Demand Response: Multiagent System Based DR Implementation

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1 Problem and Motivation

It is very crucial to come up with a real-time forecasting model which can give primary instruction to evaluate DR. Previous works have some limitations that should be overcome for better implementation. There is a strong need to come up a model for peak demand forecast because hourly power consumption forecast may miss very important information. Similarly, we also need power consumption prediction for every home as every smart home has different pattern of power consumption. Meanwhile we also need real-time energy price prediction as well as scheduler which can schedule power accordingly. These all works should be in heterogeneous.

2 Background and Related Work

Demand response is a technique which is designed to condense the peak demand and to make awareness in the people that they should consume the power when renewable energy is accessible in terms of PV panels. It is beneficial for grid operators, electrical customers, and many load serving entities. It is very difficult for an end user to have the track of dynamic pricing. So effective DR implementation always depends on its enabling technologies. Generally, in housing societies, these

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enabling technologies are present in smart home situations where smart appliances like smart meters, smart refrigerators, and washing machines worked. EMS (energy management system) is classified as one of the DR-enabling technologies which is a pure smart home topography which has the ability to control household loads very intelligently using connotation between smart appliances like smart meters, fridges, AC, washing machine, etc. Implementing the efficient DR model to see the usefulness of its policies is very effective to boost up the energy efficiency as well as power system constancy. Nowadays, research has a trend that DR implementation is moving toward distributed systems where many heterogeneous mechanisms exist [1–3]. There is a need to come up with an efficient DR model which should have the ability to implement intelligent distributed algorithms, optimizing these algorithms and load forecasting aiming to evaluate power systems on large scale.

MAS (multiagent system) is a combination of different autonomous agents working cooperatively for effective design objectives [4–6]. Every agent in MAS has heterogenous components, and each component can interact with each other. IEEE Power Engineering Society's Multi-Agent Systems Working Group passes comprehensive review from the IEEE that a multiagent system has an ability to provide two novel methods for power engineering, i.e., developing efficient systems which should be flexible and extensible and can simulate and model the algorithms [1, 7]. Generally, MAS is appropriate for developing heterogeneous components while implementing the DR application for smart grids. In this paper, we proposed multiagent system to device DR which is based on RTP. In our model, we proposed a MAS for implementing DR as a residential DR where primary participants are named as HAs and RAs as shown in Fig. 1. In Fig. 1 we can see that the black line is the power connections and the red lines are the LAN connection which is used for communication between HAs and RAs. HAs are connected with each other, so security is also retained. Every agent has heterogeneous components like residential load prediction model, price prediction model, real-time pricing, and power scheduling. There are two main purposes of our multiagent system algorithm, e.g., demand response policies and their enabling technologies. To make prediction, we used artificial neural network concept. We used LSTM to make load forecast and price prediction. The detail of our model is given below.

3 Approach and Uniqueness

3.1 Home Agent

The environment of an HA includes real-time prices prediction, real-time load forecast, scheduling the power for better energy management, and demanding the power from retailer by having the communication with its corresponding agent. We used multipurpose LSTM model in HA, which has the ability to predict each appliance load. Then the agent checks his own renewable energy in the form of

