

Knowledge-Based System to Support Plug Load Management

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ABSTRACT

Electrical plug loads comprise an increasingly larger share of building energy consumption as improvements have been made to Heating, Ventilation, and Air Conditioning (HVAC) and lighting systems. It is anticipated that plug loads will account for a significant portion of the energy consumption of Sustainability Base, a recently constructed high-performance office building at NASA Ames Research Center. Consequently, monitoring plug loads will be critical to achieve energy efficient operations. In this paper we describe the development of a knowledge-based system to analyze data collected from a plug load management system that allows for metering and control of individual loads. Since Sustainability Base was not yet occupied at the time of this investigation, the study was conducted in another building on the Ames campus to prototype the system. The paper focuses on the knowledge engineering and verification of a modular software system that promotes efficient use of office building plug loads. The knowledge-based system generates summary usage reports and alerts building personnel of malfunctioning equipment and unexpected plug load consumption. The system is planned to be applied to Sustainability Base and is expected to identify malfunctioning loads and reduce building energy consumption.

1. INTRODUCTION

Lighting and HVAC loads have typically been the top contributors to building energy consumption. However, as technology advances have made these systems more efficient, plug loads have become a relatively larger contributor to energy usage. For example, in a typical California office building lights consume around 40% of total energy, HVAC 25% and plug loads 15% (Kaneda,

Jacobson & Rumsey, 2010; Moorefield, Frazer & Bendt, 2011). These proportions change in a high-performance building, where unregulated plug loads can correspond to more than 50% of total energy consumption (Lobato, Pless, Sheppy & Torcellini, 2011). With the decreasing trend in lighting and HVAC energy consumption and with more dependence on computer and electronic equipment, plug and process loads are taking up an increasingly larger slice of the building energy use pie.

In terms of plug load energy consumption, it has been found that motivated users are key to saving energy (Kaneda et al., 2010). Employees who make use of built-in power saving functionality and turn off devices when not in use can significantly reduce energy waste, particularly during non-business hours. In other words, many of the barriers to reducing plug load energy use are behavioral, not technical.

As part of a NASA program to replace outdated and inefficient buildings, NASA Ames Research Center recently completed construction of Sustainability Base, a 50,000 sq. ft. office building designed to exceed the Leadership in Energy and Environmental Design (LEED) Platinum rating. Beyond providing an inviting workspace for employees, Sustainability Base has the following objectives:

1. To be a living, evolving research laboratory and showcase facility for sustainable building research.
2. To provide a mechanism for the demonstration and transfer of NASA aerospace technologies to the building industry.
3. To be an experimental research facility relevant to NASA's interest in developing human habitats on Mars and in space.
4. To facilitate collaboration by involving inter-governmental, academic, nonprofit, and industry partners in research on next generation sustainable building technologies and concepts.
5. To reinforce NASA's position on and support of the Executive Order on Federal Leadership in Environmental, Energy, and Economic Performance.

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In addition to investigations of technologies such as greywater recycling, data mining, prognostics, computational fluid dynamics, fuel cells, and intelligent control, NASA Ames will also examine the influence of plug load management. Since Sustainability Base was not yet occupied at the time of this study, a testbed was set up in another building on campus to perform a preliminary plug load management assessment (Poll & Teubert, 2012).

We wish to detect irregular plug load usage, malfunctioning devices, and also whether the plug load management system itself is performing as expected. In this paper, we demonstrate the development of an expert system to analyze data acquired from plug loads and to call attention to potential issues. The main contribution is the development of a modular, extensible knowledge-based system that can be easily adapted to Sustainability Base or other buildings that use plug load management.

This paper has the following structure: Section 2 discusses related work on intelligent systems applied to sustainable buildings. Section 3 describes the pilot study testbed, including test environment, plug load management devices and data collection. Section 4 describes the expert system developed to analyze the data generated by the monitoring system, concentrating on knowledge representation techniques. Section 5 presents the results of applying the expert system to the plug load data. Section 6 concludes with some lessons learned and next steps to be applied to Sustainability Base.

