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CE 295 Data Science for Energy
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Final Project Report (Team 3)

I. Title & Team Members

Title: Co-Optimization of In-Home Energy Resources
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II. Abstract

In this study we modeled and generated optimal operation schedules for smart home energy devices over a 24-hour period (March 15, 2019) located in Berkeley, CA.

First, we modeled three devices – HVAC, a water heater, and a solar photovoltaic (PV) system. We optimized the operation of the HVAC and water heater by minimizing the total daily cost using a PG&E time-of-use (TOU) rate plan.

Second, we performed a co-optimization, where we minimize total costs under different tariff structures – a harsh tariff would pay customers $0/kWh for excess solar generation, while a generous tariff would pay market price.

We found that the HVAC heating schedule varied significantly according to different tariff structures under co-optimization, while, as modeled, the water heater operating schedule remained the same. We demonstrated that there are tangible, although relatively small, benefits of co-optimization (relative to parallel optimization) through reduced consumer costs under harsher tariff regimes, although little-to-no benefit under generous tariff regimes. However, under all tariffs, we found quantifiable grid benefits via a significant reduction of on-peak consumption.

These results may be used to better inform consumer energy device operation and electricity rate design, by quantifying the value and methods of co-optimization.

III. Introduction

A. Motivation & Background

There are several key changes happening on modern grids today: The rise of renewables, the decentralization of power generation (think rooftop solar, micro-grids), and the introduction of dynamic pricing schemes, such as time-of-use rates and demand response events. In parallel to these energy trends there has been an explosion in smart home and connected IoT devices. Taken together these energy and digital trends present an exciting opportunity.

Energy devices in the home may leverage intelligent control strategies to provide value to the occupant and the grid. The occupant may enjoy lower energy bills, improved comfort, and higher ease-of-use. And utilities, with a new grid asset, may call on customers to reduce their load in high-demand times to ease grid strain, and in the long term, defer capacity and transmission upgrades.

There are several smart energy devices on the market already, you can find smart thermostats (e.g., Nest, EcoBee), smart EV chargers, smart heat pump water heaters, and smart plugs.

But these devices operate in isolation and opportunities for coordinated control and co-optimization are underexplored. Now is the best time to explore these opportunities. At the end of 2019 Amazon, Apple, and Google all committed to use a standard communication protocol (Zigbee) [13]. And in February of 2021, Google reversed its prior decision to close off Nest's API to third parties. One rising cleantech startup – Span – is building out a smart electrical panel "so you can intelligently monitor and control your home energy." Understanding what "intelligent" control should look like in the future will be critical, and is what we aim to explore in this project.

B. *Relevant Literature*

a) *System Setup*

There has been extensive research on household devices' energy consumption modeling. It is common practice for appliances to be categorized as interruptible, non-interruptible, and base with power ratings. Some papers only include the basic household devices like the washing machine, water heater, dishwasher, and air conditioner [1,15,17], while others incorporate more secondary devices like hair dryer, vacuum cleaner, coffee maker, etc., reaching over 10 total household appliances [3,6].

Energy generation and storage are also often included in system setups found in literature. [1,3,7,9] included models for renewable energy sources (PV solar panels and wind turbines), batteries, and electric vehicles (EV). [11] included a water tank as energy storage. [12] proposes and compares two system level designs i.e. home energy storage (HES) and community energy storage(CES). In both HES and CES systems heat and electricity storage are used for water and space heating utilities.

b) *Optimization Methods*

Optimization tools are broadly used across home energy modeling. In [4] and [7], mixed integer linear programming was used to optimize the electricity cost. In [11], a mixed integer nonlinear programming model (MO-MINLP) was used.

Optimization methods using meta-heuristics, that include random exploration and improving by exploitation are utilized continuously in recent years. In [3], the authors deploy the Butterfly optimization algorithm (BOA), a new optimization technique introduced by Aroa and Sing. BOA falls under the umbrella of swarm optimization algorithms, in which each agent shares its experiences with the other butterflies based on distributing the fragrance over the distance. In a similar approach, [1] proposes the dragonfly algorithm to balance the trade-off between exploration and exploitation. That balancing is achieved by emulating the static vs dynamic behavior of a swarm of dragonflies. During the static behavior, the swarm of dragonflies is organized in small groups over a specific area to make prey. In a dynamic swarm, a large number of dragonflies migrate from one place to another over a long distance in order to find the best habitat for their living.

c) *Objective Functions*

Throughout literature, there are mainly three types of objective function. The first and most common one is electricity cost minimization [1,5,6,7,9,11,15]. In these studies, dynamic pricing schemes were considered. In [9], the paper considers energy transfer both to and from the grid and minimizes the total energy cost of the smart home by buying and selling electricity to the grid under a dynamic pricing scheme. User comfort maximization was another optimization goal through modeling [3,4,5,6,11,15]. [11] integrated thermal comfort and waiting time of the users to optimize the energy usage. Peak load minimization was also considered in [4], which could avoid grid instability and possible grid failure.

