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COMPILATION OF DIVERSITY FACTORS AND SCHEDULES FOR ENERGY AND COOLING LOAD CALCULATIONS

ASHRAE Research Project 1093

Phase II Report

IDENTIFIED RELEVANT DATA SETS, METHODS AND VARIABILTY ANALYSIS

Bass Abushakra
Jeff. S. Haberl, Ph.D., P.E.
David E. Claridge, Ph.D., P.E.
Energy Systems Laboratory
Texas A&M University
College Station, Texas, 77843-3581

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ENERGY SYSTEMS LABORATORY
Building Energy Analysis Division
Texas A&M University System

EXECUTIVE SUMMARY

This is the second report of the ASHRAE 1093-RP project that reports on the progress during the scheduled *Phase II* effort. In this report, we present:

(1) *the data sets identified and acquired required for the analysis:*
We have acquired data from 45 office buildings as follows: (1) lighting and equipment data from 29 Office buildings available in the database at the ESL, (2) lighting and equipment data from 9 Office buildings from LBNL (buildings that were part of the Energy Edge project, and another project performed by LBNL), (3) typical load shapes from 7 district-heated office buildings in Swedish cities (Noren 1997). We will continue our contact with sources who originally offered help in this project.

(2) *the method adopted for classifying the Office building categories:*
We identified three Office building subcategories: (1) Small (1,001 - 10,000 ft^2), (2) Medium (10,001 - 100,000 ft^2), and (3) Large (> 100,000 ft^2) based on CBECS (1997a and b).

(3) *the relevant methods for daytyping necessary for creating the typical load shapes for energy and cooling load calculation:*
We describe the well-documented methods that were identified in the Preliminary Report and three additional methods identified during Phase II; in total, we are describing 10 methods developed in the U.S., and 1 method used in Europe. The procedure and the use of each of these methods are described, and a method is proposed for use in this project. Examination showed that none of the original methods was optimal for use in this project. Therefore, the proposed method incorporates elements of several previously developed techniques, and is presented as a step by step method to achieve the goals of this research project.

(4) *the relevant robust variability (uncertainty) analysis:*
We propose an approach to account for the variability in developing the typical load shapes, and the uncertainty in using the results based on a percentile measure of central tendency.

(5) *typical load shapes reported in the literature:*
We include typical load shapes of lighting and equipment and total electricity consumption in Office buildings that are given in the available literature. These typical load shapes will be used as reality checks after we develop the diversity factors and typical load shapes for this project.

(6) *a test to assure the non-weather dependency (seasonal variation) of the lighting and equipment data sets:*
We propose to use BWM plots of the weekly-binned lighting and equipment hourly loads as a first step in the daytyping to check for seasonal variation in the data which will suggest an additional criterion for the final daytyping (i.e., summer/winter).

(7) a proposed occupancy surrogate variable:
We propose using a surrogate variable for the occupancy typical load shapes. We derived this variable from typical lighting and equipment load shapes, by two different approaches: (1) using a transformation function, and (2) using linear regression. We propose to use the transformation approach which was shown to be more accurate in our tests.

The results obtained during *Phase II* will enable us to proceed with *Phase III*, as planned.

Phase III will cover: (1) developing the typical load shapes for the acquired data sets, using the proposed method, for both energy and cooling load calculations, (2) developing the tool-kit for deriving the new diversity factors and general guidelines for their use, and (3) developing illustrative examples of the use of the diversity factors in the DOE-2 and BLAST simulation programs.

Most of the identified methods for daytyping and generation of typical load shapes were developed to disaggregate monitored whole-building electricity consumption data (load research data) into different end-uses, to avoid the additional cost of monitoring these end-uses. After obtaining the reconciled end-uses data, the daytyping procedures were applied in order to develop typical load shapes. For this project, we identified sets of monitored lighting and equipment loads in office buildings; thus, in most cases there will be no need to disaggregate the whole-building electricity consumption into end-uses, in the data sets acquired for use in this project.

Most of the buildings include both the whole-building electricity consumption, and end-use data (Lighting, Equipment, or Lighting + Equipment), and the daytyping approaches that were developed for use with this type of data were mainly used for energy baselining and retrofit savings calculation purposes within the inverse modeling techniques. We will combine elements of these different approaches to generate the typical load shapes and diversity factors which will be used in forward energy simulation programs (DOE-2, BLAST) for energy and cooling calculation. In our analysis, we are proposing a method that combines the work that was previously performed by Abbas (1993), Thamilseran and Haberl (1994), and Dhar (1995) to best serve the purposes of this project, and assure the robustness of the results. None of these methods, individually, can be used to automatically determine the daytypes and obtain the corresponding diversity factors and typical load shapes that this research project wants to achieve. Therefore, selected procedures have been extracted from different methods and merged into a combined approach.

The work scheduled for *Phase III* of the project will be initiated based on the findings of *Phase II.* The comments of the PMSC will be taken into consideration as of whether we should try to modify our approach.

The typical load shapes that will be developed for design cooling load calculation purposes, will differ from the ones developed for energy use purposes. For design cooling load calculation, one needs to account for extremes (peaks) in the data. However, the absolute peak values of the lighting and equipment consumption may represent outliers or values that do not robustly represent the case. Therefore, we propose two approaches to develop the typical load shapes for design cooling calculations:

1. After identifying the daytypes for energy calculation, aggregate for each daytype a "Design Day" with the hours equal to the mean of the 90^{th} percentile values at each hour (1-24).

or, if there is a clear seasonal variation identified in the data,

2. Consider summer and winter seasons separately, and aggregate for each season a "Design Day" with the hours equal to the mean of the 90^{th} percentile values at each hour.

We will test these two approaches and consider other approaches as well, and recommend the approach that is judged most appropriate.

The objectives of the project will be accomplished by completion of three phases, as described in the RFP, with review and approval by the Project Monitoring Subcommittee (PMSC) provided after the first and second phases, before initiating the next phase. The results of *Phase I* of the project (Literature review and database search, Preliminary Report) are reported in the Preliminary Report (May 1999), and the results of *Phase II* of the project (Identified data sets, methods and variability analysis) are included in this report.

Phase III (Compilation of Diversity Factors and Preparing a library of diversity factors and load shapes for energy and cooling load calculations, Project Reports and Technical Papers) will proceed as soon as comments and suggestions on *Phase II* have been received.

TABLE OF CONTENTS

1. INTRODUCTION

This is the second report of the ASHRAE 1093-RP project that reports on the progress during the scheduled *Phase II* effort. In this report, we present: (1) the identified and acquired data sets required for the analysis, (2) the method adopted for classifying the office buildings category, (3) the relevant methods for daytyping necessary for creating the typical load shapes for energy and cooling load calculation, and (4) the relevant robust variability (uncertainty) analysis. We also included in this report: (5) typical load shapes reported in the literature, (6) a test to assure the non-weather dependency (seasonal variation) of the lighting and equipment data sets, and (7) a proposed occupancy surrogate variable. The results obtained during *Phase II* will enable us to proceed with *Phase III* as planned.

Phase III will cover: (1) developing the typical load shapes from the acquired data sets, using the proposed method, for both energy and design cooling load calculations, (2) developing the tool-kit for deriving the new diversity factors and general guidelines for their use, and (3) developing illustrative examples of the use of the diversity factors in the DOE-2 and BLAST simulation programs.

1.1 Work Completed in Phase I

The first report (Preliminary Report) for the ASHRAE 1093-RP project included: (1) an extended literature search of methods used to derive load shapes and diversity factors in the U.S. and Europe, (2) a survey of available databases of monitored commercial end-use electrical data in the U.S. and Europe, and (3) a review of classification schemes of the commercial building stock listed in national standards and codes, and reported by researchers and utility projects. The findings of this preliminary report were the basis for performing the next phases of the project where appropriate daytyping methods on relevant monitored data sets of lighting and equipment (and other surrogates for occupancy) could be identified and tested to develop a library of diversity factors and schedules for use in energy and cooling load simulations.

The goal of the ASHRAE 1093-RP project is to compile a library of schedules and diversity factors for energy and cooling load calculations in various types of indoor office environments in the U.S. and Europe. Two sets of diversity factors, one for design cooling load calculations and one for energy calculations will be developed.

In the Preliminary Report we described the related literature for the ASHRAE 1093-RP project. To accomplish this we have divided the previous literature into three categories: (1) existing literature on diversity factor and load shape calculations, (2) literature that reports on existing databases of monitored data in the U.S. and Europe, and (3) relevant studies about classifications of commercial buildings. In the literature on diversity factors and load shapes, we covered papers reporting the existence of databases of monitored end-uses in commercial building, methods used in developing the daytypes and load shapes, and what classification schemes were used in the commercial building sector. We reported the names of the scholars and energy analysts whom we contacted in the U.S. and Europe, who provided detailed information on existing databases on monitored end-uses in commercial buildings in the U.S.

Finally, we summarized the classification schemes of the commercial building sector that are reported in national standards and codes.

We reviewed a total of 51 sources on diversity factors and load shapes from conference proceedings and scientific journals (47), internet websites (2), standards (1), and a professional handbook (1). We also consulted 10 bibliographies related to deriving load shapes, and other subjects like commercial buildings end-uses, and we reviewed methods used to calculate uncertainty analysis.

Five papers were reviewed in which the authors reported the existence of databases of monitored commercial building end-uses, from which data was utilized to develop typical load shapes. Besides these reported databases in the literature, we conducted our own search and contacts and located various sources of monitored end-uses in commercial buildings.

For methods used in deriving load shapes of end-uses in the U.S., we reviewed 28 papers, one standard, one professional handbook, one thesis, and two reports on an organization website in which the authors described (either explicitly or briefly) different methods used in daytyping weather-dependent and weather-independent end-uses, and deriving typical load shapes, that we felt could create a basis for our analysis. For methods used in Europe, we have been able to review three papers.

From the literature on methods used in deriving load shapes of end-uses in the U.S., we identified 12 unique methods that were used when metered end-uses were not available, and/or employed some sophisticated techniques. Besides these methods, several other simpler methods were also reviewed. The simple methods were based on averages and standard deviations of typical daytypes, and were usually utilized whenever metered end-uses existed. From the few European papers on this topic which we were able to obtain, only one paper described the methodology of deriving the load shapes. However, these papers are useful in providing a basis for comparison between the energy use in commercial buildings in the U.S. and Europe.

In the Preliminary Report, we also reviewed previous literature on different classification schemes that were used in various commercial building energy-use daytyping and determination of load shapes projects. These papers reflect how utility companies and research laboratories divide the commercial building stock. We included these papers to provide an example of commercial building classification followed in the load shape studies.

Since the publication of the Preliminary Report, an extensive search was conducted in order to locate and identify databases of monitored data in the U.S. and Europe. Direct contacts through e-mail, fax, and phone calls were conducted with scholars, researchers, and energy consultants, and their responses ranged from providing us with further names and references to readiness for help with or without charge to this research project. The available databases and sources of monitored lighting and office equipment data have been compiled in a tabulated format. Major sources of data were found through the ASHRAE FIND database, EPRI-CEED, ELCAP, and the Energy Systems Laboratory database that includes data monitored under the LoanSTAR program and other contracts for buildings inside and outside the state of Texas.

We also reviewed various national standards and codes, and major public surveys to identify commercial building classification schemes proposed and followed. We proposed to follow the classification followed by the Commercial Buildings Energy Consumption Survey (CBECS) (CBECS 1997a and b), a national survey of commercial buildings and their energy suppliers, in compiling their statistics of the commercial building stock in the U.S. We based our proposal on the detailed compiled survey results of CBECS that helped us in drawing meaningful conclusions. The CBECS classification scheme agrees with that of ASHRAE Standard 90.1 (ASHRAE 1989), taking into consideration the small representation, in the whole commercial building stock, of the "Religious Worship" and the "Public Order and Safety" categories that appear in the CBECS classification.

Therefore the proposed commercial building classification in developing the diversity factors and schedules for energy and cooling load calculations will consist of the following categories: (1) Offices, (2) Education, (3) Health Care, (4) Lodging, (5) Food Service, (6) Food Sales, (7) Mercantile and Services, (8) Public Assembly, and (9) Warehouse and Storage.

1.2 Work Completed in Phase II

This is the second report of the ASHRAE 1093-RP project that reports on the progress during the scheduled *Phase II* effort. In this report, we present:

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We identified three Office building subcategories: (1) Small (1,001 - 10,000 ft^2), (2) Medium (10,001 - 100,000 ft^2), and (3) Large (> 100,000 ft^2) based on CBECS (1997a and b).

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We describe the well-documented methods that were identified in the Preliminary Report and three additional methods identified during Phase II; in total, we are describing 10 methods developed in the U.S., and 1 method used in Europe. The procedure and the use of each of these methods are described, and a method is proposed for use in this project. Examination showed that none of the original methods was optimal for use in this project. Therefore, the proposed method incorporates elements of several previously developed techniques, and is presented as a step by step method to achieve the goals of this research project.

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We propose to use BWM plots of the weekly-binned lighting and equipment hourly loads as a first step in the daytyping to check for seasonal variation in the data which will suggest an additional criterion for the final daytyping (i.e., summer/winter).

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1.3 Schedule and Work Plan

The objectives of the project will be achieved by completion of three phases, as described in the RFP, with review and approval by the Project Monitoring Subcommittee (PMSC) provided after the first and second phases, before initiating the next phase. The results of *Phase I* of the project (Literature review and database search, Preliminary Report) are reported in the preliminary report (May 1999), and the results of *Phase II* of the project (Identified data sets, methods and variability analysis) are included in this report.

During *Phase II* we have identified the relevant data sets and methods required to derive the daytypes and typical load shapes for energy and cooling load calculations

After conducting all the contacts in the U.S. and Europe, that we noted in the preliminary report, we acquired data from Office buildings in an LBNL database (9 buildings). These buildings were analyzed during the Energy Edge project (Piette et al. 1994). Besides the data from LBNL, the major source of data was the monitored data that is available in the ESL database. All the data identified is for Office buildings only (44 buildings), as required for this project. Many other buildings monitored by ESL fall within other Commercial buildings categories like Hospitals (Health Care), Lodging (Hotels, Motels), Retail, Restaurants, Classrooms and Laboratories, or buildings housing Classrooms and Offices (typical of university and college campuses). These categories were excluded from our data identification. The identified data for this project consists of monitored lighting loads, receptacle loads, or lighting and receptacles together (i.e., the difference between whole-building electricity consumption and the motor-control-center loads).

From Europe, we acquired typical load shapes from seven district-heated office buildings in Swedish cities (Noren 1997).

We reproduced and studied the relevant daytyping methods required for deriving the diversity factors and report them in this report. We also proposed methods: (1) to generate typical load shapes for energy and cooling calculation, and (2) to obtain a surrogate occcupancy variable. We also reviewed the variability (uncertainty) analysis methods reported in the literature, and proposed a method to account for the variability of the results from using the proposed method for daytyping and derivation of diversity factors.

Phase III (Compilation of Diversity Factors and Preparing a library of diversity factors and load shapes for energy and cooling load calculations, Project Reports and Technical Papers) will proceed as soon as comments and suggestions on *Phase 2* have been received. Table 1 shows the scheduled phases and tasks of ASHRAE 1093-RP as proposed in our work plan.

			1999											2000				
Phase	**Task**	**Activity / Deliverable**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**1**	**2**	**3**	**4***	**5**
1	1	Literature Review and Database search																
	2	Preliminary Report																
2	3.a	Identification of relevant existing Data sets (energy consumption and Demand)																
	3.b	Identification of methods for the Classification of buildings																
	3.c	Identification and use of relevant Statistical procedures for daytyping																
	4	Identification of robust uncertainty Analysis methodologies																
	5	Report on list of derived diversity Factors and schedules based on 3.a, 3.b,and 3.c.																
3	6.a	Compilation of the diversity Factors and load shapes																
	6.b	Development of a Tool-Kit for deriving New diversity factors, and General Guidelines for their use																
	6.c	Development of illustrative examples of the use of the diversity factors in the DOE-2 and BLAST simulation Programs																
	7.a	Draft Final Report																
	7.b	Final Project Report																
	7.c	Quarterly Reports																
	7.d	Technical Research Papers																

***** *Completion date of the project***

Table 1. Phases and Tasks of ASHRAE 1093-RP.

2. IDENTIFICATION AND ACQUISITION OF RELEVANT EXISTING DATA SETS

During *Phase I* of the project we identified all possible sources for lighting and equipment data in commercial buildings within the U.S. and Europe. During *Phase II* of the project we contacted most of these sources (when it was clear that data could be made available), and we report herein the result of this data identification and acquisition.

2.1 Previously Identified Data Sets

In *Phase I* of the project, an extensive search was conducted in order to locate and identify databases of monitored data in the US and Europe. Direct contacts through e-mail, fax, and phone calls were conducted with scholars, researchers, and energy consultants, and their responses ranged from providing us with further names and references to readiness for help with or without charge to this research project. The initial search was presented in a tabulated format in the Preliminary Report and we repeat the tables (Tables 2 to 6) in this report for illustrative purposes. Table 2 shows the names of scholars, researchers and energy consultants that we contacted during our search, and their corresponding organizations.

The available databases and sources of monitored lighting and office equipment data have been compiled in a tabulated format. Major sources of data were found through the ASHRAE FIND database (ASHRAE 1995), EPRI-CEED, ELCAP, and the Energy Systems Laboratory database that includes data monitored under the LoanSTAR program and other contracts for buildings inside and outside the state of Texas. Initial contacts with European references also produced a number of promising leads shown in Table 3. Table 3 was intended to summarize the availability of databases of monitored equipment and lighting loads in commercial buildings, both in the U.S. and Europe. The name of the contact person, the name of the organization, the type of data available and the cost to obtain this data are listed in this table.

From Europe, the only successful contact was with Mr. Guislain Burle from MD3E (a consulting firm in France). Mr. Burle proposed offering us monitored data from Commercial Buildings (Small, Medium, and Large Office buildings, University Buildings, and Hotels) including: General, Lighting, Equipment, Lighting+Equipment, Water Heating, Air-Conditioning, Lifts, and Restaurant). The offered data would be 10-minute data, 3 weeks in length, and cost US$9,840. We contacted Mr. Burle again and reminded him that we are looking for Lighting and Equipment data for Office Buildings only, and we have not heard back from him as of this moment. Other contacts in Europe have not resulted in producing any data.

The information from EPRI-CEED was very clear about the type of data available in terms of commercial building category, type of end-use, sample size, data format and length. The data can be obtained at a cost to be discussed. Table 4 lists the commercial building metered end-use data available at EPRI-CEED. These sample sizes of end-use were obtained by personal communication with Mr. John Farley. However, when we contacted EPRI-CEED during *Phase II* of this project, we were informed that they do not have a policy that allows them to provide raw data in the format we requested. They only provide processed data (i.e., in our case the typical load shapes). We concluded that this will not be of a major help to our project since our objective is to acquire raw data, and process it with different methods to produce the typical load shapes and diversity factors. Moreover, EPRI-CEED offered to provide one typical load shape for each office building category (small, medium, and large), which would be a result of averaging the whole stock of monitored data from different buildings that fall in each category. The cost for obtaining such data was approximated to be between $1,000 and $2,000 (correspondence e-mails available).

Battelle PNNL has offered access to ELCAP data that represents 80 to 90 commercial buildings in Seattle, Oregon, and Idaho. These data include whole-building electricity consumption, and various sub-metered channels. Square footage, address, city, state, and type of building are associated with the hourly data, and the data can be provided in an ASCII format. The cost for obtaining these data still needs to be determined. As of this date, we have not heard back from PNNL regarding this issue.

Table 5 was shown previously in the Preliminary Report to summarize the data that can be available for this project as compiled in the ASHRAE FIND database. This database summarizes a survey conducted in the U.S. and Canada in order to locate available measured energy use at national laboratories, universities, utility companies, cities, and energy consultant firms. We note here data on lighting and equipment loads from the Commercial building sector only (as required in this project), since the ASHRAE FIND database covers Residential buildings, Agricultural buildings, Industrial buildings, and Multiple Building Complexes, along with Commercial buildings. The data in the table is listed according to the name of the organization, building type, sample size, type of measured end-use, data format, availability of data, cost, and medium of recorded data. Thirty-four sources of data were found.

During *Phase II*, and as it was determined in Seattle (ASHRAE Annual Meeting 1999) by the PMS Committee, the project focus was on Office Buildings as compared with other commercial buildings subcategories (restaurants, schools, hospitals, etc.). Most of the ASHRAE FIND data (as seen in Table5) covers different commercial sectors and only few data sources cover the three categories of Office Buildings (small, Medium, and large), namely, the Energy Systems Laboratory, Lawrence Berkeley National Laboratory, ADM Associates Inc, and Battelle PNNL. It is worth noting also that most of the sources do not make the data available to the general public, or if they do, it would be conditional and with the agreement of the utility company or the specific clients. From these sources, we contacted LBNL through Ms. Mary Ann Piette and received a positive response.

Table 6, in the Appendix, lists all buildings monitored by the Energy Systems Laboratory (ESL) at Texas A&M University. The table shows the building name, location, square footage, weather-dependency nature of the whole-building electricity consumption, availability of lighting and equipment load, source of data (type of contract), data format, cost, and data quality. The table also shows how the lighting and equipment variables are recorded, either explicitly or implicitly (as the difference between Whole Building Electricity Consumption and Motor Control Center Consumption - AHU, Pumps). From these buildings, we chose the Office buildings only to be analyzed for the *Phase II* of the project.

USA		
	Contact	**Organization**
	Hashem Akbari	LBNL
	Mary Ann Piette	LBNL
	Mimi Goldberg	Xenergy
	Jim Halpern	Measuring and Monitoring Services
	Z. Todd Taylor	Battelle PNNL
	Ilene Obstfeld	EPRI-CEED
	John Farley	EPRI-CEED
	John McBride	NHT
	Mike Baker	SBW
	Taghi Alereza	ADM
EUROPE		
	Ari Rabl	Ecole des Mines - France
	Moncef Krarti	Ecole des Mines - France
	Arthur Dexter	University of Oxford - UK
	Geoff Levermore	University of Manchester - UK
	Prof. Bitzer	Germany
	Vic Hanby	Loughborough Universite - UK
	Mike Homes	Ove Arup & Partners - UK
	Jacques Roturier	Universite Bordeaux - France
	Peter Hill	BRE - UK
	Andrew Eatswell	BSRIA - UK
	Chris Parsloe	BSRIA - UK
	Casper Kofod	DEFU - Denmark
	Benoit Lebot	IEA
	Olivier Sidler	Independent consultant
	Veronique Richalet	(Research Lab on Energy in Buildings)
	Ghislain Burle	Independent consultant
	Thomas Gueret	France Ministry of Industry
	Marc Bons	Electricite de France
	Alain Anglade	ADEME - France
	Jean Lebrun	Universite de Liege - Belgium

Table 2. Contact list of scholars and energy analysts in the U.S. and Europe

	Name	Organization	Data Available	Remarks	Cost
Europe	Jean Lebrun	Universite de Liege - Belgium	European Ministry Council Building	Brussels - Belgium, Available	"with or without financial support"
	Guislain Burle	MD3E	Database of Office Equipment Use	France, Available	"cost depends on type of data"
	Casper Kofod	DEFU - Danmark	Office Equipment, Lighting, Occupancy	Will get back to us on May 11 99	?
USA	Mimi Goldberg	Xenergy	Waiting for final answer (100's of buildings)	Data belongs to clients	?
	Jim Halpern	Measuring and Monitoring Services	Waiting for final answer (100's of buildings)		?
	Ilene Obstfeld	EPRI-CEED	Load shapes for several categories	Southwestern Utilities	(Waiting for final answer)
	John Farley	EPRI-CEED	Load shapes for Offices	BC-Hydro - Canada	(Waiting for final answer)
	Z. Todd Taylor	Battelle PNNL	Whole building and submetered channels (90 Commercial buildings)	ELCAP data	Probable charge
	Mary Ann Piette	LBNL	We are waiting to hear back		
	Mike Baker	SBW	We are waiting to hear back		
	John McBride	NHT	5 to 10 commercial buildings in Montana and California	?	?
	Taghi Alereza	ADM	More than 10 buildings in California and Louisiana	?	?

Table 3. Response obtained from the list of contacts who have data in the U.S. and Europe which will (or may) be available for use in RP-1093.

Bldg. Type	Re-gion	Sam-ple	Total Load	HVAC	Cooling	Heating	Electric Water Heating	Food Service	Lighting - Exterior	Lighting - Interior	Refrigeration	Other
Education	NE									5		
	NW	4	4		1	3	3	4	4	4	4	5
	SE	52	52	41	11		22	12	2	21		117
	SW											
	W											
Entertain -ment	NE											
	NW											
	SE	8	8	8			4	3	2	3		15
	SW											
	W											
Grocery / Food Store	NE											
	NW	8	8		2	6	6	7	8	8	8	14
	SE	12	12	12			5	3	4	8	10	25
	SW	5	5	3	4					5	5	4
	W											
Healthcare	NE			2						2		
	NW											
	SE	5	5	1	4			2		1		13
	SW											
	W				3							
Hotel / Motel	NE											
	NW											
	SE		12	11	1			1	2	5		33
	SW											
	W				3							
Office	NE			24						18		
	NW	17	17		9	14	15	15	17	17	6	28
	SE	100	100	90	5		37	4	9	54		158
	SW	23	23	21	21		4		4	21		6
	W				9							
Restaurant	NE											
	NW	6	6	6	3	2	4	6	6	6	6	7
	SE	17	5	19	2		5	5	3	5	7	65
	SW											
	W											
Retail	NE			4						28		
	NW	15	15		8	13	13	2	11	13	6	24
	SE	88	88	79	4		22	1	13	66	5	161
	SW	18	18	15	17		5		7	15		
	W				2							

Table 4. List of available commercial building metered load data at EPRI-CEED

(Data presented as obtained from EPRI-CEED. Sample sizes do not match with number of metered end-uses for some building categories; we assume that the sample size figures should be updated to match with number of metered end-uses)

	ID#	Organization	Building Type	Sample Size (buildings)	Meas'd Light/Equip	Data Format	Available to	Charge	Data Medium
1	135	Battelle Pacific Northwest Laboratory	All Commercial	300 - 999	Light., Equip.	5 min, 15 min, Hourly	Through BPA or FOIA	No	Tape
2	213	Seattle City Light	Large Offices	1 - 9	Light.	?	?	?	?
3	362	Omaha Public Power District	All Commercial	300 - 999	Light., Equip.	5 min, 15 min	Upon Request	Nominal Fee	Disk
4	367	Energy Systems Laboratory	Large Offices, Small Offices, Schools, Colleges, Grocery Stores, Health Facilities	50 - 99 (ASHRAE FIND) (365 total as of April 99)	Light. Equip.	15 min, Hourly	General Public, ASHRAE	Fee Charged	Disk, Tape
5	650.3	The Fleming Group	Large Offices, Small Offices, Warehouses, Schools	1 - 9	Light.	15 min	?	?	?
6	650.4	The Fleming Group	All Commercial	10 - 49	Light.	Hourly	?	?	?
7	650.5	The Fleming Group	All Commercial	10 - 49	Light.	Hourly	?	?	?
8	676	Natural Resources Defense Council	Small Offices	1 - 9	Light., Predicted Equip.	15 min	General Public, ASHRAE	Minimum Charge	?
9	704	Oregon Department of Energy	Restaurants, Retail Stores, Grocery Stores, Lodging	100 - 299	Equip.	?	General Public	No	Tape
10	735	ML Systems	All Commercial	11 - 25	Light.	?	Limited	?	Summary Database
11	740	Lawrence Berkeley Laboratory	Large Offices, Small Offices, Restaurants, Retail Stores, Schools, Health Facil., Lodg.	10 - 49	Light., Equip.	Hourly	General Public	No (BPA Approval)	Tape
12	750	Sierra Pacific Power Company	Large Offices, Small Offices, Retail Stores, Grocery Stores, Schools, Lodging	100 - 299	Light., Equip.	15 min	CEED	No	?
13	813	CEI	Large Offices	1 - 9	Light.	Hourly	?	?	?
14	760	BC Hydro & Power Authority	Large Offices, Small Offices, Restaurants, Retail St., Grocery St., Schools, Colleges, Health Facil., Lodging	300 - 999	Light., Equip.	15 min	?	?	?
15	804.1	Seattle City Light	Small Offices, Retail Stores, Health Facilities	1 - 9	Light.	Hourly	?	?	?
16	1055	Northwest Energy	Grocery Stores	10 - 49	Light.	5 min	With Owner Permission	?	?
17	1061	University of Calgary Faculty of Environ. Design	Large Offices	1 - 9	Light.	?	?	?	?

	ID#	Organization	Building Type	Sample Size (buildings)	Meas'd Light/Equip	Data Format	Available to	Charge	Data Medium
18	1064	E Source	All Commercial	10 - 49	Light.	5 min	General Public	?	?
19	1077	Oak Ridge National Laboratory	Small Offices	1 - 9	Light., Equip.	Hourly		No	Disk
20	1102	Southern California Edison Company	Large Offices, Small Offices, Restaurants, Retail Stores, Grocery Stores, Warehouses	50 - 99	Light., Equip.	?	Specific Research Groups	?	Disk
21	1183	Bonneville Power Administration	Small Offices, Restaurants, Retail St., Grocery St., Warehouses, Schools, Health Facilities., Lodging	300 - 999	Light., Equip.	Hourly	General Public	No	Tape
22	1225	Duke Power Company	All Commercial	1000 or more	Light., Equip.	5 min, 15 min	Not Available (?)		Disk
23	1245	University of Michigan	All Commercial	100 - 299	Light.	5 min, 15 min, Hourly	General Public	No	Disk, Tape
24	1252	SBW Consulting Inc.	Restaurants	1 - 9	Light.	?	Through EPRI	?	Disk, Tape
25	1277	Pacific Gas & Electric Company	Small Offices, Restaurants	1 - 9	Light., Equip.	15 min Hourly	PG&E	?	?
26	1390	Green Mountain Power Company	All Commercial	10 - 49	Light.	15 min	?	?	Disk
27	1417	Sycom Enterprises	All Commercial	300 - 999	Light., Equip.	Hourly	Conditional	?	Disk
28	1534	Lambert Engineering	Schools	1 - 9	Light., Equip.	Hourly	With Utility Consent	Arranged Fee	Tape
29	1535	Midwest Power System	All Commercial	more than 100	Equip.	Hourly	Consultants or Negotiable	Negotiable	Disk
30	1576	Lawrence G. Spielvogel Inc.	All Commercial	1000 or more	Light., Equip.	Hourly	General Public, ASHRAE	Negotiable	Any
31	1856	CANETA	Large Offices	1 - 9	Light., Equip.	15 min	?	?	Disk
32	3011	ADM Associates Inc.	All Commercial	50 -99	Light.	15 min	?	?	?
33	3023	ADM Associates Inc.	Large Offices, Small Offices, Restaurants, Retail Stores, Grocery Stores, Warehouses	50 - 99	Light., Equip.	5 min, Hourly	Approval from SCE	?	Disk
34	3024	ADM Associates Inc.	Small Offices, Retail Stores, Grocery Stores, Warehouses	10 -49	Light.	Hourly	Approval from PG&E	?	Disk

Table 5. ASHRAE FIND survey of databases of Lighting and Equipment monitored electricity use in Commercial Buildings

2.2 Data Acquired

During *Phase II* of the project we recontacted many of the sources that we identified in *Phase I*, with the purpose of acquiring data from Office buildings which is the category of interest within the wider range of the Commercial buildings sector. The *Phase II* search produced a set of data from 9 Energy Edge Office buildings, through LBNL, 29 Office buildings from the ESL database, and load shapes from 7 Office buildings in Sweden. The data now in hand comprise monitored hourly lighting and receptacles (equipment) loads in small, medium, and large office buildings. This section describes the efforts undertaken to acquire the data.

2.2.1 ESL Data

Table 7 below shows the 29 office buildings monitored by the ESL. These buildings are all "pure" office buildings, where the typical offices schedule is predominant, as compared with office buildings where part of the building serves some other purpose, like classrooms and laboratories, which modifies the overall operation of the building systems.

The 29 buildings consist of:

- 21 Large Office buildings (>100,000 ft^2)
- 8 Medium Office buildings (>10,000, and < 100,000ft^2).

The 21 Large Office buildings consist of:

- 1 Federal Office building
- 2 Private Office buildings
- 15 State Office buildings
- 1 County Office buildings
- 2 Court buildings

The 8 Medium Office buildings consist of:

- 6 State Office buildings
- 1 County Office building
- 1 State Court building

An initial data quality check was performed on the data, by viewing the channels to provide a clear identification of creep, missing data gaps, turned-off periods, and sudden big changes that suggest changes in the building operation or an addition to the building. We include in Appendix (8.1) one-page descriptions of each building showing information such as the floor area, the number of stories, and the operation. In Appendix (8.2), we show sample lighting and equipment data from the monitored Office buildings in the ESL database. Samples of the graphs used for data quality checks are shown in Appendix (8.3).

No.	Category	Bldg ID#	Building	Location	Start Date	End Date	Retrofit Date	Building Area (sqft)	WBE	L&R	Data Format	Cost	Data Quality
1	Large	904	Federal Office 904	Washington D.C	1/1/94	12/31/94	N/A	1,200,000	NWD		Hourly	Free	Good
2	Large	209	State Office 209	AUSTIN	1/1/97	12/31/97	6/1/92 - 8/1/93	491,000	NWD	LITEQ	Hourly	Free	Good
3	Large	146	State Office 146	Dallas, TX	1/1/95	12/31/95	6/30/92 - N/A	473,800	WD	MCC	Hourly	Free	Good
4	Large	708	State Office 708	Capitol Complex	-	-	6/13/94 - 12/28/94	378,100	NWD		15min	Free	Bad
5	Large	710	State Office 710	Capitol Complex	1/1/98	12/31/98	7/1/94 - 12/28/94	366,805	NWD		15min	Free	Good
6	Large	952	County Office 952	Dallas County	1/1/98	12/31/98	N/A	323,232			Hourly	Free	OK
7	Large	711	State Office 711	Capitol Complex	1/1/98	12/31/98	5/6/94 - 9/9/94	317,286	NWD		15min	Free	Good
8	Large	210	State Office 210	AUSTIN	1/1/97	12/31/97	1/1/94 - 5/1/94	308,080	NWD	LIGHT, LITEQ	Hourly	Free	Good
9	Large	200	State Office 200	AUSTIN	7/1/97	7/1/98	N/A	282,499	NWD		Hourly	Free	OK
10	Large	707	State Office 707	Capitol Complex	1/1/98	12/31/98	6/13/94 - 12/28/94	281,850	NWD		15min	Free	Good
11	Large	704	State Office 704	Capitol Complex	1/1/98	12/31/98	7/22/94 - 6/23/95	200,829	NWD		15min	Free	Good
12	Large	201	State Office 201	AUSTIN	1/1/93	1/1/94	2/1/94 - N/A	182,961	NWD		Hourly	Free	OK
13	Large	203	State Office 203	AUSTIN	1/1/97	12/31/97	4/1/92 - 8/1/92	169,746	WD	LIGHT	Hourly	Free	Good
14	Large	228	State Office 208	AUSTIN	1/1/98	12/31/98	2/1/94 - N/A	151,620	NWD		Hourly	Free	Good
15	Large	229	State Office 229	AUSTIN	1/1/98	12/31/98	2/1/94 - N/A	121,654	NWD		Hourly	Free	Good
16	Large	208	State Office 208	AUSTIN	1/1/97	12/31/97	4/1/92 - 8/1/92	120,000	NWD	LITEQ	Hourly	Free	Good
17	Large	206	State Office 206	AUSTIN	1/1/96	12/31/96	4/1/92 - 9/1/92	102,000	NWD	LITEQ	Hourly	Free	Good
18	Large	963	Court 963	Butte, MT	7/1/98	7/1/99	N/A	100,000			Hourly	Free	OK
19	Large	975	Court 975	Bryan, TX	7/1/98	7/1/99	N/A	100,000	WD	MCC	Hourly	Free	Good
20	Large	984	Private Office 984	Dallas, TX	1/1/98	12/31/98	N/A	100,000		MCC	Hourly	Free	Bad (MCC)
21	Large	985	Private Office 985	Dallas, TX	10/1/98	10/1/99	N/A	100,000	WD	MCC	Hourly	Free	OK
22	Medium	226	State Office 226	AUSTIN	1/1/96	12/31/96	2/1/94 - N/A	97,030	NWD		Hourly	Free	Good
23	Medium	709	State Office 709	Capitol Complex	3/1/96	3/1/97	9/24/94 - 4/5/95	87,664	NWD		15min	Free	Good
24	Medium	205	State Office 205	AUSTIN	1/1/94	12/31/94	4/1/92 - 8/1/92	80,000	WD	LITEQ	Hourly	Free	OK
25	Medium	712	State Office 712	Capitol Complex	1/1/98	12/31/98	7/11/94 - 6/23/95	77,630	NWD		15min	Free	Good
26	Medium	227	Stata Court 227	AUSTIN	1/1/98	12/31/98	2/1/94 - N/A	72,737	NWD		Hourly	Free	Good
27	Medium	207	State Office 207	AUSTIN	1/1/93	12/31/93	4/1/94 - N/A	62,000	WD	MCC	Hourly	Free	Good
28	Medium	706	State Office 706	Capitol Complex	1/1/98	12/31/98	9/2/94 - 4/5/95	57,047	NWD		15min	Free	Good
29	Medium	951	County Office 591	Dallas County	1/1/98	12/31/98	N/A	42,385			Hourly	Free	OK

Table 7 All Office Buildings monitored at ESL and relevant to the ASHRAE 1093-RP project

2.2.2 LBNL Data

We contacted Ms. Mary Ann Piette at LBNL for data, and she referred us to Ms. Satkartar Khalsa and Mr. Bruce Nordman. LBNL provided us the data at no cost. Mr. Khalsa offered us one year worth of hourly lighting and receptacles loads data from a large Office building in San Francisco, CA. Mr. Nordman offered us two years (more or less) worth of hourly lighting and receptacles data from 8 large, medium, and small buildings monitored under the Energy Edge program; the buildings are located in Washington, California, Oregon, and Idaho. Table 8, below, shows the data acquired from LBNL. The LBNL data has already been processed and used (by LBNL), and is judged clean. We include in the Appendix (8.2) samples from the LBNL lighting and receptacles data.

