Prioritizing and Visualizing Energy Management and Control System Data to Provide Actionable Information for Building Operators

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1. *INTRODUCTION*

Since the 1970s, energy management and control systems for commercial buildings have evolved under a variety of names including: building energy management systems (or BEMS), building management systems (or BMS), energy management systems (or EMS), building automation systems (EIS), HVAC control systems, indoor environment management systems, digital direct control (or DDC), or energy management control systems. This paper describes these as energy management systems (EnMS) in accordance with the recent ISO 50001 (ISO, 2011) standard. EnMS incorporate advances in microprocessor technology and implement standard communication protocols to retrieve sensor data and correspondingly adjust heating, ventilating, air conditioning (HVAC) and lighting systems to maintain human comfort levels while minimizing energy consumption. In addition, these systems log extensive data on system operating conditions. Research shows that EnMS conserve as much as 10-40% of the energy typically consumed by commercial buildings (Ahmed, Ploennigs, Menzel, & Cahill, 2010). This represents significant cost savings for building owners because, according to the U.S. Department of Energy (DOE), over 50% of the total energy use in buildings is used for HVAC and lighting (Department of Energy, 2003). One roadblock to achieving these savings is the complexity of these systems and the resulting inability of building operators to analyze and act on EnMS data and thus realize their full potential. It has been shown that data coming from EnMS and EIS are underutilized due to improper training (Piette, Kinney, & Friedman, 2001). This information is of great value for building stakeholders but can overwhelm them if they do not know how to interpret these data. To minimize the learning curve, stakeholders will need information that is relevant to them and presented visually in an intuitive way. This will allow them to take actions that will improve energy efficiency, prolong equipment life, and most importantly maintain occupants' comfort levels.

This paper reviews how EnMS control HVAC and lighting systems to both conserve energy while maintaining human comfort and productivity. It then reviews the challenges facing building operators and other building stakeholders as they strive to balance the conserve v. comfort equation. Finally, this paper will propose methods by which building owners and stakeholders can realize the full potential of EnMS using advanced artificial intelligence and improved information visualization techniques. This discussion includes the design criteria for a graphic user interface intuitive to end-users.

2. *CAPABILITIES OF ENMS SYSTEMS*

In order for an EnMS to log and react to the current conditions of a building it requires input from comfort sensors and connections to HVAC and lighting control systems. Sensors typically deployed to address human comfort and health while minimizing energy consumption measure temperature, relative humidity (RH), occupancy, illumination, and CO_2 levels. These sensors are placed throughout the building to coincide with the different zones being controlled. The size of zones can range from an individual office space where only one person occupies that zone to a large open area where multiple people have their workspace. In the case of open spaces, current EnMS have limited capabilities to address individual comfort levels. The following are brief descriptions of how these sensors are used in practice and the level of energy savings attributed to them from the literature.

2.1 SENSORS

Temperature/RH sensors are use to monitor indoor, outdoor, supply, mixed, and zone air temperature and relative humidity. These control chilled/heated water valves and dampers in the HVAC system to provide cooling or heating as needed for the different zones. They also control economizers based on if the outside air is adequate to provide the necessary cooling/heating to the zone. Savings on economizer control can vary from 15% to 50% depending on settings and climate zone (Hatley et al., 2005).

Occupancy sensors detect activity in a zone and return a control signal that indicates occupancy status. The two technologies commonly found in these sensors are infrared and ultrasonic. There is also a hybrid of the two technologies, which overcomes some of the shortcoming of each. Infrared occupancy sensors detect line-of-sight temperatures; ultrasonic occupancy sensors use the Doppler principle to detect movement (Watt Stopper, n.d.). They do not count the actual number of occupants in the zone only the presence of occupants. These sensors are recommended where the presence of occupants of the space varies a lot throughout the day. These zones can be meeting rooms, maintenance rooms, restrooms, private offices and even open plan offices. Any zone with variable daily occupancy is a good application for occupancy sensors. These sensors are usually set to turn on the lighting fixtures and manage the 'occupied settings' for HVAC system control when the zone is occupied. In day lit spaces, advanced applications are set up as 'vacancy' sensors in terms of lighting control so that lighting is turned on manually and off automatically upon a time delay (often 5-15 minutes) after vacancy. Lighting energy savings attributed to these sensors range from 15% to 20% (Eilers, Reed, & Pigg, 1996) with additional savings from component cooling load reductions.

