MULTIPLY DATA ANALYSIS AND KNOWLEDGE-BASED METHODS TO REDUCE HVAC OPERATING AND MAINTENANCE PROBLEMS

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ABSTRACT
Recent reports have highlighted a lower than expected level of understanding by some consulting engineers and building operators concerning how to systematically track operation and maintenance problems and provide consistent advice for improving permanently a system capable of analyzing and continuously diagnosing problems after the original analysis is complete (MacDonald and Waeseman, in preparation).

One system, originally developed at a state university, student recreation center (Rec Center), reduces operation and maintenance problems by analyzing monthly consumption data with an expert system. Several papers and reports have been written that describe this particular system, called the building Energy Analysis Consultant (BEACON) system, how it was developed, its application to four complexes, and its possible future directions (Haberl and Claridge [1987]; Haberl et al. [1988]).

This paper presents additional information concerning the BEACON system, including examples of its impacts, a review of the regression analysis employed in the original BEACON system, a description of the knowledge acquisition process, and reports on recent developments to modify and streamline the algorithm. Experience with delivering the prototype software to building administrators and ideas on future directions are also presented.

INTRODUCTION
Computer and maintenance. Computers have been used to track and schedule building maintenance operations since the late 1950's. Computerized methods used to analyze maintenance problems range from graph theory and decision logic to hierarchical control, pattern recognition and expert systems. Applications of these methods include chemical process control, aircraft power control systems (Chester et al. [1984]), a diesel electric locomotive centralized expert system (Claridge and Haberl 1984), and steel and paper-pulp industrial controls (Murphy et al. 1984). This paper reviews a system developed for the armed services provided by Richardon (1985).

Expert systems, a form of artificial intelligence (AI), are symbolic computer programs that solve problems difficult enough to require a specialist or expert. Different expert system programs (or shells) use varying schemes of knowledge representation, but they all follow the same general line of reasoning. The BEACON system (and maintenance of the rule base) is provided by Richardon [1987].

BEACON's reasoning structure evolved from observed events. The structure used is simple in nature and was generated by Chester [1984], Davis [1984], and Richardon [1984].

1. identification and sampling of a control, program, or inference engine for processing the information;
2. one of the goals of the project was to eventually turn over the day-to-day operation of the system (and maintenance of the rule base) to non-technical building personnel with limited computer training. A more advanced system, which is model-driven and quasi-real-time, is now under development and will be reported on in the near future.

Development of the BEACON system required a traditional walk-through energy audit, significant background information (including building energy end-use distribution diagram and historical metered data) one or more persons that intimately knew the building systems well enough to serve as the building expert, and a minimum of 9 months to one year of daily observations of the building's performance -- all of which was used to assemble the regression model and the knowledge base.

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Knowledge acquired from maintenance experts. The second type of information required for the construction of the knowledge base consisted of knowledge gained from conversations and interviews with maintenance personnel. Our "expert" in fact, embodied several individuals, most of whom had experience with the building since its construction in the early 1970's. There are many methods in use for interviewing an expert, colliding the knowledge, inserting the knowledge into a knowledge base, and testing the code (Bart 1986). We chose formal interview (where possible) and supplemented with informal conversations (recorded during meter readings).

Knowledge acquired from the formal interviews of the maintenance personnel focused on specific problem-solution areas, for example of a problem-solution set follows:

1. the interviewer selects a specific problem for the site to be identified;
2. general questions are asked concerning the obvious signs that are used to diagnose the site-independent problem;
3. the maintenance expert then adds specific details that concern the site-specific problem;
4. the interviewer is asked into a simple decision tree and then into that of IF-THEN rules;
5. the rules that codify the domain knowledge are elicited.

The prototype expert system is reviewed by the knowledge engineer and the maintenance expert;
6. adjustment and/or changes are made as needed.

Knowledge gained from informal conversations was less structured than the formal interviews. Most meetings usually occurred during the time when the daily meter readings were taken at the Rec Center. In most of these instances the maintenance personal
were either responding to a maintenance call or performing preventive maintenance, information obtained was distilled into a decision table, inserted into the knowledge base, and tested.

