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An analysis on the energy consumption of circulating pumps of residential swimming pools for peak load management

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HIGHLIGHTS

- The average hourly energy consumption of a circulating pump is 0.7425 kW.
- The peak power and valley power of circulating pump are 0.5274 kW and 0.9612 kW.
- The peak time and valley time of circulating pumps are 9:00 and 17:00.
- Circulating pumps contribute 8.48% peak load of all neighborhoods.
- The peak load can be reduced by 8.48% by controlling circulating pumps.

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ABSTRACT

Based on an extensive dataset containing aggregated hourly energy consumption readings of residents during March 2011 and October 2012 in South Ontario, Canada, this paper estimates the energy consumption of circulating pumps of residential swimming pools (CPRSP) non-intrusively, and quantifies the impact of CPRSP on the power system. The main challenges are that, first, widely used non-intrusive appliance load monitoring (NIALM) methods are not applicable to this work, due to the low sampling rate and the lack of the energy consumption pattern of CPRSP; second, temperature-based building energy disaggregation methods are not suitable for this work, as they highly depend on the accurate base load estimation and predefined parameters. To overcome these issues, in this paper, first it is found that, during the pool season, for homes with and without swimming pools, the ratio between their base loads is approximately equal to the ratio between their temperature-dependent energy consumptions, then a novel weighted difference change-point (WDCP) model has been proposed. The advantages of the WDCP model are that, on one hand, it doesn't depend on the base load estimation and predefined parameters; on the other hand, it has no requirement on the data sampling rate and the prior information of energy consumption patterns of CPRSP. Based on the WDCP model it is shown that, the average hourly energy consumption of CPRSP is 0.7425 kW, and the minimum and the maximum hourly energy consumptions are 0.5274 kW at 9:00 and 0.9612 kW at 17:00, respectively. At the peak hour 19:00, July 21, 2011, CPRSP contributes 20.36% energy consumption of homes with swimming pools, as well as 8.48% peak load of all neighborhoods. As a result, the peak load could be reduced by 8.48% if all CPRSP are stopped during the peak hour.

1. Introduction

Peak load in a given year refers to the highest amount of electricity being consumed in an hour in the system under consideration, which determines the size of the generators, transmission lines, and transformers for a utility [1]. Peak load may exceed the maximum supply levels that the electrical energy industry can generate, resulting in energy outages and load shedding, and peak load management has received significant attention in recent years [2–5]. On the residential front, a lot of efforts have focused on studying how air conditioners (ACs) - typically the most electricity consuming home appliance - could be controlled to reduce their activities during the peak hour while the users' comfort remain at an acceptable level [6–8].

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Nomenclature

ACs	air conditioners
CPRSP	circulating pumps of residential swimming pools
WDCP	weighted difference change-point
NIALM	non-intrusive appliance load monitoring
IALM	intrusive appliance load monitoring
EvOT	energy consumption vs. outdoor temperature
RPT	the reference point temperature
Φ	the no-pool season
Ω	the pool season
B	base load
$P_{\max}$	peak load
$H_{\max}$	the peak hour
$\Re$	the aggregated energy consumption
T	the temperature-dependent energy consumption
N	the temperature-independent energy consumption
P	the CPRSP energy consumption
r	the ratio of base load of homes with and without swimming pools during pool season
k_0	the gradient of the linear regression on weighted difference of energy consumption vs. outdoor temperature
k_1 and k_2	gradients of two-phase piecewise linear regression on weighted difference of energy consumption vs. outdoor temperature
A	the angle between the two lines of two-phase piecewise linear regression

Superscripts

p	data from homes with residential swimming pool
n	data from homes without residential swimming pool

Subscripts

Φ	data during non-pool season
Ω	data during pool season

This paper considers a class of pumping system that has not been studied much, namely circulating pumps of residential swimming pools (CPRSP) and shows that it might have a significant impact on peak load in some neighborhoods in South Ontario, Canada. Current studies on the energy consumption of pumps mainly focus on the water pumping system which is widely used for irrigation. One issue of the water pumping system is the high energy consumption, applying renewable energy such as solar energy is a popular way to overcome this issue [9,10], and at present many efforts have focused on the photovoltaic water pumping system [11–14]. This paper chooses CPRSP to analyze its impact on peak load because:

- Residential swimming pools are standard backyard accessories in central-Canadian middle-class homes. There are over 700,000 residential swimming pools in Canada. In Ontario alone, the estimated number of residential swimming pools is 311,000.
- CPRSP are the second largest electrical load of homes with swimming pools, right after AC, and peak load occurs in summer in Ontario when swimming pools are in use.
- CPRSP are used to circulate water through filters in swimming pools to keep it clean. The activity period of CPRSP is typically 8–12 h a day, regardless of the weather or residents activities. Therefore, controlling the activity periods of CPRSP might be easier than for AC since it would result in very little impact on user comfort.

