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Generalizing the Electric Vehicle and Building Energy System for Smart Energy Management

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Summary

When EVs are charged in buildings, the optimization of the energy management can become a complex technical problem. Currently, the EV charging system related protocols are designed only for EVs, and the building automation protocols, such as KNX for building components. New elements, such as in-building batteries, such as Tesla Powerwalls are appearing, and local energy production through solar panels is added.

To help building energy usage optimization algorithms for these complex systems, we propose generalizing the definition of both the building components and EVs, and creating methods and protocols which allow the same simplified algorithms to be used for the modeling, simulation, and optimization of energy management. As an example, a building can be defined as a union of a multitude of energy consuming devices, energy producers (solar panels), and a storage battery (an in-building storage battery). An EV can be defined as a combination of energy consuming devices (motor, air conditioning) and a storage battery (main battery).

All of these simplified components have a set of properties, such as capacity, average use patterns, conditions, such as the ability to be used together (if the car motor is consuming energy, the car is not consuming building energy), permits, and quotas. In a building that has multiple EV owners, the optimization can be made for a union of these components and their properties. A general solver software can then be used for the optimization in a straightforward fashion.

Keywords: energy, modeling, optimization, prediction, smart charging

1 Introduction

An energy efficient future building will have its own smart energy system. In this work in progress paper we are outlining how a building could be optimized for comfort, energy efficiency and cost. We model the building to have an electrical connection to the outside ("the grid"), solar panels on the roof, electric car charging in the garage or parking lot, a building level energy storage unit (a big battery) and of course various domestic loads, such as a stove, a sauna, and lighting.

In addition to electrical systems we expect the heat system to have solar loaded geothermal heating or similar up to date solutions, however, we limit the scope of this paper to the electricity. What we do expect, instead, is some computing facilities to make the system smart. This means some data logging that allows proactive (predictive) control by having some data mass to make predictions from. From a description of the building, predicted uses and energy prices our software derives a model of the behavior of the energy system, then uses a constraint solver to optimize from that derives a plan (a schedule) for when and how much to charge EVs and when to use the house battery.

2 Generalized Modeling of Energy Systems

The energy system has a large number of objects, which either produce or consume energy, depending on various factors. These objects include EVs, Solar panels, batteries, other energy consumers. What we need is a way to define these a generic way which can be easily processed by a constraint solver. While constraint solvers have been used for load management, we propose to apply the same methods to optimize whole buildings with all the energy consuming and producing devices, batteries, and possibly further expanding this to large groups of buildings, cities, or national level optimization. To simplify the problem, we are proposing to model the energy system objects through generic capabilities. Few examples of possible objects and related capabilities follow.

- A solar panel is an object, which produces energy during specific hours, depending on weather, and the price of energy is zero.
- A grid interface is an object, which produced energy at any time, has the price of energy varies according to a preset schedule.
- A battery is an object, which has size, minimum input and output power, and state.
- An air conditioning system is an object, which uses energy, depending on the weather.
- A motor is an object, which consumes energy at specific times, for which prediction is possibly through historical information, calendar information.
- An EV is a union of battery, an air conditioning system, a motor, and has a location, known for characteristic that it can input energy from building, if its location is at the building, and it uses energy while not at the building, at 8 am and 5 pm.
- A building is a union of an EV, A solar panel, A battery, An air conditioning system.

Obviously there can be vast number of parameters and relationships. However, to do reasonably good optimization for energy system, even simple models of these objects will give reasonably good results.

2 Object Descriptions

Looking at the various electrical connections we can see that some of them provide electricity (grid, house battery, solar panels) and others consume electricity (appliances, EVs, house battery). Some of them have a price, or relation such as consuming energy is related to distance driven. The house battery can be controlled, while the solar panels and most appliances cannot. Of various possible descriptions we arrive at this:

producerconsumer(max_power, min_power, min_capacity, full_capacity, cost)
PV = producerconsumer(max_power): min_power = max_power, rest=0
HouseBattery = producerconsumer(...): cost = 0

EV = producerconsumer(...): min_power = 0, value = -2 * cost for min_capacity or -1 * cost otherwise
Sauna = producerconsumer(max_power): min_power = max_power, rest=0
Grid = producerconsumer(...): min_capacity = max_capacity = 0

We must be careful with the signs. The power of the sauna and PV are opposite as is the price of the EV and the grid (the grid is a cost and the EV is added driving distance).

