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# Automated demand response applied to a set of commercial buildings

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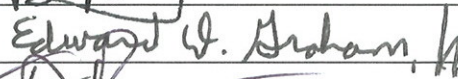| | | |
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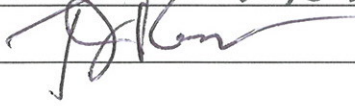


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**AUTOMATED DEMAND RESPONSE APPLIED TO A SET OF**

**COMMERCIAL FACILITIES**

BY

**DONALD F. LINCOLN**

B.S., Mechanical Engineering, University of Nebraska, 1969

M.S., Mechanical  Engineering, University of Nebraska, 1970

DISSERTATION

Submitted in Partial Fulfillment of the
Requirements for the Degree of

**Doctor of Philosophy**
**Engineering**

The University of New Mexico
Albuquerque, New Mexico

**December 2009**

# Dedication

*To my family.*

# Acknowledgments

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# AUTOMATED DEMAND RESPONSE APPLIED TO A SET OF COMMERCIAL FACILITIES

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ABSTRACT OF DISSERTATION

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## Abstract

Commercial facility demand response refers to voluntary actions by customers that change their consumption of electric power in response to price signals, incentives, or directions from grid operators at times of high wholesale market prices or when electric system reliability is jeopardized. Energy management in a commercial facility can be segregated into two areas: energy efficiency and demand response. This dissertation assesses both in two commercial facilities: one designed and constructed prior to the development of demand response principles and the second designed and constructed with modern energy controls and energy efficient materials. The energy evaluation identified opportunities for energy conservation and strategies for demand response. Next this paper presents a fuzzy method for predicting a facility's baseline load profile. The baseline load profile is the predicted energy use of a facility during a demand response event in the absence of any energy reduction. During a demand

response event, building operators or their automated control systems make adjustments to building operations with the goal of reducing the building's electric load during times of the electric system's peak electric usage.  The baseline load profile is key to assessing the actual peak load electric energy reduction from a demand response event.  Some grid operators are considering compensating commercial facilities for the energy reduction they achieve during demand response events.  In fact the Public Service Company of New Mexico, the electricity supplier to UNM, has a demand response program that would compensate in this manner.  The method described here is based on fuzzy set theory and allows the inclusion of building occupancy in the calculation.  Our method achieves greater accuracy than other methods currently in use.  Third, this study developed strategies for minimizing occupant dissatisfaction during demand response events using fuzzy cognitive mapping.  If occupant discomfort causes significant complaints to the facility operator or owner, they may direct the demand response event be discontinued and thus eliminate the electric power savings.  Assessing and predicting this potential interruption of the demand response event is not readily evaluated with crisp analytical techniques.  Thus we elected to assess this problem using fuzzy set theory as applied to cognitive maps.  Our model focuses on the University of New Mexico (UNM) campus.  Fourth, we developed the conceptual design and operation of a facility control system to manage demand response events for the campus of the University of New Mexico.  This section presents the design principles, the demand response control system logic and operation, and the economic value based on the PNM Peak Saver Demand Response Program financial incentives.

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

Energy management in a commercial facility can be segregated into two areas: energy efficiency and demand response. Energy efficiency focuses on steady state load minimization. Demand response reduces load for event driven dynamic peak load reduction (Kiliccote et al. 2006). Commercial facility demand response (DR) refers to voluntary actions by customers that change their consumption of electric power in response to price signals, incentives, or directions from grid operators at times of high wholesale market prices or when electric system reliability is jeopardized (Albadi and El-Saadany 2007). Demand response driven changes in electricity use are designed to be short-term in nature, centered on critical hours during the day when demand is high or when the electricity supplier's reserve margins are low (FERC 2007, Menniti et al. 2009).
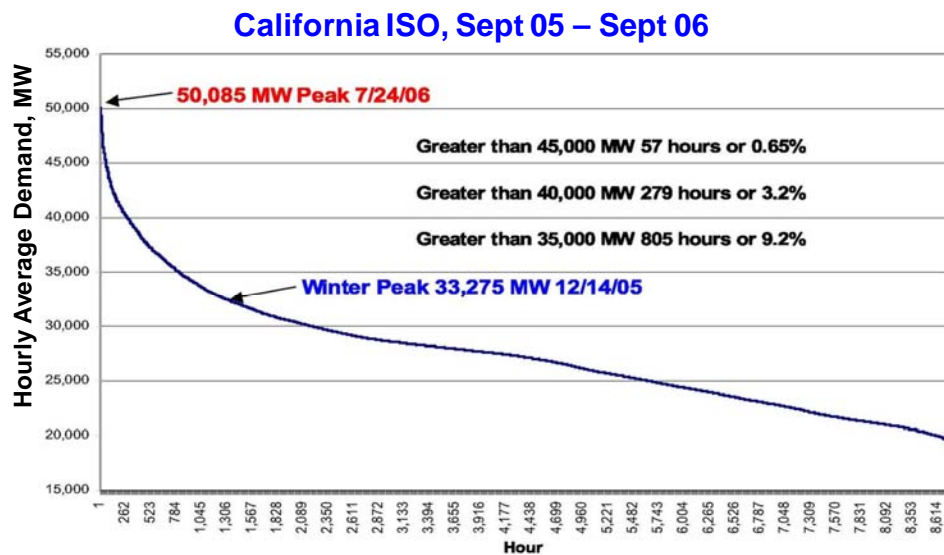


Figure 1.1: Annual hourly energy use sorted highest to lowest

Figure 1.1 shows the annual energy use by the state of California, from the California Independent System Operator for September 2005 through August 2006, for each hour sorted from highest to lowest. This curve is typical of electric supply through the world. It shows that the highest 25% of the electric load is experienced for less than one percent of the hours in the year.

The Federal Energy Regulatory Commission (FERC) adopted the following definition of demand response in 2006 (FERC 2007):

> "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."

Demand response under this definition can be categorized into two types of programs: price based programs and incentive based programs. Price based demand response programs give customers time varying rates (Aalami et al. 2008) that reflect the value and cost of electricity in different time periods (Barbose et al. 2004). These time varying rates include time-of-use (TOU) rates, critical peak pricing (CPP), and real-time pricing (RTP). Various studies have shown the selection of time varying rate policies have direct impact on customer behavior (Vapero 2007, Su and Kirschen 2009). With this knowledge of the electricity price in a given time period, customers tend to use less electricity when prices are high (Zhang and Wang 2009, Zhang et al. 2009). Incentive based demand response programs pay participating customers to reduce their electricity

use at times requested by grid operators, triggered by either grid reliability or high electricity prices (Burke and Henderson 2005).

FERC estimates the 2009 nation-wide reduction in peak demand from demand response programs to be 37 gigawatts and by 2019 to possible be as much as 188 gigawatts or 20% of the nation-wide peak demand (FERC 2009). The benefits from this on-peak reduction in energy use include:

- Reduction in wholesale power prices

- More efficient operation of power markets

- Enhanced reliability of the power system

- Environmental benefits from reduced generation

- Operational and capital cost savings from avoided new generation and deferred transmission and distribution costs

These benefits also flow to society as a whole, not just to the participants. Without a demand response mechanism, the electric supplier is forced to assume that all customers have an inelastic demand for energy and will pay any price for it. There is ample evidence this is not true. Customers, given a demand response tool, can and will manage their demand for electricity. It is expected that demand response programs in European markets will derive similar benefits (Abrate and Benintendi 2009).

This paper addresses four aspects of demand response as presented in Chapters 2 through 5. Chapter 5 utilizes the results of Chapters 2, 3, and 4 in the conceptual design of an automated demand response control system as applied to the University of New Mexico campus facilities.

First, as presented in Chapter 2, we (throughout this dissertation "we" refers to the author) assessed energy efficiency and demand response in two facilities: one designed and constructed prior to the development of demand response principles, Plaza Del Sol in 1973, and the second, Alvarado Transportation Center in 1999, designed and constructed with modern, granular energy controls. We performed an energy evaluation of these two Albuquerque, NM, USA buildings owned by the City of Albuquerque. The energy evaluation identified opportunities for energy conservation and strategies for demand response. We used these strategies in designing the Demand Response Control System as described in Chapter 5.

Second, as presented in Chapter 3, we developed a method for predicting what the energy usage of a facility during a DR event would be in the absence of the DR event. This predicted energy usage is termed the baseline load profile. During a DR event, building operators or their automated control systems make adjustments to building operations with the goal of reducing the building's electric load during times of the electric system's peak electric usage. The baseline load profile is key to assessing the actual peak load electric energy reduction from a DR event. Some grid operators are considering compensating commercial facilities for the energy reduction they achieve during DR events. In fact, the Public Service Company of New Mexico (PNM), the electricity supplier to UNM, has a demand response program that would compensate in this manner. UNM could potentially receive compensation for demand response through the PNM Peak Saver Demand Response Program. This compensation is composed of a designated and delivered capacity payment and an energy saved payment. The Program

requires UNM designate a capacity reduction quantity and UNM would receive compensation based on the portion of that designated capacity reduction actually achieved, limited to 100 percent, during demand response events. The method used to determine the baseline load profile presented in Chapter 3 is based on fuzzy set theory and allows the inclusion of building occupancy in the calculation. Our method achieves greater accuracy than other methods currently in use. We utilized this method for estimating the baseline load profile in designing the Demand Response Control System as described in Chapter 5.

Third, as presented in Chapter 4, we developed strategies for minimizing occupant dissatisfaction during demand response events using fuzzy cognitive mapping. Obviously reducing electric power consumption on a hot summer afternoon, the normal time for a demand response event, can cause some discomfort to facility occupants. If this occupant discomfort causes significant complaints to the facility operator or owner, they may direct the DR event be discontinued and thus eliminate the electric power savings. Assessing and predicting this potential interruption of the DR event is not readily evaluated with analytical techniques. Thus we elected to assess this problem using fuzzy set theory as applied to cognitive maps. We modeled this problem using the University of New Mexico (UNM) campus. The campus consists of over 200 facilities including classrooms, offices, laboratories, libraries, and residence halls, drawing over 30 megawatts of electricity at peak. We utilized the results of fuzzy cognitive mapping in the design of the Demand Response Control System as described in Chapter 5.

Fourth, as presented in Chapter 5, we developed the conceptual design and operation of a facility control system to manage demand response events for the campus of the University of New Mexico. This Chapter presents the design principles, the demand response control system logic and operation, and the economic value based on the PNM Peak Saver Demand Response Program financial incentives.

# Chapter 2

# Demand Response in Existing Buildings

## 2.1 Introduction

We performed an energy evaluation of two City of Albuquerque buildings: Plaza Del Sol (PDS) and the Alvarado Transportation Centrer (ATC). This energy evaluation identified opportunities for energy conservation and strategies for demand response. We utilized these demand response strategies in designing the Demand Response Control System as described in Chapter 5.

Plaza Del Sol is an eight story office facility with 106,000 square feet of floor space that houses approximately 300 people on the day shift, 6 people on the second shift, and 1 to 2 people on the third shift. The City organizations housed in the building include: the planning department, building permits and inspection, zoning inforcement, hydrology, land development, fire marshall, metropolitan redevelopment, neighborhood coordination, and the City 311 call center. The ATC is a two story transportation and office facility with 31,500 square feet of of floor space that houses approximately 110 people. The City functions performed in the building include: a ticketing and waiting area for transportation users, transportation customer support, the City transportation dispatch center, transportation marketing, planning and human resources. The only energy use information available for these analyses were the monthly summaries of each building's electric and natural gas consumption (City of Albuquerque 2008). We

developed an energy model for each facility which projected the heating and cooling loads for the year as well as other electric consumption each hour of the month. The energy use each hour was needed to assess demand response in the facilities. These models were then calibrated against the actual energy use. The following sections present the models' projection of currrent operation aginst the actual usage, opportunities for energy conservation, and operating strategies for demand response.

## 2.2 Facility Energy Models

The facility energy models utilized a TRNSYS computer model for the determination of the heating and cooling loads as frequently as every 15 minutes for an entire year. TRNSYS is a computer modeling tool with a graphical user interface (GUI) designed to simulate the transient performance of thermal energy systems. TRNSYS is a joint project between the University of Wisconsin-Madison Solar Energy Lab, The Centre Scientifique et Technique du Batiment (CSTB) in Sophia Antipolis, France, Transsolar Energietechnik GmBH in Stuttgart, Germany and Thermal Energy Systems Specialists (TESS) in Madison, Wisconsin. TRNSYS contains a graphical interface library of 380 components. The TRNSYS user base includes universities, national laboratories, governments, electric utilities, automobile manufacturers, and architect-engineering firms (TESS 2005).

TRNSYS uses building geometry, building wall and window materials, weather induced thermal loads, and internal thermal loads that impact the heating and cooling loads such as occupancy, building space lighting, computer equipment, etc. as input to the model. The facility energy model also includes the other building loads that are not

completely captured in the heating and cooling load calculation such as fan motors, elevators, outdoor lighting, etc.

## 2.3 Energy Evaluation

This section presents the energy models' simulation of the as-found condition of the PDS facility and the ATC facility. Subsequently, for Plaza Del Sol, we simulated several potential options, titled PDS Baseline 1 through PDS Baseline 5, for energy conservation and present the anticipated annual energy and cost savings. We did not present any energy conservation options for Alvarado Transportation Center as this facility is relatively new and includes current energy efficient materials and construction.

Table 2.1 shows the PDS actual energy use for fiscal years 2006-2008 with the electricity use in kilowatt hours (kWh) and the natural gas use in decatherms (Dth). A decatherm is ten therms or one million BTUs.

Table 2.1: Plaza Del Sol (PDS) actual energy use FY 2006-8

| | PDS Actual Usage | | | | | |
|---|---|---|---|---|---|---|
| | FY 2006 | | FY 2007 | | FY 2008 | |
| Month | Ele, kWh | Gas Dth | Ele, kWh | Gas Dth | Ele, kWh | Gas Dth |
| Jul | 229,916 | 12 | 283,184 | 19 | 264,776 | 13 |
| Aug | 219,341 | 26 | 281,618 | 14 | 256,159 | 11 |
| Sep | 186,831 | 57 | 214,641 | 81 | 209,157 | 14 |
| Oct | 162,155 | 444 | 186,048 | 622 | 184,873 | 586 |
| Nov | 137,479 | 687 | 166,856 | 1148 | 145,705 | 771 |
| Dec | 131,996 | 963 | 164,898 | 1630 | 138,654 | 1127 |
| Jan | 136,696 | 665 | 162,156 | 1568 | 145,705 | 1227 |
| Feb | 142,572 | 842 | 151,972 | 1229 | 142,180 | 1069 |
| Mar | 142,179 | 755 | 196,623 | 903 | 177,431 | 854 |
| Apr | 145,705 | 177 | 181,739 | 591 | 174,689 | 611 |
| May | 179,781 | 20 | 206,024 | 295 | 208,373 | 416 |
| Jun | 214,641 | 20 | 245,584 | 13 | 240,492 | 179 |
| | 2,029,292 | 4,668 | 2,441,343 | 8,113 | 2,288,194 | 6,878 |

Table 2.2 shows PDS total FY 2008 electricity cost and natural gas cost along with that year's average annual unit costs of $0.104 per kWh for electricity and $8.49 per Dth for natural gas. These average unit costs are used to project the cost savings for each subsequent potential energy conservation option.

Table 2.2: PDS energy costs FY 2008

| PDS Energy Costs FY 2008 | |
|---|---|
| Electric | $ 237,023 |
| Nat. Gas | $ 58,406 |
| $/kWh | $ 0.104 |
| $/Dth | $ 8.49 |
| $/sq ft | $ 2.79 |

Figure 2.1 shows the TRNSYS model used for each building.  While the form of the model is the same for both, the building construction data is customized for each.
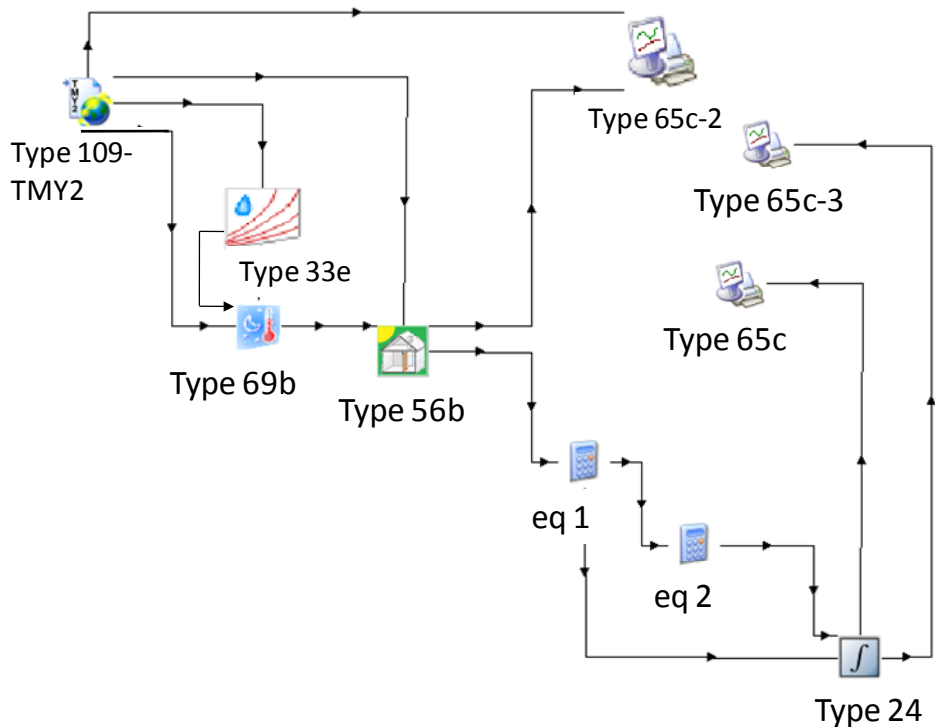


Figure 2.1: TRNSYS model for PDS and ATC

TRNSYS models are composed of components and data communication paths. The Type109-TMY2 component provides average weather data at regular time intervals thruoughout the year for many US locations including Albuquerque, NM. This component provides: the ambient dry bulb temperature and relative humidity to the thermodynamic property component Type33e; the ambient dry bulb temperature, beam radiation on horizontal, and sky diffuse radiation on horizontal to the sky temperature component Type69b; ambient temperature relative humidity, total radiation, beam radiation, and angle of incidence for all building surfaces to the multi-zone building component Type56b; and the ambient temperature to the online plotter component. The Type33e component provides the dew point temperature to the sky temperature component, Type69b. The Type69b component determines the effective sky temperature, which is used to calculate the long-wave radiation exchange between the atmosphere and the building surfaces in the multi-zone building component, Type56b. The Type56b multi-zone building component contains all of the building specific information for each building zone including wall materials, floor materials, ceiling materials, schedule of occupancy and equipment operation, number of occupants, number and type of heat generating equipment, etc. The multi-zone building component provides the zone heating and cooling loads to the calculator component, eq1, and the zone temperatures to the online plotter component, Type65c-2. The first equation component, eq1, calculates the heating and cooling values for each zone for each hour and outputs this data to the integrator component, Type24, and to the second equation component, eq2. The second equation component, eq2, sums the zone heating and cooling data to

form the total heating and cooling loads for each hour and outputs this data to the integrator component, Type24. The integrator component, Type24, accumulates the heating and cooling loads for each month and outputs the heating data to the online printer component, Type65c, and the cooling to the online printer component, Type65c-3. This is shown in Figure 2.2 and Figure 2.4.

We calibrated the electric energy with the PDS average building usage. We calibrated natural gas with the PDS average building usage similarly. During those years two conditions were present that adversely impacted facility energy usage:

- The outside air dampers were inoperable with 3 dampers stuck open and 1 damper stuck closed. Outside air is mixed with the building return air ventilation to improve the quality of the building air by diluting various gaseous irritants produced inside the building. Excess outside air will unnecessarily add to the heating and cooling load.

- The main door on the ground level, primarily used by customers and employees of the building, did not close properly and remained partially open when not in use. This caused significant air leakage from the conditioned space adversely impacting the heating and cooling load.

We included these two conditions to the Baseline 1 energy model with the results as shown in Tables 2.3.

Table 2.3: PDS Baseline 1 energy use actual to model comparison

| PDS | Electricity, kWh | | Natural Gas, Dth | |
|---|---|---|---|---|
| Month | Model | Actual Ave. | Model | Actual Ave. |
| Jul | 243,732 | 273,980 | 1 | 15 |
| Aug | 230,397 | 268,889 | 6 | 17 |
| Sep | 200,060 | 211,899 | 37 | 51 |
| Oct | 187,017 | 185,461 | 349 | 551 |
| Nov | 177,743 | 156,281 | 956 | 869 |
| Dec | 188,324 | 151,776 | 1,493 | 1,240 |
| Jan | 187,559 | 153,931 | 1,406 | 1,153 |
| Feb | 166,783 | 147,076 | 1,065 | 1,047 |
| Mar | 183,207 | 187,027 | 842 | 837 |
| Apr | 178,121 | 178,214 | 360 | 460 |
| May | 202,295 | 207,199 | 94 | 244 |
| Jun | 217,490 | 243,038 | 14 | 71 |
| Total | 2,362,728 | 2,364,769 | 6,622 | 6,553 |

Table 2.4 shows the actual average annual electric and natural gas use for the as found, PDS Baseline 1, condition of the facility. This is used to present the total annual energy use per unit area in BTUs per square foot. Since one kilowatt-hour is 3412 BTUs and one decatherm is one million BTUs, this yields 137,000 BTUs per square foot or $2.79 per square foot per year for PDS.

Table 2.4: PDS Baseline 1 average actual energy use

| Average Actual Energy Use - PDS | | |
|---|---|---|
| Ave. Ele kWh | | 1,707,742 |
| Ave. Gas, Dth | | 2918 |
| BTU/sq ft | | 82,053 |
| $/sq ft | $ | 2.79 |

Figure 2.2 shows the cumulative per month heating and cooling energy use as calculated by the TRNSYS model.

Figure 2.2: TRNSYS PDS annual heating and cooling energy

The heating energy is the energy from natural gas burned in the boiler at 75 percent efficiency (1.0 kWh of natural gas yields 0.75 kWh of heat). The cooling energy is the electric energy used by the chiller with a coefficient of performance of 4.15 (1.0 kWh used by the chiller yields 4.15 kWh of cooling).

Figure 2.3 uses these data values to show the hottest week, July 29 through August 4. The hottest hour in this week is 4:00 pm on July 31. The general shape of this cooling curve for this week is as expected, peaking each afternoon between 2:00 and 5:00 pm and falling to a minimum in the early am. Similarly the highest heating week is January 7 through January 13 with the highest heating load at 7:00 am on January 8. The general shape of this heating curve for this week is also as expected, peaking each morning between 5:00 and 8:00 am and falling to a minimum in the early afternoon.

Plaza Del Sol July 29 to Aug 4

Plaza Del Sol Jan 7 to 13

**Cooling**

**Heating**

Figure 2.3: PDS cooling/heating for hottest/coldest week in the year

The PDS input schedules and other electric loads are shown in Appendix 1-1 (Garcia & Associates 1973).

The PDS Baseline 2 model resets the outside air to a normal level of 30 percent and assumes the air infiltration through the second floor entrance is also normal at 20 percent. This reduces the annual heating load by 39 percent, having only a minor impact on the cooling load. This results in an annual energy cost reduction of $16,800 from reduced natural gas use and an annual energy use per unit area reduction to 115,000 BTUs per square foot.

In 2005 the PDS air conditioning system was modified to add a 75 ton Trane air conditioning unit on the roof of the building equipment penthouse, see Figure 2.4. The building ductwork was modified so this 75 ton air conditioning unit services the 7th and 8th floors. The building ductwork was further modified so the original 229 ton chiller, installed in the equipment penthouse, services the rest of the building. In the Baseline 2 scenario during the hottest day of the year in the weather module of the TRNSYS program, the total building required 171 tons of cooling. The chiller originally installed

in the PDS building penthouse producing a maximum of 229 tons or 25 percent more than this maximum requirement would be adequate to handle this cooling load. It appears the 75 ton additional AC unit installed on the penthouse roof was needed to



Figure 2.4: Air conditioning unit on roof of PDS equipment penthouse

compensate for maintenance issues but is not needed for cooling loads greater than the original 229 ton chiller can provide.

The PDS Baseline 3 model keeps the conditions as in Baseline 2 but assumes one of the two supply and return fans are stopped from 6:00 pm to 6:00 am Monday through Saturday and all day Sunday. This is reasonable as the building occupancy is low during these periods, less than 5 percent of the day time level, and one supply and return fan will provide adequate conditioning. This reduces the electricity use by 16 percent below PDS Baseline 2 and saves an additional $40,100 annually. The annual energy use per unit area reduces further to 102,000 BTUs per square foot.

The PDS Baseline 4 model also keeps the PDS Baseline 2 conditions but replaces the existing windows with windows similar to those installed in the Alvarado Transportation Center. The existing PDS windows are single pane one quarter inch plate glass (U = 5.7 kilojoules per hour per square meter per degree Kelvin) with no added energy conservation characteristics. The ATC windows have excellent energy loss characteristics (U = 0.4 kilojoules per hour per square meter per degree Kelvin). This reduces the electric use by 12 percent and natural gas use by 27 percent annually resulting in savings of $39,300. The annual energy use per unit area reduces to 95,300 BTUs per square foot.

The PDS Baseline 5 model keeps the conditions as in PDS Baseline 2 but assumes the two supply and return fans have variable frequency drives (VFDs) installed. The fan motors are operated at variable speeds proportional to the heating or cooling loads with a minimal power of 40 percent when heating or cooling is not required. VFDs are devices that allow electric motor speed and power reductions while maintaining a reasonable motor efficiency. Without VFDs these motors operate either at full power or, if stopped, operate at zero power. The PDS Baseline 5 model reduces the electricity use by 17 percent below Baseline 2 and saves $43,100 annually. The annual energy use per unit area reduces to 101,000 BTUs per square foot.

In summary these conservation savings are shown in Table 2.5. The total savings in Table 2.5 assumes that the reduction of Baseline 3, stopping 1 supply and return fan during off hours, is replaced with Baseline 5, installing VFDs to reduce fan power when heating or cooling is not needed.

Table 2.5: Value for each energy scenario at PDS

| PDS Baseline: | Description: | Value, $/Year | BTU/sq ft | Est. Cost |
|---|---|---|---|---|
| 2 | **Repair outside air dampers and main 2nd floor door** | **$16,800** | **115,000** | **$5,200** |
| 3 | Shutdown 1 supply fan 1 exhaust fan from 6 pm to 6 am Mon-Sat and all day Sunday | $40,100 | 102,000 | $0 |
| 4 | Replace windows with better insulating type (U = 0.4) | $39,300 | 95,300 | $5,000,000 |
| 5 | **Install VFDs on supply and return fans** | **$43,100** | **101,000** | **$69,000** |
| | Total | $99,200 | | $5,074,200 |

Table 2.6: Alvarado Transportation Center (ATC) actual energy use

| | Actual Usage | | | | | |
|---|---|---|---|---|---|---|
| | FY 2006 | | FY 2007 | | FY 2008 | |
| Month | Ele, kWh | Gas Dth | Ele, kWh | Gas Dth | Ele, kWh | Gas Dth |
| Jul | 69,760 | 58 | 69,760 | 6 | 77,360 | 64 |
| Aug | 63,360 | 50 | 63,360 | 6 | 79,680 | 70 |
| Sep | 54,720 | 73 | 54,720 | 67 | 73,600 | 107 |
| Oct | 46,720 | 206 | 46,720 | 140 | 62,160 | 178 |
| Nov | 44,960 | 292 | 44,960 | 189 | 52,720 | 261 |
| Dec | 43,680 | 340 | 47,440 | 325 | 52,160 | 316 |
| Jan | 49,120 | 380 | 47,600 | 330 | 55,280 | 369 |
| Feb | 46,080 | 305 | 44,800 | 245 | 50,000 | 281 |
| Mar | 55,920 | 273 | 54,800 | 194 | 62,960 | 254 |
| Apr | 57,280 | 162 | 53,280 | 135 | 64,320 | 169 |
| May | 63,120 | 73 | 63,200 | 68 | 74,800 | 124 |
| Jun | 66,480 | 20 | 76,160 | 43 | 81,200 | 68 |
| | 661,200 | 2232 | 666,800 | 1748 | 786,240 | 2261 |

Table 2.6 shows the Alavarado Transportation Center (ATC) actual energy use for fiscal years 2006-2008 with again the electricity use in kilowatt hours (kWh) and the natural gas use in decatherms (Dth).

Table 2.7 shows ATC total FY 2008 electricity cost and natural gas cost along with that year's average annual unit costs of $0.104 per kWh for electricity and $8.45 per Dth for natural gas. The average electricity cost for ATC is based on the PDS cost as electricity costs were not provided in the ATC monthly usage data.

Table 2.7: ATC energy costs

| ATC Energy Costs FY 2008 | |
|---|---|
| Electric | $81,769 |
| Nat. Gas | $18,897 |
| $/kWh | 0.104 |
| $/Dth | 8.45 |
| $/sq ft | $ 3.20 |

We calibrated the electric energy and the natural gas projection in the energy model with the ATC average building usage in FY 2006, FY 2007, and FY 2008. The result is shown in Table 2.8.

Table 2.8: ATC energy use actual to model comparison

| Month | Electricity, kWh | | Natural Gas, Dth | |
|---|---|---|---|---|
| | Model | FY Actual Ave. | Model | Actual Ave. |
| Jul | 77,326 | 72,293 | 0 | 43 |
| Aug | 72,360 | 68,800 | 0 | 42 |
| Sep | 61,878 | 61,013 | 6 | 82 |
| Oct | 55,293 | 51,867 | 100 | 175 |
| Nov | 49,923 | 47,547 | 287 | 247 |
| Dec | 51,402 | 47,760 | 463 | 327 |
| Jan | 51,411 | 50,667 | 429 | 360 |
| Feb | 46,558 | 46,960 | 314 | 277 |
| Mar | 52,325 | 57,893 | 227 | 240 |
| Apr | 54,401 | 58,293 | 88 | 155 |
| May | 64,976 | 67,040 | 20 | 88 |
| Jun | 70,428 | 74,613 | 1 | 44 |
| Total | 708,281 | 704,747 | 1,935 | 2,080 |

Table 2.9 shows the actual average annual electric and natural gas use for the ATC baseline condition with the total energy usage in BTUs per square foot.

19

Table 2.9: ATC actual average energy use

| Average Actual Energy Use | |
|---|---|
| Ave.Ele kWh | 704,747 |
| Ave. Gas, Dth | 2,080 |
| BTU/sq ft | **142,000** |
| $/ sq ft | $          3.20 |

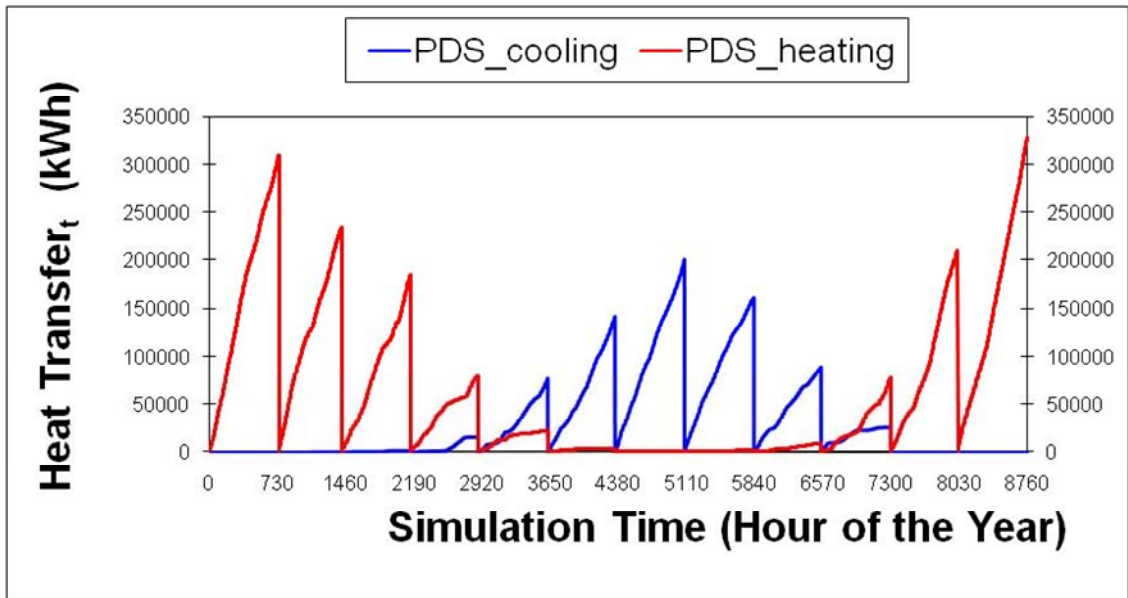Figure 2.5 shows the cumulative per month heating and cooling energy use as calculated by the TRNSYS model.  The heating energy is the energy from natural gas burned in the boiler at 75 percent efficiency (1.0 kWh of natural gas yields 0.75 kWh of heat).  The cooling energy is the electric energy used by the chiller with a coefficient of performance of 3.50 (1.0 kWh used by the chiller yields 3.50 kWh of cooling).
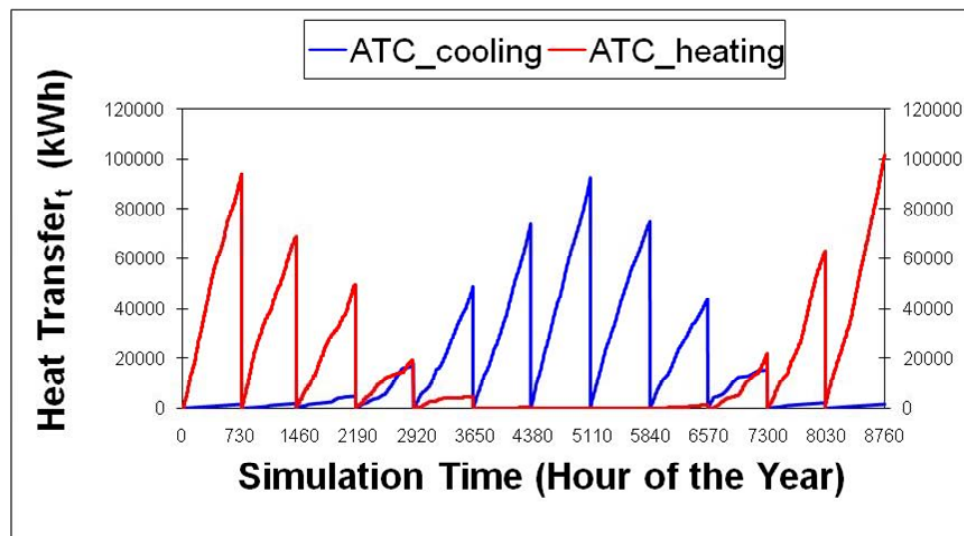


Figure 2.5: TRNSYS ATC annual heating and cooling energy

Just as shown for Plaza Del Sol, Figure 2.6 uses the Alvarado Transportation Center data to show the hottest week, July 29 through August 4.  The hottest hour in this

week is 4:00 pm on July 31. Again, the general shape of this cooling curve for this week is as expected, peaking each afternoon between 2:00 and 5:00 pm and falling to a minimum in the early am. Similarly the highest heating week is January 7 through January 13 with the highest heating load at 7:00 am on January 8. The general shape of this heating curve for this week is also as expected, peaking each morning between 5:00 and 8:00 am and falling to a minimum in the early afternoon.
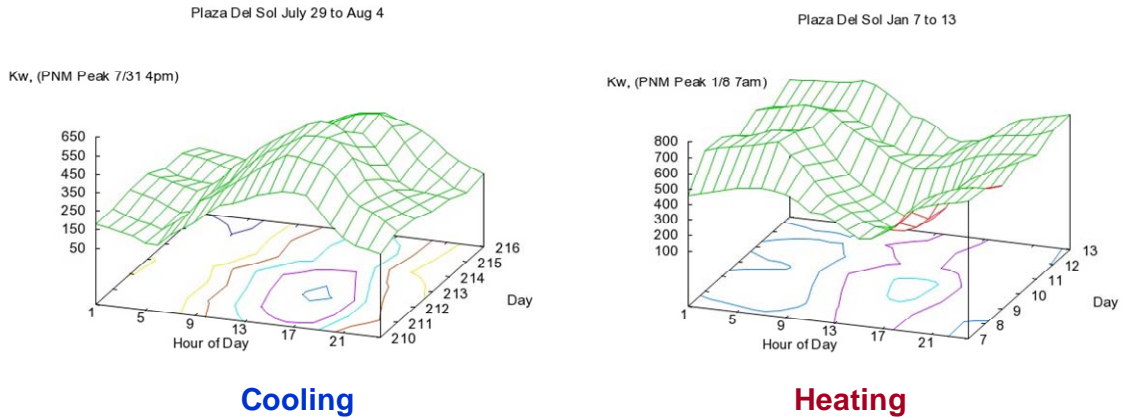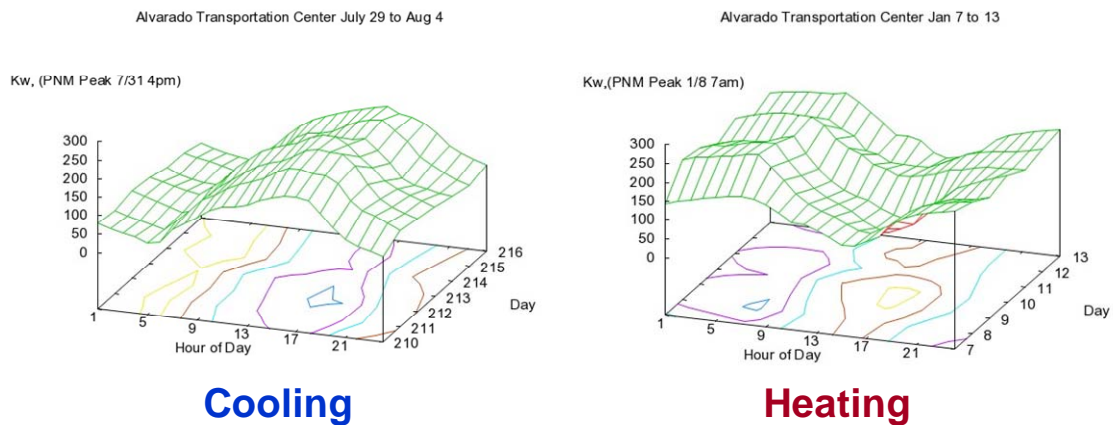


Figure 2.6: ATC cooling/heating hottest/coldest week in the year

The ATC input schedules and other loads are shown in Appendix 2.2 (Dekker et al. 1999).

## 2.4 Demand Response

Electric energy suppliers and electric energy users are working interactively to develop methods for demand response (DR) to reduce consumption during periods of peak energy use. Toyko Electric Power Company has stated that demand response can increase electric system reserve margins on peak by as much as twenty-five percent (Asano 2009). Figure 1.1 shows the annual energy use by the state of California for each

hour sorted from highest to lowest. This curve is typical of electric supply throughout the world. It shows that the highest 25% of the electric load is experienced for less than one percent of the hours in the year. Typically the time period for a demand response event is 12:00 noon to 6:00 pm (Piette 2009). During a DR program event, building operators or their automated control systems make adjustments to building operations with the goal of reducing the building's electric load during times of the electric system's peak electric usage.

