User-aided Footprint Extraction for Appliance Modelling in Non-Intrusive Load Monitoring

Roberto Bonfigli, Emanuele Principi, Stefano Squartini, Marco Fagiani, Marco Severini, and Francesco Piazza
Department of Information Engineering
Università Politecnica delle Marche, Ancona, Italy
Email: {r.bonfigli, e.principi, s.squartini, m.fagiani, m.severini, f.piazza}@univpm.it

***Abstract*—In the area of Non-Intrusive Load Monitoring (NILM), many approaches need a supervised procedure of appliance modelling, in order to provide the informations about the appliances to the disaggregation algorithm and to obtain the disaggregated consumptions related to each one of them. In many approaches, the appliance modelling relies on the consumption footprint, which is a typical working cycle of the appliance. Since the NILM system has only the aggregated power consumption available, the recorded footprint might be corrupted by other appliances, which can not be turned off during this period, i.e., the fridge and freezer in the household. Furthermore, the user needs a facilitated procedure, in order to obtain a clean footprint from the aggregated power signal in real scenario. Therefore, a user-aided footprint extraction procedure is needed. In this work, this procedure is defined as a NILM problem with two sources, i.e., the desired appliance and the fridge-freezer combination. One of the resulting disaggregated profiles of the algorithm corresponds to the extracted footprint. Then, this is used for the appliance modelling stage to create te corresponding Hidden Markov Model (HMM), suitable for the Additive Factorial Approximate Maximum a Posteriori (AFAMAP) algorithm. The effectiveness of the footprint extraction procedure is evaluated through the confidence of the disaggregation output of a real problem, using a span of 30 days data taken from two different datasets (AMPds, ECO). The experiments are conducted using the HMM from the extracted footprint, compared to the confidence of the same problem using the HMM from the true footprint, as appliance level consumption. The results show that the performance are comparable, with the worst relative F_1 loss of 3.83%, demonstrating the effectiveness of the footprint extraction procedure.**

I. Introduction

The smart home energy monitoring in residential environments is an issue that has been arousing great interest in recent years: in fact, an improved users energy awareness leads to a conservative consumption, thus to a less waste of energy and a reduction of excesses in the production phase [1], [2]. Furthermore, the plan of the usage of energy resources [3] and the battery management for the storage [4] allows the reduction of the overall energy costs.

For this purpose, the Non-Intrusive Load Monitoring (NILM) is proposed as a mean to identify the contribution of each appliance to the aggregated power demand of the electrical system. This information is useful for the user, who analyzes the percentage of the cost in the bill attributable to each appliance, in order to have a more accurate analysis of the energy cost.

Although different NILM algorithms operate on various aggregated electrical signal [5], the proposed system disaggregates the active power P_a aggregated signal, since it is the physical quantity directly related to the cost in the bill.

Among different NILM approaches, the supervised ones reach better performance [6], [7], that is the resulting disaggregated signals have a better correspondence with the true appliance energy consumption. Therefore, those methods results to be more reliable for the final user.

The supervised section in the NILM algorithms corresponds to the appliance modelling stage, as showed in Fig. 1b, where the training phase is carried out. A model is created starting from the appliance level consumption (e.g., training set), in order to represent each appliance in a parametric way, and its parameters are used in the NILM algorithm in order to disaggregate the portion of the aggregated power consumption related to each appliance, as represented in Fig. 1c.

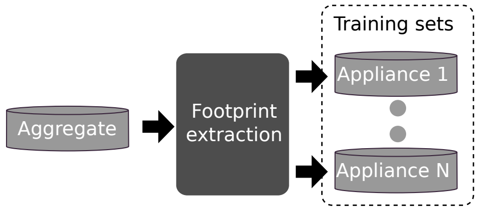
The power consumption profile of an appliance can be depicted as the repeating of a working cycle, alternated by time intervals when the appliance is turned off. The repetition rate, related to the length of the *off-intervals*, depends on the user consumption habit.

Therefore, in order to analyze the consumption features of an appliance, it is sufficient to extract the working cycle in the appliance level consumption, defined as the *footprint*, and to exploit it as training set in the appliance modelling stage.

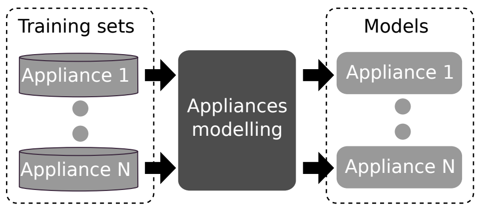
This stage of the supervised NILM chain is named *footprint extraction*, as showed in Fig. 1a.

