.

7. ACKNOWLEDGEMENTS

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