ENERGY LABORATORY

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

AN EVALUATION OF THE ORNL RESIDENTIAL ENERGY USE MODEL

Prepared by

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Abstract

This report provides an evaluation of the architecture, empirical foundation, and applications of the Oak Ridge National Laboratory (ORNL) residential energy use model. A particular effort is made to identify the strengths and shortcomings of the model for alternative uses, and to identify areas where model structure and empirical support could be upgraded. Concrete suggestions are made for improvements in model logic, strengthening the empirical basis for behavioral and technical parameters, and reducing the biases in the model arising from aggregation. The overall conclusion is that the model has the potential to provide adequate forecasts of the aggregate impacts at a regional or national level of policies whose effects on households are relatively homogeneous. There are a number of model changes which would be relatively easy to implement, and which should substantially improve forecasts of this sort. On the other hand, the aggregate architecture of the ORNL model makes it fundamentally unsuitable for applications to geographical areas smaller than DOE regions, or to policies which have a heterogeneous impact on households.

Table of Contents

EXECUTIVE SUMMARY

The Oak Ridge National Laboratory (ORNL) residential energy use model is a complex system designed to simulate the impacts of alternative energy policies on the residential sector. Its architecture represents a compromise between the need to analyze policies which are quite localized and heterogeneous in their impacts, such as mandatory insulation standards in new homes, and the requirements that data inputs and forecast outputs be defined at highly aggregate national or DOE regional levels. Totally satisfactory achievement of both objectives is beyond the reach of contemporary data and modeling art. The ORNL model is a successful exercise in the "art of the possible" which attains many, but not all, of its goals. The model is generally sound in concept and logic. Its aggregate design places fundamental limits on the kinds of questions it can sensibly address -- it is intended to provide aggregate forecasts of impacts of "uniform" policies, and should not be asked to forecast localized or heterogeneous effects. The implementation of the model contains a number of slips and modeling misjudgements which in hindsight could and should be rectified. The empirical analysis and judgement underlying model parameters is a particular area where a substantial continuing effort to upgrade the model is needed. An overall conclusion is that the ORNL model provides an adequate framework for aggregate forecasting of the impacts of homogeneous policies, but needs an immediate overhaul to repair some obvious weaknesses, and a program of long-term maintenance and upgrading. For localized forecasting of the

impacts of heterogeneous policies, as for example the impact of a credit program for insulation retrofitting in a utility service area, the ORNL is fundamentally limited by its aggregate architecture, and should not be expected to provide satisfactory results. The following paragraphs summarize the findings of the evaluation report.

Policy Analysis and Energy Use Modeling

The report attempts to provide a perspective on methods for policy analysis -- non-modeling approaches, simple "econometric" models, and complex simulation models of the ORNL type.

- o Modeling provides a useful discipline for policy analysis in which assumptions are explicit, interactions are accounted for in a logical fashion, and conclusions are reproducible. However, the state of modeling art is such that model outputs should be treated as only one input to decision-making, subject to error, and the models themselves should be treated as evolutionary.
- o In modeling, more complex or "realistic" is not necessarily better -- a model is purposely an abstraction of reality, and different policy goals may call for models of different "grains."
- o In designing models, it is useful to think of them as "factories" which transform data on economic conditions and energy policies into forecasts. Decisions on model architecture parallel the decisions required to design the processing technology and management structure of a real factory. Further, the model user faces the same problems and decisions as a real factory owner -- breakdowns and maintenance, investment to replace or upgrade processing technology, adequacy of management, R&D, and when to scrap an obsolete plant and start over.
- o Complex energy use models such as ORNL have data requirements

for calibration and operation considerably in excess of what is currently available. Several remedies are required: better documentation of judgements made in the absence of adequate data and identification of data needs, modification of models to use available data, innovative use of existing data, and a program to expand data collection in directions needed for policy modeling.

- A program of on-going validation and evaluation of results should be undertaken for energy policy models, including the ORNL model and others.

ORNL Model Structure

The ORNL model structure is designed to forecast energy consumption by major end use, taking into account appliance saturations, efficiency of appliances, and usage patterns. The unit of analysis is aggregate -- a DOE region or the nation. The model is explicitly dynamic, with equipment decisions in new construction and replacement decisions following failures.

- The model has difficulty handling aggregation correctly because the behavioral equations represent aggregates of heterogeneous households, and because of aggregation of accounts (e.g., aggregation of appliances of all vintages and efficiencies into a single old appliance category with an "average" efficiency). This is a fundamental limitation on the precision of the model due to its architecture. However, biases could be reduced by selective disaggregation and appropriate correction factors.
- The housing module is currently insensitive to energy policy, and contains some questionable model assumptions and econometrics. Remedies are to rework the model using better data (e.g., Annual Housing Survey) and statistical methods, or else to use external housing market forecasts to provide the required simulation inputs.
- Appliance efficiency decisions are assumed in the ORNL model to minimize life-cycle costs. This report gives examples showing

that joint determination by households of efficiency with utilization, durability, or capacity of appliances can result in significant biases in the ORNL approach. A number of technical suggestions are made for improving the ORNL efficiency choice module.

- The usage of owned appliances is modeled satisfactorily. Some technical improvements are suggested.
- The appliance saturation models are quite awkward, and could be both simplified and improved. There is room for substantial improvement in data sources (e.g., equipment prices) and model specification (e.g., interaction of climate, capacity, and effective price).

Model Calibration

The ORNL model requires, by crude count, 500 behavioral and technological parameters, plus approximately 450 exogenous variable values for each region analyzed. Most of the parameters and many of the exogenous values are not observed directly, and must be calibrated by indirect construction, engineering calculation, econometric estimation, or judgement. In practice, the econometric and engineering support for the calibration is weak, and the model relies heavily on judgement.

- Housing sub-model parameters are mainly estimated econometrically, with some simplistic judgements on future housing mix. Better use of available data and more careful model specification and estimation should improve this module.
- The module determining appliance efficiency utilizes engineering estimates of the tradeoff between appliance efficiency and fabrication cost, and untested assumptions on the relation of fabrication cost and price of equipment, and on life-cycle minimization without adjustments for capacity, service features, or interaction with utilization. Existing survey data sets would permit some of these assumptions to be tested and modified if they conflict with actual behavior. New data will be needed to map out fully consumer behavior with respect to efficiency,

capacity, usage, and service quality decisions. More comprehensive and better documented engineering analysis is needed.

- The appliance saturation module giving fuel shares suffers from inadequate data, particularly lack of equipment price data, and unsatisfactory model specification and statistical analysis. A simpler, more data-analytic model structure is suggested. Survey data sets along with careful construction of cost data for alternatives should yield a more plausible saturation model.
- The usage module parameters are almost entirely judgemental. Survey data sets should permit testing of these assumptions or substitution of behavioral estimates.
- The ORNL model needs much more careful and comprehensive validation than it has received so far. If a new type of airplane is designed and built, it is unthinkable that it would be put into service carrying passengers without first being carefully tested. Judgements on energy policy reached using the ORNL model can also have a profound effect on people's lives, and it should also be unthinkable that it would be used without thorough testing.

Policy Simulation Methodology

The ORNL model is currently used as a tool for baseline midterm forecasting, and for policy studies of specific programs such as insulation standards for water heaters.

- The ORNL model has few proven advantages and a number of potential pitfalls as a baseline forecasting tool, when compared to aggregate econometric forecasting models. Prudent forecasting suggests it be used only as a backup to more traditional forecasting tools until it has established a track record of superior performance.
- The ORNL is designed for policy studies, and is generally well suited to their performance. Care should be taken not to push the model beyond its design limits. It should not be used to analyze very heterogeneous or localized policies, or to attempt to answer distributional questions.

- o Despite its end-use detail, the ORNL still lacks the richness of technological description or components of behavior necessary to make policy analysis easy. For example, it is non-trivial to translate specific policies such as credit programs for insulation into technological or behavioral parameters in the model. Future model changes should take this translation problem into account.
- o The ORNL is not designed for application to small geographic areas, and is entirely inappropriate for this purpose. While the ORNL model contains many useful ideas for the analyst faced with policy analysis at the state level or below, such major structural changes would be required for it to perform acceptably at this level that the analyst would be better off starting with a clean slate.

Recommendations

This evaluation has reached the conclusion that the ORNL model is potentially a useful forecasting tool for the range of policies it is designed to handle. The model should immediately be revised to correct weaknesses and improve documentation. A program for recalibration and validation should be started. This program should include improving model specification and logic where appropriate.

- o Development of a portfolio of policy models, varying in complexity and purpose, is recommended. These should range from "simple" econometric baseline forecasting models, through the ORNL model, to "complex" microsimulation models of individual household behavior. An overall "model management plan" should be adopted to maintain a degree of commensurability and compatibility between these models, and to guide the placement of models in the portfolio.
- o Future data collection efforts for the residential sector should be expanded to provide behavioral information in four areas:household appliance efficiency decisions; improved engineering studies on the technological relationship between

cost, comfort, and energy efficiency; prices of appliances as a function of efficiency and service characteristics; and experiments with consumer response to policies for which there are no close historical analogies, such as load management devices.

Section 1

ENERGY POLICY ANALYSIS

POLICY PROBLEMS

Energy production and consumption extend through the fabric of the United States economy. Dependence on foreign suppliers, a relatively concentrated industry, non-renewable resource limits, innovations in supply technology requiring massive risky investments, and pervasive and substantial distributional consequences make the operation of the energy market a matter of national concern. Policies of government and major private sector suppliers over the remainder of this century will nave substantial impacts on the energy market, and consequently on the vitality and viability of the American economy. To make energy policy decisions on the basis of casual opinion or political ideology without careful analysis of the consequences for the economy is dangerous and foolish. The best interests of the nation will not be served either by resurrection of the ham-handed government interventions of the past in this market, or by romantic lassiz faire policies which ignore the impact of OPEC and industrial structure on the development of energy resources. A reasoned course requires weighing the benefits and costs of the spectrum of policy instruments available to government and private suppliers.

The pervasiveness and variety of energy policy impacts, and the importance of consumer accommodation of these impacts, make the measurement of benefits a difficult task. Many policies or market futures involve changes for which there is almost no historical precedent -- examples are imposition of appliance efficiency standards, electricity load management devices, and time-of-day pricing. Others involve changes which are well outside the range of historical experience -- examples are drastic changes in energy prices or in tax treatment of energy-saving equipment. In these circumstances, traditional tools of the policy analyst, reasoning by analogy with historical cases, and use of simple forecasting models which exploit the continuity and inertia of real dynamic systems, lose their effectiveness. The best alternative is, then, to turn to tools which capture the salient aspects of the structural interdependencies and limitations of the system, and thus have some promise of permitting reasonable extrapolation. Policy models provide an organizing framework for this analysis.

POLICY MODELS

The most direct way to describe and quantify the impacts of policy is to construct a model of the system under study. A well-designed model can capture the main features of the real system, while stripping away the irrelevant complexities, and provide reasonable, logically consistent forecasts of system response to new conditions. However, models can also be poorly designed, in which case they may be unable to answer the policy questions at hand, or may provide false and spuriously precise answers. Murphy's Law applied to models suggest that they usually do poorly what they are designed to do, and worse what they are asked to do.

The short history of policy models is littered with many failures and few successes. Further, most successes have been for relatively precisely defined problems (such as inventory control) rather than for policy problems involving large and complex systems, where answers are most needed. This has led to serious questioning of the usefulness of models for policy analysis. There are four answers to this criticism.

First, large-scale policy models are very complex systems which require substantial time and money to bring to maturity. I would guess that various measures used to describe system complexity would conclude that a policy model of the scale of the ORNL model is comparable in complexity to an automobile. One might expect the lead times and design costs for a well-running policy model to then also be comparable to those for an automobile. Furthermore, the policy model building industry is in its infancy, and has still not reached the point where the basic principles of good design are well articulated or widely understood. Just as it would have been tempting but incorrect to conclude on the basis of the early automobiles that they would never replace the horse, I believe it is incorrect to conclude that models will not become an effective tool in policy analysis. Two further conclusions can be drawn from the automobile analogy. First, one should expect a new policy model to be subject to the same kinds of design flaws, repairs, and recalls as a newly designed automobile. Further, the more time and budget pressure at the design stage, the more likely problems in operation. Second, just as vehicles are designed for a limited range of operation, and differentiated by purpose, policy models will have design limits. A vehicle designed to do too many things will do none well, and is inferior to an array of special-purpose machines. Similarly, a policy model designed to answer all questions is likely to be too complex and cumbersome, and will be dominated by a portfolio of simpler models with more limited objectives. Finally, it is worth repeating that development of a good policy model cannot be done "on the cheap" -- the design of software, calibration, and validation tasks require the same kinds of resources as the design of hardware, fabrication, and testing.

A second answer to criticism of policy models is that the market for model builders is open to all comers, with no standards for entry or peer review. There are certainly unqualified and unscrupulous suppliers in the market, often with the most ambitious claims and most elaborate models. The intelligent consumer of models must learn to discriminate good models and modelers from bad, and should judge the value of policy models in terms of what a discriminating consumer can obtain.

Third, the limitations of the current generation of policy models should be assessed in comparison with the limitations of policy analysis without models using traditional tools. The advantage of non-model approaches is that they can in principle take more factors into account more quickly than any formal model. The drawback is that it is difficult to maintain logical consistency and perspective in an informal analysis, to reproduce results, or to convince others that the analysis is unbiased. That the assumptions and weaknesses of a formal model are more explicit and vulnerable than the implicit assumptions of informal analysis should be good for policy analysis, although possibly uncomfortable for the analyst.

Fourth, legitimate reservations about the usefulness of current policy models should be separated from a "kill the messenger" response to unpalatable model forecasts.

Section 2

APPROACHES TO ENERGY USE MODELING

MODELING STRATEGY

The purpose of developing a policy simulation model is to provide a device which can produce plausible quantitative forecasts of the impacts of alternative energy policies. This establishes certain features the simulation system should have — it should accept as inputs the policy alternatives of interest, ideally in a form in which they are naturally described by policy makers. It should provide as outputs the full range of information required to assess impacts, through time and across economic actors.

Any forecasting system, whether simple or complex, can be viewed as a "black box" in which background factors and policies are linked and modulated to produce forecasts; see Figure 2-1. The internal workings

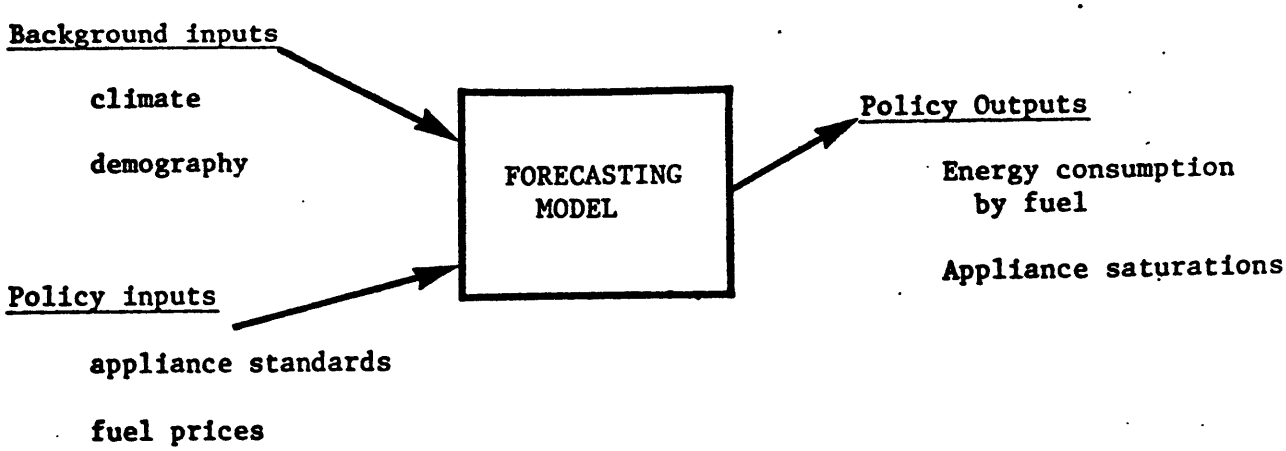


Figure 2-1 A Simulation Model

of the black box may be constructed from historical data on technology and behavior using econometric/statistical techniques, or by some method of engineering design and simulation. One criterion for assessing the plausibility of a forecasting model is realism in process: Are the detailed technical and behavioral linkages inside the black box realistic descriptions of how energy-using equipment is acquired and operated, and how this behavior is influenced by external factors? A second criterion for assessing plausibility is realism in performance: Is the model successful in "backcasting" response to historical events?

In general, satisfaction of one of these criteria is neither necessary nor sufficient for satisfaction of the other. A complex model whose elements each appear to be plausible descriptions of the linkage process may contain falacies of composition or "ecological" instabilities which result in implausible performance. It is extremely difficult to design large dynamic models without unintentionally building in unstable feedbacks which lead to implausible long-run behavior. On the other hand, a model with a good record for realism in performance may exploit inertia in the real system and be right for the wrong reasons.

Realism in performance is the bottom line for a forecasting model. Since the whole objective of modeling is to abstract the key linkages of reality, it is not the case that a more realistic model is always better. When the task of the analyst is primarily to prepare baseline forecasts or consider policies which are mild variations on historical experience, there are many advantages to simplistic econometric/time series analysis models which exploit system continuity. On the other hand, when policy alternatives depart radically from historical experience, it is reasonable to expect that a realistic process model will extrapolate more plausibly than a simpler forecasting system. These comments have two implications. First, it may be useful for the analyst to have a portfolio of simulation models ranging from simple models designed primarily for short term baseline forecasting to complex process models designed primarily for long term forecasts of the impacts of significant policy innovations. Second, in any specific simulation model, it is desirable to build in a structure in which short-run baseline behavior is modulated by historical continuities and long-run behavior under alternative policies is bounded by realistic process linkages.

A second feature of the "black box" containing the forecasting model is its flexibility in being able to address a wide range of policy alternatives, or provide outputs answering a wide range of policy questions. A related characteristic is the robustness of the system in being able to respond to policy questions not anticipated at the time of design. Generally, the more flexible or robust a model, the more complex it must be made to capture the required degree of realism in process, and the greater burden in time and cost placed on the analyst. Most of the energy simulation models developed to date, including the Oak Ridge National Laboratory model reviewed in this paper, have been rather ambitious in accepting model complexity in order to gain flexibility. Taking a broad view, it would probably be desirable to develop limited and specialized versions of existing models, or new simplified models, for a series of more specialized policy arenas.

A final feature of the "black box" is its internal organization. A simulation system can be viewed as having a structure much like the internal organization of a firm, as illustrated schematically in Figure 2-2. The core of a simulation model is the "line" function of accepting model inputs, processing them through the equations that link inputs to outputs, and producing policy outputs. A good simulation system will be organized functionally under a supervisor which has the capacity to tailor the production process to specific tasks.

A variety of staff functions in the simulation will service the line function. An accounting and auditing function will organize input and output files, run consistency and validation checks, and maintain records of simulation model performance and cost. A processing technology function will provide and update linkage equations and system parameters, integrating information such as household survey data as it becomes available. This function is in turn served by a research and development function which evaluates model validation results and results from alternative systems, and determines where model improvements are most productive. In most current simulation models, only the line productidon function resides as software in a computer. The remaining functions are less formal, and are often not developed as part of the model design process. Good practice in systems design places more stress on integrating the supervisory and monitoring functions into the architecture of the system.

In most current energy simulation models, the line-processing function is designed as a single-purpose top-down recursive process. The same sequence of steps is performed, in the same order, no matter what the policy under consideration or the policy outputs desired. This is

SIMULATION SYSTEM ORGANIZATION

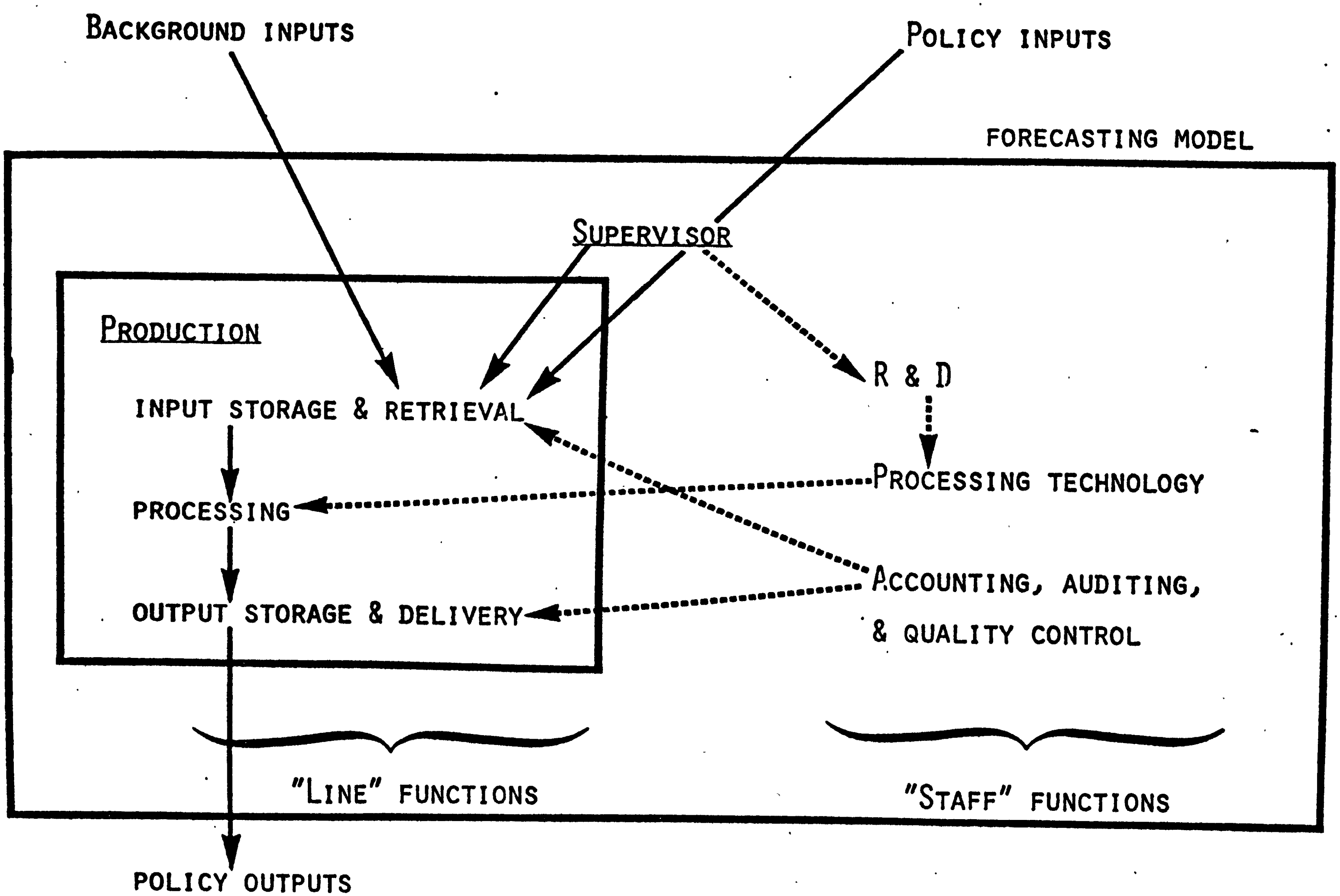


Figure 2-2

the simplest of a variety of ways of organizing a processing system. For example, one could house several independent models within one simulation system, perhaps with common input and output structures, with the supervisor assigning work to the most appropriate model. With vertical modularity and/or parallel processing, one may achieve economies in some stages of the simulation or build in redundancy to be used for consistency checking and validation. Good systems architecture will choose modular and functional model designs that are amenable to operation in various mixed modes. One ideal is to develop the models in terms of some high level "simulation language" permitting easy modification, rather than as "hard-wired" modules. However, the current generation of simulation languages do not appear to be powerful or efficient enough to handle systems of the complexity of the current energy simulation models.

