Information Technology for Energy and Maintenance Management

Luis Villafana
School of Information Mgmt. & Systems
University of California, Berkeley

Clifford Federspiel
Center for the Built Environment
University of California, Berkeley

ABSTRACT

We describe the design of a tenant interface for energy and maintenance systems (TIEMS) in commercial buildings. TIEMS is designed for use by occupants (tenants) of commercial buildings. Our hypothesis is that by allowing tenants access to information from the energy and maintenance systems and by giving them some control over these systems, energy and maintenance performance can be improved. We used interviews with potential users and existing energy and maintenance databases to guide the design. Results of a field trial demonstrate the utility of TIEMS.

We also describe the design of a maintenance and operations recommender (MORE). MORE uses information from computerized maintenance management systems (CMMS) and energy management and control systems (EMCS) to recommend what maintenance personnel should do in response to a maintenance service request. MORE integrates text descriptions of problems with sensor information related to the problem. After work orders are closed, MORE uses the information about what was actually done to solve the problem to learn how to improve its recommendations.

INTRODUCTION

Modern buildings use computerized maintenance management systems (CMMS) and computer-based energy management and control systems (EMCS). These systems contain large databases of information about historical building maintenance operations. Additionally EMCS systems contain real-time information about various subsystems important to building operations, including heating, ventilating, and air-conditioning (HVAC) systems, life-safety systems, lighting systems, and power systems.

One of the most advanced energy and maintenance systems developed to date is GEMnet (Piette, 2002). GEMnet is an integrated information technology infrastructure for energy and maintenance management. It uses a common database system for all components and an open communications protocol called BACnet (ASHRAE, 2001). GEMnet uses modern web-based technology for its user interface. However, the intended users of GEMnet only include maintenance personnel. The way that building occupants interact with GEMnet is by making a telephone call to someone in the maintenance department to request service or report a problem. The maintenance personnel manually enter the service request into GEMnet, sometimes long after the phone call has been made.

Our work on the interaction between building occupants and energy and maintenance systems (Federspiel 1998, 2001) suggests that building occupants should also be considered users of energy and maintenance systems. Until recently this has been considered an unwise, even radical, idea among facility management professionals. However, providing tenants with a user interface to energy and maintenance systems should improve thermal comfort, improve the performance of energy management strategies, eliminate some redundant service requests, and an improve the quality of data in maintenance databases. A well-designed user interface should also improve the satisfaction of the occupants with the services provided to them by maintenance personnel.

CMMS systems are used to monitor the frequency of maintenance activities and the time required to perform them. This capability is particularly useful when maintenance services are provided by third parties. EMCS systems are used to monitor energy-intensive equipment such as HVAC equipment. They monitor key system variables such as temperatures, flow rates, and pressures, and derived performance metrics such as chiller efficiency so that when alarms or problems are reported the maintenance personnel can look at these variables to diagnose the problems. There have been some efforts at integrating CMMS operations and EMCS operations. For example, some energy and maintenance systems will automatically initiate a work order in a CMMS in response to an alarm in an EMCS.

In this paper we describe the design of a Tenant Interface for Energy and Maintenance Systems (TIEMS). TIEMS is designed to operate as a component of GEMnet. The next section covers the methods we used for design.

The following section includes the results of our pre-design investigations, and a description of the design itself. We conclude with a section on expected benefits of TIEMS.

We also propose integrating CMMS data with EMCS data for the purpose of recommending to building engineers what they should do in response to a service request or problem report from an occupant. Recommender systems are commonly used to retrieve useful documents from large databases and from the internet (Resnick and Varian, 1997). In the document retrieval application, the recommender system recommends documents that match a weighted query. The recommender system either uses feedback from the user or watches the user's search patterns to determine the best set of weights for the queries. Hayes and Pepper (1989) describe a system that provides maintenance recommendations based on a decision-tree approach and a database of faults. The system provides sequential recommendations of tests that the maintenance technician should perform in order to diagnose a problem.

I. TENANT INTERFACE FOR ENERGY AND MAINTENANCE SYSTEMS – (TIEMS)

METHODS

We used four sources of information to guide the design of TIEMS: interviews with tenants, meetings with maintenance personnel, historical maintenance records, and tenant scenarios.