Illumination control sensors are used to detect the amount of natural lighting that is available for zones, often referred to as daylight harvesting. These devices are usually set to control lighting fixtures in places where the fixtures are close to natural light sources. These sensors switch or dim artificial lighting when natural lighting is sufficient to provide lighting levels for the occupant. Savings from these systems range from 0% to 89% (Acker & Van Den Wymelenberg, 2009). Low savings are often caused by poorly commissioned systems or improper user operation e.g. occupants manually closing blinds due to glare (Acker & Van Den Wymelenberg, 2010). In addition lighting zone orientation and fenestration type (side lighting vs. top lighting) can play a role in savings. In the case for side lighting, energy savings for the top quartile is about 82% of the expected value and almost half the systems installed do not save any lighting energy (Heschong, Howlett, McHugh, & Pande, 2005). On the other hand, energy saving with top lighting is highly predictable and effective (McHugh, Pande, Ander, & Melnyk, 2004).

In advanced applications, daylight harvesting system also control motorized blinds to reduce glare, provide natural desired levels of daylight, and lower cooling loads caused by direct sunlight (J.-H. Kim, Park, Yeo, & K.-W. Kim, 2009). These two forms may conflict with each other because blinds reduce natural light and artificial light must be increased but there has been research in order to integrate and optimize these two systems (Galasiu, Atif, & MacDonald, 2004). Cooling load reductions from using motorized venetian blinds compared to controlling blinds manually save about 7-15% in energy (E.S. Lee, D.L. DiBartolomeo, & S.E. Selkowitz, 1998).

CO_2 sensors are used to readout carbon dioxide levels to provide the necessary ventilation for occupants that are present at any given moment, a system referred to as demand controlled ventilation (DCV) systems. They provide the minimum level of ventilation when there is no one present and ramps up to the design occupancy ventilation level when the designed occupancy of the zone is reached. It is important to note that CO_2 is being used as a surrogate for actual occupancy levels. Unlike occupancy sensors, CO_2 sensors can sense relative zone population. With this information, ventilation can be provided to prevent the buildup of volatile organic compounds (VOCs) and other noxious pollutants that cause irritation to building occupants Savings attributed to these systems are in between 6-22% and it depends on the occupancy patterns, building type, and climate zone (Roth, Westphalen, Feng, Llana, & Quartararo, 2005).

Additional sensors can be placed in the HVAC equipment that relay information back to the building operator and to the EnMS about the equipment's status. These include state loggers that measure on/off states of motors, fans, valves, or other equipment. Potentiometers measure damper and valve positions. Differential pressure sensors that monitor filter life. Current transducers and voltage meters calibrated to calculate energy usage of components or systems. Rotational sensors that measure rpm of fans or pumps, and flow meters that measure flow rates of fluids. It is not uncommon for a complete EnMS system to have thousands of points. For example, a 185,000 SF, 11 story commercial office building studied has over 10,000 points monitored. The integration of all these sensors is important to truly gain the benefits that EnMS have to offer(Piette, Kinney, & Haves, 2001). The objective being the provision of diagnosis, prognosis and other actionable information that is useful to building operators.

2.2 PROGRAMMING CAPABILITIES

Programming capabilities are another important part of EnMS. Building operators can set the system to take into account buildings' operating schedule and individual zone schedules. For example, if a building's tenants are there only on weekdays from 7:00 am to 6:00 pm then there is no need to run the equipment to maintain zone comfort levels for the rest of the time. The equipment will run as designed for only 44 hours per week and the other 124 hours energy savings can take place. This does not mean that all the HVAC equipment will be necessarily shut down completely but the systems will not waste energy trying to maintain occupancy comfort levels (Automated Logic Corporation, 2008). These methods can save more than 15% energy usage and also prolongs the life of the equipment (Hatley et al., 2005).

