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# Explainable Multi-Agent Recommendation System for Energy-Efficient Decision Support in Smart Homes

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## Abstract

Understandable and persuasive recommendations support the electricity consumers' behavioral change to tackle the energy efficiency problem. This paper proposes an explainable multi-agent recommendation system for load shifting for the household appliances. First, we provide agents with enhanced predictive capacity by including weather data, applying state-of-the-art models and tuning the hyperparameters. Second, we suggest an Explainability Agent providing transparent recommendations. Third, we discuss the potential impact of the suggested approach.

## 1 Introduction

Europe faces a double urgency to increase energy efficiency: on the one hand, caused by the war in Ukraine, on the other hand, due to the continuous rise in electricity consumption [1]. Tackling the energy efficiency problem through consumers' behavioral change is an obvious, however challenging solution. People often need a guidance, and sometimes a soft nudge to put the intentions into actions [2], for instance, to change the timing of appliances usage. Recommender systems can suggest energy-efficient actions to facilitate such behavioral change. To increase the trust in the recommendation system, and, thus, the acceptance rate of recommendations, users need to understand why and how the model makes its predictions [3], [4]. Thus, the recommendation system should be explainable.

The existing research on explainability in recommender systems for energy-efficient smart homes is very scarce [5]. [6] provide a thorough literature review on explainability in recommender systems for other application domains. However, most existing approaches are not applicable to the smart home area because of the missing data structures. [7] design an explainable context-aware recommendation system for a smart home ecosystem. They show that displaying the advantages and the reasoning behind recommendations lead to a 19% increase in acceptance rate. To our best knowledge, the issue of explainability in multi-agent recommendation systems for energy-efficient smart homes has not been studied yet.

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Our contributions are twofold. First, we suggest an explainable multi-agent recommendation system for energy efficiency in private households. In particular, we extend a novel multi-agent approach of [8] by designing an Explainability Agent that provides explainable recommendations for optimal appliance scheduling in a textual and visual manner. Second, we enhance the predictive capacity of other agents by including weather data and applying state-of-the-art models. We also provide an overview of predictive and explainability performance. We provide a comprehensive tutorial in Jupyter Notebook in GitHub<sup>1</sup> for all the steps described in this paper and beyond.

## 2 Explainable multi-agent recommendation system

[8] introduce a utility-based context-aware multi-agent recommendation system that provides load shifting recommendations for household devices for the next 24 hours. Their system includes six agents: Price Agent (prepares external hourly electricity prices), Preparation Agent (prepares data for the other agents), Availability Agent (predicts the hourly user availability for the next 24 hours), Usage Agent (calculates the devices' usage probabilities for the prediction day), Load Agent (extracts the typical devices' loads), and Recommendation Agent (collects the inputs from the other agents and provides recommendations). The multi-agent architecture of [8] is flexible and can be easily integrated into existing smart home systems. However, the cost of the simplicity of the approach (i.e., they use Logistic Regression for the availability and usage predictions) is a relatively low prediction accuracy.

We address the limitations in [8] by enhancing the performance of the Availability and the Usage Agents. In particular, we apply the K-Nearest-Neighbours (KNN), extreme gradient boosting (XGBoost), adaptive boosting (AdaBoost), and Random Forest to predict the availability and usage probabilities. Furthermore, we use Logistic Regression (Logit) and Explainable Boosting Machines (EBM, see [9]) as inherently explainable models. We propose including the Explainability Agent in the system (see Figure 1). The explainability models are divided into local and global, depending on their capability to explain a particular instance or the entire model. Since we want to help the user understand a single recommendation, we focus on local approaches. In particular, we apply post-model approaches LIME (local, interpretable, model-agnostic explanation; [10]) and SHAP (Shapley additive explanations; [11]) as model-agnostic tools that can explain the predictions of the chosen classifiers.

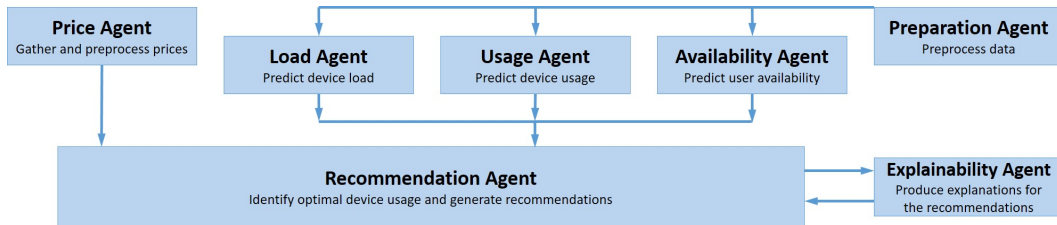


Figure 1: Architecture of the explainable multi-agent recommendation system.