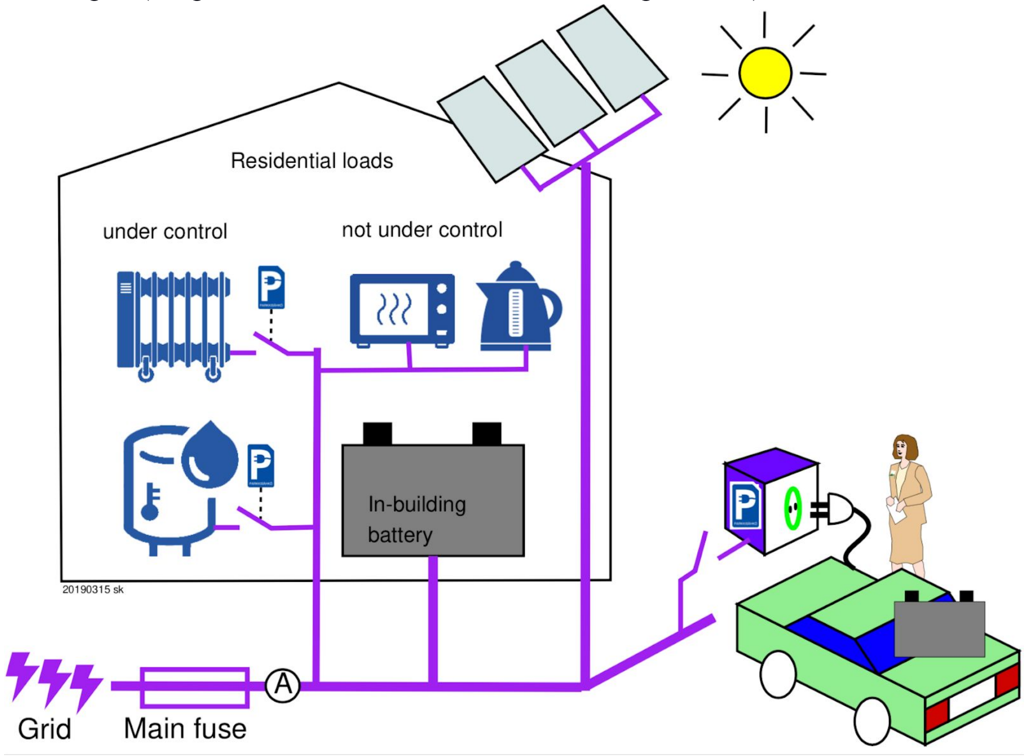

Figure1: Modeling elements

Next we consider time. The grid price depends on the market when flexible pricing is active. The sauna is used only in the evening. Electric cars can be charged only when plugged in. The output of the PV depends on how sunny it is, which depends on the time. The time dependent values come from various sources, like weather forecast combined with the time of year and latitude to figure the PV output, or driving history to estimate when an electric car will be driven how far.

For each producerconsumer object we create a table of time value vectors based on the predictive sources. For instance:
todayPV = [0, PV(max_power = 0); 6, PV(max_power = 4); 8, PV(max_power = 10)]
Indicates that midnight to 6 am, the power is zero, between 6 and 8 it is four, and after that ten. For brevity we skipped the evening.
todayGrid = [0, Grid(cost = .1); 2, Grid(cost = .12)]
Indicates that after midnight electricity costs 10 cents per kWh and after 2am it goes up to 12 cents.

3 Solving

After collecting all the values for all the electrical objects in the house for the given day (or whatever the desired planning period is) we use a software tool to create detailed constraints for the solving tool. In our prototype solver we use the freely available Z3 solver. It is an SMT solver that searches for a solution in the state space. It can handle state spaces in the millions but the smaller the state space the easier its work. Thus the somewhat counterintuitive observation that the more constraints the faster it works as the state space

generally gets smaller from additional constraints. And since we are dealing with objects in only one house in a limited amount of time the state space is not very large in any case. The tests we have conducted got solved in milliseconds.
To feed the input descriptions and time arrays to the solver we use a Python interface as part of the Parking Energy Cloud backend to translate the input into a constraint program understood by Z3. While the principle is rather straightforward the Python program is unfortunately somewhat hard to understand so in order to save the day of the reader we are not presenting it here.

In addition to simple constraints we also create calculations that sum all the costs and the amount the cars have been charged etc. These calculations are also handed to the solver, which then can be used to optimize the given values. In other words in the state space we are not only searching for the first solution but a good solution. The solution does not need to be the very best solution of any solution as long as it is a good solution and mostly the best one. In order to simplify comparing apples and oranges in the optimization phase it is a good idea to normalize all values to a common unit. While it may seem hard to compare comfort with driving distance with energy price, a rather practical solution is to consider everything through monetary value. By assigning multipliers to any other factor we can assign a monetary value and thus have a common basis for determining success.

