IRMAC: Interpretable Refined Motifs and Binary Classification for Rooftops PV Owners

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Abstract—In this paper, we seek to identify residential rooftop solar PV owners using imported energy data. To solve this problem with an interpretable, fast, secure, and maintainable solution, we propose Interpretable Refined Motifs And binary Classification (IRMAC) method, which includes a shape-based dimensionality reduction technique we call Refined Motif (RM), and a classification technique with linear complexity to identify solar owners. Furthermore, with the real data from Australia and Denmark, the proposed method is tested and verified in identifying PV owners as well as identifying electrical heating system users. The performances of the proposed method is studied and compared with various of state-of-the-art methods, where the proposed method outperformed the alternatives.

Index Terms—Motif discovery, Solar energy, Pattern recognition, Binary classification, Time series classification

I. INTRODUCTION

Rooftop solar photovoltaic (PV) systems have become a widely accepted choice for residential consumers as a renewable energy source. According to the Australian Energy Market Operator (AEMO), 33% of dwellings in South Australia own rooftop solar PV [1]. At this substantial level of rooftop PV in the distribution network, the system operators are facing unprecedented challenges in maintaining the supply and demand balance locally and system-wide due to the uncertainty of solar generation. As a result, knowing the number of residential consumers with rooftop PV at the feeder level can play an important role in infrastructure planning, day-to-day grid operation, network upgrade and demand-side management. However, identifying users with PV systems based on their hourly or half-hourly imported electricity or net load data from the grid is a major challenge, partially because of a substantial amount of time series from a large number of consumers. Also, the classification problem becomes more complex when only imported energy (which is the case in our paper) time series are available. The complexity grows exponentially when a fast, accurate and interpretable solution is needed for this classification problem.

Classification problems with long time series has been discussed in literature for decades. The existing classification methodologies can be categorised into two groups, shape-based and structure-based [2], [3]. The former approaches rely on analysing similarities of patterns of the raw numeric time series, while the latter converts the raw data with Symbolic Aggregate Approximation (SAX) or Discrete Fourier Transform (DFT) to create statistical models. Shape-based approaches are believed to be more accurate and interpretable, but are computationally expensive [2]. One solution to balance the advantages and drawbacks of the shape-based techniques is called motif extraction, which can compress the time series data while preserving the shape information for classification purposes.

Motifs, defined as approximately repeated sub-patterns in a long time series, was first proposed in 2003 [4]. Since then, motifs have been used as representative patterns for long time-series data in various data mining applications, e.g., classification, clustering, and rule discovery. However, efficient ways to extract motifs were needed as the brute-force solution was computationally untenable [5]. In 2016, an all-pair-similarity search technique, called Matrix Profile (MP), was proposed and then widely used as it could significantly decrease the spatial and temporal complexity of the motif discovery problem [6]. The core idea of MP is to record the most similar sub-patterns pair with the smallest z-normalised Euclidean distance (ED) and exploit the overlap between subsequent patterns using Fast Fourier Transform (FFT) [6]. MP then evolved into a Nearest-Neighbour-based approach and became the most dominant motif discovery approach in the literature, e.g., [5]–[8]. Another critical improvement happened in 2018, when a Scalable Time series Ordered-search Matrix Profile (STOMP) algorithm was proposed, which significantly decreased the temporal complexity of motif discovery by enabling parallel computing and GPU acceleration [9]. Since then, motif-based classification techniques have been widely used in finance, bioinformatics, and economics due to their robustness, low computational power requirement and interpretability.

Compared to the research fields above, only a few research studies have investigated the application of motif-based classification methods in power system related problems [10]–[12]. In these studies, motif-based discovery methods were applied...
to smart meter energy consumption data to identify regular behaviours, rules extraction and solar PV panel installations identification, respectively. All three research used SAX to represent the time series data as discrete code sequence, from where the repeated code segments were extracted as motifs. However, as discussed above, similar to motifs, SAX is a representation technique for dimensionality reduction [2], [13]–[15]. The issue with this approach is the loss of shape information that is critical in binary classification problems such as the one in this paper. Furthermore, SAX technique is vulnerable to identifying small amplitude changes on sub-patterns and missing important information in a given segment [15].

