# Agent-based Modeling and Neural Network for Residential Customer Demand Response

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***Abstract*—In this paper, both bottom-up and top-down models for demand response with agent-base approach and neural networks have been investigated. Simulations have been carried out with practical load data from the UK and Canada. Results show that each approach has its advantages and disadvantages depending on difference application scenarios.**

***Keywords-Residential customer, demand response, agent, neural network, decision making***

## I. Introduction

Demand response, also named customer response, is one of the main focuses in smart grid deployment to increase energy efficiency, provide more market trading opportunities through more customer participation in power system operation. In demand response, power utility releases information with economic incentives to its customers. Customers change their electricity consuming behaviors by responding to the information, leading to variation in total power system load. The load information will be sensed by utility with electricity meters. The operational procedure of demand response is shown in Figure 1 below.

Reviewing the current literatures, models for load profile establishment in demand response could be classified into two categories, namely, the bottom-up modeling and top-down modeling. Bottom-up modeling, like models introduced in references [1] to [6], decouples the load into appliances' level. In this level, models simulate the behaviors' variation towards each appliance by economic consideration under a certain scheme of demand response. The total load and consumption is thus constructed by loads from all appliances. Top-down modeling, like models as reported in reference [7], summarizes all impact factors by micrographic quantization. The relations between impact factors and model output are established by an equivalent mapping. In the following section, modeling details are revealed and comparative analysis between these two models is considered.

Considering different requirements on load variation, demand response's schemes could be classified into 2 types: Time-based Demand Response and Incentive-based Demand Response [8]. Time-based Demand Response includes various time-based dynamic pricing, such as Time-of-Use (TOU) and Real-Time Pricing (RTP). Incentive-based Demand Response mainly concerns with the emergent requirement from utility. In the following section, Time-based Demand Response will be investigated.

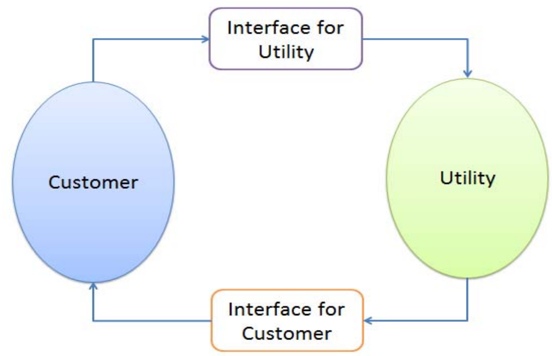


Figure 1. Operational procedure of demand response

## II. Bottom-up Modeling – Agent-Based Modeling

From bottom-up point of view, loads from a group of customers are constructed by each customer individually, while loads of each customer are constructed by possessed appliances, as shown in Figure 2 below.

Agent-based model is a type of computational models for

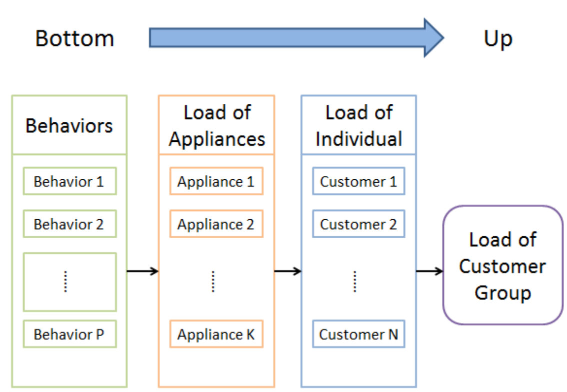


Figure 2. Relationship in bottom-up modeling

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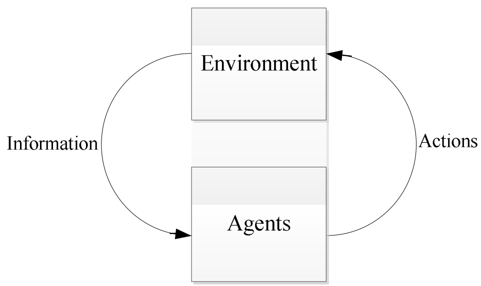


Figure 3. Agent-based model interaction process

simulating the statistical effect of actions and interactions among agents towards their environment. Each agent represents an individual with independent power for its own decision making. Inputs of decision processes are information sensed from environment. After the processes, agent updates its actions by decision made in each step. Environment represents the aggregation of all passive impact factors influencing agents' decision making. So in general, agent-based model simulation is the simulation of an interacting system between environment and agent group. Figure 3 shows the process of interaction.

