Fall 1982

A RESIDENTIAL ELECTRICAL LOAD MODEL

CHARLES FRANCIS WALKER

8320660

Walker, Charles Francis

A RESIDENTIAL ELECTRICAL LOAD MODEL

University of New Hampshire PH.D. 1982

University
Microfilms
International 300 N. Zeeb Road, Ann Arbor, MI 48106

PLEASE NOTE:

In all cases this material has been filmed in the best possible way from the available copy. Problems encountered with this document have been identified here with a check mark _√_.

1. Glossy photographs or pages _____
2. Colored illustrations, paper or print _____
3. Photographs with dark background _____
4. Illustrations are poor copy _____
5. Pages with black marks, not original copy _____
6. Print shows through as there is text on both sides of page _____
7. Indistinct, broken or small print on several pages _√_
8. Print exceeds margin requirements _____
9. Tightly bound copy with print lost in spine _____
10. Computer printout pages with indistinct print _____
11. Page(s) __________ lacking when material received, and not available from school or author.
12. Page(s) __________ seem to be missing in numbering only as text follows.
13. Two pages numbered __________. Text follows.
14. Curling and wrinkled pages _____
15. Other ______________________________

A RESIDENTIAL ELECTRICAL LOAD MODEL

BY

CHARLES F. WALKER
B.E.E., THE COOPER UNION, 1953
M.S.E.E., UNIVERSITY OF NEW HAMPSHIRE, 1970

DISSERTATION

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Doctor of Philosophy
in Engineering

September, 1982

This dissertation has been examined and approved.

Dissertation Advisor
John L. Pokoski, Professor, Electrical & Computer Engineering,
Signal Processing Area, Engineering Ph.D. Program

Ronald R. Clark, Professor/Chairman, Electrical & Computer
Engineering, Signal Processing Area, Engineering Ph.D. Program

Filson H. Glanz, Associate Professor, Electrical & Computer
Engineering, Signal Processing Area, Engineering Ph.D. Program

David E. Limbert, Associate Professor, Mechanical Engineering,
Signal Processing Area, Engineering Ph.D. Program

Robert W. Goodrich, Ph.D., Research and System Planning,
Northeast Utilities Service Company

AUGUST 2, 1982
Date

Dedicated

To my wife, Helen

ACKNOWLEDGEMENT

I want to first thank Dr. John Pokoski, the Chairman of my Committee, for his patience, guidance, encouragement and assistance in completing this work.

I also want to thank the other members of my Committee, Dr. Ronald Clark, Dr. Filson Glanz, Dr. David Limbert and Dr. Robert Goodrich for their assistance and suggestions.

I want to especially thank Dr. Goodrich for providing information on the availability of reference material, especially the test results associated with the Connecticut Light and Power Company Residential Load Test, which were used extensively in developing the work. I want to thank the Associates Program for providing the funding to obtain the data of the Residential Load Test.

I want to thank Dr. Sivaprasad for his assistance with procedural matters.

I also want to thank Nan Collins and Barbara Layne for typing the manuscript.

TABLE OF CONTENTS

LIST OF FIGURES

Figure	Title	Page
4.15	Customer Load Curve for the Large Load Group-Test Data for Friday	104
4.16	Cross Correlation Function-Large Load Group-Model to Test Data	106
4.17	Cross Correlation Function-Large Load Group-Test Data to Test Data-Different Days	107
4.18	Forecast Load Curve for Large Load Group with Additional Water-Heaters	109

LIST OF TABLES

ABSTRACT

A RESIDENTIAL ELECTRICAL LOAD MODEL

by

CHARLES F. WALKER

UNIVERSITY OF NEW HAMPSHIRE, SEPTEMBER 1982

This work develops a time varying residential electric load model based on the philosophy that the availability of people to turn on electrical appliances and their tendency to do so at particular times are significant factors in determing the time varying nature of the residential load. Additional contributions to the load are the result of peoples availability and tendency to perform direct actions (e.g. dish washing) that indirectly cause electrical appliances (e.g. water heaters) to turn on and off under the control of their sensors. The availability and tendencies of the residents also affect, to some extent, the contribution to the load caused by weather conditions since the residents determine the settings of heating and cooling devices.

A general availability function is developed to estimate the number of persons available in the residence at a particular time. Proclivity (tendency) functions are developed to specify the probability that an appliance will be used at a particular time by an available person or that the person will perform an action which will result in the operation of some appliance.

Models for individual appliances, selected on the basis of their load significance, are developed using the foregoing functions together with operating characteristics of the appliances and estimates of power consumption for prevalent sizes. The individual appliance models are combined into a residential model with provisions for specifying characteristics of the residence. The model is used to simulate individual residences and groups of residences. Heating and cooling loads are not included in the simulation. The load curves generated by the simulation are compared to test data obtained during the Connecticut Light and Power Company Residential Load Test [1] for equivalent residences and groups of residences. The results indicate that the model has potential for estimating the time varying residential electric load.

CHAPTER I

INTRODUCTION

1.1 Statement of Problem

This work describes the development of a residential electrical load model. A comprehensive load model allows an electric utility to adequately predict the magnitude and time variation of its load and therefore enables it to operate its generation capacity more efficiently. A load model, if it contains provisions for adjusting those parameters which can be expected to change with time, is an indispensable tool for accurate short and long term utility capacity planning. The reason for concentrating on a residential load model is that this section of the load is the most difficult to predict, since it involves many items of equipment and many individual decisions. The commercial and industrial sections of the load on the other hand, can be more easily predicted because of the lesser number of variables that affect them.

The residential model involved developing a number of elemental appliance models which describe the operation of individual types of residential electrical equipment. The development of the individual models is described in Chapter 2. These models required the development of availability functions for household inhabitants and functions defining their proclivity (tendency) to use various equipment at particular times. These elemental models were then incorporated into a combined model. The development of the combined model is described in Chapter 3. This required investigating the interrelationships between daily aspects of living and then combining the elemental models in a correlated pattern to fit these aspects.

The combined model has been programmed for operation on a digital computer. Load curves obtained by exercising the model have been compared to load curves for similar residences obtained in a load test [1] conducted on the Connecticut Light and Power Company residential load and the results are presented in Chapter 4. Recommendations for further work are included in Chapter 5.

1.2 History and Background

Some of the approaches that had been used in "near-term" load modeling were based on an analysis of previous system load data with a prediction of overall change based on periodicity and weather effects [2,3,4]. In general, no specific relationship between physical equipment and load was made for "demand" models although equipment characterization is utilized in "response" models [5].

More recently Woodward [6], proposed a model based in part on physical elements [for example, domestic water heaters] and in part on functional elements (for example, lighting load as determined by wattage per square foot and the area involved). His "switching" functions are based on element response to a combination of environmental functions and life-style functions, which are different for each category. He combines all of the elements of one type as one potential load. This is fractionally switched, partially by a life style function which uses a multiple harmonic expansion to describe the function. The initial parameters needed for the function would be obtained from a year's worth of empirical data.

The development of other physically based models was reported in [7] through [11]. These include various forms of aggregate component models with a "usage" function for each. The usage function includes or implies customer input, assumed to be specified elsewhere or obtained from empirical data or generated by various probability functions [7,8,9]. Boeing Computer Services indicates they consider summing individual component models to obtain a residence load and summing residence loads to obtain a feeder load to be too complex a process. They propose a customer-level model based on cyclic and environmental time functions from which component level information could be extracted [10]. A circuit based model, in which the coefficients of the describing differential equations are parameters represented by stochastic processes, has also been proposed [11].

References [12] and [13] describe end use models in which the basic load curves for residential appliances are developed by analysis of recordings of actual use of the appliances.

The model proposed herein treats each piece of equipment as an individual load. It treats the individual switching actions as stochastic in nature and develops the switching functions based on the availability and proclivities of persons together with automatic switching functions which are, in part, triggered by their actions.

A residential load is the sum of the individual appliance load and an area load is the sum of the loads of individual residences. The basic approach used will be summarized in the remainder of Chapter 1. Following chapters will discuss these issues in greater detail.

1.3 Element Definition

An element, in the context of this work, is a device, or an assemblage of devices, that represents the smallest load that will be switched ON or OFF an electrical system at one time. An example of an element is a household refrigerator. An example of an assemblage, acting as one element, is a singly switched section of the lighting load for a retail store. The amount of electricity used by these elements, when they are operating, is generally known. The switching ON and OFF of these elements determines the variation in the utility load curve.

1.4 The Switching Functions

The basic elemental model includes a function which describes the connecting and disconnecting of the device to the system. This function is usually developed from a number of basic functions which are interrelated. In this work the basic functions are called "availability" functions, "proclivity" functions and "normal-cycle" functions. The availability function indicates the probability that someone is available to operate a switch to connect a device to the system. The proclivity function indicates the probability that the person will operate the switch at a particular time. The "normal-cycle" function determines when the device is switched ON or OFF as a result of information observed by its sensors. Availability and proclivity functions also are associated with the probability that someone will perform an act, at a particular time, which will lead eventually to a device being automatically connected to the system. A refrigerator is an example of the inter-relationship between the three basic functions. The refrigerator switches on and off automatically when the inside temperature rises as a result of heat which infiltrates due to the outside ambient temperature and also a result of heat which enters when someone is "available" and has a "proclivity" to open the door.

1.4.1 The Availability Functions

The availability of people to turn on residential electrical equipment depends on a number of factors. An adult person will not be "available" while that person is asleep, or while traveling to and from work, or while at work. The person's availability at home will also be affected by the probability of shopping or of outside recreation. Working, shopping and recreation hours are generally affected by the time of day and the day of the week. The availability function must consider all of these factors. Similar factors affect the availability of children and adults who normally remain home.

For an individual person an availability function on a weekly, 1/4 hour by 1/4 hour basis, would consist of a 672 element vector [7x96] indicating when that person is at home and awake. The vector would contain a "1" for each 1/4 hour the person is at home and awake and a "0" for all other 1/4 hours. In determining which element is a "1" and which a "0" the person's normal work shift, normal travel hours and normal sleeping hours for that work shift must be modified by probabilities of departure from normal routine and for the hours away from home due to shopping and recreational activities.

For a "general" person, a general availability function can be developed. This takes into consideration the percentage of persons in an area on the various work shifts, including children at shcool, their generalized travel, shopping and recreational times as well as generalized sleeping times. The probability of departure from the norm must also be applied in this case. This would result in a "quantized" function having values in the range "0.0" to "1.0" which when multiplied by the number of persons in a household will give a generalized availability of persons for that type of household.

1.4.2 The Proclivity Functions

Given the fact that a person is available, there is a tendency to do certain things at certain times. This does not preclude doing these things at other times but there is a greater probability of doing them at one time than another. Such tendencies determine, for example, when people eat, when they watch television, when they wash clothes and when they perform other tasks that result in the use of electrical energy. Some of these tendencies are controlled by standard factors such as the work shift but others are controlled, to a large extent, by convention or habit. In order to develop a "tendency function" or, as it will be called in this work, a "proclivity function", it is necessary to obtain information, on a sampling basis, of when people normally do certain things. As an example, surveys are periodically conducted of the size of television audiences as a function of the time of day, so that advertisers will know the potential audience available to watch their commercials. The proclivity functions developed in this work are based on a survey performed as part of the Connecticut Light and Power Company Residential Load Study [1] previously mentioned, or on estimates as to when various actions are performed, if survey data was not available.

1.4.3 The Normal-Cycle Function

Various types of residential electrical equipment are automatically turned ON and OFF by environmental or other sensors. Some sensors, such as those on air-conditioners and humidifiers, respond to ambient conditions of temperature and humidity in the residence. Others respond to deviation from a preset temperature in a particular unit such as a refrigerator or a water heater. Functions of this type will be referred to as "normal-cycle" functions in this work. In modeling this type of equipment, functions must also be developed which are based on the reasons for the change in temperature. For a water heater, as an example, a function that describes how hot water is used is required to determine when and for how long the heater is connected to the power system.

1.5 The Combined Model

The switching functions outlined in Section 1.4 are utilized in the development of the elemental (appliance) models to specify the probability of the appliance being ON or OFF.

The individual elemental models are then incorporated into a combined model which determines the load for a residence.

CHAPTER II

ELEMENTAL MODEL DETERMINATION

2.1 Residential Elemental Models

In general, the demand model of a residential element can be characterized as a combination of a number of factors. These include:

1) The wattage taken by the element when operating
2) The basic duty cycle of the element (if one exists)
3) The effect of weather on the basic cycle
4) The effect of people's actions on the basic duty cycle including:
   a) the effect of people's living habits on the time of performing the actions, (proclivities).
   b) the availability of people to perform the actions.

Not all factors affect all elements and the weightings are generally different for the different elements.

In this chapter, some models include more detail than others. This was done to illustrate the level of complexity to which the analysis could be carried. To minimize computer time in a "production" model, each sub-model should have a complexity appropriate to the desired accuracy of the overall model simulation.

2.1.1 Selection Criteria

The diversity in the stock of electrical goods owned by various households requires basic elemental models in the domestic area to be defined for that equipment, which by size and/or saturation, make a significant contribution to the load. Such elements would include space heating, water heating, refrigeration and similar loads. Groups of other elements such as entertainment or grooming could be treated as combined elemental models. The above approach is perferable to defining an "average" house as a primary element since it allows for changes in saturation of particular elements due to regional and economic differences when determining combined loads. It also permits easier modification of the model if the efficiencies of the primary elements are changed as for example the improved energy efficiency of solid state television or of better insulated refrigerators.

2.1.2 Diversity Within Element Types

Because there is a wide range of sizes encountered in many residential appliances provision was made in the individual models to vary appropriate parameters to suit the differences. In the computer coding for the model the parameters are defined as variables, whose values can be specified in data statements.

2.2 Switching Functions

After defining a basic element the switching functions that describe its use must be established. As an example the on-times and off-times of a refrigerator are determined by a number of factors including the effectiveness of the thermal insulation, the effect of ambient temperature, the opening of the door, the humidity and the reloading of the refrigerator.

If the function is represented by a set of interrelated subfunctions based on contributing factors, the expected value of the total can be estimated as a function of time. Typical subfunctions to be considered are:

a) Heat-entry function: the on-off cycle due to leakage and heat conduction at standard ambient conditions.

b) Temperature function: the effect of temperature and humidity on the off-time.

c) Door opening function: the additional on-time caused by opening the door.

d) Reloading function: the additional on-time caused by restocking the refrigerator.

2.2.1 Switching Function Selection

An analysis of the factors which cause the device to be turned on and off must be made, to determine the switching functions which affect a particular element. For example, the lighting load is affected principally by the number of people available to require lighting and to turn the lights on. However the number of lights turned on is also generally affected by the time-of-day, by habit and by the number of rooms in the house. Thus the model for the lighting element should contain an 'availability' function, a function based on time-of-day and a function which relates lighting load to house size.

2.2.2 Variation in Switching Functions

A function which describes the "potential" for people to be at home on a weekday will be different from that which describes the "potential" on a weekend day or holiday. In addition, the actual "availability" will generally be different for each weekday and each weekend day since the probability of people engaging in away-from-home activities is normally different for each day. Seasonal and weather factors also affect the actual availability.

Similarly, seasonal and to some extent weather factors have an effect on when people tend to do various tasks. As with the "availability" function the probability that something will be done is more likely on one particular weekday or weekend day than on another. Consequently, the weekday and weekend day "tendency" functions should be given an appropriate probability weighting to specify the actual "proclivity" function for a particular day.

2.3 Development of the Major Functions

The first basic switching function is the "availability" function since, at least to some degree, this function affects the switching of all the elements. Second in importance are the "proclivity" functions since they normally affect a number of elements. More peculiar to individual loads are the "normal-cycle" functions since they are concerned basically with one item of equipment. These basic functions are developed in the following sections.

2.3.1 The Availability Function

The maximum availability of a person at home is constrained by the times the person gets up, leaves for work, is able to return from work and goes to bed. Some allowance must be made to account for the deviation from typical times on a day to day basis. It is postulated that this deviation takes the form of a normal distribution about the typical times with a standard deviation, "sigma", which is larger for the less critical times. Times for getting up and leaving for work are generally more critical than the times of returning from work and for going to bed.

When the function is to be used to describe a generalized person, the variation must be increased to account for the different travel times to and from work for people living in the geographical area being modeled. In addition, if one function is to be used to describe the area availability, different optimal times must be used to suit the various work shifts, suitably weighted in proportion to area population on each shift. The block diagram of Figure 2.3.1.1, illustrates the development of the availability functions used in the residential load model.

In the development of the general availability functions, and the other functions described in later sections, del T is one quarter hour and all times "T" are expressed as a number of quarter hours. This was done to suit the form of the data used from the load test [1]. The functions shown in Figure 2.3.1.1 are defined as follows:

1) Ptw(n) and Pfw(n) are density functions which describe the distribution of travel times to and from work for a given shift and so affect the leave time density function Plt(T) and arrive home density function Pah(T). Evans [8] indicates that the residential density of workers decays exponentially with distance from the worksite. Heggie [9], presents data for a "Journey-to-Work-Behaviour" study which indicates that, after a minimum time offset, the travel time distribution is similarly exponential.

The travel time functions (Ptw(n), Pfw(n)) used in this

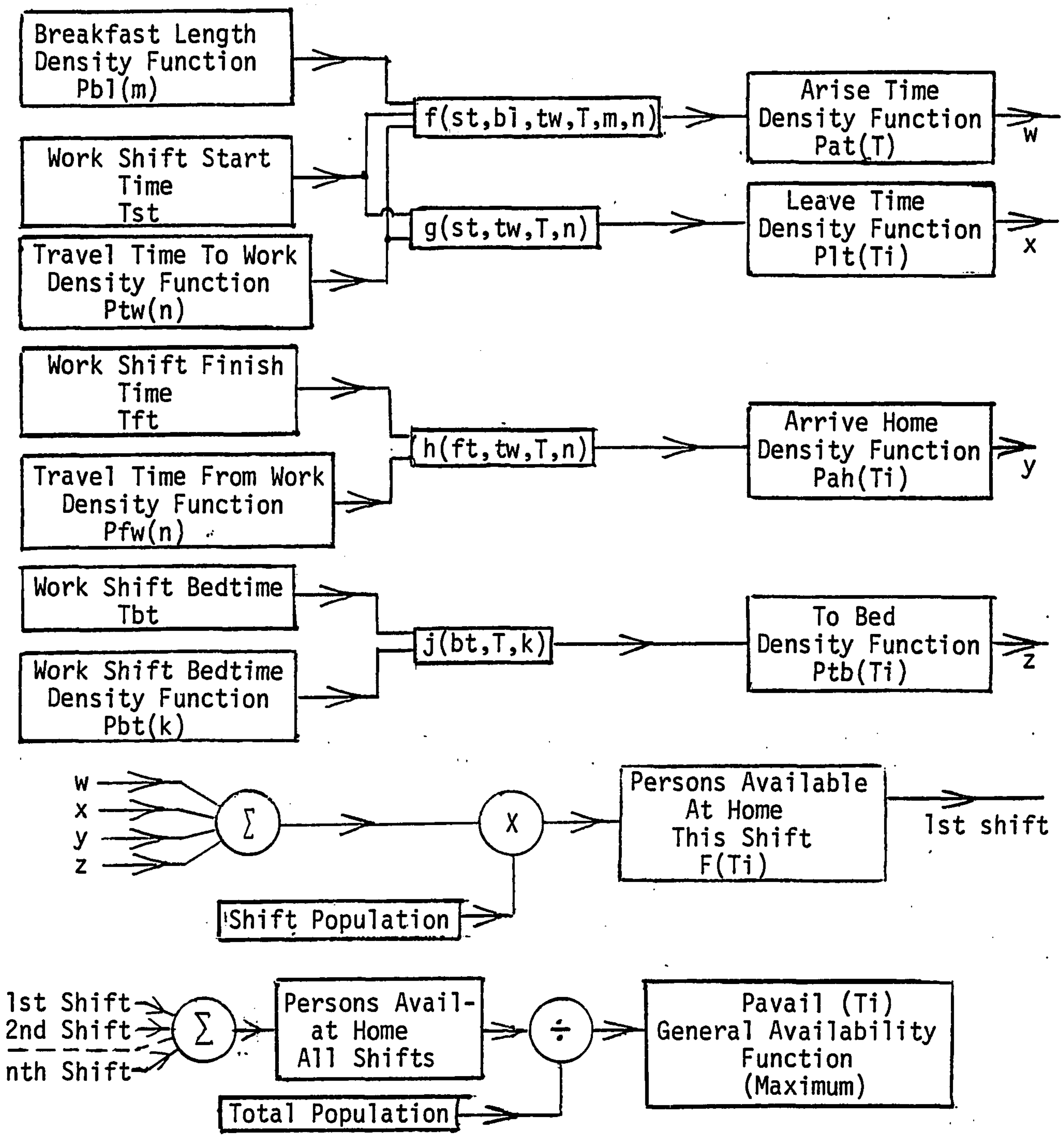


Figure 2.3.1.1 Block Diagram - Maximum

Availability Function

development are exponential after an offset of del T (1/4 hour) as a reasonable minimum time to travel to work even for the closest workers. The exponential decay requires that 99.3% of the workers have travel times within 5 time constants plus the offset. The value of the time constant is an input parameter. For example, if del T is used as the time constant, essentially all the workers will have a travel time of 1-1/2 hours or less with the majority having travel times of 1/4 to 1/2 hour. This seems to be a reasonable expectation for the normal day shift. Because of greater uncertainty in the afternoon and night shifts with respect to eating, sleeping and recreation habits a longer time constant is more appropriate to these shifts.

The function Ptw(n) gives the fraction of people who have travel times to work n period long and thus must leave between n and n+1 periods before the start time. Since the residential model is a discrete time model, the function is a discrete function with the requirement that the total distribution, for a normalized function, sum to one over the whole time span. Taking into consideration the one period offset, then

$$\mathrm{Ptw}(n) = \mathrm{Ptw}(\mathrm{Tst}-\mathrm{Ti}) = \frac{1}{\mathrm{Tau}} \int_{x=n-1}^{x=n} e^{-x/\mathrm{Tau}} dx$$

$$= - [e^{-h/\mathrm{Tau}} - e^{-\frac{(h-1)}{\mathrm{Tau}}}]$$

and

$$\sum_{n=1}^{nmax} \mathrm{Ptw}(n) \cong 1.0$$

where: Ptw(n) = the fraction of people that have travel times n periods long.

Tst = the shift start time

Ti = the present time period

n = the number of time periods before the shift start time

Tau = the time constant for travel time distributions

nmax = (1+5Tau): the maximum number of time periods during which people will be traveling before the shift start time. The 1 provides for the minimum time offset and the 5 yields the five time constants.

As an example (as used for the day shift in the model):

For: Tau = del T (i.e. one time period)

and: Tst = 32 (equivalent to 8:00 AM)

When: Ti = 28 (equivalent to 7:00 AM)

Then: n = 4

and: Plt(28) = q(st,tw,n,T)

= Ptw(32-28)

= Ptw(4)

= -[exp(-4/1)-exp(-3/1]

= 0.03

Where Plt(Ti) is defined as the fraction of people leaving for work during period Ti. Thus, 3% of the people who start work at 8:00 AM are assumed to leave home between 6:45 AM and 7:00 AM.

The travel time from work function, Pfw(n) defined as the fraction of people having travel times from work n periods long, is similar to the travel time to work function, Ptw(n). A minimum of one time period beyond the shift finish time is specified and the time constant, Tau, for the exponential distribution of the travel times can be specified to suit the shift or other considerations. This determines Pah(Ti), defined as the fraction of people arriving home at time Ti.

2) The breakfast length function, Pbl(m), which also includes time for any other at home activites before leaving for work, is defined as the fraction of persons who get up m periods before they leave for work. When added to the travel time it establishes the wake up time (arise time). It is assumed to have a normal distribution about a mean length of time which the average person requires between the time they get up and the time they leave for work. The standard deviation about the mean is specified as a number of time periods. Once again, because of the discrete nature of the model the densities Pbl(m) are discrete and are in fact the cumulative distribution over each del T. Because 99.75 of the cumulative distribution occurs between plus or minus three standard deviations σ [16] the range of Pbl(m) is six standard deviations before each leaving time as established by Ptw(n).

3) The arise time function is defined as the fraction of people who get up at time Ti. Thus, Pat(Ti) is the summation of the joint probabilities Ptw(n) x Pbl(m) for all values of m and n such that:

$$Ti = Tst - n \text{ del } T - m \text{ del } T$$

Where: Ti = the present time period

Tst = the shift start time

del T = one time period (1/4 hour)

$1 \leq n \leq nmax$

$0 \leq m \leq mmax$

nmax = 1 + 5 Tau

mmax = 2 x 3 sigma

For example:

If: Tau = del T = 1

and: sigma = del T = 1

Then: nmax = 1 + 5 = 6

and: mmax = 2 x 3 = 6

If: Tst = 32 (8 AM)

When: Ti = 24 (6 AM)

Then: 24 = 32 -n del T - m del T

= 32 - 6 - 2

= 32 - 5 - 3

= 32 - 4 - 4

= 32 - 3 - 5

= 32 - 2 - 6

and: Pat(Ti) = f(st,bl,tw,T,m,n)

Pat(24) = Ptw(5) x Pbl(2) + ... + Ptw(2) x Pbl(6)

4) The "to bed" density function Ptb(Ti), defined as the fraction of people who go to bed at time Ti, depends on the bedtime probability function, Pbt(k), taken as a normal distribution about a mean bedtime, Tbt, associated with each "shift". Thus:

Ptb(Ti) = Pbt(k) = Pbt(Tbt - Ti);

$-3\ \sigma \geq k \geq 3\ \sigma$

Different mean bedtimes and different standard deviations can be specified to suit considerations peculiar to each shift.

5) F(Ti) defines the number of persons, for one shift, who can be available at home at a particular time. It is a cumulative function and thus:

$$F(Ti) = F(Ti-1) + (Pat(Ti) - Plt(Ti) + Pah(Ti) - Ptb(Ti)) \times \text{Shift Population}$$

6) TF(Ti) defines the number of persons, for all shifts, who can be available at home at a particular time. It is therefore the sum of the F(Ti) for each shift.

7) Dividing TF(Ti) by the total area population gives the maximum availability function Pavail(Ti) which is the "general" fraction of people who can be available at home at a particular time.

The Fortran program for the availability function is included as Appendix B. It has the flexibility of allowing various values, in increments of del T, to be assigned to the standard deviation (sigma) and the time constant (Tau) which might be more suitable to different shifts. For example, in the model a time constant of one time period (1/4 hour) was used for the travel time to work for the first shift and a time constant of two time periods (1/2 hour) was used for the 2nd shift. Similarly the standard deviation, σ, for the "breakfast length" function for the two shifts were also taken as one and two periods respectively. The work shifts for weekend days and holidays are, in general, different than those for weekdays and therefore a different set of statistics are entered in obtaining the function for weekend days. For the case of those work shifts that do not work on Saturday or Sunday, dummy start and stop times can be entered and both the leave for work function

Plt(Ti) and the return from work function Pah(Ti), are set equal to "0" for all T. An example of the maximum availability function for a weekday is shown in Figure 2.3.1.2. (The function is shown continuous in the figure but is implemented as a discrete function in the model).

To account for the greater likelihood of people being away from home at certain times and on certain days for activities other than the work shift, the maximum availability function, Pavail (Ti), is modified by a probability function Paway(Ti), which is defined as the probability of being away from home for reasons other than work or school, based on the time of day and whether the day is a weekday, or weekend day or a holiday. It takes into consideration the times when activities are generally available and when people are more likely to do things outside the home. In the model only two away probability functions are used, one for weekdays and one for weekend days. A more comprehensive approach would result in a different away probability function for each day of the week and for holidays, with additional input form the time of year.

Therefore the maximum availability function is adjusted by applying the probability for the particular day and time. In addition, since the actual number of people available at home during a particular time period, Ti, depends on whether the probability that they are at home is realized, a test is performed to determine how many of the residents are actually away during each interval. Since the process of being away is random with time dependent probability, the model used in computing the number of people at home begins by comparing a randomly drawn percentage to the "away probability", Paway(Ti), at time Ti. If the former is not within the range of the latter, the decision is made that those who

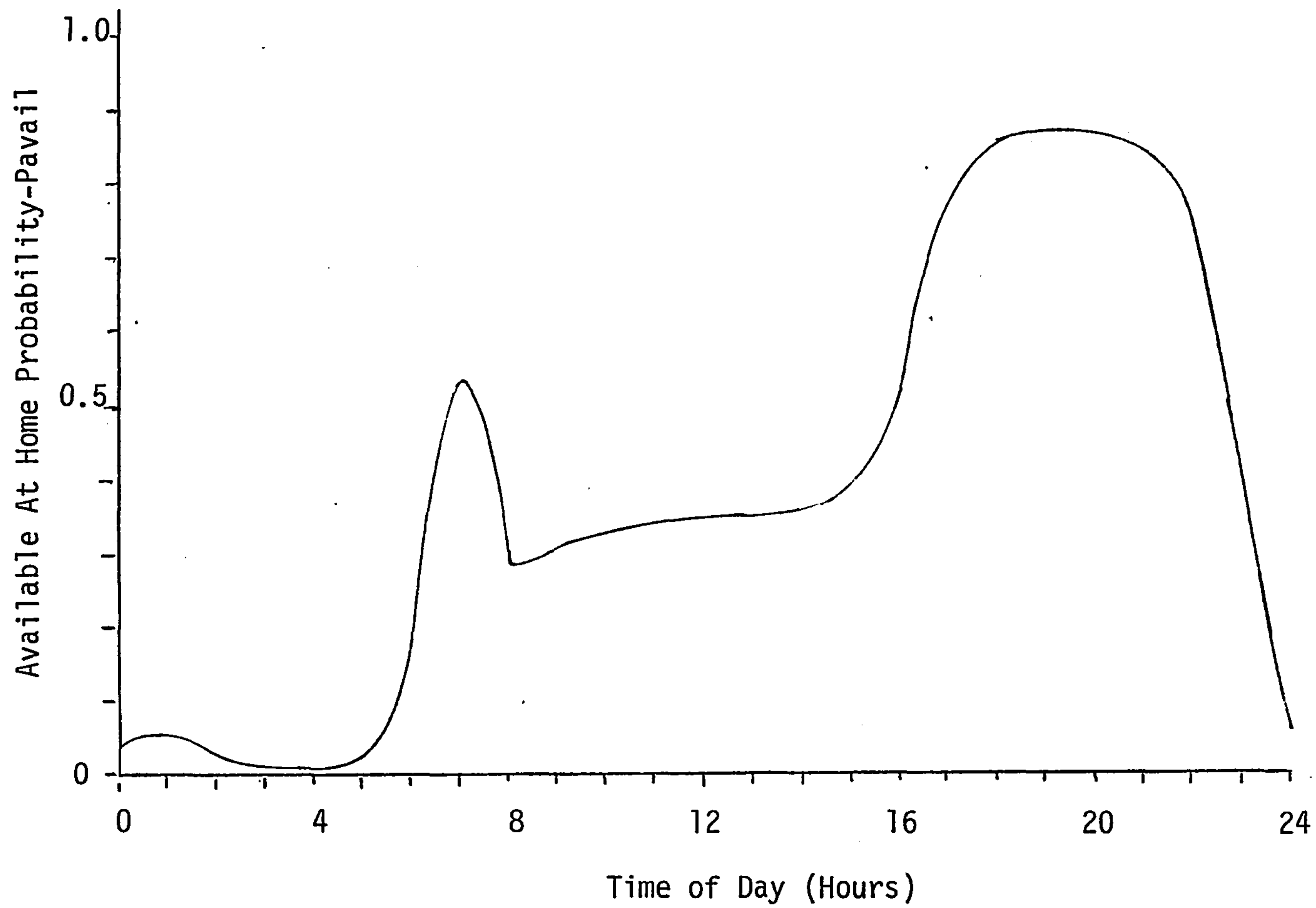


Figure 2.3.1.2. Typical Weekday General Availability Function

could be home, are home during this period. If the former is within the range of the latter the decision is that some of the residents are away. A second test is then made to determine how many are away. The likelihood of a larger number of potentially available persons being away is less than that of a smaller number being away. This factor, W(I), is a weighting factor, used in the test to decide how many persons are away. This test also uses a randomly selected percentage as the comparator.

When using the generalized availability function, Pavail(Ti), the computed number of persons will generally not be an integer. A final test is therefore made, using the rounding convention, to convert to an integer number of persons.

The block diagram which describes the function is given in Figure 2.3.1.3 and the definition of the variables follows it.

2.3.2 Proclivity Functions

Some of the proclivity functions developed for use in the residential model are based on the results of the Connecticut Light and Power Company Residential Load Test [1], which included a demographic survey. The data which was useful in developing proclivity functions for particular appliances were answers to the following questions which were asked in the demographic survey:

1) How many times a week do you use a particular appliance in the summer?
2) In which time frames is the appliance normally used on a weekday and on a weekend day?
3) How many hours is it used on an average day?
4) What are the answers to items 1 through 3 for the winter?

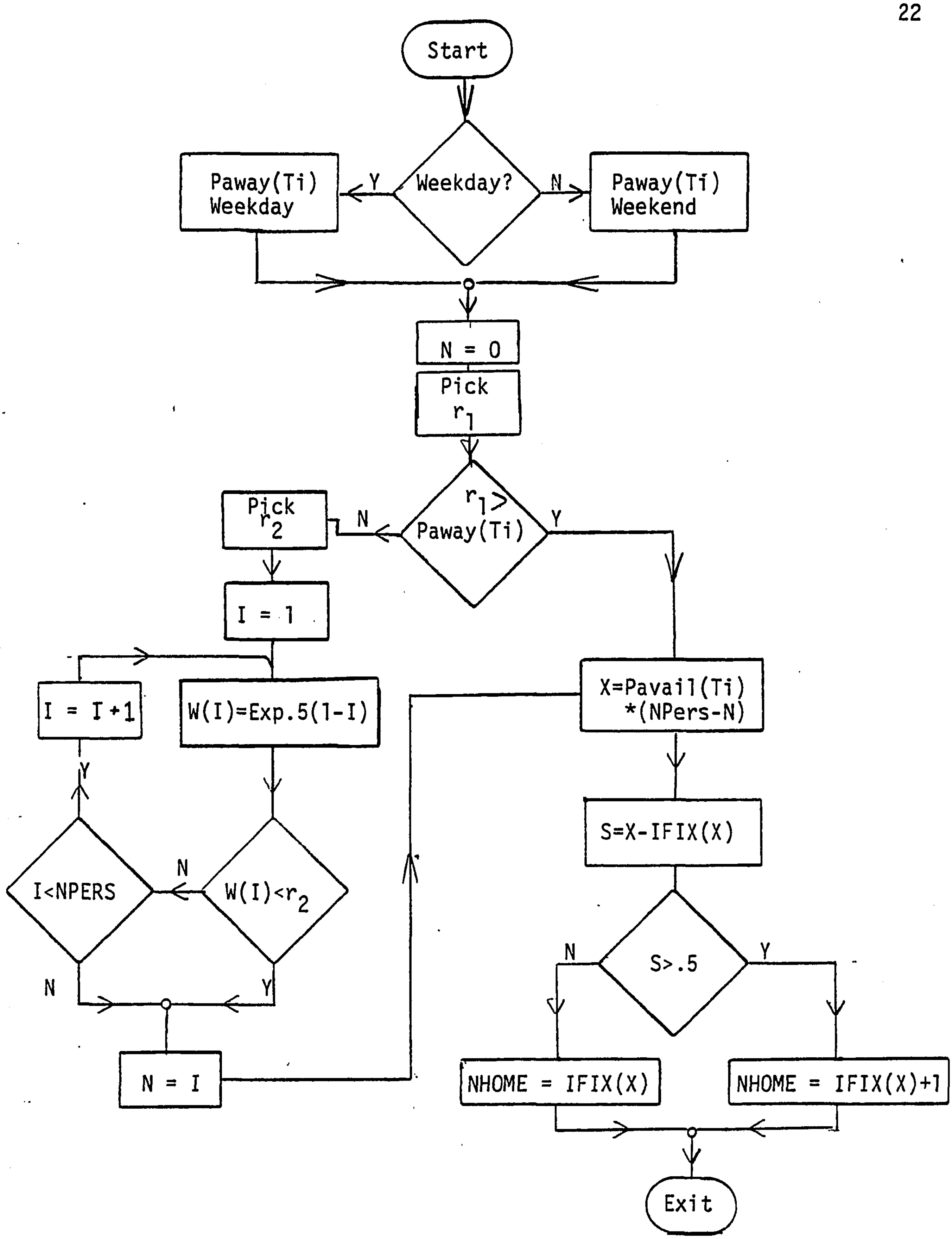


Figure 2.3.1.3 Function NAVAIL

(Legend on next page)

Pavail (T_i)	=	Fraction of people who could be available at home.
Paway (T_i)	=	The probability of being away for reasons other than work or school.
r_1	=	Random decimal
r_2	=	Random decimal
NPERS	=	Number of persons living in the residence
W(I)	=	"Weighting" function for number of residents away at one time.
N	=	Number of residents away.
$X(T_i)$	=	"Real" value of number of people available at home consists of an integer part (INT) and a decimal part (DEC).
NHOME	=	Rounded off value of X.

Legend for Figure 2.3.1.3

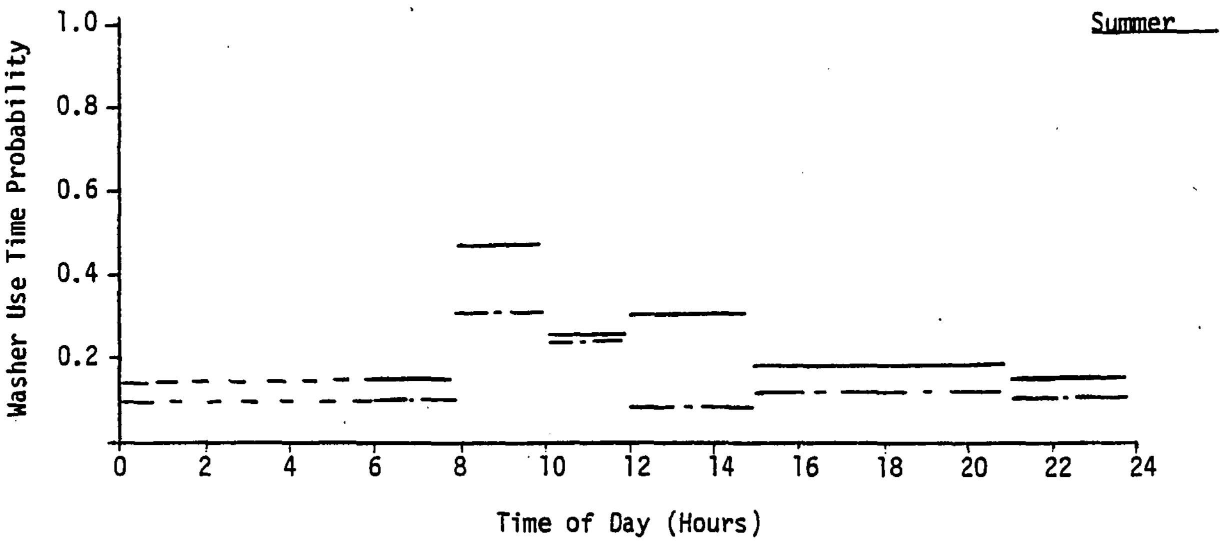
The survey delineated specific time frames (which will be indicated in the development) to be answered by a yes or no. The primary purpose of the load test was to determine the elasticity of "time of day" use to "off-peak" time pricing schedules and the time frames were chosen to more readily reflect any changes. The data is therefore not as specific as could be desired but it still gives a reasonable basis for developing proclivity function.

The method used is illustrated by the development of the proclivity functions for automatic clothes washing machines. Separate functions were developed for summer and winter weekdays and weekend days for this appliance.

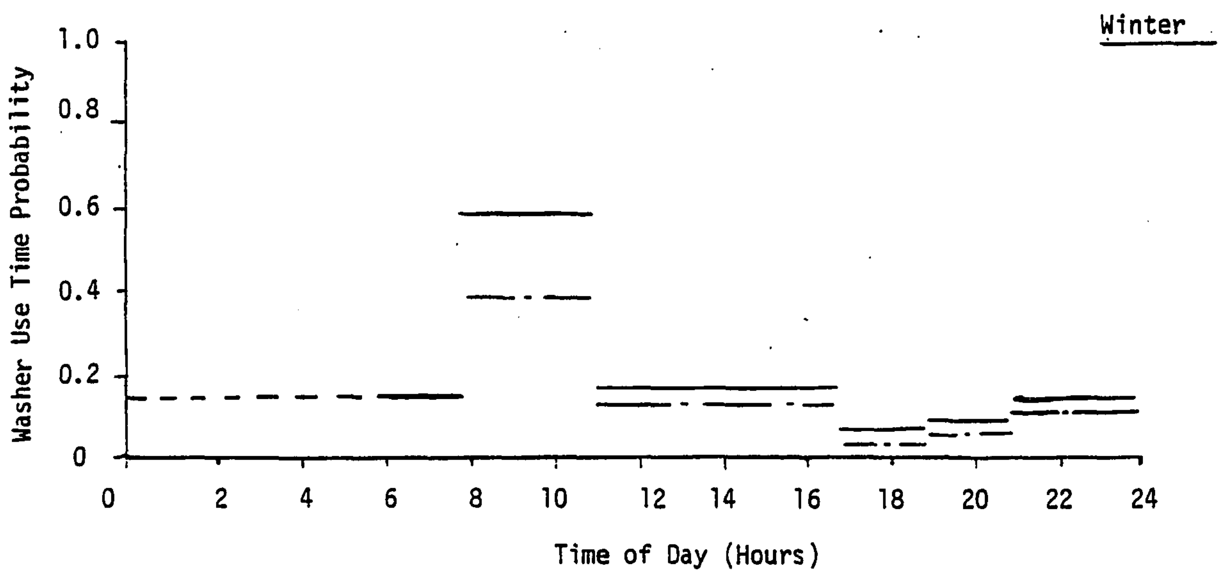
The development began by compiling the responses of all households having clothes washing machines. The survey provided data as to the estimated number of times the appliance was used in a week, the number of hours used on a weekday and on a weekend day and the estimated time frames of use. From the compiled data, averages were computed for times of use, hours of use and specific time frame of use. This data is presented in semigraphical form in Figure 2.3.2.1.

The approach used in applying the time frame data in developing the proclivity functions was as follows:

1) The usage data for the hours 9PM to 8AM was assumed to apply, more realistically, between 9PM and Midnight and again between 6AM and 8AM.
2) An incremental density function whose cumulative distribution is 1.0 over one day was developed by dividing the given percentage during each particular time interval, Ti, by the sum of the percentages for all time intervals in the day. This



Average: Times On/Week-5.59; Weekend Hours -1.0; Weekday Hours - 1.48.



Average: Times On/Week-5.0; Weekend Hours -.99; Weekday Hours - 1.41

——— Weekday

—— . —— Weekend Day

Number - 189

(Sample - 220)

Figure 2.3.2.1 Survey Data for Clothes Washer Use function is the basic proclivity function for using clothes washers. The computer flow diagram which developes this, and similar proclivity functions, is given in Figure 2.3.2.2.

It should be noted that the program computes the value for each of the 96 1/4 hour increments in the day. Utilization of the average times per week and average hours per use data is discussed in the elemental model development in Section 2.4.

A plot of the proclivity function output by the computer program is shown in Figure 2.3.2.3.

A second type of proclivity function, the tendency to do something which indirectly affects the use of one or more electrical appliances, is illustrated by the development of a meal time proclivity function. The times at which meals are eaten affects the use of the electric range, additional use of the refrigerator and the use of hot water from the electric hot water heater for personal washing and the washing of dishes. It therefore affects the models of a number of different appliances. The survey [1] generated data as to when meals were eaten by each hoursehold. As was done for the other data, totals for each time period were compiled. From these totals relative densities were computed for each Ti. The tabular analysis of the data and the development of the function is shown in Figure 2.3.2.4.