As motifs based applications have only become feasible in the last couple of years, there are some knowledge gaps on state-of-the-art motifs discovery methods. First, for MP and other ED-based methods, one weakness is the lack of temporal dynamics consideration. Second, current motifs discovery methods always extract the most significant features, and hence are incapable to apply to different problems [5], [7], [8]. Third, extracting exact repeated patterns still remain an unsolved problem. Last but not least, there is a lack of discussion on how to effectively use the extracted motifs and preserve the high flexibility for classification purposes in the literature.

Besides the shape-based and structure-based methods, some research tried to classify electricity consumers by analysing their electricity consumption time series with machine learning (ML) techniques, e.g., [16]–[18]. While ML techniques can generally handle extremely complex systems and can infer from incomplete data, their application in power system operation, as a safety-critical system, casts a doubt. ML-based models cannot be easily interpreted, its behaviour cannot be anticipated, and they completely neglect the domain knowledge and physical models [19], [20]. Furthermore, the huge number of parameters in most ML techniques, e.g., Deep Neural Network (DNN), make them suffer from the curse of dimensionality and long training time [21]. On the contrary, the motif-based methods project the data into a much lower relevant representational space to eliminate the curse of dimensionality [21]. The authors in [11] discussed how shape-based methods can be used in energy consumption data analysis for reliable and interpretable applications.

To fill the gap in knowledge, we propose a highly flexible motif discovery method, which enables users to bring in domain knowledge to identify the most repeated motif patterns. To the best of our knowledge, this is the first motif discovery method that can extract motif containing the requested features that might not be the most significant to the shape, whilst considering the time dynamics and preserving the interpretability. With the extracted exact motifs as inputs, then we construct a linear single neuron model to classify the users by their motif. This methodology is later used in a comprehensive simulation study to solve the rooftop PV owners identification problem in this paper, with high performance on accuracy and speed. To show the robustness of the proposed method, a second problem is solved by identifying electric heater users in a dataset.

This paper is organised as follows: Section II explains the proposed methodology including motifs discovery, classification, and implementation. The simulation studies are reported in Section III and the results are analysed in detail. The paper is concluded in Section IV and future works are outlined.

II. THE PROPOSED METHODOLOGY

The proposed methodology is summarised in the high-level block diagram in Fig. 1. First, an accurate and fast motif extracting method, called Refined Motif (RM) hereafter, is developed to reduce the dimension of the electricity time series. In the RM method, a different pattern similarity measurement is proposed by combining power system domain knowledge with temporal dynamics of the time series to extract features. In addition, unlike the Nearest-Neighbour-based methods looking for the closest patterns, the RM technique discovers the most repeated patterns. Second, with the exact motif discovered by the RM method, a linear-complex classification model is proposed to identify rooftop solar PV users, which includes weight parameters and a threshold to provide classification results. The rest of the section will introduces the two middle steps in detail.

![High-level block diagram of the proposed classification method](image)

**A. Refined Motif (RF) Method**

To address the lower accuracy and lack of temporal dynamics representation in the previous motif discovery methods, we propose a new method for pattern distance measurement, which is inspired by Dynamic Time Warping (DTW). Although DTW has long been proven to outperform ED measure in terms of accuracy and detecting temporal dynamics, i.e. time shifting and time stretch [3], the ED was the preferred pattern similarity measure in motif discovery research, e.g., [5]–[9], due to lower complexity. The ED and DTW measures are given in (1) and (2), respectively, where two sub-patterns X and Y have the same length, m, are compared by ED and DTW.

\[
ED(X, Y) = \sqrt{\sum_{i=1}^{m} (X_i - Y_i)^2}. \tag{1}
\]

\[
DTW(X, Y) = \sqrt{\gamma_{i,j}}, \tag{2}
\]

where \(X_i\) is the \(i^{th}\) point in \(X\), \(Y_j\) is the \(j^{th}\) point in \(Y\), \(\gamma(i, j)\) is the cumulative distance of \(X\) and \(Y\) from 1 to \(m\):

\[
\gamma_{i,j} = (X_i - Y_j)^2 + \min\{\gamma_{i-1,j-1}, \gamma_{i-1,j}, \gamma_{i,j-1}\}. \tag{3}
\]