C. *Study Focus*

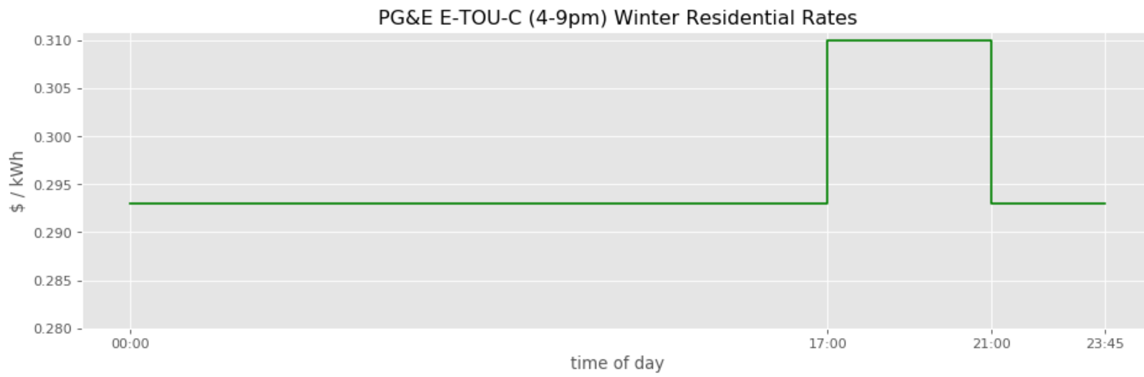
Our project will investigate opportunities for co-optimization between different home energy devices and appliances, aiming to minimize costs subject to device constraints. The goal is to understand and prove how homeowners can optimally reduce energy consumption from multiple sources in unison, reducing customer costs, flattening the electricity “duck” curve, and contributing to energy sustainability efforts.

Challenges to managing this particular energy system optimization project include over-simplifying constraints, accurately accounting for multiple objectives, and selecting the most optimal optimization method.

IV. Technical Description

A. *Time-of-Use Electricity Prices*

The PG&E residential time-of-use rate plan (E-TOU-C) was used which has lower prices before 4pm and after 9 pm ($0.293 / kWh) and higher prices from 4-9 pm ($0.31 / kWh).



B. *Solar Panel Modeling*

The solar photovoltaic (PV) power output was estimated using historic solar irradiation data and several assumptions about the configuration of the PV system. The 15-minute interval irradiation data was gathered from the National Renewable Energy Laboratory’s (NREL) National Solar Radiation Database (NSRDB) [16].

The following equations were used to estimate the power generated by the PV system.

$$P_{solar} = (n_{panels} * A_{panel} * S_{module} * \eta)/1000$$

$$S_{module} = GHI * (sin(\alpha + \beta) / sin(\beta))$$

$$\alpha = 90 - \phi + \delta$$

$$\delta = 23.45 * sin(\frac{360}{365}(284 + d))$$

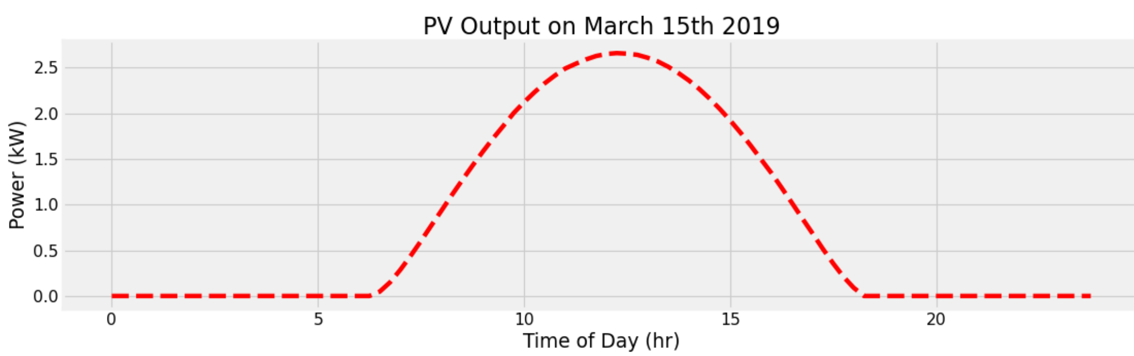
P_{solar} → is the power generated by the PV system $[kW]$

n_{panels} → is the number of PV panels [ ] ( )

A_{panel} → is the total area of each PV panel $[m^2]$

S_{module} → is the solar irradiation incident on each panel's surface $[W/m^2]$
η → is the efficiency of the PV [ ]
GHI → is the global horizontal irradiance $[W/m^2]$
α→ is the elevation angle [ ]
β→ panel tilt angle, measured from the horizontal [ ]
ϕ → is the latitude [ ]
δ→ is the declination angle [ ]
d→ is the day of the year [ ]

System parameter values:
$n_{panels} = 8$
$A_{panel} = 1.63\ m^2$
$\eta = 0.185$
$\beta = 45°$



C. *HVAC Optimization*

[8] provided a model of HVAC using the area of windows, ceiling, and walls into account. The model aims to minimize the cost while maximizing the comfort level. [14] provided a simpler model compared to [8], with only the area of the walls considered. Meanwhile, [14] considered the wall temperature separate from the air temperature, and adding an extra layer on the thermal resistance of the outer wall and the inner wall. It also took thermal energy from the sun into consideration.

