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INTELLIGENT SYSTEM FOR PREDICTING BEHAVIOR OF ELECTRICAL ENERGY CONSUMPTION

Naama Methab ATHAB[1]; Osman Nuri UÇAN[2]; Oğuz BAYAT[3]; Saadaldeen AHMED[4]

Electrical and Computer Engineering & Altinbaş University, Iraq
Electrical and Computer Engineering & Altinbaş University, Turkey
Electrical and Computer Engineering & Altinbaş University, Turkey
Information Technology & Altinbaş University, Iraq
eng.naama@gmail.com, osman.ucan@altinbas.edu.tr, oguz.bayat@altinbas.edu.tr, saadaljanabi95@gmail.com

ABSTRACT: This paper will explore the intelligent system that could predict the usage and saving of electricity and it plays a major role in the smart home era, since can provide benefits with regard to comfort, safety and energy savings to electricity consumers. Many authors have already explored residence monitoring and prediction systems, however, very few approached the residence detection for predicting the energy consumption and prediction by using smart meter data. In this work, it can be achieved by using solely electricity consumption data and integrating it into an intelligent system. Also, we address the problem of generalizing a classification model, i.e., we analyze the possibility of using a single classification model to monitor residence in multiple households. We found that a residence detection accuracy and predict the usage was possible by using a generic classification model. Regarding residence prediction, we showed that it is possible to predict residence in multiple households, by using solely electricity consumption data. In addition to a higher energy efficiency, residence monitoring also provides more safety to the consumers. If a high electricity consumption is verified in periods that are not supposed, residence monitoring systems can be used as an intruder's detector, by sending alarms in real time to the smartphones of the occupants. If we analyze residence at the room-level, residence monitoring systems can also be used for health monitoring applications.

Keywords: occupancy prediction, residence detection, electricity consumption, smart meter, opportunistic sensing, intelligent system

1. INTRODUCTION

In terms of operations that take place in industry, with the advance in the statistics field and with the appearance of new fields such as the Internet of Things (IoT) and machine learning, energy utilities have now the possibility of providing these benefits to the customers. One way of providing these benefits to the customers is by controlling automatically their electrical appliances depending if the house is occupied or not. According to [1], however, the author states that these savings have been difficult to realize since households typically do not manually adjust the thermostat several times a

day. Also, smart thermostats, such as the NEST thermostat, attempts to solve this problem by automatically programming itself based on occupancy patterns that it learns by a built-in motion sensor [2]. However, the relatively high cost represents a major disadvantage of the thermostat. According to [3], Non-Intrusive Occupancy Monitoring is possible by using smart meters and allows utilities to determine: 1) Developing an intelligent system to predict the energy usage and to show how much a programmable thermostat would benefit in each home and 2) To suggest an optimal customized thermostat schedule system for usage. In this work, we do not focus on analyzing the savings potential of smart thermostats, but on investigating how viable is it to monitor and predict residence by using solely smart meter data. In terms of developing an intelligent system, this represents a problem that can be solved through supervised classification algorithms. These algorithms are trained by using input and output information. In this case, the input information represents the electricity consumption data and the output represents the residence data. After having a classification model, we use solely the electricity consumption data (input) and we compare the residence data generated by the model (output) with the real residence data (ground truth residence). Then, classification performance metrics are defined to measure the residence detection performance. By analyzing similar works, we decided to use the neural network, support vector machines and random forest models as our methods for residence detecting/monitoring.
However, to the best of our knowledge, no single work analyzed the possibility of using a single and generic classification model to detect residence in multiple households. For electricity consumers, this represents a major interest, since they would benefit from residence monitoring applications (such as home automation) without the need of monitoring the real residence through direct systems (e.g. motion sensors).

1.1 Problem Statement

The present work proposes to investigate the viability of detecting and predicting residence and behavior by using solely the electricity consumption data, obtained from smart meters. To this end, we installed an intelligent system service in 5 households by the data collected, in order to collect both electricity consumption and residence data, which is necessary to perform our experiments. This service represents an energy management system for the residential sector, provided by an intelligent system. Intelligent system allows customers to visualize their electricity consumption data (both aggregated and device-level) and also provide energy management functions using the dataset that includes data of five households, such as billing of sub metering and remote control and automation of their equipment's.