In this case, the complexity of ED is \(O(m)\), while it is quadratic, \(O(m^2)\), for DTW. Consequently, for a long time series with total length \(n\) and sub-pattern length \(m\), with
one data point sliding step, the motif discovery complexity is $O(n^2m)$ and $O(n^2m^2)$ for ED and DTW, respectively. Furthermore, z-normalised ED between two time series sub-patterns can be calculated by their dot product, hereby using the Fast Fourier Transform (FFT) divide and conquer to reduce the complexity from $O(n^2m)$ to $O(n^2)$ (best case $O(n^2)$), which is called MASS algorithm [6].

Comparing the two methods, the ED seems to be a fair trade-off between complexity and accuracy, especially when $m$ is large. However, the nature of specific problems, such as PV owners identification, necessitates more complex measures. For instance, seasonality will affect the PV generation magnitude and duration such that two clear-sky days in summer and winter may be seen as two different patterns using simple distance measures as a result of the patterns’ stretches.

Since the accuracy of decisions always outweighs other criteria in critical systems, and motif discovery is an offline process, we prefer the DTW measure to the ED measure. For the same reason, we use the most accurate DTW method rather than computationally-improved DTW algorithms, e.g. Dynamic Timewarp Barycenter Averaging and Fast Dynamic Time Warping [22], which are faster but less accurate as a trade-off between accuracy and computational speed.

Considering the fact that a PV system generates energy in a daily repetition, the sub-pattern size $m$ should be equal to the number of samples in a day. Also, PV systems generation profiles present a daily cycle. Therefore, we change the pattern search sliding window length from 1 to $m$. The wider sliding window requires the pattern similarity measurement to be robust to pattern shifting due to the seasonal changes in the sunrise and sunset times. As a cumulative distance measure, DTW can work perfectly under time shifting. As a result, the time complexity of the DTW-based motif discovery method reduces from $O(n^2m^2)$ to $O(n^2m)$. More importantly, it makes every sub-pattern start and end at the same time, which ensures that the motifs extracted from different users are comparable.

Another issue in the existing motifs discovery methods is that one can only search for the most significant feature inside the sub-pattern. As a result, extracting motifs from one year of imported electricity data potentially leads to finding the most repeated consumption pattern that dominates the 24 hour daily cycle. This is because the PV generation is only available during daylight hours, the patterns of which may be undermined by the stronger 24-hour load patterns. We show in Section [11] that current motifs discovery methods are incapable to extract motifs in such cases. In this regard, we propose a weighted mask matrix in the original DTW, called refined Dynamic Time Warping (r-DTW) method hereafter as (4)-(5), where $X$ and $Y$ are two sub-patterns, $\phi(i,j)$ is the cumulative distance of $X$ and $Y$, and $W$ is a proposed weight matrix for customising the extracted features by assigning different weight to temporal data.

$$ r-\text{DTW}(X,Y) = \sqrt{\phi_{i,j}}, \quad (4) $$

$$ \phi_{i,j} = W_{i,j}(X_i - Y_j)^2 + \min\{\phi_{i-1,j-1}, \phi_{i-1,j}, \phi_{i,j-1}\}, \quad (5) $$

$$ \tilde{w}_t = \begin{cases} 
1, & t = \text{daytime}, \\
0, & t = \text{nighttime},
\end{cases} \quad (6) $$

$$ W_{i,j} = \max\{||\tilde{w}_i||, ||\tilde{w}_j||\}. \quad (7) $$

For using r-DTW to identify PV generation patterns, we need to emphasise the daytime patterns. As a result, the weighted matrix $W_{i,j}$ in (4) is set as binary in (6) and (7), where $w_t$ is a binary mask vector for the sake of simplicity. For electric heating users identification, no mask was applied in the experiment due to the lack of comprehensive information, but theoretically, the weighted matrix can be set based on their heater usage probability distribution.

