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Collaborative Filtering-based Electricity Plan Recommender System

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***Abstract*—Owning to electricity market deregulation, residential customers now enjoy the freedom to choose their preferred electricity retailers. This paper investigates the application of recommender system, a fast-developing technique in machine learning, into the task of recommending electricity plans for the individual residential customer. Based on a collaborative filtering strategy, an electricity plan recommender system (EPRS) is developed. By providing easily obtainable data of some household appliances, residential customers of the EPRS are recommended with predicted ratings of different plans, which can provide effective guidance to customers in the selection of suitable plans and proper tariffs. Different numerical tests are carried out to evaluate the performance of the EPRS. The EPRS outperforms other strategies in the accuracy of recommendation result and is verified to be a promising solution to electricity plan recommendation task.**

***Index Terms*—Collaborative filtering, electricity market, electricity plan, flexible pricing, recommender system.**

NOMENCLATURE

A. Abbreviation

CDI	Cluster dispersion indicator
CFRS	Collaborative filtering recommender system
COS	Cosine similarity
DR	Demand response
EPRS	Electricity plan recommender system
EUC	Euclidean similarity
J-COS	Jaccrad-Cosine Similarity
J-EUC	Jaccrad-Euclidean Similarity
J-wEUC	Jaccrad-weigthed Euclidean Similarity
KDE	Kernel density estimation
PDF	Probability density function
RMSE	Root mean square error
SG	Single-rate
TOU	Time-of-use

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B. Parameters

ω_a	Confidential weight of appliance a
ω_a^{VCDI}	verified-cluster dispersion indicator of appliance a
$\omega_{\min}$	Minimum confidential weight
h	Bandwidth for kernel density estimation
k	Number of nearest neighbors
N	Number of top-N plans
Q	Number of clusters of all training users

C. Functions, Indices and Sets

F^D	Intra-set distance function
F^K	Kernel function for kernel density estimation
F^U	Utility function of recommender system
$\boldsymbol{I}_m^N$, $\hat{\boldsymbol{I}}_m^N$	Set of real top-N items, top-N items recommended to user m
$\boldsymbol{U}_m^k$	Set of k-nearest neighbors of user m
a	Index of appliance
$\boldsymbol{A}$, $\boldsymbol{A}_m$	Set of all the appliances, appliances operated by user m
$\boldsymbol{c}_a$	Set of $c_a^{(q)}$ for all the possible q
$\boldsymbol{c}_{a(q)}$	Centres of $\boldsymbol{f}_{a(q)}$
$\boldsymbol{c}_m$, $\bar{\boldsymbol{c}}_m$	Set of plan charges on user m, average value of $\boldsymbol{c}_m$
$\boldsymbol{F}$, $\boldsymbol{F}_{tr}$	Set of features of all the users, features of training users
$\boldsymbol{f}_{a(q)}$	Set of operation features of appliance a given by all the users in $\boldsymbol{U}_{tr(q)}$
i	Index of plan
$\boldsymbol{I}$, $\boldsymbol{I}_m$	Set of all the items, item rated by user m
l	Index of power record
$\boldsymbol{P}$	Set of power use records
q	Index of training users cluster
$\boldsymbol{R}$, $\boldsymbol{R}_{tr}$	Set of ratings of all the users, ratings of training users
$\boldsymbol{r}_m$, $\bar{\boldsymbol{r}}_m$	Set of plan ratings given by user m, average value of $\boldsymbol{r}_m$
u, m, n	Indices of user
$\boldsymbol{U}$, $\boldsymbol{U}_{tr}$, $\boldsymbol{U}_{te}$	Set of all the users, training users and testing users
$\boldsymbol{U}_{tr(q)}$	q-th cluster of all training users
$\boldsymbol{U}_{tr(q)\text{-a}}$	Set of users in $\boldsymbol{U}_{tr(q)}$ who can supply operation feature to appliance a

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D. Variables and Matrix

c_{mi}	Charge of plan *i* on user *m*
f_{ma}	Operation feature of appliance *a* used by user *m*
p	Power use
P_l	The *l*-th power use record in ***P***
r_{mi}, $\hat{r}_{mi}$	Real and predicted rating given by user *m* to plan *i*
s_{mn}, s_{mn}^{J}, $s_{mn}^{\omega E}$	General, Jaccard and weighted Euclidean similarity between user *m* and user *n*
u_{tr}, u_{te}	Training user, testing user

I. Introduction

MODERN power systems have experienced a series of deregulation since 1882 to introduce full competition at different stages of electricity supply chain. In many countries, electricity tariffs have been deregulated in the retail markets, and the benefits of electricity retail competition have been clearly observed. The end-users, especially residential customers, have gradually understood their household energy-consumption practices. With more attractive tariffs and greater customer service, residential customers have more options to lower their power expenditures through demand response (DR) activities or selecting suitable electricity retailing plans. Together with flexible pricing tariff, DR minimizes the electricity expenditure of a customer through rescheduling operation time of household appliances [1-4], reducing load during critical peak hours [5, 6], or transferring to onsite distributed generators [7, 8], etc. Challenges hindering the wider applications of DR among residential customers are the loss of comfort, the change in living pattern, and concerns about handing over the controllability to the system operator. Also, the efficiency of DR would be greatly impaired by an electricity plan improperly selected. If a customer demands high power consumption in peak hours but selects a plan with higher peak-hour charge, it is quite possible that shifting to a plan with lower peak-hour charge can be more economical than just performing DR. In this case, selecting suitable electricity plan becomes a simple and effective strategy for energy expenditure reduction without altering the original living pattern.

In a highly competitive electricity retail market, tens or hundreds of electricity plans are issued by different retailers, which makes plan selection a troublesome task [9]. Currently, a few tools have been developed to help customers in selecting cost-effective electricity plans. These tools make recommendations in either direct or indirect manner. Direct manner is popular in online plan recommendation platforms, like Energy Made Easy, iSelect, Power to Choose, and Check24 [10-13]. The basic principle is looking for cheaper electricity plans by directly comparing costs of all the plans. The cost of a plan is calculated from total electricity usage of a customer and the charge rates of the plan. Generally, total electricity usage is estimated as the corresponding values shown in recent electricity bills. When recent bills are inaccessible, which is usually the case for new settlers, total electricity usage is derived from other information like the number of occupants, the number of bedrooms. A major problem of direct methods is that the estimation of total electricity use is inaccurate due to the ignorance of many other key factors affecting energy consumption, like the operation frequency of household appliances. Another drawback is that these tools fail in recommending pricing tariff. Customers have to select a particular tariff themselves and then can receive advices on plans attaching to the selected tariff.

Different from directly comparing costs of all plans, indirect methods recommend a customer electricity plans preferred by other customers with similar energy consuming patterns. In [14, 15], a target customer, which is the customer looking for recommendation, is firstly assigned to a predefined customer cluster according to some electricity consumption factors. This target customer is then advised of the plans found cost-effective to members of this cluster in prior. One drawback of these approaches is the lack of personalization. Customers assigned to the same cluster always receive same recommendation result. To achieve personalized recommendation, [16, 17] applied collaborative filtering recommender system (CFRS) in electricity plan selection process. In these works, once a target customer is classified into a cluster, the similarity between this customer and each member in the cluster is evaluated through comparing key energy consumption features. Based on the derived similarity values, the potential preference of the target customer for each plan is estimated and most preferred plans are recommended. The weakness of existing indirect plan recommendation methods is that they are over-optimistic about the abilities of residential customers in estimating abstract features of energy consumption, e.g. shape factors and monthly energy consumption in different season. Lacking accurate estimated energy consumption feature values, the suggestions given by these indirect plan recommendation methods are unreliable.