1.2 Occupancy and Electricity Consumption Data

In a decade, homes were instrumented with smart meters and data was collected every second during months. They told to the participants to register which appliances they have used at what time. It was demonstrated that smart meters have the potential to provide relevant information about the households, such as: how many people are in the home, sleeping routines and eating routines. The major limitation of this study is that these conclusions were obtained by visual inspection of the electric load curves. Despite the simplicity of this study, the authors concluded that the algorithm performed well. However, this approach may not be feasible in households that have appliances with patterns of high consumptions at night (e.g., electric water heater) since the threshold would be higher and lead to a worst classification. Furthermore, authors refer that machine learning algorithms would perform better than the threshold-based method. Due to the lack of these datasets, authors of [4] decided to perform an extensive ECO data collection in 5 households in different parts of world months. In addition to the aggregate electricity consumption data, this dataset also contains data from PIR sensors and smart plugs. Ground truth occupancy data was obtained through a tablet computer. This was a preliminary study that used standard classification techniques to evaluate the occupancy detection accuracy with information provided only by smart meters. In this work, 10 features were extracted from the dataset and 4 classification models were used. The study showed that occupancy detection accuracies over 80% are feasible in most of the scenarios.

2. BACKGROUND

Most of the existent work in this field extract few features and uses them all in the classification process. However, when dealing with high dimensionality data, some classifiers may not perform well. Thus, it is important to use a technique to reduce the high dimensionality of the data. It was analyzed two methods with the objective of selecting the most describing features of the data to measure the consumption of electricity: sequential forward selection (SFS) and principal component analysis (PCA).

Sequential forward selection (SFS) is a direct and nonparametric method to determine the best subset of d measurements out of a set of D total measurements. In the first iteration it is found the best feature that maximizes the performance of the algorithm. At each iteration it is included one more feature that maximizes the performance. The process stops until all the features have been selected or a number of d features have been reached.

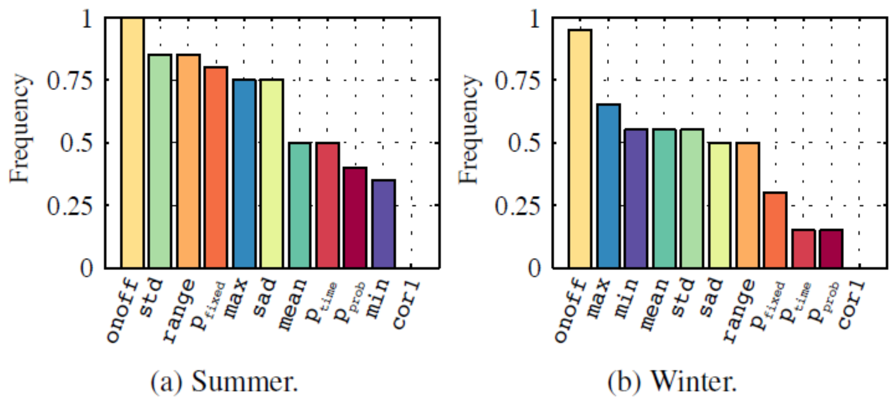

Figure 1: *Frequency of the features chosen by Sequential forward selection (SFS) algorithm for a certain household and classification method.*

Another way to select the optimal feature set through a brute-force evolution of all possible combinations, however, this process complexity grows exponentially with the number of features. As explained before, the device-level electricity consumption represents a good indicator of occupancy, specially of the interactive loads. Thus, the importance of measuring this consumption has been growing in the literature and many works has already focused on this field. There are two ways to measure this consumption. The first way consists on using physical devices, smart plugs that measures the device consumption. The second way is through a non-intrusive load monitoring (NILM) algorithm. According to [1], the frequency of the data is the most important factor to identify correctly those appliances. The author states that, hourly data typically identifies three end-user's categories, such as: loads that correlate with outdoor temperature, continues loads and loads that depend on the time (e.g. pool pumps and outdoor lighting). Data frequency from one minute to one second (1 Hertz) allows to identify 8 appliances types (e.g. Refrigerator, Heaters, Washers and dryers), data in multiple kHz of frequency identify between 20-40 appliance types. Finally, data in the MHz frequency range has the potential to identify close to 100 distinct appliances, such as different types of lights.