Once the schedules are set, another feature of EnMS can be taken advantage of. This feature is called optimal start/stop and is used to pre-cool or pre-heat zones before they are occupied or stop cooling or heating before they become unoccupied using the building's thermal inertia to maintain comfort conditions until the scheduled end of occupancy. Some EnMS actually "learn" if the zones reach comfort levels before occupancy starts. The system will adjust if comfort levels are reached too late or too soon (Automated Logic Corporation, 2008). EnMS does this by logging the time it takes to reach the predetermined set point as a function of outdoor air temperature. If the set point is reached before the zone is occupied then the system will start its functions later to reach the set point on schedule the next day. If its reached late it will start sooner in the future. Also, when the proper economizer and controls are in place the system will use outside air when it is beneficial to do the pre-cooling/pre-heating (Automated Logic Corporation, 2008).

Another feature in EnMS that can be implemented easily is the ability to apply dynamic set points for HVAC equipment. These set points are adjusted to reduce power requirement in the equipment and are used in jurisdictions where energy prices change throughout the course of the day. The temperature set points can be relaxed in several levels as demand peak for the utility company is reached (Automated Logic Corporation, 2008). In the same way, set points for the chilled and hot water can be adjusted depending on load conditions of the building. This will increase the efficiency of chillers and boilers when they perform at part-load conditions that result from varying outdoor temperature (Hatley et al., 2005).

Demand Response (DR) is an additional feature that can help avoid peak demand charges. When DR is enabled in EnMS, the system will shed or shift loads to reduce energy consumption at peak demand. For example, EnMS can shift HVAC equipment to operate during off-peak hours and benefit from thermal inertia during peak demand hours. This method of DR is called load shifting. When the system dims lighting or uses dynamic set points to reduce energy consumption during peak demand it is called load shedding. In addition to reducing energy usage, utility companies pay incentives for buildings that are enrolled in DR programs (Newsham & Birt, 2010). Normally, building managers need outside help to effectively analyze their buildings' loads to find which loads are adequate for DR programs (Hatley et al., 2005).

3. *PROBLEMS ASSOCIATED WITH ENMS SYSTEMS*

The features mentioned above are examples of common practices in programming EnMS. Systems get more complicated when EnMS are integrated with energy information systems (EIS). EIS refer to additional software, data acquisition hardware, and communication systems that provide energy performance data of the building (Motegi, Piette, Kinney, & Dewey, 2003). These data contain information for all the building's stakeholders to improve energy efficiency, comfort levels, and reduce troubleshooting time for HVAC equipment (Seidl, 2006).

The problem with EIS is that they provide a lot of data to the building's stakeholders, the building owner, building operator, and occupants, but not a lot of information that can be acted upon easily or tailored to specific stakeholders. Figure 1 shows 16 zone temperatures for a single floor and there is additional data available that is associated with the floor. For example, data from air-handling units which show supply air temperature, coil temperatures, damper and valve positions, and CO_2 levels did not fit on the same graph. Figure 2 shows values captured from the same floor mentioned in figure 1 related to lighting systems using an energy management system that is specifically designed for lighting systems. The system integrates its capabilities to include daylight harvesting, zone scheduling, and load shedding with occupancy sensors and illumination sensors to provide savings in lighting energy consumption. This control system presents data in graphs along with baseline energy use to inform building managers how much energy they save when using the system. For an untrained individual, all of these data can be so overwhelming that they will not use it at all. In one study, Haris Doukas et al state "to the best of our knowledge, the buildings' energy management's systems operational data of a building are in many cases simply recorded without being further processed and analyzed, in terms of assisting the selection of possible energy-savings measures" (Doukas, Nychtis, & Psarras, 2009). These data are mostly used as a monitoring system,