There are a few works on the analysis on the energy consumption of CPRSP [15,16]. In these works, end-uses have been recorded directly through specific meters for each use, which can be considered as an intrusive appliance load monitoring (IALM) issue. However, this paper estimates the CPRSP energy consumption non-intrusively from the aggregated energy consumption measured by single smart meter installed in the residential house. Generally, non-intrusive appliance load monitoring (NIALM) methods or energy disaggregation methods are used for such issue. Compared with IALM which measures each appliance's energy consumption with a specific meter, NIALM has many advantages, such as lower cost of installation and maintenance, smaller space requirements and greater reliability [17]. Currently there are plenty of NIALM methods [17–29]. Among these methods, most of them are event-based, meaning that appliances are monitored by detecting the change of some steady-state [19,23–25] or transient-state features [17,21,29] related to current or voltage, and then corresponding energy consumptions are estimated by supervised [17,20] or unsupervised [19,23] methods, depending on whether prior information is available. However, all of these NIALM methods cannot be used for the CPRSP energy consumption, due to the very low sampling frequency (hourly data) and no prior information on CPRSP in this work. Although most of steady-state signatures based NIALM methods do not emphasize the importance of the sampling frequency, an implicit assumption is that the sampling frequency needs to be high enough to capture most of state changes of major appliances [19,20,24,30], or the prior information of use patterns of appliances must be available [18]. From another aspect, the estimation of the CRPSP energy consumption can be converted to estimations of base load and the temperature-dependent energy consumption, and some temperature-based building energy disaggregation methods such as degree days [31,32] and change-point models [33,34] may be used. However, degree days methods highly depend on the reference temperature point (RTP), which is usually chosen empirically, and an inappropriate RPT will greatly reduce the accuracy of degree days methods [31]. Meanwhile, to use change-point models, three key issues need to be identified: the number and locations of change points, as well as the gradient of each linear regression. However, for some the energy consumption vs. outdoor temperature (EvOT), these parameters are determined empirically, making the estimation unreliable.

To estimate the energy consumption of CPRSP non-intrusively, this paper proposes a novel weighted difference change-point (WDCP) model. Compared with other NIALM methods, the proposed WDCP model has no requirement on the sampling rate and prior information of energy consumption patterns of CPRSP. Meanwhile, compared with typical building energy consumption disaggregation methods such as basic change-point models and degree-day methods, the proposed WDCP model doesn't depend on the base load estimation, as well as user defined parameters. The contributions of this paper can be summarized as follows.

First, based on a dataset containing hourly energy consumption readings of labeled 1005 residential buildings in South Ontario, Canada from March 2011 to October 2012, this paper finds that, during the pool season, for homes with and without swimming pools, the ratio between their base loads is approximately equal

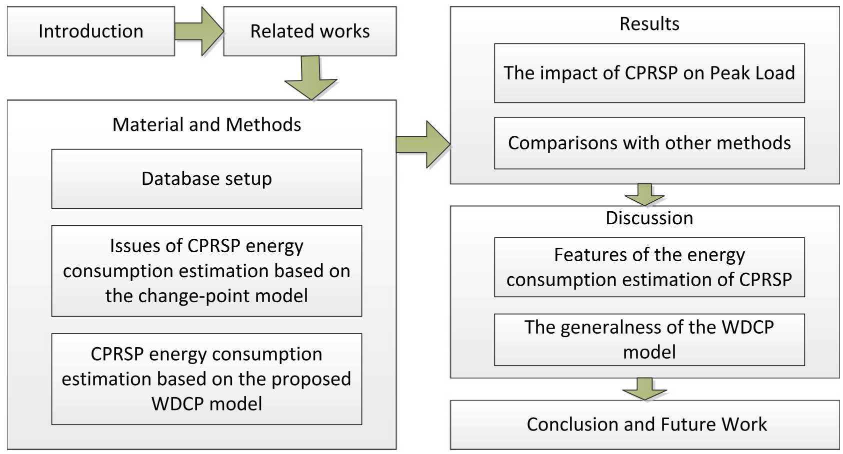


Fig. 1. The schematic overview of the whole paper.

to the ratio between their temperature-dependent energy consumptions.

Second, a novel WDCP model has been proposed, based on which it is shown that, the average hourly energy consumption of a poop pump is 0.7425 kW, the minimum and the maximum hourly energy consumptions are 0.5274 kW and 0.9612 kW, and corresponding hours are 9:00 and 17:00, respectively. Meanwhile, during the peak hour 19:00, July 21, 2011, CPRSP contributes 20.36% energy consumption of homes with swimming pools, and 8.48% peak load of neighborhoods. Therefore, if all CPRSP all stopped during the peak hour, the peak load will be reduced by 8.48%.