In literature, different approaches have been proposed to extract the appliance working cycle features from the aggregated data. An unsupervised method, based on spectral clustering, is proposed in [8]: the most different activation occurrences, which can be denoted in the aggregated power, are saved; then, they are grouped between the most similar, using the clustering technique. A bayesian approach is used in [9], [10]: a generic bayesian model for the appliance category is defined; then, it is fitted on the activation within the aggregated power, using a threshold schema on the likelihood function. Most of those approaches have limitations, concerning the aggregated power, where the appliance activation can be overlapped and it can cause trouble in the extraction phase.

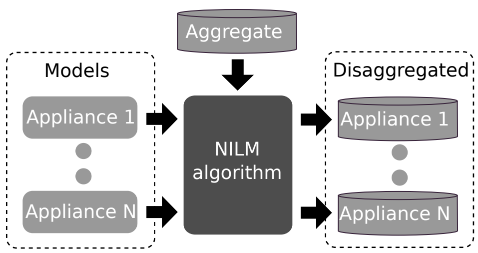
To overcome this, in a real scenario, the user interaction with the system can be considered, in order to improve the reliability of the footprint extraction: in those cases, the user



(a) The footprint extraction stage.



(b) The appliance modelling stage.



(c) The disaggregation algorithm stage.

Fig. 1: The Supervised NILM chain.

needs a facilitated procedure to determinate the appliance activation instant and an easy way to interact with the energy monitoring system. Therefore, in this work a *user-aided* footprint extraction procedure is proposed.

The easiest way to extract the footprint from the aggregated power is to use the appliance alone, turning off all the other devices in the electrical network, as described in [11]. This approach results to be the more reliable for the user, thus it is adopted in the presented work.

The appliance modelling stage employs the footprint, in order to represent the appliance consumption behavior: despite several works deal with model for the classification, such as SVM, k-NN [12] or deep neural networks [13], the Hidden Markov Model (HMM) is a widespread modelling technique [14]–[16], since it is able to represent the behavior of the appliance in working states and to regulate the transition with a probability value. This representation is close to the real appliance mode of operation, where each working state corresponds to a power consumption value.

In this work, the disaggregation algorithm is based on HMM, in particular the AFAMAP (Additive Factorial Approximate Maximum a Posteriori) algorithm [8] is used.

The unavailability of the appliance level consumption, for extract the footprint, represents one of the main issue in the NILM supervised approach. In real scenarios, only the aggregated power consumption is available to the user. Therefore, the footprint extraction stage aims to extract the appliance footprint from the aggregated power: this work aims to investigate the performance of a footprint extraction procedure based on the HMM and AFAMAP algorithm.

The outline follows. The problem formulation is described in Section II, whereas Section III introduces the footprint extraction procedure. The appliance modelling stage is described in Section IV, and Section V presents the experiments and the obtained results. Section VI draws the work conclusions.

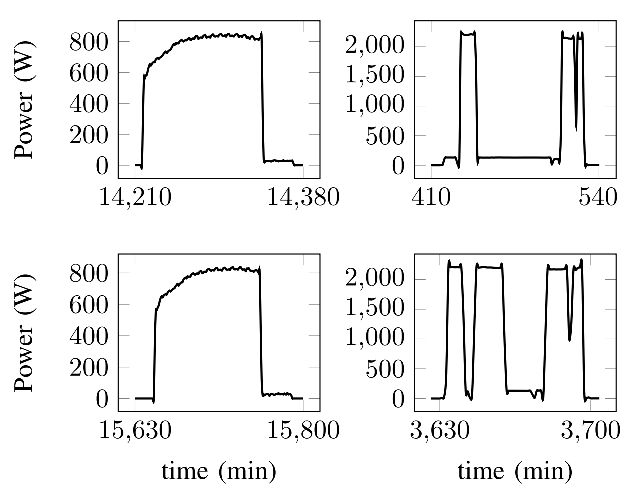
II. Problem Formulation

In this section, the concept of appliance footprint is described, along with some examples related to a real dataset. Furthermore, since the application scenario of the NILM is related to domestic context, specific issues are introduced.