For Plaza Del Sol, DR cannot be performed automatically as the building HVAC equipment does not have the necessary digital based control and communication systems. So for this DR evaluation we assumed that either the appropriate automatic controls and communications are installed or the building operator performs these control functions manually at the specified times. The PDS demand response was modeled for the following three options. The first and third options raised the building temperature control range from 22 °C – 24 °C (72 °F – 76 °F) to 24 °C – 26 °C (76 °F – 79 °F) for the demand response period 12:00 noon – 6:00 pm. The second option stopped the chiller and operated the building in an evaporative cooling mode for the demand response period 12:00 noon – 6:00 pm. The individual scenarios for the three options are:

1. Fan energy was reduced to 50 percent by stopping one supply and return fan.

2. The chiller was stopped and the building temperature was controlled by operating the air washers in an evaporative cooling mode.

3. The fan energy was controlled to 40 percent of normal by reducing the proposed VFD controllers from 60 hertz to 24 hertz.

The result for the first option is shown in Figure 2.7. The maximum power reduction was 115 kilowatts and the total energy reduction during the DR period below the baseline was 20 percent or 623 kilowatt hours.
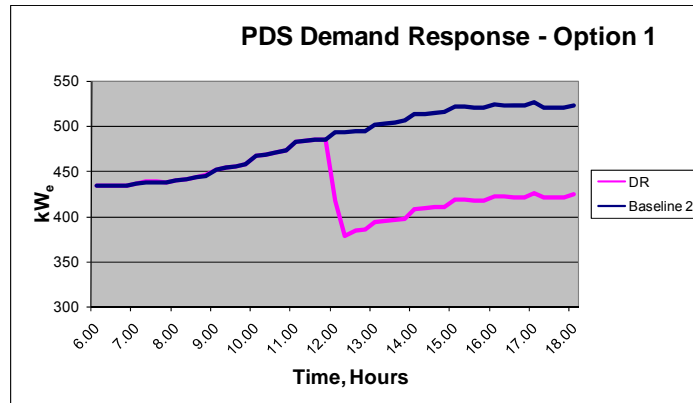


Figure 2.7: PDS demand response – option 1

The result for the second option is shown in Figure 2.8. The building's return air system must exhaust 63,400 cubic feet per minute during the DR event as evaporative cooling requires that recirculation be minimized to minimize the air relative humidity. Under these assumptions, the building's air temperatures are controlled in the range of 24 °C (79 °F) to 28 °C (82 °F) and relative humidity ranges from 40 percent to 65 percent.
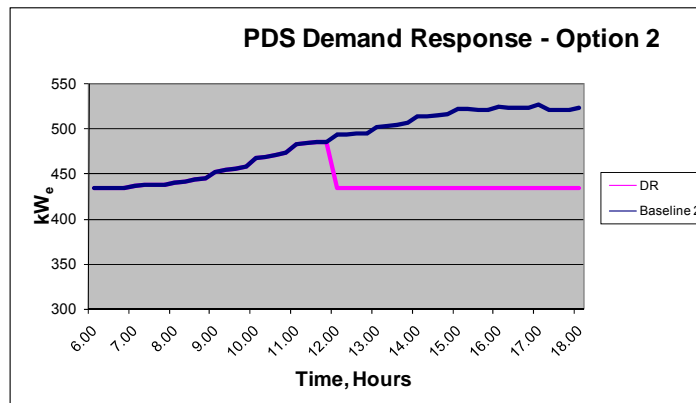


Figure 2.8: PDS demand response - option 2

The maximum power reduction was 88 kilowatts and the total energy reduction during the DR period below the baseline was15 percent or 476 kilowatt hours.

The result for the third option is shown in Figure 2.9. The maximum power reduction was 133 kilowatts and the total energy reduction during the DR period below the baseline was 24 percent or 732 kilowatt hours.

We were curious to see if pre-cooling PDS in the morning (Xu et al. 2007) would increase the power savings during a DR event. Using the TRNSYS energy model with the third option conditions for PDS, we brought the building temperature down to 68 °F prior to initiating the demand response event but detected no difference in power savings without pre-cooling. This is likely due to the low energy efficiency of the building.
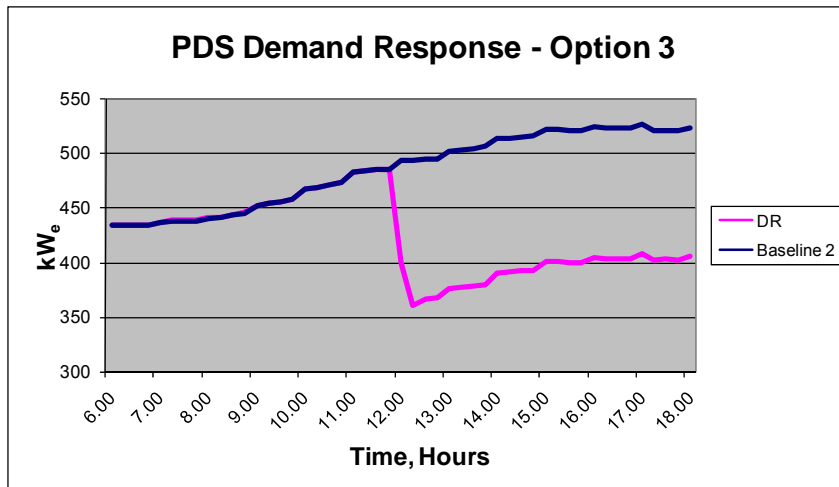


Figure 2.9: PDS demand response – option 3

Demand response for the Alvarado Transportation Center can readily be performed automatically as the HVAC equipment does have digital based controls and communication. The ATC demand response was modeled for the following two options. Both options raised the building temperature control range from 20 °C – 22 °C (68 °F –

72 °F) to 24 °C – 26 °C (76 °F – 79 °F) for the demand response period 12:00 noon –

6:00 pm on July 31, the hottest of the days in the weather model.  The second option

stopped the 53.17 ton AC unit and operated the building only with the 71.75 ton AC unit

for the demand response period 12:00 noon – 6:00 pm.  The individual scenarios for these

options are:

1.  Raise temperature set point range only.  No other reductions.

2.  Raise the temperature set point range and also shutdown the smaller of the AC

    units (53.17 ton) and only cool the facility with the larger unit (71.75 tons).

The result for the first option is shown in Figure 2.10.  The maximum power

reduction was 121 kilowatts and the total energy reduction during the DR period was 18

percent or 506 kilowatt hours.
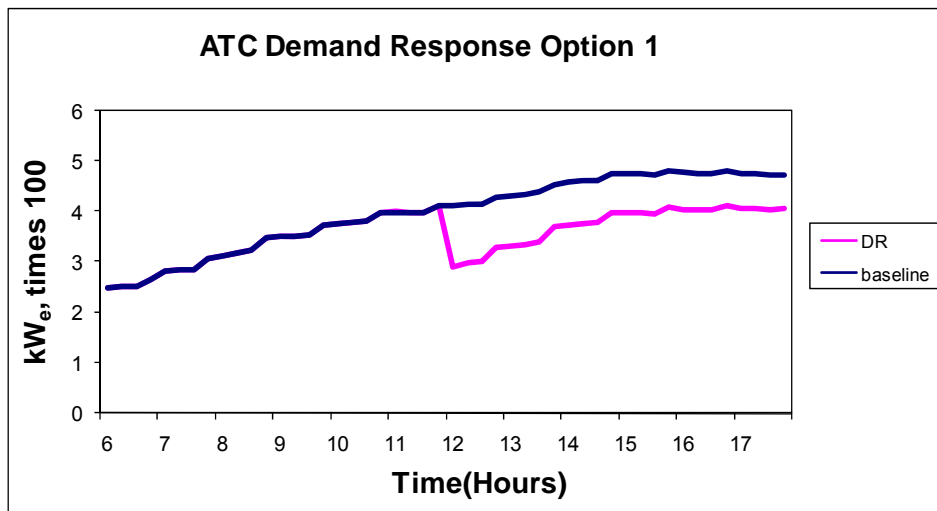


Figure 2.10: ATC demand response – option 1

The result for the second option is shown in Figure 2-11.  The maximum power

reduction was 125 kilowatts and the total energy reduction during the DR period was 26

percent or 649 kilowatt hours.
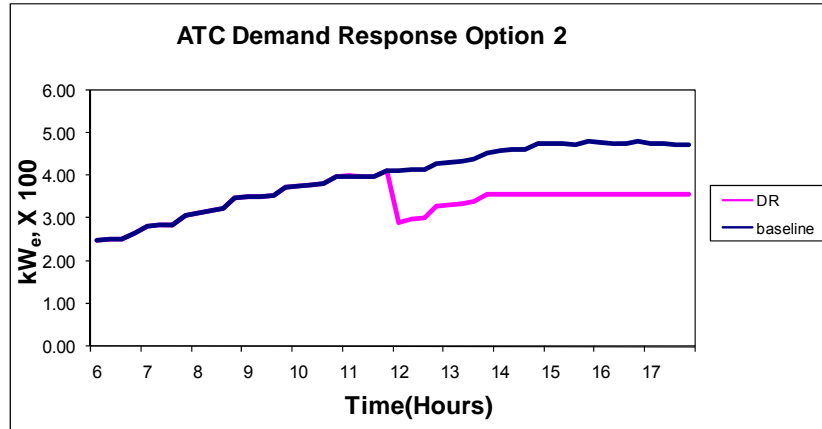
Figure 2.11: ATC demand response – option 2

## 2.5 ATC Photovoltaic Generation Potential

Due to the high availability of solar energy in the southwest, the Alvarado Transportation Center is a site with the potential for a solar photovoltaic (PV) electric generating system. The ATC has an annual average electric energy use in one day of 1930 kilowatts-hours. This was used to establish the size of the potential PV system. The PV generating potential in the Albuquerque area is 6.25 watts per square meter per day (NREL 2006) with efficiency of 0.135 for polycrystalline PV material (Wormser and Strong 2007). This would require approximately 2290 square meters or 24,600 square feet of PV panels to supply the ATC daily use. It should be noted that the flat portion of the ATC roof is only 5000 square feet or 465 square meters. The rest of the roof is sloped tile and not architecturally appropriate for mounting PV panels. Some other location would be required for the panels such as the top of covered parking or covered walkways. The cost for covered parking and walkways would be quite high and not likely worth the investment.

## 2.6   Conclusions

Plaza Del Sol has the opportunities for improvement in day-to-day energy use as shown in Table 2.10.

Table 2.10: PDS summary of energy improvements

| Description: | Value, $/Year | BTU/sq ft | Est. Cost |
|---|---|---|---|
| **Repair outside air dampers and main 2nd floor door** | **$16,800** | **115,000** | **$5,200** |
| Shutdown 1 supply fan 1 exhaust fan from 6 pm to 6 am Mon-Sat and all day Sunday | $40,100 | 102,000 | $0 |
| Replace windows with better insulating type (U = 0.4) | $39,300 | 95,300 | $5,000,000 |
| **Install VFDs on supply and return fans** | **$43,100** | **101,000** | **$69,000** |
| Total | $99,200 | | $5,074,200 |

Shutdown of the supply and return fans during nights and Sundays is not warranted if VFDs are installed on these fans.  Also the replacement of the windows will have a significant capital cost and likely is not justified economically.  Therefore the most reasonable improvements and their savings are shown in **bold** in Table 2.10.

No energy improvements were recommended for the Alvarado Transportation Center as this facility is relatively new and includes current energy efficient materials and construction.

The Plaza Del Sol demand response Option 3, raising the temperature control range to 76 °F to 79 °F and controlling the supply and return fan energy to 40 percent of

normal using VFD controllers gives the greatest demand response power reduction. This option will necessitate adding automatic control and communication equipment for the demand response to be effective.

The Alvarado Transportation Center demand response Option 1, raising the temperature set points, has the least intrusive result. Option 2, while 8 percent better in energy reduction, will result in higher temperatures than the 76 °F to 79 °F and cause discomfort to City employees and the public.

# Chapter 3

# Baseline Load Profile

## 3.1   Introduction

This Chapter focuses on predicting what the energy usage of a facility during a demand response event would be in the absence of any energy reductions.  This predicted energy usage is termed the Baseline Load Profile (BLP) (Couglin, et al. 2008).  This chapter shows the development of a fuzzy set theory approach for determining the baseline load profile and compares the accuracy of this approach to the current industry approach.  We utilized the baseline load profile method presented in this chapter in designing the Demand Response Control System as described in Chapter 5.

Fuzzy set theory provides a conceptual framework similar to ordinary sets but is more general and has a wider scope of applicability.  It provides a natural way of dealing with problems in which the imprecision is the absence of sharply defined criteria of class membership (Zadeh 1965). This is shown in Figure 3.1 (Ross 2004).  Set **A** in Figure 3.1 is a classical or crisp set with element "a" included in set **A** and element "b" excluded from set **A**.  The fuzzy set **A**, also shown in Figure 3.1, is different in that element "c" is only partially included in the fuzzy set.  Figure 3.2 shows examples of a crisp set for tall people and a fuzzy set for tall people.  In the crisp set for tall people, those less than 5' 10" are excluded from the set and those 5' 10" or taller are included in the set.  In the fuzzy set for tall people, those individuals who are 5' 10" tall have a 0.5 membership in

the fuzzy set for tall people, those that are 6' 0" tall have a 0.8 membership in the fuzzy

set for tall people, and those 6' 2" or taller have a 1.0 membership in the fuzzy set for tall
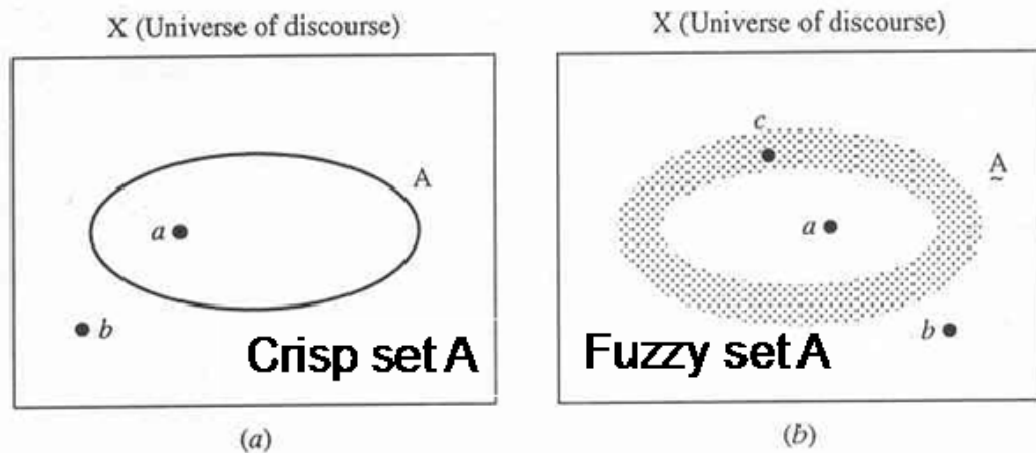
people.



Figure 3.1 Example of a classical (crisp) set (a) and a fuzzy set (b)
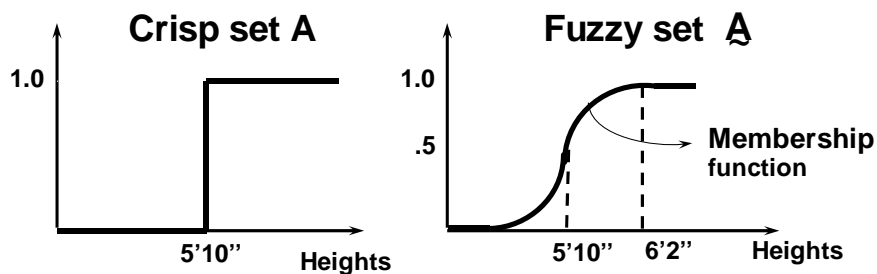


Figure 3.2: Classical (crisp) and fuzzy sets for tall people

Fuzzy sets form the building blocks for fuzzy IF-THEN rules having the general form "IF

X is **A** THEN Y is **B**," where **A** and **B** are fuzzy sets. A fuzzy system is a set of fuzzy

rules that converts inputs to outputs. Fuzzy systems are rule-based systems that may be

constructed from a collection of linguistic rules; in general they are non-linear mappings

of inputs to outputs (Ross 2004).

During a DR program event, building operators or their automated control systems make adjustments to building operations with the goal of reducing the building's electric load during times of the electric system's peak electric usage. The baseline load profile (BLP) is key to assessing the actual peak load electric energy reduction from a DR event. Some grid operators are considering compensating commercial facility operators for this energy reduction they achieve during DR events.

## 3.2 Methods

The California Energy Commission (CEC) has funded research (Couglin et al. 2008) to assess the accuracy of algorithms for determining estimates for building electric load usage profiles (BLP) for commercial facilities participating in demand response (DR) programs. This research, performed by Laurence Berkeley National Laboratory (LBNL), tested seven BLP algorithms on a sample of 33 buildings located in California for actual energy use data from May 2005 through October 2006. LBNL selected proxy DR event days as the hottest 25 percent of the non-holiday or weekend days in this May through October period. After performing statistical analysis of each BLP algorithm on the conditions of the proxy event days, LBNL determined the "simple average over the highest 3 out of 10 previous days with morning adjustment" (referred to as LBNL Best here) to be most accurate (Coughlin et al. 2008).

We duplicated this calculation using Dane Smith Hall and compared the results to a fuzzy approach using the modified learning from example (MLFE) methodology with a recursive least square (RLS) improvement (Ross 2004) but with facility occupancy included as an additional input.

We selected the proxy event days based on the hottest 25 percent of the non-holiday or weekend days in August and September 2006.  The hottest days were selected from the National Oceanic and Atmospheric Administration (NOAA) weather information at the Albuquerque Sunport weather station.  Next we gathered the Dane Smith energy use data from the UNM Energy Management and Control System (EMCS) information for the hours of 9:00 am through 6:00 pm for each of the proxy event days.  This resulted in 21 data sets for each of the peak energy hours.  This report presents only the 4:00 pm hour to demonstrate the methodology, but the results show all three peak hours, 3:00 pm, 4:00 pm, and 5:00 pm.  Table 3.1 presents the energy use and occupancy data for the 4:00 pm hour.  The numbers in the "Day" column range from 48 to 91 and represent the dates numbered sequentially.  Day 48 represents August 17, 2006 and Day 91 represents September 29.  The field labels are defined as follows:

$al(d.h)$ – actual load (kW) during this day and hour

$pl(d,h)$ – the average of the 3 highest hourly loads (kW) of the previous 10 days

Occ. – the occupancy at this day and hour

$al(d,10)$ – the actual load on this day at 10:00 am

$al(d,10)$ – the actual load on this day at 11:00 am

The LBNL Best algorithm is applied to this data as follows:

- $pl(d,h)$ = the predicted load.  This is the average of the actual load for this hour for the 3 highest actual loads over the previous 10 days.

- $d$ = the day

- $h$ = the time at the beginning of the hour

Table 3.1: Data sets for the 4:00 pm hour

| Day | al(d,h) | pl(d,h) | Occ. | al(d,10) | al(d,11) |
|-----|---------|---------|------|----------|----------|
| 55 | 182.46 | 174.78 | 554 | 175.67 | 178.08 |
| 52 | 177.88 | 119.21 | 556 | 176.29 | 187.46 |
| 60 | 182.54 | 179.06 | 759 | 179.71 | 181.50 |
| 61 | 181.67 | 180.96 | 619 | 178.79 | 187.33 |
| 48 | 119.29 | 112.21 | 759 | 103.00 | 103.42 |
| 62 | 183.58 | 182.22 | 554 | 172.79 | 175.17 |
| 67 | 183.54 | 182.86 | 759 | 165.50 | 172.96 |
| 68 | 174.38 | 183.19 | 619 | 181.75 | 187.75 |
| 73 | 171.67 | 183.22 | 556 | 163.83 | 180.04 |
| 74 | 176.00 | 183.22 | 759 | 167.00 | 170.04 |
| 76 | 174.79 | 181.04 | 554 | 173.96 | 172.00 |
| 77 | 165.58 | 178.19 | 128 | 165.21 | 175.17 |
| 88 | 179.92 | 179.89 | 759 | 170.08 | 174.58 |
| 89 | 175.50 | 180.78 | 619 | 174.71 | 177.71 |
| 91 | 155.42 | 180.78 | 128 | 165.79 | 175.42 |
| 49 | 91.96 | 119.21 | 128 | 98.08 | 96.71 |
| 59 | 175.92 | 179.06 | 556 | 172.25 | 183.00 |
| 63 | 161.62 | 182.86 | 128 | 181.96 | 187.63 |
| 75 | 171.54 | 182.93 | 619 | 178.71 | 178.67 |
| 81 | 183.75 | 178.19 | 759 | 172.50 | 175.67 |
| 90 | 170.42 | 180.78 | 554 | 170.42 | 168.92 |

The LBNL authors (Couglin et al. 2008) recommend a correction factor for this prediction (pl) based on the conditions in the morning of the DR event (hours 10:00 am and 11:00 am) as follows:

$$c(d) = \frac{al(d,h=10)+al(d,h=11)}{pl(d,h=10)+pl(d,h=11)} ,$$
(3.1)

where:

al(d,h) – the actual load for the day and the hour

pl(d,h) – again, the average of the 3 highest actual loads at this hour over the 10 previous days.

33

Thus the corrected predicted load (pl') during the peak energy hours (3:00: pm through 5:00 pm) is:

$$pl'(d,h) = c(d) \times pl(d,h) \qquad (3.2)$$

We calculated the predicted load (pl') for each of the peak hours of 3:00 pm, 4:00 pm, and 5:00 pm based on the LBNL Best algorithm described herein for each set of test data.  Table 3.2 shows the input data and the LBNL Best results for the 4:00 pm hour.

Table 3.2: LBNL Best predicted load for 4:00 pm

| Day | al(d,10) | al(d,11) | pl(d,10) | pl(d,11) |
|-----|----------|----------|----------|----------|
| 49  | 98.08    | 96.71    | 107.12   | 110.89   |
| 59  | 172.25   | 183.00   | 176.82   | 186.51   |
| 63  | 181.96   | 187.63   | 179.00   | 187.04   |
| 75  | 178.71   | 178.67   | 181.39   | 187.57   |
| 81  | 172.50   | 175.67   | 180.31   | 182.65   |
| 90  | 170.42   | 168.92   | 178.04   | 182.12   |

| Day | cl(d) | pl(d,h) | pl'(d,h) |
|-----|-------|---------|----------|
| 49  | 0.89  | 119.21  | 106.51   |
| 59  | 0.98  | 179.06  | 175.07   |
| 63  | 1.01  | 182.86  | 184.63   |
| 75  | 0.97  | 182.93  | 177.19   |
| 81  | 0.96  | 178.19  | 170.93   |
| 90  | 0.94  | 180.78  | 170.32   |

The fuzzy set theory approach utilizes the modified learning from example (MLFE) methodology to generate the initial Gaussian membership functions and the recursive least square algorithm to improve their accuracy.  MLFE is a multiple input and single output system comprised of a collection of if-then rules where the rules are in the form of a premise clause and a consequence.  These rules are of the form (Ross 2004):

IF premise$_1$ and premise$_2$ and premise$_3$ and premise$_4$ THEN consequence,  (3.3)

where:          premise$_1$ = the fuzzy set for $x_1$ of Table 3.3

premise$_2$ = the fuzzy set for $x_2$ of Table 3.3

premise$_3$ = the fuzzy set for $x_3$ of Table 3.3

$$\text{premise}_4 = \text{the fuzzy set for } x_4 \text{ of Table 3.3}$$

$$\text{consequence} = \text{the output parameter y of Table 3.3}$$

This approach allows one to readily add an input variable, in this case facility occupancy, to improve the prediction. In the case of Dane Smith Hall occupancy for any given day and hour varies from less than 100 people to over 800 people. This population variation should strongly impact the facility's energy use. All data was normalized to the range of 0 to 1 by dividing each input and output data set by the largest member of that set. Fifteen data sets were used to train the MLFE/RLS methodologies and six data sets were used to test the accuracy of the two approaches, LBNL Best versus the fuzzy set theory approach. The 15 training data sets and the 6 testing data sets are shown in Table 3.1 prior to normalization. They are further defined in Table 3.3.

Table 3.3: MLFE inputs ($x_i$) and output (y)

| y | actual energy use for the day and hour, al(d,h) |
|---|---|
| $x_1$ | the 3 hour averages used in the LBNL Best, pl(d,h) |
| $x_2$ | Dane Smith occupancy for the day and hour, Occ. |
| $x_3$ | actual energy usage at 10:00 am for the day, al(d,10) |
| $x_4$ | actual energy usage at 11:00 am for the day, al(d,11) |

The MLFE algorithm calculates the membership functions for each of the four inputs. The Gaussian membership functions describing the input fuzzy sets are of the form (Ross 2004):

$$\mu(x_j) = e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2} \text{,}$$ 

$\hspace{10cm}$ (3.4)

where: $\hspace{2cm}$ $j = 1$ to n (the number of inputs – 4)

$\hspace{4cm}$ $i = 1$ to R (the number of membership functions)

$\hspace{4cm}$ $\mu(x_j)$ is a membership function describing input $x_j$

$\hspace{4cm}$ $c_j^i$ is the jth input's center for the ith rule

$\hspace{4cm}$ $\sigma_j^i$ is the jth input's relative width for the ith rule

The rule base is initialized using values for the first rule's center, $c_j^{i=1}$, as the first input data value. The relative width, $\sigma_j^{i=1}$, of the first rule must be set manually as this information cannot be determined from the input data.

The fuzzy model produced by MLFE uses a product t-norm for the conjunction of multiple antecedents in the premise as:

$$\mu_i(x) = \prod_{j=1}^{n} e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2}$$

$\hspace{10cm}$ (3.5)

where: $\hspace{2cm}$ $\mu_i(x)$ is the membership value of the input x in the $i_{th}$ rule

$\hspace{4cm}$ $c_j^i$ and $\sigma_j^i$ are the center and the spread for the $j_{th}$ input and $i_{th}$ rule

$\hspace{4cm}$ n is the number of inputs

$\hspace{4cm}$ $i = 1$ to R (the number of membership functions)

This is the mathematical representation of the function of the word "and" in equation (3.3).

The implication represented by the word "then" in equation (3.3) along with the weighted average defuzzification is used for the output as:

$$f(x \mid \Theta) = \frac{\sum\limits_{i=1}^{R} b_i \prod\limits_{j=1}^{n} e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2}}{\sum\limits_{i=1}^{R} \prod\limits_{j=1}^{n} e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2}} \quad , \tag{3.6}$$

$f(x|\Theta)$ is the defuzzified output and is a function of:

$x_j$ is the current input training vector

$\Theta$ is the vector containing the rule parameters for each input rule ($b_i$, $x_j$, $c_j^i$, and $\sigma_j^i$)

$b_i$ is the value defining the output for the $i^{th}$ rule

$x_j$, $c_j^i$, and $\sigma_j^i$ are as defined in equation (3.4)

It is determined that an additional rule is needed if the prediction error for the current model is equal to or greater than the user defined test factor ($\varepsilon_f$) as:

$$| f(x \mid \Theta) - y | \geq \varepsilon_f , \tag{3.7}$$

where:        $y$ is the actual output from the training data set

$f(x,\Theta)$ is the calculated model output described in equation (3.6)

$\varepsilon_f$ is the user specified accuracy.

If an additional rule is needed, the centers for the new rule are set to the next training data inputs, $x_j^i$, and the relative widths are determined by the MLFE algorithm based on achieving an appropriate overlap between membership functions. This overlap is set by a user defined weighting factor ($\omega$):

$$\sigma_j^i = \frac{1}{\omega} |c_j^{i'} - c_j^{min}|, \tag{3.8}$$

where: $c_j^{i'}$ are the current input training data set, $x_j^i$

$c_j^{min}$ are the nearest membership function centers to the new membership function centers $c_j^{i'}$

$\omega$ is the user defined Gaussian membership function width weighting factor

This process of adding additional rules using the next training data set repeats until equation (3.7) is satisfied.

The MLFE methodology generated membership functions for the four inputs as shown graphically in Figures 3.3 through 3.6. The weighting factor ($\omega$) determines the amount of overlap between the membership functions. For the 4:00 pm hour, a weighting factor of 0.055 yielded the best accuracy. The test factor ($\varepsilon_f$) regulates the number of membership functions or rules the MLFE methodology generates. Again for the 4:00 pm hour, a test factor of 0.06 generated 5 rules and yielded the best accuracy.

The RLS algorithm uses Gaussian membership functions as input, optimizes these membership functions based on the training data, and yields the predicted output for the test data sets as a delta function. This is performed by iteratively estimating the value of the output as follows:

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\,\xi\left(x^k\right)[y^k - (\xi\left(x^k\right))^T\hat{\theta}(k-1)] \ , \qquad (3.9)$$

with regression vector:

$$\xi\,(x) = \frac{\Pi_{j=1}^{n}\,e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2}}{\Sigma_{i=1}^{R}\,\Pi_{j=1}^{n}\,e^{-\frac{1}{2}(\frac{x_j - c_j^i}{\sigma_j^i})^2}} \qquad , \qquad (3.10)$$

and the covariance matrix:

$$P(k) = \frac{1}{\lambda}\{I - P(k-1)\,\xi\,(x^k)[\lambda\,I + (\xi\left(x^k\right))^T P(k-1)\,\xi\,(x^k)]^{-1}(\xi\left(x^k\right))^T\}P(k-1),$$

The above equation is equation number (3.11)

where: $\qquad\qquad P(0) = \alpha\mathbf{I}$

$\qquad\qquad\qquad \alpha = 100$ here

$\qquad\qquad\qquad \mathbf{I} = $ the identity matrix (RxR)

$\qquad\qquad\qquad \lambda = 1$ here to weight all training data equally

The RLS code was set to cycle through the training data set 100 times.
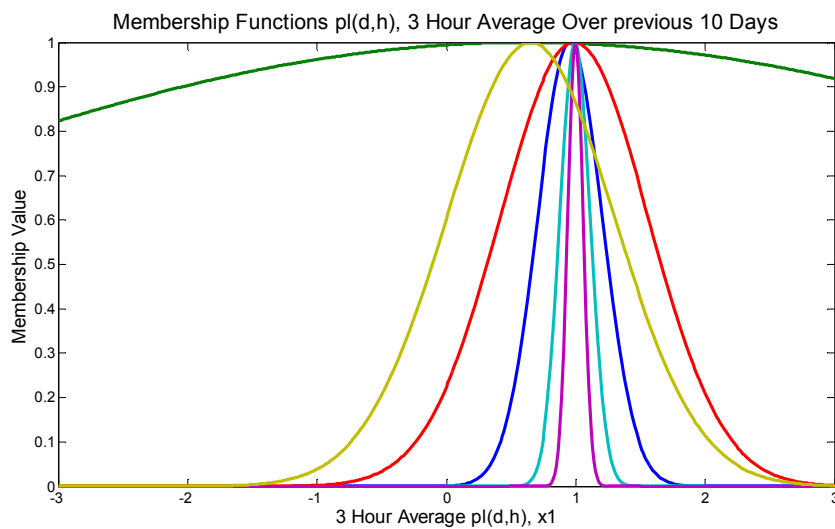


Figure 3.3: The 3 hour averages pl(d,h) memberships
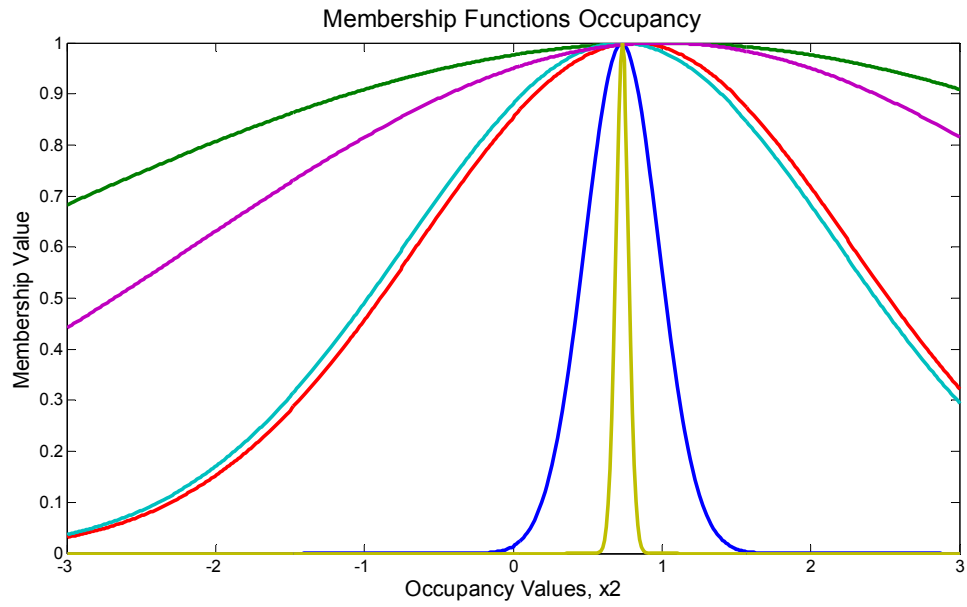
Figure 3.4: Occupancy memberships
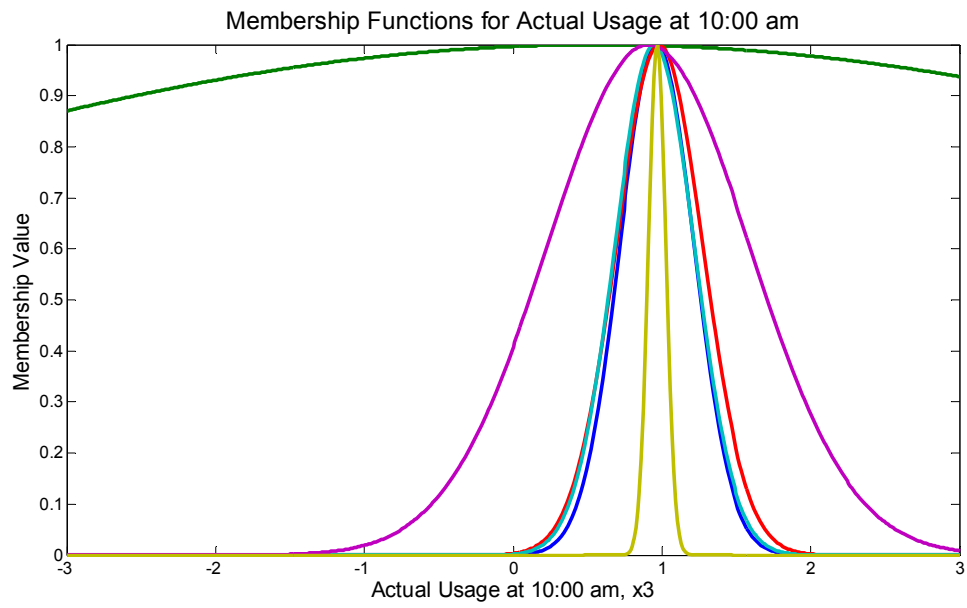


Figure 3.5: Actual usage at 10:00 am membership
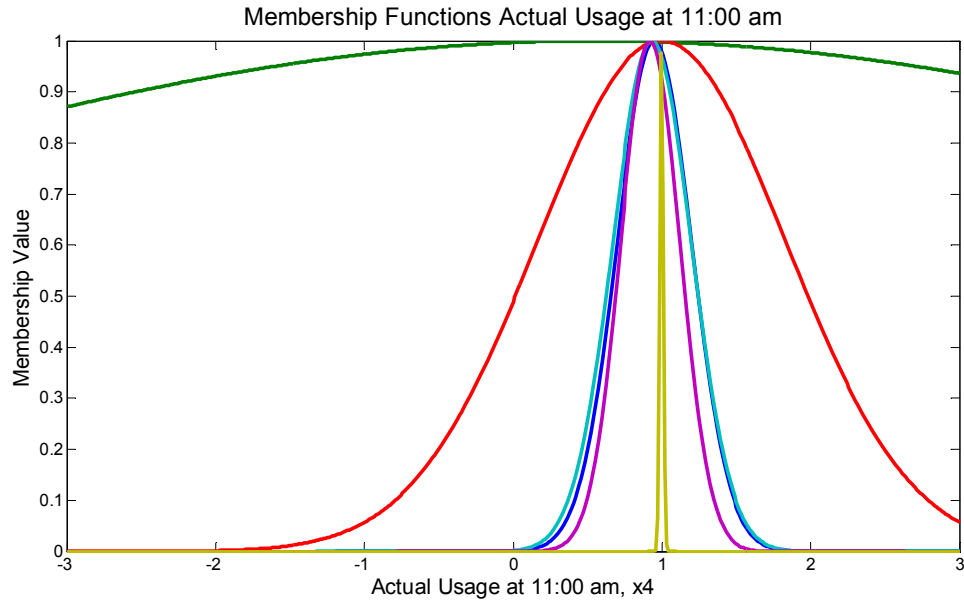
Figure 3.6:  Actual usage at 11:00 am membership

## 3.3   Discussion and Results

The accuracy of each methodology ($e_p$) is simply the difference between the actual electric load (al) for the hour from the testing data output minus the predicted electric load (pd) squared and shown in equation (3.12).  These were then summed and divided by 6, the number of test data sets (m):

$$e_p = \sum \frac{[al(d,h) - pd(d,h)]\text{^}2}{m} \qquad (3.12)$$

We calculated this accuracy for both the MLFE/RLS methodology and the LBNL Best methodology.  These accuracies of the results for the LBNL Best algorithm, pl'(d,h)

from Table 3.2, and the fuzzy approach are shown in Table 3.4 for the three peak hours.

Figures 3.7, 3.8, and 3.9 compare the two methods point by point for these three hours.