HVAC is one of the major energy consumption load in and household, hence for improving energy efficiency optimizing and scheduling the thermal load demand from the grid is necessary. We address the problem of optimal HVAC energy use at home while considering the thermal comfort zone of residents.

The thermal model for the house adopted incorporates different sources of heat gain and loss, making some simplified assumptions which lowers the complexity of the in-depth physical model while maintaining overall accuracy.

The following equation details the house thermal model considered:

$$C\frac{dT_{in}}{dt}=\frac{1}{R_t}(T_{out}-T_{in})+\emptyset_{H/A}+A(1-p)\emptyset_{ir}+n_{ac}V_{house}\rho_{air}C_2(T_{out}-T_{in})/3600$$

$C,\ C_2$ → is the capacity of the total indoor air's heat ,

R_t → indicates the total resistance against heat flow to the outside of the room or thermal energy from heater/air-conditioner ,

T_{in} → is the room temperature ,

T_{out} → is the outside temperature ,

$\emptyset_{H/A}$ is the thermal energy flow of the heater/air-conditioner ,

A → is the area of the window of the room ,

p → is the part of the irradiation of sun which is directly observed by inner layer of indoor walls [],

$\emptyset_{ir}$ → is the thermal energy from sun ,

n_{AC}→ number of air change

The main heat exchange sources considered are solar energy, thermal exchange with the outside environment due to temperature difference between inside and ambient environment and the heat exchange due to HVAC air circulation.

The above continuous state model is changed to discrete step state model by using zero order hold (ZOH) and the resulting difference equations obtained are :

$$T(t_{k+1})=A_dT(t_k)+B_du(t_k)$$

where $A_d=e^{A\Delta t}=e^{\left(-\frac{1}{CR}-\frac{n_{ac}V_{house}\rho_{air}C_2}{3600C}\right)\Delta t}$

$$B_d=\int_0^{\Delta t}e^{A\tau}Bd\tau$$

where $\Delta t=t_{k+1}-t_k$

$$=\int_0^{\Delta t}e^{\left(-\frac{1}{CR}-\frac{n_{ac}V_{house}\rho_{air}C_2}{3600C}\right)\tau}\frac{1}{C}\left[\frac{1}{R}+\frac{n_{ac}V_{house}\rho_{air}C_2}{3600}\ 1\ A(1-p)\right]d\tau$$

$$=\frac{1}{C}\left[\frac{1}{R}+\frac{n_{ac}V_{house}\rho_{air}C_2}{3600}\ 1\ A(1-p)\right]\int_0^{\Delta t}e^{\left(-\frac{1}{CR}-\frac{n_{ac}V_{house}\rho_{air}C_2}{3600C}\right)\tau}d\tau$$

$$=\frac{1}{C}\left[\frac{1}{R}+\frac{n_{ac}V_{house}\rho_{air}C_2}{3600}\ 1\ A(1-p)\right]\frac{1}{\left(-\frac{1}{CR}-\frac{n_{ac}V_{house}\rho_{air}C_2}{3600C}\right)}\left(e^{\left(-\frac{1}{CR}-\frac{n_{ac}V_{house}\rho_{air}C_2}{3600C}\right)\Delta t}-1\right)$$

$$u(t_k) = \begin{bmatrix} T_{out}(t_k) \\ \emptyset_{H/A}(t_k) \\ \emptyset_{ir}(t_k) \end{bmatrix}$$

It can be observed from the input vector above, we have two exogenous input i.e. $T_{out}(t_k)$ and $\emptyset_{ir}(t_k)$, which depends on the weather data of the day and one controllable input $\emptyset_{H/A}(t_k)$, which is what we are trying to optimize.

The energy consumption of the HVAC thermal energy (cooling/ heating) supplied and can be written as:

$$\emptyset_{H/A} = P_{heat} z_{heat} + P_{cool} z_{cool}$$

Where the heating and cooling power of the HVAC system i.e. (P_{heat} and P_{cool}) is fixed and the variable that determines the energy consumption is z_{heat} and z_{cool} that works as and operation status switch for HVAC (z_{heat} = 1 , when heating is on , otherwise 0 , similarly and z_{cool}=1 , when cooling is on and 0 otherwise).
The day chosen for the analysis done in this study March 15 2019, which is a relatively cold day as can be seen from the weather data, hence only heating load was considered in the HVAC system.

$$\emptyset_{H/A} = P_{heat} z_{heat}$$

The optimization objective takes the energy consumption of the HVAC and minimizes the cost associated with operating cost of the HVAC.

$$min\, z(t) \sum_{t=1} p(t).\, P_{heat} z(t)$$

As reported in [14], the human thermal comfort level is between 18◦ C to 24◦ C and optimum temperature is 21◦ C. To insure that indoor temperature is maintained within this comfort zone, additional constraint, i.e., comfort constraint is also considered.

$$\left| T_{in} - T_{set} \right| \geq \Delta T_{thers}$$

T_{set} is taken as 21◦ C ΔT_{thers} is taken as 3◦ C. Hence in the HVAC optimization the following constraints are applied:

$$T\left(t_k\right) \leq T_{max}, T\left(t_k\right) \geq T_{min}$$

The physical values of the parameters, taken in the HVAC models are summarized in the table below and are referred from [8],[14].

