Electrical Power and Energy Systems 103 (2018) 224–232

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

Classifier economics of Semi-Intrusive Load Monitoring

Fangyuan Xu[a], Baifu Huang[a], Xin Cun[a], Fenghua Wang[b], Haoliang Yuan[a,*], Loi Lei Lai[a,*], Alfredo Vaccaro[c]

[a] Guangdong University of Technology, Guangzhou, China
[b] State Grid Zhejiang Electric Power Co. Ltd, China
[c] University of Sannio, Italy

ARTICLE INFO

Keywords:
Load monitoring
Machine learning
Classifier evaluation
Smart grid
Smart meter

ABSTRACT

Non-Intrusive Load Monitoring (NILM) and Semi-Intrusive Load Monitoring (SILM) are fast developing techniques for devices operation recognition in system monitoring. Many traditional researches focus on feature space improvements for better recognition accuracy and classifier/meter quantity reduction. But practically, cost of each classifier/meter will influence the optimal NILM/SILM solution. A feature space with better accuracy in NILM may require more cost than a SILM solution with multiple classifiers with simpler feature spaces. Facing this issue, this paper initiates a new classifier network construction method for NILM/SILM. Instead of creating a classifier for NILM or SILM, this method helps decision maker to select different types of classifiers and optimally allocates the classifiers' positions. In this method, economics of each type of classifier is considered to ensure decision maker's cost reduction. A combinatorial optimization problem is established on a tree-type model to the optimized classifier network. Numerical studies on a public data set REDD and an industrial operational data are implemented to support the feasibility of the method.

1. Introduction

1.1. Technical background

Information and Communication Technologies (ICT) and Intelligent Data Analytical Technologies (IDAT) become a new trend for various industries' development. On one hand, Internet of Things (IoT) provides high degree linkage among multiple devices, which devices can talk to each other [1–3]. On the other hand, the fast developing artificial intelligent techniques have improved capabilities of devices' coordination [4–6]. Following this trend, more and more new implementations with ICT and IDAT appear in multiple industries.

Non-Intrusive Load Monitoring (NILM) is one of the ICT & IDAT implementing cases in power system. Other than recognizing devices' operation status by device-based specified metering data traditionally, NILM receives information of detail power profiles at the aggregated point and find out devices operation status by a machine-learning based classifier [7–8,18]. Facing requirement on devices operation monitoring, NILM only contains a local meter and a local data analyzing unit, instead of constructing a data transmission network and more than one meter in traditional monitoring system. So intuitively, NILM can decrease the construction cost of load monitoring system [9–11]. Moreover, installing one meter at the aggregated point is said to have less privacy violation than distributing a specified meter for each device inside consumers [12–14]. Relevant researches keep placing effort on NILM development. Longjun creates a view on V-I Trajectory for NILM with 1% minimal error with Adaboost framework [15]. Chang presents a novel NIFM algorithm to improve the associated recognition accuracy and the average test accuracy of using the proposed method is higher than 98.13% in DLGF [16]. Kong introduces a Hybrid Programing Method to improve the NILM efficiency and push the NILM being used in the daily life [17].

NILM is still a developing technology. Facing different devices combination, NILM may not always achieve a good enough accuracy. For example, the Type I devices are classified with a high accuracy but the other type devices like Dishwasher are with a lower accuracy in [19]. Some NILM schemes only perform well on distinguishing special devices [20]. Generally speaking, performance of NILM will decrease when more devices are integrated together. Because devices with similar power profile may confuse classifier's recognition. Thus, Tang has introduced a method named Semi-Intrusive Load Monitoring (SILM) [21]. SILM does not accumulate all devices' recognition into one aggregated point. Instead, by considering performances of classifiers, SILM select several aggregated points with classifiers. Each classifier only classifies the operating status of a section of devices. Thus, each classifier will not suffer overburdening task and the total recognition

* Corresponding authors.
E-mail address: Hunteryuan@126.com (H. Yuan).

https://doi.org/10.1016/j.ijepes.2018.05.010
Received 28 February 2018; Accepted 9 May 2018
0142-0615/

accuracy will increase.

Saving construction cost of load monitoring system is one of the most attracting advantages from NILM and SILM. Various researches on NILM or SILM is trying to decrease the cost by decreasing numbers of metering points [22–23]. Some researches have quantized the cost reduction [11,24]. But most researches assume that the cost of meter is same/similar with each other. In fact, meter cost with different metering functions fluctuates significantly in the market. If a meter with advanced power profile metering costs too much, NILM system with high cost metering function may cost even higher than traditional load monitoring system. Furthermore, accuracy of traditional load monitoring system is nearly 100% with only active power metering. So NILM and SILM may appear to be even worse than traditional load monitoring method on both accuracy and construction cost. Decision maker of load monitoring requires new methods with consideration on both accuracy and construction cost to support their solution design.