FIGURE 2: 16 ZONE TEMPERATURES FROM FLOOR 7. AUTOMATED LOGIC WEBCTRL

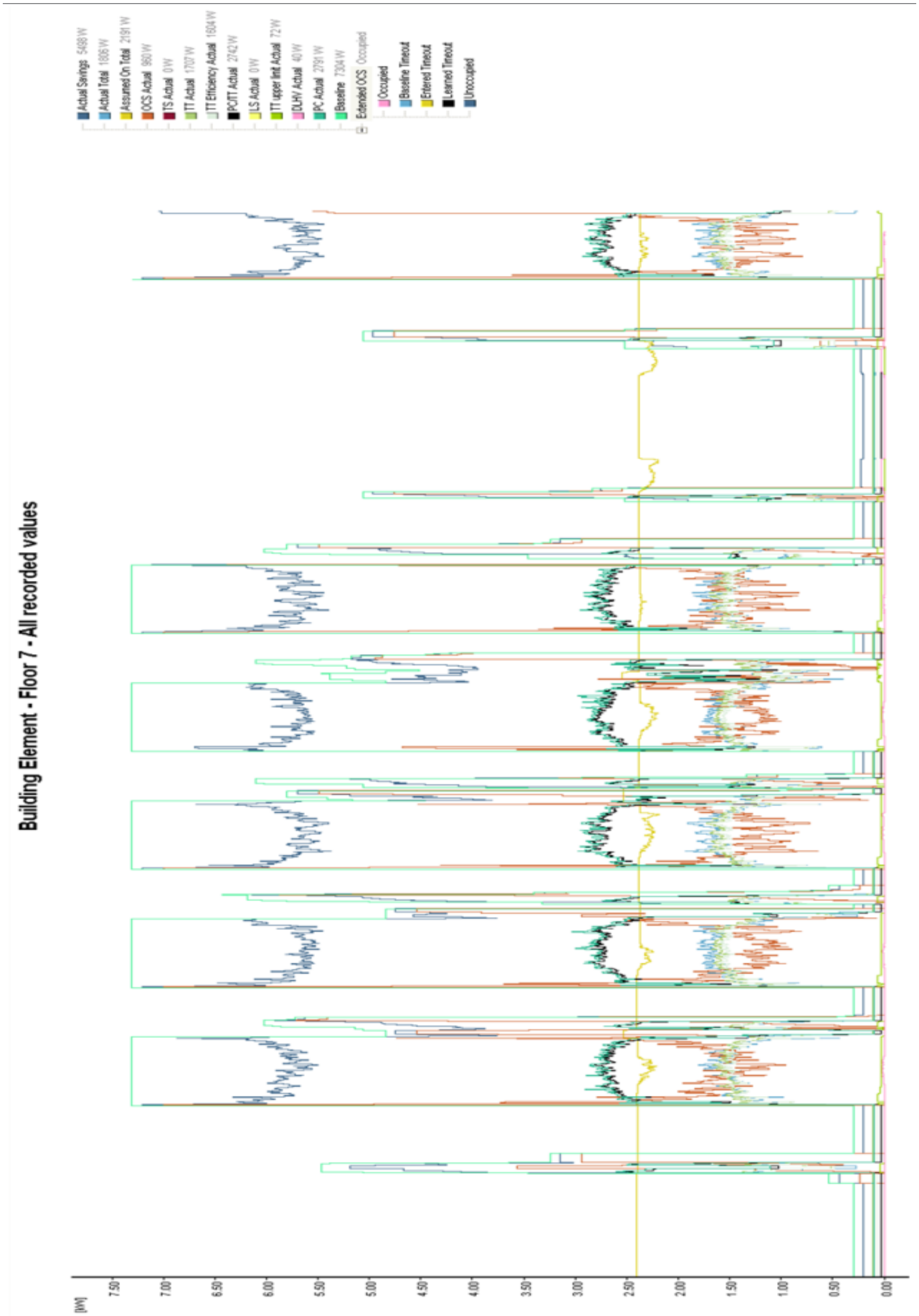

FIGURE 2: LIGHTING ENERGY MANAGEMENT SYSTEM DATA FOR FLOOR 7

forgoing opportunities to establish building characteristics and trends in which they can aid with the continuous improvement for the life of the system (Ahmed et al., 2010).