A. The appliance footprint

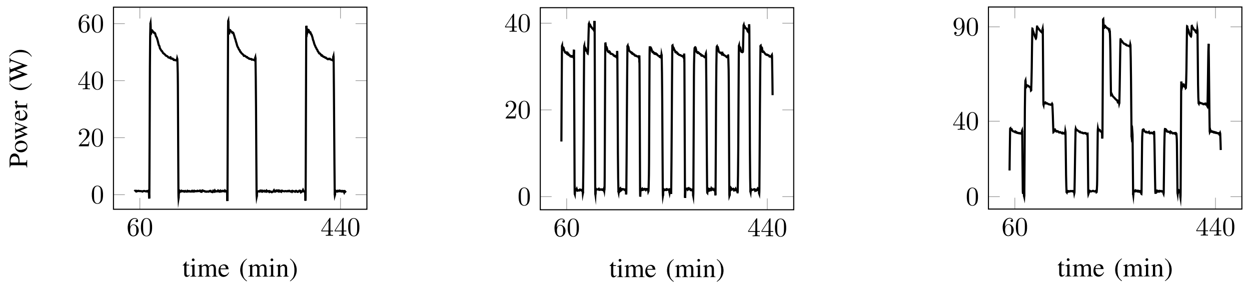
A working cycle of an appliance is the interval between the power on and the power off by the user. In this time interval, the appliance power consumption signal is defined as *footprint*. Some examples of footprint taken from the ECO dataset [17] are shown in Fig. 2, that reports the power consumption traces recorded from the appliances located inside different Swiss households.

The usage of an appliance differs every time, especially in the case of equipments with different usage modes: e.g., the operating cycles of a washing machine can be set in a different way each time, or the operation of the dishwasher may vary according to the selected rinsing cycle. The different usage mode of the same appliance reflects on different footprint, as shown in Fig. 2b: the power levels in the two footprint of the dishwasher are the same, but they appear in different orders, which demonstrate that the working state composing the appliance working cycle are unique, but they are employed in different orders, based on the user habits. Therefore, it is necessary to record different occurrence of the appliance



(a) Dryer, household 1. (b) Dishwasher, household 2.

Fig. 2: Alike and different footprints for the same appliance, in ECO.



(a) Fridge, household 1. (b) Freezer, household 1. (c) Fridge-freezer combination, household 1.

Fig. 3: Power consumption of continuously turned on appliances, in ECO.

footprint, in order to explore the different user habits in the appliance usage.

On other hand, this aspect is not significant for appliances with easier working principle, and a less complex circuit composition. In this case, the usage pattern of the appliance can not be different in times, thus the footprint appears to be similar in each occurrence, as shown in Fig. 2a: the footprint of the dryer follows the same trend in time, which demonstrates the unique working cycle of the appliance and the unique way of usage by the user.

B. The domestic context

The footprint extraction is a necessary step in supervised NILM algorithms. In this context, the user exploits the aggregated power sensing system. An easy method to record the appliance footprint is to switch off all the appliances in the household and to turn on only the appliance of interest [5], [11]. In this way, the aggregated power consumption corresponds to the appliance one.

The appliance switch on and off are detected by using a threshold schema on the active power consumption: when the value exceeds a threshold, the current is flowing in the circuit and the appliance is turned on, whereas when the value is below, the appliance is turned off. A threshold equal to the value of 50 W is a good choice for most datasets, nevertheless this value depends on the type of appliance and the activation power consumption. The samples between those two events are saved as the power consumption data related to the footprint. Multiple usages of the same appliance define different occurrences of the footprint.

In a household not all appliances can be turned off, e.g., the fridge and the freezer have to be continuously powered in order to maintain the food inside in safe condition. As shown in Fig. 3a and Fig. 3b, their power consumption are continuous in time, with a periodic working cycle. In this scenario, the aggregated consumption presents a continuous component, resulting from the sum of the fridge and freezer consumption, as shown in Fig. 3c. This signal can be modeled as the consumption of a unique model, representing the combination fridge-freezer as a composed appliance.

The presence of this component in the aggregated power does not allow to acquire a *clean* footprint of the appliance of interest, since all the appliances power signals are summed up on the aggregated power. Therefore, the footprint results to be *corrupted* and a procedure to clean it is needed.

III. The footprint extraction algorithm

In this section, the procedure to extract a clean footprint is presented, introducing the idea and the implementation details related to a real NILM application.

A. The idea

In order to clean a corrupted footprint, a procedure to separate the fridge-freezer consumption from the appliance footprint one is needed.

The fridge-freezer contribution can be recorded on the aggregated power turning off all the other appliances in the household: in this way, the characterization of the fridge-freezer combination is not afflicted by noise or other appliances consumption, thus the extracted model results to be highly reliable and accurate.

The steps to be followed are the following:

1) the consumption of the fridge-freezer combination is recorded, in a adequate span of time to collect enough data for the modelling;
2) a corrupted version of the appliance of interest footprint is acquired;
3) the extraction procedure is applied to the recorded footprint, using the a priori knowledge of the fridge-freezer model and a generic model of the appliance.