No.	Category	Building Name	Location	Start Date	End Date	Retrofit Date	Building Area (ft2)	L&R	Source	Data Format	Cost	Data Quality
1	Large Office	Bellevue	Bellevue, WA	Oct-90	Sep-91		389,000	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
2	Large Office	160 Sansome	San Francisco, CA	May-98	Jun-99		100,000	Light, Recep	LBNL	Hourly	Free	OK
3	Medium Office	Director	Portland, OR	Jan-91	Aug-92		79,700	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
4	Medium Office	EPUD	Eugene, OR	Nov-88	Sep-92		24,838	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
5	Medium Office	East Gate	Bellevue, WA	Aug-90	Jun-92		23,728	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
6	Medium Office	West Yakima	Yakima, WA	Nov-88	Apr-90		16,221	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
7	Small Office	Dubal	Portland, OR	Dec-87	Aug-89		8,512	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
8	Small Office	East Idaho	Idaho Falls, ID	Jun-88	Mar-90		5,300	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK
9	Small Office	STS	Ellensburgh, WA	Jan-89	Apr-92		4,266	Light, Recep	Energy Edge, LBNL	Hourly	Free	OK

Table 8 Energy-Edge Office Buildings provided by LBNL for ASHRAE 1093-R

2.2.3 Lund Institute of Technology Data

We obtained the thesis of Mr. Corfitz Noren at Lund Institute of Technology - Sweden (Noren 1997), which includes the processed data used in the developed typical load shapes. Mr. Noren has also published two papers (Noren and Pyrko 1998a) and (Noren and Pyrko 1998b) which we reviewed in the Preliminary Report. The raw data was unretrievable since Mr. Noren graduated and left the institute. We contacted Dr. J. Pyrko, C. Noren's advisor who could not help us. However, the thesis clearly documents the method for developing the typical load shapes. The processed data for the load shapes for six categories of Swedish Commercial Buildings are available in a Spreadsheet Format, and in Graphs. These data represents whole-building electric data for 7 district-heated office buildings in an urban area in South Sweden.

2.3 Potential Data

In addition to the data from LBNL and ESL, there is still a potential for acquiring more data by contacting three sources again, if this is deemed of sufficient priority, by the PMSC. The three sources are: (1) EPRI-CEED, (2) Battelle PNNL (ELCAP data), and (3) European data. Below, we explain the circumstances of our *Phase II* communication with these sources.

2.3.1 EPRI-CEED Data

The information from EPRI-CEED was very clear about the type of data available in terms of commercial building category, type of end-use, sample size, data format and length. However the data are obtainable at a cost. When we contacted EPRI-CEED during *Phase II* of this project, we understood that they do not have a policy that allows them to provide raw data. They only provide processed data, i.e., in our case the "typical load shapes". This will be of limited help to our project since we prefer to acquire raw data, and process it with clearly defined methods to produce the typical load shapes and diversity factors. Moreover, EPRI-CEED offered to provide one typical load shape for each office building category (small, medium, and large), which would be a result of averaging the whole stock of monitored data from different buildings that fall in each category. The cost for obtaining such data was approximated to be between $1,000 and $2,000 (correspondence e-mails available). We will contact EPRI-CEED again if the PMSC requests that we do so.

2.3.2 Battelle PNNL (ELCAP) Data

During *Phase I* of the project, Battelle PNNL, through Mr. Todd Taylor, has indicated their willingness to offer access to ELCAP data that represents 80 to 90 commercial buildings in Seattle, Oregon, and Idaho. These data include whole-building electricity consumption, and various sub-metered channels. Square footage, address, city, state, and type of building are associated with the hourly data, and the data can be provided in an ASCII format. The cost for obtaining this data was yet to be determined. We will try again to obtain the data from Battelle PNNL, if the PMSC asks us to do so.

2.3.3 European Data

From Europe, the only completed contact was with Mr. Guislain Burle from MD3E (a consulting firm in France). Mr. Burle proposed offering us monitored data from Commercial Buildings (Small, Medium, and Large Office buildings, University Buildings, and Hotels) including: General, Lighting, Equipment, Lighting+Equipment, Water Heating, Air-Conditioning, Lifts, and Restaurant). The data sets would have a 10 minutes frequency, and are 3 weeks in length, and cost US$9,840. We contacted Mr. Burle again and reminded him that we are looking for Lighting and Equipment data only, and for Office Buildings only. We have not heard back from him as of this moment. We will pursue the contact with MD3E if the PMSC feels this is important.

Other contacts in Europe, i.e., Universite de Liege, and DEFU (a consulting firm in Denmark) have not resulted in any data. We will continue to pursue the European contacts, with the Universite de Liege and DEFU, if the PMSC feels this is important.

3. IDENTIFICATION OF METHODS FOR THE CLASSIFICATION OF BUILDINGS

Commercial buildings are classified according to different criteria by national standards and agencies. In the Preliminary Report we listed major classification schemes of the commercial building sector that were used by various national laboratories and agencies, and published in standards. Our survey of the classification schemes covered: ASHRAE FIND (ASHRAE 1995), ASHRAE Standard 90.1(ASHRAE 1989), CBECS (CBECS 1997a and b), NAICS (NAICS 1997), ELCAP (ELCAP 1989 and Gillman et al. 1990), BECA (Wall et al. 1984), and EPRI -CEED. However, after the ASHRAE meeting in Seattle (June 1999), the PMSC asked us to perform our analysis on only the Office building category.

3.1 Previously Identified Categories

In the Preliminary Report, we proposed to follow the classification followed by the Commercial Buildings Energy Consumption Survey (CBECS), a national survey of commercial buildings and their energy suppliers, in compiling their statistics of the commercial building stock in the U.S. We based our proposal on the detailed compiled survey results of CBECS, that helped us in drawing meaningful conclusions. The CBECS classification scheme agrees with that of ASHRAE Standard 90.1, taking into consideration the small representation, in the whole commercial building stock, of the "Religious Worship" and the "Public Order and Safety" categories that appear in the CBECS classification. Therefore, we determined in *Phase I* that the commercial building classification that we will follow in developing the diversity factors and schedules for energy and cooling load calculations will consist of the following categories:

1. Offices
2. Education
3. Health Care
4. Lodging
5. Food Service
6. Food Sales
7. Mercantile and Services
8. Public Assembly
9. Warehouse and Storage.

3.2 Office Buildings

After the ASHRAE meeting in Seattle (June 1999), the PMSC suggested that we perform our analysis on the Office building category only. Therefore, we will used data from Office buildings only for this project, but we will divide the Office buildings into three subcategories, based on CBECS:

- Small (1,001 - 10,000 ft^2)
- Medium (10,001 - 100,000 ft^2)
- Large (> 100,000 ft^2).

4. IDENTIFICATION OF RELEVANT METHODS FOR DAYTYPING

In this report 8 of the 12 methods, listed in the Preliminary Report, for daytyping and generation of typical load shapes of lighting and equipment loads in Office buildings are documented. Three additional methods have since been identified during the *Phase II* work. From these 11 well-defined methods we are proposing to use a specific procedure that combines features of several previously used methods together, to produce a robust technique for daytyping and generation of typical load shapes.

4.1 Previously Identified Methods

In the Preliminary Report, we identified a total of 12 existing methods for daytyping and determining load shapes of end-uses. These 12 methods consist of 4 deterministic methods and 8 statistical methods. Moreover, these methods are either based on engineering simulations and monitoring (Total Electricity Consumption), or totally based on monitored energy uses. Table 9, below, shows the 12 methods.

Method's Name	Nature*	Basis**	Weather-dependent	Weather-independent	Reference
Stephan-Demming Algorithm	Deterministic	Engineering/ Monitoring	X	X	(SRC 1988, ref. Eto et al.1990)
End-use Disaggregration Algorithm (EDA)	Deterministic	Engineering/ Monitoring	X	X	(Akbari et al. 1988)
Conditional Energy Demand (CED)	Statistical	Monitoring	X	X	(Parti et al. 1988)
Variance Allocation	Deterministic	Engineering/ Monitoring	X	X	(Schon and Rodgers 1990)
Bi-level Regression	Statistical	Engineering/ Monitoring	X	X	(SSI 1986, ref. Eto et al. 1990)
Statistically Adjusted Engineering approach (SAE)	Statistical	Engineering/ Monitoring	X	X	(CSI, CA, ADM 1985, ref. Eto et al. 1990)
Mean / Standard Deviation / Regulatory Index	Statistical	Engineering/ Monitoring		X	(Katipamula and Haberl 1991)
Temporal Synoptic Index (TSI)	Statistical	Monitoring	X		(Hadley 1993)
Heuristic Pattern Recognition Algorithm	Deterministic	Monitoring	X	X	(Margossian 1994)
Inverse Binning Method	Statistical	Monitoring		X	(Thamilseran and Haberl 1994)
Temperature-binning Daytyping	Statistical	Monitoring	X		(Bou-Saada and Haberl 1995), (Noren and Pyrko 1998)
Pattern Group Assignment	Statistical	Monitoring	X	X	(Emery and Gartland 1996)

* *Deterministic Methods*: Methods that rely on exact reconciliation to an hourly control total, which is provided by the hourly whole-building load research data. The starting point for the reconciliation is an engineering simulation which is relied upon by the earliest load shape estimation methods. The methods typically rely on much more detailed information to develop the simulation input (i.e., minimizing the extensive reliance on engineering judgement) (Eto et al. 1990).

Statistical Methods: Methods that typically rely on regression techniques that correlate explanatory variables with the hourly control total (measured total electricity use). These variables need not all be physical and the reconciliation to the control total is usually expressed in goodness of fit.

** *Engineering methods*: Methods based on pure simulations of whole-building energy use and/or different end-uses.

Monitoring Methods: Methods that involve monitored whole-building energy use.

Note: Simple average and standard deviation deterministic methods, based on metered end-uses, are not included in this table. Only methods that disaggregate whole-building energy use to derive typical load shapes for end-uses are listed, besides some other sophisticated approaches.

Table 9. Existing methods for daytyping and determining load shapes of end-uses.

In Table 9, the first *Deterministic* method listed for deriving load shapes is the Stephan-Deming Algorithm (SRC 1988, ref. Eto et al. 1990), which is a statistical adjustment procedure in which elements of an end-use matrix are adjusted when the terminal values (i.e., total hourly loads) are known. When only the hourly whole-building load is known, a weighted distribution of the difference between the measured total and the sum of the simulated end-uses, based on the magnitude of the original simulated estimates, is applied.

The second *Deterministic* method listed uses the Energy-use Disaggregation Algorithm (EDA) (Akbari et al. 1988) which is an engineering method that primarily utilizes the statistical characteristics of the measured hourly whole-building load and its statistical dependence on temperature. In the EDA the sum of the end uses is constrained at hourly intervals to be equal to the measured whole-building load, providing a reality check not always possible with pure simulation. The intent of the method is to supply reasonable end-use breakdowns when detailed information is scarce. This method is a hybrid method that uses monitored data, statistical disaggregation, and a prorating based on a simulation.

The third *Deterministic* method listed is the Variance Allocation method (Schon and Rodgers 1990) which is a hybrid engineering/ statistical approach to end-use load shape estimation for the commercial sector. The method: (1) identifies systematic biases in engineering model hourly end-use load estimates, (2) adjusts the engineering model to significantly reduce these biases for individual building end-use estimates, and (3) uses a variance-weighted approach to reconcile adjusted engineering estimates with whole-building metered data. To reconcile the sum of the hourly end-use load estimates with each individual facility's hourly research data, the variances observed for each regression coefficient are used. The difference between simulated and metered totals is prorated based on statistical variation in the simulated end-use loads. The largest and most variant end-uses receive the largest portion of the difference between the engineering simulation and the metered whole-building load.

The fourth *Deterministic* method listed is the Heuristic Pattern Recognition Algorithm (Margossian 1994) which is used to disaggregate premise-level load profiles. This algorithm uses as input 5-minute or 15-minute residential premise-level load data, and also requires as input connected load estimates of the cooling, heating and water heating appliances. The algorithm first scans the premise-level load profile and identifies all spikes in the profile that are large enough with respect to the connected load of the space conditioning appliance, and categorizes these spikes with various attributes such as shape, timing, magnitude, and duration. In a second stage, the classification stage, the algorithm decides whether or not to attribute each of the identified spikes to the space conditioning appliance. The resulting spikes comprise the end-use load profile for the space conditioning appliance on that day. For example, the load profile of the water heating appliance is derived from the residuals of the premise-level load profile, after subtracting the space conditioning appliance load profile, using the scanning and classification stages.

The first *Statistical* method listed is the Conditional Energy Demand (CED) technique (Parti et al. 1988). In this technique the end-use metered consumption information are used only for comparison to the CED estimates of end-use load shapes. The CED carries out the disaggregation of the total load into its end-use components by applying Multiple Linear Regression (MLR) analysis to a data set composed of total load data, survey and weather information. The model breaks down the hours of the day into four general hourly categories: (1) Night, (2) Morning, (3) Midday, and (4) Evening.

The second *Statistical* method listed is the Statistically Adjusted Engineering approach (SAE) (CSI, CA, ADM 1985, ref. Eto et al. 1985) which is very close to the *Deterministic* methods. First an engineering simulation is developed to provide an initial estimate of end-use loads. Next, the initial estimates are regressed against control totals, which are averages of hourly energy use for typical days. The estimated coefficients can then be thought of as adjustment factors that reconcile the initial estimates to the control total.

The third *Statistical* method listed is the Bi-level Regression approach (SSI 1986, ref. Eto et al.1986) which involves two levels of time series and cross section regression analyses. In the first level, the hourly load of individual households is regressed against both weather-related variables, and sine and cosine functions which capture daily, weekly, and seasonal periodicity in loads that are independent of weather. In the second level, the coefficients estimated in the first level (separately for each household) are regressed as a group against customer characteristics.

The fourth *Statistical* method listed is the Mean/Standard Deviation/Regulatory Index method (Katipamula and Haberl 1991). The method identifies typical daytypes for a building, using monitored non-weather-dependent electricity use. Load shapes are generated from the data for each typical daytype. In deriving the daytypes, the mean and the standard deviation of the energy use at each hour for the entire data group were calculated, and a Regularity Index (RI) is calculated and checked against a maximum acceptable value (10%) for each hour. If the RI for all 24 hours exceeds the 10% value, hourly data is summed to daily totals and the mean and standard deviation of the daily consumption are calculated. Three daytypes are then identified as follows: (1) LOW-D days with daily consumption lower than Y (10%) times one standard deviation below the mean; (2) HIGH-D days with daily consumption higher than Y times one standard deviation above the mean; and (3) NORMAL-D , the remaining days. The daytypes are then subdivided to LOW-LOW D, LOW-HIGH D, LOW-NORMAL D, HIGH-LOW D, HIGH-HIGH D, HIGH-NORMAL D, NORMAL-D, NORMAL-LOW D, AND NORMAL-HIGH D.

The fifth *Statistical* method listed is the Temporal Synoptic Index approach (TSI) (Hadley 1993) for weather-dependent data which uses a combination of principal component analysis (PCA) and cluster analysis on the resultant principal components (PC's), to identify days which are considered meteorologically homogeneous. Once the number of daytypes is specified, each day in the data set analyzed can be assigned to a specific, unique daytype and the average values of each meteorological variable calculated for each daytype. Each weather-daytype is defined in terms of the daily average of the dry-bulb and wet-bulb temperature, extraterrestrial and total global horizontal radiation, clearness index, and wind speed. The unique character of each weather daytype is established by: (1) the mean value of each of the original weather variables within each daytype; (2) the frequency of occurrence of the daytype by month; and (3) the diurnal variation of each variable within each daytype. The statistical techniques followed in this method might be helpful in deriving weather-independent load shapes.

The sixth *Statistical* method listed is the Inverse Binning approach (Thamilseran and Haberl 1994) for non-weather-dependent loads. In this method the general pattern of the energy use is identified graphically to show the effect of weekdays-weekends and holidays and the periodicity of the peak consumption. Then Pearson's correlation technique is used to identify the correlation between dependent and independent variables. The "hour of the day" is used as a bin variable in the non-weather-dependent loads model. Duncan's, Duncan-Waller's and Scheffe's multiple comparison tests are used to aggregate the data into daytypes that have means with statistically insignificant differences. The technique includes the following steps: (1) identification of general patterns of data (from database), (2) checking for temperature dependency of Hour of the Day (HOD) dependency, (3) checking for data quality and outliers identification, (4) identification of comprehensive daytypes, (5) checking for impact of ON/OFF mode, (6) calculation of binned energy, (7) correction for missing bins, (8) checking for need for thermal lag, (9) checking for need for humidity sub-binning, (10) final calculation of binned energy and correction for missing bins.

The seventh *Statistical* method listed is the Temperature-binning Daytyping technique

(Bou-Saada and Haberl 1995). With this method, the whole-building electricity consumption of an electrically heated-cooled building was categorized into three weather-daytypes (below 45°F, between 45 °F and 75°F, and above 75°F). An average heating profile was chosen to represent all hours when temperatures were below 45 °F, an average cooling profile was selected for temperatures above 75 °F, while non-HVAC profile was assigned for all hours between a temperature of 45 °F and 75 °F. For the non-HVAC profile, two representative days, weekday and weekend days, were chosen by visual inspection of the data. Disaggregation of the non-weather-dependent electric load was then performed by reviewing site plans, hand measurements during site visits and personal interviews. In a similar way, Noren and Pyrko (1998) presented load shapes developed for different mean daily outdoor temperatures and different daytypes; standard weekdays and standard weekends. The load shapes are presented as non-dimensional normalized 1-hour loads. The methodology consisted of calculating the normalized load by dividing the measured load at time *t* by the mean annual load. Then the data are split into different groups, depending on the daytype. The data in every group are sorted by hour, and every hour sorted into different temperature intervals. Six different integrals for mean daily outdoor temperature were used to sort the data. A mean normalized value of the load can be calculated for every hour and each temperature interval, by dividing the calculated normalized load by the total number of observations at time t for a category at specified temperature interval. The statistical techniques used in these two methods can prove helpful in deriving the diversity factors for this project.

Finally, the eighth *Statistical* method listed is the Pattern Group Assignment (Emery and Gartland 1996) which groups together days with common behavioral load shapes or patterns, instead of grouping energy behaviors together based on the day of the week, as in daytyping algorithms. Pattern codes are assigned in reference to the frequency distribution of a certain behavior. With this technique, there is flexibility in the level of detail available to the pattern code. Different numbers of sections, and different numbers and designations of time periods can be chosen depending on the data and the level of accuracy needed. Once the pattern codes are assigned to each day, the days are iteratively assigned to groups. In the first iteration, days with the same pattern code are grouped together. In the second and proceeding iterations, groups with similar pattern codes and the lowest combination errors are combined until there are no more groups with sufficiently similar pattern group codes.

In summary, daytyping and load shape determination methods that have been reviewed are unique, however only 8 of them were reproducible. The Stephan-Deming Algorithm (SRC. 1988, ref. Eto et al. 1990), the Bi-level Regression (SSI 1986, ref. Eto et al. 1990), the Heuristic Pattern Recognition Algorithm (Margossian 1994), and the Pattern Group Assignment method (Emery and Gartland 1996) could not be reproduced without additional documentation.

4.2 Typical Load Shapes Samples from the Literature (U.S. and Europe)

In this section we show the typical load shapes of Office buildings taken from the literature covered in *Phase I* of the project. Some original graph captions (as they appeared in the references) are changed for illustrative purposes. Each graph is referenced in the new caption. These typical load shapes will be used as reality checks after we develop the diversity factors and typical load shapes for this project.

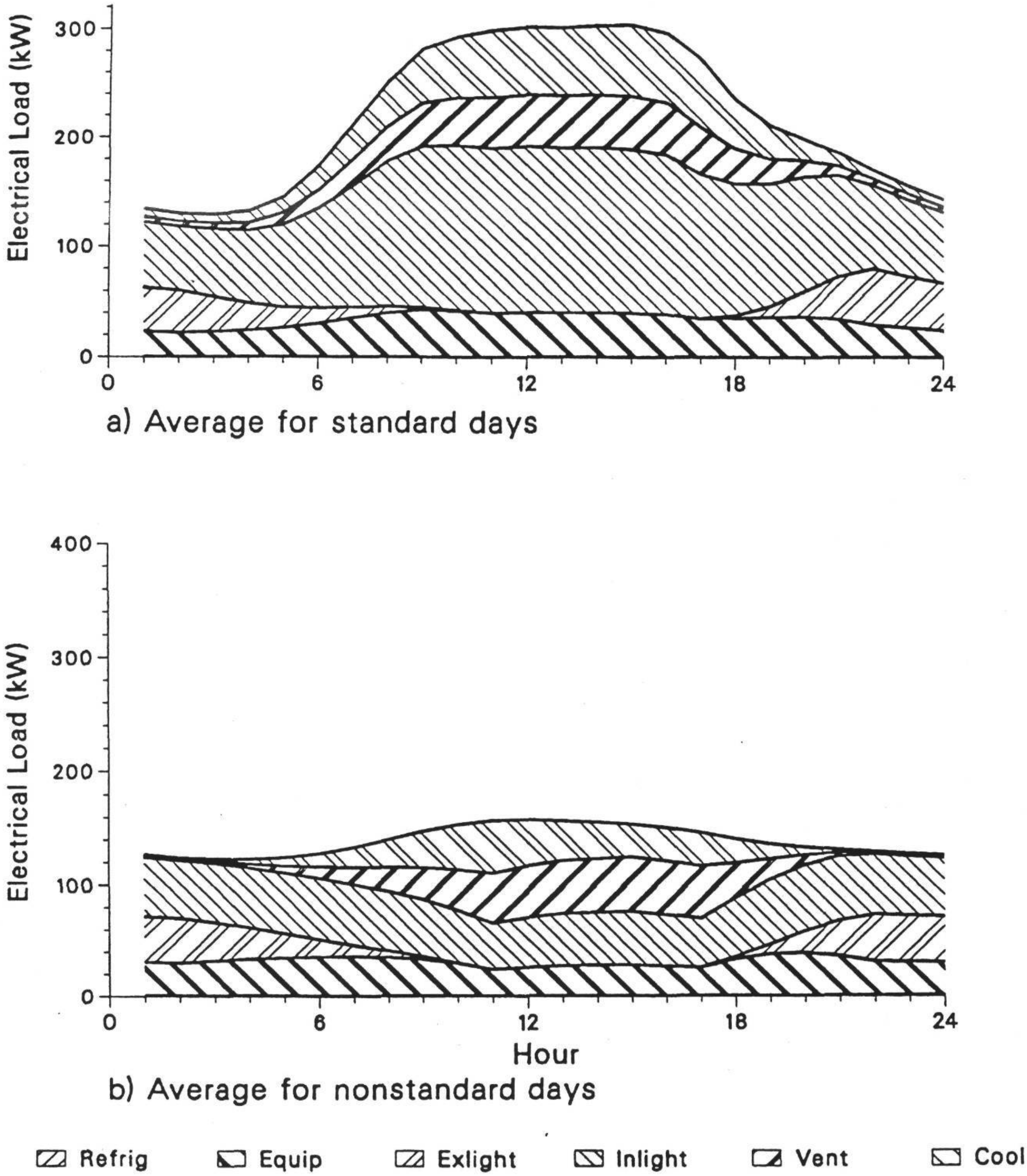


Figure 1. Reconciled Load Shapes for Large Office Buildings (Akbari et al. 1989)

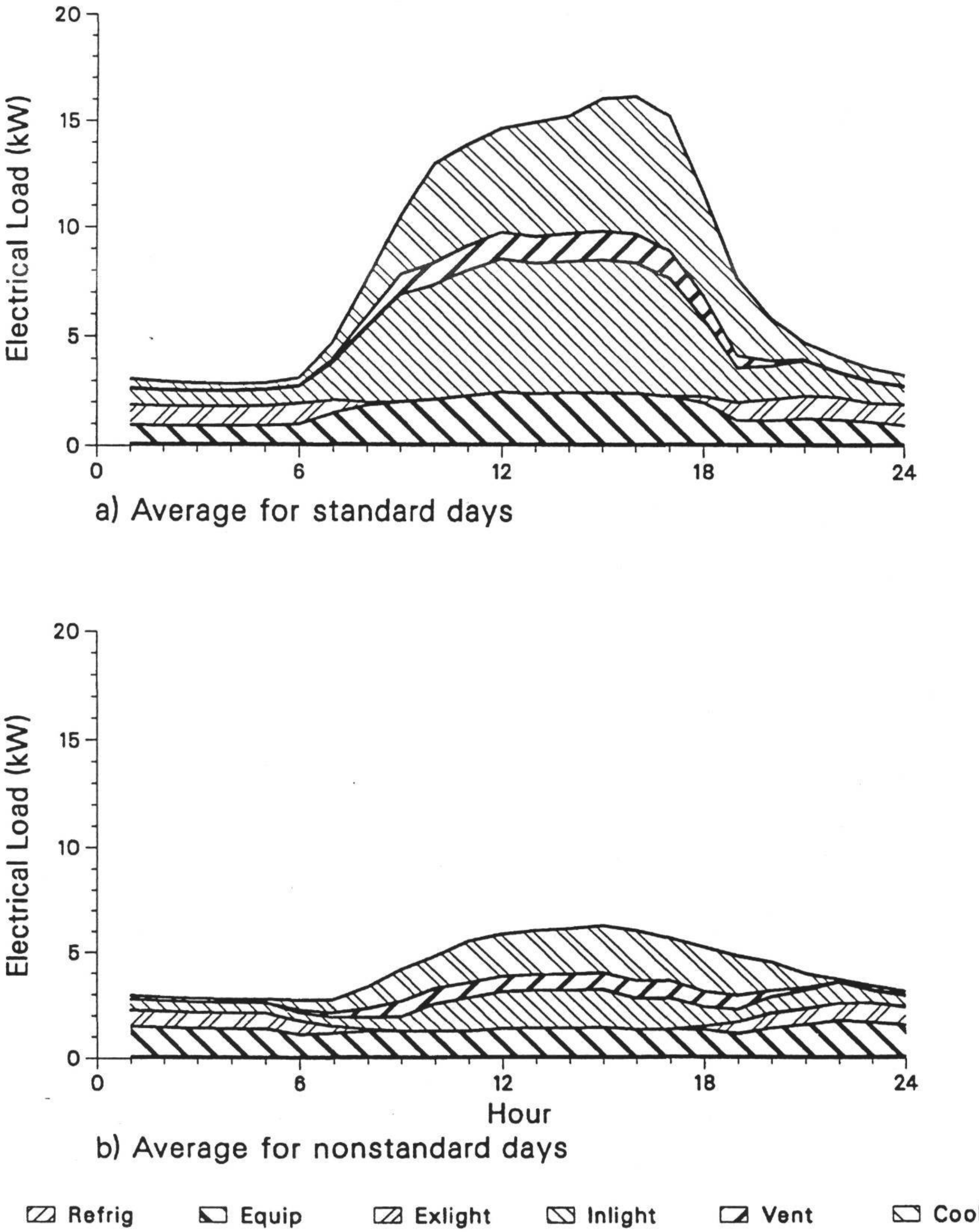
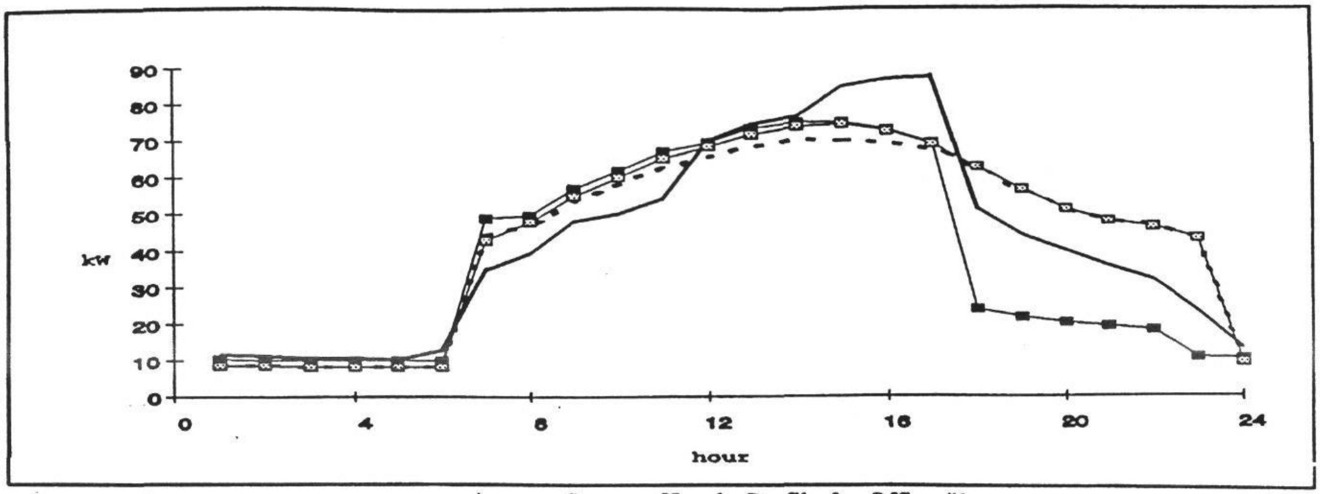
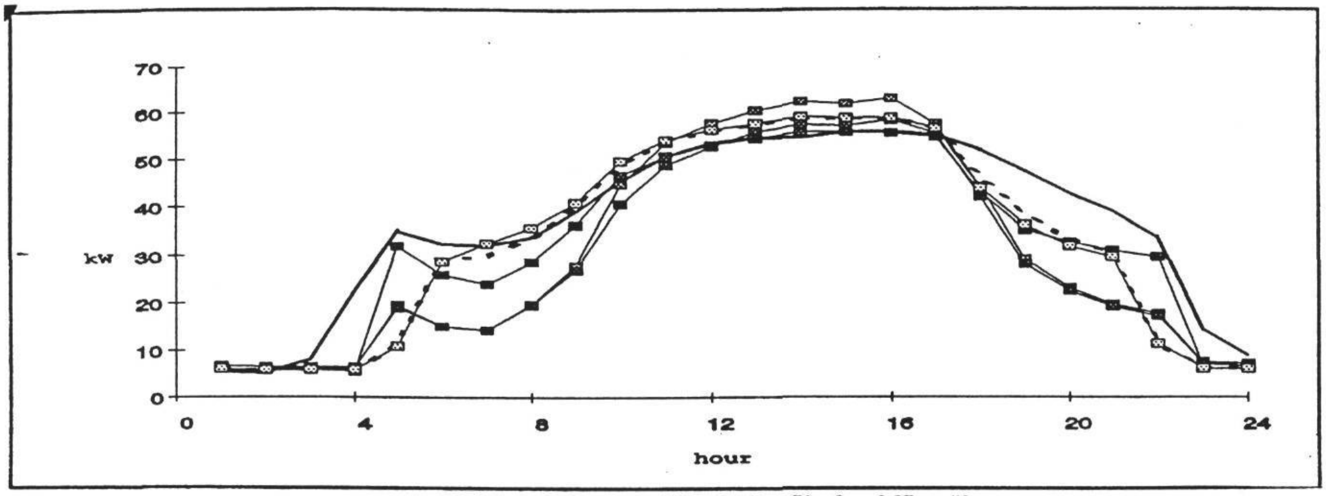


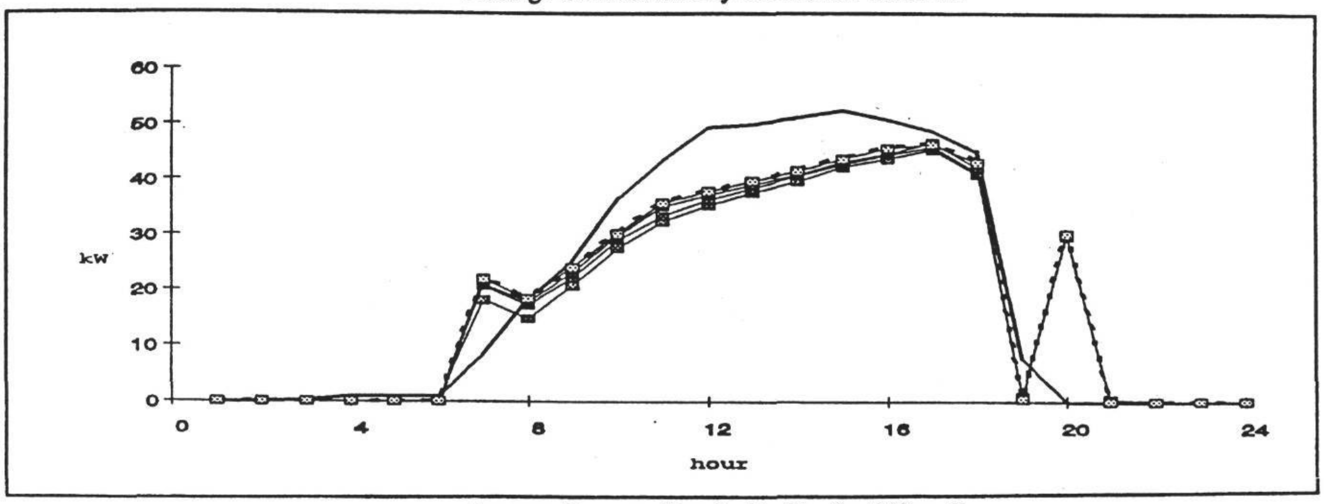
Figure 2. Reconciled Load Shapes for Small Office Buildings (Akbari et al. 1989)



Average Summer Hourly Profile for Office #1



Average Summer Hourly Profile for Office #2



Average Summer Hourly Profile for Office #3

Figure 3. Average Summer Typical Load Shapes of Medium Office Buildings (Alereza and Faramarzi 1994)

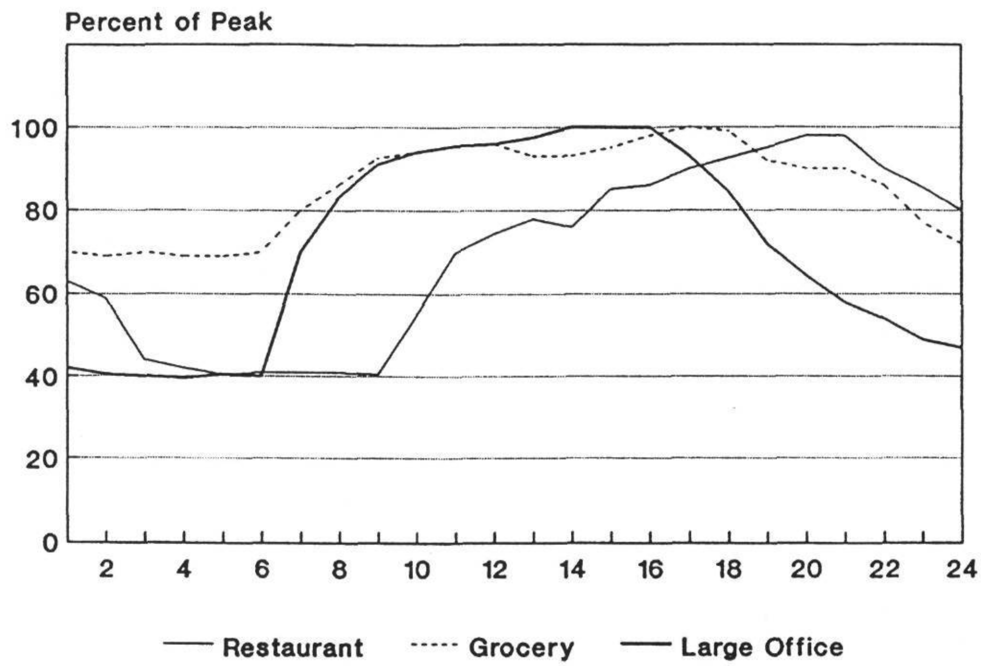


Figure 4. Typical Whole-Building Load Shapes for Commercial Buildings (Baker 1990)