INPUTS AND OUTPUTS

A key question in simulation design is the extent to which the system should be "vertically integrated" to accept inputs and provide outputs in the "natural language" of policy analysts. A fully vertically integrated system will be highly user oriented; however, building in user convenience usually requires building in rigidities which may limit what the system can do. The best solution to this problem is to provide the user with an operating language which defaults to a very simple form for inexperienced users, but with flexibility for experienced users who choose to override the defaults. This has so far not been an issue for energy policy models, which have mostly been written without consideration for user operation.

A second aspect of simulation model inputs and outputs is that large quantities of data are often involved, requiring data base management. If the simulation system runs within the environment of a good data base manager, then the latter system can be used to provide some of the user-oriented capacities desired, such as provision for modifying and checking inputs and summarizing and tabulating outputs. It is a good idea to choose a data base manager which has the capacity to do some arithmetic and statistical calculations, to aid in constructing inputs and summarizing outputs. There are advantages in using a standard data manager language, such as SAS, SPSS, QUAIL, or TROLL.

STRUCTURE

The usefulness of modular functional structure in design of the simulator processing system has already been stressed. Ideally, a processor can be organized as a "job shop" in which flexibility and robustness in handling a variety of policy problems are achieved by employing a selection of appropriate modules. The capacity to "hand-craft" critical steps and use standard or simplified outputs for non-critical steps is an advantage.

One way of achieving flexibility and economy in the same system is to have interchangeable modules which process the same intermediate inputs and outputs at various levels of precision and complexity. For example, one may have a very precise module which forecasts appliance purchases by explicit aggregation over a large simulated population, and a simpler alternative which forecasts the same behavior directly for regional aggregates. A second example is a simple "reduced form" module which forecasts energy consumption as a function of price, in place of more complex modules for appliance purchases, determination of appliance efficiency, and appliance usage.

It is possible to develop interchangeable modules independently, perhaps by drawing blocks of equations from various existing systems. However, an approach which has a better chance of preserving the integrity of the system is to develop the simpler modules as models of their more complex alternatives. For example, a simple model for aggregate appliance purchases could be estimated as a response surface fitted to inputs and outputs of the disaggregate model. In this way, one could construct a consistent hierarchy of models in which the very precise and complex modules would be utilized only when they are critical to a particular policy analysis.

These ideas have been applied piecemeal in many simulation systems. For example, the "Elasticity Estimator" module in the Oak Ridge National Laboratory model can be interpreted as providing a response surface for a more complex system (in a "staff" rather than a "line" capacity). However, they have not been applied systematically, at least for energy policy simulators, and there are some research questions involved in their implementation: Is it practical in sequential modular calculations to go from a simplified "coarse" module to a complex "fine" one, without compromising the consistency of the complex calculation, and what is the best way to make the transition? In fitting simple response surfaces to complex modules, how should real data at the grain of the response surface be weighed, and how should this information be used in assessing and upgrading the complex module?

CALIBRATIONS

The calibration of contemporary energy simulation model parameters in the presence of a variety of innovative policies has placed an impossible burden on model builders. Behavioral response parameters are required in areas where data have never been collected or the appropriate experiments have never been performed. Technical parameters are required in areas where the experiments or working models required for careful analysis are unavailable. The possible responses are to restrict model structure and limit model objectives, or to make up model parameters, depending on downstream consistency checks to limit the damage caused by poor judgements. Quality control with the second alternative is very difficult. Widespread and sometimes cavalier judgements about model parameters are a weakness in current energy forecasting models which should be flagged by careful documentation and checked against data wherever possible.

The statistical and specification errors certainly present in complex data-poor systems should be faced resolutely, and not ducked by use of spuriously precise judgemental or engineering parameters. Error transmission should be modeled and reported as part of simulation outputs. The demand of policy-makers for point estimates is legendary (Lyndon Johnson said in response to bounds on a GNP forecast, "Ranges are for cattle.") Novertheless, modelers only damage their own cause by implying false precision. Instead, non-model analysts must be invited to step through decision trees to establish error distributions for their forecasts.

VALIDATION

The need for policy tools has led to the uncritical use of simulation models without adequate testing and validation. Energy policy simulators are complex systems which are relatively innovative and untested. If these models are to be an input to important policy decisions, then it is important that they be right and that they be widely accepted as reliable.

A common method for validation is within-calibration-period forecasting compared with actual outcomes. This is a useful exercise, but requires two cautions. First, since model development and calibration is an on-going process, it is important to freeze the system and conduct arms-length validation on outputs which have not previously been used in calibration. Second, in a parameter-rich system, it is very easy to over-fit in the calibration period and thereby lose accuracy in the forecast period.

A valuable validation method is to backcast prior to the calibration period. If the model cannot simply be reversed and run backward in time, then it must be provided with starting values and exogenous variables for the backcast period. Validation is sufficiently important to make availability of these variables a consideration in model design.

Sensitivity analysis of model parameters and equation specifications is a useful way to learn about model characteristics and consistency. However, note that while sensitivity analysis may invalidate a model by showing that it is implausibly sensitive (or insensitive) to some factors, it cannot by itself validate a model.

The most valuable information on validity comes from the cumulative experience in using the model for policy forecasting. The primary difficulty is that the policy user has little day-to-day interest in model validation or in systematic data collection for validation. Impressionistic reports on model performance are clearly often biased. A serious evaluative effort requires a systematic arms-length monitoring of policy applications and consequences.

Section 3

DATA LIMITS ON ENERGY USE MODELS

CALIBRATION REQUIREMENTS

An energy simulation model is required to forecast baseline energy consumption by fuel and year given exogenous forecasts on demography, income, and prices; and to forecast the variations in consumption induced by various policies such as fuel price changes, time-of-day electricity pricing, appliance standards, or insulation tax credits. Behavioral models of response require either historical or experimental analogies from which parameter values can be inferred. In addition, a simulation model requires baseyear starting values.

At the level of geographical aggregates such as states, time series data are generally available on energy expenditures and physical consumption levels, incomes, prices, and demographic variables. These permit calibration of some baseline forecasting models, but lack the detail on interactions necessary to calibrate even baseline models with full end-use disaggregation. For many policy alternatives, indirect evidence on response can be deduced by translation into price equivalents; however the behavioral-engineering judgements required for the translation are often difficult to justify.

Cross-section surveys of individual households which have recently become available permit calibration of more detailed behavioral models of appliance choice and consumption. However, these are generally not sufficient to determine appliance efficiency and provide a behavioral foundation for the current life-cycle cost minimizing models of appliance efficiency choice. These data do not provide time-of-day information.

AVAILABLE DATA

Time-series cross-section data by state on residential energy consumption and economic variables is available from published U.S. government sources. In particular, a data base has been compiled by Oak Ridge National Laboratory. State appliance holding data is generally available only in census years. However, recent Annual Housing Surveys provide considerable data on appliances for selected regions.

There are a number of cross-section surveys available which describe the energy consumption behavior of individual households:

(1) BLS consumer expenditure survey, 1972

(2) WCMS survey, 1973 and 1975

(3) MRI survey, 1976

(4) NIECS survey, 1980

The BLS data is now somewhat dated, and lacks critical variables for analysis of appliance choice. The MRI data provides reasonable appliance detail, but its use has been limited by data quality. The WCMS and NIECS surveys provide good quality data with reasonable appliance detail. None of these surveys provide sufficient detail for a full calibration of a stock-purchase-replacement model for appliances, or of a behavioral model of appliance efficiency choice. Load data is also absent. The WCMS data has been used fairly extensively in energy demand studies, although apparently not in the version of the Oak Ridge National Laboratory model currently used in policy studies. The NIECS data has only recently become available.

In addition to these surveys, there are extensive data available from time-of-day electricity pricing experiments and from utility customer surveys required by state regulatory agencies for the PURPA process. Major data preparation efforts would be required in most cases to ensure data quality, provide additional variables, and recode information to a form suitable for model calibration.

General use of energy simulation models for policy analysis will require a continuing program of data collection for calibration and validation. The particular areas in which new data are needed are appliance replacements, appliance efficiency decisions, end use specific load curves, behavioral response to load management programs and related non-price regulatory mechanisms, and product and market data on appliance availability and prices.

Section 4

OVERVIEW OF THE ORNL MODEL

OBJECTIVES

The ORNL model is designed to provide forecasts of residential energy use at highly aggregate national or DOE regional levels. It is intended for analysis of policies which are quite localized and heterogeneous in their impacts, such as mandatory insulation standards in new houses. To some extent, these objectives are incompatible, given the limits of contemporary data and modeling art. On one hand, it is possible to carry out detailed engineering studies of the impact of policies such as insulation standards at the "test house" level. However, it is extremely difficult to project such impacts up to a regional level -- the required demographic and behavioral data are simply unavailable. On the other hand, it is possible to develop fairly satisfactory aggregate-level models to forecast the impacts of policies which are relatively uniform, such as energy price shifts due to a tax on imported oil. However, it is very difficult to assess the impacts of heterogeneous policies such as insulation standards within an aggregate model. To do so requires some assumption on how these effects aggregate, and these conditions tend to be ad hoc and subject to significant aggregation errors.

The ORNL model is a compromise intended to satisfy the most pressing requirements for regional forecasts of the impacts of heterogeneous policies. The unit of analysis is aggregate -- all consumers in a region. However, energy consumption is disaggregated by end use -- refrigerators, gas water heaters, etc. The end use disaggregation permits the assessment of policies which affect individual appliances, at least in principle. A model of this sort will in general have difficulty handling aggregation appropriately -- if a policy affects the purchase and operation of gas water heaters, the aggregate impact of changing usage and saturation is generally a non-linear function of the effects on individuals. These aggregation problems are eased somewhat in the ORNL model by permitting some demographic variation, by type of fuel used, for example. However, the ORNL model specification has not been designed to minimize aggregation problems.

The primary output of the ORNL model is total residential energy consumption, classified by fuel. What the model cannot provide is information on the distributional impacts of energy policy by geographical area other than region (e.g., urban/rural) or by demographic group (e.g., rich/poor, young/old, owners/renters). Thus, while the model can provide the demand detail necessary to drive a planning model for energy production, it does not produce all the outputs necessary to carry through a full benefit-cost analysis of policy.

INPUTS

The ORNL model forecast changes from base year energy consumption, taking into account changing demographics, economic conditions, and technological possibilities for conservation. Simulation inputs fall into three broad catagories: base year data on all variables (including variables which become model outputs in forecast years such as appliance saturation levels and energy consumption), rates of change for variables exogenous to the model such as population and fuel prices, and behavioral and technological parameters which translate exogenous variable changes into model output changes such as changes in energy consumption. Table 4-1 lists the principle inputs. A crude count of dimensions gives 153 technological parameters, 971 behavioral parameters, 636 base year values, and 8840 exogenous forecast values. In practice many of these values are redundant, either because they are not used in the model (e.g., because of excluded fuel/appliance combinations), are assumed to be zero or have common values, or are obtained by a relatively simple interpolation as part of the pre-processing of the input files. There is an obvious ambiguity in the number of inputs depending on at what stage in pre-processing they are counted. I estimate that 500 behavioral and technological parameters which are uniform across regions, plus approximately 450 base year data points plus inputs to preprocessed exogenous forecasts for each region must be determined by engineering or econometric study or by substantive judgemental assumption. In practice, most of these values in the ORNL model have a significant judgemental component, based on indirect and weak engineering or econometric evidence. This is inevitable in any attempt to construct a model of this complexity from existing data, but is also grounds for extreme caution in applying model outputs.

Ordinarily one anticipates that base year values of variables and exogenous forecasts are readily obtainable and non-controversial. However, a number of the base variables in the ORNL model correspond poorly or not at all to published data sources. In particular, base year energy consumption by end use is not obtainable, even approximately, on any systematic basis. When confronted with such a problem, the model-builder should make this level of detail endogenous to the model, so the exogenous driving variables are publicly measured and reported.

Table 4-1. ORNL Model Inputs

Variable	Symbol	Type[1]	Dimension	Input[2]
New equipment market shares e.g. const.	a	BY	240	A,B
Air cond. - space heat load reduct. ratio	acc	T	3	A,B
Appliance mkt. share elast. w.r.t. op. cost	ao	B	400	A,B
Usage elast. w.r.t. op. cost	au	B	160	A,B
Interest rates for PV cost minimization	b	B	320	A,B
Equipment market shares, 1970	c70	BY	120	A,B
New equipment market shares, 1970	cn70	BY	80	A,B
Market share equation "slope" coeff.	coef	B	80	
Ratio of regional to nat'l. new equip. mkt. shares	crat	BY	32	A,B
New equipment technological parameter	oealfa	T	32	A,B
New equipment technological parameter	oebeta	T	32	A,B
New equipment technological parameter	oeinf	T	32	A,B
Annual average energy use, new equip., 1970	eu70	BY	120	A,B
Ratio of short to long run usage elasticities	gan	B	1	B
A market penetration rate parameter	nval	B	1	B
A horizon after which life-cycle cost is min.	nyr	B	1	B
New construction technological parameters	otalfa	T	12	A,B
New construction technological parameters	otbeta	T	12	A,B
New construction technological parameters	otinf	T	12	A,B
New equipment prices, relative	peg	F	3720	A
New equipment prices, 1970	]g70	BY	120	A,B
Interest rate	rate	BY	1	B
Interest rate	ratei	BY	1	
Interest rate	ratet	BY	1	B
Retrofit technological parameters	rtalfa	T	3	B
Retrofit technological parameters	rtbeta	T	3	B
Retrofit technological parameters	rtinf	T	3	B
Ratio of 1969 to 1970 usage factors	ru	BY	4	A,B
Maximum saturation	sat	B	8	
Average equipment lifetimes	teg	T/B	8	A,B
Lifetime of investments in thermal shell	ttin	T	1	B
New equipment installations, 1970	un70	BY	32	
Real prices for fuels plus income	x	F	155	B
Fuel prices plus income, 1970	x70	BY	5	B
Average size of existing housing units	ehs	F	93	B
Average annual energy use, new equip., before adjust.	eun	F	3720	B
Thermal integrity of retrofit homes	rti	F	24	B
Number of homes which are retrofit	rtr	F	93	B

Table 4-1. ORNL Model Inputs (cont.)

Total number of occupied housing units	stoke	F	93	B
Total number of new housing units	stokn	F	93	B
Fractions of new homes with room/central AC	f	F	2	B
"Status quo" new equipment energy use	eun70	F	72	B
Size of new housing units	nhs	F	31	B
Average thermal integrity, new structures	tin	F	744	B

Notes:

1. Types are base year data (BY), technological parameters (T), behavioral parameters (B), and exogenous forecasts (F).

2. Named variables are those defined in program documentation. Input A indicates the variable is documented as an input. Input B indicates the variable is included in a file of initial values.

The alternative, apparently adopted in the ORNL model, is to use judgement and scattered end use results to fill in the base year data.

OUTPUTS

The ORNL model is designed to forecast residential energy consumption, classified by 5 fuel types, 3 dwelling types, and 8 end uses, for 31 years starting from 1970. Table 4-2 lists the classification for which these forecasts are provided. Auxiliary outputs are expenditures on new equipment, classified by fuel, end use, dwelling type, and year; expenditures on retrofitting space heat in existing dwellings, classified by fuel, dwelling type, and year; expenditures on new dwelling thermal integrity, classified by fuel, dwelling type, and year; retrofit fuel market shares, classified by dwelling type and year; and total number of new equipment units installed, classified by fuel, dwelling type, end use, and year.

Table 4-2. ORNL Classifications for Outputs

Fuel type:	electricity, gas, oil, other, none
Dwelling type:	single-family, multi-family, mobile home
End use:	space heating, air conditioning (room, central), water heating, refrigeration, freezing, cooking, lighting, other
Year:	1970 to 2000

In addition, the model contains a number of variables used internally which could be obtained as outputs if needed, such as indices of efficiency and usage levels of equipment and structures. The model cannot provide any disaggregation of outputs by sub-regional geography (e.g., urban/rural or climate zone) or by demographic group (e.g., young/old or rich/poor).

STRUCTURE

The ORNL model has a block recursive structure, illustrated schematically in Figure 4-1. Base year data, exogenous variable forecasts, and behavioral parameters drive a housing submodel which produces forecasts of new construction by dwelling type, and average size. The outputs of this model plus base year data, exogenous base costs, and parameters drive the simulation model, which gives as outputs forecasts of energy consumption classified by fuel, dwelling type, end use, and year.

A more detailed schematic diagram of the housing sub-model is given in Figure 4-2. This model first predicts the ratio of households to total population, then allocates these households to regions. Based on the 1970 dwelling stock by type (single-family, multiple-family, mobile home), very crude assumptions on the 2000 dwelling mix, linear interpolation of the mix, and number of regional households, the model constructs a demand for dwellings of each type. New construction of each type is assumed to equal demand for that type less existing stock after (exogenous) retirements. Finally, a model predicts average size of new single family dwelling units. The housing sub-model is <u>not</u> sensitive to energy policy.