The process of signal separation can be interpreted as a disaggregation problem with 2 sources: therefore, the same NILM algorithm, which is executed after the footprint extraction and the appliance modelling step, can be exploited for the footprint extraction step, as well. In order to obtain the disaggregated traces, the NILM algorithm requires both the model of the fridge-freezer combination and of the appliance of interest. The first one is available, whereas the appliance model is not available, because the footprint extraction step precedes the appliance modelling step. Therefore, it is necessary to provide a generic model, which represents the class related to the appliance of interest, and which is suitably fitted on the specific appliance features, e.g., a priori knowledge of the maximum power consumption, in order to represent it as good

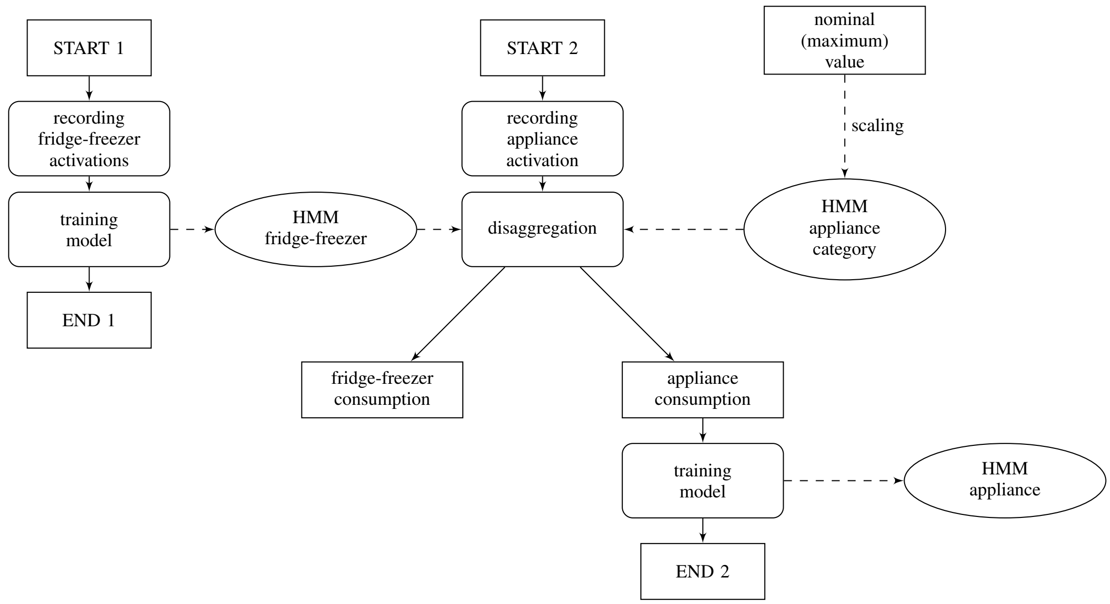


Fig. 4: Footprint extraction algorithm flowchart.

as possible. This procedure introduces an uncertainty in the appliance modelling stage, which might be the cause of the error in the footprint extraction stage.

B. Implementation details

In this work, the NILM algorithm chosen for the disaggregation step is the *AFAMAP* proposed by *Kolter and Jaakkola* [8]: the algorithm requires the HMM of each appliance that contributes to the aggregated power signal.

The HMM [18] of an appliance is represented by the following parameters:

- the hidden states $x \in 1, \dots, m$;
- the symbols emitted μ_j, where $j = 1, \dots, n$;
- the symbol emission probability matrix $\boldsymbol{M}^{n \times m}$;
- the state transition probability matrix $\boldsymbol{P} \in [0,1]^{m \times m}$;
- the starting state probability vector $\boldsymbol{\phi} \in [0,1]^m$.

In the algorithm, it is assumed that each state x of the HMM corresponds to a working state of the appliance $\{\mathrm{ON}_1, \mathrm{ON}_2, \dots, \mathrm{OFF}\}$, so that the number of states m is equal to the number of symbols n with $\boldsymbol{M} \equiv \boldsymbol{I}^{m \times m}$, and each symbol μ_j corresponds to the value of power consumption of the working state. The probability of transition between the working states of the appliance is proportional to the number of transitions from one state to the other within the footprint, i.e., when the transition is not allowed, the probability is equal to zero. Finally, the starting working state corresponds to the OFF state, because the footprint starts at the turning on instant.