This paper proposed a smart electricity plan recommender system (EPRS) adapted from CFRS. As a fast-developing technique in machine learning area, the CFRS has been widely applied in e-commerce like Amazon and Netflix in recent years to make recommendations on commodities rich in historical transaction records, like books, movies and TV programs [18-23]. The CFRSs in e-commerce perform by deriving potential preferences of a customer on unpurchased goods from historical transaction data of this and other customers, according to the practical experience that similar users display similar preferences in purchasing activities. This experience is also shared by electricity customers, of who similar in electricity consumption pattern prefer same cost-effective retailing plans. Therefore, CFRS popular in e-commerce is also a promising method to issue personalized recommendation on electricity plans. However, unlike consumers of books or movies, an electricity customer tends to remain with a same retailer for a same electricity plan for a few years, thus has quite limited electricity plan transaction records. Therefore, when applying CFRS in electricity plan recommendation problem, similarity evaluation methods used in e-commerce CFRSs are no longer suitable.

In this paper, a tailored weighted similarity metric is proposed for EPRS to evaluate the similarity between two elec-

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tricity customers through comparing some easily obtainable electricity consumption features. Given derived similarity values, similar customers are retrieved as neighbours of the target customer seeking for suggestions. The potential preferences of the target customer to different plans are then derived from the preferences of the neighbours. Top-N favourite plans are recommended. The proposed EPRS effectively solves challenging issues suffered by existing electricity plan recommendation strategies and provides a reliable, accurate and convenient approach. This paper mainly contributes in the following aspects. (1) It frees customers from estimating abstract electricity consuming factors and thus improves the convenience and the accuracy of the recommendation task. Compared to the inaccessible inputs like peak-average ratio of the power use required by existing electricity plan recommendation strategies, the only input variable of the EPRS is the weekly operation duration of household appliance, the value of which can be easily and accurately estimated by residential customers. With the input values more accessible and accurate, the EPRS outperforms other strategies in the recommending accuracy. (2) The EPRS further improves the recommending accuracy largely through the application of CFRS with the weighted similarity metric. The similarity between any customer pair is effectively evaluated by the Jaccard-weighted Euclidean metric, based on which the EPRS issues highly customized recommendations. Unlike the same recommendations supplied by other strategies to users attributed in a same cluster, the customization enables the EPRS to serves more accurate recommendations. (3) The EPRS instructs customers in the selection of pricing tariffs, which benefits the popularization of flexible tariff and further helps to improve the competitive and healthy operation of electricity market. Unlike other strategies, the EPRS performs without tariff type selected in prior. Electricity plans with different tariffs are compared together, which provides customer a better understanding on the tariff type most suitable for them.

The rest of the paper is structured as follows. In Section II, the basic knowledge of the CFRS is briefly introduced. The proposed electricity plan recommender system is presented in Section III, followed by three case studies reported in Section IV. Section V concludes the paper.

II. Basic Knowledge of Collaborative Filtering Recommender System

A. Principle and Classification of Recommender System

Recommender systems can be generally modelled by a utility function $F^U: \boldsymbol{U} \times \boldsymbol{I} \rightarrow \boldsymbol{R}$, which presents the mapping from set $\boldsymbol{U}$ and $\boldsymbol{I}$ to set $\boldsymbol{R}$. The element of $\boldsymbol{U}$ is user, which is denoted by u and stands for a customer purchasing products. The element of $\boldsymbol{I}$ is item, which is denoted by i and stands for a product available to be recommended. To evaluate the preference of a user u to an item i, term *rating* is introduced and denoted by r_{ui}. $\boldsymbol{R}$ is the set of r_{ui} for all the possible u and i. Recommender system acts by using utility function F^U to predict potential ratings given by a user to all the candidate items. Items with higher ratings are recommended if a higher rating is supposed to indicate a strong preference.

Numerous strategies have been developed to achieve utility function F^U. An effective and widely-applied solution is collaborative filtering technique, which is divided into three classes, namely neighbourhood-based, model-based and hybrid method [21, 24-29]. To provide reliable recommendations to a user, a neighbourhood-based method first searches for neighbours, which are set of users with similar patterns as this user. Ratings of these neighbours are then applied to predict potential ratings given by this user to some item. Differently, the model-based method derives a user-item model from available rating data, which is then used for rating prediction. And hybrid collaborative filtering is a combination of neighbourhood-based and model-based approaches.

One innate difficulty for electricity plan recommendation is the low-frequency of plan consumption, i.e. residential customers tend to use same electricity plan for several years rather than changing plans frequently. In this case, it is impossible to collect rich ratings on a diversity of plans for customers seeking for recommendations, thus it is difficult to apply the model-based method. However, the neighbourhood-based collaborative filtering is still a promising solution to plan recommendation, thus it is used in this paper. A brief introduction to the neighbourhood-based method is provided in the following sections.

B. Similarity Evaluation and K-Nearest Neighbors

Neighbourhood-based collaborative filtering searches for neighbours of a user by evaluating the similarities between this user and other users. To derive the similarity of a user pair, features of two users are compared. For recommender systems in e-commerce, rating given by a user to an item is the typical feature for similarity evaluation. Table I lists some commonly used similarity metrics in the neighbourhood-based collaborative filtering algorithms [19].

TABLE I
Popular Similarity Metrics for Recommender Systems

Metric	Mathematical expression
Euclidean	$s_{mn} = 1 - \left\Vert \boldsymbol{r}_m - \boldsymbol{r}_n \right\Vert_2^*, \boldsymbol{r}_m = \{r_{mi}\}, \boldsymbol{r}_n = \{r_{ni}\}, i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n$
Cosine	$s_{mn} = \sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} r_{mi} r_{ni} \bigg/ \left(\sqrt{\sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} r_{mi}^2} \sqrt{\sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} r_{ni}^2} \right)$
Pearson	$s_{mn} = \sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} (r_{mi} - \bar{\boldsymbol{r}}_m)(r_{ni} - \bar{\boldsymbol{r}}_n) \bigg/ \left(\sqrt{\sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} (r_{mi} - \bar{\boldsymbol{r}}_m)^2} \sqrt{\sum_{i \in \boldsymbol{I}_m \cap \boldsymbol{I}_n} (r_{ni} - \bar{\boldsymbol{r}}_n)^2} \right)$
Jaccard	$s_{mn} = \lvert \boldsymbol{I}_m \cap \boldsymbol{I}_n \rvert / \lvert \boldsymbol{I}_m \cup \boldsymbol{I}_n \rvert$

In this table, subscripts m and n indicate users, and subscript i indicates item. Notation s_{mn} denotes similarity between user m and n. Notations r_{mi} and r_{ni} denote ratings on item i given by user m and n. Notations $\boldsymbol{r}_m$ and $\boldsymbol{r}_n$ denotes sets of ratings given by user m and n on items co-rated by these two users. Notation $\boldsymbol{I}_m$ and $\boldsymbol{I}_n$ denote set of items rated by user m and n. And superscript * indicates normalized value. Overline indicates mean value. Similarity values derived from the listed metrics range between 0 and 1. The users are ranked based on the similarity values. The users with first k largest similarity values to a user are defined as k-nearest neighbors of this user.