Physical Parameters	
Capacity of the total indoor air's heat	C=8.12 [kWh/°C] C2=1214.4/ρ_{air} [J/(kg*°C)]
Heating power of the HVAC [kW]	P_{heat}=60*A_{floor}/1000
Total resistance against heat flow [°C/kW]	R_t=8.02
Area of the floor/window [m²]	A_{window}=4 A_{floor}=100
Volume of the house [m³]	V_{house}=300
Part of the irradiation of sun directly observed by window	P=0.995
Air density [kg/m³]	ρ_{air}=1.2
Number of air change of the house [1/hr]	n_{air}=0.35
Minimum temperature	T_{min}=20
Maximum temperature	T_{max}=24
Initial temperature	T_o=21

D. Water Heater Optimization

In modeling the electric water heater (EWH) device, we based our work off [17] and utilized a 15 minute time step. We only modeled the cold water that enters the tank and mixes with present hot water (red outline in Fig. 1); thus, we neglect water mixing post-heating and assume the output water temperature is satisfactory for the user.

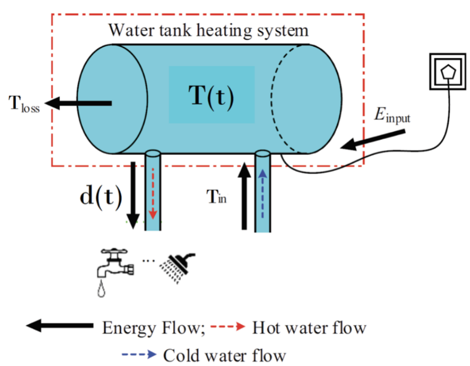


Fig. 1: Energy Flow inside Electric Water Heater

We represent the usage of a 50 gallon water tank for two, discrete tasks: a shower and washing machine cycle. Each water demand has a constant, predetermined flow rate and usage time; the shower (1.6 gpm) runs for 15 minutes from 9-9:15 AM and the washing machine (2.0 gpm) runs for 45 minutes from 6-6:45 PM.

The water inside the EWH is treated as a single body with uniform temperature and instantaneous heat transfer. Applying energy conservation and thermodynamic principles, the temperature inside the water heater can be determined and controlled via multiple constraints and a penalty function.

The following three constraints were employed in the optimization:

1. The initial temperature inside the water heater is a predetermined value T_o.

$$T(0) = T_0$$

2. The temperature inside the water heater must never exceed a predetermined maximum temperature T_{max}.

$$T(t+1) \leq T_{max}$$

3. The temperature inside the water heater can be expressed in state space form and accounts for hot water demands d(t) as well as water heater input temperature T_{in} effects. The state and input matrices model the thermodynamics of the system, with beta representing the input matrix importance factor, which accounts for feasibility.

$$T(t+1) = \underbrace{e^{\frac{-\Delta t}{RC}}}_{A}\left[\frac{M-d(t)}{M}T(t) + \frac{d(t)}{M}T_{in}\right] + \underbrace{\beta QR\left(1-e^{\frac{-\Delta t}{RC}}\right)}_{B}u(t)$$

The objective function employed in the optimization can be decomposed into cost and penalty components. The cost component models the pricing of utilizing the water heater based on TOU pricing p(t). The penalty component penalizes the system when the temperature inside the water heater falls below a predetermined minimum temperature T_{min}; a penalty function was employed rather than a hard constraint, as a hard constraint drove the problem to become infeasible due to thermodynamic constraints. The optimization variables are the temperature inside the water heater T(t) and the state (on/off) of the water heater u(t).

$$\min_{u(t),T(t)} \sum_{t=1}^{n} \underbrace{(p(t)\cdot Q\cdot u(t)\cdot dt)}_{\text{Cost Function}} + \underbrace{\frac{1}{2}\alpha\left[\max_{T(t)}(0, -T(t+1)+T_{min})\right]^2}_{\text{Penalty Function: } T(t+1)\geq T_{min}}$$

The physical parameters, variables, and factors we incorporated into our optimization (referenced above) are as follows:

Physical Parameters	
Thermal Resistance	R = 1.52 ˚C/kW
Thermal Capacitance	C = 863.4 kWh/˚C
Heat Capacity	Q = 4 kW
Heater Mass	M = 50 gal
Initial Temperature	T_0 = 60 ˚C
Minimum Temperature	T_{min} = 55 ˚C
Maximum Temperature	T_{max} = 65 ˚C
Input Temperature	T_{in} = 25 ˚C

Factors	
Penalty Function	α = 1
Input Matrix	β = 10,000

Variables	
Temperature [˚C]	T (t)
State [0,1]	u(t)
TOU Pricing [$/kWh]	p(t)
Demand [gal]	d(t)

E. *Co-Optimization*

In the sections above we have generated an optimal schedule for each device separately. We will now incorporate all three devices (PV, HVAC, water heater) into our optimization.