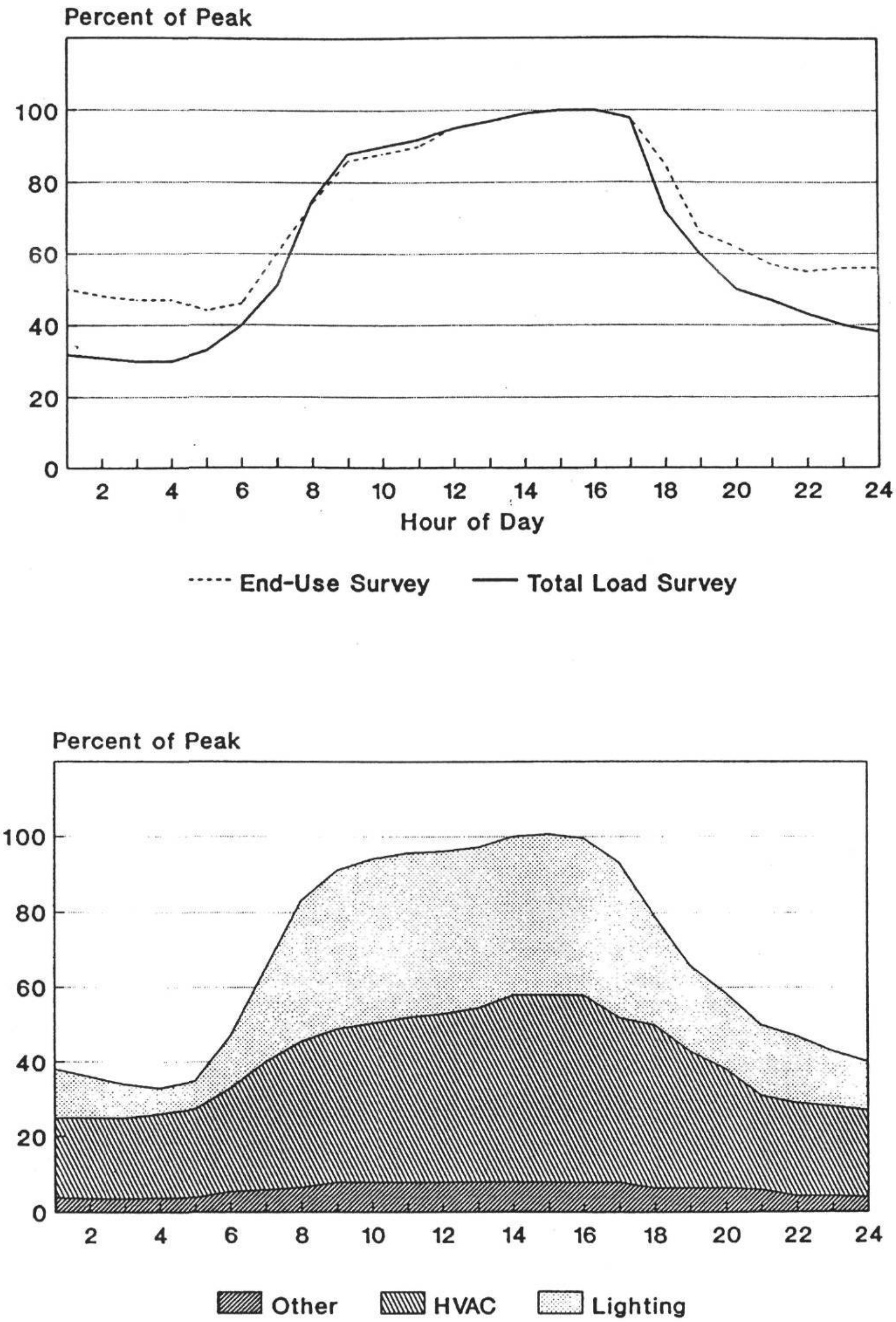


Figure 5. Typical Load Shapes (July Weekdays) for Large Office Buildings (Baker 1990)

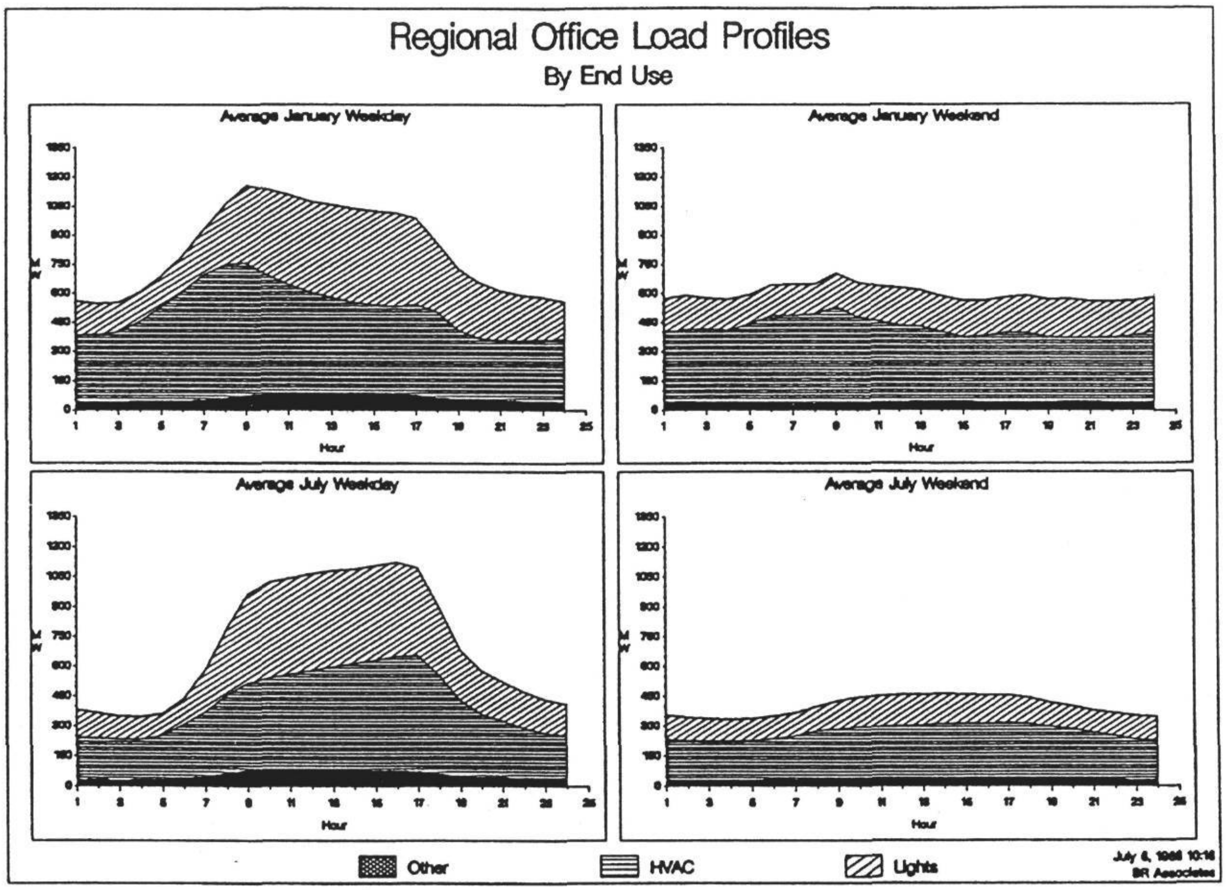


Figure 6. Typical Load Shapes of Office Buildings in the Pacific Northwest (Baker and Guliasi 1988)

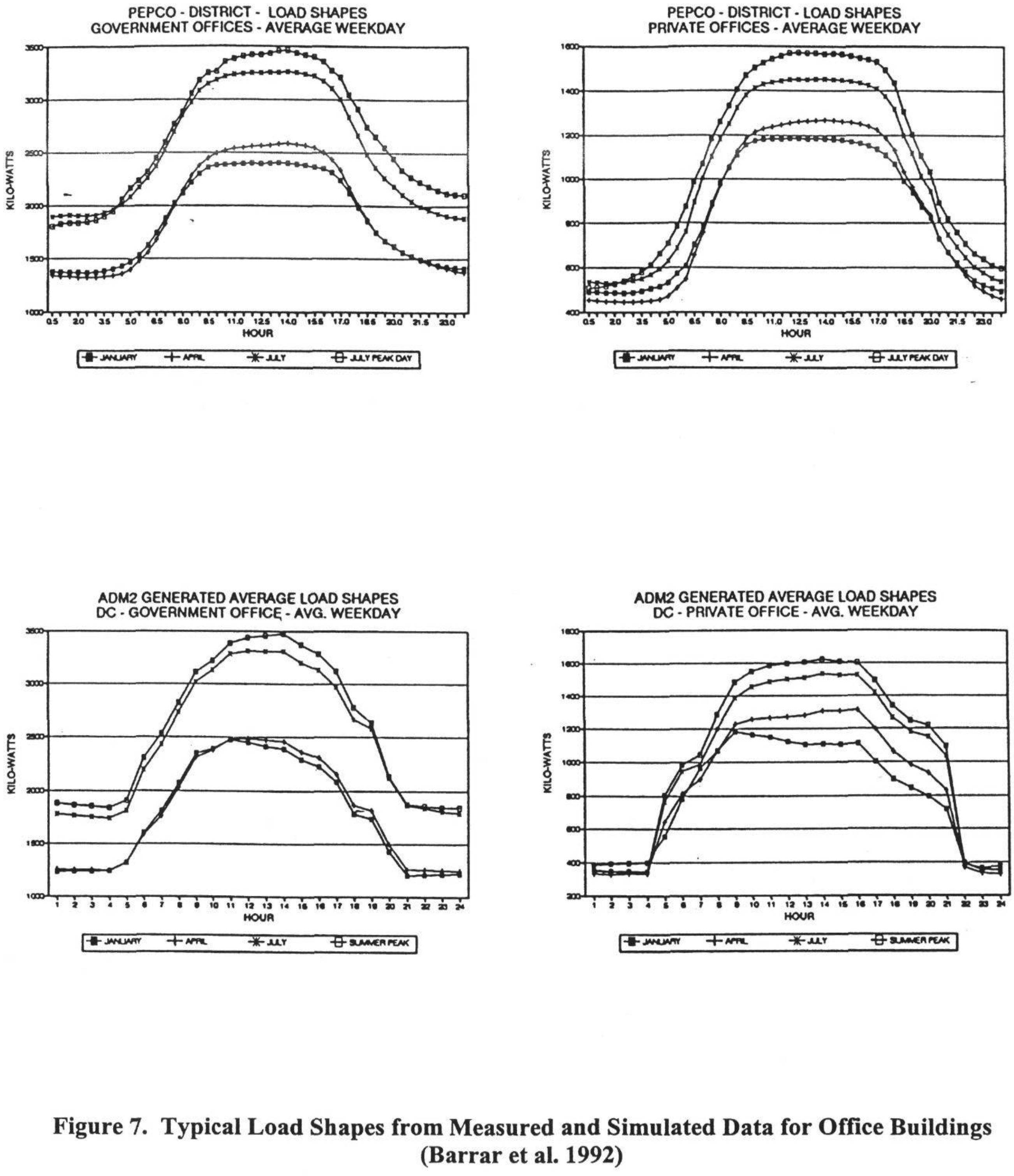


Figure 7. Typical Load Shapes from Measured and Simulated Data for Office Buildings (Barrar et al. 1992)

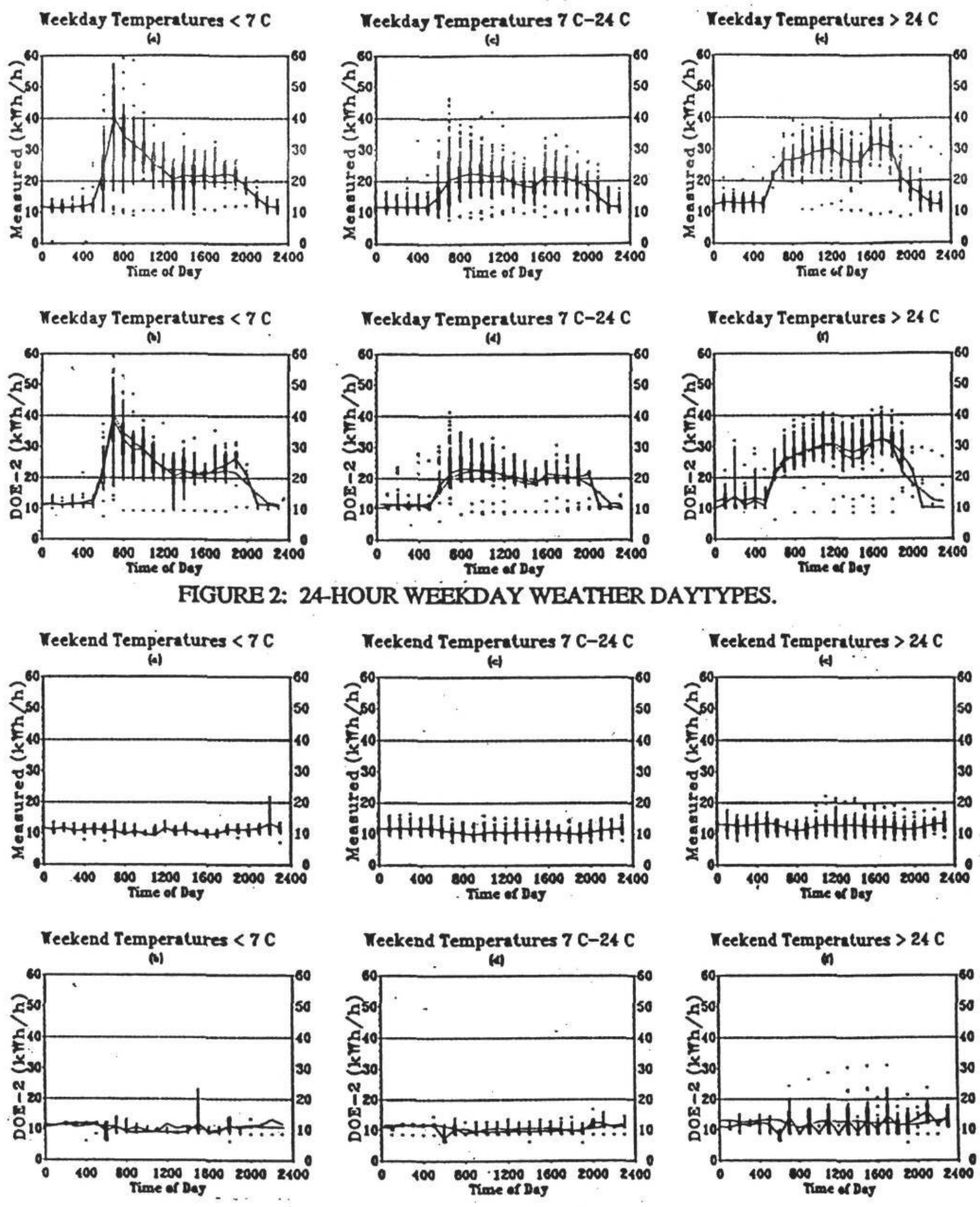


Figure 8. Typical Load Shapes Derived with a Weather-Daytyping Approach (Bou-saada and Haberl 1995)

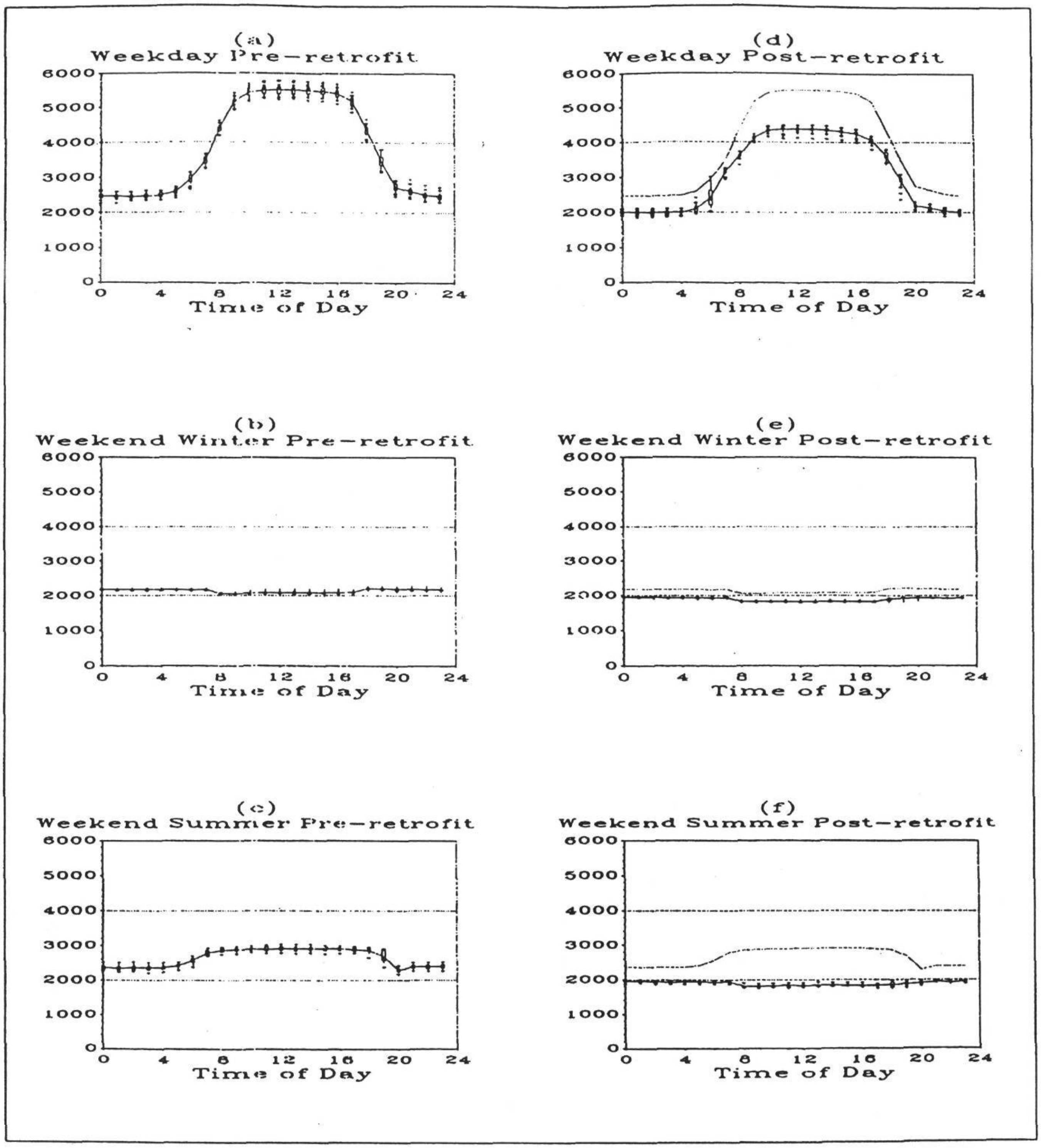
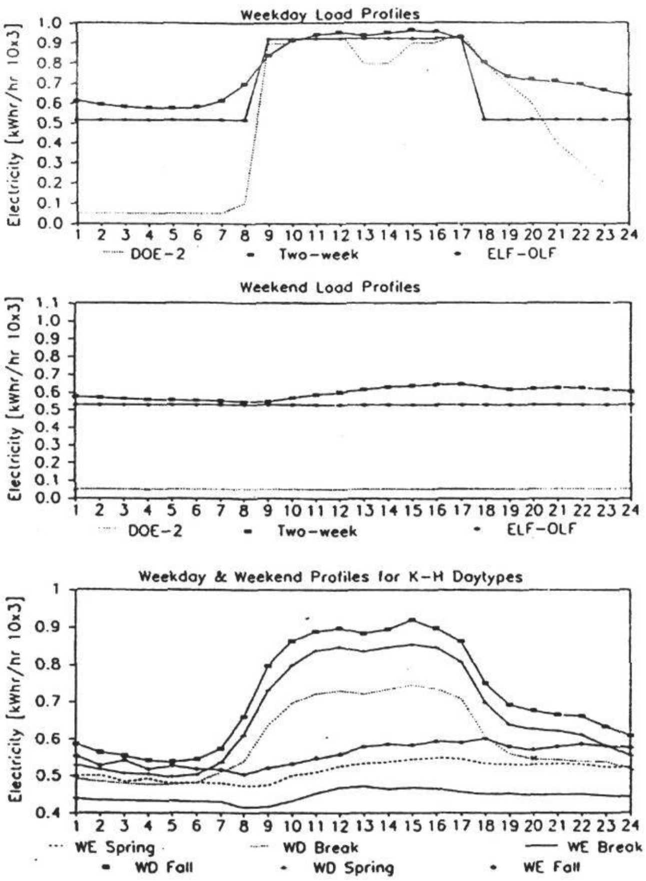


Figure 9. Typical Load Shapes for a Large Federal Office Building (Bou-saada and Haberl 1996)



Weekday and weekend day-type profiles for the EC. Day-type profiles are shown in this figure that represent the DOE-2, ELF-OLF, two-week auditor's monitoring profiles for the weekday (upper graph) and weekend (middle graph), and day types generated with day types from the full data set (bottom graph).

Figure 10. Typical Load Shapes for a Large Institutional Building (Bronson et al. 1992)

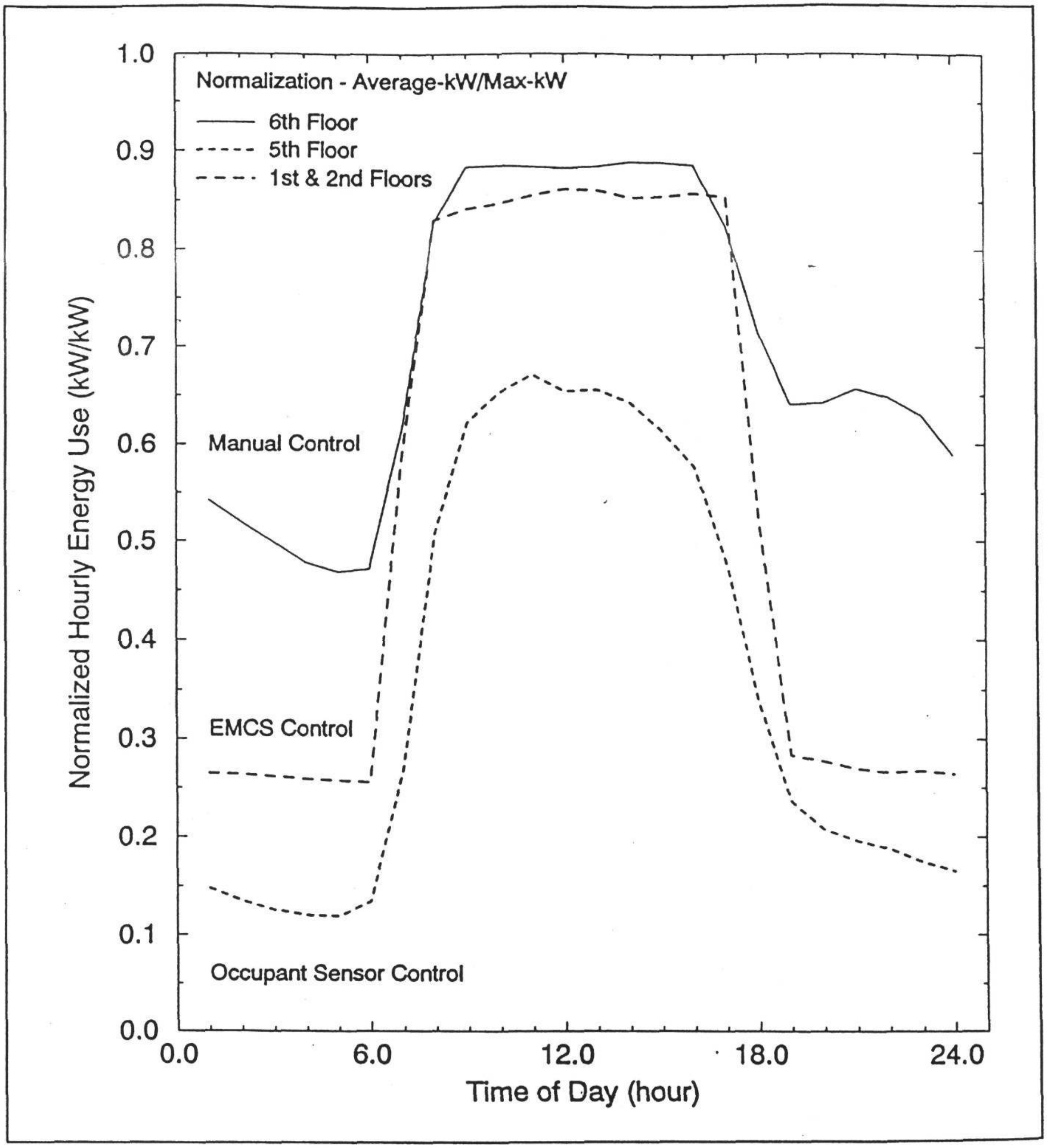
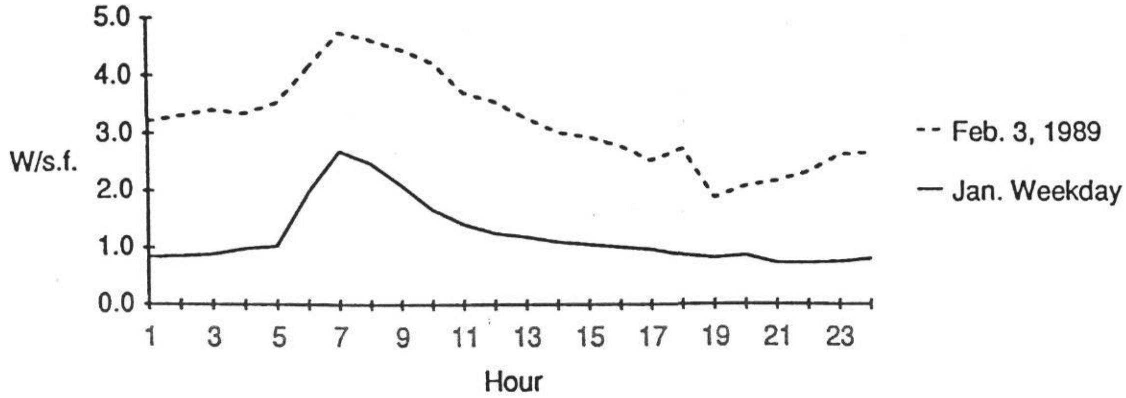
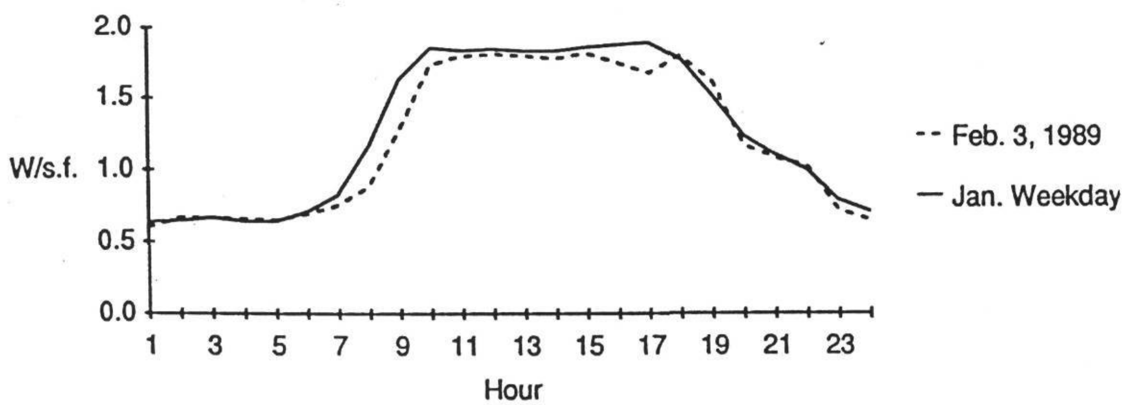


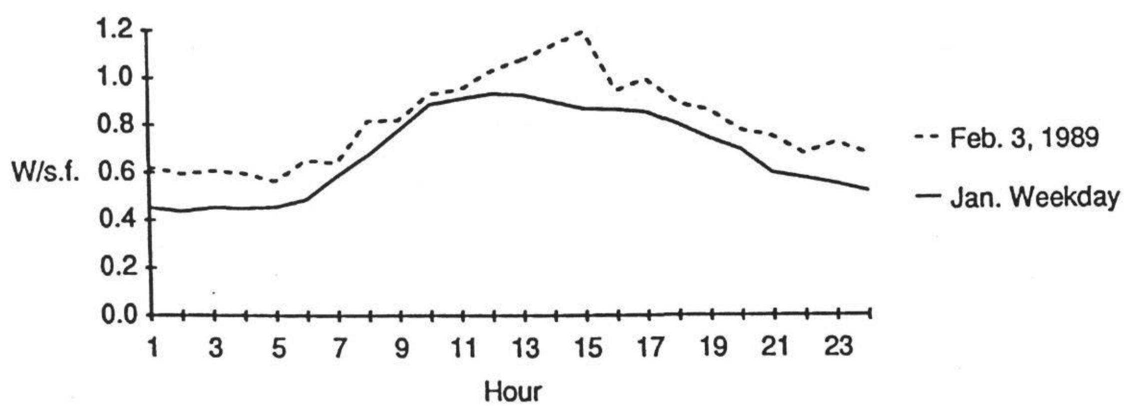
Figure 11. Typical Load Shapes for a Medium Office Building (Energy Edge) (Diamond et al. 1992)



Space Heat Load Shapes (n=9), Commercial Office

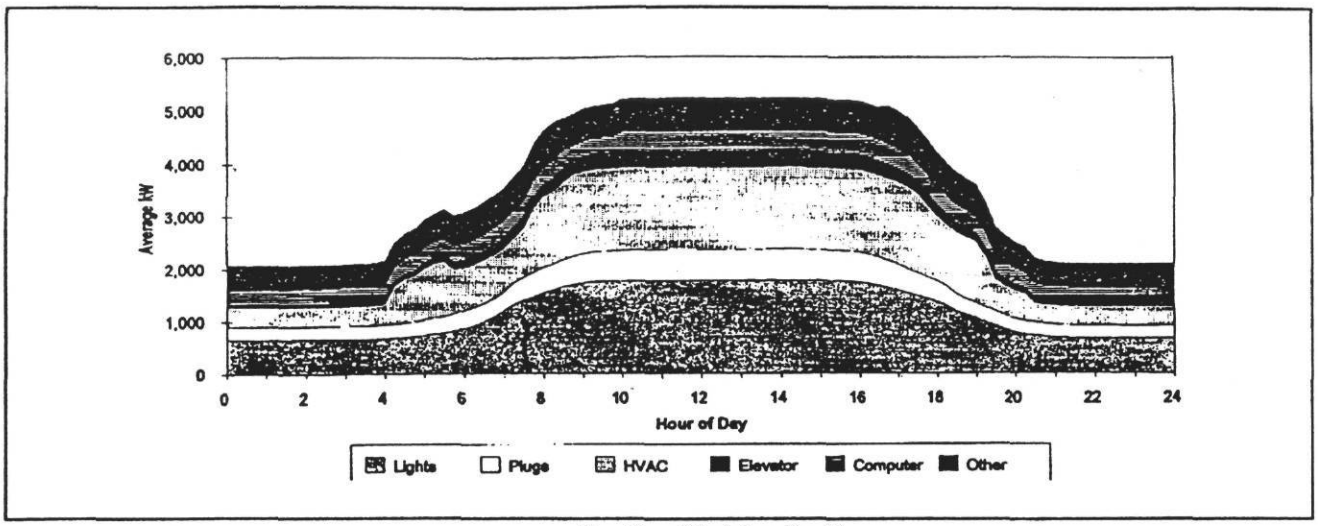


Lighting Load Shapes (n=9), Commercial Office

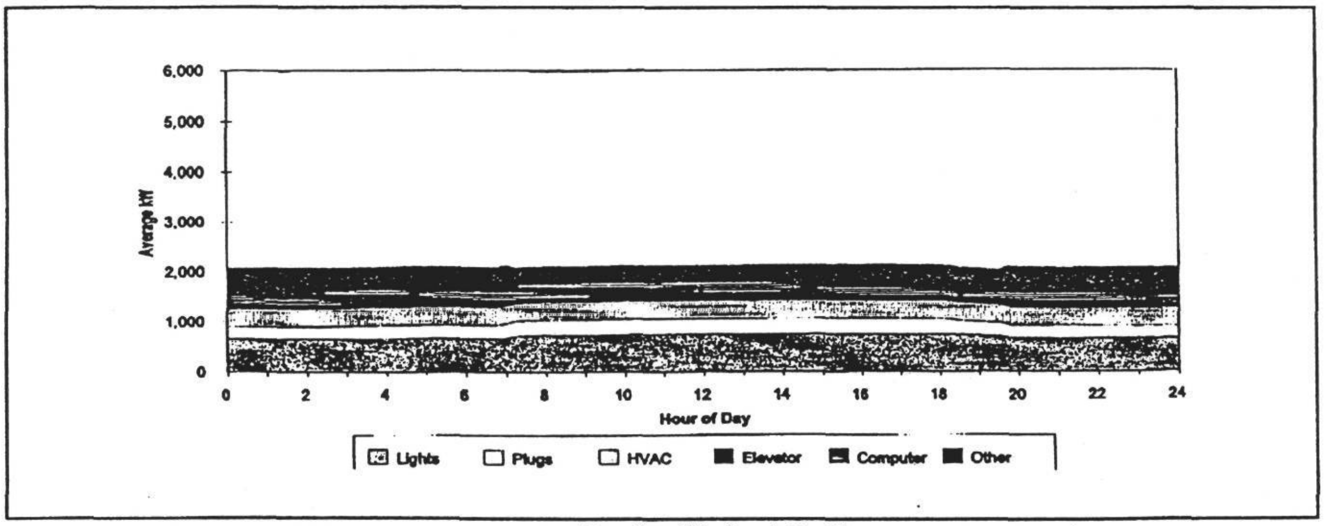


Other Load Shapes (n=9), Commercial Office

Figure 12. Typical Load Shapes of Whole-Building Electric, with Electric Space Heating, for an Office Building (Gillman et al. 1990)

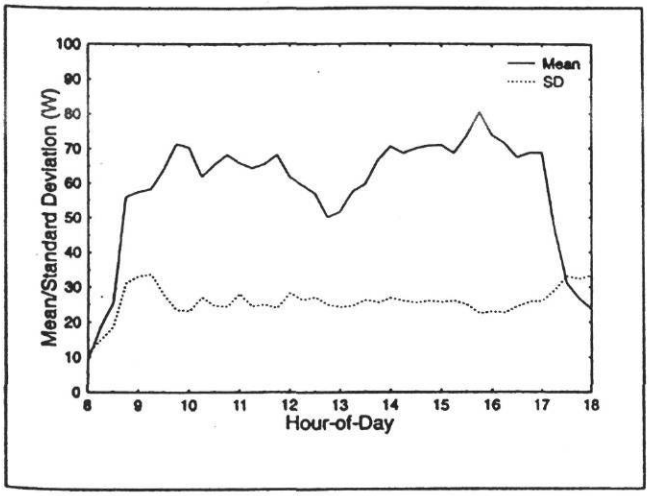


Baseline Weekday Profile



Baseline Weekend Profile

Figure 13. Typical Load Shapes for a Large Federal Office Building (Halverson et al. 1994)



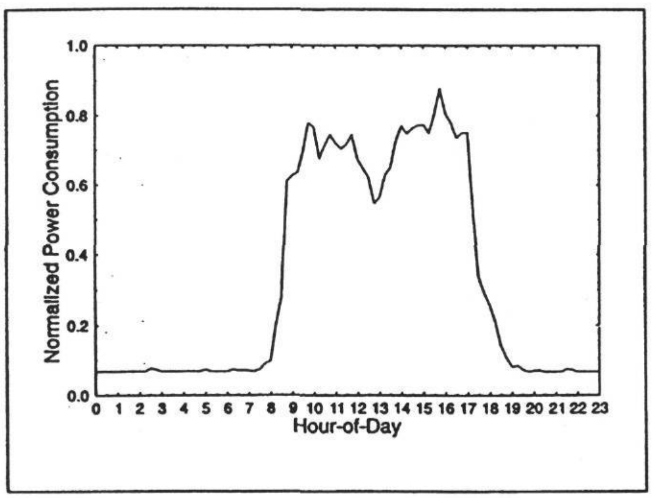


Figure 14. Typical Load Shape for an Energy-Star-Compliant PC in an Office Building (Katipamula et al. 1996)

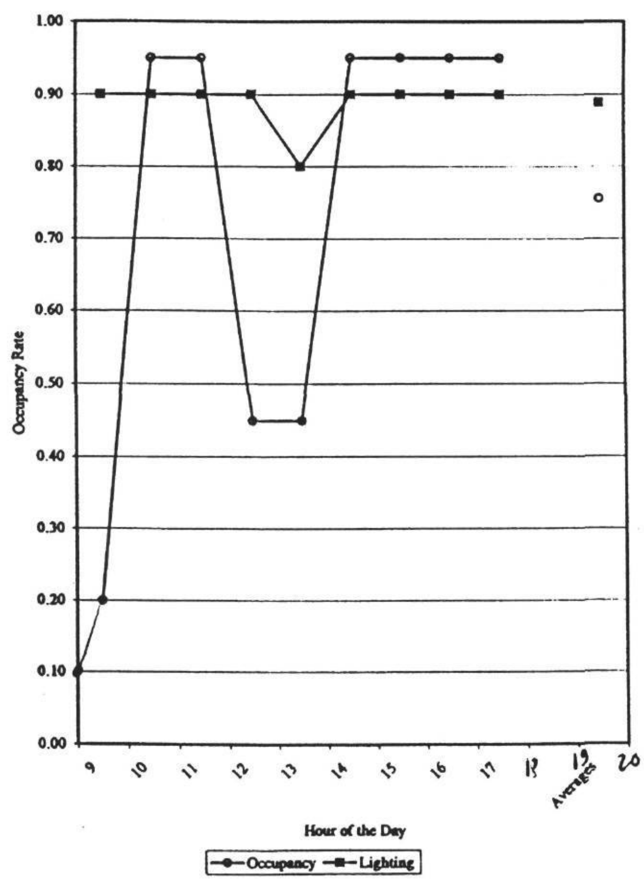


Figure 15. Typical Load Shapes of Occupancy and Lighting in an Institutional Building (Keith and Krarti 1999)