To create an explanation for a recommendation, the Explainability Agent extracts feature importance from the explainability models. We design the explanation to include two parts: (i) Usage explanation - which features lead to the specific device usage prediction for the day? and (ii) Availability explanation - which features drive the user availability prediction for the hour? We do not include an explanation for the Load Agent since we do not consider the extracted typical load profile of every shiftable device as informative to the users. As a result, the Recommendation Agent recommends the cheapest starting hour within the hours of user availability for the shiftable devices that are likely to be used on the prediction day with an explanation in a text and visual form. The system provides no recommendations if the predictions for the availability and usage probabilities are below the thresholds.

<sup>1</sup>[https://github.com/Humboldt-WI/Explainable\\_multi-agent\\_RecSys](https://github.com/Humboldt-WI/Explainable_multi-agent_RecSys)

### 3 Experimental design

We use the REFIT data set on electrical load measurements, provided in [12]. It contains the energy consumption of nine devices in Watts used in 20 households in the United Kingdom as well as aggregate energy consumption in each household over the period 2013 to 2015. Additionally, we utilize the weather data from the meteostat, provided in [13]. In particular, we use the following features: dew point, relative humidity, air temperature, average wind direction, and average wind speed. The missing values are imputed using the KNN algorithm.

We apply an exhaustive grid search over the algorithms mentioned above, excluding the EBM. The latter is computationally expensive. Overall, 87 parameter combinations are tested twice (with and without weather data) to quantify the benefit of including additional data and pursuing a fusion-based approach. We use a KernelExplainer for explaining Logit, AdaBoost, KNN and Random Forest. For XGBoost, we use the fastest version of the TreeExplainer - interventional feature perturbation [14].

To evaluate the performance of the multi-agent model we apply multiple metrics depending on the task. The Usage and the Availability Agents perform a classification task, and therefore, we evaluate their area-under-the-ROC-curve (AUC). The Load Agent is evaluated by investigating the mean squared error (MSE) of the predicted load profile to real usages. Next, we use three metrics within the Explainability Agent to reflect how well the explainability approaches work in giving accurate local explanations [15]: accuracy, fidelity, and efficiency. Accuracy shows how well the explainable model predicts unseen instances compared to the real outcome. Fidelity determines how close the prediction from the explainable model is to the black-box model’s prediction. Additionally, we calculate the mean absolute explainability error (MAEE) for every approach. The efficiency metric describes the algorithmic complexity of the explainability approaches when calculating the local explanations. Lastly, we measure the time that each method needs to calculate all the local explanations for a day and average the values for all calculations.

### 4 Results

Using the prediction methods mentioned above, we observe consistent results for the Availability Agent. It benefits less from complex models and the inclusion of weather data than the Usage Agent. Random Forest model learns at most from additional data. The range between best and worst performing models is 0.023 AUC points regardless of weather inclusion, which indicates robustness towards algorithmic choice as well as weather features. Contrarily, the Usage Agent benefits greatly from the weather data. While without the additional data, most models perform around 0.7 in AUC. The inclusion allows for substantial increases toward the performance of 0.93. Especially more complex models (i.e., Random Forest, XGBoost, Adaboost) profit from the inclusion and outperform the approach of [8]. We conclude that it is not sufficient to either include more complex models or weather data, but the combination of the two leads to the substantial performance improvements. For more details, please refer to the Appendix.

Since Random Forest and XGBoost perform similar in their respective best setup, we further analyze the AUC over ten households to investigate their stability. We notice that Random Forest slightly but consistently outperforms XGBoost. On average, XGBoost achieves an AUC of 0.884 over all prediction tasks and devices. While the Random Forest achieves an AUC of 0.891. The EBM performs similarly to the alternatives for the Availability Agent. We decide to use further Random Forest with the tuned parameters derived from the grid search.

#### 4.1 Explainability

We examine the results of the explainability evaluation by using the predictions from LIME and SHAP. SHAP generally performs better according to the higher accuracy and fidelity compared to LIME. Most strikingly, since the forecasts of the prediction algorithms and SHAP are so similar, the fidelity is almost perfect. In other words, SHAP works very well for mimicking the local behavior of the prediction model. The accuracy of LIME for the Usage Agent is not so high. The possible reason is that the predictions, e.g., for AdaBoost, are very close to the chosen cutoff of 0.5. Although LIME is only off on average about 0.0311 AUC points, it sometimes exceeds the cutoff assigning it to the wrong class. For the Availability Agent, the worse calibration of LIME does not take too much influence since the values from the prediction are more extreme. Furthermore, for most cases

SHAP creates predictions faster than LIME. Especially, LIME is not able to handle XGBoost very well while the TreeExplainer of SHAP used for XGBoost provides a very good runtime.