To solve this problem, we defined a new vector variable, P_{grid} representing the net power (kW) coming from the grid to the home in 15-minute increments:

$$P_{grid} = P_{wh} + P_{hvac} - P_{solar}$$

Where

$$P_{wh}(t) = Q \cdot u(t)$$

$$P_{hvac} = P_{heat} \cdot z(t)$$

We then defined a new total cost vector, C_{grid} where the price per kWh, $p(t)$to consume electricity remains the same, but the price paid for electricity exported to the grid is scaled by β.

$$C_{grid}(t) = \begin{cases} P_{grid}(t) \ \cdot p(t) \cdot \Delta t \quad if\ P_{grid}(t) \geq 0 \\ \beta \cdot P_{grid}(t) \ \cdot p(t) \cdot \Delta t\ \ if\ P_{grid}(t) \leq 0 \end{cases}$$

$$\beta \ \in [0, 1]$$

We then defined our objective function to be

$$min \sum_{t=1}^{n} C_{grid}(t)$$

We were able to transform this into a solvable system by introducing a slack variable, g and introducing the piecewise function into the constraints. By plugging in different values for βwe were able to evaluate how different tariff schemes impacted our optimization (see Results section).

$$min \sum_{t=1}^{n} g(t)$$

Where

$$g(t) \geq P_{grid}(t) \ \cdot p(t) \cdot \Delta t \ \ \forall\ t$$

$$g(t) \geq \beta \cdot P_{grid}(t) \ \cdot p(t) \cdot \Delta t \ \ \forall\ t$$

$$\beta \ \in [0, 1]$$

V. Results

A. Water Heater

After performing the optimization, as shown in Fig. 2 (left), we observe that the water heater was turned on three times (9.00 am - 9.15 am and 6.00 pm - 6.30 pm) and the activity was related to the water demand from the shower happening from 9 am to 9.15 am and the washing machine between

6.00 pm and 6.45 pm. The water temperature inside the electric heater, as displayed in Fig. 2 (right), barely dropped below the minimum temperature of 55 °C, meaning the implementation of the penalty function to handle the desired minimum temperature constraint performed extremely well. That is in spite of the large volumes of water proportionally extracted from the tank for the activities and instantaneously replaced with water of equal volume but of much lower temperature (25 °C). At the same time our maximum temperature constraint of 65 °C is satisfied throughout the day.

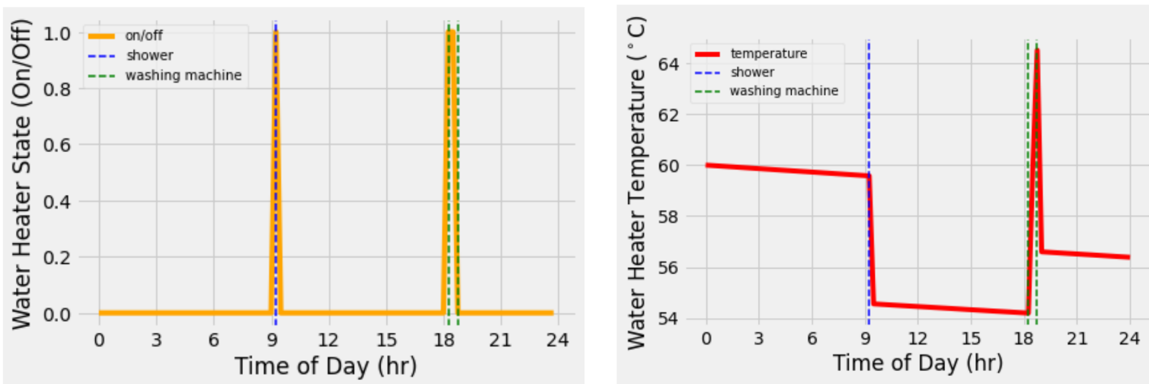


Fig. 2. Left:Water Heater State per Time of Day, Right: Water Heater Temperature per Time of Day

B. HVAC

The optimization result of the HVAC system is shown in Fig. 3. In the HVAC model, the optimal temperature was set between 21 °C and 24 °C. The initial temperature of the house was set to be 21 °C. After performing the optimization, we found that HVAC was not turned on till 3:15 am because the initial temperature was high compared to the minimum set temperature. During daytime from 9.00 am to 6.00 pm, the HVAC was turned on less frequently compared to the rest of the day because of external heat from the sun. There is a larger jump in temperature and longer heating at 4:30 pm. This is because HVAC was trying to heat more to overcome the temperature loss and increase in unit price between 5pm and 9pm. The utility price of the HVAC for the day was $7.99.