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2.1 Classification Algorithms

The inference of occupancy through the electricity consumption data represents a supervised classification problem. Supervised classification is a machine learning technique typically used for pattern recognition. A supervised machine learning algorithm is an algorithm that required label data to learn the patterns and recognize. In this work, the label data represents the ground truth occupancy.

Classification can be divided into two groups: binary (when the output has two classes, 1 or 0) and multi- class (when the output has more than two classes). In the literature, most of the related works focuses on monitoring/predicting occupancy as a binary classification (the output is occupied or not occupied) [3], and different models have been used.

Other models have been used in similar works with good results, such as neural networks [5] and random forest [5]. A review of classification techniques was performed in [5].

2.2 Existent Approaches

As it was already explained, predicting human presence can provide many benefits to electricity consumers. Many works focus on predicting occupancy for HVAC controlling in households, such as thermostats, due to the higher savings potential.

Prediction algorithms predict occupancy in two possible ways: binary level and occupancy level. Predicting the occupancy level consists on predicting how many occupants are present in a building and is typically done in office building. Predicting binary occupancy consists on predicting whenever a building is occupied or not, and represents the most commonly used approach in residential systems [6].

2.3 Schedule-Based Approaches

Schedule-based approaches can be divided in two categories. The first detect routines in the historical occupancy schedules and the second assumes that routines can be explained by daily or weekly timetable (i.e., depends with the day of the week and the time of the day). In [6], several state-of-art schedule-based algorithms were analyzed and the study concluded that, for their occupancy dataset, the Presence Probabilities (PP), Presence Probabilities Simplified (PPS) and PreHeat (PH) algorithms provided the best results.

2.4 PreHeat

In [20] it is presented the PreHeat (PH) algorithm, which is a schedule-based approach that predicts the future occupancy by analyzing the occupants' routines and finding the most similar historical patterns. In this study, five houses (3 in U.S. and 2 in U.K.) were used to analyze the benefit of controlling automatically home heating systems. Authors concluded that PreHeat algorithm allows to obtain a higher home heating efficiency (between 8% and 12% of savings in energy usage) while removing the necessity for users to program their thermostats.

Figure 2: Each vertical bar represents each day occupancy vector, divided in 15-minute intervals.

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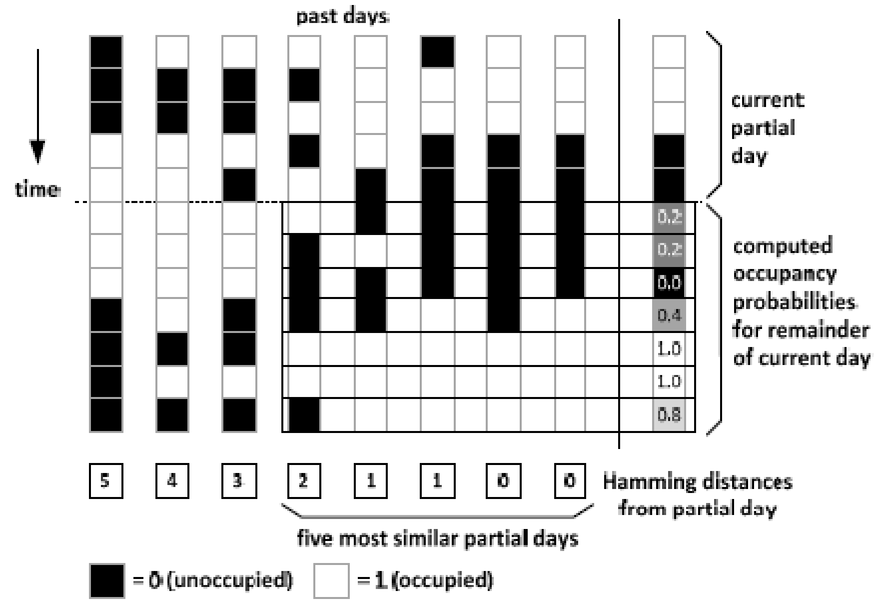

Figure 6: *PreHeat algorithm. Each vertical bar represents one-day occupancy data divided by 15-minutes intervals [6].*

Because PreHeat computes energy prediction probabilities it is necessary to define a threshold value to predict the class occupied or unoccupied. A threshold of 0.5 was chosen in this study [6] and also in a similar work [6-7] since typically it represents a good tradeoff between the true positives (correctly predicting occupancy) and false positives (predicting the house as occupied when it is unoccupied). Figure 3 shows the Receiver Operating Characteristic (ROC) curves for the 5 households (US stands for households in United States while UK for households in United Kingdom). Each line contains one circle that represents the point where threshold is equal to 0.5.