Since there is no significant difference between the fidelity of SHAP across the models, we apply SHAP with one of the most accurate algorithms while also minimizing runtime. XGBoost and Random Forest perform similarly regarding predictive performance for the Availability Agent, therefore, we also run an evaluation with the TreeExplainer for Random Forest. The resulting runtimes (Availability: 0.558, Usage: 0.0357) are also low, while there is little change with regard to the metrics. Thus, we select Random Forest and SHAP with the TreeExplainer as our final model.

## 4.2 Explainable recommendation

The recommendation for the next 24 hours is provided once a day at the same time specified by the user. To create an explanation for the recommendation, we create a feature importance ranking using Shap Values. We provide two different explanations for the Availability and the Usage Agents. We separate the features in two categories for each of the agents: features based on weather data and non-weather features. The Recommendation Agent embeds the two most important features of each group into an explanation sentence. The usage explanation is provided for each device (if its usage is recommended) since their predictions differ. Additionally, we adapt the plots provided by SHAP to inform the user about the specific impact of the features. We only display the most important features to shorten the explanation. We show an exemplary explainable recommendation in Figure 2.

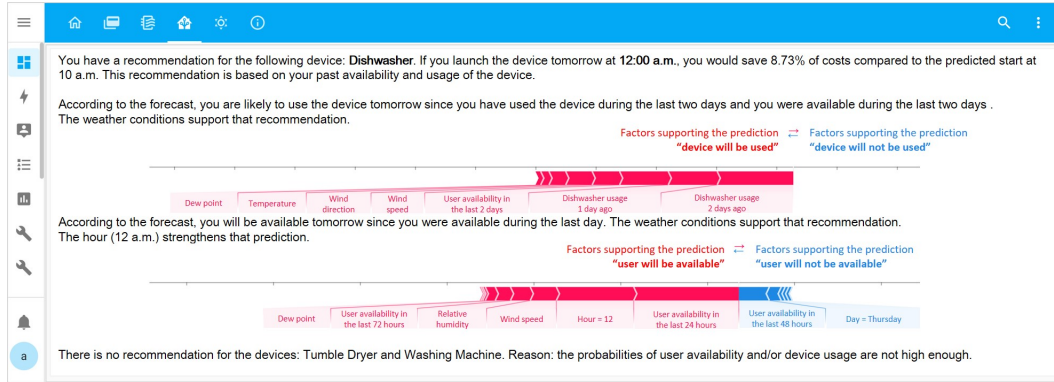


Figure 2: Exemplary explainable recommendation.

## 5 Potential impact

Our medium-term goal is to integrate the explainable recommendation system with the existing smart home platform used in German residential houses. Seeing the recommendations daily will increase the awareness of residents of their energy consumption and will encourage more climate-related actions (supporting SDG 13). The shifted load will facilitate energy efficiency in the grid (SDG 7), foster energy innovation towards sustainable development (SDG 9), reduce the environmental impact, and strengthen the households' sustainability making them inclusive, safe, and resilient (SDG 11).

## 6 Conclusions

Our results show a substantial improvement in the performance of the multi-agent recommendation system while at the same time opening up the "black box" of recommendations. Generating load shifting recommendations for household appliances as explainable increases the transparency and trustworthiness of the system. As a result, the understandable and persuasive recommendations facilitate the consumers' behavioral change in tackling the energy efficiency problem.

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## Appendix

Table A1: Performance evaluation results (in AUC) for the Availability and the Usage Agents with tuned hyperparameters including weather data

Model	Availability	Usage TD	Usage WM	Usage DW
Logit	0.836	0.728	0.703	0.684
Random Forest	<b>0.859</b>	<b>0.928</b>	<b>0.932</b>	<b>0.929</b>
AdaBoost	0.850	0.779	0.777	0.788
KNN	0.830	0.760	0.758	0.785
XGBoost	0.852	<u>0.922</u>	<u>0.925</u>	<u>0.922</u>
EBM	<u>0.854</u>	<u>0.803</u>	0.822	<u>0.842</u>

Abbreviations: TD - Tumble Dryer, WM - Washing Machine, DW - Dishwasher.  
The best performing model is in bold, the second-best - is underlined.

Table A2: Performance evaluation results (in AUC) for the Availability and the Usage Agents with tuned hyperparameters excluding weather data

Model	Availability	Usage TD	Usage WM	Usage DW
Logit	0.838	0.702	0.689	0.676
Random Forest	0.835	<u>0.713</u>	0.683	<u>0.715</u>
AdaBoost	<b>0.849</b>	0.710	<u>0.701</u>	0.680
KNN	0.826	<b>0.738</b>	<b>0.718</b>	<b>0.779</b>
XGBoost	0.845	0.712	0.682	0.710
EBM	<u>0.846</u>	0.707	0.683	0.700

Abbreviations: TD - Tumble Dryer, WM - Washing Machine, DW - Dishwasher.  
The best performing model is in bold, the second-best - is underlined.