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C. Item Recommendation and Result Evaluation

Neighbourhood-based collaborative filtering predicts the potential ratings given by a customer based on rating data of k-nearest neighbors of this user. Let k-nearest neighbors of user m form a set $\boldsymbol{U}_m^k$. The potential rating given by user m to item i is predicted according to (1).

$$\hat{r}_{mi} = \sum\nolimits_{n\in \boldsymbol{U}_m^k} s_{mn} r_{ni} \Big/ \sum\nolimits_{n\in \boldsymbol{U}_m^k} s_{mn} \tag{1}$$

Hat symbol ^ in (1) stands for predicted value. In case higher rating indicating stronger preference of user on an item, items with higher predicted rating values are recommended to the user.

The performance of recommendation can be evaluated by a variety of metrics [30]. One popular metric is the root mean squared error (RMSE), which statistically measures the error between the predicted and the real rating of all the items. (2) presents the definition of RMSE of the recommendations to user m.

$$RMSE = \sqrt{\sum\nolimits_{i\in \boldsymbol{I}} \left(r_{mi} - \hat{r}_{mi}\right)^2 \Big/ \left|\boldsymbol{I}\right|} \tag{2}$$

The other metric is precision specially for top-N recommendation, which picks out the items with first N highest estimated ratings if higher rating indicates stronger preference. These N plans are recommended in no particular order. Let $\boldsymbol{I}_m^N$ and $\hat{\boldsymbol{I}}_m^N$ be the set of top-N items for user m in real situation and predicted by the recommender system. Precision of top-N recommendation is defined a percentage derived from (3).

$$Precision = \left|\hat{\boldsymbol{I}}_m^N \cap \boldsymbol{I}_m^N\right| \Big/ N \tag{3}$$

III. The Proposed Electricity Plan Recommender System

A. Principle of the EPRS

The proposed EPRS is a recommender system supplying personalized suggestions to residential customers in selecting most suitable electricity retailing plans. This system relies on neighbourhood-based collaborative filtering method with a specially designed similarity metric. In the EPRS, *item* denotes electricity retailing plan, and *user* denotes a residential customer. In this paper, notations $\boldsymbol{U}_{tr}$ and $\boldsymbol{U}_{te}$ denote the training and testing user sets. By simply supplying several easily obtainable features, testing users can obtain reliable plan recommendations from the EPRS.

The structure of the EPRS is depicted in Fig. 1. As can be seen, a dual-stage framework, offline data extraction stage and online recommendation stage, is proposed. *1) Offline data extraction stage:* Ratings and features of each training user are extracted from total usage and appliance usage data. Ratings of all training users form a training rating set, while features of these users form a training feature set. *2) Online recommendation stage:* A testing user supplies estimated features, based on which the similarity between this testing user and every training user is evaluated. According to the derived similarity values and training rating set, the potential ratings given by the testing user is predicted. Cost-effective plans can then be determined for recommendation according to predicted ratings.

The following parts explain the details on each stage. The evaluation metric of recommendation accuracy is introduced in the last of this section.

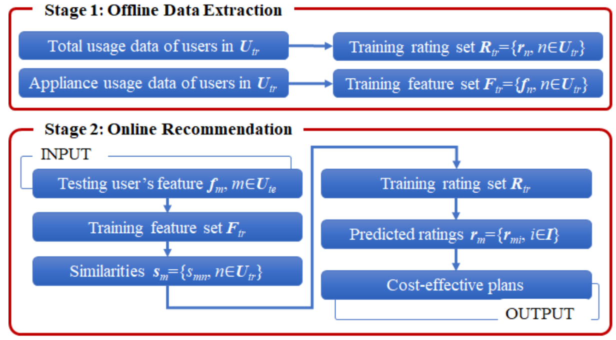

Fig. 1. Dual-stage framework for the EPRS.

B. Data Extraction

Training users contributes two datasets to the EPRS, namely training rating set and feature set. These two sets can be extracted from the power usage records of training users.

1) Training rating set extraction

Recommender systems use rating to quantify the preference of a user on an item. Since residential user's preference is highly related to the plan charge, the EPRS defines rating as the normalized price charged by a plan on a user. Let c_{ni} be the charge of plan i on user n and $\boldsymbol{c}_n$ be the vector formed by c_{ni} for all the plan i. The definition of rating r_{ni} can be presented in (4)

$$r_{ni} = \left(c_{ni} - \max\left[\boldsymbol{c}_n\right]\right) \Big/ \left(\max\left[\boldsymbol{c}_n\right] - \min\left[\boldsymbol{c}_n\right]\right) \tag{4}$$

According to (4), the lower a plan charging on the user, the lower a rating given by the user to the plan. Considering the general preference of residential customers on lower charged electricity plans, it is safe to infer that a user prefers lower rating-plans than higher rating-plans. The objective of the proposed EPRS is estimating the rating of each plan and introducing lower rating-plans to the customers.

Plan charge c_{ni} can be easily derived from the total usage record of user n and the charging rates of plan i. Total usage record is a time-series recording the electricity consumptions of a whole house.

2) Training feature set extraction

Ideally, electricity users can calculate charges of all the plans once their total usage records are available, and further search for cheaper plans by themselves. Regrettably, total usage records are not accessible in many cases, e.g. no smart meter is installed, or users cannot get access to meter data. The EPRS waives the requirement on total usage records in plan recommendation task by introducing extra features. A feature is required to represent user's electricity consuming habit, as well as to be easily obtained by users and not expose too much private information. In the EPRS, appliance weekly operation duration is set as a feature, which measures how long a household appliance is used each week on average. Compared to abstract factors like the ratio between maximum power and daily average power used in other electricity plan recommendation methods [14-17], the estimation on number of hours an appliance being used each week is much easier and tend to be

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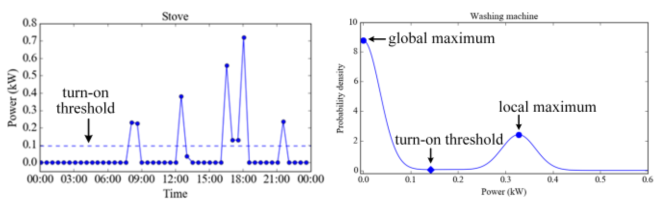
more accurate. Also, weekly operation duration of appliance is less sensitive than detailed power records thus is helpful to private protection.

The weekly operation duration of an appliance can be extracted from appliance usage record, which is a time-series recording the electricity consumed by the appliance. Fig. 2(a) shows an example of the appliance usage record during a day. As can be seen in this figure, appliance operation duration is the total time when the appliance power exceeds a turn-on threshold, which is depicted as the dashed line in Fig. 2(a). To extract the operation duration time of an appliance, it is crucial to select a suitable turn-on threshold. In many previous studies, this threshold is generally set as a constant value for all types of household appliances [31], which fails to consider two facts: turn-on threshold varies with appliance types and appliance usage records contain noises with different magnitudes. In this paper, a constant turn-on threshold is set for continuous-on appliances like refrigerator and multiple-mode appliances like desktop computer. A probability density function (PDF)-based approach is introduced to set turn-on thresholds for occasional-on appliances, like dishwasher and washing machine. For appliances occasionally used, its PDF of power shows a global maximum around 0W and a local maximum around the typical operating power, as indicated in Fig. 2(b). In this case, the turn-on threshold is set to be the power value of local minimum between the two maxima, which is marked in Fig. 2(b).