It should be noted that in the development the cumulative distribution of the function is 1.0 for each meal rather than for the whole day as in the other type of proclivity functions. Since each meal is at least semi-independent from the others, the cumulative distribution is not based on the total sample but rather on that portion of the sample

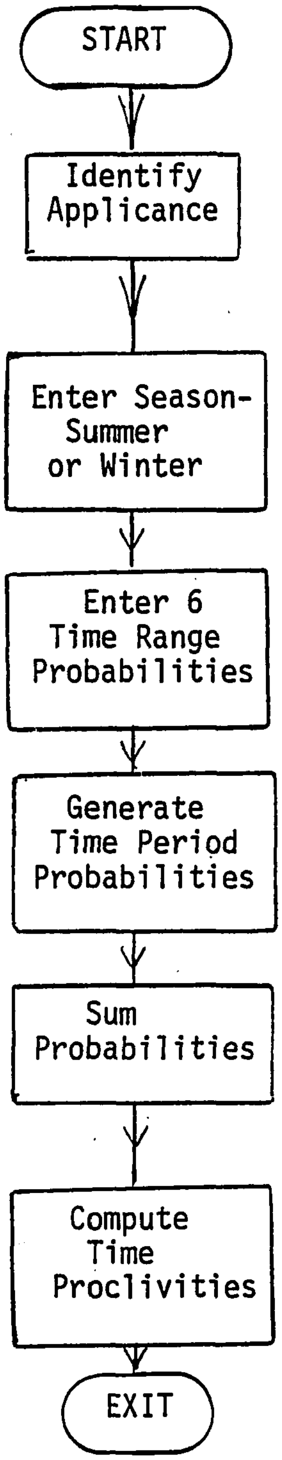


Figure 2.3.2.2 - Computer Flow Diagram for Proclivity Functions

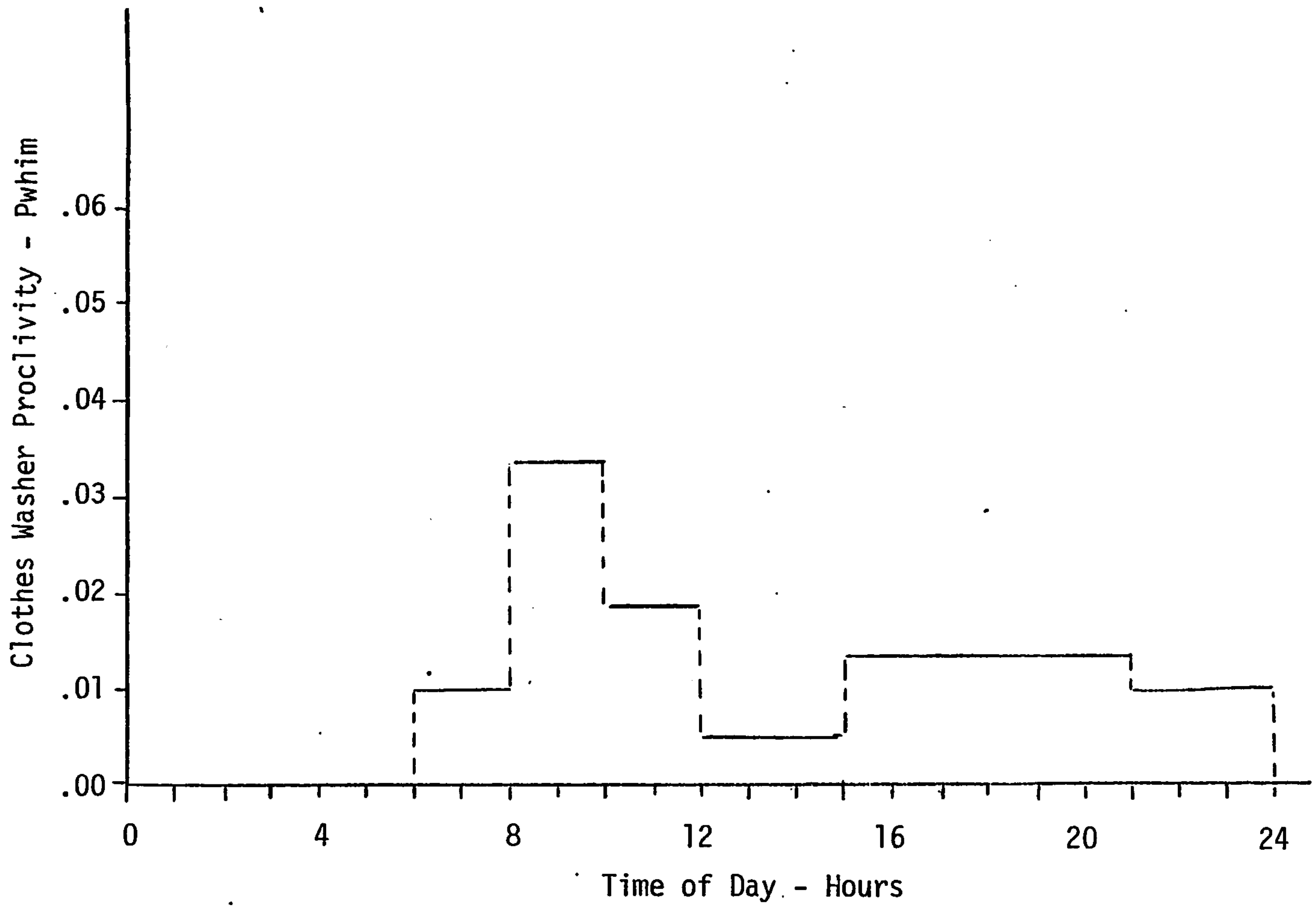


Figure 2.3.2.3 - Clothes Washer - Summer Weekday Proclivity Function

Hour of Day	0	1	2	3	4	5	6	7	8	9	10	11	12
Number of Homes at:													
Breakfast						6	14	81	75	30	6	1	
Lunch	8										1	1	103
Dinner							1		1				
Fraction Eating	.036	.0	.0	.0	.0	.027	.068	.368	.345	.136	.032	.009	.468

Hour of Day:	13	14	15	16	17	18	19	20	21	22	23	24
Number of Homes at:												
Breakfast												
Lunch	46	2										
Dinner		1		4	42	111	46	9	3			8
Fraction Eating	.209	.014	.0	.018	.191	.505	.209	.041	.014	.0	.0	.038

Number of Homes: 220

Meal 1 (Breakfast) 5 AM - 10 AM
Meal 2 (Lunch) 11 AM - 2 PM
Meal 3 (Dinner) 4 PM - 9 PM

Figure 2.3.2.4 - Meal Time Survey Data

eating a particular meal. This is based on the reasoning that if a meal is eaten at home it implies that someone is there to eat it. In the models which use this function, it is applied in conjuction with the availability function which takes the requirement to have someone at home into account.

The basic function is shown in Figure 2.3.2.5. It is shown as a continuous function in the figure but is implemented as a discrete function in the model. Its use in the various elemental models and in the composite residential model is discussed in Sections 2.4 and in Chapter 3.0. For weekend days the mealtimes are shifted 4 periods later.

2.4 Model Development

The form of the residential model is a combination of the loads due to individual appliances. Therefore the model has the flexibility that any appliances not present in a particular household can be deleted. Also any new type of applicance, which could have a significant affect on the load, can be modeled and readily included in the composite model.

For this model the individual appliances were chosen on the basis of saturation, that is the percentage of households possessing the appliance, as reported in "Merchandising" [17]; on the basis of the amount of average monthly use as reported in "Energy Facts" [18] and various public utility customer relations bulletins [19] and [20]; and on the basis of the size of the individual loads. Separate models were not developed for those appliances which essentially are a substitution for another appliance. For example, coffee-makers, broilers and micro-wave ovens are essentially a substitute for the electric range, which is modeled.

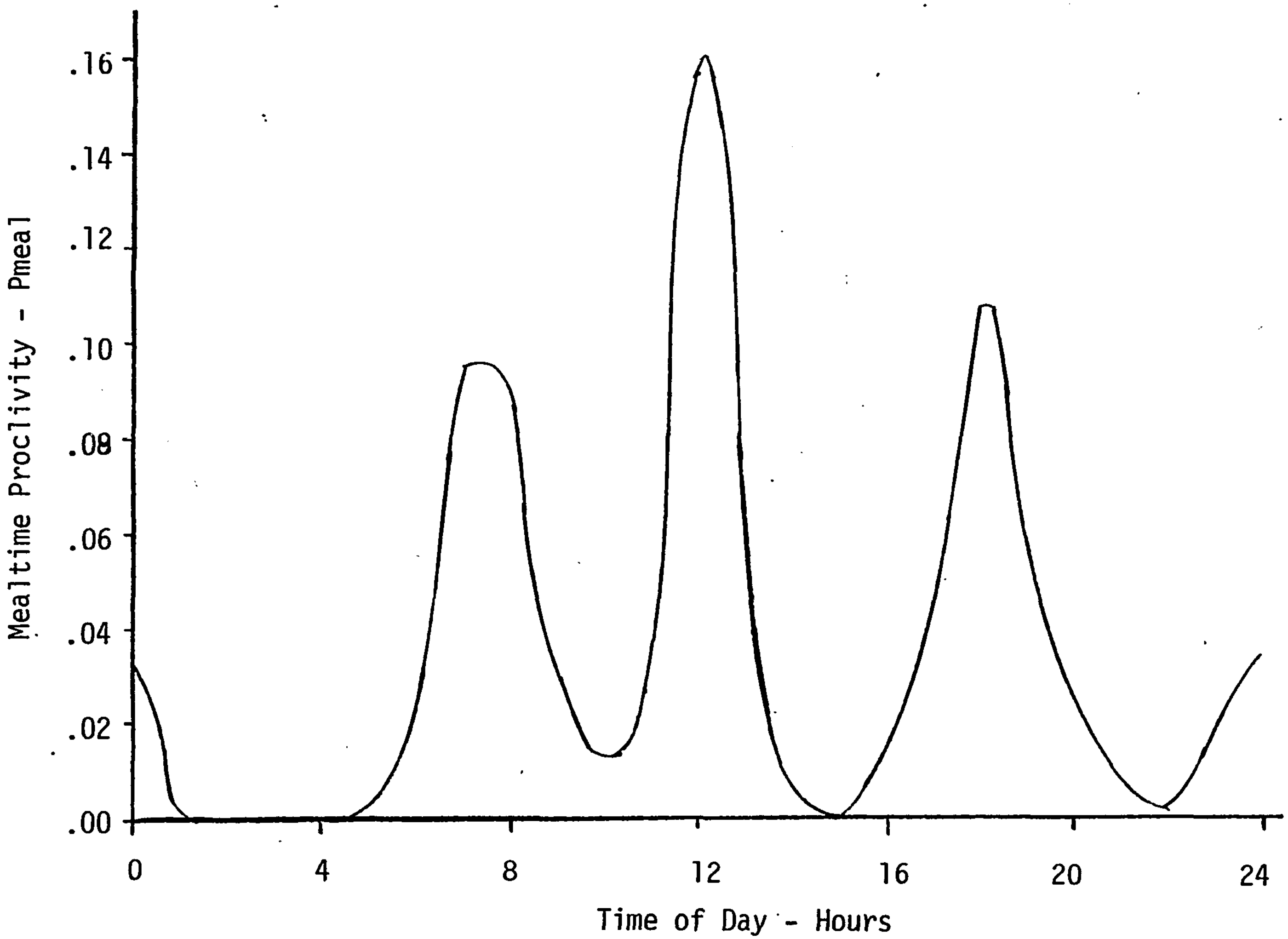


Figure 2.3.2.5 - Mealtime Proclivity Function

Some seasonal appliances such as humidifiers and dehumidifiers are grouped together where it is unlikely that both will be used together and where the switching functions have similar parameters. On the foregoing basis the following individual appliances were analyzed. The "miscellaneous" model is included to provide space in the composite model to more easily add an additional appliance if required.

1) Lighting
2) Television
3) Refrigerator
4) Electric range (or similar appliance)
5) Dish washer
6) Clothes washer
7) Clothes dryer
8) Water heater
9) Freezer
10) Air conditioner
11) Fans/Unit heater
12) Electric space heating
13) Humidifier/Dehumidifier
14) Swimming pool filter
15) Miscellaneous

Because of time constraints, all of the appliances listed have not been completely modeled or tested. Items 1 through 9, and a manual version of the dehumidifier, item 13, were included and exercised in the combined model. Items 11 and 14 were modeled but not tested. Items 10 and 12 are discussed but have not been modeled.

2.4.1 The Lighting Model

In determining a model for the residential lighting load, conventional lumens per square foot and other methods of providing adequate lighting do not indicate the amount of lighting in use at a particular time. In general this is governed by the number of people at home as well as by the size of the house. Public Service Company of New Hampshire in its periodic publication, Light Lines [20], points this out. Their estimate of the normal monthly energy consumption for lighting by an average family of four is 75 kilowatt-hours per month when living in a 5 room house, 85 kilowatt-hours in a 7 room house and 100 kilowatt-hours in a 10 room house. The major contributing factor to the lighting load is the lighting requirements of each person but additional factors are involved in a larger residence. Household members are more likely to occupy different areas in a larger house resulting in less communal lighting and there is a greater likelihood that rooms are left lighted even though not occupied.

Based on the foregoing considerations the residential lighting model has been developed as a function of the number of persons at home and the number of rooms in the residence.

The method followed in developing the parameters for the lighting model is outlined below.

1) The availability of a generalized person was averaged over a month and found to be approximatley 40 percent.

2) A nominal value of 60 watts (.06 kilowatts) was taken as the average lighting requirement for each person.

3) On the above basis the energy used by four persons in a 30 day month was then calculated to be:

Kilowatt-hour use = (# of Residents) x (average availability) x (24 hours/day) x (30 days/month) x (.06 kilowatt)

= (4 x .4 x 24 x 30 x .06)

= 69 kwhrs.

4) The parameter used for describing the average watts used for each room of the residence exceeding the number of residents was determined as follows, based on [20]:

# of Rooms	Excess Rooms	Estimated Kilowatt-hour Difference
5	1	75-69 = 6
7	3	85-69 = 16
10	6	100-69 = 31
	Total 10	Total 53

Average kilowatt-hour/Excess room = 53/10 = 5.3 KWHR

The wattage assigned to each "excess" room was based on the assumption that this lighting would be normally used only when someone was available to turn on the lights. Thus the parameter was calculated using the average availability as:

Wattage/excess room = (kilowatt-hours/room) x 1000 /(24 hours x 30 days x average avail.)

= (5.3 x 1000)/(24 x 30 x .4)

= 18 watts/room

5) To adjust the model for time-of-day considerations necessitates estimation of the difference in requirements between daylight and darkness hours. During daylight hours

the load per person and the "excess room" load are normally less than during nightime hours, with the expectation that the "excess room" load will be considerably less during daylight hours. Therefore the "average" parameters were adjusted to reflect the two conditions. As an additional consideration, during daylight hours a minimum of one person must be home to initiate the "excess room" load.

The lighting function is described by:

$$KWUSED(Ti) = .060 \times NHOME(Ti) \times Factor\ 1 + 0.018 \times (NROOMS-NHOME(Ti)) \times Factor\ 2$$

Where:

KWUSED(Ti) = Kilowatt load during period i

NHOME(Ti) = Number of persons at home and awake during period i.

NROOMS = Number of rooms in the residence

Factor 1 = .5; $32 \leq Ti \leq 68$ (i.e. daytime)

= 1.0; otherwise (i.e. nightime)

Factor 2 = .1; $32 \leq Ti \leq 68$

= 1.0; otherwise

The time spans of Factor 1 and Factor 2 are subject to seasonal adjustment.

The block diagram for the lighting model is given by Figure 2.4.1.1.

2.4.2 The Television Model

The time varying load due to television sets and similar home entertainment sources such as stereo music equipment is determined by a number of factors. These include the power taken by the sets, the number of sets in a residence, the availability of people at home to turn on

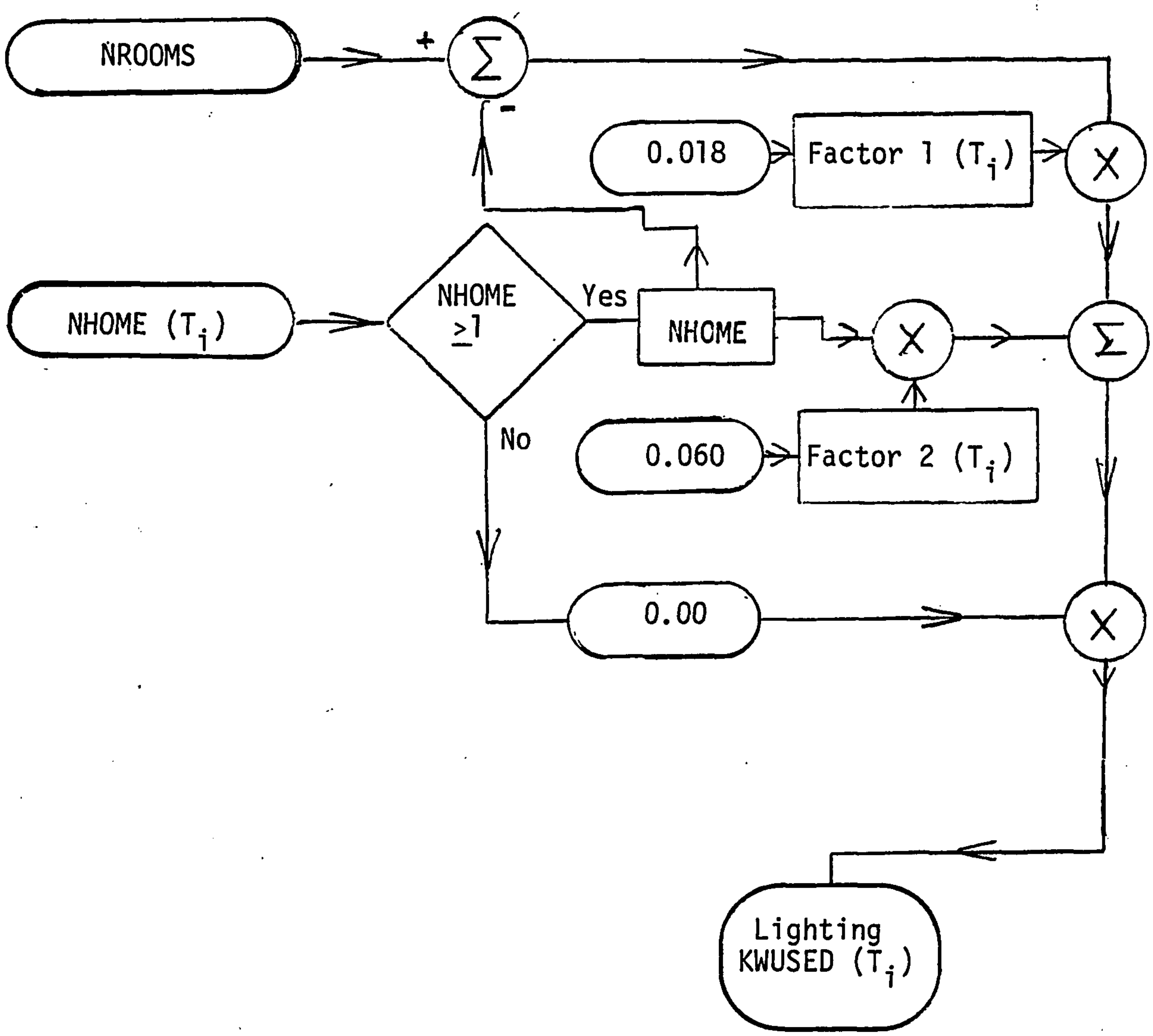
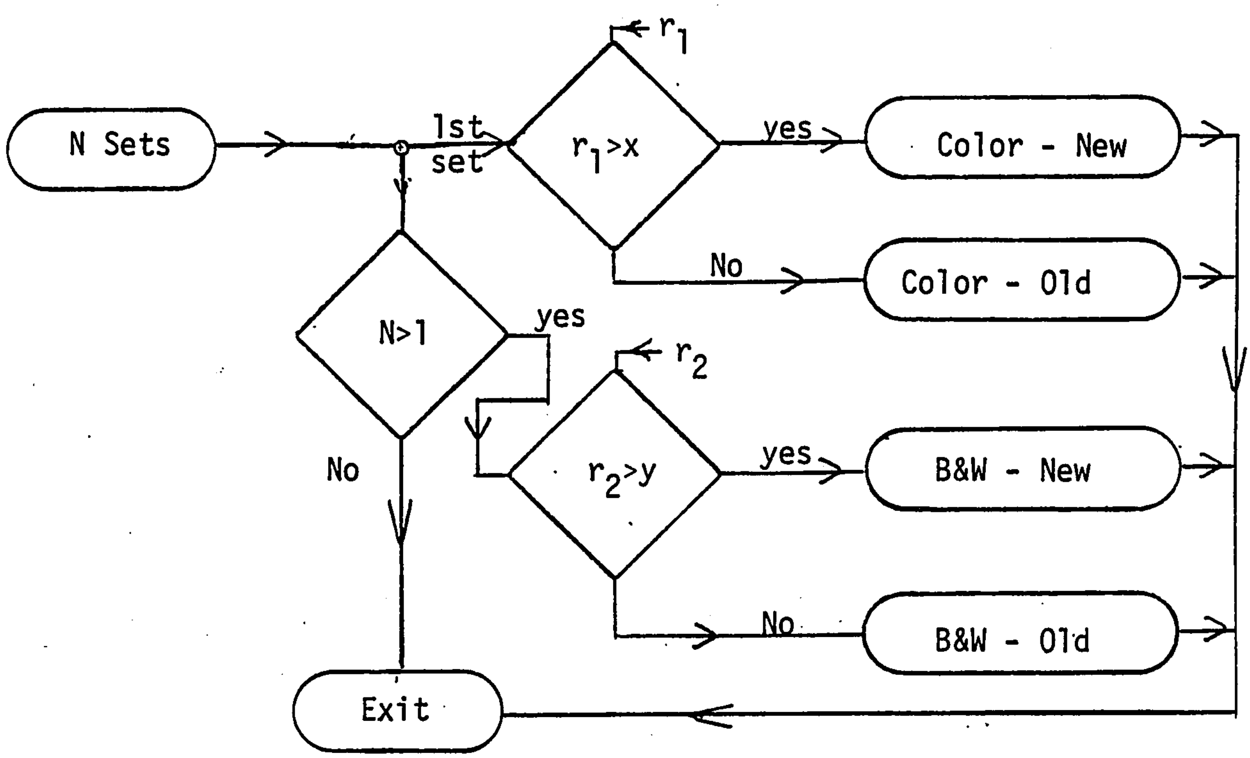


Figure 2.4.1.1 Diagram of the Lighting Model

the sets and their proclivity to do so. The power used by older television sets (tube type sets) is greater than that taken by the newer models (solid state sets). It is also greater for color sets than for black and white models. The size of the set also affects the power required. However, in order to keep the model within reasonable bounds, "average" values of wattage for the four basic types (old, new, color and black and white) were used. The parameters are changeable in the model if greater detail is desired. A diagram of the method of "assigning" the television sets for a particular residence is given in Figure 2.4.2.1. The selection of the particular wattage is done on a probability basis using the fraction of old and new sets as the criterion. When there are both color and black and white sets in a residence it is assumed the color set is used first. Also, in the general model, a "single" television set is assumed to be color but this could be changed in the parameters supplied to the model.

"Merchandising" [17] estimates the national saturation (1978) of color television sets at 85.2% and of black and white sets at 99.9% for all homes that have electricity. The actual saturation in a particular area depends to a great extent on the proximity to television stations but with the increase in Cable TV and other signal enhancing systems the eventual saturation can be expected to appraoch 100% for both types of units. The saturation percentages recorded in the Connecticut Light and Power Company Residential Load Test survey [1] were much less than those given above but the data is still considered sufficient for determining the proclivity functions for the model. The percentages recorded in the survey are listed below for information.



r_1 and r_2 = random numbers (0-1.0)

x = fraction of old color TV = .8

y = fraction of old B&W TV = .9

Figure 2.4.2.1 Diagram of TV Type Selection

Houses with television sets - 89%
Houses with B&W sets only - 21%
Houses with Color sets only - 46%
Houses with both Color and B&W - 23%

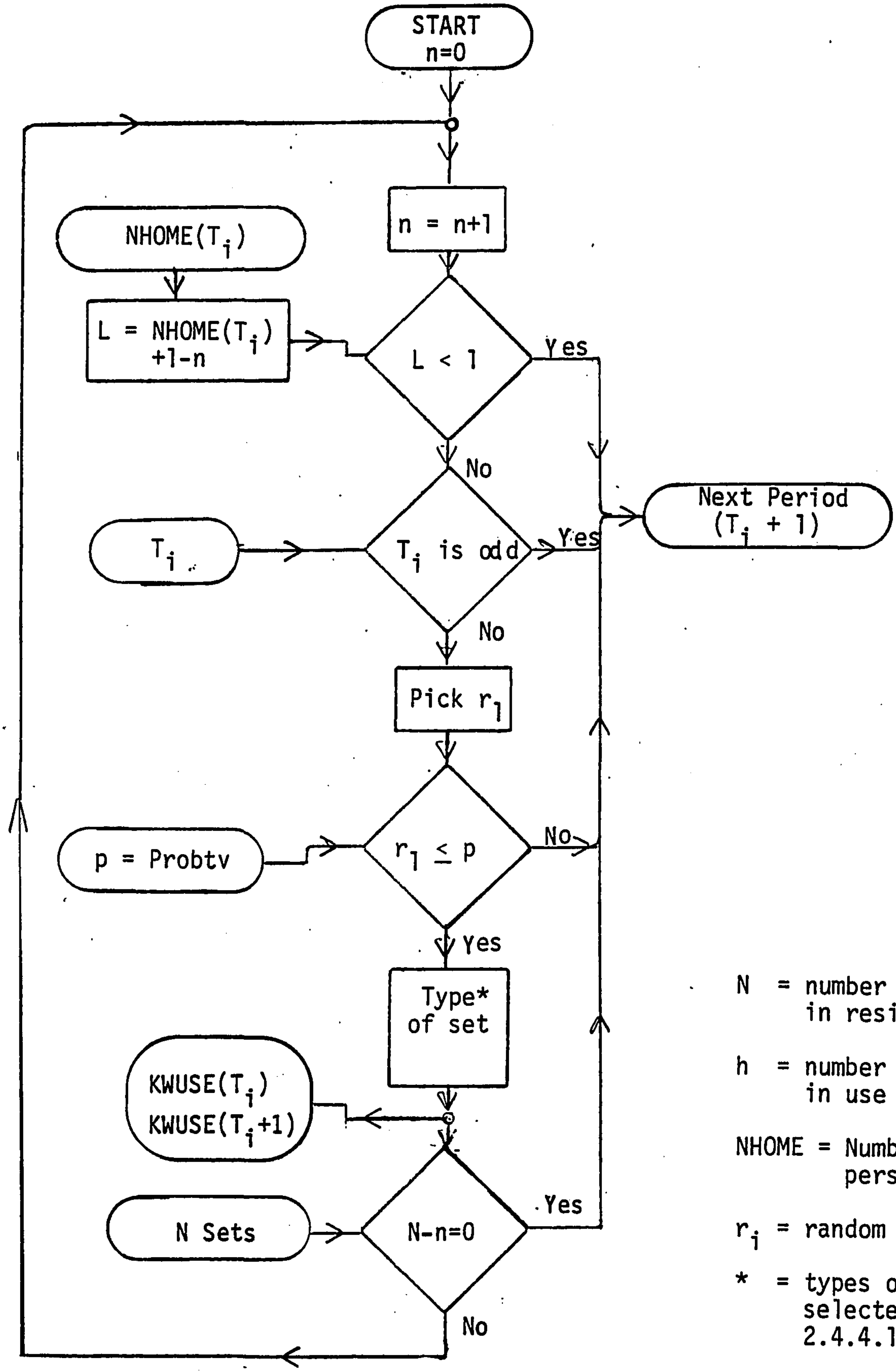
Based on data given in "Merchandising" [17] for 1979, the number of B&W sets replaced per year is approximately 5% of the total number of sets and the number of Color sets replaced is approximately 10% of all Color sets. In the model, since the major shift to solid state occurred in 1973, the percentage of old color sets was estimated to be 80% and the number of old black and white sets was estimated at 90% for a nominal year 1975 (to suit the survey dates).

Additional information obtained from Merchandising [17] indicates that the predominant size for color sets is 19 inch and for black and white is 13 inch. The nominal wattages used for these sets are:

Color (tube type) = 350 watts
Color (solid state) = 150 watts
B&W (tube type) = 100 watts
B&W (solid state) = 30 watts

The proclivity function was developed in the manner previously discussed in Section 2.3.2. The model also uses the availability function to compute the number of people at home. That function was discussed in Section 2.3.1.

Refer to Figure 2.4.2.2. During each period the model tests to see if anyone is available to watch television. Since essentially all programs start on the hour or half hour and run in half-hour increments, the test for TV "on" is made on even quarter hours and if the TV is "on" at that time it is assumed it will be on for at least one half hour, at which time another test is made.



N = number of sets in residence

h = number of sets in use

NHOME = Number of persons home

r_i = random number (0-1.0)

* = types of set selected by Figure 2.4.4.1

Figure 2.4.2.2 Diagram of Television Model

The probability of a television set being used during a particular period, Probtv, is the product of the television proclivity function and the average number of periods of use per day, as developed from the survey data. If there is more than one set in the house the tests are repeated to see if any other set is being watched.

2.4.3 The Refrigerator Model

The refrigerator model is a complex model since many factors combine to determine when it switches on and off. The basic control for the refrigerator is the thermostat which responds to a designed differential about a desired (set) refrigerator compartment temperature. In combination units (i.e. having both a refrigerator and a freezer compartment) one compressor system provides the cooling for both areas and is controlled by the setting of the refrigerator compartment thermostat. The percentage of cooling going to each area depends first on the location of the freezer, which can be inside the refrigerator compartment or be outside of it with a separate door. In the separate door type a deflector, which may be adjustable, is provided to regulate the percentage of cooling air flow to each compartment. The above discussion is based on the ASHRAE Handbook [21] and retail catalogue information.

Factors (Figure 2.4.3.1) which cause the refrigerator (and freezer) compartment temperature to rise are:

1) Heat transmission through the walls and the door gaskets due to the difference between inside and outside (ambient) temperature. The rate of heat transmission varies as the temperature difference varies and consequently has a seasonal variation, which is limited by household heating and cooling.

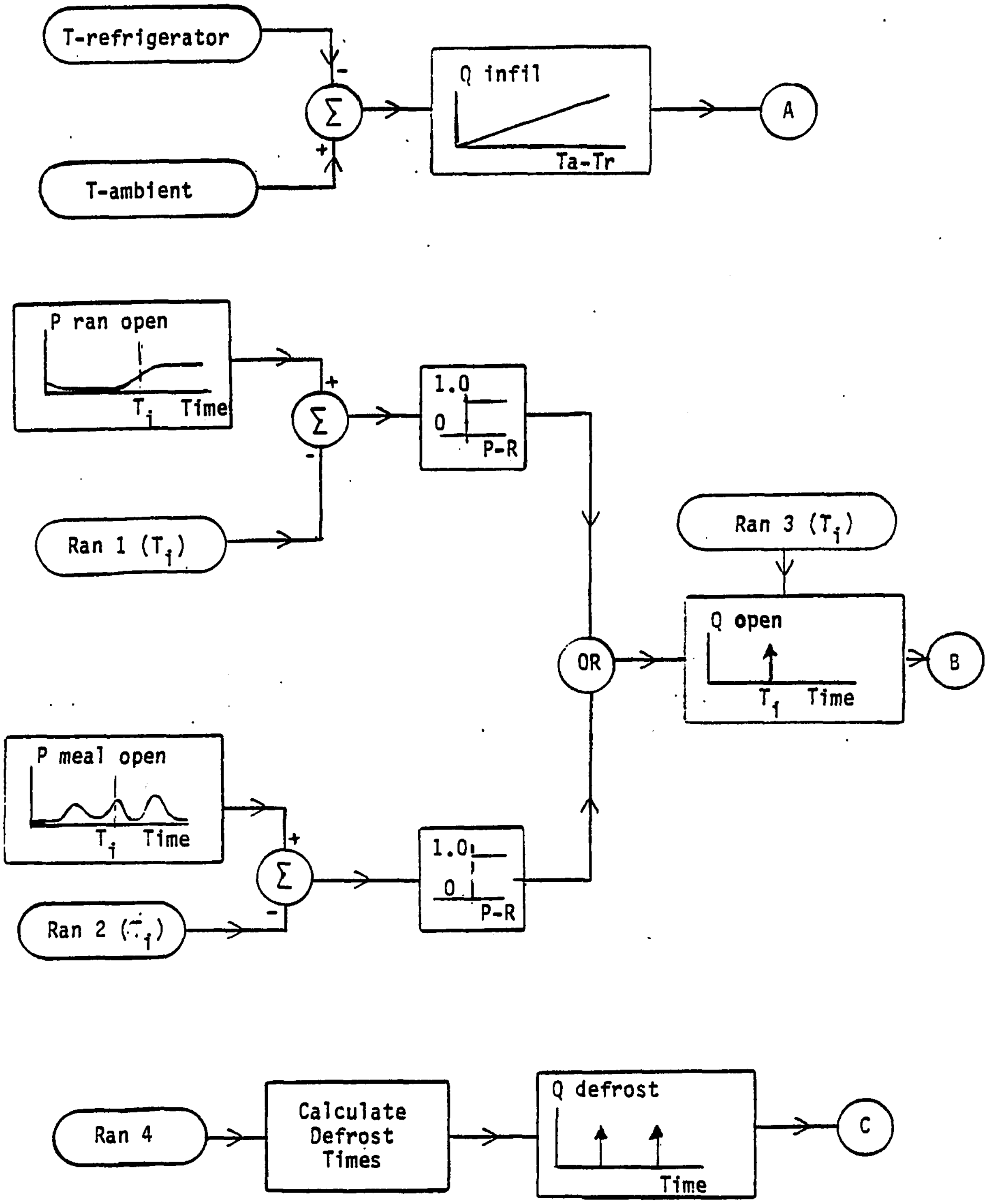


Figure 2.4.3.1 Diagram of Refrigerator Model (Sheet 1 of 2)

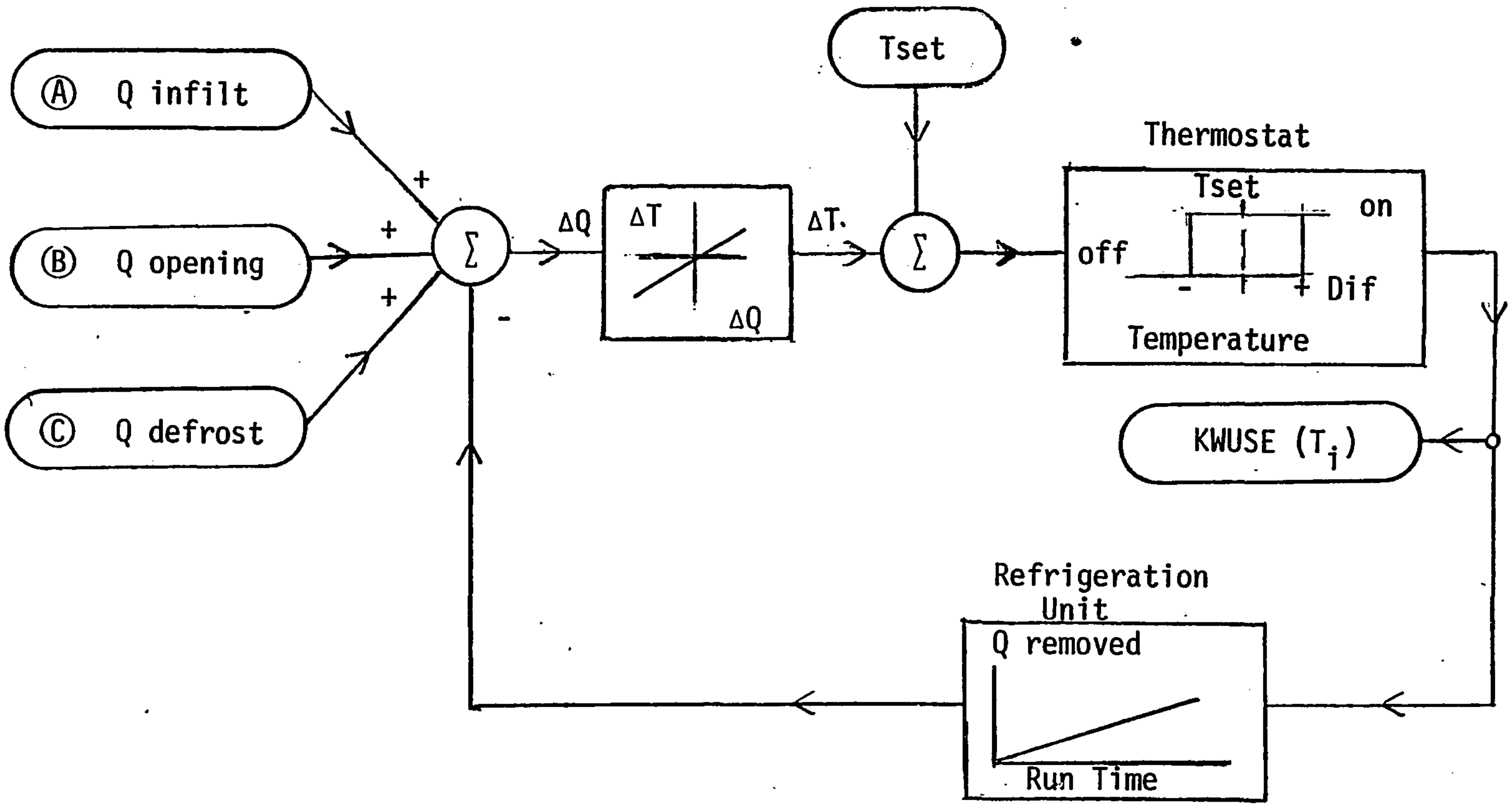


Figure 2.4.3.1 Diagram of Refrigerator Model (Sheet 2 of 2)

2) Heat entry due to door openings and air leakage around the gaskets. Particularly during humid weather, this air contains appreciable latent heat as well as sensible heat.

3) Heat entry due to power dissipated by internal fans, lights and heaters. The heaters may be used for preventing condensation on the outside of the box and/or keeping the compartments frost free (automatic defrosting).

4) Heat entry due to the heat stored in products placed in the refrigerator which must be cooled to the refrigerator or freezer compartment temperature.

The factors which affect heat removal from the refrigerator include:

1) The capacity of the compressor unit, assuming the other components such as the condenser, evaporator and the expansion device are adequately sized.

2) The temperature of the air in the vicinity of the condenser which might exceed normal ambient due to poor circulation and thus affect the heat rejection capacity of the condenser.

The run time is determined by the difference between the heat removal and heat entry rates. The off time is determined by the heat entry rate and the equivalent specific heat of the refrigerator products (since the thermostat responds to temperature). If a product is added at a higher temperature there will be additional run time until its temperature is reduced.

Because the heating and cooling rates, coupled with the heat capacity of the refrigerator and its stored products, are such that the refrigerator cycle time is often much less than 1/4 hour, the refrigerator model operates on a one minute period. The 1/4 hour load is the "average" kilowatts for that time. This is consistent with electric utility practice in determining and recording their time varying load.

The foregoing factors have been included in the model. The simplifying assumptions and the provisions for expansion are discussed below. A detailed development of the refrigerator parameters is included in Appendix 'C'.

1) The rate of heat transmission is contained in one parameter which gives the heat rate per minute per degree fahrenheit. The value used in the model is based on an average refrigerator. The parameter can be readily changed as input data to suit studies of different refrigerators. It is based on simplified calculations suggested in the ASHRAE Handbook [21]. This parameter is multiplied by the current difference between room ambient and refrigerator compartment temperature to obtain the heat added by heat transmission and leakage during the current minute. No separate parameter has been provided to specify the additional latent heat due to high humidity. However since the model responds to a summation of heats entering, this can be added at a later date with little difficulty.

2) The time of heat entry due to door openings is random throughout the day, with a greater likelihood at meantimes and when more people are home. A certain number of random openings and a certain number of openings per meal can be expected. The model includes these sub-functions as described below.

   The first sub-function compares a random number (between 0 and 1) to a probability of the door being opened. This probability is determined on the basis of an expected number of openings per day (10 in the model but the number is readily changed). Dividing this number by the number of minutes in a day gives the probability of the door being open during any one minute. Since someone must be available to open the door the above probability is "weighted" by multiplying it by the number of persons at home. This gives the probability of the door being opened at a particular time.

The second subfunction compares a random number (between 0 and 1) to the probability that the door will be opened a number of times during each mealtime period. This probability is calculated using 6 as the "expected number" of openings for each meal. (This parameter can be changed). To account for the expectation of more openings for more involved meals this number is weighted by multiplying it by the number of people at home for a particular meal. To account for the greater likelihood of openings occuring before and after the actual meal the probability is weighted toward the beginning and end of the meal period. The mealtime is determined by the mealtime proclivity function described in Section 2.3.2.1.

The amount of heat added per opening is calculated on the basis of a complete change of air per opening plus an additional random amount of heat due to a longer door opening (which causes a rise in stored product temperature) or due to the initial temperature of the product stored being higher than the refrigerator temperature.

3) The amount of heat due to fans and surface heaters is accounted for in the model by including these components in the heat added and removed subfunctions. For frost-free refrigerators a

twice daily heat load is added for frost removal. The load due to lights is included in the door opening allocation.

4) To model the rate of heat removal a subfunction based on data provided in the ASHRAE Handbook [21] is used. This specifies a fixed amount of heat removal per minute based upon the compressor capacity at standard conditions.

The parameters presently used in the model are based on the most prevalent size of refrigerator, approximately 16 cubic feet, as reported in "Merchandising" [17] but can be changed to suit other sizes. The block diagram which describes the model is given in Figure 2.4.3.1.

2.4.4 The Electric Range Model

The model for the electric range combines data on time of use extracted from the Connecticut Light and Power Company Residential Load Test survey [1] together with data for estimated monthly use published by various electric utilities, [18], [19], and [20]. Unlike most other electric loads the amount of power used when the range is switched in is not a fixed amount. The most common range has four top elements, which are continuously or stepwise variable. It also has a thermostatically controlled oven and an on or off broiler. Nominal values for the top units are 1600 watts (6 inch) and 2100 watts (8 inch). The oven and broiler units are 2500 watts each. The amount of load switched in at a particular time depends on the nature of the meal being prepared and an estimate of this amount must be made in the model.