Table A3: Performance evaluation results (in AUC) for Random Forest for the Availability and the Usage Agents for the ten households

Household	Availability	Usage TD	Usage WM	Usage DW	Usage WM2	Usage WD
h1	0.795	0.949	0.923	0.942		
h2	0.827		0.892	0.932		
h3	0.859	0.927	0.934	0.927		
h4	0.860		0.929		0.871	
h5	0.816	0.910				
h6	0.826		0.914	0.948		
h7	0.881	0.950	0.945	0.945		
h8	0.675		0.921			
h9	0.765		0.926	0.944		0.920
h10	0.820		0.950			

Abbreviations: TD - Tumble Dryer, WM - Washing Machine, DW - Dishwasher, WM2 - 2nd Washing Machine, WD - Washdryer.

Table A4: Performance evaluation results (in AUC) for XGBoost for the Availability and the Usage Agents for the ten households

Household	Availability	Usage TD	Usage WM	Usage DW	Usage WM2	Usage WD
h1	0.780	0.927	0.910	0.936		
h2	0.817		0.890	0.928		
h3	0.852	0.922	0.925	0.922		
h4	0.855		0.917		0.860	
h5	0.817	0.905				
h6	0.825		0.905	0.945		
h7	0.884	0.943	0.937	0.930		
h8	0.671		0.918			
h9	0.764		0.914	0.936		0.916
h10	0.800		0.942			

Abbreviations: TD - Tumble Dryer, WM - Washing Machine, DW - Dishwasher, WM2 - 2nd Washing Machine, WD - Washdryer.

Table A5: Performance evaluation results for Logistic Regression for the ten households from [8]

Devices Households	Availability AUC	Usage AUC			Load MSE		
		0	1	2	0	1	2
1	0.72	0.52	0.45	0.49	1224.45	511.49	3021.88
2	0.77	0.60	0.80	-	320.81	14578.80	-
3	0.80	0.65	0.65	0.65	24907.50	890.33	314.84
4	0.82	0.67	0.52	-	0.80	1793.77	-
5	0.76	0.68	-	-	37982.21	-	-
6	0.77	0.53	0.66	-	424.78	6032.65	-
7	0.83	0.79	0.80	0.81	43673.35	336.83	6845.26
8	0.62	0.77	-	-	0.35	-	-
9	0.67	0.60	0.57	0.78	30711.30	14.36	5480.13
10	0.77	0.74	-	-	647.57	-	-

The table is reproduced here from [8] to enable the direct comparison.

Legend for mapping the shiftable devices 0 - 2 is provided in Table A6.

Table A6: Legend for mapping the shiftable devices to an integer index from [8]

Household	Devices		
	0	1	2
1	Tumble Dryer	Washing Machine	Dishwasher
2	Washing Machine	Dishwasher	-
3	Tumble Dryer	Washing Machine	Dishwasher
4	Washing Machine (1)	Washing Machine (2)	-
5	Tumble Dryer	-	-
6	Washing Machine	Dishwasher	-
7	Tumble Dryer	Washing Machine	Dishwasher
8	Washing Machine	-	-
9	Washer Dryer	Washing Machine	Dishwasher
10	Washing Machine	-	-



Table A7: Explainability evaluation results for LIME and SHAP for the Availability Agent for the ten households

Model	LIME				SHAP			
	Accuracy	Fidelity	MAEE	Duration	Accuracy	Fidelity	MAEE	Duration
Logit	0.8371	0.9890	0.0265	73.748	0.8362	1	0	2.147
KNN	0.8295	0.9747	0.0194	79.695	0.8386	1	0	20.759
Adaboost	0.8369	0.9349	0.0035	50.975	0.8479	1	0	52.103
Random F.	0.8411	0.9761	0.0313	107.363	0.8451	1	0	64.853
XGBoost	0.8378	0.7971	0.1848	310.551	0.8366	1	0	0.717

The values for MAE are not displayed as they are too small. The duration is only comparable within the model since the evaluation was run on different machines with different background tasks.

Table A8: Explainability evaluation results for LIME and SHAP for the Usage Agent for the ten households

Model	LIME				SHAP			
	Accuracy	Fidelity	MAEE	Duration	Accuracy	Fidelity	MAEE	Duration
Logit	0.6761	0.8215	0.1454	2.582	0.7049	1	0	0.084
KNN	0.6928	0.8101	0.1858	2.864	0.7611	1	0	0.852
Adaboost	0.5757	0.5934	0.0311	1.859	0.8254	1	0	0.813
Random F.	0.7101	0.7988	0.1203	3.682	0.8726	1	0	0.957
XGBoost	0.6763	0.6516	0.2705	10.222	0.9353	1	0	0.230

The values for MAE are not displayed as they are too small. The duration is only comparable within the model since the evaluation was run on different machines with different background tasks.