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Hybrid Renewable Energy Tariff Selection Using Providers and Consumers Lexicographic Preferences Similarity

Shadi Farid[1], Faria Nassiri-Mofakham [2*]
1 Faculty of Computer Engineering, University of Isfahan
2 Faculty of Computer Engineering, University of Isfahan (Corresponding Author)

ABSTRACT

Due to the importance of hybrid renewable energies for green power plants, strategies are required to make the market competitive and encourage consumers to admit to using such still less available electricity compared to the power generated from fossil fuels. Promotion-based group-buying tariffs are a selling marketing tool that can be adapted for this purpose. Energy producers and consumers can express their preferences regarding hybrid renewable energies through multiple attributes and values in a conditional manner, a lexicographic representation. In this paradigm, "what to buy" and "who else might incline to buy this," is a challenging issue for a group of consumers to make a single purchase decision. To this end, an HRECS and a PLPSim method are proposed to group consumers having the most similar lexicographic preferences for purchasing the most appropriate supplier tariff. The evaluation results demonstrate that HRECS using PLPSim outperforms the existing PLPDis method regarding Normal Discounted Cumulative Gain (nDCG) as well as intra- and inter-group Davies-Bouldin dispersion.

Keywords: Hybrid renewable energy market, Tariff selection, Lexicographic preference, Similarity, Group buying.

1. INTRODUCTION

Globalization and the increase in the urban population and household energy consumption have led to an unprecedented increase in demand for electricity, and fossil fuels as a result. This has made energy production a major challenge, while the use of fossil fuels has disadvantages such as limited resources, lack of uniform distribution, and increased greenhouse gas emissions [1]. Renewable energy, such as solar, wind, biomass, geothermal, and hydropower, is an important non-finite alternative to the traditional energy for power plants to reduce fossil fuels energy consumption, and environmental and economic challenges of electricity networks [2]. However, disadvantages such as depending on the weather, incompatibility of availability fluctuations and demands time distribution, and high design cost of independent deployment of these energy systems, make their availability unpredictable, so that their single-use does not produce much energy throughout the year. Hybrid renewable energy systems (HRESs) are an energy system with more than one type of source of renewable energy (as a primary energy source) [1], and battery storage system (when the system has a power deficit) by using a power converter [3]. Electricity, like other commodities, is first produced and sold at a wholesale level before being distributed to consumers. The cost per kilowatt-hour of energy consumed from the smart energy grid is called the consumption tariff [4]. Prices fluctuate at different times due to supply and demand. In fact, they change depending on the number of sales and the number of consumers willing to buy. Also, due to fluctuations in renewable energy, one of the ways to balance production and consumption is to use multiple electricity tariffs to encourage consumers' use to be close to the optimal and desired consumption curve [5]. The electricity retail market has made consumers more flexible in choosing tariffs, competitive prices, and innovative offers from companies. For example, SP Group [6] in Singapore currently offers electricity supply companies different contracts by selecting parameters such as type of electricity consumption (domestic/industrial) and average monthly consumption. The suppliers' and consumers' preferences over energy tariffs can be described in

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attributes and values regarding energy type, demand rate, contract, and so on. For example, for saving the environment, a consumer may tolerate electricity fluctuations, if it has been only supplied using solar and wind power. These preferences are complex, combinatorial, and conditional. A potential way in computer science having high ability to represent conditional (and unconditional) preferences is lexicographic preferences (LP) [7]. That is, each party can use preference relations ($\succ$) to order the importance of candidate solutions by expressing in a lexicographic preference tree (LP-tree) or list over attributes and values [7]. On the other hand, for making competitive the hybrid renewable energy market and encouraging most consumers to adapt to using such energies, marketing strategies such as discount-based group buying can bring mass benefits to these energy producers as well [5]. However, one of the main challenges in the coalition formation is creating the coalition structure, i.e., selecting the best coalitions from a set of possible ones, so that each party joins exactly one coalition. To create a more efficient coalition [4], it should be possible to put the most similar parties in a group among the consumers who want to enjoy group-based discounts and assign an appropriate tariff to each coalition so that the maximum satisfaction of users is obtained.

This study proposes a PLPSim method for comparing lexicographic preferences over hybrid renewable energy to group the most similar consumers using the HRECS coalition formation system per every energy tariff. These methods are presented in Sections 2 and 3, and the results of the research are in Section 4.

