SmartRate: A Rating Interpretation Mechanism for Agents in Smart Grid Markets

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ABSTRACT

We present SmartRate, a trust and reputation-based decision framework for Smart Grid, based on the available ratings provided by other customers. This model considers multiple trust factors associated with the broker and the preferences of customers for each of these factors. We define a decision framework for broker selection based on multi-attribute utility function and show how learning customers' rating behaviors helps to increase a decision maker's utility. We evaluate this framework by simulating a market based on real-world data. Our results show that learning the characteristics of a rating population helps to interpret and personalize the ratings, which results in better decision making and an increase in customer satisfaction.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: multiagent systems

General Terms

Design, Experimentation, Economics

Keywords

Reputation, Trust, Rating, Behavioral Modeling, Smart Grid

1. INTRODUCTION

Smart Grids extend and modernize the existing power grid using digital communication technologies. Smart Grids enhance and facilitate the ability of small-scale producers, such as households with solar panels and windmills, to sell their production to the power grid, creating a two-way flow of electricity. Therefore, they increase renewable power production, and balance supply and demand [1].

One approach to address the technical challenge in new control mechanisms for supply-demand balance in Smart Grids is by introducing *Broker Agents*. These agents buy electricity from producers and sell it to consumers using a market mechanism, the *Tariff Market*, in which agents publish their bid and ask prices [5]. Tariff markets control balance by incentivizing broker agents. Broker agents, who are able to simultaneously gain profit and maintain the balance between supply and demand, contribute to the stability of the grid.

As in many other multi-agent systems, finding trustworthy broker agents helps customers and producers to increase their profit and/or satisfaction. However, there is no solution in the literature that defines or uses a trust and reputation model for broker agent selection in Smart Grids. In this paper, we propose a trust and reputation-based decision framework, *SmartRate*, for Smart Grid applications. In our model, customers work with brokers and provide ratings for each aspect, or *factor*, of the service they receive (price, customer service). We define a broker's *reputation* as the average ratings given by the customers of a population. These ratings depend on the customers' behavior and expectations as well as the broker's performance. Therefore, customers who want to use these ratings to find the broker who is best fit to their preferences must first learn the population's *rating behavior*, and then customize and adjust the ratings to reflect their own viewpoints. We define the *trust* of a customer in a broker using these adjusted ratings. This model is generalized for many e-commerce applications that use ratings. In this paper, we show how in a Smart Grid application, this model helps customers to select the best broker —i.e., the one that maximizes their satisfaction.

In our previous work [2] on the PRep (Probability Reputation) model, we showed the importance of learning the behavior of the agent who is providing reports or ratings. This learned information helps agents to find more trustworthy partners, resulting in higher payoffs. We incorporate the lessons from the PRep model in our proposed framework, SmartRate, by defining a *rating interpretation* procedure that takes into account the behavior of raters. Moreover, we add the following contributions: first, we propose a novel approach that uses average ratings of all raters instead of individual ratings, since individual ratings of each factor are not readily available on many websites or are hard to collect; second, we model preferences and satisfaction thresholds of customers, and multiple service factors of brokers.

Our trust-based decision framework considers ratings provided by other customers, and direct interactions with a small group of brokers to decide whether to accept a given tariff from a new broker. We simulate a Smart Grid using real-world data to evaluate our proposed decision framework. We also verify the accuracy of our model and the results on the real-world data by using a synthetic data set.

2. THE SMARTRATE MODEL

In this section, we present our decision framework, SmartRate, which models trust and reputation based on the provided ratings of broker agents in Smart Grids. We propose a rating interpretation process and utility-based approach that takes into account the behavior of rater agents.