The remainder of this paper is organized as shown in Fig. 1. Related works are given in Section 2. Material and methods are shown in Section 3. Section 4 gives the analysis of the impact of CPRSP on peak load, and the comparisons of the proposed WDCP model with other methods. In Section 5, the features and the generalness of the proposed model are discussed. Finally, Section 6 gives the conclusion and the future work.

2. Related works

The estimation of the CRPSP energy consumption can be converted to estimations of base load and the temperature-dependent energy consumption, and some temperature-based building energy disaggregation methods such as degree days and change-point models may be used. Degree days methods (cooling and heating) calculate the number of days with the temperature greater or less than the reference temperature point (RTP), to estimate the influence of temperature change on a building [31,32]. Degree days methods highly depend on RPT, which is usually chosen empirically, and an inappropriate RPT will greatly reduce the accuracy of degree days methods [31]. Change-point models are to fit piecewise linear regression models with unknown change points to a dataset whose distribution is suspected to change at change points. Change points models have been widely used in fields such as global surface temperature anomaly analysis [35] and crime analysis [36]. For the building energy disaggregation issue, change-point models are popular steady-state data-driven models, which disaggregate the temperature-dependent and temperature-independent energy consumptions based on piecewise linear regression on EvOT [33,34]. To use the change-point model, three key issues need to be identified: the number and locations of change points, as well as the gradient of each linear regression. However, for some EvOT, these three parameters are difficult to be obtained automatically, which need to be determined empirically. For example, in [33], the heating season gradient and the cooling season gradient are defined as the 90th percentile fits of the heating and cooling phase, while base load is obtained from 10th percentile fits. Obviously corresponding results highly depend on user's definitions.

From another point of view, estimating the energy consumption of CPRSP from the aggregated energy consumption can be considered as a NIALM issue, which is to disaggregate an individual appliance energy consumption from the aggregated energy consumption obtained by an main smart meter in a building. NIALM is not a novel concept, in 1989, Hart has presented the concept, prototypes, research directions, as well as the advantages and disadvantages of NIALM [17]. Compared with intrusive appliance load monitoring (IALM) which measures each appliance energy consumption with a specific meter, NIALM has many advantages, such as lower cost of installation and maintenance, smaller space requirements and greater reliability. NIALM is a very hot topic in recent years, and currently there are plenty of NIALM methods [17–29]. For NIALM methods, features selection and load disaggregation are two key issues. At present two types of features of appliances are usually used: steady-state signatures [18,19,23–25] and transient signatures[17,21,29]. Steady-state signatures of appliances are signatures when appliances are in stable states, such as the active power, the reactive power, and the power factor angle. Steady-state signatures can be obtained using meters with low sampling frequencies (e.g. 1 Hz). However, such signatures are not unique, and many appliances may have similar steady-state signatures, bringing difficulties for appliances identification [37]. Compared with steady-state signatures, transient signatures can provide more unique features. Transient signatures of appliances are the signatures captured during the state of appliances change, such as turn-on or turn off [17]. For different appliances, transient signatures such as current waveform signatures, current harmonic signatures and active power waveform may be unique, making it can be used for appliances identification. However, to capture distinctive transient signatures, a high sampling rate is required, therefore some specific designed meters need to be installed [38]. Meanwhile transient signatures are more susceptible to noises. To overcome this issue, some works combines the two types of signatures to improve the identification accuracy. In [21], the turn-on transient energy signature and traditional steady-state power signatures are used to improve the recognition accuracy and to reduce computational requirements. After obtaining signatures, superwised and unsuperwised learning or classification models can be used for load disaggregation. Superwised learning models require appliances information (e.g., an appliances signatures database) as prior. For example, Lin et al. [29] employ transient signatures (current waveform signatures, current harmonic signatures, active and reactive power signatures, and geometrical properties of V-I curves), and use quadratic 0–1 programming to identify appliances based on an appliances signatures database. Compared with superwised learning methods, unsuperwised learning methods disaggregate energy without prior information, and Hidden Markov Models have been widely used [19,23,28]. For example, Aiad and Lee [28] use Factorial Hidden Markov Model with the active power as the input, and they also consider interactions among devices. Although can work without prior, the accuracy of unsuperwised learning methods will decrease dramatically with the increase of potential appliances [23].