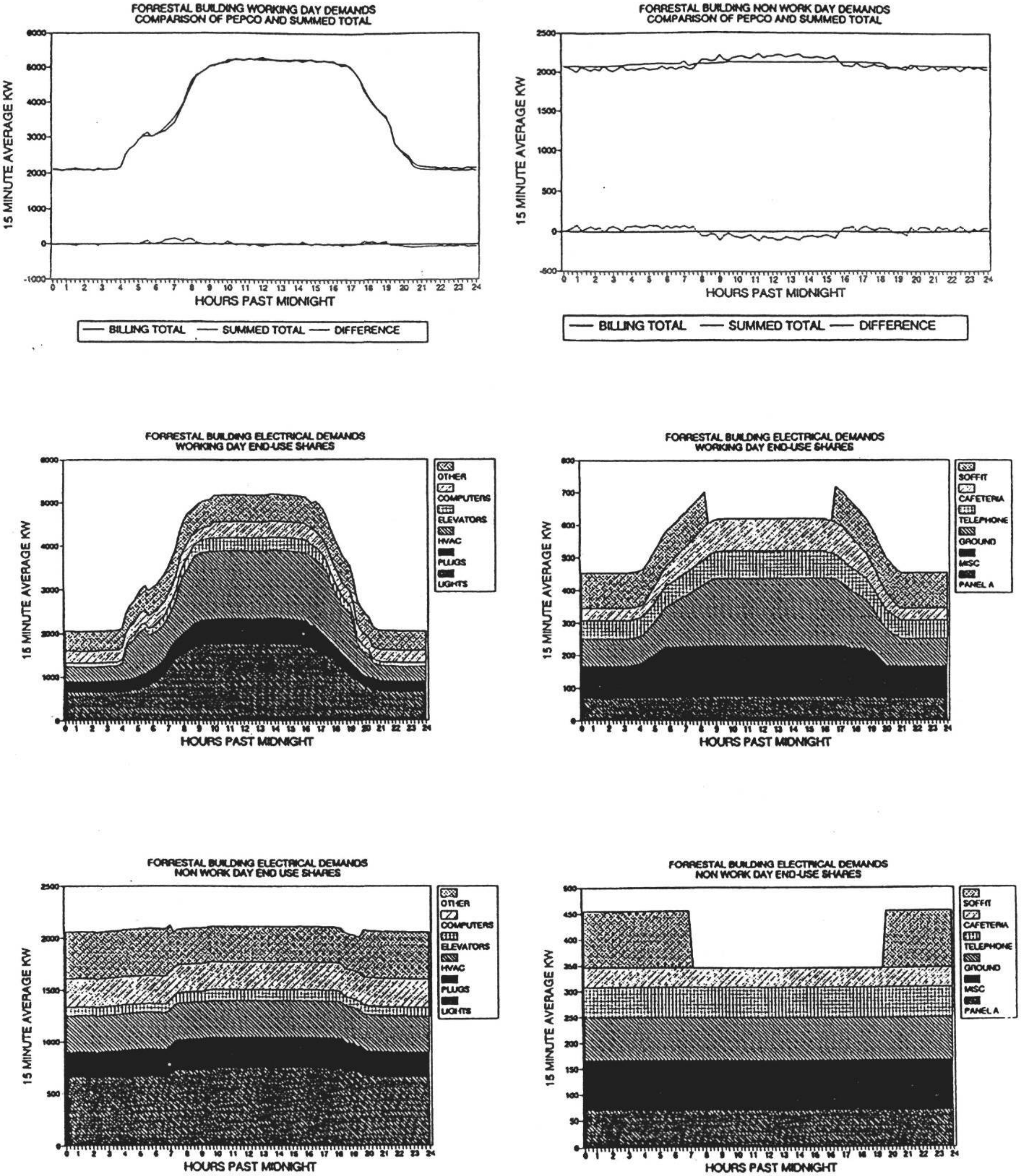


Figure 16. Typical Load Shapes for a Large Federal Office Building (Mazzuchi 1992)

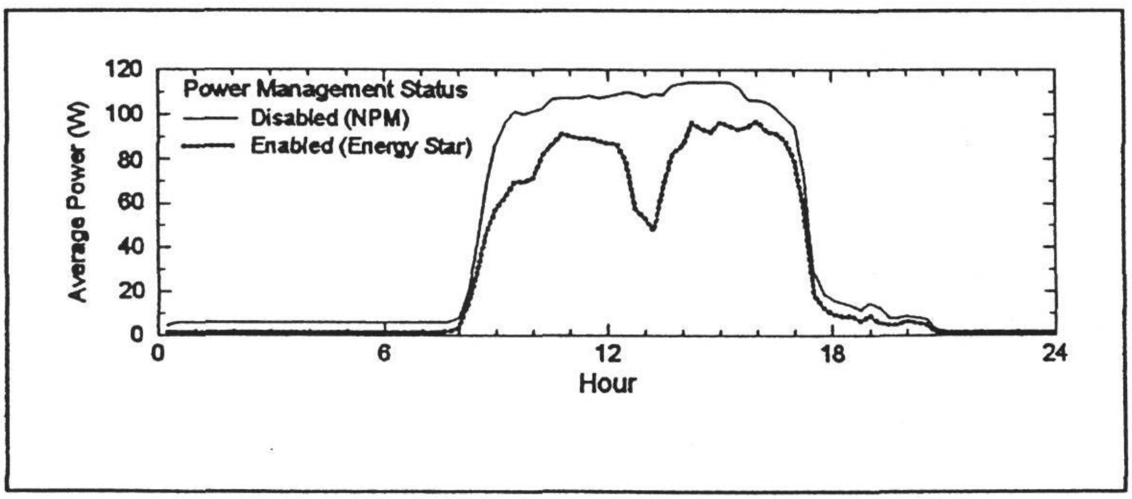


Figure 17. Typical Load Shapes of a PC in an Office Building (Nordman 1996)

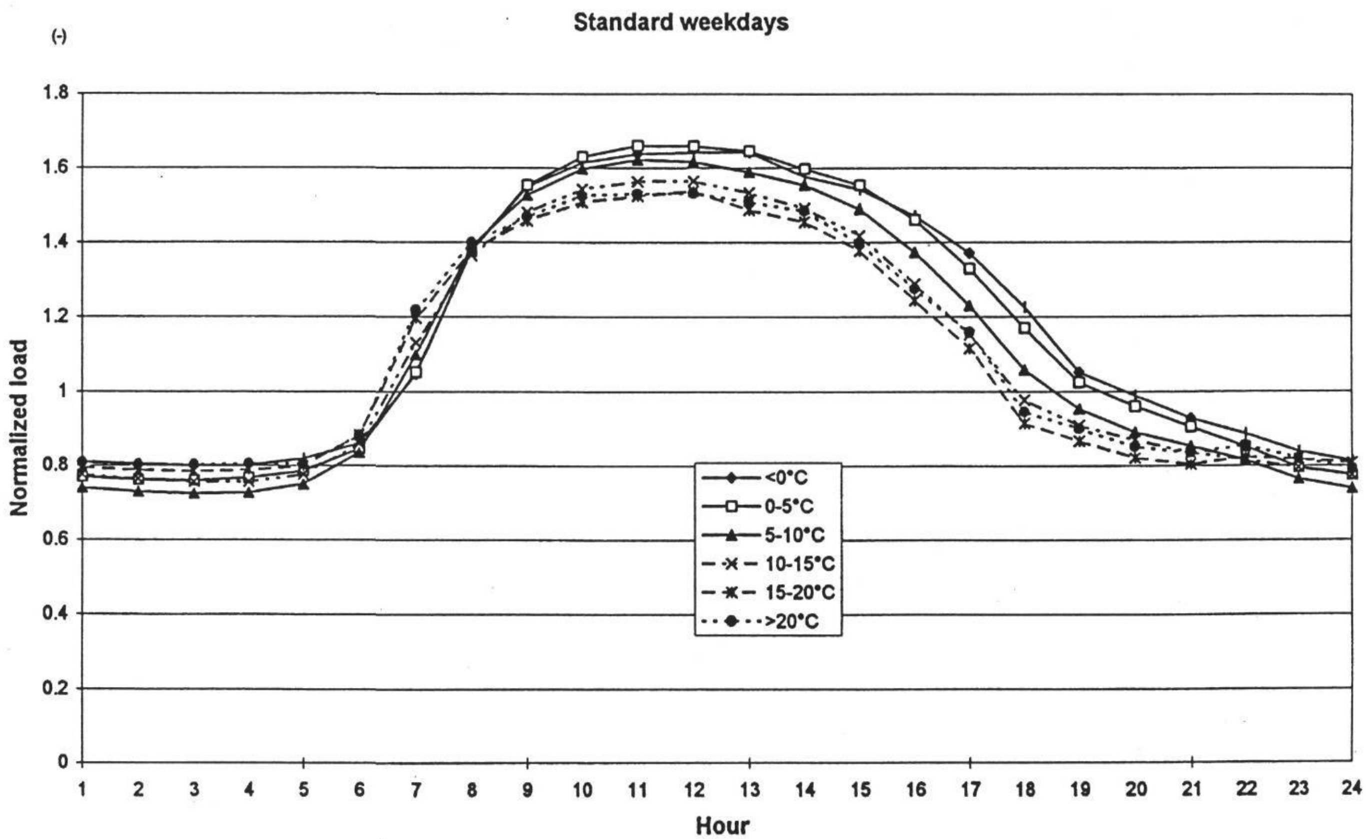


Figure 18. Typical Weekdays Load Shapes for Office Buildings in Sweden Derived with a Weather Daytyping Approach (Noren 1997)

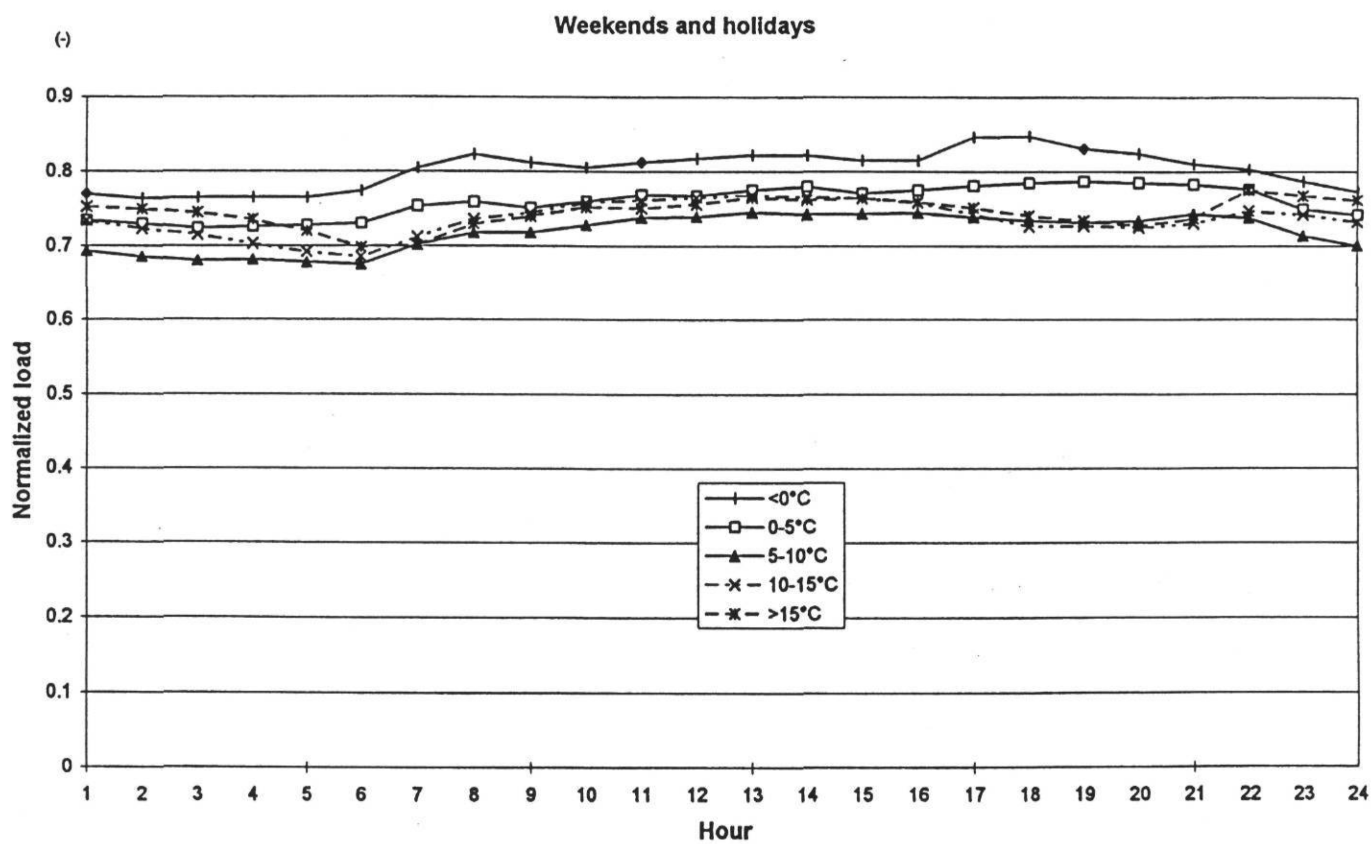
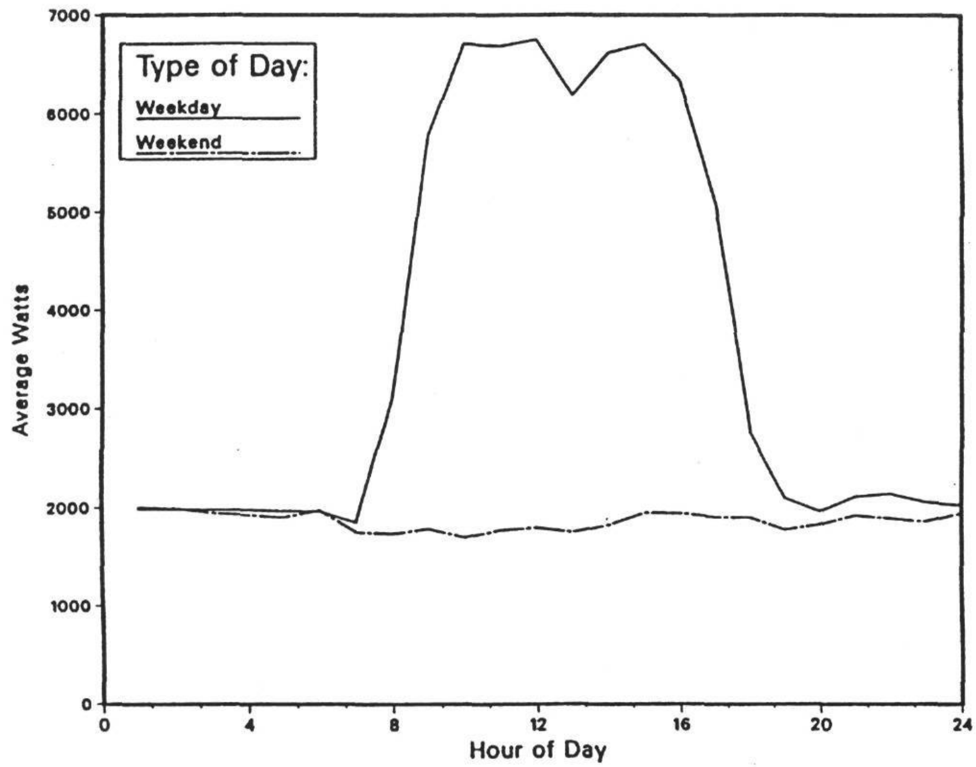
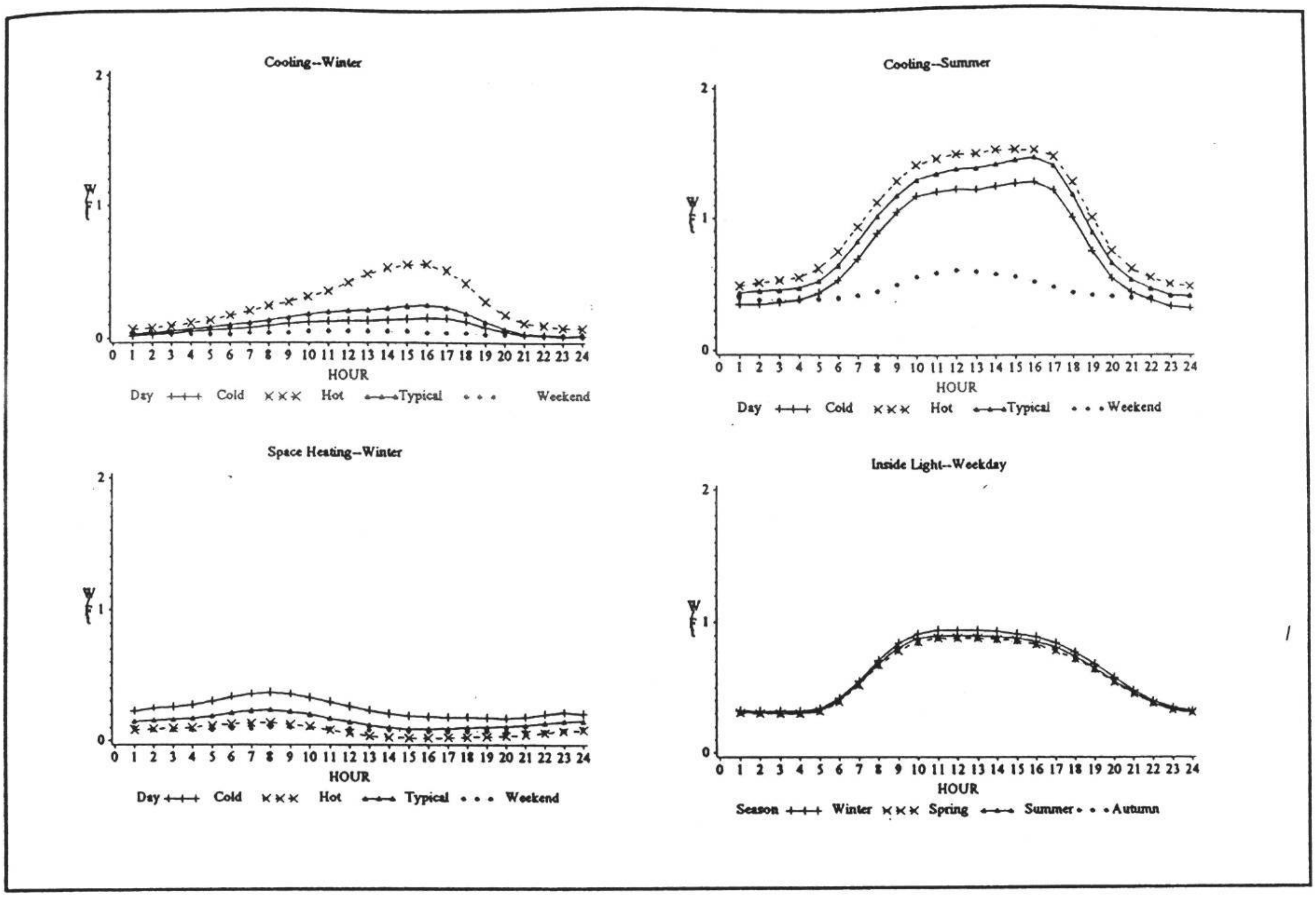


Figure 19. Typical Weekends and Holidays Load Shapes for Office Buildings in Sweden Derived with a Weather Daytyping Approach (Noren 1997)

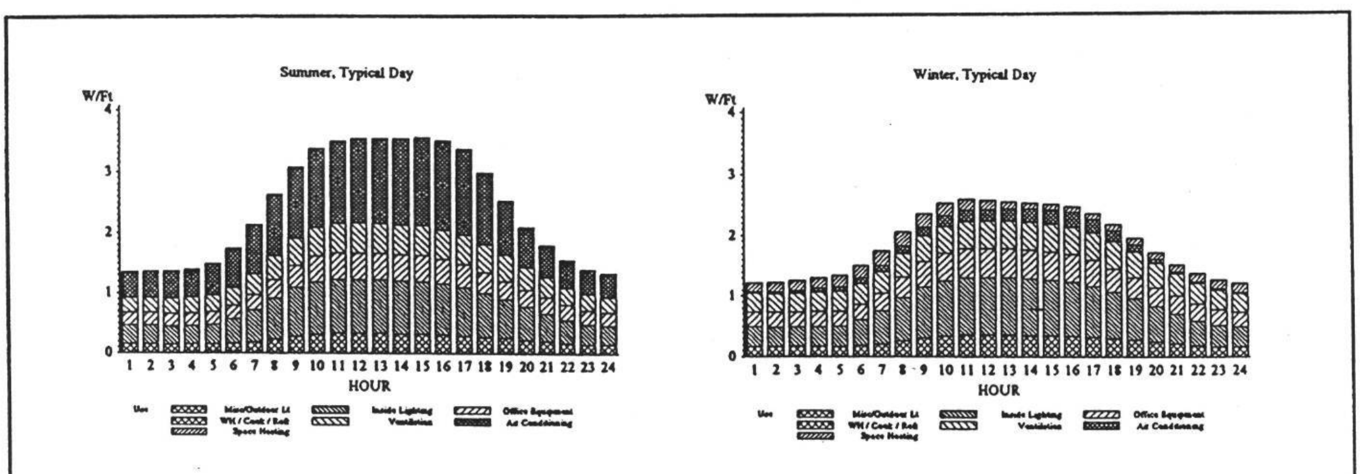


Average weekday "plugs" load profile, small office building. These data show weekday average hourly loads for April 1988 for a recently-constructed, two-story building of about 850 m^2. Computers and other office electronic equipment represent most of this load; not included is a separately metered minicomputer, which would add about 10 % to the loads shown. Data come from monitoring equipment installed by Battelle Pacific Northwest Labs.

Figure 20. Typical Load Shapes for Equipment in Small Office Buildings (Norford et al. 1988)



Adjusted End-Use Shapes for an Office Building



End-Use Composition of Loads for an Office Building

Figure 21. Typical Load Shapes of End-uses in Office Buildings (Rohmund et al. 1992)

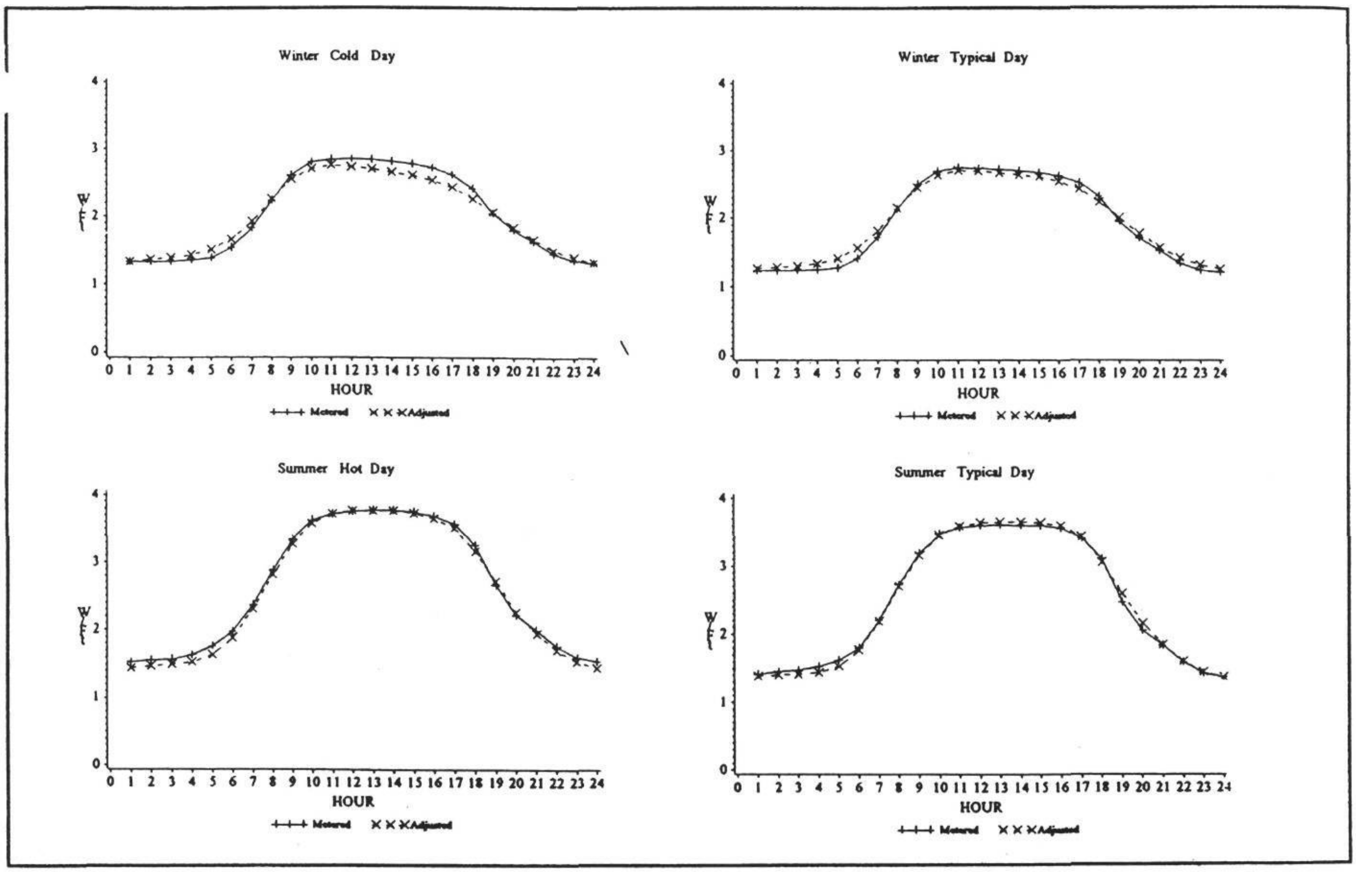
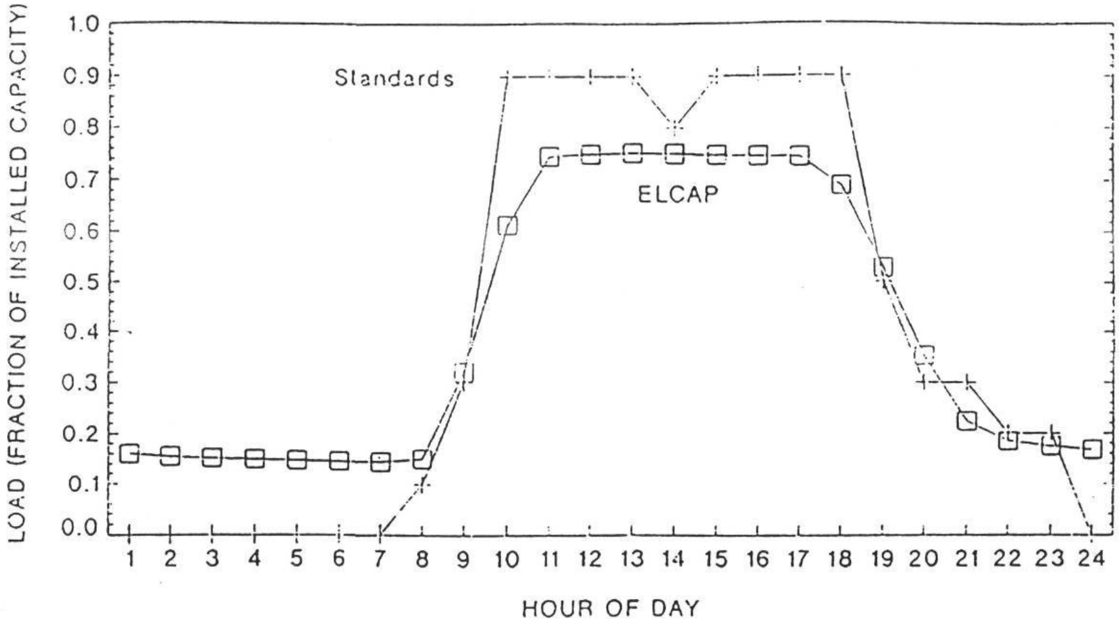
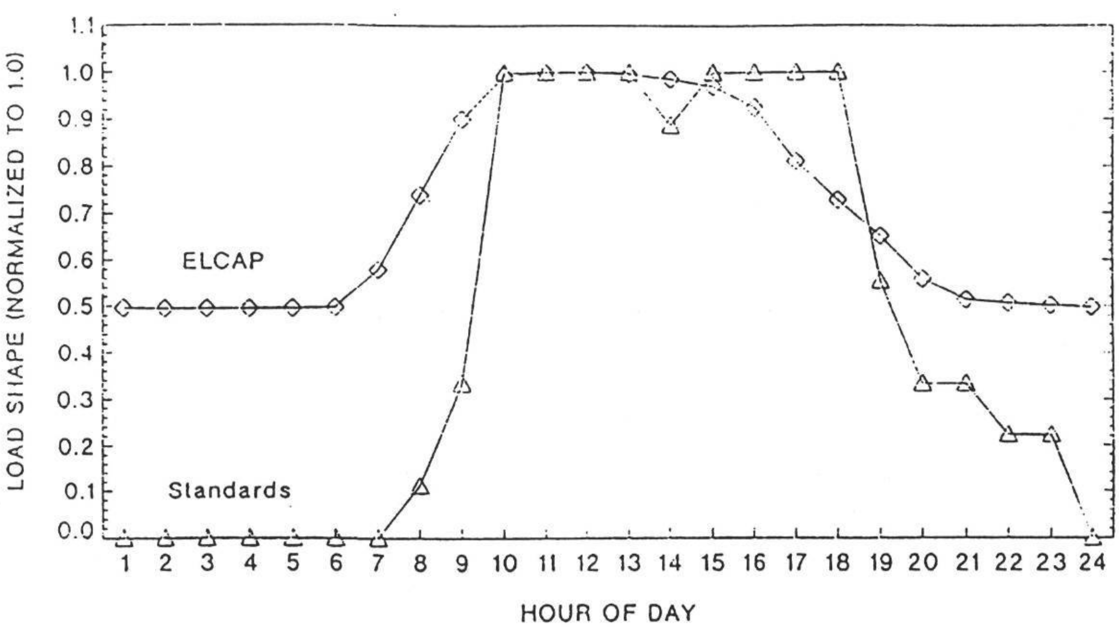


Figure 22. Typical Load Shapes of End-uses (Metered and Adjusted) in Office Buildings (Rohmund et al. 1992)

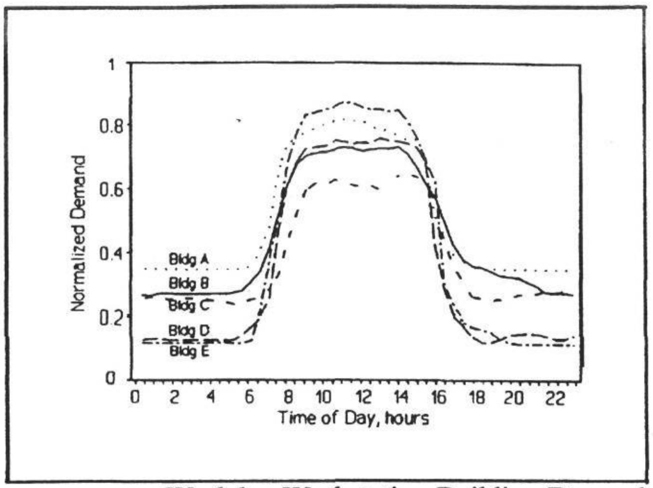


Office Building Lighting Load Profile DOE/ASHRAE Standards vs. Metered Data

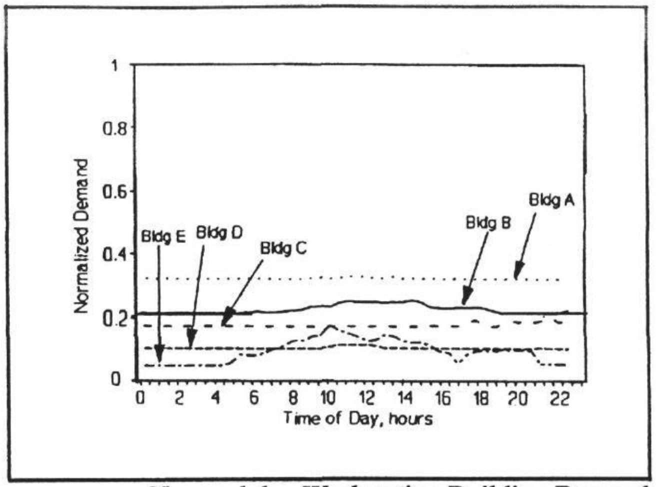


Office Building Equipment Load Profile DOE/ASHRAE Standards vs. Metered Data

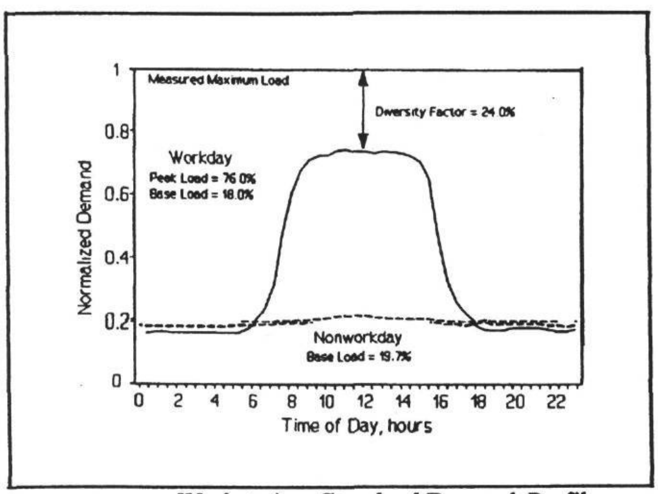
Figure 23. Typical Load Shapes for Office Buildings (Stoops and Pratt 1990)



Workday Workstation Building Demand Profiles

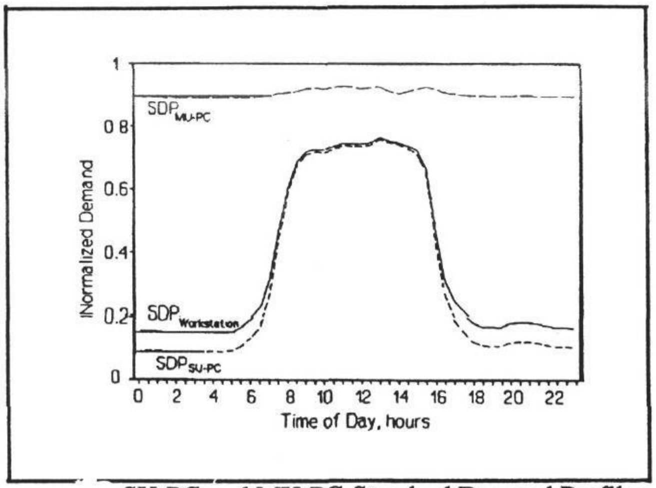


Nonworkday Workstation Building Demand Profiles

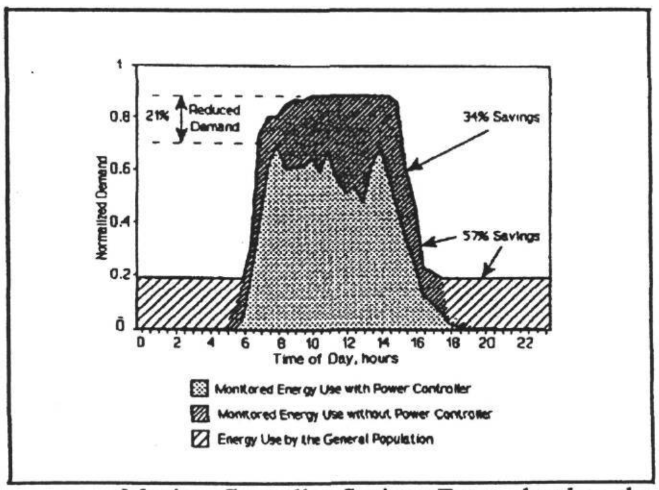


Workstation *Standard* Demand Profiles

Figure 24. Typical Load Shapes of Workstations in Office Buildings (Szydlowski and Chvala 1994)



SU-PC and MU-PC Standard Demand Profiles



Monitor Controller Savings Extrapolated to the General Population of PCs

Figure 25. More Typical Load Shapes of Workstations in Office Buildings (Szydlowski and Chvala 1994)

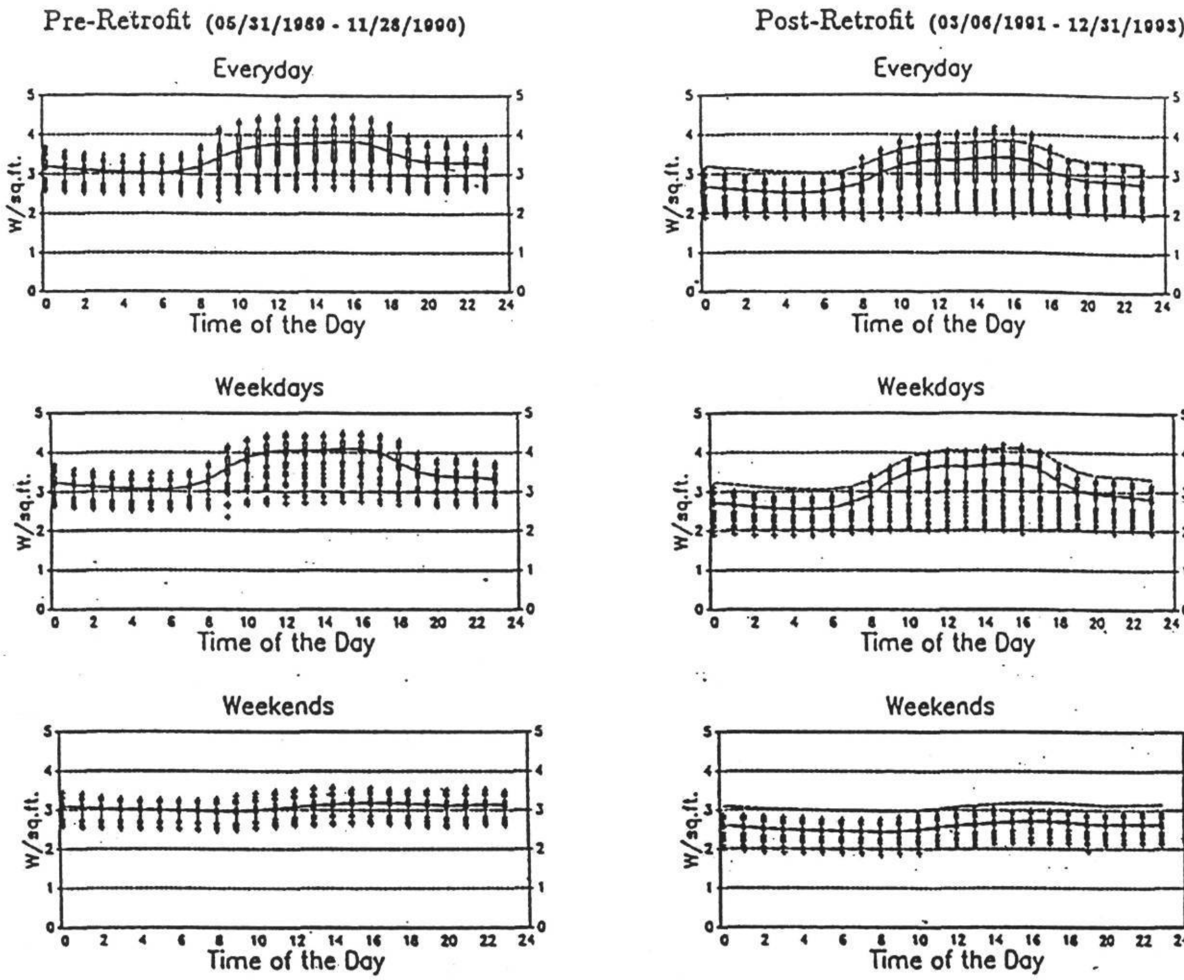


Figure 26. Typical Load Shapes for a Large Institutional Building (Thamilseran and Haberl 1994)

4.3 Reproducible Methods

Of the 12 methods identified in *Phase I* of the project, only 8 methods were possible to reproduce based on the available literature. We also identified three additional methods; the Interquartile Analysis (Abbas 1993), the Duncan's Multiple Range Test, and Frequency Univariate Analysis (Dhar 1995), and the Singular Value Decomposition (SVD) (Verdi 1989). All of these three methods are *Statistical* methods applied for daytyping and generation of typical load shapes. These 11 methods are shown in Table 10, below.