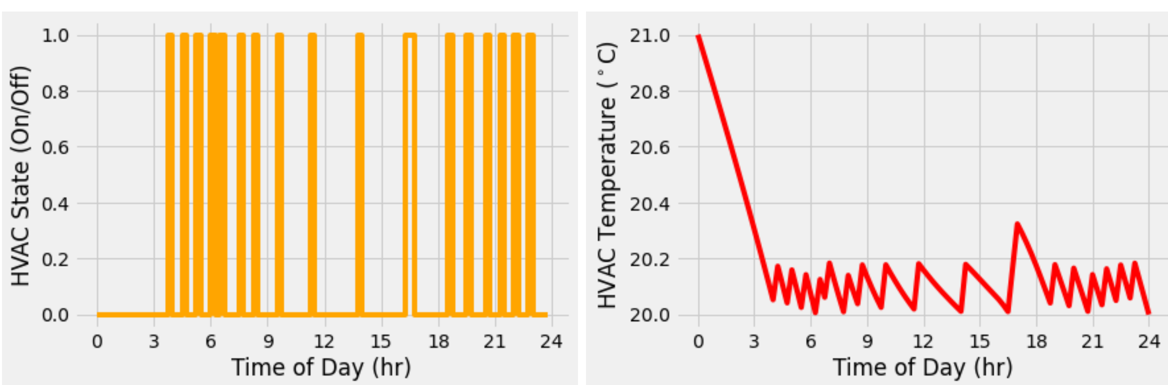
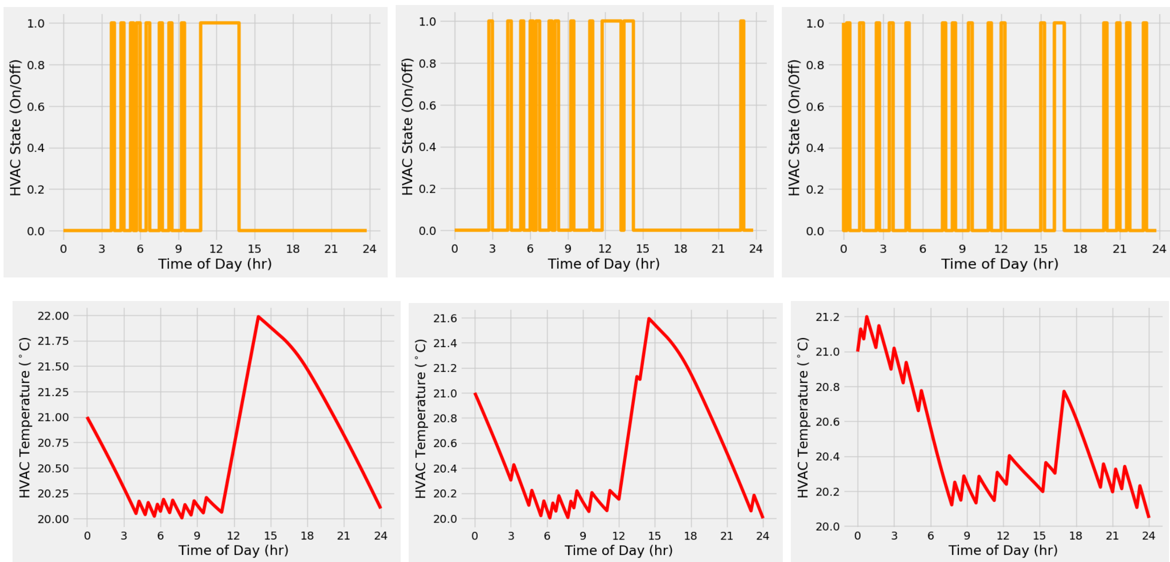


Fig. 3. Left: HVAC State per Time of Day, Right: HVAC Temperature per Time of Day

C. Co-Optimization

In Sections A and B, each device made decisions in isolation. Here we show that the solar output and tariff structures have real impacts on the optimal operating times for HVAC.

The opportunities for co-optimization are defined by the tariff structures they operate within. If excess solar exported to the grid has no value, then the optimization will strongly favor directing that solar-generated electricity to in-home devices (see 0% in Fig. 4). And, on the opposite side, if exported electricity is paid full market value (i.e. the price to export is equal to the cost to consume), then there is little-to-no-incentive to alter home device consumption to align with the times of PV output (see 100% in Fig. 4).

