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Interactive Multi-Consumer Power Cooperatives with Learning and Axiomatic Cost and Risk Disaggregation

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Abstract

This paper introduces a novel autonomous interactive learning cooperative (ILCP) who receives expected value and variance of load from consumers and participates in the electricity market on their behalf. Using an axiomatic approach, the share of each consumer's payment as well as its weight in calculating the modification of total day-ahead load are formulated. This scheme applies double-seasonal smoothing exponential, a recent load forecasting technique, and a classifier for *real-time* to *day-ahead* price direction forecasting (Gaussian Nave Bayes). In addition to this, the ILCP employs interactive cooperative algorithms for both trading cooperative and consumer side. The ILCP scheme is investigated and its performance is compared to those of non-cooperative *real-time pricing* (RTP), LCP (non-interactive learning cooperative) and CP (non-interactive non-learning cooperative). The developed system was implemented using PJM(world's largest wholesale electricity market) real-time and day-ahead data for 2013 and half of 2014; real load profiles were selected from a set of 579 residential and commercial consumers, and weather data were applied to forecasting electricity price direction. We demonstrate the advantages of ILCP to lower the average electricity cost and to reduce unit price variations.

Introduction

Putting 'smart' in electricity Demand Side Management (DSM) is one of the concerns for future electricity networks and smart grids (Ramchurn et al. 2012). Pricing schemes such as real-time or 'dynamic', in comparison to the mainstream 'flat-rated', *demand response (DS)* or *time of use (TOU)* rates, are proposed and criticized extensively in literature (Albadi and El-Saadany 2008; Borenstein, Jaske, and Rosenfeld 2002; Conejo, Morales, and Baringo 2010; Mohsenian-Rad and Leon-Garcia 2010; Allcott 2009). In addition, smart grids allow real-time interactions between utility companies and consumers which introduce intelligent autonomous agents to these markets (Davito, Tai, and Uhlaner 2010; Peters et al. 2013; Ketter, Collins, and Reddy 2013).

Though it appears that Real-Time Pricing (RTP) combined with autonomous agents is effective in demand shifting, this method is not sufficient without using sophisticated adaptive approaches to any particular situation that 'can look ahead and predict' (Allcott 2009; Piette et al. 2009). Instead, computationally efficient learning algorithms, as one of the artificial intelligence challenges, is to put intelligence in autonomous units who provide consumers with profitable opportunities (Ramchurn et al. 2012). Nonetheless, few researches have proposed and investigated cooperative and interactive mechanisms that provide consumers with DSM opportunities.

Recently proposed *cooperative for demand side management* (CDSM) model enables consumers to cooperate and participate in wholesale electricity market (Kota et al. 2012). However, this model relies on demand reduction scheme (rather than demand shifting) which can be an unrealistic assumption for regular consumers. Another cooperative idea is based on simplified wholesale market model with assumption of discrete electricity prices or group price discount beside a known and determined demand threshold for price shift (Akasiadis and Chalkiadakis 2013; Veit et al. 2013). However, these models don't address the dynamic, continuous and competitive electricity pricing in reality. In some other works, consumers are assumed to actively participate in the wholesale electricity market; nonetheless, in reality, retail electricity consumers including residential and commercial, are not allowed to join and bid in wholesale market; indeed, a good practice in demand side management is to manage aggregated behavior (Mohsenian-Rad and Leon-Garcia 2010).

In this paper we introduce a non-profit *interactive learning cooperative* (ILCP) to which residential and commercial consumers can subscribe. The ILCP receives expected value and variance of next day load profiles and participate in the electricity market on behalf of its consumer members. The rest of this paper is organized as follows: in the first section, we describe our framework; in the second and third sections, the predictive methods applied for load and price prediction are described and justified; then, the *interactive algorithms* applied to cooperative agent and consumers for load modifications are illustrated, and finally, two axiomatic models for cost and risk (load deviation) disaggregation are formulated.