(a) (b)

Fig. 2. (a) Appliance usage record during a day and turn-on threshold of this appliance (b) PDF of occasional-on appliances.

The approximation of PDF of appliance power is achieved by kernel density estimation (KDE) method, which provides a much smoother estimation than histogram approaches [32]. Let $\boldsymbol{P}$ be a series of appliance usage records. Each element P_l in $\boldsymbol{P}$ is treated as a sample of a random variable p. Here p stands for the power usage of appliance. KDE supplies the estimation on PDF of p through (5).

$$f_p(p) \approx \frac{1}{|\boldsymbol{P}|h} \sum_{P_l \in \boldsymbol{P}} F^K\left(\frac{p-P_l}{h}\right) \tag{5}$$

In (5), F^K is kernel and can be any non-negative-zero-mean function integrating to one. Gaussian function is set to be the kernel in this paper. Coefficient h is bandwidth, the value of which is selected by Scott's rule [33].

C. Similarity Evaluation

Similarity quantifies how similar of two energy consuming patterns. In this paper, similarity between two users is derived by comparing their features, i.e. appliance weekly operation durations. However, it is very common that some features are missing of different electricity users. For instance, when the power usage of an appliance is not recorded, the weekly operation duration of this appliance is not available and thus this feature is missing. These missing features causes some similarity metrics listed in Table I ineffective. To conquer this difficulty, a novel similarity metric is specially defined as in (6).

$$s_{mn} = s_{mn}^{J} s_{mn}^{\omega E} \tag{6}$$

As indicated in (6), the new metric is a hybrid of Jaccard similarity s^J and weighted Euclidean similarity $s^{\omega E}$. For convenience, metric defined in (6) is named as Jaccard-weighted Euclidean (J-wEUC) metric. Let $\boldsymbol{A}_m$ and $\boldsymbol{A}_n$ denote the set of household appliances whose operation duration is accessible to user m and n. Based on these notations, Jaccard similarity between user m and n is defined in (7).

$$s_{mn}^{J} = |\boldsymbol{A}_m \cap \boldsymbol{A}_n| / |\boldsymbol{A}_m \cup \boldsymbol{A}_n| \tag{7}$$

Let $\boldsymbol{A}$ be the set of all the appliances. The element of $\boldsymbol{A}$ is denoted as a. Let f_{ma}, f_{na} be the normalized weekly operation duration of appliance a used by user m and n. Based on these notations, weighted Euclidean similarity is defined in (8).

$$s_{mn}^{\omega E} = 1 - \sqrt{\left(\sum_{a \in \boldsymbol{A}_m \cap \boldsymbol{A}_n} |\boldsymbol{A}| \omega_a \left(f_{ma} - f_{na}\right)^2\right) \Big/ |\boldsymbol{A}_m \cap \boldsymbol{A}_n|} \tag{8}$$

Here, ω_a is called appliance confidential weight, quantifying the phenomenon that the operations of different household appliances influence the total electricity usage and further influence the plan recommendation results in different degrees. For some household appliances, the plan recommendation result would change a lot if their operation durations change, while for others, the plan recommendation results only slightly change if their operation durations change. In case all the appliances have a same confidential weight value, (8) is converted to traditional Euclidean similarity metric listed in Table I.

The confidential weight is derived in the following steps. All the users in training user set $\boldsymbol{U}_{tr}$ are firstly clustered into Q groups according to their rating values derived by (4). The q-th cluster is denoted by $\boldsymbol{U}_{tr(q)}$. Different subsets $\boldsymbol{U}_{tr(q)\text{-}a}$ can then be extracted from $\boldsymbol{U}_{tr(q)}$ for different appliance a. The element of $\boldsymbol{U}_{tr(q)\text{-}a}$ is user n in cluster $\boldsymbol{U}_{tr(q)}$ able to supply a valid operation duration value f_{na} to appliance a. Let $\boldsymbol{f}_{a(q)}$ be the set collecting f_{na} for all the user n in $\boldsymbol{U}_{tr(q)\text{-}a}$. The centre of $\boldsymbol{f}_{a(q)}$ is denoted by $c_{a(q)}$ and $c_{a(q)}$ for all the possible q form the set $\boldsymbol{c}_a$. Based on these notations, a variant cluster dispersion indicator (CDI) of each appliance a is calculated using (9).

$$\omega_a^{VCDI} = F^D(\boldsymbol{c}_a) \Big/ \sqrt{\sum_{q=1}^{Q} F^D\left(\boldsymbol{f}_{a(q)}\right) \Big/ Q} \tag{9}$$

in which, notation F^D is intra-set distance operation symbol. For any set $\boldsymbol{v}$, its intra-set distance can be calculated as (9).

$$F^D(\boldsymbol{v}) = \sqrt{\frac{1}{2|\boldsymbol{v}|} \sum_{i=1}^{|\boldsymbol{v}|} \sum_{j=1}^{|\boldsymbol{v}|} \left(v_i - v_j\right)^2} \tag{10}$$

Once ω_a^{VCDI} for all the appliances a are obtained from (10), the confidential weight for each appliance a is derived next

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using (11) and (12).

$$\omega'_a = \left(1-\omega_{\min}\right)\frac{\omega_a^{VCDI} - \min_{a\in\boldsymbol{A}}\left[\omega_a^{VCDI}\right]}{\max_{a\in\boldsymbol{A}}\left[\omega_a^{VCDI}\right] - \min_{a\in\boldsymbol{A}}\left[\omega_a^{VCDI}\right]} + \omega_{\min} \quad (11)$$

$$\omega_a = \omega'_a \Big/ \sum_{a\in\boldsymbol{A}} \omega'_a \quad (12)$$

Coefficient ω_{min} in (11) is called minimum confidential weight and is manually set between 0 and 1. When ω_{min} equals to 1, all the appliances have the same confidential weight and the weighted Euclidean similarity metric in (8) is equivalent to traditional Euclidean similarity in Table I. The optimal value of ω_{min} is selected as the one corresponds to the minimum RMSE of the recommendation results.

The derivation of ω_a defined in (9)-(11) is similar to feature selection technique and measures the correlation between the weekly operation duration of each appliance and the customers clusters in terms of plan ratings. Appliances strongly correlated to the clustering result come with larger variant CDI value. Clustering operation on users is achieved by hierarchical clustering algorithm in this paper. This method treats each user as its own cluster at first. For each cluster, a typical rating set is derived. Clusters are then successively merged together according the typical rating set [34]. The optimal amounts of clusters corresponds the elbow point of *CDI-Q* curves, in which CDI is cluster dispersion indicator measuring the clustering effectiveness.

D. Rating Prediction, Plan Recommendation and Evaluation

The ERPS applies the neighbourhood-based collaborative filtering method to predict potential ratings given by a testing user to each plan and to find cost-effective plans for recommendation. Based on the similarity metric in (6), the EPRS calculates the similarity between a testing user and each training user and selects training users with first k largest similarities as the k-nearest neighbors of the testing user. The potential rating given by the testing user to a plan can then be estimated based on rating data of these k-nearest neighbors using (1). According to the defination of rating in (4), a lower rating indicates a lower plan charge, thus a stronger preference of electricity user on the plan. In this case, plans with lower estimated ratings are recommended to the testing user in prior. In practical application, top-N mechanism, in which the first N lowest rated plans are recommended, is a wise selection. Top-N recommendation better satisfies customers' requirement in making their own choices among all the recommended candidates according to personal preferences on other factors like retailer fame and service quality.