2. INTELLIGENT SYSTEMS FOR SUSTAINABLE BUILDINGS

Knowledge-based systems have been applied to Building Energy Management Systems (BEMS), which play an important role in occupant comfort and energy consumption. In this area, Doukas, Patlitzianas, Iatropoulos and Psarras (2007) describe an intelligent decision support system using rule sets based on a typical building energy management system. The knowledge base addresses the following categories: internal comfort conditions, building energy efficiency, and decision support. The decision support module has the following functions: Interaction with the sensors for the diagnosis of the building's state; incorporation of expert and intelligent system techniques in order to select the appropriate interventions; communication with the building's controllers for the application of the decision. The system enables central management of energy consumption in buildings by translating the building energy knowledge into several rules and finally into electronic commands to actuator devices. The paper describes the adopted methodology to develop the system using expert knowledge for building energy management, the system architecture, a summary of its rules and an appraisal of its pilot application to a building. One of the main project conclusions was that expert knowledge has significant potential for improving building energy management, since

it provides the ability to modulate, with the help of the rules, intelligent interventions.

As presented above, heating and cooling requirements play a vital role in building energy demands, therefore the definition of such requirements is essential during the building design process. In this context, Ekici and Aksoy (2011) introduce an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict heating and cooling energy needs. The inputs to the inference include physical environmental parameters such as outdoor temperatures, solar radiation and wind speed and direction in addition to design parameters such as building form factor, transparency ratio, insulation thickness, and orientation. The performance of ANFIS was benchmarked with the results of conventional calculation methods of building energy requirements; the ANFIS models yielded a successful prediction rate of 96.5% for heating and 83.8% for cooling energy requirements.

Kwok, Yuen and Lee (2011) present an intelligent approach to assess the effect of building occupancy on cooling load. The reference presents a neural network that considered external (outdoor temperature, relative humidity, rainfall, wind speed, bright sunshine duration and global solar radiation) and internal factors (occupancy area and occupancy rate) as inputs; the total cooling load is the model output. The occupancy rate is derived from the total energy of primary air units, whose output of fresh air depends on the measured CO₂ level. When the number of occupants increases, the CO₂ concentration level increases and leads to an increase in fresh air supply rate. The study includes a sensitivity analysis considering three variations on the input to the neural network: only external factors, inclusion of occupancy area and addition of occupancy rate. The analysis

Equipment	No.	Equipment	No.
Desktop	6	Calculator	1
Laptop	3	Storage drive	1
Printer	7	Battery charger	1
Phone	2	Vending machines	2
Speaker	3	Space heater	1
Scanner	3	External drive	1
Monitor	7	Coffee maker	1
Hub	2	Refrigerator	1
Copier	1	Bridge	1
Shredder	3	Microwave	1
Lamp	2	TOTAL	50