Interactive Learning Cooperative

We introduce a framework based on a non-profit *interactive learning cooperative* (ILCP) to which residential and commercial electricity consumers can subscribe. The ILCP receives the next-day expected load profile and risk (expected load variance) from subscribed consumers, forecasts the aggregated load and real time electricity price, places bid in day-ahead market, informs consumers about any financial opportunities in load modifications (according to the predicted real time load and price), and applies a formulation for cost sharing and risk disaggregation to calculate consumers' payments. The ILCP collects the expected load profiles for next day from each consumer in cooperation and calculates the aggregated load and places bid in day-ahead market on their behalf. Then, in real-time market, it calculates all eventual day-ahead and real-time payments using: aggregated day-ahead bid and real-time electricity consumption, market prices, consumers expected profile announcements (received during day-ahead information exchanges), individual and aggregated imbalances. Finally, we introduce Interactive Algorithms, which enable the cooperative agent to interact with consumers and inform them of financial opportunities for profile modifications (load shifting). Being concerned with this issue, we devise interactive *request-offer-approve* algorithms for ILCP and consumer members; also, we simulate a real-world-driven consumer preferences using stochastic formulation for consumers' amount and timing of load shifting.

In this paper, a day consists of 24 time intervals consistent with settlement periods in PJM market. Each consumer informs a day-ahead expected load profile (24 sequential values) $\widetilde{L}_t^i$ per day and consumes $L_{RT(t)}^i$ in real-time, where t is the time interval and i is the consumer index. The market announces the day-ahead price ($p_{DA(t)}$) by 12PM a day before each settlement and the real-time price ($p_{RT(t)}$) after the real-time actual electricity consumption; since the later price is calculated based on real time bids by generators and consumers, cost of reserved capacity and ancillary services, etc..

Short Term Load Forecasting

(Taylor 2003) introduced the double seasonal exponential smoothing method, which has adapted Holt-Winters approach in (Chatfield 1978) for short term forecasting of electricity load. Since then, in literature its performance has been compared to other regular short term load forecasting methods such as ARIMA, SARIMA, PCA etc. (Taylor and McSharry 2007) which indicates its competitive performance in short term hourly load forecasting. Multiplicative formulation of double seasonal formulation can be described as:

$$\begin{aligned}
&S_t = \alpha(L_t/(D_{t-s1}W_{t-s2}) + (1-\alpha)(S_{t-1}+T_{t-1})\\
&T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1}\\
&D_t = \delta(L_t/(S_tW_{t-s2})) + (1-\delta)D_{t-s2}\\
&W_t = \omega(L_t/(S_tD_{t-s1})) + (1-\omega)W_{t-s2}\\
&L_{F(t)}(k) = (S_t + kT_t)D_{t-s1+k}W_{t-s2+k} \qquad (1)
\end{aligned}$$

in which S_t is the level learning part, T_t is the trend, D_t is the first seasonal component and W_t is the second seasonal component. Time interval t shows the time to which we train our model and k refers to steps ahead for forecasting.The last expression is the final forecasting formulation that combines all the above together in multiplicative approach. Our time interval parameter is hourly (24 per day), the first seasonal component is 24 hours and the second seasonal component is 168 hours (1 week). In our context, we use slightly more than one year of historical load for learning purpose. We tuned our parameters approximately $\alpha = 0.1$, $\gamma = 0.4$,$\delta = 0.5$,$\omega = 0.3$ using similar method applied in (Taylor 2010).

Price Direction Forecasting

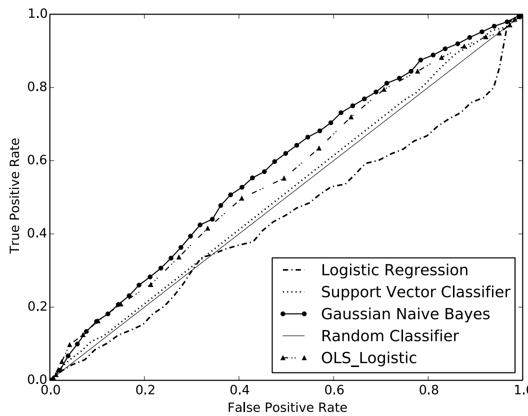
We apply different approaches to classify real-time to day-ahead price direction. Aiming for the feature variables of price direction forecasting, we use the historical day-ahead and real-time prices, $p_{RT(t)}$ and $p_{DA(t)}$, the historical weather parameters such as temperature, relative humidity, *dew* point temperature and weather categories (e.g. sunny, cloudy), and *date* parameters such as weekday and time of day. For the later parameters we converted the categorical variables to numerical datasets and combined them with numerical data for learning applications. Finally, we applied two approaches. At first, we created a price direction binary parameter (1 if price goes up and 0 otherwise), we trained our data using multiple machine learning methods such as *Logistic Regression* (LR), *Support Vector Classifier - linear kernel* (SVC) and *Gausian Naive Bayes* (GNB) and compared the results. In our second approach, in order to exploit the numerical difference between real-time and day-ahead prices, we tried *Least Square Regression* (OLS) combined with a logistic function. For each time interval, the day-ahead price is known and $\Delta Price_{(t)} = p_{RT(t)} - p_{DA(t)}$ is subject to learning:

$$\widetilde{\Delta Price}_{(t)} = \beta_0 + \beta_1 X_1 + ... + \beta_m X_m$$

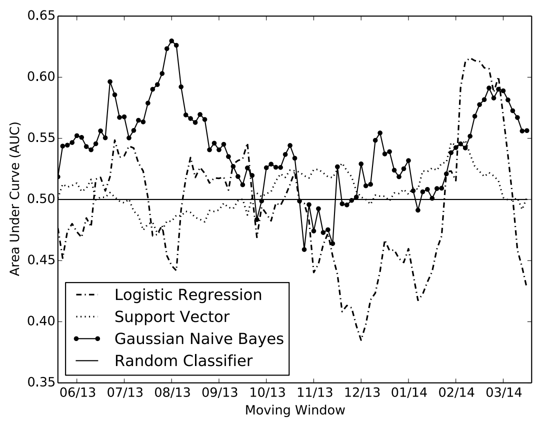
Then, a logistic function and a bias parameter is applied to classify $\widetilde{\Delta Price}_{(t)}$ direction.

$$Logistic(\Delta Price_{(t)}) = 1/(1 + e^{\Delta Price_{(t)}+B}) \qquad (2)$$

Adjusting the B parameter, we plot the ROC curve of learning *test data* according to Figure 1. Figure 1a indicates performance of well known learning methods such as logistic regression. For the sake of better comparison, we plot learning performance of these methods, moving the training window on the historical data; each time step shows 72 hours shift in learning window. However, performance of well known learning methods such as *logistic regression* is below random classifier. In theory, this looks like an opportunity to do better than random classifier using the opposite classes, but Figure 1b shows that this is not applicable since its performance is swinging between underperforming and outperforming the random classifier. According to (Mon 2014, p. 92) the participation of financial companies in the PJM market has increased significantly throughout



(a) receiver operating characteristic (ROC)



(b) area under the curve (AUC) vs moving window

Figure 1: performance of classifiers on forecasting real-time to day-ahead price direction

2013; this implies the possibility of applying regular learning algorithms on this market excessively (*herding effect* in learning). SVC has a performance slightly better than random classifier. Also, our OLS algorithm shows noticeable improvement over logistic regression and random classifier, but it falls short of GNB'. At last, GNB gives the best overall performance in terms of classification accuracy and stability.

Seeking a formulation to put both forecasting techniques in effect, we introduce *day-ahead bid coefficient (C_t)* for day-ahead aggregated bids:

$$C_t = 0.7 + 0.3 * Prob_{GNB(t)} \tag{3}$$

in which $Prob_{GNB(t)}$ is the probability score of price direction classification using GNB in time interval t. The probability 1 and 0 indicate all but ensured positive and negative price direction in order. We propose our final formulation for aggregated day-ahead bid:

$$L_{DA} = C_t * L_{F(t)} \tag{4}$$

where $L_{F(t)}$ is the forecasted load in Equation 1.

Interactive Algorithms

We introduced ILCP, which applies its cooperative, learning and interactive capabilities to modify aggregated day-ahead bid (for the sake of lower total payment for consumers). Here, we propose novel *request-offer-approve* interactive algorithms for ILCP.