From the analysis carried out in Subsection III-A, the availability of the HMM of both the fridge-freezer combination and the appliance of interest is necessary. The first one is obtained from the corresponding consumption recorded, thus it is a model with high reliability: as showed in Fig. 3c, it is a model with 4 working states, derived from the composition of the 2 working states of the fridge and the freezer. Whereas, for the appliance of interest, the model is not available, since it is derived after the footprint extraction step. Therefore, a generic HMM is exploited: it is obtained from a reference dataset, under the assumption that all the appliances of the same category acts in the same way, while passing from a working state to another, so that the transition probability matrix results the same for each appliance in the category. Furthermore, it is assumed that the number of the working states is the same for all the appliances of the same category, since the working cycle of the appliance type observed in the footprint: therefore, the number of states is defined a priori for the appliance type, such as described in Table I.

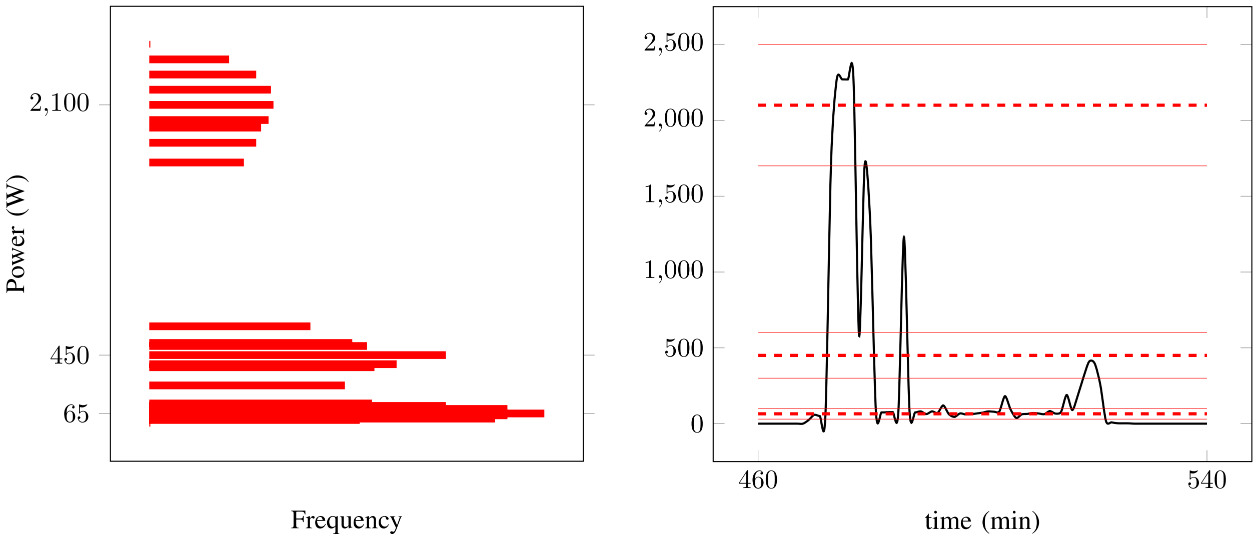
For the appliances with a number of working states greater than 2, it is assumed that the consumption values are proportional each other: therefore, the consumption values in the model are scaled based on the nominal (maximum) value, which is given a priori to the algorithm.

In this way, the HMM represents the appliance as good as possible, omitting the approximation on the consumption values of the middle working state and the approximation on the transition probability matrix.

After the AFAMAP algorithm execution, two disaggregated

TABLE I: Number of working states defined for each category of appliance.

Appliance	num. of states
Fridge	2
Freezer	2
Dryer	3
Washing machine	4
Dishwasher	3
Oven	3



(a) Histogram of the power consumption values.

(b) Footprint and clusters associated to the working states.

Fig. 5: Washing machine in ECO, household 1.

consumption profiles are obtained: the appliance one corresponds to the extracted footprint. Starting from this, the HMM representing the appliance is created, which is used in the disaggregation algorithm to solve the NILM problem.

In order to reach a good generalization in the HMM creation, the availability of different appliance footprints is necessary, as described in Subsection II-A: this process allows to mitigate the errors introduced in the footprint extraction phase. A suggested value of occurrences to record is in the order of 10.

In Fig. 4 the flowchart of the footprint extraction algorithm is depicted. The diagram is composed of two sections: in the left one, the contribution of the fridge-freezer combination is recorded, from which the HMM is obtained; in the right one, the appliance activations are recorded, to obtain the footprint and the related HMM. This procedure is repeated for each appliance footprint recorded, which needs to be extracted.

IV. The Appliance Modelling

In order to execute the AFAMAP disaggregation algorithm, it is necessary to generate the HMM of each appliance from the extracted footprints.

As first step, the power consumption values associated to each working state need to be extracted. This is achieved via a clustering procedure.

As final step, the HMM is created using the well known training techniques.