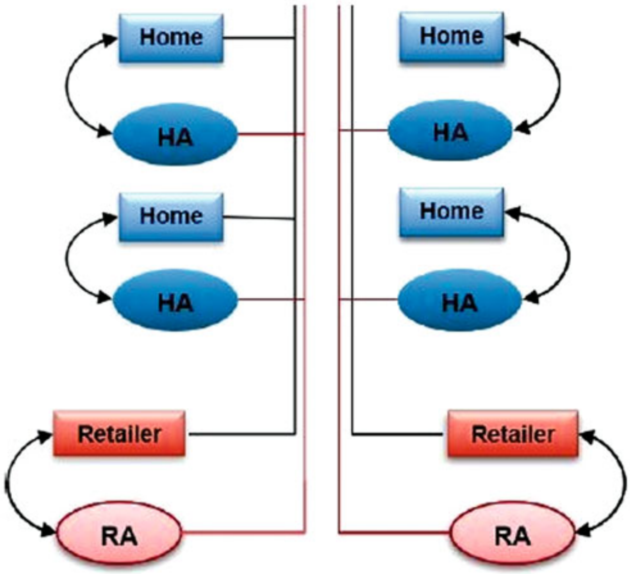

Fig. 1 Overview of proposed model

batteries or solar. If the predicted load is manageable, then electricity request is scheduled by the control load action, or if it is not manageable, then it can ask for power by making demand to RA immediately. LSTM model also predicts the overall load used in home and by using RTP predicts the price of electricity. It also has the ability to predict the solar energy. The primary purpose of the control load action is to minimize electricity bills which are based on our predicted real-time prices or our DLC requests.

3.2 Retailer Agent

The features of a retailer agent atmosphere comprise of real-time prediction of used electricity, available power, aggregated loads, service scope, and the manpower capacity. An RA has the functionality to aggregate power demand based on HA demand according to their services and purchases electricity from wholesale market. After that RA then trades power to the HAs according to their need in a retail market. Sometimes according to firm circumstances such as abundant renewable energy, transmission limitations, and power deficiency, the RA may demand DLC.

Our idea emphasizes on ideal implementation of residential DR in a distribution network; therefore, we also introduced WMA (wholesale market agent) and GA (generator agent). RAs demand power from the wholesale market agent, and generator agent according to their capacity. The electricity generation capacity after

Table 1 This table is showing specific software and hardware specification during the experiment

Name	Experiment environmental parameters
OS	Windows 10
CPU	Intel(R)Core(TM)i5-3570CPU@3.40GHZ3.80GHZ
GPU	NAVIDIA GeForce GTX1050
RAM	24GB
DT	Python 3.6 (PyCharm)

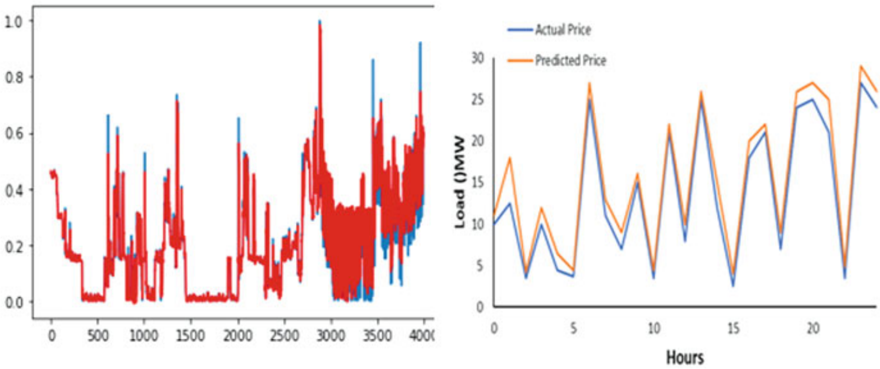

Fig. 2 Simulated MAS results

having the lowest price will be allocated first in the market. In conclusion, this mechanism influences the market in stable state, and a peripheral price is attained.

4 Simulation and Result Discussion

In order to test the performance of proposed MAS, we need agent execution environment. We need LSTM model for predicting load and prices of electricity. We run our LSTM model on PC having the attributes described in Table 1. We used LSTM models to predict load, price, and energy with real-time data. provided by US power control department for training and testing of LSTM model. We used real-time data provided by US power control department for training and testing of LSTM model. To implement MAS-based DR, we consider one RA which is responsible for 100 HAs in a spread network. While implementing we accept that the RA can demand and obtain enough energy from a wholesale market and all broadcast restrictions are fulfilled. In our MAS, the retail market is balanced with respect to budget, i.e., the RA cannot generate revenues. As in our model home, agents can schedule the manageable power to abate the electricity prices, so Fig. 2 shows its simulated LSTM model results. First figure is the predicted price, and the second figure is the predicted load.

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