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Tech Note: Smart Home – Modeling the Internet-of-Things with SysML

Part 4 Smart Home to Smart Grid

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Abstract

This is the fourth in a series of technical notes describing the application of Model-Based Systems Engineering (MBSE) to the specification, design, procurement and evaluation of an Internet-of-Things (IoT) system. This section explores the use of the Smart Home model created in the earlier notes in the context of a Smart Grid utility system, both in terms of the transmission and use of power pricing information in shifting power consumption patterns and in the use of external Big Data analytics to optimize system performance. The emphasis is on the advantages of the object-oriented nature of SysML models in a System-of-Systems model rather than specific algorithms of data analysis and use.

Introduction

One great benefit of SysML in Model-Based Systems Engineering (MBSE) is its object-oriented or modular approach to modeling. In the first three parts of this series of Tech Notes, we created a model of a Smart Home as an example of the Internet-of-Things (IoT), including a parametric model which was used to evaluate cost and power consumption. But we appreciated that many of the benefits of the Smart Home would only be realized in the context of larger "Smart Systems".

In Part 4, we use the earlier model with only minimal changes as an element in a Smart Domain, allowing us to look at the impact of the larger domain on the individual home and, in reverse, the impact of many smarter homes on the larger domain. In doing so, we will make contact with two areas of widespread interest and investigation.

Smart Grid

The Smart Grid for electrical power generation and distribution is a broad set of concepts with potentially revolutionary impact on energy consumption, cost, system resiliency and the environment. One common aspect of these ideas is that dynamic energy pricing information can be transmitted continuously to the individual energy users, residential, commercial and industrial:

- Electricity consumption can be shifted to periods of greater availability and lower cost
- The need for generation and distribution capacity can be reduced
- Adoption of time-varying renewable energy sources is simplified.

The Smart Grid benefits enormously from the Smart Home, where a distributed network of sensors and actuators is a highly adaptive system that can make use of the information from outside.

The Smart Grid does introduce elements of uncertainty into the analyses we need to perform. Volatile energy prices and the availability of solar and wind energy require that risk assessment be incorporated into calculation of cost and performance. Monte Carlo simulations and other stochastic analyses need to be available to the MBSE user.

Data Analytics

An envisioned benefit of the IoT is that data generated within a system like the Smart Home can be sent outside the system for analysis. The outside analysis, benefiting from the experience of many users, proprietary analysis algorithms and greater processing power, can find patterns in the user data that enable it to optimize performance, minimize cost, improve reliability, etc.

In our earlier notes, we described an HVAC system where individual zones could be controlled independently. Two possibilities for control schemes were allowed. The zones could be individually preprogrammed to heat or cool on a specific schedule, as many homes are today. Second, the local occupancy of each zone could be determined from the motion sensors of the Security subsystem, making it possible to turn off HVAC to empty rooms.

While both control schemes have the potential to save energy (and money) by reducing heating and cooling to unused space, both have obvious drawbacks. Preprogrammed schedules may not reflect real use of the space, while on/off control of rooms only when occupied cannot anticipate when a room

will be occupied or empty in the future and control the temperature accordingly. As an alternative, consider a data analysis provided by the Smart Grid, which takes the occupancy and temperature data from the home, analyzes it over many cycles, and provides an optimized pattern for the individual zones for the Smart Home. This, in combination with local modification by the homeowner, provides the best combination of comfort and cost.

Constructing a Smart Domain

We begin by creating an IoT Domain block, composed of one-to-many Smart Homes plus other systems with which these homes could potentially communicate:

- Entertainment Company, which provides audio programming to the home Audio Subsystem
- Alarm Company, which provides protective services to the home based on alarm information from the security subsystem
- Smart Grid, which provides electrical power and other services to several of the home subsystems.



This structure is illustrated in Figure 1 and Figure 2.