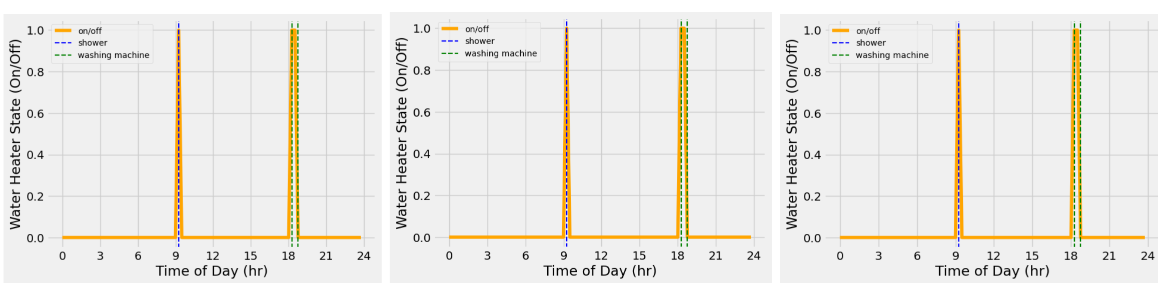


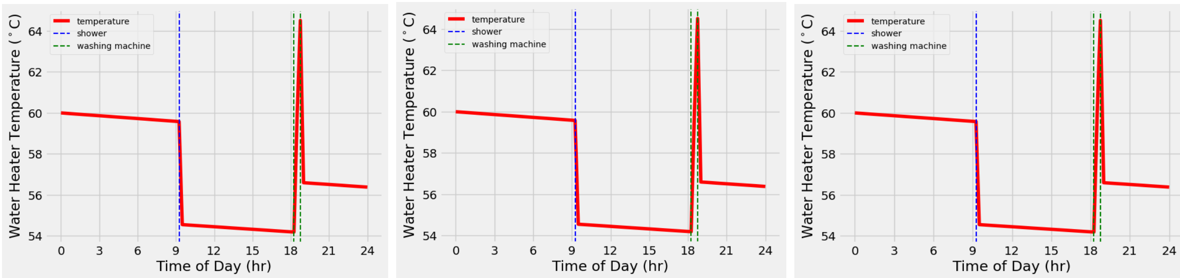
β =0% (Excess solar has no value) ----------------------------> **β =50%** (Excess solar is paid full grid price) **β =100%**

Fig. 4. Top: HVAC State at Different % Paid for Exported Solar

Bottom: HVAC Temperature at Different % Paid for Exported Solar

While co-optimization significantly alters the control schedule for HVAC as βchanges, we see no impact on the water heater's state. This is likely because the water heater is quite powerful, and so there is little room to preheat water without exceeding the maximum temperature (65° C). This is especially true given our duty cycle period (15 minutes) which is high for a water heater.





β =**0%** β =**50%** β =**100%**

(Excess solar has no value) --------------------------------> (Excess solar is paid full grid price)

Fig. 5. Top: Water Heater State at different % Paid for Exported Solar

Bottom: Water Heater Temperature at different % Paid for Exported Solar

Above we explore how co-optimization impacts devices' schedule. We can also explore the broader impacts on customer cost and on the grid.

In Fig. 6, we see that customer cost decreases linearly with β - the higher the price paid for excess solar, the lower the cost for the customer.

But, we see that as βincreases, so does on-peak electricity consumption. However, the difference is relatively small, there is less than a 0.3% jump in on-peak consumption between $\beta = 0\%$and $\beta = 100\%$. Also note that the relationship is non-linear - the on-peak percentage is near constant until $\beta \approx 60\%$, at which point the on-peak percentage jumps by ~0.28% .

Fig. 6 shows the tradeoff between consumer and grid interests for different β*s*.

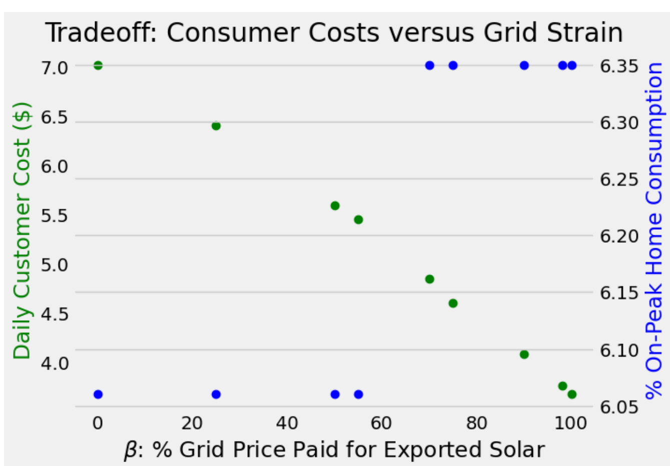


Fig. 6. Customer Costs and On-Peak Consumption vs β

Here we explore the net value of co-optimization relative to parallel optimization. We found that there was a slight net consumer benefit of co-optimization, with the most significant value at lower β values (see Fig. 7). Surprisingly, we found that co-optimization underperformed parallel optimization at higher βvalues, however this was likely due to the slight differences in optimization solvers used for co-optimization (MOSEK) and parallel optimization (XPRESS).