A. *The clustering procedure*

Clustering refers to the method of partitioning data which are usually gathered near typical values. As result, the samples are split up and assigned in groups in accordance with a distance metric. Then, each group is represented by the *centroid*, namely the unique value in the center of the group, which therefore represents all the elements related to the same group.

In the case of power consumption, the values in the footprint are distributed around the typical value of consumption of each state, as showed in Fig. 5a: 3 groups of data can be observed from the histogram, which represent the 3 clusters. The OFF state, with 0 W power consumption value, is added at the end of the procedure, because the related samples are not considered throughout the data recording: indeed, in order to record the appliance activation using the threshold schema, only the samples which exceed the threshold are considered.

Consequently, the clustering algorithm is executed on the data. In this work, *k-means* [19] has been chosen: it requires only the parameter m as input, corresponding to the number of desired clusters to be obtained. This value has been set for each appliance type as defined in Table I (i.e., the values in the table include the OFF state, thus they have to be decreased by 1). The algorithm selects the starting point to randomly initialize the clusters within the data, and it finds the centroid of each defined group following an iterative procedure.

Recording many footprints allow to reach a proper solution during the iterative procedure in the algorithm: indeed, this kinds of algorithm operates more effectively when a significant amount of data is available for each cluster to find.

The cluster centroid represents the power consumption value of the appliance in that working state: the inference of a gaussian variable on the data related to the same cluster is carried out. The resulting mean value corresponds to the centroid of the cluster and the variance determines the width of the cluster, as shown in Fig. 5b.

The levels with high variability are susceptible of great variance in the consumption value, e.g., the state with higher consumption, while the levels with lower variability have a tighter interval, e.g., the OFF state, as shown in Fig. 5. The variability in the levels is an information representative of the appliance category, as well as of the user usage habits.

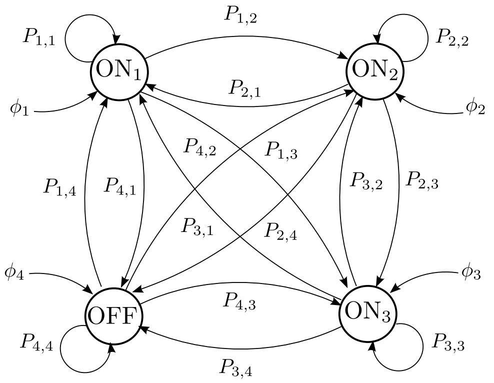


Fig. 6: A 4 states HMM.

TABLE II: An example of the HMM transition probability matrix.

		Destination state			
		ON$_1$	ON$_2$	ON$_3$	OFF
Start state	ON$_1$	0.832	0.085	0.081	0.002
	ON$_2$	0.080	0.690	0.202	0.028
	ON$_3$	0.012	0.028	0.916	0.045
	OFF	3.1e-05	2.7e-05	0.002	0.998

B. The Hidden Markov Model

The HMM is a representation method based on the Finite State Machine (FSM), in which the transitions between the states are regulated by a probability matrix, proportional to the time of permanence in the states and the number of times the model pass from a state to another one. Fig. 6 shows an example of HMM with 4 states.

The transition probability matrix $\boldsymbol{P}$ is obtained using the *Baum-Welch* [18] training algorithm: in the specific case when $\boldsymbol{M} \equiv \boldsymbol{I}^{m\times m}$, only the number of states m composing the HMM and the observed sequence of symbols have to be specified to the algorithm. Each HMM state is assigned to a power consumption state, therefore to a cluster resulting from the procedure described in Subsection IV-A.

Table II shows the transition probability matrix related to the washing machine footprint showed in Fig. 5b. The highest values in the matrix are the ones located on the diagonal, which represent the probability of remaining in the same state, respect to the transition to another one: indeed, for the state where the permanence time is low, this value is lower than the one of the state where the permanence time is higher. The highest value is the one related to the OFF state, because the activation of the appliance occurs after a long time in which it is turned off.

Since the pause interval between two footprint is not recorded, the user has to establish the time interval between two appliance activations, e.g., the typical time of use in the daytime or the number of activations per day of the appliance, in order to calculate the OFF interval and to use this value for the calculation of the transition probability related to the OFF state.

The probability value which tends to zero denotes that the transition is unlikely. In the practice, it is recommended to avoid zero probability value, because it is evaluated in $\log$ scale in the AFAMAP algorithm, and it tends to infinity. It is recommended to fix the value to a little quantity, e.g., $\simeq 10^{-5}$.