Another key improvement in the RM method is the capability to find the most repeated sub-patterns in the long time series instead of the approximated one. MP-based methods save the similarity value of a sub-pattern to its nearest neighbour, and extract the sub-patterns with the largest similarity value as the motif, namely the most similar sub-pattern pairs in the long time series. To find the most repeated sub-patterns, however, we propose a Similarity Profile (SP), shown in Fig [2] which counts the number of similar patterns in the time series to the current sub-pattern. When two sub-patterns are repeated the same number of times, we use the normalised average similarity value to choose the dominant sub-pattern. A pattern is assumed similar when its r-DTW distance to the current pattern is smaller than a predefined threshold, $T$. The process can be presented by:

$$ c_{i,j} = \begin{cases} 
1, & d_{i,j} \leq T, \\
0, & d_{i,j} > T,
\end{cases} \quad (8) $$

where the $c_{i,j}$ is the similarity index, which is 1 when day $i$ and day $j$ have an r-DTW, $d_{i,j}$, below the Threshold value, $T$. The threshold can be set dynamically, e.g., using the median of all r-DTW distances in the table, or simply a fixed educated guess. A dynamic threshold enhances the adaptability of the RM for different users. As a result, the dynamic threshold changes with the new incoming data, which means that updating the users’ SP requires recalculating all r-DTW distances in $m^2$ iterations. Unlike with a dynamic threshold, updating SP with a fixed threshold takes only one iteration. Hence, the dynamic threshold leads to a less scalable solution for long time series. For this reason, we prefer the fixed threshold approach for RM discovery in this paper to preserve the low complexity of updating motifs.

After populating the table for all $N$ days, we can find the average r-DTW for each day, i.e., $\tilde{d}_i$, by

$$ \tilde{d}_i = \frac{\sum_{j=1}^{N} d_{i,j}}{N-1}. \quad (9) $$

Also, we can calculate the total similarity indices for each day, i.e., $\tilde{c}_i$, for day $i$ as:

$$ \tilde{c}_i = \sum_{j=1}^{N} c_{i,j}. \quad (10) $$
Finally, SP for each day, $SP_i$, can be obtained considering the impact of total similarity indices and average r-DTW for day $i$ as:

$$SP_i = \hat{c}_i - \frac{\hat{d}_i}{\max(d_{i,j})}. \tag{11}$$

In (11), the total similarity indices $c_i$ are integers representing the number of similar patterns with current day $i$, while the average r-DTW distance $\hat{d}_i$ is normalised by $\max(d_{i,j})$ to be the secondary impact factor for SP, which will differentiate the days with same similarity indices. Therefore, the proposed SP can provide both similarity indices (integral part) and average similarity (fractional part) of every daily pattern, and the largest value suggests the best motif.

| Day 1 | Day 2 | ⋮ | Day N |
|-------|-------|---|-------|
| Day 1 | $<c_{1,k}, d_{1,k}>$ | ⋮ | $<c_{1,N}, d_{1,N}>$ |
| Day 2 | $<c_{2,2}, d_{2,2}>$ | ⋮ | $<c_{2,N}, d_{2,N}>$ |
| ⋮     | ⋮     | **max** | ⋮     |
| Day N | $<c_{N,1}, d_{N,1}>$ | ⋮ | $<c_{N,2}, d_{N,2}>$ |

| Day 1 | $SP_1$ | ⋮ | Day N |
|-------|-------|---|-------|
| Day 1 | $SP_1$ | ⋮ | $SP_N$ |

Fig. 2: Our proposed Similarity Profile (SP)

### B. Motif-based Linear Classification Function

To use the extracted RMs as classifiers, a simple Neural Network (NN) solution is proposed to classify the users while preserving the interpretability of the IRMAC solution. The proposed classifier contains a single neuron with linear function and the Sigmoid function, where $I$ is the input data with $k$ users’ motifs of length $m$, and $\vec{a}_1, b_1, a_2, a_2$ are the weights and biases of the linear function and the Sigmoid function, $\vec{U}_{sn}$ is the output vector from the linear function with length $k$, and vector $\vec{U}_{sig}$ with length $k$ is the Sigmoid classification outputs for $k$ users.