We interviewed eight tenants from three different agencies in a U.S. federal building before and after deploying the interface to determine their needs. We asked questions designed to provide information about how the complaint reporting process currently works, their satisfaction with the current process, their needs for changes, and whether or not they would be receptive to our proposed design ideas. After deploying the interface we interviewed tenants to learn about their perception of the interface and whether it met their needs.

We held meetings with the building energy and maintenance staff to discuss our concepts for the design of the user interface. We described our previous research results, proposed our design for TIEMS, and asked for their feedback.

We analyzed data from several maintenance databases. We looked for sensor data recorded in these databases, and we studied the problem descriptions and descriptions of actions taken.

We used the statistical test described in Fleiss (1981) for comparing two Poisson parameters to test whether or not there is evidence that the service request rate after deploying the user interface is different than the service request rate prior to deploying it. The null hypothesis for this test is that the rates are equal. The test statistic is as follows:

$$s = \frac{\left|\frac{k_A}{k_A + k_B} - \frac{T_A}{T_A + T_B}\right| - \frac{1}{2(k_A + k_B)}}{\sqrt{\frac{\frac{T_A}{T_A + T_B}\left(1 - \frac{T_A}{T_A + T_B}\right)}{k_A + k_B}}} \tag{1}$$

where k_A is the number of service requests prior to deploying the user interface, k_B is the number of service requests after deploying the user interface, T_A is the duration over which service requests were counted prior to deploying the user interface, and T_B is the duration over which service requests were counted after deploying the user interface. Under the null hypothesis, s is approximately standard normal.

To test the impact of TIEMS on labor hours reported by maintenance engineers, we used the two-sample t-test and the robust rank order test, which is described by Siegel and Castellan (1988). The robust rank-order test is a non-parametric equivalent of the two-sample t-test.

RESULTS

From the initial interviews with tenants, we learned the following:

1. All tenants currently report service requests by telephone. Office assistants usually report problems on behalf of others.
2. The average satisfaction level with the reporting process was 2 on a scale of 1 to 5 with 1 being the most satisfied and 5 the least satisfied.

3. All tenants complained about not being able to track the status of service requests. Some tenants would prefer to check status at a web site, while others would like to receive email. Some tenants want to be able to check indoor temperatures from a browser, and some tenants would like to be able to access maintenance notices from a browser or by email.
4. Tenants sometimes submit more than one service request for the same problem because they cannot track the status of their service requests and because they think it will reduce the response time.
5. Two-thirds of the tenants surveyed said they would use a web-based service request form.
6. One of the tenants said that they would be more likely to report problems if it were easier to report them.

From the post deployment interviews with tenants and building operators we learned that:

1. Tenants want to use a computer interface to enter complaints.
2. All Tenants like the feature of tracking complaint status.
3. Although any tenant could create a user profile and submit complaints directly into the maintenance system, agencies selected one administrative assistant to submit complaints and track these for the office.
4. The complaint status feedback is sufficient for some tenants but others require more information. One tenant stopped using TIEMS because it did not provide enough feedback for her. She wanted to know what parts were being ordered while the service request was open.

Maintenance personnel told us that it is common for maintenance or construction activities to produce many redundant service requests.

From results in (Federspiel 1998, 2001), and GSA maintenance databases we learned the following:

1. Temperature complaints are the most common service request.
2. In well-controlled buildings, half of the temperature complaints occur when the temperature is within the bounds specified in (ASHRAE 1992).
3. Data quality in maintenance databases is poor. Most of the fields are populated by hand, and service requests are relayed between two or three people before they are entered in the database.

Based on these findings, we included four key features in TIEMS. The first is the ability to check the status of service requests. User's can check the status of all service request they submitted and filter the display by status condition.

The second feature checks for redundant service requests. TIEMS searches for service requests submitted from the same location during the past two hours and displays them when a service request is submitted. The design intent is to eliminate redundant service requests. TIEMS does not prevent the user from submitting the request because it is possible that a second service request will contain important information about a problem that was not contained in the first service request.

The third feature of TIEMS is a list of notices that the maintenance personnel feel will convey useful information to the tenants. Tenants only see notices that apply to their location. Maintenance personnel can specify the length of time that the notices run. Notices are meant to notify tenants of possible maintenance activities that may be causing their complaint. Notices may also assist building operators with the ability to respond to ongoing energy saving activities. If building operators decide to shed energy load during a hot day, they have the ability to warn tenants of higher building temperatures.