There are some tools in the market that seek out to resolve the problem of data being presented without being organized to make improvements to the system. These include EnergyWitness (IDS Interval Data Systems, Inc., 2008), EnergyICT (EnergyICT, 2011), Facilimetric (Noveda Technologies, Inc, 2011), Energy Expert (Energy WorkSite, 2011), EfficiencySMART (EnerNOC, 2011) and PACRAT (Santos, Brightbill, & Lister, n.d.). These tools monitor data, make trends, and some will even analyze data. For example, Energy Expert will use bin data methodology to predict energy usage based on weather forecasting but it does not control EnMS (Energy WorkSite, 2011). Adjustments or improvements to equipment must be done manually. PACRAT, performance and continuous re-commissioning analysis tool, is a tool that integrates with EnMS to diagnose problems, give recommendations on how to fix them, and provides a list of consequences if problems are not addressed on time (Santos et al., n.d.). EnerNOC uses a combination of algorithms and experienced energy analysts to make recommendations to their clients to improve energy usage and time of usage to prevent demand charges. Their EfficiencySMART system can make simple recommendations like enabling setbacks or more involved projects that require the replacement of equipment (EnerNOC, 2011). The presentation of data in these tools can range from simple trend graphs (EnergyWitness) to dashboards that show almost real time energy consumption of a building (Facilimetric, EfficiencySMART) to custom reports, but they require additional fees or software (EnergyICT, EfficiencySMART). All seem to have the capacity to collect data at the equipment level and have a detailed report on energy consumption within a building. It is just a matter of installing the necessary sensors or meters.

From the above-mentioned systems, EfficiencySMART and PACRAT are tools that provide actionable information. The rest rely on the experience of the operator to interpret, analyze, and improve building performance based on the way these tools present their collected data. . However, building operators commonly lack the experience and time to use the information gained or use more advanced features of EnMS (Hatley et al., 2005; Piette, Kinney, & Friedman, 2001). Features include load shedding, load shifting, diagnosing, and prognosis. The objective of the proposed EnMS toolset is to provide these advanced features by distilling the knowledge needed to accomplish it. These strategies must not compromise comfort, health, and productivity and that is why EnMS require a set of rules established by the operator to accomplish automatic load shedding/shifting effectively (Powerit Solutions, 2011). Rules need to establish equipment that will not cause negative consequences when power is reduced or shut down completely. For instance, productivity can go down if comfort levels are not in an acceptable range. According to ASHRAE standard 55-1992, the acceptable temperature range for zones in the winter is 68-75°F and 73-79°F for the summer (ASHRAE, 1992). Air speed can range from 55 fpm to 120 fpm depending on the zone temperature (ASHRAE, 1992). In regards to lighting, IESNA recommends a range of 30-50 footcandles for most modern offices (IESNA, 2011). Maintaining comfort during demand response events is critical for the continuation of this practice, thus supporting the concept of individual comfort feedback to EnMS.

4. THE PROPOSED METHODS

The scope of this work is to build an EnMS toolset that will aid building stakeholders in improving the energy efficiency of their buildings by using data that is available from EnMS. This research proposes to use Computational Intelligence techniques, specifically Artificial Neural Networks (ANN) and Fuzzy Logic tools to process the vast quantity of data available from an EnMS to make actionable information that can more easily be used by a building operator, manager, or occupant. These techniques were chosen for their generalizing capability (neural networks as universal approximators and classifiers), and capability of dealing with imprecision (fuzzy logic capable of encoding linguistic and quantitative uncertainties). Research needs to start by assessing the current knowledge of building operators for controlling EnMS. In addition, any known strategies operators use, if any, to collect, store, and analyze building performance data to implement energy efficiency measures (EEM) need to be documented. Finally, any shortfalls of their current EnMS and how they would like it to be addressed will also be important to know. The results of this data collection will inform how to proceed with a toolset that provides actionable information with appropriate visualization tools that are relevant to the different stakeholders. It will also provide guidance for additional sensor hardware that may be required in existing building or guidance for new building design and control of comfort parameters and the role of user feedback.

4.1 INTERVIEWS

Interviews with building operators and/or building owners will give an understanding of their current knowledge level with EnMS. This information will be deduced when they provide their current strategies to collect, store, and analyze data. They will also need to explain what features and functions their EnMS provide. This is important because the more experienced a building operator, the more features he/she will be able to name in theory. Another important aspect to note when conducting these interviews is the amount of time building operators or owners spend each day to make any modifications or to diagnose any problems with the EnMS. The goal of these interviews is to document any difficulties operators and owners are having with EnMS or actionable information they wish they could obtain from building performance data. Finally, the interviews must be conducted in a non-threatening manner and make it clear that the objective this toolset is to help them perform their job more effectively.