The daytyping required in this project requires that extensive time-series data sets of lighting and equipment (without the presence of weather-dependent heating and cooling inputs) be processed to determine the typical daytypes required for energy analysis and for determination of design cooling loads.

The first four methods, the End-use Disaggregation Algorithm (EDA) (Akbari et al. 1988), the Conditional Energy Demand (CED) (Parti et al. 1988), the Variance Allocation (Schon and Rodgers 1990), and the Statistically Adjusted Engineering Approach (SAE) (CSI, CA, ADM 1985, ref. Eto et al. 1990), were mainly used to disaggregate the Whole-Building Electricity consumption into end-uses. The fifth method, the Temporal Synoptic Index (TSI) (Hadley 1993) is a weather daytyping technique which is not generally required in daytyping the lighting and equipment loads. The sixth method, the Singular Value Decomposition (SVD) (Verdi 1989), was mainly used to reduce the number of data points required to describe a set of data from different buildings.

The only well documented and reproducible European method that we were able to identify is the Temperature Binning Method that was used at Lunds Institute of Technology in Sweden (Noren 1997, 1998a and b). However, the foundation of this daytyping method is the binning according to predetermined temperature ranges. Even though the temperature dependency (seasonal variation) of the lighting and equipment loads should be evaluated, this European method, by itself, is not sufficient to be applied in our project, as we need additional procedures in order to determine the typical load shapes of the lighting and equipment loads.

This leaves only the following four methods, Mean / Standard Deviation / Regulatory Index (Katipamula and Haberl 1991), Interquartile Analysis (Abbas 1993), Inverse Binning Method (Thamilseran and Haberl 1994), and Duncan's Multiple Range Test and Frequency Univariate Analysis (Dhar 1995), which are appropriate for the daytyping needs of this project. The main characteristics of all the 11 methods are discussed in detail in the following sections and in the Appendix (8.5).

	Method's Name	Nature*	Basis**	Weather-dependent	Weather-independent	Reference
1	End-use Disaggregration Algorithm (EDA)	Deterministic	Engineering/ Monitoring	X	X	(Akbari et al. 1988)
2	Conditional Energy Demand (CED)	Statistical	Monitoring	X	X	(Parti et al. 1988)
3	Variance Allocation	Deterministic	Engineering/ Monitoring	X	X	(Schon and Rodgers 1990)
4	Statistically Adjusted Engineering approach (SAE)	Statistical	Engineering/ Monitoring	X	X	(CSI, CA, ADM 1985, ref. Eto et al. 1990)
5	Mean / Standard Deviation / Regulatory Index	Statistical	Engineering/ Monitoring		X	(Katipamula and Haberl 1991)
6	Temporal Synoptic Index (TSI)	Statistical	Monitoring	X		(Hadley 1993)
7	Interquartile Analysis	Statistical	Monitoring	X	X	(Abbas 1993)
8	Inverse Binning Method	Statistical	Monitoring		X	(Thamilseran and Haberl 1994)
9	Duncan's Multiple Range Test, and Frequency Univariate Analysis	Statistical	Monitoring	X	X	(Dhar 1995)
10	Temperature-binning Daytyping	Statistical	Monitoring	X		(Bou-Saada and Haberl 1995), (Noren and Pyrko 1998)
11	Singular Value Decomposition (SVD)	Statistical	Monitoring	X	X	(Verdi 1989)

* *Deterministic Methods*:

Used when monitored end-uses are not available, these methods rely on exact reconciliation to an hourly control total, which is provided by the hourly whole-building load research data. The starting point for the reconciliation is an engineering simulation which is relied upon by the earliest load shape estimation methods. The methods typically rely on much more detailed information to develop the simulation input (i.e., minimizing the extensive reliance on engineering judgement) (Eto et al. 1990).

Statistical Methods:

1. Used when monitored end-uses are not available, these methods typically rely on regression techniques that correlate explanatory variables with the hourly control total (measured total electricity consumption). These variables need not all be physical and the reconciliation to the control total is usually expressed in goodness of fit.
2. Used when monitored end-uses are available, these methods use different statistical and mathematical methods for daytyping.

** *Engineering methods*:

Methods based on pure simulations of whole-building energy use and/or different end-uses.

Monitoring Methods:

Methods that involve monitored whole-building energy use.

Notes:
1. Simple average and standard deviation deterministic methods, based on monitored end-uses, are not included in this table.
2. Methods 1 to 4 are developed to disaggregate whole-building energy use (when measured end-uses are not available) to derive typical load shapes for the end-uses.
3. Methods 5 to 10 represent sophisticated approaches for daytyping, that can be used in deriving typical load shapes for end-uses.

Table 10. Existing Reproducible methods for daytyping and determining load shapes of end-uses.

4.3.1 Documented Methods of Daytyping and Generation of Typical Load Shapes

From previous work, we identified 4 well-documented methods that were used in daytyping required for energy baselining and retrofit savings calculations. Various elements of these methods are applicable to this project. These 4 methods are: (1) Mean / Standard Deviation / Regulatory Index (Katipamula and Haberl 1991), (2) Interquartile Analysis (Abbas 1993), (3) Inverse Binning Method (Thamilseran and Haberl 1994), and (4) Duncan's Multiple Range Test and Frequency Univariate Analysis (Dhar 1995).

4.3.1.1 Mean / Standard Deviation / Regulatory Index

Katipamula and Haberl (1991) developed a method, that uses a Mean/Standard Deviation/Regulatory Index, that identifies typical daytypes for a building, using monitored non-weather-dependent electricity use. Load shapes are generated from the data for each typical daytype. In deriving the daytypes, the mean and the standard deviation of the energy use at each hour for the entire data group are calculated, and a Regularity Index (RI), which is a measure of grouping within a sample that determines if the data are tightly grouped, is calculated and checked against a maximum acceptable value (10%) for each hour,

$$RI = \frac{100 \times Std.Deviation}{HourlyMean} \qquad (1)$$

If the RI for all 24 hours exceeds the 10% value, hourly data is summed to daily totals and the mean and standard deviation of the daily consumption are calculated. Three daytypes are then identified as follows: (1) LOW-D days with daily consumption lower than Y (10%) times one standard deviation below the mean; (2) HIGH-D days with daily consumption higher than Y times one standard deviation above the mean; and (3) NORMAL-D , the remaining days. Then the grouped daily data is sorted in Weekdays/Weekends groups. The weekdays are then checked for including any Vacation, Holiday, Special Event, and classified as such. Then, the weekday group is sorted into Monday through Friday, and the weekend group is sorted into Saturday and Sunday groups. The mean and standard deviation for each hour are then calculated for each group. This will result in a total of 7 load shapes in each daytype: LOW-D, HIGH-D, and NORMAL-D. The data then are regrouped (Monday through Sunday), for instance, Monday-Tuesday, Monday-Tuesday-Wednesday, and so on, and checked for having a relative difference in the mean at each hour across the group less than 10%. This procedure is repeated until no additional groups can be formed. After this regrouping, the mean and standard deviation for each group are calculated. If the RI at each hour for all the new groups is less than 10%, then the typical load shapes are generated. If not, the procedure is applied again in a recursive fashion, and the daytypes are then subdivided to LOW-LOW D, LOW-HIGH D, LOW-NORMAL D, HIGH-LOW D, HIGH-HIGH D, HIGH-NORMAL D, NORMAL-D, NORMAL-LOW D, AND NORMAL-HIGH D. As a result, the hourly load average profile for each daytype is generated.

This is a labor-intensive technique and involves some subjectivity when 10% of the standard deviation below or above the mean is considered for variability in the data. We believe that the Interquartile Analysis (Abbas 1993) and other statistical tests like the Duncan's Multiple Range test, and the Univariate Analysis (Thamilseran and Haberl 1994, and Dhar 1995) produce more robust daytypes, and corresponding typical load shapes.

4.3.1.2 Interquartile Analysis

Abbas (1993) developed graphical indices for building energy data to help building energy analysts to efficiently view and analyze large amounts of hourly building energy consumption data. These graphical indices were based upon statistical analysis of the data. Different types of graphical representation of the data were proposed. The most relevant type of graphs developed by Abbas are the Box-Whisker-Mean plots, which use the Interquartile Analysis technique. These plots were developed for daily data, and weekly data. The daily data is obtained by binning the hourly data of the year (hour 1 to hour 24) for "weekdays", "weekends", and "all days", which provides a graphical identification of the *diurnal variation* of the data. The daily data are obtained by binning the hourly data of the year into 53 weeks, which provides a graphical representation of the *seasonal variation* of the data. Figure 27 shows a flowchart of Abbas' method. Figure 30 below shows the BWM plot developed for weekly data.

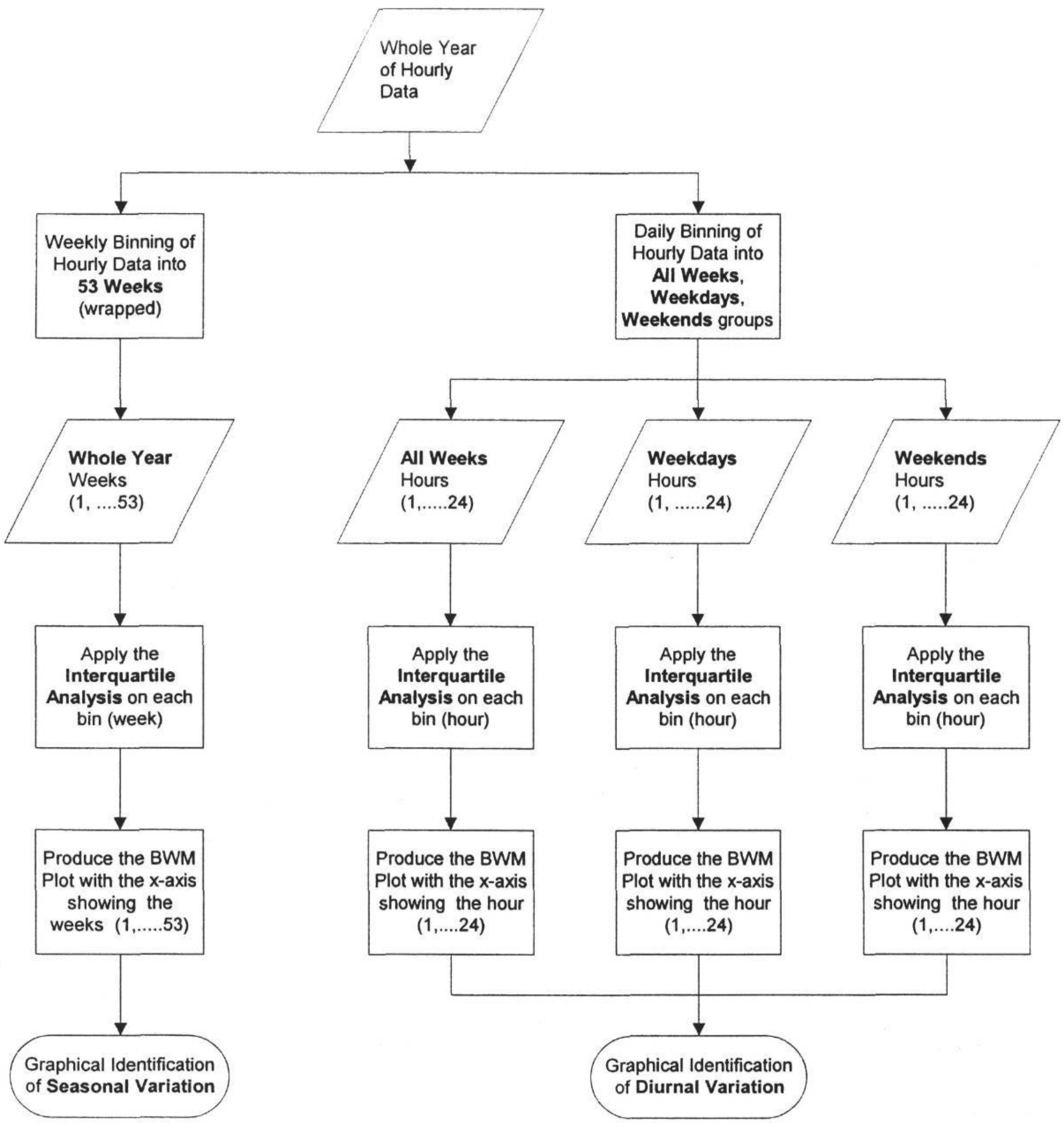


Figure 27. Interquartile Analysis (Abbas 1993)

While the BWM plots produces a simple daily binning of the data into the "weekdays", "weekends", and "all days" groups, it cannot make any distinction between different days in the same group, and thus this technique is not, by itself, sufficient for daytyping. However, it is very useful as a first step in the daytyping, for outlier rejection, and for checking for any seasonal variation in the data sets.

4.3.1.3 Inverse Binning Method

Thamilseran and Haberl (1994) developed a binning approach for non-weather-dependent loads for the purpose of calculating retrofit savings. The general pattern of the energy use is identified graphically to show the effect of weekdays-weekends and holidays and the periodicity of the peak consumption. Then the Pearson's correlation technique is used to identify the correlation between dependent and independent variables. The "hour of the day" is used as a bin variable in the non-weather-dependent loads model. Duncan's, Duncan-Waller's and Scheffe's multiple comparison tests are used to aggregate the data into daytypes that have means with statistically insignificant differences. The technique includes the following steps: (1) identification of general patterns of data (from database), (2) checking for temperature dependency of Hour of the Day (HOD) dependency, (3) checking for data quality and outliers identification, (4) identification of comprehensive daytypes, (5) checking for impact of ON/OFF mode, (6) calculation of binned energy, (7) correction for missing bins, (8) checking for need for thermal lag, (9) checking for need for humidity sub-binning, (10) final calculation of binned energy and correction for missing bins, (11) prediction of baseline energy use. Figure 28, below, shows the flowchart of the Inverse Binning method. Bou-Saada et al. (1996) applied the methodology developed by Thamilseran and Haberl (1994) successfully to provide an overview of the lighting retrofit and the resultant electricity and thermal savings at the DOE Forrestal Building. Their study determined that three 24-hour daytype profiles would be required to characterize the electricity use for the baseline period; a weekday profile, a winter weekend profile, and a summer weekend profile.

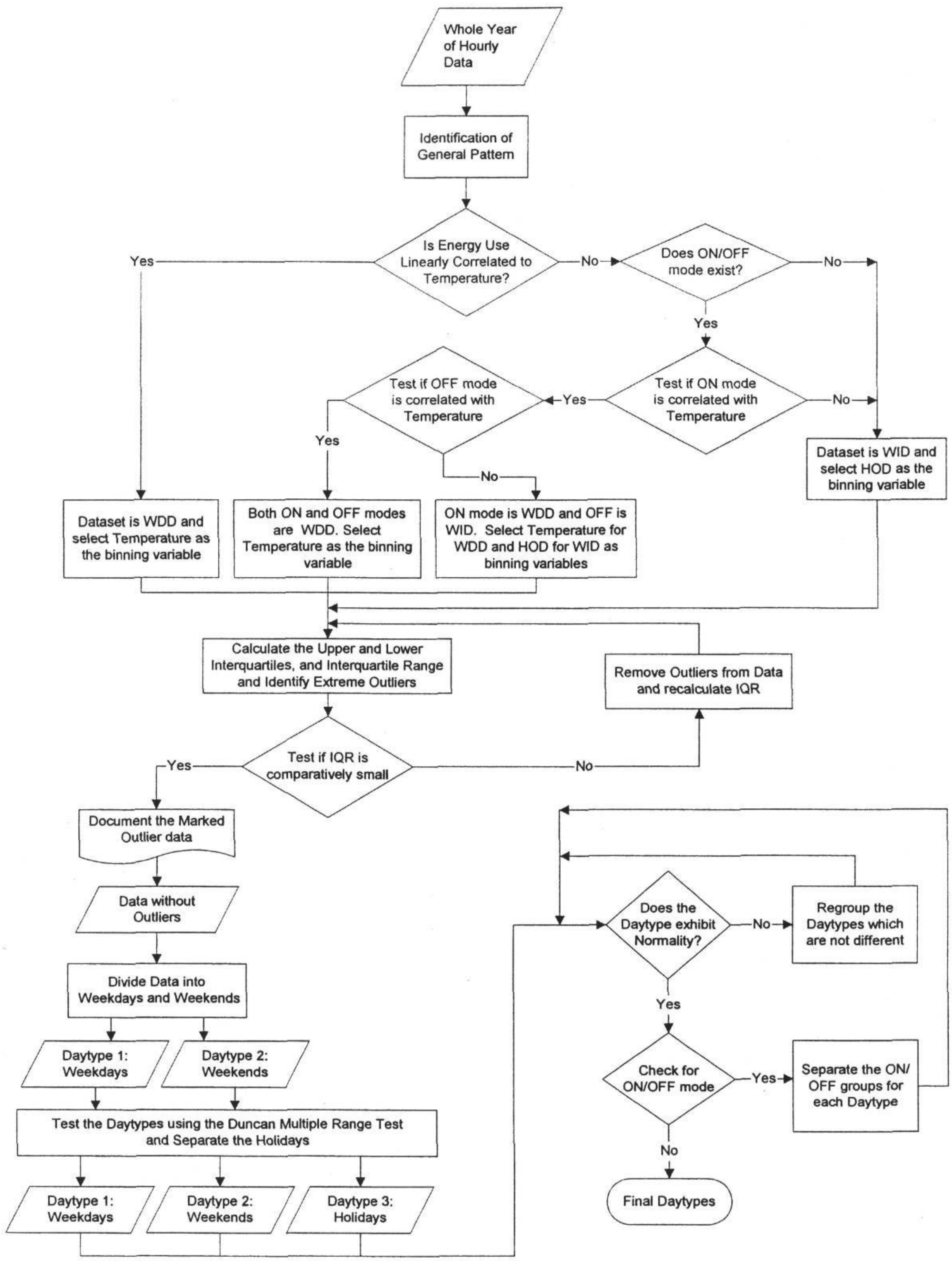


Figure 28. Inverse Binning Method (Thamilseran and Haberl 1994)

The procedures used in the Inverse Binning method are very helpful in reaching robust daytypes. These procedures include checking for: (1) Temperature-dependency, (2) Hour of Day - dependency, (3) ON/OFF modes, and (4) Outlier rejection.

4.3.1.4 Duncan's Multiple Range Test, and Frequency Univariate Analysis

Dhar (1995) developed a procedure for daytyping of building energy use where the whole year of hourly data is divided into daytypes based on the calendar: weekdays, weekends, holidays, and Christmas (for the special characteristics on the Christmas breaks). After grouping the data, a Duncan's Multiple Range test is applied to determine if the daily mean energy use of different daytypes are in fact different. Daytypes of same daily mean are then aggregated to obtain the Primary daytypes. The Univariate Analysis of each important frequency for each primary daytype is then performed, to check the presence of a consistent Multimodal Distribution. In the absence of the multimodal distribution, the primary daytypes are retained as Final daytypes. If the multimodal distribution exists in the data, Duncan's test is applied again to aggregate the daytypes with the same mean energy use in order to obtain the Final daytypes. Figure 29, below, describes Dhar's daytyping procedure.

Duncan's Multiple Range test and the Univariate Analysis will be used in our analysis for daytyping and generation of typical load shapes, in addition to other technique also required for refinement, and described in earlier sections (4.3.1.1 to 4.3.1.3).

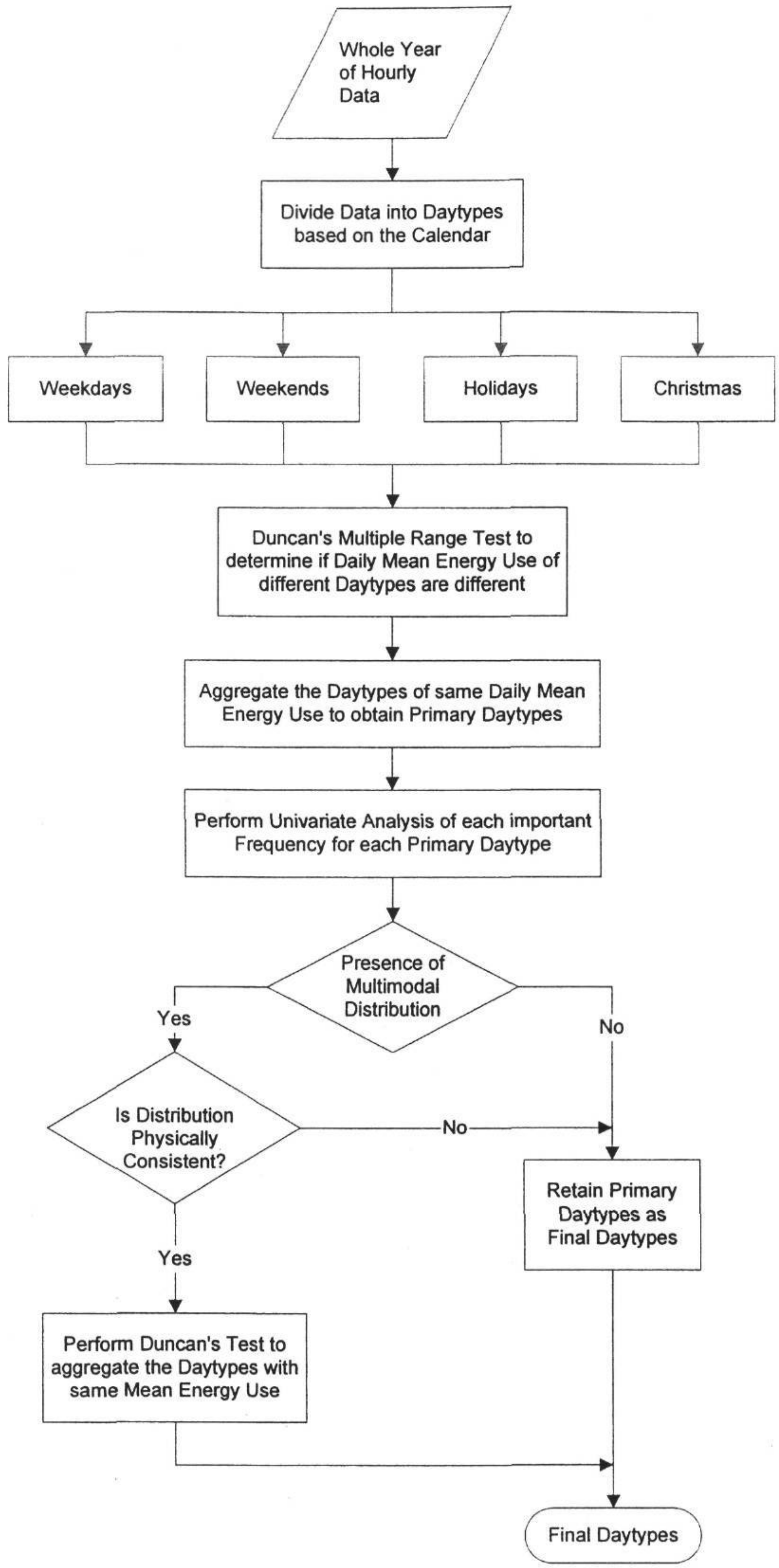


Figure 29. Duncan's Multiple Range Test, and Frequency Univariate Analysis (Dhar 1995)

4.3.2 Other Well-Documented Methods in the U.S. and Europe

From the U.S. we identified six well documented methods used for generating typical load shapes, the End-use Disaggregation Algorithm (EDA) (Akbari et al. 1988), the Conditional Energy Demand (CED) (Parti et al. 1988), the Variance Allocation (Schon and Rodgers 1990), the Statistically Adjusted Engineering Approach (SAE) (CSI, CA, ADM 1985, ref. Eto et al. 1990), the Temporal Synoptic Index (TSI) (Hadley 1993), and the Singular Value Decomposition (SVD) (Verdi 1989). The main characteristics of each of these methods are described in the Appendix (8.5). The first four methods were mainly used whenever *only* the total electricity consumption (Whole-Building Electric) is monitored, and engineering simulation were required to disaggregate the total into end-uses. The fifth method (TSI) is a weather daytyping technique which is not necessarily required in daytyping the lighting and equipment loads. The sixth method (SVD) was mainly used to reduce the number of data points required to describe a set of data from different buildings.

The only well documented and reproducible European method that we were able to identify is the Temperature Binning Method that was used at Lunds Institute of Technology in Sweden (Noren 1997, 1998a and b). However, the foundation of this daytyping method is the binning according to predetermined temperature ranges. Even though the temperature dependency (seasonal variation) of the lighting and equipment loads should be evaluated, this European method, by itself, is not sufficient to be applied in our project, as we need additional procedures in order to determine the typical load shapes of the lighting and equipment loads. This European work mixes normalization, and binning techniques and is somewhat similar to the weather-daytyping used by Bou-Saada and Haberl (1995). The main characteristics of the Temperature Binning Method is described in the Appendix (8.5).

4.3.3 Other Methods

It is worth adding at the end of this section (Reproducible Methods), one unique study in which the authors developed average and peak occupancy profiles for an office building. Keith and Krarti (1999) summarized a methodology used to develop a simplified prediction tool to estimate peak occupancy rate from readily available information, specifically average occupancy rate and number of rooms within an office building. The study was carried on in a laboratory campus with three similar two and three story buildings in Boulder, CO, comprising approximately 1200 rooms, with 1174 having individual occupancy sensors. A total of 195 sensors were selected, and the raw data included each room's status as either "occupied" or "unoccupied", and an associated time/date stamp taken from the central facility management computer, at nominal 15 minutes intervals, for a 12-month period.

The average occupancy rate was defined as the average over a period of one month, for either the entire 9-hour workday period (8:00 AM to 5:00 PM) or for each hour separately. Calculations were performed with every 5-minute period within the daily period of interest over the month, counting the occupied and unoccupied records for all the rooms in the specified set. The average occupancy rate is equal to the number of occupied records divided by the number of both occupied and unoccupied records. The average hourly occupancy is the monthly average of the occupancy rate in that particular hour of all workdays. Therefore for any given set of rooms, there are nine average hourly occupancy rates associated with each month. To determine the peak occupancy rate, numerous combinations of linear terms were evaluated, starting with just the two independent variables of average occupancy rate and number of rooms, and increasing the number and variety of terms to develop the best fit.

A multiple linear regression model of peak occupancy rate was finally developed which is a function of average occupancy rate, number of rooms, and other variables which are combinations of these two variables. Predicting the peak occupancy rate can help in determining potential savings due to occupancy-sensing lighting controls, in order to avoid errors in predicting the effect on peak demand. The paper shows the derived average and peak typical occupancy profiles for the case study office building. This is a unique paper where the occupancy variable was measured and studied to develop typical occupancy load shapes. However, the results are based on measurements conducted in one site only. The derived typical load shapes for occupancy and consumption are shown in Section 4.2 (Typical Load Shape Samples from the Literature - U.S. and Europe), above. Although few such efforts of monitoring the occupancy variable with different techniques exist, acquiring such data on a large scale was not possible for the purpose of our project, and therefore we are proposing a surrogate occupancy variable.

4.4 Proposed Methods to Generate the Typical Load Shapes

Most of the identified methods for daytyping and generation of typical load shapes involved approaches to disaggregate the monitored whole-building electricity consumption data (load research data) into different end-uses to avoid the additional cost of monitoring these end-uses. After obtaining the reconciled end-uses data, the daytyping procedures were applied in order to develop the typical load shapes. For this project, we identified sets of monitored lighting and equipment loads in office buildings, thus, in most cases there is no need to disaggregate the whole-building electricity consumption.

Moreover, most of the buildings monitored by the ESL include both the whole-building electricity consumption, and the end-use data (Lighting, Equipment, or Lighting + Equipment), and the daytyping approaches that are developed using these data were mainly used for energy baselining and retrofit savings calculation purposes within the inverse modeling techniques (for instance, regression, Fourier series, bin methods, neural networks, etc.). We will therefore apply several different approaches in a combined way to generate the typical load shapes and diversity factors which will be used in forward energy simulation programs (DOE-2, BLAST) for energy and cooling calculation. It is worth noting that these approaches complement each other in achieving one robust daytyping technique that will enable us to produce the typical load shapes for energy and cooling calculation.

4.4.1 Typical Load Shapes for Energy Calculations

We are proposing to combine three methods for daytyping. These three methods (Abbas 1993, Thamilseran and Haberl 1994, and Dhar 1995) complement each other in identifying a robust daytyping technique.

The Interquartile Analysis which provides the BWM plots in Abbas (1993), will be performed as an initial step for identifying general patterns in the data, before applying more sophisticated daytyping techniques, as the graphical representation of the data is generally able to reveal problems (i.e., outliers, drift, etc.) before the data is analyzed statistically.

The Inverse Binning technique described in Thamilseran and Haberl (1994) provides several other features useful in identifying the daytypes, namely:

- Examines for existence of ON/OFF modes
- Examines for Hour of Day dependency
- Identifies linear correlation to outdoor temperature
- Outlier rejection
- Daytyping using Duncan's Multiple Range Test.

The third technique that will be used is Univariate Analysis (Dhar 1995) that will ascertain the existence of a Multimodal Distribution in the data after running Duncan's Multiple Range Test. If a Multimodal Distribution is found, Duncan's test should be performed again and the daytypes will be reaggregated based on similar mean energy use in order to obtain the final "distinguished" daytypes.

Finally, by using the weekly-binned BWM Graphs from Abbas (1993) as the first step in the data analysis, we will be able to determine the "indirect" weather dependency of the Lighting and Equipment data sets; in other words, the seasonality of the data. The seasonality of the lighting and equipment loads in a commercial buildings are basically explained by the variation in the Occupancy and the Length of day between a Summer Day, and a Winter Day. The BWM weekly graph will show if such variation exists. Figure 30, below, suggests such variation for the building whose data are plotted.

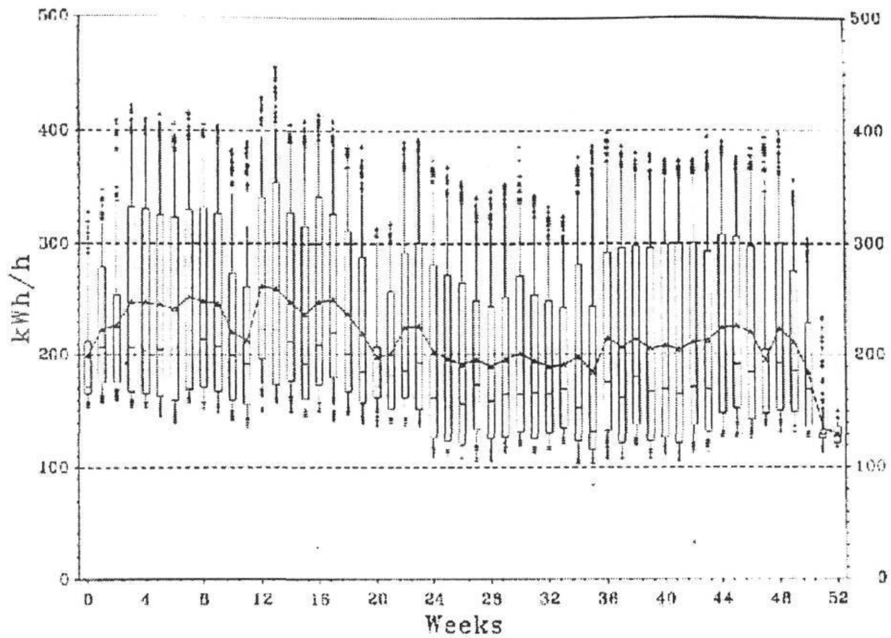


Figure 30. Seasonal Variation of the energy use (Abbas 1993)

The steps of the daytyping and typical load shapes generation will include:

Step 1. Perform a Weekly-binning of the whole-year of data for identifying any seasonal variation that would dictate additional Primary Daytypes (i.e., one for each season).

Step 2. Check for linear correlation to outdoor temperature for possible weather binning of the data.

Step 3. Check for the existence of ON/OFF modes.

Step 4. Select "Temperature" as the binning variable for the weather-dependent days, and the "Hour of Day" as the binning variable for weather-independent days.

Step 5. Perform Interquartile Analysis on the data.

Step 6. Remove outliers.

Step 7. Divide data into Daytypes based on calendar.

Step 8. Perform Duncan's Multiple Range test to determine if daily mean of different daytypes are different.

Step 9. Aggregate the Daytypes of same daily mean to obtain the primary Daytypes.

Step 10. Perform Univariate Analysis on each important Frequency for each primary Daytype.

Step 11. Perform Duncan's Test again if a Multimodel Distribution of the data exists.

Step 12. Obtain final Daytypes.

4.4.2 Typical Load Shapes for Cooling Calculations

The typical load shapes that will be developed for design cooling load calculation purposes, will differ from the ones developed for energy use purposes. For design cooling load calculation, one needs to account for extremes (peaks) in the data. However, the absolute peak values of the lighting and equipment consumption may represent outliers or values that do not robustly represent the case. Therefore, we propose two approaches to develop the typical load shapes for design cooling calculations:

1. After identifying the daytypes for energy calculation, aggregate for each daytype a "Design Day" with the hours equal to the mean of the 90^{th} percentile values at each hour (1-24).

or, if there is a clear seasonal variation identified in the data,

2. Consider summer and winter seasons separately, and aggregate for each season a "Design Day" with the hours equal to the mean of the 90^{th} percentile values at each hour.

We will test these two approaches and consider other approaches as well, and recommend the approach that is judged most appropriate.

4.5 Proposed Surrogate Occupancy Variable

An effort to monitor the occupancy variable (Keith and Krarti 1999) developed average and peak typical occupancy load shapes. However, acquiring such data on a large scale is not possible for this project, and therefore we are proposing a surrogate occupancy variable, in order to produce typical occupancy load shapes.

To develop a surrogate occupancy variable, we investigated Lighting and Equipment load schedules (diversity factors) determined by a previous study (Bronson 1992) for the Engineering Center at Texas A&M University based on the daytyping method of Katipamula and Haberl (1991), described above, and the ELF/OLF technique developed by Haberl and Komor (1990a). The data used to determine these schedules (diversity factors) was monitored by the ESL. In (Bronson 1992), the author generated occupancy profiles (for 12 different zones of the case-study building) for the determined daytypes based on a walk-through survey in the building. Figure 31, below, shows the Average Occupancy profiles that we derived from the 12 different profiles used by Bronson (1992), and Figure 32 shows the typical load shapes for lighting and equipment for the specified daytypes.