The fourth important feature of TIEMS is the ability to check indoor temperatures. This feature is made possible and relatively simple by the fact that GEMnet control devices communicate using an open protocol called BACnet. GEMnet polls thermostats every five minutes and places the data in a circular buffer. TIEMS displays the most recent temperature value from the GEMnet database corresponding to the location specified by the user. User's choose a default location that becomes part of their profile. If temperature data are available, then TIEMS shows users the temperature at the complaint location when they submit a service request.

A site diagram and screen shots of individual web pages are shown in Federspiel and Villafana (2003a). The features described above are distributed throughout TIEMS. For example, when a tenant logs in he or she is immediately show a table of service requests previously submitted, and the temperature for their default location is shown in a sidebar.

We implemented TIEMS in two office buildings operated by GSA. Three lead users were given access to TIEMS. Figure 1 shows the number of service requests submitted to GSA by these lead users. Prior to October, all service requests were submitted by phone. Based on the test statistic in Equation 1 we found no statistically significant difference between the frequency of service requests submitted before TIEMS was deployed compared to after it was deployed.

The chief engineer at the test site told us that he thought TIEMS reduced the number of labor hours required to handle service requests because TIEMS provided better data about the nature of reported problems. He said that there were cases where it took them an hour just to determine what the problem was or who had submitted the service request when they were submitted by phone. We compared the number of labor hours reported for service requests submitted through TIEMS with the labor hours of service requests reported by phone. Table 1 shows the results. The table shows several comparisons because there were suspicious values in many of the records. The first row compares the two populations after records with zero labor hours were eliminated. The second row compares the two populations after records with labor hours less than 0.5 hours were eliminated. The third row compares the two populations after records with labor hours less than 0.5 hours and greater than zero were adjusted to 0.5 hours. The first column includes all maintenance workers, while the second column only compares work orders handled by GSA; the work orders handled by a subcontractor were eliminated. GSA thought that the fairest comparison was elimination of all records with labor hours less than 0.5 hours and handled by GSA. All of the comparisons show that the average labor hours for service requests submitted through TIEMS were slightly less than the average labor hours for service requests submitted by phone, but none of the differences are statistically significant.

II. MAINTENANCE AND OPERATIONS RECOMMENDER (MORE)

METHODS

The maintenance recommender works by making comparisons, by predicting the outcome of comparisons, and by learning from observations. This section describes methods currently used by MORE to perform these functions.

We assume that for every service request there is a set of N descriptors that could be sensor data, time, location, problem codes, or a text description of a problem or action taken. The data could be represented by Table 1. Actions could be either a set of codes corresponding to actions, a text description of actions taken, or both.

Text Processing

Some of the information in CMMS systems that will be used by the recommender is text, so we need a way to process text. Specifically, we need a way to compare text descriptions of problems and text descriptions of actions taken with standard queries.

We use concepts from the field of information retrieval (IR) that have been developed for comparing the relevance of text documents for making these text comparisons. Three common IR models used for assessing the relevance of documents are: 1) probabilistic models, 2) vector-based models, and 3) extended Boolean models. Probabilistic models and vector models are best suited to retrieving information from large collections of large documents. In a CMMS database, the “documents” consist of short text descriptions of problems or actions taken in response to problems; collections in the CMMS context are the sets of problem descriptions and actions. Even long descriptions in a CMMS database are short by IR standards. We have used both the vector model and the Extended Boolean model to process text from maintenance databases. For details on IR models, see Baeza-Yates and Ribeiro-Neto (1999) or Manning and Schutze (1999). For a description of how these models can be applied to maintenance data, see Federspiel and Villafana (2003b).

These text processing methods allow us to produce numeric values from text inputs. These numeric values are called similarity indexes. They usually take a value from zero to one. We use these values as the direct inputs to MORE.

Sensor processing

Some of the data available to the recommender are from sensors. We scale the sensor data prior to using them as inputs to MORE. The scaling involves subtracting a location value and dividing the difference by a scaling term. The location value could be the mean value of historical data, and the scaling term could be the standard deviation of historical data.