3. Material and methods

3.1. Dataset setup

To quantify the energy consumption of CPRSP, and measure the impact of the use of CPRSP on power system, a utility in South Ontario has monitored the hourly energy consumption of 31,000 meters from March 2011 to October 2012. The dataset contains these readings as well as the meter locations and the types of buildings in which the meters are installed, (e.g., residential, commercial and industrial). Meanwhile, hourly weather data is obtained from Weather Canada (weather.gc.ca), and linear interpolation is carried out when some weather data is lost. From the dataset it can be seen that the peak hour occurs on July 21, 2011, which is Thursday. As statistical properties of load during weekdays are usually different from that during weekends [5], this paper only considers data during weekdays. As in Ontario Canada, residential swimming pools are typically install outdoor, for 1110 residential meters in a specific neighborhood, ground truth data is manually added on building features observed using satellite imagery, and Google Earth is used to label whether a home has a swimming pool or not manually. Two examples of the way to label data are given in Fig. 2, where the house in left figure (Coordinates: 4219′50.6″N 8253′42.1″W) has no pool while the house in the right figure (Coordinates: 4219′40.9″N 8253′35.9″W) has a pool. Finally, after ignoring some images with uncertainty, altogether 1005 residential buildings have been labeled, among which 346 with swimming pools and 659 without swimming pools.

In Canada, CPRSP are used to circulate the water through filters in the swimming pools to keep it clean. Previously CPRSP were run continuously for the whole season. Due the consideration of the electricity cost, timers are installed to reduce the activity period of CPRSP. Nowadays, the activity period of CPRSP is typically 8–12 h a day, regardless of the weather or residents activities. Therefore, from a statistical point of view, the use pattern of CPRSP can be assumed to be daily cycle during Ω.

To estimate the CPRSP energy consumption, some definitions using in this paper are given as follows:

No-pool season Φ and **pool season** Ω: in Ontario generally people use their pools from May to September. However, since it is difficult to know exactly when pools are being opened and closed, to make it no ambiguity, the non-pool season Φ is defined from November 15, 2011 to February 29, 2012. Similarly, the pool season Ω is defined from July 1, 2011 to August 30, 2011, as well as from July 1, 2012 to August 30, 2012, during which all pools are expected to be opened. Note that in other locations, definitions of Φ and Ω would be probably different.

Base load B: generally base load refers to the energy consumption for the basic daily tasks and is supposed to be continuous 24 h a day. In this paper, base load is defined as the total energy consumption of homes excluding the energy consumption related to the outdoor temperature (e.g. the energy consumption by AC or heaters), as well as the CPRSP energy consumption if swimming pools exist.

Based on definitions of Φ, Ω and B, the average hourly energy consumptions of homes with and without swimming pools during Φ and Ω can be written as:

$$\begin{aligned}\Re^p_\Phi &= T^p_\Phi + N^p_\Phi \\ &= T^p_\Phi + B^p_\Phi\end{aligned} \tag{1}$$

$$\begin{aligned}\Re^n_\Phi &= T^n_\Phi + N^n_\Phi \\ &= T^n_\Phi + B^n_\Phi\end{aligned} \tag{2}$$

$$\begin{aligned}\Re^p_\Omega &= T^p_\Omega + N^p_\Omega \\ &= T^p_\Omega + (B^p_\Omega + P^p_\Omega)\end{aligned} \tag{3}$$

$$\begin{aligned}\Re^n_\Omega &= T^n_\Omega + N^n_\Omega \\ &= T^n_\Omega + B^n_\Omega\end{aligned} \tag{4}$$

where $\Re$ is the aggregated energy consumption, T and N are temperature-dependent and temperature-independent energy consumptions, respectively, B is base load, and P is the CPRSP energy consumption. All of them are hourly average values. Superscripts p and n indicate homes with or without swimming pools, subscripts Φ and Ω indicate it is in Φ or Ω. Eq. (3) means that for homes with residential swimming pools, during Ω, the temperature-independent energy consumption N^p_Ω consists of two components: B^p_Ω and P^p_Ω. In other situations as depicted in Eqs. (1), (2) and (4), the temperature-independent energy consumption N is equal to the corresponding B.