To evaluate the recommendation result, the RMSE metric defined in (2) is used to statistically compare the true and estimated value of ratings of all the plans. The precision metric defined in (3) is applied to evaluate top-N recommendation. A lower RMSE or a higher precision indicates a more accurate recommendation result on electricity plan.

E. Differences between EPRS and CFRSs in E-commerce

Although developed from neighbourhood-based CFRSs, the EPRS distinguished itself from other recommender systems in e-commerce in two aspects. First, the similarity evaluation methods are different. The similarity between two customers is evaluated by comparing their preferences on co-rated goods in e-commerce while by comparing weekly operation durations of household appliances in EPRS. This difference is caused by the severe shortage of rating data given to electricity plans by electricity customers. Second, the preference evaluation methods are different. In e-commerce, multiple factors influence the final rating to a commodity given by a customer. In EPRS, the rating is assumed only related to relative price of a plan.

IV. Case Studies

In this part, the results of three numerical tests are presented to evaluate the recommendation accuracy of the EPRS. In case study 1 and 2, the EPRS carries out recommendation on electricity plans following the same tariff, i.e. single-rate (SG) tariff in first test and time-of-use (TOU) tariff in second test. In case study 3, the EPRS makes recommendation on a combination of both the SG and TOU electricity plans.

A. Dataset Description

The testing data is divided into two parts, user and item data. User data comes from Smart Grid Smart City (SGSC) project, which is a smart grid project gathering smart meter data for 13,735 residential customers in New South Wales, Australia during 2010 and 2014 [35]. From the SGSC dataset, 730 customers are selected for the numerical tests. These customers satisfy two requirements. First, they can provide total power usage records for a certain period (30 days in this paper). Second, they can supply meter readings for at least four commonly applied household appliances during the same period. Totally, 10 appliances are considered in the tests, namely microwave (Micro), oven, stove, dishwasher (Dish), washing machine (Wash), cloth dryer (Dryer), television (TV), computer (CPU), air conditioner (AC) and hot water system (Water).

Item data in the tests is extracted from 62 electricity plans released by 15 local retailers in the middle of 2017 for residential customers in New South Wales. Among all the plans, half of them use SG tariff, which is a kind of fixed electricity pricing. The other half use TOU tariff, which is a representation of flexible pricing in Australia.

B. Set Up

Before the tests, ratings and features for all the 735 customers are extracted beforehand from their smart meter readings. These customers are then randomly and evenly divided into five groups for the sake of 5-fold cross validation, i.e. there are 147 testing users and 588 training users in each fold.

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The process of numerical test entails two steps. The first step is coefficient setting. In this step, coefficient k for k-nearest neighbours is set to be an integer between 1 and the size of training group $|\boldsymbol{U}_{tr}|$. The other coefficient, minimum confidential weight ω_{min}, is set to be a number between 0 and 1. With ω_{min} known, appliance weight ω_a for each appliance a is extracted from the data of training group. A trial-and-error approach is applied in this step to exact the optimal value of k and ω_{min}. It should be noticed that different values could be set as k and ω_a in different test cases. The pseudocode for this step is presented below.

Step 1: Coefficient setting for each fold

Input: Training rating set $\boldsymbol{R}_{tr}$ and training feature set $\boldsymbol{F}_{tr}$; true rating values r_{mi} for all the testing user m and all the plan i; features f_{ma} for all the testing user m and all the household appliance a.

1. For ω_{min} in [0,1]:
   1) Cluster training users in set $\boldsymbol{U}_{tr}$ into Q groups according to ratings of each user in training rating set $\boldsymbol{R}_{tr}$.
   2) Extract ω_a of all the appliances a from $\boldsymbol{F}_{tr}$ using (9)-(12).
   3) For user m in testing user set $\boldsymbol{U}_{te}$:
      Calculate similarity s_{mn} for all the user n in training user set $\boldsymbol{U}_{tr}$ using (6).
   4) For k in [1, $|\boldsymbol{U}_{tr}|$]:
      a) For user m in testing user set $\boldsymbol{U}_{te}$:
         i. Find k-nearest neighbors $\boldsymbol{U}_m^k$.
         ii. Estimate rating $\hat{r}_{mi}$ given by user m to all the plan i using (1).
         iii. Calculate RMSE between $\boldsymbol{r}_m$ and $\hat{\boldsymbol{r}}_m$ using (2).
      b) Calculate average and maximum value of RMSEs for the recommendation results to all the user m in testing user set $\boldsymbol{U}_{te}$.
   5) Plot maximum RMSE-k curve, average RMSE-k curve.
2. Set the value of k according to maximum RMSE-k curves and average RMSE-k curves.
3. Plot average RMSE-$\omega_{\min}$ curve based on the selected value of k.
4. Set the value of $\omega_{\min}$ according to the average RMSE-$\omega_{\min}$ curve.
5. Calculate ω_a for all the appliances by substituting $\omega_{\min}$ into (11).

Output: coefficient k, ω_{min} and ω_a

The second step is formed by plan recommendation and result evaluation. In this step, the EPRS estimates the potential ratings to all the plans given by each testing users according to the rating and feature data of training users. The difference between real and predicted ratings of a testing user is quantified by RMSE metric. In order to get a comprehensive evaluation,

Step 2: Plan recommendation and result evaluation for each fold

Input: Training rating set $\boldsymbol{R}_{tr}$ and training feature set $\boldsymbol{F}_{tr}$; true rating values r_{mi} for all the testing user m and all the plan i; features f_{ma} for all the testing user m and all the household appliance a.1. For u_{te} in $\boldsymbol{U}_{te}$:
   1) Calculate similarity s_{mn} for all the user n in training user set $\boldsymbol{U}_{tr}$ using (6).
   2) Find k-nearest neighbors $\boldsymbol{U}_m^k$.
   3) Estimate rating $\hat{r}_{mi}$ given by user m to all the plan i using (1).
   4) Calculate RMSE between $\boldsymbol{r}_m$ and $\hat{\boldsymbol{r}}_m$ using (2).
   5) Given different N, calculate precision based on $\boldsymbol{I}_m^N$ and $\hat{\boldsymbol{I}}_m^N$ using (3).
2. Calculate the average value of RMSE and precision of recommendations to the user m in testing user set $\boldsymbol{U}_{te}$.

Output: $\hat{\boldsymbol{r}}_m$ for all testing user m; average RMSE; average precision

both the average and maximum value of RMSEs for all the testing users are calculated. The pseudocode for the second step is showed below.

In each testing case, the recommendation result received by the EPRS is compared to the results achieved by other four strategies different in similarity metrics. Metrics for comparison are Euclidean (EUC), Cosine (COS), Jaccard-Euclidean (J-EUC, the multiplication of Jaccard and Euclidean similairity) and Jaccard-Cosine (J-COS, the multiplication of Jaccard and Cosine similairity). The performance of equal-similarity strategy, in which all the training users have the equal similarity with the testing user, is also tested and set as the base value for comparison.