Sensor data are used to assess the system state. Since problems occur in different places and with different systems, the sensor values should be from the same kind of sensor, not just the same sensor itself. This implies that sensors of the same kind exist. It would not be possible using this method to use the sensors corresponding to a hot complaint from a space heated by a hydronic system with the sensors corresponding to a hot complaint from a space heated by a forced-air system.

We assume that MORE has been configured so that it knows whether or not a descriptor is sensor data or text. We also assume that the fields in the database corresponding to a particular kind of sensor data do not change. This could easily be accomplished by making a column in a table in the database always correspond to a kind of sensor (e.g., duct static pressure). The recommender does not figure out data types by itself.

Predicting actions

To make recommendations, MORE associates inputs with outputs. In principle, this mapping function could be any effective mapping function. In Federspiel and Villafana, we demonstrated the use of a linear mapping that associated the similarity of input descriptors with the similarity of the text descriptions of actions.

We have found that predicting action similarity does not work well because the quality of text in maintenance databases is poor. Text in maintenance databases frequently contains abbreviations, misspelled words, and short descriptions. For example, three text strings of actions that we found in one database are as follows: TO MANUAL&ADJ.AH5 CD, ADJ C/D S/P RM 101C, TS BROKIN, ADJ TS. Low quality text implies that the action similarity indexes are not an accurate estimated of the true similarity of actions.

We have also found that linear associations between inputs and outputs do not work well. The relationships between problem descriptors and actions taken are nonlinear.

We propose using codified actions as outputs. Codified actions could be embedded in a user interface, making the task of recording actions quicker and more reliable. Codified actions also offer the opportunity for MORE to produce actionable recommendations that could be automated in some cases.

We also propose using neural networks for mapping input descriptors to output action codes. Neural networks can be used to model arbitrarily complex, nonlinear relationships between inputs and outputs. They also have the ability to learn as new data become available.

Learning

The recommender learns to improve its predictions by adjusting the weights of the neural network so that the difference between predicted and computed action codes is a small as possible. This weight adjustment can be accomplished using any one of a number of different algorithms. In subsequent sections we use a Levenberg-Marquardt algorithm to train the network in batch mode (all at once).

RESULTS

In this section we demonstrate the performance of MORE using the data set analyzed by Federspiel (1998). This data set contains six input descriptors: time of day, day of week, building, gender (derived from name of caller), problem code, and space temperature. When someone calls to report a problem, the operator who takes the call sometimes takes an action that is codified. That action is taken prior to dispatching a field technician, so it becomes an input descriptor for MORE. Some of these descriptors take multiple values, so the number of input nodes of the neural network is 28.

The data set included a total of 15 action codes. These were reduced to 9 by grouping a number of them that occurred infrequently into an “other category”. The outputs of the neural network were codified using the binary code for the numeric value of the action code, reducing the number of output nodes in the network to 4. The output nodes used logistic activation functions.

We tested networks with a number of hidden layer nodes. We found that the best performance came from a network the same number of hidden layer nodes as output layer nodes, which was four.

The data set consisted of 2109 input-output pairs. We divided the data set into a training set with 1055 input-output pairs, and a validation set with 1054 input-output pairs. Figure 2 shows histograms of both data sets.

The most common action in this set was “no action”, followed by “adjust thermostat” and “major repair”. In the validation set, “no action” occurred 33% of the time. If MORE knew nothing about the problem descriptors, or had no way to use the descriptors to predict actions, then it should always recommend “no action” because that recommendation would maximize its success rate absent of any way to process the conditional information provided by the descriptors.

MORE successfully recommends the correct action 45% of the time. This is not a large increase in the success rate, but it is a statistically significant increase. Figure 3 shows the success rate of MORE for each of the actions. MORE successfully predicts the success rate of the frequent actions more than half of the time, correctly recommending “no action” 66% of the time.

DISCUSSION

TIEMS

The results of the field trial illustrate two important points. The first is that even the most active lead users sometimes still need to use the telephone to report service requests. The other has to do with "nuisance" service requests. Some facility managers are concerned that allowing tenants to submit service requests via the internet will increase the number of service requests submitted. There is no evidence from our field trial data that this is happening. Although GSA feels that TIEMS helps reduce the number of labor hours required to handle service requests, the available data do not provide conclusive evidence that such an effect exists.

