Perceived-Value-driven Optimization of Energy Consumption in Smart Homes

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Residential energy consumption has been rising rapidly during the last few decades. Several research efforts have been made to reduce residential energy consumption, including demand response and smart residential environments. However, recent research has shown that these approaches may actually cause an increase in the overall consumption, due to the complex psychological processes that occur when human users interact with these energy management systems. In this article, using an interdisciplinary approach, we introduce a perceived-value driven framework for energy management in smart residential environments that considers how users perceive values of different appliances and how the use of some appliances are contingent on the use of others. We define a perceived-value user utility used as an Integer Linear Programming (ILP) problem. We show that the problem is NP-Hard and provide a heuristic method called COndensed DependencY (CODY). We validate our results using synthetic and real datasets, large-scale online experiments, and a real-field experiment at the Missouri University of Science and Technology Solar Village. Simulation results show that our approach achieves near optimal performance and significantly outperforms previously proposed solutions. Results from our online and real-field experiments also show that users largely prefer our solution compared to a previous approach.

CCS Concepts: • **Human-centered computing → Collaborative and social computing design and evaluation methods**;

Additional Key Words and Phrases: Smart homes, energy consumption, perceived-value driven optimization

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1 INTRODUCTION

Residential energy consumption constitutes a significant fraction of the total usage. As an example, in the U.S. in 2014, residential users consumed 1.4 trillion kilowatt-hours of electricity, which

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amounts to 38% of the net consumption by all sectors including commercial (36%) and industrial (26%) [2]. Moreover, according to the U.S. Department of Energy, electricity consumption in the residential sector is expected to increase by 13.5%, by 2040 [1].

Numerous efforts have been made to reduce residential energy consumption. *Demand response* has been proposed in the context of power management systems, where the price of electricity is changed over time to alter user behavior and ultimately reduce the occurrence of high consumption peaks [10]. Although relatively easy to implement, thanks to the diffusion of advanced metering infrastructure (AMI) [7], the effectiveness of demand response methods is not clear [16, 17, 21], and it can even lead to an increase of energy consumption [16]. Another drawback is that this strategy treats uniformly across users inattentive to their special needs and psychological, behavioral, and ritual aspects. For example, it puts some users at a greater risk than others, such as low-information users, individuals with medical or cognitive impairments, or those with overburdened time demands.

A recent alternative to achieve user-side smart energy management is based on exploiting novel technologies, such as the paradigm of the Internet of Things (IoT) [9, 43, 54]. According to this paradigm, smart appliances of our everyday life are equipped with micro-controllers, transceivers, and suitable protocols to become part of the Internet and will ubiquitously proliferate in homes, realizing the so-called *smart homes*. Such smart environments will allow fine-grained energy monitoring and control, thus enabling advanced methods to save energy [12–15]. One basic approach is to increase user awareness by providing feedback about energy consumption, e.g., Berkeley Energy Dashboard [38], AlertMe [4], and HeatDial system [23]. However, it has been shown through experimental studies that in the long term, these approaches provide only limited benefits [23, 25] and may penalize users with limited technological capabilities or resources. Recently, several researchers investigated the use of smart appliances to perform *user activity recognition* and *prediction* and consequently optimizing the energy consumption [8, 12, 32, 35, 49, 51–53].

Although smart environments have the potential to reduce and optimize residential energy consumption, previous approaches have *largely neglected* the psychological and behavioral factors that influence the energy consumption in these environments. As an example, the utility perceived by the user is often based on engineering-defined metrics that are uniform across users and are based on oversimplified assumptions that ignore the complexity of human behavior. In fact, users can be highly heterogeneous, and the usage and availability of different appliances may have various, non-uniform impacts on the users' psychological well-being. Supported by recent research in the social behavioral science domain [16, 17, 21, 24], in this article we claim that:

> The success of smart residential environments in improving our everyday life, while achieving desirable goals such as reducing energy consumption, can be achieved **only** by interdisciplinary approaches that merge psychological models, to capture the complexity of human nature, with computationally efficient optimization techniques.

Following our claim, in this article we propose an energy management system for smart residential environments realized through the IoT paradigm that specifically takes into account psychological dimension of the user. In particular, we define a *psychological model* that considers five dimensions of user well-being, as well as dependency between appliances resulting from user routines, habits, or desires to use some appliances together. We use behavioral science methodologies, including *large-scale online experimental surveys*, to which we refer as *online experiments* in the rest of the article. We conduct a series of online experiments, with representative sample populations recruited through Amazon Mechanical Turk [5], to quantify generic perceptions of appliances in terms of the above model under different energy shortage contexts (e.g., when operating on a power generator or shared renewable sources) and to identify sample appliance dependencies.

Given such psychological model, we consider an *energy constrained* smart environment in which user has a maximum energy budget that can be consumed by active appliances. This represents several scenarios, for example, where the user has set a maximum limit on the monthly energy expenditures or where the smart home belongs to a micro-grid operating in islanding mode. We define a *perceived-value user utility* based on the psychological model and formulate an optimization problem that maximizes such utility given constraints on the energy budget and appliance dependencies. We show that this problem is NP-Hard and propose an algorithm named, COndensed DependencY (CODY), based on the graph condensation theory.

We tested our approach with synthetic and real graphs representing the appliance dependencies. CODY shows superior performance in both cases, providing performance close to the optimum. Additionally, this approach considerably outperforms a recently proposed method that does not address psychological dimension, referred to as knapsack-based solution [9], as well as a baseline Greedy approach. We further validate CODY versus the knapsack approach through two experiments, one online and one in-person experiment at the Missouri University of Science and Technology Solar Village. The goal of these validations is to compare human perceptions of the optimization algorithms' output. Moreover, the in-person experiment enables a personalized solution tailored for the participant's own appliances, utility values, and dependencies. Results show that by including our psychological modeling in the optimization process, users overwhelmingly prefer our solution.

2 USER PSYCHOLOGICAL MODEL

In this section, we describe the user psychological model on the basis of our perceived-value driven energy optimization framework.

2.1 Importance of Appliances

The first goal in developing the psychological model is to identify the perceived importance of electric home appliances (e.g., coffee makers, home security systems, home medical devices, home electronics, etc.). Previous works synthesize the importance as a single numerical value, for example, proportional to the energy consumed by an appliance [41], or proportional to the length of time an appliance is used [9]. However, such modeling choice necessarily oversimplifies the complexity of human behavior.

An important construct influencing human behaviors and interactions with the world is the pursuit or maximization of "well-being." Philosophers argue that well-being is a state that humans generally tend toward [19], and arguably most of the purposeful activities humans engage in are in some sense meant to promote well-being to varying degrees. Griffin argues further that well-being is less an objective static quantity and more an ongoing process of maximization, with the tools, objects, and activities that lead to well-being having different values at different times relative to other tools, objects, and activities [19]. He refers to it as "fulfillment of informed desire," and as those desires may change, so may the degree of well-being they elicit when fulfilled. While research has certainly investigated the impact of a great many end-user technologies on well-being, these are generally considered on an individual technology level and within the context of the design and use of that particular object. Research has not looked directly at something we might consider a mundane aspect of human life and that is how we perceive the collection of appliances in a home as contributing to well-being relative to one another. In other words, how are appliances ranked or prioritize in terms of their importance in contributing to our well-being, especially when access to those appliances might be temporarily limited by energy constraints either within or beyond our control.

In determining how to measuring the contribution of appliances to some notion of "well-being" it is important to acknowledge that there are two broad aspects of well-being, namely *state of mind* and *state of the world* [19], and that within these two aspect there are further subtypes of well-being, such as physical well-being and psychological well-being. Because of the diverse functionality and purpose of home appliances, it is possible that users will perceive some appliances as contributing to one aspect of well-being more than another. Further complicating this matter is that users might hold some subtypes of well-being as more important than others. To better capture some of these nuances, rather than measuring well-being as a single question or dimension, we first measure the contribution of appliances toward five subtypes of well-being that have been discussed in scholarly literature as unique contributors to overall well-being and were also likely to be easily understood and contemplated by a broad audience. We then create a weighted composite score across these multiple dimension to arrive back at a single score for overall well-being for each appliance. Specifically, for state of mind, we include psychological well-being [40] and moral well-being [19]; for state of the world, we include physical well-being and economic well-being [20]; and, finally, we include social well-being that intersect both aspects [27]. This is not to imply that these are the only forms of well-being or that each are uniquely distinct and mutually exclusive to one state or the other; instead, they are included to create a more nuanced measure that will add refinement to our utility measurement for overall well-being.