Data: historical load and market price data
Result: day-ahead bid
while *not in the last time interval and it is 12pm* **do**
  collects day-ahead profiles;
  for *every consumer agent* **do**
    send consumers the day-ahead price;
    receive the consumers' offers;
  end
  rank consumers according to their contribution ;
  go to the first ranked consumer;
  while *aggregated load constraints is not violated* **do**
    add to aggregated modification;
    go to the next consumer
  end
  forecast the next day aggregated load;
  modify day-ahead bid;
  calculate aggregated deviation;
  disaggregate load deviation;
  calculate current payments for all consumers
  previous announcement, modifications and price;
end

Algorithm 1: interactive algorithm of ILCP

We devised an interactive scheme where the autonomous trading cooperative unit sends expected price signal to all the consumers and receives their offer which is a daily zero sum load shifting with positive and negative values for load reductions and increments respectively. On the other side, we model consumers' offering behavior using a stochastic algorithm which receives the financial opportunities, finds the plausible pairs of time intervals (for shifting) according to its own financial constraint, and chooses a pair with a probability relative to its potential financial benefit (Algorithm 2). Sum of all of the individual changes shows the final load shifting curve achieved by interactive cooperative. The ILCP sends the price signal using the day-ahead price and real-time price predictive method (Equation 1), predicts aggregated load (Equation 4) and places day-ahead bids and calculates payments using the cost disaggregation approach (Equation 8) and risk sharing approach (Equation 5). We implemented interactive Algorithms 1 and 2 for ILCP and consumers.

Axiomatic Risk Disaggregation Model

In cooperative scheme, in more than one situation the sum of expected loads announced by consumers is different from day-ahead bid by cooperative. Then, the cooperative needs to disaggregate any deviation (risk) between all of those consumers. Some reasons for this deviation, which necessitate this formulation, are *risk management*, *load forecast-*

Data: Day-ahead and real-time prices
Result: profile modification offer
Select consumer threshold;
while *not in the last time interval and day-ahead price received* **do**
  rank day-ahead time interval prices;
  calculate *max price difference*;
  while *max price difference* $>$ *threshold* **do**
    assign the top and bottom price to separate lists
    remove those from price ranking calculate *max price difference*
  end
  randomly pair top and bottom list elements;
  p=*selection probability* by relative *pair price difference*;
  for *i in pairs* **do**
    if *random number*$\leq$ *p* **then**
      select randomly among [10, 20, 30] percent for modification update total modification;
    else
      continue the loop;
    end
  end
  send offer to cooperative;
end

Algorithm 2: interactive algorithm of consumers

ing, *price forecasting and day-ahead bid modifications*. We propose the following axioms for deviation disaggregation:

Axiom 1 - Directed: individual deviation shall have the same sign as the aggregated deviation.

$$sgn(L^i_{DA(t)} - \widetilde{L}^i_t) = sgn(L_{DA(t)} - \widetilde{L}_t)$$

Axiom 2 - Fixed-Sum: sum of individual deviations shall be equal to aggregated deviation:$\sum_{i=1}^{N} L^i_{DA(t)} = L_{DA(t)}$

Axiom 3 - Increasing: given other conditions, the individual deviation amount shall be partially increasing to both individual announced load variance and expected load.

$$\frac{\partial(L^i_{DA(t)} - \widetilde{L}^i_t)}{\partial\sigma^i_t} > 0, and\ \frac{\partial(L^i_{DA(t)} - \widetilde{L}^i_t)}{\partial\widetilde{L}^i_t} > 0$$

where σ^i_t and $\widetilde{L}^i_t$ are respectively the 'relative load variance' (normalized by the load value) and 'expected load value' announced by consumer i to ILCP in day-ahead information exchange for time interval t. We define the formulation for calculation of day-ahead share of each consumer (disaggregation) as:

$$L^i_{DA(t)} = \widetilde{L}^i_t + \sigma^i_t * \widetilde{L}^i_t * (L_{DA(t)} - \widetilde{L}_t) / \sum_{j=1}^{N} \sigma^j_t * \widetilde{L}^j_t \quad (5)$$

where $L_{DA(t)}$ is calculated using Equaiton (4), $\widetilde{L}_t = \sum_j \widetilde{L}^j_t$; $L^j_{DA(t)}$ and $\widetilde{L}^j_t$ are respectively day-ahead bid and announced expected load by consumer j for time t.

This formulation ensures all of the above axioms. It is *Directed* since if $L^i_{DA(t)} - \widetilde{L}^i_t$ has the same sign with $L_{DA(t)} - \widetilde{L}_t$. It is fixed-sum in formulation since $\sum_{j=1}^{N} L^j_{DA(t)} = L_{DA(t)}$. And the deviation function is increasing with both announced variance and expected load.