Figure 4-1. Structure of ORNL Model

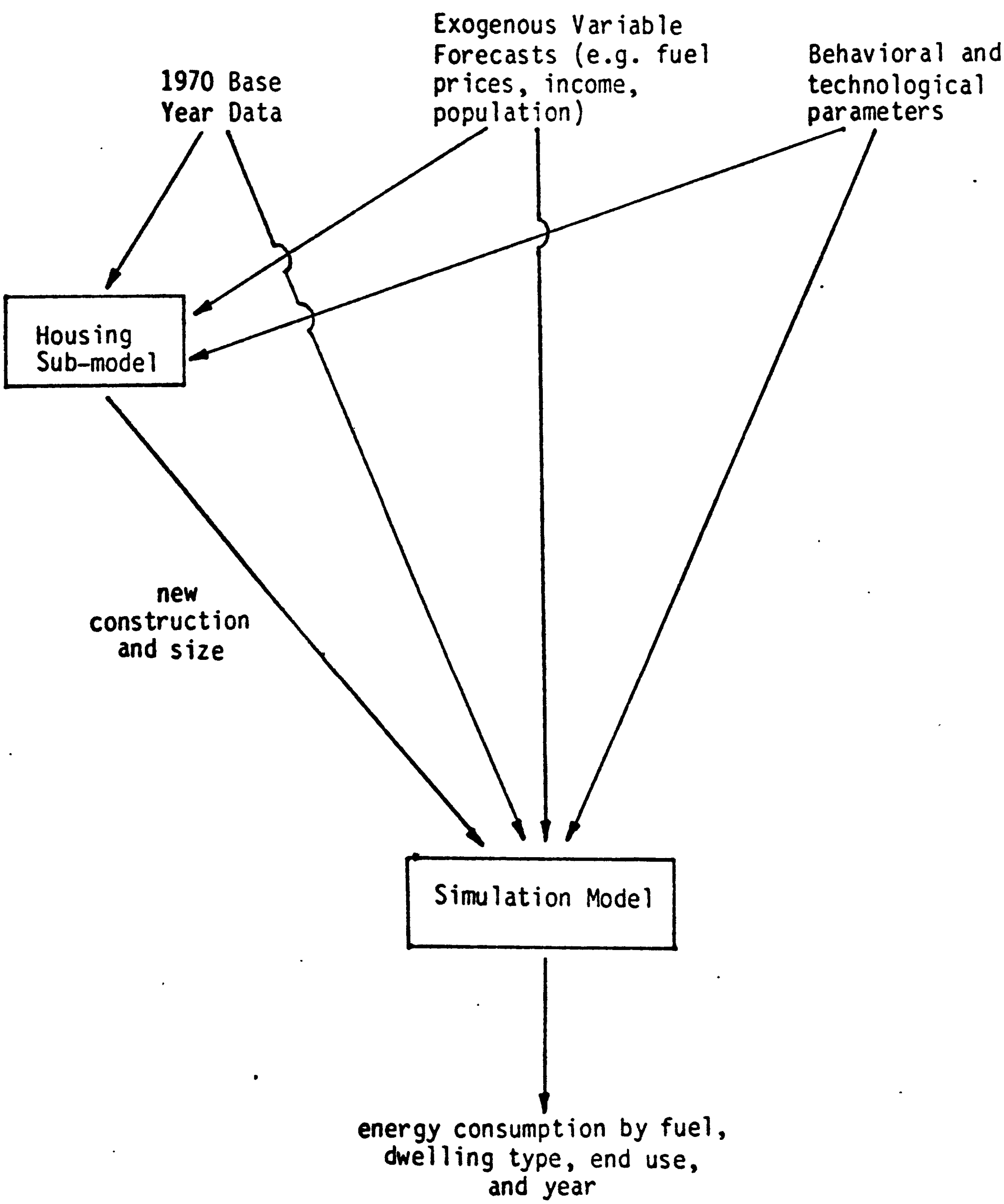


Figure 4-2. Structure of Housing Sub-Model

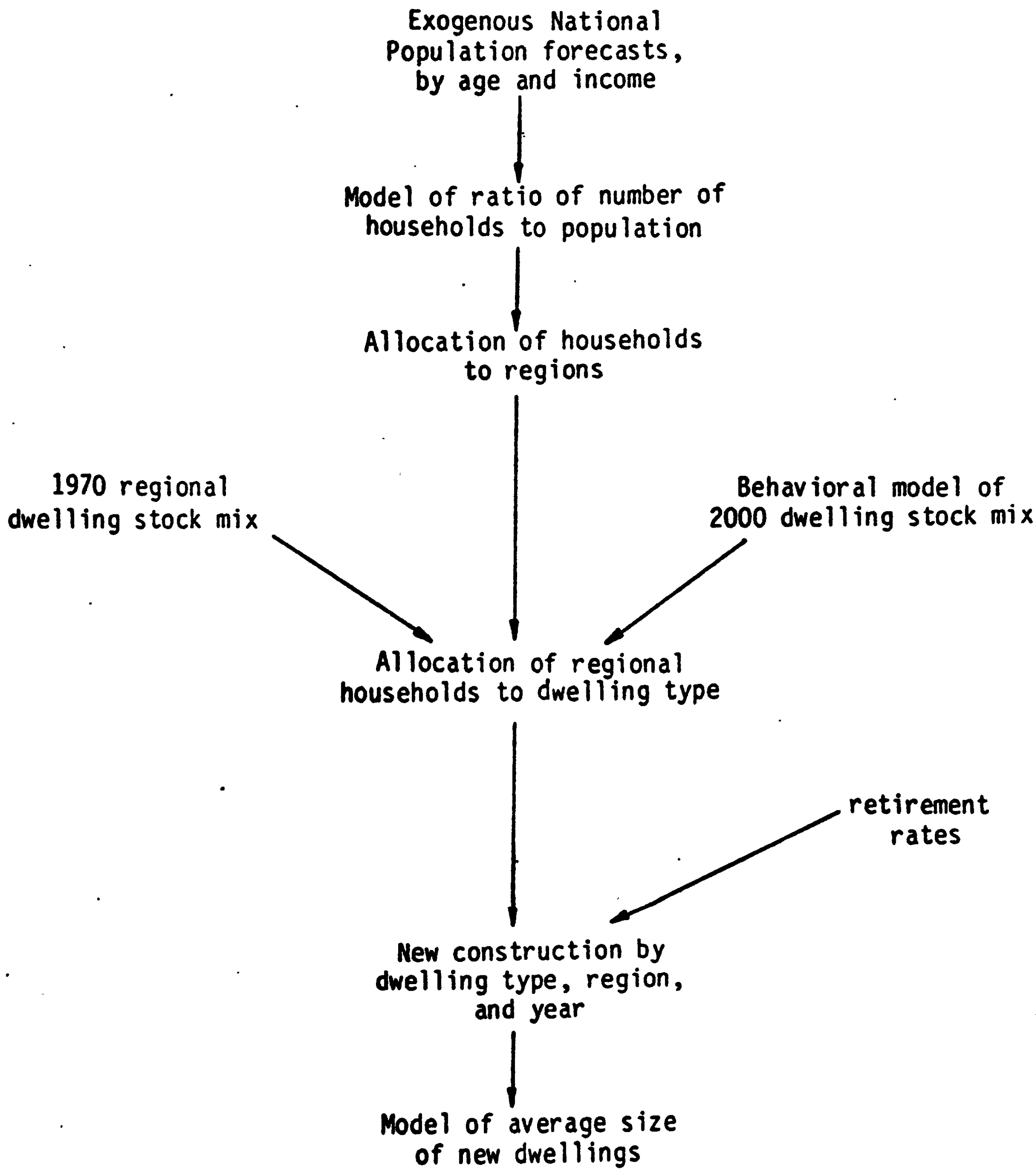
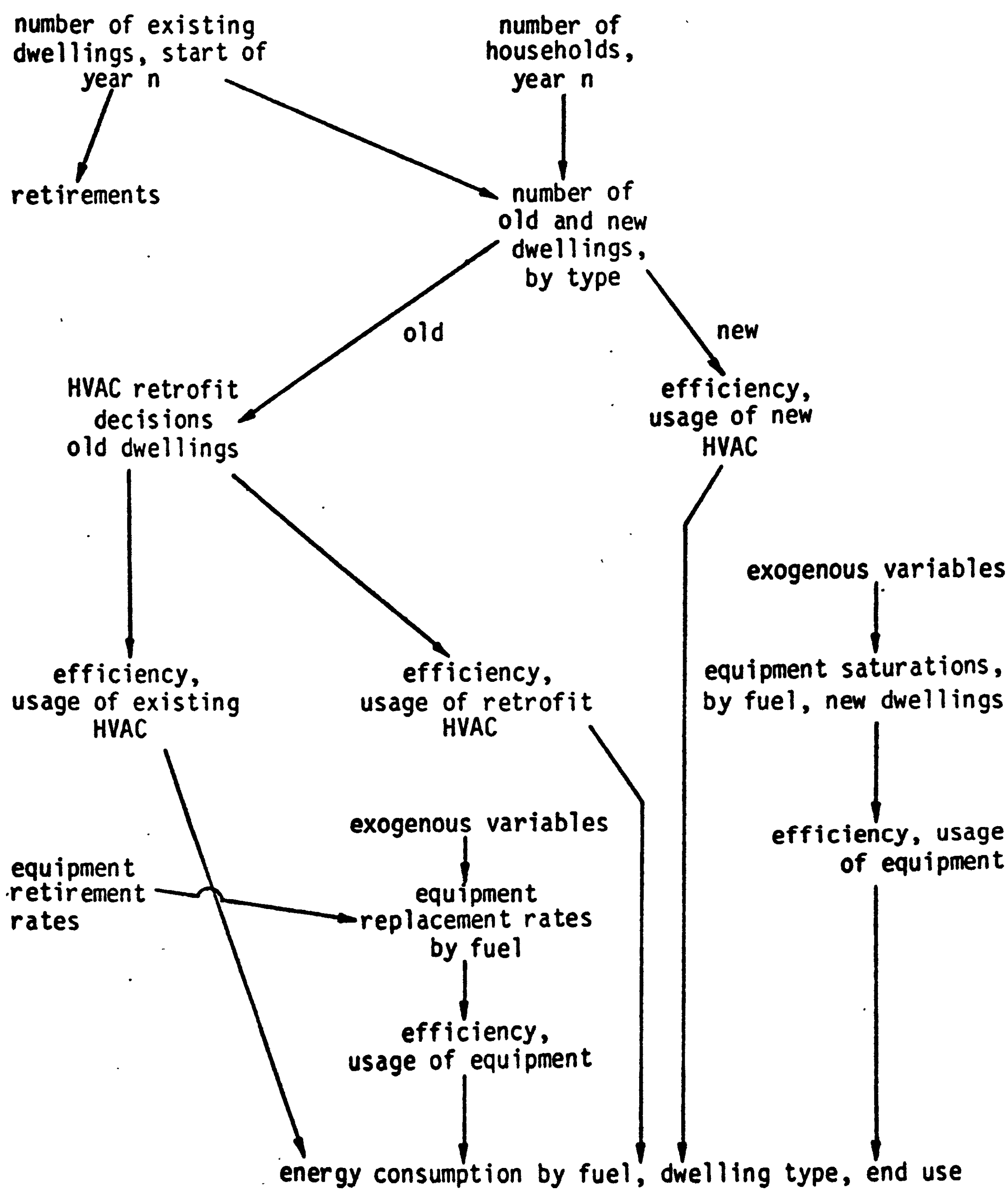


Figure 4-3 gives a more detailed schematic diagram of the simulation model. The principle underlying this model is that residential energy consumption is the sum of consumptions by end use: heating-ventilating-air-conditioning (HVAC), refrigerators, etc. Further, the energy consumption of equipment such as a refrigerator is determined by its efficiency and by the intensity with which it is used. Knowing the number of units of a type of equipment and its efficiency and utilization, its energy consumption can be computed. This picture is complicated because energy policy impacts old and new equipment differently. Therefore, the model keeps track of existing stocks, replacements in existing dwellings, and installations in new dwellings. Quite a few modeling compromises are made here to isolate decisions and avoid interdependencies, and to limit the scale of information required. The result is almost certainly some degree of aggregation error, plus some potentially serious misspecifications of behavioral response.

CALIBRATION

The ORNL model contains a large number of technological and behavioral parameters which could be determined with a satisfactory degree of precision only with very careful empirical study, including probably rather substantial engineering and behavioral experiments. In practice, ORNL has carried out limited engineering and econometric studies which shed some light on a selection of these parameters. This analysis is not generally extensive enough nor sufficiently well documented to be definitive. Beyond this, judgement has been used to set many parameters.

Figure 4-3. Structure of Simulation Model



As a practical matter, substantial judgemental input is probably mandatory in a model of this complexity, given the current state of data. However, it would be highly desirable to document judgements, isolate speculative parameters, and identify weak points in order to focus further research. Calibration of the ORNL model is discussed in further detail in Section 6.

VALIDATION

Complex models such as the ORNL model tend to have systemic characteristics which are not detectable in calibration. For example, a complex model with a dynamic structure may compound negligible misspecification errors at the individual equation level into unstable transients which cause forecasts after some period of time to become totally unrealistic. On the other hand, such a system may have a "dynamic imperative" which makes the system quite insensitive to some specification errors. Thus, it is quite important to carry out an extensive model validation.

The usual method of validation is to forecast, or backcast, outside the calibration period, and compare the forecast error with an absolute standard of accuracy or with alternative models using the same information. The most critical and interesting test is the ability of the model to make long term forecasts using only the base year information, since this most closely parallels policy applications.

A second validation procedure examines the sensitivity of forecasts to variations in model parameters or equation specifications. When there are classical or Bayesian measures of precision associated with model parameters, it is possible to formalize this and establish confidence bounds on the model forecasts.

The ORNL model has not been systematically validated. Hirst-Carney (1978) report on a within-calibration-period validation for six years starting in 1960 or starting in 1970. Since the model parameters are essentially tuned into reproduce historical experience through this period, this is more a test of the completeness of the tuning than a validation test. The tuning problem is greatly compounded by the methods used to supply missing base year values. The authors adjust these inputs "until the model's predictions for the first few years after the simulation begins are reasonably accurate." A better validation test, but still within calibration period, has been carried out by Freedman, Rothenberg, and Sutch (1980). They find that a five-year forecast from 1970 by the ORNL model is more accurate for electricity consumption, but less accurate for consumption of all other fuels, than a naive model that forecasts 1970 consumption levels to remain constant.

In some ways, the preceding result may be too stringent a test of the ORNL model. First, in building a complex policy model like the ORNL model, one is probably willing to sacrifice baseline predictive accuracy in order to obtain reasonable predictions of relative impacts of alternative policy scenarios. Second, the place where a non-linear dynamic system will shine, if it is working well, is in long-run forecasts where substantial exogenous changes and long-run responses can be anticipated. For example, if one could run a 1960 base naive forecast against the ORNL model for the 17 year period until 1976, with the latter model initialized "fairly" using only 1960 data, it is likely the ORNL model performance would look better. However, the apparent failure of the ORNL model to pick up short run responses to price shocks in the early 1970's in the Freedman analysis may indicate that the ORNL model seriously underestimates short run price response.

Hirst-Carney (1978) have also done a limited sensitivity analysis of selected model parameters. They argue that forecasts attenuate fairly strongly the percentage impact of changes in key parameters. However, such a conclusion is very sensitive to the base chosen for the comparison. For example, a more relevant quantity for policy analysis may be the forecast of the relative reduction in consumption due to a conservation program, and this may be quite sensitive to parameter changes. Using the Hirst-Carney forecasts in year 2000 (Hirst-Carney, 1978, Fig. 27, p. 66 and Fig. 28, p. 67), one obtains Table 4-3. In this table the effect of a variation of 25 percent in the key parameters to give the low and high cases chosen by Hirst-Carney implies variations in the predicted policy impact of the conservation program around 30 percent. By this policy-relevant standard, the model is quite sensitive to parameter specification. Freedman, Rothenberg-Sutch (1980, p. 14) suggest that the sensitivity analysis should be extended to base year variables, lag coefficients, interest rates, and functional forms.

POLICY APPLICATIONS

The ORNL model is currently being used in two policy applications. First, it is being used by EIA as a demand driver for the Midterm Energy Forecasting System. In this mode, it is apparently used primarily to make baseline forecasts at the DOE region level. Second, it has been used by ORNL to carry out a series of impact analyses of specific energy

Table 4-3. Sensitivity Analysis for Conservation Impact

year 2000	Low Paramaters			Nominal Parameters			High Parameters		
consumption (10^{15} BTU)	Base	Cons.	Impact	Base	Cons.	Impact	Base	Cons.	Impact
Electricity	16	14.1	1.9	17	14.5	2.5	18.2	14.8	3.4
Gas	4.6	3.8	0.8	5	4.1	0.9	5.8	4.6	1.2
Oil	1.7	1.6	0.1	1.9	1.7	0.2	2.1	1.8	0.3
Total	23	19.8	3.2	25	20.6	4.4	27	21.2	5.8

policies. Table 4-4 lists some of these studies.

The study of regional impacts of water heater options by O'Neal, Carney, and Hirst is a prototypical policy analysis using the ORNL model. The policy scenarios analyzed are (1) baseline, (2) efficiency improvements in conventional heaters, (3) electric heat pump water heaters, and (4) solar water heaters with electricity backup, with or without a tax subsidy. The outputs of the study are (undiscounted) cumulative energy savings in Btu for each DOE region, and net economic benefit (= present value of fuel bill reductions less incremental capital cost). The primary effort is to develop the technological tradeoffs available in each scenario. For efficiency improvements in conventional heaters, an engineering calculation is done, and is assumed to apply nationally. Water heat pump efficiency is weather-sensitive; however, this was apparently not accounted for in the regional analysis. Solar water heaters are extremely weather-sensitive, a factor handled in the analysis by using climate in one city in each DOE region. The potential for a significant bias is obvious here -- Denver climate is not representative of Fargo, N.D. in Region 8, and Atlanta, Georgia is not representative of Miami in Region 4. Thus, this particular scenario is at the edge where a regionally aggregate model may be inadequate to reflect the interaction of climate and policy impact.

The new water heating technologies are restated in ORNL model inputs in terms of shifts in a three-parameter approximation to the available efficiency-envelope. This step may again introduce some bias; the authors comment that they "were unable to find values for the three parameters to accurately fit both conventional and solar water heaters." This is a model deficiency. It would be better to have the flexibility to describe the efficiency-cost tradeoff as it comes from the scenario.

Table 4-4. ORNL Policy Applications

Author	Topic	Report
Ellison	Impact of heat pumps, combined with thermostat adjustments	ORNL/CON.4
Hirst-Carney	Federal residential energy conservation programs	ORNL (1977)
O'Neal-Carney-Hirst	Regional analysis of water heating options	ORNL/CON-31
Pilati	Energy Conservation potential of Winter thermostat adjustments	ORNL/NSF-EP-80

It is necessary to specify in the model the penetration of the new technology. The assumption is made that within fuel type, the technology with the lowest life-cycle costs is chosen. Thus, in region 4, all new water heaters will be heat pump, or solar, or conventional, rather than some mixture. Some ad hoc adjustments are made to reduce inconsistencies in market share equations across fuels. The ORNL model is then run under the alternative scenarios to produce regional forecasts of the impacts on energy consumption and net economic benefit.

Section 5

EVALUATION OF MODEL STRUCTURE

END USE APPROACH

The strategy of the ORNL model is to forecast energy consumption by end use, and then aggregate over end uses to obtain overall consumption. This approach has several attractive features. First, there is considerable intuition and casual experience with the characteristics of individual appliances, and they are amenable to engineering study. For example, inspecting the rating of a refrigerator motor and timing its cycle can give a quick, and not grossly inaccurate estimate of its operating cost. Furthermore, for the analysis of policies which affect different appliances differently, such as appliance-specific efficiency standards, this level of disaggregation is essential. Finally, to the extent that the behaviors determining the ownership, replacement, and use of different appliances are independent, it is a useful simplification to analyze them separately, and then add them up to get total energy consumption.

However, end use analysis also has drawbacks. The scale of the model is now multiplied by the number of appliances. End use specific consumption levels are not readily observed, and a careful study of individual appliance characteristics and usage requires detailed data collection and analysis. Further, there are some important exceptions to the proposition that behaviors affecting different appliances are independent. First, households tend to treat heating-ventilating-air-conditioning (HVAC) systems and decisions on the thermal shell interdependently. Second, there is an obvious link between water heater usage and the use of appliances such as dishwashers and washing machines. Third, the overall type and size of dwelling and the availability and installation cost of natural gas or 220V service is a common factor in the fuel type and usage decisions of several appliances. Finally, there is the "phantom appliance" problem: the end use approach may tend to under-forecast future energy consumption because it fails to allow for the introduction of appliances not currently in existence or in widespread use. The historical pattern in this century has been the steady introduction of energy using appliances, from washing machines to hot tub heaters. The argument is made that energy economics and the technology of electronic control have caused a sharp break from historical trends. On the other hand, this may be a transient, and one may well see before year 2000 the penetration of new appliances that increase energy consumption or offset reductions in consumption achieved elsewhere.

The ORNL model considers 8 end-use categories: space heating, air conditioning (sub-divided room/central), water heating, refrigeration, freezing, cooking, lighting, and others. The miscellaneous category includes such disparate uses as dishwasher, clothes washer and dryer,TV, swimming pool pumps and heaters, irons, portable electric heaters, pumps, tools, and farm equipment. The ORNL model covers only energy use in the home — transportation is excluded.

The model analyzes separately each end use; e.g., the fuel choice on space heating is independent of the air conditioning decision, and the usage levels for hot water and other are independent. This is almost certainly the source of some specification error for the two cases given as an example. There is a clear relationship between the choice of a heating system with or without ducting, and the choice of central air conditioning. Consumption of hot water is strongly affected by a dishwasher or clothes washer.

Energy consumption in each end use is modeled as the result of the number of units of equipment held, the efficiency of the equipment (measured in energy consumed per unit of service), and the intensity of utilization. The heart of the model is the accounting relationship

$$\text{(V.1)} \quad \begin{matrix}\text{Energy consumption,}\\ \text{end use k, dwelling}\\ \text{type l, fuel i}\end{matrix} = \begin{matrix}\text{Number}\\ \text{of}\\ \text{units}\end{matrix} \times \begin{matrix}\text{Average}\\ \text{Energy/}\\ \text{Service}\\ \text{Ratio (ESR)}\end{matrix} \times \begin{matrix}\text{Average}\\ \text{Utilization}\\ \text{rate (U)}\end{matrix} .$$

If either the energy service ratio or the utilization rate is constant over all units of equipment in the category, then this accounting relationship is valid. Otherwise, it is an approximation containing an aggregation bias due to the fact that the product of averages is not equal to the average of products. In general, one would expect a negative correlation between ESR and U, because a priori a household anticipating heavy utilization will find it advantageous to purchase a more efficient appliance, and ex post the more efficient appliance will be more attractive to use. This aggregation bias may be substantial. For example, if ESR and U are jointly lognormally distributed, each varies in the population with a standard error of the same magnitude as its mean, and the correlation of ln ESR and ln U is -0.3, then the accounting relationship above will be biased downward by 19 percent. The ORNL model reduces aggregation biases somewhat by considering separate categories for existing equipment, retrofit equipment, and new equipment. However, the mechanics used by the model to combine these categories may reintroduce bias.

In operation, the ORNL model has one module to predict number of units of equipment (by fuel, dwelling type, and status: existing, retrofit/replacement, new). A second module uses the accounting relationship to predict consumption, carrying through adjustments of ESR and U. These modules will be examined in the following sections.

THE HOUSING MODULE

The housing module of the ORNL model forecasts number of households in a region, additions to housing stocks required to accomodate these households, and the average size of new dwellings. The structure of the module was outlined in Figure 4-2. First, number of households, classified by age group, is predicted for each region and year by multiplying regional population in the classification by predicted proportion which are heads of households. The latter prediction is obtained from a regression on national age-specific marriage and divorce rates and income. Next households are allocated among three dwelling types (single-family, multiple-family, mobile home) in proportions determined by linear interpolation between existing 1970 housing type shares and assumed year 2000 housing type shares. Third, new construction of each dwelling type is assumed to equal demand determined by the allocation of households less the supply of existing dwellings of that type after retirement of an exogenously set fraction. Finally, size of new single family dwellings (in square feet) is forecast using a regression of square footage on income, persons per household, cost ($/sq. ft.), and regional dummies. The method used to forecast size of multi-family and mobile home dwellings is not documented. However, inputs to the simulation module provided by ORNL contain the following representative values:

Percentage Increase in Square Footage over 1970

	Single-Family	Multiple-Family	Mobile Home
1980	2.2	2.7	7.2
1990	7.6	9.1	21.8
2000	13.4	15.6	35.0

The primary deficiency of the ORNL housing module from the standpoint of policy analysis is that it is insensitive to energy policy. In practice, both housing type and size decisions are likely to show some sensitivity to energy costs. An approach which would be consistent with the logic of other parts of the ORNL model would be to assume housing type and size choices are functions of life-cycle costs of housing acquisition and space conditioning. Such models could be calibrated using the census data already employed in this module and elsewhere.

A few other features of the housing module could potentially be improved. First, it is not clear that marriage and divorce rates are predetermined in the equation determining proportion of heads of households, or that reliable external forecasts for these variables are available. Second, rates of retirement or conversion of existing dwellings may be sensitive to net demand and to energy price changes. Third, new construction may not respond instantaneously to excess demand, and this may influence type choice, and possibly even rate of household formation. Finally, the equations for housing size should incorporate energy cost, and the econometric estimation of these equations should take into account self-selection by housing type.