Acknowledging that participants might have slightly different interpretations of the five aspects of well-being described in the previous paragraph, we also provided a basic definition for each term. To increase the likelihood that the definitions were accessible to a broad adult population, we conducted an informal polling[1] to assess readability of the definitions. Based on the literature we collected 25 of short, plain English phrases that had been associated with defining each type of well-being (5 for each) and subsequently asked college students to rank the phrases in terms of ease of understanding and readability. The top three phrase choices for each well-being type were then selected and combined into a single sentence as shown below.

- **Physical well-being:** The appliance contributes to feelings of being safe from harm, having a healthy body, and taking care of one's body.
- **Psychological well-being:** The appliance contributes to personal happiness, acceptance, and the pursuit of goals.
- **Economic well-being:** The appliance helps control financial status and standard of living and supports financial independence.
- **Moral well-being:** The appliance helps the user choose right from wrong, exercise good character, and to do what the user perceives to be the right thing.
- **Social well-being:** The appliance helps form relationships with others, contributes to supporting and being supported by others, and contributes to a sense of belonging.

To mathematically represent this information, let us consider a set of n appliances $\mathcal{A}$ for a given user u. We denote by a_i an appliance in $\mathcal{A}$, for $i = 1, \ldots, n$. The importance of a_i for u is defined in terms of the following *five dimensions* of user well-being.

According to our model, appliances are ranked with respect to each dimension of well-being. Specifically, for an appliance a_i, we define the value d_k^i as its ranking in the kth dimension,

[1]Informal polling was conducted on a college campus as part of a course requirement and included approximately 200 students. The IRB Chair was consulted, and this task was not reviewed as it was deemed pilot research aimed at refining study materials for future research and not at formulating new knowledge or generalizable findings.

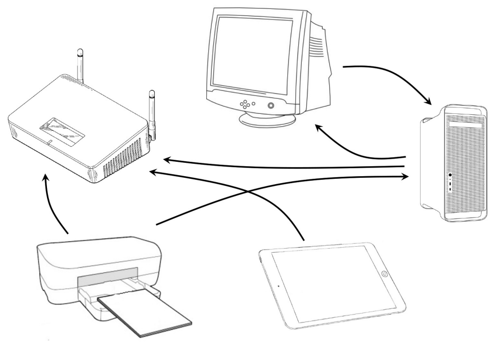


Fig. 1. Example of dependency graph between electric appliances.

$k = 1, \dots, 5$. Dimensions are also weighted to identify the most relevant well-being factors for that user. The weights of the kth dimension is defined by $r_k \in [1, 100]$.

We consider five different *energy availability contexts* to identify potential changes in the perceived importance of appliances. Specifically, the contexts are a standard condition with no mention of energy conservation and four contexts in which they were trying to limit their energy use, namely use of a power generator, reduction of energy bill, concerns with how human-made energy is impacting the environment, and where the smart house is one among several other houses sharing energy from a local solar or wind powered generator.

We conducted a large-scale online experiment, involving 1,500 subjects through the online participant recruitment service provided by Amazon Mechanical Turk to quantify the perception of several appliances in terms of the above model. Results are described in Section 6.1.

2.2 Dependency between Appliances

The contribution of an appliance to the psychological well-being of a user may not be fully independent from other appliances. Specifically, we identify dependency as described in the following. We make use of an example of a typical home office setting with appliances such as a computer, a monitor, an internet router, a wireless printer, and a tablet. Figure 1 shows the appliances in our example.

An appliance may *need* other appliances to work or to be able to provide any benefit for the user. In our example, the router and the tablet can work independently. Conversely, the computer and the monitor are mutually dependent, while the wireless printer needs both the computer and the router to work. Moreover, the user may have routines, habits, or desires to use some appliances together. Consider our example where the user accesses the Internet through the tablet and the computer. Even though the tablet and computer can independently contribute partially to user well-being, if the wireless router is not available, then their contribution may be significantly impaired. In this case, we say that as a consequence of these user factors both the computer and the tablet have a dependency with the router.

We formalize the concept of dependency through a directed graph. In particular, given the set $\mathcal{A}$ of appliances for a user u, we define the dependency graph $G = (\mathcal{A}, E)$. Intuitively, there is an edge $(a_i, a_j) \in E$ if appliance a_i has dependency with a_j.

Due to the transitive nature of dependency, if an appliance a_i depends on an appliance a_j, which in turn depends on another appliance a_l, then a_i also needs a_l to function, although indirectly. In our example, the printer needs the computer, which in turn needs the screen. As a result, the printer can provide full utility to the user *only* if both the computer and the monitor are available.

2.3 Perceived-Value User Utility

We now define a *Perceived-Value user utility* that considers the model for appliance importance and dependency. Specifically, given a set of appliances $S \subseteq \mathcal{A}$, we want to quantify user perceived utility $U_{SB}(S)$ taking into account the five psychological dimensions, as well as the dependency between the appliances in S.

In this article, we assume that the utility $U_{SB}(S)$ is a scalar, and therefore for each appliance a_i we define an individual appliance utility u_i that combines the ranking in each dimension of well-being for a_i, as well as the weight of the dimensions for that user. The formula adopted is given by

$$u_i = \sum_{k=1}^{5} e^{1-d_k^i} \frac{r_k}{\sum_{j=1}^{5} r_j}, \tag{1}$$

where, d_i^k represents the ranking of the appliance a_i in the kth dimension, $k = 1, \ldots, 5$. Also, r_k denotes the weights of the kth well-being dimension. Research related to ranking data suggests that transformation of ranked values is often needed [28, 45]. In fact, the distance between higher ranked items may be greater than lower rank items, meaning that in a ranked set of 21 items, while a difference between items ranked 1st and 2nd may be close to one, the distance between items ranked say 20th and 21st may be closer to zero. Because we have a large number of ranked items, we applied a transformation using a negative exponential function to minimize the distance between items ranked highest (i.e., closer to 21).

It is worth mentioning that we investigated the sensitivity of the results to the choice of the utility function. To this aim, we examined our proposed algorithm with different types of utility functions, namely linear, quadratic, and exponential. The results were exactly the same for all functions. It shows that the outcomes are independent of the utility absolute values while they merely depend on the ranking of the appliances from user's point of view.

If the appliance a_i is in the set S, then the utility u_i represents the *maximum* utility it can provide. However, this occurs only if *all* its dependency are satisfied, i.e., if all the appliances from which a_i depends in G are also in S. To model this aspect, we introduce a variable $z_i \in \{0, 1\}$, which is equal to 1 only if all dependencies of a_i are satisfied in S. The calculation of z_i is described in Section 3.

Summarizing the above discussion, given a set $S \subseteq \mathcal{A}$ of appliances, the Perceived-Value User Utility $U_{SB}(S)$ is defined as follows:

$$U_{SB}(S) = \sum_{a_i \in S} u_i z_i. \tag{2}$$

It is worth noting that the user utility may vary over time. This can easily be handled by our model by introducing time slots (e.g., an hour). However, for ease of presentation, we omit the time dimension in this article.

3 PROBLEM FORMULATION

In this article, we consider an *energy constrained* scenario. Examples of this scenario include a user who wants to reduce his or her energy bill, a smart home during a blackout operating with energy from a local generator, and a smart house that is part of a micro-grid working in islanding mode, i.e., running only on batteries or renewable sources.

We formalize the energy constraint with a maximum power allowance B (measured in watts) that cannot be exceeded. Each appliance a_i has a maximum power rating e_i that represents the energy consumption of that appliance when in use. Note that the assumption of such fixed consumption is realistic, as the energy consumption of an appliance tends to plateau around a constant value over time, as shown by several load disaggregation papers [30, 55].

Our problem consists of finding the best set of appliances S^* that provides the maximum perceived-value user utility, given the energy budget B and the appliances' dependencies. We formulate the problem as a Mixed Integer Linear Program in the following:

$$\underset{x_i}{\text{maximize}} \quad \sum_{i=1}^{n} u_i z_i, \tag{3}$$

$$\text{subject to :} \quad z_i \leq x_i, \tag{4}$$

$$z_i \leq \begin{cases} \sum_{j=1}^{n} \frac{z_j y_{ij}}{Y_i} & \text{if } Y_i > 0, \\ 1 & \text{otherwise,} \end{cases} \tag{5}$$

$$\sum_{i=1}^{n} x_i e_i \leq B, \tag{6}$$

$$x_i \in \{0, 1\}, z_i \in \{0, 1\}. \tag{7}$$

The problem takes as input the dependency in the form of binary constants y_{ij}. The constant y_{ij} equals 1 if appliance a_i has dependency with appliance a_j. We define Y_i as the total number of dependencies of a_i, that is, $Y_i = \sum_{j=1}^{n} y_{ij}$.