Axiomatic Cost Sharing Model

According to (PJM 2014), total payment is calculated based on day-ahead bid, real-time consumption and market prices:

$$P_{(t)} = L_{DA(t)} * p_{DA(t)} + (L_{RT(t)} - L_{DA(t)}) * p_{RT(t)} \quad (6)$$

where $L_{DA(t)}$ is the day-ahead load bid in day-ahead market, $p_{DA(t)}$ is the day-ahead electricity unit price, $L_{RT(t)}$ is the real-time load consumption, and $p_{RT(t)}$ is the real-time electricity unit price. In this formula, the day-ahead bid and real-time consumption values can be either individual or aggregated. For aggregated cases (which includes ILCP), in order to disaggregate the total payment among consumers, we apply and devise few reasonable axioms. (Herzog, Shenker, and Estrin 1997) each of which describes an aspect of a cost sharing:

Axiom 1 - Increasing: given other consumers' load, a consumer's payment shall be strictly increasing corresponding to its own consumption.

$$P^i_{(t)a} > P^i_{(t)b}\ for\ \forall L^i_{RT(t)a} > L^i_{RT(t)b}$$

Axiom 2 - Fixed sum: in a non-profit cooperative, sum of all payments shall be equal to Equation 6: $\sum_{i=1}^{N} P^i_{(t)} = P_{(t)}$

Axiom 3 - Continuity: given other consumers' load, for a consumer, small variation in consumption should result in small variation in payment:

$$\forall L_{RT0} \in \mathbb{R}\ \lim_{L_{RT} \to L_{RT0}} P^i(L_{RT}) = P^i(L_{RT0})$$

Axiom 4 - Responsibility: any aggregated cost or benefit in payment due to a load deviation shall be charged or credited to contributors to that deviation: assume that $\Delta L^i_{(t)} = L^i_{RT(t)} - L^i_{DA(t)}$ and $\Delta L_{(t)} = L_{RT(t)} - L_{DA(t)}$ are individual and aggregated load deviations. Notice that individual day-ahead bid ($L^i_{DA(t)}$) is calculated according to Equation (5). Then this axiom states that:

$$P^i_t = \begin{cases} f(p_{DA}(t)) & \text{if } sgn(\Delta L^i_t) \neq sgn(\Delta L_t) \\ f(p_{DA}(t), p_{RT}(t)) & \text{if } sgn(\Delta L^i_t) = sgn(\Delta L_t) \end{cases}$$

According to the above axioms, we divide the solution into two scenarios. The first one occurs if the total imbalance and the individual imbalance are in opposite directions in which case the formulation is:

$$P^i_{(t)} = L^i_{RT(t)} * p_{DA(t)} \quad (7)$$

and the second scenario is when imbalances have the same direction:

$$P^i_{(t)} = L^i_{RT(t)} * p_{DA(t)} + \Delta L^i_{(t)} * (p_{RT(t)} - p_{DA(t)}) * \sum_{j=1}^{N} \Delta L^j_{(t)} / \sum_{j \in S_{II}} \Delta L^j_{(t)} \quad (8)$$