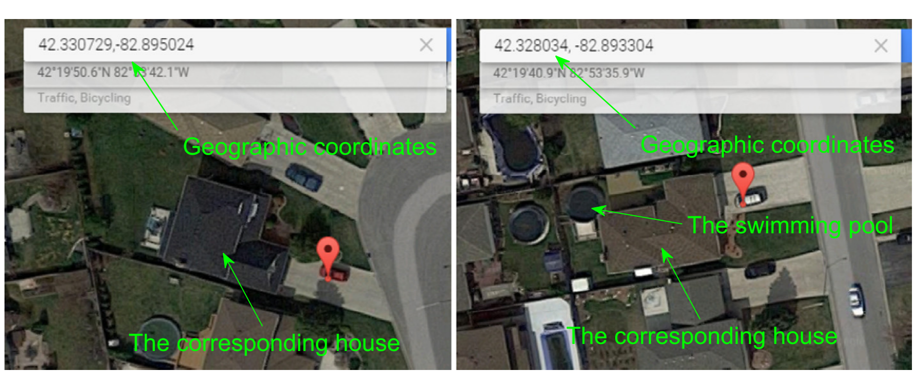
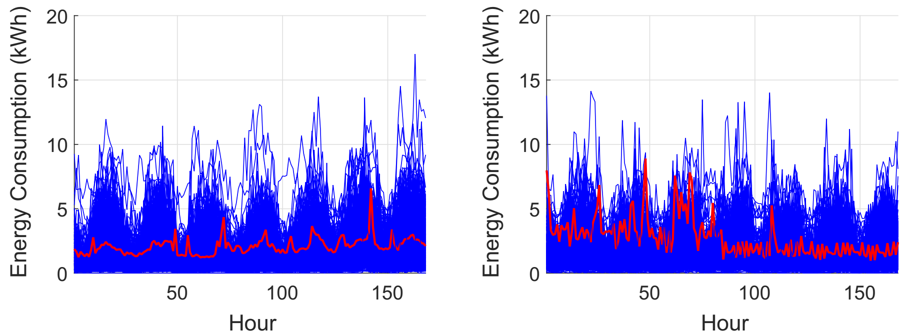
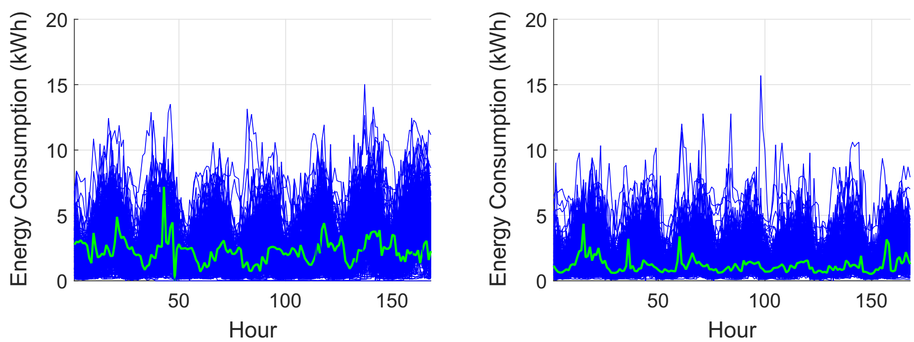


Fig. 2. Two examples of the way to label data using Google Earth, where the house in left figure has no pool while the house in the right figure has a pool (Accessed date: 2016-11-6).



(a) 2011.08.27 - 2011.09.02 without pool (b) 2011.12.25 - 2011.12.31 without pool

Fig. 3. Raw profiles of energy consumptions of homes without swimming pools during one week, where blue curves are raw profiles, while red curves in a and b are profiles of a single home without the swimming pool during different periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) 2011.08.27 - 2011.09.02 with pools (b) 2011.12.25 - 2011.12.31 with pools

Fig. 4. Raw profiles of energy consumptions of homes without swimming pools during one week, where blue curves are raw profiles, while green curves in a and b are profiles of a single home with a swimming pool during different periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Peak Load P_{max} and Peak hour H_{max}: peak load P_{max} refers to the highest amount of electricity being consumed in an certain hour, and peak hour H_{max} is the corresponding time.

As profiles of energy consumptions of homes with and without swimming pools are available, one may consider that the CPRSP energy consumption could be obtained from the difference between them. Figs. 3 and 4 give raw profiles of energy consumptions of homes without swimming pool, where data in Figs. 3a and 4a are from August 27, 2011 to September 02, 2011 (pool season), and data in Figs. 3b and 4b are from December 25, 2011 to December 31, 2011 (no-pool season). In Figs. 3 and 4, blue curves are raw profiles. In Fig. 3a and b, the red curves are profiles of a single home without the swimming pool during different periods. In Fig. 4a and b, the green curves are profiles of a single home with a swimming pool during different periods.

From Figs. 3 and 4 it can be seen that although overall distribution of profiles of energy consumptions is periodic daily, the distribution of that of a single home is complex, and the CPRSP energy consumption could not be obtained from differences between energy consumption profiles of different periods.

