Modeling and Optimization of a Smart Home System

Tobias Rodemann
Honda Research Institute Europe GmbH, Offenbach/Main

Torsten Schwan, Dresden University of Technology,
Institute of Automotive Technologies

Kurzfassung

Durch die Herausforderungen des Klimawandels, steigender Preise fossiler Brennstoffe und einer Neubewertung des Risikos der Kernkraft, werden neue, innovative Ansätze zur Stromproduktion, -speicherung und -nutzung benötigt. Intelligente Häuser, sogenannte Smart Homes, können einen wichtigen Beitrag leisten, da sie Stromproduktion (durch PV oder BHKWs), mit Energiespeicherung und Verbrauch lokal integrieren können. Die Kombination mit der (elektrischen) Mobilität bietet dabei das Potential zu weiteren Effizienzsteigerungen. Um dieses Potential zu analysieren und eine optimale Konfiguration und Steuerung zu ermöglichen, wurde auf Basis der Green Building Library ein Smart Home System plus Elektrofahrzeug simuliert und evaluiert. Dieser Artikel beschreibt das Simulationskonzept, stellt erste Ergebnisse vor und gibt einen Ausblick über die geplante Systemoptimierung.

Abstract

New innovative approaches for electricity production, storage, and consumption are needed to respond to growing concerns on climate change, increasing fossil fuel prizes, and the re-evaluation of the risk of nuclear power after the Fukushima accident in Japan. Intelligent houses, so called smart homes, might contribute to these efforts, since they can locally integrate and coordinate energy production, storage, and consumption. Further efficiency gains are possible through the integration of (electric) mobility. In order to analyze this potential, we simulated a smart home system with an integrated electric vehicle using the Green Building Library. This article describes simulation concepts, presents some initial results and outlines our approach for system optimization.

Section 1: Introduction and Motivation

In Germany, Japan, and other countries the networks of electricity production, transmission, storage and usage are being substantially modified due to growing concerns on climate change, increasing fossil fuel prizes, and the phase-out of nuclear power after the Fukushima accident. Renewable sources of energy have to replace conventional (fossil and nuclear) sources and societies need to reduce their energy demand in areas like production, households, and mobility. In this context, Honda has recently unveiled the Honda Smart Home System (HSHS, Fig. 1) in Japan's Saitama prefecture near Tokyo. The HSHS combines energy production through photo-voltaic (PV) and micro combined heat and power generators (mCHP) with battery storage and e-mobility devices like electric vehicles or fuel cell cars. The operation of the house is controlled and coordinated by a central smart control unit, the Smart e-Mix Manager (SeMM).

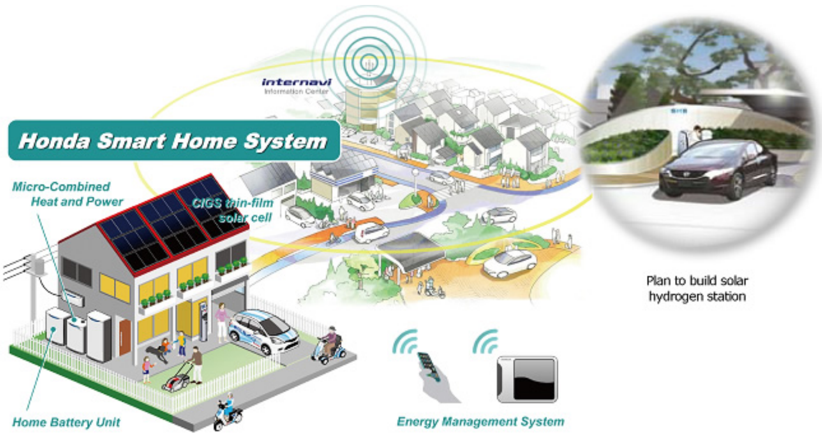


Figure 1: Honda Smart Home System

Section 2: Simulation System

In order to understand the interaction of the different modules with the home's owners and the environment, a detailed simulation of the HSHS is needed. For Honda as a mobility company a building-centered simulation environment is not sufficient since Honda aims at providing a green and affordable mobility by integrating cars and home appliances.