$$\vec{U}_{sn} = \vec{I} \cdot \vec{a}_1 + b_1, \tag{12}$$

$$\vec{U}_{sig} = \frac{1}{1 + e^{-(\vec{U}_{sn} \cdot a_2 + b_2)}}. \tag{13}$$

Hence, by (12) and (13), the classification problem can then be represented as:

$$\vec{U}_{sig} = \frac{1}{1 + e^{-(\vec{I} \cdot \vec{a}_1 \cdot a_2 + a_2 \cdot b_1 + b_2)}}. \tag{14}$$

Since the Sigmoid function is an increasing function, and $a_2, b_1, b_2$ are constant scalars and biases that do not affect the comparison relationships among users, (14) can be further simplified to $\vec{I} \cdot \vec{a}_1$, which has linear complexity, i.e. $O(k)$, where $k$ is the number of users. In addition, this weight vector has values that align with our domain knowledge, which will be further discussed in Section III.

### C. Further Advantages of the Proposed Method

The proposed classification method can be implemented as shown in Fig. 3. The imported energy time series will be cleansed in the pre-processing stage before applying r-DTW to obtain the SP. The extracted motif of each user is then the input to the single neuron NN. The trained model is a linear function that can be used for new users’ motifs directly.

Furthermore, the proposed method can be implemented in a hierarchical structure, where the end-users at the edge of the grid can extract motifs at their end. As a result, six key advantages can be expected using the proposed method, as listed in the following sub-section.

First, it is storage efficient since only the extracted motif needs to be stored instead of the long time series consumption data of each user. Second, it needs low communication bandwidth as the end users communicate the motif to the cloud system instead of the whole time series. Third, the fast processing speed can be achieved since motifs discovery is conducting at users’ ends in parallel, whereas the classification method is a linear function taking only motifs as inputs. Forth, the cost for the central entity, e.g., aggregator, can significantly decrease because of the low storage and computation capacity requirement. Fifth, moderate abnormal patterns of each end users cannot influence the performance of the proposed method since only motifs can be extracted and used for classification purpose.

The sixth advantage of the proposed IRMAC method is the high security in terms of facing data leakage and data flaws. The high-resolution consumption data is considered sensitive as one can easily identify the household occupany, lifestyle and the usage of different appliances from that. With the proposed method, however, only motif, i.e. one day’s partial data, for each user is communicated to the aggregator and recorded in their databases. In case of data leakage, only one day’s worth of motif data of the end users is exposed. This is not a significant privacy threat because motifs don’t contain the full information on end-users’ lifestyles and occupancy. Also, the proposed method is more robust to false or missing data at the users’ ends compared to ML based methods since those abnormal behaviours occur irregularly and will not affect the most repeated patterns, i.e. motifs. Additionally, the false data of one user cannot affect other users due to the fact that motifs discovery for each end user is highly independent.

Finally, the proposed RM method is easily maintainable. For instance, updating the model to include new users’ data only requires the motif from the new user rather than recomputing previous motifs for all consumers and refining the models. Also, the process of updating a single user’s motif only requires a single iteration by comparing the new incoming data with the existing sub-patterns to update the SP. Therefore, we do not need to repeat the entire motif discovery process for a user to update its motif. It is worth noting that the proposed RM method is applicable to other electricity user’s type detection problems such as heating types classification, which will be discussed in Section III. In summary, the
The proposed method is fast, computationally efficient, secure from the end-user’s perspective, scalable and interpretable.

![Diagram](image-url)

**Fig. 3: Block diagram for the proposed IRMAC method**

### III. Simulation Results

To show the applicability of the proposed IRMAC method, the experiments are conducted on two datasets to solve two different binary classification problems: 1) finding rooftop solar PV among residential consumers, and 2) finding residential consumers with electrical heating systems. In the first dataset, we have half-hourly PV generation and load demand data of 300 residential consumers from the East coast of Australia [24]. The database contains one year’s worth of gross solar PV generation, general electricity consumption, and electricity consumption profile of a controlled appliance (likely a off peak hot water system), which leads to an electricity usage surge around mid-night. We also know the capacity of PV panels in each household. We have done a quality check on the data. The dataset is further divided into imported energy from the grid for 300 solar and 300 non-solar users. As discussed in Section II, we use the imported electricity rather than the actual electricity demand because of two reasons: 1) Some utilities in the world, e.g., Watts in Denmark who is our industry partner, only have access to imported data from the grid for their consumers, and 2) detecting rooftop PV using net demand data can be trivial in many cases.