Knowledge acquired from daily observations. Information gained from daily observations consisted mostly of daily log book entries taken since August 1985. Specific issues of interest were inspected each day and noted in the log book. Special events were also noted. Such entries were used to identify operationally caused equipment-malfunctions that may have led to an unknown event and/or to verify previously assembled diagnostic rules.

In addition, the knowledge base was supplemented by two other means: 1. expected patterns in many event signatures could be calculated from design conditions; and 2. over-consumption events could be treated by forcing systems to malfunction and observing how actual consumption deviated from the predicted consumption.

Assembly and testing of the knowledge base. Figure 3 illustrates the decision table used to construct the knowledge base. Our decision table was composed of three primary parts: a conditions section, an event matrix and a conclusion section. Condition(s) consisted primarily of three types of data: 1. the daily consumption signatures; 2. the daily influence parameters; and 3. other observations noted in the log book (e.g., hockey games, special events, etc.). The consumption signature data and the influence parameters were used to calculate the comparative difference between actual and modeled consumption calculated for each of the meters in the building. The influencing parameters were those parameters that significantly affected consumption (e.g., average outdoor temperature, occupancy, etc.).

The event matrix is a sparse matrix of conditions that are used to specify each event. The matrix can have a confidence factor attached to each condition that is recorded. The conclusions contain a diagnosis of the problem based on the knowledge base interpretation of the observed conditions. The form for a conclusion is a sentence-like structure.

The example of an observed event relates to an uncontrolled draining of the pool that would occur every morning (e.g., during a lease-related event) when the power outage occurs. Information gained from daily observation coincide with the expert system by asking the following questions: 1) is there an operationally caused equipment malfunction? 2) is there an over-consumption event signature? 3) are there any other observations noted in the log book? 4) has there been a change in the filters (1,000 to 5,000 gallons)? Has the pool been serviced? Has there been an unusual routine in the emergency generator (a natural gas fueled backup that cuts in on low voltage)?

The assembly and testing of the knowledge base. During our observations at the Rec Center we found that there were many different types of over-consumption events in the original system, which indicated that the emergency generator would drain the pool (at times the pool would be empty). These conditions were identified as a leak due to a power outage. These conditions occurred several times during the period of observations, were consistently spotted by the expert system, and hence are assigned a high confidence factor.

Defining significant over-consumption events. In order to define significant over-consumption events in the original system, a leak due to a power outage, these conditions were identified and assigned a high confidence factor. Significant was defined as having a measurable event. Either, "significant" or "non-significant" was meant to signify a measurable event. The problem events were defined to have a duration of up to 5.000 gallons per day? Is the total pool water consumption in excess of 10,000 gallons in one day? Has there been a change in the filters (1,000 to 5,000 gallons)? Has the pool been serviced? Has there been an unusual routine in the emergency generator (a natural gas fueled backup that cuts in on low voltage)?

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several days. "Trends" were defined to be sustained, measurable shifts in consumption. A significant event, therefore, was an observed event that can be related to an operational, system, or equipment cause. A non-significant event is an event that causes over-consumption, but is not operationally or maintenance related. For example, planned, extended hours (special events) were viewed as non-significant events. Significant events were usually observed by one of two methods:

1. observing the event during the daily inspections and then relating it to the resulting over-consumption,
2. observing an over-consumption signature and discovering the offending event by interviewing maintenance personnel.

Significant events were opened (or documented) in the database for special analysis. The sustained occurrence of a significant trend, typically required the reconstruction of the consumption predictions, otherwise repeated warnings become bothersome.

CONSTRUCTING THE CONSUMPTION PREDICTORS

General. The consumption predictors from the original prototype model were a staple set of regression-based equations that model the energy usage for a given day using the influencing parameters. The consumption predictors used for the Rac Center have been previously reported (Haberl 1986; Haberl and Claridge 1987; Haberl et al. 1988). This discussion will focus on how they were constructed as an introduction to the new developments using the PRISM predictors.