V. Computer simulations

The experiments have been conducted using different datasets: the first one for the generic model extraction, and the second one for testing the footprint extraction algorithm. The disaggregation experiments have been conducted on the same dataset, to evaluate the effectiveness of the footprint extraction algorithm, compared to the use of the true appliance level consumption, to create the appliance model.

The general model has been extracted using the *AMPds* dataset [20]. The experiments on footprint extraction and disaggregation are conducted on the *ECO* dataset [17], considering the households 1 and 2, whose appliances are:

- household 1: dryer, washing machine;
- household 2: dishwasher, oven.

The experiments include the the fridge-freezer combination, present in each household.

A. The footprints extraction

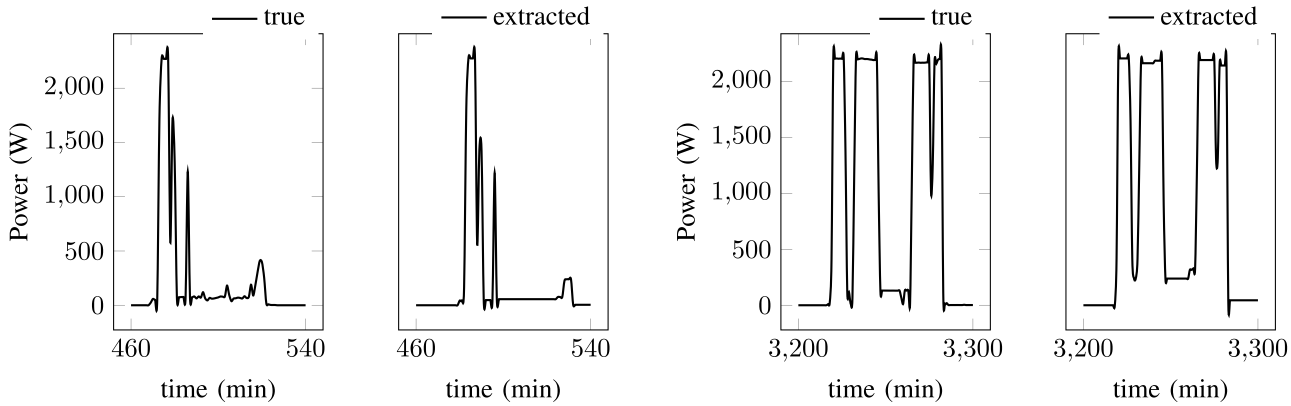
Fig. 7 shows two example of extracted footprints, compared to the original ones. In both cases, a good correspondence between the temporal trends can be noticed, which denotes that the model representing the fridge-freezer combination has a high reliability and it allows to extract the appliance footprint contribution in a suitable way. However, for several portions of the footprint, the correspondence with the power level is not correct: this might be due to the incorrect power levels of the general model, which are obtained from a scaling operation respect to the nominal consumption value. Indeed, the error is introduced in the middle power levels, while for the maximum power level the correspondence is exact. In the entire process, the uncertainty introduced from the disaggregation algorithm, used to separate the footprint from the consumption of the fridge-freezer combination, needs to be considered.

B. The disaggregation results

The experiments have been conducted on a portion of 30 days of the ECO dataset. To evaluate the effectiveness of the footprint extraction procedure, the disaggregation results have been evaluated using:

- the models created using the appliance level consumption, available in the dataset (*true* footprint);
- the models created using the *extracted* footprint, following the procedure described in Section III.

The disaggregation results have been evaluated using the Precision (P) and Recall (R) metrics, defined in [21] in state and energy based sense. To compare the performance of the entire disaggregation system, the F-score (F_1) metric averaged across the appliances (AAA) has been used.



(a) Washing machine in ECO, household 1.

(b) Dishwasher in ECO, household 2.

Fig. 7: Comparison between the true and the extracted footprint for some appliances.

TABLE III: Disaggregation performance in ECO, household 1.

Metric		Fridge-freezer	Dryer	Washing machine	AAA	Footprint
State based	P	0.506	0.657	0.909	0.691	True
	R	0.568	0.821	0.948	0.779	
	F_1	**0.536**	**0.730**	**0.928**	**0.732**	
	P	0.483	0.622	0.880	0.661	Extracted
	R	0.531	0.788	0.937	0.752	
	F_1	**0.506**	**0.695**	**0.908**	**0.704**	
Energy based	P	0.955	0.488	0.849	0.764	True
	R	0.815	0.972	0.978	0.922	
	F_1	**0.879**	**0.650**	**0.909**	**0.835**	
	P	0.953	0.422	0.809	0.728	Extracted
	R	0.790	0.976	0.982	0.916	
	F_1	**0.864**	**0.589**	**0.887**	**0.811**	

TABLE IV: Disaggregation performance in ECO, household 2.