Table 3.4:  Accuracy comparisons

| Peak Hour | LBNL Best | MLFE/RLS |
|-----------|-----------|----------|
| 3:00 pm | 109 | 42 |
| 4:00 pm | 120 | 40 |
| 5:00 pm | 166 | 98 |
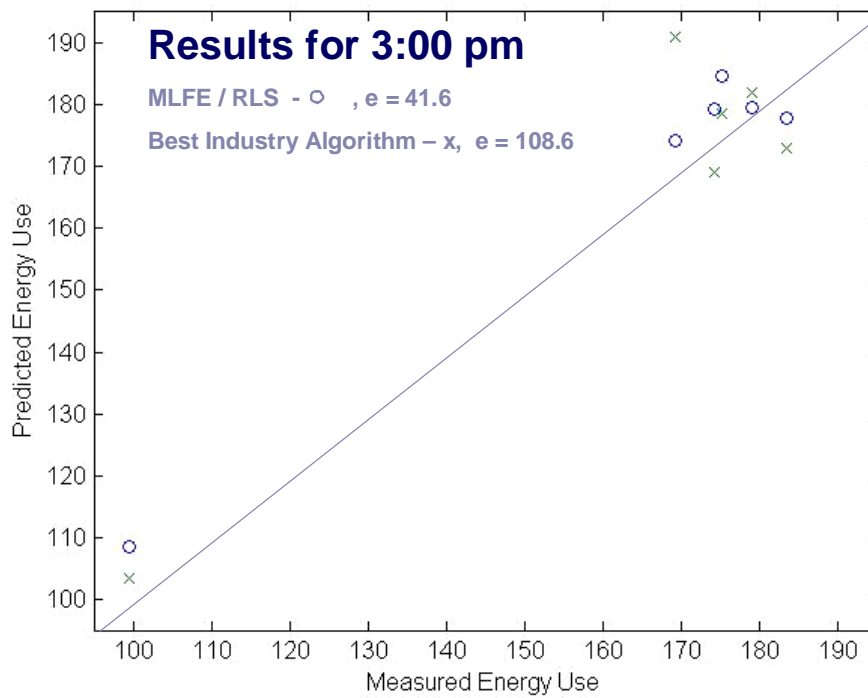


Figure 3.7:  Test data comparisons for 3:00 pm
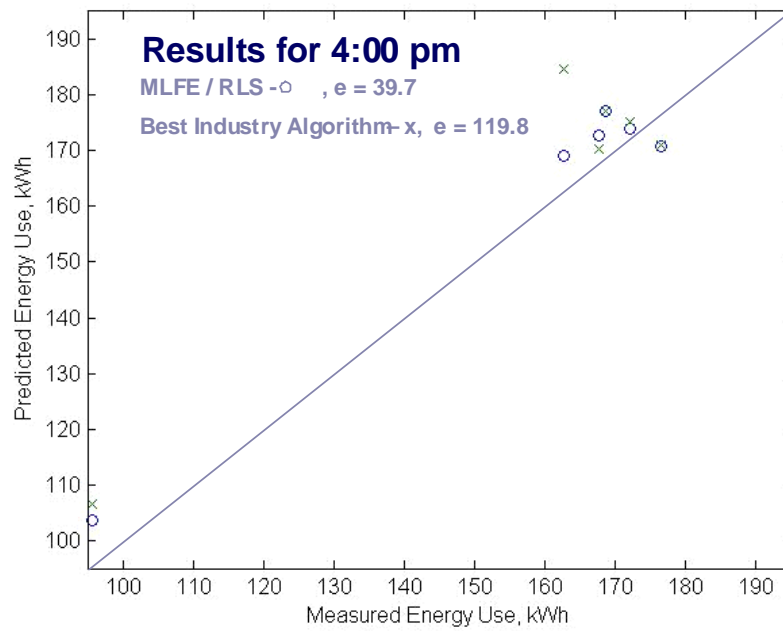
Figure 3.8: Test data comparisons for 4:00 pm
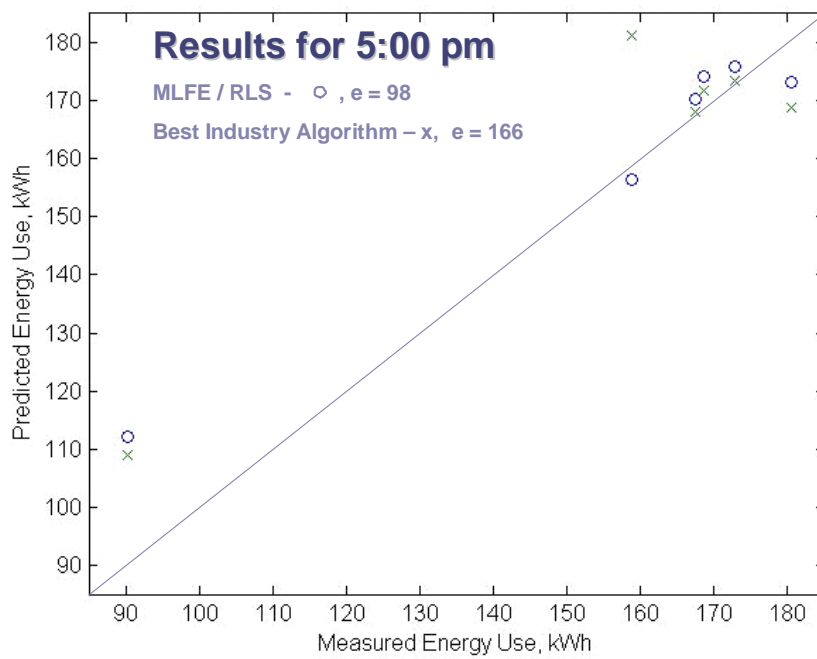


Figure 3.9: Test data comparisons for 5:00 pm

## 3.4  Conclusions

The fuzzy approach was significantly more accurate than the LBNL Best algorithm.  This was partially because the fuzzy approach takes into account the Dane Smith Hall building occupancy.  Occupancy variation in the range of 100 people to 800 people in a classroom building is a significant driver for energy use.  This is due to the heat given off by the occupants and the additional lighting required in high occupancy periods.

The fuzzy approach has an additional advantage due to the relationship between the inputs and outputs.  The fuzzy system allows the natural non-linearity of the inputs to be reflected in the output.  The LBNL Best algorithm forces a linear relationship between the inputs and output.  Forced linearity in modeling a non-linear system cannot match the accuracy of an intrinsically non-linear modeling system.

The largest effort in the BLP modeling is gathering and appropriately processing the input information.  Both modeling algorithms use the same input information and therefore suffer equally with this difficulty.  While the LBNL Best algorithm is somewhat simpler to apply to the input data, current software tools such as MATLAB™, which was used in modeling the MLFE/RLS methodology, was fast and straight forward.  The significant increase in accuracy clearly justifies this additional effort.

# Chapter 4

# Evaluation of Commercial Facility Demand Response Using a Genetically Evolved Fuzzy Cognitive Map

## 4.1   Introduction

Demand response programs reduce electric energy use on or near the electric peak usage period typically on summer days (Valero et al. 2007).  Electric suppliers only impose demand response events for a limited number of days, typically 10 to 15 days each year.  Electric customers' participation in demand response events are voluntary. Obviously reducing electric power consumption on a hot summer afternoon, the normal time for a demand response event, can cause some discomfort to facility occupants.  If this occupant discomfort causes significant complaints to the facility operator or owner, they may direct the DR event be discontinued and thus eliminate the electric power savings.  Assessing and predicting this potential interruption of the DR event is not readily evaluated with traditional analytical techniques.  Thus we elected to assess this problem using fuzzy set theory as applied to cognitive maps.  We modeled this problem using the University of New Mexico (UNM) campus.  The campus consists of over 200 facilities including classrooms, offices, laboratories, libraries, and residence halls,

drawing over 30 megawatts of electricity at peak. We utilized the results of this fuzzy cognitive mapping evaluation in the design of the Demand Response Control System as described in Chapter 5.

Fuzzy cognitive maps provide a heuristic approach for analyzing complex strategic situations to improve decision making processes. Fuzzy cognitive maps have been applied to a vast array of problems from technical to political. These include biological processes, electric circuits, control systems, equipment failure modes and effects analysis, social and political situations, organizational strategic planning, etc. Fuzzy cognitive maps are a form of neural networks which lend themselves to analysis using neural network techniques as well as genetic algorithms.

Cognitive maps (CM) were introduced by Robert Axelrod in 1976 as a means of formalizing and improving the decision process for policy makers. CMs are directed graphs that show the interconnection of the nodes, representing concepts, with interconnecting arrows reflecting the causes between concepts. Concepts typically represent processes, actions, events, values, goals, or policies (Kozko 1992). The use of simple binary relationships (i.e., increase and decrease) is done in a conventional (crisp) CM. CMs offer a number of advantages that make them attractive as models for engineering planning and concept development. CMs have a clear way to visually represent causal relationships, they expand the range of complexity that can be managed, they allow users to rapidly compare their conceptual models with reality, they make evaluations easier, and they promote new ways of thinking about the issue being evaluated.

A fuzzy cognitive map extends the simple binary relationship of a CM to include various degrees of increase or decrease (small decrease, large increase, almost no increase, etc.). An FCM extends the idea of conventional CMs by allowing concepts to be represented linguistically with an associated fuzzy set, rather than requiring them to be precise. This extension allows fuzzy numbers or linguistic terms to be used to describe the degree of the relationship between concepts in the FCM (Ross 2004).

This dissertation presents mathematical approaches to model fuzzy cognitive maps by three methods: crisp inputs with crisp interconnecting weights, crisp inputs with fuzzy interconnecting weights, and fuzzy inputs with fuzzy interconnecting weights. The paper applies these modeling approaches to a simplified example of the UNM campus DR issue, composed of seven concepts, to demonstrate each method. Finally this paper presents a genetically evolved approach to evaluating a fuzzy cognitive map composed of twenty concepts based on the author's work in commercial facility electric demand response as applied to the University of New Mexico campus. The results show potential drivers of facility occupant dissatisfaction and potential approaches to reducing this dissatisfaction and its impact on the demand response event.

## 4.2  Methods

Figure 4.1 and Figure 4.1a show the fuzzy cognitive map (FCM) representing the University of New Mexico (UNM) strategy as applied to the campus while it undergoes a demand response (DR) event.

47
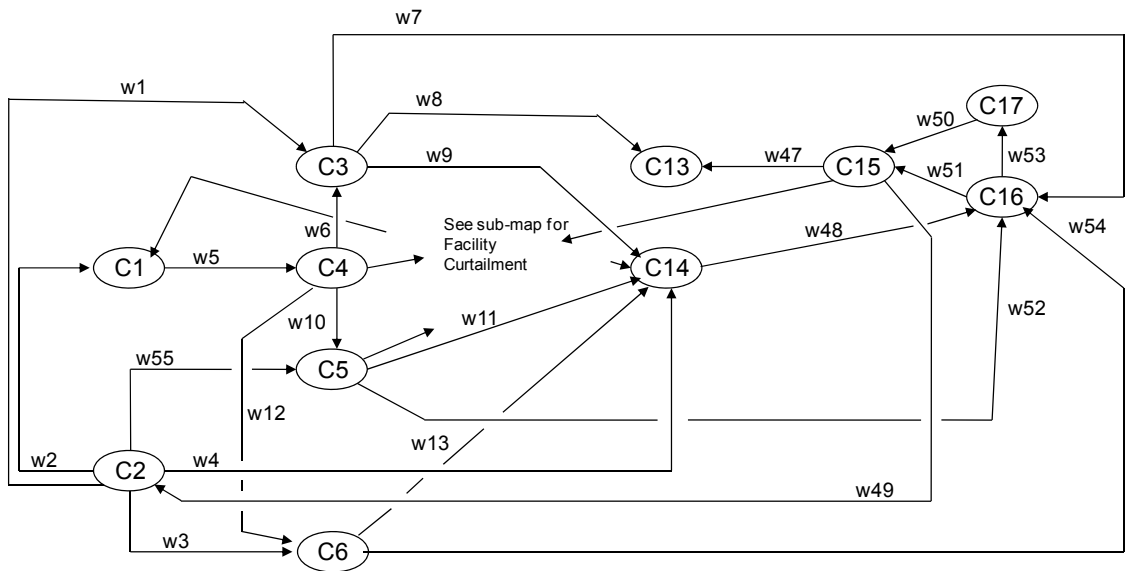
Figure 4.1: Commercial facility FCM representing the University of New Mexico

strategy as applied to the campus while it undergoes a demand response event
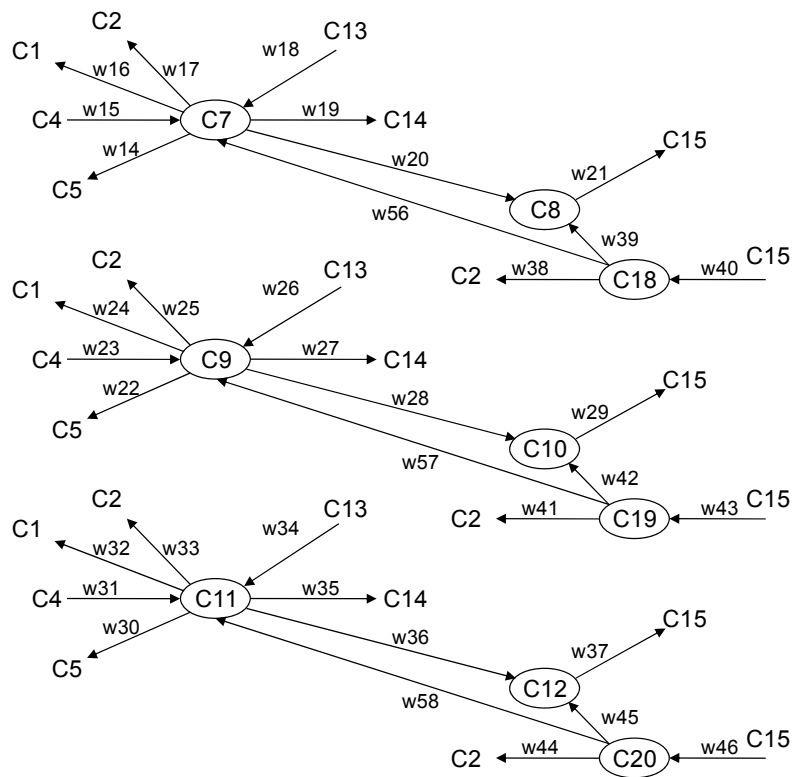


Figure 4.1a: Sub-map for facility curtailment shown in the middle of Figure 4.1

Figure 4.2 shows the simplified version of this FCM used herein to demonstrate the three analysis approaches.
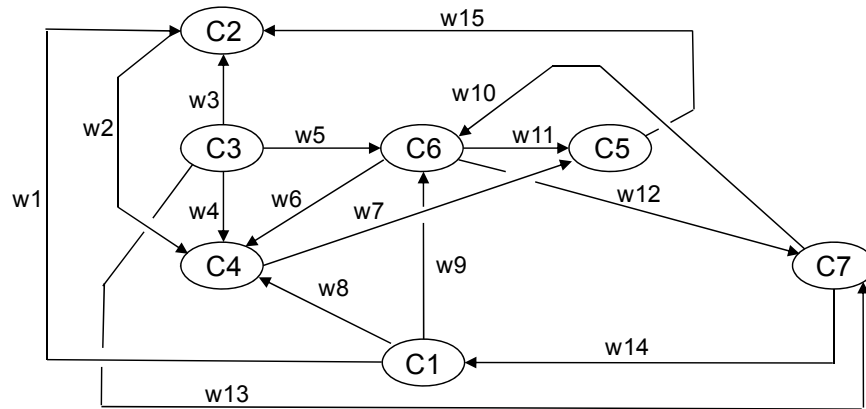


Figure 4.2: Simplified example FCM used to demonstrate the analysis methodologies

FCMs are made up of nodes that represent concepts and interconnected arrows that represent the causal connections among the concepts (Ross 2004). Concepts' activation levels range from -1 to +1 and their causal connections are also weighted from -1 to +1. The arrow points from the causing concept to the concept being caused either positively or negatively. For example in Figure 4.2, concept C1 causes concept C6 while concept C7 causes concept C1.

The following describes each of the seven concepts that make up the FCM of Figure 4.2. Section 4.3.4 contains the detailed descriptions of the concepts for the FCM of Figure 4.1 and Figure 4.1a.

C1 - Level of UNM electricity demand. This is a measure of the quantity of electricity the UNM campus is consuming in total. An activation level of +1 indicates a high level of electric demand and therefore consumption, an activation level of 0

49

represents a light level of electric consumption, and an activation level of -1 represents a very light level of consumption.

C2 – UNM generates electricity internally. UNM has a co-generation gas turbine in the Ford Utilities Center capable of producing 6,000 kilowatts of electricity, approximately a third of the base campus usage, and supplying this to the campus electricity distribution system. An activation level of +1 represents full power output for the co-generation turbine, 0 represents a medium power output, and -1 represents little to no internal power generation.

C3 – PNM sends UNM a demand response energy curtailment signal. A high demand response signal from UNM represents a request for a demand response event. An activation level of +1 represents the high demand response signal is present, 0 represents a medium demand response signal, and -1 represents a low or no demand response signal.

C4 – UNM stores energy. UNM facilities store energy by storing hot or chilled water in insulated storage tanks for use at a later time. This is commonly done by commercial facilities at night when electric rates are low for use during the day when prices are higher (Furusawa et al. 2009). An activation level of +1 represents energy storage at the maximum rate, 0 represents storage at a moderate rate, and -1 represents no storage.

C5 – UNM external (supplied by PNM) electric energy usage. This concept represents the amount of the campus energy usage that is supplied by PNM as opposed to that supplied by the Ford Utilities Center co-generation turbine or stored hot or chilled

water.  An activation level of +1 represents a high level of PNM electricity usage, 0 represents a moderate level of usage, and -1 represents a low level of use.

C6 – Curtail facility electric energy usage.  This is the level of electric energy usage UNM reduces based on the request for curtailment by UNM.  An activation level of +1 indicates a high level of electric curtailment, an activation level of 0 represents a moderate level of electric curtailment, and an activation level of -1 represents no curtailment of electric energy use.

C7 – Occupant dissatisfaction.  This concept indicates the amount of dissatisfaction registered by the campus occupants due to the energy curtailment.  Energy curtailment can result in higher internal temperatures, reduced air circulation, and lower lighting levels which can lead to occupant dissatisfaction (Inge 2008).  An activation level of +1 represents a high level of dissatisfaction, a level of 0 represents minor dissatisfaction, and -1 represents no dissatisfaction.

The following sections present the methods for assessing this fuzzy cognitive map under three conditions:

1. Crisp Analysis

2. Crisp Inputs with Fuzzy Weights

3. Fuzzy Inputs with Fuzzy Weights (GEFCM)

Section 4.3 will apply these methods to the simplified, seven concept FCM of Figure 4.2 and discuss the results.  In addition Section 4.3 will apply the third method, GEFCM, to

the FCM of Figure 4.1 and Figure 4.1a on which this simplified example is based and present the results.

4.2.1   Crisp Analysis

Initially we analyzed this FCM using crisp initiating activation levels and interconnecting weights.  Figure 4.3 shows the crisp interconnecting weights as supplied by our subject matter expert, the author in this case.  The causal connection matrix, also termed the adjacency matrix, for these weights is shown in Figure 4.4.  The causal connection matrix represents the weight interconnections in the FCM.  The rows in the causal connection matrix represent the causing concept and the columns represent the caused concept.  The intersection of the causing row and the caused column contain the interconnecting weight.  The four input vectors, shown on the following page, were used to determine the four stable output concept activation levels using the (-1 0 +1) approach (Ross 2004).  This approach takes the input vector and multiplies it times the causal connection matrix, Figure 4.4, to generate the output vector.  The output vector is normalized by replacing the activation levels for the output vector elements with the input concept activation levels; activation levels less than -1 are replaced with the value -1; and activation levels greater than +1 are replaced with the value +1.  This normalized output vector now replaces the input vector and is multiplied times the causal connection matrix to form a new output vector.  This process is repeated until the new input vector matches the old input vector.  In addition we tested the (0 +1) approach (Kozko 1997, Kandasamy and Smarandarche 2003).  This approach is like the (-1 0 +1) approach but all outputs less than or equal to 0 are normalized to 0.  The results, as one would expect,

are similar to the (-1 0 +1) approach with each concept activation level of -1 replaced with 0.
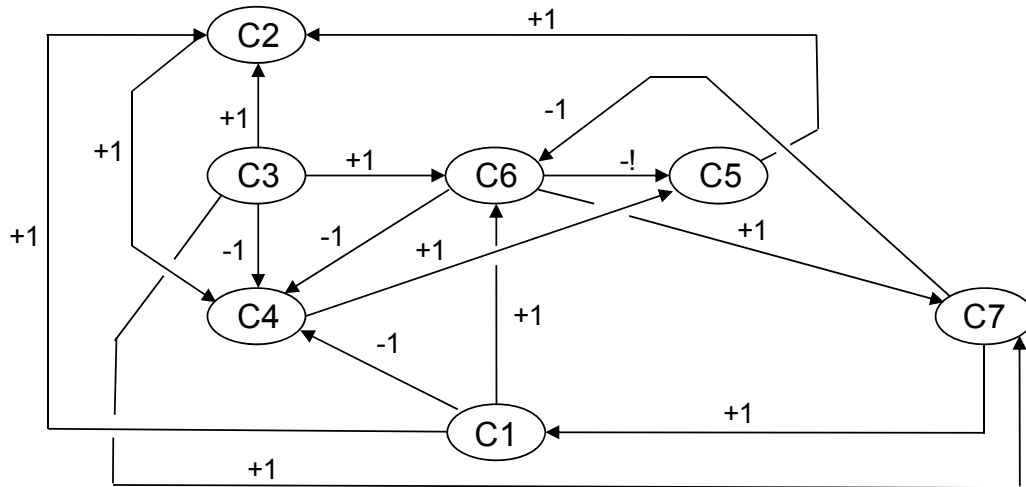


Figure 4.3: Simplified example FCM with crisp weights

|   | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0 | -1 | 0 | 1 | 0 |
| 2 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| 3 | 0 | 1 | 0 | -1 | 0 | 1 | 1 |
| 4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | -1 | -1 | 0 | 1 |
| 7 | 1 | 0 | 0 | 0 | 0 | -1 | 0 |

Figure 4.4: Crisp causal connection matrix

## 4.2.2   Crisp Inputs with Fuzzy Weights

Next we developed linguistic modifiers for the causal weights connecting the concepts.  The linguistic modifiers and their weight definitions are as follows:

- Definitely causes                                               1.0

- Strongly causes                                               0.8

- Moderately causes                                          0.5

- Weakly causes                                                0.2

- Does not cause                                               0

- Weakly causes the negative of the concept         -0.2

- Moderately causes the negative of the concept     -0.5

- Strongly causes the negative of the concept       -0.8

- Definitely causes the negative of the concept      -1.0

Figure 4.2 shows the FCM with the causal weights labeled, w1 through w15. Based on physical insight, the author, as the subject matter expert, assigned the weights to each of these connections as shown in Table 4.1:

| w1 | 0.8 | w9 | -0.5 |
|----|-----|-----|------|
| w2 | 0.2 | w10 | 0.5 |
| w3 | 0.8 | w11 | -0.5 |
| w4 | -0.8 | w12 | 0.2 |
| w5 | 0.8 | w13 | 0.2 |
| w6 | -1.0 | w14 | 0.5 |
| w7 | 0.8 | w15 | 0.2 |
| w8 | -0.5 | | |

Table 4.1: Weight assignments

For example, the level of UNM electricity consumption, C1, strongly causes (w1 = 0.8) UNM to generate electricity internally with the co-generation gas turbine in the

Ford Utilities Center, C2. If UNM is curtailing electricity usage, C6, this definitely causes the negative (w6 = -1) of UNM storing energy, C4.

|   | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| 1 | 0 | 0.8 | 0 | -0.5 | 0 | 1 | 0 |
| 2 | 0 | 0 | 0 | 0.2 | 0 | 0 | 0 |
| 3 | 0 | 0.8 | 0 | -0.8 | 0 | 0.8 | 0.2 |
| 4 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0 |
| 5 | 0 | 0.2 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | -1 | -0.5 | 0 | 0.2 |
| 7 | 0.5 | 0 | 0 | 0 | 0 | -0.2 | 0 |

Figure 4.5: Fuzzy causal connection matrix

The causal connection matrix for this fuzzy cognitive map is shown in Figure 4.5.

Again following the basic method of analysis used previously, the input vector is multiplied times the causal connection matrix, Figure 4.5, to generate the output vector. The output vector is normalized by replacing the activation levels for the output vector elements with the input concept activation levels, replacing activation levels less than -1 with the value -1, and replacing activation levels greater than +1 with the value +1. This normalized output vector now replaces the input vector and is multiplied times the causal connection matrix to form a new output vector. This process is repeated until the new input vector agrees to within some error value with the old input vector.

4.2.3   Fuzzy Inputs and Weights

Two professors at the University of Cyprus, A. S. Andreou and N. M. Mateou, and their various co-authors have pioneered the development of genetically evolved

fuzzy cognitive maps using neural network techniques and genetic algorithms in their evaluation (Mateou and Andreou 2008, Mateou et al. 2005, Andreou et al. 2004, Andreou et al. 2003) which they termed genetically evolved fuzzy cognitive maps GEFCM). A. K. Tsadiras and K. G. Margaritis of the University of Macedonia introduced the certainty neuron and its transfer function (1999, 1996) central to the fitness evaluation, see equation (4.4), required in the GEFCM.

Certainty neurons use the strength of the system's weight matrix and the strength of the system's decay mechanism as a two variable transfer function. This provides the certainty neurons with memory capabilities that decay with subsequent iterations (Andreou et al. 2004). This makes them useful in specific classes of artificial neural networks such as fuzzy cognitive maps. The certainty neuron transfer function (CNFCM) appropriate for FCMs is (Tsadiras and Margaritis 1999):

$$A_i^{t+1} = f(A_i^t, S_i^t) - d_i A_i^t , \tag{4.1}$$

where:

$$S_i^t = \sum_{j=1}^{N} A_j^t W_{ij} , \tag{4.2}$$

$A_i^t$ is the activation level of concept i at iteration t

$d_i$ is the decay factor for each activation level

N is the number of concepts in the FCM

$W_{ij}$ is the causal connection matrix (Mateou and Andreou 2008)

Terms where $i = j$ should be excluded from this calculation for $S_i^t$. In fact $W_{ij}$ for $i = j$ is always zero because in FCMs no concept causes itself. Thus this term is always zero. The function (f) for equation (3.1) is defined as follows:

$$f(A_i^t, S_i^t) \quad = \quad A_i^t + S_i^t\,(1 - A_i^t) \qquad \text{if } A_i^t \geq 0,\ S_i^t \geq 0$$

$$\text{or} \quad = \quad A_i^t + S_i^t\,(1 + A_i^t) \qquad \text{if } A_i^t < 0,\ S_i^t < 0 \ \&\ abs(A_i^t \leq 1,\ S_i^t \leq 1)$$

$$\text{or} \quad = \quad \frac{(A_i^t + S_i^t)}{[1 - \min(A_i^t, S_i^t)]} \qquad \text{otherwise} \qquad\qquad (4.3)$$

All elements of the FCM participate in each iteration of the transfer function. Each new concept activation level ($A_i^{t+1}$) iteration calculation includes each previous concept activation level ($A_i^t$) and the entire interconnection weight ($W_{ij}$) matrix.

The CNFCM transfer function, with a random initiating value, $A_i^{t=0}$, between -1 and +1 and a pre-established causal connection matrix, $W_{ij}$, with each element also in the range of -1 to +1, will usually approach constant, stable values as t goes to t maximum ($A_i^{t=tmax}$). The causal connection matrix ($W_{ij}$) is an NxN square matrix (N is the number of concepts in the FCM) made up of the weights between the concepts (Andreou et al. 2004). We utilized 250 as the appropriate number of iterations, $t_{max}$, as we found that if stability was to be achieved, it was normally achieved prior to this number of iterations. Tsadiras et. al. (1999) stated that the decay factor should be in the range of 0 to 0.4 as decay factors larger than this cause the system to collapse to zero due to the heavy decay mechanism. We used 0.10 as the decay factor for each activation level, $A_i^t$, as this gave reasonable results and was the value utilized by Mateou et. al. (2008).

The CNFCM can yield three possible results: stability, bounded limit cycle, or unbounded limit cycle (Andreou et al. 2004). Figure 4.6 shows an example of a CNFCM result stable prior to 50 iterations.
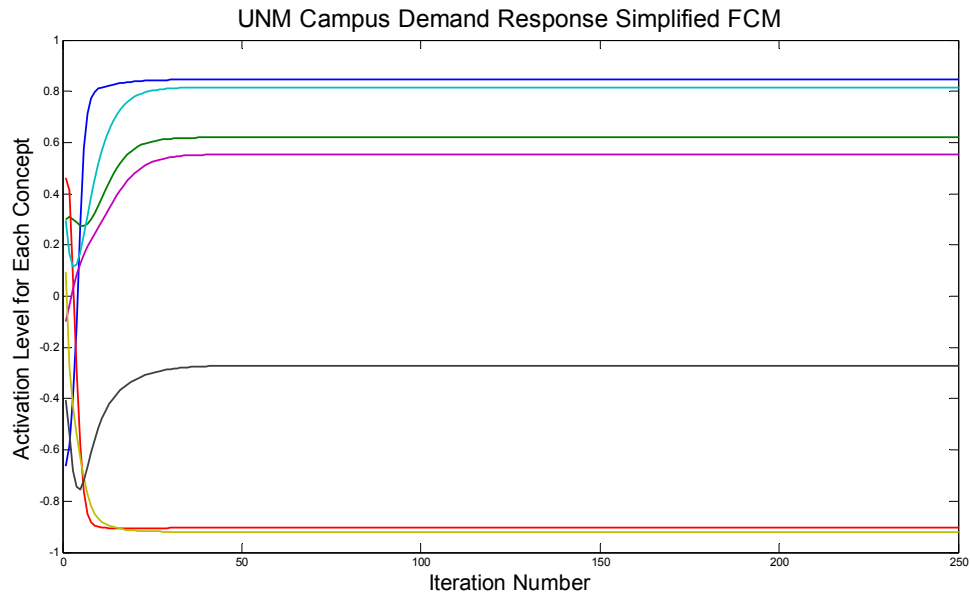
Figure 4.6: Example of CNFCM result that is stable after 50 iterations

Bounded limit cycle is defined as (Andreou et al. 2004) an oscillating value with a total amplitude less than or equal to 75% of the maximum total amplitude (+1- -1 = 2) or a value of 1.5 (Mateou and Andreou 2006). Figure 4.7 shows an example of a bounded limit cycle CNFCM result for a single concept.
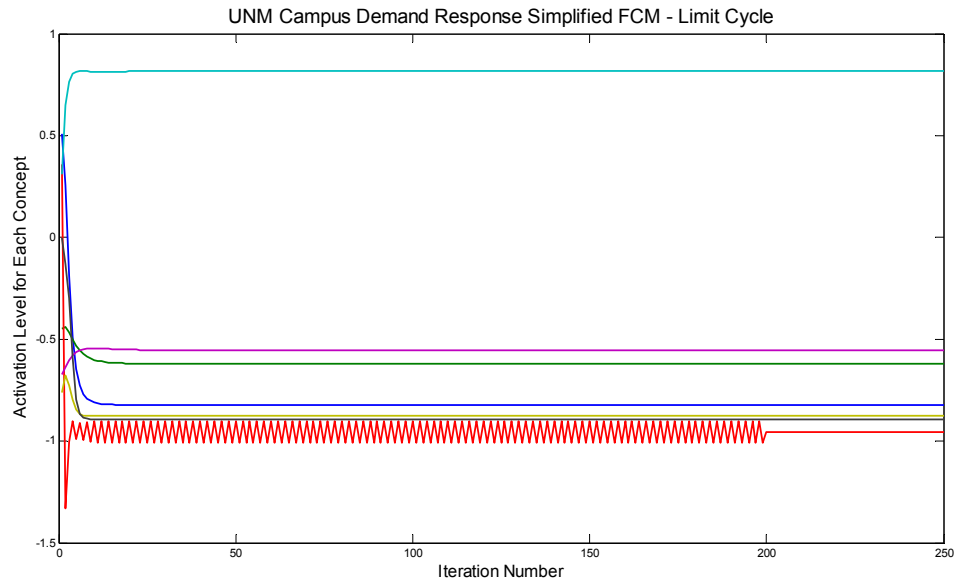
Figure 4.7: Bounded limit cycle CNFCM result

An unbounded limit cycle result is defined as an oscillation exceeding 75% of the maximum total amplitude (Andreou et al. 2004). An unbounded limit cycle event is in some cases completely chaotic. The maximum total amplitude is (1 - - 1 = 2) so an unbounded limit cycle result has a periodic amplitude exceeding 1.5. Figure 4.8 shows an example of the unbounded limit cycle CNFCM result. A bounded limit cycle result is useful by stabilizing it as the mean of the oscillation. This is shown in the last 50 iterations of Figure 4.7. A unbounded limit cycle result is not useful.
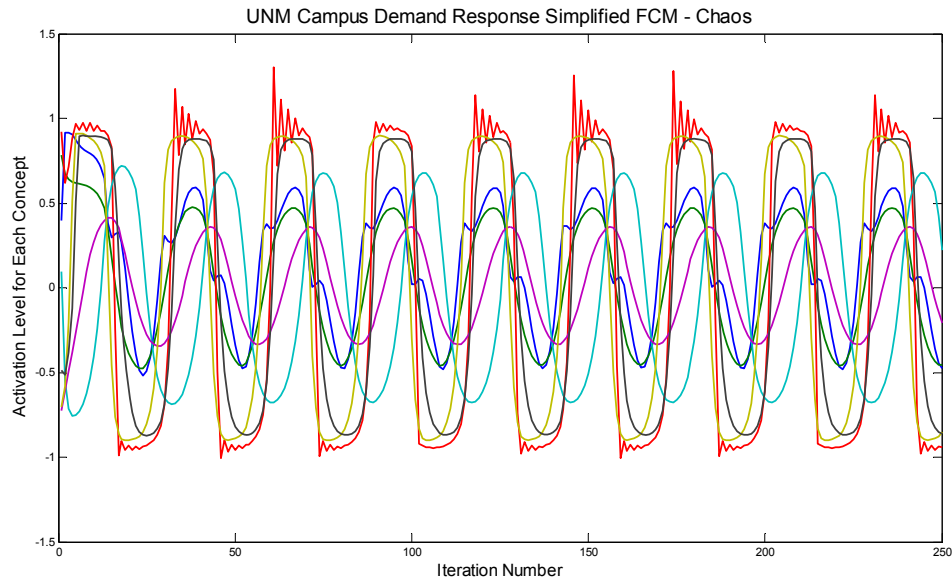
Figure 4.8: Unbounded limit cycle CNFCM result

We utilized a genetic algorithm (GA) to calculate optimum causal connection weights in the FCM based on the desired activation levels, $A_i$, of one or more of the FCM concepts. These concepts' desired activation levels establish the goal for the genetic algorithm. The Genetically Evolved Fuzzy Cognitive Map (GEFCM) uses the genetic algorithm to adjust the weights and recalculates the concept activation levels. The best set of weights is the set which yields the best fit to the desired activation levels (Mateou and Andreou 2009). The defuzzification process, following the activation level ranges in the concept descriptions in Section 4.2 for the simplified FCM, yields the meaning of the analysis.

The fitness function that the GA uses to determine if it has achieved the optimum causal connection weights is based on the CNFCM method described in the previous section. In particular the fitness function calculates the value of the activation levels ($Aa_i$) for each population member developed by the GA at each generation. It uses the

60

causal connection weights determined by the GA for each concept at the $250^{th}$ iteration from equations (4.1), (4.2), and (4.3). As shown in equation (4.4), the fitness for each member is the difference between this calculated activation level ($Aa_i$) and the desired activation level ($Ad_i$) for the controlling scenario's concepts.

$$\text{Fitness} = \text{sqrt}[\ (Ad_1 - Aa_1)^2 + (Ad_2 - Aa_2)^2 + \ldots + (Ad_n - Aa_n)^2\ ], \qquad (4.4)$$

where:        $Ad_i$ is the desired activation level for concept $C_i$

                 $Aa_i$ is the CNFCM calculated activation level for concept $C_i$

                 n is the number of the desired activation level(s)

The lower the fitness value the closer the causal connection weights are to the optimum value and thus the better the individuals in each population. In the event the CNFCM result is an unbounded limit cycle, this result is rejected. The GA takes the best individuals and saves them for the next generation and performs crossover or mutation operations on the rest. The GA then repeats the fitness tests on the new generation. This process continues until the fitness value is less than a pre-established fitness limit or the maximum number of generations is met. This will yield a set of causal connection weights that supply a set of activation levels locked to the desired predetermined scenarios. The activation levels of the concepts not included in the set of desired activation levels are of most interest to the analyst. They give the reaction of the FCM to the concepts included in the desired scenario.

For example, in the simplified FCM of Figure 3.2 shown with the seven concepts, let our desired concepts be:

- A high level of UNM electric demand, C1 = 1.0

61

- PNM sends UNM the demand response signal, C3 = 1.0, and

- UNM occupant dissatisfaction is high, C7 = 1.0.

The genetic algorithm establishes values for each of the fifteen interconnecting weights for each member of this generation. The fitness function uses these fifteen weights to calculate the seven activation levels for the FCM following equations (4.1), (4.2), and (4.3) after 250 iterations with the seven decay factors, $d_i$, all equal to 0.1. The fitness function then compares these calculated activation levels for C1, C3, and C7 to our desired activation levels (1.0, 1.0, and 1.0) calculating a fitness value according to equation (4.4). The genetic algorithm uses this fitness value in establishing the worthiness of each generation member in developing the next generation. This process continues until the minimum fitness is reached or until the maximum number of generations is exceeded.

## 4.3  Results and Discussion

### 4.3.1  Crisp Analysis for Simplified FCM

Four input vectors were used to establish four stable output activation concepts using the (-1 0 +1) approach described in Section 4.2.1.

The first input vector [**1**, 0, **1**, 0, 0, 0, **1**] holds three concepts at a constant value as shown in bold. These three concepts represent the following:

C1      Level of UNM electricity consumption is high,

C3      PNM sends UNM the DR curtailment signal, and

C7      Occupant dissatisfaction is high.

A stable output was achieved after three iterations with the result [1, 1, 1, -1, -1, 1, 1]. This represents, in addition to the input above:

C2     UNM generates electricity internally at the maximum level,

C4     UNM stores no energy,

C5     UNM external (PNM) electric energy usage is low due to the Ford Utilities Center co-generation turbine operating at the maximum level,

C6     Full DR by UNM to curtail electric energy use even though occupant dissatisfaction was so high.

For the (0 +1) approach the result was [1, 1, 1, 0, 0, 1, 1], which only differs at C4 and C5 as -1 is not allowed.

The second input vector [**1**, 0, **1**, 0, 0, 0, **0**] holds the same three concepts at a constant value but C3 is 0 as shown in bold. These three concepts represent the following:

C1     Level of UNM electricity consumption is high,

C3     PNM sends UNM the DR energy curtailment signal, and

C7     There is no occupant dissatisfaction.

The stable output was also achieved after three iterations and resulted in [1, 1, 1, -1, -1, 1, 0]. This represents:

C2     UNM generates electricity internally at the maximum level,

C4     UNM stores no energy,

C5     UNM external (PNM) electric energy usage is low

C6     Full DR by UNM to curtail electric energy use as occupant dissatisfaction was non-existent.

For the (0 +1) approach the result was [1, 1, 1, 0, 0, 1, 0], which only differs at C4 and C5 as -1 is not allowed.

The third input vector [**0**, 0, **1**, 0, 0, 0, **0**] holds the three input concepts at the constant values shown in bold. These represent:

C1    Level of UNM electricity consumption is low,

C3    PNM sends UNM the DR energy curtailment signal, and

C7    There is no occupant dissatisfaction.

The stable output was achieved after four iterations and resulted in [0, 0, 1, -1, -1, 1, 0]. This represented:

C2    UNM generates electricity internally at the half power level,

C4    UNM stores no energy,

C5    UNM external (PNM) electric energy usage is low as the campus demand is low, and

C6    Full DR by UNM to curtail electric energy use as occupant dissatisfaction was non-existent.