Table 2 lists the equations that form the internal model used in the prototype. Two sets of equations were necessary for the period July 1986 to June 1987, since the "wind" variable was eliminated from the regression and significant trends occurred during that period (increases of over 10 percent). The building's "other steam" consumption is currently sensitive to the outside air temperature, the city water temperature, the resurfacing of the ice rink, the wind (dropped after January 1987), the number of people using the facilities, and the scheduled hours of operation. The prototype predictors had an R-squared of 0.92 to 0.98 and a standard error of 3.4 to 3.6 MMBtu/day (8 percent of average monthly usage).

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March and May. However, a non-temperature dependent seasonality can be detected during the months of October, November, and December. These events are well described by a PRISM analysis, although some predictors are difficult to trace to physical conditions even though they provided a good fit.

2. Applying regression techniques blindly to a data base often creates obvious units. One must be careful to choose units that are computationally efficient and yet remain acceptable as engineering units. For example, the first prototype (label2) was inefficient and yet remained acceptable as engineering units.

3. Correlations among independent variables caused problems. They expanded the data base, slowed computation, and decreased the accuracy of predictors. For example, the first prototype (label2) was inefficient and yet remained acceptable as engineering units.

4. Linearization, using polynomials, sometimes created severe inaccuracies at the upper and lower limits. Also, certain linearization techniques could not be translated to physical conditions even though they provided a good fit.

5. The Princeton Scorekeeping Method (PRISM) was chosen over other methods (MacDonald and Wasserman, in preparation) because it provides several daily parameters, has well-documented statistical procedures (Coldberg 1982), and is based on engineering principles and has significant potential for adaptation (Pels 1986).

The Princeton Scorekeeping Method (PRISM) is a statistical procedure originally developed to monitor heating energy usage in housing. PRISM requires whole-building metered data, billing period dates, and average daily temperatures for a given building. PRISM produces a weather-adjusted annual consumption (ACC) which is composed of three primary parameters that describe temperature dependent and temperature independent (or baseload) consumption (Pels 1986). One parameter, the baseload consumption (a), is a measure of the appliance or temperature independent energy consumption. A second parameter, the balance point temperature of the model, is the calculated temperature below which the building requires heating to maintain comfort conditions. The third parameter is the heating degree days (B) or the amount of energy the building requires for each degree difference between the outside air temperature (Tout) and the balance point temperature (Tbp). The basic PRISM approach solves for these parameters by regressing against a range of balance point temperatures. The following equation was used:

\[ \text{B} = \text{a} + \text{b} \times (\text{Tout} - \text{Tbp}) \]

where \(\text{B}\) is the heating degree days, \(\text{a}\) is the baseload consumption, \(\text{b}\) is the heating slope, \(\text{Tout}\) is the outside air temperature, and \(\text{Tbp}\) is the balance point temperature. The main assumption is that the building is a constant volume at steady state.

One of the key features of the PRISM approach is that it is relatively simple to use and requires a minimum of data input. The model is based on engineering principles and has significant potential for adaptation (Pels 1986). The PRISM approach is useful for identifying the effects of different design strategies on energy consumption. For example, it can be used to estimate the energy savings that can be achieved by changing the design of a building.

The problem with the PRISM approach is that it is not always possible to estimate the energy savings that can be achieved by changing the design of a building. This is because the PRISM approach is based on engineering principles and has significant potential for adaptation (Pels 1986). The PRISM approach is useful for identifying the effects of different design strategies on energy consumption. For example, it can be used to estimate the energy savings that can be achieved by changing the design of a building.
The lower line shows the comparative (PRISM-actual) other steam consumptions, upper line represents the actual consumption and minutes (compared to 8+ hours for the prototype) which reduces our computation time significantly.

Table 2 - Prototype and PRISM-based Predictors for the 1987-94 Center.

Comparative (PRISM-actual) other steam consumptions for the period July 1986 to June 1987 are shown. The upper lines represent the actual consumption and predicted consumption. The lower line shows the comparative consumption with the housing upper and lower limits as defined by one standard deviation.