Metric		Fridge-freezer	Dishwasher	Oven	AAA	Footprint
State based	P	0.741	0.926	0.977	0.881	True
	R	0.781	0.980	0.984	0.915	
	F_1	**0.760**	**0.952**	**0.980**	**0.898**	
	P	0.735	0.855	0.972	0.854	Extracted
	R	0.773	0.974	0.982	0.910	
	F_1	**0.754**	**0.911**	**0.977**	**0.881**	
Energy based	P	0.983	0.873	0.973	0.943	True
	R	0.944	0.983	0.984	0.970	
	F_1	**0.963**	**0.925**	**0.979**	**0.956**	
	P	0.981	0.816	0.975	0.924	Extracted
	R	0.939	0.982	0.988	0.970	
	F_1	**0.960**	**0.891**	**0.982**	**0.946**	

The parameters used in the AFAMAP algorithm were the same employed in [21]. The disaggregation window parameter has been set $T = 60$ min.

The disaggregation results are showed in Table III and Table IV. For both metrics, the algorithms achieve good performance: the best results are reached in the household 2 experiment, with a F_1 of 0.898 in state based sense, and 0.956 in energy based sense. This is due to the relatively simple problem studied in those cases: a disaggregation problem with only 3 appliances, with highly distinguishable values of power consumption, reveals to be solvable with high accuracy. The experiments in Table IV shows a better performance respect to the Table III one: the reason is the appliances footprints and the resulting HMMs composition. Indeed, the second problem is composed of models with a lower number of states (e.g., 3 states for the dishwasher, 3 states for the oven, respect to the 3 states for the dryer and 4 states for the washing machine), thus the disaggregation problem results to be simpler in the resolution, and the overall performance reaches higher values. This trend was already introduced from the author of the disaggregation algorithm [8], who shows that the higher is the number of states related to the HMM, the higher is the complexity of the problem definition, and lower is the disaggregation performance due to the more difficult resolution. Regarding the first problem, the fridge-freezer combination has the consumption values close to the dryer ones, which leads to an ambiguity during the problem resolution and a lower performance for the total problem. In general, the appliance with the better performance is the one with the higher power consumption value: for the first problem the washing machine, for the second one the oven.

In both experiments the results corresponding to the true footprint show higher performance respect to the extracted footprints ones: it means that the footprint extraction procedure introduces an error in the appliance modelling stage, which results in a error during the disaggregation algorithm resolution. Nevertheless, the results of the extracted footprint experiments show performance with an admissible relative loss: for the household 1 experiment, the relative loss results of 3.83% in state based sense, and 2.87% in energy based sense, while for the household 2 experiment, it results of 1.89% in state based sense, and 1.05% in energy based sense .

In conclusion, the models obtained after the footprint extraction procedure show a good correspondence with the original ones, which means that the footprint extraction is sufficiently reliable. Therefore, the footprint extraction algorithm introduced in this work provides a convenient procedure to the user for modelling the appliance at the cost of an acceptable loss in disaggregation performance.

VI. Conclusion

In this work, a footprint extraction procedure has been introduced as a solution for the appliance modelling in real NILM scenarios. Indeed, in order to create the appliance model and to use this in the disaggregation algorithm, the user needs to record the appliance consumption profile. A facilitated procedure is needed, in order to obtain a clean footprint from the aggregated power signal in real scenario: therefore, a user-aided footprint extraction procedure is defined. The solution introduced here relies on the availability of a general model for the appliance category to obtain the clean footprint. This is the starting point of the modelling stage: in this work the AFAMAP algorithm has been used, which relies on the HMM for the appliance modelling. The resulting models have been tested in a disaggregation problem, and they have been compared with the same problem solved using the true appliance model, i.e., the models created using the actual footprint from the appliance level consumption. The results have showed a moderate performance reduction compared to the ideal case due to the footprint extraction stage.

For those reasons, the footprint extraction procedure introduced in this work can be considered as an effective method for the user employment in a real NILM scenario.

In the future works, the separation of the model representing the fridge-freezer combination in the single component will be evaluated, since the AFAMAP algorithm shows a better working in the problem resolution using models with lower number of states. In addition, a more complex model for the power consumption in the working state can be exploited, in order to better represent the operational working of the appliance: for example, a Gaussian Mixture Model (GMM) might represents a working state with a probability distribution shape of the power consumption value more complex respect to a simple Gaussian form. Moreover, more experiments will be performed using different datasets in literature, in which a more detailed study about the generalization performance can be carried out, specially for the generic model selection.

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