For residential customers, each agent is appropriate for a family representation as each family contains an independent appliances set and utilization pattern. Traditionally, people establish their control behaviors for their activities requirement. For example, people turn on TV are mainly related to customers' life-style, which could be separated into the statistical Home Activity Distribution (HAD) and the Activity Constraints (AC).

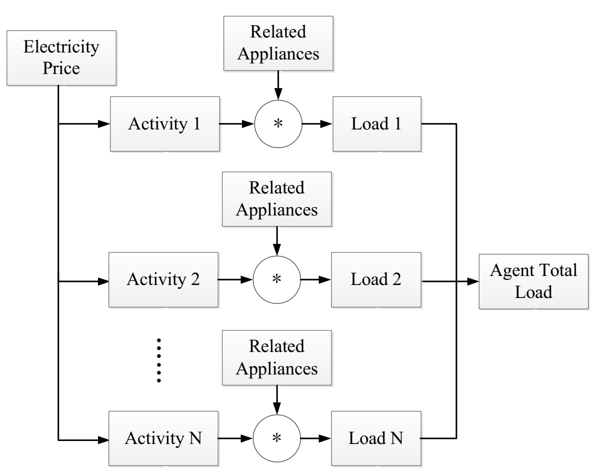


Figure 4. Impact from bidirextional information flow

### A. *Home Activity Distribution (HAD)*

Appliances are switched on as a result of human activity requirement. So an appliance's switching on probability SP at a certain time step is influenced by the relevant activity distribution at this time step. UK 2000 Time Use Survey is a typical activity distribution [8]. Table I introduces the relation between some typical appliances and the activities covered by UK 2000 Time Use Survey.

### B. *Activity Constraints (AC)*

Residential customers' activity will contain constraints that limit the behaviors. One constraint is the 'family member at home'. In a certain time step, difference in family member at home may lead to different devices' utilization. E.g. computers are more probable to be turned on when more people are out of bed. Some appliances will be turned off when people fall in sleep.

TABLE I. MAPPING BETWEEN HOME APPLIANCES AND RELATIVE ACTIVITIES

| Appliances | Relative Activities |
|---|---|
| Cooking Equipment | Unspecified food management |
| | Food preparation |
| | Other specified food management |
| Dish Washer | Dish Washing |
| TV | Unspecified TV watching |
| | Watching a file on TV |
| | Watching Sport on TV |
| | Other specified TV watching |
| Vaccum Cleaner | Cleaning dwelling |
| Tumble Dryer | Wash and dress |
| | Laundry |

In the directional information flow (Figure 5), utilities pass economic-related information, such as electricity price, to customers. The price information influences residential customers' activity status. The altered activities status, require different usages of appliances to fulfill customers' needs in activities. Finally the usages of appliances construct the total

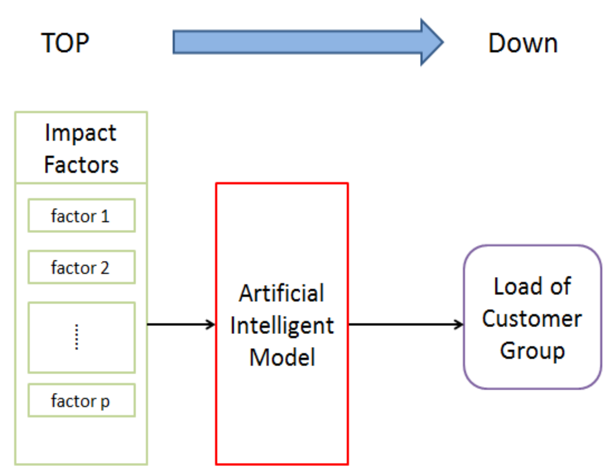


Figure 5. Rerlationship in top-down model

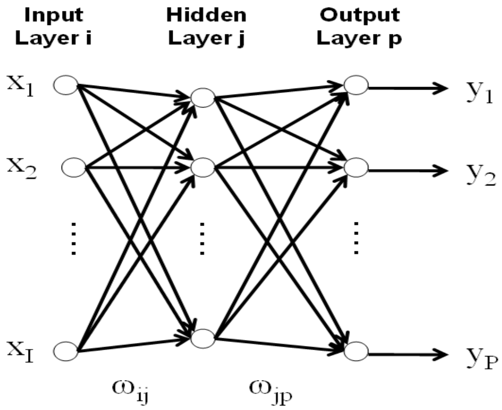


Figure 6. Model of Multi-Layer Perceptron

load of one customer. Figure 4 shows the impact from bidirectional information flow. Customers change their activities by responding to different electricity price. It is the way that customers respond to demand response scheme.