For the (0 +1) approach the result was [0, 1, 1, 0, 0, 1, 0] which only differs at C4 and C5 as -1 is not allowed.

The forth input vector [**1**, 0, **1**, 0, 0, 0, 0] holds two concepts at the constant value shown in bold. These represent:

C1    Level of UNM electricity consumption is high and

C3    PNM sends UNM the DR energy curtailment signal.

The stable output was achieved after three iterations and resulted in [1, 1, 1, -1, -1, 1, 1]. This represents:

C2      UNM generates electricity internally at the maximum level,

C4      UNM stores no energy,

C5      UNM external (PNM) electric energy usage is reduced to low from the DR event. The campus consumption is high but internal electric generation supplies much of the load.

C6      UNM curtails electric energy use from a full demand response event.

C7      The campus occupants register dissatisfaction from the electric load reduction.

For the (0 +1) approach the result was [1, 1, 1, 0, 0, 1, 1)] which only differs at C4 and C5 as -1 is not allowed.

### 4.3.2    Crisp Inputs with Fuzzy Weights for the Simplified FCM

The same four input vectors were used with the causal connection matrix of Figure 4.5 to determine the stable output vectors following the approach of Section 4.2.2. The error value used in comparing the new input vector to the old input vector after normalization was 0.01.

The first input vector [**1**, 0, **1**, 0, 0, 0, **1**] holds three concepts at a constant value as shown in bold. These three concepts represent the following:

C1      A high level of UNM electricity consumption.

C3      PNM sends UNM the DR energy curtailment signal.

C4      Occupant dissatisfaction is high.

The stable output was achieved after four iterations and resulted in [1, 1, 1, -1, -1, 1, 1].

This represented, in addition to the input above:

C2      UNM generates electricity internally at the maximum level,

C4      UNM stores no energy,

C5      UNM external (PNM) electric energy usage is low due to high internal generation and DR.

C6      Full DR by UNM to curtail electric energy use.

The second input vector [**1**, 0, **1**, 0, 0, 0, **0**] holds the same three concepts at a constant value but C3 is 0 also as shown in bold. These three concepts represent the following:

C1      Level of UNM electricity consumption is high,

C3      PNM sends UNM the DR energy curtailment signal, and

C7      There is no occupant dissatisfaction.

The stable output was also achieved after three iterations and resulted in [1, 1, 1, -1, -1, 1, 0]. This represented:

C2      UNM generates electricity internally at the maximum level,

C4      UNM stores no energy,

C5      UNM external (PNM) electric energy usage is low

C6      Full DR by UNM to curtail electric energy use as occupant dissatisfaction was non-existent.

For the (0 +1) approach the result was [1, 1, 1, 0, 0, 1, 0] which only differs at C4 and C5 as -1 is not allowed.

The third input vector [**0**, 0, **1**, 0, 0, 0, **0**] holds the three input concepts at the constant values shown in bold. These represent:

C1      A light level of UNM electricity demand.

C3      PNM sends UNM the DR energy curtailment signal only.

C7      There is no occupant dissatisfaction.

The stable output was achieved after five iterations and resulted in [0, 0.60, 1.00, -1.00, -1.00, 0.80, 0]. This represented:

C2      UNM generates electricity internally at a medium high level.

C4      UNM stores no energy.

C5      UNM external (PNM) electric energy usage is low as the campus demand is low and internal generation is medium high.

C6      Nearly full DR by UNM to curtail electric energy use.

The forth input vector [**1**, 0, **1**, 0, 0, 0, 0] holds two concepts at the constant value shown in bold. These represent:

C1      Level of UNM electricity demand high,

C3      PNM sends UNM curtailment signal, and

The stable output was also achieved after four iterations and resulted in [1, 1, 1, -1, -1, 1, 0.4]. This represented:

C2      UNM generates electricity internally at the maximum level,

C4      UNM stores no energy,

C5      UNM external (PNM) electric energy usage is moderately low due to internal electric generation and the DR event.

C6 Full DR by UNM to curtail electric energy use.

C7 There is moderate occupant dissatisfaction.

### 4.3.3 Genetically Evolved Approach for the Simplified FCM

The first step in the GEFCM approach of Section 4.2.3 is to calculate the concept

activation levels of the CNFCM based on the causal connection matrix from our subject

matter expert, in this case the author, Figure 4.5. The initial concept values ($A_i^{t\,=\,0}$) are

random numbers between -1 and +1 and the iterations continued for 250 steps. The

results of this CNFCM calculation are in Figure 4.9
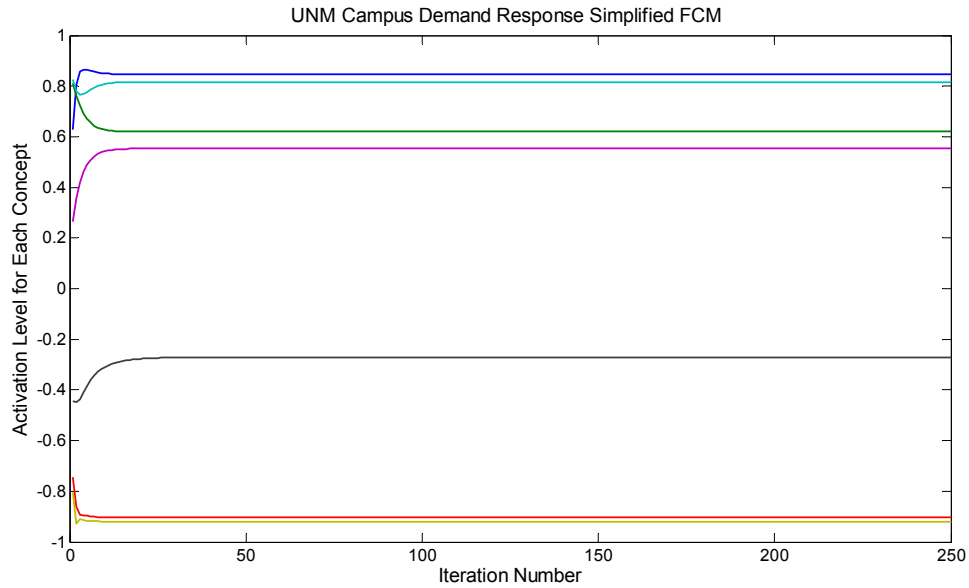


Figure 4.9: CNFCM result from Table 4.1 weights

with the stable concept activation values shown in Table 4.2.

Table 4.2: CNFCM activation levels

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | 0.85 | 0.62 | -0.90 | 0.82 | 0.55 | -0.92 | -0.27 |
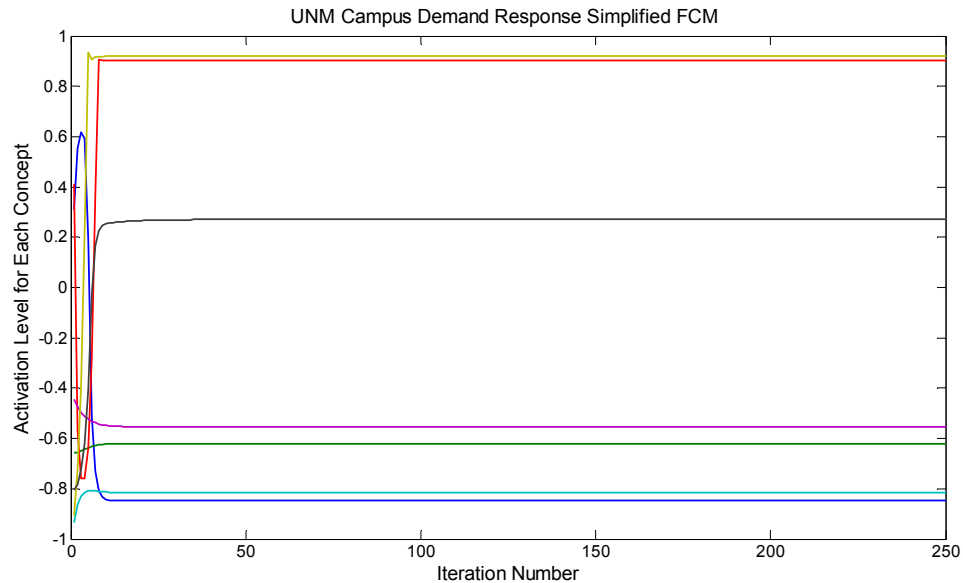
Figure 4.10: CNFCM result from Table 4.1 – 2nd outcome

Table 4.3: CNFCM activation levels – 2nd outcome

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | -0.85 | -0.62 | 0.90 | -0.82 | -0.55 | 0.92 | 0.27 |

Figure 4.9 shows a stable CNFCM result which indicates the basic design of the fuzzy cognitive map and the author's estimate of the weights are reasonable. It should be noted that a random initiating set of activation levels results in two possible outcomes; one is the negative of the other. Figure 4.10 shows the second of these two possible outcomes for our simplified example. This does not pose a problem in using the CNFCM random initiating set of activation levels in the fitness function for the genetic algorithm as the negative result will have poor fitness and be rejected.

We ran the GEFCM with the desired activation level for each of the four scenarios of Sections 4.3.1 and 4.3.2. The MATLAB™ Genetic Algorithm Toolbox 2.0 (GATool)

by The MathWorks, Inc. performed the GA functions with the CNFCM fitness function evaluating each individual developed by the GATool to assess its fitness level. In the MATLAB™ GATool, elite count specifies the number of individuals that are guaranteed to survive to the next generation. Crossover fraction specifies the fraction of the next generation, other than elite individuals, that are produced by crossover. The remaining individuals, other than elite individuals, in the next generation are produced by mutation. We set the population size to 20, the elite count to 2, and the crossover fraction to 0.95.

For the first scenario we ran the GEFCM with the fitness function of equation (3.4) for the GATool seeking solutions with C1 at 1.0, C3 at 1.0, and C7 at 1.0. We repeated this GEFCM run 120 times with all input parameters identical for each run to assess repeatability. A plot of the results of these runs is shown in Figure 4.11.
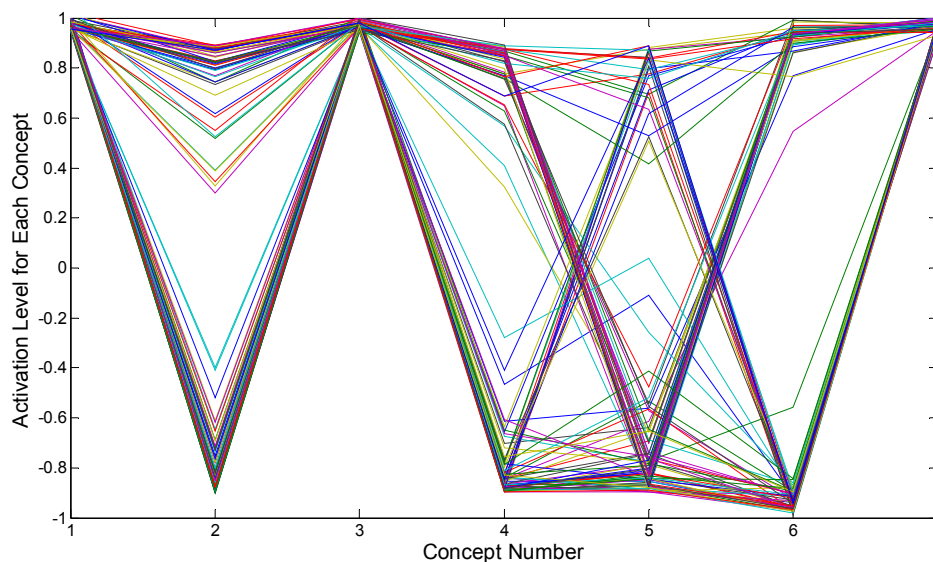


Figure 4.11: Plot of 120 runs of GEFCM

70

A plot of 120 purely random values between -1 and +1, with C1, C3, and C7 held at 1.0, is shown in Figure 4.12.
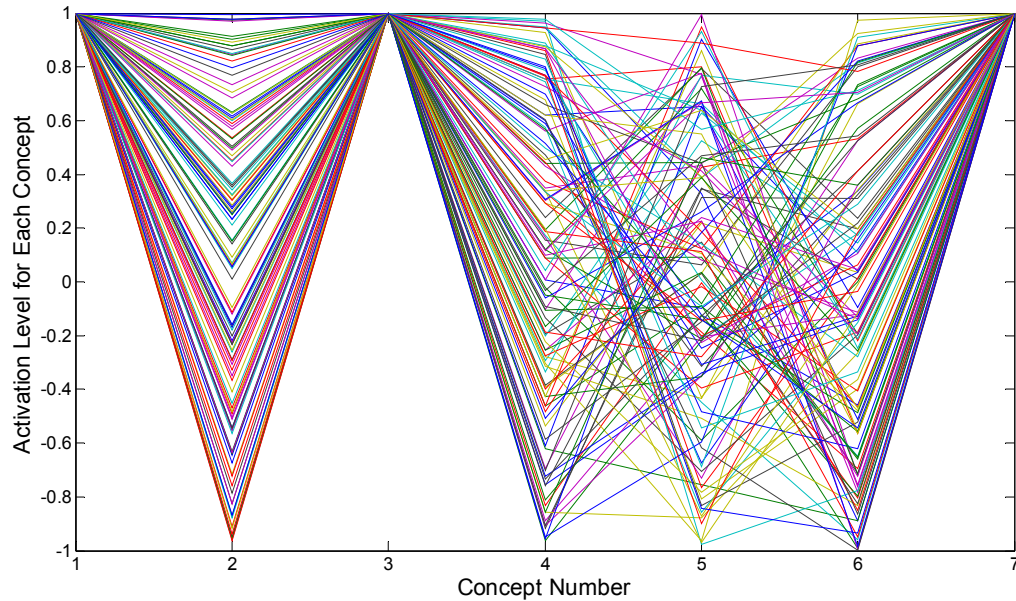


Figure 4.12: Plot of 120 random concept values

Clearly the data in Figure 4.11 has some sort of a pattern when compared to the random values of Figure 4.12. To identify the pattern in the data of Figure 4.11, we next chose to seek clusters in these 120 data sets using k-means clustering.

Given a set of data vectors ($\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_n$), k-means clustering (Duda et al. 2001), also termed c-means clustering (Ross 2004), partitions n sets of data into k clusters so as to minimize the within cluster sum of the square distances between the cluster center and the cluster members. In our case $\mathbf{x}$ is 120 data sets containing the seven concepts, C1 – C7, generated by the GEFCM. The clustering process is:

$$\sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - c_i\|^2$$

where                 k is the number of clusters

                             j is the index for the 1-7 concepts

                             $x_j$ are the data sets in each cluster

                             $S_i$ contains the cluster members

                             $c_i$ is the cluster center of each $S_i$

To initialize this algorithm, k cluster centers are chosen randomly from the data ($x_1$, $x_2$, …, $x_n$). Then the algorithm assigns each data set to the cluster with the lowest sum of the square distance between the data members and the cluster center. The algorithm next recalculates the cluster centers ($c_i$) and repeats the process with these new cluster centers as the initiating cluster centers. This continues until the cluster centers do not change.

We performed the k-means clustering using the "kmeans" function in the MATLAB™ Statistical Toolbox. To estimate an appropriate number of clusters, we ran
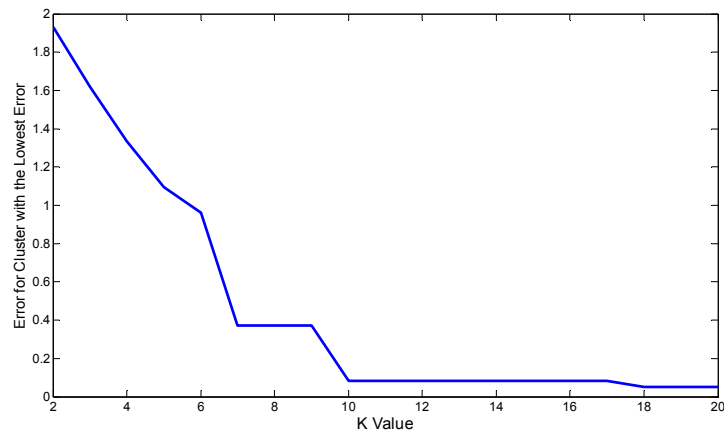


Figure 4.13: K-means clustering on GEFCM data for k from 2 to 20

our actual data from the 120 GEFCM runs and plotted the lowest error cluster for values of k from 2 to 20. This is shown in Figure 4.13.

We chose a value of k equal to 14 as best suited to our data. Since the k-means clustering methodology initiates with a randomly chosen first set from our data as the initial estimate of the cluster centers, there is some variation in the final clusters. We chose the best cluster of the 14 as the one with the lowest error sum between the center and each cluster member divided by the number of cluster members. Again to ensure repeatability we ran the clustering on the total set of data fifty times. With repeated runs of the MATLAB™ kmeans routine, we found cluster centers with essentially identical values (+ or − 0.00005). We chose the best cluster centers from the fifty results as the ones that repeated the most.

Our initial input vector with C1, C3, and C7 as 1.0 resulted in the cluster centers of Figure 4.14 and Table 4.4.
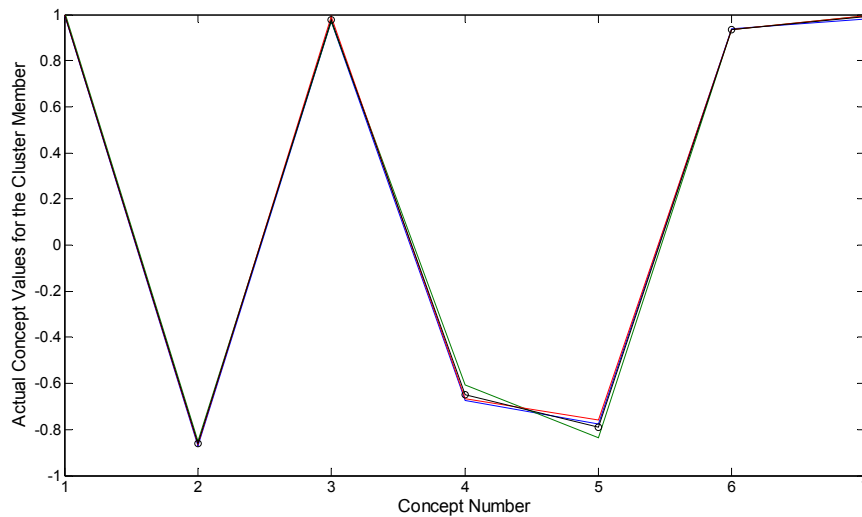


Figure 4.14: Concept activation levels for C1, C3, and C7 = 1

73

Table 4.4: Concept activation levels for C1, C3, and C7 = 1

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | 1.00 | -0.86 | 0.98 | -0.65 | -0.79 | 0.94 | 0.99 |

The three input concepts activation levels represent the following:

C1     A high level of UNM electricity consumption.

C3     PNM sends UNM the DR energy curtailment curtailment signal.

C7     Occupant dissatisfaction is high.

The GEFCM output repeated 11 times (the second best was 7 repeats) in the 50 repeat clustering calculations. The concept activation levels represented, in addition to the input above:

C2     UNM generates very little electricity internally,

C4     UNM stores very little energy,

C5     UNM external (PNM) electric energy use is low due to the release of stored energy and the energy reduction from the demand response event.

C6     UNM curtails electric energy use to support the demand response event.

Our second input vector with C1 and C3 as 1.0 and C7 as 0 resulted in the cluster centers of Figure 4.15 and Table 4.5.

Table 4.5: Concept activation levels for C1 & C3 =1 and C7 = 0

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | 0.95 | -0.87 | 0.96 | -0.86 | -0.86 | 0.86 | 0.00 |
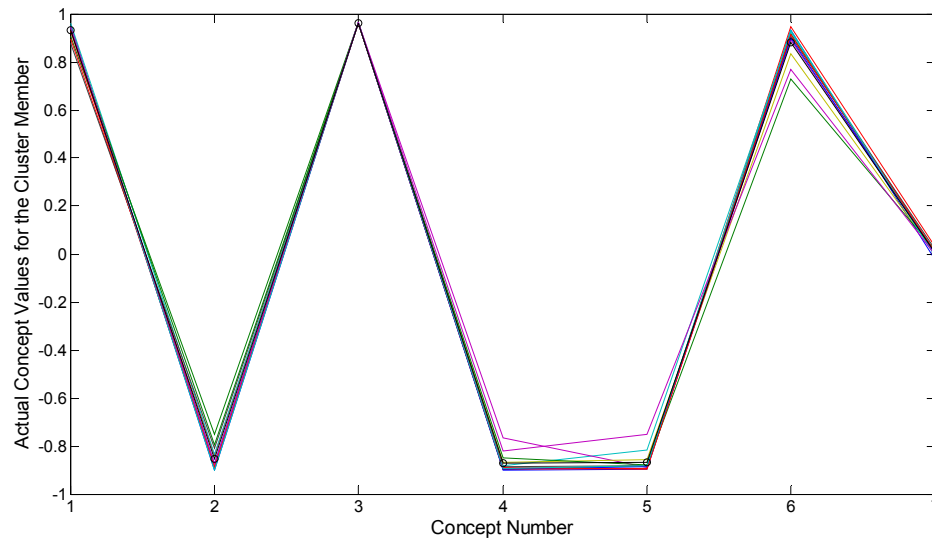
Figure 4.15: Concept activation levels for C1 & C3 =1 and C7 = 0

The three input concepts activation levels represent the following:

C1    A high level of UNM electricity consumption.

C3    PNM sends UNM the DR energy curtailment signal.

C7    Occupant dissatisfaction is minor.

The GEFCM output repeated 8 times (the second best was 5 repeats) in the 50 repeat clustering calculations.  The concept activation levels represent, in addition to the input above:

C2    UNM generates very little electricity internally,

C4    UNM stores very little energy,

C5    UNM external (PNM) electric energy use is low due to the release of stored energy and the energy reduction from the demand response event.

C7    UNM curtails electric energy use to support the demand response event.

Our third input vector with C1 and C7 as 0 and C3 as 1 resulted in the cluster centers of Figure 4.16 and Table 4.6.
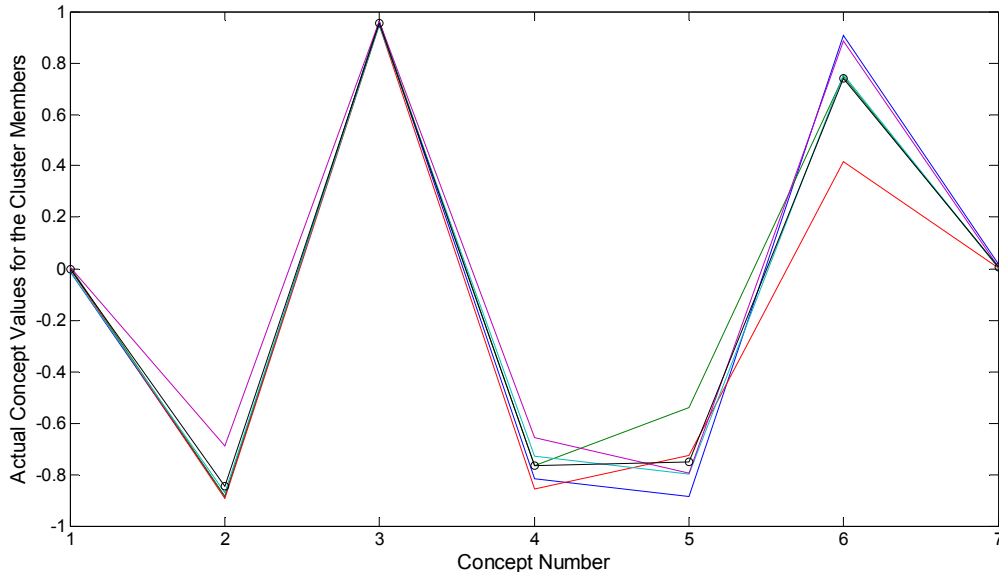


Figure 4.16: Concept activation levels for C1 & C7 =0 and C3 = 1

Table 4.6: Concept activation levels for C1 & C7 =0 and C3 = 1

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | 0.00 | -0.85 | 0.96 | -0.77 | -0.75 | 0.74 | 0.00 |

The three input concepts activation levels represent the following:

C1     A light level of UNM electricity consumption.

C3     PNM sends UNM the DR energy curtailment signal.

C7     Occupant dissatisfaction is minor.

The GEFCM output repeated 28 times (the second best was 7 repeats) in the 50 repeat clustering calculations.  The concept activation levels represent, in addition to the input above:

C2     UNM generates very little electricity internally,

76

C4     UNM stores very little energy,

C5     UNM external (PNM) electric energy use is fairly low due to the light level of UNM electric consumption and the energy reduction from the demand response event.

C6     UNM curtails electric energy use to support the demand response event.

Our fourth input vector with C1 and C3 as 0.90 resulted in the cluster centers of Figure 4.17 and Table 4.7.
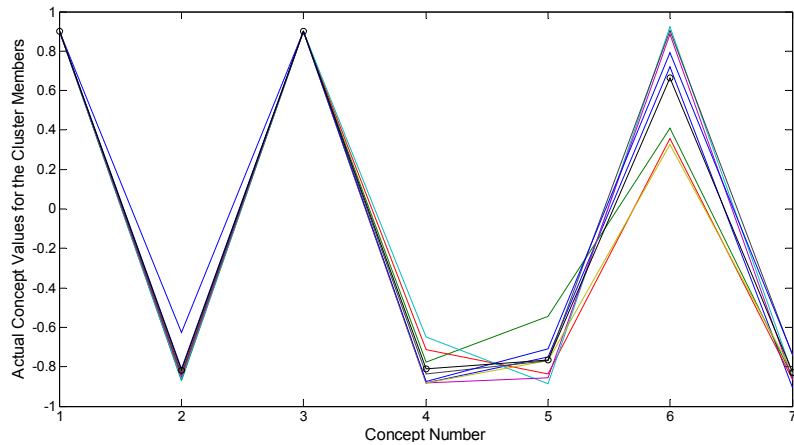


Figure 4.17: Concept activation levels for C1 and C3 = 0.9

Table 4.7: Concept activation levels for C1 and C3 = 0.9

| Concept | C1 | C2 | C3 | C4 | C5 | C6 | C7 |
|---|---|---|---|---|---|---|---|
| Activation Level | 0.90 | -0.82 | 0.90 | -0.81 | -0.77 | 0.66 | -0.83 |

The two input concepts activation levels represent the following:

C1     A high level of UNM electricity consumption.

C3     PNM sends UNM the DR energy curtailment signal.

The GEFCM output repeated 32 times (the second best was 5 repeats) in the 50 repeat clustering calculations.  The concept activation levels represent, in addition to the input above:

      C2      UNM generates very little electricity internally,

      C4      UNM stores very little energy,

      C5      UNM external (PNM) electric energy use is fairly low due to the release of stored energy and the energy reduction from the demand response event.

      C6      UNM curtails electric energy use to support the demand response event.

      C7      Occupants of the facility have a dearth of dissatisfaction.

### 4.3.4   Genetically Evolved Approach for the More Comprehensive FCM

Figure 4.1 and Figure 4.1a show the more detailed Fuzzy Cognitive Map representing the University of New Mexico (UNM) strategy as applied to the campus facilities while they undergo a demand response event.

The twenty concepts that make up this FCM represent:

C1 – Wholesale price of electricity.  This is the pricing level PNM pays for purchased power or receives for power sold in the wholesale electric market.  An activation level of +1 represents a very high pricing level, a value of 0 represents a moderate pricing level, and a value of -1 represents a low pricing level.

C2 – Level of UNM facility demand.  This is a measure of the quantity of electricity the UNM campus is consuming in total.  An activation level of +1 indicates a high level of electric consumption, an activation level of 0 represents a light level of

electric consumption, and an activation level of -1 represents a very light level of consumption.

C3 – UNM generates electricity internally. UNM has a co-generation gas turbine in the Ford Utilities Center capable of producing 6,000 kilowatts of electricity, approximately a third of the maximum campus usage, and supplying this to the campus electricity distribution system. An activation level of +1 represents full power output for the co-generation turbine, 0 represents a medium power output, and -1 represents little to no internal power generation.

C4 – PNM sends UNM the DR curtailment signal. PNM signals a request for a demand response event. An activation level of +1 represents the high DR signal is present, 0 represents a medium DR signal, and -1 represents no DR signal.

C5 – UNM stores energy. UNM facilities store energy by storing hot or chilled water in insulated storage tanks for use at a later time. This is commonly done by commercial facilities at night when electric rates are low for use during the day when prices are higher (Dayanian et al. 1989). An activation level of +1 represents energy storage at the maximum rate, 0 represents storage at a moderate rate, and -1 represents no storage.

C6 – Supply stored energy to UNM facilities. UNM supplies the energy stored at night to UNM facilities during the day when energy prices are higher. An activation level of +1 represents energy supply at the maximum rate, 0 represents supply at a moderate rate, and -1 represents no supply.

C7 – Curtail facility electric energy usage for classrooms/office facilities. This is the level of electric energy usage UNM classrooms/office facilities reduce based on the request for curtailment by UNM. An activation level of +1 indicates a high level of electric curtailment, an activation level of 0 represents a moderate level of electric curtailment, and an activation level of -1 represents no curtailment of electric energy use.

C8 – Classroom/office occupant dissatisfaction. This concept indicates the amount of dissatisfaction registered by the classroom/office occupants due to the energy curtailment. Energy curtailment can result in higher internal temperatures, reduced air circulation, and lower lighting levels. An activation level of +1 represents a high level of dissatisfaction, a level of 0 represents minor dissatisfaction, and -1 represents no dissatisfaction.

C9 – Curtail facility electric energy usage for library facilities. This is the level of electric energy usage UNM reduces in library facilities based on the request for curtailment by UNM. An activation level of +1 indicates a high level of electric curtailment, an activation level of 0 represents a moderate level of electric curtailment, and an activation level of -1 represents no curtailment of electric energy use.

C10 – Library occupant dissatisfaction. This concept indicates the amount of dissatisfaction registered by the library occupants due to the energy curtailment. Energy curtailment can result in higher internal temperatures, reduced air circulation, and lower lighting levels. An activation level of +1 represents a high level of dissatisfaction, a level of 0 represents minor dissatisfaction, and -1 represents no dissatisfaction.

C11 – Curtail facility electric energy usage for residence halls. This is the level of electric energy usage UNM reduces in residence halls based on the request for curtailment by UNM. An activation level of +1 indicates a high level of electric curtailment, an activation level of 0 represents a moderate level of electric curtailment, and an activation level of -1 represents no curtailment of electric energy use.

C12 – Residence Hall occupant dissatisfaction. This concept indicates the amount of dissatisfaction registered by the residence hall occupants due to the energy curtailment. Energy curtailment can result in higher internal temperatures, reduced air circulation, and lower lighting levels. An activation level of +1 represents a high level of dissatisfaction, a level of 0 represents minor dissatisfaction, and -1 represents no dissatisfaction.

C13 – Override the electric curtailment signal. UNM at its option may decide to reduce or even cease energy curtailment during a demand response event. An activation level of +1 represents a full override of the demand response request or no energy reduction during the demand response event, an activation level of 0 represents a moderate level of electric usage reduction, and an activation level of -1 represents no override of the demand response request.

C14 – UNM external (supplied by PNM) electric energy usage. This concept represents the amount of the campus energy usage that is supplied by PNM as opposed to that supplied by the Ford Utilities Center co-generation turbine or stored hot or chilled water. An activation level of +1 represents a high level of PNM electricity usage, 0 represents a moderate level of usage, and -1 represents a low level of use.

C15 – UNM administration operation. UNM administration establishes occupancy levels for UNM facilities. In addition, occupant dissatisfaction due to discomfort or other issues may cause the UNM administration to take action to curtail the demand response event, thus stopping energy reduction activities. An activation level of +1 represents a high level of UNM administration intervention, 0 represents a moderate level of UNM administration intervention, and -1 represents no UNM administration intervention.

C16 – UNM operation costs. This concept represents the level of UNM operating costs due to all factors including electric energy use. An activation level of +1 represents a high level for operating costs, 0 represents a moderate level for operating costs, and -1 represents a low level for operating costs.

C17 – UNM Board of Regents direct operating cost reductions. The UNM Board of Regents has fiduciary responsibility for the University (UNM Board of Regents 2004) and may direct the UNM administration to reduce operating costs, if costs are too high or are politically unacceptable. An activation level of +1 represents UNM Regents direct intervention, 0 represents UNM Board of Regents concern and suggestion to UNM administration to reduce operating costs, and -1 represents no UNM Board of Regents concern intervention.

C18 – Classroom/office occupancy levels. An activation level of +1 represents a high occupancy level, 0 represents a medium occupancy level, and -1 represents a low occupancy level.

C19 – Library occupancy levels. An activation level of +1 represents a high occupancy level, 0 represents a medium occupancy level, and -1 represents a low occupancy level.

C20 – Residence hall occupancy levels. An activation level of +1 represents a high occupancy level, 0 represents a medium occupancy level, and -1 represents a low occupancy level.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | w5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | w2 | 0 | w1 | 0 | w55 | w3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w8 | w9 | 0 | w7 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | w6 | 0 | w10 | w12 | w15 | 0 | w23 | 0 | w31 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w11 | 0 | w52 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w13 | 0 | w54 | 0 | 0 | 0 | 0 |
| 7 | w16 | w17 | 0 | 0 | w14 | 0 | 0 | w20 | 0 | 0 | 0 | 0 | 0 | w19 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w21 | 0 | 0 | 0 | 0 | 0 |
| 9 | w24 | w25 | 0 | 0 | w22 | 0 | 0 | 0 | 0 | w28 | 0 | 0 | 0 | w27 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w29 | 0 | 0 | 0 | 0 | 0 |
| 11 | w32 | w33 | 0 | 0 | w30 | 0 | 0 | 0 | 0 | 0 | 0 | w36 | 0 | w35 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w37 | 0 | 0 | 0 | 0 | 0 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0 | w18 | 0 | w26 | 0 | w34 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w48 | 0 | 0 | 0 | 0 |
| 15 | 0 | w49 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w47 | 0 | 0 | 0 | 0 | w40 | w43 | w46 |
| 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w51 | 0 | w53 | 0 | 0 | 0 |
| 17 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w50 | 0 | 0 | 0 | 0 | 0 |
| 18 | 0 | w38 | 0 | 0 | 0 | 0 | w56 | w39 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 19 | 0 | w41 | 0 | 0 | 0 | 0 | 0 | 0 | w57 | w42 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 20 | 0 | w44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | w58 | w45 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Figure 4.18: Causal connection matrix

The first step in the GEFCM approach described in Section 4.3.3 is to calculate the concept activation levels of the FCM using the certainty neuron transfer function

(CNFCM) of equations (4.1) to (4.3). The fuzzy causal connection matrix for this calculation, $W_{ij}$ in equation (4.2), is shown in Figure 4.18.

Table 4.8 shows the weights developed by our subject matter expert, again the author, used in the fuzzy causal connection matrix.

Table 4.8: Weights used for CNFCM

| Weight | Value | Weight | Value | Weight | Value | Weight | Value |
|--------|-------|--------|-------|--------|-------|--------|-------|
| w 1 | 0.8 | w 16 | -0.2 | w 31 | 0.8 | w 46 | 0.5 |
| w 2 | 0.2 | w 17 | -0.3 | w 32 | -0.5 | w 47 | 0.8 |
| w 3 | 0.5 | w 18 | -0.8 | w 33 | -0.3 | w 48 | 0.2 |
| w 4 | 0.5 | w 19 | -0.5 | w 34 | -0.2 | w 49 | 0.2 |
| w 5 | 0.5 | w 20 | 0.6 | w 35 | -0.3 | w 50 | 0.5 |
| w 6 | 0.5 | w 21 | 0.8 | w 36 | 0.4 | w 51 | 0.5 |
| w 7 | -0.5 | w 22 | -0.8 | w 37 | 0.8 | w 52 | 0.3 |
| w 8 | -0.2 | w 23 | 0.8 | w 38 | 0.8 | w 53 | 0.8 |
| w 9 | -0.5 | w 24 | -0.2 | w 39 | 0.5 | w 54 | -0.3 |
| w 10 | -0.4 | w 25 | -0.3 | w 40 | 0.5 | w 55 | -0.8 |
| w 11 | 0.5 | w 26 | -0.2 | w 41 | 0.8 | w 56 | 0.5 |
| w 12 | 0.4 | w 27 | -0.3 | w 42 | 0.5 | w 57 | 0.5 |
| w 13 | -0.5 | w 28 | 0.3 | w 43 | 0.5 | w 58 | 0.5 |
| w 14 | -0.8 | w 29 | 0.8 | w 44 | 0.8 | | |
| w 15 | 0.8 | w 30 | -0.8 | w 45 | 0.5 | | |
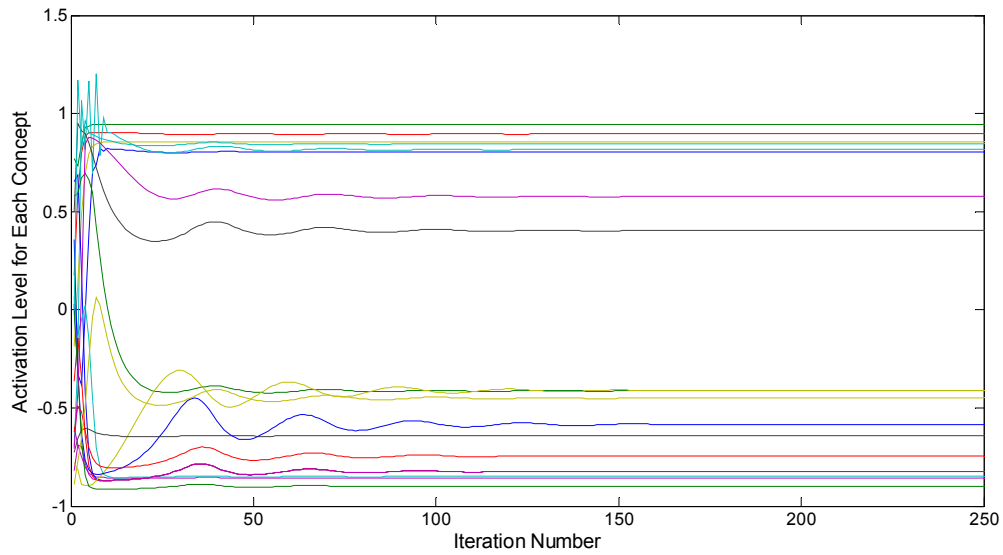


Figure 4.19: CNFCM result with weights of Table 4.8

The twenty initial concept values ($A_i^{t=0}$) are random numbers between -1 and +1. The iterations continue for 250 steps. The results of this CNFCM calculation are shown in Figure 4.19 with the stable concept activation values shown in Table 4.9. Appendix 4-1 contains the listing of the MATLAB™ code used to perform the CNFCM calculation.

Table 4.9: Activation levels for CNFCM

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|------|------|------|------|------|------|------|------|------|------|
| 0.80 | 0.94 | 0.90 | 0.82 | -0.86 | 0.86 | 0.40 | -0.82 | -0.41 | -0.82 |

| C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 | C19 | C20 |
|-------|-------|-------|-------|-------|-------|-------|------|------|-------|
| -0.85 | -0.82 | -0.41 | -0.64 | -0.58 | -0.90 | -0.75 | 0.84 | 0.58 | -0.45 |

This result is indicative of a real potential solution for the FCM with the following defuzzified meaning for each concept:

C1     The wholesale price of electricity is at a high level.