Secondly, the imported energy data used in the electric heating system identification problem is obtained from our industry partner [25]. The dataset contains 10,000 residential consumers all across Denmark. After data pre-processing, we picked 1052 consumers in the same region. The sample dataset had 893 users with no electric heating system and 159 users with electric heating systems. It is an unbalanced dataset for modelling purposes. To analyse this unbalanced data, the F-score, as a widely accepted measure of balance between the precision and the recall in unbalanced datasets for binary classification [26], is used as a performance measure.

1) **Solar PV Users Identification**: Based on Occam’s razor theory, sophisticated methods make sense only when a problem cannot be solved with a direct or an intuitive solution. As a result, we compare the proposed RM method with several intuitive and complex methods as follows:

   a) Full ML:
      - Support vector machines (SVM)
      - K-Nearest Neighbors algorithm (k-NN)

   b) Two DNN Methods:
      - Multi-layer perceptron (MLP): A simple DNN with 5 layers sequential model containing relu and dropout.
      - Time Series Convolutional Neural Network (1D-CNN): A state-of-the-art DNN specifically designed for time series classification, which outperforms other ML solutions [27].

2) Intuitive:
   a) Counting Zeros (CZ): The general understanding is that a consumer with rooftop PV does not import energy in the middle of the day most of the times; hence resulting in numerous zero entries in the imported electricity time series. In this method, we examine this intuitive idea to identify solar PV owners. From the box plot in Fig. 4, we can see that most of the non-solar users have less than 2,000 zero entries, while the majority of solar users have more than 2,000 zeros. Therefore, we use this value to classify consumers in this approach.
   b) Average Daily Profile: To challenge the RM method, we replaced extracted motifs with average daily profiles of each user. Similar to IRMAC, we used a single neuron NN for the classification problem in this case.

3) Motif-based methods:
   a) STOMP Motifs: The most dominant motifs discovery method in the literature, which uses one interval step size pairwise ED with MP.
   b) IRMAC: This is our proposed method.

![Box plot](image-url)

**Fig. 4: Box plot for the “Counting Zeros (CZ)” method**

For the East coast of Australia data, only summertime imported electricity data is selected to have the strongest solar generation pattern in the time series, which also reduces the motif discovery time in the motifs-based methods. With extracted motifs from SP as inputs, we devote 448 motifs to the training set and the remaining 150 motifs to the testing set. The calculated weight vector from the single neuron NN is shown in Fig. 5, which is obtained with the initial value...
of weight mask set based on sunset and sunrise time, with a 90% accuracy for the testing set. The overall trend of the weight profile matches our domain knowledge of the solar PV generation characteristics. This weight profile can guide us in calibrating the weight mask vector for SP by limiting the window to 10 am to 4 pm and using the same mask on the weight vector for classification. These calibrations improved the IRMAC’s accuracy to 96% on the testing dataset. Two solar users have been detected as non-solar users, i.e. False Negative (FN), and four non-solar users have been detected as solar users, i.e. False Positive (FP).

![Weight vector obtained during single neuron NN training](image)

**Fig. 5:** Weight vector obtained during single neuron NN training

Different classification methods are compared in Table I. In general, the Motif-based methods and full ML techniques outperform the intuitive methods. The better performance of IRMAC over Average method indicates that the extracted motifs contain significant features of the PV generation compared to the annual average values. Within the motif-based methods, STOMP is incapable of finding valid motifs for two reasons. First, the total load feature is dominant in an entire daily profile, thus the most significant feature is not from solar generation. Second, The STOMP motifs use a one step sliding window, which mixes the night time patterns with the distance counting.

By comparing the accuracy and F-score in Table I, the Time Series CNN outperforms other methods. However, it has the longest computation time. Note that the motif discovery computation time is not reported in the table. This is because motif discovery is processed in parallel for each user at their end; thus the actual classification time in the IRMAC method is only the time needed for the linear classification function. In addition, the motif discovery will be carried out once and it takes about 20 s for each user from summertime’s data. After that, we only need to update the motif by incoming daily data, which requires 300 ms for each user on average. Therefore, the motif discovery time should be separated from the actual classification problem, which takes 1.03 ms to solve. In conclusion, the proposed IRMAC method outperforms the other techniques considering the computational time and accuracy.