The objective function is the Perceived-Value User Utility discussed in Section 2.3. The binary decision variables of the problem are $x_i \in \{0, 1\}$, for $i = 1, \ldots, n$, where x_i equals 1 if it is selected, and 0 otherwise. We recall that z_i is equal to 1 if appliance a_i has all the dependencies satisfied. To ensure this, the constraint in Equation (4) forces a_i to provide utility only if all the dependencies are selected. Besides, the constraint in Equation (6) ensures that the power budget is not violated, while the constraint in Equation (7) defines the variables' domains.

The following theorem shows that our problem is NP-Hard, motivating the need for an efficient heuristic.

Theorem 3.1. *The optimization problem is NP-Hard.*

Proof. We provide a reduction from the NP-Complete 0-1 knapsack problem [11]. Let us consider a general instance of knapsack: a set of elements $\mathcal{A}$, each element $a_i \in \mathcal{A}$ has a value v_i, a cost c_i, and a budget B. The goal is to find a set of elements $S^* \subseteq \mathcal{A}$ such that the elements in S^* provide maximum value and incur a cost within the budget B. Given the general knapsack instance, we can create an instance of our problem as follows. We create an appliance a_i for each element in $\mathcal{A}$. We set the utility as $u_i = v_i$ and the power consumption $e_i = c_i$.

We consider dependency. Therefore, since there are no dependencies $Y_i = 0$, the constraint in (5) reduces to $z_i \leq 1$, and the only active constraint on z_i is Equation (4), $z_i \leq x_i$. As a result, the utility u_i is provided entirely if and only if the appliance a_i is selected ($x_i = 1$), independently from other appliances.

In this setting, since dependencies are not present, our problem looks for the best set of appliances S^* such that the sum of their utility is maximum, and their cumulative power consumption is within the budget B. As a result, the elements of the knapsack corresponding to the appliances in S^*, also represent the optimal solution to the knapsack problem. Therefore, our problem is at least as difficult as knapsack, and it is therefore NP-Hard. □

Note that, in our current model, the user cannot override the system decisions, and thus it is extremely important to optimize the selection of appliances according to the user needs. As a consequence, the energy budget constraint guarantees that such budget is not exceeded. In our future work, we will consider the possibility of overriding the system's decisions, thus potentially exceeding the energy budget. Furthermore, we would like to point out that in a real context, where a specific smart home and user is considered, the problem described in this section, including the user psychological model, the dependencies, and the set of appliances should be tailored to that specific home and user. In this article, we used large-scale surveys to show that our psychological model is meaningful; that is, there exist statistically significant difference in how users perceive different appliances. We also included a real-field experiment at the Missouri S&T Solar Village to evaluate our approach and to show how it works in practice. Finally, the problem discussed in this section may arise in different scenarios, which are mostly characterized by the entity that sets the energy budget. As an example, in our previous work we consider the budget be set by the load serving entity (i.e., the utility company), to prevent cascading failures in smart grids [9]. Nevertheless, such budget could also be set by the user to reduce his/her energy bills.

An average home generally contains several tens of appliances. Nevertheless, our method can be also applied to community complexes or office buildings, where the number of appliances is much higher than a single home (note that lighting in different rooms should be counted as different appliances). In the following, we propose a polynomial heuristic to find a suboptimal solution efficiently. Depending on the specific context and number of appliances, we may use the ILP formulation or the heuristic.

4 THE CODY ALGORITHM

In this section, we propose the CODY algorithm to solve the optimization problem described in Section 3. The algorithm is based on the theory of graph condensation [22, 42, 46]. Specifically, given the dependency graph, CODY performs graphs operations to obtain an *equivalent* condensed graph. The selection of appliances is performed on the reduced graph, making it more effective and efficient. In the following, we first provide some background on graph condensation and then introduce the algorithm.

4.1 Graph Condensations

As mentioned in Subsection 2.2, we model dependencies between appliances through a directed graph $G = (\mathcal{A}, E)$. In this graph, nodes are appliances and there is an edge (a_i, a_j) if a_i needs a_j to work or the user has a strong preference towards using them together. According to our perceived-value user utility function $U_{SB}()$, given a set of appliances $S \subseteq \mathcal{A}$, an appliance provides utility only if all its dependencies are satisfied by the appliances in S. As a result, for example, a *cycle* in this graph identifies a set of appliances that should be selected all together; otherwise, their individual utility would be zero. Therefore, we can merge such appliances in one single *super-appliance*, i.e., one single node in the graph representing all of them. This basic idea is developed in the following by using the concept of *Strongly Connected Component* and is at the basis of the graph reduction.

Definition 4.1 (Strongly Connected Component (SCC) [11]). Given a directed graph $G = (V, E)$, a strongly connected component (SCC) is a maximal subgraph $\hat{G} = (\hat{V}, \hat{E})$ such that for each $u, v \in \hat{V}$ there exists a path from u to v, and from v to u, in $\hat{G}$. In other words, any two vertices in an SCC are mutually reachable.

It is well known that any directed graph can be decomposed into a set of disjoint SCCs $\hat{G}_1, \ldots, \hat{G}_k$ [22, 46]. This set can be computed efficiently by using Tarjan's algorithm, which is based on depth-first search (DFS) traversal of the graph [46].

In the context of this article, an SCC in the dependency graph G identifies a set of appliances that mutually rely on each other. As a result, selecting any subset of them does not increase the perceived-value user utility. For this reason, we reduce the dependency graph by condensation into a single super appliance node s_i all appliances belonging to the SCC $\hat{G}_i$ of G, that is:

$$s_i = \{a_j : a_j \text{ belongs to the } i^{\text{th}} \text{ SCC } \hat{\mathrm{G}}_\mathrm{i} \text{ of the graph } G = (\mathcal{A}, E)\}.$$

By using such super appliances, we can shrink the dependency graph by generating the *condensation graph* as follows.

Definition 4.2 (Condensation graph [42]). The Condensation of a directed graph $G = (\mathcal{A}, E)$ is a Directed Acyclic Graph (DAG) $G' = (\mathcal{A}', E')$, where:

- $\mathcal{A}' = \{s_i : s_i$ is a SCC of the $G\}$;
- $E' = \{(s_i, s_j) : \exists(u, v) \in E$ such that $u \in s_i, v \in s_j\}$.

In fact, vertices in Condensation graph are super appliances. Note that a super appliance, s_i, has dependency to s_j if and only if s_i contains at least one appliance that is dependent to any appliance in s_j. However, there is no appliance in s_j that depends on an appliance in s_i, since both s_i and s_j are maximal by definition of SCC. It is possible to prove that the condensation graph G' is unique.

THEOREM 4.3. *Given a directed graph, $G = (\mathcal{A}, E)$, the reduced version of this graph obtained by taking condensation is unique.*

PROOF. The SCCs of a directed graph are unique [46]. Therefore the condensation graph is uniquely defined following the steps in Definition 4.2. □

The CODY algorithm performs the selection of appliances on the condensed graph G', therefore working at the granularity of the super appliances. Potentially, this may reduce the solution space and result in sub-optimal solutions, since the algorithm looses the ability of selecting appliances individually. In the following theorem, we prove that the optimal set of appliances that maximizes the utility function in the original graph G corresponds to the same optimal solution calculated in the condensed graph G' at the granularity of super appliances.

THEOREM 4.4. *The set of appliances S^*, optimal solution of the optimization problem in Equation (3) calculated on the dependency graph $G = (\mathcal{A}, E)$ is also the optimal solution of the same problem calculated on the condensed graph $G' = (\mathcal{A}', E')$.*

PROOF. According to the optimization problem in Equation (3), an appliance a_i can contribute with its utility to the solution only if all its dependencies are satisfied, i.e., if $z_i = 1$. This occurs only if, in turn, also the dependencies of a_i's dependencies are satisfied, and so on, recursively. Let $Y : n \times n$ be the matrix containing the dependency information, i.e., the elements $y_{i,j}$ defined for the optimization problem. We can calculate the *transitive closure* of Y as $Y^n = \overbrace{Y \times Y \times \cdots \times Y}^{\mathrm{n}}$. The matrix Y^n contains 1 in position i, j only if it is possible to reach a_j from a_i in G, i.e., a_i depends on a_j, either directly or indirectly.