EFFICIENCY DECISIONS

The ORNL model assumes that appliance efficiency is determined by life cycle cost minimization, taking into account the tradeoff between capital and operating cost for various levels of efficiency. The key ingredients of this analysis are the schedules of efficiency vs. cost postulated to be available in the market, and assumptions on household discount rates and expectations about future energy prices, durability, and intensity of use.

Before analyzing the specifics of the ORNL model, it is helpful to review the basic logic of consumer decisions on the characteristics and usage of consumer durables. The consumer ordinarily has choice along several dimensions: energy efficiency, durability, capacity, and various aspects of service quality (quietness, appearance, convenience, flexibility). For example, in the refrigerator purchase decision the consumer will consider efficiency, storage capacity, and convenience features such as automatic defrost. As in this example, there is often a trade-off between efficiency and service quality. Thus, the consumer typically does not face a simple trade-off between capital and operating costs with capacity and service quality fixed. Rather, the consumer can be expected to optimize jointly with respect to capacity, service quality, and efficiency.

An economic consumer can be expected to approach the capacity-service quality-efficiency decision as a problem of maximizing preferences, considered over the lifetime of the household, subject to a lifetime budget constraint. When decisions are not fully reversible, as in the case of consumer durables with substantial installation costs or inadequate resale markets, the purchase decision must be evaluated in terms of its strategic consequences. This can be interpreted as requiring the consumer to solve a dynamic programming problem in which current choices are evaluated in terms of their strategic consequences when future decisions are optimal. When elements of uncertainty about future energy prices or equipment failures are introduced, the programming problem is stochastic, and consumer expectations become a key ingredient. In practice, such a problem may be too complex for the consumer (or analyst) to solve, and some hueristic may be adopted. In the following commentary, we shall not attempt any general solution of this optimization problem, but rather concentrate on special features which may help to illuminate the adequacy of the minimum life cycle cost criterion assumed in the ORNL model.

Exercise 1. Suppose an appliance of fixed life L, and consider the simplest problem of intertemporal untility maximization subject to an intertemporal budget constraint, with future prices known with certainty. We use the following notation:

(v.2) t = time, $0 \leqq t \leqq L$

h = energy service ratio (ESR), giving the energy consumption of the appliance per unit of service

$x(t)$ = rate of utilization of the appliance

$p(t)$ = real energy price

ρ = rate of impatience

r = interest rate

$y(t)$ = real rate of expenditure

W = wealth

(v.3)
$v(y(t), hp(t))$ = instantaneous indirect utility as a function of real rate of expenditure and energy price per unit of service

(v.4) $C(h)$ = purchase price of appliance

The consumer's problem is

$$\text{(v.5)} \quad \max_{y,h} \int_0^L e^{-\rho t} v(y(t), hp(t))\, dt$$

$$\text{(v.6)} \quad \text{subject to } C(h) + \int_0^L e^{-rt} y(t)\, dt = W.$$

The utilization rate, given by Roy's identity, is

$$\text{(v.7)} \quad x(t) = -\frac{v_2(y, hp)}{v_1(y, hp)}$$

The first-order condition for intertemporal maximization is

$$\text{(v.8)} \quad v_1 (y(t), hp(t)) = \lambda e^{-(r-\rho)t}$$

and for optimal ESR is

$$\text{(v.9)} \quad \int_0^L e^{-\rho t} v_2(y(t), hp(t))\, p(t) dt = \lambda C'(h)$$

or

$$\text{(v.10)} \quad \int_0^L e^{-\rho t} p(t)[-x(t)\, e^{-(r-\rho)t}] dt = C'(h),$$

implying

$$\text{(v.11)} \quad C'(h) + \int_0^L e^{-rt} p(t)x(t)dt = 0$$

This is precisely the first-order-condition for minimization of life-cycle cost for the appliance conditioned on the chosen utilization rate x(t). However, in general the ESR and utilization are determined jointly, and the effect of price changes on the ESR may be moderated by adjustments in the utilization rate.

Suppose, for example, the instantaneous indirect utility function has the form

$$\text{(v.12)} \quad v(y(t), hp(t)) = \frac{1}{1-\beta} \left[y(t) - \frac{\gamma (hp(t))^{1-\alpha}}{1-\alpha} \right]^{1-\beta}$$

with α, β, $\gamma > 0$. Then

$$\text{(v.13)} \quad x(t) = \gamma (hp(t))^{-\alpha}$$

Note that α is the elasticity of utilization with respect to the price of energy. Substituting this expression in the first-order-condition for minimization of life-cycle cost yields

$$\text{(v.14)} \quad C'(h) + \gamma h^{-\alpha} \int_0^L e^{-rt} p(t)^{1-\alpha} dt = 0$$

If $C(h) = c_0 h^{-\mu}$, then the optimal ESR satisfies

$$\text{(v.15)} \quad \mu c_0 h^{-\mu-1+\alpha} = \gamma \int_0^L e^{-rt} p(t)^{1-\alpha} dt$$

or

$$\text{(v.16)} \quad h = [\mu c_0/\gamma \int_0^L e^{-rt} p(t)^{1-\alpha} dt]^{\frac{1}{1+\mu-\alpha}} .$$

The impact of a uniform one percent increase in energy price is a $(1-\alpha)/(1+\mu-\alpha)$ percent net decrease in ESR. The magnitude of this expression decreases as α increases from zero (where utilization is perfectly price-inelastic). For $\alpha \geq 1$, utilization is sufficiently price elastic so that an energy price increase sharply lowers utilization, and consequently makes it desirable to raise the ESR.

Consider, for example, central air conditioners. Typical parameter estimates for this appliance are $\mu = 1.0$ and $\alpha = .85$, implying an elasticity of ESR with respect to energy price of -0.13 and with respect to purchase price level of 0.87. These differ substantially from the respective values -0.5 and +0.5 of these elasticities calculated under the assumption of a fixed level of utilization (α=0). Also, the elasticity of energy consumption with respect to energy price is -0.87, in contrast to an elasticity of -0.5 when utilization is price-inelastic.

Exercise 2. Consider the case of discretionary retirement of appliances. From the preceding exercise, we obtain the expected result that if the elasticity of usage with respect to energy price is low, then expected growth in energy prices leads to more efficient fixed-life appliances. Intuitively, if appliances can be retired and replaced voluntarily, one would expect a partially offsetting effect in which households reduce the length of time they plan to hold an appliance before it is replaced with a unit with more appropriate energy consumption characteristics. This decrease in planned lifetime has two effects. First, the chosen ESR is more appropriate for current energy prices than in an appliance chosen strategically for optimization over a longer lifetime. Second, the reduction in planned lifetime generally raises the attractiveness of appliances with higher ESR.

To examine this by example, use the model and notation of exercise 1, except now assume for simplicity that households and appliances are infinitely lived, and all replacements are voluntary.
The objective function is

$$(v.17) \quad U = \sum_{i=0}^{\infty} \int_{L_i}^{L_{i+1}} v(y(t) - \gamma\frac{(p(t)h_i)^{1-\alpha}}{1-\alpha})\, e^{-\rho t}\, dt,$$

where L_i is the date of the ith replacement, $L_0 = 0$.
This is maximized subject to the budget constraint

$$(v.18) \quad W = \sum_{i=0}^{\infty} e^{-rL_i}\, [C(h_i) + \int_{L_i}^{L_{i+1}} e^{-r(t-L_i)}\, y(t)dt],$$

by choice of h_i, $y(t)$, and L_i.

The first-order-conditions are

$$\text{(v.19)} \quad v'(y(t) - \gamma \frac{(p(t)h_i)^{1-\alpha}}{1-\alpha}) e^{-\rho t} = \lambda e^{-rt}$$

$$\text{(v.20)} \quad \gamma \int_{L_i}^{L_{i+1}} p(t)^{1-\alpha} v'(y-\gamma \frac{(p(t)h_i)^{1-\alpha}}{1-\alpha}) e^{-\rho t} dt + \lambda C'(h_i) h_i^{\alpha} e^{-rL_i} = 0$$

or

$$\text{(v.21)} \quad \gamma \int_{L_i}^{L_{i+1}} p(t)^{1-\alpha} e^{-r(t-L_i)} dt + h_i^{\alpha} C'(h_i) = 0$$

implying the life-cycle cost minimizing condition

$$\text{(v.22)} \quad \int_{L_i}^{L_{i+1}} p(t)x(t) e^{-r(t-L_i)} dt + C'(h_i) = 0,$$

and

$$\text{(v.23)} \quad v(y(L_i^-)-\gamma \frac{(p(L_i)h_{i-1})^{1-\alpha}}{1-\alpha}) e^{-\rho L_i} - v(y(L_i^+) - \gamma \frac{(p(L_i)h)^{1-\alpha}}{1-\alpha}) e^{-\rho L}$$

$$+ \lambda e^{-rL_i} (rC(h_i) - y(L_i^-) + y(L_i^+)) = 0$$

From (v.19),

$$\text{(v.24)} \quad y(L_i^-) - y(L_i^+) = \gamma \frac{p(L_i)^{1-\alpha}}{1-\alpha} [h_{i-1}^{1-\alpha} - h_i^{1-\alpha}]$$

and (v.23) implies

$$(v.25)\quad rC(h_i) = \gamma \frac{p(L_i)^{1-\alpha}}{1-\alpha}\,[h_{i-1}^{1-\alpha} - h_i^{1-\alpha}].$$

Equations (v.21) and (v.25) are difference equations in L_i and h_i. To simplify their analysis, consider the case $\alpha < 1$, $C(h) = c_0 h^{-\mu}$, and $p(t) = p_0 e^{gt}$. Then these equations have a solution with $L_{i+1}-L_i=L$ constant and $h_i = K\exp[-iLg(1-\alpha)/(1+M-\alpha)]$ with K a constant. Substituting yields the equations

$$(v.26)\quad \gamma p_0^{1-\alpha}\,\frac{(1-e^{-(r-g(1-\alpha))L})}{r-g(1-\alpha)} = c_0 \mu K^{-(1+\mu-\alpha)}$$

$$(v.27)\quad rc_0K^{-\mu} = \frac{\gamma}{1-\alpha}\,p_0^{1-\alpha}\,K^{1-\alpha}(e^{g(1-\alpha)^2L/(1-\alpha+\mu)} - 1)$$

Eliminating K,

$$(v.28)\quad 1-e^{-(r-g(1-\alpha))L} = \frac{\mu(r-g(1-\alpha))}{r(1-\alpha)}\,(e^{g(1-\alpha)L/(1-\alpha+\mu)} - 1)$$

This equation can be solved numerically for L, and has the property that increasing the rate of growth of energy price g leads to a decrease in L, as expected. For the central air conditioner, the assumptions of infinite life, no maintenance cost gradient, and no technical progress plus parameter values μ=1.0, α=.85, r=.1, and g=.15 imply a voluntary replacement interval of 60 years, and an elasticity of replacement interval with respect to g at this point of 0.8. If g rises and p_0 is fixed, then the ESR h_0 falls. However, if one considers combinations of p_0 and g such that the present value of the cost of a constant unit stream of energy consumption is fixed, then increasing g causes h_0 to fall for small g, but causes h_o to rise for g approaching the interest rate r.

If in this exercise one considered increasing maintenance cost with appliance age, or technical progress improving the cost-efficiency tradeoff, retirement interval would decrease.

The introduction of uncertainty about future energy or equipment replacement prices substantially complicates the optimization problem. The objective function (v.17) is modified to permit risk aversion and the strategic possibility that plans can be modified in light of added information as it is received. No attempt will be made here to solve this stochastic dynamic programming problem. However, it should be noted that risk aversion will in most cases induce a conservative response to increased uncertainty, with reduced expected life (and an associated increased ESR) giving greater flexibility.

Exercise 3. Consider the case where appliances have characteristics such as capacity or service quality which are subject to choice. Assume for simplicity a fixed appliance life L. Assume the consumer has a direct instantaneous utility function $u=U(S,K,z)$ of S=units of service provided by the appliance, K=appliance capacity (or service quality), and z=consumption of other goods. Units of service satisfies $S=HK$, where H=hours of usage. The consumer faces a price p(t) per unit of energy. If the energy-service ratio (ESR) is h, then the price per hour of use is $p(t)hK$. The instantaneous consumer problem is to maximize $U(HK, K, z)$ in H,z subject to $z+p(t)hKH=y(t)$, where y(t)=instantaneous expenditure. Let $u=V(y(t), p(t)hK,K)$ denote the indirect instantaneous utility function giving the value of the maximized direct utility. Roy's identity implies the optimal $H(t)$ satisfies $H(t)=-V_2/V_1$, and hence energy consumption $x(t)$ satisfies $x(t)=-hKV_2/V_1$.

The consumer's life-cycle optimization problem is

$$\text{(v.29)} \quad \underset{y(.),h,K}{\text{Max}} \int_0^L e^{-\rho t} V(y(t),p(t)hK,K)dt$$

$$\text{subject to} \quad \int_0^L e^{-rt} y(t)dt + C(h,K) = W.$$

The first-order conditions for this maximization are

$$\text{(v.30)} \qquad e^{-\rho t} V_1(y(t), p(t)hK,K) = \lambda e^{-rt},$$

$$\text{(v.31)} \qquad \int_0^L e^{-\rho t} p(t)KV_2 dt = \lambda C_1$$

or

$$\text{(v.32)} \qquad \int_0^L e^{-rt} p(t)x(t)dt + hC_1(h,K) = 0$$

and

$$\text{(v.33)} \qquad \int_0^L e^{-\rho t} p(t)hV_2 dt + \int_0^L e^{-\rho t}V_3 \, dt = \lambda C_2$$

or

$$\text{(v.34)} \qquad \int_0^L e^{-rt} p(t)x(t)dt + KC_2(h,K) = \frac{1}{\lambda} \int_0^L e^{-\rho t} V_3 \, dt$$

The condition (v.32) states that given capacity and units of service, the consumer chooses the ESR h to minimize life-cycle cost, as in the previous examples. However, condition (v.34) involves both life-cycle cost and preferences, stating that capacity will be increased until the marginal life cycle cost per unit of capacity equals the dollar value of the marginal utility gain from added capacity. Qualitatively, one would expect higher energy prices to discourage the purchase of high capacity or high service quality appliances which consume extra energy. This should induce larger price elasticities than Exercise 1. For example, higher electricity prices may induce smaller refrigerators and fewer energy-consuming service quality features such as automatic defrost or ice makers. The picture may be complicated by the technological and market relationship between ESR, capacity, and service quality. For example, there is a strong complementarity between air conditioner capacity and efficiency, and strong substitutability between capacity and hours of use. For water heaters, efficiency can be increased by lowering recovery rate, which lowers service quality. This can be offset (with some offset of the efficiency gain) by increasing capacity.

Suppose the instantaneous indirect utility function has the form

$$\text{(v.35)} \qquad V(y(t),p(t)hK,K) = \frac{1}{1-\beta}\left(y(t) - \frac{\gamma}{1-\alpha}(p(t)hK)^{1-\alpha}\right)^{1-\beta} + \frac{\delta}{1-\theta}K^{1-\theta}$$

with $\alpha,\beta,\theta,\gamma,\delta > 0$. Suppose appliance purchase cost has the form

$$\text{(v.36)} \qquad C(h,K) = c_0 h^{-\mu} K^{\eta},$$

with $c_{\ }, \mu, \eta > 0$. Then $x(t) = \gamma p(t)^{-\alpha}(hK)^{1-\alpha}$. Define (v.37) $$\pi = \int_0^L e^{-rt}\, p(t)^{1-\alpha}\, dt$$

(v.38) $$R = \delta(1-e^{-\rho L})/\rho$$

(v.39) $$Q = (1-e^{-(\rho+(\beta-1)r)L/\beta})\beta/(\rho+(\beta-1)r)$$

Then the first-order conditions, from the budget constraint, (v.32), and (v.34), are

(v.40) $$\gamma\pi(hK)^{1-\alpha} = \mu c_0 h^{-\mu} K^{\eta}$$

(v.41) $$\left(\frac{\mu+\eta}{\mu}\right) \gamma\pi(hK)^{-\alpha} = RK^{-\theta}/\lambda$$

(v.42) $$\frac{1-\alpha+\mu}{\mu(1-\alpha)}\, \gamma\pi(hK)^{1-\alpha} = W-\lambda^{-1/\beta}Q$$

To obtain the price elasticities, it is sufficient to differentiate these conditions and solve. One obtains, for a permanent proportional change in energy prices,

(v.43) $$\frac{\partial \ln K}{\partial \ln p} = -(1-\alpha)(\mu+\varepsilon(1+\mu))/\Delta$$

(v.44) $$\frac{\partial \ln(hK)}{\partial \ln p} = -(1-\alpha)(\varepsilon\theta+(1+\varepsilon)(\mu+\eta))/\Delta$$

(v.45) $$\frac{\partial \ln x}{\partial \ln p} = -\alpha-(1-\alpha)^2(\varepsilon\theta+(1+\varepsilon)(\mu+\eta))/\Delta,$$

where $\varepsilon = \frac{1}{\beta}\lambda^{-1/\beta} Q/(W-\lambda^{-1/\beta}Q)$ and

(v.46) $$\Delta = \theta\varepsilon(1-\alpha+\mu) + (1-\alpha(1+\varepsilon))(\eta+\mu).$$

For typical parameter values, an increase in energy price reduces capacity, energy consumption per hour of use, and overall energy consumption. For example, typical values for air conditioners are μ=1.0, η=0.4, α=.85. The expression $\lambda^{-1/\beta}Q$ equals the present value of expenditure on other goods z. If life cycle cost for the appliance is 10 percent of wealth, then $\varepsilon=9/\beta$. Then for typical values β=0.5 and θ=2 (corresponding to a relatively sharp determination of capacity), one has an elasticity of capacity with respect to price of -0.275, an elasticity of energy consumption per hour of use with respect to price of -0.465, and an elasticity of total energy consumption with respect to price of -0.92. (By contrast, the elasticity of total energy consumption with respect to price in Exercise 1 without capacity adjustments is -0.87.) Generally, greater flexibility in choice of capacity will increase price elasticities. For example, taking θ=1.2 in the example above yields elasticities of -1.61, -1.99, and -1.15 for capacity, energy consumption per hour of use, and total energy consumption respectively.

Two general conclusions can be drawn from this exercise. First, the ability of the consumer to adjust capacity or service quality may contribute substantially to overall price elasticity; this effect is not captured by the choice of efficiency level to minimize life-cycle cost. Second, an engineering analysis of the relationship between appliance attributes and cost should take into account the significant impact of capacity.

I now review the determination of efficiency in the ORNL model. This system forecasts the efficiency of the equipment in each end use and the thermal integrity of the housing shell. In principle, the calculation is straightforward: consumers are assumed to choose efficiency to minimize life-cycle cost, with some partial adjustment introduced to capture market imperfections. The life-cycle cost calculation takes into account expected usage, which in turn depends on energy prices. Hence, this approach is in principle consistent with the utility-maximizing behavior described in Exercise 1. However, it does not consider optimization with respect to capacity (Exercise 3), or voluntary replacement decision (Exercise 2).

The efficiency calculations for heating, air conditioning, and the thermal shell are interrelated. Efficiency decisions for the remaining end uses are assumed to be made independently. Since the latter calculations are simpler, they will be discussed first. For concreteness, consider water heaters. For each fuel type, the life cycle cost of a new water heater is the sum of initial cost and present value of operating cost. Initial cost is expressed as a simple function of the energy/service ratio h,

$$C(h) = c_0 + b\left(\left(\frac{1-h_0}{h-h_0}\right)^{1/\alpha} - 1\right), \tag{v.47}$$

where in 1970 h is normalized to one and c_0 is the new equipment price. Equipment capacity, service quality (e.g., recovery rate), and durability are assumed fixed and not subject to choice. The parameters a, b, and h_0 are fitted to engineering data on the material and fabrication costs of achieving alternative energy service ratios. The assumption is then made that this also gives the locus of market prices. Several features of manufacturing behavior suggest that the connection of manufacturing cost and price is less simple: Consumer equipment manufacturers are relatively concentrated, and appear to follow mark-up pricing rules to cover development and administrative overhead at anticipated production levels. As a consequence, the markup over cost is least on "popular" models, and the engineering analysis may underestimate the cost of moving to efficient but historically low demand models. The ORNL model could be strengthened by establishing firmly the relationship between engineering cost calculations and market prices.

The present value of operating cost is defined by

(v.48) present value operating cost = present worth factor x fuel price x Energy/Service Ratio (h) x Expected usage

Several features of this formula deserve comment. First, the present worth factor is defined assuming fixed equipment life and an interest rate individualized for each end use. In reality, equipment survival curves have ogive shapes, and empirical survival curve data could be incorporated into the present worth factor calculation. This still does not address the choice problems posed by stochastic survival or voluntary retirements. Economic theory would suggest a common interest rate for most consumer decisions (an exception may be distinctions between portable appliances and those attached to the dwelling, since the latter may share some of the tax and credit benefits of home mortgages); the alternative assumption in the ORNL model needs justification.

Second, fuel price is taken at the date of purchase, corresponding to the assumption that consumers expect no future changes in real price. Since influencing consumer expectations may be an important aspect of energy policy, this is a point where refinement of the ORNL model could be beneficial. Also, maintenance cost should be included in operating cost.

Third, expected usage is taken to equal average 1970 base year usage for the appliance, an undocumented input to the program. This excludes joint determination of efficiency and usage level of the sort treated in Exercise 1, and suggests that in the later years of a simulation or for extreme policy scenarios the model may calculate efficiency choice on the basis of assumed usage which differs markedly from actual usage. An easy partial remedy would be to set expected usage equal to one year lagged actual usage (net of last year's energy/service ratio). A full remedy would require efficiency and usage to be determined jointly, as in the exercises.

The optimal energy/service ratio is determined by minimizing life-cycle cost, and can be derived analytically. The ORNL model assumes this optimum will be attained gradually. Two partial adjustment mechanisms are introduced (in sequence). First, due to "market imperfections," consumers are assumed to purchase less than optimally efficient equipment. The modeling choice for representing this partial optimization is awkward, leading to an equation requiring iterative solution: "Observed" efficiency levels in 1970 when compared to the computed optimal level implies a difference (D) in observed and optimal life-cycle cost. This difference is assumed to persist into the future, possibly attenuated when fuel costs rise or time passes. No behavioral justification for this assumption is given. The second partial adjustment assumes adaptive adjustment in energy/ service ratios to the level determined by the first stage -- in ORNL runs,

(v.49) $\quad h_n = .25\ h^* + .75h_{n-1}$,

where h_n is the ESR in year n and h^* is the ESR determined in the first stage.