1.2. Original contribution

Facing the issue above, this paper initiates a new classifier network construction method for SILM. Instead of creating a classifier for NILM or SILM, this method helps decision maker to select different types of classifiers and optimally allocates the classifiers' positions. In this method, economics of each type of classifier is considered to ensure decision maker's cost reduction, including cost of feature metering and classifier hardware constructions. A combinatorial optimization problem is established on a tree-type model to the optimized classifier network. In this model, NILM becomes a special SILM case with 1 classifier only. Numerical studies on a public data set REDD and an industrial operational data are implemented to support the feasibility of the method.

The content of this paper is summarized below. Section 2 provides a technical introduction for NILM and SILM. The classifier network construction is introduced in Section 3. Based on this network, the tree-type combinatorial optimization problem construction is shown in Section IV. Two numerical case studies are selected to verify the effect of proposed method in Section V.

2. Typical feature space of SILM

NILM or SILM analyzes devices' operation status from the power information at the aggregated point.

From Fig. 1, all power operational information downstream devices are accumulated at the aggregated point with classifiers. Theoretically, voltage and current obey Thevenin Theorem. Classifiers should fully

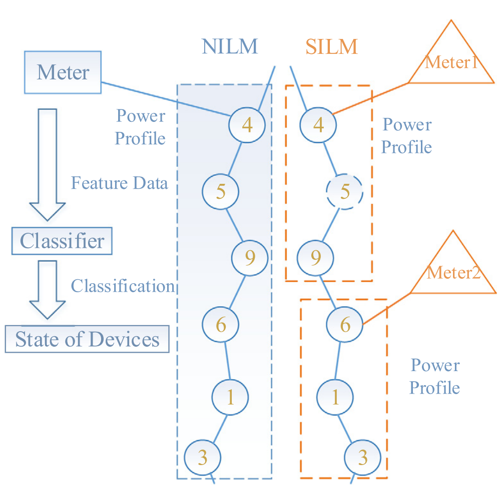

Fig. 1. SILM/NILM monitoring structure.

recognized devices' operational differences on power profile information to differentiate operational status. At the initial stage of NILM, Massachusetts Institute of Technology (MIT) has summarized 4 types of appliances with different operational patterns [32], including ON/OFF appliances (Electric Kettle, Toaster), Finite State Machines (Electric Fan, Air Conditioning, Washing Machine), Continuously Variable Consumer Device (Speaker Box, Dimmer Light), and Permanent Consumer Device.

Facing different types of appliances, various features are abstracted to portray each downstream devices. The most popular features are introduced below.

- **Active Power**. Although the focusing point of NILM researches are different, active power appears to be a common feature under their feature space [11,25]. This feature represents the energy consuming speed and performs well when number of downstream devices is small. The meter price of active power metering only is the lowest in the market.
- **Reactive Power**. Reactive power is preferred by several NILM researches together with active power [25,26]. Meters with reactive power measuring is higher than those with active power only.
- **Time & Frequency Domain Characteristics**. Features under this title includes Vrms, Irms, Ipeak and harmonics of voltage and current. It improves the accuracy from models with only reactive power and active power [27]. These features are abstracted by high sampling frequency and thus the metering function cost is much higher than that with active power and reactive power only.
- **Transient Related Features**. Typical features under this title include transient power, Start-Up Current Transients and High Frequency Sampling of Voltage Noise [28]. Transient monitoring requires not only high sampling frequency but also a suitable capture triggering scheme for waveforms. The processed data is large and cost for the metering function is usually the most expensive.

Classifiers in NILM or SILM with different feature spaces require different cost of metering functions. Table 1 shows a sample of price for meters in Fig. 2.

3. Modelling of SILM classifier network

3.1. Problem definition

There are many types of implementations for SILM. Owners of SILM or NILM aim to construct monitoring system with less construction cost and sufficient accuracy. So construction cost and accuracy are the two main factors for SILM system installation consideration.

In terms of accuracy, nearly all types of classifiers will suffer accuracy reduction with large scale of devices. Because large scale of devices will have a high probability on containing similar performing devices (or even several same type of devices). It is difficult for classifier to separate devices with similar features. A preliminary experiment is selected to reveal this phenomenon in Fig. 3.

Random forest is selected as classifiers in this experiment. A public dataset REDD is selected for analysis [29]. Two feature spaces are selected for preliminary experiments. The feature space1 has the P and Q. The feature space2 contains the fundamental to the 8th harmonic

Table 1
Price sample of meters in Fig. 2.

Meter	Product No.	Market Price
Fig. 2(a)	DDS1531	$200
Fig. 2(b)	DTS3533	$300
Fig. 2(c)	PAC4200	$1000
Fig. 2(d)	ION7650	$2500