To analyze the performance of the PP algorithm, Figure 3 shows a table with the confusion matrix at the equal error point. It is possible to see that, when the algorithm infers that the occupants are at home, 64% of the times it predicts correctly. When it infers that the occupants are away, 65% of the times if predicts correctly.

		Inferred	
		home	away
Actual from GPS	home	64%	36%
	away	35%	65%

Figure 3: *Confusion matrix containing the probability accuracies for the PP algorithm.*

In this work, we use three supervised machine learning algorithms for detecting/classifying occupancy: neural networks, support vector machines and random forest. To predict occupancy, we use the Presence Probabilities Simplified algorithm.

3. METHODOLOGY

Many methodologies exist to solve data mining problems, such as: CRISP-DM (CRoss Industry Standard Process for Data Mining), SEMMA (Sample, Explore, Modify, Model, and Assess) and KDD (Knowledge Discovery in Databases). According to a 2014 poll, presented in [6], CRISP-DM is the most popular methodology for data mining projects. CRISP-DM was chosen as the methodology for our work since it focuses on delivering real value for business and answering to their needs.

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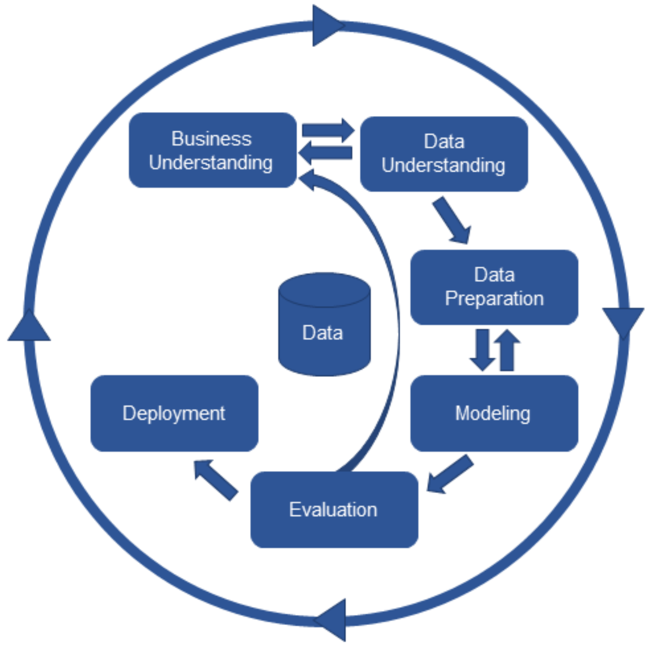

Figure 4: *Six phases of the methodology.*

3.1 Machine Learning Algorithms

As shown before, machine learning is a relevant method of data mining. There are two types of machine learning methods: supervised learning and unsupervised learning [8].

Supervised Learning

In supervised learning, it is used a labeled dataset, which is a dataset containing both input and output data, used to train a model. The labeled data allows the model to compare and adjust its parameters so that the performance is maximum. In Figure 5, it is illustrated the working principle of supervised learning.The input matrix is represented by (x1, x2…, xn), where each element represents a vector, with many records, for a given feature of *n* features. The output or target variables are denoted by (y1, y2…, yn). In our case we only have one output variable and its value can be 1 (when a house is occupied) or 0 (when a house is unoccupied).