2.1 Utility Calculation and Preferences

The aim of our model is to increase customer satisfaction; therefore, we start by defining our utility function to quantify satisfaction. We define the utility of a customer by his satisfaction with the service he has received from a broker. We first model each broker's performance on each factor of the service that it is providing to the customers. We denote a broker, B_l, and its performance on the factors of the service that it provides by $\beta_l = \{\beta_{l1}, ..., \beta_{lM}\}$, where M is the number of factors of the service, and β_{li} represents how well factor i is provided, on a scale from 0 to 1. We define the utility of a single service factor i of broker B_l, by the performance that the broker has on that factor, β_{li}, where β_{li} is the performance of the broker on factor i. Note that u_{li} is the same for all customers and has the same range as β_{li}, i.e., from 0 to 1.

In our SmartRate model, we consider all service factors in computing the overall utility of a broker, which requires a multi-attribute utility, or MAU, function. In utility theory, an additive MAU function incorporates a customer's preferences by defining a set of scaling factors proportional to those preferences. The scaling factor is multiplied by an attribute's utility (a broker's performance for a given service factor in our case) and these values are combined for all attributes to obtain the overall utility. We define the preferences of a customer, k, for service factors (e.g., price, quality, and customer service) as $Pref_k = \{Pref_{k1}, ..., Pref_{kM}\}$.The values for these preferences are defined such that the summation of all preferences of a customer k is equal to 1.

Keeney [4] showed that a MAU function has an additive form when the sum of the scaling factors equals 1. Therefore, we define an additive utility function for the customer k to show his satisfaction with broker B_l, as:

$$U(k,l) = \sum_{i=1}^{M} Pref_{ki} \times u_{li}, \tag{1}$$

2.2 The Rating Model

In our rating model, customers receive service from brokers (and interact with brokers) by accepting their tariffs. Then, customers rate brokers based on the experience that they have had with those brokers for each of their service factors. In most rating websites, a common approach is to assign numerical values to the ordered categories of ratings. In our model, each customer k is modeled as computing his satisfaction in broker B_l for a factor i as:

$$y_{kli} = \beta_{li} x_{ki}, \tag{2}$$

where x_{ki} is the factor multiplier of customer k for factor i, and β_{li} is the provided service performance for factor i for this customer. In essence, x_{ki} reflects how much a customer cares about a specific factor or how "hard to please" he is about that factor. To model the ratings in this work, a customer maps this satisfaction level to a scale-based rating, R, using a defined set of thresholds $\{\alpha_0, \alpha_1, ..., \alpha_r\}$, where $\alpha_0 < \alpha_1 < ... < \alpha_r$ and each threshold corresponds to a rating from 1 to r. These α thresholds are assumed to be the same among the customers of a rating population. The actual satisfaction y and thresholds α are not directly observable, but we show how they can be inferred indirectly through the posted ratings, R.

In our model, we assume an inverse relation between $Pref_{ki}$ and rating factors x_{ki}. This assumption comes from the fact that a lower factor multiplier x_{ki} means that the customer will be harder to please in that specific factor and is expecting a high performance from the broker in order to give a good rating. This implies that this factor has high preference for the customer, which results in the inverse relation. The ratings of all customers in a population are reported to a centralized system (see Figure 1); these individual ratings are not visible to other customers. In the centralized system, the available ratings for each factor and each broker are accumulated and are averaged by the number of ratings provided for that factor.

2.3 Learning Preferences and Thresholds

Figure 1 explains the learning process of our model using a scenario involving brokers and customers. In this scenario, C stands for a new customer, who is looking to find a reputable broker, given a population of customers, who have rated broker (or service provider) B_l. C is presumed to have previously accepted tariffs from a few brokers (e.g., $B1$ and $B2$) and to have observed the performance of different aspects of their service (e.g., reliability, price). That is, C has experienced and learned $B1$ and $B2$'s service factors (β_{B1} and β_{B2}) through direct interactions with them. Now, C needs a new service and wants to switch to another broker, such as $B3$. C wants to use the ratings posted on the central system in order to see if it is better to switch to $B3$, or continue using $B1$ or $B2$. Therefore, C needs to predict $B3$'s performance on the service factors, and must learn the population's rating characteristics.