C. Test Results and Discussion

1) Coefficient setting

a) Coefficients for SG plan recommendation

Two coefficients of the EPRS, the number of nearest neighbours k and minimum appliance weight ω_{min}, are set for SG plan recommendation test and Fig. 3 presents the setting process. In first two subfigures, Fig. 3(a) and (b), the relationships between average RMSE and k, as well as between maximum RMSE and k, are depicted in curves in cases of different ω_{min} values between 0 and 1. The mini-figrues display part of the curves when k is no larger than 20. As can be seen in these subfigures, when ω_{min} is set differently, neither average RMSE-k nor maximum RMSE-k curve changes obviously. According to this observation, it is safe to set coefficient k independently of coefficient ω_{min}. Considering notches shown in both Fig. 3(a) and (b), k is set to be 5 for SG plan recommendation to ensure lower values for both average and maximum RMSE. Fig. 3(c) presents the relationship between average RMSE and ω_{min} when k equals to 5. Based on this figure, ω_{min} is set to be 0.6 in this testing case, which responds to the minimum point of average RMSE-ω_{min} curve. With the selected ω_{min}, appliance confidential weights ω_a are further derived by substituting ω_{min} into (10) and the results are listed in Fig. 3(d). As can be seen, stove, computer and hot water system have first three largest confidential weights. This accurately indicates deeper influences of these three household appliances on the total electricity usage in the house.

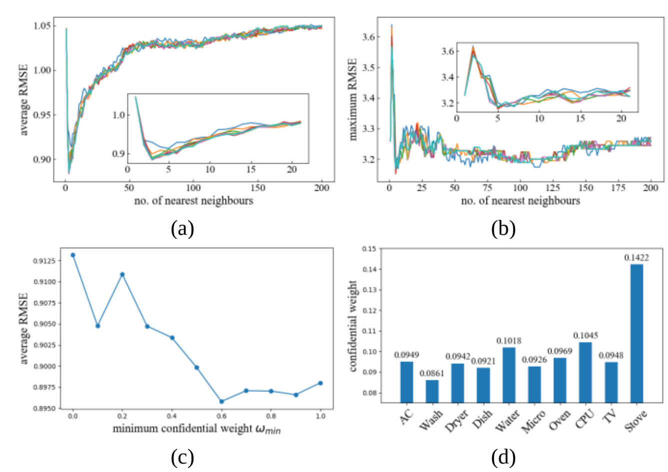

Fig. 3. Coefficient setting for SG plan recommendation test (a) average RMSE-k curves under different ω_{min} values between 0 and 1 (b) maximum RMSE-k curves under different ω_{min} values between 0 and 1 (c) average-RMSE-ω_{min} curves when k is 5 (d) confidential weights for 10 household appliances when ω_{min} is 0.6.

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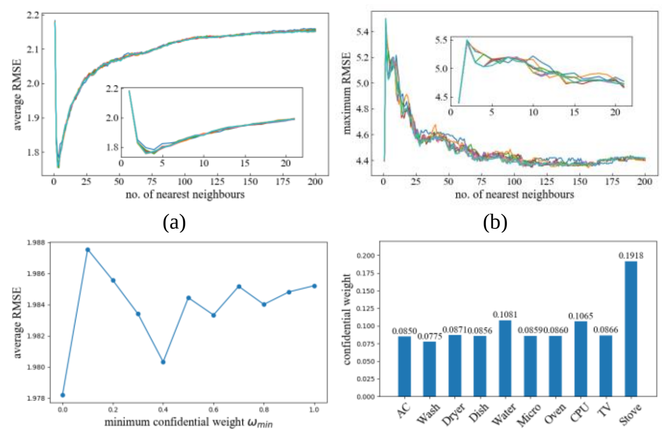
b) Coefficients for TOU Plan Recommendation

Fig. 4 presents the coefficient setting process for TOU plan recommendation test. In Fig. 4(a) and (b), the relationship between average RMSE and k as well as between maximum RMSE and k curves in case of different ω_{min} is depicted in curves. Same as the SG testing case, these two subfigures also reveal the independence of k from ω_{min}. Therefore, k is set regardless of ω_{min}. Like the Fig. 3(a), a notch appears in Fig. 4(a) when k is around 4, thus 4 is a promising choice for k to ensure a lower average RMSE. However, maximum RMSE is quite high when k is around 4. Noticed the sharp decrease in maximum RMSE when k increases to 25, k is set to be 20 for TOU plan recommendation. In this case, both average and maximax RMSE have lower values. Fig. 4(c) plots the relationship between average RMSE and ω_{min} curve when k equals to 20. Two lowest average RMSE values appear when ω_{min} equals to 0 and 0.4. Since average RMSE increases sharply when ω_{min} increases from 0 and 0.1, 0 is not a suitable choice for ω_{min}. Therefore, ω_{min} is set to be 0.4 for TOU plan recommendation. Fig. 4(d) lists all the appliance confidential weights ω_a in case ω_{min} is 0.4. Appliances with first three largest weights are stove, hot water system and computer, which indicates the operation feature of these three appliances largely affect TOU plan recommendation result.



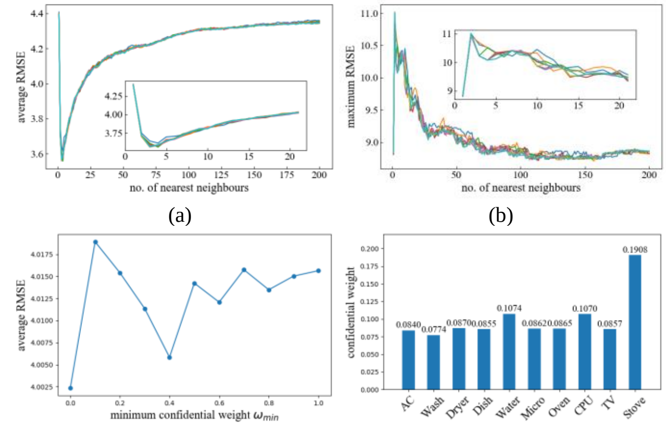
(a) (b)

(c) (d)

Fig. 4. Coefficient setting result for TOU plan recommendation test (a) average RMSE-k curves under different ω_{min} values between 0 and 1 (b) maximum RMSE-k curves under different ω_{min} values between 0 and 1 (c) average-RMSE-ω_{min} curves when k is 20 (d) confidential weights for 10 household appliances when ω_{min} is 0.4.

c) Coefficients for TOU and SG Plan Recommendation

Fig. 5 presents the coefficient setting process for combined TOU and SG plan recommendation test. As showed in Fig. 5(a) and (b), average RMSE-k curves and maximum RMSE-k curves almost shows no difference when different ω_{min} are applied. The value of k is set to be 20, independent of ω_{min}. Once k is set, minimum confidential weight ω_{min} is then selected to be 0.4 according to average RMSE-ω_{min} curve given in Fig. 5(c). Appliance weights ω_a are then derived and listed in Fig. 5(d). Same to the first two testing cases, appliances with three highest weights in this test are stove, hot water system and computer. It is reasonable since stove and hot water system in most families in Australia have higher ratings. For the larger confidential weight of computer, one promising explanation is that the longer operation duration of computer indicates a longer home-stay time and the more possible other household appliances used during this time.