C2     The level of UNM facility demand is high.

C3     UNM generates electricity internally at the full power output.

C4     PNM sends UNM a DR energy curtailment signal.

C5     UNM stores no energy.

C6     UNM supplies stored energy to the campus facilities.

C7     UNM curtails energy for the classroom/office facilities at a fairly high level.

C8     The classroom/office occupants are not dissatisfied.

C9     UNM curtails energy for the libraries at a fairly low level.

C10    The library occupants are not dissatisfied.

C11    UNM does not curtail energy for the residence halls.

C12     The residence hall occupants are not dissatisfied.

C13     UNM does not override the electric curtailment signal much.

C14     UNM external (supplied by PNM) electric energy usage is moderately low due to high internal generation, high supply of previously stored energy, and the energy curtailment from demand response.

C15     While the UNM administration does establish the facility occupancy levels, it does not intervene in the demand response event.

C16     UNM operation costs remain low.

C17     UNM Board of Regents has no concerns.

C18     The classroom/office occupancy is high.

C19     The library occupancy is medium high.

C20     The residence hall occupancy is fairly low.
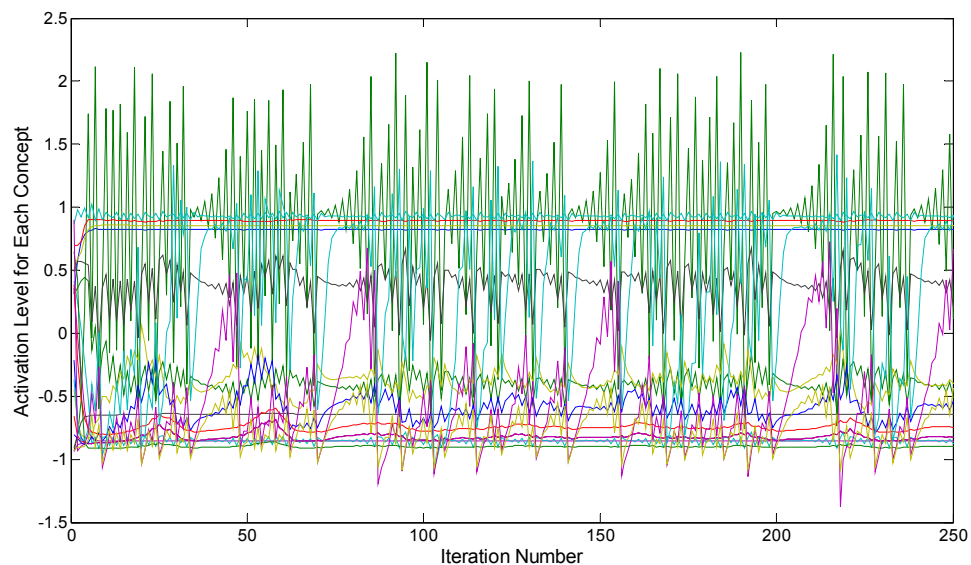


Figure 4.20: Unbounded limit cycle CNFCM result

86

One indicator that the FCM is constructed reasonably and the weights are appropriate is the stability of the CNFCM calculation. By simply revising weights w2 from 0.2 to 0.9, w6 from 0.5 to 0.95, and w10 from -0.4 to -0.95 in Table 3.8, we generate the CNFCM result of Figure 4.20. This is clearly an unbounded limit cycle result and therefore is not useful in the FCM analysis.

For the first scenario we ran the GEFCM with the fitness function of equation (4.4) for the GATool seeking solutions with C1 at 0.80, C2 at 0.94, and C4 at 0.82 to represent the wholesale price of electricity at a high level, UNM using electricity at a high level, and the PNM DR signal present. In addition we set the occupancy values of C18, C19, and C20 at 0.8 to represent high occupancy levels for the classroom/office facilities, libraries, and residence halls. We allowed the GEFCM to calculate activation levels for the other fourteen concepts. We repeated this GEFCM run 150 times with all
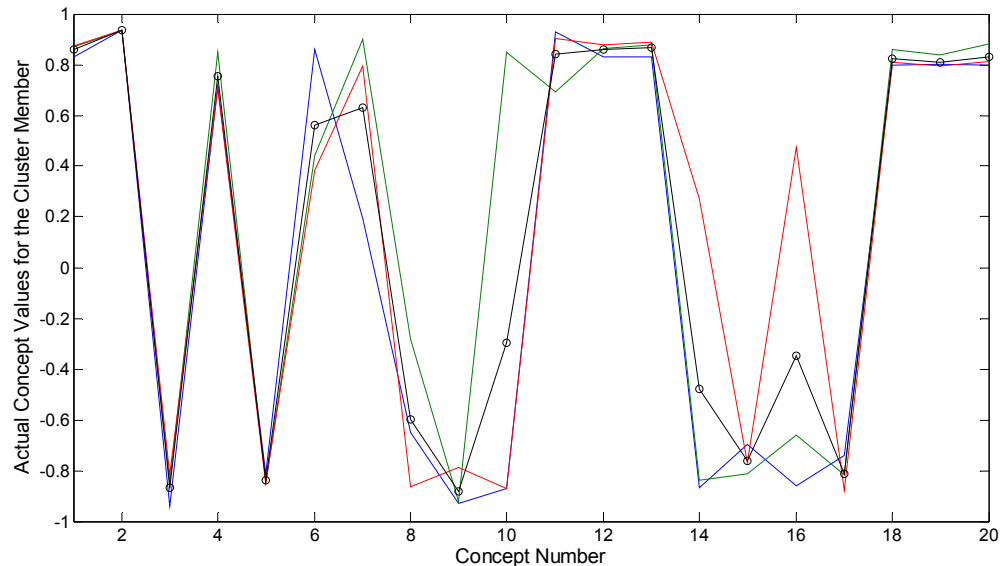


Figure 4.21: Concept activation levels for high UNM demand (or high energy use), DR requested bu PNM, and high occupancy in all facilities

input parameters identical for each run and clustered this data into 18 clusters. The cluster that repeated the most after 50 clustering runs is shown in Figure 4.21 with the stable concept activation levels shown in Table 4.10.Appendix 4-2 shows the MATLAB™ code listing for the 150 GEFCM calculations. Appendix 4-3 shows MATLAB™ code listing for the clustering calculation.

Table 4.10: Concept activation levels for high UNM demand (or high energy use), DR requested bu PNM, and high occupancy in all facilities

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|------|------|-------|------|-------|------|------|-------|-------|-------|
| 0.86 | 0.94 | -0.87 | 0.76 | -0.84 | 0.56 | 0.63 | -0.60 | -0.88 | -0.30 |

| C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 | C19 | C20 |
|------|------|------|-------|-------|-------|-------|------|------|------|
| 0.84 | 0.86 | 0.87 | -0.48 | -0.76 | -0.35 | -0.81 | 0.82 | 0.81 | 0.83 |

These resulting activation levels represent the following:

C3     UNM generates no electricity internally.

C5     UNM stores no energy.

C6     UNM supplies stored energy to UNM facilities at a fairly high rate.

C7     UNM curtails electricity to classrooms/office facilities at a fairly high rate.

C8     The classroom/office facility occupants register fairly minor

        dissatisfaction.

C9     UNM does not curtail electricity to libraries.

C10    Library occupants' dissatisfaction is indeterminate but likely very low.

C11    UNM curtails electricity to residence halls.

C12    The residence hall occupants register strong dissatisfaction.

C13    UNM overrides the curtailment signal.

C14     UNM usage of PNM supplied electricity is moderate to low due to the use

of stored energy even though the DR event was overridden.

C15     UNM administration does not intervene in the demand response event.

C16     UNM operation costs remain low.

C17     The UNM Board of Regents direct little to no administrative changes.

Under this scenario, calling for the DR event (C1, C2, and C4 high) with high occupancy

(C18, C19, and C20 also high), the strong occupant dissatisfaction caused the DR event

to cease.  We see that high occupancy has a strong impact on occupant dissatisfaction and

thus brings significant political pressure to reduce or even cease the DR event.

For the second scenario we ran the GEFCM with the fitness function of equation

(4.4) for the GATool seeking solutions again with C1 at 0.80, C2 at 0.94, and C4 at 0.72

to represent the wholesale price of electricity at a high level, UNM using electricity at a

high level, and the PNM DR signal present.  This time we set the occupancy values of

C18, C19, and C20 at 0.8, -0.2, and -0.8 to represent classroom/office occupancy high,

library occupancy medium to low, and residence hall occupancy low.  We repeated this

GEFCM run 150 times with all input parameters the same for each run and clustered this

data into 15 clusters.  The cluster that repeated the most after 50 clustering runs is shown

in Figure 4.22 with the stable concept activation levels shown in Table 4.11.

Table 4.11:  Concept activation levels for high UNM demand (or high electric energy

usage), DR requested by PNM, and varied facility occupancy

| C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 |
|------|------|-------|------|-------|-------|-------|------|-------|-------|
| 0.79 | 0.93 | 0.69 | 0.72 | -0.23 | -0.78 | -0.89 | 0.14 | -0.89 | -0.62 |

| C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 | C19 | C20 |
|------|------|-------|-------|------|-------|------|------|-------|-------|
| 0.89 | 0.08 | -0.19 | -0.78 | 0.70 | -0.42 | 0.62 | 0.80 | -0.20 | -0.80 |
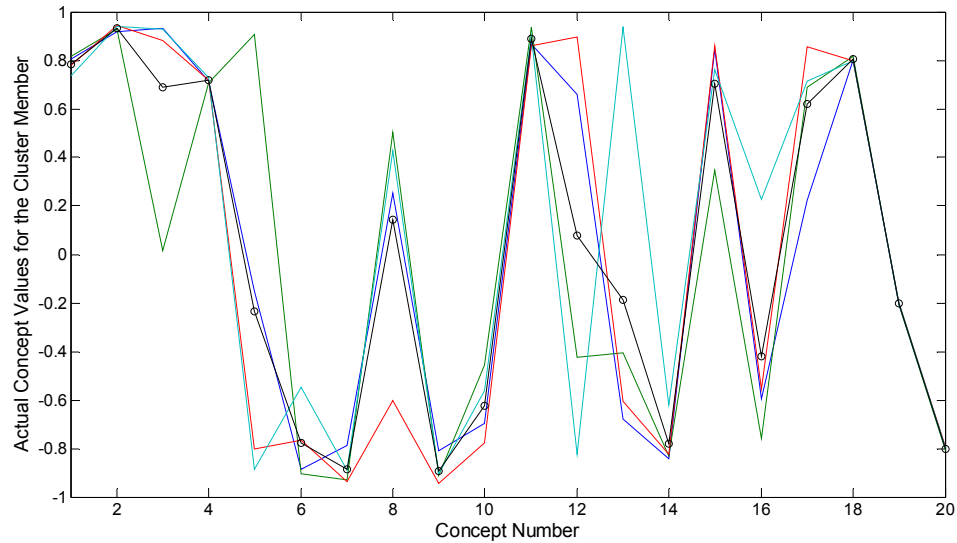
Figure 4.22:  Concept activation levels for high UNM demand (or high electric energy

usage), DR requested by PNM, and varied facility occupancy

These resulting activation levels represent the following:

C3      UNM generates electricity internally at a fairly high level.

C5      UNM energy storage is indeterminate but likely low.

C6      No stored energy is supplied to UNM facilities.

C7      UNM curtails little energy in classroom/office facilities.

C8      The classroom/office occupants are still dissatisfied.

C9      UNM does not curtail energy to the libraries.

C10     The library occupants register slight dissatisfaction.

C11     UNM curtails electricity to residence halls.

C12     The residence hall occupants' dissatisfaction is indeterminate but likely

        low.

C13    The DR event override is moderate to low but pressure does exist from the Administration and even the Regents to cease the DR event.

C14    UNM external (supplied by PNM) electric energy usage is moderately low due to the internal electric generation and partial continuance of the DR event.

C15    UNM administration intervenes to moderate the DR event but does not cause it to cease.

C16    UNM operation costs remain moderately low due to the internal electric generation.

C17    UNM Board of Regents has moderately strong concern due to the classroom/office occupants' dissatisfaction.

Under this scenario, calling for the full DR event (C1, C2, and C4 high) with high classroom/office occupancy, medium library occupancy, and low residence hall occupancy caused the UNM administration to pressure the DR event reduction. Again we see that high occupancy has a strong impact on occupant dissatisfaction and thus brings significant political pressure to reduce the impact of the DR event.

## 4.4  Conclusions

Fuzzy cognitive maps provide a heuristic approach for analyzing complex situations to improve the decision making process. The genetically evolved method for FCM analysis adds additional dimensions to this analysis. It allows the analyst to fix the activation level of one or more concepts in the FCM and resolve the activation levels of

the rest of the concepts in the map. The solutions to the FCM appear in families or groups and are identified using clustering techniques.

Fuzzy cognitive maps allow us to model the human and political reactions to electric power reduction which occur in a demand response event and estimate the impact these reactions can have on the event. We found that facility occupancy levels have a strong impact on the level of dissatisfaction and therefore on the imposition of limits by the university administration on the amount of power reduction allowed during the demand response event. This analysis suggests that the organizers of the demand response event will achieve greater success if occupancy level is understood and considered in planning the demand response event. The analysis implies that once dissatisfaction emerges, it tends to drive a strong political intervention that would be absent with a low dissatisfaction level. In other words, if the dissatisfaction level is kept low, the demand response event will not be impacted negatively and power reduction goals will be met. The analysis indicates that high occupancy facilities should receive less power reduction than those with moderate occupancy levels and low occupancy facilities will tolerate the highest power reduction.

The analysis suggests additional exploratory work. The impact of lighting reduction on occupant dissatisfaction is not well understood. It appears that reducing lighting in a windowed area of a facility on a bright sunny day, the type of day typical for a demand response event, would have no impact on occupant dissatisfaction. In addition reducing lighting by twenty to forty percent in hallways and corridors may have no impact on occupant dissatisfaction. Studies of these areas on real facilities with various

occupancy levels would provide useful data that could be incorporated into future fuzzy cognitive map analysis.  Additionally, studies of occupant dissatisfaction under various occupancy levels for small increases in temperatures coupled with increases in air flow would be useful.  It may be that increasing air flow slightly with increasing temperatures may minimize the occupant dissatisfaction. This would add a new strategic element in managing demand response events.

# Chapter 5

# The Demand Response Control System

This Chapter presents the conceptual design and operation of a facility control system to manage demand response events (DR Control System) for the Albuquerque campus of the University of New Mexico. The development of the conceptual design of this DR Control System utilizes the results of the previous three chapters.

## 5.1 Background

The University of New Mexico Albuquerque campus is situated on 650 acres, inhabited by 25,000 people, and contains more than 230 facilities that total approximately 6,360,000 square feet. The campus draws approximately 30 megawatts of electric power at peak. Typically UNM maintains these facilities at 74 °F in the summer and 70 °F in the winter.

Beginning in 2001, UNM commenced a utility infrastructure investment program intended to reduce the use of energy associated with campus electric use, heating, and cooling. The core of the investment was the renovation of the Ford Utilities Center, which included the installation of a 6 MW co-generation turbine/generator, waste heat recovery boilers, and absorption chillers. The co-generation unit recovers a substantial fraction of the waste heat, using it for steam and chilled water production, resulting in an overall energy efficiency of approximately 70%. The co-generation unit currently meets approximately 40% of the campus base load electric energy needs and 65% of the heating

needs. A new Energy Management and Control System (EMCS) was also installed in the 2001 renovation, having the capability of monitoring and controlling facility energy use on campus from a remote location.

There are two different types of controls in the EMCS. They are both direct digital control systems installed by Energy Control Inc. and are capable of being monitored through the Internet. One of the systems (I/NET Seven) is manufactured by TAC. I/NET Seven is an older system that utilizes a proprietary communication protocol. In order for a user to view the I/NET Seven system over the Internet, the user must have the I/NET Seven software running on their computer. The second system is the Delta Control System. The Delta system utilizes BACnet as its communication protocol. BACnet is an open protocol designed by ASHRAE. The Delta system at the University of New Mexico is capable of serving up web pages without special software on the user's computer (Mammoli et al. 2007).

The DR Control System includes a subset of these University of New Mexico campus facilities (69 in total). These facilities are all connected to the District Energy System and metered through the EMCS. They constitute 75% of the total campus building area and over 90% of the energy use. The complete list of these facilities, termed the DR Facilities, and their area is given in Appendix 5-1.
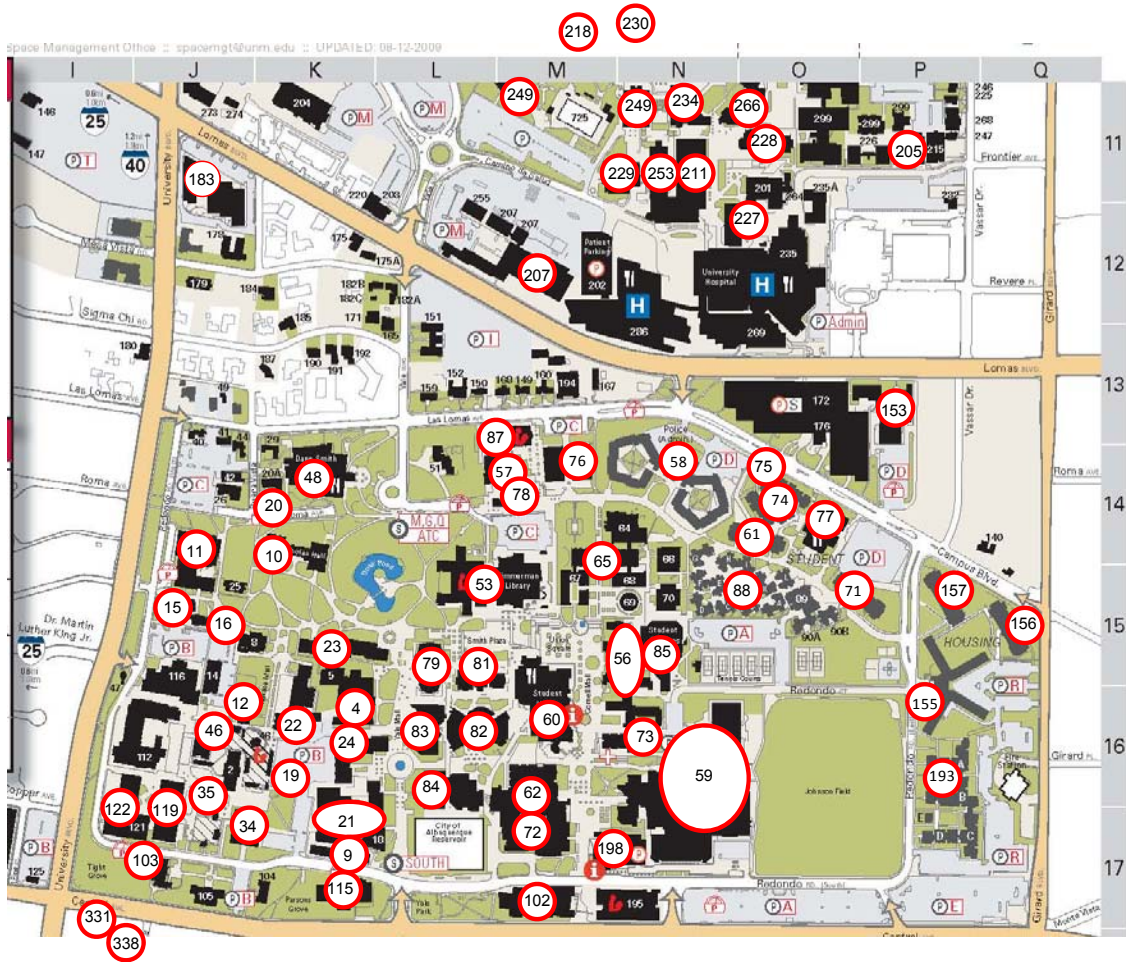
Figure 5.1: UNM campus map showing the DR facilities

Figure 5.1 shows the UNM campus map with a red circle around each of the DR

Facilities. The average building area for these DR Facilities is 71,050 square feet. The

average year of construction is 1964, with a standard deviation of approximately 20

years. However, the HVAC and lighting of several older buildings have been upgraded.

For example, Scholes Hall, a 50,000 sq. ft. historic office building constructed in 1936,

underwent major renovation including an entire HVAC retrofit in 2006 (Mammoli et al.

2007).

The DR Control System is based on two design and equipment assumptions. The System first assumes the heating, ventilating, and air conditioning (HVAC) in each facility is a variable air volume (VAV) system. This type of HVAC system delivers a variable quantity of conditioned air at a constant temperature (typically 55 °F for cooling) to the building space. The VAV controller varies the air flow to achieve the space temperature called for by the EMCS controlled thermostat set point temperature. In periods when little air flow is required, the fan speed is reduced by a variable frequency control device (VFD) thus saving considerable electricity. The majority of HVAC systems in these facilities have VAV Systems and the remainder will eventually be retrofitted with them. Next the DR Control System assumes the lighting in these facilities can be partially reduced by the EMCS. These lighting reductions occur in areas with sunny windows or other conditions where lighting reduction will not significantly impact occupants. None of the existing facilities have lighting designed to allow these reductions. None-the-less, these lighting reductions have very high value in a DR event. Each kilowatt reduction in electric use in lighting adds another kilowatt reduction in the air conditioning load.

## 5.2 Comparison of Unit Commitment Issues to Demand Response

In the early conceptualization of the DR Control System, we chose to compare opportunities for reducing electric power use in a group of commercial facilities during a DR event to issues in power generation unit commitment. Unit commitment refers to the

schedule for loading or unloading electric generating units to a power grid while minimizing the total operation cost and satisfying the unit and grid constraints (Wood 1996). These constraints include the generating units' ramp rate limits, minimizing the fuel costs, meeting emission requirements, and minimum up and down time limits for the generating units each hour of the day. With the unit commitment schedule, generating companies must satisfy customer load demands, maintain transmission flows, and keep bus voltages and reactive power within their permissible limits (Ma and Shahidehpoor 1999). In particular the goal is to minimize production costs during each hour of the day according to equation (5.1) (Chen 2002):

$$PC = \sum_{i=1}^{N} \sum_{t=1}^{H} \left[ I_i(t) F_i\big(P_i(t)\big) + S_i(t) \right] \qquad (5.1)$$

where:

$N$ = number of units, $i$

$H$ = number of hours, $t$

$I_i$ = 0 if unit off, 1 if unit is on

$F_i(P_i(t))$ is the cost for hour $t$ and unit $i$

$S_i(t)$ is the startup cost for unit $i$ at hour $t$ if appropriate

We hoped to identify opportunities for similar engineering optimization in controlling commercial facility electric loads in the DR event. These generating unit production costs need to be minimized under the constraints listed on the left side of Table 5.1

(Huang and Huang 1997). The right side of the table contrasts the unit commitment issues with the related commercial facility power reduction issues during a DR event.

Table 5.1: Unit commitment principles contrasted to DR

| Power Unit Commitment | Commercial Power DR Reduction |
|---|---|
| a) System power balance (Merlin and Sandrin 1983):<br><br>$P_D(t) = \sum_{i=1}^{N} I_i(t)P_i(t)$<br><br>where $P_i(t)$ is power of unit i at t | Total Power Reduction, $\Delta P_d(t)$, in All Facilities at hour t,:<br><br>$\Delta P_d(t) = \sum_{j=1}^{H}[P_j^{noDR}(t) - P_j^{DR}]$<br><br>Where:<br><br>$P_j^{noDR}(t)$ is the baseline load profile for facility j (if no DR event) at hour t (this is calculated as shown in a previous section).<br><br>$P_j^{DR}(t)$ is the facility j power use during the DR event at hour t. |
| b) Reserve requirement R(t):<br><br>$R(t) \le \sum_{i=1}^{N} I_i(t)r_i(t)$ where $r_i(t)$ is the reserve margin from unit I (Kurban and Filik 2009) | Reserve margin, also termed spinning reserve, refers to the ability of a generating unit to pick up additional electric load if the power grid requires this. Demand response will increase this margin. |

Table 5.1: Unit commitment principles contrasted to DR

| Power Unit Commitment | Commercial Power DR Reduction |
|---|---|
| c) Unit Generation Limits: <br><br> $P_i^{min} \le P_i \le P_i^{max}$ | Unit generating limits are the maximum and minimum power output that a generating unit can produce. In a multi-unit power system, DR will not significantly impact these limits. |
| d) Unit Startup And Shutdown Times (Jenkins 2007) | In a multi-unit power system, DR will not significantly impact these limits. |
| e) Unit Ramp Rates (Li 2007) | Reduction in facility power is instantaneous and has no ramp rate limits. |
| f) Emission Limits | Reduction in facility power generally reduces emissions, depending on the power source. |
| g) Transmission Flow Limits (Congestion) (Yalcinoz 1999) | Reduction in facility power reduces transmission and distribution power flows and therefore reduces congestion. |

Table 5.1: Unit commitment principles contrasted to DR

| Power Unit Commitment | Commercial Power DR Reduction |
|---|---|
| h) Minimize Reactive Power At Each Bus (Seyedrasoul 1996) | Reactive power control can be an issue in a DR event (Markushevich and Chan 2009), but the UNM campus has very minimal reactive power charges from PNM. Reduction in electric use will have no impact on these charges. |

As evidenced in the above table, the engineering optimization required by the unit commitment problem is not generally applicable to demand response for the UNM campus. In other situations, transmission and distribution power flows and reactive power control may be issues. We developed the design philosophy for the demand response event as described in the following section.

## 5.3  DR Event Control Philosophy

This section presents the conceptual design principles the DR Control System will follow and the basis for these principles.

Demand response events typically occur during the period of 12:00 noon to 7:00 pm on normal working days for one or more hours (Coughlin 2008). Electric suppliers only schedule one demand response event in any given day (Kiliccote et al. 2006). Thus the DR Control System will assume a DR event can initiate at the beginning of any hour between 12:00 noon and 6:00 pm and end at any hour from 1:00 pm to 7:00 pm following

the event initiation. Thus the DR event could last from one hour to seven hours in hourly increments (Roos and Kern 1996).

As we saw in the previous section, occupant dissatisfaction potentially has a powerful impact on the success of the demand response event. In addition we also saw that facility occupancy level is a significant factor in driving dissatisfaction. Other work on controlling multiple facility DR events assumes facilities either participate fully in the DR event or abstain (Piette et al. 2006, Piette et al. 2007). Taking this into account in our DR Control System design, we first need to determine the planned occupancy levels in each of the DR Facilities. UNM has established maximum occupancy levels for each facility and schedules occupancy for each classroom on the campus each semester. In addition the UNM administration tracks office, laboratory, and residence hall assignments.

Fuzzy set theory has been successfully applied to many types of closed loop, feedback type control systems (Ross 2004). In these control systems, outputs provide feedback to the system inputs to achieve a desired system response. We did not utilize a closed loop control system in the DR Control System. The DR Control System is an open loop control system where the desired system output is clearly understood and the system inputs can be pre-determined to achieve these outputs directly.

We utilized the occupancy information to establish hourly linguistic occupancy levels for normal working days. We have assumed each weekdays' occupancy level is the same for simplicity in demonstrating the DR Control System operation. The hourly linguistic occupancy information is defined as:

- Low (L)                 < 20% of full capacity

- Medium (M)         20% to 60% of full capacity

- High (H)              60% to 90% of full capacity

- Very High (S)      > 90% of full capacity

A facility population table appears in Appendix 5-2. This table provides the occupancy input to the DR Control System. The DR Control System uses this linguistic population information to control facility temperatures during the DR event as follows:

- Low (L)                 raise facility temperature to 80 °F

- Medium (M)         raise facility temperature to 78 °F

- High (H)              raise facility temperature to 76 °F

- Very High (S)      leave facility temperature at 74 °F

To further avoid occupant dissatisfaction, any facility may choose to not participate in either the lighting reduction or the temperature increase of the DR event. This will be reflected in the input to the DR Control System. Appendix 5-5 shows this participation table.

## 5.4  Control System Design

This section describes the design and operating principles for the DR Control System and presents its software code.

Figure 5.2 shows a diagram of the UNM EMCS with each individual Building Controller, the Building Utility Monitoring Panel (BUMP), and the Control Portal. The DR Control System allows a single control signal from the electric supplier (here PNM) to initiate and control the demand response event from start to finish (Piette et al. 2007).
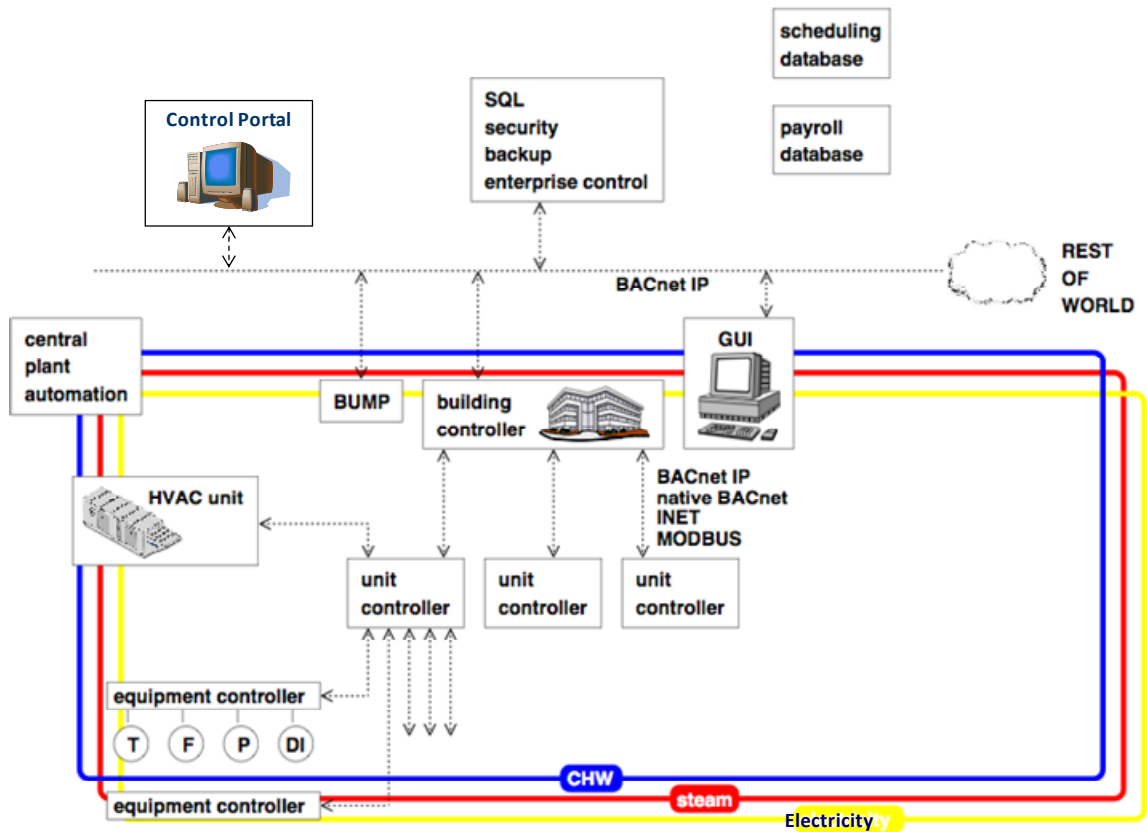
Figure 5.2: Diagram of the UNM Energy Management and Control System (EMCS)

The DR Control System is software residing on the Control Portal that manages the overall demand response event, outputs the lighting reduction and temperature set points to the building controllers, and monitors the progress of the event from the BUMPs (Koch and Piette 2007). This layout is similar to commercial control systems currently in use (LeMay et al. 2008, Schisler et al. 2008)

The DR Control System requires three key pieces of information prior to initiating the demand response event:

1.    The electric power reduction goal for the event or

2.    The goal to reduce electric power use by the maximum amount subject to the non-participation constraints and the population level temperature constraints.

3.    The start and end times for the event.

This information can be pre-established and updated as appropriate independently of the demand response event.  In addition to the above DR event initiating information, we must establish a table that defines the linguistic population for each facility for each potential hour of the demand response period, 12:00 noon to 7:00 pm (Piette et al. 2009). Appendix 5-2 shows an example of this table.  We must also establish a table with each facility's lighting power reduction potential in kilowatts and each facilities cooling power reduction for each potential thermostat set point.  Appendix 5-3 shows an example of this table.  The lighting load for each facility is assumed to be 1.1 watts per square foot.  We assume we can reduce this by 40 percent during the DR event.  The cooling load decrease in power is assumed to be 0.314 watts per square foot per degree Fahrenheit increase. This is the average power decrease we found during the simulated DR events using the TRNSYS models for Plaza del Sol and the Alvarado Transportation Center in Chapter 2.

Figure 5.3 shows the DR Control System software flow chart and is  described in the following section.  In the event the DR Control System is to achieve a specific power reduction goal, it first calculates the maximum power reduction available from lighting reduction alone.  Prior to establishing the maximum lighting power reduction, the DR Control System queries each participating building controller to determine each building's available lighting reduction.   Lighting reduction is available only if the

targeted lighting is energized. The DR Control System sets the maximum power reduction from lighting equal to the sum of the available lighting reduction in each DR Facility based on this query.
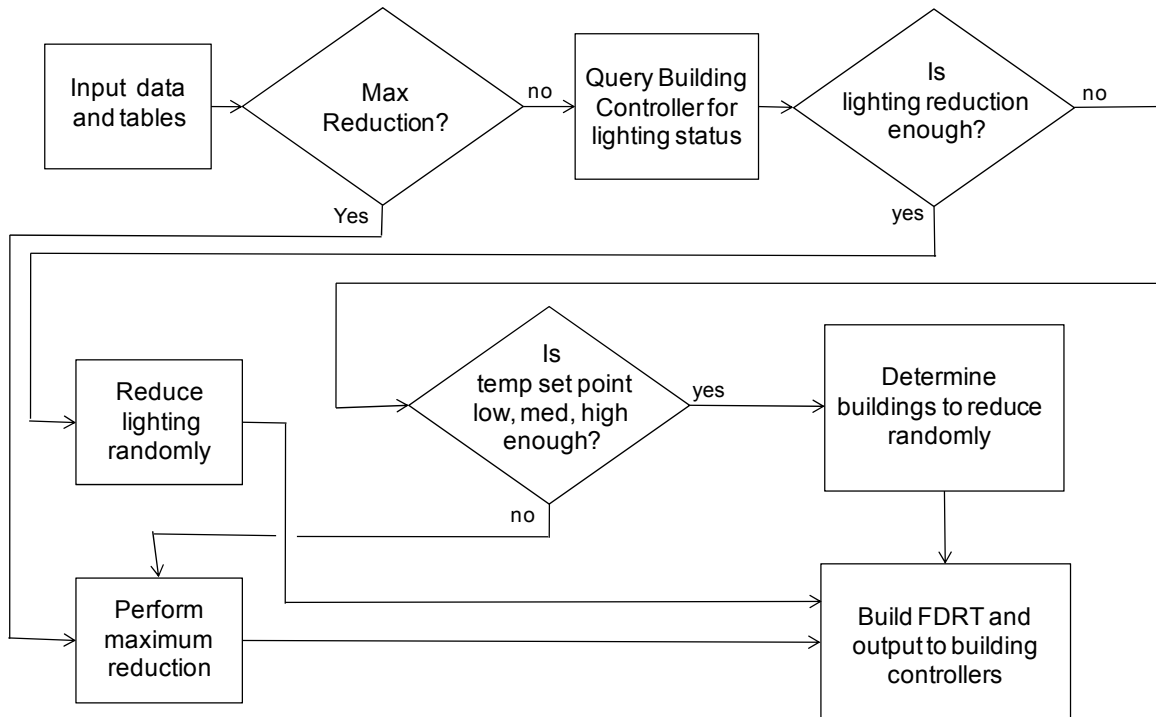


Figure 5.3: Flow chart for the DR Control System

If this maximum lighting power reduction exceeds the power reduction goal, the DR Control System, choosing each facility randomly, selects enough facilities to achieve the reduction goal. The facilities are selected randomly as opposed to from a preselected list to spread the impact of the DR event among facilities as fairly as possible. It then instructs the selected facility building controllers to reduce lighting. If the maximum available lighting reduction is less than the power reduction goal, then the DR Control System calculates the maximum power reduction available from thermostat set point

increases from those facilities with a low population during that hour. If the following conditions occur:

- maximum lighting power reduction,
- the low population facility thermostat set point increase, and
- The maximum power reduction exceeds the power reduction goal.

Then the DR Control System selects all facilities for lighting reduction and randomly selects low population facilities for set point increase until the power reduction goal is achieved. It then instructs all of the participating facility building controllers to reduce lighting and the selected facility building controllers to increase thermostat set points. This process continues with the medium and high population facilities until the power reduction goal is met.

In the event the DR Control System is to achieve the maximum power reduction, it instructs all building controllers to reduce lighting and increase temperature set points based on the buildings' participation and population.

Appendix 5-4 shows the listing of the MATLAB™ code used for the DR Control System. The code utilizes five function files, similar to subroutines in Fortran, which perform the following:

1. DRCinput – establishes the DR Control System input values for the desired reduction in power in kilowatts (-1 indicates the maximum power reduction), PDR; the number of DR Facilities (69 here), nmax; the DR event start time, nstart; the DR event end time, nend; and the potential number of hours in the DR event (here 7), h.

107

2.  DRCtables – takes the MS Excel spreadsheet, FacilityData.xls, and builds the MATLAB™ data file, FacData.mat, which contains the facility data shown in Appendix 5-1, the population data shown in Appendix 5-2, the facility lighting and temperature power reduction information shown in Appendix 5-3, and the facility participation table shown in Appendix 5-5.

3.  FacRandomizer – builds a random order for the DR Facilities for power reduction goals for DR events which do not require reduction in all participating DR Facilities.  This ensures the same facilities are not always reduced in subsequent DR events.

4.  FacLightRed – checks each building controller to determine the lighting power reduction that is achievable based on lights that are not currently off.

5.  DRCoutput – outputs the power reduction signals for each hour to the MS Excel spreadsheet, FDRTable.xls.

We tested the DR Control System with the following three sets of example inputs.

1.  The maximum lighting reduction is 2806 kilowatts so we chose a reduction goal of 2000 kilowatts to show an example of only lighting power reduction.  Figure 5.4 shows the facilities the DR Control System randomly selected for reduction for this example with the yellow circles. Facilities with white circles are not impacted by the DR event.  Table 5.2 shows the details of the results of the lighting reduction at 1:00 pm.

2.  We directed the DR Control System to perform the maximum reduction for the period of 1:00 pm to 2:00 pm.  Figure 5.5 shows the facility status with red circles for a set point of 80 °F, pink circles for a set point of 78 °F, blue circles for a set point of 76 °F, yellow circles for lighting reduction and a set point of 74 °F, and white circles for no lighting reduction and a set point of 74 °F.  In this situation, all facilities that are participating in the lighting reduction have their lighting reduced.  Those with white circles are not participating in the lighting reduction as presented in the table in Appendix 5-5.  Table 5.3 shows the details of the results of the lighting reduction at 1:00 pm.