Now, given a solution $S \subseteq \mathcal{A}$, an appliance $a_i \in S$ can contribute to the utility $U_{SB}(S)$ calculated on the dependency graph G only if all the appliances in $D_i = \{a_j \mid Y^n[i, j] = 1\}$ are in S. Let us now consider the condensation graph G' and the super appliance s_k containing a_i. Clearly, D_i contains all the appliances in s_k, plus some additional dependencies that are not part of the strongly connected component s_k. Nevertheless, such additional dependencies are kept in the condensation graph G' as edges between super appliances. As a result, the value of the utility $U_{SB}(S)$ is the same when calculated for the original dependency graph G and for the condensed graph G'. Since this applies to any set $S \subseteq \mathcal{A}$, it is also true for the optimal solution to the problem. □

ALGORITHM 1: Condensed Dependency (CODY)

Input: Dependency graph, Sets of appliances' utility, u_i, and power consumption, e_i, for each $a_i \in \mathcal{A}$, budget B.
Output: Set of selected appliances S_C.
Generate the condensed graph $G' = (\mathcal{A}', E')$;
$S_C = \emptyset$;
$R = \mathcal{A}'$;
while $R \neq \emptyset$; **do**
  Let $\mathcal{A}'_0$ be the set of nodes in $\mathcal{A}$ with zero outdegree;
  $s_i^* = \underset{s_i \in \mathcal{A}'_0}{\text{argmax}} \frac{U_{SB}(S_C \cup \{s_i\}) - U_{SB}(S_C)}{C(\{s_i\})}$;
  if C $\left(S_C \cup \{s_i^*\}\right) \leq B$ **then**
    $S_C = S_C \cup \{s_i^*\}$;
    Remove s_i^* from the reduced graph;
    $R = R \setminus \left\{\{s_i^*\}\right\}$;
  end
  else
    $R = R \setminus \{s_i^*\}$;
  end
end
Return S_C

4.2 Appliance Selection

CODY selects the appliances iteratively, given the condensed graph G'. This phase of the algorithm exploits the fact that the graph G' is a DAG, and in a DAG there is always at least a node with zero outdegree [11]. These super nodes[2] have no dependencies, and thus they can directly contribute to the utility. Let $\mathcal{A}'_0$ be the set of super appliances with zero outdegree at the current iteration. The algorithm selects the super node s^* that maximizes the increase in the objective function divided by the cost of adding all appliances in s^*. These appliances are added to the solution S_C only if the budget is not exceeded. Subsequently, all appliances in s^* are removed from G'. As a result, at the next iteration there will be new super nodes with zero outdegree in $\mathcal{A}'_0$. The algorithm terminates as soon as there are no more nodes that can be selected. The pseudo code for the CODY algorithm is provided in Algorithm 1.

4.3 Algorithm Complexity

The complexity of CODY is dominated by two consecutive steps, first calculating the condensed graph and then the selection of appliances. We recall that $|\mathcal{A}|$ and $|E|$ represent the number of appliances and the number of edges in the original dependency graph, respectively. To obtain the condensed graph G', we first need to find all the strongly connected components in the original graph G. This can be done using the Tarjan algorithm, with complexity of $O(|\mathcal{A}| + |E|)$ [46]. Subsequently, we need to merge all nodes of a SCC into a single super node. The complexity of this step depends on the data structure used to represent the dependency graph. As an example, with an adjacency matrix it can be done in $O(|\mathcal{A}|^2)$. The while loop for selecting appliances removes one appliance from the set R at each iteration. Therefore, the loop executes at most $O(|\mathcal{A}|)$ iterations. At each iteration, finding the best appliance requires to calculate the function $U_{SB}()$ for each appliance in $\mathcal{A}'_0$. Given a set $S_C \subseteq \mathcal{A}'$, calculating $U_{SB}(S_C)$ requires to verify for every super appliance in S_C if all the dependency are satisfied within S_C. By keeping a simple data structure that stores the direct and indirect dependencies of every appliance, such as the *transitive closure* Y^n described

[2]Super node and super appliance are used interchangeably in this article.

in Theorem 4.4, this can be done in $O(|S_C|^2)$. Therefore, finding the best appliance s_i^* requires overall $O(|\mathcal{A}|^3)$, since $|S_C| \leq |\mathcal{A}'_0| \leq |\mathcal{A}|$. The overall complexity of the while loop is then $O(\mathcal{A}^4)$. As a result, the complexity of the CODY algorithm is $O(|\mathcal{A}| + |E| + |\mathcal{A}|^2 + |\mathcal{A}|^4) = O(|\mathcal{A}|^4)$.

5 COMPARISON ALGORITHMS

In this section, we describe two approaches that we use for comparison with the CODY algorithm. The first approach has been recently proposed in Reference [9], while the second one is a baseline Greedy approach, which we introduce here, that does not exploit graph reductions.

5.1 A Recently Proposed Knapsack-based Solution

Similarly to the problem studied in this article, the authors of Reference [9] considered the problem of maximizing user satisfaction in an energy constrained scenario. However, this work has a simplified model to define such satisfaction, based on the concept of *importance factor* of appliances. Specifically, the authors define $\lambda_i \in [0, 1]$ as the fraction of time that a user uses the appliance a_i. The importance factor γ_i of appliance i is defined as:

$$\gamma_i = \frac{\lambda_i}{\sum_{h=1}^{n} \lambda_h}. \tag{8}$$

Therefore, γ_i represents the relative usage time of appliance a_i with respect to the other appliances. The approach assumes that the importance factor γ_i measures the contribution of appliance a_i to the utility of the user. Therefore, given a set of appliances S, the utility that results from using such appliances $\sum_{a_i \in S} \gamma_i$.

Given the importance factors and an energy budget B, the approach solves the knapsack-based problem in Equation (9), where the x_i and e_i have the same meaning as the formulation of our problem in Section 3,

$$\underset{x_i}{\text{maximize}} \sum_{i=1}^{n} \gamma_i x_i, \tag{9}$$

$$\text{subject to} \sum_{i=1}^{n} x_i e_i \leq B. \tag{10}$$

This approach has two main limitations: It largely oversimplify the concept of user utility, and it overlooks the existence of dependencies between appliances. For these reasons, it achieves lower performance as described in Section 6. Note that even if solving the problem in Equation (9) is NP-Hard, we solved it optimally in the experiments for fair comparison.

5.2 Greedy Approach

In this subsection, we describe a baseline Greedy algorithm that we use for comparison with CODY. The algorithm follows the standard heuristic approach to solve of the knapsack problem [11]. Nevertheless, we use the function $U_{SB}()$, defined in Equation (2), to calculate the utility of the appliances to take into account the perceived value factors as well as the dependencies.

The algorithm works in iterations and starts from an initial empty solution $S_G = \emptyset$. At each iteration it chooses an appliance, among those not already in S_G, which maximizes the ratio between the perceived-value user utility over the appliance's power rating. In other words, it chooses the appliance $a_i \in A \setminus S_G$ that maximizes $\frac{U_{SB}(S_G \cup \{a_i\})}{e_i}$. Such appliance is chosen if the energy budget is not exceeded by adding it to S_G. The pseudo-code of the algorithm is shown in Algorithm 2.

ALGORITHM 2: Greedy Approach

Input: Dependency graph, Sets of appliances' utility, u_i, and power consumption, e_i, for each $a_i \in \mathcal{A}$, budget B.
Output: Set of selected appliances S_G.
$S_G = \emptyset$;
$R = \mathcal{A}$;
while $R \neq \emptyset$; **do**
  $a_i^* = \underset{a_i \in \mathcal{A} \setminus S_G}{\text{argmax}} \frac{U_{SB}(S_G \cup \{a_i\})}{e_i}$;
  if $C(S_G \cup \{a_i^*\}) \leq B$ **then**
    $S_G = S_G \cup \{a_i^*\}$;
  end
  $R = R \setminus \{a_i^*\}$;
end
Return S_G

6 EXPERIMENTAL RESULTS

In this section, we describe the results of our perceived-value driven framework for energy management. We first discuss the large-scale online experiment used to quantify our perceived-value model presented in Section 2. Then, we compare the performance of the CODY algorithm with the approaches described in Section 5 as well as with the optimal solution, using synthetic and realistic dependency graphs. Furthermore, we use online surveys to validate the benefits of our approach as perceived by human subjects. Finally, we evaluate the performance of the proposed algorithm through an in-person experiment realized at the Missouri University of Science & Technology Solar Village. In this in-person experiment, a personalized list of appliances, dependency graph, and the utility values are derived for each considered smart home and user. All human subjects experiments described in this section were approved through Missouri University of Science & Technology's Institutional Review Board (IRB). The codes and data regarding the experiments in this article are available at https://github.com/khamesi/Perceived-Value-User-Utility.git.

6.1 Large-scale Online Experiment

To investigate user perceptions and behaviors as they relate to the use of electric appliances, we conducted a large-scale online experiment with the goal of investigating whether users generally find certain appliances more important than others and whether these perceptions change under different energy contexts.