There would appear to be several advantages to replacing the adjustment mechanism just described with something computationally simpler and behaviorally appealing. First, consumers appear to utilize relatively high interest rates when evaluating alternatives. This may be due to credit constraints, uncertainty about the effectiveness of promised energy efficiency, or the inability of mobile consumers to capture the full value of efficient appliances in imperfect second hand markets. This can be captured in the model simply by minimizing life-cycle cost with a correspondingly low present worth factor. The second adjustment (v.49) seems unnecessary, but could be retained if it is realistic to argue that there are significant delays in delivering equipment with desired efficiency levels to the market.

The determination of the efficiencies of heating and air conditioning equipment and the thermal integrity of the shell follows the same pattern as the water heater calculation, with the added complication that the decisions are interrelated by the effect of thermal integrity on heating and air conditioning operating cost. The most logical way to carry out this computation would be to write down the joint life-cycle cost of these three decisions and optimize jointly. This could be done by solving for the equipment efficiencies as functions of the level of thermal integrity, substituting these expressions back in to get joint life-cycle cost as a function of thermal integrity alone, and finally optimizing in this decision variable. Note that since the dwelling and equipment have different assumed lives, it is necessary to make some adjustments to the life cycle cost formula to express all costs to a common horizon. This in turn requires assumptions on how the prospect of future decisions affects current choice, making the problem in principle a dynamic programming problem. A simpler and perhaps realistic approach would be to assume stationary expectations so that joint life cycle cost is written as a renewal equation:

$$\text{(v.50)} \quad LCC = \sum_{k=0}^{2} C_k(h_k)/(1-e^{-rt_k}) + p_f(h_1 h_o u_1 + h_2 h_o u_2)/r,$$

where

LCC = joint life-cycle costs including present value of replacement costs (to an infinite horizon)

h_0 = ESR (inefficiency) of the thermal shell

h_1 = heating ESR

h_2 = air conditioning ESR

$C_k(h_k)$ = capital cost

p_f = fuel price

U_k = expected usage in end use k

L_k = equipment life

r = interest rate

This formulation has the unrealistic feature that surviving equipment is assumed to move when the dwelling is replaced. Alternately, one could consider LCC only for dwelling life and assume premature retirement of surviving equipment:

$$\text{(v.51)}\quad LCC = C_0(h_0) + C_1(h_1)\sum_{t=0}^{t} e^{-rtL_1} + C_2(h_2)\sum_{t=0}^{t_2} e^{-rtL_2}$$
$$+ p_f(h_1h_0u_1 + h_2h_0u_2)\,(1-e^{-rL_0})/r,$$

where t_k is the largest integer less than L_0/L_k. For L_0=25 and values of r around 0.1, these formulae will have virtually identical solutions.

The computation actually carried out by the ORNL model differs from the procedure outlined above in several respects. First, the computation is done sequentially rather than jointly. Heating and air conditioning equipment efficiencies are calculated by minimizing their respective life-cycle costs, with thermal integrity set at its value in the previous period. Capital and operating costs in these calculations are defined and computed in the same manner as the water heater calculation discussed earlier, and the earlier comments on the limitations of the procedure apply. An additional factor in the definition of expected usage of heat and air conditioning is dwelling size, which is appropriate. However, heating and cooling equipment capacity is assumed to be independent of dwelling size. This is clearly an error which in the presence of growing dwelling sizes leads to an underestimate of capital cost. For example, an increase of 13.4 percent in the size of single family homes by the year 2000 can be expected to cause an increase in air conditioner equipment cost of 5.2 percent (at the historical elasticity of cost with respect to capacity of 0.4). As for other equipment, a two-phase partial adjustment mechanism is introduced for short-run response and the effect of "market imperfections."

Once heating and air conditioning efficiencies are calculated, the thermal integrity of the shell is computed by minimizing the expression:

$$\text{LCC} = \begin{array}{l}\text{Initial}\\ \text{cost of}\\ \text{thermal}\\ \text{improvements}\end{array} + \begin{array}{l}\text{present}\\ \text{worth}\\ \text{factor}\end{array} \cdot \begin{array}{l}\text{Thermal}\\ \text{ESR for}\\ \text{heating}\end{array} \cdot \begin{array}{l}\text{fuel}\\ \text{price}\end{array} \cdot \begin{array}{l}\text{Expected}\\ \text{heating}\\ \text{usage}\end{array} \tag{v.52}$$

$$+ \begin{array}{l}\text{present}\\ \text{worth}\\ \text{factor}\end{array} \cdot \begin{array}{l}\text{Thermal}\\ \text{ESR for}\\ \text{cooling}\end{array} \cdot \begin{array}{l}\text{fuel}\\ \text{price}\end{array} \cdot \begin{array}{l}\text{Expected}\\ \text{cooling}\\ \text{usage}\end{array}$$

In this formula, the present worth factor is calculated for an assumed dwelling life of 25 years. The thermal ESR for cooling is assumed to vary from its 1970 base as a fraction of the variation of the ESR for heating. Fuel prices are taken at the date of construction, with no adjustment for expectations. Expected usage quantities are set to 1970 values. Dwelling size does <u>not</u> enter expected usage in this formula.

This calculation has several deficiencies. First, unless cost of thermal improvements is proportional to dwelling size, the term for dwelling size will enter the determination of optimal thermal ESR. Further, this term should enter life-cycle cost difference calculations if the first partial adjustment mechanism of the ORNL model is utilized. Second, fixing expected usage at 1970 levels excludes the tradeoff between usage and efficiency of the sort considered in Exercise 1 and implicit in the usage elasticities permitted later in the simulation model. This will tend to lead the model to forecast too high a level of optimal efficiency.

Third, the ORNL calculation excludes the present value of future heating and cooling equipment replacements in the life cycle cost optimization, which biases downward significantly the cost of added efficiency. Compare (v.51) with the equations optimized by the ORNL model. For simplicity, ignore the difference in heating and cooling ESR. The first-order conditions for optimization of (v.51) are

$$\text{(v.53)}\quad C_o'(h_o) + p_f[h_1u_1+h_2u_2](1-e^{-rL_o})/r = 0$$

$$\text{(v.54)}\quad C_k'(h_k)\sigma_k + p_f h_o u_k(1-e^{-rL_o})/r = 0 \qquad (k=1,2)$$

where $\sigma_k = \sum_{t=0}^{t_k} e^{-rtL_k}$. For the assumed equipment lifetimes L_o=25, L_1=15, L_2=10 and r=.06, one has $1-e^{-rL_o}$=.777, σ_1=1.41, and σ_2=1.85. In comparison, the first-order conditions for the optimization in the ORNL model are

$$\text{(v.55)}\quad C_k'(h_k) + p_f h_o u_k(1-e^{-rL_k})/r = 0, \qquad (k=1,2)$$

$$(v.56)\quad C_0'(h_0) + p_f[h_1u_1+h_2u_2](1-e^{-rL_0})/r = 0,$$

where we ignore the modest error caused by solving the equations (v.55) using lagged h_0 rather than solving the system simultaneously. For the assumed values, $1-e^{-rL_1}=.593$ and $1-e^{-rL_2}=.451$. For the system (v.55)-(v.56) to give the same solution as the correct jointly optimized system (v.53)-(v.54), it would be necessary to increase C_1 by 7.6 percent and C_2 by 7.4 percent. This error and the previous two errors in the ORNL calculation all go in the direction of underestimating the relative capital cost of increasing efficiency.

Fourth, the ORNL model does not solve the system (v.55)-(v.56) separately for the classes of consumers without air conditioners, with central air conditioners, and with room air conditioners, but rather obtains a single solution of (v.56) for a "representative" consumer holding fractions of a central and a room air conditioner (equal to 25 percent and 55 percent, respectively, in the ORNL inputs). These saturations may deviate substantially from the penetrations of air conditioners under alternative energy scenarios, so this method may employ a biased formula for average life-cycle costs. More importantly, the solution of this non-linear optimization problem for average costs may deviate from the average of the solutions for alternative households. The ORNL input parameters imply that the elasticity of the optimal thermal ESR with respect to total utilization is -0.75. Expected usage from the ORNL inputs for a single-family home, gas heat is

127.2 mil. Btu for heating, 28.8 mil. Btu if a room AC, and 52.7 mil. Btu if a central AC. The impacts on the optimal thermal ESR are summarized below:

type consumer	proportion	relative ESR	
gas heat only	.20	1.0	average
room air cond.	.55	0.858	0.865
central air cond.	.25	0.771	
"representative"	---	0.857	

In this case, the optimum for the representative consumer deviates by 0.008 from the average of the relative ESR for the various consumer types. This results in an error of 0.8 percent in the energy consumption forecast.

Fifth, it should be noted that the introduction of the partial adjustment mechanisms in the determination of equipment efficiencies leads in the second step to the calculation of an "optimal" thermal ESR which is lower than would result from joint optimization of life cycle costs. The partial adjustment toward this solution may then be going too far relative to the true joint optimum. In terms of logic, simplicity, and computational ease, there appear to be strong arguments for simultaneous solution of the heating, cooling, and thermal efficiency and usage decisions, and for incorporation of market imperfections in the consumer discount rate. This modification would change the heart of the computer code of the ORNL model, but would be consistent with its underlying logic and input requirements.

USAGE

Given appliance holdings, and the fuel type and efficiency of these appliances, the consumer will adjust intensity of utilization in light of prevailing income and prices. In a model of intertemporal utility maximization with perfect foresight, utilization decisions will be planned ex ante, and efficiency will be set commensurately. More generally, utilization will be determined by ex post utility maximization, given efficiency levels set by earlier strategic decisions. One simple approach would be to approximate this adjustment by a constant elasticity response,

$$\text{(v.57)} \quad \ln U_n = (1-\gamma)\ln U_{n-1} + \gamma\alpha_1 \ln F + \gamma\alpha_2 \ln Y - (1-\gamma)\ln U_{1969}$$

where U_n=intensity of use in period n, F=cost per unit of intensity (normalized to one in 1970), α_1 and α_2 are long run elasticities, and γ is a partial adjustment rate. The ORNL model uses essentially this approach, but places bounds on the range of intensity of use, $0.5<U<1.5$, by replacing lnU throughout (v.57) by $0.25 \ln(u-0.5)/(1.5-U)$. This is unobjectional, although the non-constant elasticities of this transformation may make calibration of the parameters more difficult.

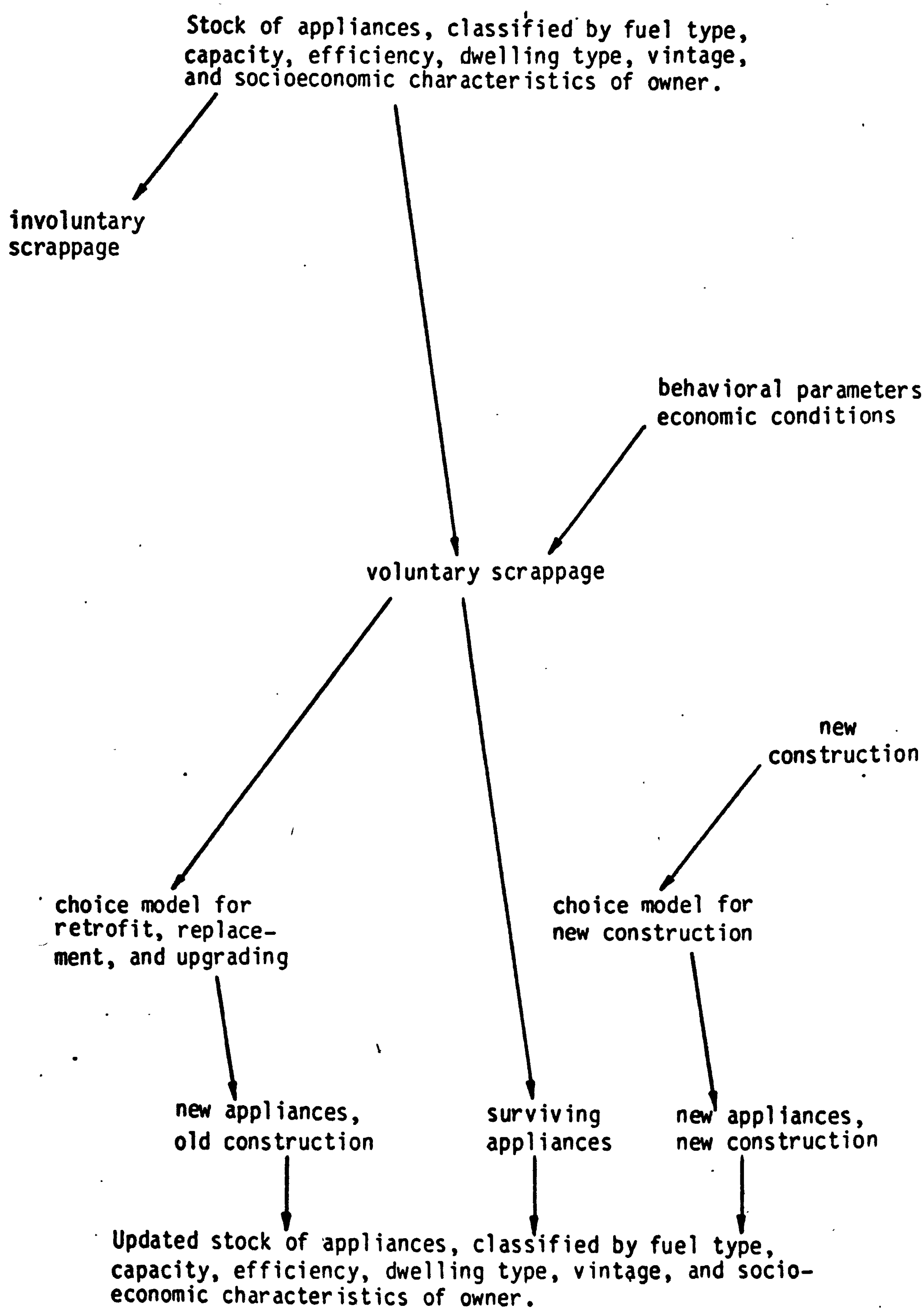
The variable F in this analysis incorporates the efficiency decisions discussed in the preceding section.

APPLIANCE SATURATION MODELS

The ORNL model predicts number of appliances by predicting total number of households in a class and proportion of households owning the particular type of appliance (saturation). Perhaps the best way to discuss this model is to first outline a realistic description of appliance choice behavior, and then indicate the assumptions and compromises necessary to go from this to the ORNL module. Figure 5-1 gives the flows one would expect to be associated with individual behavior. First note that capacity, efficiency, and vintage are properly characteristics of an appliance determined at time of purchase, and should ideally be analyzed as part of the appliance choice module. Further, to avoid aggregation bias, the full classification of appliances should be maintained.

Second, existing stocks are reduced by involuntary scrappage, which is primarily a technological function of age, and by voluntary scrappage. The latter is a behavioral function of economic conditions, and is particularly sensitive to mobility and turnover rates since most retrofitting is done at the time of moves. Note that there may be an important distinction between scrappage and gross retirements. There are active second-hand markets in some appliances, and voluntary retirement decisions by some households may lead to units being recycled. The result may be a different socioeconomic composition of household holding particular types of appliances, and at the end of the chain an increase in appliance saturations or scrappage of appliances with quite different capacity, efficiency, and vintage characteristics than those initially supplied to the second-hand market. For example, a sizable fraction of

Figure 5-1. A Description of Appliance Choice Behavior



the voluntary refrigerator retirements creating demand for new units are recycled, and replace or supplement refrigerators of older vintage and smaller capacity. Consequently, an appliance with poor capacity-efficiency characteristics relative to current energy prices may stay in the system a long time, with succesive owners absorbing capital losses on resale which reflect the inappropriateness of the appliance characteristics. The reduced second hand price makes the appliance attractive in terms of life-cycle costs conditions to successive buyers. This phenomenon has been extensively studied only for used cars, where old "gas guzzlers" remain in operation at purchase prices which make their life-cycle costs attractive to low-income buyers. In principle, it would be possible to replicate the used car studies for refrigerators, ranges, washing machines, and other appliances which have active second-hand markets. Short of this, it may be feasible to model voluntary scrappage, ignoring inter-household transfers, without introducing unacceptable biases. Note that in calibration of any of these models, it is essential to distinguish scrappage and resale data.

After scrappage, the stock of surviving appliances is determined, with the same classification detail as before, taking into account any significant shifts in the distribution of a particular type of appliance across dwelling types and socioeconomic classes. The vacancies created by scrappage are inputs to a choice model for replacement, retrofit, and upgrading decisions in existing dwellings. At this point, fuel type, capapcity, and efficiency of replacement units is determined. Inputs to this decision are purchase, installation, and operating costs of alternative appliances, and the household's evaluation of the quality of service provided. As part of this decision, the household will form expectations on future prices and utilization. A classical economic decision-maker will choose the appliance characteristics to maximize lifetime utility subject to a lifetime budget constraint. Note that this is not the same as minimization of life cycle costs except in the extreme case that service quality and utilization are fixed. Beyond this, if there is uncertainty about the future and the possibility of ex post revision of operating plans, the consumer's maximization problem becomes a stochastic dynamic programming problem. It is probably beyond the realm of practicality to incorporate a decision model of this complexity in a simulation system. However, any practical consumer decision model should be viewed as an approximation to the full stochastic dynamic program, and should mimic its most important qualitative features.

In addition to replacement decisions in existing dwellings, there may be net additions; e.g., increasing penetration of room air conditioners in existing, non-air-conditioned dwellings. The decision process on such upgrading presumably parallels that for replacement.

The most important differences in appliance choices between existing and new dwellings is probably not in behavioral parameters, but rather in differences in availability and cost of alternatives. Appliance choices in existing dwellings are often severely constrained by availability or installation costs of fuels, size limitations, etc.

Next consider appliance choices in new dwellings. There is a delicate question of who makes these decisions, depending on the structure of the market for new structures. One (extreme) possibility is that all structures are built to order, so that the household makes all appliance decisions, taking into account construction costs. A more plausible possibility is that some structures are built to stock, but the supply of dwellings is perfectly elastic and builders are highly sensitive to profit signals, so the household can choose among appliance portfolios by choice of dwelling at competitive prices. This has the same final effect as dwellings built to order -- households determine appliance shares. The last possibility is that supply is not perfectly elastic, and builders build to stock without clear signals on household preferences. Then the prices of dwellings will adjust to reflect the ex post desirability of their appliance portfolio, witn builders taking windfall gains or losses if they guess right or wrong on future economic conditions and tastes. In this case, the mix of appliance types in new housing reflects builder's decisions, which are influenced by the builder's expectations about households and by the builder's economic environment, including financing of new construction. From the point of view of buyers, dwelling price adjusts to make the life cycle costs of alternatives comparable. This last possibility raises one real problem and one modeling problem. The real problem is that the lag in builder response to changes in household expectations may be long. The modeling problem is that in the last case, a model of new appliance shares as a function of economic conditions is a reduced form which may be inappropriate for forecasting if the new housing market structure shifts, and may be specified incorrectly if economic factors affecting builders are important.

The final step in Figure 5-1 is to collect the various sources of appliance stock changes and produce an updated cross-classified appliance stock.

The next question is how the ORNL appliance saturation model works, and how it related to the "ideal" module just presented. The sources for this description are Hirst-Carney (ORNL/CON-24, 1978) and Lin-Hirst-Carney (ORNL/CON-3, 1976), plus program documentation.

The starting point of the ORNL appliance model is an econometrically estimated model of equipment ownership, classified by type of equipment and fuel type, as a function of equipment and fuel prices. The estimation is done principally on 1970 Census data at the state level, and is described in Lin-Hirst-Carney. The specification chosen is of the form

$$\text{(v.58)} \quad \log\left(s_i^k/(1-s_i^k)\right) = \alpha_i^k + \beta_i^k X + \varepsilon_i^k$$

where s_i^k is the share of fuel i among appliances of type k, X is a vector of income, fuel prices, and appliance prices, and α, β are parameters. This is estimated as a multivariate system across fuels by three-stage least squares subject to the parameter restrictions

$$\text{(v. 59)} \quad \sum_i \bar{s}_i^k (1-\bar{s}_i^k)\, \beta_i^k = 0,$$

where $\bar{s}_i^k$ is the 1970 national share of fuel i. The purpose of this restriction is to ensure that "on average" the fitted shares will sum to one. In the estimation, the $\bar{s}$ are treated as arithmetic rather than as random variables.

When the fitted share equations are used in the simulation program, they are normalized so that the shares in any region and year sum to one. Consequently, the model finally used to forecast appliance saturations is

$$\text{(v.60)} \quad \hat{s}_i^k = [1 + \exp(-\hat{\alpha}_i^k - \hat{\beta}_i^k X)]^{-1} / \sum_j [1 + \exp(-\hat{\alpha}_j^k - \hat{\beta}_j^k X)]^{-1} ,$$

where $\hat{\alpha}$, $\hat{\beta}$ are the estimated parameters.

This model has several severe shortcomings. First, note that the final forecasting model (v. 60) is in fact a multinomial logit model

$$\text{(v.61)} \quad s_i^k = e^{V_i^k} / \sum_j e^{V_j^k} \quad ,$$

where the scale function V_i has the unconventional non-linear form

$$\text{(v. 62)} \quad V_i^k = -\ln[1 + e^{-\alpha_i - \beta_i X}]$$

rather than the standard linear-in-parameters form

$$\text{(v.63)} \quad V_i^k = \theta_i^k + \psi_i^k X \quad .$$

Lin-Hirst-Carney claim that their model is based on the conditional multinomial logit model of discrete behavior developed by McFadden, modified to relax restrictions on cross-elasticities imposed by the multinomial logit form. However, their model is inconsistent in both form and logic with McFadden's treatment, which emphasizes the derivation of the multinomial logit model from individual preference maximization and leads to scale values V_i^k which are functions solely of attributes of alternative i and household characteristics. It is this last property which restricts cross-elasticities. The standard multinomial logit functional form (v. 61), with scale values (v. 63) which depend on attributes of all alternatives, imposes no cross-elasticity restrictions. It is unnecessary to adopt the non-linear form (v. 62) to achieve flexible cross-elasticities.