Figure 1 IoT Domain Block Definition Diagram, including Home block developed in Parts 1 through 3

Our focus in this example is directed towards the interaction between the Smart Grid and the home HVAC subsystem. As shown in Figure 2, the HVAC subsystem communicates information about temperature, power usage, and zone occupancy to the Smart Grid. In addition to electrical power, the grid returns information about the power cost, as well as a predicted zone occupancy pattern based on analysis of past data.



Figure 2 IoT Domain Internal Block Diagram showing connections between Home and outside systems

Analyzing Cost Savings from Smart Domain

One objective of this larger model is to evaluate how communication between the home's HVAC subsystem and the Smart Grid could reduce both the home's power consumption and the cost of that power. As in Part 2, we will put these parametric analyses into their own analysis blocks which reference the structural components and their value properties.

The analysis block structure is shown in Figure 3, with the new elements added to the analysis highlighted in purple. Note that these analyses are for the individual Smart Home, not for the entire domain. Only two modifications are made to the Smart Home model described in the first three parts.

- A new value property, shiftAllowance, is added to the HVAC Controller block. This represents a user-determined willingness to shift HVAC power consumption to periods of low power cost, where 1 represents no shift allowed and 0 represents complete shift to low cost periods, i.e. no HVAC when the power cost is high.
- A second new value property, perLowCost, is added to the HomeHVACAnalysis block. This represents the fraction of HVAC power consumption that would occur during low power cost periods <u>without shift</u>, i.e. if shiftAllowance above were set to 1.

The Smart Grid block provides 4 new parameters necessary for the calculation. costLow and costDiff are the base cost of electricity and the premium to the base cost during high use periods, respectively. The occupancy pattern information calculated by the grid for the home is represented by two value properties, occAvg and occVolatil (both values range from 0 to 1). These may be thought of as placeholders for a more complete occupancy pattern data structure, which is beyond the scope of this example, as is the algorithm by which this pattern is calculated. It is sufficient to say that these represent the data necessary for the home to optimize its HVAC performance to balance comfort with power consumption.



Figure 3 Analysis Block Definition Diagram – new analysis blocks shown in purple

The OptimizedHomeHVACAnalysis block contains the calculations for calculating power consumption based on the use of this optimized occupancy data returned by the Smart Grid data analysis utility. This is shown in the parametric diagram in Figure 4. The constraint OccupOptimFac takes the occupancy pattern and calculates occOptimFactor, a value between 0.8 and 1. This is used by the second constraint, OptHomePower, to reduce the HVAC power for the unoptimized Home.



Figure 4 Parametric diagram for Optimized HVAC Power Consumption, based on occupancy analysis

The CostSavingsAnalysis block calculates the cost of the HVAC power consumed for both unoptimized (dailyCostUnopt) and optimized (dailyCostOpt) HVAC programming. An additional factor is applied to the optimized cost when the Smart Grid offers demand pricing, i.e. different pricing during different times of day. The shiftAllowance factor in the parametric diagram in Figure 5 is used by the PowerShift constraint to increase the percentage of power consumed during low cost periods



Figure 5 Parametric diagram for Cost Savings Analysis, comparing a home with optimized occupancy programming and shifting of consumption to a home without either feature.

(perLowOptim vs perLowCost). The constraint block DailyPowerCost is used twice, the first to calculate the daily cost for a home with no occupancy optimization and no demand shifting, second for the optimized and shifted HVAC usage patterns. The final constraint CostDiff calculates the difference in daily cost between the two alternatives.

Running the model

In Figure 6, The ParaMagic browser shows results for one set of inputs. The target value shows a cost differential of \$2.79 per day for the effect of the smart home optimization and power shifting relative to the baseline, for an ambient temperature of 60 degrees F and a set of internal zone setpoints of 68-77 F. Raising the outside temperature to 80 approximately doubles the cost savings to \$6.34 per day.