(a) (b)

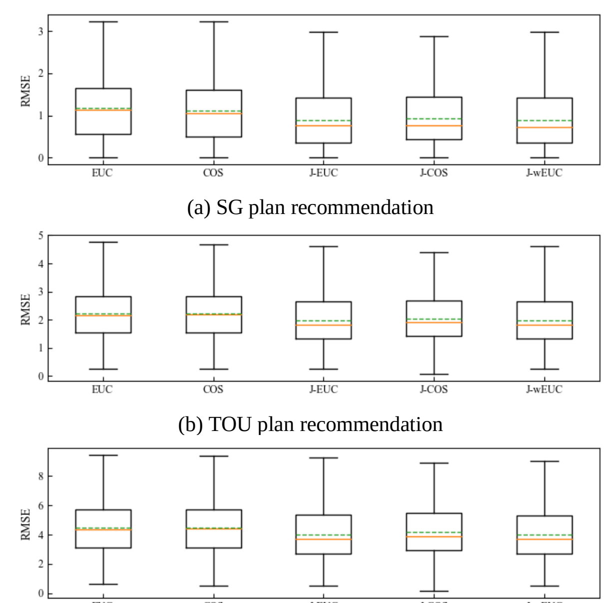
(c) (d)

Fig. 5. Coefficient setting result for SG and TOU plan recommendation test (a) average RMSE-k curves under different ω_{min} values between 0 and 1 (b) maximum RMSE-k curves under different ω_{min} values between 0 and 1 (c) average-RMSE-ω_{min} curves when k is 20 (d) confidential weights for 10 household appliances when ω_{min} is 0.4.

2) *Recommendation results for all the tests*

a) Effectiveness of the EPRS

Fig. 6 presents the statistical features of RMSE of plan recommendation results received when different similarity metrics applied. The yellow solid line and green dashed line indicate the median and the average value of RMSEs. To facilitate the comparison, the exact average RMSE values are listed in Table II. The average RMSE received by equal-similarity strategy, in which all the training users have the equal similarity with the testing user, is also presented in Table II.



(a) SG plan recommendation

(b) TOU plan recommendation

(c) Combined TOU and SG plan recommendation

Fig. 6. The influence of similarity metric on RMSE in three testing cases (a) SG plan recommendation (b) TOU plan recommendation (c) TOU and SG plan recommendation.

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TABLE II
AVERAGE RMSE RECEIVED BY EPRS (WITH J-WEUC) AND OTHER RECOMMENDATION STRATEGIES IN THREE NUMERICAL TESTS*

Similarity metric	SG	TOU	TOU and SG
EUC	1.1818	2.2064	4.4537
COS	1.1245	2.2054	4.4525
J-EUC	0.8980	1.9852	4.0156
J-COS	0.9453	2.0418	4.1781
J-wEUC**	0.8958	1.9803	4.0059
Equal-similarity	1.3083	2.4439	4.7544

**k* equals to 5, 20, 20 for SG, TOU, TOU and SG recommendation test
**ω_{min} equals to 0.4, 0.6, 0.6 for SG, TOU, TOU and SG recommendation test

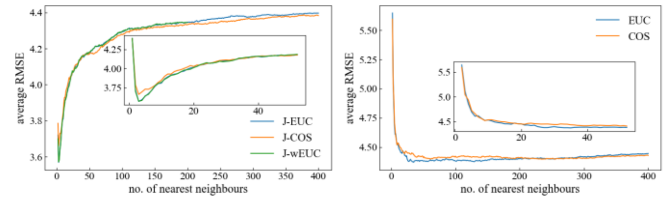
Through comparing three subfigrues in Fig. 6, it can be noticed that no matter which similarity metric is applied, recommendations for SG tariff-based plans always have the lowest errors, while for TOU tariff-based plans have higher errors and for TOU and SG tariff-based plans have highest errors. The difficulty in recommending combined TOU and SG plans is caused by two factors. Firstly, recommendation candidates contain TOU plans, in which charging rate is time-varied other than fixed. Therefore, features in addition to appliance weekly operation duration are required for a reliable recommendation. Secondly, more plans attend in TOU and SG plan recommendation test than other two tests. With more recommendation candidates, it is fair for a lower accuracy received.

In spite of abovementioned difficulties, collaborative filtering-based strategies with different similarity metrics still outperform the equal-similarity strategy in all three tests, as showed in Table II. This verifies that by considering the variation in the similarities between different user pairs, the collaborative filtering-based methods can improve the accuracy of electricity plan recommendation.

The accuracy can be further improved by applying more efficient similarity metric. Fig. 6 compares the recommendation effects of five different similarity metrics, from which two conclusions can be drawn. Firstly, Jaccard-based metrics (J-EUC, J-COS and J-wEUC) serves better recommendations than non-Jaccard-based metrics (EUC and COS). Secondly, J-wEUC metric outperforms other two Jaccard-based metrics (J-EUC and J-COS) in plan recommendation. According to the definition of J-wEUC in (6)-(8), the high efficiency of J-wEUC is attributed to the confidential weight integrated into the Euclidean similar metric. Benefited from J-wEUC, the EPRS is able to provide recommendation service with higher accuracy than other strategies.

b) Influence of Jaccard Metric

Fig. 7 presents average RMSE-*k* curves received in combined TOU and SG plan recommendation test when different similarity metrics applied. The advantage of Jaccard-based metrics (J-EUC, J-COS and J-wEUC) in recommending accuracy is obvious in this figure. The other phenomenon is that when Jaccard-based metrics applied, fewer nearest neighbours (a smaller *k*) are required to ensure a lower error. Oppositely, a larger *k* is necessary for a lower error if non-Jaccard-based metrics applied. The same observation can be found in plan recommendation tests for SG plans alone or TOU plans alone, the results of which are not presented here due to the space limitation. Since it is computational effective for rating estimation operation in (1) with fewer nearest neighbours, the introduction of Jaccard metric in similarity evaluation improves the response speed of plan recommender system. Therefore, EPRS applies Jaccard metric in similarity evaluation for a better performance and introduces confidential weights to make a further improvement.

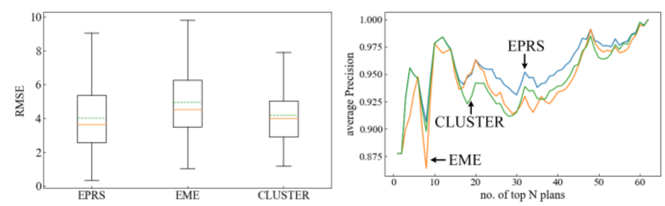


(a) (b)

Fig. 7. Relationships between average RMSE and *k* derived in TOU and SG plan recommendation test when different similarity metrics applied (a) Jaccard-based metrics: J-EUC, J-COS, J-wEUC. ω_{min} is 0.4 in case of J-wEUC (b) non-Jaccard-based metrics: EUC, COS.

c) Comparison to current methods

The EPRS is compared to the method applied in Energy Made Easy (EME) [10] and the strategy developed in a cluster-based recommender system (CLUSTER) [15] in terms of recommendation performances. 80 customers in a same localised zone are selected for this test. For concision of this paper, only the results of TOU and SG plan recommendation test are presented. As indicated in both Fig. 8(a) and (b), EPRS outperforms other two methods when evaluated by both RMSE and precision metrics. Besides, according to the relationship between precision and the number of top-N plans given in Fig. 8(b), with the increase of *N*, the precision also rises in a fluctuated way.



(a) (b)

Fig. 8. Performances of EPRS, EME and CLUSTER method in TOU and SG plan recommendation test (a) RMSE: ω_{min} is 0.6 and *k* is 20 in case of EPRS (b) The relationship between the number of top-N plans and average precision.