6.1.1 Experimental Design. Participants first read an informed consent letter advising them on their rights, expectations, and compensations. Participants were then randomly assigned to one of the *energy availability contexts* described in Section 2. They were presented with a description of the energy scenario and a single definition of one of the five aspects of well-being. They were instructed to inspect a list of appliances on the left side of the screen and to indicate their perceived value and importance of these appliances in achieving those aspects of well-being. They made this indication by dragging and dropping items from the appliance list into an empty box on the right in ranked order of how important each was to that particular aspect of well-being described. Participants were encouraged to rank at least five items (with a pop-up message appearing if they ranked fewer than five) but were told they could rank as many appliances as they liked. This was repeated for the remaining four aspects of well-being (presented in random order) while the energy context always remained the same for the participant. Critically, we also asked participants to indicate how important each of the five aspects of well-being were to their overall well-being so that their responses could be combined in Equation (1).

Note that in developing the survey materials for this large-scale online experiment in which participants would indicate the perceived value of home electrical appliances in contributing to well-being, we recognized it was not possible to predict precisely which appliances each individual participant would have in their current home; at the same time, providing an exhaustive list of all possible appliances would be cumbersome for participants to go through. As such, a generic subset of appliances were presented. To help determine which appliances to include in the generic subset, we conducted an informal poll of college students[3] in which they listed all of the appliances they would expect to see in various rooms of a typical home in the U.S. (e.g., kitchen, living room, bedroom, and so on). Of over 200 separate responses, 99 unique electrical appliances were listed by respondents. A subset of 21 appliances were selected, accounting to 98.7% of total variance in responses. The subset was double-checked against industry and market data on home appliance retailers to confirm that the highest selling household appliances in the U.S. were included in the list [33].

Finally, participants were asked a set of manipulation check questions to ensure that they paid attention during the study (participants who received 50% or less on the manipulation check were not included in the final analysis).

6.1.2 Participants. Participants were recruited using Amazon Mechanical Turk [5]. A power analysis using G*power [18], assuming a moderate effect size and alpha error probability of .05 indicated a sample size of approximately 1,400. Nearly 1,600 participants responded to the survey request; after participants who scored less than 50% on the attention check questions were eliminated from the dataset, our total sample size was 1,457. The mean age was 35.74, with a standard deviation of 11.3. and 52.3% of the subjects were male, while 47.7% were female. The ethnicity distribution was as follows: 75.4% White, 13.5% Asian, 8.5% African American, 1.4% American Indian or Alaskan, and 1.1% Other. The education distribution was: 10% High School or Less, 34% Some College, 56% Bachelor's or Higher. The employment status distribution was 65% paid employees, 17% self-employed, 6% unemployed looking, 8% unemployed not looking, and 4% students. Finally, the income distribution was 29% under $29,999, 60% between $30,000 and $99,999, and 11% over $100,000.

6.1.3 Summary of Results. An aggregated overall well-being score was calculated for each user appliance as described in Section 2.3. We then conducted a series of Analysis of Variance (ANOVA) tests to identify differences in how appliances were perceived as contributing to overall well-being across our five energy availability contexts. We were most interested in determining whether appliances in the standard energy availability context were ranked systematically (as opposed to randomly), and if so, whether there were departures from that rank order in any of the other four energy availability conditions. We observed a statistical significant difference in terms of mean utility value for the higher ranked appliances in the standard condition (see Table 1), and we found the rank order of these appliances (for example, Computer, Cell phone, Television, Refrigerator, and Air Conditioner) remained generally the same across the different energy contexts. This suggests that perceptions about these appliances remains stable even in the times of energy shortage. Further analysis of these behavioral findings and their psychological implications are forthcoming but are beyond the scope of this article. Here, we do not attempt to generalize about particular rank order changes across the conditions or about the objective utility values of each appliance. Instead, we demonstrate the value participants perceive in appliances, in terms of how they contribute to overall well-being, is not random, and instead, participants perceived some appliances as being significantly more valuable than others. We were able to assign a generic relative utility value for

[3]Described in footnote 1.

Table 1. Summary of Survey Results for Highest-ranked Appliances

		ANOVA			
Appliance	Rank	$U_{SB}()$	F (4,1452)	p	Effect size (η_p^2)
Computer	1	4.260	3.003	.018	.008
Phone/CellPhone	2	4.260	3.778	.005	.010
Television	3	2.138	5.390	.000	.015
Refrigerator	4	2.060	4.230	.002	.012
Air/Conditioner	5	1.618	2.646	.032	.007

each appliance that quantifies users' overall perceptions about these appliances in relation to each other across multiple dimensions of well-being and energy contexts.

6.2 User Utility Maximization

We now study the performance of CODY using both synthetic and realistic appliance dependency graphs. To this purpose, we compare through simulations the performance of CODY with the approaches described in Section 5, as well as to the optimal solution of the optimization problem in Section 3, denoted by OPT in the figures. Then, we conducted an online experiment to compare the perception of the solutions found by CODY and the knapsack approach across different contexts.

6.2.1 Synthetic Dependency Graphs. We use synthetic graphs to investigate the performance of the considered approaches under different dependency graphs structures, e.g., number of nodes and edge density. To this purpose, we adopt the Erdős–Rényi (ER) model [34] and the Barabási-Albert (BA) model [3]. These models generate graphs with completely different characteristics. Specifically, ER generates a graph with a binomial degree distribution, while BA returns a scale-free graph with power-law degree distribution. To generate the dependency graph based on the ER model, we first create a graph with the number of nodes equal to the number of desired appliances, denoted by n. Hence, for each ordered pair of nodes (u, v), we use the edge probability to determine if u depends on v and create an edge in the graph accordingly. Differently, in the BA model, we start with an initial empty graph with $m_0 = \lceil \frac{n}{2} \rceil$ nodes. The rest of the nodes are added to the graph one at a time. Each new node is connected to m existing nodes with a probability proportional to their current degree. The edge probability value in the ER model can vary between 0 and 1, while the value of m in the BA model can vary between 0 and $\lfloor \frac{n}{2} \rfloor$. An increase of these parameters results in an increased density of the dependency graph. The appliances' individual utility is picked at random in the interval $[10, 100]$. Note that since in the synthetic dependency graphs nodes do not correspond to actual real appliances, we use the same utility value for appliances for all approaches, including the knapsack-based approach proposed in Reference [9]. In the experiments with realistic dependency graphs detailed in Subsection 6.2.2, we instead use the utility values derived by our perceived-value driven models. Finally, the power rating values for each appliances are chosen randomly in an interval $[20, 3000]$. Note that this represents a realistic interval for power ratings according to the experiments in Reference [39].

Figures 2 and 3 illustrate the results under different values of available energy budget for ER and BA model, respectively. For the ER graphs, we use 25 appliances and an edge probability of 0.1, while for the BA model, we adopt 30 appliances and $m = 5$. As observed, our proposed algorithm, CODY, achieves a utility close to the optimal, OPT, under all budget settings. All algorithms provide similar user utility in case of very low or very high energy budgets. This happens because when the budget is low, very few appliances can be selected, while when the budget is high, all appliances

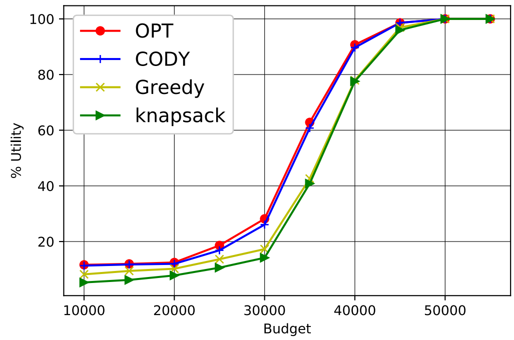


Fig. 2. ER model: Num. of appliances = 25, Edge Probability = 0.1.

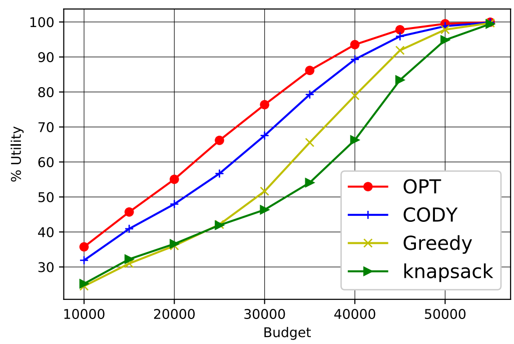


Fig. 3. BA model: Num. of appliances = 30, m = 5.