To further study the proposed method, Fig. 6 shows the histogram of the results from the test dataset, where all results from the Sigmoid function are coloured by their real user types. While the IRMAC model will classify the users with a value below 0.5 as non-solar users and otherwise as solar users, we can observe two FN on the far left and four FP on the right. Most of the results are located at the two ends, showing IRMAC model is likely to give a confident result. However, among the falsely detected users, two FN and one FP are located at the far ends, which means the proposed method has high confidence in classifying them correctly. It requires further analysis as follows.

First, we compare the FN and FP average motifs with the average motifs of solar and non-solar users in Fig. 7. We can see that the falsely detected solar users have irregular profiles compared to their respective groups. For example, while solar users have a relatively flat and close to zero motif shape during the daytime, the FN cases have a significantly higher profile during the same time. It means that these two FN cases have either a very low-capacity PV system or they have exceptionally high demand during daytime. This is investigated by looking at the gross solar energy generation,

**TABLE I: Performance of different methods in PV owner classification problem**

|         | Full ML | SVM | KNN | ID-CNN | MLP Average | CZ | 50% | 90% |
|---------|---------|-----|-----|--------|-------------|----|-----|-----|
| Accuracy| 89.4%   | 72% | 97.3% | 94.6% | 87% | 94.6% | 50% | 90% |
| F-score | 0.897   | 0.71 | 0.973 | 0.945 | 0.86 | 0.944 | 0.56 | 0.96 |
| Time, s | 1.93    | 0.5 | 212  | 15.3  | 0.001 | 4.2  | 18  | 0.001 |

**Fig. 6:** A histogram of the IRMAC method testing results

**Fig. 7:** Average motifs of different users’ groups
demand, and solar panel capacities of the two FN users. First, we noticed that the two FN users have 1.0 kW PV systems. Furthermore, from the generation-consumption ratio plot in Fig. 8 we observe that the two FN users have the lowest daytime generation-demand ratio. This indicates that our method cannot identify the solar users with high electricity demand and low solar production.

Fig. 8: The ratio of total PV production to the total daytime consumption for solar users

2) Electrical Heating System Users Identification: For heating system classification, the intuitive method has been developed based on the fact that we expect electrical heating system users to import more energy from the grid during winter. To test this hypothesis, we first plot the load duration of each group of consumers during the summer and winter seasons separately in Fig. 9.

The higher imported energy can be observed for electrical heating system users compared to non-electrical heating users. The difference between summer load duration and winter load duration for each user is then measured by ED, and a threshold is set to identify the user’s type as Fig. 10. This method is called Load Duration (LD) method.

For comparison, we use the same classification methods from the solar users identification problem (except for the CZ that is replaced by the LD method). For obvious reasons, only winter data is used for the motif-related methods. The accuracy and computational time of the different methods are reported in Table II. It shows that the proposed IRMAC method is almost as accurate as the best methods, but it requires less computation time. Also, it proves that the proposed binary classification method is robust and could be applicable to other problems.

IV. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel shape-based method to identify the rooftop PV owners from their imported electricity data. This method is proven to be reliable and can be applied to
As future work, we intend to develop an RM-based method for multi-class classification problems that has numerous applications in power systems, e.g., identifying users with electric vehicles, solar PV and stationary batteries. We also would like to develop an adaptable motif updating technique to reduce the fears over security breaches.

TABLE II: Performance of different methods in the electric heating system identification problem

|       | Full ML | Intuitive | Motif-based |
|-------|---------|-----------|-------------|
|       | SVM     | KNN       | MLP         | STOMP       | IRMAC      |
| Accuracy | 95%     | 93%       | 95%         | 94%         | 92%        | 94.4%      |
| F-score | 0.79    | 0.72      | 0.767       | 0.73        | 0.73       | 0.642      | 0.749      |
| Time, s | 0.46    | 0.61      | 2.32        | 4.34        | 0.002      | 0.002      | 67         | 0.002      |

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