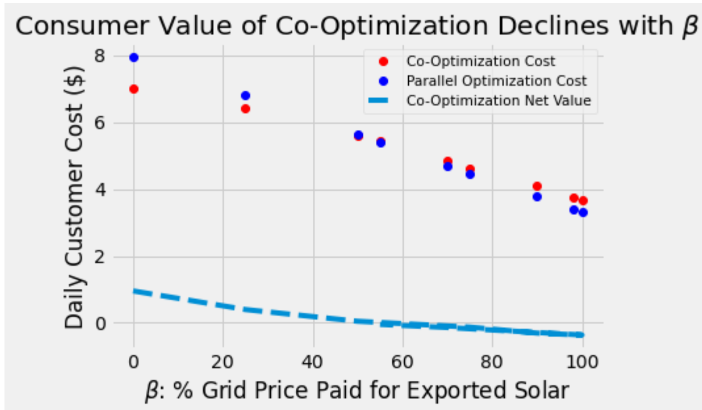


Fig. 7. Daily Customer Costs under Co-Optimization and Parallel Optimization vs β

Although the consumer cost benefit of co-optimization was only slight (and even non-existent at higher βvalues), we see substantial grid benefits - the reduction of on-peak device consumption is significant and consistent across all values of β(Fig. 8).

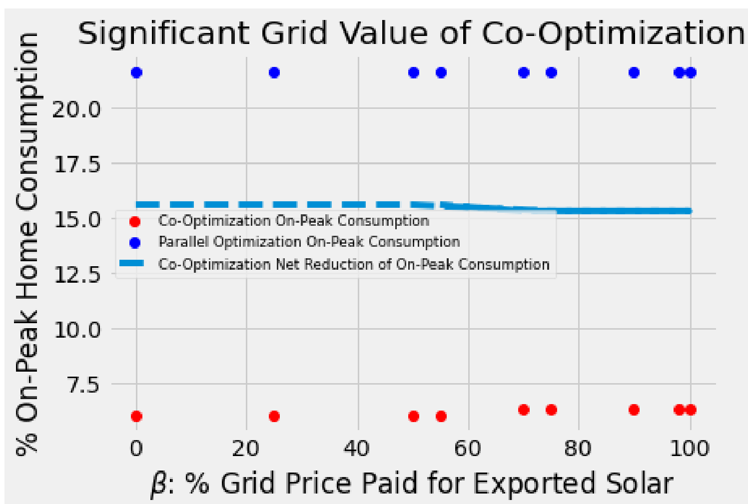


Fig. 8. On-Peak Consumption under Co-Optimization and Parallel Optimization vs β

VI. Discussion

We demonstrated how to model and design an optimal schedule for HVAC and water heater systems.

We also demonstrated that incorporating PV solar output and tariffs into a co-optimization model can significantly affect when devices use electricity, the total cost paid by the consumer, and the on-peak electricity consumption. These results are informative in two key ways:

(1) Automated Decision-Making for Consumers: A centralized decision-making algorithm, with information from the PV system and all home energy devices, has the potential to make more intelligent decisions on behalf of the consumer.

(2) Tariff Design: There is ongoing discussion in California about the future of solar tariffs (i.e. NEM 3.0). Our methodology and results provide useful context to inform tariff design and show that decreasing the amount paid for excess solar will increase consumer costs while only slightly reducing customers' on-peak consumption.

Improving both automated decision making and tariff design will help to enable the future of low-carbon, flexible, and decentralized electricity grid.

Future Steps

- Adjust time steps to better reflect the duty cycle of the water heater.
- Investigate and adjust HVAC inputs. The system modeled may be undersized.
- Explore implementation of real-time control and optimization.
- Model and incorporate other smart-home energy devices, such as dishwasher and air conditioner.
- Expand model to include additional times and locations.
- Introduce uncertainty into demand of devices to create a more robust, realistic model and framework.

VII. Summary

This project aimed to co-optimize home energy appliances and devices, and resultantly produce a daily cost-optimal load profile for various energy devices in one's home. This study explored the methods and benefits of co-optimization relative to parallel optimization.

In the first part of the study we modeled three devices – HVAC, a water heater, and a solar photovoltaic (PV) system. For each of these devices we used assumed certain equipment characteristics and user consumption patterns.

Using mixed integer programming (MIP), we optimized the operation of the HVAC and water heater by minimizing the total daily cost using a PG&E time-of-use (TOU) residential rate plan and generated the appropriate daily load profile for each device.

In the second part of the study, we performed a co-optimization, where we minimize total costs under different tariff structures – a harsh tariff would pay customers $0/kWh for excess solar generation, while a generous tariff would pay the market price for exported solar electricity.

We found that the HVAC heating schedule varied significantly according to different tariff structures under co-optimization, while, as modeled, the water heater operating schedule remained the same. We demonstrated that there are tangible, although relatively small, benefits of co-optimization (relative to parallel optimization) through reduced consumer costs under harsher tariff regimes, although little-to-no benefit under generous tariff regimes. However, under all tariffs, we found a significant reduction in on-peak electricity consumption, suggesting that co-optimization may provide substantial grid benefits over a parallel optimization.

These results may be used to better inform consumer energy device operation, by quantifying the value and methods of co-optimization. Similarly, the results can inform tariff and rate structure design by quantifying the tradeoffs of consumer cost and grid value under different cost regimes.

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