Table 1. List of equipment monitored

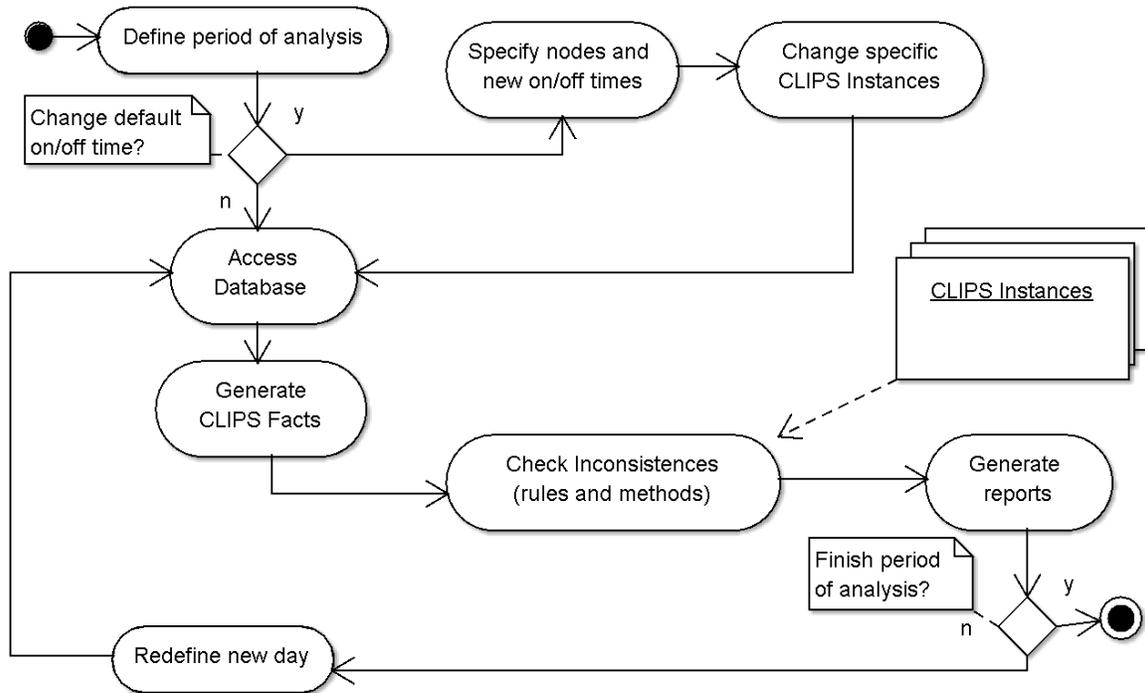


Figure 1. UML activity diagram of expert system prototype

demonstrates the importance of occupancy data in the building cooling load prediction. From these few examples, it is clear that there is a need for applications of intelligent systems for sustainable buildings.

3. TESTBED FOR PLUG LOAD MANAGEMENT

In preparation for deploying a plug load management system to Sustainability Base, a pilot study was conducted in another office building on the NASA Ames campus (Poll & Teubert, 2012). The plug load management system included 15 power strips, with 4 channels (receptacles) per strip. Each channel is metered and can also be commanded on or off. Power strips wirelessly transmitted data to and commands from a cloud-based data service via bridges connected to the building local area network. Minimum, mean, and maximum power draws for one minute intervals were recorded to a database. In order to collect a representative set of data, the power strips were located in different locations, including offices, a copy room, and a break room. Table 1 lists the types and number of equipment monitored.

Channels had various power consumption profiles and operating modes (e.g., standby, idle, active). Both the number of channels and power consumption characteristics will change in the future deployment to Sustainability Base, requiring that the knowledge-based system be easily adaptable.

Power consumption data were collected over a period of several weeks to establish a usage baseline. Then, schedule-

based control was used to power off and on groups of devices at different times according to occupants' work schedules. In addition to employing time-based rules, changes were made to the energy saver settings of certain devices (e.g., time to standby mode, screen saver behavior).

4. EXPERT SYSTEM PROTOTYPE FOR PLUG LOAD ANALYSIS

One of the main objectives of the plug load testbed was to gain practical experience that could be transferred to Sustainability Base, which was in the final stages of commissioning at the time of this study. Consequently, one of the first decisions made in developing the expert system prototype was to create a knowledge-base that could be easily adapted to the future setup, which will have a different set of plug loads compared to the testbed.

The expert system prototype was developed in CLIPS (Giarratano & Riley, 1994) using a combination of rules, semantic network and object-oriented modeling.

Figure 1 presents the expert system prototype UML activity diagram. The knowledge-base is composed of two parts: 1) CLIPS Instances (setup dependent); 2) Rules and Methods (setup independent), as discussed later. For graphical output, a JavaScript library was used (Dygraphs, 2011).

The choice of CLIPS as developmental framework was guided by the following factors:

- CLIPS Object-Oriented Language (COOL) module allows to take full advantage of object-oriented modeling;

Element	Description
Define period of analysis	User definable period of analysis during which all instance attributes are kept the same.
Change default on/off times	Each load has time-based on/off attributes pre-defined in the instance set. These attributes are key to identifying inconsistencies, since a load can be operating when it shouldn't or vice-versa.
Access database	Generate facts by extracting only relevant attributes from the database, such as channel, initial time and average power.
CLIPS Instances	Comprising the core of the system, instances define specific methods (e.g., calculate time spent in each power mode) as well as attributes that describe load behavior such as status, power, abnormal range, etc.
Check inconsistencies	Set of rules and methods to accomplish the following functions: Alert loss of communication if load doesn't report measurement for more than 20 minutes. Alert failure of schedule-based on/off rules: triggers a message if a load is on when it should be off or conversely, if a load is off but should be on. Alert abnormal power consumption: triggers a message if load is consuming power out of any previously defined range or if the load is consuming power in a range for longer than expected (e.g., transition to standby mode after 60 minutes). Alert possible channel change: triggers a message if power consumption pattern indicates that a different load may have been plugged into a channel. In this case, the system writes a message to the end of the daily report, indicating the time when the change was detected and which channel(s) was switched.
Generate Reports	Present power mode transitions: records a message if load changes modes (e.g., on to off, standby to idle, idle to active). Present percentage of time in different power modes: records duty cycle information for each channel. Present overall energy consumption per day: record the total kilowatt-hour energy consumption for each channel. Calculate wasted-energy: records energy consumption of phantom loads. Graphical reports for different fault modes.