MORE

We have described the design of a new system for providing recommended actions for maintenance personnel responding to problems reported by building occupants. MORE uses information stored in a CMMS database, integrates CMMS data with sensor data from EMCS systems, and learns to improve its performance with time.

In the example, input descriptions and output actions were codified. It is still likely that many maintenance databases will contain text. We propose using text problem descriptions and text action descriptions by comparing these descriptions with a set of standard queries. The text would be processed using one of the methods described above. The standard queries could be designed based on a combination of term frequencies in the text collections and application specific information about the building maintenance process. They could be designed with similar terms in the same query, producing a simplified thesaurus.

A key advantage of using codified actions instead of trying to predict action similarity is that a recommender that predicts codified actions can produce actionable recommendations. Actions such as "raise thermostat setpoint" can be automated using a standard value by which to raise the setpoint. Many control actions such as adjusting setpoints are benign enough that they could be implemented even if the probability of a successful recommendation is not very high.

It may be useful to add hysteresis to the output nodes so that no recommendation is given unless the output is sufficiently high or low. For example, a deadband of 0.2 around the midpoint output value of 0.5 could be used to define a "no recommendation" output state. In this case, an output value between 0.3 and 0.7 would result in "no recommendation". This would increase the probability of success when recommendations are made, making it possible to confidently automate recommendations that can be automated.

We assume that sensor data are readily and automatically available at the time that a problem is reported. Today this is generally not the case. To get sensor data into the CMMS database today, most systems would require the maintenance engineer to go to the control system, manually record relevant sensor values then manually enter them into the CMMS system. Through TIEMS this would be done automatically. The user interface uses this code to query a database for the most recent space temperature sensor value from the problem location. In that particular case, the temperature sensor values are available in a database because the controls are BACnet compliant. A program that can communicate with BACnet compliant devices polls all of the space temperature sensors (and other sensors) periodically and stores them in a circular buffer.

MORE uses feedback from recorded actions to learn. This does not require that the actions taken are always correct, but MORE will learn faster if they are correct, and the reliability of its recommendations will be better if the actions are correct. One way to ensure that MORE gets high-quality actions is to only make recommendations and learn from actions taken by experts. It is common for the name of the person performing maintenance to be recorded in a CMMS database. Ad hoc criteria such as years of experience, years working at this particular site, or a quality rating from a manager could be used to determine whether or not MORE uses the actions taken by a particular maintenance engineer. Another mechanism for ensuring the quality of recorded actions would be to survey the person who reported the problem to see whether or not the problem was solved, and how well it was solved. The results of the survey could be used to filter out incorrect actions and to place more weight on actions that result in high occupant satisfaction. However, care would have to be taken to ensure that factors which could result in low satisfaction, such as a slow response, do not reduce the occupants' assessments of whether or not the actions solved the problem.

We have designed a system that provides recommendations, not diagnoses. There are three good reasons for this. The first is that most of the information available in CMMS systems describes actions. It is much less common for maintenance engineers to describe the cause of problems. The second reason is that it may be possible to solve a problem without knowing the cause. It is arguably more important to solve problems than to know why problems occurred. In some cases the path to the root cause may be so long that deciding exactly what caused the problem is an arbitrary act of stopping somewhere along this path. The third reason is that it may be possible to automate some actions, significantly reducing the labor required to perform maintenance. However, if causes were routinely reported in a CMMS database, then the same procedure we have described for recommending actions could be used for recommending likely causes.

III. CONCLUSIONS

TIEMS Benefits

We expect the following benefits from TIEMS:

1. Fewer duplicate service requests
2. Better energy management resulting from better temperature control
3. Improved occupant satisfaction with maintenance services
4. Tenant acceptability to the use of computers to report complaints

Service request tracking should eliminate duplicate service requests, improving maintenance productivity because technicians won't be dispatched more than once for the same problem. The temperature checking feature of TIEMS should make it easy to identify whether or not a temperature problem is because of equipment failure or disagreement with temperature-related energy management practices. Giving tenants more access to and control of the process should increase their satisfaction with the process.

MORE Benefits

We have shown how CMMS data and EMCS data can be integrated to recommended actions to maintenance and operations personnel in response to a problem reported by occupants. The recommender has the following features:

1. Integrates text information from a CMMS with sensor data from an EMCS.
2. Learns to improve its recommendations without requiring anyone to rate past recommendations.