3.  Finally, we requested a reduction of 8000 kilowatts for the period of 2:00 pm to 5:00 pm.  Figure 5.6 shows the facility status for the period 4:00 pm to 5:00 pm with red circles for a set point of 80 °F, pink circles for a set point of 78 °F, blue circles for a set point of 76 °F, yellow circles for lighting reduction and a set point of 74 °F, and white circles for no lighting reduction and a set point of 74 °F.  In this situation, all facilities that are participating in the lighting reduction have their lighting reduced.  Those with white circles are not participating in the lighting reduction as presented in the table in Appendix 5-5.  Table 5.4 shows the details of the results of the lighting reduction at 4:00 pm.
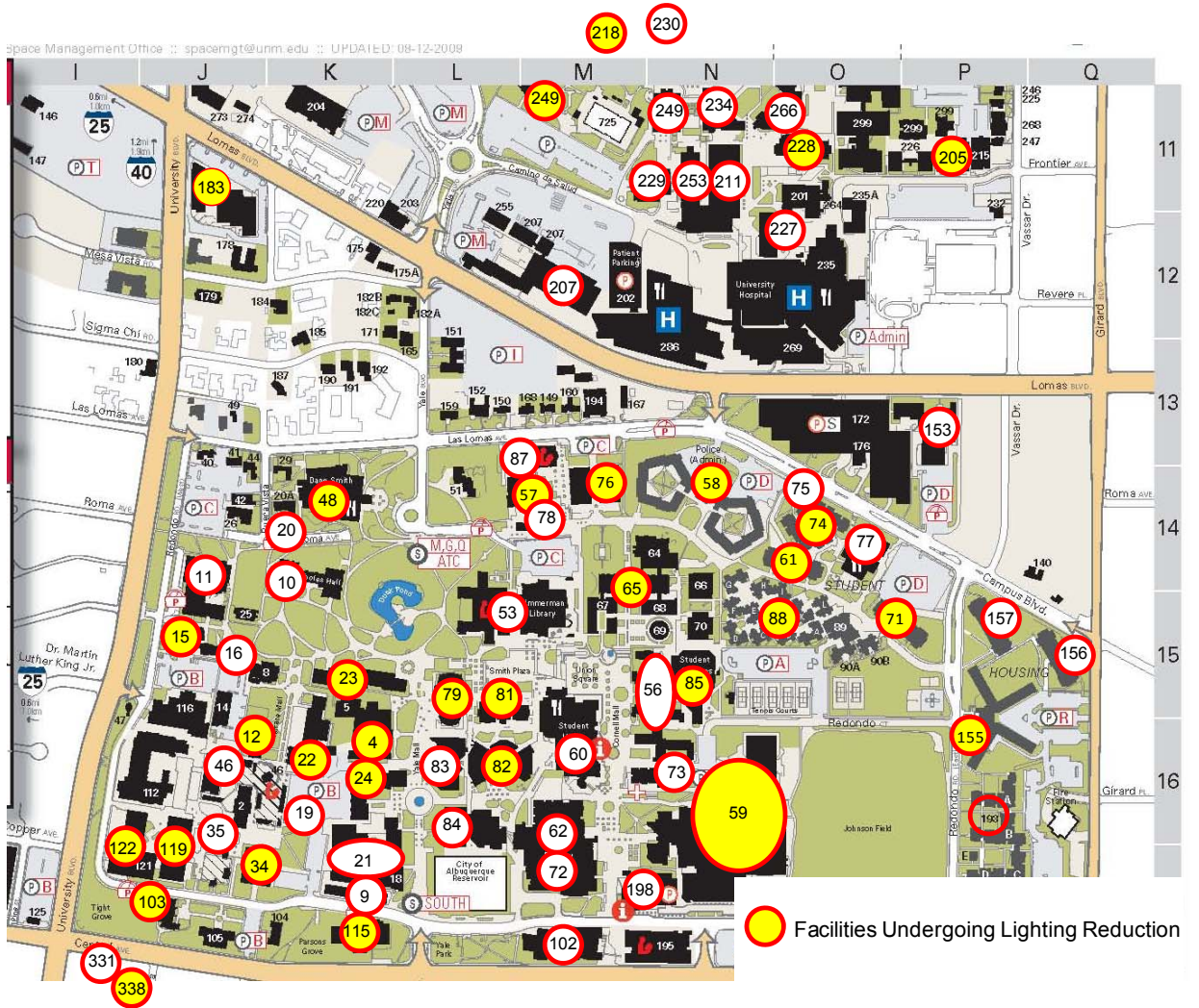
Figure 5.4: Targeted demand response reduction of 2000 kilowatts at 1:00 PM
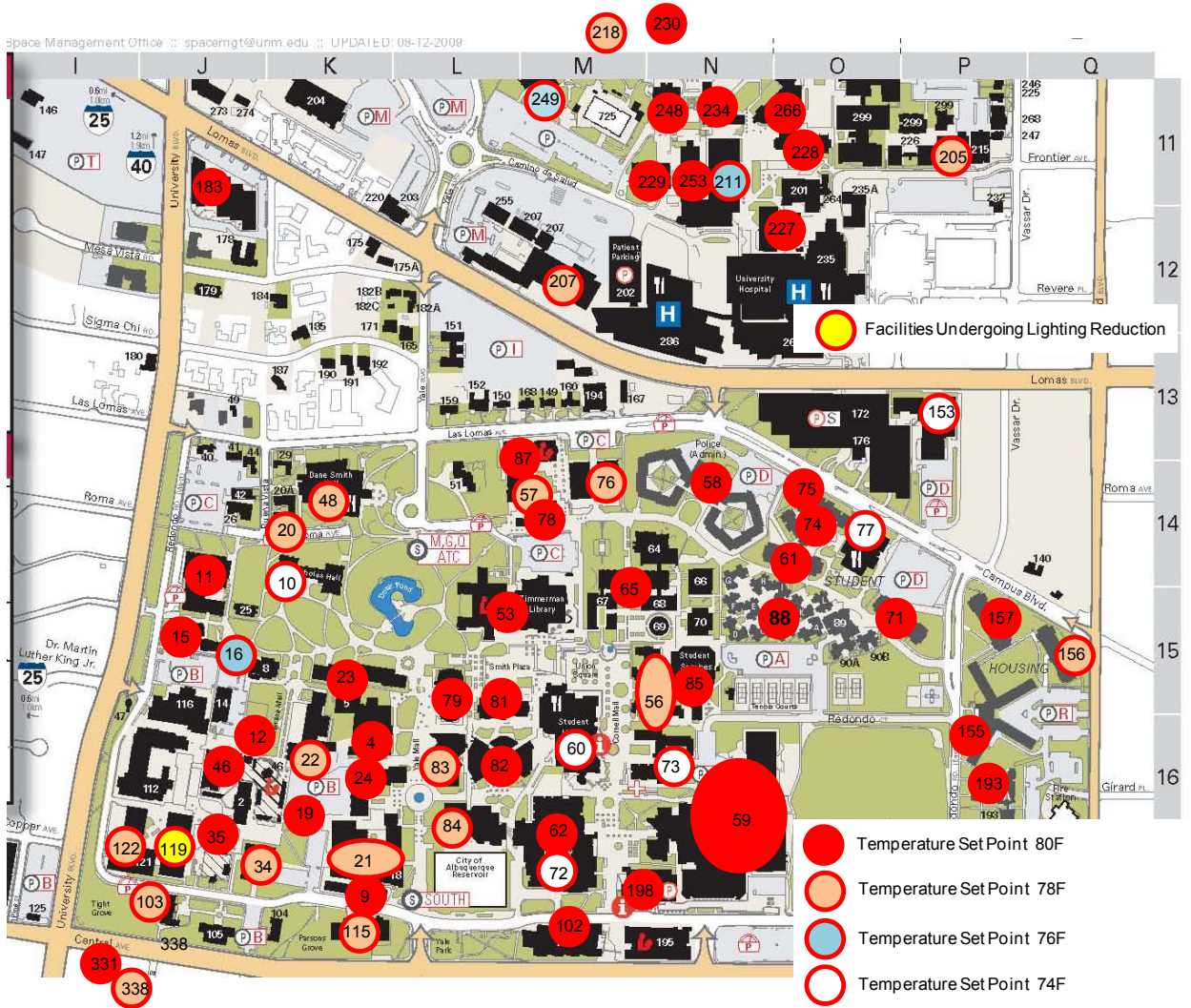
Figure 5.5: Maximum demand response reduction at 1:00 PM
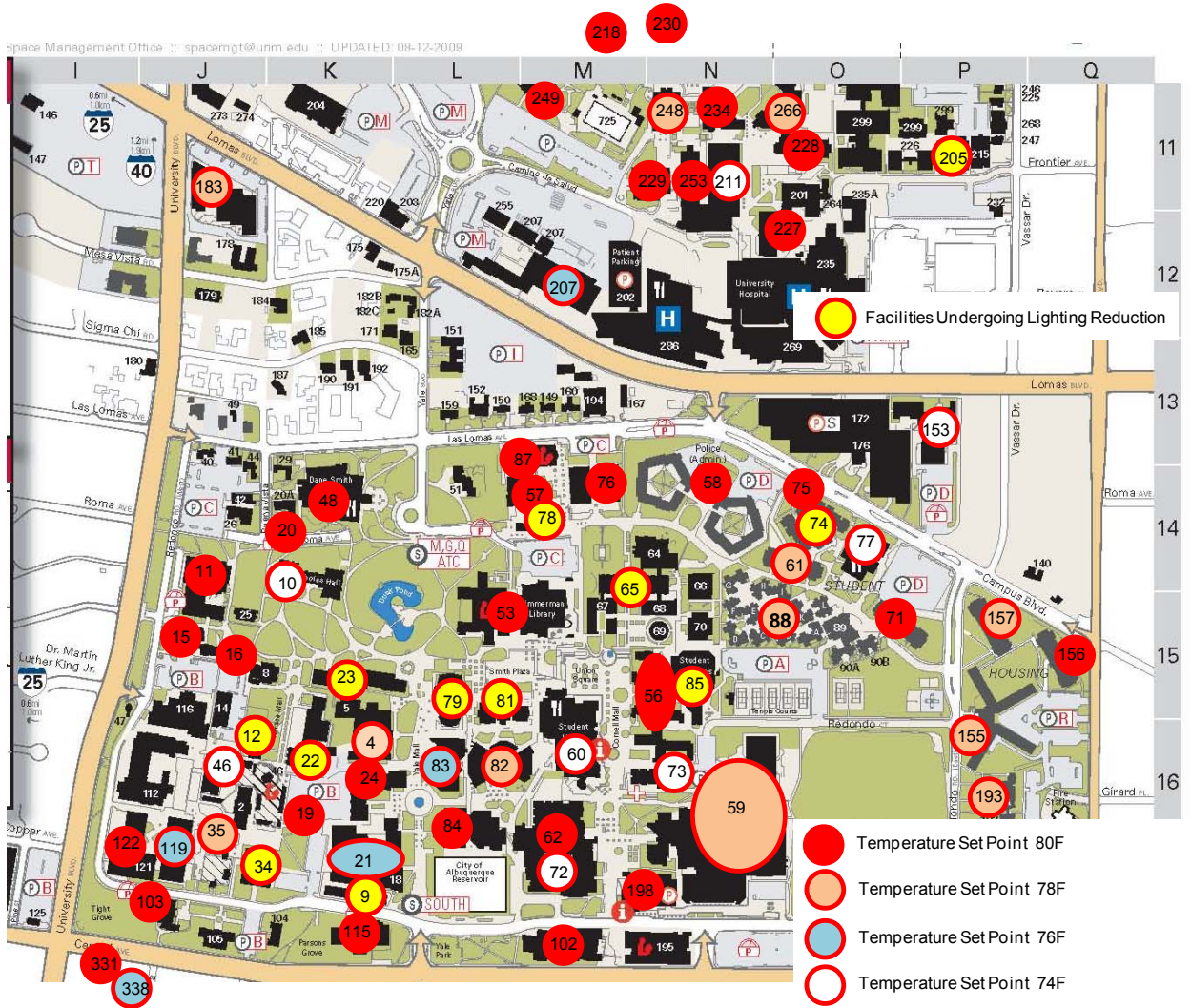
Figure 5.6: Targeted demand response reduction of 8000 kilowatts at 4:00 PM

Table 5.2: Results of the lighting reduction at 1:00 PM

| # | Bldg # | Light, yes/no | Temp, °F | Power, kW | # | Bldg # | Light, yes/no | Temp, °F | Power, kW |
|---|--------|---------------|----------|-----------|---|--------|---------------|----------|-----------|
| 1 | 157 | 0 | 74 | 0.0 | 36 | 81 | 1 | 74 | 62.4 |
| 2 | 76 | 1 | 74 | 40.8 | 37 | 59 | 1 | 74 | 285.3 |
| 3 | 12 | 1 | 74 | 8.5 | 38 | 115 | 1 | 74 | 28.1 |
| 4 | 11 | 0 | 74 | 0.0 | 39 | 77 | 0 | 74 | 0.0 |
| 5 | 84 | 0 | 74 | 0.0 | 40 | 74 | 1 | 74 | 38.6 |
| 6 | 16 | 0 | 74 | 0.0 | 41 | 34 | 1 | 74 | 44.8 |
| 7 | 211 | 0 | 74 | 0.0 | 42 | 122 | 1 | 74 | 61.8 |
| 8 | 19 | 0 | 74 | 0.0 | 43 | 9 | 0 | 74 | 0.0 |
| 9 | 253 | 0 | 74 | 0.0 | 44 | 56 | 0 | 74 | 0.0 |
| 10 | 218 | 1 | 74 | 139.6 | 45 | 23 | 1 | 74 | 41.3 |
| 11 | 229 | 0 | 74 | 0.0 | 46 | 102 | 0 | 74 | 0.0 |
| 12 | 227 | 0 | 74 | 0.0 | 47 | 230 | 0 | 74 | 0.0 |
| 13 | 4 | 1 | 74 | 27.5 | 48 | 193 | 0 | 74 | 0.0 |
| 14 | 21 | 0 | 74 | 0.0 | 49 | 60 | 0 | 74 | 0.0 |
| 15 | 83 | 0 | 74 | 0.0 | 50 | 24 | 1 | 74 | 66.7 |
| 16 | 22 | 1 | 74 | 71.9 | 51 | 228 | 1 | 74 | 84.5 |
| 17 | 153 | 0 | 74 | 0.0 | 52 | 156 | 0 | 74 | 0.0 |
| 18 | 198 | 0 | 74 | 0.0 | 53 | 79 | 1 | 74 | 58.2 |
| 19 | 155 | 1 | 74 | 82.6 | 54 | 207 | 0 | 74 | 0.0 |
| 20 | 48 | 1 | 74 | 86.0 | 55 | 35 | 0 | 74 | 0.0 |
| 21 | 75 | 0 | 74 | 0.0 | 56 | 88 | 1 | 74 | 111.5 |
| 22 | 249 | 1 | 74 | 24.6 | 57 | 71 | 1 | 74 | 36.6 |
| 23 | 46 | 0 | 74 | 0.0 | 58 | 61 | 1 | 74 | 35.0 |
| 24 | 57 | 1 | 74 | 19.2 | 59 | 10 | 0 | 74 | 0.0 |
| 25 | 65 | 1 | 74 | 114.4 | 60 | 78 | 0 | 74 | 0.0 |
| 26 | 248 | 0 | 74 | 0.0 | 61 | 73 | 0 | 74 | 0.0 |
| 27 | 119 | 1 | 74 | 66.3 | 62 | 85 | 1 | 74 | 85.2 |
| 28 | 62 | 0 | 74 | 0.0 | 63 | 82 | 1 | 74 | 34.9 |
| 29 | 87 | 0 | 74 | 0.0 | 64 | 53 | 0 | 74 | 0.0 |
| 30 | 266 | 0 | 74 | 0.0 | 65 | 72 | 0 | 74 | 0.0 |
| 31 | 234 | 0 | 74 | 0.0 | 66 | 183 | 1 | 74 | 61.6 |
| 32 | 15 | 1 | 74 | 33.1 | 67 | 205 | 1 | 74 | 25.7 |
| 33 | 103 | 1 | 74 | 14.5 | 68 | 338 | 1 | 74 | 52.8 |
| 34 | 58 | 1 | 74 | 69.0 | 69 | 331 | 0 | 74 | 0.0 |
| 35 | 20 | 0 | 74 | 0.0 | | | **Total Kilowatts** | | 2,013 |

Table 5.3: Results of the maximum demand response reduction at 1:00 PM

| # | Bldg # | Light, yes/no | Temp, °F | Power, kW | # | Bldg # | Light, yes/no | Temp, °F | Power, kW |
|---|--------|---------------|----------|-----------|---|--------|---------------|----------|-----------|
| 1 | 157 | 1 | 80 | 113.0 | 36 | 81 | 1 | 80 | 195.9 |
| 2 | 76 | 1 | 78 | 99.1 | 37 | 59 | 1 | 80 | 896.1 |
| 3 | 12 | 1 | 80 | 26.6 | 38 | 115 | 1 | 78 | 68.1 |
| 4 | 11 | 0 | 80 | 100.7 | 39 | 77 | 0 | 74 | 0.0 |
| 5 | 84 | 0 | 78 | 96.6 | 40 | 74 | 1 | 80 | 121.3 |
| 6 | 16 | 1 | 76 | 22.7 | 41 | 34 | 1 | 78 | 108.7 |
| 7 | 211 | 0 | 76 | 110.3 | 42 | 122 | 1 | 78 | 150.1 |
| 8 | 19 | 0 | 80 | 15.6 | 43 | 9 | 1 | 80 | 55.2 |
| 9 | 253 | 0 | 80 | 206.4 | 44 | 56 | 1 | 78 | 239.0 |
| 10 | 218 | 1 | 78 | 338.8 | 45 | 23 | 1 | 80 | 129.8 |
| 11 | 229 | 0 | 80 | 154.0 | 46 | 102 | 0 | 80 | 88.3 |
| 12 | 227 | 0 | 80 | 202.9 | 47 | 230 | 0 | 80 | 15.8 |
| 13 | 4 | 1 | 80 | 86.4 | 48 | 193 | 1 | 80 | 340.1 |
| 14 | 21 | 1 | 78 | 244.9 | 49 | 60 | 0 | 74 | 0.0 |
| 15 | 83 | 1 | 78 | 151.0 | 50 | 24 | 1 | 80 | 209.4 |
| 16 | 22 | 1 | 78 | 174.5 | 51 | 228 | 1 | 80 | 265.5 |
| 17 | 153 | 0 | 74 | 0.0 | 52 | 156 | 1 | 78 | 87.5 |
| 18 | 198 | 1 | 80 | 10.0 | 53 | 79 | 1 | 80 | 182.7 |
| 19 | 155 | 1 | 80 | 259.4 | 54 | 207 | 1 | 78 | 137.2 |
| 20 | 48 | 1 | 78 | 208.8 | 55 | 35 | 1 | 80 | 63.8 |
| 21 | 75 | 1 | 80 | 121.5 | 56 | 88 | 1 | 80 | 350.3 |
| 22 | 249 | 1 | 76 | 42.2 | 57 | 71 | 1 | 80 | 115.0 |
| 23 | 46 | 0 | 80 | 337.2 | 58 | 61 | 1 | 80 | 109.9 |
| 24 | 57 | 1 | 78 | 46.5 | 59 | 10 | 0 | 74 | 0.0 |
| 25 | 65 | 1 | 80 | 359.2 | 60 | 78 | 1 | 80 | 90.0 |
| 26 | 248 | 1 | 80 | 160.9 | 61 | 73 | 0 | 74 | 0.0 |
| 27 | 119 | 1 | 74 | 66.3 | 62 | 85 | 1 | 80 | 267.6 |
| 28 | 62 | 0 | 80 | 330.4 | 63 | 82 | 1 | 80 | 109.5 |
| 29 | 87 | 0 | 80 | 101.5 | 64 | 53 | 0 | 80 | 452.0 |
| 30 | 266 | 1 | 80 | 159.6 | 65 | 72 | 0 | 74 | 0.0 |
| 31 | 234 | 1 | 80 | 181.9 | 66 | 183 | 1 | 80 | 193.5 |
| 32 | 15 | 1 | 80 | 103.8 | 67 | 205 | 1 | 78 | 62.3 |
| 33 | 103 | 1 | 78 | 35.3 | 68 | 338 | 1 | 78 | 128.2 |
| 34 | 58 | 1 | 80 | 216.6 | 69 | 331 | 1 | 80 | 14.1 |
| 35 | 20 | 1 | 78 | 22.2 | | | **Total Kilowatts** | | 10,154 |

Table 5.4: Results of the targeted demand response of 8000 kilowatts at 4:00 PM

| # | Bldg # | Light, yes/no | Temp, °F | Power, kW | # | Bldg # | Light, yes/no | Temp, °F | Power, kW |
|---|--------|---------------|----------|-----------|---|--------|---------------|----------|-----------|
| 1 | 157 | 1 | 78 | 87.4 | 36 | 81 | 1 | 74 | 62.4 |
| 2 | 76 | 1 | 80 | 128.3 | 37 | 59 | 1 | 78 | 692.5 |
| 3 | 12 | 1 | 74 | 8.5 | 38 | 115 | 1 | 80 | 88.2 |
| 4 | 11 | 0 | 80 | 100.7 | 39 | 77 | 0 | 74 | 0.0 |
| 5 | 84 | 0 | 80 | 144.8 | 40 | 74 | 1 | 74 | 38.6 |
| 6 | 16 | 1 | 80 | 41.7 | 41 | 34 | 1 | 74 | 0.0 |
| 7 | 211 | 0 | 74 | 0.0 | 42 | 122 | 1 | 80 | 194.2 |
| 8 | 19 | 0 | 80 | 15.6 | 43 | 9 | 1 | 74 | 17.6 |
| 9 | 253 | 0 | 80 | 206.4 | 44 | 56 | 1 | 80 | 309.2 |
| 10 | 218 | 1 | 80 | 438.4 | 45 | 23 | 1 | 74 | 41.3 |
| 11 | 229 | 0 | 80 | 154.0 | 46 | 102 | 0 | 80 | 88.3 |
| 12 | 227 | 0 | 80 | 202.9 | 47 | 230 | 0 | 80 | 15.8 |
| 13 | 4 | 1 | 78 | 66.8 | 48 | 193 | 1 | 78 | 262.8 |
| 14 | 21 | 1 | 76 | 172.9 | 49 | 60 | 0 | 74 | 0.0 |
| 15 | 83 | 1 | 76 | 106.6 | 50 | 24 | 1 | 80 | 209.4 |
| 16 | 22 | 1 | 74 | 0.0 | 51 | 228 | 1 | 80 | 265.5 |
| 17 | 153 | 0 | 74 | 0.0 | 52 | 156 | 1 | 80 | 113.2 |
| 18 | 198 | 1 | 80 | 10.0 | 53 | 79 | 1 | 74 | 58.2 |
| 19 | 155 | 1 | 78 | 200.5 | 54 | 207 | 1 | 76 | 96.8 |
| 20 | 48 | 1 | 80 | 270.3 | 55 | 35 | 1 | 78 | 49.3 |
| 21 | 75 | 1 | 78 | 93.9 | 56 | 88 | 1 | 78 | 270.7 |
| 22 | 249 | 1 | 80 | 77.3 | 57 | 71 | 1 | 78 | 88.9 |
| 23 | 46 | 0 | 74 | 0.0 | 58 | 61 | 1 | 78 | 84.9 |
| 24 | 57 | 1 | 80 | 60.2 | 59 | 10 | 0 | 74 | 0.0 |
| 25 | 65 | 1 | 74 | 114.4 | 60 | 78 | 1 | 74 | 28.7 |
| 26 | 248 | 1 | 78 | 124.3 | 61 | 73 | 0 | 74 | 0.0 |
| 27 | 119 | 1 | 76 | 113.7 | 62 | 85 | 1 | 74 | 85.2 |
| 28 | 62 | 0 | 80 | 330.4 | 63 | 82 | 1 | 78 | 84.6 |
| 29 | 87 | 0 | 80 | 101.5 | 64 | 53 | 0 | 80 | 452.0 |
| 30 | 266 | 1 | 78 | 123.4 | 65 | 72 | 0 | 74 | 0.0 |
| 31 | 234 | 1 | 80 | 181.9 | 66 | 183 | 1 | 78 | 149.5 |
| 32 | 15 | 1 | 80 | 103.8 | 67 | 205 | 1 | 74 | 0.0 |
| 33 | 103 | 1 | 80 | 45.6 | 68 | 338 | 1 | 76 | 90.5 |
| 34 | 58 | 1 | 80 | 216.6 | 69 | 331 | 1 | 80 | 14.1 |
| 35 | 20 | 1 | 80 | 28.7 | | | **Total Kilowatts** | | 8,024 |

## 5.5   Economic Analysis

The main incentive for commercial power users to perform demand response power reductions is financial (Roos and Kern 1996, Alvarado 2004).  UNM could potentially receive compensation for demand response through the PNM Peak Saver Demand Response Program.  This compensation is composed of a designated and delivered capacity payment and an energy saved payment.  The Program requires UNM designate a capacity reduction quantity and UNM would receive compensation based on the portion of that designated capacity reduction actually achieved, limited to 100 percent, during demand response events.  This compensation is in the range of $32.00 to $40.00 per kilowatt.  PJM Interconnection in the northeast USA provided approximately $28.00 per kilowatt in 2008 (Langbein 2009).  Under the Program UNM could also be compensated for energy reduced during the demand response events in the range of 10 to 15 cents per kilowatt hour.  In 2001, the New York Independent System Operator and the PJM Interconnection paid commercial customers $0.50 per kilowatt hour (Laurence and Neenan 2003, Corvino 2003).  The PNM Peak Saver Demand Response Program is limited to the four month period from June through September.  Only one DR event may be scheduled per day.  No single DR event may exceed six hours in length and the total DR hours in a year cannot exceed one hundred.

For the purpose of this economic analysis we shall assume the capacity compensation is $36.00 per kilowatt, the reduction achieved is 100 percent of the designated amount of 8000 kilowatts, a total of 75 hours of DR events occur in the year, and the energy compensation is 12.5 cents per kilowatt hour.  This yields an annual

capacity payment of $288,000, an annual energy payment of $75,000, yielding a total annual payment of $363,000. UNM uses approximately $10,000,000 worth of electricity annually at the North, Main, and South campuses covered by this DR Control System and thus the demand response savings would total 3.6 percent of the total electric charges per year.

In the event the automated lighting reduction is not included in the demand response control system, the designated capacity reduction would need to be reduced to 5000 kilowatts. The facility modifications required to allow automated lighting reduction from the building controllers is significant and not likely justifiable from this level of economic payback. Assuming a $10 million cost to upgrade the lighting to allow automatic DR control, the payback would exceed 50 years. Without lighting reduction, the yield is reduced to an annual capacity payment of $180,000, an annual energy payment of $47,000, yielding a total annual payment of $227,000 or 2.3 percent savings per year.

The economic payback from PNM's view point is quite different from that of UNM. Assume demand response reduces PNM's peak load of approximately 2000 megawatts by 10 percent for the 100 hours in the year that this peak occures. PNM could avoid the capital cost of adding 200 megawatts of power generating capacity and the transmission and distribution capacity to carry this power to customers. This new generating capacity would cost approximately $400 to $500 million to build. The transmission and distribution upgrades would cost approximately $100 to $200 million or more depending on right-of-way issues. The annual interest at five percent on these

projected capital costs would be approximately $35 million. PNM's annual payments to customers under the PNM Peak Saver Demand Response Program to reduce this 200 megawatts of peak power would be approximate $7.2 million or less than 25% of PNM's avoided interest. The economics of PNM's demand response program appear to be somewhat one sided.

## 5.6   Conclusions

The DR Control System design will control the demand response event for sixty-nine UNM facilities comprising approximately seventy-five percent of the total campus floor space. Each demand response event would potentially reduce campus power use up to the maximum of 8,000 to 10,000 kilowatts for the seven hour design period. The DR Control System input can be adjusted to control any amount of power reduction up to the maximum amount for any time period in one hour increments from 12:00 noon to 7:00 pm. The DR Control System first reduces facility lighting and then increases temperature set points until the input power reduction goal is met. If the power reduction input request is less than the maximum amount, the DR Control System chooses facilities for reduction randomly to spread the power reduction among the campus facilities.

The conceptual design effort suggests additional exploratory work. Upon initiation of the demand response event, the DR Control System could calculate the baseline load profiles for each facility for each demand response event hour based on input from the Building Utility Monitoring Panels. This calculation would follow the methodology presented in the previous chapter. As discussed in that chapter, the baseline load is a function of the actual environmental conditions the morning of the event, the

previous days' actual energy use, and the facility's population during the hour of the event. At the end of each DR event hour, the DR Control System could then determine each facility's actual power reduction as:

$$\Delta P_j(t) = P^{noDR}_j(t) - P^{DR}_j(t) \qquad (5.2)$$

where:

$\Delta P_j(t)$          the power reduction for facility j at DR hour t

$P^{noDR}_j(t)$          the baseline load (BLP) for facility j at DR hour t

$P^{DR}_j(t)$          the power use for facility j at DR hour t

The DR Control System would then adjust the temperature power reduction values in the table in Appendix 6-3 to more accurately reflect the current day's conditions. This would yield more accurate power reduction in future hours during this event and potentially more accurate power reduction results in future DR events.

# Chapter 6

# Summary Recommendations for Automated Demand Response and Opportunities for Additional Exploratory Work

The conclusions for each of the four aspects of demand response addressed in this dissertation are presented in this chapter. The design of the Demand Response Control System, presented in Chapter 5, utilized the results of Chapter 2, 3, and 4.

In Chapter 2 we demonstrated that many opportunities for improved energy efficiency exist in the commercial facility, Plaza Del Sol, designed and constructed more then thirty-five years ago. The outside air mixing dampers were broken. Their repair would decrease energy needed to condition the excess quantity of outside air. We recommended shutting down half of the supply and return air fans at night and on weekends as the building is only lightly occupied at these times and these fans use significant energy. Or to preclude this manual fan shutdown, we recommended installing variable frequency control devices (VFD) for these fans to reduce energy use during periods requiring less air flow. We also recommended replacing the single pane ¼ inch plate glass windows with a better insulating type.

No energy improvements were recommended for the Alvarado Transportation Center as this facility is only ten years old and includes current energy efficient materials and construction.

The ability to control demand response in Plaza Del Sol is only possible manually without upgrading the building HVAC controls. We did show that even this thirty-five year old facility could contribute significant power reduction in a demand response event. The ten year old Alvarado Transportation Center contains the appropriate digital controls for automated demand response.

The fuzzy set theory approach, Modified Learning From Experience with a Recursive Least Square improvement (MLFE/RLS), predicted what the energy usage of a facility during a demand response event would be in the absence of the event (the baseline load profile). This method, as presented in Chapter 3, was significantly more accurate than other methods currently in use. This was partially because the fuzzy set theory approach can take into account the building occupancy. Occupancy variation in the range of 100 people to 800 people in a classroom building is a significant driver for energy use. This is due to the heat given off by the occupants and the additional lighting required in high occupancy periods.

The fuzzy set theory approach has an additional advantage due to the relationship between the inputs and outputs. The fuzzy system allows the natural non-linearity of the inputs to be reflected in the output. The other methods currently in use force a linear relationship between the inputs and output. Forced linearity in modeling a non-linear system cannot match the accuracy of an intrinsically non-linear modeling system.

The largest effort in the baseline load profile modeling is gathering and appropriately processing the input information. Both modeling algorithms use the same input information and therefore suffer equally with this difficulty. While the methods currently in use are somewhat simpler to apply to the input data, current software tools such as MATLAB™, which was used in modeling the MLFE/RLS methodology, was fast and straight forward. The significant increase in accuracy clearly justifies this additional effort.

Fuzzy cognitive maps provide a heuristic approach for analyzing complex situations, as described in Chapter 4, to improve the decision making process. The genetically evolved method for FCM analysis adds additional dimensions to this analysis. It allows the analyst to fix the activation level of one or more concepts in the FCM and determine the resulting activation levels of the rest of the concepts in the map. The solutions to the FCM appear in families or groups and are identified using clustering techniques.

Fuzzy cognitive maps allow us to model the human and political reactions to electric power reduction which occur in a demand response event and estimate the impact these reactions can have on the event. We found that facility occupancy levels have a strong impact on the level of dissatisfaction and therefore on the imposition of limits by the university administration on the amount of power reduction allowed during the demand response event. This analysis demonstrates that the organizers of the demand response event will achieve greater success if occupancy level is understood and considered in planning the demand response event. The analysis implies that once

dissatisfaction emerges, it tends to drive a strong political intervention that would be absent with a low dissatisfaction level. In other words, if the dissatisfaction level is kept low, the demand response event will not be impacted negatively and power reduction goals will be met. The analysis indicates that high occupancy facilities should receive less power reduction than those with moderate occupancy levels and low occupancy facilities will tolerate the highest power reduction.

The analysis suggests additional exploratory work. The impact of lighting reduction on occupant dissatisfaction is not well understood. It appears that reducing lighting in a windowed area of a facility on a bright sunny day, the type of day typical for a demand response event, would have no impact on occupant dissatisfaction. In addition reducing lighting by twenty to forty percent in hallways and corridors during a demand response event may have no impact on occupant dissatisfaction. Studies of these areas on real facilities with various occupancy levels would provide useful data that could be incorporated into future fuzzy cognitive map analysis. Additionally, studies of occupant dissatisfaction under various occupancy levels for small increases in temperatures coupled with increases in air flow would be useful. It may be that increasing air flow slightly with increasing temperatures may minimize the occupant dissatisfaction. This would add a new strategic element in managing demand response events.

The DR Control System, described in Chapter 5, will manage the demand response event for sixty-nine UNM facilities comprising approximately seventy-five percent of the total campus floor space. Each demand response event would potentially reduce campus power use up to the maximum of 8,000 to 10,000 kilowatts for the seven

hour design period.  The DR Control System input can be adjusted to control any amount of power reduction up to the maximum amount for any time period in one hour increments from 12:00 noon to 7:00 pm.  The DR Control System first reduces facility lighting and then increases temperature set points until the input power reduction goal is met.  If the power reduction input request is less than the maximum amount, the DR Control System chooses facilities for reduction randomly to spread the power reduction among the campus facilities.

The conceptual design effort suggests additional exploratory work.  Upon initiation of the demand response event, the DR Control System could calculate the baseline load profiles for each facility for each demand response event hour based on input from the Building Utility Monitoring Panel.  This calculation would follow the methodology presented in the previous chapter.  As discussed in that chapter, the baseline load is a function of the actual environmental conditions the morning of the event, the previous days actual energy use, and the facility's population during the hour of the event.  At the end of each demand response event hour, the DR Control System could then determine each facility's actual power reduction.  The DR Control System would then adjust the temperature power reduction values in the table in Appendix 5-3 to more accurately reflect the current day's conditions.  This would yield more accurate power reduction in future hours during this event and potentially more accurate power reduction results in future DR events.