Table 2.4.4.1 lists pertinent data from the previously cited sources which were used in developing the required parameters. The reason for including data on the coffee-maker in the breakfast factor is because it accounts for the difference between the reported "breakfast" range use

FACTOR DESCRIPTION	DATA	SOURCE
Average times/day range use	2	1
Average times/day coffee-maker use	1	1
% range use - breakfast	60%	1
% coffee-maker use - breakfast (weighted)	20%	1
% range use - lunch	60%	1
% range use - dinner	90%	1
Estimated range energy/month	100 kwhr*	20
Estimated coffee-maker energy/month	8 kwhr*	20
Estimated average daily energy use (108/30)	3.6 kwhr	
Estimated percent of total for:		
Breakfast	30%	
Lunch	10%	
Dinner	60%	

Calculated Base Load per Period:

Breakfast (3 periods) 3.6 x .3 x 1/3 = .36 kw

Lunch (2 periods) 3.6 x .1 x 1/2 = .18 kw

Dinner (4 periods) 3.6 x .6 x 1/4 = .54 kw

*For an average family of four

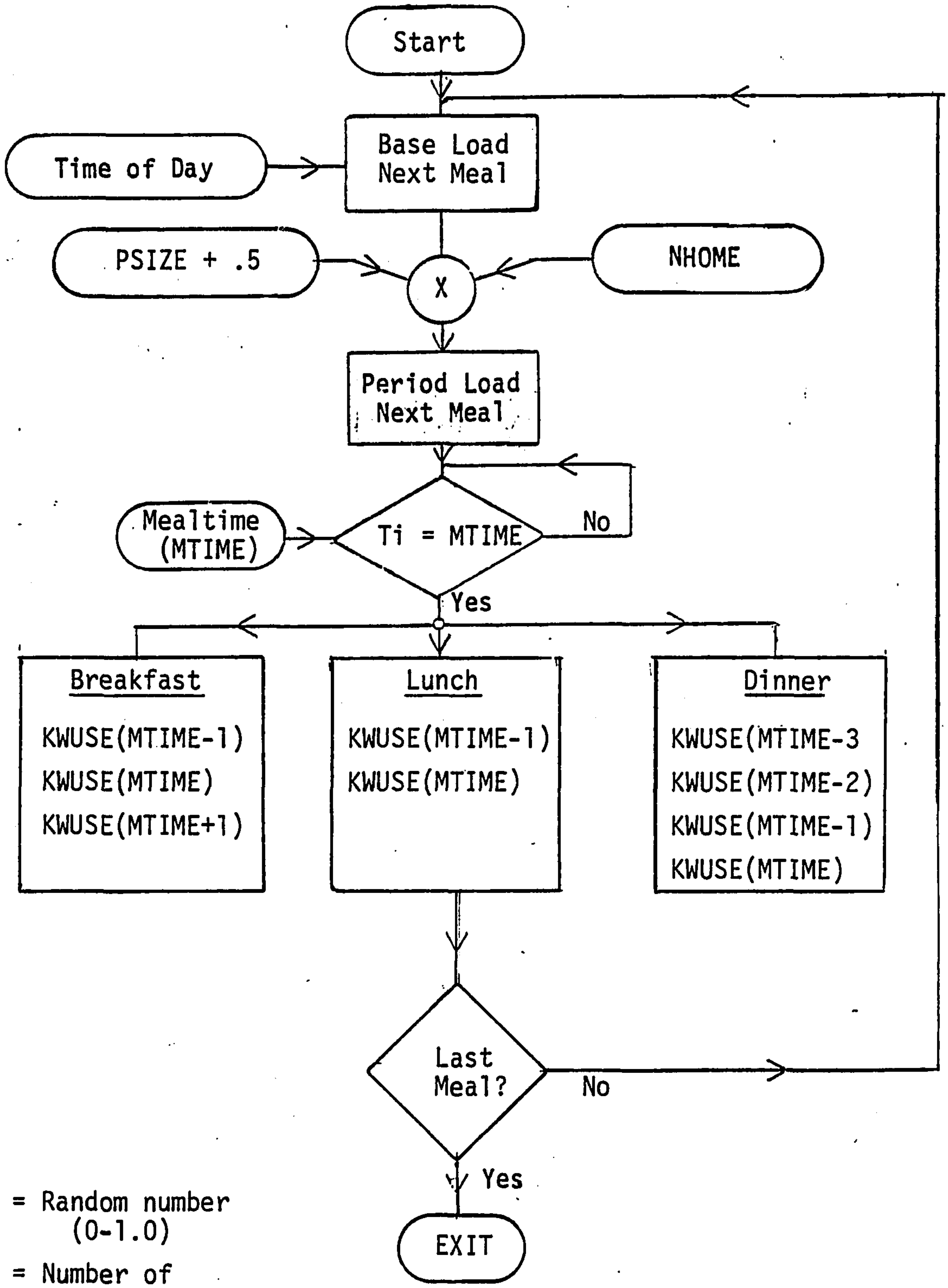
Table 2.4.4.1 Electric Range Use and Load Data and the reported "breakfast eaten" percentages given in the survey [1]. As in the other appliance models, the parameters are included in such a way that modification is readily accomplished.

A diagram of the electric range model is included as Figure 2.4.4.1. Referring to the figure the model selects the base load for the next meal, based on the time of day. This load is then multiplied by the number of persons at home and by a random factor to obtain the load connected each period. The random factor, which is the sum of .5 and a randomly selected number, PSIZE, allows the load to vary from .5 to 1.5 times its estimated nominal value.

Using the mealtime function previously described in Section 2.3.2.2, the model decides if and when a particular meal is to be eaten. If the meal is to be eaten, the model then specifies the amount of load and the periods in which it is connected. The load is applied over a number of periods consistent with the type of meal being prepared. A random component could also be included to account for other than mealtime use such as baking and snack preparation (but is not included at present).

2.4.5 The Dishwasher Model

The information developed in the Connecticut Light and Power Residential Load Test survey [1] indicates that the automatic dishwasher is used an average of slightly less than once a day (i.e. 6.3 times a week). However in addition to the electric energy which it uses directly it contributes to the hot water use (and so affects the water-heater load). It is therefore included in the model. The block diagram which describes the model is given in Figure 2.4.5.1. The probability of the dishwasher being used on a particular day is 90% on the average, based on the survey data,



PSIZE = Random number (0-1.0)

NHOME = Number of persons home.

Figure 2.4.4.1 Electric Range Model

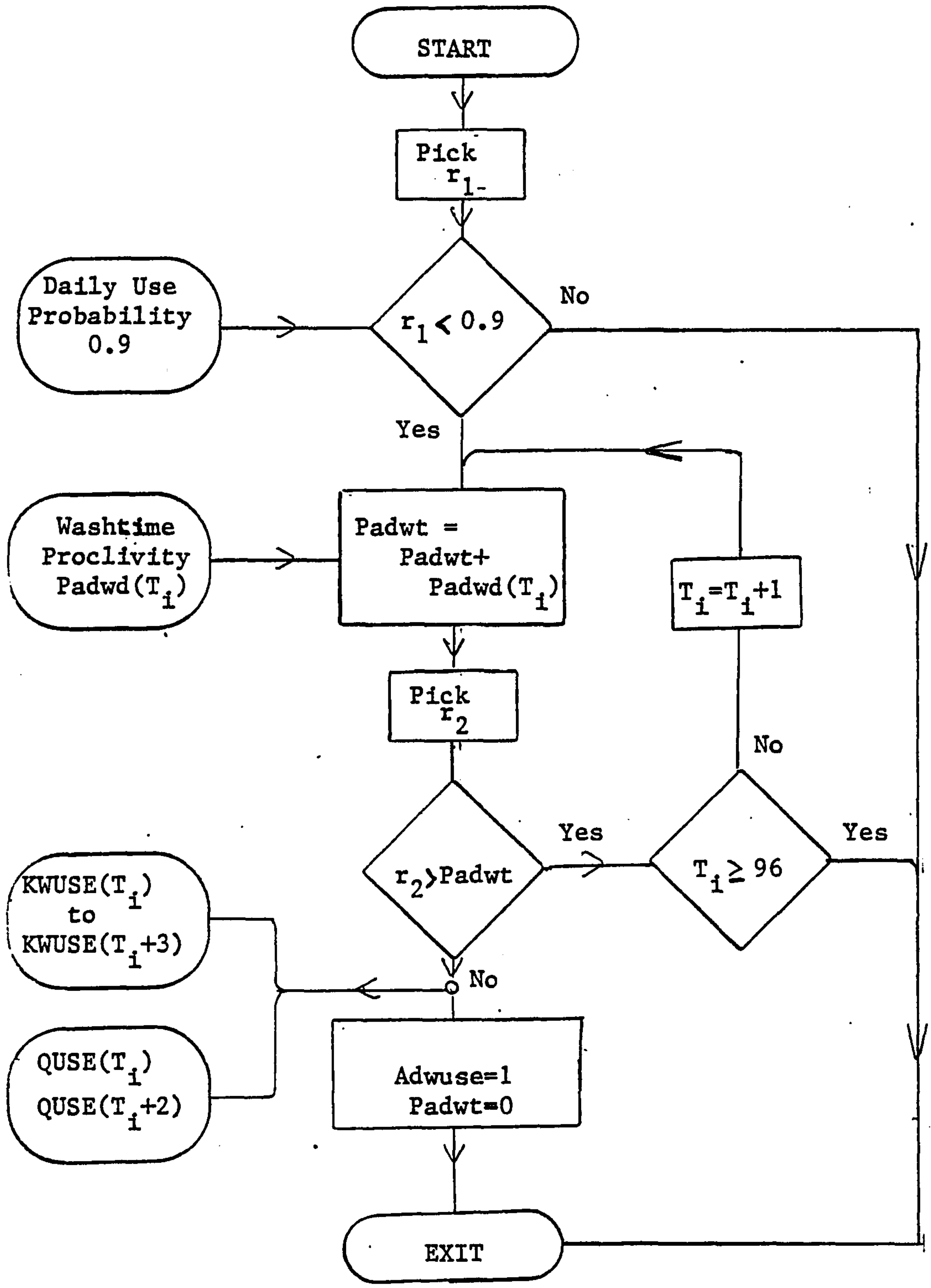


Figure 2.4.5.1 - Diagram for Dishwasher Model

data, and this is used as the first test in the model. The time of use on a particular day is based on a proclivity function for dishwashers developed in a manner similar to the one for the automatic clothes washer developed in Section 2.3.2.1. The proclivity function Padwd (T_i) shows a greater tendency to use the dishwasher at the end of the day which is certainly reasonable if it is used only once a day. To assure that the machine operates in the day specified by the first test, the "cumulative" proclivity, Padwt, is computed and tested at each period which further weights the probability of operation toward the end of the day.

When the dishwasher operates, both the electric load connected to the system and the amount of heat used (in the form of hot water) are calculated. Padwt is reset to zero and a flag, Adwuse, is set to indicate the dishwasher has been used.

2.4.6 The Clothes Washer Model

The clothes washer does not use a large amount of electric energy during the month (it is estimated at 10 kilowatt-hours) but it is associated with the operation of the dryer and the water heater both of which consume appreciable energy. For that reason it is modeled here. The model uses the proclivity curve developed in Section 2.3.2.1. An estimate of the number of washes per week based on the survey data and the number of residents is also used. Each wash is considered to last one hour and the average power for each period has been estimated. A typical washer cycle was used in the estimation.

The proclivity function, Pwhtim (T_i) is a time-of-day function. It does not indicate a preference for any particular day, or if more than one wash may be done at a particular time. Therefore two additional factors have been included. The first, Pwday (I), is the probability that the washer will be used on a particular day. This parameter is estimated by dividing the number of remaining washes by the number of remaining days in the week. The second, Swash (L), assigns the expectation that one, two or three washes will be done in succession. The total number of washes in a week is still limited based on the number of residents.

In order to estimate the amount of hot water used by the washing machine, four combinations of wash and rinse temperatures are available and the function, Tywash (k), is used to select the combination for a particular wash, on a probabilistic basis. The heat demand on the water heater is calculated from this data. The block diagram for the washer (and dryer) model are shown in Figure 2.4.6.1.

2.4.7 The Clothes Dryer Model

The model tests for the availability of an electric clothes dryer and, if the residence has one, calculates the load associatd with it. The model assumes an average run time of one hour (four periods) and that drying follows immediately after washing. The model selects the type of drying on a probabilistic basis using the function, Tydry (k), which assigns a small probability of air only or hot dry and the largest probability of warm dry. This is the type of drying recommended for "permanent press" fabrics which seem to predominate now. With energy conservation in mind a test could be readily added which would model the tendency not to use the dryer if weather permitted outside (or even inside) drying.

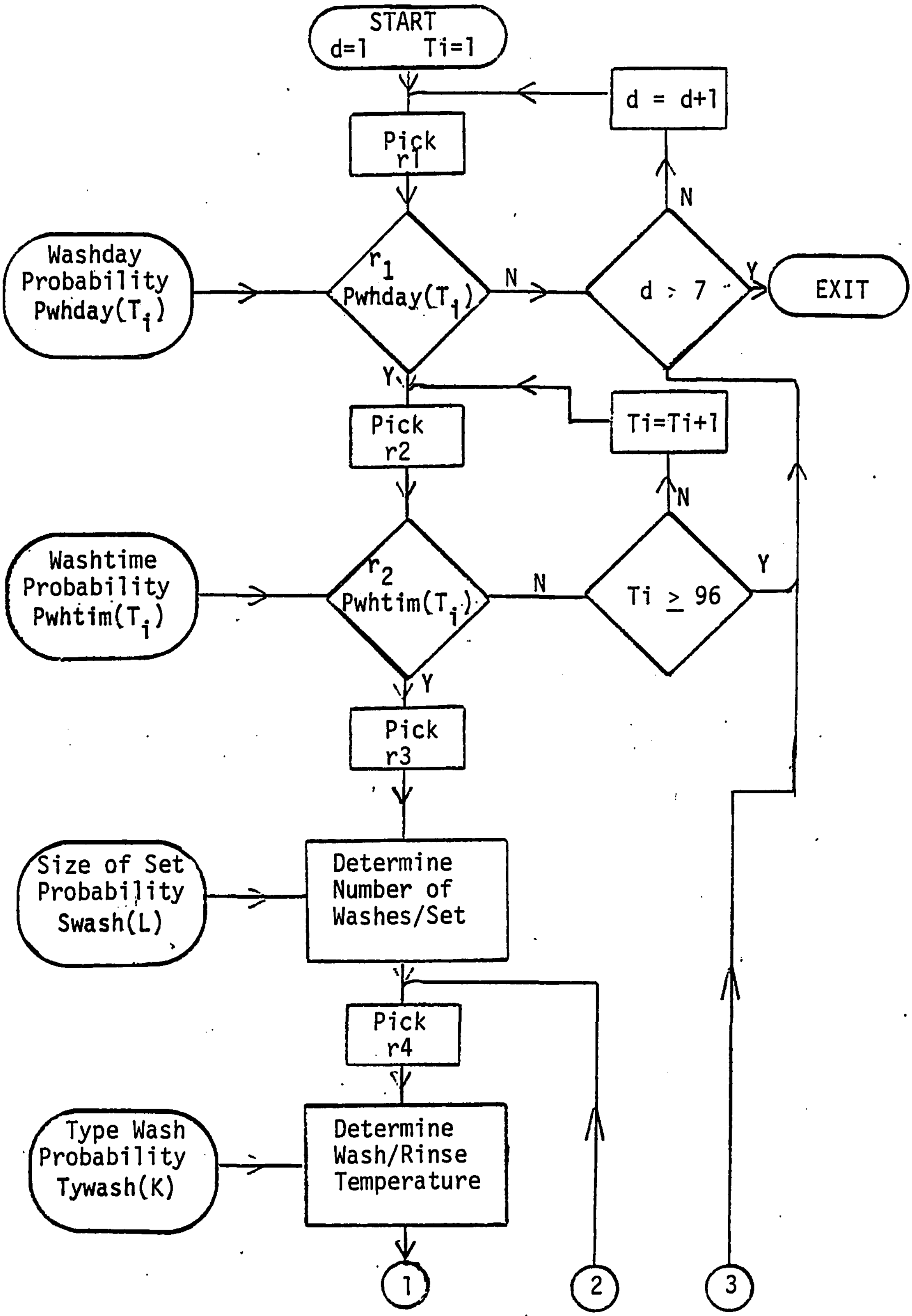


Figure 2.4.6.1 - Diagram for Clothes Washer and Dryer (Sheet 1)

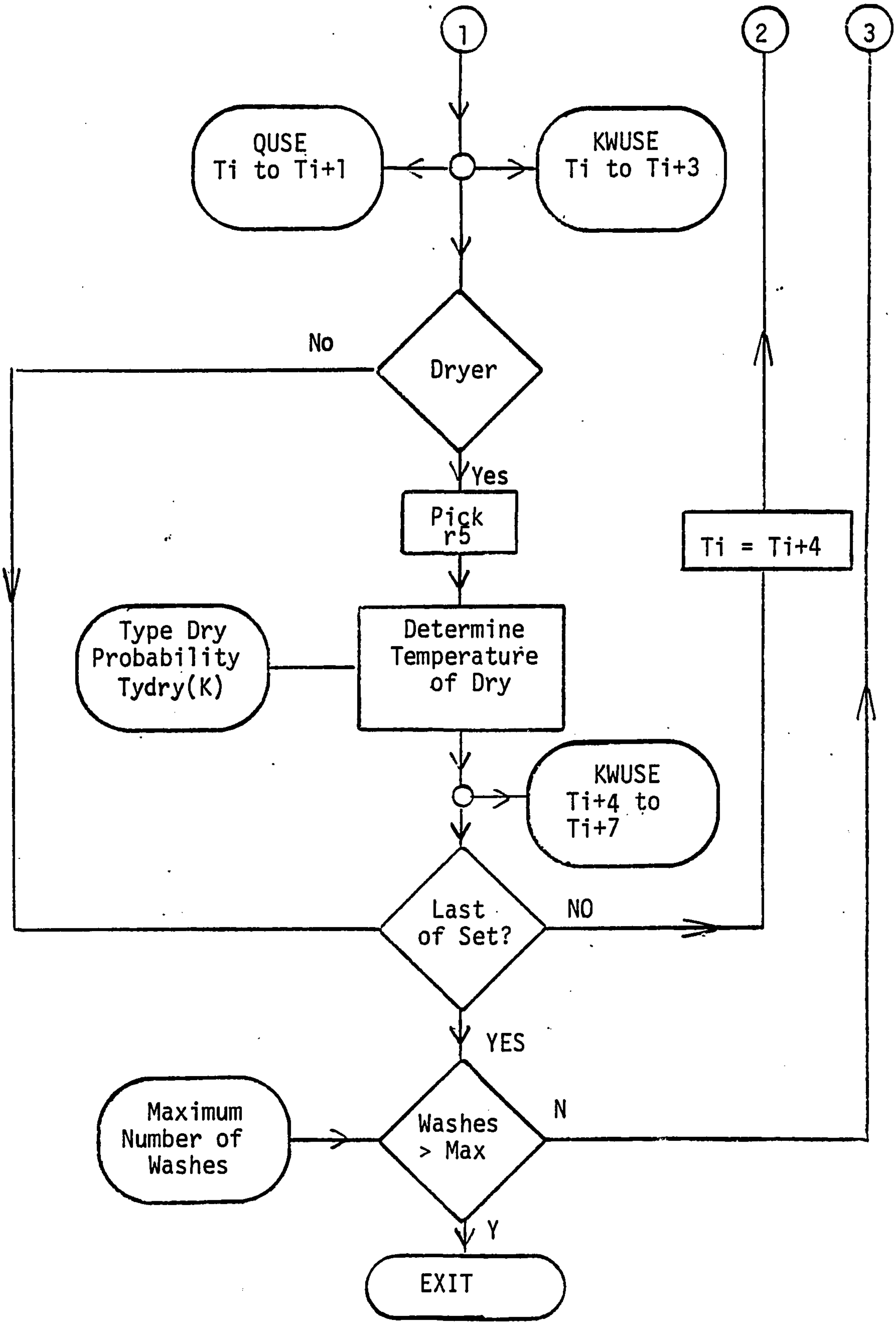


Figure 2.4.6.1 - Diagram for Clothes Washer and Dryer (Sheet 2)

2.4.8 The Water-heater Model

The water heater has a "normal cycle" which causes it to turn on and off when a thermostat senses a fixed deviation below or above a desired (set) temperature. The hot water is drawn from the top of the tank and the cold replacement water is introduced at the bottom of the tank. Although some diffusion can be expected, the tank basically operates in a stratified mode. This allows a type of operation called off-peak in which the water is heated by a low-wattage (1000 to 2000 watt) element during the hours between 9PM and 6AM when utility demand is low. A reduced rate is charged for this service. A large tank (80 gallons minimum) is usually required by the utility for this service and a larger element which can operate at any time is provided in the top of the tank. This allows heating of the upper portion if more hot water is used than was stored off-peak. Public utilities indicate that for this type of water heater 88% of the electric energy is used off-peak and only 12% is used during the day (on-peak). This seems to justify stratification principle use in the devleopment of the "normal-cycle" part of the model for the water heater.

The off-peak water heater is not the most prevalent type of water heater (because of its size). More prevalent is a two element type with equal elements. The lower element keeps the whole tank hot and the upper element only operates when so much water is used at one time that even the upper portion of the tank drops below the desired water temperature. Public utilities give a special rate for this type of service, called "quick recovery", if the tank used is larger than a certain minimum size.

There are also small tanks using one element, mostly in older mobile homes.

Modern water heaters have submerged elements which are very efficient. There are older heaters, some of which are still in use, that use an external element which heats the water by heating the bottom of the tank. The developed model is based on the submerged element type but an efficiency factor could be added to account for the older type.

The model simulates two element water heaters. Both the off-peak and the quick-recovery types can be simulated. Standard size water heaters with "average" size elements have been included. As in the other models these values can be readily changed. Other factors and approximations used in the model are listed below:

1) The model operates on the basis of a summation of heat used, lost and added, in BTU. Heat is used when hot water is used, heat is lost through the insulation and heat is added when an element is turned on.

2) The heat capacity of the water heater is determined by its liquid capacity and the difference between the desired water temperature and the temperature of the cold make-up water.

3) In a two element unit the upper thermostat (and element) controls the upper third of the tank and the bottom thermostat (and element) controls the lower two thirds of the tank. This is to be interpreted in the sense that the upper element will not come on until all the stored heat in the lower part is exhausted.

4) The assumption is made that when an amount of heat is removed from a section that would lower the overall section water temperature by the lower differential temperature, that element will be energised. It will stay on

until enough heat is added to raise the sections temperature to the set point plus the differential. This approximation is considered consistant with placement of the elements and the water heater heat balance.

5) The water heater cycle has been set at 5 minutes (i.e. 3 times in each period) to minimize temperature overshoots for large element sizes and undershoots for large water use.

6) The heat loss through conduction is based on the amount of hot water left in the tank. This is mainly significant for off-peak water heaters where the amount of hot water in the tank varies appreciably throughout the day.

To indicate the actual model complexity for the water heater, its block diagram is shown in Figure 2.4.8.1. The stochastic use function is described in Section 2.4.8.1.

2.4.8.1 The Hot Water Use Function. Water heater operation depends primarily on when hot water is used, except for the off-peak heater which operates primarily after 9PM. In order to complete the modeling of the water heater a "hot water use" function was developed. Some of the inputs were mentioned previously in the dishwasher and clothes washer models. Other important inputs include hand washing of dishes, wash basin use and bath/shower use. Figure 2.4.8.1.1 is a block diagram of the "hot water use" function showing the inputs that have been included in the model. A separate hand clothes washing use was not included because of the saturation of washing machines and the avaiaability of laundry centers. However since the final input is a summation of the various uses during each time period, additional sub-functions can be easily added.

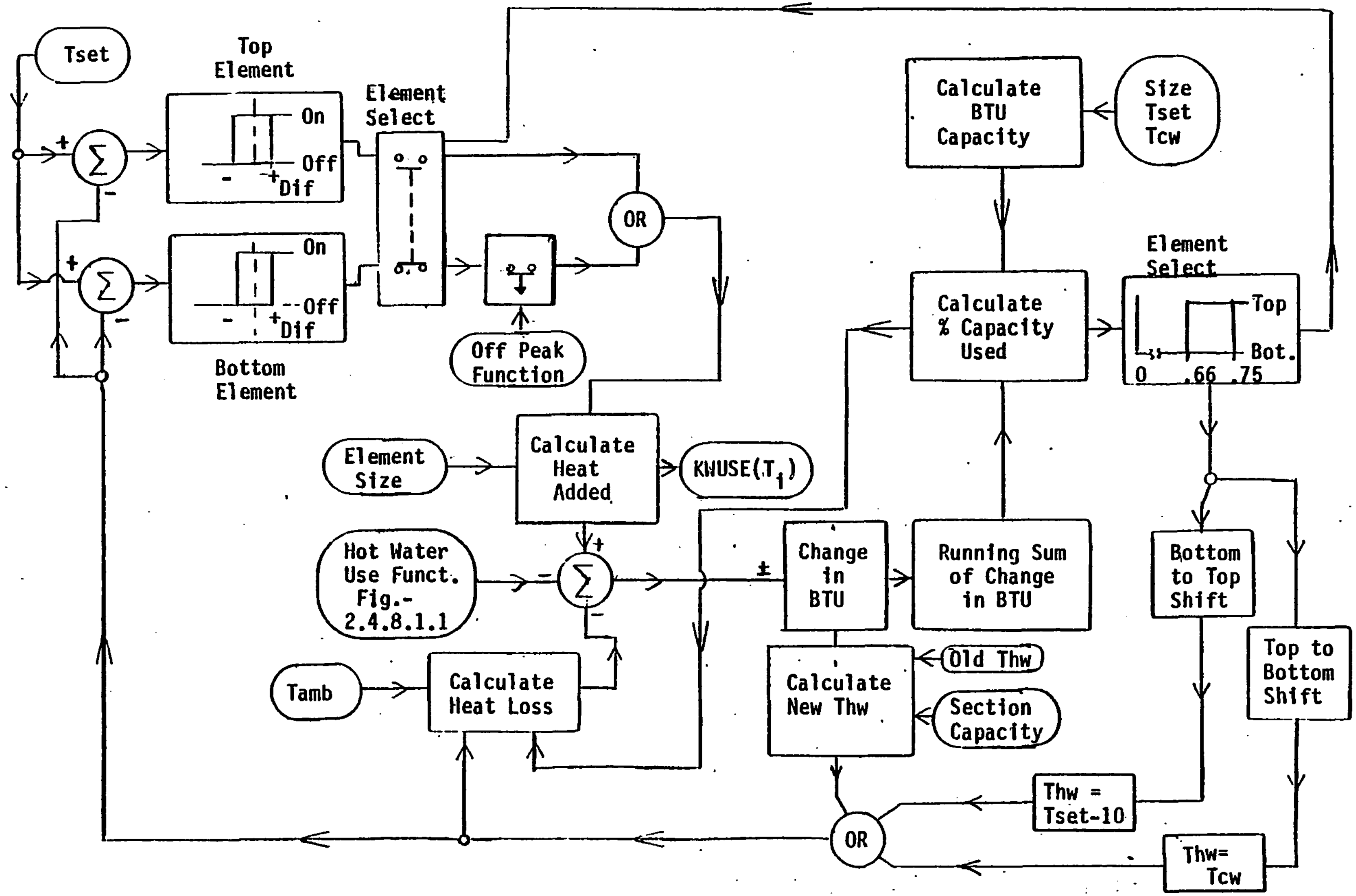
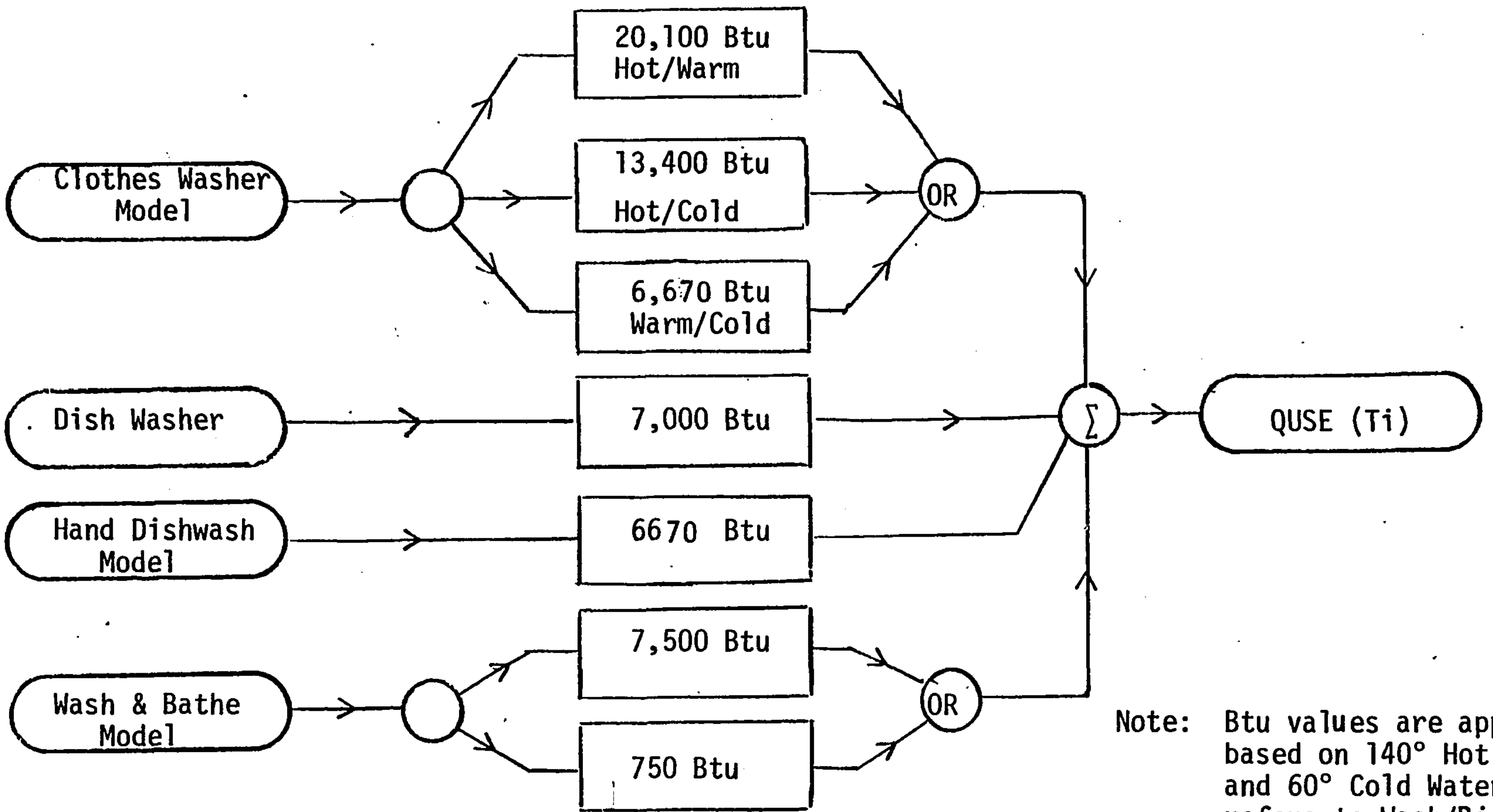


Figure 2.4.8.1 Diagram of the Water Heater Model



Note: Btu values are approximate based on 140° Hot Water and 60° Cold Water. Hot/Warm refers to Wash/Rinse temperature.

Figure 2.4.8.1.1 - Stochastic Inputs to Hot Water Use.

The amount of heat required by each use is based upon the average amount of water needed for a particular use, the temperature at which it is used and the temperature of the cold water entering the heater. Values for the amount and temperature of the water for various uses are based on data given in Hutton and Dillon [22]. Thus:

$$\text{Heat Use (BTU)} = \text{gallons use} \times 8.34 \text{ lbs/gal} \times (\text{Temp. of Water} - \text{Cold Water Temp.})$$

which for wash basin use is:

$$\begin{aligned}\text{Heat Use (BTU)} &= 2 \times 8.34 \times (105^\circ \text{ F} - 60^\circ \text{ F}) \\ &= 750 \text{ BTU/use (for TCW} = 60^\circ \text{ F)}\end{aligned}$$

As previously indicated the time of hot water use for the clothes washer and the dishwasher are determined by their proclivity functions. The wash basin and the bath/shower sub-functions were combined in one function. A flow diagram of the wash and bathe function is shown in Figure 2.4.8.1.2. It is based on the following reasoning and assumptions:

1) That people normally wash their hands before and after eating. Considering that the mealtime spans an average of six periods for each meal there is a probability of 2/6 that a person will wash during each period. This has been weighted toward the beginning and end of each mealtime. The factor is designated Pwashm and is equal to zero outside of the meal periods.
2) Each person is independent so that a test (comparison to a randomly drawn percentage) is made for each person at home.
3) In addition, a probability of two additional random washbasin uses per person per day has been assumed. This yields a probability of 2/96 of wash basin use in any period by each

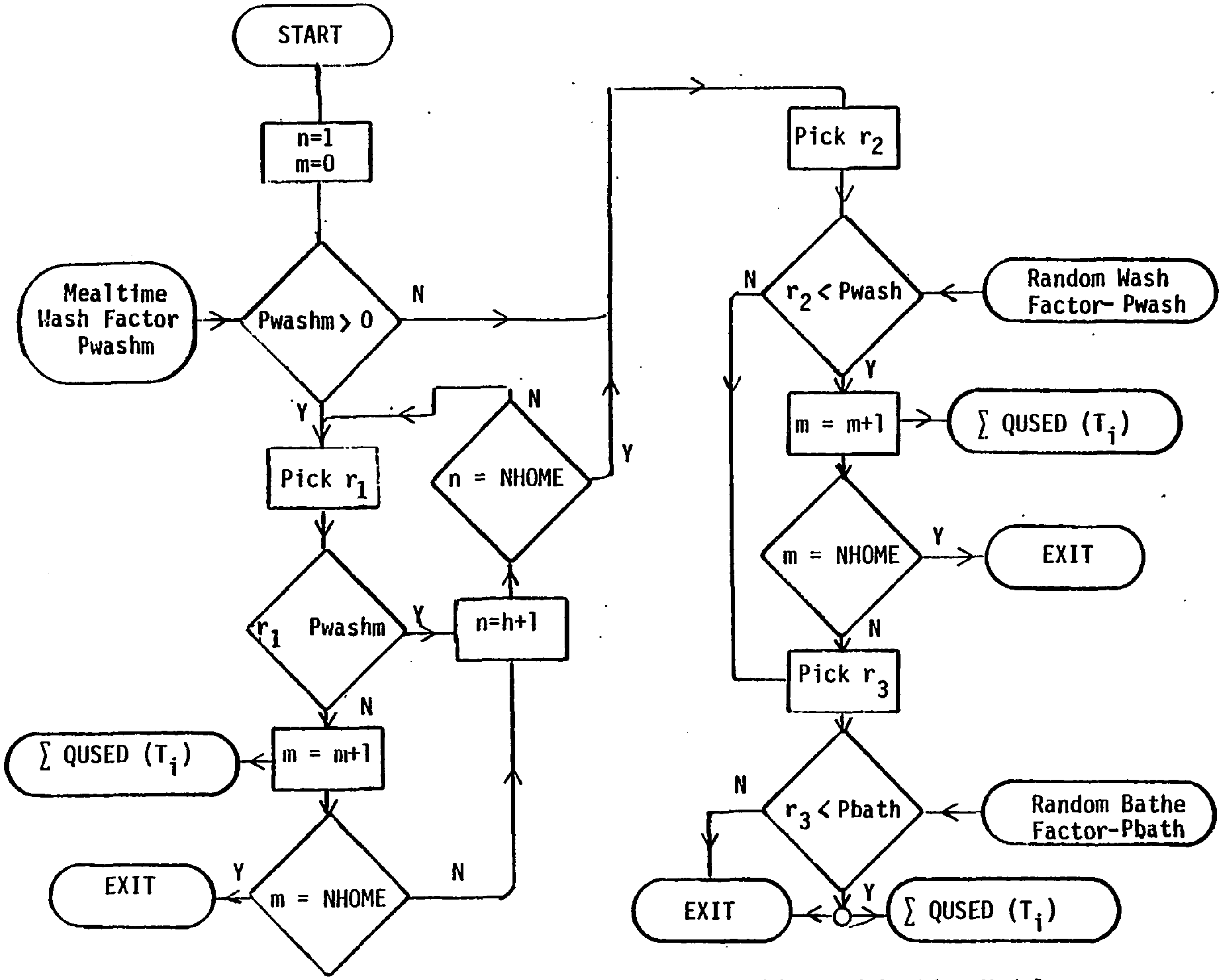


Figure 2.4.8.1.2 Diagram of Hand Washing and Bathing Model

person. This is multiplied by the number of persons at home to give the probability of wash basin use, Pwash, during a particular time period. This is tested against a random percentage. A "children" factor increases the average amount of hot water used for hand washing.

5) Bath/shower use is modeled by assuming an average of 5 uses for person per week. (This number is easily changed). This yields an unweighted probability of 5/672 where 672 is the number of periods in a week. This is weighted by (assumed) time of day and day of week preferences. When multiplied by the number of people at home it gives the probability of bath, Pbath, use in a particular period. (The daily total number of baths is also limited to one per person per day).

A function for hand dishwashing was also developed since the saturation of dishwashers is only 42% (see "Merchandising" [17]), and even when a dishwasher is available it is not always used. A block diagram of this function is shown in Figure 2.4.8.1.3 and is based on the following assumptions:

1) If there is no dishwasher or if it isn't used, the dishes will probably be done after each meal that is eaten.

2) The probability, Dadish(MT), of doing the dishes is different for different meals.

3) When they are done, the dishes are washed about an hour after the meal start (i.e. (MTime (MT)+4), where the value of MT designates the particular meal.

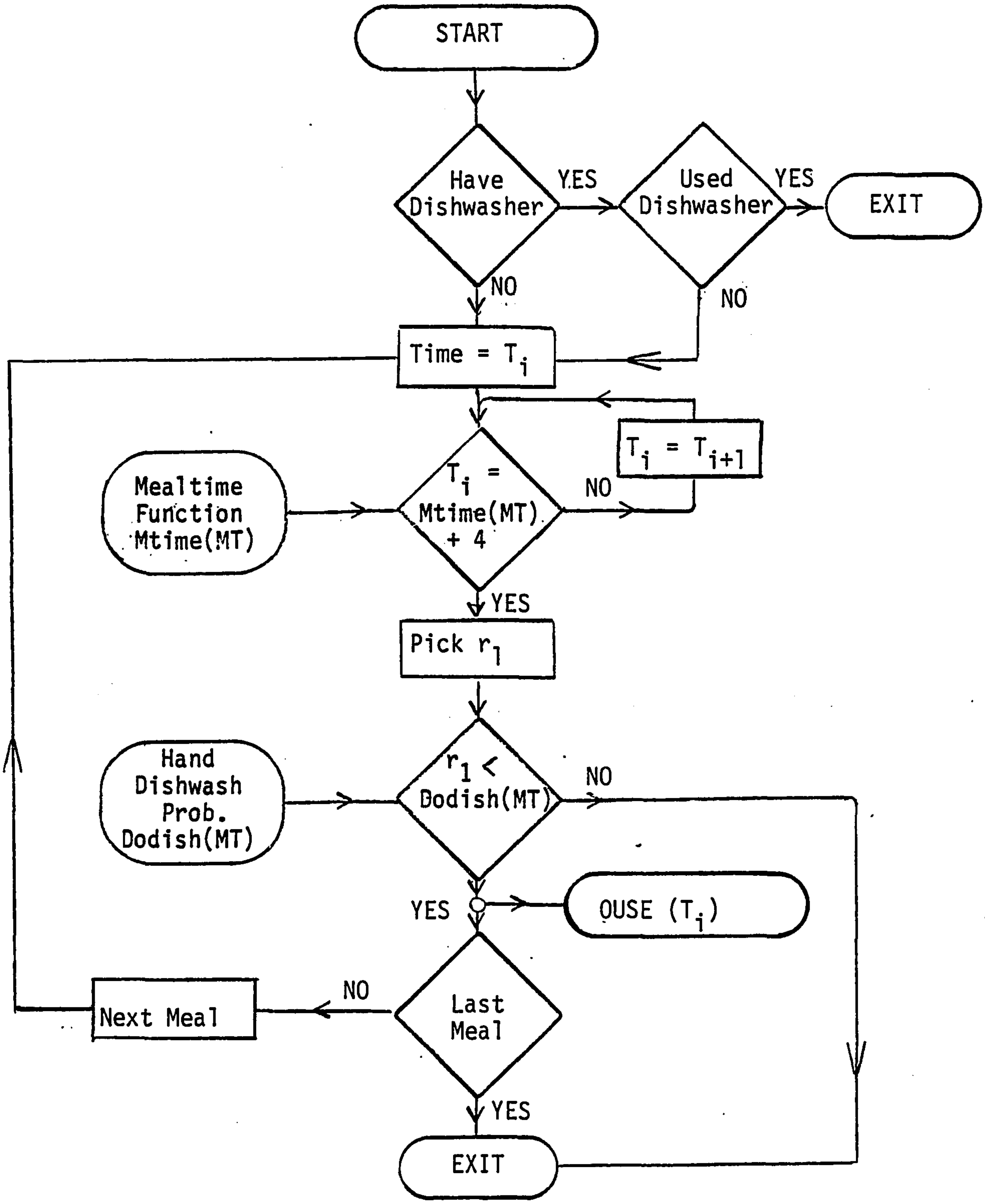


Figure 2.4.8.1.3 - Diagram of Hand Dishwashing Model

2.4.9 The Freezer Model

The normal-cycle function of the freezer model is essentially the same as the refrigerator normal-cycle function. The parameters are chosen to suit the different compartment temperature, insulation and compressor size. The freezer is often kept in an area whose ambient temperature is less than the house temperature (i.e. a basement) so that heat gains are less. The two basic types, upright and chest, gain different amounts of heat through door openings but the use function is much less than for a refrigerator.

The freezer model assumes that most of the energy is used to remove heat gained through the walls and gaskets. The use function is based on an estimate of three openings a day. A loading function based on one loading a week has been considered for a future addition but is not presently included. The model diagrams are similar to those for the refrigerator which are shown in Section 2.4.3.

2.4.10 The Air-Conditioner Model

The residential air conditioner can be a central (whole house) or unit (room) type, the predominance depending on the area weather. In either case some simplifying assumptions are needed for a viable model. If it is assumed that the size (maximum capacity) has been selected to cool the required area under the most severe (design) weather conditions, then the cooling load during any period is some fraction of the maximum capacity. The cooling load is determined by the outside temperature and solar radiation but lags the present conditions due to the residence construction and heat storage capability. The cooling load can be estimated by relating the outside weather to the design weather. The electrical power consumption can then be estimated from the cooling load and the energy efficiency rating (EER) of the unit.

Three functions "drive" the air conditioner. In hot weather areas the predominant function is the weather function. In temperate areas, where the air conditioner is not required constantly, the availability and proclivity functions would normally determine when the air conditioner was turned on. Once turned on, the weather function will have a large influence on how long it is left on.

To model an "average" residence the predominant size air conditioner for the area must be estimated and the proclivity function developed. The later will have some basis in the "comfort index". As previously indicated, the air conditioner has not been modeled.

2.4.11 The Fan Model

Due to radiation on sunny days additional heat enters the house through windows. Radiation also causes the outside surfaces of the residence to be at a higher temperature than the outside air. The inside temperature can therefore become higher than the outside air. Under these conditions attic and window fans are often used to reduce inside temperatures, especially in the afternoon and evening.

Large window fans (20 inch) use about 200 watts of power and represent a constant load. Attic fans, used in some residences, are usually larger and sometimes thermostatically controlled. The saturation of attic fans in the survey area [1] was only 10% and are not included in the model. The saturation of window and other fans was 70% and are modeled. A time of day function based on the percentages given in the survey data was used. This function indicates the fan is more likely to be used in the afternoon and evening as expected. In the model a test is also made to determine if the inside temperature is higher than the outside temperature and if it is greater than 75 degrees F. A preliminary diagram for this model is given in Figure 2.4.11. The model requires further evaluation and testing.

2.4.12 The Electric Heat Model

A model for the electric heat load of a totally electrically heated residence relates the electric energy required for a period to the heat loss of the residence for that period. The heat loss for the "whole house" can be estimated based on the house geometry, the insulation values, the windown treatment and the inside-outside temperature difference. Some time lag will result with changing temperature due to the heat storage capability of the house. In a simplified approach which neglects the temperature swing about the thermostat setting, the function driving the model would be the predicted outside temperature and the thermostat setting. For different residences both the "daytime" and "nighttime" settings will have a range of values based on a resident preference probability. The switching from "daytime" to "nighttime" settings would be governed by the availability function, considering that if no one is home the nighttime setting would probably be used. For a resistive type heating system the heat loss can be converted directly to a kilowatt load for the period. For a heat pump system a factor based on the outside temperature is also needed.