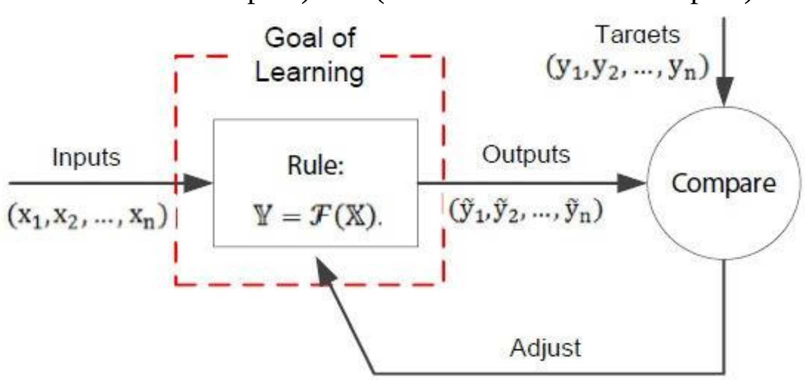

Figure 5: *Mechanism of supervised machine learning algorithms [8]***.**

The goal of supervised learning is to learn a general rule (F(X)) that maps the inputs X to outputs Y.

Unsupervised Learning

Unsupervised learning represents the methods that do not use labeled data to train the goal function (F(X)). The goal of these methods is to discover hidden patterns in the input data X by using its features (without using the target data to compare and adjust the model), as can be seen in Figure 6.

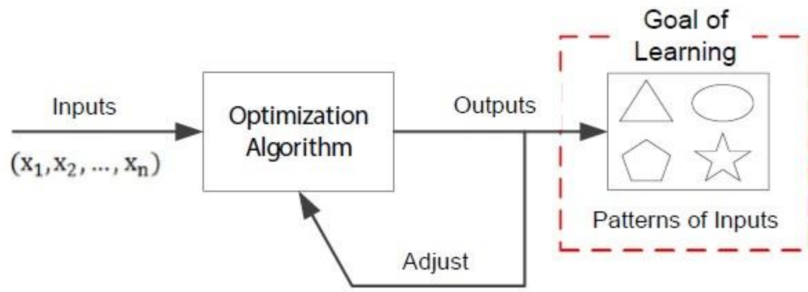

Figure 6: *Mechanism of unsupervised machine learning algorithms [8].*

For predicting behavior from the electricity consumption data, it is necessary to use a supervised classification method since unsupervised learning, alone, cannot solve this problem. For this reason, we needed to collect both electricity consumption and occupancy data and to choose our classification algorithms: neural networks, support vector machines and random forest (based on neural networks).

Our main objective consists on predicting occupancy from electricity consumption data and can be divided into two parts: 1) have a classification model that detects, with high accuracy, the occupancy of any household by using solely the electricity consumption data; 2) have a prediction model that predicts occupancy based on the detected occupancy data for an intelligent system. In the next sections we explain the theory behind each classification algorithm chosen.

3.3 Classification Evaluation

Binary occupancy classification represents a two-class classification problem since a household can be occupied or unoccupied in each interval of 15 minutes. There are four different possible outcomes for the process of occupancy classification, which can be seen in the confusion matrix, presented in Figure 7.

		Actual class (ground truth)		
		p (occupied)	*n (unoccupied)*	Total
Predicted class	*p′ (occupied)*	True Positive	False Positive	$tp+fp$
	n′ (unoccupied)	False Negative	True Negative	$fn+tn$
	Total	$tp+fn$	$fp+tn$	N

Figure 7: *Confusion matrix of a binary classifier for predicting the energy usage.*

A *true positive (tp)* occur when occupancy is correctly classified while a *true negative (tn)* refers to an unoccupied moment correctly classified. A *false negative (fn)* occurs when an occupied interval is falsely labeled as unoccupied while a *false positive (fp)* is when an unoccupied interval is falsely classified as occupied.

3.3.1 Accuracy

Accuracy is a simple metric to evaluate a classifier and can be computed by dividing the number of correct classifications by the total number of classifications, as shown in equation.

$$\text{Accuracy} = \frac{tp=tn}{tp+tn+fp+fn}$$

In order to have a baseline for comparing the obtained classification accuracy by each algorithm for a certain household, we use the Prior classifier, which assumes that the house is always occupied or unoccupied (if the house is typically occupied or unoccupied, respectively, in most of the times). For example, if a house is more than 50% of the time occupied, then prior assumes the house to be always occupied, otherwise, assumes the house to be always unoccupied.

4. RESULTS

Collected the necessary data from dataset for our study we installed a smart energy management system in five households. To obtain more information about each participant and to verify if they meet all the requirements for our analysis, we asked for each household to fill a dataset. Not having any pet and any scheduled appliance are the mandatory requisites because it would affect our analysis (since some appliances could be turned on when a household is not occupied). Table 2 contains a summary of the gathered information. Household 1 have 8 occupants while household 5 have only one. Household 4 and 5 have seems to have similar occupancy profiles during the week, since their occupants are full-time workers. However, household 4 seems to have more variability in the occupancy during the week, since one occupant have irregular work schedules. Households 1 considers its occupancy profile as very occupied during the all days of the week.