In the model, each activity is represented by a probability, which determines the switch on behavior for each related appliance. When there is a change in price, the probability changes and this will also lead to a change in the likelihood of appliances' status. Through this method, the model establishes a passage from price variation to load variations.

## III. TOP-DOWN MODELING – NEURAL NETWORK

From top-down point of view, impact factors of daily demand curve in an entire area including weather status, working days types and habitual behaviors. When specifying a certain time period, the habitual behaviors daily could be recognized as unchanged when the other two factors are fixed. In this case, artificial intelligent model, such as neural networks, is preferred for relationship learning on a set of training set to avoid detail classification of habitual behaviors into appliance's level.

Artificial Neural Network (ANN) is a model for equivalent mapping construction. By offering a set of training data from input space and output space (a set of input-target pairs), ANN can learn the pattern of relationship between input and target and so it is used as equivalent mapping between the specified input space and output space.

Multiple Layer Perceptron (MLP) is one of the ANN family members. As shown in Figure 6, there are three types of layers in the MLP's architecture, that is, the input layer, hidden layer and output layer. Input layer accepts network input from outside while hidden layers and output layer contain the perceptron neurons. Number of neurons in input layer is the dimension of input vector while dimension of output vector determines the number of neurons in output layer. The number of hidden layers and the number of neurons in each hidden layer are controllable by users. It deeply influences the complexity and the performance of MLP. Between each layer, the output from one neuron is passed to neurons in the next layer with weighting factors. In other words, Artificial Neural

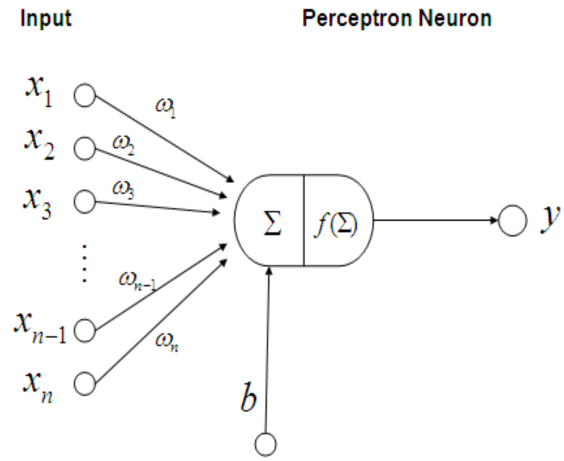


Figure 7. Perceptron neuron model

Network is processed by architecture selection and weights selection to achieve a preferred mapping between input and output data.

Figure 7 introduces the model of a single layer Perceptron. The model accepts n inputs with corresponding n weights. Neuron sums up all the input with weights then passes to a function f, which is named as activation function. b in Figure 6 is a bias.

In 1989, G. Cybenkot provide a demonstration in Reference [9], revealing that any continuous function can be uniformly approximated by a continuous neural network having only one internal hidden layer and with an arbitrary continuous sigmoidal nonlinearity in the unit hypercube. In the same year

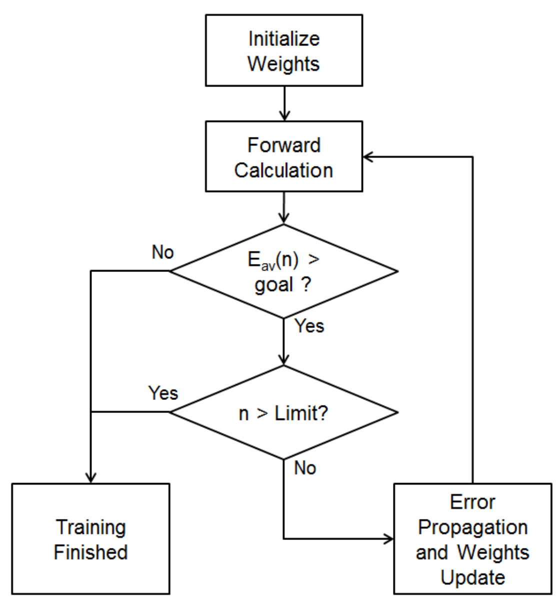


Figure 8. Back propagation training

KEN-ICHI FUNAHASHI proved the approximation realization ability of a k (≥3) – layers ANN in Reference [10]. The similar demonstration provides a mathematic insurance of the model possibility.