To study how electrified mobility and smart home systems can interact in an optimal way, the Honda Research Institute Europe and the TU Dresden, developed a model of a smart home system with an attached Plugin Hybrid Electric Vehicle (PHEV).

The simulation uses the Green Building Library [1] newly developed by ITI, EA Energie Architektur GmbH and TU Dresden. We have chosen SimulationX as a modeling tool for the following reasons:

- A tool which is compatible with standard software in automotive R&D is necessary in order to connect mobility devices to the smart home.
- The Modelica language allows an easy extension of the models.
- Using the C-Code Export function we can employ very efficient population based optimization tools running simultaneously on clusters of computing nodes.

In the simulation system (Fig. 2) we model a standard single-family home with three zones (ground floor, upper floor, and attic) with a heating system for the first two zones. The house uses a PV system for electricity and a mCHP for combined heat and electricity production. To provide enough heat even under extreme weather conditions a conventional heat boiler system is added. The house is furthermore connected to the electricity grid and employs an in-house battery to store electricity. Finally we model the house owners' mobility demands via a vehicle that runs approximately 8000 km/year or 30 km/day. The car is assumed to be docked to the house for certain periods of time, when recharging is possible. In a pre-processing step the average fuel and energy demand of the car is computed for the specific driving demands. These averages are used in the actual simulation of the smart home system. This approach is applied due to the different time-scales of car and house dynamics. The model system can be instantiated in different variations including a conventional system without PV and mCHP, using a conventional combustion engine for mobility. It is therefore possible to compare different system configurations in terms of their economic merits, environmental footprint, provided comfort and a variety of other issues.
The operation of the system depends on many factors, the two most important are user profiles and environmental conditions (e.g. weather). Both factors can change from day to day, and vary for different locations. To deal with these variations we decided to fix a specific location for all simulations (for the described results, Berlin was chosen), and simulate a complete year in order to average out seasonal changes. Despite a high simulation speed, a complete year of simulated time requires several days of simulation time. To speed up the simulation we employed the reference day method, where a small number of prototypical reference days is simulated and weighted with their relative occurrence over the course of a year. As a result, simulation time could be reduced to a couple of hours on a single computer.