Second, the method used to fit the Lin-Hirst-Carney saturation model has several shortcomings. The model is heteroscedastic with a parametric covariance structure depending on expected shares and on the size of the state observation units. The authors' estimation procedure is not efficient for this problem, and may in fact be asymptotically inferior to ordinary least squares. The parameter constraint (v. 59) complicates the estimation without making any positive contribution. The normalization of shares in the forecasting equation (v. 60) would be required whether (v. 59) were imposed or not, and reduces (v. 59) to the role of an arbitrary and unnecessary side constraint on parameters. Further, the dependence of this constraint on observed national shares makes it stochastic and most probably correlated with the equation errors, implying that the authors' estimates will contain some asymptotic bias.

A third comment concerns the empirical identification of the model. The authors do not have linearly independent equipment prices, and therefore fit equipment price parameters by imposing judgemental restrictions on β's, choosing a set of restrictions which yield "reasonable" elasticities (see ORNL/CON-3, Appendix E). This procedure lacks a statistical foundation, and erases any desirable statistical properties of the estimates obtained prior to this stage.

The authors use equipment and operating cost coefficients to calculate appliance and fuel specific implicit interest rates which are used subsequently in determining life-cycle cost. I am aware of no behavioral studies which suggest varying discount factors for different purposes; theory would suggest the contrary.

Freedman et al. note that in this model equipment is assumed to have a fixed lifetime, whereas in simulation the inconsistent assumption is made that there is a geometric failure rate for each appliance.

Finally, there are some problems in variable specification in (v.58). Fuel type is expected to be sensitive to life cycle costs, which depends on efficiency and intensity of use. For some appliances, utilization is weather-sensitive; this enters the model only through possibly unrepresentative 1970 utilization rates. A more subtle problem here is that level of utilization and fuel type are jointly determined. Then using actual utilization as an explanatory variable creates a simultaneous equations problem, while using "representative" utilization causes an errors-in-variables problem.

The model and statistical deficiencies of the Lin-Hirst-Carney analysis could be remedied relatively simply. If the standard multinomial logit (v. 61) and (v. 63) is adopted, with the normalization $\theta_1^k = 0$, $\psi_1^k = 0$, then the system of equations

$$\log\,(s_i^k/s_1^k) = \theta_i^k + \psi_i^k X + \varepsilon_i^k \qquad (i>1)$$

can be estimated by generalized least squares. Berkson and Theil have provided the appropriate transformations to adjust for heteroscedasticity and cross-equation correlation. Collinearity in equipment prices can be avoided by careful measurement, using published construction cost indicators. These vary with regional installation labor costs and with equipment capacity which depends on dwelling size, climate, and household size. Aside from the aggregation issues implicit in the use of state-level data, this approach should provide a simpler and sounder model of saturations than ORNL currently employs.

The shares model is transformed in the simulation system to forecast shares in retrofit and new construction. The computer code is complex and opaque. However, at least in terms of generalities, the ideas underlying the applications are simple:

1. Base year data on market shares by fuel and dwelling type of existing appliances is expanded to a classification by fuel, dwelling type, and old or new dwellings, by assuming the shares in each sub-classification are the same. The rather extensive code has the capacity to alter this assumption parametrically by specifying different overall new equipment fuel shares in the base year, which are then allocated in proportion to shares of existing equipment across dwelling type and vintage (new, old). Then new equipment shares are assumed to equal existing equipment shares.

2. Next the non-linear multinomial logit model (v.60) is used to forecast new equipment shares. The program does this by a series of indirect steps which obscure the core of the computation. A principal complicating factor in this computation is that the econometric model coefficients are translated into elasticities evaluated (apparently) at national mean shares and national means of the explanatory variables. These elasticities are input to the simulation model and then translated back into model coefficients. However, the second translation is carried out at the values of shares and explanatory variables prevailing in the region of application and year of simulation. This double translation is logically inconsistent -- the simulation model no longer equals the calibrated model, and there is no judgemental or common sense plausibility in the nature of the deviation. There are a number of detailed mechanical questions regarding the manner in which weighting is done and parameters are adjusted. Shares of existing equipment by dwelling type are weighted by "conventionalized" shares of "vacancies"

for equipment by dwelling type to obtain overall shares. No rationale for these particular weights is given.

The ORNL appliance share simulation could be simplified and made logically consistent by scrapping the double translation through elasticities, and using the econometric model coefficients directly. This would circumvent most of the mechanical problems.

The ORNL appliance model assumes all scrappage is involuntary, with a geometric survival curve for each appliance. This is clearly unrealistic -- energy price increases have accelerated retrofitting.

In light of this critique, what are the primary differences between the ORNL appliance model and the "realistic" choice scheme outlined in Figure 5-1? First, capacity, efficiency, and vintage detail are not kept in the ORNL model, introducing aggregation biases. Second, no possibility of voluntary scrappage, based on economic behavior, is included. Third, the choice model for new equipment fuel shares is behaviorally weak and contains logical inconsistencies. Fourth, the capacity and efficiency decisions are not analyzed as part of a joint appliance decision. Of these differences, the first and fourth are intrinsic to the architecture of the ORNL model, and cannot be changed. The second and third could be modified within current architecture by (1) fitting cleaner, more data-analytic models of fuel shares, (2) using model parameters directly, and (3) adding a voluntary retrofit model by employing some combination of judgement and econometric analysis of currently available data sets. In principle, the fuel share choice can be based on the same model of intertemporal utility maximization as the efficiency and utilization decisions -- this would impose a strong consistency on all aspects of the consumer decision, and potentially economize considerably on the number of behavioral parameters requiring estimation or judgement.

AGGREGATION ISSUES

At many points the ORNL model aggregates results in order to reduce the scope of data handling and computation. For example, all non-new dwellings are aggregated into a single class with "representative" efficiency, usage levels, and fuel share levels; room and central air conditioners are aggregated together; all income classes are aggregated to a representative level, etc. Aggregation weights correspond generally to population or energy consumption shares, and are generally sensible, although sometimes poorly documented.

Because many of the relationships in the ORNL model are non-linear, errors are introduced by the aggregation process. The reason is essentially that a non-linear function of averages is not equal to the average of the corresponding non-linear function. If the non-linearity is predominately concave or convex, then this aggregation bias tends to be systematic. As was noted in the overview of the ORNL model, the errors introduced by aggregation bias can be quite substantial.

A substantial degree of aggregation is intrinsic to the architecture of the ORNL model. Computationally feasible methods of calculating the distribution of energy consumption before aggregation require fundamentally different approaches -- classification of consumers into a large number of relatively homogeneous classes or approximating the distribution using a random sample of households. However, it should be possible to reduce aggregation bias within the ORNL model architecture. Some suggestions for doing this follow:

(1) A few aggregates could be eliminated without causing excessive computation. An example would be separate treatment of room and central air conditioners.

(2) Appliance counts should be kept by vintage class (e.g., new, 1-3 years, 4-10 year, 11+ years), to avoid aggregation over units of substantially different efficiencies.

(3) Households should be disaggregated into a few catagories by income and family size.

(4) In cases where the aggregation bias in a formula can be clearly identified, as in the case of consumption equal to the product of fuel share, energy/service ratio, and utilization, it may be possible to introduce analytic or empirical factors to reduce bias. A study of these quantities on a household by household basis could provide the foundation for a relatively realistic correction factor.

DISTRIBUTIONAL IMPACTS

The outputs of the ORNL model are summarized in Table 5-1. These permit calculation by region of the present value of the economic cost of energy consumption and various summary statistics on physical energy consumed. These figures can be disaggregated by end use, fuel, and dwelling type. However, the program does not permit disaggregation by income class, dwelling tenure, family size, or other demographic dimensions. Consequently, the ORNL model can provide the information necessary to assess energy policies in terms of overall and regional impacts, but is not designed to answer questions about the distributional impacts of policy along such dimensions as income, age, or housing tenure. Furthermore, given the nature of aggregation in the model, it is clear that policies which are quite heterogeneous in their impacts on different demographic groups are likely to be assessed with larger aggregation errors than are policies whose impact is relatively homogeneous. Consequently, the ORNL model is likely to perform best for the analysis of policies whose impact is relatively homogeneous and whose assessment depends primarily on overall impacts rather than on distributional effects.

Table 5-1 Outputs of the ORNL Model

Description	Classification*
energy/service ratio (ESR), new equipment	i, k, l, n
price of new equipment	i, k, l, n
ESR, thermal, new dwellings	i, l, n, (k=1,2)
price of thermal improvements, new	i, l, n
ESR, thermal, retrofit	i, l, n
price of thermal improvements, retrofit	i, l, n
number of units retrofit	i, l, n
market shares for exisitng equipment	i, k, l, n
number of new units	i, k, l, n
market shares for new equipment	i, k, l, n
average ESR, all equipment	i, k, l, n
average ESR, thermal, all dwellings	i, l, n
usage intensities	i, k, l, n
housing size	i, l, n, m
housing stock	l, n, m
fuel consumption	i, k, l, n

* i = fuel type

k = end use

l = dwelling type

n = year

m = new/old

Section 6

EVALUATION OF MODEL CALIBRATION METHODOLOGY

MODEL PARAMETERS

The ORNL model requires, by crude count, approximately 500 behavioral and technological parameters, and for each region analyzed approximately 450 data points giving base year values of variables plus exogenous forecasts. Most of the parameters and many of the base data points are not observed directly, and must be calibrated by indirect construction, engineering calculation, econometric estimation, or judgement. The informational requirements of the model exceed considerably what can be learned from existing data sets. Further, the model has not been structured to maximize compatability with existing data sources. Consequently, it is infeasible to take a unified approach to model calibration, or to dispense with judgemental factors. Nevertheless, all the parameters in the model should be viewed as provisional, and should be refined by further calibration exercises. A useful initial step would be to provide adequate documentation of what has been done so far.

The behavioral and technological equations in the ORNL model can be broken into four groups: housing stock, energy/service ratio, fuel market share, and usage. Generally, the approach to calibration has been to fit the housing stock and fuel market share equations by least squares regression analysis, to fit the parameters of the equations determining ESR by engineering cost calculations and normalization to 1970 base values, and to determine the usage equations by judgement. The combination of these models implies overall price and income elasticities for energy consumption. These implied elasticities are compared with "experience," which is based on historical econometric studies of energy demand and an ORNL analysis of state cross-section data (ORNL-CON-7). An ORNL module, termed the "Elasticity Estimator", carries out this computation, and permits the user to adjust detailed elasticities judgementally to reconcile imputed and estimated overall elasticities. However, the model provides no guidelines or statistical foundations for such judgemental adjustment. (Within an empirical Bayes framework, one could develop a decision criterion for parameter reconciliation which would concentrate adjustments on poorly determined parameters.)

As detailed in the discussion of model structure, a variety of partial adjustment factors are introduced to capture short run rigidities and response lags. For the most part these short-run factors are ad hoc in structure, with parameter values set on the basis of rather simplistic judgements (e.g., a widely used assumption that the ratio of short to long run elasticities is 1/4).

Suggestions for upgrading ORNL parameter estimates fall into four general catagories: (1) improve the compatability and generality of model elements, and systematically test model specification, (2) use more informative data sets, (3) improve statistical method, and (4) provide a statistical framework for combining and reconciling parameter estimates. The following sections give specific suggestions for each of the groups of behavioral and technological relationships in the ORNL model.

THE HOUSING MODULE

The housing equations are estimated from national time-series data, 1952-1976. The following questions can be raised about model specification: (1) Do energy costs affect housing type and size choice ? (2) Are marriage and separation rates exogenous to the determination of the household/population ratio? (3) Is there a cultural shift after 1970 in household formation rates? (4) Are the models specified with forecasting in mind, with trustworthy external forecasts for all exogenous variables?

The national census data used in the calibration has several drawbacks. First, data for intra-census years is partly estimated rather than measured, and the analysis may be simply approximating the Census interpolation rule. Second, there may be significant regional variations in rates of household formation, and in dwelling size choice. More informative data sets are now available, such as the Annual Survey of Housing and the National Interim Energy Consumption Survey (NIECS). However, two notes of caution are necessary regarding the use of individual household data for calibration. First, there tends to be considerable noise in individual behavior, and sample sizes and statistical methods should be chosen with this mind. Second, the use of individual data purges the calibrated model of the confounding effeacts of aggregation. This is desirable in principle. However, sometimes biases in behavioral parameter estimates resulting from calibration on aggregate data will tend to offset errors introduced by aggregation in the simulation. An example illustrates the point: Suppose a household i purchases an air conditioner if $\theta y_i + \epsilon_i > 0$, where y_i = income, θ is a behavioral parameter, and ϵ_i is an unobserved factor. Suppose y_i and ϵ_i have independent normal distributions, with means $\bar{y}$, 0 and variances σ^2, 1, respectively. The probability that an individual with income y_i purchases an air conditioner is then given by $P_i = \Phi(\theta y_i)$, where Φ is the standard normal cumulative distribution function. Estimation from a disaggregate data set will give a consistent estimate of the behavioral parameter θ. Noting that $\theta y_i + \varepsilon_i$ is normal with mean $\theta\bar{y}$ and variance $\theta^2\sigma^2 + 1$, the share of this population purchasing air conditioners is $\overline{P} = \Phi(\theta\bar{y} / \sqrt{1 + \theta^2\sigma^2})$. Estimation using regional data would give consistent estimates of $\theta / \sqrt{1 + \theta^2\sigma^2}$, which combines the effects of behavioral response and non-linear aggregation, and is less than the individual behavioral response θ. When simulation is done by applying a model $\overline{P} = \Phi(\alpha y)$ without adjusting for aggregation errors, but the parameter α is obtained from the behaviorally inconsistent estimate from regional data, the errors exactly offset. Going to a behaviorally consistent estimator of α would then uncover the aggregation bias in the simulation. This example cannot be taken as a justification for using inconsistent methods. Exact offset occurs only in special models, with the distribution of the explanatory variables stationary (i.e., unchanging). Use of consistent procedures throughout places the simulation on much firmer ground.

ENERGY/SERVICE RATIO MODULE

The key ingredients in the model determining equipment efficiencies are equations giving the capital cost of alternative efficiencies and the discount rate entering the expression for life-cycle cost which is minimized to determine demand. The cost-technology tradeoffs are calibrated using engineering calculations of materials and fabrication cost. The analysis and judgements entering these calibrations are partially documented for water heaters, and are almost totally undocumented for other equipment. Major questions about the model specification are (1) What is the interaction of efficiency, capacity, and service quality in reality, and how are the omitted capacity and service quality dimensions treated implicitly in the current analysis? (2) How stable is the cost-attribute frontier over time? If it is shifting, what are the trends? (3) What is the relationship between engineering cost and market price? How is it affected by the structure of the equipment-producing industry, the structure of the product line, and the product life-cycle? (4) How suitable is the current three-parameter formulation, compared say with explicit choice among a finite set of alternatives?

Some analysis of these questions could be carried out using construction cost and consumer price data sources. A complete study would probably require primary data collection.

FUEL MARKET SHARE

The ORNL model determining fuel market shares is estimated on state cross-section data for the census year 1960 and 1970. The model selected is a very awkward and implausible non-linear variant of a multinomial logit model, with most of the limitations of this functional form and none of its advantages. A prequisite to improving the calibration of the fuel market share model is specification of a behaviorally plausible structure. One alternative which would be computationally attractive for choice among three fuels, and sufficiently flexible to accomodate plausible patterns of cross-elasticities, would be a trinomial probit model. It is also likely that a simple linear multinomial logit model with fuel-specific cross-price effects would prove to be sufficiently accurate to be satisfactory for practical analysis. As discussed in Section 5, the latter model need not exhibit the severe restriction on cross-elasticities often attributed to logit models.

A combined cross-section, time-series analysis of state census data may prove adequate for estimation. A problem not addressed in the ORNL statistical analysis, which should be treated, is heteroscedasticity and interdependence of errors in regressions of log relative fuel shares on explanatory variables.

Because share models are intrinsically non-linear, calibration on state aggregate data (e.g., household income) will introduce an aggregation bias. One method of correcting this bias when the distribution of explanatory variables is known is to estimate an analytically (or numerically) aggregated share model as a function of parameters of the distribution of explanatory variables. Alternately, the model system could be estimated using household data (from the Census public use sample or from energy consumption surveys such as WCMS or NIECS), and then aggregated numerically.

It would be desirable in re-estimation of this system to incorporate several improvements in the model specification suggested in Section 4. Capital costs should reflect equipment market price rather than fabrication cost, and should include installation cost. Operating cost should include maintenance, and should incorporate a factor for expected changes in real fuel prices. Ideally the expected fuel price changes should themselves be behaviorally modeled as functions of historical patterns and announced energy policy. Costs should reflect expected useful appliance life, taking into account household moves, obsolescence, and resale market conditions. Consumer discount rates should, in the absence of strong behavioral evidence to the contrary, be specified at a common level across appliances and fuels, as indicated by intertemporal consumer theory. The heating-ventilating-thermal efficiency decision should be estimated as a joint choice, and the costs of alternatives should reflect the joint nature of some system costs (e.g., gas connection to main).

A deficiency of all the data sets currently available on appliance fuel choice is that they provide information on holdings rather than purchases, and hence represent decisions made at various dates in the face of different relative prices and price expectations. This fact could be turned to advantage, permitting estimation of the behavioral response to different price environments, if acquisition dates are identified and prices at date of purchase are collected. In practice, acquisition dates are unavailable for most appliances in most data sets except for recent purchases. A further complication is the purchase of appliances along with a house purchase. In this case, the total price reflects the revaluation of the appliance portfolio at the dates of the dwelling purchase to reflect the appropriateness of the appliance technology. Existing data sets generally provide no information on dwelling purchase price, or any means of attributing house price differentials to individual appliances. The collection of historical price data is also difficult. Geographic detail on fuel price is often unavailable historically, particularly for fuel oil, and location information on disaggregate data sets is sometimes limited. For these reasons, most analysis to date has estimated holdings models and made rather simplistic assumptions on the relation of holdings and purchases.

Exploitation of Annual Housing Survey data or NIECS data to study new purchases would be one useful step in quantifying fuel choice behavior. Beyond this, primary data collection would probably be required to develop fully the dynamic of appliance purchase, holdings, and resale.

USAGE

The ORNL model employs usage elasticities based on "engineering possibilities and our judgements" (ORNL/CON-24, p.27). Assumed long run usage elasticities in the ORNL model are reproduced in Table 6-1. Short-run elasticities are assumed to be half these values, so the total impact of price on usage is felt in two years.

Table 6-1 ORNL Long-Run Usage Elasticities

Appliance	Own-Price	Income
Space heating	-.4	.10
Air conditioning	-.4	.30
Water heating	-.25	.05
Refrigeration	-.05	.02
Food freezing	-.05	.02
Cooking	-.10	.04
Lighting	-.10	.10
Other	-.10	.10

There is almost no documentation of the analysis underlying these elasticities. The ORNL cites as an example of their reasoning the argument that a 1 degree F setback in winter temperature for a full 24 hour day cuts space heating fuel use by about 5%. First, this conclusion holds only for a moderate climate (such as Oak Ridge, Tenn.). Table 6-2 gives the percentage saving from a 1 degree F thermostat setback in various U.S. Cities. One sees that the saving is quite sensitive to

Table 6-2 Fuel Savings from 1 degree F Thermostat Setback

City	Heating degree days	% Saving
Chicago	6872	3.8
Duluth	10015	3.1
Dallas	2504	6.6
New York	4258	6.3
Seattle	3333	7.2

climate. If the behavioral response of comfort level to price is relatively uniform for families in different cities, then the elasticity of usage with respect to price in moderate climates will be approximately double the magnitude of the usage elasticity in cold climates. Missing from the ORNL documentation is any description of the factors which led to their implicit judgement on the behavioral response of comfort level to price. The point of this comment is that the judgements used by ORNL may have a significant impact on the forecasts produced by the model, and that careful reflection may suggest that some of these judgements are implausible. This portion of the model needs careful documentation and evaluation.

Because the functional form for usage in the ORNL model does not in fact exhibit constant elasticities, there is an ambiguity about how the assumed elasticities in Table 6-1 are translated into model coefficients.

A number of recent studies of electricity consumption have fitted appliance-specific consumption levels as functions of prices and income. While there is some difficulty in untangling the contributions of capacity, efficiency, and usage in these studies, they do provide some behavioral foundation for judgements on usage elasticities. To the extent that any pattern emerges from these studies, it suggests that usage elasticities are somewhat higher than those assumed in the ORNL model.

VALIDATION

In a complex simulation model containing judgements on equation specification as well as parameter values, and containing lagged impacts which induce model dynamics of unknown character, model validation becomes a crucial part of the calibration process. The ORNL model has been subjected to some within-sample validation. This analysis has focused primarily on adjusting parameters to fit base year data and provide "reasonable" short-run response. The long-run dynamics of the model have not been studied systematically, and the documentation currently available does not report on any "arms length" out-of-sample validation. If this model is to be used as an input to important policy decisions, then it deserves far more extensive and systematic validation and documentation.

Section 7

EVALUATION OF POLICY SIMULATION METHODOLOGY

OVERVIEW

One current use of the ORNL is as a baseline demand forecasting system driving the Midterm Energy Forecasting System. A second is to carry out a series of impact studies of specific energy policies.

As a baseline forecasting model, the ORNL model has some structural advantages over simpler "macroeconometric" energy demand forecasting systems. Because the end use detail of the model permits obvious technological limits to be built in, one would expect the long run forecasts to be more reasonable than macroeconometric forecasts. On the other hand, the complexity and lack of validation of the ORNL model make its use more risky than the traditional alternatives. This is likely to be particularly true for short-term forecasts, where macroeconometric models which exploit the "inertia" of the system are relatively reliable, and the short-run behavioral judgements and possible over-fitting to base-year data which weaken the ORNL model are not balanced by the long-run technological limits. Scientific prudence suggests that the ORNL model not be chosen over simpler models constructed explicitly for baseline forecasting until it has demonstrated clear forecasting superiority.