Table 1: *Information collected of each household from the dataset.*

Household	Num. of occupant	Weekdays occupancy	Weekend days' occupancy	Type of heating
1	8	Very occupied	Very occupied	Electric and natural gas
2	2	Unoccupied: 9h-11h; 14h-16h:	Very occupied Variable profile	Electricity (Water and space)
3	3	Unoccupied: 11h-15:30h	Very occupied	Electricity (Water)
4	2	Unoccupied: 8:30h-19:00h Variable	Unoccupied: 12h-16h Variable profile	Electricity (space), Natural gas (Water)
5	1	Unoccupied: 9:30h-19:30h	Very occupied Variable	Electricity (space) Natural gas (Water)

Some occupants of households 4 and 5 may spend one or two weekends away from the house per month. Thus, a more variable occupancy profile is associated to these households. Household 1 and 3 have similar occupancy patterns during the weekends. Using the information provided by the participants in the dataset, we divided the appliances of each household into two categories: Switch operated and other appliances, as shown in Table 2. We consider that switch-operated devices represent the appliances that, when consuming electricity, indicate that the house is occupied.

Not having any pet and any scheduled appliance are the mandatory requisites because it would affect our analysis (since some appliances could be turned on when a household is not occupied).

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The number of hidden neurons was set to 2 and 3. By also changing the feature set, ten different combinations are possible to make. Table 3 presents the training results for household 5 ordered by decreasing order of accuracy.

Table 3: *Results of the training phase of the neural network model in 5 households.*

combination	Number of hidden neurons	Feature set	AUC - *training set*	Accuracy (%) - *training set*
1	**3**	**4**	**0.9746**	**92.96**
2	2	5	0.9663	92.62
3	2	4	0.9745	92.60
4	2	3	0.9772	92.50
5	2	2	0.9765	92.33
6	3	2	0.9654	92.06
7	3	3	0.9699	91.08
8	3	5	0.9551	91.08
9	2	1	0.8794	89.14
10	3	1	0.8338	87.32

Table 4 and Table 5 contains, respectively, the false positive rate and false negative rate obtained in each household by the three models. We can verify that the lower FPR and FNR are typically obtained by the random forest classifier. Values in parenthesis represent the average misclassified minutes per day, according to the error type (false positive and false negative). We can observe that household 5 has the lower FPR (3.86%), which indicates that 25 minutes of absence, in average and per day, are wrongly classified as occupied [9].

Table 4: *False positive rate (%) obtained for each household and model and the respective misclassified minutes, in average and per day, in the optimization by household experiment.*

Household	neural network	SVM	random forest
1	97.15 (92 min)	100 (95 min)	**96.67 (91 min)**
2	31.65 (93 min)	26.61 (78 min)	**20.80 (61 min)**
3	51.7 (123 min)	56.25 (134 min)	**53.22 (127 min)**
4	53.60 (128 min)	**22.41 (106 min)**	22.51 (107 min)
5	3.93 (25 min)	4.14 (27 min)	**3.86 (25 min)**

Regarding the false negative rate, the lower value was obtained in household 4 (1.3%). This low value indicates that only 6 minutes of presence are wrongly classified as absence.

Table 5: *False negative rate (%) obtained for each household and model and the respective misclassified minutes, in average and per day, in the optimization by household experiment.*

Household	neural network	SVM [6]	Random forest [6]
1	0.8 (7 min)	**0**	0.57 (5 min)
2	7.04 (47 min)	6.91 (46 min)	**4.6 (31 min)**
3	12.29 (89 min)	13.41 (97 min)	**7.92 (57 min)**
4	5.11 (37 min)	7.14 (35 min)	**1.3 (6 min)**
5	14.14 (45 min)	15.42 (49 min)	**13.58 (43 min)**