2. ENERGY CONSUMERS COALITION USING PLPSIM SIMILARITY OF LEXICOGRAPHIC PREFERENCES

Assume an energy market in which the suppliers have offered tariffs and expressed their preferences regarding hybrid renewable energy attributes and values in lexicographic representation (Def. 1). Consumers also have lexicographic preferences to choose desired tariffs. It is also assumed that the energy resources provided by each supplier are unlimited. Every supplier may offer a different discount percentage if a sufficient number of consumers purchase her tariff, forming a buying coalition. This benefits the consumers to buy tariff in a more reasonable price, while increasing the number of consumers will increase the total profit of the supplier in the competitive energy market. In addition to the hard constraint, price, that must be met, soft constraints in this market are described using multiple negotiable criteria.

Example 1. A consumer expressed his binary preference in Fig 1, so that energy type (*D*) has been the most preferred attribute, as the consumer prefers wind (d') to solar (*d*). If Wind (d') is chosen, the demand rate (*S*) is the second most preferred attribute for him, and his demand is for the peak-time (s') and is preferable to low-time (*s*) and then contract (*E*), which is short-term (*e*) to long-term (e'), and if solar (*d*) is chosen for the energy type (*D*), the contract (*E*) and then demand rate (*S*) is preferred.

Definition 1 (Lexicographic preference). Let $\mathcal{V} = \{X_1, \dots, X_N\}$ be a set of N attributes, and $D_X = \{x \ , x'\}$ be the domain of each attribute of X if the attributes are binary. The set of combinatorial domain outcomes, which is a Cartesian product of the attribute domains, is denoted by $\prod_{X\in\mathcal{V}} D_X$. Thus, for each set of attributes $\chi \subseteq \mathcal{V}$, we indicate $D_\chi = \prod_{X\in\chi} D_X$. Formally, a lexicographic order is a total order on the set of outcomes, which is reflexive, asymmetric, transitive and all the attributes of the member of the set are related to each other. In fact, if all the members were not related to each other, then the relation of the lexicographic order is partial [7, 8]. The lexicographic order has two main elements, which are importance order (between attributes/conditional or unconditional) and local preferences (between attribute's values/conditional, unconditional, or fixed) [7].

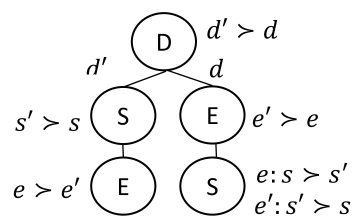

Figure 1. LP-tree

2.1 Lexicographic preference tree solution rank

By pre-order traversing the LP-tree in branches from root to leaves, starting from the left branch, all combinations of attributes and their values can be obtained, each is called a solution. Assume that attribute values are binary, so each node has two children at most. Suppliers express tariffs in complete lexicographic preferences because they know the attributes and attribute's values. However, consumers' preferences can be complete (CLP) or partial (PLP) due to lack of information or impossibility of distinguishing some attributes or values.

Definition 2 (Partial solution). If value substitution is not performed on all attributes of the problem, the ordering of these values is an incomplete or partial solution.

Definition 3 (Solution rank in lexicographic preferences). We rank lexicographic preferences solutions according to their position in the linear order of preference so that the best preference is ranked n (number of leaves, i.e. the number of solutions from the whole tree) and the worst preference is ranked 1. That is, the ranks of the solutions change from qualitative to quantitative, and then normalized (between 0 and 1) to be comparable among LP-trees with any number of leaves (Eq. 1). In zero, it eliminates the worst solution. Hence, by adding a small positive number λ (e.g., 0.1), the normalized rankings of solution α in lexicographic preferences $\mathcal{L}$, i.e. $rank(\mathcal{L},\alpha)$, is placed between λ to 1 + λ (i.e. 0.1 to 1.1) (Eq. 2). For example, $rank(Fig1, d's'e') = 0.95$ and $rank(Fig1, de's) = 0.38$.

$$normalized(index(\alpha)) = \frac{index(\alpha)-1}{n-1} \quad (1)$$

$$\boldsymbol{rank}(\mathcal{L},\alpha) = normalized(index(\alpha)) + \lambda \quad (2)$$

2.2 PLPSim similarity

The only existing method, PLPDis, for comparing two complete or partial lexicographic preferences trees T_1, and T_2 computes their distance using partial Kendall distance [8]. It forgets the absence of attributes in partial trees; i.e., it computes the distance of T_1 with T_2 the same as of its horizontal mirror T_1' with T_2, for example. For addressing this problem, we introduce the rank of solutions (Definition 3) and by adapting, extending, and improving CPSim [9] to lexicographic preferences, present the PLPSim method that distinguishes between tree branches as well as the importance and preference of solutions of the LP-tree in computing the similarity of complete and incomplete preferences (PLP). For two LP-trees LPT_i and LPT_j represented by graphs T_i and T_j, Eq.(3) computes PLPSim of LPT_j to LPT_i by computing the average of three fractions. In which, sv_{LPT_i,LPT_j}, se_{LPT_i,LPT_j}, v_{LPT_i}, e_{LPT_i}, sr_{LPT_i,LPT_j} and r_{LPT_i} are the number of shared variables between T_i and T_j, the number of shared edges between T_i and T_j, the number of variables in T_i, the number of edges in T_i, and the sum of the product of the rank of the shared solutions between the two trees T_i and T_j. $r_{LPT_i} = \sum_{\alpha\in O_i} rank(\alpha, LPT_i)^2$ and $sr_{LPT_i,LPT_j} = \sum_{\alpha\in SO_{T_i,T_j}} rank(\alpha, LPT_i) \times rank(\alpha, LPT_j)$.