The second use of the ORNL model, analyzing policy scenarios, conforms to its primary design purpose. The end use detail of the model and its ability to capture the dynamics of appliance acquisition make it particularly suitable for analyzing the impacts of policies which affect specific appliances.

Some features of the ORNL model limit its policy applications. Because the model operates on geographical aggregates (DOE regions), it is difficult to analyze policies which have highly localized and heterogeneous impacts within a region, such as support of solar technologies which are sensitive to micro-climate, or lifeline rates which affect only a segment of the population. Further, model outputs are limited to these geographical aggregates. Thus, the model can forecast the impact of natural gas price deregulation by DOE region, but cannot forecast the distribution of this impact by income group or by the service areas of various natural gas distributors. For many energy policies which are national in scope, the geographical detail of the ORNL model will be quite adequate, and distributional impacts are of secondary interest. For these, the ORNL model should provide satisfactory forecasts. For these applications, it would be desirable to incorporate the corrections and enhancements discussed previously, and validate the model carefully.

For policy studies requiring distributional impacts, the ORNL model will be useful only with fundamental architectural changes or with ad hoc methods for distributing aggregate impacts. It should be noted that the first alternative is not beyond the bounds of practicality -- the accounts maintained by the model could be disaggregated by a few income classes, and the behavioral equations could as a first approximation be assumed uniform across classes. There would be a substantial task to provide base-year data and exogenous forecasts by income class. The ad hoc approach seems less promising, in that the ORNL model provides "representative" impacts based on implicit assumptions about distributional homogeneity. Any ad hoc assumption on differential impacts introduces a modeling inconsistency whose consequences are almost certainly unpleasant.

The energy policies for which the ORNL model might be used fall into four broad categories — policies affecting energy prices, voluntary conservation policies, mandatory conservation policies, and seasonal/time-of-day (STD) rates for electricity. The suitability of the model for each area is discussed in turn.

POLICIES AFFECTING ENERGY PRICES

The ORNL model accepts as inputs exogenous forecasts of prices of various fuels. No allowance is made in the behavioral equations or inputs for non-linear price structures, such as block rate structures or two-part tariffs for electricity and gas. Hence the ORNL model interprets fuel prices as average = marginal prices. In terms of model architecture, no changes would be required to extend the scope of the model to handle two-part tariffs. In this case, marginal prices would be inputs, and the incomes input would be adjusted downward by the fixed charge portion of the tariff. There remains a behavioral question as to whether the current appliance choice, efficiency, and usage models would adequately describe consumer response to two-part tariffs.

A variety of price-related policy issues affect only overall price levels, and not rate structure. Examples are decontrol of oil or natural gas prices, taxation of oil imports, and alternative scenarios for OPEC pricing policy and development of new oil or non-oil energy resources. For these alternatives, the ORNL model detail should be adequate. Of particular interest is the impact of price scenarios on appliance saturations and fuel choices, and the long-run consequences for energy consumption levels and flexibility. The ORNL model should be able to provide this information by region with acceptable accuracy.

The ORNL model has two deficiencies as a tool for analyzing pricing scenarios. First, the behavioral equations employ simplistic (and sometimes inconsistent) assumptions on price expectations and behavioral response to expectations. In practice, consumer perceptions of future prices and the effect of announcements or public committments to price policies may be important policy issues. The ORNL model cannot provide satisfactory answers to questions of how energy consumption patterns will respond to different tactics for introducing and publicizing price policies. A second deficiency of the ORNL model as a tool for analyzing pricing policy is that it represents only one segment of one side of the energy market, residential energy demand at home. Transportation, commercial, and industrial demand are outside the model, as is supply. Consequently, the feedbacks from demand to price through the equilibration of demand and supply that occurs in the real world are not easily accounted for in operation of the ORNL model. Put another way, it is awkward to analyze prices and consumption levels in energy markets without marrying the ORNL model to commensurate models of other demand segments and supplies, and simulating market equilibria. The ORNL model does not appear to have been designed with such a marriage in mind, and so far as I am aware compatible mates are not on the horizon.

For price policies which affect rate structures or apply only to segments of the population, such as introduction of inverted block rate structures or lifeline rates, the ORNL model is not designed to provide satisfactory forecasts. (An exception where the model should work is policy affecting appliance-specific rates, such as special rates for electric heat or for all-electric homes, which with easy modifications could be analyzed within the end-use specific format.) The model will also have trouble handling broad price policy changes when their impact is heterogeneous within a region. For example, a policy alternative which retards oil price increases should have a heterogeneous impact between utility service areas on electricity prices, due to the impact of various utility fuel mixtures on fuel adjustment cost clauses.

As discussed earlier, it is not feasible within the spirit of the current ORNL model architecture to disaggregate below the regional or state level. Consequently, the aggregation biases implicit in analyzing policies which are heterogeneous at the utility service area level limit fundamentally the usefulness of the model. On the other hand, it is feasible, although not trivial, to modify current model architecture to distinguish two or three income classes, permitting analysis of policies such as lifeline rates and some more general inferences on the distributional impacts of policy.

VOLUNTARY CONSERVATION POLICIES

A voluntary conservation policy is one in which government or energy suppliers subsidize the development, production, installation, or information about energy-efficient appliances or dwelling modifications. The consumer then faces a market choice of whether to acquire a more energy-efficient unit. Examples are tax credits for home insulation, labeling of appliance efficiencies, and utility-supplied energy audits or credit.

The ORNL model can in principle provide satisfactory forecasts of the impacts of many voluntary conservation policies. The primary task in this application is to link the specific policy to the model inputs which affect efficiency choices. Within the model, the two proximate inputs to efficiency decisions are the parameters of the curve describing the capital cost of equipment at various efficiencies, and the discount factor which determines the behavioral tradeoff between capital and operating cost. These inputs are not direct market variables, and hence substantial analysis is required to translate market changes implied by policies into parameter changes. An example is the ORNL analysis (ORNL-CON-31) of the impact of various conservation policies on water heaters, where extensive work is needed to refit the three-parameter efficiency-cost curve for water heaters to the alternatives presumed available under different scenarios. Becuse this curve reflects an engineering calculation of fabrication cost rather than market price, there is further room for errors to enter. Similarly, since the discount factors reflect some (unknown) combination of market and behavioral factors, it is not immediately obvious how they would be modified by policies making credit available for energy investments, or subsidizing interest rates.

The translation required above could be reduced considerably by moderate architectural changes to make the ORNL model run directly off a file of alternative appliances projected to be available in the marketplace, and by reestimating behavioral models to identify a market component and a behavioral premium in consumer discount factors. This will work best for policies affecting appliance market price or credit cost. Accurate forecasts of the impacts of improving consumer information or relaxing direct credit constraints are beyond the capacity of the ORNL model, and at best can only be obtained by very intensive, expensive, and problem-specific market research methods.

MANDATORY CONSERVATION STANDARDS

A mandatory conservation standard is one in which government requires that new appliances or dwellings meet specific design standards. Examples are insulation or burner efficiency standards on water heaters, and insulation standards for dwellings constructed with government-insured mortgages.

The ORNL model is well-suited for forecasting the impacts of mandatory standards. The modules determining efficiency accept minimum and maximum efficiency bounds which can be set to reflect mandatory standards. The program modification suggested in the preceding section to input directly a list of available appliances could accommodate mandatory standards even more readily.

One potential problem in analyzing mandatory standards in the ORNL model is the question of the interactions between efficiency and other appliance attributes such as capacity and service quality, and behavioral response in these dimensions to efficiency standards. For example, there appears to be a strong technological relationship between the efficiency and capacity of room air conditioners. Will minimum efficiency standarus for this appliance lead to oversizing, and consequent inefficient usage patterns? Another example is water heaters, where burner efficiency standards have reduced recovery rates, with a consequence that consumers may move to larger units to maintain service level.

SEASONAL AND TIME OF DAY PRICING AND LOAD MANAGEMENT

An important area of energy policy has been the management of electric loads and reduction of peak capacity requirements by introduction of seasonal and time-of-day (STD) pricing, or direct load management methods such as timed or interruptable service. Analysis of behavioral response to such policies requires an understanding of how consumers utilize appliances through time, and the extent to which they will reschedule activities to accommodate peak prices or periods of unavailable service. Of particular importance is the long run penetration of appliances such as storage water heaters or air conditioners which facilitate shifting activities out of peak. While STD experiments are beginning to shed some light on this behavior, there is still no consensus on STD response patterns, particularly the critical question of the extent to which peak shaving is accompanied by valley filling.

The ORNL contains no module to forecast residential load or STD response, and is unable to address policy questions in this area. It would probably be feasible within the framework of current ORNL model architecture to introduce appliance-specific relative load curves to allocate total appliance energy consumption over time. With appropriate input modifications, this allocation could be made sensitive to STD prices. This is the approach proposed by Hausman, Kinucken, and McFadden (1979). A much more difficult task would be introduction of feedbacks from STD consumption to the forecasts of total appliance usage and forecasts of long run decisions on appliance characteristics. These do not appear feasible in the ORNL framework, but must be addressed if the basic question of the relation between relative load shape and total consumption is to be answered.

Section 8

RECOMMENDATIONS

REVISIONS AND EXTENSIONS OF THE ORNL MODEL

The detailed review of the ORNL model has pointed out a number of weaknesses which could be corrected with modest effort, and are worth correcting if the model is to be used for policy analysis. The most limited and critical revision would be to clean and document the computer code for the model, and eliminate logical inconsistencies, as detailed in Section 5. Some of the suggested revisions require fairly substantial changes in equation specification in some modules. For the most part, these could be implemented without new calibration, and would require new computer code only at well-defined program locations. However, some modifications may affect data management in the program. While these changes could probably be made on a piecemeal basis, I recommend that when changes are made, the architecture of the model be reviewed with an eye to rationalizing the input and output data management and improving program flexibility.

A more ambitious revision of the ORNL model would reexamine the calibration of model equations, and bring data now available to bear to reduce unsupported judgements and refine behavioral estimates. It is critically important that this not be done for the model in its current form with basic flaws in logic and specification, but rather on a revised model after the cleaning and respecification recommended in the first paragraph.

Beyond the corrections and revisions suggested above, there are several directions in which the ORNL model could be usefully extended. These extensions should be compatable with the general architecture of the program:

a. Make housing behavior dependent on energy prices.

b. Disaggregate by two or three income classes.

c. Add a module to produce appliance-specific seasonal and daily load curves.

ALTERNATIVE MODEL DEVELOPMENT

In addition to refinement of the ORNL model, a program for general improvement of policy simulation methods would benefit from the following:

1. Continue development of large general purpose simulation models using micro-simulation methods, as a way of overcoming the aggregation biases and blindness to heterogeneities inherent in geographically aggregated models like the ORNL model.

2. Explore development of a family of compatable simplified models which could be operated in a "mix and match" mode with large general purpose simulation models.

3. Integrate seasonal and time-of-day experiment data and models into end use consumption simulation.

DATA COLLECTION

Currently available data on energy behavior is not yet adeqeuate to construct a judgement-free simulation system. There are four areas in which specific data are needed:

1. Survey data on household appliance efficiency decisions, and on voluntary replacement of appliances;

2. Improved engineering studies on the technological relationship between cost, comfort, and energy efficiency in structures and HVAC systems, and on the production cost of other appliances of various efficiencies, capacities, and service qualities;

3. Market price studies of the purchase, installation, and maintenance costs of appliances of various efficiencies;

4. Experiments with consumer response to voluntary conservation programs, load management devices, information programs, tax incentive and credit programs, and other policies for which there are no close historical analogies.

VALIDATION

The ORNL model should be the subject of a continuing program of validation. Particularly useful would be an effort to monitor policy applications of the model, policies adopted, and model accuracy in predicting results. A second, but more costly, form of validation would be to seek policy case histories, run the model with the information available at the time of an actual policy decision, and compare model recommendations and predicted outcomes with those actually observed.

Section 9

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This research was supported by the Electric Power Research Institute through the M.I.T. Energy Laboratory. I have benefited from discussions with Carl Blumstein, Roger Bohn, Glenda Earl, David Freedman, Andrew Goett, Mark Levine, and David Wood. However, I am solely responsible for the conclusions in this paper.

I have attempted to make this an objective review of the Oak Ridge National Laboratory (ORNL) model, judged on its own merits. My opinions on desirable and undesirable features in energy policy simulation models are influenced by my own experience in designing simulation models in this area. Some of the limitations and suggestions for improvements of the ORNL model coincide with innovations in the simulation models witn which I have worked, some made with benefit of hindsight from experience with the ORNL model. Other suggestions concern deficiencies shared by the ORNL model and my models. I have not in this report drawn any overall conclusions on the merits of the ORNL model in comparison with other models including those with which I have been involved. It is my opinion that at this stage of development, policy analysis is best served by continued investment in refining and reworking a portfolio of parallel simulation models.

To clarify the relationship between the ORNL model and the models I have helped design, I shall give brief descriptions of the latter: First, I designed an electric utility simulation model built by Teknekron, Inc. for the National Commission on Water Quality in 1975. This model operates at the state aggregate level, and does not forecast end use consumption or appliance holdings. Second, I designed an electricity demand model developed by Cambridge Systematics, Inc. as a subcontractor to Teknekron for the Federal Energy Administration in 1977. This model forecasts residential electricity consumption for eight residential appliance portfolios, plus appliance saturations, at the state level. Housing construction and appliance efficiency decisions are implicit, and their effects cannot be isolated for policy analysis. This model had three features not contained in the ORNL model: commercial and industrial demand as well as residential demand was forecast; the size distribution of residential electric bills within a state was forecast, permitting analysis of lifeline rates; and the residential appliance-portfolio-specific load curve was forecast, permitting analysis of load management and peakload pricing policies. This model was constructed to drive a full-scale industry simulation model which has never been implemented. Consequently, the demand forecasting system has never been used or validated.

Third, I am a designer of the Residential End-Use Energy Policy System (REEPS) developed by Cambridge Systematics for the Electric Power Research Institute in 1981. This model was designed in light of experience with the ORNL system, and shares a number of its features -- comparable end-use detail, explicit modeling of new construction and appliance purchase behavior, determination of appliance efficiencies to minimize life-cycle cost. The primary difference is that the REEPS model operates on a simulated population of individual households rather than on regional aggregates. It thereby avoids the aggregation problems inherent in the ORNL model. The cost is introduction of statistical sampling error which for some outputs can be reduced to an acceptable range only by using a large and expensive simulated population. The

REEPS model can be operated at a national level, but is primarily designed for simulation at a state or utility service area level. Validation of this model is incomplete. Many of the innovations in model specification and estimation in the REEPS Model could be utilized in a reworking of the ORNL model. Until such time as the regional scale of the ORNL model is shown to be clearly superior or inferior to the household scale of the REEPS model in all policy applications, a conservative research-strategy would be to continue parallel development of the models.

Section 10

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Appendix

COMMENT: An Evaluation of the ORNL Residential Energy Use Model*

by

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1. Introduction

We are pleased to have been given an opportunity to comment upon an evaluation of the residential end-use model developed here at Oak Ridge National Laboratory. This evaluation is one of several critical analyses of the ORNL model—including critiques by John Herbert;[1] David Freedman, Thomas Rothenberg, and Richard Sutch;[2] and Robert Weatherwax.[3] What distinguishes Daniel McFadden's analysis from the others is that he is generally more thorough, and that he accompanies his criticisms with remedial suggestions. Because some of these criticisms were cited previously (by other critics), and because some of his recommendations had previously suggested themselves as ways of better depicting policy impacts, we have been working in many of the areas of weakness noted. On the other hand, there are other areas where McFadden's comments have prompted either remedial modifications or contemplation of remedial modifications to come. That we have been pursuing model development in areas of weakness cited suggests an appropriate format for our comments—that of discussing recommendations in terms of data availability, sensibility, and implementation results and/or problems.

Therefore, in Section II we shall look at McFadden's recommendations which appear only to be implementable with more and "better" data than

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[1]John H. Herbert, "Selected Comments on the ORNL Residential Energy Use Model," DOE/EIA/TR-0244, June 1980.

[2]David Freedman, Thomas Rothenberg, and Richard Sutch, "Analysis Quality Report on Midterm Energy Demand: The Hirst-Carney ORNL Model for the Residential Sector," reported submitted to NBS under contract NB805BCA0492, June 1981.

[3]Robert Weatherwax, "Task 2.3: Comparison of the Capabilities of the ORNL and CEC Residential Energy Consumption Forecasting Models," <u>Information Validation of Energy Consumption in California, Final Report</u>, Report No. ERG-81-1, July 1981.

currently exists. In Section III, we discuss areas of evaluation in which we question the practical sensibility of recommendations made. In Section IV, we report those areas in which we are implementing, or have implemented, McFadden's suggestions.

In following this format, we shall be specific and non-comprehensive. We shall not attempt to respond to every issue raised. But in Section V, we shall conclude our remarks with some brief comments about modeling philosophy.

II. Model Shortcomings Related to Data Shortcomings

The ORNL residential model's original development was by Eric Hirst and Janet Carney. Hirst has been recently involved in data analysis and program evaluation. After reviewing McFadden's evaluation, Hirst has discussed with us several areas where remedial suggestions seem to outrun data availability.

(1) McFadden's discussion of efficiency choices is excellent. His examples are very helpful in clarifying the importance of different aspects of these decisions. We shall later discuss implementation of McFadden recommendations concerning usage in efficiency choice, and simultaneous optimization.

But he also suggests that we try to incorporate (in our models) relationships among capacity and service quality, as well as efficiency, capital cost, and usage. We agree that this is desirable, but know of no data on service quality and of very little data on capacity. The engineering portions of the model could be expanded to include capacity for heating equipment, air conditioners, and perhaps, water heaters and refrigerators. As McFadden points out, this is a particularly important consideration for heating/air conditioning systems. As will be described later, we have instituted an implicit capacity adjustment (as a function of new housing size) for space conditioning and water heating.

(2) McFadden also suggests that we not use fixed equipment lifetimes. Yet, so far as we know, data on decay rates for household equipment and appliances are sparse and non-comprehensive.[4] Moreover, McFadden agrees that empirical survival curve data "does not address the choice problems posed by stochastic survival or voluntary retirements." His "Exercise 2" very nicely illustrates these problems. And surely, this is an area in which the future will be sufficiently unlike the past to make the fabrication of an econometric relationship (determining lifetimes) a tenuous proposition.

(3) McFadden recommends the inclusion of maintenance costs in life cycle cost. We are unaware of the existence of significant data on these costs.

(4) McFadden comments that "it is essential to distinguish (equipment) scrappage and resale data." We agree, but know not where to find such distinguishing data.

The issues of appliance filtering and scrappage were also discussed by Freedman, et. al. They comment that:

> Exponential scrappage may not be a good model for the actual retirement process, on empirical grounds. Also, there are some logical difficulties. The scrappage factor q applies uniformly across the stock, to efficient stoves as well as

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[4]See, for example, data on cooking, refrigeration, freezing, and washing and drying in—Consumer and Food Economics Institute, "Life Tables for Major Household Appliances—July 1972 Survey," Agricultural Research Service, U.S. Department of Agriculture, Hyattsville, Md., July 1975.

> inefficient ones. This is questionable on economic grounds: rational consumers might get rid of the bad stoves first. Another problem is that the scrappage factor depends only on the appliance, not on the fuel type. This may be unrealistic. Finally, the decision to buy an appliance is linked in a peculiar way to the scrappage process. Thus, consumers with no freezers are represented in the model as having "other/none" -fired freezers. Every eighteen years, such shadow appliances break down, and only then do their owners get to buy real freezers. (Eighteen years is the assumed lifetime for freezers.)[5]

The authors' first point is well taken, and is germane to McFadden's commentary in that it identifies the primary "scrappage" deficiency for the residential model as a "macro-simulation model." We believe that it is less important that the model keep track of appliance filtering than it is that stock appliance efficiencies accurately reflect the efficiencies of appliances retired. To this end, we are incorporating the necessary bookkeeping in the "housing-stock-vintage" model currently under development (and discussed below).

On the other hand, the authors' last point is specious, and is an example of the fallacy of composition. Appliance choices are not associated with particular micro-decision-unit-households tracked over the lifetimes of their appliance stocks. The amorphous non-ownership category receives an opportunity to be increased or diminished in each year of model simulation.

(5) McFadden recommends "scrapping the double translation through elasticities, and using the econometric model coefficients directly." This particular comment begs the question of data sufficiency to supply all the necessary partial derivatives of fuel-and-equipment choice

[5]Freedman, op. cit., p. 12 fn.

relative to its determinants. The elasticity filter ("Elasticity Estimator") was employed so that Hirst and Carney could apply judgment about relationships among household fuel-and-equipment demands—in the face of spotty data. It would be more difficult—and foolhardy—to apply judgmental assessments to coefficient magnitudes. Nonetheless, we believe that McFadden is correct on logical-consistency grounds, and his (later) suggestion of a Bayesian framework implies recognition of the data deficiencies.

A related logical-consistency issue is raised in McFadden's comment that "the second translation is carried out at the values of shares and explanatory variables prevailing in the region of application and year of simulation." Translation in the year of simulation has never been true of the Oak Ridge version of the residential model. However, Lawrence Berkeley Laboratory uses a modified version which makes this logically inconsistent translation.

III. Model Shortcomings Related to the Practical Sensibility of Proposed Solutions

There are recommendations in two areas in which we have reservations about the sensibility and feasibility of the modifications required:

(1) McFadden recommends a feedback loop from energy prices and policies to housing numbers and size. Such a loop would include life-cycle cost consideration of housing acquisition and space conditioning. We have three reservations:

a. No program sponsor has expressed interest in financing such an endeavor.

b. It's unlikely that we would find much statistical relation between household formation/housing choice and energy prices. We had considerable difficulty (and little success) in predicting housing choice as a function of housing price (let alone energy price).

c. Perhaps, the "detectable" relationship exists between household formation/housing choice and energy prices/monetary authority-and-credit-market-response to energy price changes. However, modeling this relationship would imply confidence in our ability to supply "credit-restrictiveness" explanatory variables over the forecast horizon of the residential model. Merely developing a minimal number (i.e., boundary cases) of monetary scenarios would seem to be intractable.