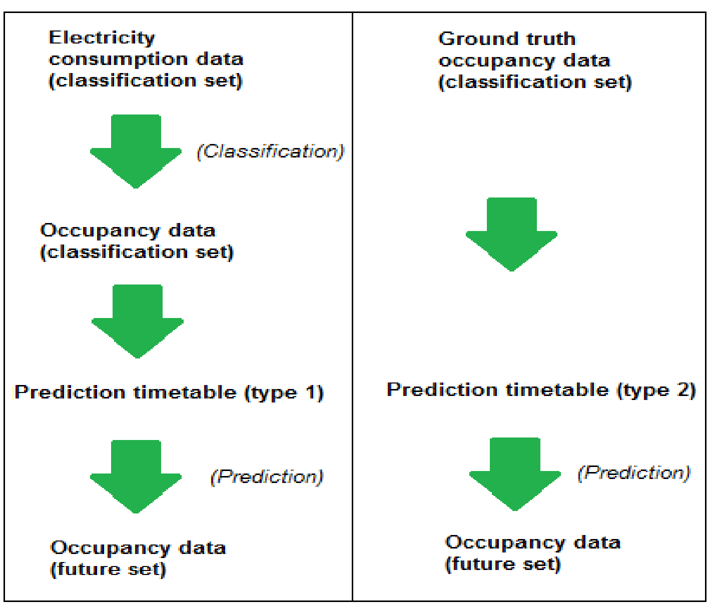

Figure 8: *Schematic representation of the construction and application of the two types of prediction timetables.*

5. DISCUSSION

To summarize, we consider that two conditions are fundamental in order to make it viable to predict occupancy by using solely electricity consumption data and a schedule-based approach: 1) It is necessary to have a classification model that generates occupancy data with a high accuracy (very similar to the ground truth occupancy) and 2) Households should have similar patterns of occupancy during each weekday and hour of the day [13]. For the sake of simplicity, To summarize the results obtained in the occupancy prediction experiment, Figure 45 illustrates the occupancy prediction accuracy obtained in households 2, 4 and 5, in the two previous experiments:1)Prediction by household/self-test (type 1): for each household, we apply the respective best classification model to generate occupancy data. Then we construct the prediction timetable using this generated occupancy data and test the prediction accuracy.2) Prediction by household/self-test (type 2): for each household, we construct the prediction timetable based on the ground truth occupancy data. Then, we test the prediction accuracy.3) Prediction in other households/other's-test (type 1): we use the best overall classifier (neural network model of household 3) to detect occupancy in households 2, 4 and 5. Then, we construct the prediction timetable using this generated occupancy data and test the prediction accuracy.

6. CONCLUSION

We analyzed how accurate can occupancy be monitored through electricity consumption data. To do this, we first extracted 8 features (most of them related with the electricity consumption). Then, 5 different feature combinations were used to train three classification algorithms (neural network, support vector machines and random forest), for each household. However, the authors analyzed 35 features and used the principal component analysis as feature selection method. For households with high levels of occupancy (e.g. more than 75%), we verified that the obtained accuracy does not represent a relevant improvement when comparing to a random choice (e.g. assuming that the household is always occupied). We consider that in households with a high occupancy level, more periods of low power consumption and power variability may exist when the household is occupied [12]. Thus, a lower correlation between occupancy and the electricity consumption may exist, which reduces the occupancy detection accuracy. To analyze the viability of using a single classification model to monitor occupancy in multiple households, we tested, for each household, the classification models trained in the remaining household. We observed that a single classification model can be used to monitor occupancy in 4 out of 5 participants. The only exception is for the household with the higher level of occupancy (more than 90%), which provided a classification accuracy equal to the Prior method. This result is fabulous, but definitely indicates that it is possible to generalize classification algorithms and motivates researchers to investigate in more detail this area.

6.1 Future Work

To increase the occupancy monitoring accuracy obtained through smart meter data, we consider that households could be grouped (e.g. through a clustering method) according to their similarities. Then, a different classification model could be used to monitor occupancy in each group of households [14]. Also, different models could be used according to the season, since the electric consumption behavior of the occupants tends to be different in the summer and in the winter. Another possibility to increase the occupancy monitoring accuracy is by combining smart meter data with data from mobile phones. For example, in addition to the electricity consumption data, obtained from smart meters, it could be also used data from GPS systems and wireless network traffic. In times where occupants are at home but no electrical devices are consuming, the GPS system could correctly identify presence.

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