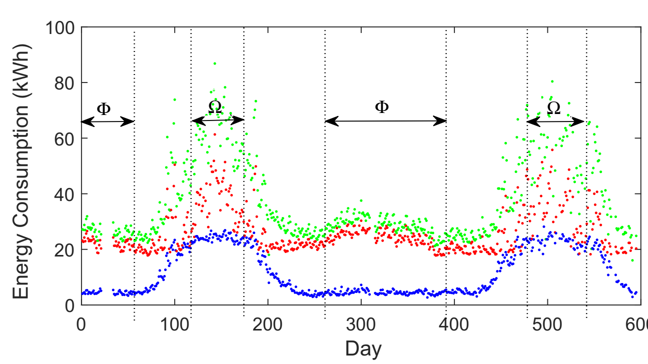


Fig. 5. Daily average energy consumption profiles of homes with and without CPRSP over the whole period, where green points, red points and blue points are daily average energy consumption of homes with CPRSP, without CPRSP, and differences between them. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 5 gives daily average energy consumption profiles of homes with and without swimming pools over the whole period, where green points, red points and blue points are daily average energy consumption of homes with CPRSP, homes without swimming pools, and differences between them. From Fig. 5 it can be seen that during Φ, values of blue points are around 5 kW h. However, they should be close to 0 if they are considered as the CPRSP energy consumption. The reason is that homes with residential swimming pools are usually richer and bigger than homes without swimming pools, making the fact that excluding the CPRSP energy consumption, the energy consumption of homes with swimming pools is still larger than that of homes without swimming pools, due to the different lifestyle such as additional TVs and a second refrigerator, as discussed by Fisher[16].

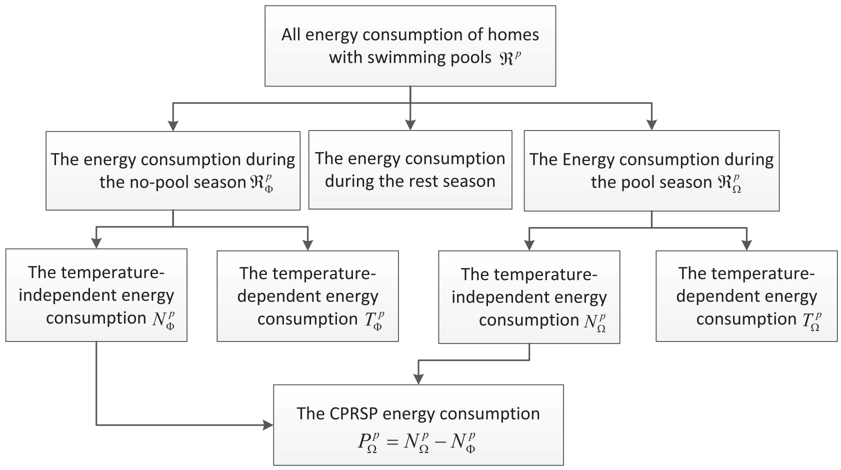


Fig. 6. The flowchart of the straightforward method to estimate the CPRSP energy consumption.

3.2. CPRSP energy consumption estimation based on the change-point model

As the base load is temperature-independent, it can be considered remaining the same during Φ and Ω. Therefore, if N^p_Φ and N^p_Ω are obtained, then P^p_Ω can be estimated by:

$$\begin{aligned} P^p_\Omega &= N^p_\Omega - B^p_\Omega \\ &= N^p_\Omega - B^p_\Phi \\ &= N^p_\Omega - N^p_\Phi \end{aligned} \tag{5}$$

According to the above analysis, the flowchart of a straightforward method of estimating the CPRSP energy consumption is given in Fig. 6, which includes three steps. In the first step, the energy consumption of homes with swimming pools $\Re^p$ is divided into three groups, the energy consumption during the no-pool season $\Re^p_\Phi$, the energy consumption during the pool season $\Re^p_\Omega$, and the energy consumption during the rest season. In the second step, $\Re^p_\Phi$ is disaggregated into two parts, the temperature-independent energy consumption N^p_Φ, and the temperature-dependent energy consumption T^p_Φ. Meanwhile, $\Re^p_\Omega$ is also disaggregated into two parts, the temperature-independent energy consumption N^p_Ω, and the temperature-dependent energy consumption T^p_Ω. In the third step, the CPRSP energy consumption P^p_Ω can be obtained by:

$$P^p_\Omega = N^p_\Omega - N^p_\Phi \tag{6}$$

To disaggregate the temperature-independent and temperature-dependent energy consumptions, degree days methods [31,32] and change-point models [33,34] are usually used. However, in degree days methods, RTP must be predefined, and an inappropriate RPT will significantly reduce the estimation accuracy[31], therefore in this paper the change-point model is used.

The change-point model is to fit a piecewise linear regression model with unknown change points to a data set whose distribution is suspected to change at change points. According to ASHRAE (the American Society of Heating, Refrigerating, and Air-Conditioning Engineers) [31], a whole change-point model is shown in Fig. 7, where the red[1] line with the gradient below 0 indicates a temperature-dependent heating period, the green line with the gradient close to 0 indicates a temperature-independent period, and the blue line with the gradient above 0 indicates a temperature-dependent cooling period. Using the change-point model, it is easy to aggregate temperature-independent and temperature-dependent energy consumptions, as well as analyze the influence of the outdoor temperature on the energy consumption. Note that for some EvOT, change-point models may have only one or two types periods, meanwhile each type period may have occur multiple times [33].