D. Further discussions

1) Recommendations on tariff type selection

The result of combined SG and TOU plan recommendation test indicates that the EPRS helps to popularize TOU tariff among electricity retailing market. Unlike tradition online platforms which only make recommendations for plans based on the same tariff, the proposed EPRS compares the predicted ratings of all the plans regardless of the tariff type each plan follows. Customers receive predicted rating of each plan from the EPRS and thus are clear about how many TOU plans come in top-rating ones. In this paper, a customer is defined more suitable to TOU tariff when more than half of the 10 cheapest plans for this customer follow TOU tariff. According to the true rating data, averagely 22 out of 147 testing users in each cross-validation fold are suitable for TOU. According to the

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predicted rating data given by the EPRS in SG and TOU plan recommendation test, averagely 19 out of 147 testing users in each fold are suitable for TOU, which is quite close to the real ratio. Inspired by the EPRS, these 19 testing customers are more possible to select TOU plans other than SG plans. With more customers of TOU tariff, it become easier for peak shaving and valley filling in power system, which helps to improve the stability of the system as well as the competitive operation of the electricity market.

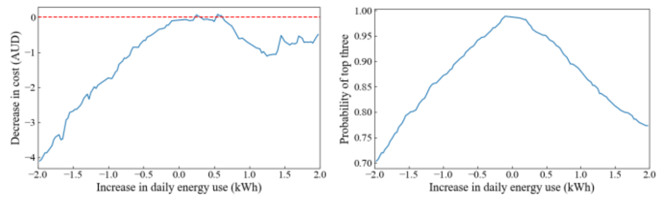
2) Term of Validity

Compared to the orders of DR strategies updated at high frequencies like 5min [2, 4] or 1 hour [3], the recommendations made by the EPRS have longer terms of validity, which are generally half to two years or even longer. In the EPRS, the electricity plans evaluated are released in form of hedge contract, which locks electricity prices for a specified time (generally half to two years in Australia [9]) no matter the significant price volatility in the spot market. Customers are required to set their favourite contract period in prior, based on which the EPRS compares all the electricity plans with the given contact period. Since all the plans have locked their prices for the same period, the recommendations of the EPRS are valid in this period.

The long validity of the recommendations of the EPRS also appears when customers change their electricity consuming habits due to factors like new appliances purchased. Based on the new consuming habits, the recommendations issued by the EPRS may be different from the previous ones. However, switching to a cheaper plan according to the new recommendations is very likely not profitable since the energy cost saved usually cannot cover extra changes for plan switching service. This phenomenon is verified through a simple test on 735 customers in SGSC dataset and 31 single-rate plans. The increase of daily electricity use for each customer ranges from -2kWh to 2kWh. The EPRS made recommendations for these customers in two rounds, namely before and after the daily electricity use changes. Customers are supposed to always select the cheapest plan in each round. The charges for switching plans is 22.66 dollars [36]. Fig. 9(a) presents the average decrease in electricity cost through switching plan. According to this figure, the average decrease in the cost is negative (which means the cost increases) for most cases except when daily electricity use increases with 0.3kWh and 0.6kWh. Fig. 9(b) depicts the probability of the cheapest plan in the first recommendation round remaining in the top three cheapest in the second round, which indicates that the original plans recommended by the EPRS are still cost-effective when the daily electricity use changes.

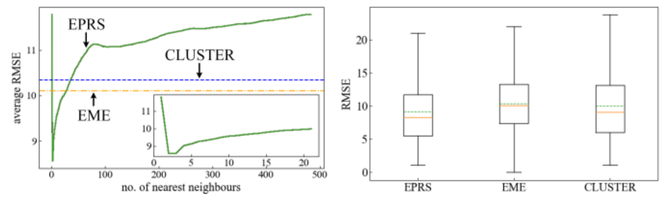
3) Effectiveness on other databases

The inputs of the EPRS are household appliances' weekly operation durations, which are expected to be the statistical means over a year to eliminate the influence of season. This period was shortened to one month in previous case studies due to the shortage of records in SGSC dataset. To make up the difficulty of availability of data in SGSC, the performance of EPRS was also tested on another dataset name Dataport [37] and compared to the performances of EME [10] and CLUSTER [15]. Fig. 10 evaluates the recommendations for 736 residential customers in Texas from Dataport dataset on 96 SG plans. The appliance weekly operation duration of each customer is derived from the smart meter records for a whole year. As indicated in Fig. 10(a), the relationship between average RMSE and the number of nearest neighbours k displayed in this test is similar to the ones showed in case studies on SGSC dataset. As indicated in Fig. 10(b), EPRS outperformed other two methods with respect to the recommendation accuracy.



(a) (b)

Fig. 9. (a) The average decrease in cost when switch from the cheapest plan in first recommendation round to the cheapest plan in second round (b) The average probability the cheapest plan in the first round remains in the top 3 cheapest plans in the second round.



(a) (b)

Fig. 10. Performances of EPRS, EME and CLUSTER method in SG plan recommendation test for customers in Dataport dataset (a) The relationships between average RMSE and the number of nearest neigbours (b) Statistics for RMSE when the number of nearest neigbours is 5.

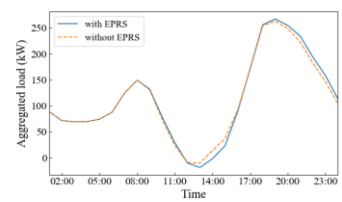


Fig. 11. The aggregated DLP of 200 residential customers after optimization.

4) Influence on aggregated load

The influence of the EPRS on aggregated load demand is briefly investigated by a test on 200 residential customers collected in the SGSC dataset from the same district. Each customer equips with 2kW solar panel and 5.7kWh energy storage system (ESS). 31 TOU plans are available for selection. According to the past power records and the selected plan for each customer, the electricity expenditure is minimized through the optimization strategy developed by [38]. The optimization was carried in two scenarios. Each customer selects the cheapest plan recommended by the EPRS in first scenario (with EPRS) while randomly selects a plan in second scenario (without EPRS). The aggregated daily load profile (DLP) of these 200 customers after optimization is presented in Fig. 11. As can be seen, aggregated DLPs in two scenarios are same in the shape but slightly different in lowest and highest peaks.

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V. Conclusions

This paper investigates the application of recommender system, a fast-developing technique in machine learning, into the task of recommending electricity plans for individual residential customers. An electricity plan recommender system is proposed based on collaborative filtering algorithm. The EPRS conquers three shortcomings in current electricity plan recommendation strategies. Firstly, the EPRS frees users from supplying abstract and detailed electricity usage records by requiring other easily obtainable features instead. Secondly, the accuracy is obviously improved by the newly developed metric. Thirdly, customers of the EPRS are advertised with predicted ratings of different plans, based on which customers are able to select most suitable plans with proper tariff. Our test cases confirm that the EPRS generally outperforms other strategies in different plan recommendation tasks. Lower RMSE and higher precision of the recommendation results ensure a better electricity expenditure reduction ability for customers. The introduction of appliance confidential weight into weighted Jaccard-Euclidean metric works well on the missing feature problem and supplies reliable evaluation on similarity between users. The tariff recommendation ability is also verifeid effective and expected to facilitate the widespread of flexible pricing tariff. Further research will polish the EPRS in the aspects of recommendation accuracy and calculation speed. Specifically, novel metric and mega data will be investigated to better measuring similarity. Fast nearest neighbours detecting skill will be introduced. On the other hand, a comprehensive study on the influences of plan recommendation on the retailing market policy, on demand response techniques as well as on the aggregate load demand will be taken.

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