C examines the population's ratings for various factors of $B1$ and $B2$. Using already learned β_{B1} and β_{B2} performance values, C computes the population's rating (or satisfaction) threshold and the multipliers for each of the service factors using an ordered probit model, as explained next.

Let us assume that a population rates their satisfaction with a particular service factor by means of an ordered categorical variable R with r possible outcomes, $j = 1, ..., r$. The ratings are based on an underlying latent variable (satisfaction), which is denoted by y. As we explained, the satisfaction may differ from one population to another, or even

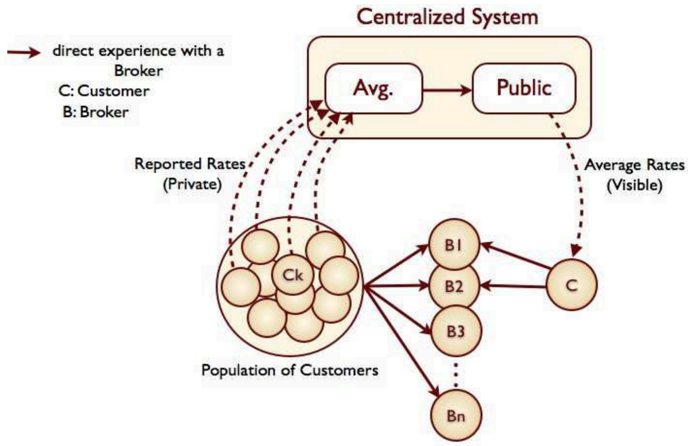

Figure 1: Basic scenario.

from one service to another, depending on the factor multipliers $x = \{x_1, ..., x_K\}$. For any service factor i:

$$y_i = \beta_i x_i + p_i, \tag{3}$$

where p_i is an independent disturbance term. In the case of a probit model, these disturbances are assumed to be normally distributed with mean zero and variance one, $p_i \sim n(0,1)$. We introduce an indicator variable z_{ji} for each of the possible outcomes of the provided ratings, R, as follows: $z_{ji} = 1$, if $R_i = j$, and 0 otherwise. For each respondent i, the probability of a particular rating j is obtained as by:

$$\begin{aligned} P(z_{ji} = 1) &= P(\alpha_{j-1} < y_i < \alpha_j) \\ &= P(\alpha_{j-1} < \beta_i x_i + u_i < \alpha_j) \\ &= P(\alpha_{j-1} - \beta_i x_i < u_i < \alpha_j - \beta_i x_i) \\ &= \Phi(\alpha_j - \beta_i x_i) - \Phi(\alpha_{j-1} - \beta_i x_i), \end{aligned} \tag{4}$$

with $\Phi()$ representing the cumulative normal distribution. The parameters x_i and α_j can be estimated by maximum likelihood. The log likelihood function is specified as:

$$L(\beta, \alpha_1, ..., \alpha_{r-1}) = \sum_{i=1}^{n} \sum_{j=1}^{r} z_{ji} ln[\Phi(\alpha_j - \beta_i x_i) - \Phi(\alpha_{j-1} - \beta_i x_i)]. \tag{5}$$

We calculate the optimal solution that maximizes these functions in order to obtain estimates of the unknown parameters $x_i = \{x_1, ..., x_M\}$ and $\alpha_1, ..., \alpha_{r-1}$.