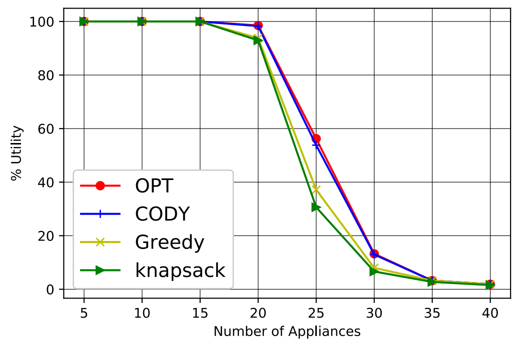


Fig. 4. ER model: Edge Probability = 0.1, Budget = 35000.

can be selected, regardless of the selection algorithm. The knapsack approach does not consider appliance dependencies; as a result, even though it optimally solves an NP-Hard problem, the lack of dependency consideration results in a low user utility. However, the Greedy takes into account the dependencies in the calculation of the objective function; however, by neglecting the fact that all appliances belonging to one super appliance should be picked together to contribute to the user utility, Greedy results in a poor performance.

Figures 4 and 5 show the results by increasing the number of available appliances. Here, we set the budget to 35000 and the edge probability to 0.1 for ER model and budget of 30000 and m equal to 5 for the BA model. Similarly to the previous scenario, all the approaches perform similarly

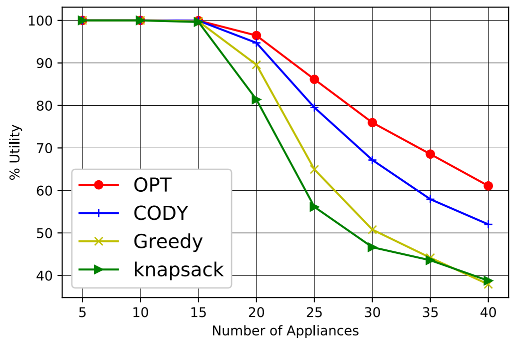


Fig. 5. BA model: $m = 5$, Budget = 30000.

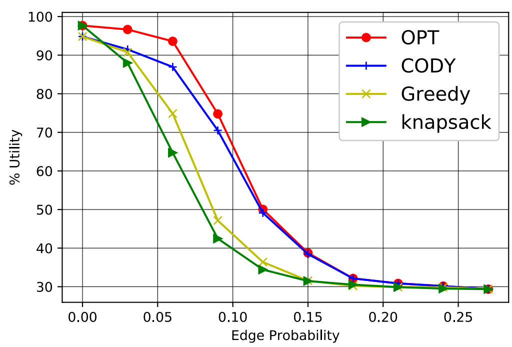


Fig. 6. ER model: Num. of appliances = 25, Budget = 35000.

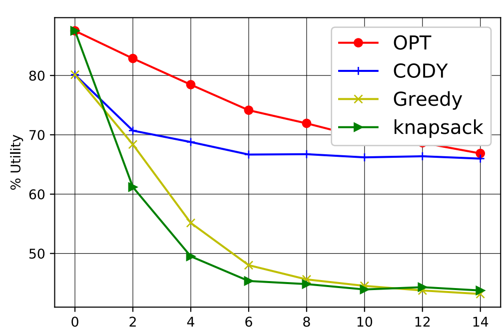


Fig. 7. BA model: Num. of appliances = 30, Budget = 30000.

when the number of appliances is very low or too high with respect to the budget. However, as the number of appliances increases, CODY demonstrates its superiority compared to the other approaches. Specifically, CODY achieves near optimal utility under the ER model, while it is within 16% of the optimal value under the BA model. This is due to the relatively reduced number of strongly connected components that occur under the BA model with respect to the ER model for a given number of appliances in the graph.

Figures 6 and 7 illustrate user utility under different edge densities in synthetic dependency graphs. The edge density is varied by increasing the probability p in the ER model and by increasing m in the BA model. Note that in the case of edge density equal to zero, there is no dependency, and therefore the problem reduces to a standard knapsack problem. Hence, the knapsack approach achieves optimal solution in such cases. Nevertheless, once the edge density increases, knapsack performance drastically degrades. It is worth mentioning that in a very dense dependency graph, each appliance depends on most of the others, making the budget insufficient to pick all of them and thus it provides a low utility. Therefore, increasing the edge density degrades the performance of all the approaches in general. Hence, for a similar reason as before, the CODY approach provides superior performance compared to the other algorithms and converges to the optimal solution as the edge density grows. As a matter of fact, Figure 7 clearly highlights the superiority of the CODY algorithm in relatively dense dependency graphs.

To summarize, the simulations results show that the CODY algorithm attains the highest user utility close to the optimal value (OPT), achieved by solving the optimization problem in Section 3. Such notable results are obtained due to the fact that the CODY approach considers dependencies between appliances and makes decision in a way that all appliances in the solution contribute to the final utility. Additionally, it gives preference to appliances that provide high utility compared to their power rating requirements.

6.2.2 Real Dependency Graphs. To validate our approach in a more realistic setting, we designed a survey to identify a realistic dependency graph that better reflects actual home appliance dependencies. It may be tempting to derive a set of "real-world" dependencies intuitively, without asking actual users. For example, the utility or value of a WiFi router is most likely dependent on the availability of the device that needs internet connectivity such as a computer. However, some dependencies will undoubtedly be highly specific to individual users and other dependencies may be less black and white. For example, one users may perceive a clothes washer to be useless if the hot water heater is not also available, while another user, who only does cold-water washes, may not share this perception. We examine these types of personalized dependencies in our final experiment, but as an interim step to validate our general approach in handling dependencies information, we conducted an online survey to gather a variety of opinions about critical or strongly preferred dependencies for a subset of 21 appliances.

Experimental design. Participants first read an informed consent letter advising of their rights, expectations, and compensations. Participants were then presented with a randomly assigned appliance from the predefined list set and asked to consider whether they would normally use that appliance in concert with other appliances. Responses were captured using a drag-and-drop format with the complete list of appliances on the left side of the screen (minus the randomly assigned appliance) and two empty boxes on the right side of the screen. Participants were asked to consider whether they felt any items from the left were critical or strongly preferred to be used at the same time as the assigned appliance. Participants were provided definitions of these two terms where a critical appliances was characterized as one that, without such the assigned appliance "would not work as intended, or would be useless to you," and a strongly preferred appliances was characterized as one that, without such the assigned appliance "would be less enjoyable, less useful, or otherwise unsatisfying." If any item(s) from the list on the left was perceived as one of these two, then participants were asked to drag that item into either the box labelled "critical" or the box labelled "strongly preferred." Participants could drag and drop as many appliances as they liked. This was repeated for an additional four randomly assigned appliances for a total of five appliances per participant.

Participants. Participants who had previously taken part in experiment 6.1.1 were invited through Amazon Mechanical Turk to complete this survey. The survey was opened up to the first 100 respondents. Because the task was somewhat repetitive and arduous, we only asked participants

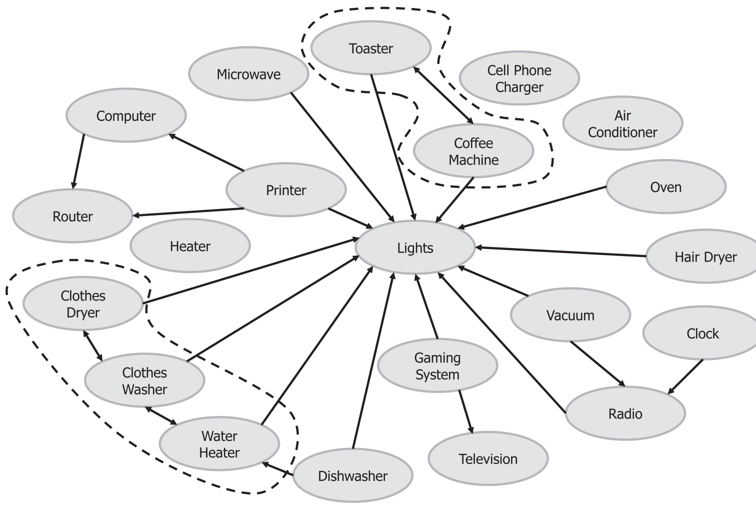


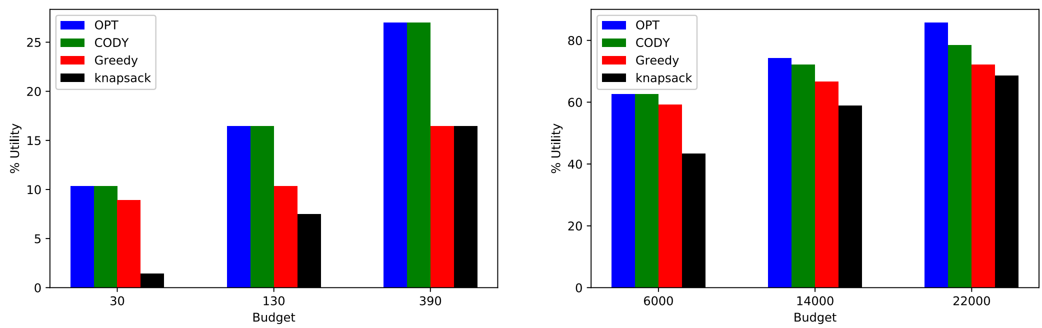
Fig. 8. Dependency graph based on real data. The super appliances are indicated by dash lines.

to consider five randomly assigned appliances out of the set of 21. This sample size was chosen to ensure that each appliance was considered by at least 10 participants. No participants were eliminated from the dataset. The mean age was 38.78, 40% of the subjects were female, and the ethnicity distribution was 89% white, 14% Black or African American, and 2% Asian; income and education demographics were not collected for this survey.

