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I. Motivation

Optimization problems are solvable if it is possible to define a solution space and an objective function. Unfortunately there exist many application scenarios where it is impossible to define a objective function due to incomplete information. Therefore, the application of standard techniques to find an adequate solution is unfeasible. One of this application scenarios is reducing the energy consumption e of a user u carrying out a task or activity a by using a set of tools t in a determined state s and following a certain workflow w.

To carry out the desired activity or task, the user has the choice between different tools to use or workflows to follow. In general, the selected set of tools and workflows directly influence the energy consumption of the task or activity to carry out. Given the constraint that the user is not willing to reduce his comfort or productivity, it is impossible for him to decide whether his selection of tools and workflows was optimal with regards to the energy consumption. Making such an optimal decision would require global a priori knowledge of all available tools or workflows for a given task as well as their energy consumption.

For a single user, it is simply impossible to collect this information. But things look different if multiple persons join their forces to collect required supporting points by monitoring their energy consumption during different activities. In the literature, a setup where users contribute sensor data to a common body of knowledge is called participatory sensing. Having these supporting points, these could be used as a priori knowledge to numerically approximate the objective function for different tasks, tools and workflows. Having such a formal description of the optimization problem is the key requirement to find more energy efficient solutions or even allow deep automatic energy consumption analysis.

II. Problem Definition

The goal of this work is to minimize the energy consumption e of arbitrary tasks or activities a carried out by or on behalf of humans u using a set of tools or appliances t in a certain state s by following a workflow w by selecting combinations with minimal energy usage. Hereby the constraint must hold not to negatively influence the user's productivity or comfort. All valid reductions of energy consumption could be achieved either by process, tooling or behavioral changes.

III. Research Gap

As defined by Pierce [1], there are four methods to reduce the energy consumption. Namely, these are:

1) Switch off not required energy consumers
2) Trim appliances to their most energy efficient state
3) Select the most energy efficient tool for a task
4) Replace an appliance with a more energy efficient device

This enumeration given by Pierce is focused on direct human actions to save energy and thus it might be incomplete. Nevertheless it clearly illustrates the solution space. More generally spoken, energy saving could be achieved either by tooling changes, organizational changes or workflow changes.

In practice, many related works focus on switching off not required consumers or influence the room temperature based on the occupancy. Exemplary, Kleimingers [2] goal is to control the heating based on the occupancy in an environment. Other researchers [3] used occupancy informations to influence the air conditioner based on the occupancy. As shown by Milenkovic [4], is also possible to switch off standby loads if they are located in an unoccupied room. All these publications rely on a special case with a given objective function for the energy consumption and the possibility to verify for constraint violations: If a room is not occupied, the heating or cooling power could be reduced without somebody noticing it. Therefore, the binary decision whether a energy consumption is useful or not is solvable in this case.

Unfortunately, things look different in the area of energy saving by tooling changes or organizational changes. In such a scenario, the user can save energy by switching to the most energy efficient appliance or by replacing inefficient devices with more energy efficient ones. Although having a high energy saving potential of up to 23% (according to Laitner [5]), it is difficult to realize these potentials because there is no objective function which states the energy consumption for different appliances with different usages patterns. The user has simply no possibility to determine whether his selected devices or workflows for a certain task are an energy efficient choice. Even if (new) appliances are labeled with their energy consumption, there exists a large stock of unlabeled legacy appliances and the manufacturer ratings might not reflect the reality. The goal of my work is to close this information gap.

IV. Approach

In the last few paragraphs a high level motivation for this work was given and my research gap was carved out. In this section I explain the concrete goals of my work and also draft possible ways to achieve these goals. The plan of this work is to build a system which is capable of measuring the electricity consumption on device level granularity together with the user's occupancy and activity. Then the hereby measured data is exchanged with an online data repository to build a body of supportive data. In exchange to their energy usage data, the users get detailed reports showing their personalized energy saving potential. This work will focus on the electricity consumption, because this parameter is easy to measure and the electricity consumption is a significant, rising part of the overall energy consumption in our post-industrial society.

To achieve the above mentioned goals, my plan is to build a measuring platform consisting of state of the art distributed smart meters and smart phones. The distributed smart meters could be used to measure the energy consumption and operating state on appliance level granularity. In conjunction, the smart phones will be used to sense the user's presence as well as his activity. This system should work autonomously without requiring user interaction. In first publications, I've shown possibilities so sense the activity of users [6] and also the operating state of electrical appliances [7] based on their electricity consumption. Next, my plan is to install multiple measurement platforms in residential environments to collect real world data. Although the measurement platforms could be installed in other environments, residential areas have the advantage of many different activities happening there which involve the usage of various electricity consuming appliances. Nevertheless, the system could be adapted to other domains or environments with minor changes.

Having an extensive body of knowledge about the energy consumption of diverse appliances used by different users with differing workflows, this data could be analyzed. The first step in this phase is to probabilistically approximate an objective function stating the electricity consumption of certain tasks or activities carried out using specific tools in a well-defined state. This approximation is required, because the collected data will contain ambiguous energy consumptions for the same input parameters due to fabrication variances and differences in the environment which are out of scope for my measurement system. This approximation could be achieved with state of the art regression methods. Also, unsupervised clustering algorithms could be used to filter and remove outliers prior to the approximation. As modeling the user's workflow might be a challenging task on its own, I will try to approximate the users workflow based on the activities duration.

With an appropriate model of the objective function, it finally becomes possible to minimize the electricity consumption as function of the specified variables. More concrete, my plan is to find the most energy efficient tool or appliance for a certain task or activity. Building upon that, my system can calculate the saving potential for all other users who are using a suboptimal appliance and report this recommendation to the owner of the appliance. The whole system could be evaluated by calculating percentage of found saving potentials. To do so, my plan is to benchmark the system against human energy consultants.

V. Challenges

Amongst others, my research project focuses two mayor challenges, namely incomplete contextual information and privacy concerns. A short explanation of these challenges will be given in this section. In contrast to the electricity consumption, the users current activity is neither directly measurable nor a closed list. Therefore, even the best user activity detection methods need training and provide probabilistic results. These algorithms may work well in small scale but it is unclear whether they are feasible in a real world installations. Furthermore, collecting electricity consumption and activity informations in a shared body of knowledge certainly raises privacy concerns. As shown in different publications, this kind of data is full of sensitive information about the habits of the users who provided the data. Although the main focus of this work is not privacy preserving, my goal is to cause no mayor privacy issues. The best I can do to protect the privacy is to carefully specify the amount and quantity of data which is at least required to find energy saving potentials. Together with pseudonymization, anonymization and temporal shuffling this should be sufficient to preserve the privacy of the users.

VI. Formal Research Question

- RQ1 How can I approximate an objective function e = f(a, t, s, w) stating the energy consumption for a large set of different activities carried out by different users?
- RQ2 Which concrete contextual parameters are required for this approximation and how could I measure these in large scale with many users?
- RQ3 Given an objective function f, how can I optimize the energy consumption without violating the given constraints?
- RQ4 How could one limit the information content of collected data to a minimal amount?

References

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