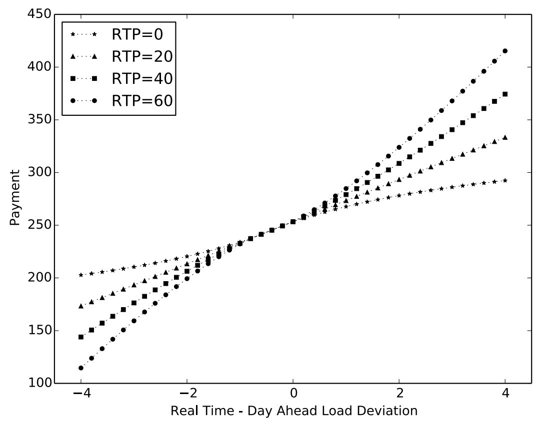


Figure 2: Monte-Carlo simulation of payment sharing axiomatic Formulation

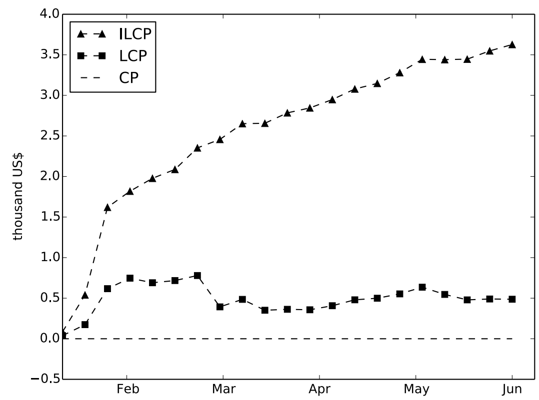


Figure 3: cumulative savings of cooperatives over RTP during 2014 trading period

where S_{II} indicates set of consumers for Scenario II. This formulation satisfies all of the four axioms. Axiom1 is true because:

First, we assume $\Delta L^i_{(t)} > 0$, for the sake of simplicity we put:

$$f = \Delta L^i_{(t)} * \sum_{j=1}^{N} \Delta L^j_{(t)} / \sum_{j \in S_{II}} \Delta L^j_{(t)}$$
$$= (x - c)(x + \alpha)/(x + \beta)$$

when $x = L^i_{RT(t)}$, $c = L^i_{DA(t)}$, $\alpha < \beta$ and $x > c$ (since the denominator is sum of only positive deltas). Then, we prove that the first derivative of payment function is strictly positive:

$$df/dx = (x^2 + 2\beta x + \alpha\beta - c\beta + c\alpha)/(x^2 + 2\beta x + \beta^2)$$

since $\alpha\beta - c\beta + c\alpha < \alpha\beta - c\beta + c\beta = \alpha\beta < \beta^2$ then $df/dx < 1$ and since $dP^i_{(t)}/dx = p_{DA(t)} + (p_{RA(t)} - p_{DA(t)}) * df/dx$ and $p_{RT(t)} \geq 0$ then $dP^i_{(t)}/dx > 0$. Similar logic applies to the $\Delta L^i_{(t)} < 0$ case. The formulation is fixed sum and the sum is equal to Formula 6 since:

$$\sum_{j=1}^{N} P^j_{(t)} = L_{RT(t)} * p_{DA(t)}$$
$$+ (p_{RA(t)} - p_{DA(t)}) * (L_{RT(t)} - L_{DA(t)}) = P_{(t)}$$

Also, this formula is a continuous function of $L^i_{RT(t)}$(axiom 3), the second term in the formula relies on the fraction of individual imbalance to sum of imbalances with similar direction (axiom 4). Figure 2 illustrates the dynamic of a individual payment corresponding to its own load deviation from day-ahead bid for few real-time prices.

Experimental Results

We study the performance of *interactive learning cooperative* using the real world electricity day-ahead and real-time prices, the real residential and commercial measured load profile, and a variety of weather parameters of Pittsburgh (a central PJM city, geographically). We collected 547 residential sample load profiles and 32 commercial ones out of which we used 100 and 10 profiles respectively. In our simulation, for the sake of having baseline for comparison, we define three other schemes:

- *Real-time pricing* (RTP): each consumer places bid in the day-ahead market individually and the payoff is calculated according to a his day-ahead bid, real-time consumption, and market prices.
- *Cooperative* (CP): it simply aggregates the load profiles of consumers and places bids in the day-ahead market, calculates the real-time consumption by each consumer and applies the cost sharing formula (Equation (8)) to disaggregate total payment among consumers. However, this scheme doesn't apply aggregated load and market price predictive models and interactive algorithms.
- *Learning Cooperative* (LCP): this scheme is the ILCP without the interactive algorithms. So, it combines all the functionalities of above CP scheme with aggregated load and market price predictive models (Equations (1) and (4)).

Real world datasets of PJM electricity market and load profiles are used for our experimental results. To better compare the results, we consider the same set of consumers for each type of cooperative. Consequently, aggregated load in each time interval is the same for all of our schemes. For trading time frame, we select 3600 hourly time intervals (out of 13104) starting from early 2014. For the LCP, we consider relearning period of 240 hours. This indicates that the trading agetns fits its *GNB* classifier every 10 days. We assume that in PJM geographical area, weather data are linearly correlated point to point and that weather forecasting is reasonably accurate up to the next 36 hours at each time interval.