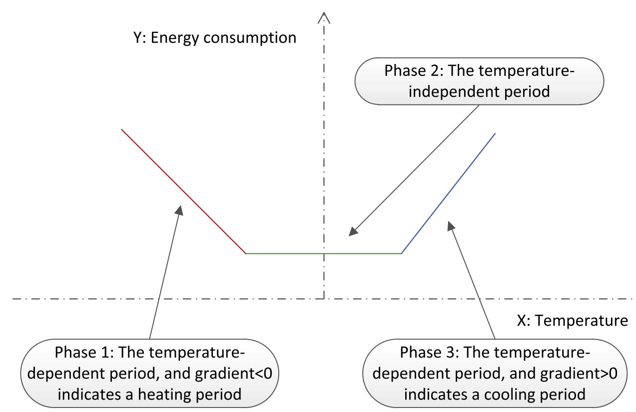


Fig. 7. The basic three-phase change-point model.

Change-point models estimate the base load by obtaining regression parameters on the temperature-independent period at the bottom of EvOT. Fig. 8 gives EvOT of houses with swimming pools over the whole period, where blue points, red points and green points indicate Φ, Ω and the transition period, respectively.

From Fig. 8 it can be seen that EvOT of houses with swimming pools during Φ has the temperature-dependent hearting period and maybe have the temperature-independent period, and during Ω it has the temperature-dependent cooling period and maybe have the temperature-independent period. However, during Φ and Ω the temperature-independent periods are ambiguous, which means that reliable N^p_Φ and N^p_Ω cannot be obtained using the change-point model based on such EvOT, as discussed in [33], therefore the basic change-point model is not suitable to estimate the CPRSP energy consumption.

3.3. Weighted difference change-point model based CPRSP energy consumption estimation

To estimate the CPRSP energy consumption P^p_Ω, an assumption is given:

[1] For interpretation of color in 'Fig. 7', the reader is referred to the web version of this article.

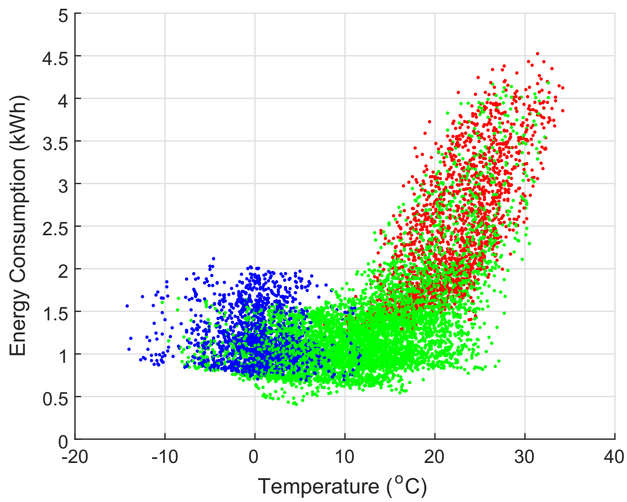


Fig. 8. EvOT of houses with swimming pools over the whole period, where blue points, red points and green points indicate Φ, Ω and the transition period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A 1. For homes with and without swimming pools, the ratio of their base loads is approximately equal to the ratio of their temperature-dependent energy consumptions during Ω:

$$\frac{B_\Omega^p}{B_\Omega^n} = \frac{T_\Omega^p}{T_\Omega^n} = r \tag{7}$$

where r is the ratio.

Proof. According to Eq. (3):

$$\begin{aligned}\Re_\Omega^p &= T_\Omega^p + P_\Omega^p + B_\Omega^p \\ &= T_\Omega^p + P_\Omega^p + r \times B_\Omega^n \\ &= T_\Omega^p + P_\Omega^p + r \times (\Re_\Omega^n - T_\Omega^n) \\ &= P_\Omega^p + r \times \Re_\Omega^n + (T_\Omega^p - r \times T_\Omega^n)\end{aligned} \tag{8}$$

Rewriting Eq. (8), P_Ω^p can be obtained:

$$P_\Omega^p = (\Re_\Omega^p - r \times \Re_\Omega^n) - (T_\Omega^p - r \times T_\Omega^n) \tag{9}$$

If and only if A.1 holds, then:

$$T_\Omega^p - r \times T_\Omega^n = 0 \tag{10}$$

And then the CPRSP energy consumption can be obtained by:

$$P_\Omega^p = \underbrace{\Re_\Omega^p - r \times \Re_\Omega^n}_{\textit{the weighted difference}} \tag{11}$$

Note that as the CPRSP energy consumption P_Ω^p is temperature-independent, if and only if A.1 holds, $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature should be temperature-independent, in other word, it should be close to a linear horizontal distribution. Therefore, if a specific r can be obtained which makes $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature close to a linear horizontal distribution, then A.1 holds. □

The estimation of r can be formatted as an optimum issue:

$$\min_r \quad \left\{ \left| \frac{k_0 \times (k_1 - k_2)}{1 + k_1 \times k_2} \right| \right\}, \quad k_1 \times k_2 \neq -1 \tag{12}$$

$$s.t. \quad 0.3 \leqslant \frac{L_{cp} - L_{\min}}{L_{\max} - L_{\min}} \leqslant 0.7 \tag{13}$$

where k_0 is the gradient of the linear regression on $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature, k_1 and k_2 are gradients of the two lines of the two-phase piecewise linear regression on $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature. Eq. 13 is the constraint on the location of the change-point of the two-phase piecewise linear regression, where L_{min}, L_{max} and L_{cp} are the minimum temperature, the maximum temperature, and the temperature of the change point. Eq. (13) is used to make the location of the change point around the middle of the whole dataset, to make the result robust.