4.2 COMPUTATIONAL INTELLIGENCE TECHNIQUES

Computational intelligence techniques have been successfully applied to many engineering problems. Some of their main advantages are intelligent system analysis, improved and more effective system modeling capabilities, automated knowledge extraction and pattern recognition (Haykin, 2008). Artificial Neural Networks (ANNs) and Fuzzy Logic Systems (FLSs) are proposed to be integrated with the EnMS for processing the gathered large multi-dimensional datasets and fusing this information into actionable information usable by the building operators, managers and occupants.

ANNs constitute a well established computational model, which is inspired by the biological neural system. The feed-forward ANN consists of multiple simple processing units - neurons, structured in single or multiple layers and interconnected via directed edges, as shown in Figure 3. By propagating an input signal through the connected neurons, the response signal is obtained in the output layer. The input signals can be connected to the preprocessed data feed from various building sensors. The ANN can be seen as a massive parallel distributed processor. One of the key features of ANN is their ability to learn and adapt its structure to the non-linear distribution of the provided multi-dimensional input data (Linda & Manic, 2009).

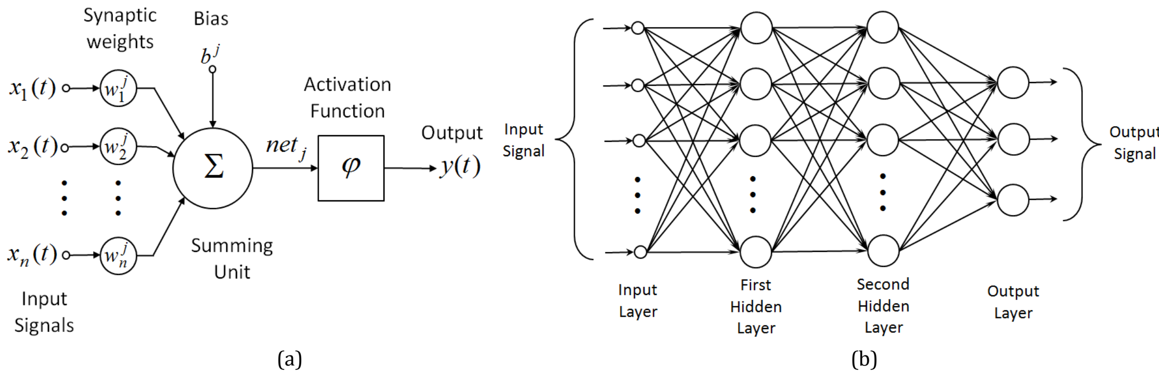

FIGURE 3: MODEL OF ARTIFICIAL NEURON (A), AND FEED-FORWARD ARTIFICIAL NEURAL NETWORK (B).

To reduce the complexity of outputs and integrate all the inputs of the system, it is purposed to use FLS and ANN controller methods to address issues that building operators are confronted with, in particular controllers that will learn and adapt to the changing conditions of buildings as well as those of the occupants. With FLS, there must be a set of rules programmed into the controller so when these conditions are met the controller can initiate an action (A. Dounis, 1995). The list can get large and complex for many inputs. With ANNs, there are three layers that interact to produce one or two outputs from all the inputs of an EnMS (Kwok, Yuen, & Lee, 2011). The first layer is all the inputs of the system. These are usually taken from the measurements of the EnMS sensors and can include weather forecasts, occupant input, and historical data. These inputs also need to be independent variables or not a function of another input (Kwok et al., 2011). The middle layer makes connections between the inputs and 'learns' how each input is correlated to each other. The third layer is one or two outputs that act on a system. A hybrid of these can also be used. Neural networks would be the initial data reduction tool and the FLS rules will optimize the results of a few outputs from the neural networks (see Figure 4). No matter how it is used, FLS and ANN controllers vary depending on the application but are considered to be the best option to optimize systems (A. I. Dounis & Caraiscos, 2009).