A comprehensive residential electric heating load model must also consider the tendency to leave areas unheated and to use auxiliary heat sources. A comprehensive model may not be practical for electric heating

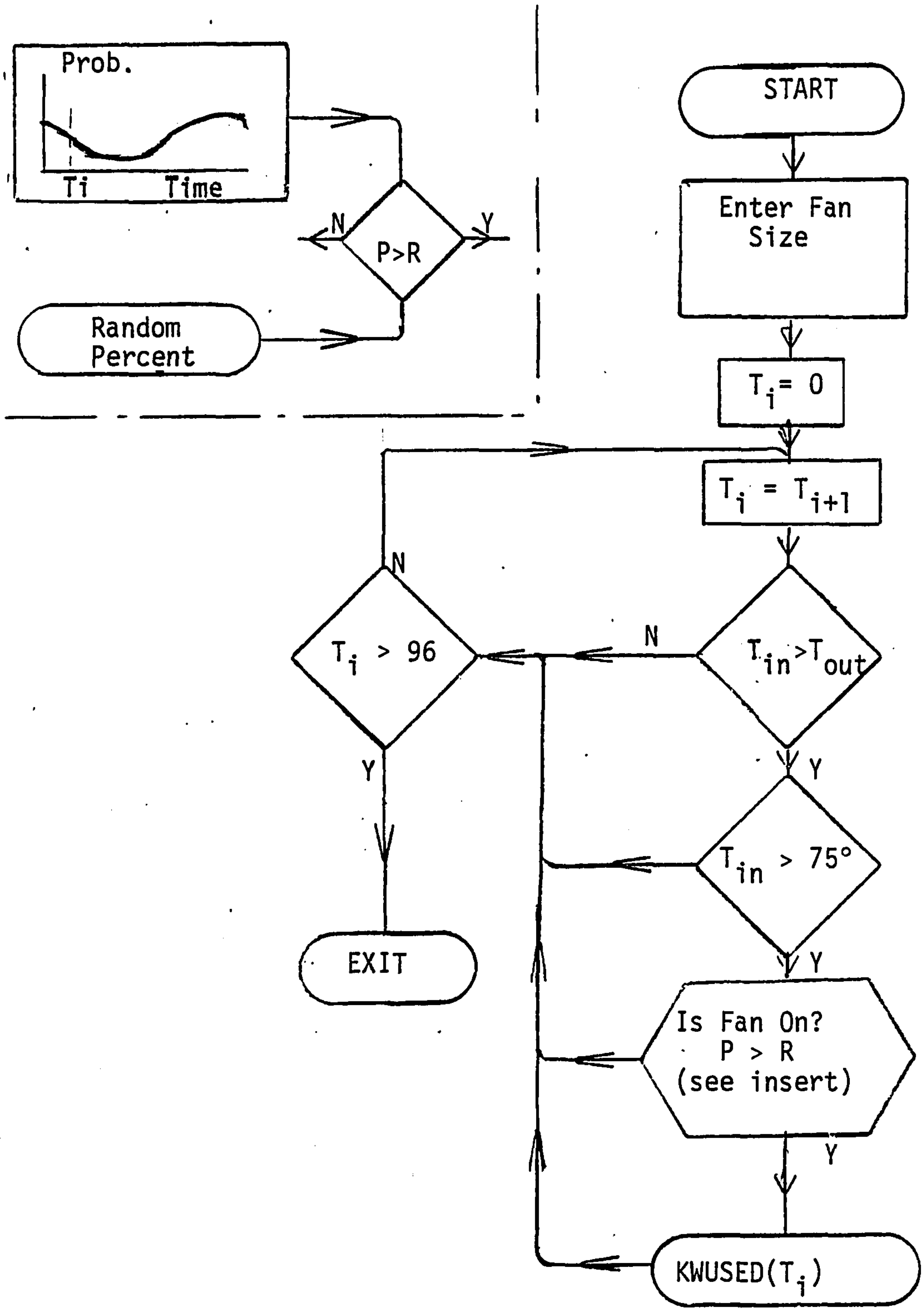


Figure 2.4.11 Diagram of Fan Model

for this reason but a possible approach would be to introduce a "use factor" to modify the "whole house" loss to account for the unheated areas and a function to describe the heat added by the auxiliary source in each period. The electric load would then be based on the net heat required for the period. Determining and modeling the distribution of the "use factor" and the distribution and time dependence of the auxiliary heat function are subjects for future work.

2.4.13 The Humidifier/Dehumidifier Model

The humidifier operates primarily during the winter months. Low humidity in a residence is normally the result of infiltrating cold outside air being heated to the inside temperature. Very low humidity results when the outside humidity is low and is particularly severe in residences having forced hot air heating systems.

Residential humidifiers are of many types including passive units installed in the ducts of hot air systems. Electrically operated units range from simple vaporizers to large (18 gallons per day) automatically controlled units.

No saturation data for humidifiers is available in Merchandising [17]. The survey data [1] indicates that the percentage of residences having humidifiers is small (17%) but, where installed, have an 82% probability of being on approximately 20 hours a day. Even the largest units do not represent a very large load (approximately 100 watts) but the load is constant. Therefore a simplified model is included.

The dehumidifier operates primarily during the summer months. High humidity in a residence results from dampness entering through the basement walls, water using activities such as showers, clothes drying and high outside humidity. High humidity in the above ground spaces is often accompanied by high temperatures and is usually reduced by the use of air-conditioning. High humidity in below ground spaces is usually associated with moderate temperatures and is normally reduced by use of dehumidifiers. The saturation of dehumidifiers is approximately 40% nationwide [17] and in the survey area [1]. The survey data indicate a use of about 19 hours a day with the use probability ranging between 75% and 90%. Dehumidifiers represent a more substantial load than humidifiers since they contain a refrigeration unit. They are included in this simplified model. A diagram of a possible model is given in Figure 2.4.13. The model checks to see if the unit is turned on by comparing the appliance use probability, Phon, to a random number. If the unit is turned on an automatic unit is controlled by the humidity, while a manual unit runs continuously. Only a manual dehumdifier is included in the model at this time.

2.4.14 The Swimming-pool Model

For in-ground pools and for large above-ground pools the water filter pump represents a large continuous load. Filters can be run 24 hours a day but are normally run only as long as required to give satisfactory water conditions. Usually this is about 12 hours a day in the survey area based on manufacturers recommendations and electric utility estimates of monthly energy use [20]. The unit may be left off during inclement weather or for other reasons and a random factor, Pswim, is used to determine if the pool is used, and if it is used, at what time it is turned off and on, has been included in the model.

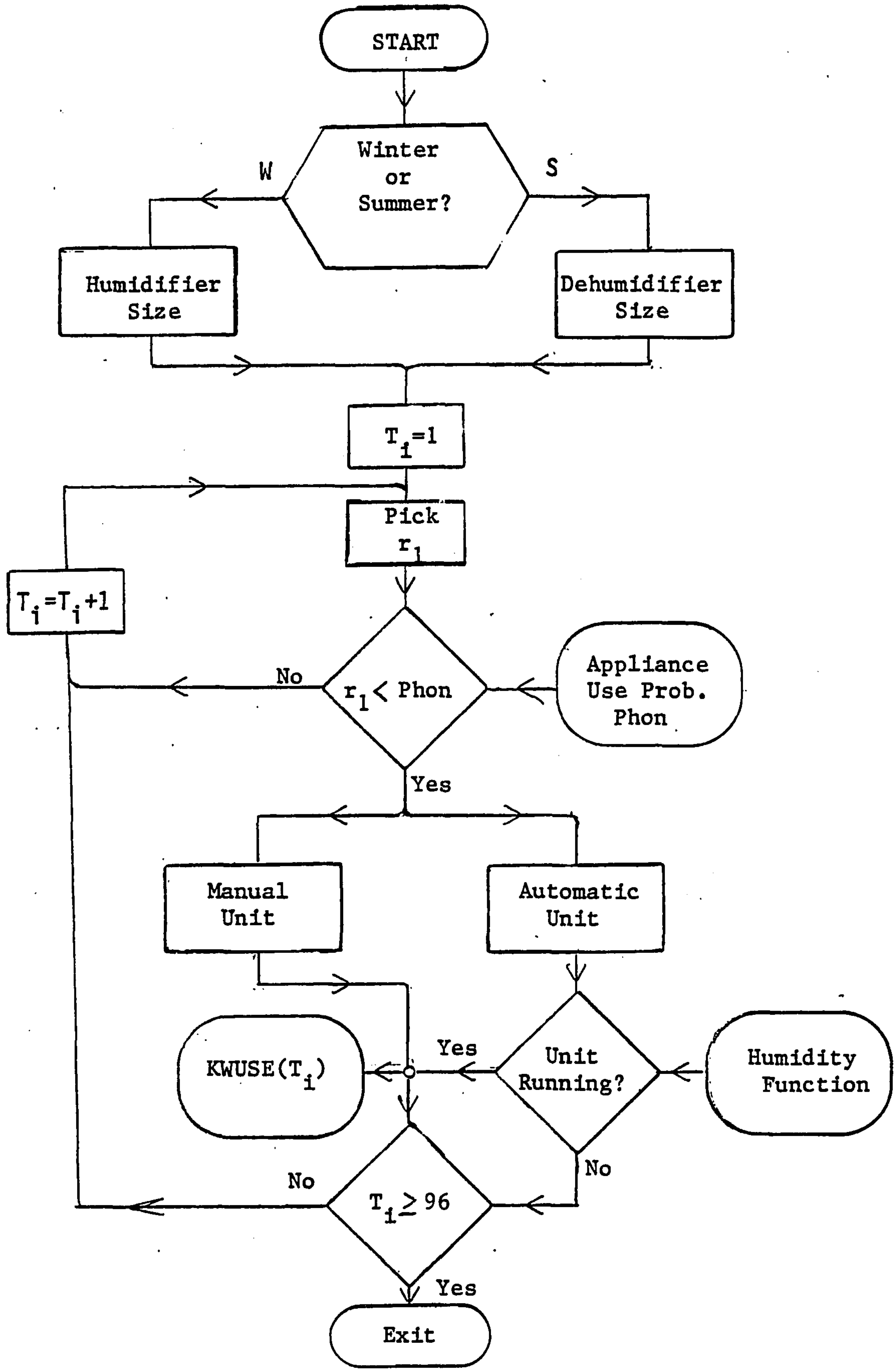
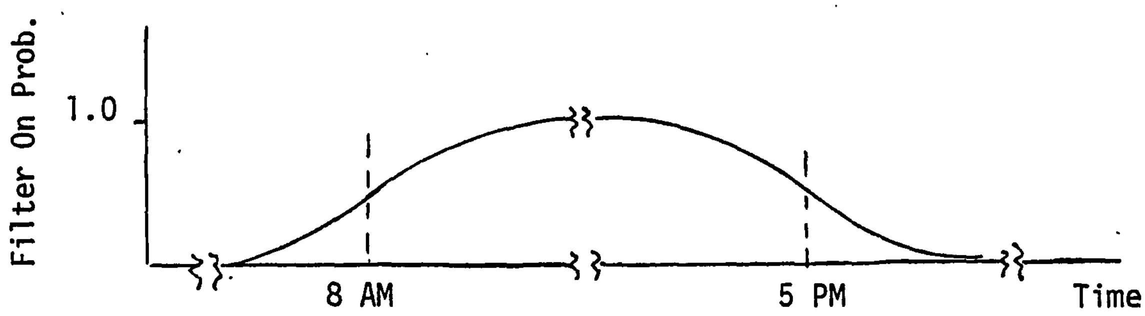


Figure 2.4.13 Diagram of Humidifier/Dehumidifier Model

The model is a simple one as shown in Figure 2.4.14. The turn-on time was assumed to have a normal distribtuion about 8AM and the turn-off time to have a normal distribution about 8PM. The standard deviation is taken as three time periods (3/4 hours). An average value of 600 watts was used as the filter electrical load. (All values are changeable).

This model was not included in the test.



Filter On Probability Function

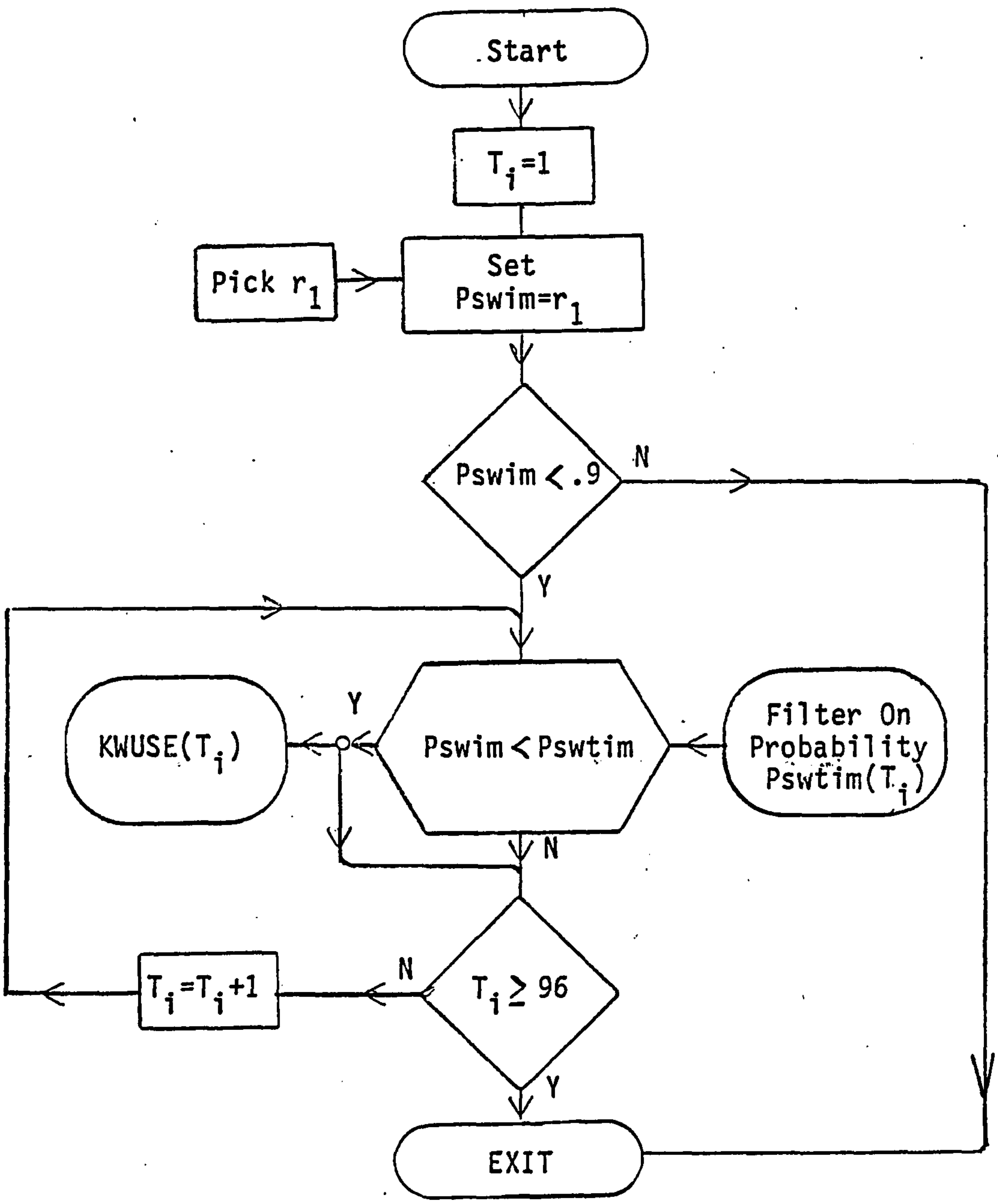


Figure 2.4.14 Diagram of Swimming-Pool Model

CHAPTER III

THE COMBINED MODEL

3.1 Considerations in Combining the Elemental Models

The number of persons available at home during a particular period affects the probability and the level of operation of appliances during that period. In addition, some functions, like the mealtime function, affect more than one appliance, such as the electric range, refrigerator and water heater, in the same or adjacent periods. Therefore the model was designed to operate each appliance model during each period, bypassing those elements that are not owned by the residence or elements like the dishwasher, which once operated, have constraints on the next operating time.

Some appliances, like a refrigerator, run different amounts of time during different fifteen minute intervals. In this case one call of the subroutine for the refrigerator model, when mixed with other pertinent information (e.g. meal times) generates the power demand for that device for that period. Other appliances, like a washing machine, overlap several periods, once started. In this case, the total energy is calculated during the first period, and the calculated amounts of power demand are saved for summation during later periods.

3.2 Implementation of the Combined Model

The combined model is implemented by a Fortran program which is included in Appendix A. Figure 3.1 is a block diagram outlining the basic sections of the program. The blocks have been numbered to facilitate the identification.

The operation of most of the blocks is self-evident. The data read in blocks 2 and 5 was generated by other programs and stored in files as outlined in Section 2.3.1. The files can be modified by running these programs with other statistical data. Block 7 "preserves" the running total when the load for a group or groups of houses is required. The computations of blocks 9 and 10, discussed in Sections 2.4.8.1 and 2.4.2 respectively, are statistical estimates. When the values are established they remain unchanged for the residence and are therefore included at this point.

Certain counters are used to keep track of operations on a particular day, such as dishwasher use or next mealtime. Block 12 resets these counters to zero for the next day.

Blocks 18 and 19 calculate the next mealtime when the time is one period before the earliest time for that meal, (i.e. based on the mealtime statistics used the earliest breakfast time would be 4:30 AM, time period 18).

Blocks 21 and 22 set the pattern for all appliances. The calculation is bypassed if the appliance has not been specified in the residence parameters. Otherwise, the probability of the appliance being in use is examined. If the appliance is used the resulting load is computed and stored. The stored data is combined and is output at the end of the run or sets of runs.

Hotwater use, estimated by Items b, c, d and e of Block 25 are totaled in Item f for use in computing the power demand of the hotwater heater, Item g.

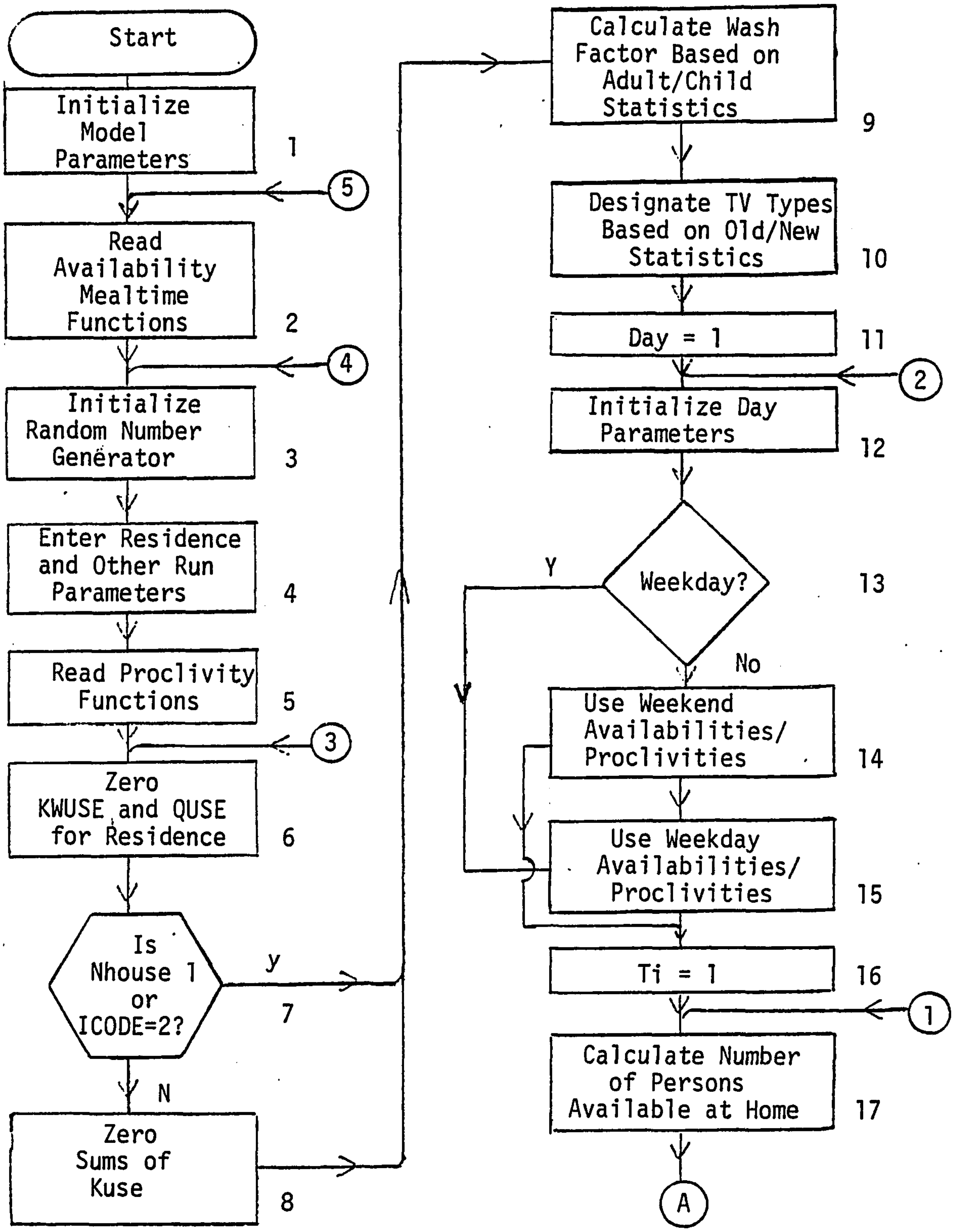


Figure 3.1 Flow Diagram for Combined Model (Sheet 1 of 3)

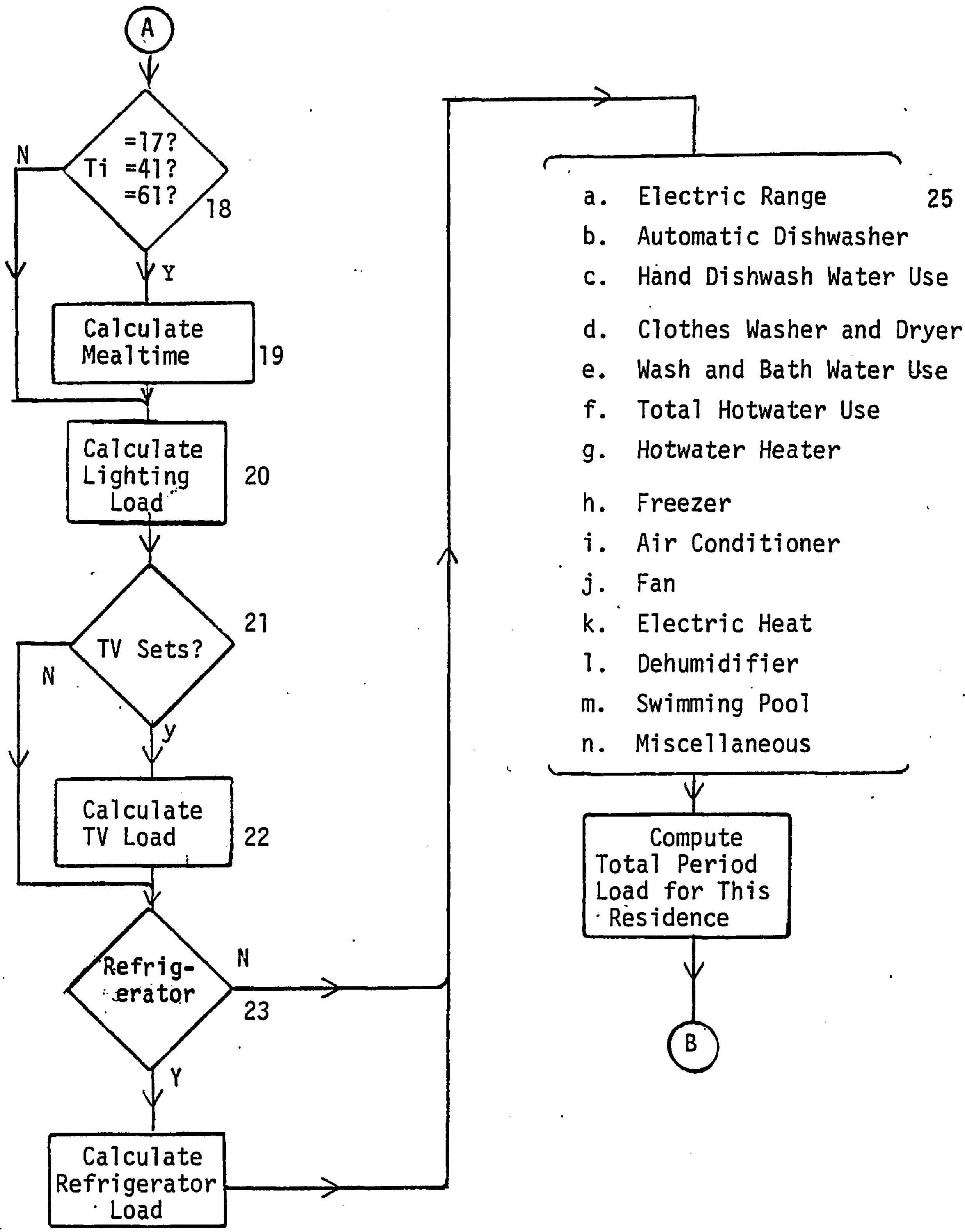
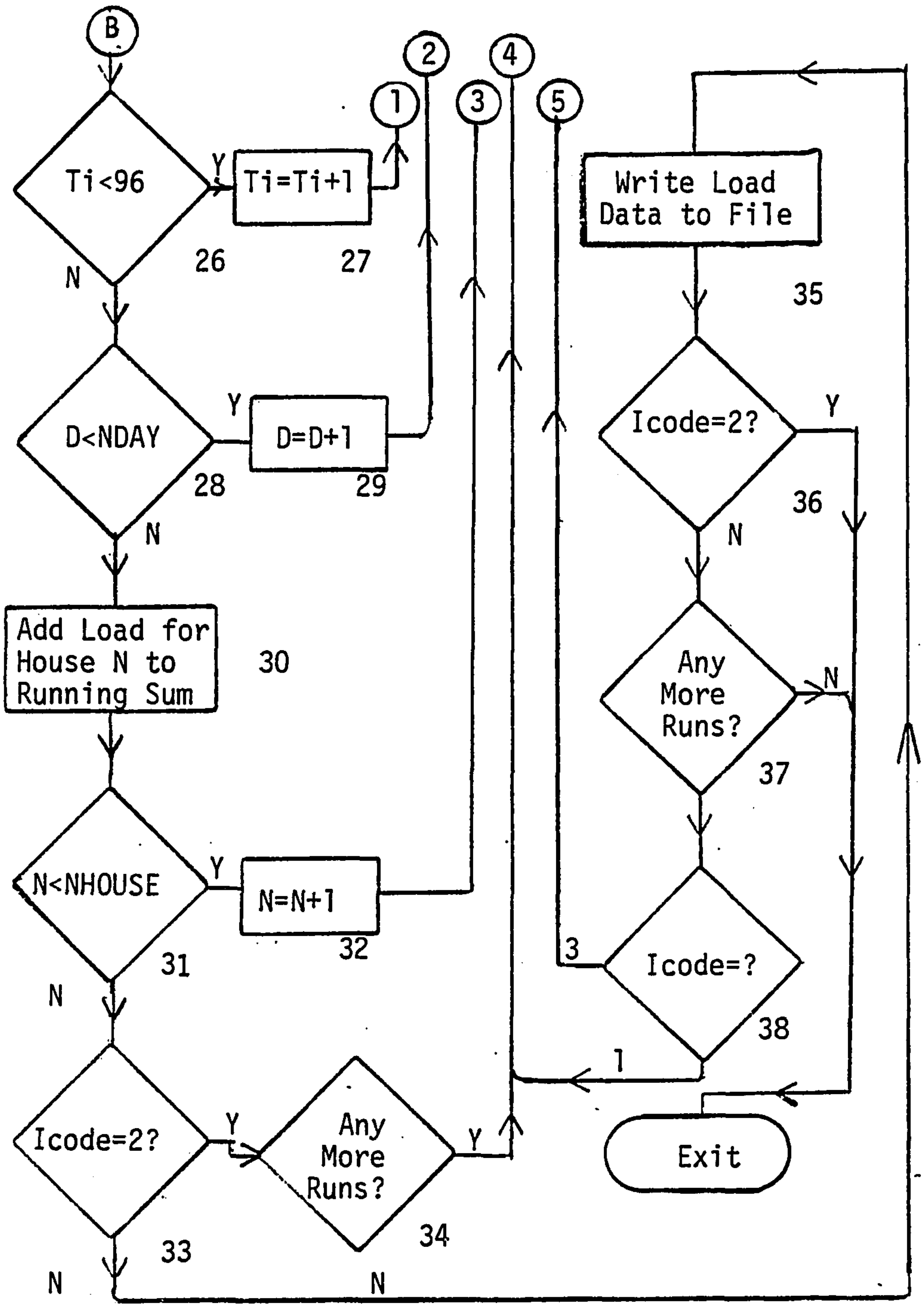


Figure 3.1 Flow Diagram for Combined Model (Sheet 2 of 3)



Lendend: Icode 1 - Same Availability Function - Separate Totals

Icode 2 - Same Availability Function - One Total

Icode 3 - Different Availability Functions - Separate Totals.

Figure 3.1 - Flow Diagram for Combined Model (Sheet 3 of 3)

3.3 Totalization of Results

A "run" consists of a number of houses of one configuration, usually for seven days. For "Icode=1", the total is written to file after each run and the next run uses the same availability function. For "Icode=2", the totals are written to file after all runs are completed, and all runs use the same availability function. "Icode=3" provides for separate run totals with different availability functions for each run.

3.4 Summary

The combined model brings together the variables and parameters which are common to many of the elemental models. It allows residences with various configurations of appliances to be modeled. It provides for combining different configurations into a group model by totaling the results of a number of runs. It also provides for output of the data for analysis and plotting.

CHAPTER IV

MODEL EVALUATION

4.1 Considerations in the Evaluation

The time-varying electric load for a single family residence depends on many probabilities as discussed in the model development, Chapters II and III. Consequently it is reasonable to expect that the load curve for a particular residence, while maintaining certain general characteristics, will not have the same shape each day. Also, the amount of variation in the hour-by-hour and day-to-day load curves depends, to a large extent, on the types of electric appliances owned by the household. A household with few electric appliances will have a relatively small time-of-day and day-to-day variation. On the other hand, residences with many large appliances can be expected to have larger variations in their load curves, since larger loads, such as washers and dryers, are connected for relatively short periods of time and are normally used only once or twice a week. As another example a water heater element can require 5000 watts but may only be on for ten or fifteen minutes at a time.

In accordance with the "law of large numbers" the average value of a large number of observations of a stochastic process will approach the "expected" value (probability) as the number of observations increases. (See Schmidt [16]). If the availability and proclivity functions, postulated in the model development, are significant factors in determining residential load variation then the average of a number of days for one residence should agree more closely with a similar average for the test data than do the daily load curves for that residence. Also, on an ensemble basis, the load curve for a group of similar residences for a particular day has the expectation of being in closer agreement with their load curve for a similar day, than will the curves for one residence.

4.2 Types of Measures

A model for the residential load based on availability and proclivity probabilities (assumed to be significant factors in the residential load) should display variations in the day-to-day load similar to the real load. Visual comparison will indicate if the general characteristics are similar but some quantitative method is needed to help determine the significance of the agreement between the model and the actual load curve. A variety of quantitative measures could be used depending on the primary purpose of the model. For example, only the daily peak load, or the weekly total load might be checked. On the other hand, a comparison each fifteen minutes may be important. One measure of agreement is how well the model can predict, on a day to day basis, the total energy used by a residence or group of residences. For a single residence the agreement can be expected to have a wide range of differences. However, the range should be at least of the same order of magnitude as the range of difference in actual day to day use of the residence being modeled. As the sample size is increased the day to day energy use should be more consistent (for similar weather conditions) and the model prediction should agree more closely.

Since a primary goal of the model is to predict the hour by hour variation in the load, some measure of the agreement for this aspect is also needed. Visual comparison of a model predicted load curve to a test data load curve will indicate if there is general agreement of characteristics. However, a quantitative measure is needed to determine improvement in the agreement as the test sample increases from a single residence to a group of residences. The agreement here should also be of the same order of magnitude as exists between test data for similar samples on similar days.

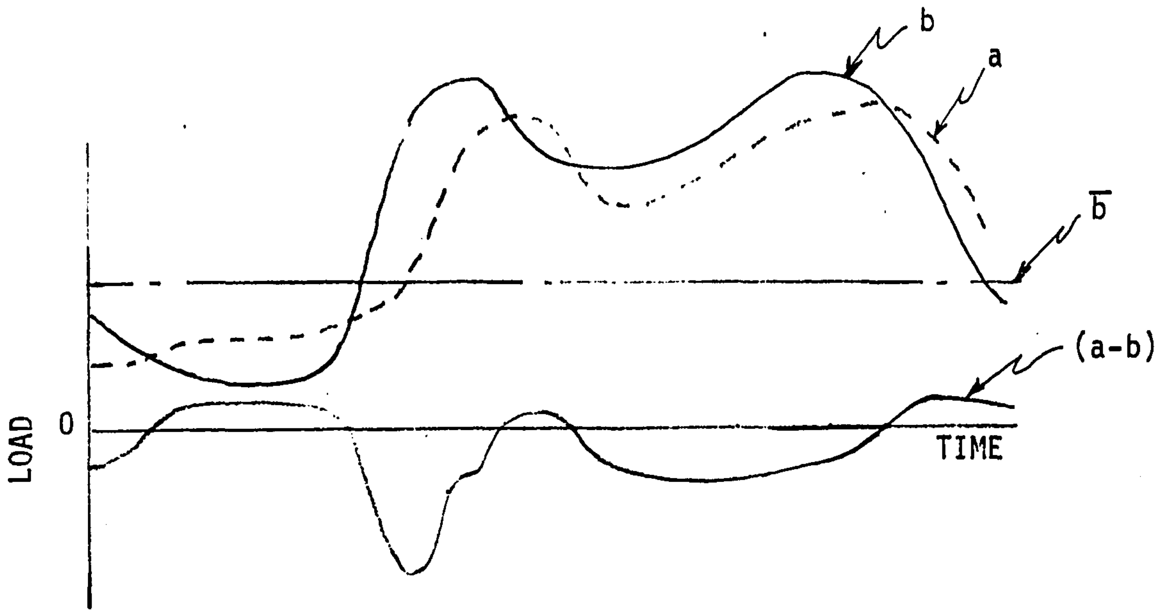
Standard methods of investigating the relationship between paired sets of data include regression analysis and cross-correlation. Both of these measures involve factors associated with variation of the model data from its mean as well as the variation of the test data from its mean. However, in determining how well a model prediction tracks the actual load, another measure, independent of the mean of the model, is more appropriate. The size of the variation of the model curve about the test data curve, defined as the sum of the squares of the point by point difference between the model and test curves, is a measure of how well the model performs on a time basis. A large variation indicates poor agreement while a small variation signifies better agreement. For a particular sample the variation of the model data from the test data should have values similar in magnitude to the variation between test data for similar days.

In order to compare the results of modeling different size samples, some method of normalizing the variation is needed. To divide the point by point difference by the point by point test data would result in unrealistic weighting for test data near zero. Therefore the average load, which is a measure of the load magnitude, was used as the normalizing factor. Figure 4.1 defines a normalized variation factor which is used in comparing the relative agreement of the model to test data for different sample sizes. A smaller normalized variation factor signifies a better agreement.

In order to have a more familiar standard by which to judge the significance of the normalized variation factor, graphs of the cross correlation between model and test data are also included for the group loads.

4.3 The Small Load Residence

Using the foregoing criteria the model was tested against test data from the Connecticut Light and Power Company Residential Load Test [1] for various types of loads. Figure 4.2 is a load curve for a small load residence. According to the survey data the customer (Identification number 1103011) lives alone and has appliances consisting of a refrigerator and a television set. However, there are peaks in the load curve around mealtime that indicate the customer has at least one cooking appliance not listed in the survey. Figure 4.3 is a load curve predicted by the model for this residence. Visually comparing this curve to Figure 4.2 shows that the model curve has characteristics similar to the customer load curve displaying periods where only intermitent refrigerator operation is indicated and periods where the more constant load associated with lighting and television are indicated. The customer's refrigerator is obviously smaller than the "average" refrigerator used in the model and the customer's availability is obviously different than that of the "general" availability function used. This is to be expected when comparing a particular test to a stochastic model. Better agreement, on a



a = predicted load curve

b = test data load curve

$\overline{b}$ = average load of test curve

n = number of periods

$$\text{Normalized Variation Factor} = \frac{\Sigma_1^n (a_i - b_i)^2}{n\,\overline{b}^2}$$

Note: A smaller variation factor signifies better agreement with the test curve.

Figure 4.1 Definition of the Normalized Variation Factor

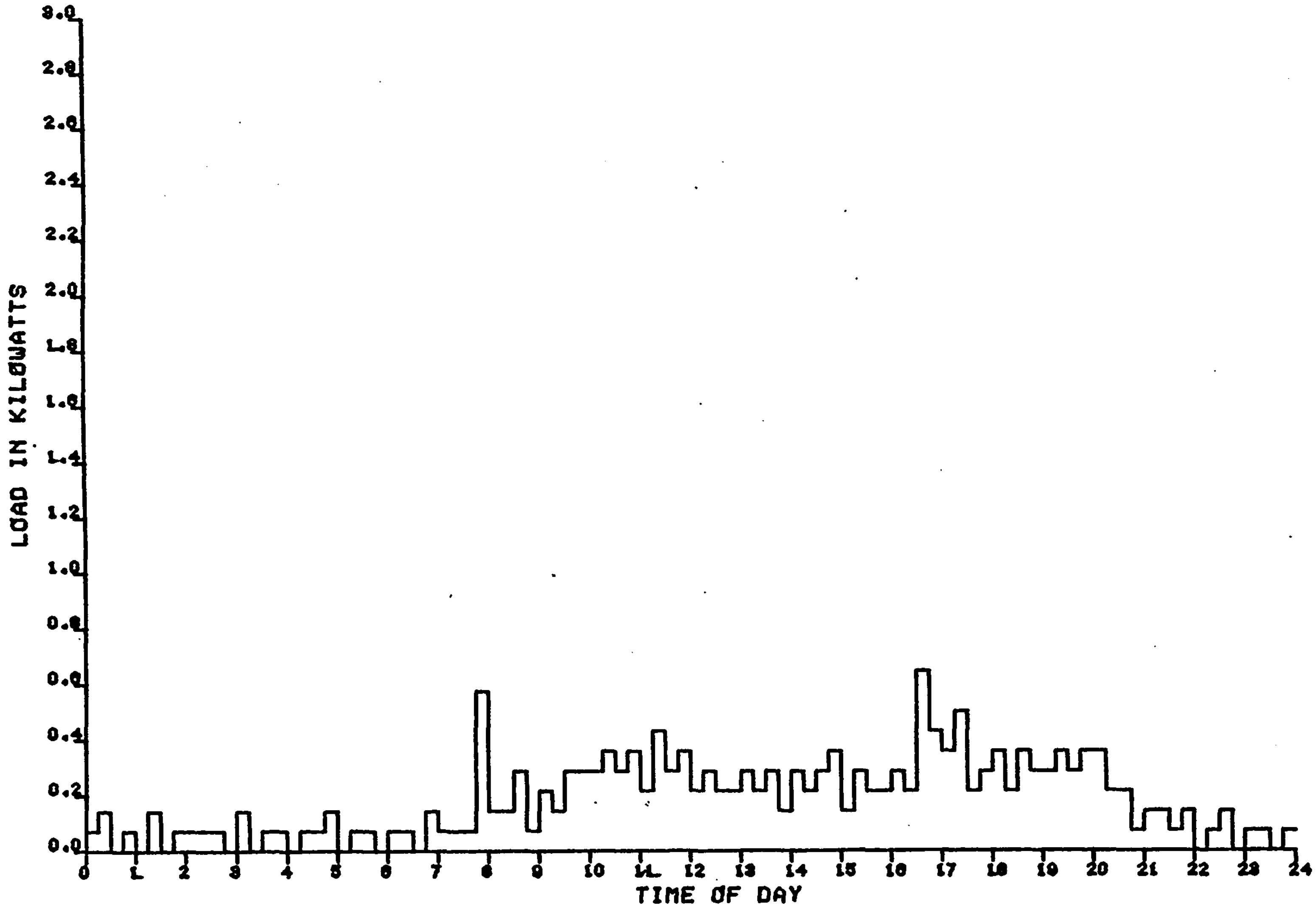


Figure 4.2 - Customer Load curve for a Small Load Residence

Test Data for Tuesday

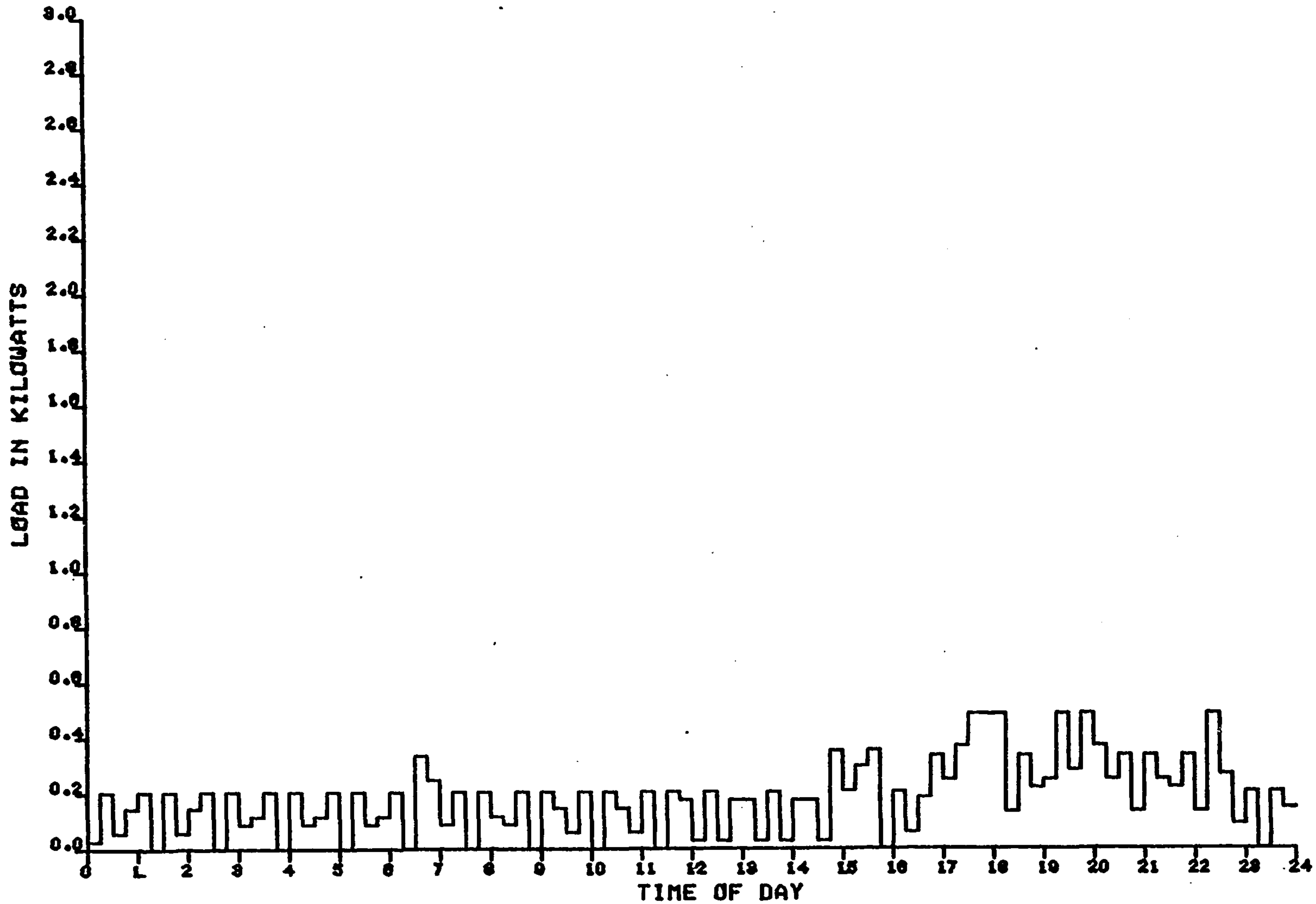


Figure 4.3 - Model Load Curve for Small Load Residence
Predicted Data for Tuesday

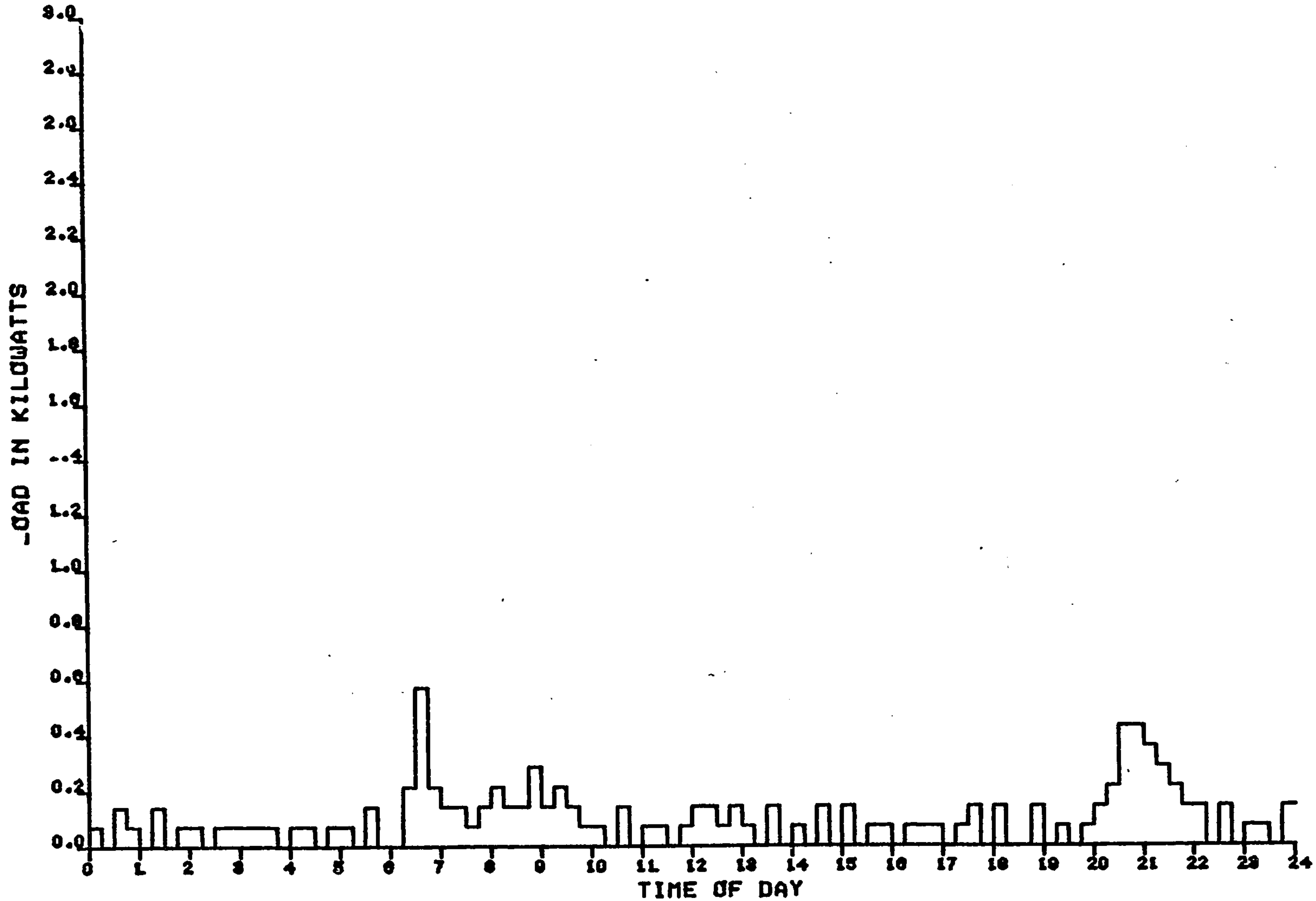


Figure 4.4 - Customer Load Curve for Small Load Residence
Test Data for Wednesday

one-to-one basis, can be expected using the same model with different refrigerator parameters and a particularized availability function. However the purpose here is to demonstrate that the model, even with general parameters, gives results which are not unreasonable. Figure 4.4 demonstrates that there can be wide differences in the load curves of the same customer on different days.