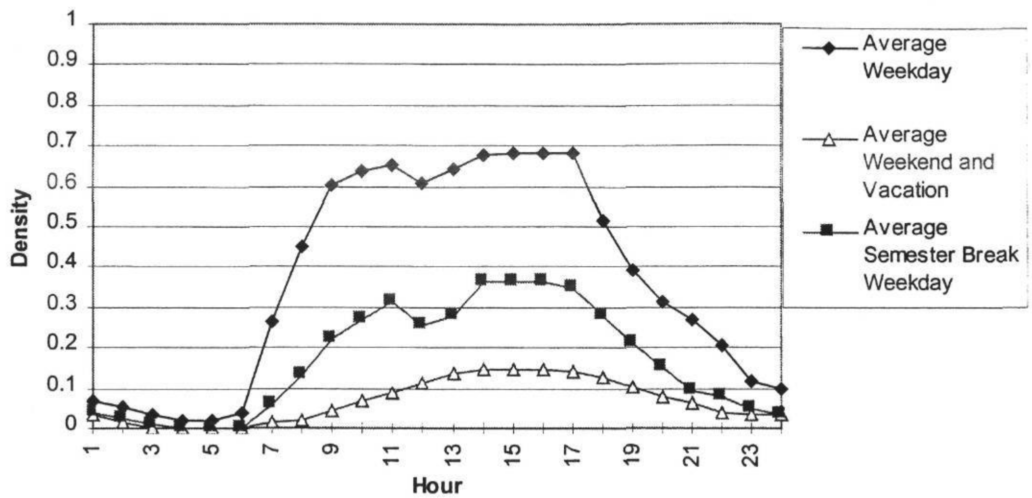


Figure 31. Average Occupancy profiles derived from a walk-through survey in the Engineering Center (Bronson 1992)

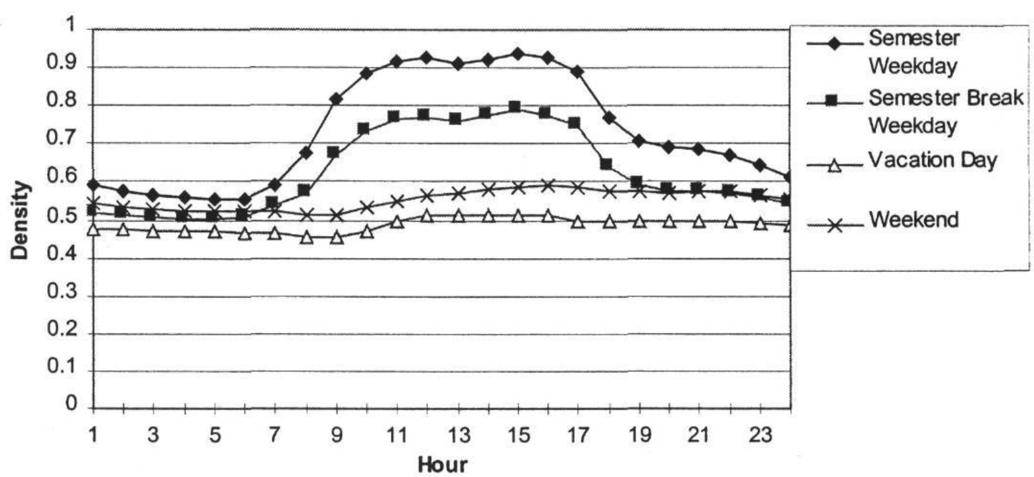


Figure 32. Average Typical Load Shapes of Lighting and Equipment Loads in the Engineering Center (Bronson 1992)

After examining the occupancy and the lighting and equipment profiles and analyzing the data, we found a strong correlation, through a linear regression analysis, between the occupancy and the lighting and equipment variables, as one would intuitively expect. The details of the linear regression analysis are covered in details in the Appendix (8.6). This strong correlation lead us to establish a relationship between these two variables, the occupancy, and the lighting and equipment. The proposed function, which is a *linear transformation* of the lighting and equipment data, provides a *surrogate occupancy* variable, as follows:

$$Occup = Occup_{Max}\left(\frac{LTEQ - LTEQ_{Min}}{LTEQ_{Max} - LTEQ_{Min}}\right) \tag{15}$$

where: Occup = Hourly Occupancy Density (fraction of 1)
$Occup_{Max}$ = Maximum Hourly Occupancy Density
LTEQ = Hourly Lighting and Equipment Load Density
LTEQMin = Minimum Hourly Lighting and Equipment Load Density
$LTEQ_{Max}$ = Maximum Hourly Lighting and Equipment Load Density

In Equation (15), the maximum occupancy ($Occup_{Max}$) can assume any value, for instance, 1, 0.7, or even 1000 (for example, if the total number of occupants is required), and can never result in a negative value as with the linear regression models shown above.

This simple manipulation of the lighting and equipment typical load shapes, which reflects the strong correlation between the occupancy and the lighting and receptacles loads, produced profiles reasonably similar to the occupancy profiles obtained by the walk-through survey, which suggests accepting the results of a surrogate variable for the true occupancy variable. Physically, the data manipulation is explained by the fact that the lighting and equipment load is strongly correlated (and in fact driven) by the occupants, with the difference of having some lights and equipment left "ON" during the unoccupied hours. Figures 33 to 35 show the proposed derived surrogate occupancy profiles as compared with the profile generated with the walk-through survey. This method is proposed for discussion with the PMSC.

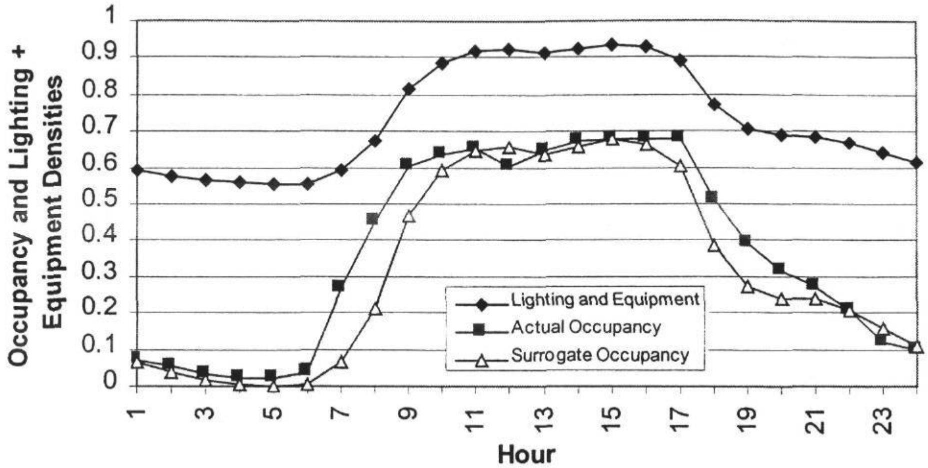


Figure 33. Proposed Derived Surrogate Occupancy Profile for the Weekdays Daytype.

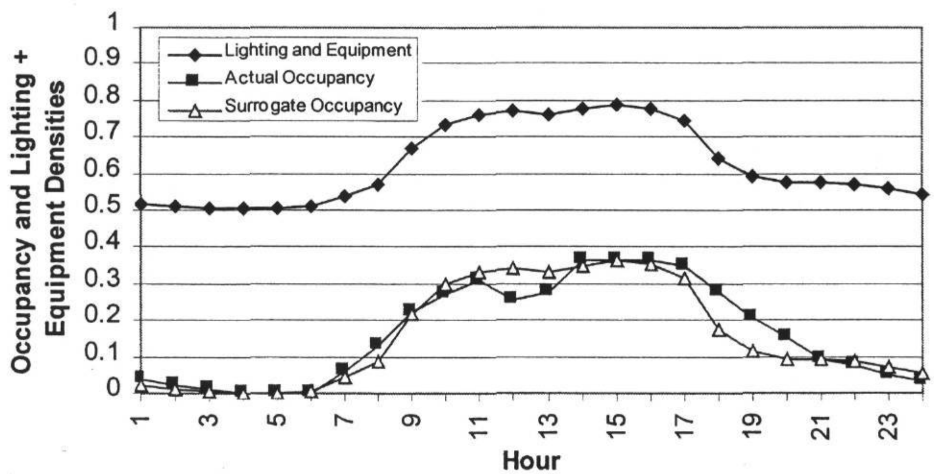


Figure 34. Proposed Derived Surrogate Occupancy Profile for the Weekdends and Vacations Daytype.

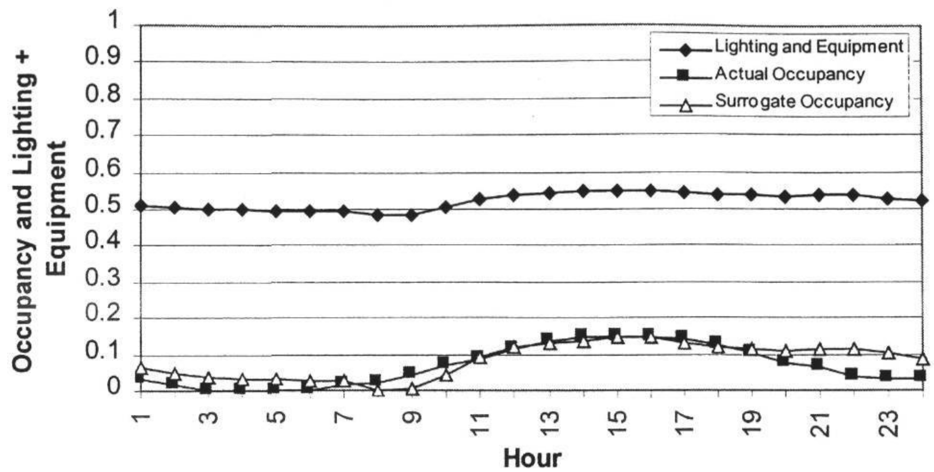


Figure 35. Proposed Derived Surrogate Occupancy Profile for the Semester Breaks Weekdays Daytype.

5. IDENTIFICATION OF RELEVANT ROBUST VARIABILTY ANALYSIS METHODOLOGIES

Akbari et al. (1989) categorized the uncertainty in developing typical load shapes in three major groups:

- Input data, for instance, load research data
- Estimation Method, for instance, aggregation of load research data by building type to obtain average whole-building load shapes, development and use of statistical weighting factors, and regression of weather whole-building load against weather data.
- Post-processing of the Typical Load Shape Method Results, for instance, averaging hourly end-use data into load shapes for the daytypes, and estimation of final load shapes.

Reddy et al. (1992 and 1998) divided the uncertainty (errors) in regression models in three groups: (1) *Model Mis-specification*, caused by inclusion of irrelevant, or exclusion of important, regressor variables, using a linear when a non-linear model is needed, and incorrect order of model (2) *Model Prediction Errors*, which are random errors, with no bias, and (3) *Model Extrapolation Errors,* when a model is used to predict outside the domain of the original data from which it had been identified. Besides the errors, there are also the *Measurement Errors* (Reddy et al. 1999) that result from: (1) calibration errors, (2) data acquisition errors, and (3) data reduction errors. Reddy et al.'s work provided a clear understanding for various sources of errors when regression models are used for baselining, and proposed equations to quantify the uncertainty in calculating retrofit savings.

Although we are using measured data for this project, we will not deal with the *Measurement Errors* as to account for the imbedded uncertainty in the data sets, since we are proposing an approach for outlier removal in the daytyping method, and we assume that the rest of data is *precise*. We will also account for the errors emerging from the modeling (calculations and daytyping techniques) a described below.

To account for the variability of the results, Noren and Pyrko (1997, and 1998a and b) showed the final typical load shapes as three curves: (1) Mean, (2) Mean + One Standard Deviation, and (3) Mean - One Standard Deviation.

The band between "*mean + one standard deviation*" and "*mean - one standard deviation*" is equal to a 68.27% Confidence Interval, which provides the range in which the "true value" exists with a defined probability. The confidence limits are calculated for each hour in the typical load shape. The mean can be defined with any confidence level using the following equation:

$$\overline{X} \pm z_c\left(\frac{\sigma}{\sqrt{N}}\right) \tag{16}$$

where: $\overline{X}$ = the Mean for each hour (1 to 24)

z_c = the Critical Value of the confidence level (found tabulated in Statistics textbooks)
σ = the Standard deviation for each hour (1 to 24)
N = sample size (for each hour, the number of days in each daytype).

The confidence interval defined in Eq. (16) is appropriate when the data shows a *Normal Distribution*, which is not necessarily the case with the lighting and equipment data distribution. We binned the lighting and equipment hourly data for the whole year used in a previous study (Bronson et al. 1992) to show the frequencies and the cumulative percentages of the whole data set (Figure 36). The histogram shows clearly that the data does not exhibit *a Normal Distribution*, rather the data suggest a *Multimodal Distribution*. Therefore, it is more appropriate to account for the *Confidence Interval* of the results with a *Percentiles Measure of Central Tendency*, instead of the *mean* and the *standard deviation*.

The typical load shapes will be presented as mean values, bound by the 25th and the 75th percentiles. This interval, or band, covers 50% of the data that is used to define a typical value for each hour. The 25th and the 75th percentiles will be calculated for each hour, and the confidence limits will be calculated for each hour as follows:

$$\frac{1}{2}\left(P_{25}+P_{75}\right)\pm\frac{1}{2}\left(P_{75}-P_{25}\right) \tag{17}$$

where: $(1/2)(P_{25}+P_{75})$ is a measure of central tendency, and
$(1/2)(P_{75}-P_{25})$ is the semi 25-75th percentile range.

We are also proposing to use a new way of comparing the final results, i.e., the typical load shapes of lighting and equipment loads with the "actual" measured data from different buildings categories, i.e., small, medium, and large Office buildings. First, a "typical year" of hourly lighting and equipment typical load shapes will be developed, by multiplying the calculated diversity factors of each daytype by the corresponding intensities (for instance, the results found in 822-RP) and projecting the results over the whole year. The differences between this "typical year" of lighting and equipment loads and a whole year of "actual" data will be accounted for in the following fashion:

(1) binning the data (for instance, in 10kWh/h bins) and obtaining the frequencies in each bin, and the corresponding cumulative percentages (Figure 36, below), and

(2) calculating the percentiles for the whole set of hourly data.

This procedure will be performed on both, the "typical year" and the "actual year" of hourly lighting and equipment loads, and the variability will be accounted for by calculating the Coefficient of Variance of the Root Mean Square Error (CV_{RMSE}%) and the Mean Bias Error (MBE%) of: (1) the frequency of the data, (2) the cumulative percentages, and (3) the percentiles. The results will determine how representative the typical load shapes are, of the actual lighting and equipment loads in office building.

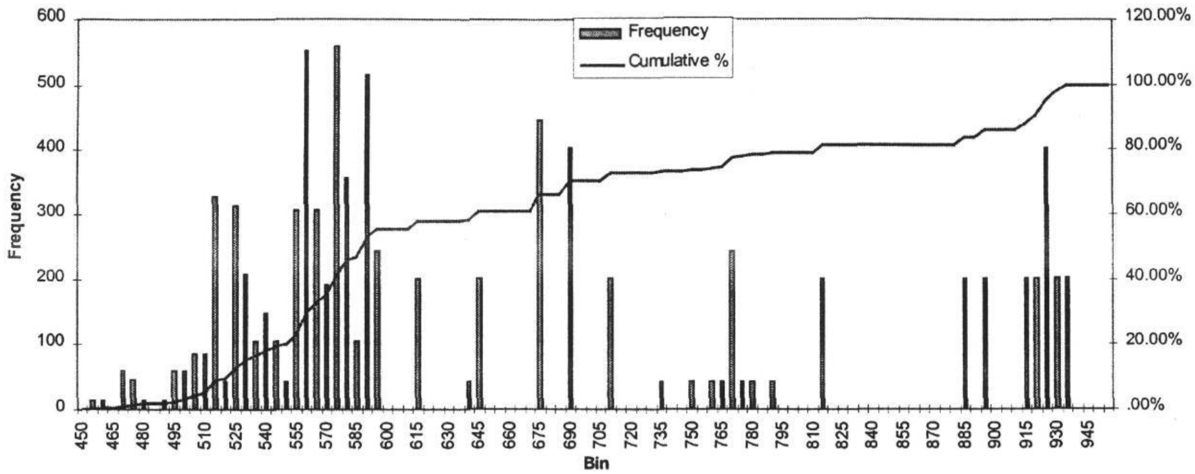


Figure 36. Histogram of a Whole-year of Hourly Lighting and Equipment Loads (data generated with a DOE-2 simulation for the Engineering Center)

Moreover, another way of comparing the frequencies in the whole-year of data generated with the typical load shapes, and those associated with a monitored data sate will be performed by comparing the frequencies (shown in Figure 36, above), by using the χ^2 statistic as follows:

$$\chi^2 = \sum_{j=1}^{k} \frac{(t_j - a_j)^2}{a_j} \tag{18}$$

where: j is the data bin (for instance, 10kWh.h), and k is the total number of bins
t_j is the typical frequency
a_j is the actual frequency

If $\chi^2 = 0$, the typical and actual frequencies agree exactly; while $\chi^2 > 0$, they do not agree exactly. In practice, χ^2 can be computed and compared with critical values such as $\chi^2_{0.95}$ or $\chi^2_{0.99}$, designating the 0.05 and 0.01 significance levels respectively and which are found tabulated in statistics textbooks. If the results are greater than a certain defined critical value, than one can conlcude that the typical frequencies differ significantly from the actual frequencies obtained from a certain monitored data set.

It is worth adding that when consulting the tables in a textbook, one should use a *Degree of Freedom*, herein found as:

$$\nu = k - 1 \tag{19}$$

where; ν is the degree of freedom, and
k is the total number of bins

6. CONCLUDING REMARKS

We would like to mention that we have not tested all the daytyping methods as we proposed in the Preliminary Report against the Predictor Shootout I (Kreider and Haberl 1994) and Predictor Shootout II (Haberl and Thamilseran 1996) data sets which were used by contestants from within and outside the U.S. to test different energy use prediction methods. This is because we felt no need to test each and every method identified, after it became clear what each method was developed for; for instance, the EDA (Akbari et al. 1988), CED (Parti et al. 1988), SAE (CSI, CA, ADM 1985, REF. Eto et al. 1990), and Variance Allocation (Schon and Rodgers 1990) methods were utilized when only the total electricity consumption is monitored in a building. Thus, these techniques were proposed and used to avoid the additional cost of monitoring the end-uses. However, when the end-uses are monitored (like in the data that we acquired for this project), there is no need to use the engineering simulations and combine them with the monitored total electricity consumption, in order to accurately disaggregate the total and "produce" the reconciled end-uses, which then are processed to produce the typical daytypes.

Moreover, in our analysis, we are proposing a method that combines the work that was previously performed to best serve the purposes of this project, and assure the robustness of the results. None of these methods, individually, can be used to automatically determine the daytypes and obtain the corresponding diversity factors and typical load shapes, that this research project seeks to achieve. Therefore, different parts of each method will be extracted and combined into an approach that will accomplish the objectives of this project.

The comments of the PMSC will be taken into consideration as to whether or not we should try to modify our approach. Meanwhile, the work scheduled for *Phase III* of the project will be initiated based on the findings of *Phase II*.

7. REFERENCES

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8. APPENDIX

This appendix includes samples of: (1) Descriptions of the Buildings in the ESL Database, (2) Files of Lighting and Equipment Raw Data, (3) Graphs for Data Quality Checks, and (4) a table containing all Buildings Monitored by the ESL.

8.1 Descriptions of the Buildings in the ESL Database

In this appendix, we are presenting a sample of building descriptions that is adopted in the report as developed by the ESL to document each building site. In the final report of this ASHRAE project, we will provide similar building description pages to document all buildings used in the analysis.

Descriptions of Building # 205 in the ESL database

Building Envelope:
- 80,000 sq.ft
- 6 floors, offices, data processing and computer facility.
- major remodeling and renovation in 1988
- walls: masonry, with a cast stone on north face and a brick-veneer facing on the remaining.
- windows: single glazed with interior blinds
- roof: flat

Building Schedule:
- offices: 7:30 am to 6:00 pm (M-F)

Building HVAC:
- 6 constant volume multi-zone AHUs (2-20hp, 2-15hp, 2-7.5hp)
- 2 constant volume dual duct AHUs (2-65hp)
- 2 chillers (1-110 hp, 1-15hp)
- 2 cooling tower (1-6hp, 1-2hp)
- 1 constant volume condensate pump
- 6 chilled water pumps (3-5hp, 1-20hp, 1-7.5hp, 1-15hp)
- 3 computer room AC (3-40hp)
- 3 hot water heaters (small hp)
- 14 return fans (28 hp total)

HVAC Schedule:
- 24 hrs/day

Lighting:
- 100% fluorescent 34-W

Installed Retrofits:
- Replace exit signs - started Apr. 1993, completed Dec. 1993
- Chiller lead lag modification - canceled

Other Information:
- steam is supplied by the main physical plant located at Sam Houston building

Descriptions of Building # 201 in the ESL database

Building Envelope

- 182,961 sq. ft.
- Ten story building constructed in 1958
- Contains offices as well as the central power plant which provides chilled water, steam, and electricity to several of the capitol complex buildings
- Walls: Texas granite, Roof: n/a
- Windows: single pane, but sealed to minimize infiltration

Building Schedule

- 7:30 am to 6:00 pm during the week

Building HVAC and Equipment

- 2-75 AHUs, 2-50 hp AHUs, 1-10 hp AHU, 1-5 hp AHU, 2-1.5 hp AHUs, 1-2 hp AHU, 3-3 hp AHUs

HVAC Schedule

- 8760 annual hours of operation

Lighting

- 2 and 4-lamp high efficiency 2x4 fluorescent fixtures
- 50-170 watt incandescent lamps

Proposed Maintenance and Operation Measures

- No quantifiable O&Ms identified. However, a quantifiable O&M for utilization of the existing Honeywell 1000 EMS was identified

Proposed Retrofits

- Install motion sensors to control bathroom lighting
- Retrofit incandescent lamps with compact fluorescents
- Provide timed control for domestic hot water pump
- Reduce lighting levels in corridors
- Replace existing inlet vanes in AHUs for AC1 and AC2 with variable frequency drives. Shut off AHUs during unoccupied periods
- Replace incandescent exit signs with electroluminescent exit signs

Status of Retrofits

- Installed motion sensors-cancelled
- Provide timed control for domestic hot water pump-completed Sep. 1994
- Reduce lighting levels in corridors-completed May 1993
- Installation of variable frequency drives-started Feb. 1994, completed Sep. 1994
- Replaced incandescent exit signs with electroluminescent exit signs-completed May 1993
- Incandescent lamps retofitted with compact fluorescents-completed May 1993

Descriptions of Building # 146 in the ESL database

Building Envelope:
- 473,800 sq.ft.
- fourteen story structure constructed in 1966 with two stories below grade
- steel and concrete structure with marble fascia
- windows: N/A
- roof: built-up flat

Building Schedule:
- the building houses County Clerk offices, District Courts, District Attorney Staff offices and County jails
- jail (top seven floors): 24 hours per day, 7 days a week
- rest of the facility: 7:00 am to 6:00 pm Monday through Friday

Building HVAC and Equipment:
- 2 electric centrifugal chillers (750 ton each)
- 3 boilers (2 - 21,000 MMBTU/hr, 500 hp and 1 - 4200 MMBTU/hr, 100 hp)
- 1 condenser water pump (75 hp)
- 3 chilled water pumps (75 hp each)
- 1 secondary chilled water pump (75 hp)
- 2 drinking water chiller (20 hp each)
- 2 water chiller circulating pump (0.75 hp each)
- 16 double duct and single zone constant volume AHUs (AHU 1 to AHU 162, 15 hp, 10 hp, 50 hp, 40 hp, 75 hp, 40 hp, 75 hp, 40 hp, 60 hp, 15 hp, 60 hp, 15 hp, 40 hp, 40 hp, 75 hp, and 75 hp)
- 5 return air fans (2-15 hp, 1-75 hp, 1-5 hp and 1-2 hp)
- the boiler provides the stream for the heating units, as all of the domestic hot water. Steam is also provided to kitchens
- double duct units serve the lower floor, and are turned off on nights and weekends
- single zone units with terminal reheat which serve the jail area are in operation at all times

HVAC Schedule:
- double duct units - 14 hrs/day (6:00 am to 8:00 pm), 5 days/week
- single zone units - 24 hrs/day, 7 days/week

Lighting:
- mixture of 34-W fluorescent (5422 lamps) and incandescent lamps

Proposed Maintenance and Operation Measures:
- none

Proposed Retrofits:
- install reflectors and delamp fixtures
- install motion sensors to control lighting
- chiller replacement
- Energy Management System upgrade
- install VFDs on chilled water pump
- replace/rebuild faulty stream traps
- steam generation modification
- time clock control of chilled drinking
- replace fluorescent fixture at the plaza
- VAV conversion
- total loan amount for the county was $1,050,050 with an estimated annual savings of $237,989

Descriptions of Building # 146 in the ESL database (Cont'd)

Status of Retrofits:

- steam trap replacement completed in December 1991
- steam generation modification which included installation of a turn-down boiler in one of the 500 hp boiler was completed in December 1992
- chiller replacement. Installation of VFDs on chilled water pumps was completed in May 1994. Fluorescent fixture replacement is in construction stage
- all the other retrofits (energy management upgrade and VAV conversion) were cancelled

Other Information & Comments:

- electricity is supplied by Texas Utilities Electric Company and natural gas by Lone Star Gas
- electric meter is located in the basement of the building and the natural gas meter is in the basement parking lot
- the W/ft^2 scale on the electricity consumption graph (fourth page) is only valid for the total electricity consumption

8.2 Sample Files of Lighting and Equipment Raw Data

In this appendix, we show a sample of the raw data that we identified for this project. The data shown represent lighting and equipment loads for buildings monitored by the ESL, and building data provided by LBNL.

Lighting and Receptacles Data of a Medium Building in Austin (data from ESL)

Month	Day	Year	Hour	Lighting+Equipment
6	1	94	0	308.28
6	1	94	100	298.68
6	1	94	200	288.6
6	1	94	300	272.04
6	1	94	400	267.36
6	1	94	500	268.08
6	1	94	600	273.9
6	1	94	700	289.68
6	1	94	800	342.24
6	1	94	900	383.76
6	1	94	1000	395.04
6	1	94	1100	396.84
6	1	94	1200	391.32
6	1	94	1300	388.8
6	1	94	1400	383.64
6	1	94	1500	378.36
6	1	94	1600	380.28
6	1	94	1700	363.84
6	1	94	1800	326.16
6	1	94	1900	314.16
6	1	94	2000	317.28
6	1	94	2100	322.2
6	1	94	2200	323.52
6	1	94	2300	321.12
6	2	94	0	306.48
6	2	94	100	290.52
6	2	94	200	289.68
6	2	94	300	284.88
6	2	94	400	285.72
6	2	94	500	283.68
6	2	94	600	290.34
6	2	94	700	299.4
6	2	94	800	340.2
6	2	94	900	382.56
6	2	94	1000	387.12
6	2	94	1100	390.6
6	2	94	1200	387.96
6	2	94	1300	384
6	2	94	1400	380.16
6	2	94	1500	379.8
6	2	94	1600	375.6
6	2	94	1700	359.76
6	2	94	1800	321.72
6	2	94	1900	314.88
6	2	94	2000	309.72
6	2	94	2100	310.68
6	2	94	2200	319.08
6	2	94	2300	307.56

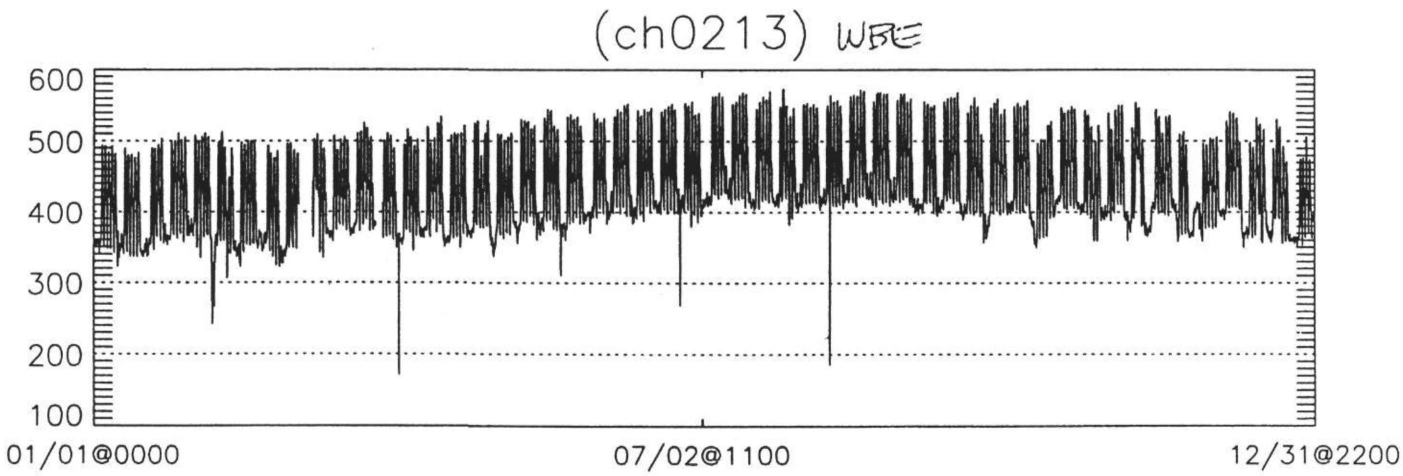
Lighting and Receptacles Data of a Large Office Building in San Francisco (data from LBNL)

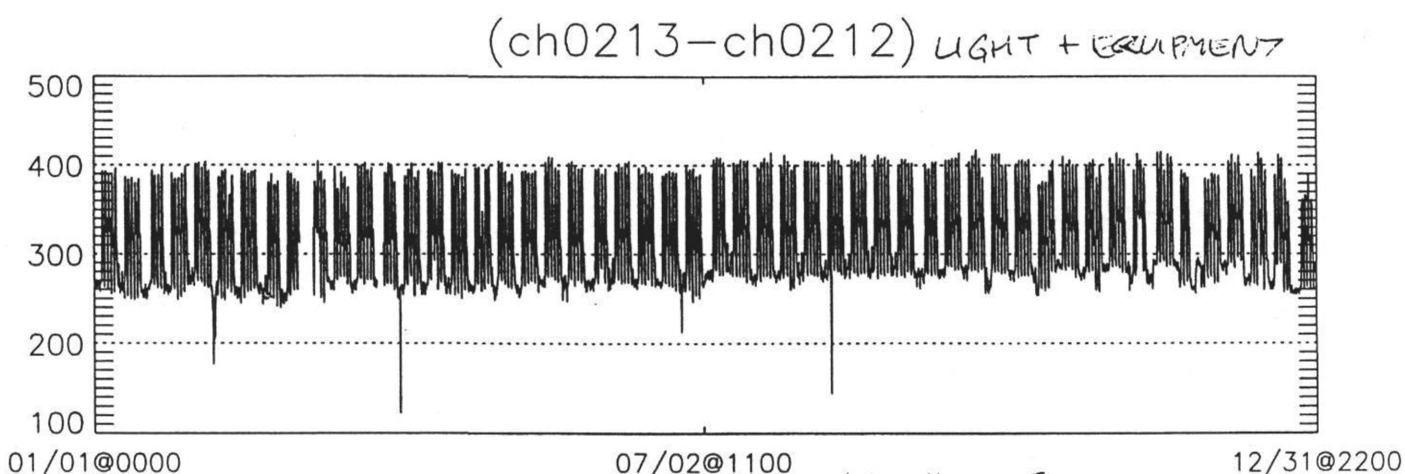
Year	Month	Day	Hour	Lighting	Receptacles
98	6	1	0	6.75487	31.3819
98	6	1	1	6.89328	31.5431
98	6	1	2	6.93858	32.1996
98	6	1	3	6.75268	32.18
98	6	1	4	6.75077	32.9877
98	6	1	5	6.74925	32.8454
98	6	1	6	12.3731	33.6796
98	6	1	7	39.5172	38.0029
98	6	1	8	77.2296	50.2497
98	6	1	9	95.1469	57.5337
98	6	1	10	96.423	61.2407
98	6	1	11	96.7877	60.5314
98	6	1	12	97.1826	61.7639
98	6	1	13	96.3251	61.3234
98	6	1	14	97.2138	60.6583
98	6	1	15	97.4494	57.2469
98	6	1	16	97.2671	57.2836
98	6	1	17	96.9543	50.4365
98	6	1	18	92.2867	45.8641
98	6	1	19	79.9656	44.1013
98	6	1	20	68.3778	40.1085
98	6	1	21	60.2195	37.4003
98	6	1	22	53.217	37.5105
98	6	1	23	46.7858	35.8003
98	6	2	0	10.9824	33.9291
98	6	2	1	6.76813	33.6745
98	6	2	2	6.76717	33.3736
98	6	2	3	6.85198	33.3731
98	6	2	4	6.94582	33.2613
98	6	2	5	6.76347	34.6358
98	6	2	6	14.8949	36.1603
98	6	2	7	45.189	40.383
98	6	2	8	78.6476	48.7897
98	6	2	9	94.5751	56.1029
98	6	2	10	97.0451	60.7968
98	6	2	11	96.7457	59.6271
98	6	2	12	96.431	61.2312
98	6	2	13	96.3857	60.8944
98	6	2	14	97.1746	61.401
98	6	2	15	97.3999	60.1412
98	6	2	16	96.9073	58.4826
98	6	2	17	94.9739	51.4962
98	6	2	18	89.0862	47.3129
98	6	2	19	75.6721	41.9467
98	6	2	20	65.8712	38.5955
98	6	2	21	58.0198	38.2965
98	6	2	22	54.1821	36.4258
98	6	2	23	35.7459	35.3986

8.3 Sample Graphs for Data Quality Checks

In this appendix, we show graphical displays of the raw data retrieved from the ESL database, which helped us in identifying clean data sets for this project.

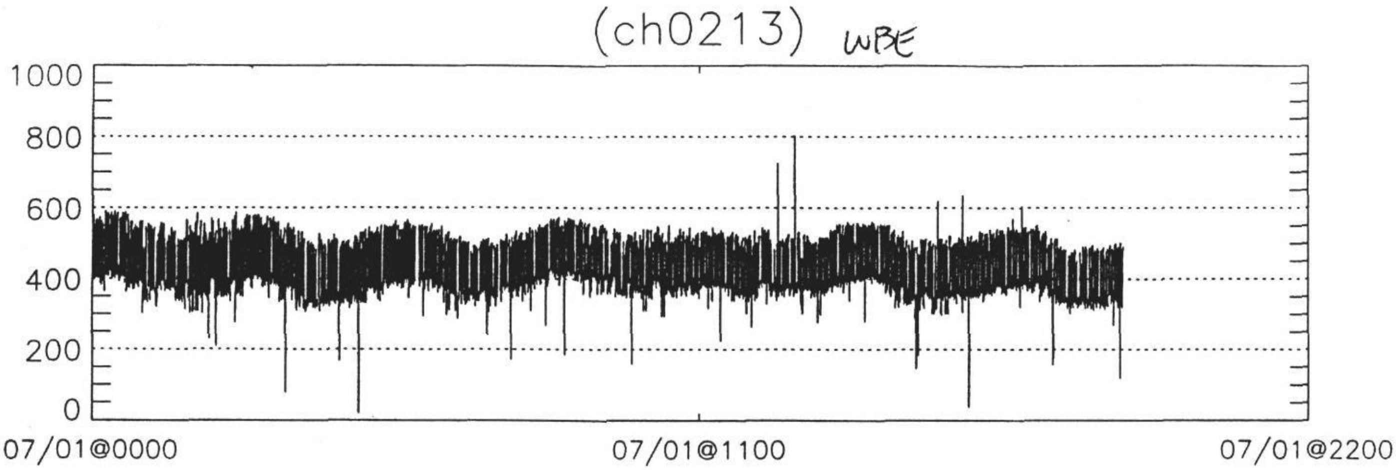
Whole-Building Electricity and Lighting+Equipment Use in Building # 205 in the ESL database

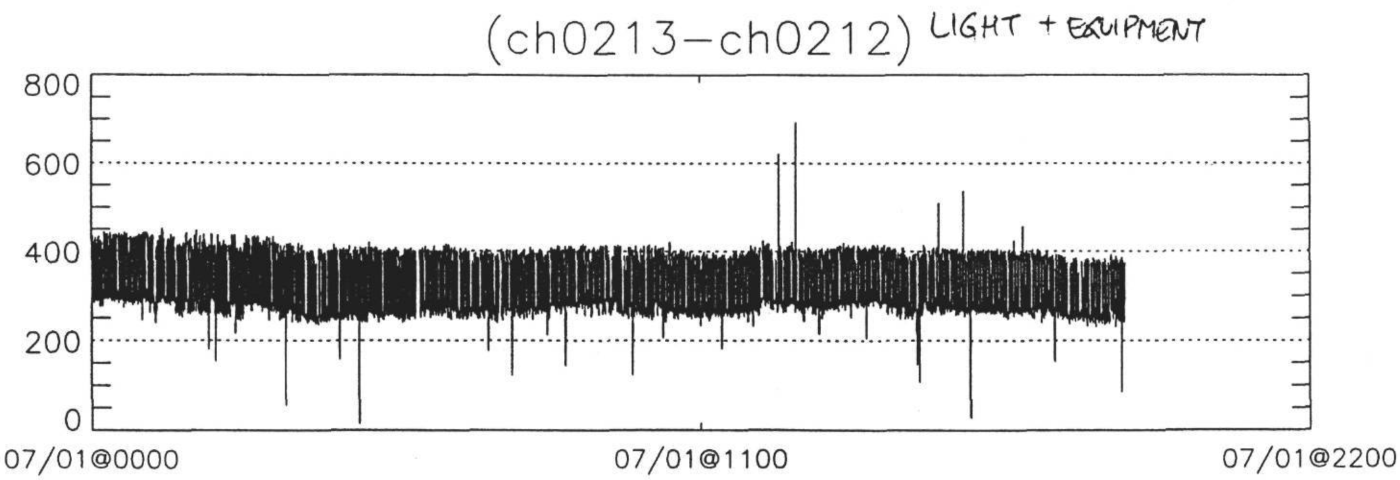




SITE # 205
01/94 - 12/94

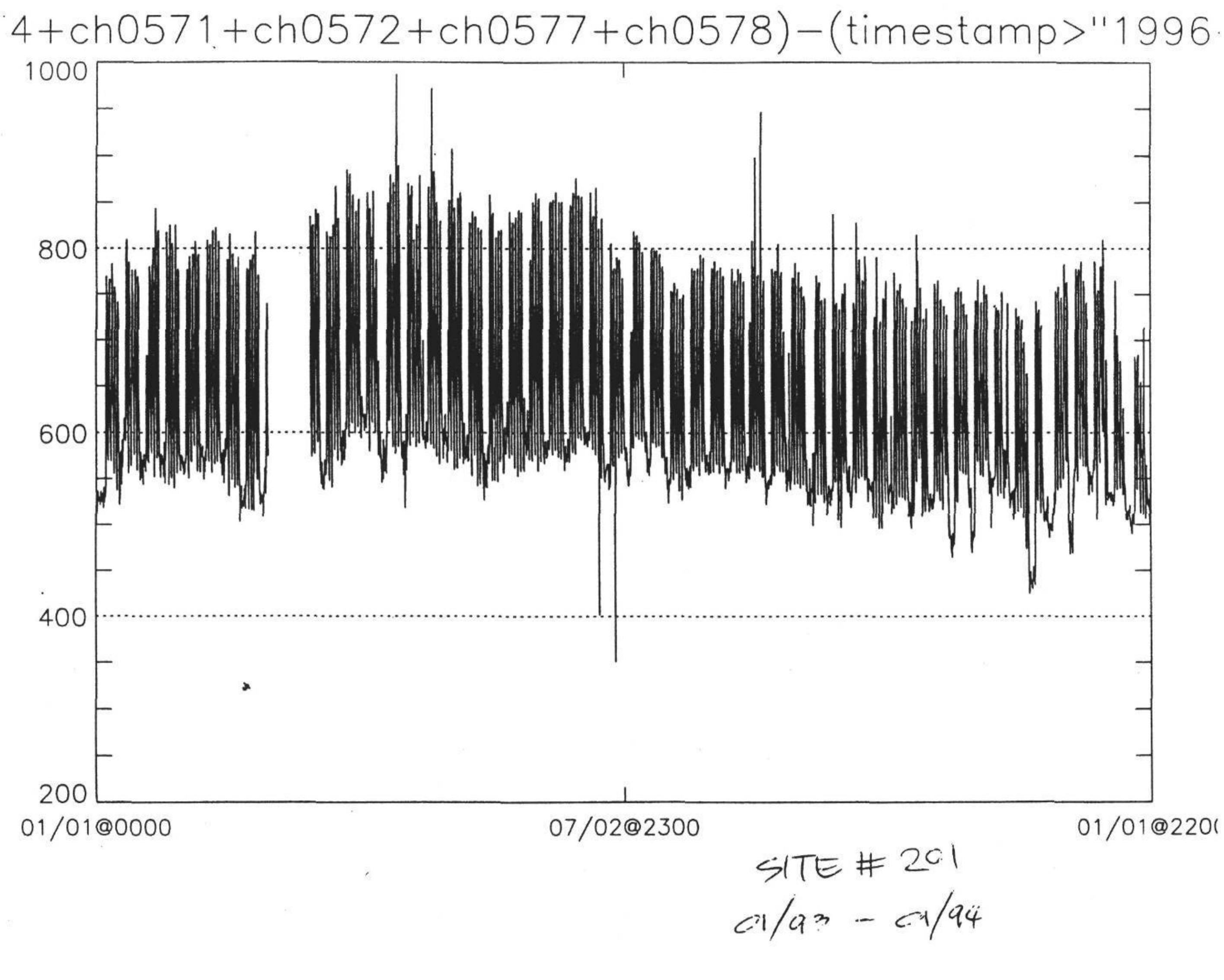
Whole-Building Electricity and Lighting+Equipment Use in Building # 205 in the ESL database (Cont'd)