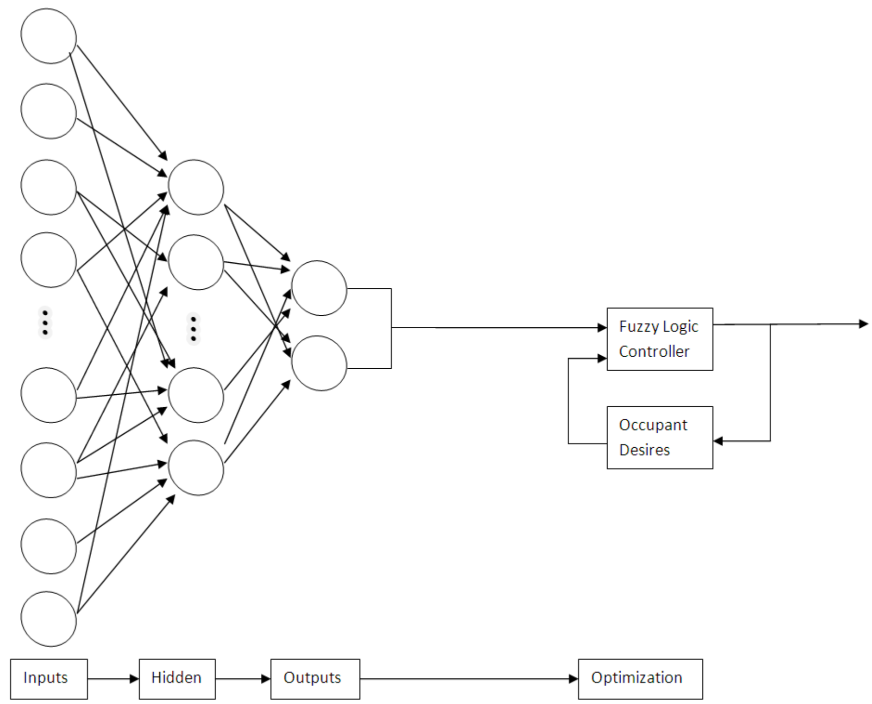

FIGURE 4: POSSIBLE CONFIGURATION OF NEURAL NETWORK AND FUZZY LOGIC CONTROLLERS FOLLOWS KWOK ET AL. 2011; DOUNIS 2009

ANNs will be used in several aspects of input data processing. First, self-organizing ANNs can be used to identify similarity and cluster different data feeds in various regions in the building and learn the optimal energy management profiles for each similar region. These energy management profiles can then be suggested to the operator as optimal solution given the previously observed historical data. The feed-forward ANNs will be used to model in real-time the dynamics of the building environment, which will enable prediction of various near-future trends and behaviors, such as peak demand. Such ANN predictor will allow for anticipating significant energy changes, e.g. pre-cool or pre-heat zones before they are occupied with higher efficiency. Furthermore, the ANN system modeling can also be used to identify abnormal behavior and deviations from the expected system performance. In this manner the ANN will provide a real-time assessment of which zones are not reaching comfort levels on time or zones that reach comfort levels too early.

FLS shave been successfully applied in various engineering areas over the past 40 years (Linda & Manic, 2011). This fact can be attributed to their ability to cope with the linguistic uncertainty originating in the imprecise and vague meaning of words. FLSs were initially developed with the intention to implement a control system capable of complex behaviors, while having a simple and human-understandable structure (Zadeh, 1975). The core of the fuzzy logic system contains linguistic fuzzy rules and knowledge. Each fuzzy rule consists of antecedent part and consequent part modeled using Fuzzy Sets (FSs). Unlike in classical Boolean logic where objects either belong to a crisp set or they do not, FSs determine the degree of belonging as a real value between 0 and 1. This real-valued degree of belonging is the fundamental concept that allows FLS to express vague and overlapping linguistic concepts or assign a single object to multiple sets with different degrees of belonging.

The unique capability of FLSs to encode human knowledge in a linguistic form will be utilized in the designed system. The initial interview records will be used to elicit fuzzy rules encoding the operators' experience. In addition, the obtained fuzzy rule base will be enhanced by learning additional fuzzy rules describing the optimal energy management actions. Furthermore, the FLS also allow for computing linguistic outputs such as “Low”, “Medium”, “High”. Providing those easy-to-understand linguistic terms to the operators might contribute the increased usability of the system and improve the utilization of the available data.