4 Executing the Plan

After running the solver to optimize the problem the unassigned variables will be assigned. The next step is then to extract the values from the produced data structure and send the results to the smart controllers of the EV chargers, house battery controllers, etc. The Parking Energy EV charging units are programmed to receive schedules. The chargers will start executing the plan. Note, however, that the plan was based on predictions. Inherently then proactive systems will have to adapt their plans when the predictions and forecasts end up differing from the actual flow of events. While the solver can be run again at any time the Parking Energy EV charging units are also capable of adapting on their own volition in a reactive collaborative manner.

5 Results

Our prototype demonstrates that the system can be described in a way outlined in this paper. It also shows that Z3 can be used to quickly derive a usable schedule. The Parking Energy charging units also are able to adapt to changing circumstances. Based on this work in progress we are continuing to further develop the system and are looking for partners in the building automation space.
We are also looking into the possibility of replaying existing execution data against partially undefined electrical configurations. Based on this we could for instance instead optimize for cost and find out how large the house battery needed to be in the past for optimal performance and cost.

6 Further Work

In our current work we have used very simple objects. Adding more refined information, better ways to define objects, generalize historical data collection for automated predictions, and other such improvements will offer plenty of further research and practical work.

6.1 Definition of objects and rules

Clear and unambiguous way of defining objects and their characteristics, and how to present rules need to found. The current way of describing the objects presented in this paper are early ideas.

6.2 Refining objects

Currently the objects have been defined with simplistic assumptions. There is nothing stopping adding more capabilities and constraints. We could define weather information as a set of constraints, and any object could have dependencies to that information, for example, solar production and EV energy consumption can be derived from weather constraints.

6.2 Dynamic Constraints

Constraints can be dynamic, such as building can have loads which cannot be predicted. Our current modeling has been based on time slots, such as each hour, and finding a solution for each hour. However, with dynamic loads, it is possible to define constraints which depend on other constraints in a way, that it would result in a conditional constraint, say, EV charging which can be controlled quickly, would drop power, when building electrical system sees additional dynamic load, such as water kettle. We need to do further work on how to define these dynamic constraints in a general way.

6.2 Learning

For any object we can automatically collect information, such as its historical behaviour, and use that to add further constraints for the solver to work on.

6.3 Scalability and locality

In our initial work we are looking at a single building, with limited number of objects. However, there is no limitation in the idea itself, it could, in theory to be expanded to optimize much larger concepts, even energy system of whole countries. The first step towards this would be adding larger number of objects.

As various objects can have a very large number of characteristics, and each object, say all cars, will be represented as a separate object, the object space will grow quite large, requiring a very scalable solver. Thus the problem should and to our view can be efficiently split to smaller combinations of objects for which a local solution can be found with problem to be solved will stay small enough. The object space locality for a building could be a set of the building and objects directly related to it, and any other objects which interact with it, such as national grid, electricity provider, EVs parked in it. Parking Energy uses similar concepts in its distributed load management, such as EV charging stations in the parking area talking to each other to find the best solution for EV charging within the constraints. We are not yet using a solver for this, however, our distributed load management could be seen as a solver by itself.

7 Conclusions

Combining knowledge of energy systems in a building and EV charging allows combined optimization and scheduling of EV charging. In addition to access to data and predictions some algorithms are also needed. This paper outlined how an SMT solver could be used to efficiently implement the algorithms. The work presented here forms a base for further work in this area.

References

[1] H.Suonsivu et. Al., Resource Efficient EV Charging Infrastructure in Real Estate Environment, EVS30, Stuttgart, Germany, October 9 - 11, 2017

[2] Tian Mao et. Al., Intelligent Energy Management Algorithms for EV-charging Scheduling with Consideration of Multiple EV Charging Modes, Energies 2019, 12, 265; doi:10.3390/e12020265

[3] Ming Zeng et. Al., Optimal Planning for Electric Vehicle Charging Station Considering the Constraint of Battery Capacity, International Conference on Artificial Intelligence: Technologies and Applications (ICAITA 2016)

[4] M. Hadi Amini et. Al., Fully Distributed Cooperative Charging for Plug-in Electric Vehicles in Constrained Power Networks, https://arxiv.org/pdf/1806.11190

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