2.4 Learning Service Factors

In the previous subsection, C estimated the population's rating behavior i.e., x and α. Now, C needs to estimate a new service provider's factors, β, using this learned information. In our scenario, Figure 1, C now looks for B3's ratings given by the population to learn the service factors of a given service from B3, $\beta_{B3} = \{\beta_1, ..., \beta_M\}$. Using Equation 5, and knowing the learned population's rating behavior for different factors of a service $x = \{x_1, ..., x_M\}$ and the satisfaction threshold, $\alpha_1, ..., \alpha_{r-1}$, C can estimate the maximum likelihood of $\beta_{B3} = \{\beta_1, ..., \beta_M\}$. Now, C uses this estimated value β_{B3} for the last step, which is decision making and tariff selection. In order to make a decision as to whether to switch to another broker or stay with the current one, C computes the expected utility of B3 using Equation 1, and compares it with the observed utility of his current broker. The broker who provides highest utility will satisfy C the most, and will therefore be selected as C's future broker.

Table 1: Customer satisfaction study

Retailer	Bill	Price	Comm.	Cust. Srv.
Ambit Energy	4	4	5	4
Amigo Energy	4	4	4	4
Bounce Energy	3	4	3	2
Cirro Energy	4	4	3	4

Table 2: Service factors (β) observed by C

	Bill	Price	Comm.	Cust. Srv.
Ambit Energy	0.5	0.65	1.0	0.5
Amigo Energy	0.45	0.6	0.7	0.5
Bounce Energy	0.3	0.7	0.6	0.15

3. MARKET SIMULATION

We have developed a market simulation using data from a rating website for Texas electricity retailers [3]. To verify our results and our assumptions from the real-world data and to measure the accuracy of our model, we developed another market simulation using synthetic data as well.

3.1 Real-World Data

The Texas electricity retailers website [3] provides a customer satisfaction study for Texas residential electricity retailers using performance ratings for different factors of the service provided by each electricity retailer in 2011, as shown in Table 1. In our experiment, we show how customer C, decides whether he will stay with his current electricity provider or will switch to a new retailer, whose performance has not yet been experienced (by C). This decision will be made by comparing the expected utility from the new retailer with the experienced utility of the current retailer. To make this comparison, C needs to learn the rating characteristics of the population that has provided ratings on the website. Then, by using the learned characteristics and the posted rated performance for the new retailer, C will estimate the performance of the new retailer on each factor. Finally, C will decide which retailer is the best, based on its preferences and all of the learned performance factors.

To evaluate our model, we introduce two baselines. First, we define a naive approach to select the best broker by summing up the ratings of each broker. This approach, U^{N1}, does not consider each customer's preference for factors, so it does not personalize the ratings based on a customer's viewpoint. The second baseline, U^{N2} is similar to the first one, but it multiplies the customer's preferences by the provided ratings, and then sum up these values for all factors.

We assume that customer C in Figure 1, has purchased electricity from a few retailers (i.e., Ambit Energy, Amigo Energy, and Bounce Energy) and has already observed their performance for each service factor. The results of this observed performance are shown in Table 2. Now, suppose that C is currently with retailer "Bounce Energy," wants to explore whether it is worth switching to "Cirro Energy."We as-

Table 3: Actual and learned characteristics

	Bill	Price	Comm.	Cust.
Actual avg. pref.	0.2	0.25	0.33	0.22
Learned avg. pref.	0.22	0.25	0.31	0.22
Actual avg. factor mults.	5.0	4.0	3.0	4.5
Learned avg. factor mults.	4.62	3.95	3.19	4.62

sume that the actual factor multipliers are the values shown in Tables 3 and actual thresholds are 0, 1.0, 2.0, and 3.0. Using Equation 5, C learns the threshold (which are 0, 1.01, 1.77, and 3.04) and factor multipliers of the population. At this stage, C has learned the population's factor multipliers (Table 3), and can estimate the performance of each factor of the service given by Cirro to the population using Equation 5. The results of the learned factor performance of Cirro Energy are 0.52, 0.61, 0.44, and 0.52.