4.3 VISUALIZATION

To understand the underlying inter-dependencies and unique attributes within the collected data, visual data mining tools such as Self-Organizing Maps will be used. Self-Organizing Maps are powerful visual data mining tools which can be coupled with other computational intelligence techniques to provide methodologies that aid the user to identify spatial distributions, important attributes, similarity and uniqueness within the database, etc. (Wijayasekara, Linda, & Manic, 2011). Using these techniques users are able extract information about important attributes that contribute to the distribution of the database.

Once the data is analyzed, the results need to be presented in a way that is intuitive, relevant to the user, and easily adjustable to accommodate individual preferences. This suggests that interactivity with presentation of data will be important because many users may one particular type of information, but a smaller set may need to add additional reports or remove certain pieces of information. A report done by University College Cork agrees with the claim by saying that the user graphic interface should be tailored to the respective building stakeholder (Stack, Tumwesigye, E. Menzel, & Wang, 2009). For example, the building owner may want a general overview of energy consumption of a specific building or specific sub-system within the entire EnMS to assign energy use to their respective tenants and control costs. By using sub-meters, owners can assign costs for tenants’ energy use. In turn, tenants will have an incentive to reduce energy that does not exist with the triple net (NNN) leasing method. The owner can then compare energy consumption on month-to-month basis. This will help the owner be more involved with implementing/approving energy efficient measures for the building as a whole. Another stakeholder, the building operator, would want to use collected data to analyze zones, equipment performance, and diagnose any problems with the system while maintaining comfort levels. The operator can have different air temperatures of the HVAC system on an hourly basis. Yet another stakeholder, the occupant, is also included because their comfort is highly correlated with their satisfaction and productivity (A. I. Dounis & Caraiscos, 2009).The occupant can provide feedback to the operator to fulfill his/her comfort needs (Stack et al., 2009). The occupant would like to see current conditions of the zone and have controls to equipment that is relevant to his/her zone e.g. lights, temperature, and ventilation(Karjalainen & Lappalainen, 2011). In the future it could be possible for occupants to provide feedback directly to the EnMS and as an additional input to the advanced learning algorithms described above. This targeting of information will provide data that is relevant to the different stakeholders and reduce the complexity of what they encounter.

5. DISCUSSION

Initial interviews support claims made by Piette 2001 and Hatley 2005 regarding building operators’ lack of knowledge on how to act on building performance data. For example, one interviewee was simply unaware of the full capabilities of the building EnMS system. Another reported that current practice is to implement energy efficiency measures only when equipment needs replacing and “replace it with the best technology that they can afford”. This suggests that this owner is unaware of or unable to control operational efficiencies but rather expects to replace equipment to achieve efficiencies. These data lead us to conclude that building operators would benefit from more transparent and easy to understand visualization tools. For example, such a system would allow operators --from a quick glance-- to figure out which zones are not reaching comfort levels on time or which zones reach comfort levels too early, e.g. when the space is unoccupied. These graphics might also show building operators performance deviation over time. And, because building operators wish to avoid typically high peak demand utility charges, they would benefit from forecasts of peak demand based on the weather, historical performance data, and tenant schedules. Currently, EnMS do not integrate these data to control HVAC and lighting equipment, consequently some building operators make building adjustments in response to the weather based on intuition, what one interviewee calls, 'sailing the building'. Advanced visualization tools could also show building operators how individual pieces of equipment perform in real time. Finally, such tools would support trend analysis that will lead to continuous improvement of the entire system.

6. CONCLUSION

Advanced visualization tools that display building performance data such that building operators can act would greatly advance the realization of the EnMS potential. Such tools will enable proactive building control to conserve energy while maintaining occupant comfort and productivity. To recap, this toolset will integrate existing EnMS inputs, weather data, building performance characteristics, occupant feedback and compare these data to optimized energy consumption models. In turn, this toolset will display data such that building operators can act to maintain occupants comfort and to make any necessary modifications if parameters change over the course of the different seasons. The goal of the toolset is to simultaneously increase comfort while saving additional energy where possible.

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