ParaMagic(R) 18.0 - co							
Name	Qualified Name	Туре	Causality	Values			
CostSavingsAnalysis 	IoT_v10::Instance01::costSavingsAnls IoT_v10::Instance01::optHomeAnls	CostSavingsAnalysis \$ \$ Real OptimizedHomeHVACAnalysis Real KW	target ancillary ancillary ancillary ancillary ancillary	2.791 18.472 21.263 0.444 0.852 5.208			
Tha Pha P	IoT_v10::Instance01::homeAnls IoT_v10::Instance01::grid	HomeHVACAnalysis Real KW Deg_F ZoneHVACAnalysis[1,?] Smart Grid \$pKwhr \$pKwhr Real Real	given ancillary given given given given given	0.5 6.11 60 0.05 0.12 0.25 0.8			
É E zha □ E hctrla □ □ cost □ shiftAllowance Expand Collapse All	IoT_v10::Instance01::homeHVACController	ZoneHVACAnalysis[1,?] HVAC Controller \$ Real Solve Reset Pres	given	100 0.9 late to SysML			
root (CostSavingsAnalysis)							
Name Local cd1 Y dpcopt Y dpcunopt Y ps1 Y	Redefined Relation dailyCostDiff=dailyCostUno dailyCostOpt=ohha.opt_po dailyCostUnopt=ohha.hha. ohha.hha.perLowCost=1-h	pt-dailyCostOpt wer*(perLowOptim*ohha.sga. power*(ohha.hha.perLowCost* ctrla.shiftAllowance*(1-perLow	costLow+(1 ohha.sga.co Optim)	Active			

Figure 6 ParaMagic browser after solution of CostSavingsAnalysis

There is a problem with simple deterministic models like this in a dynamic pricing scenario. If the base and premium costs vary, and the time premium costs are charged is varied, a distribution of values in the cost savings can be expected. Introducing this element of uncertainty into the analysis can be done in a number of ways. One approach is a Monte Carlo simulation, which is easy to set up with the ParaMagic tool.

In Table 1, we treat three inputs as normal distributions, each with a mean value and a standard deviation (sigma). We use MS Excel to generate a series of trials, each trial shown as a row in a spreadsheet with randomized values for the three stochastic inputs. One thousand trials are created, but only the first ten are shown in Table 1. The remaining given values are fixed, using the same values as in Figure 6. The batch execution is carried out in the same way as the trade study in Part 3 and the final value for cost savings is written to the last column. The entire calculation took approximately ten minutes on a standard laptop.

Monte Carlo Simulation - Cost Savings Analysis

Inputs

	mean	sigma
base cost (\$/KWhr)	0.12	0.03
differential cost (\$/KWhr)	0.05	0.02
percent low cost power	0.5	0.1

Results

Trial	base cost	differential cost	percent low cost power	cost savings (\$)
1	0.065	0.005	0.525	1.43
2	0.096	0.060	0.434	2.34
3	0.102	0.043	0.512	2.37
4	0.090	0.014	0.437	2.01
5	0.111	0.060	0.510	2.63
6	0.141	0.084	0.544	3.35
7	0.136	0.062	0.596	3.14
8	0.077	0.054	0.419	1.90
9	0.117	0.064	0.643	2.72
10	0.176	0.062	0.529	4.04

Table 1 Monte Carlo simulation results

The results for the thousand trials are plotted as a histogram in Figure 7. While the center of the distribution is near the same \$2.79 value calculated in Figure 6, one standard deviation is about \$1.



Figure 7 Monte Carlo results in histogram form

Summary

Two of the benefits widely ascribed to the Internet-of-Things are its ability for local smart systems to communicate with broader systems and its ability to generate large databases which can be exported, analyzed, and fed back for better performance. In this tech note, we have shown how both use cases can be described and analyzed within a SysML modeling environment, using a local model that was created independently of the larger domain.

In future notes in this series, we will show how a SysML IoT model can be federated to models in other tools. This includes linking to CAD models, e.g. a CAD model of the Smart Home itself, and more sophisticated simulation models, e.g. a Simulink model of power consumption variation over a daily cycle.

About the Author

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