Comparison of Predictors.

The PRISM predictors surpassed our initial expectations. The PRISM predictions (compared to 6 hours for the prototype) were equally identified and therefore did not affect the performance of the expert system. The PRISM predictors follow the change in heating envelope. The linearized prototype predictors follow the change in heating slope. The PRISM predictor did not.

Second, and most important, when we compared the over-consumption events using the prototype with the PRISM over-consumptions, no acceptable number of variates were equally identified and therefore did not affect the performance of the expert system. The PRISM predictors actually performed better during summertime periods. This is evident when one compares the June to August portion of the comparison line of Figure 7 versus Figure 6.

Finally, ongoing efforts have identified two variates, occupancy and scheduling (included in the prototype), that show promise of being adapted to a PRISM approach. We currently are investigating how we can extend the PRISM methodology to include these variates.

Discussion

General. Our efforts on the campus, and at other facilities (Haberk and Vajda 1986), encourage us to believe that a rule-base, expert system model can be modified from its current labor intensive, "nice specific" application to a more straightforward, "elite independent" application by using a modeling approach for predicting daily consumption. Therefore, we believe that such an approach, once fully developed, will provide a fast, efficient method for producing daily feedback to building operators concerning their energy use, and that will reduce operation and maintenance problems in buildings. Ongoing BEACON research is focused on resolving this issue. Our current efforts involve improving, documenting, and automating the knowledge base of the expert system, refining their structure, and streamlining the simulations, production of the rule-base, and documenting the production of the rule-base, and documenting the nature of some important features of the expert system. The performance of the expert system is useful for trouble-shooting, is a good weekly management tool, can be adapted to budgeting requirements, and justifies the time needed to collect and process the data. The graphics are the best of the entire system.

BEACON seemed somewhat static, (not as well-adapting as it could be) and is impossible for them to adjust in-house when it drifts out of calibration. The expert system in BEACON is rarely used. The administrators, lack faith in the expert system when the first wrong "conclusion" is reached. It is important that the expert system is able to adjust itself in-house with the building by looking at the charts themselves. On the other hand, the graphics are the best of the entire system, the expert system is useful for trouble-shooting, is a good weekly management tool, can be adapted to budgeting requirements, and justifies the time needed to collect and process the data. The graphics are the best of the entire system.

Areas for Future Research. Previous papers (Haberk and Claridge 1987, Haberk et al. 1988) reported a number of areas of future research. We now add the following to the list:

1. Current BEACON applications lead us to believe that a rule-base approach (with limited, may not be the most efficient method of diagnosing problems. Other methods of diagnostic reasoning have been reported (Chester et al. 1984; Richardson 1985) which may be more efficient. Our current efforts involve improving, documenting, and automating the knowledge base of the expert system. The performance of the expert system is useful for trouble-shooting, is a good weekly management tool, can be adapted to budgeting requirements, and justifies the time needed to collect and process the data. The graphics are the best of the entire system. The knowledge base is needed before a commercial/marketable product could be developed.

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3. In addition to previous efforts (Dohrmann 1986) a thorough, industr-wide survey should be conducted by ASHRAE (and others) to determine what kinds of operational and maintenance problems prevail (in a broad class of buildings) and what results these problems (i.e., personnel profiles,
energy use and diagnosing the development of differences in the personnel at different buildings. For example, age, education level, technical training, computer training, and methods employed to resolve problems. Proficiency is a state and not a skill — all need to be further quantified.

CONCLUSION

This paper reports on the process of developing an expert system (BEACON) for monitoring building energy use and diagnosing the development of potential problems. The knowledge base structure and knowledge acquisition methods used in the BEACON prototypes are described. Efforts to streamline the production of a regression-based internal model may mean this system will be easier to use in the future. Initial results are encouraging and help point the direction for continued research efforts. This work shows that significant energy savings can result when good energy conservation measures are followed-up with continuous energy monitoring, tracking and diagnosis. Finally, this work demonstrates that energy audits can be enhanced with diagnostic performed on metered consumption data.

REFERENCES


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