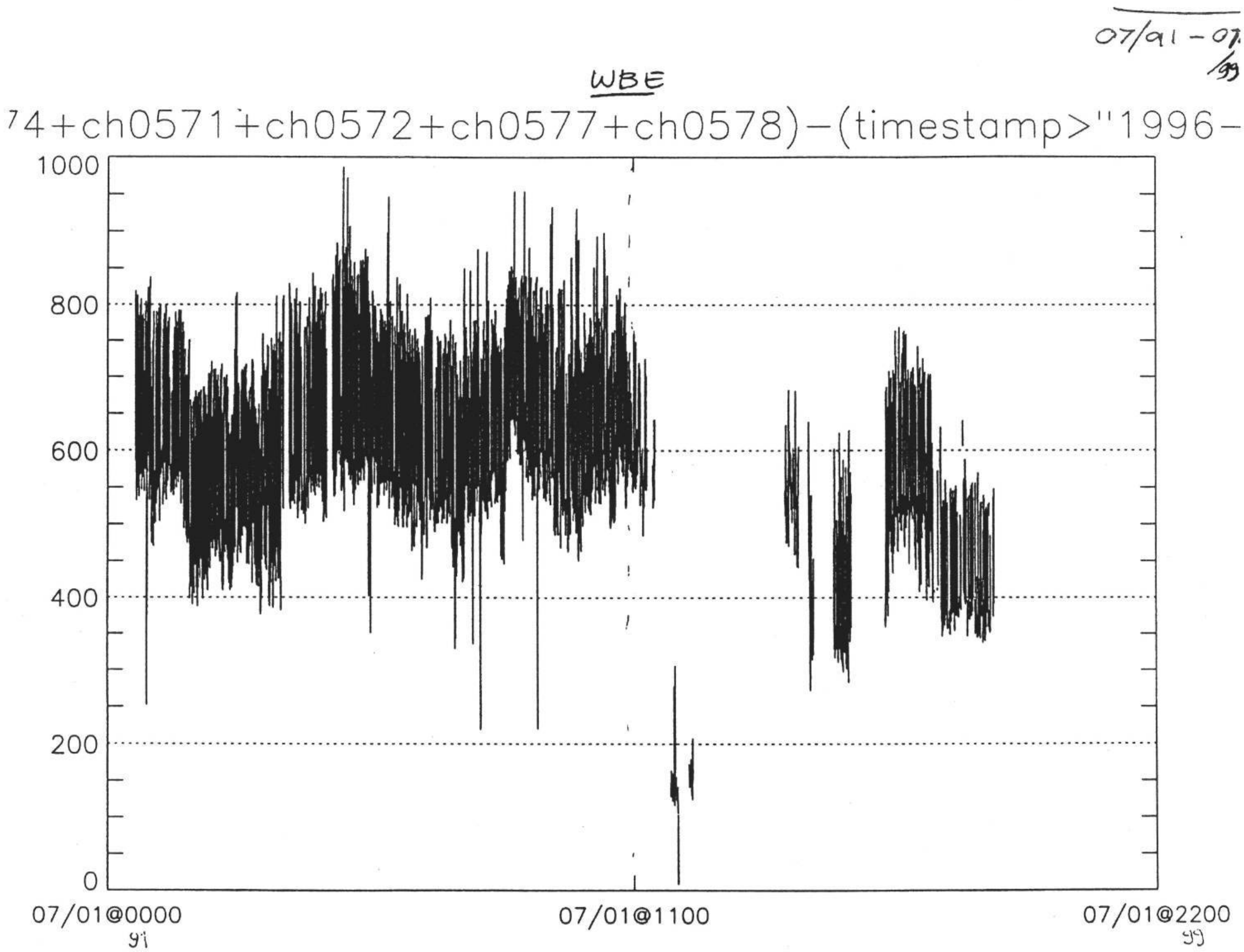


SITE 205
07/91 - 07/95

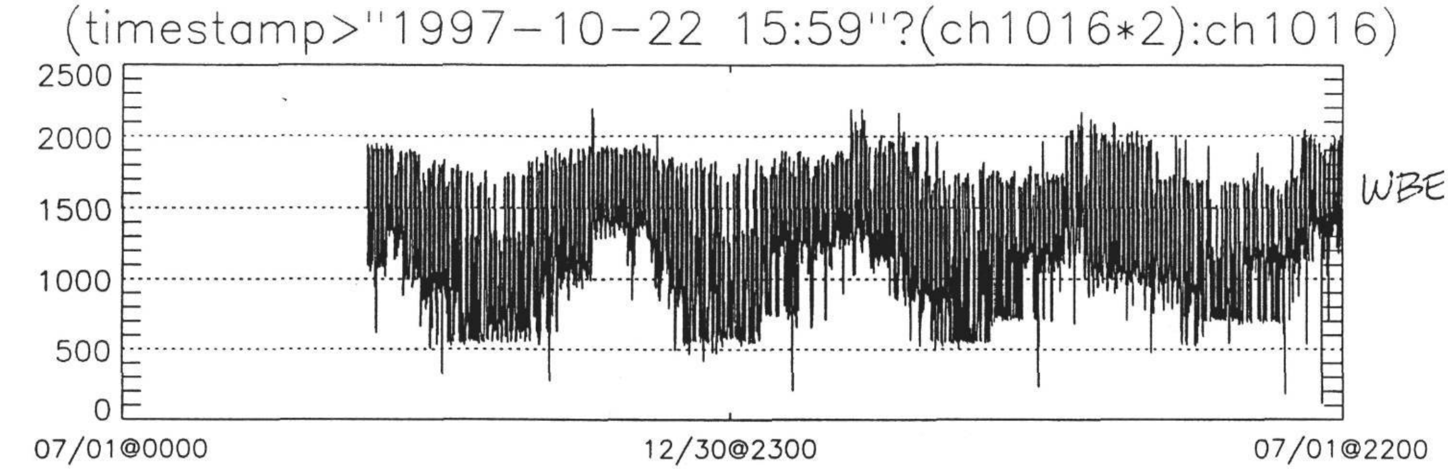
Whole-Building Electricity Use in Building # 201 in the ESL database

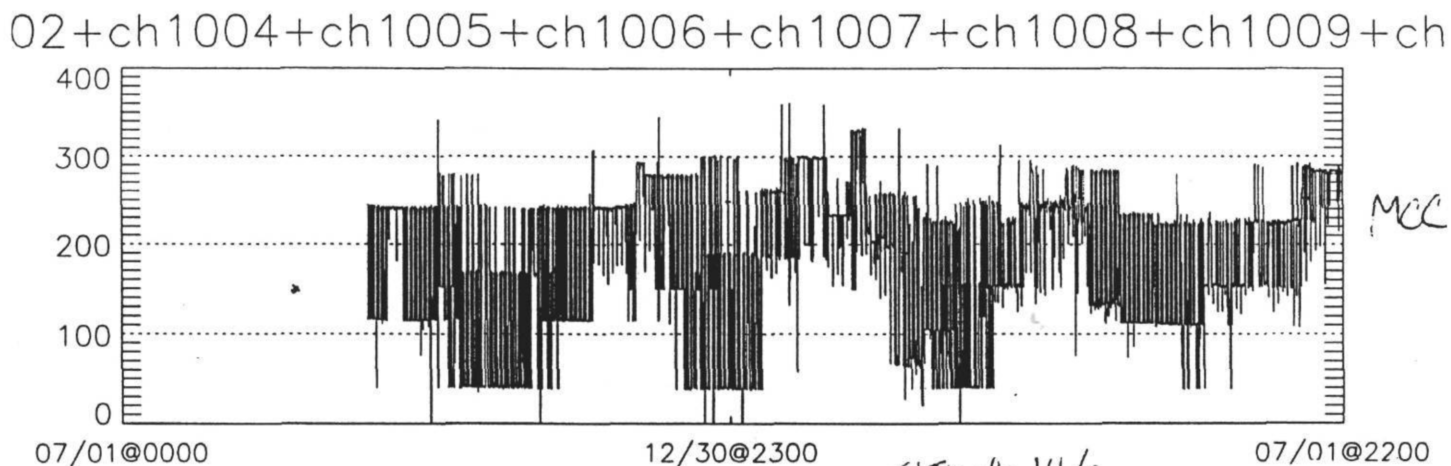


Whole-Building Electricity Use in Building # 201 in the ESL database (Cont'd)



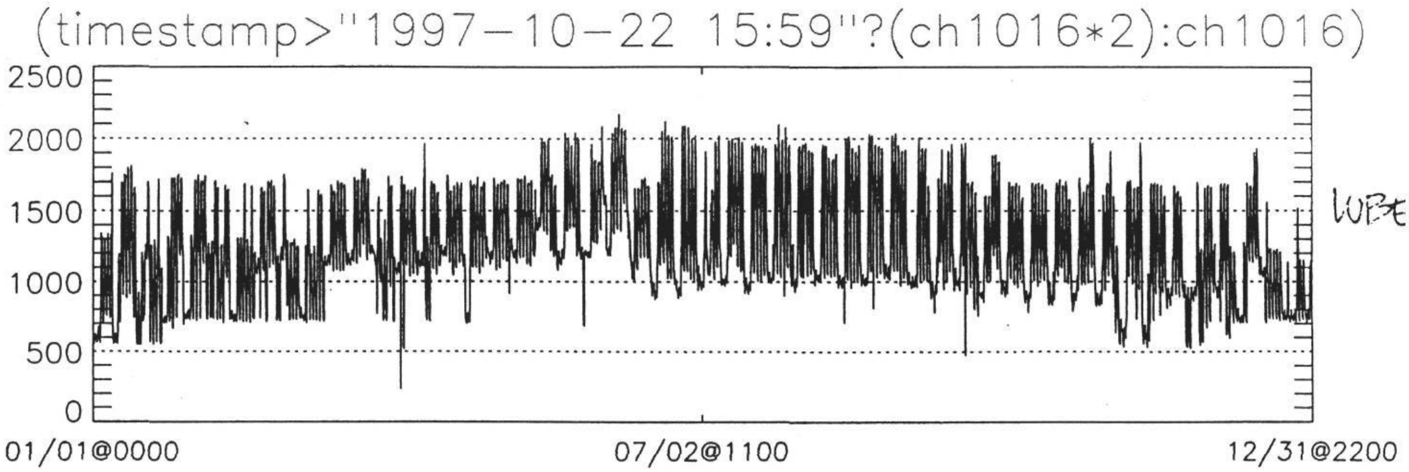
Whole-Building and Motor Control Center Electricity Use in Building # 146 in the ESL database

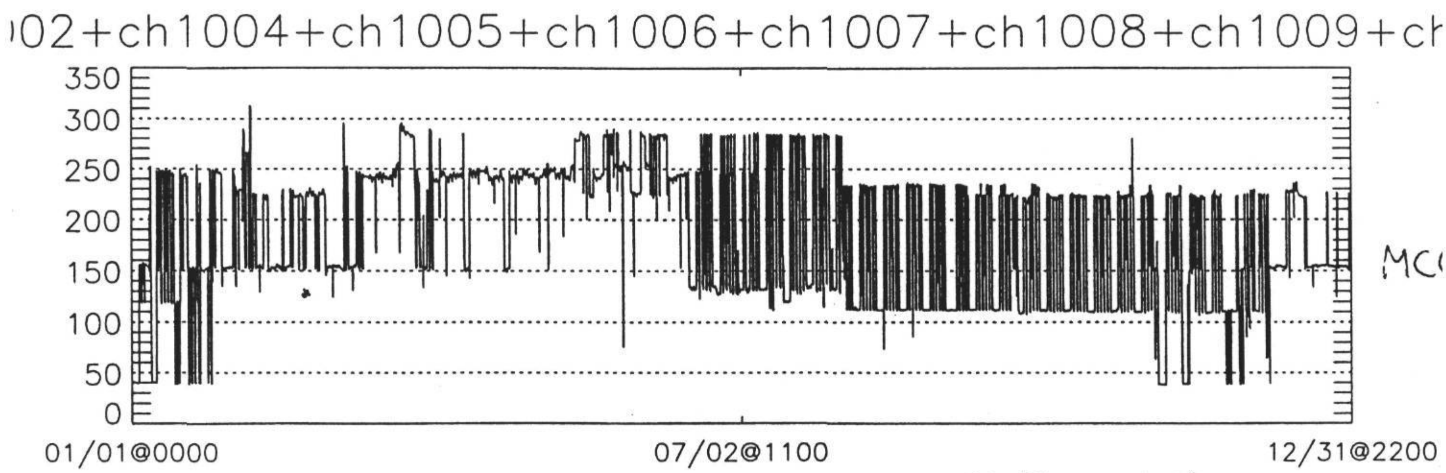




SITE # 146
07/91 - 07/96

Whole-Building and Motor Control Center Electricity Use in Building # 146 in the ESL database





SITE # 146

01/95 - 12/95

8.4 All Buildings Monitored by ESL

In this appendix, we show all buildings monitored by ESL, whose data are available in the database. Table 6 includes information on how the lighting and receptacles data can be calculated, if not measured directly.

Category	Logger ID	Building	Building Location	Building Area (ft^2)	WBE	L&R	Source	Data Format	Cost	Data Quality
	1	Zachry Engineering Center	TAMU, CS, TX	324,400	NWD	LITEQ	LoanSTAR			
	100	Sanchez E. Building	UT, Austin, TX	251,161	NWD	WBE-MCC	LoanSTAR			
	101	University Teaching Center		152,690	NWD	WBE-MCC	LoanSTAR			
	102	Perry Castaneda Library		483,895	NWD	WBE-MCC	LoanSTAR			
	103	Garrison Hall		54,069	NWD	WBE-MCC	LoanSTAR			
	104	Gearing Hall		61,041	NWD	WBE-MCC	LoanSTAR			
	105	Waggener Hall		57,598	NWD	MCC	LoanSTAR			
	106	Welch Hall		439,540	NWD	MCC	LoanSTAR			
	107	Burdine Hall		103,441	NWD	MCC	LoanSTAR			
	108	Nursing Building		94,815	NWD	MCC	LoanSTAR			
	109	Winship/Steindam Logger		109,064	NWD		LoanSTAR			
	110	Painter/Hogg Logger		128,409	NWD		LoanSTAR			
	111	University Hall	UT, Arlington, TX	123,450	NWD	MCC	LoanSTAR			
	112	Business Building		149,900	NWD	LIGHT, LITEQ	LoanSTAR			
	113	Fine Arts Building		223,000	NWD	LITEQ	LoanSTAR			
	114	Winship Hall	UT, Austin, TX	109,064	NWD	sav_leq	LoanSTAR			
	115	R.A. Steindam Hall		56,849	NWD		LoanSTAR			
	116	Painter Hall		128,409	NWD		LoanSTAR			
	117	W.C. Hogg Building		48,905	NWD		LoanSTAR			
	118	Garrison Hall		54,069	NWD		LoanSTAR			
	119	Gearing Hall		61,000	NWD		LoanSTAR			
	120	MSB Logger 1	Houston, TX	887,187			LoanSTAR			
	121	MSB Logger 2								
	122	MSB Logger 3								
	123	MSB Logger 4								
	124	Medical School Building			NWD	LIGHT				
	125	University of Texas Pan Am	Edinburg, TX	909,642	WD		LoanSTAR			
	126	Stroman High School	Victoria, TX	210,500	WD		LoanSTAR			
	127	Victoria High School		257,014	WD		LoanSTAR			
	128	Sims Elementary School	Fort Worth, TX	62,400	WD	LIGHT	LoanSTAR			
	129	Dunbar Middle School		51,693	WD	LIGHT	LoanSTAR			
	130	Texas Department of Health	Austin, TX	299,700	WD		LoanSTAR			
	131	MDA Cancer Center Boiler Room	Houston, TX	412,872	WD		LoanSTAR			
	132	Basic Research Building		120,376	NWD					
	133	Old Clinic \& Lutheran Pv.		499,013	NWD					
	134	New Clinic		276,466	NWD					
	135	MDA Logger 4								
	136	M. D. Anderson Cancer Center		1,522,193	NWD	WBE-ChW P	LoanSTAR			
	137	University of Texas at Dallas	Richardson, TX	481,549	NWD		LoanSTAR			
	138	University of N. Texas Health Science Center	Fort Worth, TX	496,000	NWD		LoanSTAR			
	139	Texas A\&M University at Galveston	Galveston, TX	420,868	NWD		LoanSTAR			
	140	UTHSC-SA Logger	San Antonio, TX				LoanSTAR			

	141	Dental School		484,019	NWD		LoanSTAR			
	142	Medical School		606,097	NWD		LoanSTAR			
	143	Delmar College	Corpus Christi, TX	636,702	WD		LoanSTAR			
	144	Midland County Courthouse	Midland, TX	90,100	WD		LoanSTAR			
	145	Ward Memorial Hospital	Monahans, TX	37,000	WD	MCC	LoanSTAR			
	146	Government Center	Dallas, TX	473,800	WD	MCC	LoanSTAR			
	147	SWTSU-E Logger		637,223	WD		LoanSTAR			
	148	SWTSU-W Logger			WD					
	149	Southwest Texas State University								
	150	TSTC Harlingen	Harlingen, TX	245,258	WD	Non-Mech	LoanSTAR			
	151	Austin State Hospital	Austin, TX	845,435	NWD		LoanSTAR			
	152	Nacogdoches High School	Nacogdoches, TX	202,615	WD	LIGHT	LoanSTAR			
	153	Chamberlain Middle School		66,778	WD	LIGHT	LoanSTAR			
	154	PCL Hot Deck Fans Logger	Austin, TX				LoanSTAR			
	155	Whole Campus	Harlingen, TX	139,193			LoanSTAR			
	160	Oppe Elementary School	Galveston, TX	80,400	WD	MCC	LoanSTAR			
	161	Weis Middle School		80,769	WD	MCC	LoanSTAR			
	162	Parker Elementary School		81,742	WD	MCC	LoanSTAR			
	163	Morgan Elementary School		76,798	WD	MCC	LoanSTAR			
	164	Rosenberg Elementary School		63,044	WD	MCC	LoanSTAR			
	165	College of Business Administration	UT-Austin, TX	242,857	NWD	MCC	LoanSTAR			
	166	Graduate School of Business		146,763	NWD	MCC	LoanSTAR			
	167	Main Building		328,752	NWD	LITEQ	LoanSTAR			
	168	Engineering II		246,102	NWD	LIGHT	LoanSTAR			
	169	Davis Hall		101,580	WD	LITEQ	LoanSTAR			
	170	Nursing Hall		155,004	NWD	LIGHT	LoanSTAR			
	171	Life Science Building		213,672	NWD	Non-Light,LIGHT	LoanSTAR			
	172	Library		201,040	NWD	LIGHT	LoanSTAR			
	173	UTA Thermal Energy Plant	UT-Arlington	31,555	WD		LoanSTAR			
	174	Thermal Energy Plant Logger 2								
	175	Thermal Energy Plant Logger 3								
	176	Thermal Energy Plant			WD	MCC	LoanSTAR			
	177	Geology Building	UT-Austin, TX	127,000	NWD	MCC	LoanSTAR			
	178	Jester Hall		157,270	NWD	LIGHT	LoanSTAR			
	179	Taylor Hall		100,773	NWD	MCC	LoanSTAR			
	180	Whole Campus								
	181	Battle Hall		47,166	NWD	LIGHT	LoanSTAR			
	182	Batts Hall		56,190	NWD		LoanSTAR			
	190	TAMUK- Central Plant-1	TAMU Kingsville	1,695,000	WD		LoanSTAR			
	191	TAMUK- Central Plant-2			WD		LoanSTAR			
	192	TAMUK- College Hall			NWD		LoanSTAR			
	193	TAMUK- Whole Campus			NWD		LoanSTAR			
	194	TAMUK- Turner-Bishop Hall			NWD		LoanSTAR			
	200	Capitol Building	AUSTIN	282,499	NWD		LoanSTAR			
	201	Sam Houston Building	AUSTIN	182,961	NWD		LoanSTAR			

	202	S.F. Austin Plant	AUSTIN	470,000	WD		LoanSTAR			
	203	John H. Reagan	AUSTIN	169,746	WD	LIGHT	LoanSTAR			
	205	James E. Rudder	AUSTIN	80,000	WD	LITEQ	LoanSTAR			
	206	Insurance Building	AUSTIN	102,000	NWD	LITEQ	LoanSTAR			
	207	Insurance Annex	AUSTIN	62,000	WD	MCC	LoanSTAR			
	208	Archives Building	AUSTIN	120,000	NWD	LITEQ	LoanSTAR			
	209	W.B. Travis	AUSTIN	491,000	NWD	LITEQ	LoanSTAR			
	210	L.B. Johnson	AUSTIN	308,080	NWD	LIGHT, LITEQ	LoanSTAR			
	211	J.H. Winters	AUSTIN	503,000	WD		LoanSTAR			
	212	Capitol Extension	AUSTIN	592,781	NWD		LoanSTAR			
	213	Sam Houston Physical Plant	AUSTIN	1,925,780	WD		LoanSTAR			
	214	S.F. Austin Building	AUSTIN	470,000	WD		LoanSTAR			
	220	Treasury Building	AUSTIN	203,672	WD		LoanSTAR			
	221	William P. Hobby Building	AUSTIN	546,749	WD		LoanStar			
	222	William P. Hobby Building								
	223	William P. Hobby Building								
	224	William P. Hobby Building								
	226	Central Services Building	AUSTIN	97,030	NWD		LoanStar			
	227	Supreme Court Building	AUSTIN	72,737	NWD		LoanStar			
	228	Price Daniels Building	AUSTIN	151,620	NWD		LoanStar			
	229	Tom C. Clark Building	AUSTIN	121,654	NWD		LoanStar			
	230	Austin Convention Center	AUSTIN	174,456	WD		LoanStar			
	231	Austin Convention Center Logger #2	AUSTIN	108,000			LoanStar			
	232	A-Lab	AUSTIN	56,000			LoanStar			
	233	Records Building	AUSTIN	33,000	NWD		LoanStar			
	234	Main Building (G, F, K Buildings)	AUSTIN	81,000	NWD		LoanStar			
	235	Small Labs (A-400, A-500, A-600)	AUSTIN	15,700	NWD		LoanStar			
	236	Brown Heatly Building	AUSTIN	262,905	WD		LoanStar			
	237	W. P. Clements Building	AUSTIN	484,077	WD		LoanStar			
	238	McDermott Library (UTD)	Richardson, TX	NA	NA	NA				
	239	Green Center (UTD)	Richardson, TX	NA	NA	NA				
	240	Police Department Headquarters	AUSTIN	110,000	WD		LoanStar			
	241	Municipal Court Building	AUSTIN	44,155	WD		LoanStar			
	242	John Henry Faulk Building	AUSTIN	110,663	WD		LoanStar			
	243	Waste Water Facility	AUSTIN	10,000	NWD		LoanStar			
	244	WFH Whole Campus	Wichita Falls	495,802	NWD	LIGHT	ESL			
	245	WFH Buildings 683 \& 700		81,164	NWD	MCC	LoanStar			
	246	TSH Whole Campus	Terrel, TX	644782			LoanStar			
	247	TSH Bldgs. 537, 725, 686 and 682			WD		LoanStar			
	248	TSH Medical Facility (Building 673)		49,651	WD		LoanStar			
	249	TSH Mech Room (Building 676)		72,140	WD		LoanStar			
	250	TSH Mech Room (Building 680)		88,750	WD		LoanStar			
	251	Waco Center for Youth	Waco	124,033	WD		LoanStar			
	252	Dobie Middle School	AUSTIN	128,693	WD		LoanStar			
	253	Lanier High School	AUSTIN	283,843	WD		LoanStar			

	254	Crocket High School	AUSTIN	312,648	WD		LoanStar			
	260	McDermott Library	Richardson, TX	211,798			LoanStar			
	261	Green Center	Richardson, TX	135,796			LoanStar			
	262	Jonsson Center	Richardson, TX	134,055			LoanStar			
	263	MED I	Fort Worth, TX	261,000			LoanStar			
	264	MED II	Fort Worth, TX	125,000			LoanStar			
	265	MED III	Fort Worth, TX	110,000			LoanStar			
	300	School of Public Health	Houston	233,738	NWD	MCC	ESL			
	301	Physical Education Building	Texas City, TX	58,678	NWD		LoanStar			
	302	Student Center	Texas City, TX	23,558	NWD		LoanStar			
	303	Fine Arts Building	Texas City, TX	24,106	NWD		LoanStar			
	304	Auto/Diesel Laboratory	Texas City, TX	22,230	NWD		LoanStar			
	305	Math/Science Building	Texas City, TX	18,827	NWD		LoanStar			
	306	Administration Building	Texas City, TX	21,274	NWD		LoanStar			
	307	Technical/Vocational Building	Texas City, TX	96,216	NWD		LoanStar			
	308	Learning Resource Center	Texas City, TX	56,000	NWD		LoanStar			
	309	Welding Technology Laboratory	Texas City, TX	8,400	NWD		LoanStar			
	310	Main CUP	Houston, TX	1,147,500	WD	MCC	LoanSTAR			
	311	Satellite CUP	Houston, TX	212,500	WD	MCC	LoanSTAR			
	312	Bell Building	Houston, TX	55,878	NWD	LITRE	LoanSTAR			
	313	Whole Campus	Houston, TX	1,700,000	-		LoanSTAR			
	315	Texas Woman's University	Houston, TX	253,175			LoanSTAR			
	320	College of the Mainland	Texas City, TX	339,167	WD		LoanSTAR			
	321	College of the Mainland					LoanStar			
	322	University of Houston - Clear Lake (Boyou Bldg.)	Houston, TX	460,576	WD		LoanSTAR			
	325	Valle Verde Campus	El Paso, TX	406,805	WD		LoanSTAR			
	326	Rio Grande Campus	El Paso, TX	102,422	WD		LoanSTAR			
	327	Trans Mountain Campus	El Paso, TX	154,000	WD		LoanSTAR			
	328	Denton State School	Denton, TX	431,580	NWD		LoanSTAR			
	329	Vernon State Hospital	Vermon, TX	265,049	WD		LoanSTAR			
	330	Abilene State School	Abilene, TX	612,052	WD		LoanSTAR			
	331	San Angelo State School	Carlsbad TX	497,091	NWD		LoanSTAR			
	332	Central Plant (San Angelo State School)			WD		LoanStar			
	333	Big Spring State Hospital	Big Spring, TX	351,892	NWD		LoanSTAR			
	334	Big Spring State Hospital (mecr site 2)	Big Spring, TX				LoanSTAR			
	335	Lubbock State School	Lubbock, TX	321,357	NWD		LoanSTAR			
	336	Rusk State Hospital	Rusk, TX	577,601	NWD		LoanSTAR			
	337	Corpus Christi State School	Corpus Christi, TX	263,918	NWD		LoanSTAR			
	338	Brenham State School Whole Campus	Brenham, TX	362,249	NWD		LoanSTAR			
	339	Brenham State School - Bldg 501 (Admin)		9,681	NWD		LoanSTAR			
	340	Brenham State School - Bldg 502 (Infirmary)		20,487	NWD		LoanSTAR			
	341	Brenham State School - Bldg 503 (Austin Unit)		38,981	NWD		LoanSTAR			
	342	Brenham State School - Bldg 504 (Fannin Unit)		38,981	NWD		LoanSTAR			
	343	Brenham State School - Bldg 505 (Childress Unit)		43,519	NWD		LoanSTAR			
	344	Brenham State School - Bldg 506 (Driscoll Unit)		38,981	NWD		LoanSTAR			

	345	Brenham State School - Bldg 507 (Recreation)		30,310	NWD		LoanSTAR			
	346	Brenham State School - Bldg 523 (Bowie Unit)		40,865	NWD		LoanSTAR			
	400	John Sealy North	Galveston, TX	54,494	NWD	MCC	LoanSTAR			
	401	Clinical Sciences		124,870	NWD	MCC	LoanSTAR			
	402	Basic Sciences		137,856	NWD	MCC	LoanSTAR			
	403	Moody Library		67,380	NWD	MCC	LoanSTAR			
	404	John Sealy South Towers		373,085	NWD	MCC	LoanSTAR			
	491	Evans Library (Old)	TAMU, CS, TX		NWD	MCC	TAMU Campus			
	492	Evans Library Complex	TAMU, CS, TX		NWD		TAMU Campus			
	493	Cushing Library	TAMU, CS, TX	812,289	NWD		TAMU Campus			
	494	E. Langford Architecture Center	TAMU, CS, TX	102,105	NWD		TAMU Campus			
	495	Old Architecture	TAMU, CS, TX	69,947	NWD		TAMU Campus			
	496	Biological Sciences Building	TAMU, CS, TX	96,083	NWD		TAMU Campus			
	497	Teague	TAMU, CS, TX	63,515	NWD	MCC	TAMU Campus			
	498	Reed McDonald	TAMU, CS, TX	80,218	NWD		TAMU Campus			
	499	Heldenfels Hall	TAMU, CS, TX	104,949	NWD		TAMU Campus			
	500	Zachry Engineering Center	TAMU, CS, TX	324,400	NWD		TAMU Campus			
	502	Main Plant 1	TAMU, CS, TX				TAMU Campus			
	503	Main Power Plant E.	TAMU, CS, TX				TAMU Campus			
	504	South Satellite Plant	TAMU, CS, TX				TAMU Campus			
	505	West Campus	TAMU, CS, TX				TAMU Campus			
	506	W. Campus 2 Pl.	TAMU, CS, TX				TAMU Campus			
	507	W. Campus Switching St.	TAMU, CS, TX				TAMU Campus			
	509	Harrington Tower	TAMU, CS, TX	130,844	NWD		TAMU Campus			
	510	Blocker	TAMU, CS, TX	257,953	NWD		TAMU Campus			
	511	Oceanography and Meterology	TAMU, CS, TX	180,316	NWD		TAMU Campus			
	512	Kleberg Animal \& Food Sciences	TAMU, CS, TX	165,031	NWD		TAMU Campus			
	513	New Chemistry Building	TAMU, CS, TX	115,797	NWD		TAMU Campus			
	514	Chemistry (1959)	TAMU, CS, TX	205,393	NWD		TAMU Campus			
	515	Bright Building	TAMU, CS, TX	148,837	NWD		TAMU Campus			
	516	CE/TTI Tower	TAMU, CS, TX	157,844	NWD		TAMU Campus			
	517	Petroleum Eng (Richardson)	TAMU, CS, TX	113,700	NWD		TAMU Campus			
	518	Engineering/Physics Lab	TAMU, CS, TX	115,288	NWD		TAMU Campus			
	519	Halbouty Geosciences	TAMU, CS, TX	120,874	NWD		TAMU Campus			
	520	Engineering Research Center	TAMU, CS, TX	177,704	NWD		TAMU Campus			
	521	Clinical Sciences (Vet)	TAMU, CS, TX	103,440	NWD		TAMU Campus			
	522	Vet Med Hospital	TAMU, CS, TX	140,865	NWD		TAMU Campus			
	523	Vet Med Center Addition	TAMU, CS, TX	114,666	NWD		TAMU Campus			
	524	Soil \& Crop/Entomology	TAMU, CS, TX	158,979	NWD		TAMU Campus			
	525	Medical Sciences Building	TAMU, CS, TX	169,859	NWD		TAMU Campus			
	526	Horticulture-Forest Sciences	TAMU, CS, TX	118,648	NWD		TAMU Campus			
	527	Biochemistry/Biophysics	TAMU, CS, TX	166,079	NWD		TAMU Campus			
	528	New Business Building	TAMU, CS, TX	192,001	NWD		TAMU Campus			
	529	State Headquarters	TAMU, CS, TX	123,961	WD		TAMU Campus	15min		
	530	TI Building	TAMU, CS, TX	153,000	WD		TAMU Campus			

	531	Chemistry (1972)	TAMU, CS, TX	205,393	NWD		TAMU Campus		
	532	Halbouty Geosciences (New)	TAMU, CS, TX	120,874	NWD		TAMU Campus		
	533	Harrington Lab	TAMU, CS, TX	61,860	NWD		TAMU Campus		
	534	Plant Science	TAMU, CS, TX	84,831	NWD		TAMU Campus		
	535	EV Adams Band Hall	TAMU, CS, TX	55,248	NWD		TAMU Campus		
	536	Academic	TAMU, CS, TX	82,555	NWD		TAMU Campus		
	537	Biological Science Building E	TAMU, CS, TX	62,273	NWD		TAMU Campus		
	538	Academic Administration	TAMU, CS, TX	69,898	NWD		TAMU Campus		
	539	Anthropology	TAMU, CS, TX	51,592	NWD		TAMU Campus		
	540	Agriculture Engineering	TAMU, CS, TX	62,228	NWD		TAMU Campus		
	541	Cyclotron	TAMU, CS, TX	80,646	NWD		TAMU Campus		
	542	Civil Engineering Building	TAMU, CS, TX	56,537	NWD		TAMU Campus		
	543	Dulie Bell	TAMU, CS, TX	51,802	NWD		TAMU Campus		
	544	Vet Sciences Building	TAMU, CS, TX	61,319	NWD		TAMU Campus		
	545	Vet Hospital	TAMU, CS, TX	96,416	NWD		TAMU Campus		
	546	Health Center Addition	TAMU, CS, TX	50,015	NWD		TAMU Campus		
	547	Vet Med Admin Bldg	TAMU, CS, TX	94,680	NWD		TAMU Campus		
	548	M. E. Shops (Thompson)	TAMU, CS, TX	81,404	NWD		TAMU Campus		
	549	Southern Crop Improvement Facility	TAMU, CS, TX	59,621	NWD		TAMU Campus		
	550	Ocean Drilling Facilities	TAMU, CS, TX	60,000	NWD		TAMU Campus		
	551	West Campus Library	TAMU, CS, TX	68,125	NWD		TAMU Campus		
	552	Medical Sciences Library	TAMU, CS, TX	84,183	NWD		TAMU Campus		
	553	Offshore Technology	TAMU, CS, TX	40,014	NWD		TAMU Campus		
	554	West Campus (old)	TAMU, CS, TX				TAMU Campus		
	560	Wells Hall	TAMU, CS, TX	67,283	NWD		TAMU Campus		
	561	Rudder Hall	TAMU, CS, TX	67,283	NWD		TAMU Campus		
	562	Eppright Hall	TAMU, CS, TX	67,283	NWD		TAMU Campus		
	563	Appelt Hall	TAMU, CS, TX	82,767	NWD		TAMU Campus		
	564	Lechner Hall	TAMU, CS, TX	59,541	NWD		TAMU Campus		
	565	Underwood Hall	TAMU, CS, TX	81,730	NWD		TAMU Campus		
	566	Commons	TAMU, CS, TX	57,500	NWD		TAMU Campus		
	568	Krueger Hall	TAMU, CS, TX	112,133	NWD		TAMU Campus		
	569	Dunn Hall	TAMU, CS, TX	112,133	NWD		TAMU Campus		
	570	Mosher Hall	TAMU, CS, TX	155,430	NWD		TAMU Campus		
	571	West Dorm - Aston Hall	TAMU, CS, TX	113,388	NWD		TAMU Campus		
	572	Clayton Williams Alumni Center	TAMU, CS, TX	56,000	WD		TAMU Campus		
	573	Read Building	TAMU, CS, TX	149,895	NWD		TAMU Campus		
	574	Kyle Field	TAMU, CS, TX	149,895	NWD		TAMU Campus		
	575	G. Rollie White Annex	TAMU, CS, TX	153,886	NWD		TAMU Campus		
	576	Koldus Student Services	TAMU, CS, TX	111,022	NWD		TAMU Campus		
	577	Cain Hall Kitchen	TAMU, CS, TX	92,812	NWD		TAMU Campus		
	578	Rudder Auditorium	TAMU, CS, TX	302,240	NWD		TAMU Campus		
	579	Duncan Dining Hall	TAMU, CS, TX	75,849	NWD		TAMU Campus		
	580	G. Rollie White	TAMU, CS, TX	177,838	NWD		TAMU Campus		
	581	Memorial Student Center	TAMU, CS, TX	177,838	NWD		TAMU Campus		