The measures for comparison include the aggregated saving in total payment, average electricity unit price, and unit price variation during the test period. Since all of our trading agents are non-profit, any presumable trading profit trans-

	ILCP	LCP	CP	RTP
Total Payment (USD)	102918.7	106058.6	106545.5	106545.5
Average Electricity Unit Price (USD/MWH)	67.06	69.11	69.42	69.42
Consumers Unit Price Relative Std (percent)	2.3175	2.3151	2.3122	2.3157

Table 1: simulation results for non-profit cooperative

lates to a lower electricity unit price. Figure 3 shows the weekly cumulative savings of our cooperative agents. First of all, CP doesn't show any payoff over *real-time pricing*. This is because no imbalance or transaction fee is directly applied to agents who buy electricity in PJM market; also, the day-ahead bid doesn't place any obligation for actual transaction in real-time. In other words, if the day-ahead bid is less or more than real-time consumption, the difference in the real-time price will be charged or credited to the trading agent in order. As soon as we place those fees or obligations (that is usual in some other wholesale markets) in our model, the cooperative scheme starts to show advantage over RTP baseline in terms of total payment (assuming a normal distribution for consumer profiles, the relative aggregated load's deviation is lower than those of individuals). The LCP shows about 0.5% saving during the trading period. Nonetheless, market disturbances has major effects on its performance. The ILCP gives more than 3.4% total cost reduction and performs well during periods in which LCP falters (e.g. late Febuary). This indicates ILCP's steady advantage over other cooperatives and RTP scheme. Further, since the total daily load consumption is equal for all schemes, ILCP offers lower average electricity prices to its consumers proportionately.

For more comprehensive comparison, we need a measure for price variation which compares the weighed average of relative standard deviation of unit prices over trading period. Having this goal in mind, our measure should have this definition:

$$RelativeStd = \sum_{t=1}^{T} upriceStd_t / \sum_{t=1}^{T} L_{RT(t)} \tag{9}$$

in which $upriceStd_t = std\{UnitPrice_t^j : j = 1toN\}$, T is number of time steps and N is number of consumers.

Figure (4) shows the position of our non-profit cooperatives and RTP in the *average price value vs relative price standard deviation* space. Though theoretically, CP cannot give any advantage over RTP in terms of average electricity price, it shows advantage in terms of lower relative price variations among consumers. The reason for this lies in Equation (8) in which the variation of payment for small variations of real-time load is proportionate to day-ahead price rather than the real-time price. LCP gives slightly lower average price and relative variance than RTP's. The ILCP shows considerable advantage in terms of unit price but not unit price variations. This is because consumers have different preferences and thresholds for cooperation, so, the financial incentive encourages those with low price thresholds to shift their load profile and lower their unit price while it is not the case for all; this issue reduces the overall unit price but increase the unit price variation.

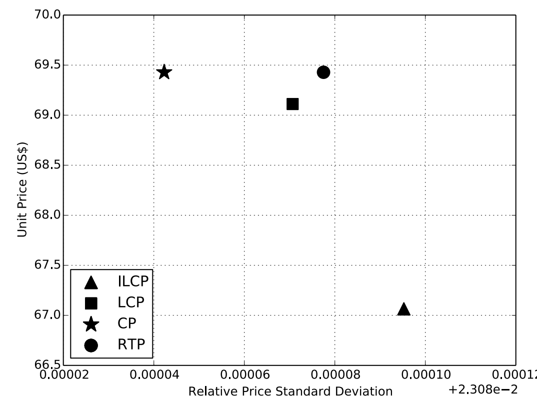


Figure 4: average electricity unit price value vs relative standard deviation for cooperatives and RTP

Conclusion

In this paper, we contributed to (i) a framework for interactive learning cooperative scheme (ii) axiomatic model for cost sharing, (iii) axiomatic model of risk disaggregation, (iv) interactive algorithms and (v) predictive models of aggregated load and real-time market price with learning from historical load and price data. We tested and validated our contributions with real world historical data of PJM markets and realistic consumer profiles. We demonstrated the performance of ILCP compared to LCP, CP, and RTP schemes. In future, we extend this model to simulate the behavior of trading and consumer agents and its implications.

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