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# Acronyms

| | |
|---|---|
| AC | Air conditioning |
| ASHRAE | American Society of Heating, Refrigeration, and Air Conditioning Engineers |
| ATC | Alvarado Transportation Center |
| BLP | Baseline Load Profile |
| BUMP | Building Utility Monitoring Panel |
| BYU | British Thermal Unit |
| CM | Cognitive map |
| CNFCM | Certainty neuron fuzzy cognitive map |
| CPP | Critical Peak pricing |
| CSTB | The Centre Scientifique et Technique du Batiment |
| DR | Demand Response |
| Dth | Decatherm |
| EMCS | Energy Management Control System |
| FCM | Fuzzy cognitive map |
| FERC | Federal Energy Regulatory Commission |
| GEFCM | Genetically evolved fuzzy cognitive map |
| HVAC | Heating, Ventilating, and Air Conditioning |
| ISO | Independent (Transmission) System operator |
| kWh | Kilowatt Hours |

| | |
|---|---|
| LBNL | Lawrence Berkeley National Laboratory |
| MLFE | Modified learning from experience |
| MW | Megawatt |
| MW | megawatt |
| PDS | Plaza Del Sol |
| PNM | Public service Company of New Mexico |
| PV | Photovoltaic |
| RLS | Recursive least square |
| RTP | Real Time pricing |
| sq ft | Square Feet |
| TESS | Thermal Energy Systems Specialists |
| TOU | Time of Use |
| TRNSYS | Transient System Simulator |
| UNM | University of New Mexico |
| UNM | University of New Mexico |
| VAV | Variable air volume |
| VFD | Variable Frequency Device |

# Appendices

Appendix 2-1: Plaza Del Sol Schedule

| | Floor 1 | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| Staff Day Shift M-S | 19 | | | 7am-5pm M-F |
| Hearing Room | 20 | | | 8am-Noon M W F |
| Lights | | | | |
| A | 154 | 14784 | 42282 | 7am-6pm M-F |
| A Emerg | 6 | 192 | 1682 | 24/7 |
| B | 30 | 1020 | 2917 | 7am-6pm M-F |
| B Emerg | 4 | 136 | 1191 | 24/7 |
| | | 16132 | | |
| Computers | | | | |
| PC | 19 | *140* | 6916 | 7am-5pm |
| Copiers | 4 | 1600 | 4160 | 7am-5pm |
| Printers | 4 | 400 | 1040 | 7am-5pm |
| | 4 | 40 | 146 | 5pm-7am |
| FAX | 3 | 225 | 585 | 7am-5pm |
| | 3 | 30 | 109 | 5pm-7am |
| Other Equipment | | | | |
| Refrigerator | 1 | 770 | 6745 | 24/7 |
| Oven | 1 | 1565 | 1221 | 11am - 2pm M-F |
| Pop Cooler | 2 | 1540 | 13490 | 24/7 |
| Ceiling Fans | 4 | 1056 | 1922 | 7:30am - 2:30pm M-F |

Appendix 2-1: Plaza Del Sol Schedule

| | Floor 2 | | | | Floor 3 | | | |
|---|---|---|---|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched | Quantity | Watts | kWh/yr | Sched |
| Staff | 40 | | | 7am-5pm M-F | 26 | | | 7am-5pm M-F |
| Walkin Cust | 10 | | | 7am-5pm M-F | | | | |
| | | | 0.023986 | | | 3480 | | 94 |
| | | 14183 | | | | 45240 | | |
| Lights | | 15092 | 1160.923 | | | 15690 | | |
| A | 146 | 14016 | 40086 | 7am-6pm M-F | 148 | 14208 | 40635 | 7am-6pm M-F |
| A Emerg | 6 | 192 | 1682 | 24/7 | 7 | 224 | 1962 | 24/7 |
| B | 21 | 714 | 2042 | 7am-6pm M-F | 29 | 986 | 2820 | 7am-6pm M-F |
| B Emerg | 5 | 170 | 1489 | 24/7 | 8 | 272 | 2383 | 24/7 |
| Computers | | | | | | | | |
| PC | 35 | 140 | 12740 | 7am-5pm | 26 | 140 | 9464 | 7am-5pm |
| Copiers | 6 | 2400 | 6240 | 7am-5pm | 2 | 800 | 2080 | 7am-5pm |
| | 6 | 1800 | 6552 | 5pm-7am | 2 | 600 | 2184 | 5pm-7am |
| Printers | 8 | 800 | 2080 | 7am-5pm | 4 | 400 | 1040 | 7am-5pm |
| | 8 | 280 | 1019 | 5pm-7am | 4 | 140 | 510 | 5pm-7am |
| Dwg Printers* | | 0 | | 7am-5pm | | 0 | | 7am-5pm |
| FAX | 3 | 225 | 585 | 7am-5pm | 2 | 150 | 390 | 7am-5pm |
| | 3 | 30 | 328 | 5pm-7am | 2 | 20 | 146 | 5pm-7am |
| Other Equipment | | | | | | | | |

Appendix 2-1: Plaza Del Sol Schedule

| | Floor 4 | | | | Floor 5 | | | |
|---|---|---|---|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched | Quantity | Watts | kWh/yr | Sched |
| Staff | 34 | | | 7am-5pm M-F | 27 | | | 7am-5pm M-F |
| Lights | | 15094 | | | | 14456 | | |
| A | 139 | 13344 | 38164 | 7am-6pm M-F | 126 | 12096 | 34595 | 7am-6pm M-F |
| A Emerg | 9 | 288 | 2523 | 24/7 | 10 | 320 | 2803 | 24/7 |
| B | 34 | 1156 | 3306 | 7am-6pm M-F | 54 | 1836 | 5251 | 7am-6pm M-F |
| B Emerg | 9 | 306 | 2681 | 24/7 | 6 | 204 | 1787 | 24/7 |
| Computers | | | | | | | | |
| PC | 34 | 140 | 12376 | 7am-5pm | 34 | 140 | 12376 | 7am-5pm |
| Copiers | 3 | 1200 | 3120 | 7am-5pm | 2 | 800 | 2080 | 7am-5pm |
| | | 0 | 0 | 5pm-7am | | 0 | 0 | 5pm-7am |
| Printers | 6 | 600 | 1560 | 7am-5pm | 10 | 1000 | 2600 | 7am-5pm |
| | | 0 | 0 | 5pm-7am | | 0 | 0 | 5pm-7am |
| Dwg Printers* | 2 | 550 | | 7am-5pm | | 0 | | 7am-5pm |
| FAX | 2 | 150 | 390 | 7am-5pm | 2 | 150 | 390 | 7am-5pm |
| | 2 | 20 | 73 | 5pm-7am | 2 | 20 | 73 | 5pm-7am |
| Other Equipment | | | | | | | | |

Appendix 2-1: Plaza Del Sol Schedule

| | Floor 6 | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| Staff Day Shift M-F | 63 | | | 7am-5pm M-F |
| Staff 2nd Shift M-F | 6 | | | 5pm-12am M-F |
| Staff 3nd Shift M-F | 1 | | | 12am-7am |
| Staff Day Shift S/S | 6 | | | 7am-5pm S/S |
| Staff 2nd & 3rd Shift S/S | 1 | | | |
| Lights | | 13760 | 13754 | |
| A | 141 | 13536 | 118575 | 24/7 |
| A Emerg | 7 | 224 | 1962 | 24/7 |
| B | 0 | 0 | | |
| B Emerg | 0 | 0 | | |
| Computers | | | | |
| PC | 52 | 140 | 18928 | 24/7 |
| PC | 11 | 140 | 4404 | 7am-5pm M-F |
| Copiers | 2 | 800 | 2080 | 7am-5pm |
| | 2 | 600 | 2184 | 5pm-7pm |
| Printers | 6 | 600 | 1560 | 7am-5pm |
| | 6 | 210 | 764 | 5pm-7pmM-F |
| FAX | 2 | 150 | 390 | 7am-5pm |
| | 2 | 20 | 73 | 5pm-7pm |
| Other Equipment | | | | |
| 27 Tons A/C Units | | | | |
| Refrigerator | 1 | 770 | 6745 | 24/7 |
| Microwave | 2 | 1200 | 936 | 3 hours per day |
| Toaster Oven | 1 | 2470 | 1927 | 3 hours per day |
| Pop Cooler | 1 | 770 | 6745 | 24/7 |

Appendix 2-1: Plaza Del Sol Schedule

| | | Floor 7 | | | | Floor 8 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Quantity | Watts | kWh/yr | Sched | Quantity | Watts | kWh/yr | Sched |
| Staff Day Shift M-F | | 22 | | | 7am-5pm M-F | 27 | | | 7am-5pm M-F |
| Lights | | | | | | | | | |
| | A | 138 | 13248 | 37889 | 7am-6pm M-F | 134 | 12864 | 36791 | 7am-6pm M-F |
| | A Emerg | 6 | 192 | 1682 | 24/7 | 6 | 192 | 1682 | 24/7 |
| | B | 22 | 748 | 2139 | 7am-6pm M-F | 30 | 1020 | 2917 | 7am-6pm M-F |
| | B Emerg | 7 | 238 | 2085 | 24/7 | 6 | 204 | 1787 | 24/7 |
| Computers | | | | | | | | | |
| | PC | 22 | *140* | 8008 | 7am-5pm | 27 | *140* | 9828 | 7am-5pm |
| | Copiers | 5 | 2000 | 5200 | 7am-5pm | 2 | 800 | 2080 | 7am-5pm |
| | | 5 | 1500 | 5460 | 5pm-7am | 2 | 600 | 2184 | 5pm-7am |
| | Printers | 7 | 700 | 1820 | 7am-5pm | 9 | 900 | 2340 | 7am-5pm |
| | | 7 | 245 | 892 | 5pm-7am | 9 | 315 | 1147 | 5pm-7am |
| | FAX | 3 | 225 | 585 | 7am-5pm | 2 | 150 | 390 | 7am-5pm |
| | | 3 | 30 | 109 | 5pm-7am | 2 | 20 | 73 | 5pm-7am |
| Other Equipment | | | | | | | | | |

Appendix 2-1: Plaza Del Sol Other Loads

| M-11 | Description | HP | Season | Eff. | OP hrs/year | kWh/yr |
|---|---|---|---|---|---|---|
| 3 | Cooling Tower Fan Motor | 7.5 | Cooling | 0.840 | 983 | 6544 |
| 3A | Cooling Tower Fan Motor | 7.5 | Cooling | 0.840 | 983 | 6544 |
| 6 | Supply Fan Motor | 70.0 | All | 0.902 | 8760 | 506,876 |
| 7 | Supply Fan Motor | 70.0 | All | 0.902 | 8760 | 506,876 |
| 8 | Return Fan Motor | 20.0 | All | 0.885 | 8760 | 147,604 |
| 9 | Return Fan Motor | 20.0 | All | 0.885 | 8760 | 147,604 |
| 10 | Exhaust Fan Motor | 3.0 | All | 0.700 | 8760 | 27,992 |
| 11 | Heating Water Pump Motor | 7.5 | Heating | 0.840 | 3227 | 21,483 |
| 12 | Heating Water Pump Motor | 7.5 | Heating | 0.840 | 3227 | 21,483 |
| 13 | Cooling Water Pump Motor | 15.0 | Cooling | 0.855 | 983 | 12,858 |
| 14 | Cooling Water Pump Motor | 15.0 | Cooling | 0.855 | 983 | 12,858 |
| 15 | Condenser Pump Motor | 20.0 | Cooling | 0.885 | 983 | 16,563 |
| 16 | Condenser Pump Motor | 20.0 | Cooling | 0.885 | 983 | 16,563 |
| 17 | Heating Water Pump Motor | 5.0 | Heating | 0.840 | 3227 | 14,322 |
| 22 | Exhaust Fan Motor | 1.5 | All | 0.788 | 8760 | 12,433 |
| 27 | Exhaust Fan Motor | 0.3 | All | 0.600 | 8760 | 3,625 |
|  | Elevator Motors - 3 | 25.0 | 35% Oper  7am-6pm M-F | 0.855 | 2860 | 65,469 |

Appendix 2-2: Alvarado Transportation Center Schedule

| | Floor 1 Customer Service | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| Staff Day Shift M-F | 9 | | | 7am-7pm M-F |
| Customers | 20 | | | 7am-7pm M-F |
| Staff Sat | 4 | | | 7am-6pm Sat |
| Customers Sat | 10 | | | 7am-6pm Sat |
| Lights | | | | |
| H 100w | 4 | 400 | 1498 | 7am-7pm M-Sat |
| A/B 32w | 27 | 2592 | 9704 | 7am-7pm M-Sat |
| C/D 32w | 4 | 256 | 958 | 7am-7pm M-Sat |
| F 32w | 17 | 1088 | 4073 | 7am-7pm M-Sat |
| G 32 | 3 | 192 | 719 | 7am-7pm M-Sat |
| | | | | |
| Computers | | | | |
| PC | 9 | 140 | 4717 | 7am-7pm M-Sat |
| Copiers | 1 | 400 | 1498 | 7am-7pm M-Sat |
| | | | | |
| Printers | 1 | 100 | 374 | 7am-7pm M-Sat |
| | | 40 | 150 | 7pm-7am M-Sat |
| FAX | | 0 | 0 | |
| | | 0 | 0 | |
| Other Equipment | | | | |
| Refrigerator | 3 | 2310 | 20236 | 24/7 |
| Oven | 1 | 1565 | 1221 | 11am - 2pm M-F |
| Small Warmers | 3 | 300 | 936 | 6am-6pm |
| Microwave | 1 | 600 | 468 | 11am - 2pm M-F |
| Ice Maker | 1 | 390 | 1217 | 6am-6pm M-F |
| Freezer | 1 | 150 | 1314 | 24/7 |

Appendix 2-2: Alvarado Transportation Center Schedule

| | Floor 1 Police Station | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| Staff | 6 | | | 24/7 |
| Customers | 2 | | | 24/7 |
| Lights | | | | |
| | 9 | 864 | 7569 | 24/7 |
| | | 0 | 0 | |
| | | 0 | 0 | |
| | | 0 | 0 | |
| Computers | | | | |
| PC | 6 | 140 | 7358 | 24/7 |
| Copiers | 1 | 400 | 3504 | 24/7 |
| Printers | 1 | 100 | 364 | 7am-5pm |
| FAX | 1 | 75 | 273 | 7am-5pm |

Appendix 2-2: Alvarado Transportation Center Schedule

| | Floor 2 | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| **Dispatch and Customer Service** | | | | |
| Day Shift 8am-5pm | 6 | | | 8am-5pm M-F |
| Day Shift 4am-5pm | 12 | | | 4am-5pm M-Sat |
| Second Shift 5pm-12 midnight | 5 | | | 5pm-12am M-Sat |
| | | | | |
| Marketing/Planning | 15 | | | 8am-5pm M-F |
| IT and Facilities | 8 | | | 8am-5pm M-F |
| HR | 6 | | | 8am-5pm M-F |
| Meeting Room | 25 | | | 10am-12n M W |
| | 25 | | | 2pm-4pm T Th |
| Lights | | | | |
| A/B at 32w | 192 | 18432 | 28754 | 7am-12am M-Sat |
| T at 75w | 73 | 5475 | 8541 | 7am-12am M-Sat |
| Meeting Room A/B | 10 | 960 | 200 | 10am-12n M W |
| Meeting Room A/B | 10 | 960 | 200 | 2pm-4pm T Th |
| | | | | |
| Computers | | | | |
| PC | 12 | 140 | 7358 | 24/7 |
| PC | 6 | 140 | 1966 | 8am-5pm M-F |
| Copiers | 3 | 1200 | 3120 | 7am-5pm |
| Printers | 6 | 600 | 1560 | 7am-5pm |
| | | 0 | 0 | 5pm-7pmM-F |
| FAX | 3 | 225 | 585 | 7am-5pm |
| | | 0 | 0 | 5pm-7pm |
| Other Equipment | | | | |
| | | | | |
| Refrigerator | 1 | 770 | 6745 | 24/7 |
| Microwave | 1 | 600 | 468 | 3 hours per day |
| Toaster Oven | 1 | 250 | 195 | 3 hours per day |
| Pop Cooler | 2 | 1540 | 13490 | 24/7 |

Appendix 2-2: Alvarado Transportation Center Schedule

| | Floor 2 Server Rooms | | | |
|---|---|---|---|---|
| | Quantity | Watts | kWh/yr | Sched |
| **Lights** | | | | |
| Assume Off | | 0 | 0 | 24/7 |
| | | 0 | 0 | 24/7 |
| | | 0 | | |
| **Computers** | | | | |
| Servers Room1 | 16 | 2880 | 25229 | 24/7 |
| Servers Room 2 | 6 | 1080 | 9461 | 24/7 |

| | Number | watts | kWh/yr | Schedule |
|---|---|---|---|---|
| **Outside Lights** | | | | |
| H 100w | 57 | 5700 | 20,748 | 8pm-6am 7 Days |
| J 150w | 2 | 300 | 1,092 | 8pm-6am 7 Days |
| K 150w | 2 | 300 | 1,092 | 8pm-6am 7 Days |
| L 100w | 27 | 2700 | 9,828 | 8pm-6am 7 Days |
| M 150w | 10 | 1500 | 5,460 | 8pm-6am 7 Days |

Appendix 2-2: Alvarado Transportation Other Loads

| Sh 139 | Description | HP | Notes | | Eff. | OP hrs/year | kWh/yr |
|--------|-------------|------|--------|------|-------|-------------|--------|
| AC-1 | 861,000 BTUH | | 71.75 | Tons | | | |
| AC-2 | 638,000 BTUH | | 53.17 | Tons | | | |
| 1 | Supply Fan | 40.0 | | | 0.885 | 2860 | 96,380 |
| 2 | Supply Fan | 25.0 | | | 0.885 | 8760 | 184,504 |
| 1 | Return Fan | 10.0 | | | 0.855 | 2860 | 24,941 |
| 2 | Return Fan | 7.5 | | | 0.840 | 8760 | 58,317 |
| 45 | Exhaust Fans | 0.5 | | | 0.700 | 8760 | 4,665 |
| 46 | Exhaust Fans | 0.3 | | | 0.700 | 8760 | 2,333 |
| 47 | Unit Heaters - 40 | 0.033 | | | 0.700 | 2080 | 2,954 |
| | Elevator | 3.0 | | | 0.855 | 780 | 2,041 |
| CP-1 | Circulating Pump | 2.0 | | | 0.788 | 2496 | 4,723 |
| CP-2 | Circulating Pump | 2.0 | | | 0.788 | 2496 | 4,723 |

146

Appendix 4-1: MATLAB™ Code Listing for the CNFCM Calculation

```matlab
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%
%    CNFCM_UNMBv8d.m
%    CNFCM for UNM Campus Demand Response Big FCM
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
% Set up for v8d weights  9/11/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
clear all;
close all;
clc;


%
%   Build W the causal connection  matrix (CCM)
%
ICN =  20;      %       the number of rows or columns in the CCM
%   w=(1:45)
%    1    2     3     4     5    6      7     8     9    10   11    12     13
%   14   15    16    17    18   19    20    21    22    23   24    25     26
%   27   28    29    30    31   32    33    34    35    36   37    38     39
%   40   41    42    43    44   45    46    47    48    49   50    51     52
%   53   54    55    56    57   58
w = [0.8  0.9  0.5  0.5   0.5  0.95 -0.5 -0.2 -0.5 -0.95  0.5   0.4 -
0.5...
    -0.8  0.8 -0.2 -0.3 -0.8 -0.5  0.6  0.8 -0.5  0.8 -0.2 -0.3 -0.2...
    -0.3  0.3  0.8 -0.3  0.8 -0.5 -0.3 -0.2 -0.3  0.4  0.8  0.8  0.5...
     0.5  0.8  0.5  0.5  0.8  0.5  0.5  0.8  0.2  0.2  0.5  0.5  0.3...
     0.8 -0.3 -0.8  0.5  0.5  0.5];
%
%  1     2    3    4    5     6    7     8    9   10    11     12   13   14    15
%  16   17   18   19   20
W =[0    0    0  w(5)   0    0    0     0    0    0    0     0    0    0     0
...
    0    0    0    0     0;
%  Row 1
  w(2)   0  w(1)  0 w(55) w(3)  0     0    0    0    0     0    0  w(4)   0
...
    0    0    0    0     0;
%  Row 2
    0    0    0    0     0    0    0     0    0    0    0     0  w(8) w(9)   0
...
  w(7)   0    0    0     0;
%  Row 3
    0    0  w(6)  0 w(10) w(12) w(15) 0 w(23)  0  w(31)  0    0    0     0
...
    0    0    0    0     0;
%  Row 4
    0    0    0    0     0    0    0     0    0    0    0     0    0  w(11)  0
...
```

```matlab
 w(52)  0    0    0     0;
%  Row 5
     0    0    0    0    0    0    0     0    0    0    0     0    0  w(13)  0
...
 w(54)  0    0    0     0;
%  Row 6
w(16) w(17)  0    0  w(14)  0    0   w(20)  0    0    0     0    0  w(19)  0
...
     0    0    0    0    0;
%  Row 7
     0    0    0    0    0    0    0     0    0    0    0     0    0    0  w(21)
...
     0    0    0    0    0;
%  Row 8
w(24) w(25)  0    0  w(22)  0    0     0    0  w(28)  0     0    0  w(27)  0
...
     0    0    0    0    0;
%  Row 9
     0    0    0    0    0    0    0     0    0    0    0     0    0    0  w(29)
...
     0    0    0    0    0;
%  Row 10
w(32) w(33)  0    0  w(30)  0    0     0    0     0    0  w(36)  0  w(35)  0
...
     0    0    0    0    0;
%  Row 11
     0    0    0    0    0    0    0     0    0    0    0     0    0    0  w(37)
...
     0    0    0    0  0;
%  Row 12
     0    0    0    0    0    0  w(18)   0  w(26)  0  w(34)  0    0    0     0
...
     0    0    0    0    0;
%  Row 13
     0    0    0    0    0    0    0     0    0    0    0     0    0    0     0
...
 w(48)  0    0    0     0;
%  Row 14
     0  w(49)  0    0    0    0    0     0    0    0    0     0  w(47)  0     0
...
     0    0    0    0    0;
%  Row 15
     0    0    0    0    0    0    0     0    0    0    0     0    0    0  w(51)
...
     0  w(53)  0    0    0;
%  Row 16
     0    0    0    0    0    0    0     0    0    0    0     0    0    0  w(50)
...
     0    0    0    0    0;
%  Row 17
     0  w(38)  0    0    0    0  w(56) w(39)  0    0    0     0    0    0     0
...
     0    0    0    0    0;
%  Row 18
```

```
     0 w(41) 0    0    0   0   0       0 w(57) w(42) 0      0    0  0    0
...
     0    0   0    0    0;
%  Row 19
     0 w(44) 0    0    0   0   0       0    0     0 w(58) w(45)  0  0    0
...
     0    0   0    0    0];
%  Row 20
%
%
%A0 is the initial activation vector generated randomly
%
%
A0 = 2*rand(1,ICN)-1;    %Build random numbers in the range -1 to +1
%
%   Initialize Variables
Imax = 250;    %This is the maximum number of iterations
A(1:Imax,1:ICN) = 0;
A(1,1:ICN) = A0;
index(1:Imax) = 0;
index(Imax) = Imax;
%
S(1:Imax,1:ICN) = 0;
%   d is a decay factor
d(1:ICN) = 0.1;

e(1:Imax,1:ICN) = 0;       %Indicator for the f function test
%   Build the Activation Matrix
for t=1:Imax-1
    index(t) = t;
    for i=1:ICN
        for j=1:ICN
            if i==j
                temp = 0;           % This is the corrected code
            else
                temp = A(t,j)*W(i,j);
            end
            S(t,i) = S(t,i)+temp;   % To here
        end
        if A(t,i)>=0 & S(t,i)>=0
            f(t,i) = A(t,i)+S(t,i)*(1-A(t,i));
            e(t,i) = 1;
        elseif abs(A(t,i))>1 & abs(S(t,i))>1
            f(t,i) = (A(t,i) + S(t,i))/(1-min((A(t,i)), (S(t,i))));
%abs removed
            e(t,i) = 2;
        else
            f(t,i) = A(t,i) + S(t,i)*(1+A(t,i));
            e(t,i) = 3;
        end
        A(t+1,i) = f(t,i) - d(i)*A(t,i);
    end
end
%
```

```matlab
MaxA = max(A((Imax-50):Imax,:));
MinA = min(A((Imax-50):Imax,:));
RangeA = MaxA - MinA;
for m = 1:ICN
    if RangeA(m) > 1.5        % Chaos
        Chaos(m) = 1;
    elseif RangeA(m) < 0.01 % Stable
        Chaos(m) = -1;
    else                % Limit Cycle
        Chaos(m) = 0;
    end
end
%%
%   Average the last 50 Iterations
%
%B = mean(A((Imax-50):Imax,:));
%for k=(Imax-50):Imax
%     A(k,:) = B;
%end
%%
plot(index,A,'k', 'linewidth', 1);
xlabel('Iteration Number','fontsize',16);
ylabel('Activation Level for Each Concept','fontsize',16);
title('UNM Campus Demand Response Full FCM ','fontsize',18);
%
%
```

## Appendix 4-2: GEFCM MATLAB™ Code Listing

```matlab
%
%   UNMbRv8a is the main m file (GA Runner) that runs the GA Tool irmax
times
%   This is to identify repeatability in the GEFCM calculation among
the
%   irmax runs.  Revise storage locations in 15 & 29
%
%%%   Initialize the variables for the GA Runner %%%
%
EndNote = 'The GA Runner is now done.';
ICN = 20;        %  Input, the number of concepts
Imax = 120;      %  Input, the number of repeats
nw = 58;         %  Input, the number of weights
wbr(1:Imax, 1:nw) = -2;
AIr(1:Imax, 1:ICN) = -2;
fitr(1:Imax) = -1;
save UNMbData8ac4 wbr AIr fitr
%
%   Start the GA Runner
%
for ir = 1:Imax
    UNMbI(ICN, nw, Imax)
    ir
    GAUNMb8a
    load fitnessUNMb fitness nSave W w A AImax
    load fitBchaos nChaos
    wbr(ir,:) = w;
    AIr(ir,:) = AImax;
    fitr(ir) = fitness;
    Nsave(ir)=nSave;
    Nchaos(ir)=nChaos;
    save UNMbData8ac4 wbr AIr fitr Nsave Nchaos
end
EndNote
%   EOF

function [X,FVAL,REASON,OUTPUT,POPULATION,SCORES] =  GAUNMb8a
%%   This is an auto generated M file with modifications for the UNM
Simplified FCM to do optimization with the Genetic Algorithm and
%    Direct Search Toolbox. Use GAOPTIMSET for default GA options
structure.
%       GAUNMb8a.m
% Revised 8/20/2009 DFL
%
%%Fitness function
fitnessFunction = @UNMBfitnessv8a;
%%Number of Variables
nvars = 58;
%Linear inequality constraints
Aineq = [];
Bineq = [];
%Linear equality constraints
```

151

```matlab
Aeq = [];
Beq = [];
%Bounds
LB(1:nvars) = -1;
UB(1:nvars) = +1;
%Nonlinear constraints
nonlconFunction = [];
%Start with default options
options = gaoptimset;
%%Modify some parameters
options = gaoptimset(options,'PopInitRange' ,[-1 ; 1 ]);
options = gaoptimset(options,'PopulationSize' ,20);
options = gaoptimset(options,'PlotInterval' ,10);
options = gaoptimset(options,'EliteCount' ,2 );
options = gaoptimset(options,'CrossoverFraction' ,0.95);
options = gaoptimset(options,'Generations' ,500);
options = gaoptimset(options,'FitnessLimit' ,5e-10);
options = gaoptimset(options,'StallGenLimit' ,150);
options = gaoptimset(options,'StallTimeLimit' ,500);
options = gaoptimset(options,'TolFun' ,0);
options = gaoptimset(options,'TolCon' ,1e-007);
options = gaoptimset(options,'MutationFcn' ,@mutationadaptfeasible);
%options = gaoptimset(options,'Display' ,'off');
options = gaoptimset(options,'PlotFcns' ,{ @gaplotbestf @gaplotrange
});
%%Run GA
[X,FVAL,REASON,OUTPUT,POPULATION,SCORES] =
ga(fitnessFunction,nvars,Aineq,Bineq,Aeq,Beq,LB,UB,nonlconFunction,opti
ons);


function fitness = UNMBfitnessv8a(w)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%UNM Simplified Fitness Function
%
%   Fitness Function for UNM Campus Demand Response Big FCM
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
% w = w(1) to w(58)      UNMBigData  revision 8/20/2009 DFL Partial
% nChaos tracking on
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%   Initialize Variables
Imax = 250;   %This is the maximum number of iterations
ICN =  20;    %    the number of rows or columns in the CCM
%    nSave counts the number of fitness improvements
load fitnessUNMb fitness nSave;   %load the best fitness so far
load fitBchaos nChaos;
fitness_old = fitness;       % save it for testing the latest value
fitness = 0;
%   Based on CNFCM and original weight assignments
```

```
Adesired = [0.8 0.94 0.82 0.72 0.65 0.95 -0.17 0 0 0  0 0.7 0  0  0 ...
             0   0   0.8  0.8  0.8];
%            1     2    3    4    5    6    7  8 9 10 11 12 13 14 15
%            16   17   18   19   20
%
%
%   Build W the causal connection  matrix (CCM)
%~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
~~~~
%
%~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
~~~~
%
%                           Columns
%   1   2    3    4   5    6    7    8    9    10   11    12   13   14   15 16
17
%
%   1    2    3    4    5    6    7    8    9    10    11    12    13    14    15
%   16   17   18   19   20
W =[0    0    0  w(5)  0    0    0    0    0    0     0     0     0     0     0
...
     0    0    0    0    0;
%   Row 1
  w(2)  0  w(1)  0 w(55) w(3)  0    0    0    0     0     0     0  w(4)   0
...
     0    0    0    0    0;
%   Row 2
     0    0    0    0    0    0    0    0    0    0     0     0  w(8) w(9)   0
...
  w(7)   0    0    0    0;
%   Row 3
     0    0  w(6)  0 w(10) w(12) w(15) 0 w(23)  0   w(31)   0     0     0     0
...
     0    0    0    0    0;
%   Row 4
     0    0    0    0    0    0    0    0    0    0     0     0     0  w(11)  0
...
 w(52)   0    0    0    0;
%   Row 5
     0    0    0    0    0    0    0    0    0    0     0     0     0  w(13)  0
...
 w(54)   0    0    0    0;
%   Row 6
w(16) w(17)  0    0  w(14)  0    0  w(20)  0    0     0     0     0  w(19)  0
...
     0    0    0    0    0;
%   Row 7
     0    0    0    0    0    0    0    0    0    0     0     0     0    0 w(21)
...
     0    0    0    0    0;
%   Row 8
w(24) w(25)  0    0  w(22)  0    0    0    0  w(28)  0     0     0  w(27)  0
...
```

153

```matlab
      0    0    0    0     0;
%  Row 9
      0  0    0      0     0    0     0      0   0      0    0      0    0    0 w(29)
...
      0  0    0    0     0;
%  Row 10
w(32) w(33) 0    0  w(30) 0     0      0   0      0    0  w(36)  0  w(35)  0
...
      0  0    0    0     0;
%  Row 11
      0  0    0    0     0    0     0      0   0      0    0      0    0    0 w(37)
...
      0  0    0     0  0;
%  Row 12
      0  0    0    0     0    0  w(18)    0 w(26)    0  w(34)  0    0    0      0
...
      0  0    0    0     0;
%  Row 13
      0  0    0    0     0    0     0      0   0      0    0      0    0    0      0
...
 w(48) 0    0    0     0;
%  Row 14
      0 w(49) 0    0     0    0     0      0   0      0    0      0 w(47) 0      0
...
      0  0    0    0     0;
%  Row 15
      0  0    0    0     0    0     0      0   0      0    0      0    0    0 w(51)
...
      0 w(53) 0    0     0;
%  Row 16
      0  0    0    0     0    0     0      0   0      0    0      0    0    0 w(50)
...
      0  0    0    0     0;
%  Row 17
      0 w(38) 0    0     0    0 w(56) w(39)  0      0    0      0    0    0      0
...
      0   0    0    0     0;
%  Row 18
      0 w(41) 0    0     0    0     0      0 w(57) w(42) 0      0    0    0      0
...
      0  0    0    0     0;
%  Row 19
      0 w(44) 0    0     0    0     0      0   0      0 w(58) w(45)  0    0    0
...
      0   0    0    0     0];
%  Row 20
%
%
%A0 is the initial activation vector
%
%Build the initial activation vector of random numbers in the range -1
to 1
A0 = 2*rand(1,ICN)-1;
%
```

```
A(1:Imax,1:ICN) = 0;
A(1,1:ICN) = A0;
index(1:Imax) = 0;
index(Imax) = Imax;
%
S(1:Imax,1:ICN) = 0;
%   d is a decay factor
d(1:ICN) = 0.1;
%
%   Build the Activation Matrix
for t=1:Imax-1
    index(t) = t;
    for i=1:ICN
        for j=1:ICN
            if i==j
                temp = 0;              % This is the corrected code
            else
                temp = A(t,j)*W(i,j);
            end
            S(t,i) = S(t,i)+temp;    % To here
        end
            if A(t,i)>=0 & S(t,i)>=0
                f(t,i) = A(t,i)+S(t,i)*(1-A(t,i));
            elseif abs(A(t,i))>1 & abs(S(t,i))>1
                f(t,i) = (A(t,i) + S(t,i))/(1-min((A(t,i)), (S(t,i))));
%abs removed
            else
                f(t,i) = A(t,i) + S(t,i)*(1+A(t,i));
            end
        A(t+1,i) = f(t,i) - d(i)*A(t,i);
    end
end
%
%
%   Determine if the A is Chaos (1), Stable (-1), or Limit Cycle (0).
%
%
MaxA = max(A((Imax-50):Imax,:));
MinA = min(A((Imax-50):Imax,:));
RangeA = MaxA - MinA;
for m = 1:ICN
    if RangeA(m) > 1.5      % Chaos
        Chaos(m) = 1;
    elseif RangeA(m) < 0.01 % Stable
        Chaos(m) = -1;
    else             % Limit Cycle
        Chaos(m) = 0;
    end
end
%
%   Average the last 50 Iterations
%
B = mean(A((Imax-50):Imax,:));
for k=(Imax-50):Imax
```

155

```matlab
    A(k,:) = B;
end
%
AImax(1:ICN)=A(Imax,1:ICN);
%
%This section records and does not store if any of the ICN values are
Chaos
cc=0;
for n=1:ICN
    if Chaos(n)>=1;
        cc = 1;
    else
    end
end
if cc >= 1;
    nChaos = nChaos + 1;
    save fitBchaos nChaos
else
end
%
%   Calculate the fitness value for the GA Tool - Square root of the
sum of
%   the squares
%
fitness = sqrt((A(Imax,4)-Adesired(4))^2 + (A(Imax,1)-Adesired(1))^2
...
        + (A(Imax,2)-Adesired(2))^2+(A(Imax,18)-Adesired(18))^2 ...
        + (A(Imax,19)-Adesired(19))^2+(A(Imax,20)-Adesired(20))^2);
%   Only save the best fitness if not chaotic
if cc < 1
    %   Save the best fitness value
    if (fitness_old - fitness)>0
        nSave = nSave + 1;
        save fitnessUNMb fitness nSave W w A AImax;
    else
    end
else
end
save CHAOS nChaos;
%
%   EOF
```

Appendix 4-3: Clustering MATLAB™ Code Listing

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%   UNMs K Means Clustering - Main Program
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%   Save in MATLAB in My Documents - UNMbKMrepeat.m
%
%       DFL 9/9/2009
%
%   This routine runs the K Means Clustering maxR times and saves the
best
%   cluster center for each(lowest SUMD/CountIDX).  Then the function
%   (FindKMrepeats) returns the most repeat values (ircnt) in
CenterBest.
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
clear all;
close all;
clc;
nPlot = 1;   %   1 plot; 0 do not plot Center Best and all members
nRC = 3;     %The concept to test for repeats
ICN = 20;    %The number of concepts
nw = 58;     %The number of weights
K = 16; % The number of clusters
irmax = 120;    %   The number of data sets (points)
w = 0.25;    %Cleaner factor such that fitr>w are eliminated
maxR = 50;   %Number of identical repeats of the K Means Clustering
ep = .00005;       %delta for equality of cluster centers
load UNMbData8ac4 wbr AIr fitr
%
%   Cleaning Routine for fitr > w; nirmax is the new number of data
points
[UseAIr, fitrn, iPlace, nirmax] = Cleaner(AIr, fitr, ICN, irmax, w);
%
X = UseAIr;
%Calculate Cluster Information
for k=1:maxR
    [IDX,C,SUMD] = kmeans(X,K,'emptyaction','singleton');   %no error
on empty cluster
%   Keep track of the original UNMsData location in
%                          iPos(1:maxR,1:2,1:nirmax).
    iPos(k,1,1:nirmax) = iPlace;
    iPos(k,2,1:nirmax) = IDX;
%   Count how many data sets in each cluster (CountIDX)
    CountIDX(1:K) = 0;
    for ik = 1:K
     for jk = 1:nirmax
        if IDX(jk) == ik
            CountIDX(ik) = CountIDX(ik)+1;
        else
```

157

```matlab
            end
         end
      end
%   Calc the distance error per data set (point) in each cluster
      for i = 1:K
          ErrorD(i) = SUMD(i)/CountIDX(i);
          %          ErrorD is zero for a cluster with 1 member
          if CountIDX(i) == 1
              ErrorD(i)=10;
          else
          end
      end
%
%   Test for smallest ErrorD and save it (Cent, CountIDX, number)
%
      ErD(k) = min(ErrorD);        % based on ErrorD
       for i=1:K
          if CountIDX(i) > 1
          if abs(ErD(k)-ErrorD(i))<ep
              N(k) = i;
              NumM(k)=CountIDX(i);
          else
          end
          else
          end
      end
      Cent(k,1:ICN) = C(N(k),1:ICN);
      CIDX(k,1:K)=CountIDX(1:K);
end
[RCnbest, indx, mcnt, CenterBest, ircnt, indC] =...
    FindKMrepeats(maxR, ep, Cent, ICN, nRC);
save UNMsKMdata
K            % Number of clusters
CenterBest   %Average of all members of the best cluster
ircnt        %Number of repeats that repeat the most
Error=ErD(indC)   %Error in the most repeated set
indC         %Location in 1:maxR of the last best(most) repeat
nCluster=NumM(indC)      %Number of members in CenterBest
RCnbest      %The value of each Cn that repeated
mcnt         %Number of times RC2best repeated
%   Plot the Center Best and its members if nPlot = 1
if nPlot == 1
      %   Keep track original UNMsData entries that form this best
cluster
      index=1;
      for i=1:nirmax
          if iPos(indC,2,i) == N(indC)
              %   array has the kth values for the best cluster members
              %   in UNMsData
              array(index) = iPos(indC,1,i);
              index=index+1;
          else
          end
      end
```

158

```matlab
    icntBC = index-1;      %The number of data sets in UNMsData that make
                           %    up the best center
    for i=1:icntBC
        n=array(i);
        AIrCB(i,1:ICN) = AIr(n,:);    %contains all of the members of CB cluster
        w(i,1:nw) = wbr(n,:);
    end
    iICN(1:ICN)=[1:ICN];
    iw(1:nw)=[1:nw];
    AIrCBT = AIrCB';           % Transpose issue only if matrix is square
    %    Plot the best cluster data and centers
    plot(iICN,AIrCBT,iICN,CenterBest,'ko-')    %Black circle and line thru centers
    xlabel('Concept Number','fontsize',16);
    axis([1 ICN -1 +1])
    ylabel('Actual Concept Values for the Cluster Member','fontsize',16);
    title('UNM Campus DR Cluster  K=14 C1=0.80 C2=0.94 C4=0.82 C18=0.80 C19=-0.2 C20=-0.80','fontsize',16);
else
end


%   EOF



function [UseAIr, fitrn, iPlace, nirmax]= Cleaner(AIr, fitr, ICN, irmax, w)
%   Cleaning Routine for fitr > w; nirmax is the new number of data points
%   Cleans the spikes (>w) from the data
%   Used in K Means Clustering of the GEFCM runs
%   UseAIr(nirmax,ICN); fitrn(nirmax); nirmax is number of cleaned elements
%   AIr(irmax,ICN); fitr(irmax); w is shown above.
%   ICN number of concepts, irmax number of identical runs of the GEFCM.
%   iPlace(1:nirmax) tracks the original location of the ICN data set.
%   DFL 3/7/2009
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ic = 0;
nirmax=irmax;
for ir = 1:irmax
    ip(ir)=ir;
    if abs(fitr(ir))>w
        ic=ic+1;
        bad(ic)=ir;
    else
    end
end
for iclean=1:ic
    i=bad(iclean)-(iclean-1);
```

```matlab
        for n=i:(nirmax-1);
            AIr(n,1:ICN)=AIr((n+1),1:ICN);
            fitr(n)=fitr(n+1);
            ip(n) = ip(n+1);
        end
        nirmax = nirmax-1;
    end
%   The data is cleaned of fitr>w and has only nirmax elements
%
%   Build data arrays based on the new number of data points.
    for n=1:nirmax;
        fitrn(n)=fitr(n);
        UseAIr(n,1:ICN) = AIr(n,1:ICN);
        iPlace(n)=ip(n);
    end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%   Plot the new fitr(nirmax) to test code
%for i = 1:nirmax
%    Irun(i) = i;
%end
%    plot(Irun, fitrn)
%    axis([1 nirmax 0 1]);
%    xlabel('Run Number');
%    ylabel('Fitness for Each Run');
%    title(['UNM Campus Demand Response Simplified - Fitness Cleaned
']);
%   function EOF

function [RCnbest, indx, mcnt, CenterBest, ircnt, indC] =...
    FindKMrepeats(maxR,ep,Cent,ICN,nRC)

%   Find and return (UNMbKMrepeat.m) the repeat values where:
%       RCnbest(indx) - all Cn repeat values
%       mcnt number of repeats (also indx)
%           If mcnt(1) = 1 then no repeats.
%           Check mcnt manually to determine if multiple
repeats!!!!!!!!!
%       CenterBest(ICN) - most repeats (only if no duplicate repeats)
%       ircnt number of CenterBest repeats
%       indC - location in the 1:maxR runs of the last most repeats
(maybe)
%   The inputs are:
%       maxR - number of K Means runs with identical input
%       ep - test value for repeats (0.0001) typically
%       Cent - results of the repeat K Means runs
%       nRC - the concept to use for repeats
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%
%           DFL 7-22-2009
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
```