The first feature allows the recommender to use information from building occupants in a systematic way, effectively utilizing occupants as virtual sensors. The second feature allows the recommender to adapt to the building operations without the undesirable need to rely on explicit ratings of its performance.

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Table 1: Labor hours comparison between TIEMS and phone.

	All workers				Removed contractors			
	TIEMS, hours	Phone, hours	pu	pt	TIEMS, hours	Phone, hours	pu	pt
All nonzero entries	1.207	1.233			1.040	1.033		
No entries < 0.5	1.398	1.568	0.398	0.205	**1.071**	**1.193**	0.552	0.32
Small entries set to 0.5	1.270	1.329			1.052	1.087		

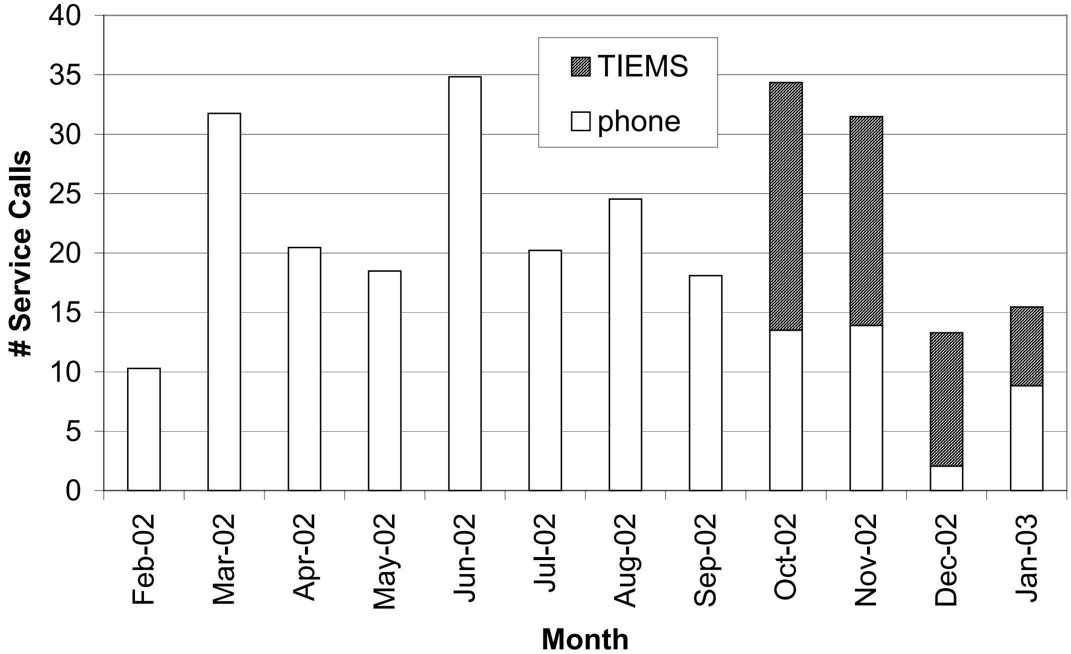

Figure 1: Number of service requests submitted by a lead user.