Table 2. Knowledge base elements of expert system prototype

- The representation paradigm was chosen based on previous experiences in developing expert systems for different engineering domains, including hydraulic system (Silva & Back, 2000), cogeneration power plant design (Matelli, Bazzo & Silva, 2009; Matelli, Bazzo & Silva, 2011), and natural gas transportation modeling (Starr & Silva, 2005);
- The combination of object-oriented modeling, semantic network, and rules in an incremental approach allows modularity, expandability, and robustness;
- The framework allows for a rapid prototyping by the knowledge engineer, which was a benefit in this case, given previous experience and time limitations.

The prototype was designed to process raw data and generate summary reports and graphs with useful information for either building operators or occupants. Table 2 lists the prototype elements (presented in Figure 1) and their rationale. The primary functions can be summarized as:

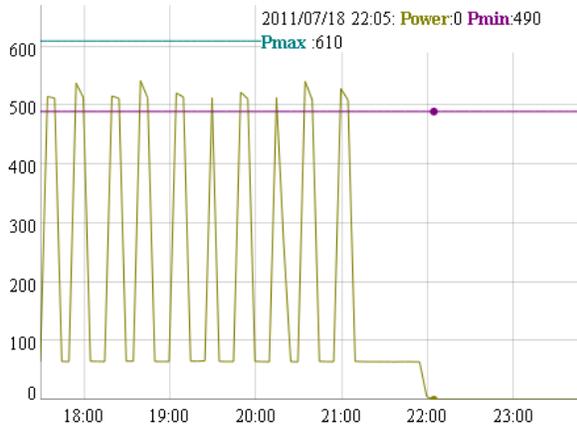
1. Alert loss of communication
2. Alert failure of schedule-based on/off rules
3. Alert abnormal power consumption

4. Alert possible channel change
5. Present power mode transitions
6. Present percentage of time in different power modes
7. Present overall energy consumption per day

Since we did not have much a priori information regarding the different types of loads, and due to the fact that most attributes are shared by all loads, we chose to generate all load instances from the main class. However, as the system evolves and more detailed information is obtained regarding differences among loads, it is possible to modify the class structure – adding sub-classes such as desktop, laptop, printer, etc., and redefining the current instances according to these new sub-classes. Such expansion would greatly increase the ability to define specific methods without requiring a considerable change in system code. Even with the current structure, it is possible to treat different loads in a specific manner. For example, the calculation of abnormal consumption, i.e., out of a pre-defined power range, was implemented for the photocopier. In order to do that, the `abnormal_range` attribute value was defined for this instance. Some loads required special treatment. Desktops computers did not have schedule-based control applied because removing power without a proper shutdown

Channel: 14.1 (Drink vending machine)

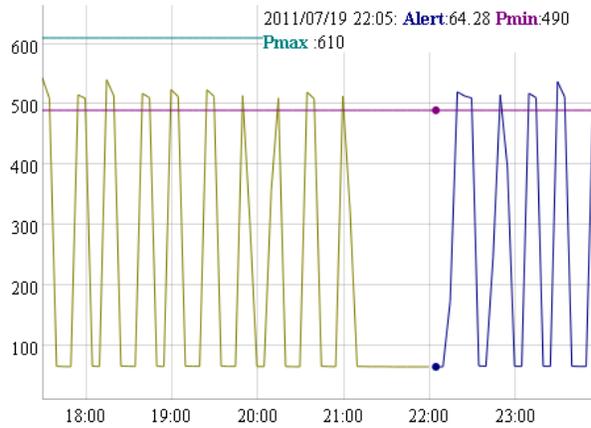
Power consumption [W]



a) Channel switches off at 10 pm

Channel: 14.1 (Drink vending machine)

Power consumption [W]



b) Channel fails to switch off at 10 pm

Figure 2. Example of schedule-based rules

sequence could result in data loss or damage to the computer.

Additionally, turning off some printers during non-business hours was found to use more energy than leaving the device in standby mode because of high power consumption for the warm-up and idle modes.

5. RESULTS

The prototype system was implemented and tested using data gathered from the plug load management system. All functions listed in Table 2 were tested by comparing the daily reports created by the prototype system to the recorded data.

Figure 2 shows outputs from one of the functions that checks for inconsistencies. Figure 2a plots the typical behavior, which shows that channel 14.1 was turned off with a schedule-based rule at 10 pm on July 18. However, on the next day, the same channel remained on after this time. Figure 2b shows that an Alert has been triggered at 22:05 (see alert message in upper right of graph), indicating that the schedule-based rule has failed.