In addition to the load curves included herein, load data for the model and for the customers were compared for each day of a test week and for the weekday average of these load curves. (For the "large load" group, the model and test data load curves for the week are included as Appendix "D" for additional information). Comparison of the customer's load curves for different days was also made. Table 4.1 is a listing of the results of the evaluation for a number of different tests. Line 1 of the table is concerned with the small load residence test.

The energy use for the small load residence predicted by the model differed from the actual energy used by the customer by percentages ranging from approximately 2 percent to 163 percent. The energy used by the customer differed by percentages ranging from 3 percent to 165 percent when comparing the energy used on different days. (The 165 percent is the result of comparing the difference between days to the low value day). Thus the model energy agreement has about the same range as the day to day difference in the test data. This is not unexpected in a stochastic process. The difference, 23 percent, between the weekday average energy use for the model and the customer lies in the lower end of the range as could be expected with a larger sample.

The normalized variation factor exhibits similar characteristics. The range of the factors obtained for the variation of the model curve

	DAILY ENERGY USE Range of Differences			NORMALIZED VARIATION FACTOR Range of		
	Model to Customer Day to Day	Different Customer Day	Model to Customer 5 Day Avg.	Model to Customer Day to Day	Different Customer Day	Model to Customer 5 Day Avg.
1. Single Residence Small Load	2-163%	4-165%	23%	5.8-.7	8.14-.65	0.4
2. Single Residence Large Load	1-44%	4-58%	20%	1.83-.69	1.65-.66	0.29
3. Residence Group Small Load	1-17%	0-19%	1%	.21-.09	.15-.07	0.07
4. Residence Group Large Load	1-22%	0-13%	11%	.13-.08	.05-.03	0.08
5. Residence Group (Sum of Small and Large Load Groups)	1-20%	1-22%	8.1%	.10-.06	.07-.02	0.06

Table 4.1 - Summary of Daily Energy Use Differences and Normalized Variation Factors

about the test curve is slightly lower than the range of factors relating one test curve to another. However the ranges are very similar indicating that the model is capable of predicting the variation, for this sample, at least as well as the variation between test days. The variation factor, 0.4, which compares the model weekday average to the weekday average of the test data is lower than the range of single day values, indicating better period by period agreement. Since increasing the sample size in a stochastic process has the potential for smoothing the variations, the lower variation factor is consistent with expectations. The value should be at least in the lower end of a wide range to be significant.

4.4 Large Load Residence

Line 2 of Table 4.1 contains similar comparative data for another single residence, Customer ID 1300151. Figure 4.5 through 4.7 are load curves for this residence which has a larger electric load and a family size of five. The electrical appliances include two refrigerator-freezers, a freezer, two television sets, an electric range, a clothes washer and dryer, a dishwasher, a water heater, two air conditioners and a dehumidifier. The model was compared to customer data for September in order to minimize the effect of cooling load and does not include operation of the air conditioner. Weather data indicated cool, humid weather; therefore the dehumidifier was included in manual operation.

The second line of Table 4.1 shows that the range of the difference between the daily energy use predictions and the test data is 1 to 44 percent while the range of differences between test data for different days was 4 to 58 percent. For both cases the range is about 1/3 of that found for the small load residence. Again the percent

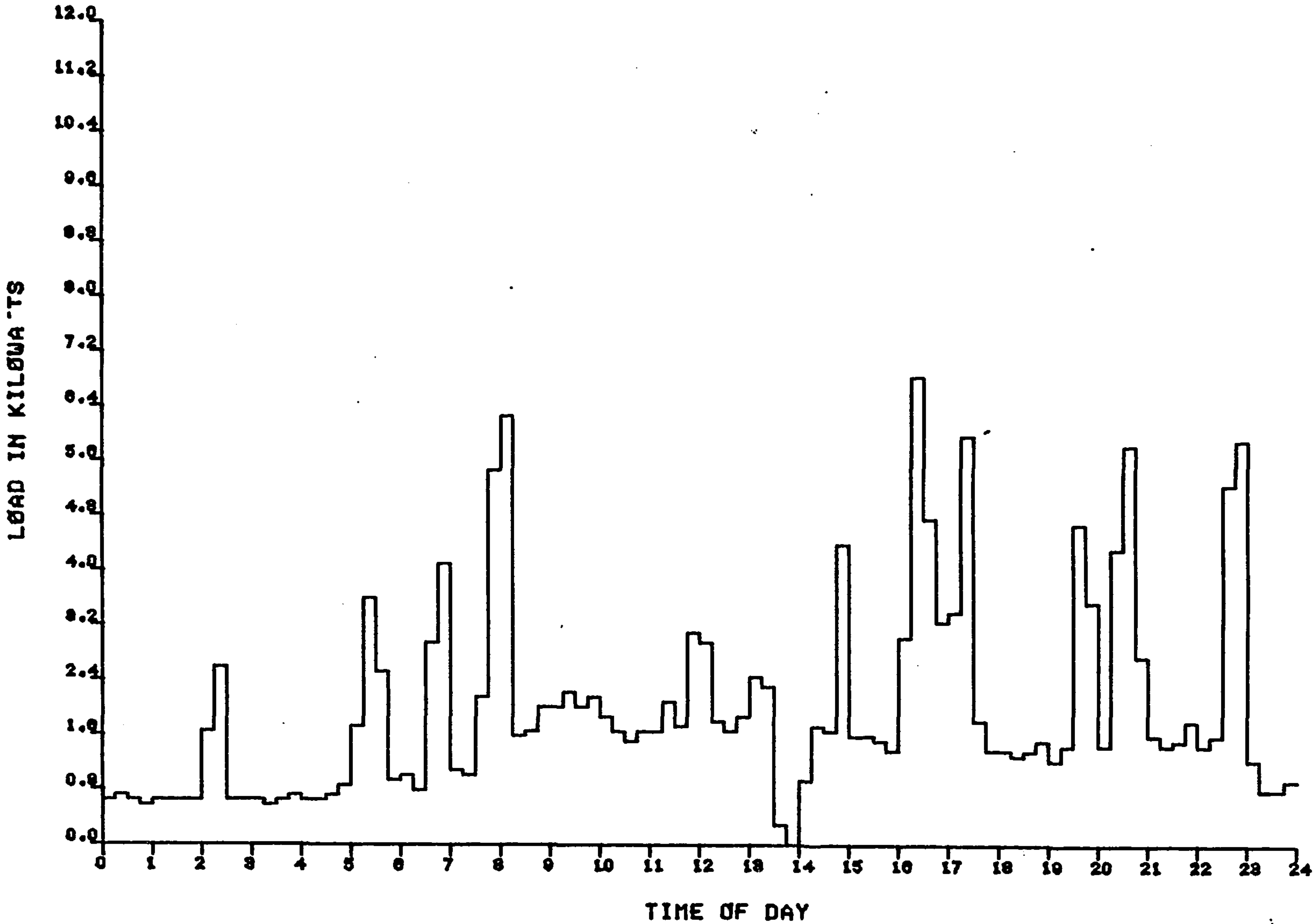


Figure 4.5 - Customer Load Curve for a Large Load Residence
Test Data for Tuesday

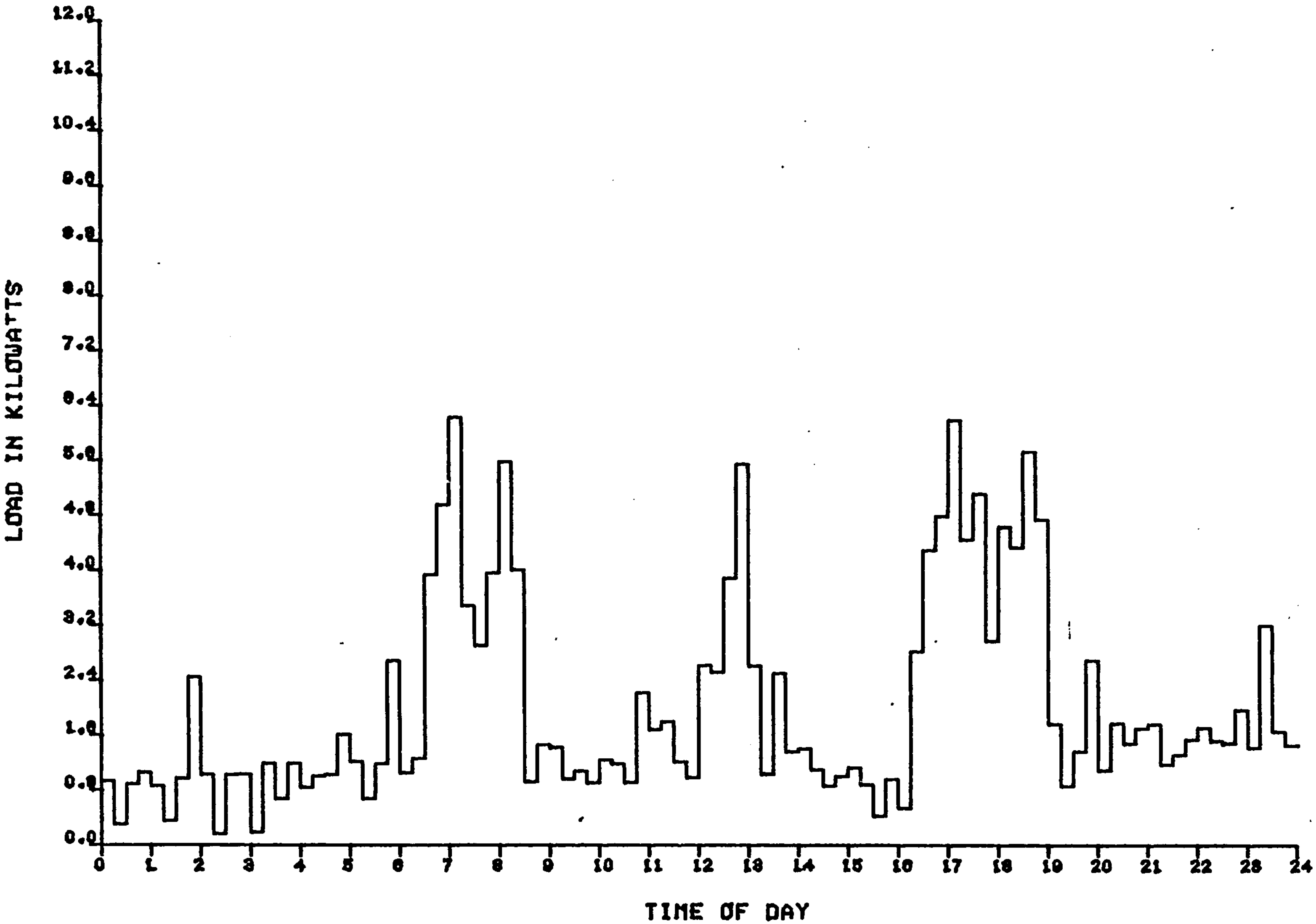


Figure 4.6 - Model Load Curve for a Large Load Residence
Predicted Data for Tuesday

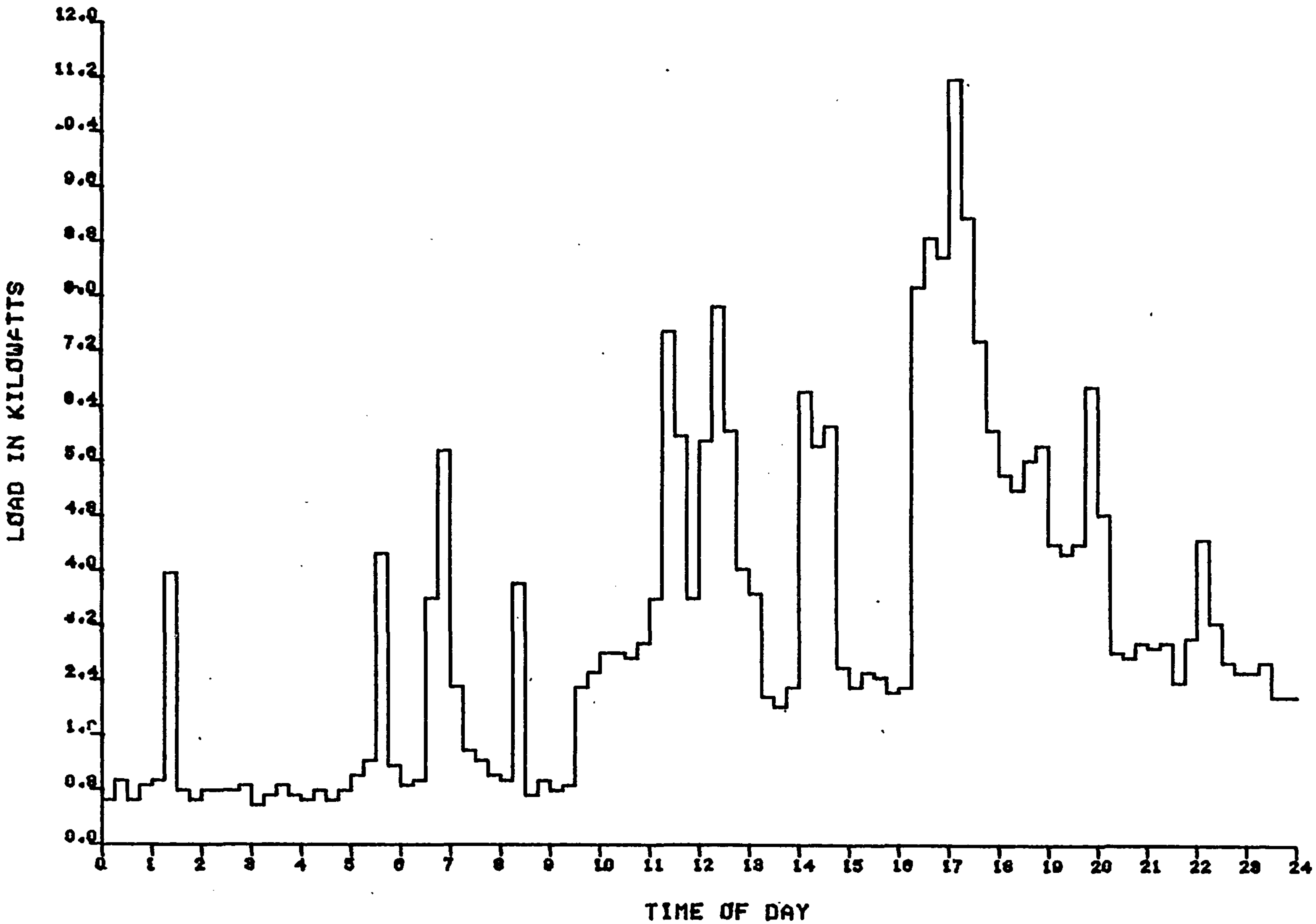


Figure 4.7 - Customer Load Curve for a Large Load Residence
Test Data for Friday

difference for the 5 day averages, 20 percent, lies toward the lower end of the difference range. The improvement in the range of energy use can be attributed in part to the larger base load since part of the energy use by the refrigerators, freezer and water heater are independent of the availability and proclivities of the residents. The range of the normalized variation factor when comparing the model to the customer data is lower than that of the small load residence. The day to day customer data range is also smaller. The upper bound of both ranges are about 1/4 that of the small load residence. Although the larger base load results in a smaller range of energy use and a larger average load, visual comparison of Figures 4.5 and 4.7 demonstrate that large variations are still present between day to day load curves for the same residence. This is due to large loads being connected for short periods at different times. For a large number of residences, and their model, the time of application of similar loads will normally vary, resulting in less variation of the total load. The fact that the comparison for the five day averages gives a smaller variation factor than either of the single day ranges indicates that the model does improve with a larger sample.

4.5 Group Models

Lines 3, 4 and 5 of Table 4.1 provide comparative data for a group of 38 small load customers (ID 1199999), a group of 44 larger load customers (ID 1399999) and the combination of these two groups. The models are again being compared to Connecticut Lighting and Power Company Residential Load test data. However the model for each group is a generalized model. That is to say the number of persons and the number of each kind of appliance reported in the survey were tabulated for each group. Then a model was assembled distributing the total number of persons and the total of the applicances so as to minimize the number of different household configurations and a generalized availability function was used. For example, for the "smaller load" group the 38 residences were reduced to 7 configurations. For large scale practical applications this method is necessary since it allows operation of the model with demographic and appliance saturation data, which is more available than individual residence data. To preserve the averaging effect of larger numbers each configuration was run a number of times equal to the number of houses it represented so that all appliances were represented (i.e. the model was run 38 times).

4.6 The Small Load Group Model

Figures 4.8, 4.9 and 4.10 are model and customer group load curves for the "small load" group. Line 3 of Table 4.1 contains the comparison data for this group. On a day to day basis the maximum difference between model and customer group energy use is 17 percent. This is an improvement of about a factor of three over the single residence "large load" case, demonstrating the averaging affect of a larger sample, despite the simplifications made in the model. The energy use agrees with the 19 percent range of the day to day customer group. Further agreement is shown by a reduction to a 1 percent difference when the "5 day average" energy use of the model is compared to the customer group. The model load curve Figure 4.9, when compared to the test data curves Figures 4.8 and 4.10, indicate the model underestimated the "night" load by about 25 percent. Since the night load represents a base load, which for this group consists mainly of the normal-cycling of refrigerators, refrigerator

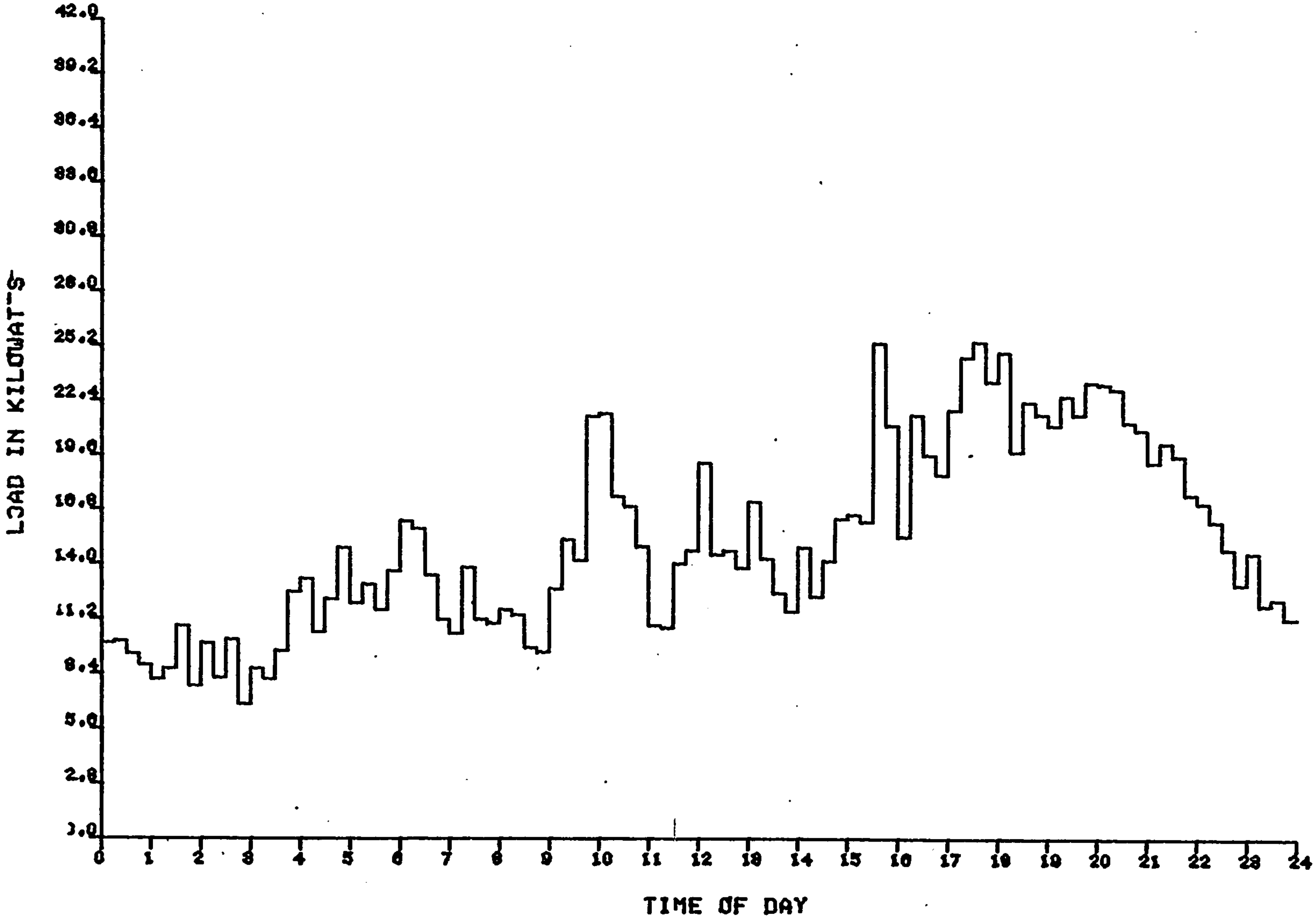


Figure 4.8 - Customer Load Curve for the Small Load Group
Test Data for Wednesday

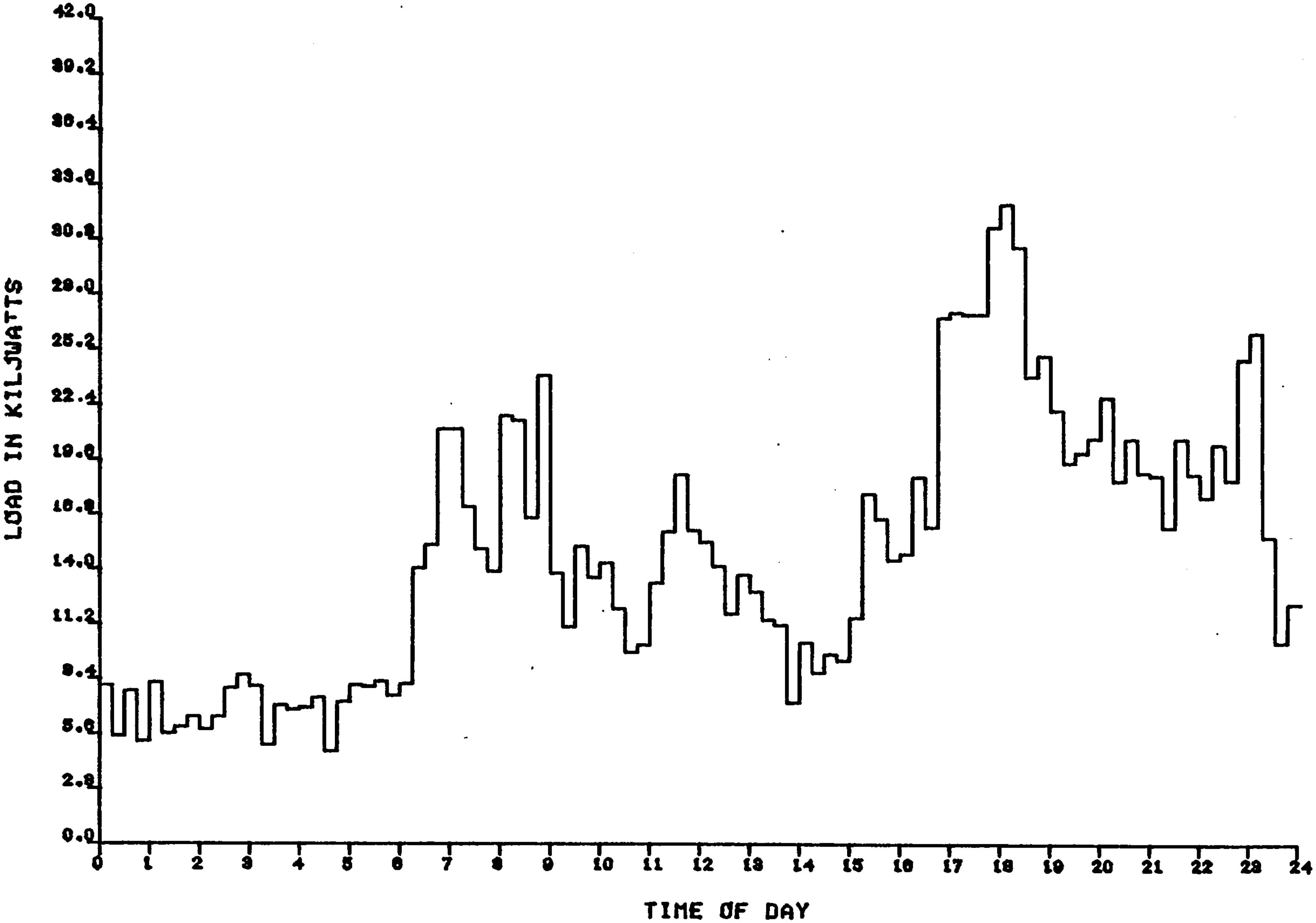


Figure 4.9 - Model Load Curve for the Small Load Group
Predicted Data for Wednesday

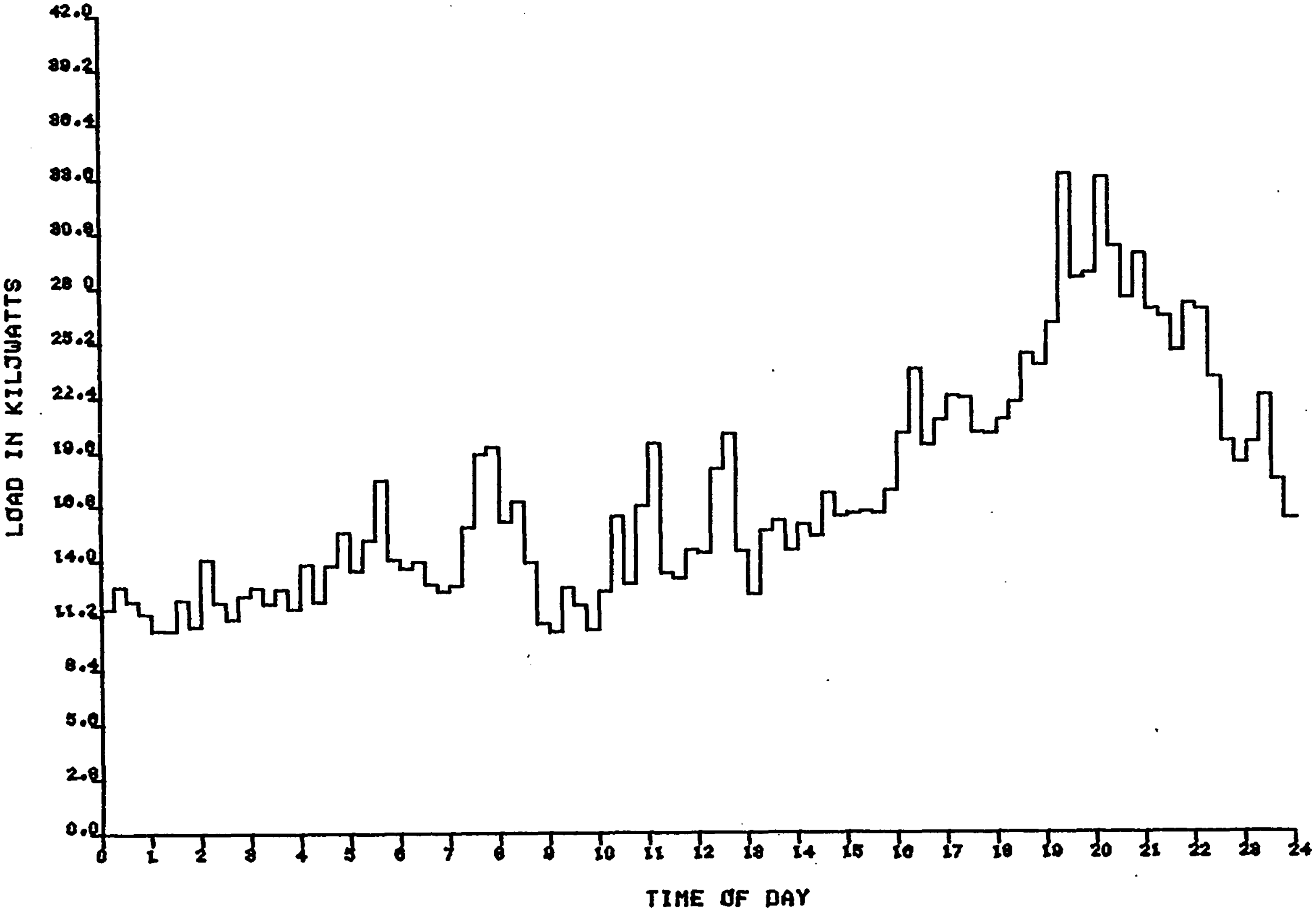


Figure 4.10 - Customer Load Curve for the Small Load Group
Test Data for Friday

parameters may need revising. On the other hand the peak load values predicted by the model for the group are consistantly higher than the test data by an average of 21 percent. Comparing Figures 4.8 and 4.9 reveals that, in particular, the morning peak and the evening peak are wider for the customer group than for the model. This would result in less concurrence of electric range and water heater loads so that the peaks would be smaller even though the total energy use is the same. It is an indication that the availability and mealtime functions may need adjusting.

The range of normalized variation between the model and test data shows almost an order of magnitude improvement over the single residence case and the range only varies by a factor of 2 (.2-.1). This indicates closer agreement on a day to day basis between the model's prediction and the test data curves. In addition the variation for the '5 day average' is within the range of the variations of the day to day test data. This, together with the smaller values of the normalized variation, demonstrates that the model's ability to predict improves with sample size.

Finally, Figure 4.11, the graph of the cross correlation function of the model data of Figure 4.9 and the test data of Figure 4.8, shows that the maximum correlation occurs with only a three period lag and is within 15 percent of the value of the cross correlation for the two test days shown in Figure 4.12. This is a further indication of the model's potential for predicting the load curve.

4.7 A Large Load Group Model

Figures 4.13, 4.14 and 4.15 are load curves applicable to the "large load" group. This group was modeled in the same way as the "small load" group. Line 4 of Table 4.1 shows that the results are of the same

```
CCF - CORRELATES*  C4  (T) AND  C11  (T+K)

           -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
             +----+----+----+----+----+----+----+----+----+----+
 -12   0.390                          XXXXXXXXXXX
 -11   0.462                          XXXXXXXXXXXXX
 -10   0.524                          XXXXXXXXXXXXXX
  -9   0.574                          XXXXXXXXXXXXXXX
  -8   0.585                          XXXXXXXXXXXXXXXX
  -7   0.602                          XXXXXXXXXXXXXXXX
  -6   0.648                          XXXXXXXXXXXXXXXXX
  -5   0.650                          XXXXXXXXXXXXXXXXX
  -4   0.647                          XXXXXXXXXXXXXXXXX
  -3   0.669                          XXXXXXXXXXXXXXXXXX
  -2   0.665                          XXXXXXXXXXXXXXXXXX
  -1   0.655                          XXXXXXXXXXXXXXXXX
   0   0.652                          XXXXXXXXXXXXXXXXX
   1   0.647                          XXXXXXXXXXXXXXXXX
   2   0.604                          XXXXXXXXXXXXXXXX
   3   0.555                          XXXXXXXXXXXXXXX
   4   0.575                          XXXXXXXXXXXXXXX
   5   0.538                          XXXXXXXXXXXXXX
   6   0.504                          XXXXXXXXXXXXXX
   7   0.506                          XXXXXXXXXXXXXX
   8   0.476                          XXXXXXXXXXXXX
   9   0.428                          XXXXXXXXXXXX
  10   0.399                          XXXXXXXXXXX
  11   0.360                          XXXXXXXXXX
  12   0.333                          XXXXXXXXX
 --
```

C4 = Model Data - Wednesday
C11 = Test Data - Wednesday
K = Time Lag in Periods

* Reference 23

Figure 4.11 - Cross Correlation Function - Small Load Group
Model to Test Data

```
CCF - CORRELATES* C11  (T) AND  C13  (T+K)

          -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
            +----+----+----+----+----+----+----+----+----+----+
 -12   0.157                         XXXXX
 -11   0.196                         XXXXXX
 -10   0.254                         XXXXXXX
  -9   0.337                         XXXXXXXXX
  -8   0.366                         XXXXXXXXXX
  -7   0.413                         XXXXXXXXXXX
  -6   0.442                         XXXXXXXXXXXX
  -5   0.483                         XXXXXXXXXXXXX
  -4   0.531                         XXXXXXXXXXXXXX
  -3   0.574                         XXXXXXXXXXXXXXX
  -2   0.613                         XXXXXXXXXXXXXXXX
  -1   0.630                         XXXXXXXXXXXXXXXXX
   0   0.687                         XXXXXXXXXXXXXXXXXX
   1   0.730                         XXXXXXXXXXXXXXXXXXX
   2   0.769                         XXXXXXXXXXXXXXXXXXXX
   3   0.766                         XXXXXXXXXXXXXXXXXXXX
   4   0.765                         XXXXXXXXXXXXXXXXXXXX
   5   0.766                         XXXXXXXXXXXXXXXXXXXX
   6   0.764                         XXXXXXXXXXXXXXXXXXXX
   7   0.756                         XXXXXXXXXXXXXXXXXXXX
   8   0.735                         XXXXXXXXXXXXXXXXXXX
   9   0.696                         XXXXXXXXXXXXXXXXXX
  10   0.666                         XXXXXXXXXXXXXXXXXX
  11   0.643                         XXXXXXXXXXXXXXXXX
  12   0.611                         XXXXXXXXXXXXXXXX
 --
```

C11 = Test Data - Wednesday
C13 = Test Data - Friday
K = Time Lag in Periods

* Reference 23

Figure 4.12 - Cross Correlation Function - Small Load Group
Teat Data to Test Data - Different Days

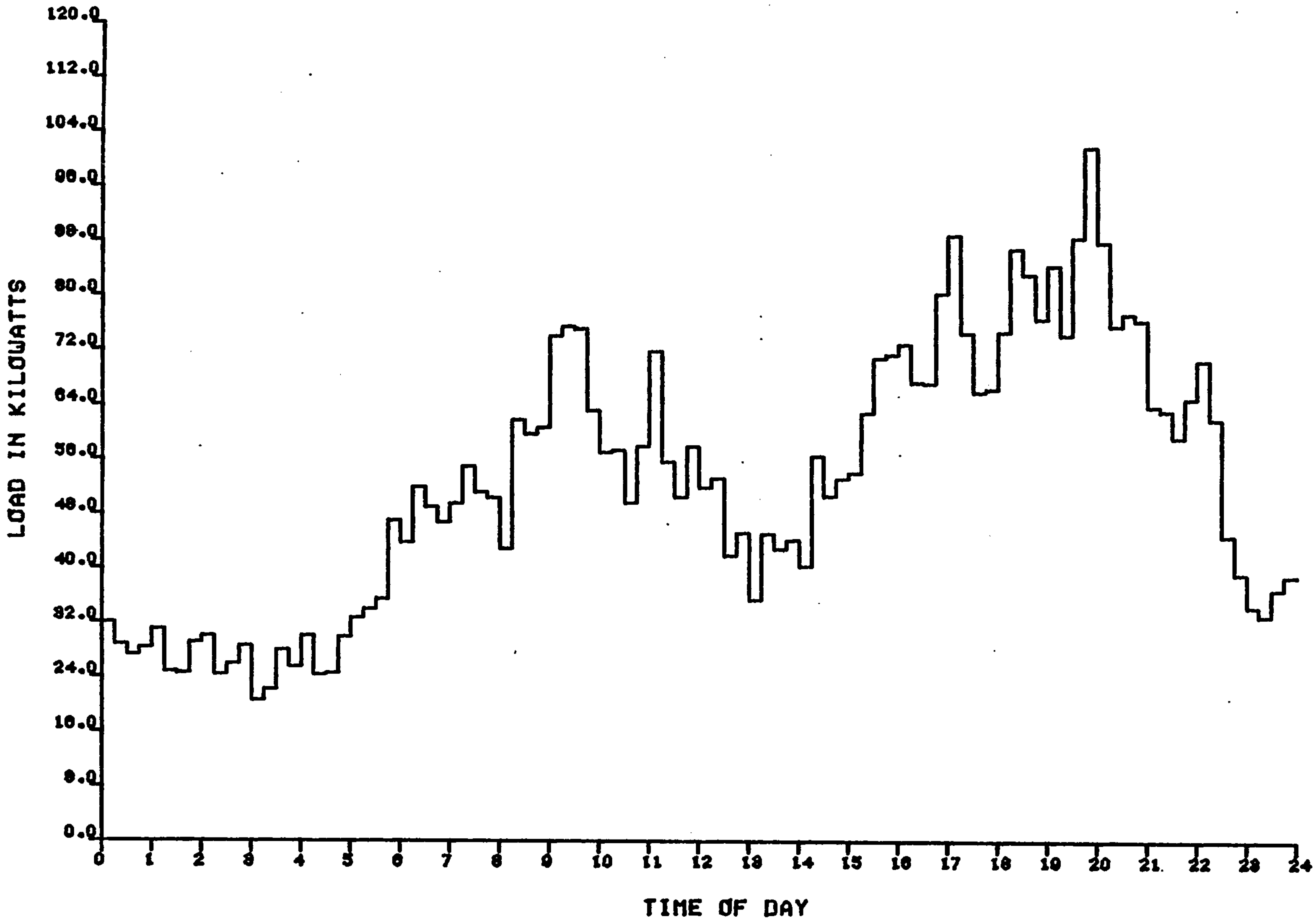


Figure 4.13 - Customer Load Curve for Large Load Group
Test Data for Wednesday

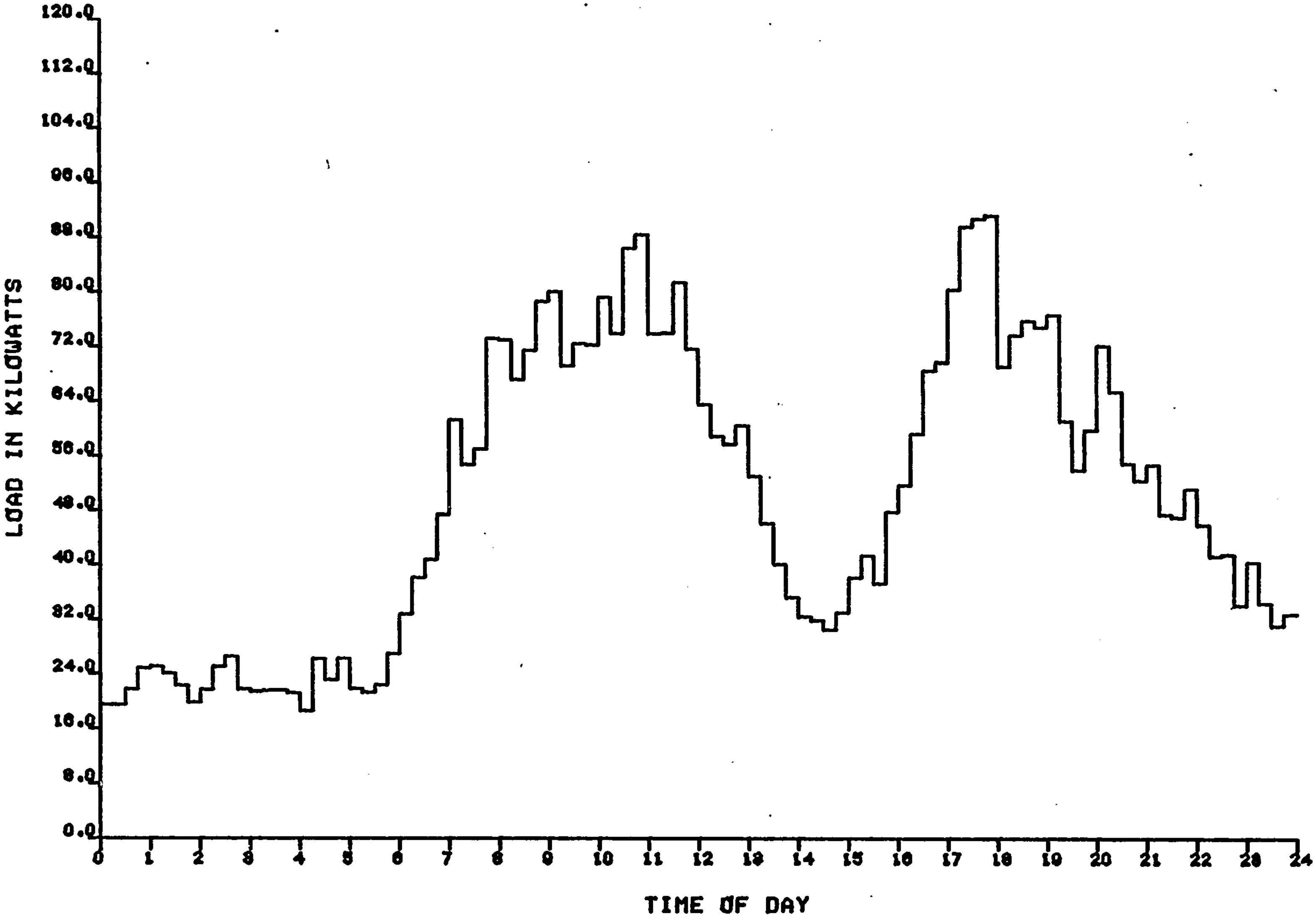


Figure 4.14 —Model Load Curve for the Large Load Group
Predicted Data For Wednesday

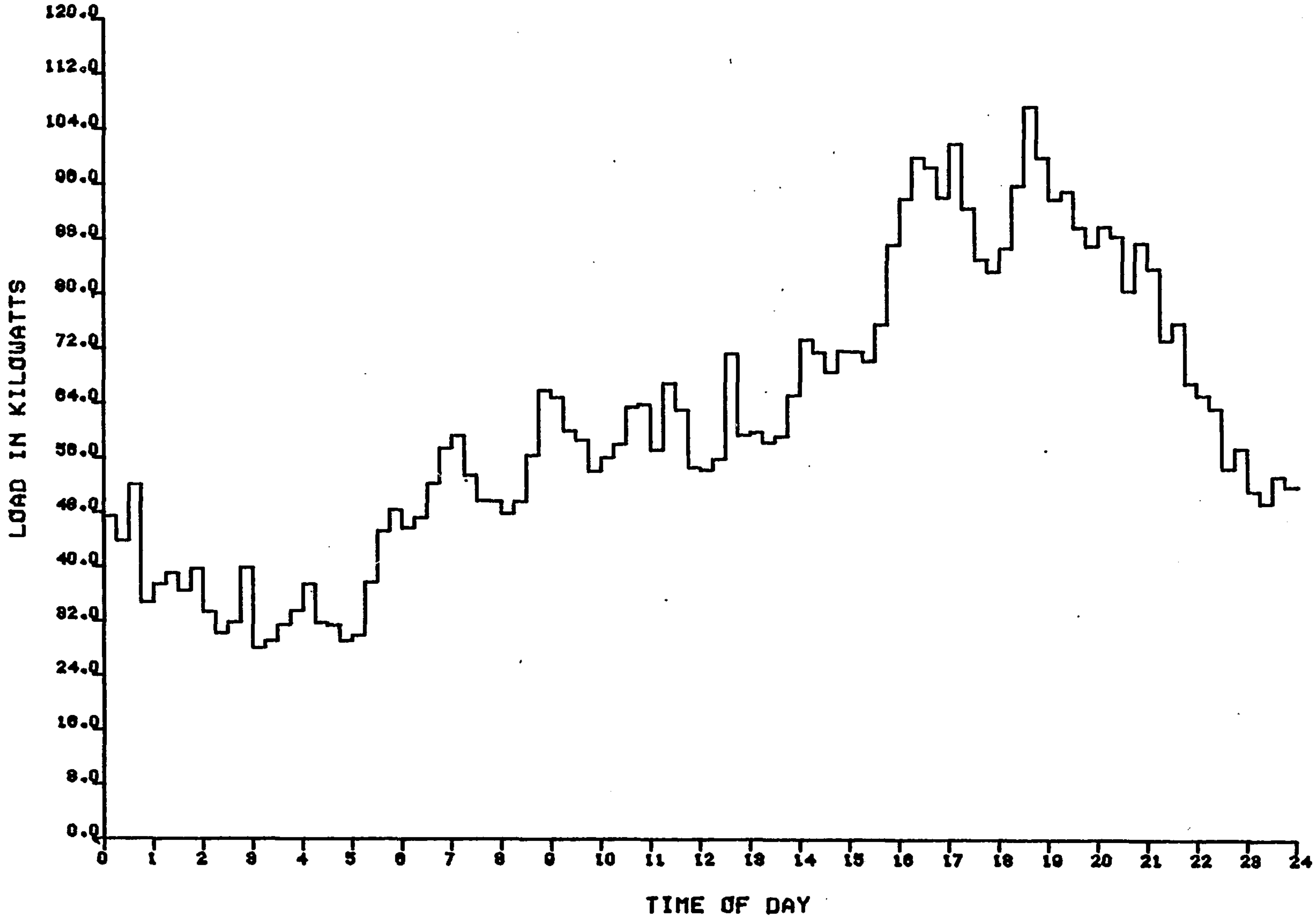


Figure 4.15 - Customer Load Curve for the Large Load Group
Test Data for Friday

order of magnitude as the "small load" group. They show about the same energy difference range and a factor of two improvement in the variation range over the "small load" group. These results are an indication that the model performance is affected more by sample size than by the size of the load being modeled. For a model of a stochastic process this would be expected.