Customer C also has its own preferences as 0.1, 0.4, 0.4, and 0.1. Now that C has learned the service factors for a new retailer (i.e., β of Cirro), he computes the utility gaining from switching to this new retailer (Cirro) from the current retailer (Bounce), and the results are 0.524 and 0.565 respectively. Therefore, customer C, as a rational agent, will stay with the current retailer instead of switching to Cirro. The main reason behind this decision is that customer C gives high preferences to the second and third service factors, and in both cases Bounce performs much better than Cirro. The ratings alone fail to catch this difference, as both retailers have received the same rating from the population on the second and third factors. The naive utility functions show this shortcoming clearly. Without the SmartRate model, customer C can use one of the naive utility functions to compute the utility gained by switching to Cirro Energy. If C uses either U^{N1} or U^{N2} to calculate the utilities, he will switch to Cirro. So, looking only at population's ratings, even if they are detailed, may not lead to the best choice.

3.2 Synthetic Data

We developed a market simulation based on synthetic data to show that even without having access to the details of ratings, we can accurately estimate the true performance of brokers. We also verify the correctness of our average preference assumption in the previous experiment; that is, assuming the average preference of customers, when we do not have access to each of the customer's preferences. Also, we study the accuracy of our learning model by computing the error rate in learning the performance of service factors and the population preferences.

In this experiment, we assume 1000 customers ($C1$,...,$C1000$ in Figure 1) with random preferences for four factors of service (billing, price, communication, and customer service). The value of each preference is between 0 and 1, and the summation of preferences of each customer is equal to 1. We have 30 brokers ($B1$, ...,$B30$) offering electricity service, and random performance values (between 0 and 1) are assigned to each service factor of each retailer. Customers individually rate the performances of those brokers they have interacted with, based on their own preferences and an overall threshold. Each customer sends the given rate for each factor of a broker to a centralized system. In the centralized system, the available ratings for each factor and each broker are accumulated and are averaged by the number of ratings provided for that factor. Finally, the average ratings for each factor of each broker are posted on a website.

Now, customer C has experienced a few brokers' performances directly (e.g., $B1$, $B2$, $B3$) in the past. Now, he decides to explore other options (about brokers) and switch to another broker if he finds them more satisfying (i.e., the one who increases his utility). C looks at the average ratings for brokers that he has experienced already, ($B1$, $B2$, $B3$). C applies these observed brokers' performance on each factor in Equation 5, and he learns the preferences of the population (the average preferences of all customers), and the thresholds. Note that he does not have access to each individual's ratings. Using this learned population's preference $\{x_1, ..., x_4\}$ and the satisfaction threshold $\{\alpha_1, ..., \alpha_4\}$, C estimates the likelihood of the performance for the other brokers (i.e., $\beta_1, ..., \beta_4$) using Equation 5.

We have compared learned population's preference with the actual preference of the population, and their average error is only 0.0225. We also compared the actual and learned alphas; the average error is 0.317. Additionally, we compared the actual and learned performance of service factors. The average error of this estimation for all the brokers and their factors is 0.06. This shows that our model estimates brokers' performances relatively accurately by using only the average preferences of the population.

4. CONCLUSIONS AND FUTURE WORK

We proposed a trust and reputation-based decision framework for Smart Grids. SmartRate models multiple service factors of brokers and preferences of customers. It also considers ratings provided by other customers and direct interactions with brokers to decide whether to accept a tariff from a broker. We have also shown how the learning factor multipliers and satisfaction thresholds of a population help to increase a customer's utility, which yields an increase in customer satisfaction. We evaluated our decision framework by simulating a market based on real-world data from an electricity retailer website. The results demonstrate that learning the characteristics of a rating population helps to interpret and personalize the ratings. All the above result in better decision making and increase customer utility and satisfaction. Although SmartRate has been tailored for Smart Grids, the proposed model is generalized and can be applied to many e-commerce applications that use ratings.

In our future work, we will investigate how to deal with new factors for the existing brokers (e.g. "is sustainable") and how to adapt old data. Additionally, we plan to consider dynamic factors such as time, or "recency" in our model.

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