ANN requires training before applications. Through repeatedly amendment, ANN adjusts its mapping towards the mapping in the training data set. Figure 8 introduces back propagation training, which is one of a typical training algorithm for ANN. Until meeting the goal or exceeding the iteration limit, ANN will update its weights in each iteration.

In this model, load-related factors are set as input. ANN is trying to establish an equivalent mapping between these factors to load.

- **Weather Condition:** Weather status has a great impact on human comfort so that there is an impact on power devices selection and their utilization amount and time length.
- **Day Style:** People perform different lifestyle in working days and holidays.
- **Demand of the Previous Point:** Provide a reference for forecast.
- **Time Points Index:** Power consumption appears to be different at each specific hour in a day.

## IV. SIMULATION

### A. *Simulation from Bottom-up Model*

A case study related to the UK was selected for verifying the bottom-up model. The selected case study is on UK residential customers. Types of home area appliances taken into account include Heating equipment, Lighting, Computers, Washing Machine, Cooking equipment, TV, Dishwasher and Electric Shower. The appliances ownership is from a typical study as reported in [10]. Appliances power is taken from Centre for Sustainable Energy. Home Activity Distribution (HAD) and Activity Constraints (AC) are based on data from UK 2000 Time Use Survey as given in [8], with variation frequency in 1 hour. Table II offers correlations between appliances and HAD in [8]. As limited by data source, the AC covers consideration of 'family member at home' and 'out of bed family member at home'. Appliances like washing machine and dishwasher are probable switched on only when family is not 'empty'. Appliances like heating, computers, TV, lighting and so on are probable switched on when home is not 'empty' and people are not sleeping. There is another constraints specified for lighting that is the light must be turned off between 09:00 to 16:00. The case study generates 1000 agent samples in the simulation with time step of 1 minute. The whole simulation targeted on load in winter so all the data are selected from winter. Simulation environment was based on Anylogic Professional 6.8 while Matlab was used as the analysis software. The simulation result is shown in Figure 9.

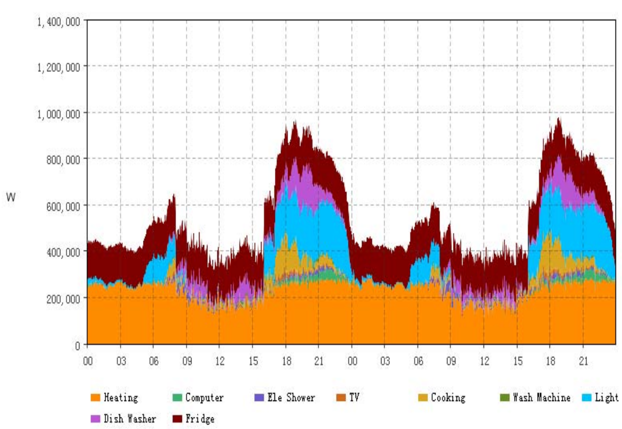


Figure 9. Simulation result from bottom-up model

### B. *Simulation from Top-down Model*

As previous sections mentioning, the hourly short-term load forecast problem in this section is the power demand forecast of Ontario province in Canada from Nov 11th, 2008 to Oct 31st, 2009. The ANN training data is from Nov 11th, 2005 to Oct 31st, 2008, which covers data for 3 years before the target period. 15% of training data is picked out as validation set for early stopping against over-fitting. The training algorithm is back propagation with training parameters as listed in Table II.

TABLE II. ANN TRAINING PARAMETERS

| | |
|---|---|
| **Training Goal** | $1\times10^{-5}$ |
| **ANN Neurons in Hidden Layer** | 20 |

The training process and the simulation result are revealed in Figures 10 and 11. The average daily Mean Absolute Percentage Error (MAPE) between the result from testing set and target is 1.25%.