Summary of Results. We aggregated the results and generated a dependency between two appliances using a threshold of 15%, defining the minimum percentage of users that identified such dependency as critical or strongly preferred. This results in a dependency graph with 21 appliances and 26 edges, as depicted in Figure 8. The figure also shows the strongly connected components identified by our algorithm. This clearly refers to the activity of washing and drying clothes using warm water. We tried different settings of the thresholds and obtained similar results. For OPT, CODY, and Greedy, we adopted the utility values from the first online experiment described in Section 6.1. Conversely, for knapsack, we used the length of time an appliance is used on average to determine its utility [29, 48], as assumed by this approach [9]. Finally, we use realistic data for power consumption from the datasets of Home Energy Saver by Lawrence Berkeley National Laboratory and Tracebase [29, 39].

Figure 9(a) and (b) presents the performance comparison under different budget scenarios. In Figure 9(a), we envision a home running on a generator during a blackout and therefore with very limited energy availability. As illustrated, similarly to synthetic graphs, the CODY algorithm outperforms other approaches also under real dependency graphs and utility values. Compared to the knapsack approach, which does not consider perceived-value, the user utility achieved by CODY is significantly higher. This shows the importance of considering our perceived-value to quantify the utility rather than the amount of time an appliance is used, as well as the dependencies between appliances.

In addition, Figure 9(b) presents the performance of different algorithms for higher budget regime. This scenario may refer to a smart home running on renewable energy stored in batteries. Also in this case, CODY shows superiority over other algorithms. However, in this case, knapsack is less penalized as the budget allows to pick more appliances and therefore achieves higher utility.



(a) Low budget (b) High budget

Fig. 9. Performance comparison of different algorithms under different budget scenarios.

6.2.3 User Perception—Online Experiment. Using the generic appliance utility values and dependencies derived previously, we conducted a second online experiment with a new set of participants to investigate broad user perceptions of the solutions provided by CODY relative to those provided by knapsack. This approach not only informs perceived performance of CODY but also aids in understanding whether the generic utility values and dependencies are generalizable to some degree, which in turn, informs whether default settings for such a system would be meaningful in future scenarios when customized utility values are not immediately available. Fully personalized appliance lists, utility values, and dependencies are used in our third and final experiment described in Section 6.2.4.

Experimental design. Participants first read an informed consent letter advising of their rights, expectations, and compensations. Participants were randomly assigned to an experimental condition in which they read one of three possible scenario's manipulating the *Duration* of the power shortage as either 1 hour, 4 hours, or 12 hours. The following is an example of the experimental condition:

> Imagine you are at home, early in the morning on a mild day when a power outage in your area occurs. This shortage is expected to last for about (Duration). However, rather than having no power in the house at all, the home you are living in is equipped with a smart energy management system and smart appliances that allow the power company to supply power to a few specific appliances.

Participants were then advised they would be presented with sets of appliances to review and that they should indicate which of the two sets they would most prefer if they were the only appliances that could be powered for during the next hour (or 4 hours or 12 hours). Nine sets of appliances were derived using either the CODY or knapsack. For CODY, we used the real dependency graphs discussed in Section 6.2.2.

These appliance sets were rendered to the participants in both text form and as icons (see Figure 10). Two sets were shown at a time, a CODY solution and a knapsack for a given budget amount, and only one budget was shown per page. To make the comparison between the two as simple as possible, the appliances in each set were in the same order with new or unique appliances always at the end of the set. After indicating their preferred appliance sets, participants answered three manipulation and attention check questions as well as demographic questions.

Participants. Once again, participants were recruited using Amazon Mechanical Turk [5] from the pool of volunteers who had previously completed Experiment 6.1.1. A power analysis using

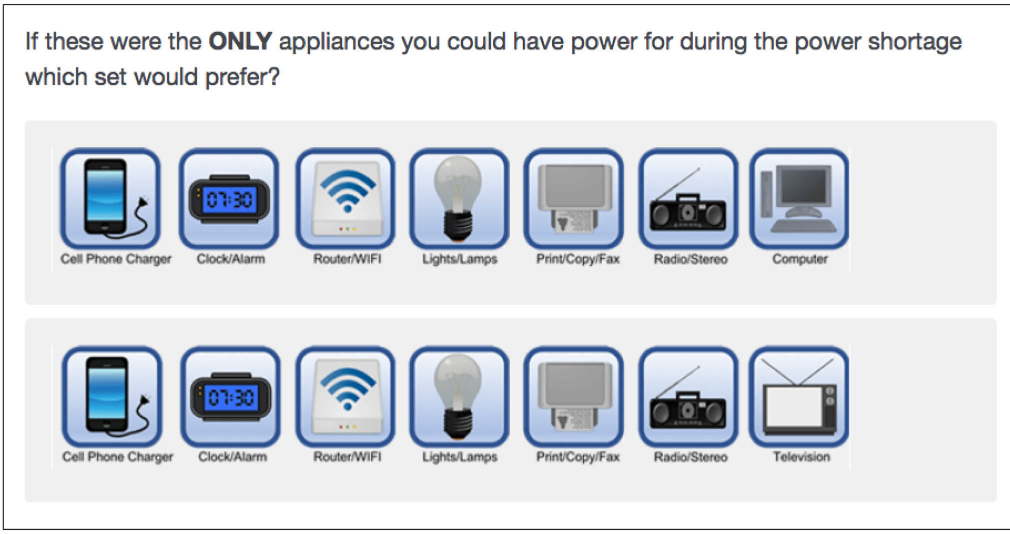
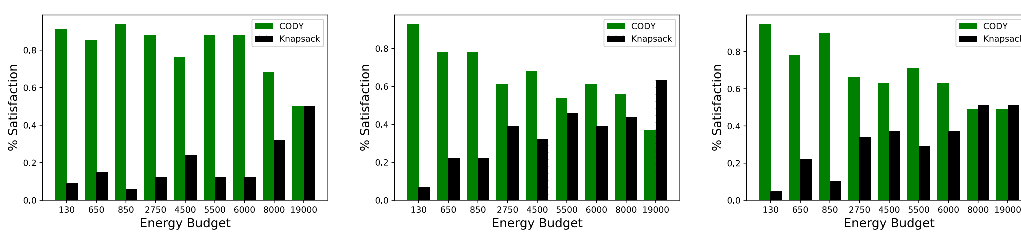


Fig. 10. A snapshot from the online experiment for the energy budget of 850.



(a) One hour (b) Four hours (c) Twelve hours

Fig. 11. User satisfaction under different budget constraint and different time durations.

G*power [18], assuming a small effect size and alpha error probability of .05 indicated a sample size of approximately 110. Approximately 120 participants responded to the survey request, after four participants who scored less than 50% on the attention check questions were eliminated from the dataset, our total sample size was 114. The sample was 66% male, Mean age 34 years (SD 9.87), 86% White, 6% Black or African American, 3.6% Hispanic, 3.4% Asian, 1% Other. In terms of education and income, 92.8% reported having a Bachelor's or Higher and 53.4% reported making less than $49,999, 33.6% reported $50,000–$99,000, and 12.9% reported making more than $100,000.

Summary of Results. Figure 11(a), (b), and (c) shows user responses under different energy budgets for 1, 4, and 12 hours scenarios, respectively. As observed, CODY largely outperforms the knapsack algorithm in the majority of scenarios. Both methods demonstrate close performance in case of higher energy budget, similarly to Figure 9(b), since most appliances are listed as available. We can also observe variability with respect to the duration of the energy shortage. These results suggest the need for further research in which the time dimension is specifically taken into account.