The model tends to underestimate the night load for this group by about 17 percent and the peak loads by about 9 percent. Again, parameters of night load appliances may need adjustment but considering the simplifications made in the test, the agreement is felt to be reasonable.

Figure 4.16 graphs the cross correlation for the large load group model Figure 4.14 and its test data Figure 4.13. The maximum correlation occurs at a lag of one period and the value is within 15 percent correlation coefficient for the two test days as shown in Figure 4.17.

4.8 Results of Combining the Load Data

The load data for the two groups was combined on a period by period basis. The results of the analysis of the totals are recorded on Line 5 of Table 4.1. The energy value comparisons have about the same range as the individual groups but the variation factors again show improvement associated with a larger sample.

4.9 Forecasting With The Model

In order to demonstrate how the model could be used to forecast the effect of a change in the saturation of a class of appliances, another simulation was made. The "large load" group model was modified under the assumption that all houses had water heaters, which increased the

```
                                    *
  CCF - CORRELATES   C4   (T) AND   C11   (T+K)

              -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
                +----+----+----+----+----+----+----+----+----+----+
-12   0.167                             XXXXX
-11   0.229                             XXXXXXX
-10   0.304                             XXXXXXXXX
 -9   0.395                             XXXXXXXXXXX
 -8   0.478                             XXXXXXXXXXXXX
 -7   0.544                             XXXXXXXXXXXXXXX
 -6   0.586                             XXXXXXXXXXXXXXXX
 -5   0.623                             XXXXXXXXXXXXXXXXX
 -4   0.661                             XXXXXXXXXXXXXXXXXX
 -3   0.708                             XXXXXXXXXXXXXXXXXXX
 -2   0.747                             XXXXXXXXXXXXXXXXXXXX
 -1   0.747                             XXXXXXXXXXXXXXXXXXXX
  0   0.736                             XXXXXXXXXXXXXXXXXXX
  1   0.719                             XXXXXXXXXXXXXXXXXXX
  2   0.703                             XXXXXXXXXXXXXXXXXXX
  3   0.666                             XXXXXXXXXXXXXXXXXX
  4   0.625                             XXXXXXXXXXXXXXXXX
  5   0.588                             XXXXXXXXXXXXXXXX
  6   0.535                             XXXXXXXXXXXXXX
  7   0.491                             XXXXXXXXXXXXX
  8   0.456                             XXXXXXXXXXXX
  9   0.404                             XXXXXXXXXXX
 10   0.337                             XXXXXXXXX
 11   0.284                             XXXXXXXX
 12   0.239                             XXXXXXX
```

C4 = Model Data - Wednesday
C11 = Test Data - Wednesday
K = Time Lag in Periods

* Reference 23

Figure 4.16 - Cross Correlation Function - Large Load Group
Model to Test Data

```
CCF - CORRELATES* C11  (T) AND  C13  (T+K)

         -1.0 -0.8 -0.6 -0.4 -0.2  0.0  0.2  0.4  0.6  0.8  1.0
           +----+----+----+----+----+----+----+----+----+----+
-12   0.424                         XXXXXXXXXXXX
-11   0.467                         XXXXXXXXXXXXX
-10   0.510                         XXXXXXXXXXXXXX
 -9   0.560                         XXXXXXXXXXXXXXX
 -8   0.603                         XXXXXXXXXXXXXXXX
 -7   0.637                         XXXXXXXXXXXXXXXXX
 -6   0.681                         XXXXXXXXXXXXXXXXXX
 -5   0.736                         XXXXXXXXXXXXXXXXXXX
 -4   0.767                         XXXXXXXXXXXXXXXXXXXX
 -3   0.804                         XXXXXXXXXXXXXXXXXXXXX
 -2   0.839                         XXXXXXXXXXXXXXXXXXXXXX
 -1   0.856                         XXXXXXXXXXXXXXXXXXXXXX
  0   0.866                         XXXXXXXXXXXXXXXXXXXXXXX
  1   0.864                         XXXXXXXXXXXXXXXXXXXXXXX
  2   0.828                         XXXXXXXXXXXXXXXXXXXXXX
  3   0.785                         XXXXXXXXXXXXXXXXXXXXX
  4   0.744                         XXXXXXXXXXXXXXXXXXXX
  5   0.714                         XXXXXXXXXXXXXXXXXXX
  6   0.684                         XXXXXXXXXXXXXXXXXX
  7   0.640                         XXXXXXXXXXXXXXXXX
  8   0.585                         XXXXXXXXXXXXXXXX
  9   0.532                         XXXXXXXXXXXXXX
 10   0.478                         XXXXXXXXXXXXX
 11   0.432                         XXXXXXXXXXXX
 12   0.400                         XXXXXXXXXXX
--
```

C11 = Test Data - Wednesday
C13 = Test data - Friday
K = Time Lag in Periods

* Reference 23

Figure 4.17 - Cross Correlation Function - Large Load Group

Test Data to Test Data - Different Days

number of water heaters by 63 percent. Figure 4.18 is the resulting load curve. It should be compared to Figure 4.14 for the unmodified model. Comparison of the curves shows a change in average "night" load of about 4 kilowatts. However the peak load, at about 6 PM, increases by 18 kilowatts, a change of about 29 percent over the previous peak load. The smaller change in the "night" load is the energy required to replace the heat loss through the insulation, while the large change in peak load results from additional hot water use which the model attempts to predict.

4.10 Conclusions

Based on the results described in the foregoing evaluations the model appears able to predict the energy use and the period by period power demand to a degree comparable with the range of values experienced by the actual loads. This does not include heating and cooling loads which, because the test data used in the comparison was for the second week in September, are believed to have been negligible.

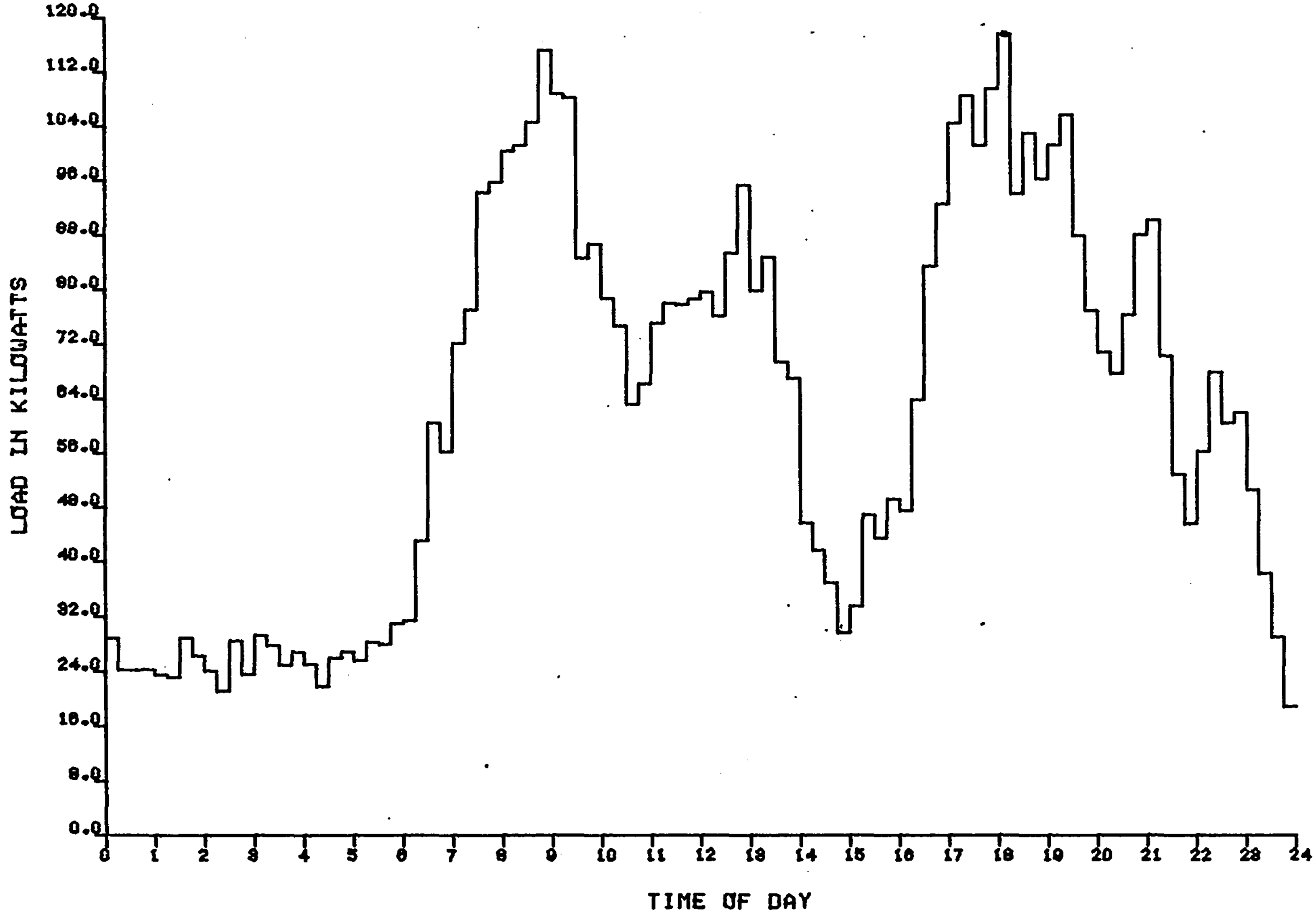


Figure 4.18 - Forecast Load Curve for Large Load Group Model
with Added Water-Heaters

CHAPTER V

SUMMARY AND RECOMMENDATIONS

5.1 Summary of Work Accomplished

A residential load forecasting model using availability, proclivity and normal-cycle functions was developed based on an evaluation of the probable reasons for the time dependency of the residential load. These functions were utilized in a residential model in determining the probability that specific appliances will be connected to the power system during particular time periods. This dictated that the form of the model include the individual appliances as sub-models.

Since the model is probabalistic, a "monte-carlo type" approach was used in determining when appliances are connected. Because operation of some appliances depends on other actions in the residence, the basic model represents an individual residence configuration with provision for specifying residence parameters.

Using the family size and stock of appliances for individual residents recorded during the Connecticut Light and Power Company Residential Load Test [1], two single family residences and two groups of residences were modeled. Load curves generated by these models were compared to the load data recorded for the residences and groups of residences whose statistics were used in constructing the models. Results obtained were consistent with day to day differences which occurred in the recorded test data. The model to test data agreement improved with sample size just as the test data to test data agreement improved with sample size. This tends to confirm the stochastic nature of the residential load.

In the group tests the model used an "equivalent set" of residences to test the feasibility of using demographic and appliance saturation data in the model.

The overall evaluation indicates the model has reasonable potential for predicting the time varying residential load curve.

5.2 Recommendations for Further Work

The potential demonstrated by the model warrants continued investigation and testing. Further work on the model is recommended in the following areas:

1. Additional tests should be conducted for the same and similar groups of loads to test the effect of parameter adjustments and the repeatability of results.
2. Models for the weather sensitive loads should be completed and tested.
3. To enhance the practicality of the model, the optimum sample size required to obtain consistent results while minimizing computer run time should be investigated.
4. Additional methods of measuring the agreement of the model load curve with a test load curve should be investigated.
5. When the weather sensitive models are completed the ability of the model to predict the monthly and/or annual energy use should be included as an independent comparison.

APPENDIX A

FORTRAN PROGRAM FOR THE RESIDENTIAL LOAD MODEL

```
C       FILE: RMODEL

        IMPLICIT REAL(K)

        DIMENSION KWUSE1(7,96),KWUSE2(7,96),KWUSE3(7,96),KWUSE4(7,96),
        1KWUSE5(7,96),KWUSE6(7,96),KWUSE7(7,96),KWUSE8(7,96),
        2KWUSE9(7,96),KWUS10(7,96),KWUS11(7,96),KWUS12(7,96),
        3KWUS13(7,96),KWUS14(7,96),KWUS15(7,96),KWUSET(7,96)

        DIMENSION KWSUM1(7,96),KWSUM2(7,96),KWSUM3(7,96),KWSUM4(7,96),
        1KWSUM5(7,96),KWSUM6(7,96),KWSUM7(7,96),KWSUM8(7,96),
        2KWSUM9(7,96),KWSM10(7,96),KWSM11(7,96),KWSM12(7,96),
        3KWSM13(7,96),KWSM14(7,96),KWSM15(7,96),KWSUMT(7,96)

        DIMENSION QUSE1(7,96),QUSE2(7,96),QUSE3(7,96),QUSE4(7,96),
        1QUSE5(7,96),QUSET(7,96)

        DIMENSION PA(2,96),PMF(2,96),PBDAY(7),PBTIME(96),JDFRS1(2),
        1PAWAY(2,96),AITEM(15),CODE(15),NUMDAT(3),NHM(96),JDFRS2(2)

        DIMENSION COLTV(2),BWTV(2),CLTVSD(2,96),TREF(2),
        1EATPRB(3),KWRANG(3),KWRANT(3),DODISH(3),PADWD(2,96),
        2PWHDAY(8),TYWASH(4),SWASH(3),PWHTIM(2,96),TYDRY(3),
        3TOUT(96),TIN(96),SUNFAC(96),PFAN(96),HUMID(96),PSWTIM(96)



        DATA TAMB/72./,TREF/36.,38./,TRFDES/37./,RFEPS/2./,USTEP/1./
        DATA A/9.10,B/.12/,C/.044/,KWREF/.005/,ONE/10./
        DATA TFRZ/0./,TFRDES/0./,FRZEPS/2./
        DATA E/8.0/,F/.073/,G/.04/,KWFRZ/.0059/,THREE/3./,BWTV/100.,30./
        DATA COLTV/350.,150./,EATPRB/.8,.75,.9/,KWRANG/.36,.18,.54/
        DATA THW/150./,TCW/60./,DODISH/.9,.75,.9/,ADLSAT/.65/
        DATA PBDAY/1.12,.84,.84,1.12,.84,1.12,1.12/
        DATA PBTIME/24*.1,16*2.0,24*.6,16*1.2,12*2.0,4*1.0/
        DATA SWASH/.1,.9,1./,KWWASH/.75/,KWDRY/5./
        DATA TYWASH/.2,.6,.9,1./
        DATA TYDRY/.05,.9,1./
        DATA WATDIF/1./,WATSIZ/2./,IELSET/2/,SMQNET/-0.0/
        DATA TSET/150./,HTLOS/0.5/,HUMID /96*72./

        DATA   (PAWAY(1,J),J=1,96)/32*.1,16*.3,40*.5,8*.2/
        DATA   (PAWAY(2,J),J=1,96)/32*.1,16*.2,16*.3,12*.1,12*.3,8*.1/
        DATA PSWTIM/26*0.,.005,.022,.066,.147,.297,.489,.680,.830,
        1.912,.956,.973,.977,23*1.0,.977,.973,.956,.912,.830,.680,
        2.489,.297,.147,.066,.022,.005,23*0./
        DATA PFAN/8*.75,40*.15,12*.2,24*.6,12*.75/
        DATA   CODE/"1,"2,"4,"10,"20,"40,"100,"200,"400,"1000,"2000,
        1"4000,"10000,"20000,"40000/



        OPEN(UNIT=20,FILE='PAVAIL.DAT',ACCESS='SEQIN')
        OPEN(UNIT=23,FILE='RMODEL.OUT',ACCESS='SEQOUT')
   1    OPEN(UNIT=24,FILE='PMEAL.DAT',ACCESS='SEQIN')

        DO 10 J=1,2
        READ(20,*) (PA(J,L),L=1,96)
        READ(24,*) (PMF(J,L),L=1,96)
```

```
   10   CONTINUE

        SKWHRS=0
        NSTOTL=0
        TOTKWH=0.
        NFRZTL=0
        QUSUM=0.
        NBATH=0
        NFAC=0

C       INITIALIZE RANDOM NUMBER GENERATOR
        CALL TIME(X,Y)
        N=IFIX(Y*1000.-1000.)
        DO 15 I=1,N
        TEMP=RAN(U)
   15   CONTINUE

C       NOTE: WRITE STATEMENTS ARE SUPPRESED (BY USE OF "C"),
              SO THAT PROGRAM CAN BE RUN WITH CARD INPUT.

C       WRITE(5,20)
   20   FORMAT( ' ENTER EQUIPMENT CODE AS A 5 DIGIT OCTAL NUMBER')
        READ(2,25) AITEMS
   25   FORMAT(O5)
        DO 30 I=1,15
        AITEM(I)=AITEMS.AND.CODE(I)
   30   CONTINUE
C       WRITE(5,35)
  35    FORMAT(' ENTER REFRIG TYPE,NUMBER AND TV NUMBER')
        READ(2,*)IREF,NREF,NTV
C       WRITE(5,40)
   40   FORMAT(' ENTER NUMBER OF PERSONS, ROOMS, DAYS, HOUSES, ICODE')
        READ(2,*) NPERS,NROOMS,NDAYS,NHOUSE,ICODE

        OPEN(UNIT=21,FILE='PROB.DAT',ACCESS='SEQIN')

        NUMDAT(1)=111
        NUMDAT(2)=311
        NUMDAT(3)=411

        CALL DATA(NUMDAT(1),CLTVSD)
        CALL DATA(NUMDAT(2),PWHTIM)
        CALL DATA(NUMDAT(3),PADWD)

        DO 2200 NRUNS=1,NHOUSE

C       ZERO USE DATA FOR EACH HOUSE.
        DO 50 I=1,7
        DO 50 J=1,96
        KWUSE1(I,J)=0.0
        KWUSE2(I,J)=0.0
        KWUSE3(I,J)=0.0
        KWUSE4(I,J)=0.0
        KWUSE5(I,J)=0.0
        KWUSE6(I,J)=0.0
        KWUSE7(I,J)=0.0
        KWUSE8(I,J)=0.0
        KWUSE9(I,J)=0.0
        KWUS10(I,J)=0.0
```

```
      KWUS11(I,J)=0.0
      KWUS12(I,J)=0.0
      KWUS13(I,J)=0.0
      KWUS14(I,J)=0.0
      KWUS15(I,J)=0.0
      KWUSET(I,J)=0.0
      QUSE1(I,J)=0.0
      QUSE2(I,J)=0.0
      QUSE3(I,J)=0.0
      QUSE4(I,J)=0.0
      QUSE5(I,J)=0.0
      QUSET(I,J)=0.0
      QUSUM=0.0

C     ZERO RUNNING SUM OF USE DATA ON FIRST RUN ONLY.

      IF(NRUNS.GT.1.OR.ICODE.EQ.2)GOTO 50

      KWSUM1(I,J)=0.0
      KWSUM2(I,J)=0.0
      KWSUM3(I,J)=0.0
      KWSUM4(I,J)=0.0
      KWSUM5(I,J)=0.0
      KWSUM6(I,J)=0.0
      KWSUM7(I,J)=0.0
      KWSUM8(I,J)=0.0
      KWSUM9(I,J)=0.0
      KWSM10(I,J)=0.0
      KWSM11(I,J)=0.0
      KWSM12(I,J)=0.0
      KWSM13(I,J)=0.0
      KWSM14(I,J)=0.0
      KWSM15(I,J)=0.0
      KWSUMT(I,J)=0.0
   50 CONTINUE

      QDEF1=0.
      QDEF2=0.
      LWASH=0
      IADULT=0
      IDAY=0

      JDFRS1(1)=0
      JDFRS1(2)=0
      JDFRS2(1)=0
      JDFRS2(2)=0
      IF(IREF.EQ.1)GOTO 52
      PDEF=RAN(U)
      JDFRS1(1)=IFIX(PDEF*48.)
      JDFRS1(2)=JDFRS1(1)+48
      PDEF=RAN(U)
      JDFRS2(1)=IFIX(PDEF*48.)
      JDFRS2(2)=JDFRS2(1)+48

C     ESTIMATE NUMBER OF ADULTS/CHILDREN
   52 DO 55 LK=1,NPERS
      PTYPE=RAN(U)
      IF(PTYPE.LE.ADLSAT)IADULT=IADULT+1
   55 CONTINUE
      NUNITS=IADULT+(NPERS-IADULT)*2
```

```
      WASHFC=(NUNITS*1.)/NPERS
C     WRITE(5,*) WASHFC

C     COMPUTE TYPE OF TV
      PROB=RAN(U)
      NCOL=1
      IF(PROB.GT..80) NCOL=2
      PROB=RAN(U)
      NBW=1
      IF(PROB.GT..90) NBW=2

      DO 2200 I=1,NDAYS
      IVAL=I
      IF(I.GT.7) IVAL=I-7
      ADWUSE=0.0
      MTIME=0
      MT=0
      JW=1
      ONE1=10.
      ONE2=3.
      THREE=3.
      NSTOTL=0
      NFRZTL=0
      QUSUM=0.0
      NFAC=0
      NBATH=0

      DO 1600 JTIME=1,96

      IWDAY=2
      IF(IVAL.EQ.1.OR.IVAL.EQ.7)IWDAY=1


C     COMPUTE NUMBER OF PERSONS HOME & AWAKE
      NHOME=NAVAIL(PA(IWDAY,JTIME),PAWAY(IWDAY,JTIME),NPERS)
      NHM(JTIME)=NHOME

C     COMPUTE MEALTIME
      JVAL=JTIME
      MSHIFT=0
      IF(IVAL.EQ.1.OR.IVAL.EQ.7)MSHIFT=4
      LBREK=17+MSHIFT
      IF(JTIME.EQ.LBREK) CALL MEAL(IWDAY,JVAL,24,PMF,NHOME,EATPRB,
      11,MTIME)
      LUN=41+MSHIFT
      IF(JTIME.EQ.LUN)CALL MEAL(IWDAY,JVAL,20,PMF,NHOME,EATPRB,2,MTIME)
      LDIN=61+MSHIFT
      IF(JTIME.EQ.LDIN)CALL MEAL(IWDAY,JVAL,24,PMF,NHOME,EATPRB,
      13,MTIME)

C     COMPUTE LIGHTING LOAD
  100 IF(AITEM(1).EQ."0)GOTO 200
      FACT1=.06*1.0
      FACT2=.018*1.0
      IF(JTIME.GT.32.AND.JTIME.LT.68) FACT1=.06*.5
      IF(JTIME.GT.32.AND.JTIME.LT.68) FACT2=.018*.1
      NEXRMS=NROOMS-NHOME
      IF(NHOME.LT.1)NEXRMS=0
      KWUSE1(IVAL,JTIME)=(NHOME*FACT1)+(NEXRMS*FACT2)
```

```
C       COMPUTE TELEVISION LOAD
  200   IF(AITEM(2).EQ."0)GOTO 300
        IF(NHOME.EQ.0)GOTO 300
        DO 250 NT=1,NTV
        PROB=RAN(U)
        PROG =(JTIME/2.)-IFIX(JTIME/2.)
        IF(PROG.NE.0.)GOTO 300
        PROBTV=CLTVSD(IWDAY,JTIME)*(1+(NHOME-NT)*.2)*23.
        IF(PROB.GT.PROBTV) GOTO 300
        TVWATT=COLTV(NCOL)
        IF(NT.GT.1) TVWATT=BWTV(NBW)
        KWUSE2(IVAL,JTIME)=KWUSE2(IVAL,JTIME)+TVWATT/1000.
        KWUSE2(IVAL,(JTIME+1))=KWUSE2(IVAL,(JTIME+1))+TVWATT/1000.
  250   CONTINUE

C       COMPUTE REFRIGERATOR LOAD
  300   IF(AITEM(3).EQ."0)GO TO 400
        NRR=1
        CALL REFRIG(JVAL,TAMB,TREF,TRFDES,RFEPS,USTEP,A,B,C,KWREF,
       1ENGY,ONE1,NHOME,NSTOC,NSTOTL,TOTKWH,MTIME,NRR,JDFRS1,QDEF1)
        KWUSE3(I,JTIME)=KWUSE3(I,JTIME)+ENGY*4.
        IF(NREF.EQ.1)GOTO 400
        NRR=2
        CALL REFRIG(JVAL,TAMB,TREF,TRFDES,RFEPS,USTEP,A,B,C,KWREF,
       1ENGY,ONE2,0,NSTOC,NSTOTL,TOTKWH,MTIME,NRR,JDFRS2,QDEF2)
        KWUSE3(I,JTIME)=KWUSE3(I,JTIME)+ENGY*4.

C       COMPUTE ELECTRIC RANGE LOAD
  400   IF(AITEM(4).EQ."0)GOTO 500
        IF(JTIME.GE.LBREK.AND.JTIME.LT.LUN)MT=1
        IF(JTIME.GE.LUN.AND.JTIME.LT.LDIN)MT=2
        IF(JTIME.GE.LDIN.AND.JTIME.LT.(LDIN+24))MT=3
        PSIZE=RAN(U)
        KWRANT(MT)=KWRANG(MT)*NHOME*(.5+PSIZE)
        IF(JTIME.EQ.MTIME) CALL ELRANG(IVAL,JVAL,MT,KWUSE4,KWRANT)

C       COMPUTE AUTOMATIC DISH WASHER LOAD
  500   IF(AITEM(5).EQ."0)GOTO 550
        IF(JTIME.EQ.1)510,520
  510   PADW=RAN(U)
  520   IF(PADW.GT.0.9)GOTO 550
        IF(ADWUSE.EQ.1.0)GOTO 600
        CALL AUDISH(IVAL,IWDAY,JVAL,THW,TCW,KWADW,QUSE5,KWUSE5,PADWD,
       1ADWUSE)

C       COMPUTE HOT WATER USE FOR HAND DISHWASHING
  550   IF(JTIME.EQ.(MTIME+4))CALL HDDISH(IVAL,JVAL,QUSE1,MT,THW,TCW,
       1DODISH)

C       COMPUTE CLOTHES WASHER AND DRYER LOAD AND HOT WATER USE
  600   IF(AITEM(6).EQ."0)GOTO 800
        NMWASH=IFIX((1.5*NPERS)+.5)
        IF(LWASH.GE.NMWASH)GOTO 800
        IF(I.GT.IDAY.AND.JTIME.EQ.1)610,640
  610   PDAY=RAN(U)
        PWHDAY(I)=(NMWASH-LWASH)/(8-I)
        IF(PDAY.LT.PWHDAY(I))630,800
  630   IDAY=I
        NTEMP=LWASH
```

```
  640    IF(IDAY.NE.I) GOTO 800
         IF(LWASH.GT.NTEMP) GOTO 800
         CALL CLWASH(IDAY,JVAL,PWHTIM,SWASH,TYWASH,TYDRY,
         1KWWASH,KWDRY,THW,TCW,AITEM,KWUSE6,KWUSE7,QUSE3,JW,NMWASH,
         2LWASH)

C        COMPUTE ELECT. HOT WATER HEATER LOAD
  800    IF(AITEM(8).EQ."0) GOTO 900

C        COMPUTE HOT WATER USE FOR WASH AND BATHE
         CALL WASHNB(IVAL,JVAL,MTIME,WASHFC,PBTIME,PBDAY,NHOME,
         1THW,TCW,QUSE2,NFAC,NBATH,NPERS)

         CALL TOTQUS(IVAL,JVAL,QUSE1,QUSE2,QUSE3,QUSE5,QUSET,
         1QUSUM)

         CALL WATHET(IVAL,JVAL,THW,TCW,QUSET,TSET,WATDIF,WATSIZ,
         1IELSET,SMQNET,UHSTEP,HTLOS,KWUSE8,TAMB)

C        COMPUTE FREEZER LOAD
  900    IF(AITEM(9).EQ."0) GO TO 1000
         CALL FREEZR(JVAL,TAMB,TFRZ,TFRDES,FRZEPS,USTEP,E,F,G,KWFRZ,
         1ENGY,THREE,NHOME,NFRZ15,NFRZTL,FRZKWH,MTIME)
         KWUSE9(I,JTIME)=ENGY*4.

C        COMPUTE AIR CONDITIONER LOAD
 1000    IF(AITEM(10).EQ."0) GOTO 1100

C        COMPUTE FANS/UNIT HEATER LOAD
 1100    IF(AITEM(11).EQ."0) GOTO 1200
         IF(TIN(JTIME).LT.TOUT(JTIME)) GOTO 1200
         IF(TIN(JTIME).LT.75.) GOTO 1200
         PROB=RAN(U)
         IF(PROB.LE.PFAN(JTIME)) KWUS11(IVAL,JTIME)=FANSIZ
         CONTINUE

C        COMPUTE ELECTRIC SPACE HEAT LOAD
 1200    IF(AITEM(12).EQ."0) GOTO 1300

C        COMPUTE HUMIDIFIER/DEHUMIDIFIER LOAD
 1300    IF(AITEM(13).EQ."0) GOTO 1400
         PDHON=RAN(U)
         IF(PDHON.GT.0.9) GOTO 1400
         IF(HUMID(JTIME).GT.65.) KWUS13(I,JTIME)=.65

C        COMPUTE SWIMMING POOL LOAD
 1400    IF(AITEM(14).EQ."0) GOTO 1500
         IF(JTIME.EQ. 1) 1410,1420
 1410    SWDAY=0.0
         PSWM=RAN(U)
         IF(PSWM.LT.0.9) SWDAY=1.0
 1420    IF(SWDAY.EQ.0.0) GOTO 1500
         SWFAC=0.0
         IF(PSWM.LT.PSWTIM(JTIME)) SWFAC=1.0
         KWUS14(IVAL,JTIME)=SWFAC*.6

C        COMPUTE MISC. LOAD
 1500    IF(AITEM(15).EQ."0) GOTO 1600
         KWUS15(IVAL,JTIME)=0.0

 1600    CONTINUE
```

```
C       COMPUTE TOTAL KW LOAD
        DO 2000 JT=1,96
        JL=JT
        CALL TOTLKW(IVAL,JL,KWUSE1,KWUSE2,KWUSE3,KWUSE4,KWUSE5,
        1KWUSE6,KWUSE7,KWUSE8,KWUSE9,KWUS10,KWUS11,KWUS12,KWUS13,
        2KWUS14,KWUS15,KWUSET)
 2000   CONTINUE

C       COMPUTE RUNNING SUM OF LOADS.
        CALL SUMKW(IVAL,KWUSE1,KWSUM1)
        CALL SUMKW(IVAL,KWUSE2,KWSUM2)
        CALL SUMKW(IVAL,KWUSE3,KWSUM3)
        CALL SUMKW(IVAL,KWUSE4,KWSUM4)
        CALL SUMKW(IVAL,KWUSE5,KWSUM5)
        CALL SUMKW(IVAL,KWUSE6,KWSUM6)
        CALL SUMKW(IVAL,KWUSE7,KWSUM7)
        CALL SUMKW(IVAL,KWUSE8,KWSUM8)
        CALL SUMKW(IVAL,KWUSE9,KWSUM9)
        CALL SUMKW(IVAL,KWUS10,KWSM10)
        CALL SUMKW(IVAL,KWUS11,KWSM11)
        CALL SUMKW(IVAL,KWUS12,KWSM12)
        CALL SUMKW(IVAL,KWUS13,KWSM13)
        CALL SUMKW(IVAL,KWUS14,KWSM14)
        CALL SUMKW(IVAL,KWUS15,KWSM15)
        CALL SUMKW(IVAL,KWUSET,KWSUMT)

 2200   CONTINUE

        IF(ICODE.EQ.2)GOTO 2550

C       NOTE: ONLY THE "TOTAL" LOAD IS WRITTEN TO FILE FOR
              A TEST RUN. REMOVE THE APPROPRIATE C(S) IF
              SPECIFIC APPLIANCE LOADS ARE DESIRED.
 2250   DO 2400 J=1,NDAYS
C       WRITE(23,*) (KWSUM1(J,L),L=1,96)
C       WRITE(23,*) (KWSUM2(J,L),L=1,96)
C       WRITE(23,*) (KWSUM3(J,L),L=1,96)
C       WRITE(23,*) (KWSUM4(J,L),L=1,96)
C       WRITE(23,*) (KWSUM5(J,L),L=1,96)
C       WRITE(23,*) (KWSUM6(J,L),L=1,96)
C       WRITE(23,*) (KWSUM7(J,L),L=1,96)
C       WRITE(23,*) (KWSUM8(J,L),L=1,96)
C       WRITE(23,*) (KWSUM9(J,L),L=1,96)
C       WRITE(23,*) (KWSM10(J,L),L=1,96)
C       WRITE(23,*) (KWSM11(J,L),L=1,96)
C       WRITE(23,*) (KWSM12(J,L),L=1,96)
C       WRITE(23,*) (KWSM13(J,L),L=1,96)
C       WRITE(23,*) (KWSM14(J,L),L=1,96)
C       WRITE(23,*) (KWSM15(J,L),L=1,96)
        WRITE(23,*) (KWSUMT(J,L),L=1,96)
C       WRITE(23,*) (QUSE1(J,L),L=1,96)
C       WRITE(23,*) (QUSE2(J,L),L=1,96)
C       WRITE(23,*) (QUSE3(J,L),L=1,96)
C       WRITE(23,*) (QUSE5(J,L),L=1,96)
C       WRITE(23,*) (QUSET(J,L),L=1,96)
 2300   CONTINUE
        WRITE(23,2500)AITEMS,NPERS,NROOMS,J,NHOUSE,
        1KWREF,WATSIZ,HTLOS
 2400   CONTINUE
```

```
C 2550  WRITE(5,2600)
 2600   FORMAT( ' ANYMORE RUNS?  IF -YES- ENTER A  1, IF -NO- ENTER A  0
        1',/)
 2550   READ(2,*)JAGAIN
        IF(JAGAIN.NE.1.AND.ICODE.EQ.2)GOTO 2250
        IF(JAGAIN.NE.1)GOTO 3000
        CLOSE(UNIT=21,FILE='PROB.DAT',ACCESS='SEQIN')
        IF(ICODE.NE.3)GOTO 10
        CLOSE(UNIT=24,FILE='PMEAL.DAT',ACCESS='SEQIN')
        GOTO 1
 3000   CONTINUE
        STOP
        END

        SUBROUTINE TOTLKW(I,J,KWUSE1,KWUSE2,KWUSE3,KWUSE4,KWUSE5,
        1KWUSE6,KWUSE7,KWUSE8,KWUSE9,KWUS10,KWUS11,KWUS12,KWUS13,
        2KWUS14,KWUS15,KWUSET)
        IMPLICIT REAL(K)
        DIMENSION KWUSE1(7,96),KWUSE2(7,96),KWUSE3(7,96),KWUSE4(7,96),
        1KWUSE5(7,96),KWUSE6(7,96),KWUSE7(7,96),KWUSE8(7,96),
        2KWUSE9(7,96),KWUS10(7,96),KWUS11(7,96),KWUS12(7,96),
        3KWUS13(7,96),KWUS14(7,96),KWUS15(7,96),KWUSET(7,96)
        KWT=0.0
        KWT=KWUSE1(I,J)+KWUSE2(I,J)+KWUSE3(I,J)+KWUSE4(I,J)
        KWT=KWT+KWUSE5(I,J)+KWUSE6(I,J)+KWUSE7(I,J)+KWUSE8(I,J)
        KWT=KWT+KWUSE9(I,J)+KWUS10(I,J)+KWUS11(I,J)+KWUS12(I,J)
        KWUSET(I,J)=KWT+KWUS13(I,J)+KWUS14(I,J)+KWUS15(7,96)
        RETURN
        END

        FUNCTION NAVAIL(X,Y,NPERS)
        N=0
        P1=RAN(U)
        IF(P1.GT.Y)GOTO 5
        P2=RAN(U)
        DO 2 I=1,NPERS
        IF(P2.GT.EXP(.5*(1-I)))GOTO 3
    2   CONTINUE
    3   N=I
    5   A=X*(NPERS-N)
        S=A-IFIX(A)
        IF(S.GE.0.5)GOTO 10
        NAVAIL=IFIX(A)
        GOTO 20
   10   NAVAIL=IFIX(A)+1
   20   CONTINUE
        RETURN
        END

        SUBROUTINE TKWHRS(IVAL,KWUSET,KWHRS)
        REAL KWUSET,KWHRS
        DIMENSION KWUSET(7,96)
        KWHRS=0.0
        DO 10 I=IVAL,IVAL
        DO 10 J=1,96
        KWHRS=KWHRS+KWUSET(I,J)
   10   CONTINUE
        KWHRS=KWHRS/4.
        RETURN
```

```
      END

      SUBROUTINE TOTQUS(I,J,QUSE1,QUSE2,QUSE3,QUSE5,QUSET,QUSUM)
      DIMENSION QUSE1(7,96),QUSE2(7,96),QUSE3(7,96),QUSE5(7,96),
     1QUSET(7,96)
      QUSET(I,J)=QUSE1(I,J)+QUSE2(I,J)+QUSE3(I,J)+QUSE5(I,J)
      QUSUM=QUSUM+QUSET(I,J)
      RETURN
      END

      SUBROUTINE WASHNB(I,JTIME,MTIME,WASHFC,PBTIME,PBDAY,NHOME,
     1THW,TCW,QUSE2,NFAC,NBATH,NPERS)
      DIMENSION PBTIME(96),PBDAY(7),QUSE2(7,96),WFAC(7)
      DATA WFAC/.0,1.,1.,.5,.5,1.,1./
      FACT=(105.-TCW)/(THW-TCW)
      BTUHW=2.*8.34*(THW-TCW)*FACT*WASHFC
      BTUBAT=20.*8.34*(THW-TCW)*FACT
      NUM=0
      IF(JTIME.GT.3)LTIME=3+JTIME-MTIME
      MULT=-(LTIME.GE.1.AND.LTIME.LE.6)
      PWASHM=(2./6.)*WFAC(1+(LTIME*MULT))*MULT
      IF(PWASHM.EQ.0.0)GOTO 30
      DO 10 N=1,NHOME
      PROB=RAN(U)
      IF(PROB.GT.PWASHM)GOTO 10
      QUSE2(I,JTIME)=BTUHW+QUSE2(I,JTIME)
      NUM=NUM+1
      NFAC=NFAC+1
   10 CONTINUE
      IF(NUM.EQ.NHOME)20,30
   20 RETURN
   30 PWASH=(NHOME-NUM)*(2./96.)
      PROB=RAN(U)
      IF(PROB.GT.PWASH)GOTO 50
      QUSE2(I,JTIME)=BTUHW+QUSE2(I,JTIME)
      NUM=NUM+1
      NFAC=NFAC+1
      IF(NUM.EQ.NHOME)40,50
   40 RETURN
   50 IF(NBATH.GE.NPERS)GOTO 60
      PBATH=NHOME*(5./672.)*(PBDAY(I)*PBTIME(JTIME))
      PROB=RAN(U)
      IF(PROB.GT.PBATH)GOTO 60
      QUSE2(I,JTIME)=BTUBAT+QUSE2(I,JTIME)
      NBATH=NBATH+1
   60 RETURN
      END

      SUBROUTINE SUMKW(IVAL,KWUSEI,KWUSUM)
      REAL KWUSEI,KWUSUM
      DIMENSION KWUSEI(7,96),KWUSUM(7,96)
      DO 10 J=1,96
      KWUSUM(IVAL,J)=KWUSUM(IVAL,J)+KWUSEI(IVAL,J)
   10 CONTINUE
      RETURN
      END

      SUBROUTINE DATA(NUMREC,VARABL)
      DIMENSION VARABL(2,96)
      N=0
```

```
 50     READ(21,100)NUM
100     FORMAT(1X,'RECORD NUM.',1X,I4)
        IF(NUM.EQ.NUMREC)GOTO 110
        DO 105 I=1,13
        READ(21,120)
105     CONTINUE
        GOTO 50
110     READ(21,120)
120     FORMAT(57X)
        N=N+1
        DO 150 J=1,12
        K=(J-1)*8+1
        READ(21,140)(VARABL(N,L),L=K,(K+7))
150     CONTINUE
140     FORMAT(1X,8F7.4)
        NUMREC=NUMREC+1
        IF(N.EQ.1)GOTO 50
        RETURN
        END

        SUBROUTINE REFRIG(JTIME,TAMB,TACT,TDES,EPS,UNSTP,
        1A,B,C,WATTS,ENGY,OPEN1,NHOME,NSTOC,NSTOTL,TOTKWH,
        1MTIME,NR,JDFRST,QDEF)
        DIMENSION POPEN(7),TACT(2),JDFRST(2)
        DATA POPEN/.0,1.,1.,.5,.5,1.,1./
        DELTIM=1.
        ENGY=0.0
        NSTOC=0
        OPEN2=0.

        IF(JTIME.EQ.JDFRST(1))GOTO 140
        IF(JTIME.EQ.JDFRST(2))GOTO 140

        DO 130 I=1,15
        DELT1=TACT(NR)-TDES
        IF(DELT1.GE.EPS.AND.UNSTP.EQ.0.0)GO TO 100
        IF(DELT1.GT.-EPS.AND.UNSTP.EQ.1.0)GO TO 100
        IF(DELT1.LE.-EPS.AND.UNSTP.EQ.1.0)GO TO 110
        IF(DELT1.GT.-EPS.AND.UNSTP.EQ.0.0)GO TO 110
        GO TO 120
100     UNSTP=1.0
        GO TO 120
110     UNSTP=0.0
120     ENGY=ENGY+UNSTP*WATTS*DELTIM
        QREM=A*(1+.03*(110.-TAMB))*UNSTP
        DELT3=TAMB-TACT(NR)
        QIN=B*DELT3

        PROB1=(OPEN1/1440.)*NHOME
        LTIME=0
        IF(JTIME.GT.3)LTIME=3+JTIME-MTIME
        MULT=-(LTIME.GE.0.AND.LTIME.LE.6)
        PROB2=(NHOME*6./90.)*POPEN(1+(LTIME*MULT))*MULT
        X=RAN(U)
        IF(X.LE.PROB2) GO TO 450
        IF(X.LE.PROB1) GO TO 400
        QRANDM=0.0
        GO TO 600
400     OPEN1=OPEN1-1.0
        GO TO 470
```

```
450     OPEN2=OPEN2+1.
470     Y=0.
        NSTOC=NSTOC+1
        DO 500 J=1,6
        Y=Y+RAN(1.)
500     CONTINUE
        QRANDM=Y*5.+15.
600     QNET=QIN-QREM+QRANDM+QDEF
        IF(QNET.LE.0.)QDEF=0.
        IF(UNSTP.EQ.1..AND.QDEF.GT.0)GOTO 125
        DELT2=C*DELTIM*QNET
        TACT(NR)=TACT(NR)+DELT2
        GOTO 130
125     QDEF=QNET
130     CONTINUE
        GOTO 150
140     ENGY=.200
        QDEF=683
        TACT(NR)=40.
150     NSTOTL=NSTOTL+NSTOC
        TOTKWH=TOTKWH+ENGY
        RETURN
        END

        SUBROUTINE FREEZR(JTIME,TAMB,TACT,TDES,EPS,UNSTP,
        1A,B,C,WATTS,ENGY,OPEN1,NHOME,NSTOC,NSTOTL,TOTKWH,
        1MTIME)
        DELTIM=1.
        ENGY=0.0
        NSTOC=0
        DO 130 I=1,15
        DELT1=TACT-TDES
        IF(DELT1.GE.EPS.AND.UNSTP.EQ.0.0)GO TO 100
        IF(DELT1.GT.-EPS.AND.UNSTP.EQ.1.0)GO TO 100
        IF(DELT1.LE.-EPS.AND.UNSTP.EQ.1.0)GO TO 110
        IF(DELT1.GT.-EPS.AND.UNSTP.EQ.0.0)GO TO 110
        GO TO 120
100     UNSTP=1.0
        GO TO 120
110     UNSTP=0.0
120     ENGY=ENGY+UNSTP*WATTS*DELTIM
        QREM=A*(1+.03*(110.-TAMB))*UNSTP
        DELT3=TAMB-TACT
        QIN=B*DELT3

        PROB1=(OPEN1/1440.)*NHOME
        X=RAN(U)
        IF(X.LE.PROB1) GO TO 400
        QRANDM=0.0
        GO TO 600
400     OPEN1=OPEN1-1.0
        GO TO 470
470     Y=0.
        NSTOC=NSTOC+1
        DO 500 J=1,6
        Y=Y+RAN(1.)
500     CONTINUE
        QRANDM=Y*5.+15.
600     QNET=QIN-QREM+QRANDM
        DELT2=C*DELTIM*QNET
```

```
      TACT=TACT+DELT2
      TIME=TIME+DELTIM
130   CONTINUE
      NSTOTL=NSTOTL+NSTOC
      TOTKWH=TOTKWH+ENGY
      RETURN
      END

      SUBROUTINE MEAL(IWDAY,JTIME,K,PMF,NHOME,EATPRB,M,MTIME)
      DIMENSION PMF(2,96),EATPRB(3)
      PMFT=0.
      PROB=RAN(U)
      IF(PROB.LE.EATPRB(M)) GOTO 10
      RETURN
 10   DO 20  J=JTIME,(K+JTIME)
      PMFT=PMFT+PMF(IWDAY,J)
      IF(PROB.GT.PMFT) GOTO 20
      MTIME=J
      RETURN
 20   CONTINUE
      RETURN
      END

      SUBROUTINE ELRANG(I,JTIME,MT,KWUSE4,KWRANG)
      REAL KWUSE4,KWRANG
      DIMENSION KWUSE4(7,96),KWRANG(3)
      M3=-((MT-3).EQ.0)
      M1=-((MT-1).EQ.0)
      KWUSE4(I,(JTIME-3))=KWRANG(MT)*M3
      KWUSE4(I,(JTIME-2))=KWRANG(MT)*M3
      KWUSE4(I,(JTIME-1))=KWRANG(MT)
      KWUSE4(I,JTIME)=KWRANG(MT)
      KWUSE4(I,(JTIME+1))=KWRANG(MT)*M1
      RETURN
      END

      SUBROUTINE AUDISH(I,IWDAY,JTIME,THW,TCW,KWADW,QUSE5,KWUSE5,
      1PADWD,ADWUSE)
      REAL KWUSE5
      DIMENSION QUSE5(7,96),KWUSE5(7,96),PADWD(2,96)
      BTUADW=15.*8.34*(THW-TCW)
      PROB=RAN(U)
      PADWT=PADWT+PADWD(IWDAY,JTIME)
      IF(PROB.GT.PADWT)10,20
 10   RETURN
 20   ID=I
      JT=JTIME
      QUSE5(ID,JT)=BTUADW/2.
      KWUSE5(ID,JT)=.4
      IF(JT.GE.96)CALL NEXDAY(ID,JT)
      KWUSE5(ID,(JT+1))=.4
      IF((JT+1).GE.96)CALL NEXDAY(ID,JT)
      KWUSE5(ID,(JT+2))=.9
      QUSE5(ID,(JT+2))=BTUADW/2.
      IF((JT+2).GE.96)CALL NEXDAY(ID,JT)
      KWUSE5(ID,(JT+3))=.9
      ADWUSE=1.
      PADWT=0.
      RETURN
      END
```

```
      SUBROUTINE HDDISH(I,JTIME,QUSE1,MT,THW,TCW,DODISH)
      DIMENSION QUSE1(7,96),DODISH(3)
      BTUHDW=10.*8.34*(THW-TCW)
      PROB=RAN(U)
      IF(PROB.GT.DODISH(MT))10,20
   10 RETURN
   20 QUSE1(I,JTIME)=BTUHDW
      RETURN
      END

      SUBROUTINE CLWASH(IDAY,JTIME,PWHTIM,SWASH,TYWASH,
     1TYDRY,KWWASH,KWDRY,THW,TCW,AITEM,KWUSE6,KWUSE7,QUSE3,J,MWASH,
     2LWASH)
      REAL KWWASH,KWDRY,KWUSE6,KWUSE7
      DIMENSION PWHTIM(2,96),SWASH(3),KWUSE6(7,96),
     1KWUSE7(7,96),QUSE3(7,96),TYWASH(4),TYDRY(3),
     1WASH(4),RINS(4),HTFAC(3),AITEM(15)
      DATA WASH/20.,20.,10.,0./,RINS/10.,0.,0.,0./
      DATA HTFAC/1.,.5,0./
      J=JTIME
      ITIME =JTIME
      I=IDAY
C     WRITE(5,*) IDAY
      PTIME=RAN(U)
      ND=2
      IF(I.EQ.1.OR.I.EQ.7)ND=1
      FACTOR=(MWASH-LWASH)/2
      IF(PTIME.LE.(PWHTIM(ND,J)*FACTOR))250,200
  200 RETURN
  250 PWASH=RAN(U)
      DO 300 L=1,3
      IF(PWASH.LE.SWASH(L)) GOTO 400
  300 CONTINUE
  400 IF(L.GT.(MWASH-LWASH))L=MWASH-LWASH
      NMWASH=L
      LWASH=LWASH+L
      DO 425 N=1,NMWASH
      PWASH=RAN(U)
      DO 500 K=1,4
      IF(PWASH.LE.TYWASH(K))520,500
  500 CONTINUE
  520 QUSE3(I,(J-1))=WASH(K)*8.34*(THW-TCW)
      KWUSE6(I,J)=KWWASH
      IF(J.EQ.96)CALL NEXDAY(I,J)
      KWUSE6(I,(J+1))=KWWASH/3.
      QUSE3(I,(J+1))=RINS(K)*8.34*(THW-TCW)
      IF((J+1).EQ.96)CALL NEXDAY(I,J)
      KWUSE6(I,(J+2))=KWWASH/1.5
      J=J+4
      IF(J.GT.96)CALL NEXDAY(I,J)
  425 CONTINUE
      IF(AITEM(7).EQ."0)GOTO 450
      I=IDAY
      JT=ITIME+3
      IF(JT.GE.96)CALL NEXDAY(I,JT)
      DO 430 IQ=1,NMWASH
      PDRY=RAN(U)
      DO 530 K=1,3
      IF(PDRY.LE.TYDRY(K))540,530
```

```
  530   CONTINUE
  540   DO 435 IT=1,4
        KWUSE7(I,(JT+IT))=KWDRY*HTFAC(K)
        IF((JT+IT).GE.96)CALL NEXDAY(I,JT)
  435   CONTINUE
        JT=JT+4
        IF(JT.GT.95)CALL NEXDAY(I,JT)
  430   CONTINUE
        IDAY=I
C       WRITE(5,*)IDAY,LWASH,J,JT
  450   RETURN
        END

        SUBROUTINE NEXDAY(I,J)
        I=I+1
        IF(I.GT.7)I=I-7
        J=J-96
        RETURN
        END


        SUBROUTINE WATHET(I,JTIME,THW,TCW,QUSET,TSET,DIF,WATSIZ,
       1IELSET,SMQNET,USTEP,HETLOS,KWUSE8,TAMB)
        REAL KWUSE8
        DIMENSION ELSIZE(8),IOFFPK(96),QUSET(7,96),KWUSE8(7,96)
        DATA ELSIZE/3.0,3.0,4.5,4.5,5.5,5.5,5.5,2.0/
        DATA IOFFPK/24*1.,60*0.,12*1./
C       NEED INITIAL VALUES FOR TSET,TCW,THW,TAMB,DIF,IELSET,
C       SMQSET, HETLOS, AND USTEP.
        IF(I.EQ.1.AND.JTIME.EQ.1)THW1=THW
        ELENGY=0.0
        IF(WATSIZ.EQ.1.)GOTO 2000
        IF(WATSIZ.EQ.2.)GOTO 2025
        IF(WATSIZ.EQ.3.)GOTO 2050
        GAL=80.
        TOPEL=ELSIZE(7)
        GOTO 2075
 2000   GAL=30.
        TOPEL=ELSIZE(1)
        BOTEL=ELSIZE(2)
        GOTO 2075
 2025   GAL=52.
        TOPEL=ELSIZE(3)
        BOTEL=ELSIZE(4)
        GOTO 2075
 2050   GAL=80.
        TOPEL=ELSIZE(5)
        BOTEL=ELSIZE(6)
 2075   BTUCAP=GAL*8.34*(TSET-TCW)
        DO 2275 L=1,3
        IF(WATSIZ.EQ.4.)BOTEL=ELSIZE(8)*IOFFPK(JTIME)
        DELT1=TSET-THW1
        IF(DELT1.GE.DIF.AND.USTEP.EQ.0.)GOTO 2100
        IF(DELT1.GT.(-DIF).AND.USTEP.EQ.1.)GOTO 2100
        IF(DELT1.LE.(-DIF).AND.USTEP.EQ.1.)GOTO 2125
        IF(DELT1.LT.DIF.AND.USTEP.EQ.0.)GOTO 2125
        WRITE(5,2110)
 2110   FORMAT(1H,'THERE IS AN ERROR')
        GO TO 2300
 2100   USTEP=1.0
```

```
      GOTO 2150
 2125 USTEP=0.0
 2150 IF(IELSET.EQ.1) GOTO 2175
      ELEMNT=BOTEL
      DFBTU=1.0/(GAL*.66*8.34)
      GOTO 2200
 2175 ELEMNT=TOPEL
      DFBTU=1.0/(GAL*.33*8.34)
 2200 ELENGY=ELENGY+(ELEMNT/12.0)*USTEP
      QADDED=3417.*(ELEMNT/12.0)*USTEP
      QLOSS=HETLOS*(TSET-TAMB)
      QNET=QADDED-QLOSS-(QUSET(I,JTIME)/3.)
      DELT2=QNET*DFBTU
      THW1=THW1+DELT2
      IF(THW1.LE.TCW) THW1=TCW
      SMQNET=SMQNET+QNET
      IF(THW1.GE.(TSET+5.).AND.IELSET.EQ.1) GO TO 2250
      IF(BTUCAP.LE.(-SMQNET)) SMQNET=(-BTUCAP)
      PUSED=-SMQNET/BTUCAP
      IF (PUSED.GT.1.0) PUSED=1.0
      HETLOS=GAL*(1.-PUSED)*(.02)/3.
      IF(PUSED.GE..75.AND.IELSET.EQ.2) GOTO 2225
      IF(PUSED.LE..66.AND.IELSET.EQ.1) GOTO 2250
      GO TO 2260
 2225 IELSET=1
      THW1=TSET-10.
      GO TO 2260
 2250 IELSET=2
      THW1=TCW
 2260 CONTINUE
 2275 CONTINUE
C     WRITE (5,2290) PUSED,THW1,IELSET,USTEP,SMQNET,QLOSS,QUSET(I,JTIME)
C     1,QADDED
C 2290 FORMAT(1H,F7.4,F7.2,I2,F4.1,F10.1,F6.1,F10.1,F8.1,/)
      KWUSE8(I,JTIME)=ELENGY*4
      THW=TSET
      IF(PUSED.GE.1.) THW=TCW
 2300 RETURN
      END
```