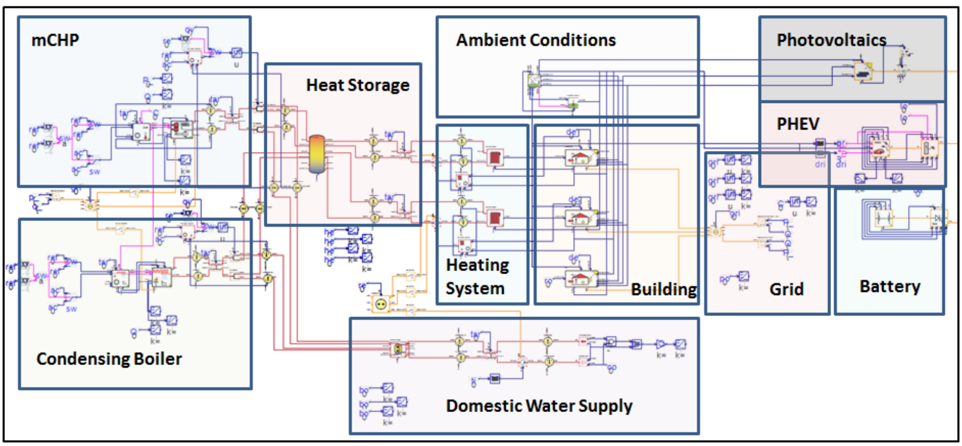


Figure 2: Implemented renewable energy system in SimulationX

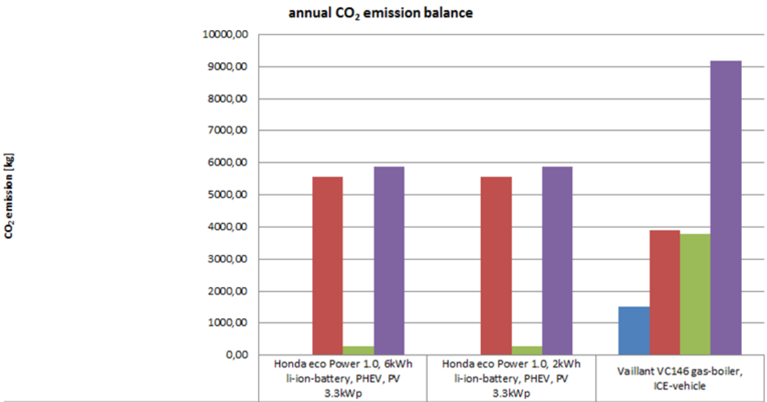
Environmental data like climate data, user profiles (e.g. daily electricity demand), and driving patterns can be specified using simple Excel sheets. The simulator provides its outputs also in Excel format in order to ease data analysis and visualization. This approach also greatly simplifies adaptation of the model to other locations or usage patterns.

Section 3: Results

Using the simulator we computed costs, emission levels and primary energy balances of different renewable and conventional energy configurations. Although renewable configurations employing PV, mCHP and PHEV are more expensive, the data shows that they also result in substantially lower CO2 emissions (see Fig. 3). We also found that a simple strategy that charges the electric vehicle from the battery which in turn is charged by the PV system can provide a high share of 'green' (CO_2 free) electricity for mobility. The exact percentage strongly depends on the size of the battery that is installed in the HSHS. Using a parameter scan for battery size we could identify the optimal dimension of the battery in terms of a cost per CO_2 reduction trade-off.

Outlook

Using the simulator model we plan to perform an automatic optimization of the system configuration considering multiple optimization criteria. We want to employ a class of newly developed algorithms from the field of evolutionary optimization, so called Evolutionary Many-Objective Optimization (EMAO) algorithms (see e.g. [2, 3]). These algorithms, which are based on concepts inspired from natural evolution, provide a population of Pareto optimal solutions which represent different compromises on the set of conflicting objectives. The target is to analyze the potential of the system in different configurations and to understand the correlations between the different objectives.



	Honda eco Power 1.0, 6kWh li-ion-battery, PHEV, PV 3.3kWp	Honda eco Power 1.0, 2kWh li-ion-battery, PHEV, PV 3.3kWp	Vaillant VC146 gas-boiler, ICE-vehicle
CO2 emission benzine (vehicle) [kg]	21,67	21,17	1519,16
CO2 emission domestic gas (CHP and condensing boiler) [kg]	5575,14	5575,46	3884,65
CO2 emission electricity [kg]	276,47	281,04	3771,75
total annual CO2 emmission [kg]	5873,28	5877,67	9175,57

Figure 3: Comparison of total emissions

References

[1] René Unger, Torsten Schwan, B. Mikoleit, Bernard Bäker, Christian Kehrer, and Tobias Rodemann:
"Green Building" – Modeling renewable building energy systems and electric mobility concepts using Modelica,
Proceedings of the 9th International Modelica Conference

[2] Kaname Narukawa and Tobias Rodemann:
Examining the Performance of Evolutionary Many-Objective Optimization Algorithms on a Real-World Application,
Proceedings of The Sixth International Conference on Genetic and Evolutionary Computing (ICGEC), 2012

[3] Nicola Beume, Boris Naujoks, and Michael Emmerich:
SMS-EMOA: Multiobjective selection based on dominated hypervolume
European Journal of Operational Research, 2007