Users general preference for CODY solutions compared to Knapsack may be attributed to both differences in utility and for the consideration of dependency. For example, under the energy budget of 850, the knapsack appliance list includes "Cell Phone/Phone Charger, Clock/Alarm, Router, Lights/lamp, Printer/Copy/Fax/Scanner, Radio/Stereo, Television." However, the appliance

Table 2. User Perception—Online Experiment: Binomial Comparisons of CODY to Knapsack with Output Organized by Condition (Duration) Using Test Probability of .50

Budget	1 hr (N = 34, df = 33)		4 hr (N = 41, df = 40)		12 hr (N = 41, df = 40)	
	Mean	SE	Mean	SE	Mean	SE
130	0.91**	0.049	0.93**	0.041	0.95**	0.033
650	0.85**	0.062	0.78**	0.065	0.78**	0.029
850	0.94**	0.041	0.78**	0.065	0.9**	0.056
2750	0.88**	0.056	0.61	0.077	0.66	0.056
4500	0.76*	0.074	0.68*	0.074	0.63	0.029
5500	0.88**	0.056	0.54	0.079	0.71*	0.030
6000	0.88**	0.056	0.61	0.077	0.63	0.030
8000	0.68*	0.081	0.56	0.078	0.49	0.029
19000	0.50	0.087	0.37	0.076	0.49	0.033

Note that "**" refers to $p < .001$, and '*' to $p < .05$.

list given by CODY is "Cell Phone/Phone Charger, Clock/Alarm, Router, Lights/lamp, Printer/Copy/Fax/Scanner, Radio/Stereo, Computer." Inattentive to the concept of appliance dependency, knapsack picks the printer that may be less useful in the absence of a computer. Furthermore, even if a computer may not be used for a significant time during the day (causing it to rank low in utility under knapsack), it is perceived as the *most* important appliance according to our results described in Section 6.1. By considering the length of time as a measurement of importance and considering appliances independently, knapsack misrepresents user perceptions of the overall utility of appliances. A snapshot of the survey corresponding to this budget and the appliances lists is depicted in Figure 10.

Finally, we show in Table 2 a statistical analysis of the results obtained through *hypothesis testing*, specifically with binomial comparison. The purpose is to show the observed difference in the preference given to CODY versus knapsack is statistically meaningful. The test assumes the probability of picking CODY over knapsack to be .5; it compares the observed proportion, i.e., how often participants actually picked CODY over knapsack and indicates whether it is significantly different from the expected proportion given the sample size. CODY outperforms knapsack in all scenarios, except for the budget 19000. However, when the budget is very high, the two approaches return a very similar set of appliances, generating no meaningful preference in the perception of the returned sets.

6.2.4 User Perception—Real-field Experiment. Finally, we investigate our proposed model through a real-field experiment at the Solar and Eco Village community located at Missouri University of Science and Technology campus. This is a planned community composed of student-designed solar homes, occupied on a yearly basis by students, faculty, or temporary residents. We conducted a small-scale experiment with residents living in and around the village. In this experiment, we were able to gather user's fully customized data for the appliance list, utility values, and dependencies.

Experimental design. Participants first read an informed consent letter advising of their rights, expectations, and compensations. The study took place in three parts. First, we conducted an in-person interview with each participant to gather a list of the user's appliances currently in the home. We asked the participants to estimate their duration of use for each appliance on a daily, weekly, or monthly basis (used to derive the appliance utilities used by knapsack), and, finally, we asked the users to indicate any critical dependencies for all of the appliances in their home after

Table 3. User Perception—Real-field Experiment: Binomial Comparisons of Our Solution to Knapsack Organized by User, Showing the Observed Probability for Selecting Our Solution and the Significance Values Assuming a Test Probability of .50

User	Number of comparisons	Observed Probability (Our solution)	Significance (p)
1	18	0.78	0.031
2	12*	1.0	<0.001
3	18	0.78	0.031
Group	48	0.83	<0.001

An omnibus test for the group is also included. "*" Note that user 2 only ranked 14 appliances as being valuable so we had to exclude unranked appliances from the algorithm that resulted in fewer unique solutions for comparison.

explaining critical dependencies in the same manner they were explained in Section 6.2.2. After the in-person interview was complete, we repeated experiment 6.1 using the standard energy context, to assess user perceptions about the relative values of each appliance they had in their homes. This allowed us to obtain user preference for the 4-hour and 12-hour conditions, this time using the information gathered from the interview and survey in the previous steps. So, for each user, the list of appliances were customized based on their unique appliances, estimated duration of use, perceptions about utility, and perceptions about dependencies. However, they were offered knapsack solutions customized based on their estimated duration of use. Energy consumption data was held constant for appliances across the approaches. The final comparisons were made about one week after the initial interview and utility survey was completed.

Participants. Three residents were able to participate in the final experiment. Although the sample size was small, each participant provided 12–18 comparisons for a final total of 48. The residents were all female, with a mean age of 21 (standard deviation of 1.73), and primarily identified as white. Residents were offered up to $30 for completing all three components of the study.

Summary of Results. Residents had between 33 and 35 appliances in their homes with mean of 33.7 and standard deviation of 0.94. Across both the 4- and 12-hour scenarios and across all budgets, the three participants each preferred the proposed approach in this work more often than the knapsack solution. Table 3 shows results of binomial comparisons (as described in Section 6.2.3) by user, where the probability of picking each list is once again assumed to .5. All three tests suggest the user's preference for the perceived-value utility proposed in this work over knapsack is statistically significant. As a group, participants preferred our approach 83% of the time, and this result was also statistically significant ($p < .001$).

7 RELATED WORK

According to many works in the literature, the energy management problem in a smart home, focusing on the selection of the best subset of appliances to use in a given time interval, can be formulated as a multi-objective optimization problem [6]. Among the components included in such a formulation, the cost of energy consumed by appliances is obviously predominant, followed by the users' well-being. The energy consumption is generally modeled according to an unbiased evaluation, while the model of users' well-being is characterized by a high heterogeneity among different works. The most common approaches are (i) the adoption of a weighted sum of the objective functions, with a set of weights that explicitly defines the tradeoff between cost and comfort, as in References [31, 36]; (ii) the use of a pure multi-objective optimization based on the Pareto Dominance criterion, as in References [26, 41]; and (iii) the formulation of some criteria as constraints to be respected, and the optimization of a single objective function, as in References [37, 44, 47, 50]. The last approach, the second most common in the literature according to Reference [6], is also adopted in this work, since it is well suited to model real scenarios characterized by a constraint on energy consumption.

The authors of Reference [31] adopt an approach based on stochastic dynamic programming and they propose to fuse energy cost and user's comfort in a single objective function. The user's well-being is simply represented as a variable whose value is inversely proportional to the distance between the current environmental conditions (e.g., temperature) and the range preferred by the user. Such simplified model is very common in the literature focused on the interaction between smart homes and smart grids, but it is not suitable for modeling complex scenarios where a wider set of appliances is used.

In Reference [41], a pure multi-objective optimization system is proposed to select a fair tradeoff between minimizing the total energy cost and maximizing the utility perceived by users, through a Pareto dominance analysis. Here, the user's well-being is modeled through a variable that estimates the utility perceived by the user as a function directly dependent from the amount of consumed energy. The work described in Reference [26] presents a multi-objective problem in which the maximization of user's well-being, expressed as preferred range of environmental characteristics to be satisfied, is combined with the minimization of energy cost and pollution emissions.

The authors of Reference [37] propose an algorithm to identify the optimal scheduling of household appliances that respects the priorities expressed by the user and his or her comfort levels, once again expressed as preference range of environmental characteristics. The energy consumption is modeled as a constraint on the total energy consumption that must be maintained below a demand limit, as in this article.

The authors of Reference [50] model the problem of finding the appliances optimal scheduling by exploiting a game-theoretic approach, in which the user's well-being are related to the respect of time intervals during which he or she prefers to use a specific appliance; the most pressing preferences are expressed as constraints, while the others are included into the goal function to be optimized together with the minimization of the energy cost. Such user's well-being model, does not consider the dependencies among appliances.

In conclusion, to the best of our knowledge, previous works oversimplify user psychological perception of appliances and do not take into account the dependencies between appliances. The interdisciplinary approach of our work is the first that specifically takes into consideration psychological dimensions for energy optimization in smart environments.

8 CONCLUSION

In this article, we studied the problem of energy optimization in smart environments by incorporating previously unexplored social and behavioral aspects. Specifically, we derived the perceived importance of appliances through a psychological model and quantified it using real data from large-scale online experiments. The psychological model also includes dependencies between appliances formalized through a dependency graph. Then, we formulated an optimization problem to maximize the perceived-value user utility under an energy budget constraint. We showed that the problem is NP-Hard and therefore proposed a heuristic called CODY to solve the problem efficiently. CODY exploits a graph condensation technique that efficiently contracts the dependency graph and turn it into a unique directed acyclic graph. Results show that CODY outperforms previously proposed approaches on different types of synthetic and real datasets. Furthermore, we used an online and real-field experiments to compare CODY with a knapsack approach using human subjects. Results show that CODY is superior as it better captures user perceptions and needs under several budget constraints.

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