APPENDIX B

FORTRAN PROGRAM FOR THE AVAILABILITY FUNCTION

```
C         FILE: AVAIL.FOR
C         INTEGER VALUES SPECIFY A PARTICULAR 1/4 HOUR. (I.E. 33
C         IS 8:15 A.M.BASED ON 96 1/4 HOURS IN A 24 HOUR DAY.)
C         NTI=THE INTEGER VALUE CF THE PRESENT TIME
C         NST=THE INTEGER VALUE CF SHIFT START TIME
C         NFT=THE INTEGER VALUE CF SHIFT FINISH TIME
C         NTAUS= THE INTEGER VALUE OF THE SHIFT START 'TIME CONSTANT'
C         NTAUF=THE INTEGER VALUE OF TH SHIFT END 'TIME CONSTANT'
C         NA=THE INTERGER VALUE CF THE EARLIEST ARISE TIME
C         NL=THE INTGER VALUE OF THE LAST LEAVE FOR WORK TIME

C         NSIGBL AND NSIGBT CAN BE 1,2 OR 4 (DELTA T)
          DIMENSION DAT(24),DAT1(6),DAT2(12),DAT4(24),TF(96),
          1F(192),PAT(192),PLT(192),PAH(192),PBT(192),PAVAIL(96),
          2PBL(24),PLTT(24)

          DATA DAT1/.0215,.1259,.3413,.3413,.1259,.C215/
          DATA DAT2/.0049,.0166,.0440,.0819,.1498,.1915,.1915,
          1.1498,.0819,.0440,.C166,.0049/
          DATA DAT4/.0017,.0032,.0060,.0106,.0173,.0267,.0388,
          1.0431,.0679,.0819,.0928,.0987,.0987,.0928,.0819,
          2.0679,.0431,.0388,.0267,.0173,.0106,.0060,.0032,.0017/

          OPEN(UNIT=20,FILE='PAVAIL.DAT',ACCESS='SEQOUT')

          WRITE(5,15)
     15   FORMAT(1H ,'HOW MANY SETS?')
          READ(5,*) ISETS
          NSETS=2*ISETS

          DO 700 NDAY=1,NSETS

C         INITIALIZE THE FUNCTION
          DO 20 K=1,96
          TF(K)=0.
          PAVAIL(K)=0.
     20   CONTINUE
          TPOPUL=0.0

C         WRITE(5,10)
C     10  FORMAT(1H ,'HOW MANY SHIFTS?',/)
          READ(2,*) NSHIFT

          DO 500 J=1,NSHIFT

C         WRITE(5,30)
C     30  FORMAT(1H ,'ENTER DATA FOR THIS SHIFT-POPULATION,START TIME,
C         1END TIME,TAU START,TAU END,SIGMA BREAKFAST,BEDTIME,
C         2SIGMA BEDTIMME',/)

          READ(2,*)POPUL,NST,NFT,NTAUS,NTAUF,NSIGBL,NBT,NSIGBT

C         INITIALIZE THE INTERMEDIATE VARIABLES
          DO 40 K=1,192
          PAT(K)=0.
          PLT(K)=0.
          PAH(K)=0.
          PBT(K)=0.
          F(K)=0
     40   CONTINUE
```

```
      MMAX=6*NSIGBL
      NMAX=1+(5*NTAUS)
      NAHMAX=1+(5*NTAUF)
      KMAX=3*NSIGBT
      NA=NST-NMAX
      IF((NA-MMAX).LE.0) NA=96+NA
      IF(NFT.EQ.200) NA=NST
      NL=NA+NMAX-1
      IF(NFT.EQ.200) NL=NA+1
      IF(NFT.NE.200.AND.NFT.LT.NA) NFT=NFT+96
      NBTT=NBT
      IF(NBT.LT.NFT.OR.(NBT-KMAX).LT.0) NBT=NBT+96
      IF(NFT.EQ.200) NBT=NBTT
C     WRITE(5,*) NA,NL

      DO 400 NTI=1,192

C     COMPUTE "ARISE TIME" PROBABILITIES

      IF(NA.GT.NTI.OR.NTI.GE.NL) GOTO 100
      N=NL-NTI


      T1=-(1.*(N-1))/NTAUS
      T2=-(1.*N)/NTAUS
      PLTT(N)=EXP(T1)-EXP(T2)
      IF(NFT.EQ.200) PLTT(N)=1.0

      DO 100 M=1,MMAX
      IF(NSIGBL.EQ.1) DAT(M)=DAT1(M)
      IF(NSIGBL.EQ.2) DAT(M)=DAT2(M)
      IF(NSIGBL.EQ.4) DAT(M)=DAT4(M)
      PBL(M)=DAT(M)
      PAT(NTI-M)=PAT(NTI-M)+PLTT(N)*PBL(M)
C     WRITE(5,*)PAT(NTI-M),M
  100 CONTINUE

C     COMPUTE "LEAVE FOR WORK" PROBABILITIES

      IF(NFT.EQ.200)GOTO 300
C     INDICATES NO WORK SHIFT.

      IF (NTI.LT.NA.OR.NTI.GE.NL) GOTO 200
      L=NL-NTI
      T3=-(1.*(L-1))/NTAUS
      T4=-(1.*L)/NTAUS
      PLT(NTI)=EXP(T3)-EXP(T4)
  200 CONTINUE

C     COMPUTE "ARRIVE HOME" PROBABILITIES

      IF(NTI.LE.(NFT+1).OR.NTI.GT.(NFT+NAHMAX))GOTO 300
      L=-(NFT+1-NTI)
      T5=-(1.*L)/NTAUF
      T6=-(1.*(L-1))/NTAUF
      PAH(NTI)=-EXP(T5)+EXP(T6)

  300 CONTINUE
```

```
C       COMPUTE "BEDTIME" PROBABILITIES

        IF(NTI.LT.(NBT-KMAX).OR.NTI.GT.(NBT+KMAX))GOTO 400
        ML=KMAX+NBT-NTI
        IF(NSIGBT.EQ.1) DAT(ML)=DAT1(ML)
        IF(NSIGBT.EQ.2) DAT(ML)=DAT2(ML)
        IF(NSIGBT.EQ.4) DAT(ML)=DAT4(ML)
        PBT(NTI)=DAT(ML)
C       WRITE(5,*) PAT(NTI),PLT(NTI),PAH(NTI),PBT(NTI),NTI

  400   CONTINUE

C       COMPUTE THE CUMULATIVE DISTRIBUTION FUNCTION

        F(1) = (PAT(1)-PLT(1)+PAH(1)-PBT(1))*POPUL
        DO 450 NTI=2,192
        F(NTI)=F(NTI-1)+(PAT(NTI)-PLT(NTI)+PAH(NTI)-PBT(NTI))*POPUL
C       WRITE(5,*) F(NTI),NTI
  450   CONTINUE

C       FOLLOWING TAKES CARE OF TIMES AFTER MIDNIGHT

        DO 430 NTI=1,96
        F(NTI)=F(NTI)+F(NTI+96)
        IF(F(NTI).LT.0.)F(NTI)=0.
  430   CONTINUE

        DO 475 NTI=1,96
        TF(NTI)=TF(NTI)+F(NTI)
  475   CONTINUE

        TPOPUL=TPOPUL+POPUL

  500   CONTINUE

        DO 600 NTI=1,96
        PAVAIL(NTI)=TF(NTI)/TPOPUL
        IF(PAVAIL(NTI).LT.0.001)PAVAIL(NTI)=.001
  600   CONTINUE

        WRITE(20,*) (PAVAIL(L),L=1,96)
  700   CONTINUE
        STOP
        END
```

APPENDIX C

PARAMETER DEVELOPMENT FOR REFRIGERATORS (FREEZERS)

Refrigerator and Freezer Models

1. The basic relationship for the refrigerator and freezer models is given by:

   QNET = QIN - QREM + QRAN + QDEF

   where:

   QNET = net heat gain (+) or removed (-)

   QIN = heat gain through the walls and gasgets as well as internal fans and heaters, where applicable

   QREM = heat removed by the refrigeration unit

   QRAN = heat added by random opening of the door(s)

   QDEF = heat added to defrost the evaporator on automatic defrost models. (Not used in freezer models at present).

2. The refrigeration unit is switched on and off when QNET changes the refrigerator (or freezer) temperature by the differential temperature, $\pm$ 2°F. (See paragraph 7 for further details).

3. QIN is calculated each minute in the program as:

   QIN = B * (Tambient - Tunit)

   B = the heat gain parameter for the refrigerator

   The value of "B" for a particular refrigerator (and the equivalent parameter "F" for a freezer) is calculated as follows:

   a) Calculate the total "wall" area of the unit, wall thickness and determine insulation type.

b) Using a), calculate the heat gain per hour by conduction based on a 110°F "standard maximum" ambient temperature and unit temperatures of 32°F (refrigerator sections) and 0°F (freezers and freezer sections).

c) Estimate other heat gains due to leakage (and to internal fans and surface heaters where applicable).

d) Then:

$$B = \frac{\text{Total BTU/Hour heat gain (at 110°F)}}{60 \times (110 - \text{Treference})} \text{ BTU/Min °F}$$

$$QIN = B \times (\text{Tambient} - \text{Tunit}) \text{ BTU/Min}$$

Where: Treference = 32°F for refrigerators

= 0°F for freezers

Tunit = actual temperature of refrigerator or freezer.

For the 16 cubic foot refrigerator used in the model, the total BTU/hour heat gain used was 546 BTU/hour based on the ASHRAE Handbook [21]. The value of "B" used, based on this, is 0.12 BTU/Min°F.

For a combination unit, using the refrigerator section temperature, QIN will be somewhat underestimated at low ambient temperature based on this simplified parameter.

4. QREM is calculated each minute in the program as:

$$QREM = A * (1+.03(110-\text{Tambient})) * \text{USTEP BTU/Min}$$

A = Refrigerator heat removal parameter ("E" for the freezer)

USTEP = "On-Off Switch", controlled by the refrigerator section temperature.

The value of "A" for a particular refrigerator ("E" for a freezer) is determined on the basis that the refrigerator is designed to run continuously when the ambient temperature is 110°F (at which time the condensing temperature is assumed to be 132°F). At a lower ambient temperature more heat will be rejected per minute, with less energy expended, since the capacity of the compressor/condenser unit increases with a lower condensing temperature (which results from a lower ambient temperature). At the same time the input power required is reduced. (This assumes the condenser, evaporator and expansion device support the increased capacity). In order to take into account the increase in capacity and the reduction in power at lower ambient temperatures, the value "A" is multiplied by a factor based on this "combined" effect, due to the variation from the maximum design temperature (110°F). Based on data from Reference 21 used in the model, an estimate of 3% increase in effective capacity per degree reduction in ambient temperature was estimated. (This value is probably optimistic and depends strongly on the characteristics of the refrigerators components).

The value of "A" is calculated as follows:

$$A = \frac{\text{Total BTU/Hour heat gain (at 110°F)}}{60}$$

$$= \frac{546}{60} = 9.10 \text{ BTU/Min} \quad \text{(for model used)}$$

5. QRAN is determined each minute in the program:

a) A "monte-carlo" check is made to see if the door is opened. (See Section 2.4.3.2)).

b) If the door is opened the amount of heat added is estimated to be:

$$QRAN = (5.0 * y) + 15 \quad BTU$$

Where: y = the sum of 6 random numbers (0 to 1.0)

$5*y$ = the estimate for longer openings and warm products based on reasonable guesses)

15 = an estimate for one air change and the heat due to the light.

Thus if the door is held open a long time and/or warm items are added to the unit, QRAN could be as large as 45 BTU.

6. QDEF, and its affect on the operation depends on the unit. The defrost operation used in the model is as follows:

a) Two defrost cycles are used per day, the times for a particular house being the same for each day.

b) 800 watts are applied for 15 minutes (equivalent of 683 BTU). The refrigerator temperature is constrained to stay at 40°F maximum (based on observation).

c) The refrigeration unit removes this amount of energy during the following periods in addition to the amount normally removed. (Note: Some of this heat goes out with the melted frost but this was neglected in the model).

7. Referring to paragraph 2, the ON-OFF times of the unit are controlled by a parameter "C" ("F" in the freezer), which gives the change in temperature of the unit per BTU.

   Thus: DELT2 = C*QNET

   and: New Temperature = Old Temperature + DELT2

   The value of "C" depends to some extent on the "loading" of the unit. (The unit will cycle more often when lightly loaded). For use in the model a "nominal" value was calculated based on the following:

   a) The temperature change between "ON" and "OFF" is 4° F (i.e. the differential is $\pm$ 2° F)

   b) A typical "OFF" time at 70°F ambient is 20 minutes (approximately 80% of the cycle time) with no door openings.

   c) Then 4° = 20 DELT2 = 20(C*QNET)

      Where: QNET(70°) = QIN(70°) (i.e. no openings)

      and $$C = \frac{4}{20\ QIN(70°)}\ °F/BTU$$

      Use C $\approx$ .044°F/BTU

8. The energy used per minute by the refrigerator (freezer) is contained in the parameter KWREF(KWFRZ). The refrigerator model "loops" 15 times in each period in its subroutine and the "energy" is summed for the number of minutes the unit is "ON" in the period. This value is multiplied by 4 to give the average kilowatts for the period. (Since the period is 1/4 hour).

   ENGY = ENGY + KWREF(USTEP)

   KWUSED(Ti) = 4.0*ENGY (in main program)

   the parameter is calculated as follows:

$$KWREF = \frac{\text{rating of compressor, surface heaters and fans}}{\text{60 Min/Hour}} \quad \text{KWHours/Min}$$

The rating of the compressor can be obtained from manufacturer's data based on calorimeter tests or can be estimated based on a typical cooling efficiency of 3 BTU/Watt hour [21].

Surface heaters, inside fan and condenser fan were estimated to use 50 watts for the model. Calorimeter data for the 16 cubic foot refrigerator/freezer indicated a 250 watt load for a 546 BTU/Hour output. Based on this, the value used in the model was:

$$KWREF = \frac{.250 + .050}{60} = .005 \text{ KWHours/Min}$$

APPENDIX D

ADDITIONAL LOAD CURVES FOR LARGE LOAD GROUP PREDICTED DATA AND LARGE LOAD GROUP TEST DATA

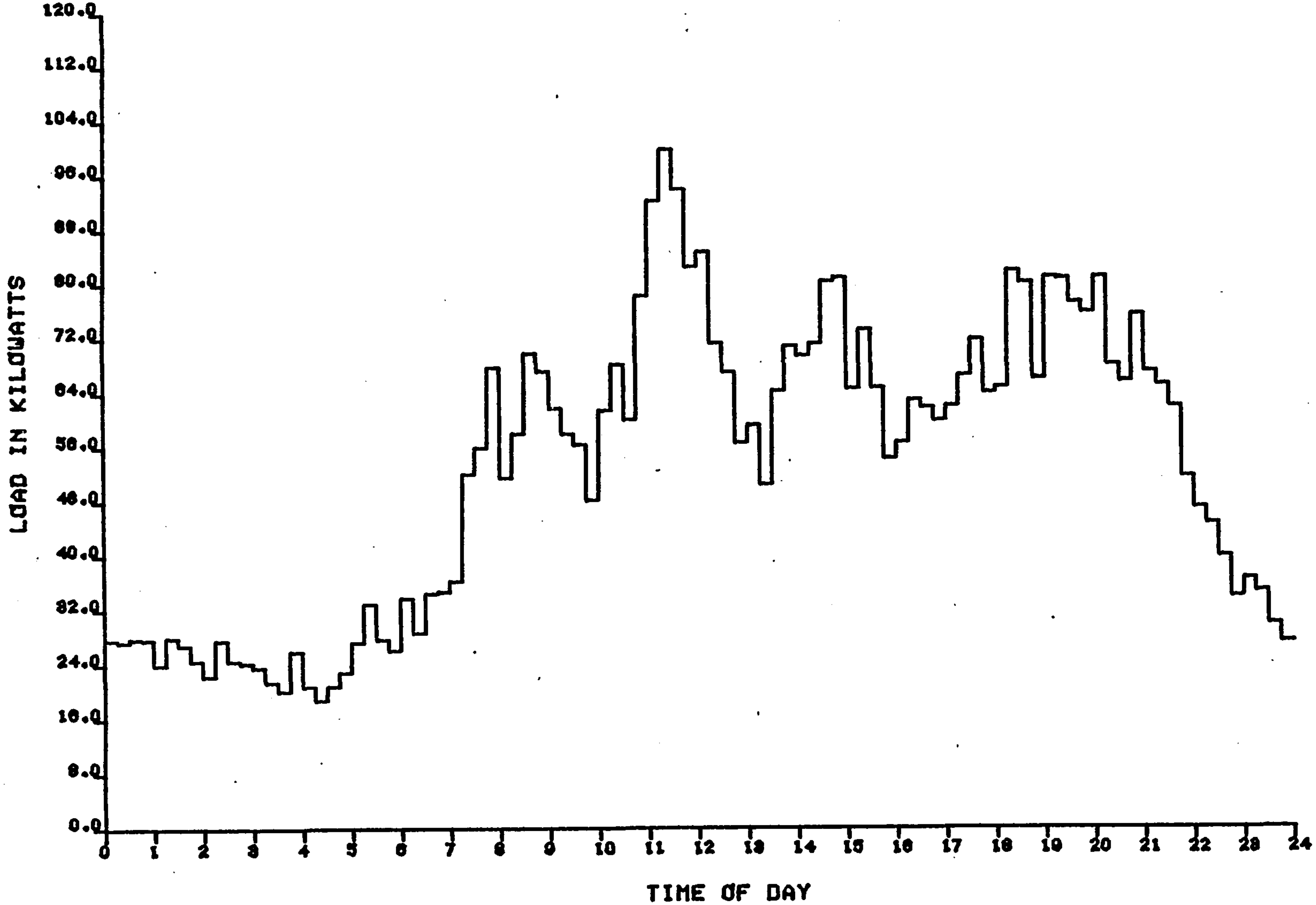


Figure D-1 - Customer Load Curve for Large Load Group
Test Data for Sunday

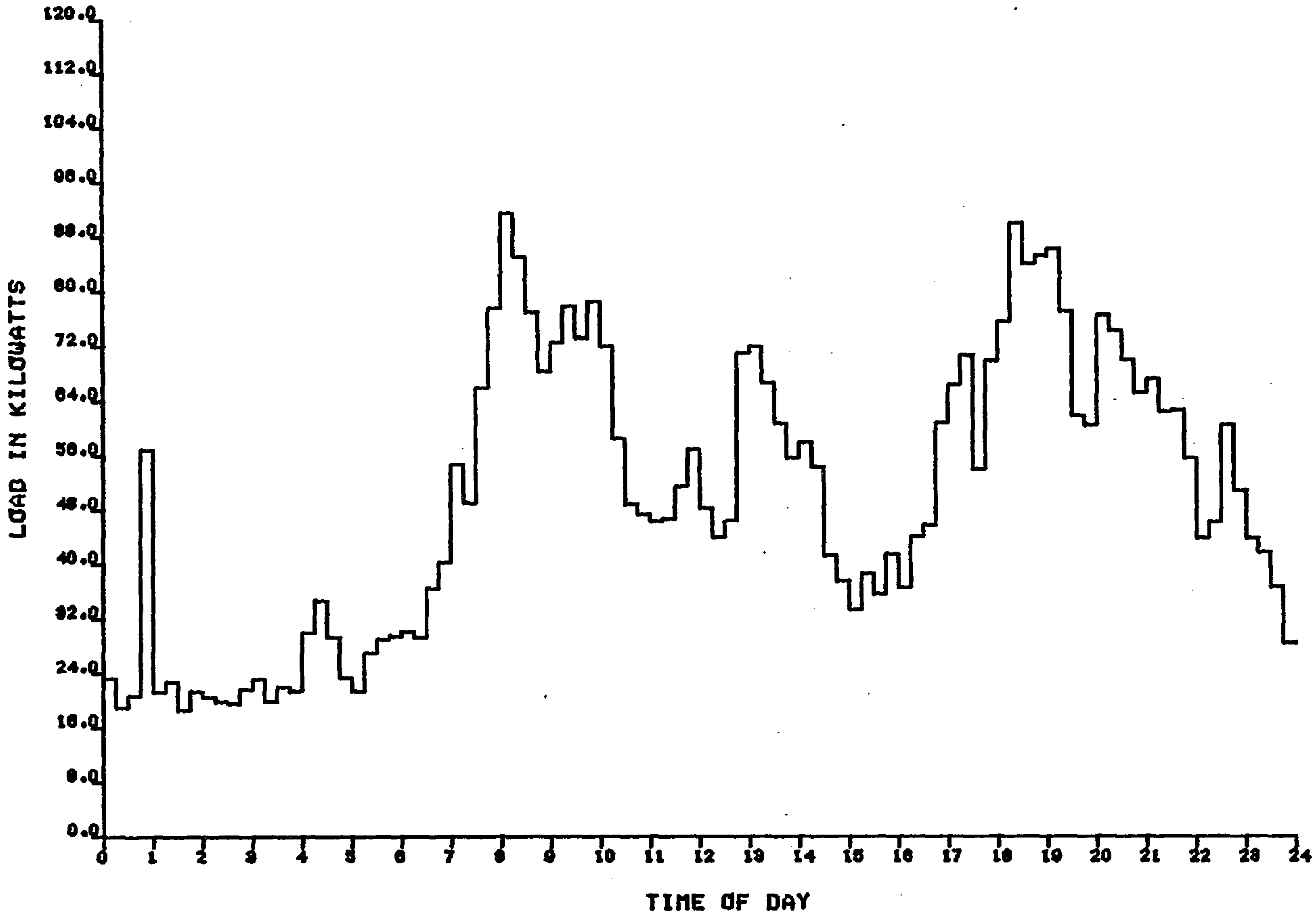


Figure D-2 —Model Load Curve for the Large Load Group
Predicted Data For Sunday

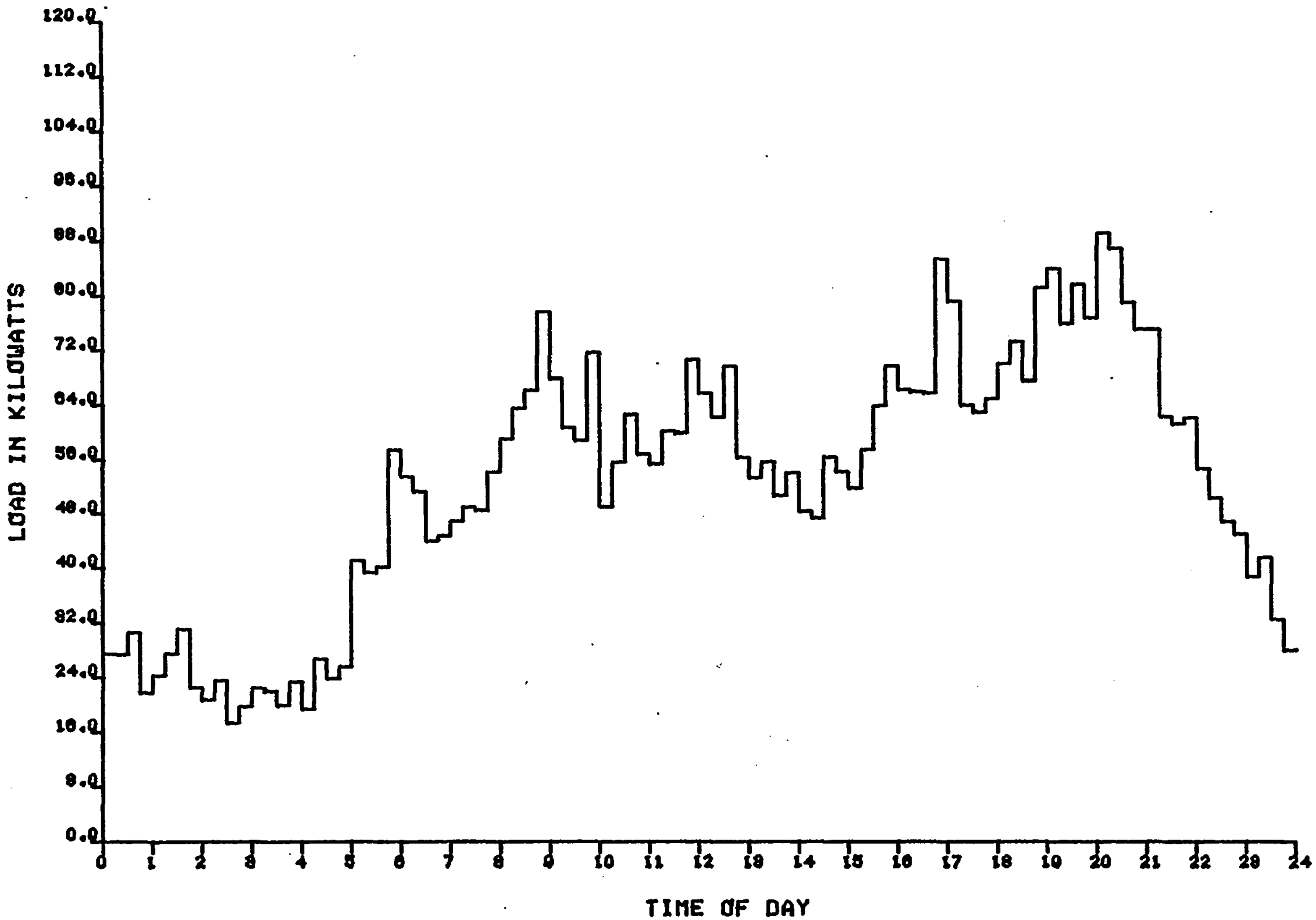


Figure D-3 - Customer Load Curve for Large Load Group
Test Data for Monday

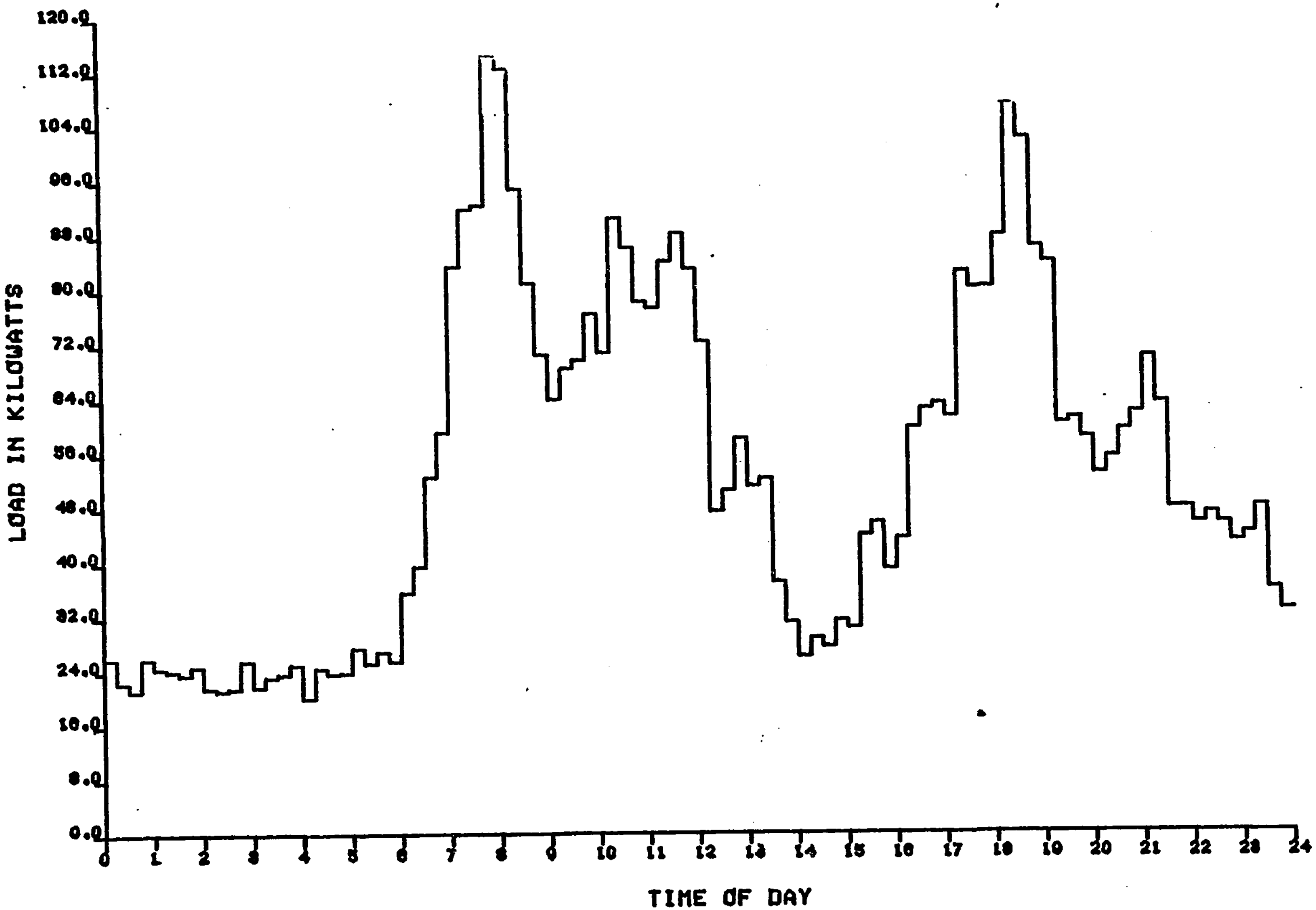


Figure D-4 —Model Load Curve for the Large Load Group
Predicted Data For Monday

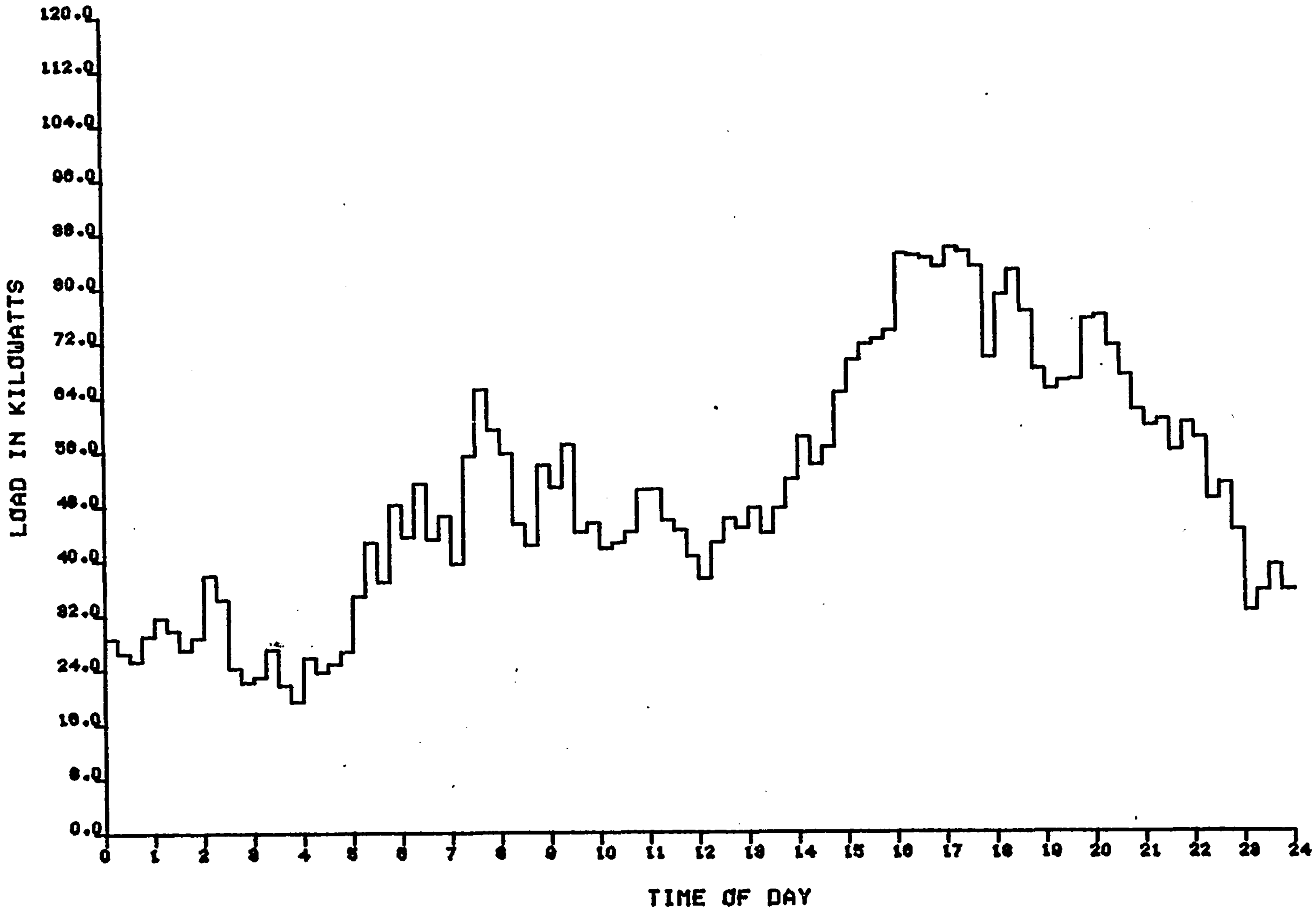


Figure D-5 - Customer Load Curve for Large Load Group
Test Data for Tuesday

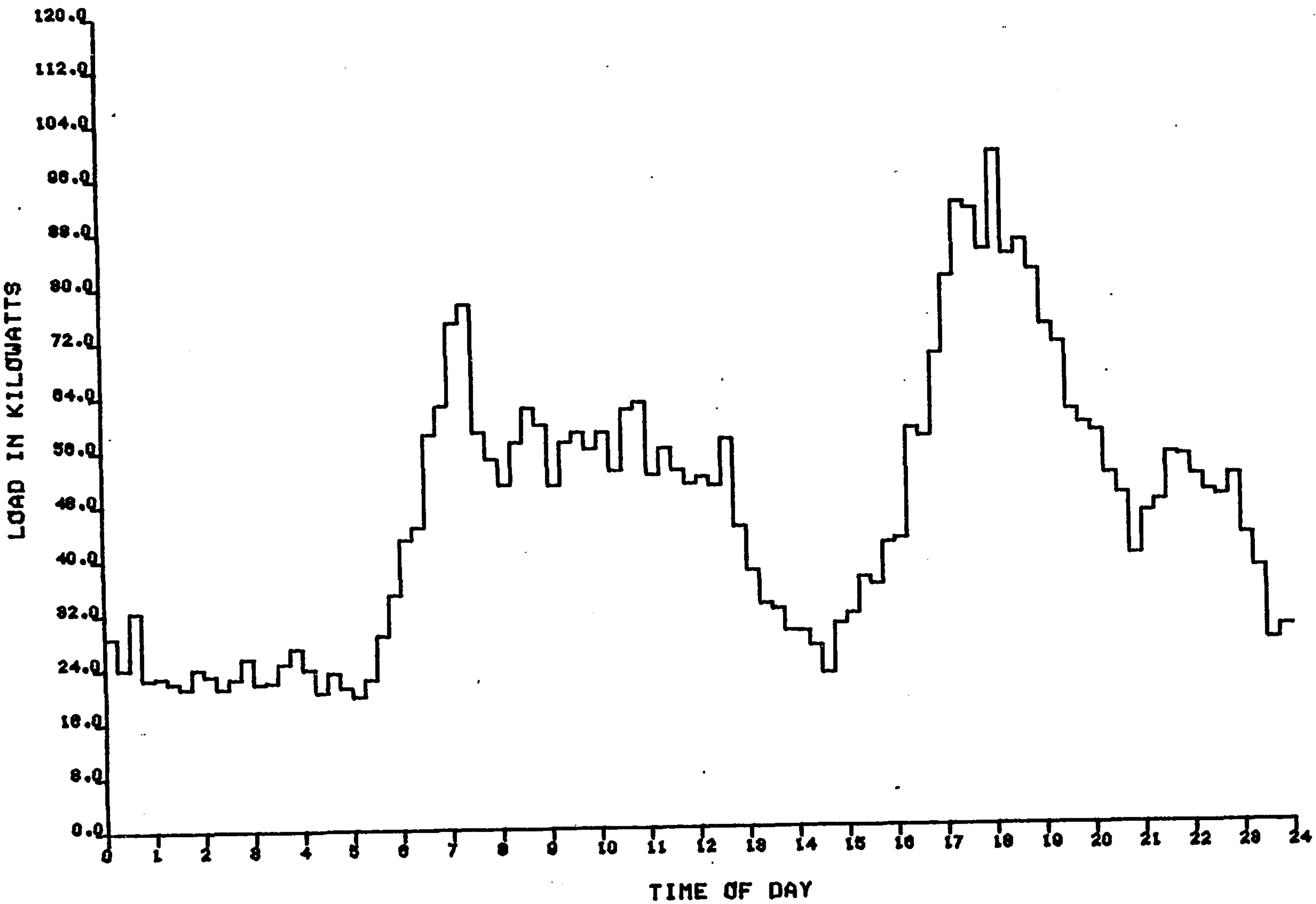


Figure D-6 —Model Load Curve for the Large Load Group
Predicted Data For Tuesday

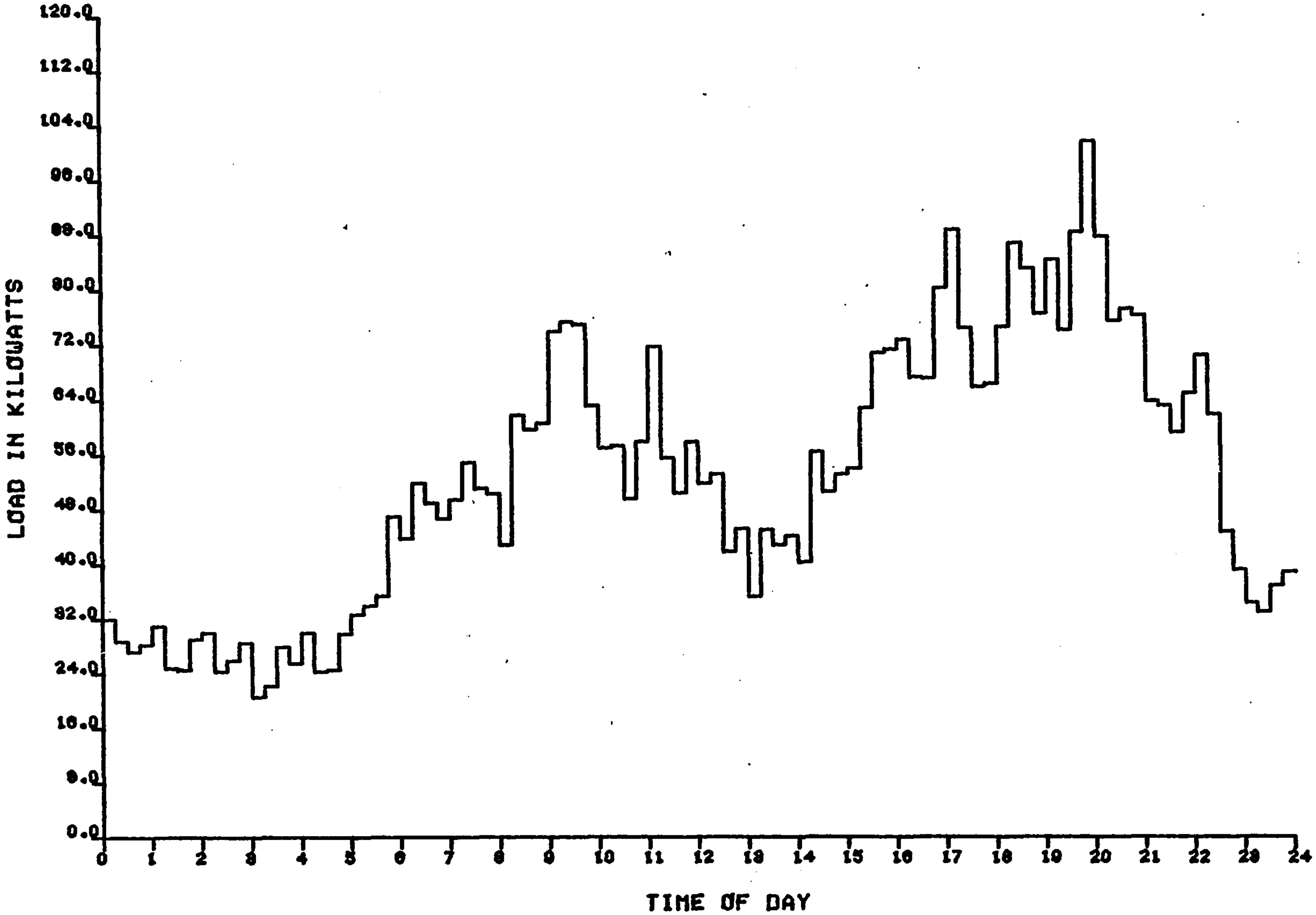


Figure D-7 - Customer Load Curve for Large Load Group
Test Data for Wednesday

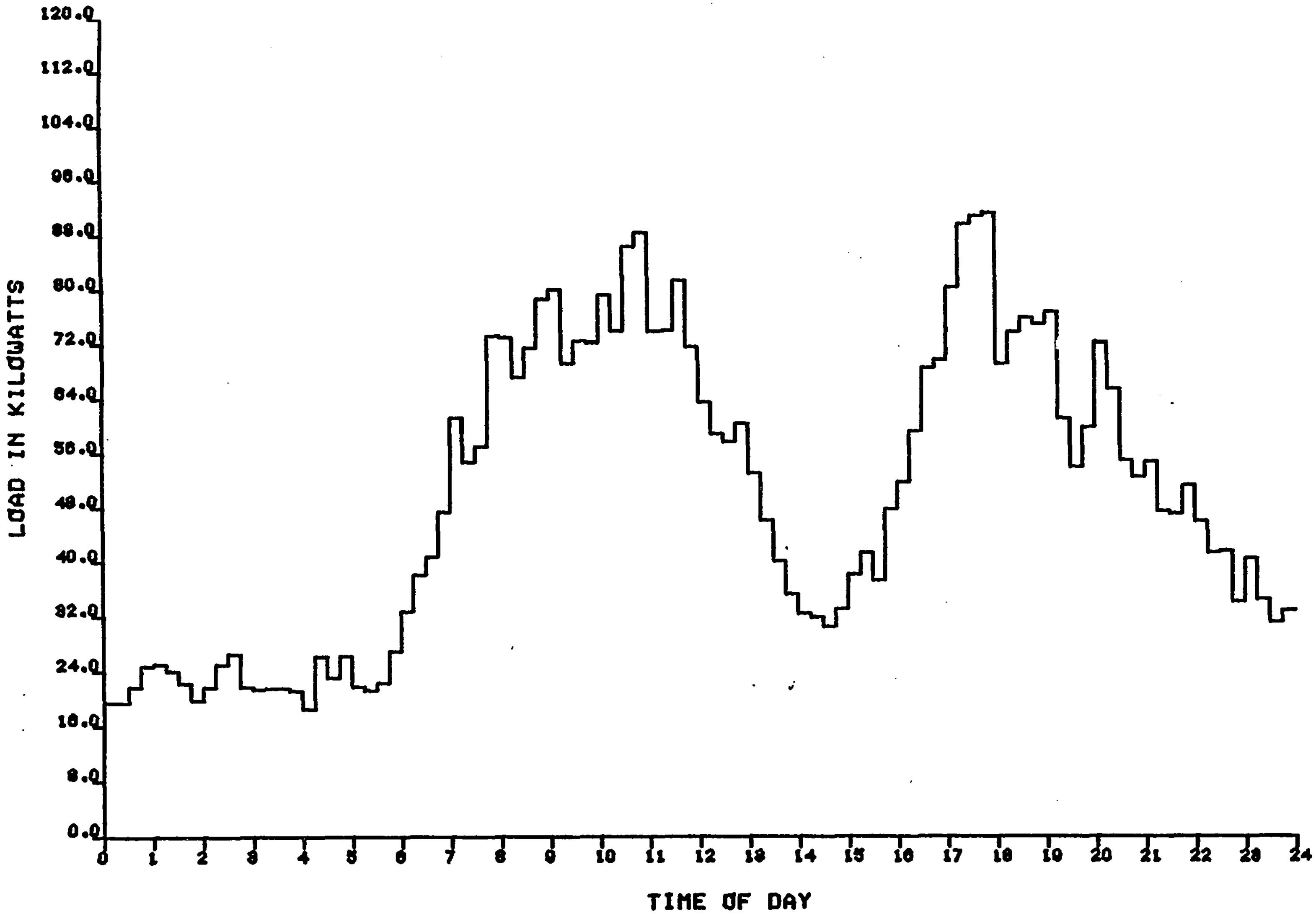


Figure D-8 —Model Load Curve for the Large Load Group
Predicted Data For Wednesday

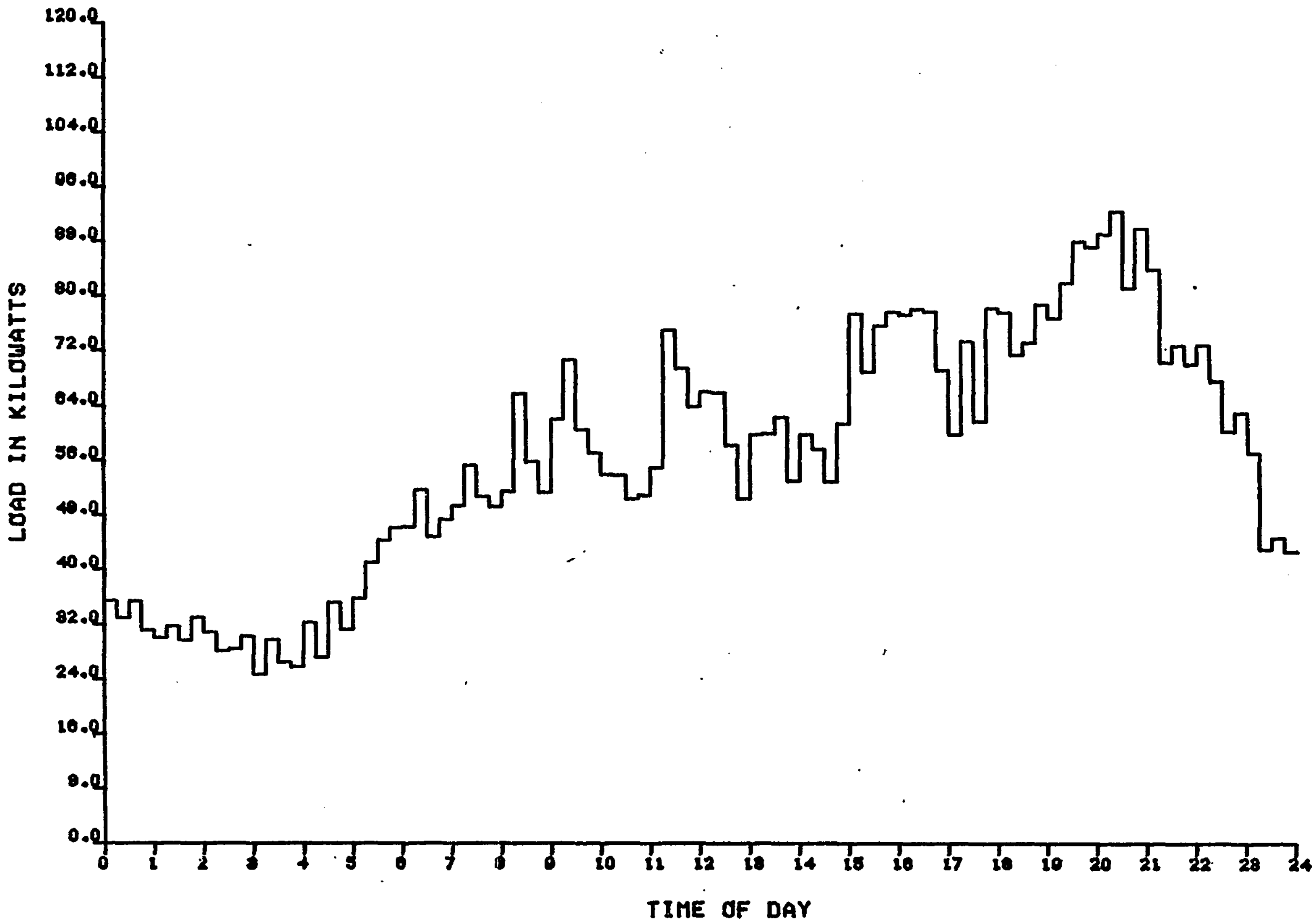


Figure D-9 - Customer Load Curve for Large Load Group
Test Data for Thursday

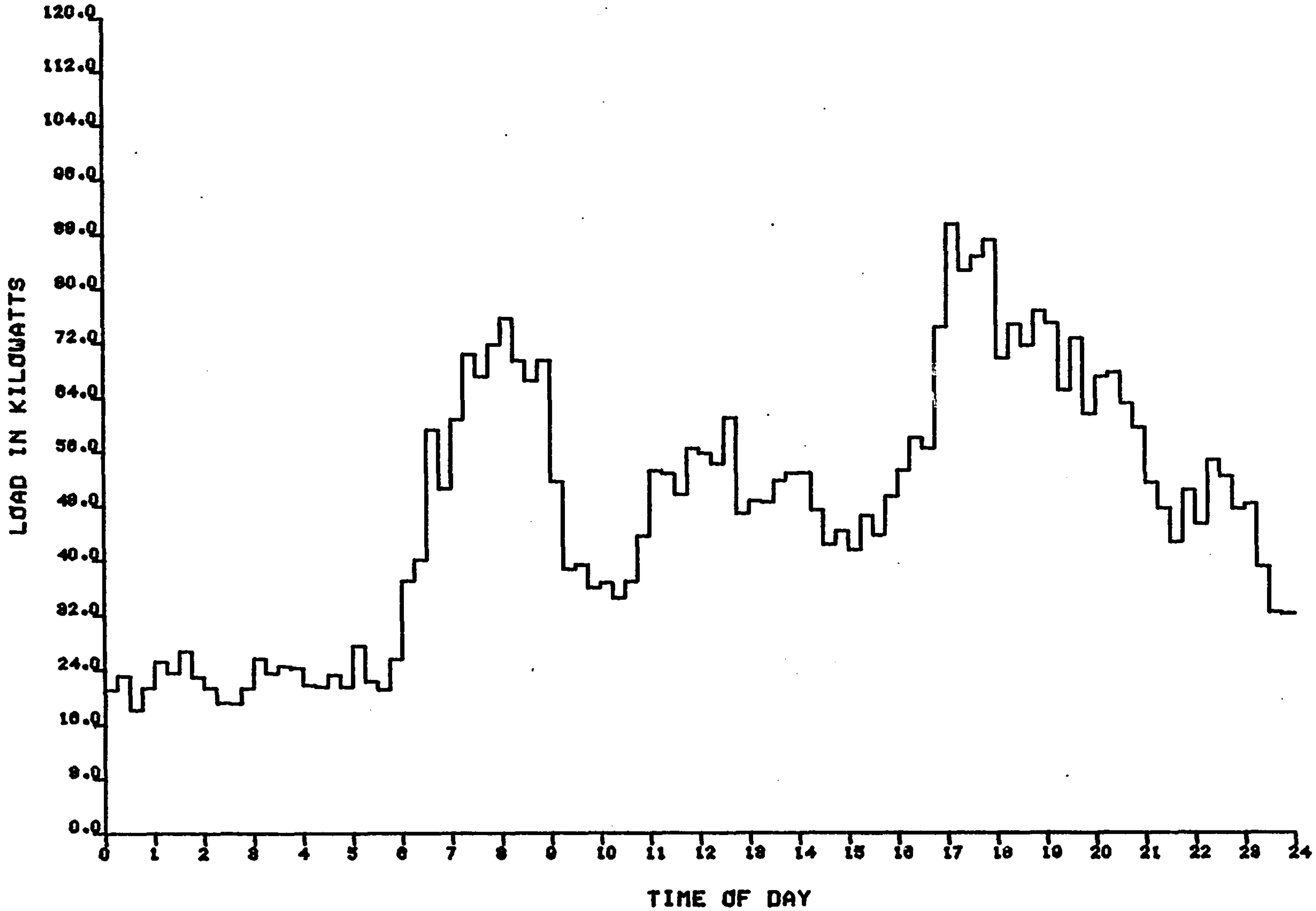


Figure D-10 —Model Load Curve for the Large Load Group
Predicted Data For Thursday

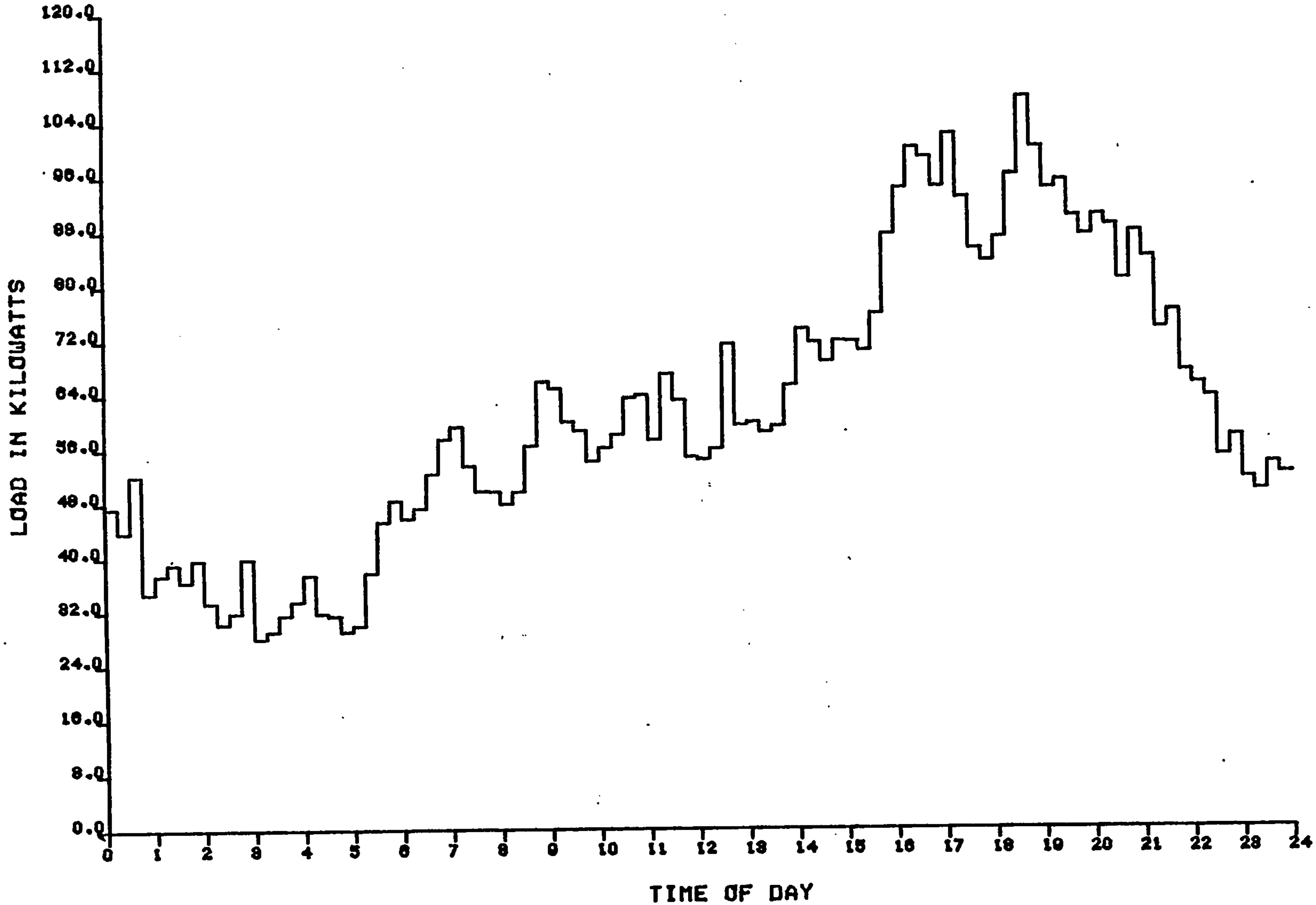


Figure D-11 - Customer Load Curve for the Large Load Group
Test Data for Friday

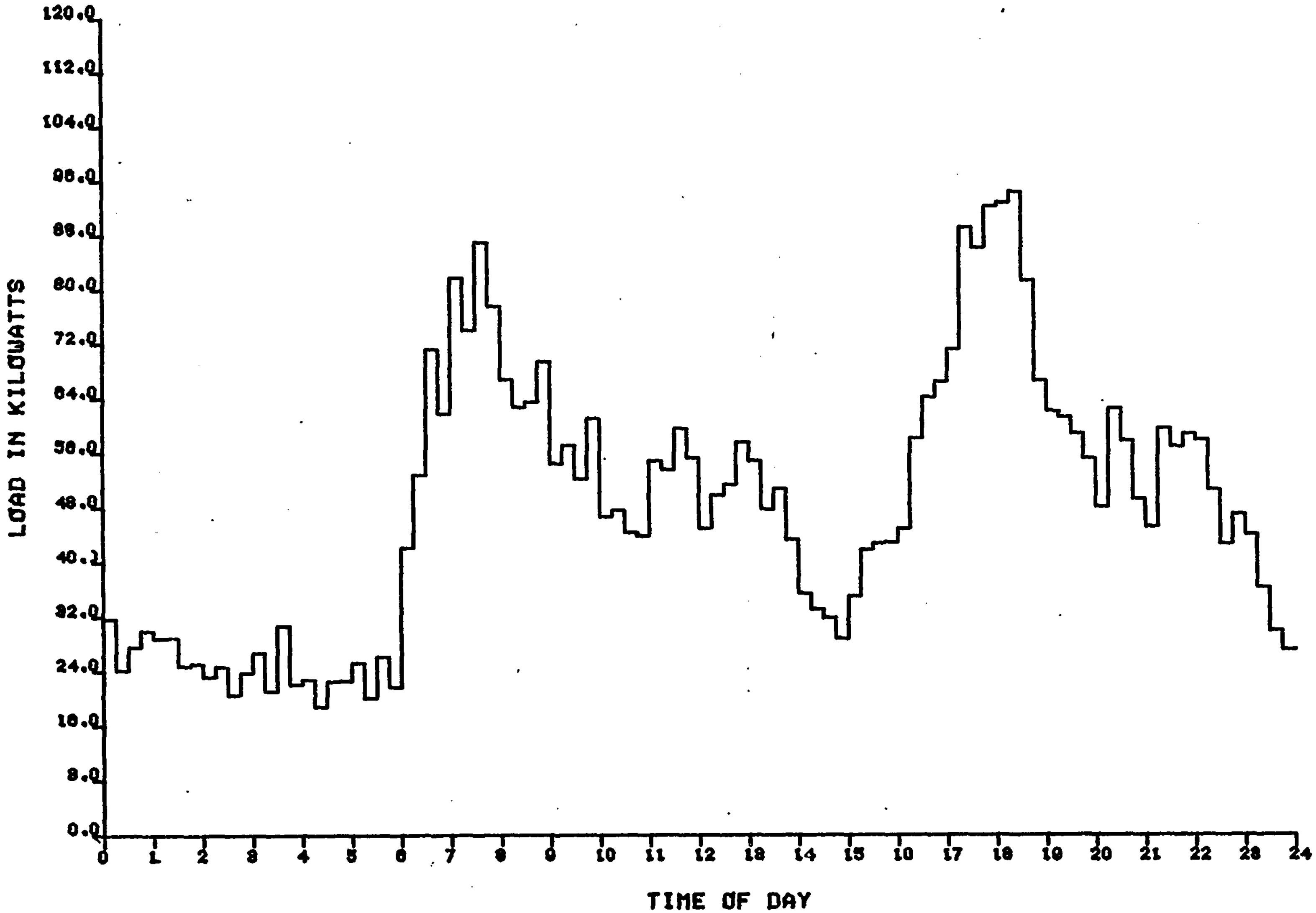


Figure D-12 —Model Load Curve for the Large Load Group
Predicted Data For Friday

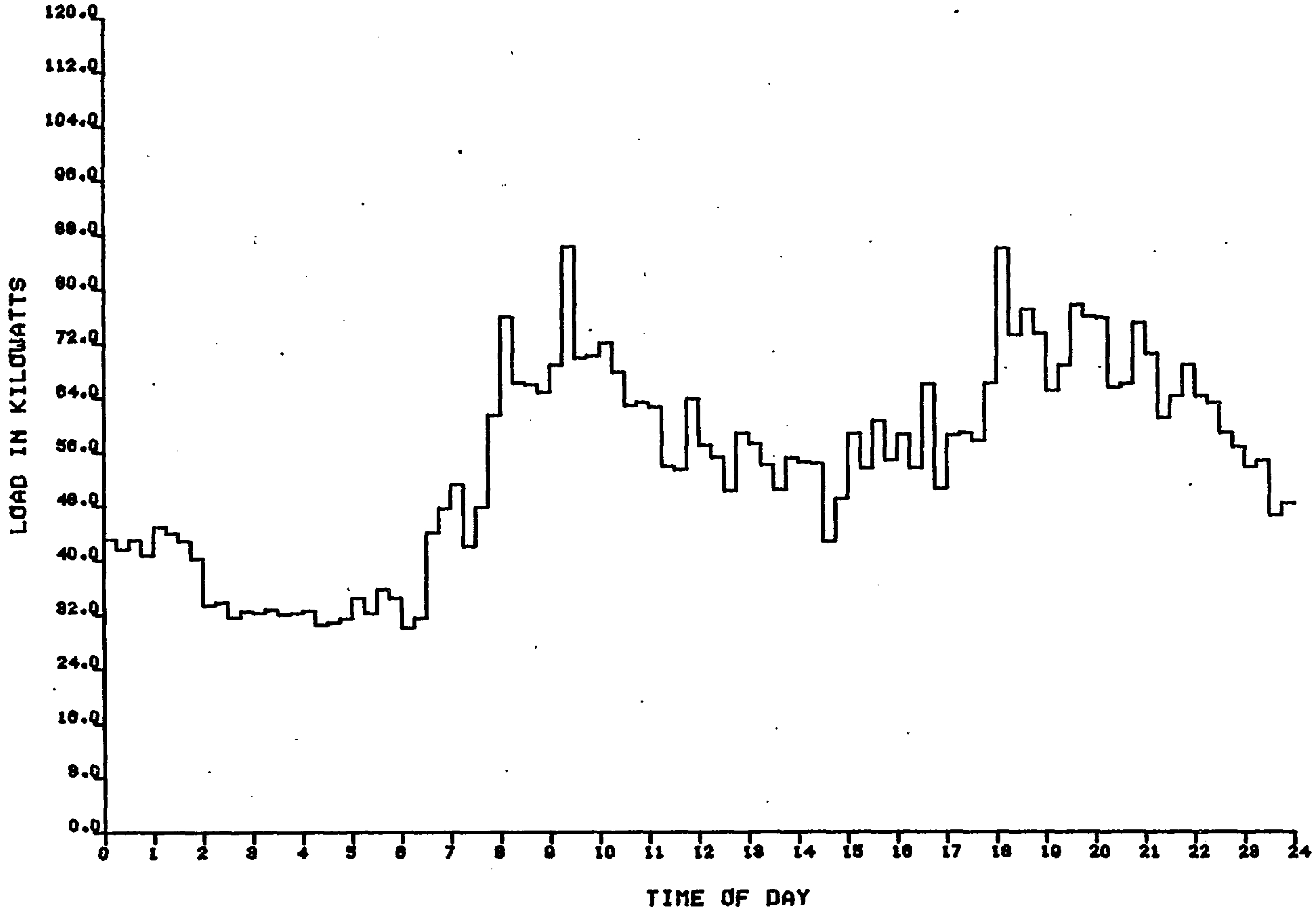


Figure D-13 - Customer Load Curve for Large Load Group
Test Data for Saturday

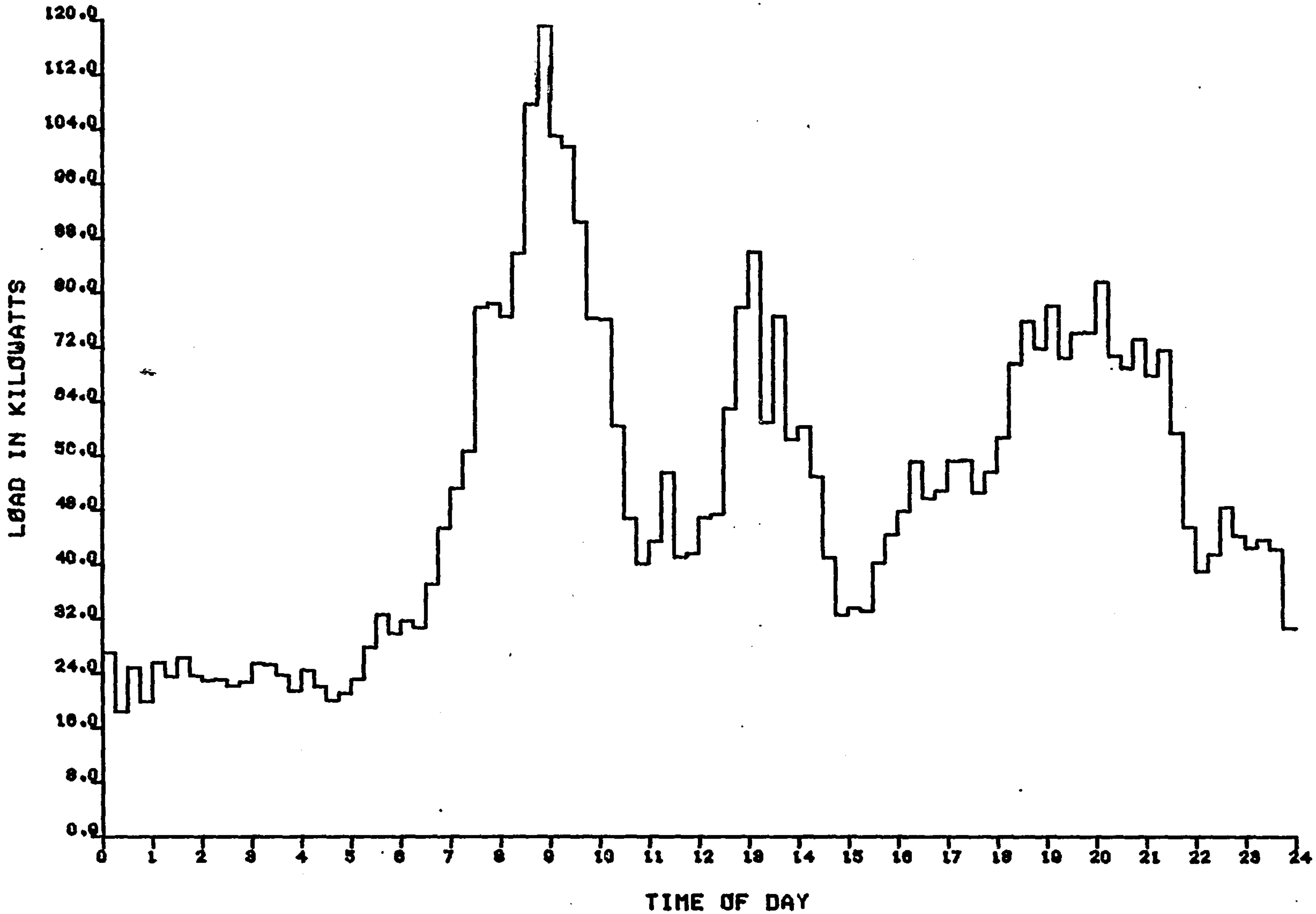


Figure D-14 —Model Load Curve for the Large Load Group
Predicted Data For Saturday

LIST OF REFERENCES

REFERENCES

1. Connecticut Light and Power Company Residential Load Test Data; Connecticut Peak Load Pricing Test; Conducted by the Connecticut Public Utilities Control Authority, the Connecticut Department of Planning and Energy Policy, the Connecticut Office of Consumer Counsel and Northeast Utilities. May 1977.

2. P.D. Matthewan and H. Nicholson, "Techniques for Load Prediction in the Electricity-Supply Industry", Proc., of the IEE, Vol. 115, No. 10, October 1968, pp. 1451-57.

3. P. Gupta and K. Yamada, "Adaptive Short-Term Forecasting of Hourly Loads Using Weather Information", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-91, Sept. - Oct. 1972, pp. 2085-94.

4. S. L. Corpening, N. D. Peppen and R. J. Ringles, "Experience with Weather Sensitive Load Models for Short and Long-Term Forecasting", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-92, Nov. - Dec. 1973, pp. 1966-72.

5. M. Y. Akhtar, "Frequency-Dependent Power System Static-Load Characteristics", Proc. IEEE, Vol. 115, No. 9, September 1968, pp. 1307-14.

6. J. B. Woodward, Jr., "Electric Load Modeling", Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, Massachusetts, September 1974.

7. N. W. Simons, F. C. Schweppe, et. al., "Component-Based Load Models", Engineering Foundation Conference, Henniker, New Hampshire, August 1979.

8. A. S. Debs and C. Y. Chong, "Structure Oriented Load Models", Engineering Foundation Conference, Henniker, New Hampshire, August, 1979.

9. S. K. Jones and C. W. Brice, "Stochastically Based Physical Model Loads", Engineering Foundation Conference, Henniker, New Hampshire, August 1979.

10. D. Nelson, D. Newman, et. al., "Aggregation Oriented Load Models", Engineering Foundation Conference, Henniker, New Hampshire, August 1979.

11. P. A. Frick, "Parametric Stochastic Representation of Loads", Engineering Foundation Conference, Henniker, New Hampshire, August 1979.

12. C. W. Gelling and B. W. Taylor, "Electric Load Curve Synthesis - A Computer Simulation of an Electrical Load Shape", IEEE Trans. on Power Apparatus and Systems, PAS-100, June 1981.

13. John H. Broehl, "An End Use Approach to Demand Forecasting", IEEE Trans. on Power Apparatus and Systems, PAS-100, June 1981.

14. Evans, Alan W., "The Economics of Residential Location", St. Martins Press, 1973.

15. Heggie, Jan G., "Modal Choice and the Value of Travel Time", Oxford University Press, 1976.

16. Schmidt, Marty J., "Understanding and Using Statistics, Basic Concepts", D. C. Heath and Company, 1975.

17. "Electrical Products - 10 year Saturation Levels (and other tables)", Merchandising, March 1979 and March 1981.

18. "Energy Facts", Library of Congress, November 1973 (based on "Annual Energy Requirements of Electrical Household Appliances", Electrical Energy Association, New York).

19. "Bright Ideas on Saving Electricity", Granite State Electric Company, October 1975.

20. "Estimated KWH Use for Household Appliances", Lite Lines, Public Service Company of New Hampshire, September 1978.

21. "ASHRAE Handbook - Fundamentals (1977) and Equipment (1979)", American Society of Heating, Refrigeration and Air-Conditioning Engineers.

22. W. Hutton and W. M. Dillon, "Hot Water Supply", Scott-Choate Publishing Company, 1951.

23. T. A. Ryan, Jr., "Minitab II Reference Manual", The Pennsylvania State University, 1980.