The system also generates verbose report, whose snippet is presented in Figure 3. Firstly, Figure 3 presents each time a mode transition takes place, anomalies such as a possible change in channels, consumption in an abnormal range, and loss of communication. The next part presents a table with percentages of time spent in different modes. The final note calls attention to items which require inspection.

Although the loads were modeled as a single class, it is possible to study distinct behaviors. For example, for channel 5.0 there is a special rule that checks to see if the

device transitions to standby mode after 60 minutes of inactivity. As shown in Figure 4a, the copier transitions to standby mode (~60W) as expected. Figure 4b shows that on the next day at 14:35 it failed to transition to standby mode and had excessive power draw for the remainder of the day. In terms of expansion and use in Sustainability Base, only the template to database access and the instance set need to be changed. Neither task requires a skilled programmer

Report corresponding to date:20110728

6.3 @12:30 mode change on to idle power= 4.61

11.3 @12:30 mode change standby to on power= 1.3

...

@12:45 9.3 consumed power out of all ranges (phantom, standby, idle and active). Possible change in the channel has occurred. Check the user. Power= 88.15

...

5.0 @13:30 consuming in abnormal range:Power:265.05

...

4.0 @22:00 loss of communication

...

Channel	Total kWh	% on	% off	%other modes (*)
1.0	1.88	30.43	0.00	69.56
1.1	0.17	0.72	16.67	82.61
...				
15.0	0.15	33.33	60.15	6.52
15.1	0.10	34.06	60.15	5.80

* includes phantom, standby and idle modes

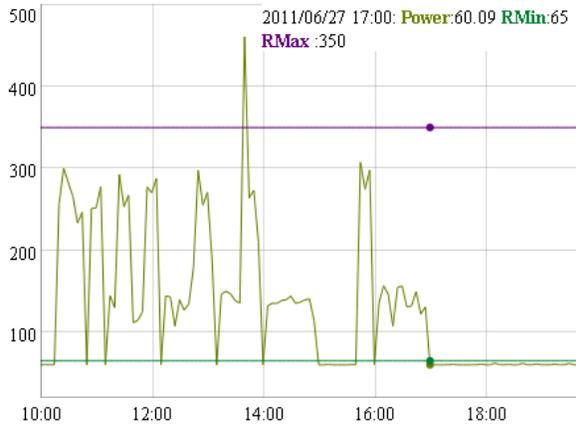
Attention: it is possible channels were changed because @ 12:45 channel 9.3 consumed power 88.15 out of its normal ranges. Check other channels in the same node.

Attention: it is possible channels were changed because @ 12:45 channel 9.1 consumed power 27.58 out of its normal ranges. Check other channels in the same node

Figure 3. Example text report

Channel: 5.0 (photocopier)

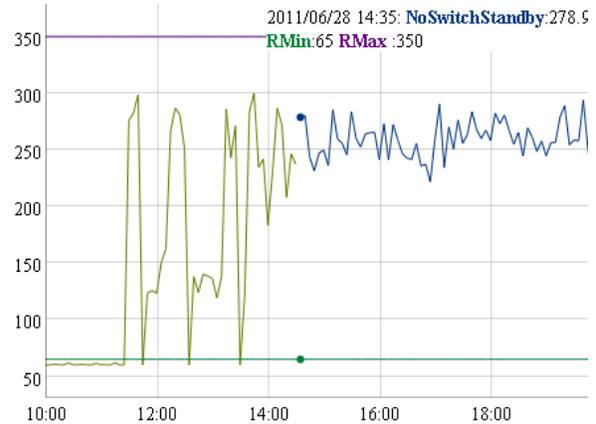
Power consumption [W]



a) Normal transition

Channel: 5.0 (photocopier)

Power consumption [W]



b) Failure to transition

Figure 4. Examples of transition to standby

because the rules/methods do not refer to specific instances; they are independent from the operational setup. The knowledge base proved to be extensible as it incorporated additional attributes as the specifications increased in complexity. Future work will implement plug load subclasses to include specific information allowing a modular expansion.

6. CONCLUSION

The paper presents the development of a knowledge based system to analyze plug loads, which are becoming increasingly important in high-performance buildings. The system processes data acquired from a plug load monitoring system, triggers alerts and generates reports. The alerts call attention to malfunctioning equipment, failure of schedule-based rules, or changes in use pattern. The reports summarize plug load power consumption statistics. Providing such feedback to occupants is expected to identify malfunctioning equipment and reduce the energy consumption of Sustainability Base.

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