	582	MSC Annex	TAMU, CS, TX	368,935	NWD		TAMU Campus			
	583	Sbisa Dining Hall	TAMU, CS, TX	137,913	NWD		TAMU Campus			
	586	Clements Hall	TAMU, CS, TX	62,156	NWD		TAMU Campus			
	587	Haas Hall	TAMU, CS, TX	69,668	NWD		TAMU Campus			
	588	McFadden Hall	TAMU, CS, TX	62,156	NWD		TAMU Campus			
	589	Neely Hall	TAMU, CS, TX	69,668	NWD		TAMU Campus			
	590	Hobby Hall	TAMU, CS, TX	62,156	NWD		TAMU Campus			
	591	McKenzie Terminal	TAMU, CS, TX	32,188	WD		TAMU Campus			
	593	Recreational Sports \& Natorium	TAMU, CS, TX	289,000	NWD		TAMU Campus			
	599	A&M westinghouse data	TAMU, CS, TX	NA	NA					
	601	Torres Unit	Huntsville, TX	NA	NA					
	602	Boyd Unit	Huntsville, TX	NA	NA					
	604	Stevesson Unit	Huntsville, TX	NA	NA					
	605	Brisco Unit	Huntsville, TX	NA	NA					
	606	Lynaugh Unit	Huntsville, TX	NA	NA					
	607	Smith Unit	Huntsville, TX	NA	NA					
	608	Wallace Unit	Huntsville, TX	NA	NA					
	609	Roach Unit	Huntsville, TX	NA	NA					
	610	Neal Unit	Huntsville, TX	NA	NA					
	611	Jordan Unit	Huntsville, TX	NA	NA					
	612	Dalhart Unit	Huntsville, TX	NA	NA					
	701	Power Plant Chillers	Capitol Complex	42,116	WD		Minnesota			
	702	Power Plant			WD					
	703	Administration Bldg.	Capitol Complex	80,000	WD		Minnesota			
	704	Judicial Building	Capitol Complex	200,829	NWD		Minnesota			
	705	Health Building	Capitol Complex	197,260	WD		Minnesota			
	706	Ford Building	Capitol Complex	57,047	NWD		Minnesota			
	707	State Office Bldg.	Capitol Complex	281,850	NWD		Minnesota			
	708	Dept. of Transportation Bldg.	Capitol Complex	378,100	NWD		Minnesota			
	709	Veterans Building	Capitol Complex	87,664	NWD		Minnesota			
	710	Capitol Building	Capitol Complex	366,805	NWD		Minnesota			
	711	Centennial Building	Capitol Complex	317,286	NWD		Minnesota			
	712	Criminal Apprehension Bldg.	Capitol Complex	77,630	NWD		Minnesota			
	713	Capitol Square Building	Capitol Complex	225,479	WD		Minnesota			
	714	Somsen Hall	Winona S U, MN	176,221	WD		Minnesota			
	715	Phelps Hall	Winona S U, MN	41,058	NWD		Minnesota			
	716	Pasteur Hall	Winona S U, MN	60,752	NWD		Minnesota			
	717	Kryzsko Building	Winona S U, MN	108,825	NWD		Minnesota			
	718	Whole Campus	Winona S U, MN	1,263,428			Minnesota			
	719	Lourdes Hall	Winona S U, MN	50,000	NWD		Minnesota			
	721	Howell Hall	Winona S U, MN	23,117	NWD		Minnesota			
	722	Prentiss Hall	Winona S U, MN	45,503	NWD		Minnesota			
	723	Memorial Hall	Winona S U, MN	142,241	NWD		Minnesota			
	724	Performance Art Center	Winona S U, MN	86,291	NWD		Minnesota			
	725	Maxwell Library	Winona S U, MN	87,567	NWD		Minnesota			

	726	Watkins Hall	Winona S U, MN	35,805	NWD		Minnesota			
	727	Morey Hall	Winona S U, MN	36,015	NWD		Minnesota			
	728	Gildemeister Hall	Winona S U, MN	37,389	NWD		Minnesota			
	729	Minne Hall	Winona S U, MN	56,182	NWD		Minnesota			
	730	Stark Hall	Winona S U, MN	91,000	NWD		Minnesota			
	731	Sheehan Hall	Winona S U, MN	74,268	NWD		Minnesota			
	901	College Station Store	C.S. TX							
	904	USDOE Forrestal Building	Washington D.C	1,200,000	NWD		ESL			
	905	Forrestal Logger 1					ESL			
	906	Forrestal Logger 2					ESL			
	907	Day Care Center					ESL			
	908	Campbell Logger					ESL			
	913	Bryan Store	Bryan, TX				ESL			
	920	FEMP					ESL			
	921	FEMP					ESL			
	922	Neil Kirkman Building A-Wing	FL				ESL			
	923	Neil Kirkman Building B-Wing	FL				ESL			
	924	Neil Kirkman Building C-Wing	FL				ESL			
	930	Riverside	TAMU, C.S				ESL			
	931	Habitat Humanity Houses	Houston, TX				ESL			
	932	Habitat for Humanity Bryan	Bryan, TX				ESL			
	941	Ft. Hood					ESL			
	946	Ft. Hood					ESL			
	948	Ft. Hood					ESL			
	949	Fort Hood Weather Station					ESL			
	950	Toronto Reference Library	North York, Ontario	300,000			ESL			
	951	Administration (and JFK)	Dallas County	42,385			ESL			
	952	Records Complex	Dallas County	323,232			ESL			
	953	Decker Correctional	Dallas County	193,323			ESL			
	954	Health \& Human Services	Dallas County	319,883			ESL			
	955	Health \& Human Services (Logger 2)								
	956	Cook/Chill Warehouse	Dallas County	345,532			ESL			
	957	Lew Sterrett Complex	Dallas County	1,850,802			ESL			
	960	Matagorda County Courthouse								
	961	Midwestern State University	Dallas County	697,800			ESL			
	962	Butte Jail	Butte, MT				ESL			
	963	Butte Courthouse Complex								
	964	Butte Courthouse (Lighting)								
	965	Butte Courthouse Logger 4								
	970	Sam Houston Elementary	Bryan, TX	62,000	WD		Rebuild America			
	971	Bryan High School	Bryan, TX	229,033	WD	MCC	Rebuild America			
	972	Rayburn Middle School	Bryan, TX	198,443	WD	MCC	Rebuild America			
	973	Brazos Center	Bryan, TX	45,000	WD	LITRE	Rebuild America			
	974	Brazos County Courthouse Annex	Bryan, TX	20,288	WD		Rebuild America			
	975	Brazos County Courthouse	Bryan, TX	100,000	WD	MCC	Rebuild America			

	980	St Paul Place	Dallas, TX	100,000	WD		ESL			
	981	Harwood Center	Dallas, TX	750,000	WD		ESL			
	982	9700 Richmond	Dallas, TX	89,000	WD		ESL			
	983	3300 Gessner	Dallas, TX	65,500	WD		ESL			
	984	McKinney Place	Dallas, TX	100,000		MCC	ESL			
	985	Pittman Atrium	Dallas, TX	100,000	WD	MCC	ESL			
	986	Brooke Army Medical Center	Fort Sam Houston	1,200,000	WD		ESL	15 min		

Legend:

WBE **Measured Whole Building Electricity Consumption**
NWD for buildings without Chillers
WD for buildings with Chillers
L&R **Measured Lights and Receptacles**
WBE-MCC L&R derived from the difference between measured Whole Building Electricity and Motor Control Center (Pumps) Consumptions
LIGHT Measured Lighting consumption
LITEQ Measured Lighting and Equipment consumption
EQUIP Measured Equipment consumption

Table 6. All buildings monitored by ESL

8.5 Other Documented Methods in the U.S. and Europe

From the U.S. we identified six well documented methods used for generating typical load shapes, the End-use Disaggregation Algorithm (EDA) (Akbari et al. 1988), the Conditional Energy Demand (CED) (Parti et al. 1988), the Variance Allocation (Schon and Rodgers 1990), the Statistically Adjusted Engineering Approach (SAE) (CSI, CA, ADM 1985, ref. Eto et al. 1990), the Temporal Synoptic Index (TSI) (Hadley 1993), and the Singular Value Decomposition (SVD) (Verdi 1989). The first four methods were mainly used whenever *only* the total electricity consumption (Whole-Building Electric) is monitored, and engineering simulation were required to disaggregate the total into end-uses. The fifth method (TSI) is a weather daytyping technique which is not necessarily required in daytyping the lighting and equipment loads. The sixth method (SVD) was mainly used to reduce the number of data points required to describe a set of data from different buildings.

The only well documented and reproducible European method that we were able to identify is the Temperature Binning Method that was used at Lunds Institute of Technology in Sweden (Noren 1997, 1998a and b). However, the foundation of this daytyping method is the binning according to predetermined temperature ranges. Even though the temperature dependency (seasonal variation) of the lighting and equipment loads should be evaluated, this European method, by itself, is not sufficient to be applied in our project, as we need additional procedures in order to determine the typical load shapes of the lighting and equipment loads. This European work mixes normalization, and binning techniques and is somewhat similar to the weather-daytyping used by Bou-Saada and Haberl (1995).

The main characteristics of these 7 methods are described below.

8.5.1 End-use Disaggregation Algorithm (EDA)

The Energy-use Disaggregation Algorithm (EDA) developed by Akbari et al. (1988) is a *Deterministic* method that relies on exact reconciliation to an hourly control total, which is provided by the hourly whole-building load research data. It is mainly used when the end-uses in a building are not monitored.

The starting point for the reconciliation is an engineering simulation of the sort relied upon by the earliest load shape estimation methods. The method typically relies on much more detailed information to develop the simulation input (minimizing the extensive reliance on engineering judgement). The intent of the method is to supply reasonable end-use breakdowns when detailed information is scarce. This method is a hybrid method that uses monitored data, statistical disaggregation, and prorating based on a simulation. The EDA is an engineering method which primarily utilizes the statistical characteristics of the measured hourly whole-building load and its statistical dependence on temperature. In the EDA the sum of the end uses is constrained at hourly intervals to be equal to the measured whole-building load, providing a reality check not always possible with pure simulation. The primary component of the EDA is the regression of hourly load with outdoor dry bulb temperature. Two season-specific (summer and winter sets of temperature regression coefficients are used to cover the temperature dependency of the building load. Twenty-four regression models (one for each hour) are developed for each season. The temperature regression equations are used to separate the load predicted by the regression, L_{REG}, into a temperature-dependent part, L_{TD}, and a temperature-independent part, L_{TI}. The temperature-dependent load is attributed to space conditioning equipment. The temperature-independent load is the sum of loads such as lighting and miscellaneous equipment, as well as temperature-independent cooling at the base temperature T_{BASE}.

The temperature-independent load is then prorated according to the loads predicted by a simulation developed based on a building audit. If the actual load at a particular hour on a particular day does not perfectly lie on the best-fit regression line, then the difference Δ between the actual load L_{ACT} and L_{REG} is split between the two parts of the load.

As described in (Akbari et al. 1988), the EDA consists of 5 steps (repeated for each hour of the day) as follows:

Step 1. Calculate the nominal load (L_{REG}), estimated from the regression, separately for Summer and Winter, at T_{ACT} (actual measured outside temperature over the same period of time of measuring the whole-building load (L_{ACT}):

$$L_{REG} = a_i + b_i\, T_{ACT} \qquad (2)$$

where i = s for summer, and w for winter.

Step 2. The regressed load is divided into a temperature-independent (base) load (L_{TI}), and a temperature-dependent load (L_{TD}). Since T_{BASE} is most clearly defined in winter, and it is assumed not to vary by season L_{TI} is defined by the winter regression to be:

$$L_{TI} = a_w + b_w T_{BASE} \qquad (3)$$

and L_{TD} = is then found from:

$$L_{TD} = L_{REG} - L_{TI} \qquad (4)$$

Step 3. Prorate the base load (LTI) according to the fractions (f) provided by the simulation performed at TBASE. For example, temperature-independent conditioning is found from:

$$L_{CTI} = f_C\, L_{TI} \qquad (5)$$

Similarly,

$$L_{LIGHT} = f_{LIGHT}\, L_{TI} \qquad (6)$$

and so on, for the rest of the temperature-independent loads. The nominal load (L_{REG}) has now been broken down into end-uses.

Step 4. The end-uses will now be adjusted so that they sum to the actual measured load (L_{ACT}), rather than to L_{REG}. Of the difference Δ between L_{ACT} and L_{REG}, a fraction $\chi\Delta$ is attributed to conditioning and the remainder, $(1 - \chi)\Delta$, is proportionately distributed to the non-conditioning end-uses. χ is the fraction of the total statistical variation around the regressed load that is attributable to conditioning, and is found for the summer from:

$$\chi = \frac{\sigma_C}{\sigma_C + \sigma_{NC}} \qquad (7)$$

χ is assumed to be 0.25 for the winter, assuming that the cooling energy use then is entirely a function of internal loads, and that the cooling equipment has a COP of 3.

Step 5. The measured load (LACT) has now been completely disaggregated into end-uses. The conditioning end-use is composed of a temperature-dependent element, temperature-independent element, and a fraction of the residual:

$$LC = L_{TD} + L_{CTI} + \chi\Delta \qquad (8)$$

The EDA method was applied to buildings in the cooling mode (seven buildings in Southern California). It does not account for nonlinearities of load, latent load, heat storage, special load management options such as cool storage and daylighting, and temperature or seasonal dependencies in end-uses other than conditioning loads. However, the intent of the method is to supply reasonable end-use breakdowns when detailed information is scarce. This method is a hybrid method that uses monitored data, statistical disaggregation, and prorating based on a simulation. The method is fundamental and can be used when disaggregation of the whole-building electricity (WBE) consumption is required (buildings where only the WBE is monitored).

8.5.2 Conditional Energy Demand (CED)

The Conditional Energy Demand (CED) approach (also called the Conditional Demand Approach (CDA)) is essentially a correlation analysis of the energy use of many separate premises against the energy using equipment in each of these premises. The analysis seeks to determine the difference in observed load due to the presence of a given energy-using device, all other things being held equal. The difference is taken to be the energy contribution of the device. The technique was first applied to annual and monthly billing data. With the availability of whole-building load shape data, the technique was extended to an hourly time step.

Parti et al. (1988) used the Conditional Energy Demand (CED) technique which allows for the development of estimated residential appliance-specific energy usage and conservation effects without placing end-use meters on the appliances. End-use metered consumption information was used only for comparison to the CED estimates of end-use load shapes. The specific objectives of this load research project were: (1) to measure the contribution to system hourly load of the residential class, (2) to measure the components of this load resulting from the operation of room ACs and refrigerators on the peak day, (3) to determine the effect of substituting more energy efficient ACs and refrigerators, and (4) to attempt to develop a model for estimating end-use profiles based on total load and demographic data without the need for end-use metering.

The CED carries out the disaggregation of the total load into its end-use components by applying Multiple Linear Regression (MLR) analysis to a data set composed of total load data, survey and weather information. In the MLR estimating equation, the hourly residential load, E_h, is written as the sum of the hourly end-use demand functions for room AC, frost-free refrigerators, non-frost-free refrigerators, pool pumps, central AC, an "unspecified" category, at hour "h". In the MLR model, the hourly AC variable is obtained using regression models function of estimates of building thermal mass temperatures, building indoor air temperature, and energy consumed by end-uses other than AC. The refrigerators variables are also obtained using regression models function of the capacity of the refrigerators. The model breaks down the hours of the day into four general hourly categories: (1) Night (12AM-6AM), (2) Morning (7AM-9AM), (3) Midday (10AM-5PM), and (4) Evening (6PM-11PM). Load shapes were developed based on the MLR model and the time categories schemes.

The CED is a statistical method that involves many estimates and weights for appliances derived from engineering studies, estimated efficiencies for the HVAC system, and estimates for the internal loads generated by occupancy, lighting, equipment, and solar radiation. This technique, although not available in a detailed documentation, could also be useful in generating end-use loads when only whole-building loads are available.

8.5.3 Variance Allocation

To provide a cost-effective alternative to end-use metering for electric utilities, Schon and Rodgers (1990) have applied a hybrid engineering/statistical approach to end-use load shape estimation for the commercial sector. The authors developed a method which: (1) identifies systematic biases in an engineering model's hourly end-use load estimates, (2) adjusts the engineering model to significantly reduce these biases for individual building end-use estimates, (3) uses a variance-weighted approach to reconcile adjusted engineering estimates with whole-building metered data, and (4) offers to estimate end-use load shapes at an order of magnitude less cost than that end-use metering.

The authors stated that end-use metering alone provides only descriptive data and provides no predictive modeling component. Alternatively, the engineering models provide the predictive modeling component missing from the end-uses. Moreover, the statistical methods that rely on existing end-use and whole building hourly loads have the advantage of capturing the behavioral components of the building operation, in the whole-building load variations. Thus, the hybrid method combines the advantages of both engineering and statistical methods. The method was applied for work at Florida Power and Light (FPL). Hourly data which were collected in 457 statistically sampled commercial facilities. Biases in the engineering models of end-uses, developed using the ASHRAE CLTD method, were identified from regressing whole-building metered loads on individual end-use load estimates at each hour:

$$L_t = \alpha_t + \sum_j \beta_{jt} E_{jt} + err_t \tag{9}$$

where, L_t is the actual whole-building load at time t
E_{jt} is the estimated end-use load (from engineering models) at time t
j is the index for each end-use

If the engineering models were unbiased, the coefficients β_{jt} would be equal to 1 and α_t would be equal to 0.

Finally, to reconcile the sum of the hourly end-use load estimates with each individual facility's hourly research data, using the variances observed for each regression coefficient β_{jt}. The CV (standard deviation of β_{jt} /mean β_{jt}) of each end-use represents the uncertainty in the end-use estimate at hour *t*. This uncertainty in coefficient β_{jt} can be used in a variance-weighted reconciliation applied to each hour in the form of:

$$F_{it} = \left(CV_{jt} E_{jt}\right)^2 / \sum_j \left(CV_{jt} E_{jt}\right)^2 \tag{10}$$

The factor F_{jt}, for each end-use j and hour t is used to prorate the difference between simulated and metered totals based on statistical variation in the simulated end-use loads. The largest and most variant end-uses receive the largest portion of the difference between the engineering simulation and the metered whole-building load.

The variance allocation approach, thus, is an allocation rule, and involves prorating the difference between the simulated and control totals based on the observed statistical variation in the simulated end-use loads. The basic intuition for this approach is that loads which are highly variable are more likely to account for any differences between a point estimate (simulated) of their magnitudes than loads which are relatively stable. This approach was applied to a study of commercial buildings in the Florida Power and Light Company service territory. This approach could also be useful in generating end-uses load shapes.

8.5.4 Statistically Adjusted Engineering Approach (SAE)

The Statistically Adjusted Engineering approach (SAE) (CSI, CA, ADM 1985, ref. Eto et al. 1990) is very close to the *Deterministic* methods. It is yet another method where the whole-building electricity use needs to be disaggregated in order to obtain different end-uses. First an engineering simulation is developed to provide an initial estimate of end-use loads. Next, the initial estimates are regressed against control totals, which are averages of hourly energy uses for typical days. The estimated coefficients can then be thought of as adjustment factors that reconcile the initial estimates to the control total. In other words, correlational analysis is used to perform the allocation of differences statistically, whereas, in the deterministic methods the allocation is performed deterministically. This method is a *Statistical Method*, and typically relies on regression techniques that correlate explanatory variables with the hourly control total. These variables need not all be physical and the reconciliation to the control total is usually expressed in goodness of fit.

Schrock (1997) stated that SAE models which are a subclass of the CED models are used to quickly reconcile engineering estimates with a known total. In the SAE model a known total is regressed against end-use estimates, and a coefficient is obtained for each end-use. The regression is performed for each hour separately (1 to 24). Next, each end-use is multiplied by the reciprocal of the associated coefficient.

This approach could also be used to generate synthetic end-use loads.

8.5.5 Temporal Synoptic Index (TSI)

Hadley (1993) employed a Temporal Synoptic Index (TSI) approach for weather-dependent data which uses a combination of principal component analysis (PCA) and cluster analysis on the resultant principal components (PC's), to identify days which are considered meteorologically homogeneous. The new weather variables, Principal Components (PC's) reduced the number of original weather variables required for determining the daytypes. Daily values for these PC's are then calculated. Days with similar daily PC values are grouped into "clusters" that are meteorologically homogeneous.

Hadley used this technique to determine the response of the HVAC system of four buildings, monitored as part of ELCAP project, to different weather conditions. Once the number of daytypes has been specified, each day in the data set analyzed can be assigned to a specific, unique daytype and the average values of each meteorological variable calculated for each daytype. The weather data was obtained from the National Weather Service (NWS). Each weather-daytype was defined in terms of daily averages of the dry-bulb and wet-bulb temperature, extraterrestrial and total global horizontal radiation, clearness index, and wind speed. The unique character of each weather daytype was established by: (1) the mean value of each of the original weather variables within each daytype; (2) the frequency of occurrence of the daytype by month; and (3) the diurnal variation of each variable within each daytype. In Hadley's work, twenty different daytypes were specified arbitrarily which resulted in some daytypes that were not significantly different from others. Finally, average hourly heating and cooling profiles were generated for each of the weather daytypes for three different buildings.

The Principal Component Analysis and the Cluster Analysis can be performed using commercial statistical packages. This technique proved to be useful for daytyping of weather-dependent data. However, for weather-independent data, like lighting and equipment, this technique becomes unnecessary.

8.5.6 Singular Value Decomposition (SVD)

The Singular Value Decomposition (SVD) reduces the necessary amount of data (herein, required to explain the variety of commercial load shapes) to only a few vectors containing the matrix's eigenvalues, shapes and scaling. Press et al. (1992) stated that in many cases where Gaussian elimination and Lower triangular-Upper triangular (LU) decomposition fail to give satisfactory results, the SVD techniques will precisely diagnose the problem. In some cases, the SVD solves the problem and gives a useful numerical answer, although not necessarily the answer that one thinks he/she should get. The SVD also is a method for solving Linear Least Square problems where the problem is either overdetermined (number of data points greater than number of parameters) or underdetermined (ambiguous combinations of parameters exist).

Verdi (1989) used this technique to develop typical load shapes. Verdi applied the SVD to a single matrix representative of all buildings (11 buildings were considered), and also to matrices representing individual buildings. In both cases, i.e., all buildings, or individual buildings, the rank necessary to describe differences across buildings or within a single building was minimized. When SVD was applied to "all buildings" in one matrix, the distinction between different building classes prevailed. When the technique was applied to a single building the distinction between different days became clear.

In the way the SVD was applied in Verdi (1989), the matrix representing all buildings take the following form:

$$\begin{bmatrix} 1.........1 \\ . \\ . \\ . \\ . \\ . \\ 24.....24 \end{bmatrix} = \begin{bmatrix} 1........1 \\ . \\ . \\ . \\ . \\ . \\ 24.....24 \end{bmatrix} \times \begin{bmatrix} d_1...........0 \\ 0d_2 0.......0 \\ 00d_3 0.....0 \\ . \\ . \\ 0..... \\ 0.........0d_m \end{bmatrix} \times \begin{bmatrix} 1...................m \\ . \\ . \\ . \\ . \\ . \\ m..................m \end{bmatrix} \tag{11}$$

$$(24 \text{ x m}) \;=\; (24 \text{ x m}) \;.\; (\text{m x m}) \;.\; (\text{m x m})$$

$$[A] \;=\; [U] \;.\; [D] \;.\; [V]^T$$

where: A is the matrix of the Normalized Median Hourly values (1 to 24) for each building
U is the matrix of the Primary Load Shapes
D is the matrix of the Eigenvalues
V^T is the matrix of the Scale Factor for each building
m is the number of buildings.

To obtain the typical load shape for each building one can take the matrix formed by the following multiplication: $U_1.d_1.V_1^T$ (i.e., (24 x 1) . (1 x 1) . (1 x m)). Each column of this matrix will be the typical load shape of the corresponding building as arranged in the original A matrix.

It is worth mentioning that the convergence of the data (typical load shapes as close as possible to the original median load shapes) occurred in Verdi's study at the fifth column of the U matrix.

For matrices representing individual buildings, the index m will represents the day, thus the matrix A will be a (24 x 365) matrix, and each column represents then one day of hourly data.

This SVD technique was used by Verdi mainly to condense the number of data points of a data set, and to compare differences among building classes. Thus it is a data handling technique, rather than a robust method to define the daytypes and typical load shapes of a certain building category.

The methods described in Section 4.3.2 provide helpful insight into techniques that might be required in cases where the end-uses are not monitored (but still required), and the analysis is therefore based on the whole-building electricity consumption.

8.5.7 Temperature Binning Daytyping

Noren (1997) developed a temperature daytyping technique for developing typical load shapes for six different commercial building categories (Hotels, Warehouses/Grocery Stores, Schools with kitchens, Schools with no kitchens, Office buildings, and Health buildings). The work is also described in Noren and Pyrko (1998a and b).

In the Office building category, the authors presented and discussed typical load shapes developed based on data from 7 district-heated Office buildings in south Sweden. Load shapes were developed for different mean daily outdoor temperatures intervals and different daytypes. The daytypes were simply the "weekdays" and the "weekends and holidays". In "weekdays" daytype 5 temperature intervals were considered: <0C, 0-5C, 5-10C, 10-15C, 15-20C, >20C. For the "weekends and holidays" daytypes the 15-20C and >20C interval were combined as >15C. The load shapes were presented as non-dimensional normalized 1-hour loads.

The methodology consisted of calculating the normalized load by dividing the measured load at time *t* by the mean annual load. Then the data are split into different groups, depending on the daytype. The data in every group are sorted by hour, and every hour sorted into different temperature intervals. Different intervals for mean daily outdoor temperature were used to sort the data. A mean normalized value of the load was calculated for every hour and each temperature interval, by dividing the calculated normalized load by the total number of observations at time t for a category at specified temperature interval. Outliers in the data were detected visually and removed, basically removing obvious very high and very low values in the monitored data. This European work mixes normalization, and binning techniques and is somewhat similar to the weather-daytyping used by Bou-Saada and Haberl (1995).

Earlier, Bou-Saada and Haberl (1995) developed a weather daytyping approach that categorized the whole-building electricity consumption of an electrically heated-cooled building into three weather-daytypes (below 45°F, between 45 °F and 75°F, and above 75°F). An average heating profile was chosen to represent all hours when temperatures were below 45 °F, an average cooling profile was selected for temperatures above 75 °F, while non-HVAC profile was assigned for all hours between a temperature of 45 °F and 75 °F. For the non-HVAC profile, two representative days, weekday and weekend days, were chosen by visual inspection of the data. Disaggregation of the non-weather-dependent electric load was then performed by reviewing site plans, hand measurements during site visits and personal interviews. Weather-dependent daytyping will only be used in our analysis if only the whole-building electricity consumption is monitored, and shows to be strongly weather-dependent.

8.6 Correlation Between Occupancy and Lighting and Equipment Loads

After examining the occupancy profiles and the lighting and equipment load profiles, we performed a simple linear regression of the occupancy variable (OCCUP) as a function of the lighting and equipment variable (LTEQ). We obtained the following equations:

For the Weekdays daytype:

$$\mathrm{OCCUP} = 1.721\ \mathrm{LTEQ} - 0.8976 \qquad (12)$$
$$R^2 = 0.9267$$

For the Weekends and Vacations daytype:

$$\mathrm{OCCUP} = 2.0309\ \mathrm{LTEQ} - 0.9909 \qquad (13)$$
$$R^2 = 0.6958$$

For the Semester Breaks Weekdays daytype:

$$\mathrm{OCCUP} = 1.1942\ \mathrm{LTEQ} - 0.5826 \qquad (14)$$
$$R^2 = 0.9143$$

where: OCCUP: Hourly Occupancy Density (fraction of 1)
LTEQ: Hourly Lighting and Equipment value

Figures 37 to 42 show the derived surrogate occupancy profiles as compared with the profile generated with the walk-through survey. The results of the simple linear regression of the occupancy variable against the lighting and equipment loads shapes produced profiles reasonably similar to the occupancy profiles obtained by a walk-through survey, which shows the strong correlation between them.

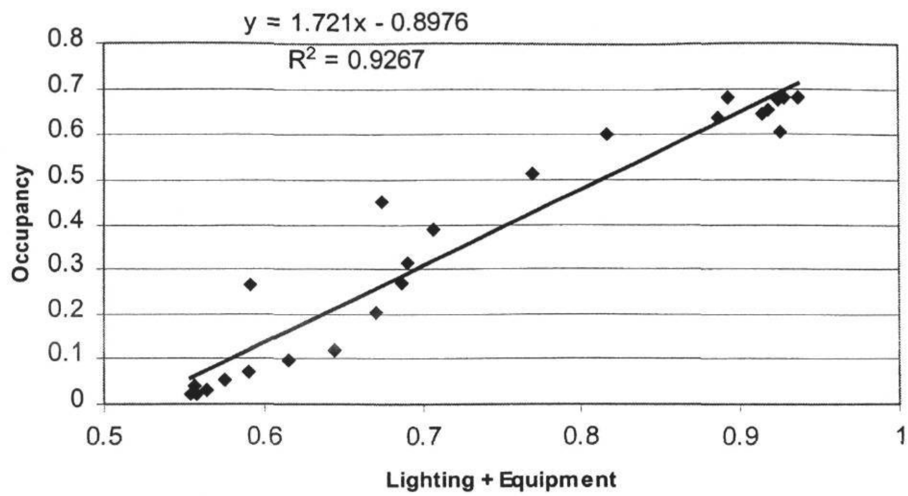


Figure 37. Linear Regression of Occupancy as a Function of Lighting and Equipment for the Weekdays Daytype.

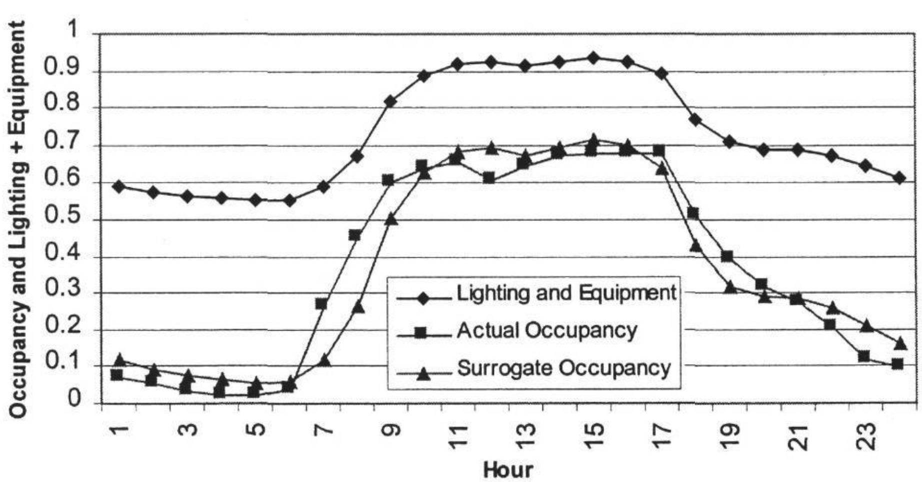


Figure 38. Derived Surrogate Occupancy Profile for the Weekdays Daytype.

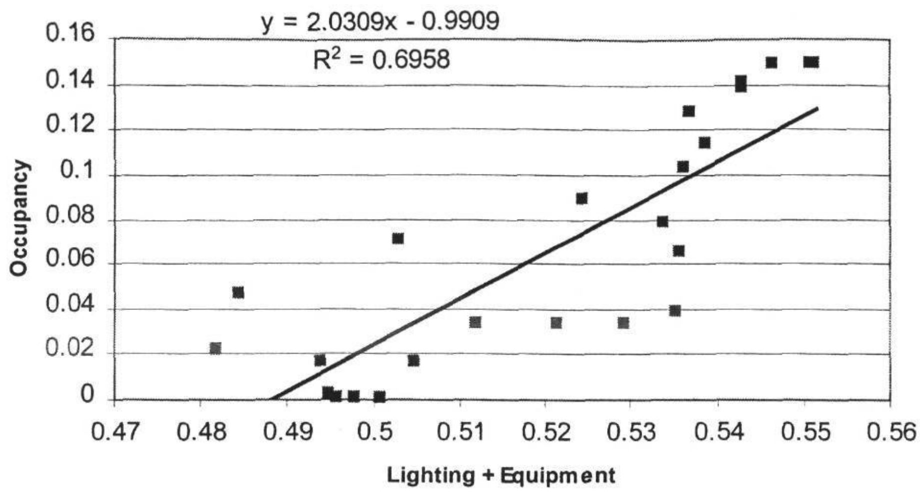


Figure 39. Linear Regression of Occupancy as a Function of Lighting and Equipment for the Weekends and Vacations Daytype.

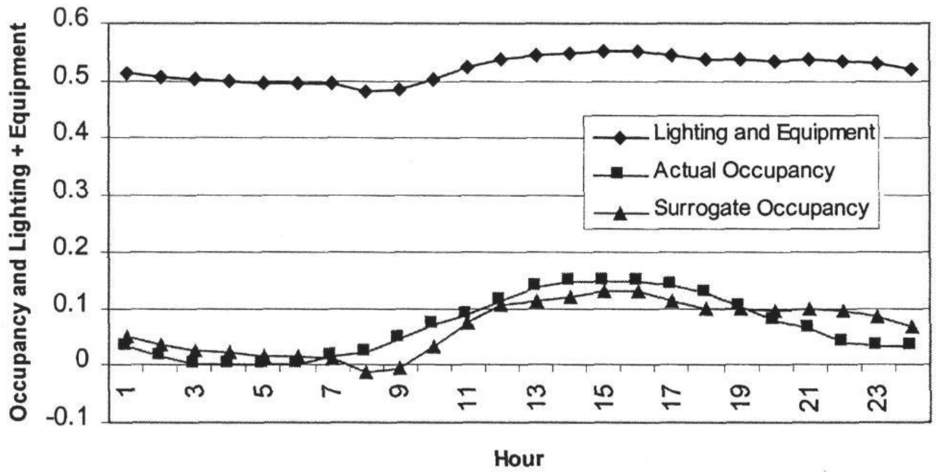


Figure 40. Derived Surrogate Occupancy Profile for the Weekends and Vacations Daytype.

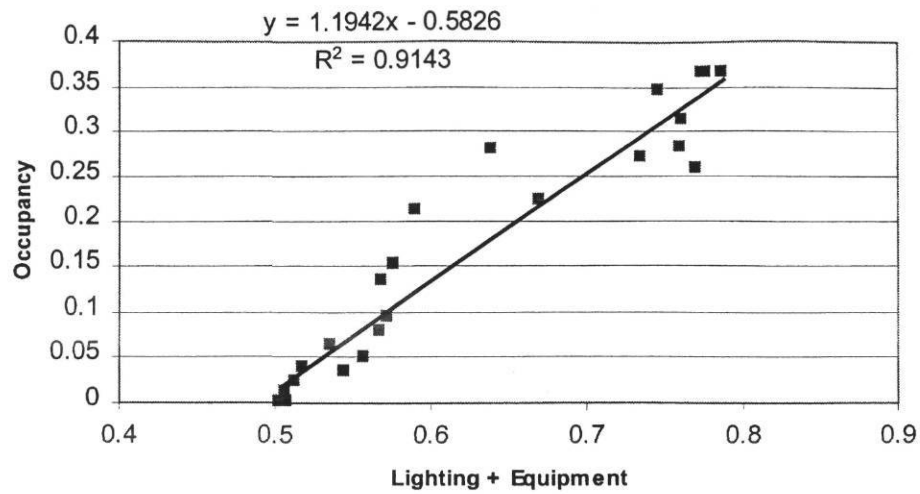


Figure 41. Linear Regression of Occupancy as a Function of Lighting and Equipment for the Semester Breaks Weekdays Daytype.

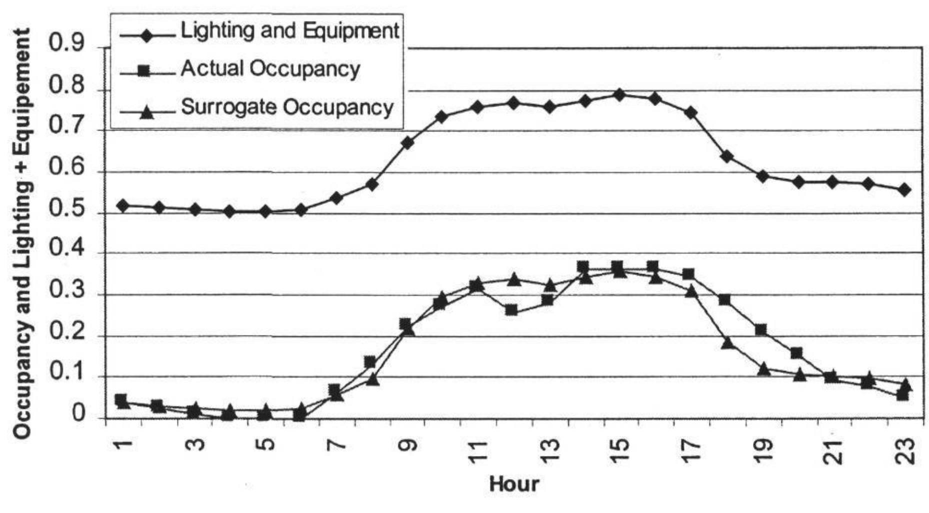


Figure 42. Derived Surrogate Occupancy Profile for the Semester Breaks Weekdays Daytype.