```matlab
%   Build m(maxR) the vector with the match(<ep) numbers or 0 if no
match
mrep=fix(maxR/2);    %max number of repeats
Cn = Cent(1:maxR,nRC);
m(1:maxR) = 0;
for j=1:maxR
    for i=(j+1):maxR
        if m(i)==0
        if abs(Cn(j) - Cn(i)) < ep
            m(i) = j;
        else
        end
        else
        end
        for n=j:maxR
            if m(n)==j
                m(j)=j;
            else
            end
        end
    end
end
%   Build mnew(maxR), ordering m sequencially and C2 also
mnew=m;
for j=1:maxR
    for i=1:(maxR-1)
        if mnew(i)>mnew(i+1)
            miold=mnew(i);
            mipold=mnew(i+1);
            mnew(i)=mipold;
            mnew(i+1)=miold;
            Cniold=Cn(i);
            Cnipold=Cn(i+1);
            Cn(i) = Cnipold;
            Cn(i+1) = Cniold;
        else
        end
    end
end
%
%   This Section builds RCC(indx) the repeating cluster centers from
most
%   to least where indx is the number of repeating centers
%   and mcnt(indx) # repeats.
indx = 1;        %-----
mcnt(1)=1;       %----- Initialize these 4 in case no repeats
indmr=1;         %-----
indC=1;          %-----
icntemp=0;
CC(1:mrep) = 2;
for j=1:(maxR-1)
    icnt = 1;
    iskip = 0;
    for in=1:indx
```

161

```
            if abs(Cn(j)-CC(in))<ep
                iskip = 1;
            else
            end
        end
        if iskip ~= 1
            if mnew(j)~=0
                for k=(j+1):maxR
                    if abs(Cn(j)-Cn(k))<ep
                        icnt=icnt+1;
                        CC(indx) = Cn(k);
                    else
                    end
                end
                if icnt~=1
                    mcnt(indx) = icnt;
                    indx=indx+1;
                else
                end
            else
            end
        else
        end
    end
    mr = max(mcnt);
    indx=indx-1;
    RCnbest(1)=2;        %Initialize in case no repeats
    for i=1:indx
        RCnbest(i) = CC(i);
        if mr == mcnt(i)
            indmr = i;
        else
        end
    end
    Cnbest = RCnbest(indmr);
    ircnt=0;
    for i=1:maxR
        if abs(Cent(i,nRC)-Cnbest)<ep
            ircnt=ircnt+1;
            indC = i;
        else
        end
    end
    CenterBest(1:ICN) = Cent(indC,1:ICN);
    %       The most repeated cluster center is "CenterBest"
    %       The number of repeats for the CenterBest is "ircnt"
    %   There is no code to test for duplicate quantities of repeats.
    %   Should test this and find the one with lowest ErrorD value.
    %   EOF
```

Appendix 5-1: Facilities in the DR Control System

| # | Bldg # | Building | SF | # | Bldg # | Building | SF |
|---|--------|----------|----|---|--------|----------|----|
| 1 | 157 | Alvarado | 40,896 | 36 | 81 | Humanities | 70,859 |
| 2 | 76 | Anderson School of M | 46,406 | 37 | 59 | Johnson Gym | 324,202 |
| 3 | 12 | Anthropology Annex | 9,614 | 38 | 115 | Journalism | 31,897 |
| 4 | 11 | Anthro Maxwell Musm | 53,461 | 39 | 77 | La Posada | 40,354 |
| 5 | 84 | Art Building | 76,876 | 40 | 74 | Laguna | 43,901 |
| 6 | 16 | Bandelier Hall West | 15,073 | 41 | 34 | Logan Hall | 50,868 |
| 7 | 211 | Basic Med Science | 175,613 | 42 | 122 | M E Building | 70,263 |
| 8 | 19 | Biology Annex | 8,269 | 43 | 9 | Marron Hall | 19,962 |
| 9 | 253 | Biomedical Researchx | 109,575 | 44 | 56 | Mesa Vista Hall | 111,870 |
| 10 | 218 | Bratton Hall | 158,622 | 45 | 23 | Mitchell Hall | 46,965 |
| 11 | 229 | CR Facility | 81,723 | 46 | 102 | New Bookstore | 46,867 |
| 12 | 227 | Cancer RT Center | 107,696 | 47 | 230 | New Mexico Law Center | 8,398 |
| 13 | 4 | Carlisle Gym | 31,270 | 48 | 193 | New Residence | 123,040 |
| 14 | 21 | Castetter-Potter | 114,642 | 49 | 60 | NM SUB | 146,100 |
| 15 | 83 | Ceria | 70,700 | 50 | 24 | Northrop Hall | 75,746 |
| 16 | 22 | Clark-Reibsomer Hall | 81,696 | 51 | 228 | Nursing & Pharmacy | 96,050 |
| 17 | 153 | Computing Cntr CIRT | 46,503 | 52 | 156 | Onate Hall | 40,961 |
| 18 | 198 | Cornell Parking | 3,600 | 53 | 79 | Ortega Hall | 66,109 |
| 19 | 155 | Coronado | 93,860 | 54 | 207 | Physics & Astronomy | 64,215 |
| 20 | 48 | Dane Smith Hall | 97,776 | 55 | 35 | Regener Hall | 23,077 |
| 21 | 75 | De Vargas | 43,976 | 56 | 88 | S R C | 126,750 |
| 22 | 249 | Dental Programs | 27,976 | 57 | 71 | Santa Ana | 41,615 |
| 23 | 46 | E E C E  CSEL | 178,987 | 58 | 61 | Santa Clara | 39,751 |
| 24 | 57 | Economics | 21,766 | 59 | 10 | Scholes Hall | 49,210 |
| 25 | 65 | Education Complex | 129,946 | 60 | 78 | Social Sciences | 32,569 |
| 26 | 248 | Family Practice | 58,213 | 61 | 73 | Student Health Facility | 42,853 |
| 27 | 119 | Farris Engineering | 75,369 | 62 | 85 | Student Services | 96,834 |
| 28 | 62 | Fine Art C & Library | 175,362 | 63 | 82 | Woodward Hall | 39,622 |
| 29 | 87 | Parish Library | 53,856 | 64 | 53 | Zimmerman Library | 239,926 |
| 30 | 266 | Health Sci & Serv | 57,760 | 65 | 72 | Popejoy Hall | 71,553 |
| 31 | 234 | Health Sci Library | 65,804 | 66 | 183 | Lobo Center | 70,000 |
| 32 | 15 | Hibben | 37,565 | 67 | 205 | RIB | 29,164 |
| 33 | 103 | Hodgin Hall | 16,511 | 68 | 338 | CHTM | 60,000 |
| 34 | 58 | Hokona | 78,365 | 69 | 331 | Crystal Growth Facility | 5,110 |
| 35 | 20 | Human Resources | 10,384 | | | | |

| | |
|---|---|
| Total Area, sq. ft. | 4,902,372 |
| Average Area, sq. ft. | 71,049 |

Appendix 5-2: Facility Population for Each Potential DR Hour

| # | Bldg # | 12:00 | 1:00 | 2:00 | 3:00 | 4:00 | 5:00 | 6:00 | # | Bldg # | 12:00 | 1:00 | 2:00 | 3:00 | 4:00 | 5:00 | 6:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 157 | L | L | L | L | M | M | H | 36 | 81 | L | L | L | H | S | M | L |
| 2 | 76 | H | M | H | H | L | L | L | 37 | 59 | L | L | L | L | M | M | H |
| 3 | 12 | L | L | L | H | S | M | L | 38 | 115 | H | M | H | H | L | L | L |
| 4 | 11 | L | L | L | L | L | L | L | 39 | 77 | S | H | M | L | L | M | S |
| 5 | 84 | L | M | M | M | L | L | L | 40 | 74 | L | L | L | H | S | M | L |
| 6 | 16 | H | M | H | H | L | L | L | 41 | 34 | H | M | M | S | H | L | M |
| 7 | 211 | H | M | M | S | H | L | M | 42 | 122 | H | M | H | H | L | L | L |
| 8 | 19 | L | L | M | L | L | M | H | 43 | 9 | L | L | L | H | S | M | L |
| 9 | 253 | L | L | M | L | L | M | H | 44 | 56 | H | M | H | H | L | L | L |
| 10 | 218 | H | M | H | H | L | L | L | 45 | 23 | L | L | L | H | S | M | L |
| 11 | 229 | L | L | M | L | L | M | H | 46 | 102 | L | L | L | L | L | L | L |
| 12 | 227 | L | L | M | L | L | M | H | 47 | 230 | L | L | L | L | L | L | L |
| 13 | 4 | L | L | L | L | M | M | L | 48 | 193 | L | L | L | L | M | M | H |
| 14 | 21 | H | M | M | S | H | L | M | 49 | 60 | S | H | M | L | L | M | S |
| 15 | 83 | H | M | M | S | H | L | M | 50 | 24 | L | L | M | L | L | M | H |
| 16 | 22 | H | M | M | S | H | L | M | 51 | 228 | L | L | M | L | L | M | H |
| 17 | 153 | L | L | L | L | L | L | L | 52 | 156 | H | M | H | H | L | L | L |
| 18 | 198 | L | L | L | L | L | L | L | 53 | 79 | L | L | L | H | S | M | L |
| 19 | 155 | L | L | L | L | M | M | H | 54 | 207 | H | M | M | S | H | L | M |
| 20 | 48 | H | M | H | H | L | L | L | 55 | 35 | L | L | L | L | M | M | H |
| 21 | 75 | L | L | L | L | M | M | H | 56 | 88 | L | L | L | L | M | M | H |
| 22 | 249 | H | M | H | H | L | L | L | 57 | 71 | L | L | L | L | M | M | H |
| 23 | 46 | L | L | L | H | S | M | L | 58 | 61 | L | L | L | L | M | M | H |
| 24 | 57 | H | M | H | H | L | L | L | 59 | 10 | H | M | H | H | L | L | L |
| 25 | 65 | L | L | L | H | S | M | L | 60 | 78 | L | L | L | H | S | M | L |
| 26 | 248 | L | L | L | L | M | M | H | 61 | 73 | H | M | H | H | L | L | L |
| 27 | 119 | H | M | M | S | H | L | M | 62 | 85 | L | L | L | H | S | M | L |
| 28 | 62 | L | L | L | L | L | L | L | 63 | 82 | L | L | L | L | M | M | H |
| 29 | 87 | L | L | L | L | L | L | L | 64 | 53 | L | L | L | L | L | L | L |
| 30 | 266 | L | L | L | L | M | M | H | 65 | 72 | L | L | L | L | M | M | L |
| 31 | 234 | L | L | L | L | L | L | L | 66 | 183 | L | L | L | L | M | M | L |
| 32 | 15 | L | L | L | L | L | L | L | 67 | 205 | H | M | M | S | H | L | M |
| 33 | 103 | H | M | H | H | L | L | L | 68 | 338 | H | M | M | S | H | L | M |
| 34 | 58 | L | L | L | L | L | L | L | 69 | 331 | L | L | L | L | L | L | L |
| 35 | 20 | H | M | H | H | L | L | L | | | | | | | | | |

Appendix 5-3: Facility Lighting and Temperature Power Reduction

| # | Bldg # | Lighting kW Red. | 76F kW Reduce | 78F kW Reduce | 80F kW Reduce | # | Bldg # | Lighting kW Red. | 76F kW Reduce | 78F kW Reduce | 80F kW Reduce |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 157 | 18.0 | 25.7 | 130.9 | 77.0 | 36 | 81 | 31.2 | 44.5 | 89.0 | 133.5 |
| 2 | 76 | 20.4 | 29.1 | 58.3 | 87.4 | 37 | 59 | 142.6 | 203.6 | 407.2 | 610.8 |
| 3 | 12 | 4.2 | 6.0 | 12.1 | 18.1 | 38 | 115 | 14.0 | 20.0 | 40.1 | 60.1 |
| 4 | 11 | 23.5 | 33.6 | 67.1 | 100.7 | 39 | 77 | 17.8 | 25.3 | 50.7 | 76.0 |
| 5 | 84 | 33.8 | 48.3 | 96.6 | 144.8 | 40 | 74 | 19.3 | 27.6 | 55.1 | 82.7 |
| 6 | 16 | 6.6 | 9.5 | 18.9 | 28.4 | 41 | 34 | 22.4 | 31.9 | 63.9 | 95.8 |
| 7 | 211 | 77.3 | 110.3 | 220.6 | 330.9 | 42 | 122 | 30.9 | 44.1 | 88.3 | 132.4 |
| 8 | 19 | 3.6 | 5.2 | 10.4 | 15.6 | 43 | 9 | 8.8 | 12.5 | 25.1 | 37.6 |
| 9 | 253 | 48.2 | 68.8 | 137.6 | 206.4 | 44 | 56 | 49.2 | 70.3 | 140.5 | 210.8 |
| 10 | 218 | 69.8 | 99.6 | 199.2 | 298.8 | 45 | 23 | 20.7 | 29.5 | 59.0 | 88.5 |
| 11 | 229 | 36.0 | 51.3 | 102.6 | 154.0 | 46 | 102 | 20.6 | 29.4 | 58.9 | 88.3 |
| 12 | 227 | 47.4 | 67.6 | 135.3 | 202.9 | 47 | 230 | 3.7 | 5.3 | 10.5 | 15.8 |
| 13 | 4 | 13.8 | 19.6 | 39.3 | 58.9 | 48 | 193 | 54.1 | 77.3 | 154.5 | 231.8 |
| 14 | 21 | 50.4 | 72.0 | 144.0 | 216.0 | 49 | 60 | 64.3 | 91.8 | 183.5 | 275.3 |
| 15 | 83 | 31.1 | 44.4 | 88.8 | 133.2 | 50 | 24 | 33.3 | 47.6 | 95.1 | 142.7 |
| 16 | 22 | 35.9 | 51.3 | 102.6 | 153.9 | 51 | 228 | 42.3 | 60.3 | 120.6 | 181.0 |
| 17 | 153 | 20.5 | 29.2 | 58.4 | 87.6 | 52 | 156 | 18.0 | 25.7 | 51.4 | 77.2 |
| 18 | 198 | 1.6 | 2.3 | 4.5 | 6.8 | 53 | 79 | 29.1 | 41.5 | 83.0 | 124.5 |
| 19 | 155 | 41.3 | 58.9 | 117.9 | 176.8 | 54 | 207 | 28.3 | 40.3 | 80.7 | 121.0 |
| 20 | 48 | 43.0 | 61.4 | 122.8 | 184.2 | 55 | 35 | 10.2 | 14.5 | 29.0 | 43.5 |
| 21 | 75 | 19.3 | 27.6 | 55.2 | 82.9 | 56 | 88 | 55.8 | 79.6 | 159.2 | 238.8 |
| 22 | 249 | 12.3 | 17.6 | 35.1 | 52.7 | 57 | 71 | 18.3 | 26.1 | 52.3 | 78.4 |
| 23 | 46 | 78.8 | 112.4 | 224.8 | 337.2 | 58 | 61 | 17.5 | 25.0 | 49.9 | 74.9 |
| 24 | 57 | 9.6 | 13.7 | 27.3 | 41.0 | 59 | 10 | 21.7 | 30.9 | 61.8 | 92.7 |
| 25 | 65 | 57.2 | 81.6 | 163.2 | 244.8 | 60 | 78 | 14.3 | 20.5 | 40.9 | 61.4 |
| 26 | 248 | 25.6 | 36.6 | 73.1 | 109.7 | 61 | 73 | 18.9 | 26.9 | 53.8 | 80.7 |
| 27 | 119 | 33.2 | 47.3 | 94.7 | 142.0 | 62 | 85 | 42.6 | 60.8 | 121.6 | 182.4 |
| 28 | 62 | 77.2 | 110.1 | 220.3 | 330.4 | 63 | 82 | 17.4 | 24.9 | 49.8 | 74.6 |
| 29 | 87 | 23.7 | 33.8 | 67.6 | 101.5 | 64 | 53 | 105.6 | 150.7 | 301.3 | 452.0 |
| 30 | 266 | 25.4 | 36.3 | 72.5 | 108.8 | 65 | 72 | 31.5 | 44.9 | 89.9 | 134.8 |
| 31 | 234 | 29.0 | 41.3 | 82.6 | 124.0 | 66 | 183 | 30.8 | 44.0 | 87.9 | 131.9 |
| 32 | 15 | 16.5 | 23.6 | 47.2 | 70.8 | 67 | 205 | 12.8 | 18.3 | 36.6 | 54.9 |
| 33 | 103 | 7.3 | 10.4 | 20.7 | 31.1 | 68 | 338 | 26.4 | 37.7 | 75.4 | 113.0 |
| 34 | 58 | 34.5 | 49.2 | 98.4 | 147.6 | 69 | 331 | 2.2 | 3.2 | 6.4 | 9.6 |
| 35 | 20 | 4.6 | 6.5 | 13.0 | 19.6 | | | | | | |

## Appendix 5-4: DR Control System MATLAB™ Code Listing

```matlab
%
%   DR_Controller.m
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%   This builds the control scheme for each facility for each hour for
%   the DR event.
%
%   DFL 9/7/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
clear all;
clc;
%  Call the function, DRCinput, that establishes the DR event input
values
%  as follows:
%       PDR – Desired reduction in power, -1 indicates the maximum
%             achievable
%       nmax – maximum number of facilities in FacilityData.xls
%       hstart – Start time of the first hour of the DR event
%       hend – Start time of the last hour of the DR event
%       h – Potential number of hours in the DR event - 7 hours
[PDR, nmax, hstart, hend, h] = DRCinput;
%
%       Call the function, DRCtables, that unloads the table
information
%       from the excel spreadsheet, FacilityData.xls, and saves it in
%       FacData.mat as follows:
%           Fpop(nmax, h+1) - Facility population table
%           FT(nmax, 3) – Facility identification table
%           FacT(nmax, 7) - Facility control table
%           PLavail(1:nmax) - The maximum lighting reduction available
from
%           each facility
%       This only needs to run if there have been changes to
%       FacilityData.xls since the last run that built FacData.mat.
%
DRCtables;
%
%       Get the DR control data tables in mat file FacData.mat
load FacData
%
%           the control logic
%   Initialize variables
PrelimSP(1:nmax,1:h) = 74;   %Intermediate storage table
PrelimSP(1:nmax,(h+1):2*h) = 0;      %ditto
PmaxLSP(1:h) = 0;                %maximum power reduction available
PplanFac(1:nmax,1:h)=0;          %Reduction for each facility each hour
PplanLSP(1:h) = 0;               %planned power reduction for the requested
PDR
Lindex(1:nmax,1:h)=0;            %Low pop index for facility and hour
```

```matlab
Mindex(1:nmax,1:h)=0;          %Medium pop index for facility and hour
Hindex(1:nmax,1:h)=0;          %High pop index for facility and hour
PmaxL(1:h)=0;                  %Low pop facility max power reduction
PmaxM(1:h)=0;                  %Medium pop facility max power reduction
50
PmaxH(1:h)=0;                  %High pop facility max power reduction
FDRT(1:nmax,h+1:2*h)=74;       %Initial temp set points for facilities in
DR
FDRT(1:nmax,1:h)=0;            %Initial power reduction for facilities in
DR
PLindex(1:nmax)=0;             %Lighting reduction index for each facility
PLmax(1:h)=0;                  %Maximum lighting power reduction
PLskip(1:nmax,1:h)=0;          %Lighting reduction even if Set Point is
skip
PLplan=0;                      %planned lighting power reduction - only
LrandFac(1:nmax)=0;            %Random fac seq number for lighting redctn
SPLrandFac(1:nmax)=0;          %Random fac seq number for low pop temp
redctn
SPMrandFac(1:nmax)=0;          %Random fac seq number for med pop temp
redctn
SPHrandFac(1:nmax)=0;          %Random fac seq number for high pop temp
redctn
finished=0;                    %Flag so max reduction not repeated if
PDR~=-1

%63
%   Build the start and end variables based on the start time and last
%   hour time from the input values from the DRCinput function.
switch hstart
    case '12:00'
        hs=1;
    case '1:00'
        hs=2;
    case '2:00'
        hs=3;
    case '3:00'
        hs=4;
    case '4:00'
        hs=5;
    case '5:00'
        hs=6;
    case '6:00'
        hs=7;
    otherwise
end
switch hend
    case '12:00'
        he=1;
    case '1:00'
        he=2;
    case '2:00'
        he=3;
    case '3:00'
        he=4;
```

167

```matlab
    case '4:00'
        he=5;
    case '5:00'
        he=6;
    case '6:00'
        he=7;
    otherwise
end
%
100
%   Fuction to set up random facility selection table,
RFacList(1:nmax),
%   for those situations where all facilities do not need to reduce
lighting
%   or thermostat set points.
[RFacList, noRepeats] = FacRandomizer(nmax);
%
Naction(1:h) = -1;
%   Naction(h) = 1  lighting reduction sufficient
%                2  lighting and temperature reduction sufficient
%                3  maximum reduction
%

    PLightMax=0;
    PLtemp(1:nmax)=0;
    %   Calc maximum power available from facilities in DR event
    %   Store amount available from each facility, 0 if not
participating
        for i=1:nmax
            if FacT(i,2) == 1
                PLightMax = PLightMax + PLavail(i);
                PLtemp(i)=PLavail(i);
            else
            end
        end
%-----------------------------------------------------------------------
---
%   Check each facility controllers to determine the level of light
energy
%   reduction that is achievable and return in PLachiev(1:nmax).
[PLachieve] = FacLightRed(PLtemp, nmax);
PLacvT = sum(PLachieve);
if PLacvT < PLightMax
    PLightMax = PLacvT;
    PLtemp=PLachieve;
else
end
%
%-----------------------------------------------------------------------
---
        PLmax(hs:he)=2*PLightMax;
    %
%
```

```
%~~~~~~~~~~~~~~~~~~if PDR = -1 do maximum
reduction~~~~~~~~~~~~~~~~~~~~~~~
%
if PDR >= 0          %   end 325
    %   reduce lighting and maybe temperatures
    %
    PLightMax2=PLightMax*2; %Both electricity and heat reduce
    if PLightMax2 < PDR      %   end 281
    %
      %------Determine max power reduction from temperature set points-
---
        for n = hs:he
            for i = 1:nmax
                if FacT(i,3) == 1   %   Eliminate the non-participants
                 switch Fpop(i,n)
%150
                       case 'L'
                           PrelimSP(i,n) = 80;
                           PrelimSP(i,(n+h)) = FacT(i,7);
                           PmaxL(n) = PmaxL(n)+FacT(i,7);
                       case 'M'
                           PrelimSP(i,n) = 78;
                           PrelimSP(i,(n+h)) = FacT(i,6);
                           PmaxM(n) = PmaxM(n)+FacT(i,6);
                       case 'H'
                           PrelimSP(i,n) = 76;
                           PrelimSP(i,(n+h)) = FacT(i,5);
                           PmaxH(n) = PmaxH(n)+FacT(i,5);
                       case 'S'
                           if FacT(i,2) == 1
                               PLskip(i,n)=2*FacT(i,4);
                               PplanFac(i,n)=PLskip(i,n);
                           else
                           end
                     otherwise
                 end
                 PmaxLSP(n) = PmaxLSP(n)+PrelimSP(i,(n+h));
                else
                end
            end %   i loop 138
            %-----Max power reduction available------------------------
---
            PmaxLSP(n) = PmaxLSP(n)+PLmax(n);
        end      %   n loop line 138
    %
    %
    %~~~~~~~~~Maximum lighting reduction and some set
points~~~~~~~~~~~~~~
        for n=hs:he
            for i=1:nmax
                if FacT(i,2) == 1
                    FDRT(i,n)=1;    %   For lighting reduction
participants
                else
```

```matlab
                    end
                end
            end
%
        %-------------------L M H set point reduction starts here------
---------
        for n=hs:he          %   end 279
                if PmaxLSP(n) > PDR
                    Naction(n) = 2;
                else
                end
                if PmaxLSP(n) <= PDR
                    Naction(n) = 3;
                else
                end
                if Naction(n) == 2 %         end 269
200
                L=0;
                M=0;
                H=0;
                PplanLSP(n) = sum(PLskip(1:nmax,n));    %skips reduce
light
                for i=1:nmax
                    ir=RFacList(i);     %   Randomize
                    if L==0
                        if Fpop(ir,n)=='L'
                            PplanLSP(n) = PplanLSP(n)+PrelimSP(ir,n+h)
...
                                       +2*PLtemp(ir);

PplanFac(ir,n)=PrelimSP(ir,n+h)+2*PLtemp(ir);
                            Lindex(i,n)=i;
                            FDRT(ir,n+h)=PrelimSP(ir,n);
                            SPLrandFac(i)=ir;
                            if PplanLSP(n)>=PDR
                                L=1;
                            else
                            end
                        else
                        end
                    else
                    end
                end
                if L==0     %   'L' is not enough
                    for i=1:nmax
                        ir=RFacList(i);     %   Randomize
                        if M==0
                            if Fpop(ir,n)=='M'
                              PplanLSP(n)=PplanLSP(n)+PrelimSP(ir,n+h)
...
                                       +2*PLtemp(ir);

PplanFac(ir,n)=PrelimSP(ir,n+h)+2*PLtemp(ir);
                            Mindex(i,n)=i;
```

170

```matlab
                                FDRT(ir,n+h)=PrelimSP(ir,n);
                                SPMrandFac(i)=ir;
                                if PplanLSP(n)>=PDR
                                        M=1;                  %   M is enough now
                                else
                                end
                            else
                            end
                        else
                        end
                    end
                else
                end
                if M==0 & L==0     %   'M' is not enough
                    for i=1:nmax
                        ir=RFacList(i);      %   Randomize
                        if H==0
                            if Fpop(ir,n)=='H'                        %
250
                                PplanLSP(n)=PplanLSP(n)+PrelimSP(ir,n+h)
...
                                        +2*PLtemp(ir);

PplanFac(ir,n)=PrelimSP(ir,n+h)+2*PLtemp(ir);
                                Hindex(i,n)=i;
                                FDRT(ir,n+h)=PrelimSP(ir,n);
                                SPHrandFac(i)=ir;
                                if PplanLSP(n)>=PDR
                                        H=1;                  %   H is enough now
                                else
                                end
                            else
                            end
                        else
                        end
                    end
                else
                end
            else
            end        %   if Naction(n) == 2   200
            if Naction(n) == 3
                for i=1:nmax
                    FDRT(i,(n+h))=PrelimSP(i,n);
                    PplanFac(i,n)=PrelimSP(i,n+h)+2*PLtemp(i);
                end
                PplanLSP(n)=PmaxLSP(n);
                finished = 1;
            else
            end
        end        %  end of n loop 191
    else
    end            %  if PLightMax < PDR 144
        %
    %----------optimize the lighting reduction----------------------
```

171

```matlab
        %
        for n=hs:he
            if Naction(n) < 0
                Naction(n) = 1;      %   Lighting reduction only
            else
            end
        end
        if Naction(hs) == 1
            LightE=0;
                    for i=1:nmax
                        ir=RFacList(i);      %   Randomize
                        if FacT(ir,2) == 1
                            if LightE == 0
                              PLplan=PLplan+2*PLtemp(ir);    %Both ele and
heat
                                PLindex(i) = i;
                                    if PLplan >= PDR
                                        LightE=1;
%300
                                    else
                                    end
                                else
                                end
                            else
                            end
                    end
                    for n=hs:he
                        for i=1:nmax
                            ir=RFacList(i);      %   Randomize
                            if PLindex(i) >= 1
                                FDRT(ir,n)=1;
                                PplanFac(ir,n)=2*PLtemp(ir);
                                LrandFac(i)=ir;
                            else
                            end
                        end
                    end
                    PmaxLSP=PLmax;
                    PplanLSP(hs:he)=PLplan;
        else
        end
        %       End of lighting optimazation
        %
end                 % if PDR >= 0   140
%-------------------Maximum Reduction (PDR=-1)----------------------
----
for n=hs:he
    if Naction(n) < 0
        Naction(n) = 3;
    else
    end
end

if Naction(hs) == 3 & finished == 0 %  Maximize the lighting reduction
```

172

```matlab
        for n=hs:he
            for i=1:nmax
                if FacT(i,2) == 1
                    FDRT(i,n)=1;           %   Set up lighting participants
                else
                end
            end
        end
    else
    end
%
%------------Now set up maximum set point reduction----------------
%
for n=hs:he
    if Naction(n) == 3 & finished == 0
            PmaxLSP(n)=0;
%350
            PmaxL(n)=0;
            PmaxM(n)=0;
            PmaxH(n)=0;
            for i = 1:nmax
              if FacT(i,3) == 1   %   Eliminate the non-participants
                switch Fpop(i,n)
                    case 'L'
                        PrelimSP(i,n) = 80;
                        PrelimSP(i,(n+h)) = FacT(i,7);
                        PmaxL(n) = PmaxL(n)+FacT(i,7);
                    case 'M'
                        PrelimSP(i,n) = 78;
                        PrelimSP(i,(n+h)) = FacT(i,6);
                        PmaxM(n) = PmaxM(n)+FacT(i,6);
                    case 'H'
                        PrelimSP(i,n) = 76;
                        PrelimSP(i,(n+h)) = FacT(i,5);
                        PmaxH(n) = PmaxH(n)+FacT(i,5);
                    otherwise
                end
              else
              end
            end
            for i = 1:nmax
                PmaxLSP(n) = PmaxLSP(n)+PrelimSP(i,n+h);
                FDRT(i,n+h) = PrelimSP(i,n);
                PplanFac(i,n)=PrelimSP(i,n+h)+2*PLtemp(i);
            end
            PmaxLSP(n) = PmaxLSP(n)+PLmax(n);
            PplanLSP(n) = PmaxLSP(n);
    else        %if Naction(n) == 3 & finished == 0
    end         %if Naction(n) == 3 & finished == 0
end             %for n=hs:he    348
%-----------------------------------------------------------------
%
%  Code to output to each facility's control system will reside here.
%  Include here an hourly calculation to determine each facility's
```

```
%  estimated load reduction (baseline load minus the actual load at the
end
%  of the hour).
%
%----------------------------------------------------------------------
%
%   Output to the spreadsheet in the current directory 'FDRTable.xls'
%
DRCoutput(FDRT, PplanLSP, PmaxLSP, PLmax, PDR,PLplan,PmaxL,PmaxM, ...
    PmaxH,PrelimSP,PLtemp,LrandFac,SPLrandFac,SPMrandFac, ...
    SPHrandFac,Naction,PplanFac)
%
%----------------------------------------------------------------------
----
%
%   EOF
401


function [PDR, nmax, hstart, hend, h] = DRCinput
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%   This inputs the DR Controller data.
%
%   DFL 8/26/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
clear all;
clc;
%   Set the input for the Demand Response (DR) event
PDR = -1;   %Desired reduction in power, kW,
%            -1 indicates the maximum achievable
nmax = 69; %maximum number of facilities in FacilityData.xls
hstart = '12:00';   %Start time of the first hour of the DR event
hend = '6:00';      %Start time of the last hour of the DR event
h = 7;              %Potential number of hours in the DR event (7
hours)
%
%   EOF


function DRCtables
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%   This inputs the DR Controller data from the excel spreadsheet
%   FacilityData.xls and saves it to a mat file (FacData.mat).
%   All are assumed located in the current directory.
%
%   DFL 8/26/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
```

174

```matlab
clear all;
clc;
nmax = 69;
h=7;
%
%    This builds the Facility Population Table, Fpop.
%
[Num, Text, FpopTemp]= xlsread('FacilityData', 'FPop', 'G2:N70');
Fpop = cell2mat(FpopTemp(1:69,2:8));
%
%    This builds the Facility Identification Table, FT.
%
[Num2, Text2, FT]= xlsread('FacilityData', 'FT', 'A2:C70');
%
%    This builds the Facility Control Table, FacT.
%
[Num2, Text2, FacTTemp]= xlsread('FacilityData', 'FacT', 'H2:N70');
FacT(1:nmax,1:7) = cell2mat(FacTTemp(:,:));
%
PLavail = FacT(:,4);
save FacData Fpop FT FacT PLavail
%
%    EOF


function [RFacList, noRepeats] = FacRandomizer(nmax)
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%   This function establishes a random order for the ordered list [1,
2,
%   ...,nmax] and returns the values in vector RFacList(1:nmax).  In
the
%   event any value in RfacList repeats, the error indicator,
noRepeats, is 1
%   otherwisw it is 0.
%
%   DFL 9/1/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
noRepeats = 0;
iset = randi(nmax,1,nmax);  %  This creats random intergers from 1 to
nmax.
for nrepeat = 1:nmax        %  This eliminates the repeate values.
    for i=1:nmax
        for j=1:nmax
            if j ~= i
                if iset(i) == iset(j)   %  Test for repeats and replace
                    iset(i) = randi(nmax,1);
                else
                end
            else
            end
        end
```

175

```matlab
            end
    end
    for i=1:nmax
            for j=1:nmax
                if j ~= i
                    if iset(i) == iset(j)   % Make sure no repeats in iset.
                        noRepeats=1;        % Bad if this is 1.
                    else
                        end
                else
                    end
            end
    end
    RFacList = iset;
    %   EOF


    function DRCoutput(FDRT,PplanLSP,PmaxLSP,PLmax,PDR,PLplan,PmaxL,PmaxM,
    ...
        PmaxH,PrelimSP,PLtemp,LrandFac,SPLrandFac,SPMrandFac, ...
        SPHrandFac,Naction,PplanFac)
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %%%%
    %
    %    This inputs the DR Controller data.
    %
    %    DFL 8/26/2009
    %
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %%%%
    %    Set the input for the Demand Response (DR) event
    LrandFac=LrandFac';
    SPLrandFac=SPLrandFac';
    SPMrandFac=SPMrandFac';
    SPHrandFac=SPHrandFac';
    PLtemp=PLtemp';
    xlswrite('FDRTable', FDRT, 'FDRT', 'D3:Q71');
    xlswrite('FDRTable', PplanLSP, 'Power', 'D3:J3');
    xlswrite('FDRTable', PmaxLSP, 'Power', 'D2:J2');
    xlswrite('FDRTable', PLmax, 'Power', 'D4:J4');
    xlswrite('FDRTable', PDR, 'Power', 'C5');
    xlswrite('FDRTable', PLplan, 'Power', 'C6');
    xlswrite('FDRTable', PmaxL, 'Power', 'D7:J7');
    xlswrite('FDRTable', PmaxM, 'Power', 'D8:J8');
    xlswrite('FDRTable', PmaxH, 'Power', 'D9:J9');
    xlswrite('FDRTable', PrelimSP, 'Prelim', 'B2:O70');
    xlswrite('FDRTable', PLtemp, 'Power', 'C12:C80');
    xlswrite('FDRTable', LrandFac, 'Power', 'E12:E80');
    xlswrite('FDRTable', SPLrandFac, 'Power', 'G12:G80');
    xlswrite('FDRTable', SPMrandFac, 'Power', 'I12:I80');
    xlswrite('FDRTable', SPHrandFac, 'Power', 'K12:K80');
    xlswrite('FDRTable', Naction, 'Power', 'D6:J6');
    xlswrite('FDRTable', PplanFac,'SumTotal','D3:J71');
    %
    %
```

```matlab
%    EOF




function [PLachieve] = FacLightRed(PLtemp, nmax)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
%
%    Check each facility controller to determine the level of energy
%    reduction that is achievable and return this value in
PLachiev(1:nmax).
%
%    DFL 8/26/2009
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%
PLachieve(1:nmax) = PLtemp(1:nmax);          %They are all achievable.
%
%    EOF
```

Appendix 5-5:  Participation Table for the DR Facilities

| # | Bldg # | Building | Light | Temp | # | Bldg # | Building | Light | Temp |
|---|--------|----------|-------|------|---|--------|----------|-------|------|
| 13 | 4 | Carlisle Gym | 1 | 1 | 36 | 81 | Humanities | 1 | 1 |
| 43 | 9 | Marron Hall | 1 | 1 | 63 | 82 | Woodward Hall | 1 | 1 |
| 59 | 10 | Scholes Hall | 0 | 0 | 15 | 83 | Ceria | 1 | 1 |
| 4 | 11 | Anthro Maxwell Musm | 0 | 1 | 5 | 84 | Art Building | 0 | 1 |
| 3 | 12 | Anthropology Annex | 1 | 1 | 62 | 85 | Student Services | 1 | 1 |
| 32 | 15 | Hibben | 1 | 1 | 29 | 87 | Parish Library | 0 | 1 |
| 6 | 16 | Bandelier Hall West | 1 | 1 | 56 | 88 | S R C | 1 | 1 |
| 8 | 19 | Biology Annex | 0 | 1 | 46 | 102 | New Bookstore | 0 | 1 |
| 35 | 20 | Human Resources | 1 | 1 | 33 | 103 | Hodgin Hall | 1 | 1 |
| 14 | 21 | Castetter-Potter | 1 | 1 | 38 | 115 | Journalism | 1 | 1 |
| 16 | 22 | Clark-Reibsomer Hall | 1 | 1 | 27 | 119 | Farris Engineering | 1 | 1 |
| 45 | 23 | Mitchell Hall | 1 | 1 | 42 | 122 | M E Building | 1 | 1 |
| 50 | 24 | Northrop Hall | 1 | 1 | 17 | 153 | Computing Cntr CIRT | 0 | 0 |
| 41 | 34 | Logan Hall | 1 | 1 | 19 | 155 | Coronado | 1 | 1 |
| 55 | 35 | Regener Hall | 1 | 1 | 52 | 156 | Onate Hall | 1 | 1 |
| 23 | 46 | E E C E   CSEL | 0 | 1 | 1 | 157 | Alvarado | 1 | 1 |
| 20 | 48 | Dane Smith Hall | 1 | 1 | 66 | 183 | Lobo Center | 1 | 1 |
| 64 | 53 | Zimmerman Library | 0 | 1 | 48 | 193 | New Residence | 1 | 1 |
| 44 | 56 | Mesa Vista Hall | 1 | 1 | 18 | 198 | Cornell Parking | 1 | 1 |
| 24 | 57 | Economics | 1 | 1 | 67 | 205 | RIB | 1 | 1 |
| 34 | 58 | Hokona | 1 | 1 | 54 | 207 | Physics & Astronomy | 1 | 1 |
| 37 | 59 | Johnson Gym | 1 | 1 | 7 | 211 | Basic Med Science | 0 | 1 |
| 49 | 60 | NM SUB | 0 | 0 | 10 | 218 | Bratton Hall | 1 | 1 |
| 58 | 61 | Santa Clara | 1 | 1 | 12 | 227 | Cancer RT Center | 0 | 1 |
| 28 | 62 | Fine Art C & Library | 0 | 1 | 51 | 228 | Nursing & Pharmacy | 1 | 1 |
| 25 | 65 | Education Complex | 1 | 1 | 11 | 229 | CR Facility | 0 | 1 |
| 57 | 71 | Santa Ana | 1 | 1 | 47 | 230 | New Mexico Law Center | 0 | 1 |
| 65 | 72 | Popejoy Hall | 0 | 0 | 31 | 234 | Health Sci Library | 1 | 1 |
| 61 | 73 | Student Health Facility | 0 | 0 | 26 | 248 | Family Practice | 1 | 1 |
| 40 | 74 | Laguna | 1 | 1 | 22 | 249 | Dental Programs | 1 | 1 |
| 21 | 75 | De Vargas | 1 | 1 | 9 | 253 | Biomedical Researchx | 0 | 1 |
| 2 | 76 | Anderson School of M | 1 | 1 | 30 | 266 | Health Sci & Serv | 1 | 1 |
| 39 | 77 | La Posada | 0 | 0 | 69 | 331 | Crystal Growth Facility | 1 | 1 |
| 60 | 78 | Social Sciences | 1 | 1 | 68 | 338 | CHTM | 1 | 1 |
| 53 | 79 | Ortega Hall | 1 | 1 | | | | | |

| 0 | Do Not Participate in the DR Event |
|---|---|
| 1 | Participate in the DR Event |