## V. RESULT ANALYSIS

By bottom-up model, customers' loads are constructed by the ownership and the usage of appliances. So this model provides dynamic presentation of each appliance in the load, revealing the reason to load dynamics at each time step. Moreover, this model is able to target on a specified consumer group, like residential customers. As shown in Figure 9, the

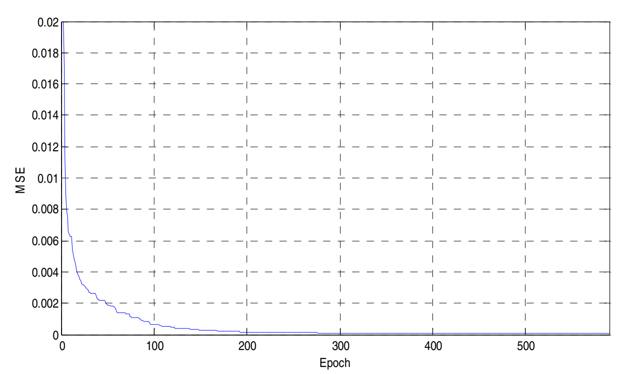


Figure 10. ANN training process

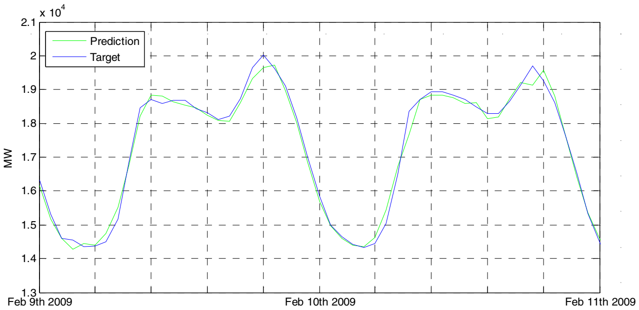


Figure 11. Compare between ANN simulation result and training target

load curve is constructed by 9 appliances. In these appliances, the usage of heater, lights and fridge dominates the consumption levels. The whole daily curve could be separated into 4 time zones: a flat zone from 00:00 am to 6:00 am, a peak zone from 6:00 am to 8:00 am, a flat zone from 8:00 am to 16:00 pm and a peak zone from 16:00 pm to 00:00 am. The main appliances constructing the peak is lighting and cooking usages.

Deployment of bottom-up model requires surveys on customers' behaviors. So the simulations may contain errors propagation from sample set in the survey. E.g. bias in appliances ownership in sample set may lead to an incomplete load curve; bias in consumers' life-style may lead to incorrect load dynamics. These factors limit the simulation accuracy. Considering the advantages, the bottom-up model achieves better performance in scheduling, planning or analytical analysis, and so will be more suitable for demand response research and planning.

With top-down model, customers' load is acquired by ANN which is trained by the selected training set. Usually the training set covers an entire area, so that the simulation considers the entire consumer group fairly and the accuracy is ensured.

But due to focusing on load approximation instead of construction, top-down model deeply limited by the training set. E.g. when training set is collected in an area, top-down model cannot separate the load into different groups of consumers as well as different appliances. As training set only represents consuming pattern in a specific period, top-down model may need to retrained by updated training set every once in a while to ensure its accuracy. Considering the advantages, the top-down model achieves better performance in practical load forecast for a specific area.

Electricity supply and demand is basically a closed loop system. The factors, like pricing, will affect the family behavior in the consumption of electricity. While the electricity demand of the families in a city or province for sure will affect the electricity supply and pricing as well. The agent-based model can be used for demand response of a family. The neural network model has succeeded to model the demand response of a province. One possible work is to integrate both to simulate the supply-demand loop. Neural network can be applied for demand forecast, it can also be applied to model a 'decision function' which is yet another agent, pricing for instance. In such case, the output of the agent-based model will be the input of the neural network, while the output of the neural network will be the input of the agent-based model.

## VI. Conclusions

Both bottom-up and top-down models have been considered for demand response investigation with agent-based approach and neural networks. With simulation results, it shows that they both have their advantages and disadvantages. It makes a contribution in the practical application of residential customer load response for real-life situation.

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