$$\boldsymbol{PLPSim}(LPT_i, LPT_j) = \frac{1}{3}\left(\frac{sv_{LPT_i,LPT_j}}{v_{LPT_i}} + \frac{se_{LPT_i,LPT_j}}{e_{LPT_i}} + \frac{sr_{LPT_i,LPT_j}}{r_{LPT_i}}\right) \quad (3)$$

2.3 HRECS Tariff Selection

We also present the HRECS coalition formation method by assigning the most similar tariff to each consumer. The sets of suppliers and consumers of hybrid renewable energy system are $S = \{s_1, \dots, s_M\}$ and $C = \{c_1, \dots, c_N\}$, respectively. Assume that each supplier s offers a tariff $A_s =< T_s, \varphi_s, q_s, d_s >$ where T_s, φ_s, q_s, and d_s are the LP-tree, the lowest acceptable price, the least number of people required for forming a coalition over the tariff, and ID of s, respectively. Each consumer c can also bids his energy requirement $B_c =< T_c, \varphi_c, d_s >$, where T_c, φ_c, and d_c are the LP-tree, the highest acceptable price, and ID of c, respectively. Therefore, consumer c can buy tariffs $\mathrm{A_s}$ that $A_s.\varphi_s \leq \varphi_c$. For the supplier s, the bids B_c can be considered if $\varphi_s \leq B_c.\varphi_c$. That is, $\forall s \in S, G_s = \{B_c | c \in C, \varphi_s \leq B_c.\varphi_c\}$. In these sets G_s, the similarity of c LP-trees is compared with s LP-tree; then, B_is that satisfy the condition are sorted in descending order of their trees similarity with T_h : $\forall h \in H, R_h = [R, B_r \,|\forall B_i, B_j \in R, 1 \leq i < j < r, score(i) \leq score(j)]$, so that, $\forall h, i, j, SIM(T_h, E_i.T_i) \geq SIM(T_h, E_j.T_j) \Leftrightarrow score(i) \leq score(j)$, where, $H = S$ or $H = C$. Matrix $\mathcal{C} = [\ (c, R_c)\ |\ c \in C]$ forms ordered lists of tariffs similar to consumers' preferences.

Having a matrix $\mathcal{C}$ from the ordered lists of tariffs in R_c for each consumer $c \in C$, the most similar tariff is allocated to each consumer for him according to Algorithm 1 (line 5). The order in which consumers' requests are processed has no effect on the outcome, and each consumer receives the only tariff that is the most similar to his or her preferences, $G(c)$, without any restrictions. According to this allocation, by inverting G, for each tariff A_s, group $\mathcal{G}(s)$ is formed from the most similar consumers possible.

Algorithm 1. Hybrid Renewable Energy Coalition System (HRECS)

1: Input: $\mathcal{C}_{N\times M}$
2: Output: $\mathcal{G}_{M\times N}$
3: Begin
4: foreach $\mathrm{c} \leq \mathrm{N}$ **do**
5: $s \leftarrow \mathcal{C}(\mathrm{c}, 1)$
6 $\mathcal{G}(s).\mathrm{append(c)}$ // i.e., add B_c to $\mathcal{G}(s)$ ~ add $A_s = R_c(1)$ to $\mathrm{G}(c)$
7: end for
8: return $\mathcal{G}$
9: End

3. RESULT

The proposed PLPSim and HRECS methods are implemented in Python 3.7.4 and run on 27 synthesized energy markets including all 2 to 10 complete lexicographic tariffs and 10 to 1000 partial lexicographic preferences of consumers over 2 to 4 binary attributes. In each experiment, the number of consumer groups is constant and equal to the number of tariffs offered in the market. The results are evaluated using Davies-Bouldin dispersion index (the less, the better; Definition 4) and Normal Discounted Cumulative Gain (nDCG; closer to 1, the better; Definition 5) and are compared with PLPDis performance. According to Fig. 2, with increasing the number of attributes, the Davis-Boldin index of PLPSim and PLPDis methods increases, where PLPDis results in a higher average. Also, the PLPSim method maintains the quality by increasing the number of attributes, on average. PLPSim also outperforms PLPDis in two other HRECSs that focus on consumers only or all parties. Extended version of the paper details this.