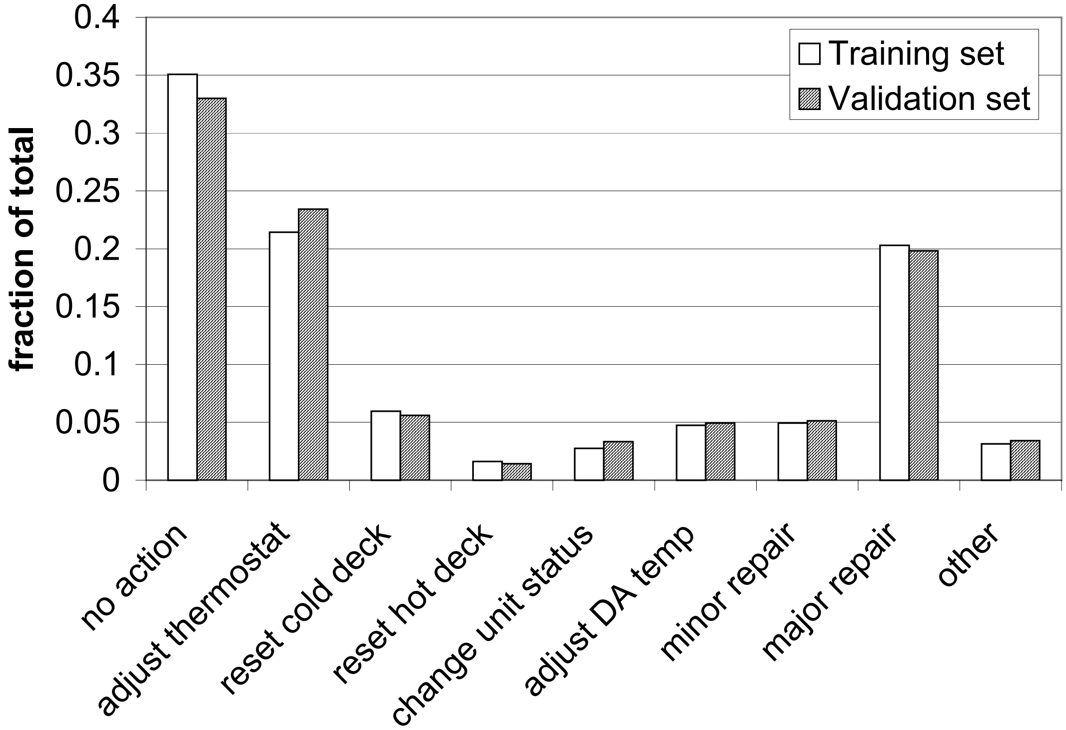

Figure 2: Histograms of the training and validation sets.

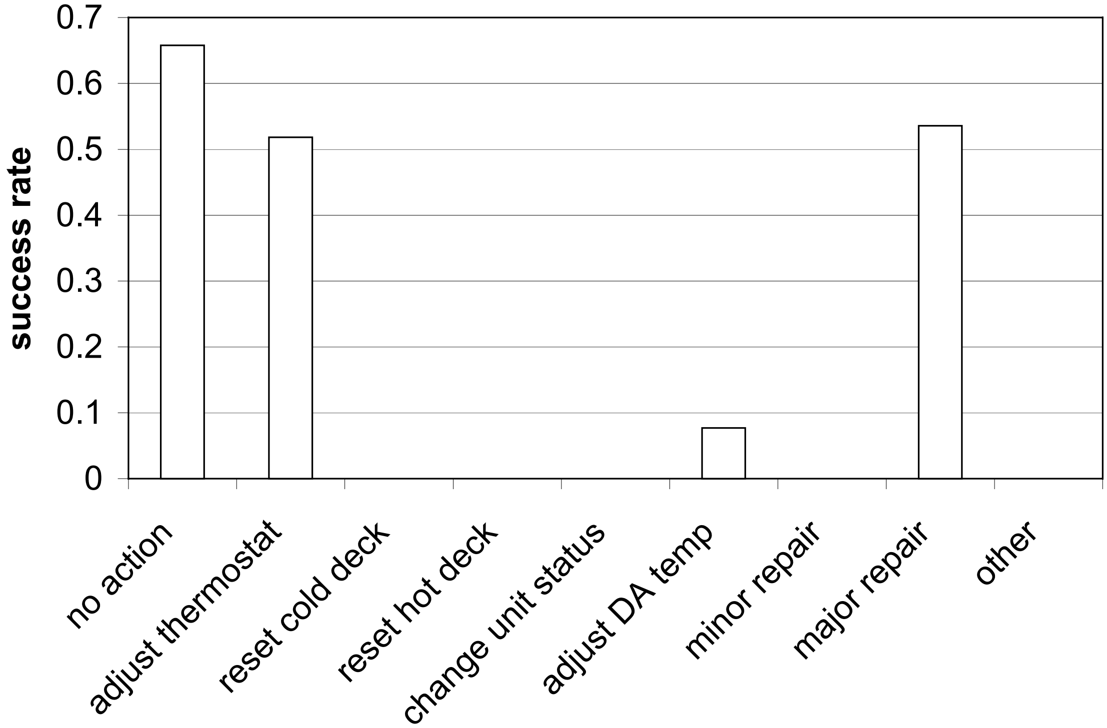

Figure 3: Success rate of MORE by action code.