(2) As a result of his very nice comparison of intertemporal utility maximization and life cycle cost minimization, McFadden recommends the joint determination of utilization and efficiency. His "Exercise 1" illustrates the desirability of this procedure. However, we have two reservations about joint determination <u>within the current life-cycle-cost-framework</u>:

a. Of course, it is trivial that the LCC minimizing utilization is zero. But also, if we simultaneously optimized subject to a long run usage constraint such as that imposed by residential model function FU with long-run coefficients employed, we would select the lower bound utilization of 0.5. Joint determination necessitates changing the objective criterion.

b. If instead, we pursue a sequential determination (as McFadden suggests as a second-best tack, and as we report implementation of below) of usage and efficiency, we confront problems with the behavioral foundations of our analysis. The "more is better" principle of non-satiation is not well suited to the analysis of "warm", and "cool," and "intensity of light." One might argue that the "current" optimal tangencies between isoamenity curves and iso-life-cycle-cost lines are at bliss points for the end uses—from which movement in any direction is sub-optimal. (Incidentally, it is not true that "current" efficiency choice in the ORNL model takes into account expected usage, as McFadden maintains. Efficiency choices are made at constant amenity levels, e.g., 70° space heat.) Short of the bliss-point extreme, convexity of preferences should perhaps explain usage variation within a restricted range—and do so in an asymmetric fashion. For example, in the light of night setback possibilities, an average usage which translates into 80° space heat may be considerably more suspect than is an average usage which translates into 60° space heat.

But again, we may find ourselves suffering from the behavioral assumption of fixed preferences; There is at least casual evidence that individuals who have become accustomed to lower thermostat settings find the former settings uncomfortable and undesirable (relative to other goods and services). Perhaps, the problem is in the oft-cited view that demand is for the end-use services; whereas, these services are "better" viewed as (substitutable) inputs in household work and leisure activities.

Notwithstanding our reservations, the McFadden comparison is persuasive in its demonstration of the necessity of considering usage in efficiency choice. Our methodology consists of minimizing life cycle cost at long run expected usage levels determined by long run usage coefficients applied to lagged values of operating cost and income determinants. Considering usage in efficiency choice (in the manner described) results in "Hicks compensated" substitution along the isoamenity curve, given the usage-induced perceived change in "energy" operating cost. Because the chosen efficiencies are still relative to a "utilization level = 1.0" isoamenity curve, and because these efficiencies determine operating costs which determine fuel-and-equipment market shares, these market shares are adjusted to reflect expected usage different from that paid for (in operating costs).[6]

[6]Daniel M. Hamblin, "Conversions from ORNL/CON-3 Estimation Coefficients to Residential Model Simulation Coefficients, Oak Ridge National Laboratory Working Paper, September 1981, pp. 17-18.

IV. Model Improvements Related to McFadden Recommendations

The consideration of usage in efficiency choice is one of many suggestions which have been implemented, or which we plan to implement. From our viewpoint, the salient characteristic of McFadden's evaluation was the number of recommendations, the implementation of which should improve the credibility of residential model simulations. The following is a list of improvements/modifications which relate to specific recommendations:

(1) Elasticity corrections "in the direction of logical consistency",

(2) Addition of housing vintage structure/endogenous retrofit consideration/energy data by income class,

(3) Associating housing-size-growth-induced increases in equipment capacity with concomitant increases in equipment prices,

(4) Considering usage in efficiency choice,

(5) Correcting interest rates employed in fuel-and-equipment switching,

(6) Elimination of duplicative lags in LCC optimum efficiency choices,

(7) Employing fuel price expectations in present value of energy cost calculations for determining LCC optima, and

(8) Simultaneous optimization with equipment replacements over the life of the structure/elimination of fractional-ownership-aggregation-error.

We shall discuss each of these in turn:

(1) Elasticity corrections "in the direction of logical consistency."

As noted above, the fuel-and-equipment-switching simulation occurs after a so-called double translation through elasticities. The existence of this double translation poses two problems:

a. Because judgment is employed to adjust the (intermediate) elasticities, the simulation coefficients are not logically consistent descendants of the estimated parameters.

b. Once judgment is given free rein, the human tendency is to employ it again and again to make predictions of the future conform to pre-conceived notions.

We would argue that the existence of the first problem (as a problem) is an artifice without the existence of the second problem. Logical consistency is a discipline imposed upon model practitioners.

The "Elasticity Estimator" filter was initially employed because the data did not seem sufficient to permit sound estimation (of 272 needed parameters) by standard econometric techniques. Eric Hirst, et. al., developed judgmental criteria which they applied to distribute overall elasticities of household fuel demands among various components.[7] On the one hand, it would be the height of an econometrician's pretentiousness to suggest that the "logical" impurity of this procedure ordains it with poorer predictions than would the direct employment of coefficients estimated from spotty data. On the other hand, (as McFadden infers) an "Elasticity Estimator" filter (or similar decision criterion) could be employed to suggest values of priors (and constraint relationships among elasticities) to be employed in a logically consistent mixed estimation or Bayesian procedure. Moreover, new data sources such as the National Interim Energy Consumption Survey (NIECS)[8] would help shift the basis for inference from judgment to evidence. What has been lacking in the

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[7] Eric Hirst, Jane Cope, Steve Cohn, William Lin, and Robert Hoskins, An Improved Engineering-Economic Model of Residential Energy Use, ORNL/CON-8, April 1977.

[8] Energy Information Administration, Residential Energy Consumption Survey: Conservation, U.S. Department of Energy, DOE/EIA-0207/3, February 1980.

pursuit of a logically consistent tack is sufficient sponsorship to get the job done.

But there is always pressure (from sponsors and others) to produce year 2000 forecasts which are consistent with pre-conceived notions. And it was discovered that Hirst's elasticities simply forecast too much electricity in the year 2000. (The existence of documentation of a sound rationale for this *ex ante* discovery is not known). But for this reason, *ad hoc* adjustments in elasticity magnitudes were made without reconciling the resultant elasticities with the "Elasticity Estimator" judgmental criteria.

Understandably, the community of residential model practitioners and consumers has felt nervous about the defensibility of all this. Therefore, we (at ORNL) re-examined the conversion procedures employed to implement fuel-and-equipment-switching simulations in the model. A number of inconsistencies were found which could affect the "severity" of switching entailed by the original elasticities. In addition, other problems and associated corrections (suggested by McFadden) impact upon switching. The fuel-and-equipment-elasticity-specific issues and corrections are discussed in an ORNL Working Paper.[9] Moreover, a comparison was made—employing a set of preliminary delivered prices (developed by Brookhaven National Laboratory) reflecting accelerated deregulation of natural gas—among three models: the model with *ad hoc* elasticity adjustments; the model with original elasticities and original "conversions"; and the model with original elasticities, corrected "conversions", and modifications associated with improvements (3), (4), (5), (7), and (8) noted above.

[9]Hamblin, op. cit.

The duplicative lags (noted in (6)) were eliminated in all three models. Table 1 reports electricity shares.

Table 1. Electricity shares* forecast by the ORNL residential model

	1985	1990	1995	2000
Uncorrected model with *ad hoc* elasticities	0.30	0.35	0.38	0.40
Uncorrected model with original elasticities	0.35	0.42	0.47	0.52
Corrected model with original elasticities	0.33	0.41	0.46	0.51

*Of delivered Btu.

Over the historical period 1978-1980, with actual values of exogenous variables, the differences among the three models' forecasts are quite small. Of course, what is needed is a comprehensive calibration and validation exercise employing the forwards-and-backwards methodology recommended by McFadden. And, of course, such an effort is invariably delayed in light of the hope that resources will come together to sponsor implementation of a logically consistent fuel-and-equipment switching methodology. But until either occurs, we recommend the "maximum-defensible-forecasting tool" currently embodied in the corrected model with Hirst's original elasticities.

(2) Addition of housing vintage structure/endogenous retrofit consideration/energy data by income class.

A comprehensive architectural modification of the model is currently underway. However, its accomplishment requires considerable expansion of the model—and promises concomitant increases in core requirements and run time. For example, energy use calculations will be embedded in a by-income-class loop; and within each class, shell and equipment choices will be relative to the birthdate of the house and the birthdate of the shell (last previous retrofit). Evidence such as that which Hausman used to infer income-class-specific discount rates employed in appliance choice[10] is suggestive of analagous income-class distinctions determining decisions to retrofit (and by how much). In an outside-the-ORNL-Residential-Model-context, the NIECS data have been utilized to estimate the influence (upon retrofit actions) of income and other factors.[11]

The anticipated "size" of this modified model appears to raise a practical compatibility issue concerning its integration into the known overgrown model which optimizes simultaneously (see improvement (8) below) across configurations of fuels assigned to end uses, e.g., all-electric-room-air-conditioned, gas-heated-centrally-air-conditioned, etc. However, future attempts to drive the model with samples of household specific micro-data would seem to necessitate the combined implementation of this improvement and improvement (8).

(3) Associating housing-size-growth-induced increases in equipment capacity with concomitant increases in equipment prices.

This very sensible recommendation not only affects equipment prices, but also, the optimal equipment efficiencies chosen and the associated energy use forecast. And in a model which optimizes simultaneously, the tradeoff between equipment efficiencies and optimal thermal performance of the shell is additionally affected. We implemented this recommendation

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[10] J. A. Hausman, "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables," The Bell Journal of Economics, 10(1), Spring 1979.

[11] Eric Hirst, Richard Goeltz, and Janet Carney, Residential Energy Use and Conservation Actions: Analysis of Disaggregate Household Data, ORNL/CON-68, March 1981.

with respect to space heating, cooling, and water heating choices in new buildings.

In response to a reviewer's comments, we have also implemented the recommendation for replacement space heating, cooling, and water heating. In this case, use of the existing-housing-size index to adjust equipment price/capacity implies the representation of a weighted average of replacements in pre-base-year households and of replacements in post-base-year households.

A worrisome aspect (of this modification) which is unaddressed by most critics is that significant energy-use-efficiency gains may stem from correcting the oversizing common in space conditioning equipment. A compensating adjustment for this factor awaits additional analysis of what equipment purchase and use data reveal.

(4) Considering usage in efficiency choice.

The methodology employed was described earlier in the discussion of our reservations about the joint determination of usage and efficiency. Implementing this improvement is subject to a caveat concerning the operating cost explanatory variable determining usage in replacement equipment. The architecture of the current model (inclusive of improvement (8) below) does not permit knowledge of lagged-stock thermal performance at the point where long run expected usage needs to be calculated. This is because the model makes calculations in several (sequential) N (= year of forecast) loops, in lieu of, in one master N loop (as will be employed in improvement (2) above). The lagged-stock thermal integrity index was taken to be 1.0 in the calculation of operating cost to determine expected long run usage of replacement equipment.

As expected, this modification has compounded impacts upon equipment efficiencies and thermal performances chosen, upon short-run usage factors, and upon energy use forecasts. Generally, in the light of increasing energy prices, less efficient equipment and shell were chosen given diminished long-run usage expectations, and more energy use was forecast than was forecast in a *ceteris paribus* case in which efficiency choice was not adjusted for usage.

(5) Correcting interest rates employed in fuel-and-equipment switching.

Much commentary from various critics has been concerned with the model's use of an array of interest rates, when economic theory seems to entail a single rate. Also, there is an underlying logical inconsistency in the model's use of interest rates which seems to have been mostly overlooked. That is, that the discount rate employed in efficiency choice is logically inconsistent with the interest rates input to determine equipment-price coefficients[12] for predicting fuel-and-equipment switching. On the one hand, the residential model (with duplicative lags removed) currently employs a single rate in efficiency choice—a rate which declines temporally as a function of average-across-fuel energy price increases. On the other hand, rates input for fuel-and-equipment switching vary in three dimensions—between those employed for new structures and those for old; among space heating (one rate), water heating (another rate), and all other end uses (a third rate); and between "own" and "cross." Were these rates to vary temporally, analagous variation in equipment price coefficients would be implied—a variation which neither

[12]Hamblin, op. cit., pp. 9-12.

McFadden (see our earlier comments on parameter conversions in the year-of-simulation *vis à vis* base year) nor we deem appropriate.

At this juncture in model development, we have implemented McFadden's suggestion that rates might be distinguished between those applying to portable appliances and those applying to attachments to the dwelling. We have therefore dropped the new vs. old rate distinction noted above, and drawn a new line between new-attached-to-the-dwelling-home-mortgage related, and all other cases. We recognize that replacement space heating, air conditioning, and water heating purchases can also benefit from mortgage-rate-conditioned financing, but we lack credible data on the preponderance of these benefits.

We are unhappy with the rate distinctions among end uses which exist independently of the attached-portable distinction. However, until we agree upon an appropriate, "defensible", single datum, we shall continue to employ the different end-use-specific rates noted in the ORNL/CON-24 model documentation.

Prior to the implementation of a logically consistent fuel-and-equipment-switching methodology, we are less sanguine about the removal of the "own" vs. "cross" rate distinction. The interest-rate-determined equipment price coefficients are a substitute good for a smaller set of very suspect equipment price coefficients estimated (in ORNL/CON-3) from very poor equipment price data. The notion of the rate distinction is that, in capitalizing expected fuel savings in equipment purchase price, a savings premium is required if the consumer must undergo the hookup-and-attendant costs of switching fuels. Hence, as a working through (with "own" and "cross" rates) of equation (14) of the (above-cited) ORNL Working Paper demonstrates,[13] the higher "cross" rates engender an inertial effect on the fuel choice associated with equipment purchases.

(6) Elimination of duplicative lags in LCC optimum efficiency choices.

We have followed McFadden's recommendation and retained the "sluggishness" in discount rate adjustment, while throwing out the adjustment in "bottom-line" efficiency away from the optimum. McFadden asserts that the latter lag is defensible "if it is realistic to argue that there are significant delays in delivering equipment with desired efficiency levels to the market." But it might also be argued that greedy profit-taking entrepreneurs might inundate markets with efficient equipment before sluggish-discount-rate consumers are "ready" to purchase. As a result, equipment would be offered at discounts unanticipated by the relative prices along our technology curves. In the light of the alternative possibilities, it seems appropriate to un-obfuscate the issue, and simply employ one lag.

(7) Employing fuel price expectations in present value of energy cost calculations for determining LCC optima.

We have expanded the model structure to accommodate an expected fuel price escalation factor in the present worth calculations. We have not yet achieved the McFadden "ideal" in an endogeneous characterization of expected fuel price changes "as functions of historical patterns and announced energy policy." Rather, we compute an average price escalation factor from the vector of forecast fuel prices input into the model.

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[13]*Ibid.*, p. 11.

This procedure may approach the "ideal" in the sense that (someone else's) behavioral determinants underlie the forecast fuel prices; however, as the forecast horizon progresses, the credibility of the procedure weakens, and in the boundary case of the last year of forecast, the fuel price escalation factor implies that the next twenty years will be just like the past twenty years.

We know of little sound evidence on the nature of consumer price expectations. A cross-sectional analysis of consumer discount rates which employs consumer-specific fuel price in determination of operating costs[14] might be interpreted as a long run characterization of behavior under rational price expectations. Rather than forecasting energy use predicated on efficiency choices which (in turn) depend upon non-falsifiable assumptions about price expectations, it might be preferable to assume rational price expectations and to examine the cost-effectiveness of policies in fulfilling the efficiency demands conditioned upon this "private" rationality. For contrast, we might obtain a conservative lower bound for conservation policy impacts with the present-value-of-energy-costs price vector obtained by applying adaptive expectations parameters to present and past values of (exogenously) forecast—and/or actual-energy-price observations.[15] Adaptive and rational expectations converge when only past values are available for prediction.

[14] Hausman, op. cit., p. 39.

[15] The seeds of this suggestion were sown in recommendations by John Holte of the Energy Information Administration.

(8) Simultaneous optimization with equipment replacements over the life of the structure/elimination of fractional-ownership-aggregation error.[16]

McFadden recommends the joint determination of space conditioning and thermal efficiency. However, given the non-trivial magnitude of water-heating costs[17] and the provision of water heaters with the structure, we have included this end use in the joint optimization problem. Simultaneous optimization also provides the opportunity for discerning shadow prices associated with energy policies which can be characterized as constraints. For example, building energy performance standards (which do or do not permit tradeoffs among the shell, space conditioning, and water heating) can be considered directly in the constrained optimization framework.

What needs to be noted about implementing this recommendation is that it considerably enlarges model structure. For each building type, simultaneous optimization (for new building equipment and thermal efficiency) is relative to sixteen configurations of fuel assignments to end uses. Table 2 delineates these assignments.

The (Table 2 noted) distinction between room air configurations and central air configurations eliminates the aggregation error inherent in the optimization of thermal integrity for a structure with a fraction of central air and a fraction of room air. Moreover, the amenability of

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[16] In implementing these structural modifications, we would like to gratefully acknowledge the programming assistance of Kathryn Ann Hall, (formerly of ORNL), and the helpful critical comments and encouragement of Richard Barnes and Eric Hirst.

[17] Residential (national) base period and forecast values of primary energy consumption in water heating are approximately three times primary energy consumption in residential air conditioning.

Table 2. Building configurations for which life cycle cost is minimized

	Heat	Room air	Central air	Water
1	Electric	Electric		Electric
2	Electric		Electric	Electric
3	Gas	Electric		Gas
4	Gas		Electric	Gas
5	Gas	Electric		Electric
6	Gas		Electric	Electric
7	Oil	Electric		Oil
8	Oil		Electric	Oil
9	Oil	Electric		Electric
10	Oil		Electric	Electric
11	Oil	Electric		Gas
12	Oil		Electric	Gas
13	Other	Electric		Other
14	Other		Electric	Other
15	Other	Electric		Electric
16	Other		Electric	Electric

the Table 2 breakdown to household-configuration-specific energy use data suggests potential for a further assault on aggregation error in the model. Another desirable "aggregation" feature that simultaneous optimization currently provides is in its allowance for less-than-baseline efficiencies (indices greater than 1.0) when marginal rates of substitution and of product transformation so dictate. A salient example is in the case of all-electric households, where efficient space heating is optimally associated with a "loose" shell. And because optimization occurs over the life of the structure, McFadden's recommendation that the present worth of equipment replacements be incorporated in the joint determination problem is followed.

For each configuration, constrained simultaneous optimization requires the joint determination of the three equipment efficiencies, shell thermal performance efficiency, and the Lagrange multiplier. Additional implicit constraints are the non-linear cost-performance isoamenity technology characterizations. The Lagrange solution method employed required implementation of a double convergence iterative technique (using a quick-convergence "golden rule" algorithm) in which convergences are on space heating thermal integrity and the Lagrange multiplier. A nice aspect of this technique, applied to the analysis of a "binding" building energy performance standard, is that the initial thermal integrity index convergence—obtained with the Lagrange multiplier set at zero—is the lower bound. It is the maximum thermal performance required, if no tradeoff help were permitted from efficient equipment choice. If desired, the shadow price associated with this extreme can be obtained by "fixing" equipment efficiencies in the constraint (only) at baseline values. The all-electric household result cited above suggests that this can be an expensive way to conserve energy.

The enlarged-mode structure required for the simultaneous optimization described necessitates almost three times as much core as the model without this modification, and needs approximately twice the run time. The latter is a function of convergence tolerances set. The tolerances currently employed are 1000 Btu's/unit/year on outside-loop constraint convergence and 500 Btu's/unit/year on inside-loop thermal performance convergence. The former is a function of the degree of integration of the simultaneous optimization into the pre-existing model structure. The modification was executed with a core-intensive minimal amount of integration. The preservation of pre-existing <u>and</u> modified structures permits one (by incrementing a counter) to contrast the predictions of sequential optimization with those of simultaneous optimization. There is also a significant tradeoff between labor (development) costs associated with integrated structural treatment of simultaneous optimization for new buildings and "vintage structure" characterization of old buildings and core requirements associated with tandem treatment of these two modifications.

Perhaps, the most glaring <u>un</u>achieved accomplishment—which would address recommendations by most model critics—is the completion of a comprehensive calibration, validation, and updated-documentation exercise. We believe that McFadden's recommendations for forward calibration/backward validation, and for sensitivity analysis on conservation program impacts are appropriate and should be incorporated in the exercise. There have been two primary hindrances to accomplishing this task:

(1) The revealed preference of sponsors has been to want calibration, validation, and documentation and not to want to pay for calibration, validation, and documentation.

(2) Eric Hirst's original brainchild is in a phase of maturation and public exposure in which problems are recognized, solutions identified, and remedial actions taken. Resource scarcity dictates that calibration, validation, and documentation be delayed until the model is as ship-shape as possible.

V. Conclusion: Modeling Philosophy

Daniel McFadden's recitation of Murphy's Law applied to models is an appropriate warning to both model builders and model consumers. It seems to be the inherent nature of things that model availability invites model question asking which ought to breach the credulity of the least cynical onlooker. And as Britton Harris likes to point out, the problem with computer models is that the GIGO acronym—Garbage In, Garbage Out—becomes anthropomorphized into Garbage In, Gospel Out. When there are three or more figures to the right of the decimal point, the impulse is overwhelming to anoint the answer with the mantel of absolute truth.

Our position is that the ORNL residential model is an imperfect, capable-of-being-improved, but nonetheless useful tool for providing insights on a limited (but significant) number of policy issues—analyzed at a reasonable cost. We hope that we (as model builders) and our sponsors (as model consumers) can and will make better predictions than our model makes. Paul Sameulson's method for beating the macro-models is appropriate. He employs the models' predictions, as well as his knowledge of the restrictive assumptions and limitations of the models, to educate his judgment about what the future holds. We hope that sponsors come to recognize that their ability to operate successfully in this mode, with respect to energy models they employ, requires the existence of up-to-date calibration, validation, and documentation.

Finally, as model builders whose products may engender further evaluations, we would like to reserve the human frailty option of occasionally mixing wrong ideas with right ideas, and bad ideas with good ideas. On this, we agree with Freud:

> Only believers who demand that science shall be a substitute for the catechism they have given up, will blame an investigator for developing or even transforming his views.[18]

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[18] Sigmund Freud, "Beyond the Pleasure Principle," The Standard Edition of the Complete Psychological Works of Sigmund Freud, Vol. 18, James Strachey and Anna Freud, Translators, London: The Hogarth Press, 1955.

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