Definition 4 (Davies-Bouldin index). Based on the average similarity in each group of consumers ($SIM_{\mathcal{G}}^{Avg}$) measured relative to suppliers tariffs, the Davies-Bouldin index (based on all $\mathcal{M} = M(M-1)/2$ pairwise checks among M groups) is $\boldsymbol{DB^{SIM}} = \frac{1}{\mathcal{M}} \times \sum_{\mathcal{G}=1}^{\mathcal{M}} D_{\mathcal{G}}$, where, $D_{\mathcal{G}} = max\left\{ R_{\mathcal{G}}^{\mathcal{G}'} \,\middle|\, R_{\mathcal{G}}^{\mathcal{G}'} = \frac{\sqrt{Var_{\mathcal{G}}^{SIM}} - \sqrt{Var_{\mathcal{G}'}^{SIM}}}{\left|SIM_{\mathcal{G}}^{Avg} - SIM_{\mathcal{G}'}^{Avg}\right|}, \forall \mathcal{G}, \mathcal{G}' \right\}$, $SIM_{\mathcal{G}}^{Avg} = \frac{\sum_{b \in B, P_b \in \mathcal{G}(\mathrm{T}_s)} SIM_{b,\mathrm{T}_s}}{\mathcal{G}(\mathrm{T}_s).q}$ and $Var_{\mathcal{G}}^{SIM} = \frac{\sum_{b \in B, P_b \in \mathcal{G}(\mathrm{T}_s)} \left(SIM_{b,\mathrm{T}_s} - SIM_{\mathcal{G}}^{Avg}\right)^2}{\mathcal{G}(\mathrm{T}_s).q}$. Low dispersion of similarity within each group and a high dispersion among the groups are desired. That is, the lower the Davis-Bouldin index, the more appropriate the consumers groupings.

Definition 5 (Society nDCG). The quality of SIM method among all consumers and suppliers is equal to the product of nDCG of consumers and suppliers, $\boldsymbol{nDCG^{SIM}} = nDCG_{\mathcal{C}}^{SIM} \times nDCG_{\mathcal{S}}^{SIM}$, where, for consumer $c \in C$, the nDCG of tariffs A_1 to A_M resulting from the SIM method is $nDCG_c^{SIM} = \frac{DCG_c^{\boldsymbol{SIM}}}{IDCG_c^{\boldsymbol{SIM}}} . IDCG_c^{\boldsymbol{SIM}}$, is similar to $DCG_c^{\boldsymbol{SIM}}$, but on the descending list of suppliers' tariffs ($\mathcal{S}$) in terms of their similarity, $DCG_c^{\boldsymbol{SIM}} = \sum_{s=1}^{M} \frac{SIM(B_c, A_s)}{log_2(s+1)}$, $IDCG_c^{\boldsymbol{SIM}} = \sum_{s \in \mathcal{S}} \frac{SIM(B_c, A_s)}{log_2(s+1)}$.

4. CONCLUSION

In this study, for grouping the consumers for the purpose of encouraging them to use renewable energy via the most appropriate tariff in a discounted cost, we presented a hybrid renewable energy coalition system (HRECS) by proposing a PLPSim method that computes the similarity of suppliers and consumers' LP-trees. It provides a management tool for planning consumption in smart grids. As future work, the reputation of energy suppliers can also be considered as their priority for allocating to consumers. Moreover, coalition can be formed with both suppliers and consumers' welfare in mind.

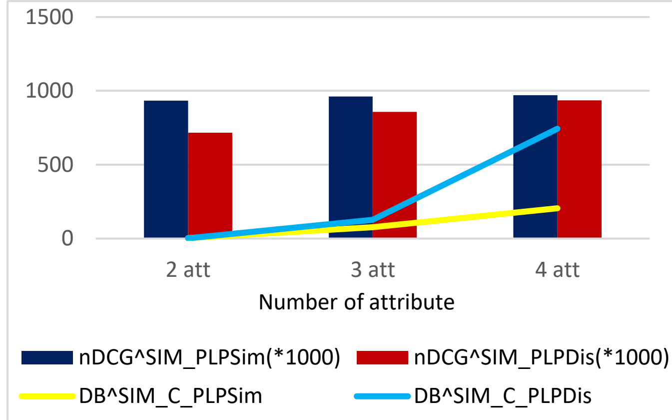

Figure 2. PLPSim and PLPDis's nDCG and Davies-Bouldin index of consumer's lexicographic preferences with 2--4 attributes.

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