Eq. (12) consists of two items, $|k_0|$ and $\left|\frac{k_1-k_2}{1+k_1\times k_2}\right|$. The first item $|k_0|$ indicates the overall direction of $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature, and minimizing $|k_0|$ will make it horizontal. The second item $\left|\frac{k_1-k_2}{1+k_1\times k_2}\right|$ is the measurement of linearity of $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature, which is actually the indicator of the angle A between the two lines of two-phase piecewise linear regression on $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature, where

$$A = \left(\arctan\left(\left|\frac{k_1 - k_2}{1 + k_1 \times k_2}\right|\right)\right) \times \frac{180}{\pi} \tag{14}$$

The idea of $\left|\frac{k_1-k_2}{1+k_1\times k_2}\right|$ is that if A is close to 0, then the two-phase piecewise linear regression could be replaced by a linear regression, which means good linearity of $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. outdoor temperature.

Note that Eq. (12) cannot be solved by general optimization methods such as least squares, as $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. out temperature changes with r. In this paper, the interior-point algorithm [39] is used to search the optimum of r, meanwhile Sizer [40] is used to obtain parameters of the change-point in the two-phase piecewise regression. Results are shown in Table 1 and Fig. 9.

Table 1 gives estimated r, k_0 and A for each hour, and Fig. 9 gives corresponding EvOT, where red points and green points indicate the energy consumption of homes with and without swimming pools, and blues points are results of the WDCP model. Due to space limitation, only results of Hour 1, Hour 7, Hour 13 and Hour 19 are given in Fig. 9.

From Fig. 9 it can be seen that, during different hours, EvOT of homes with pools, as well as EvOT of homes without pool are different, respectively. For example, except Hour 7, EvOT of homes with pools (red points) and EvOT of homes without pool (green points) at Hour 1, 13 and 19 are loose, and it is difficult to determine such distributions are linear or not. As a result, linear regressions on such distributions are unreliable. In contrast, EvOT of $\Re_\Omega^p - r \times \Re_\Omega^n$ (blur points) are much more compact, and regressions on such distributions should be more reliable. From Table 1 it can be seen that, the maximum absolution of k_0 is 1.544×10^{-6}, and the maximum absolution of A is 1.104°, which indicate that $\Re_\Omega^p - r \times \Re_\Omega^n$ vs. out temperature is horizontal and linear, therefore assumption A.1 holds, and the WDCP model can be used to estimate the CPRSP energy consumption. Furthermore, compared with distributions of red points and green points, the distribution of blue points is more compact, therefore the linear regression on such distribution should be more robust and reliable. As the proposed method relies on the weighted difference between change-point models, it is so-called the WDCP model.

4. Results

4.1. The impact of CPRSP on peak load

Energy consumption profiles of all homes can be obtained from the dataset directly. It can be found that the peak load occurs at 19:00, July 21, 2011, and in this section the energy consumption during July 21, 2011 is analyzed.

To reflect the impact of the use of CPRSP on homes with swimming pools, Fig. 10 gives profiles of the hourly average

Table 1
The estimated r, k_0 and A for each hour.

Hour	1	2	3	4	5	6
r	1.2607	1.2580	1.2426	1.2585	1.2077	1.1830
k_0 (10^{-6})	−1.083	1.544	−0.660	1.500	0.426	0.956
$A(^\circ)$	0.3181	0.3378	0.2351	0.4421	0.3035	0.3525
Hour	7	8	9	10	11	12
r	1.1337	1.2019	1.1975	1.2348	1.2148	1.1906
k_0 (10^{-6})	−0.5501	0.2801	−1.867	0.2876	−0.3710	−1.864
$A(^\circ)$	0.5474	0.3485	0.6971	0.3576	0.9300	0.8241
Hour	13	14	15	16	17	18
r	1.1684	1.1243	1.0731	1.0852	1.0492	1.0627
k_0 (10^{-6})	−0.5909	−0.3059	−0.1884	0.6736	−0.5141	0.6413
$A(^\circ)$	0.6748	1.095	0.9304	0.3913	0.3571	0.1962
Hour	19	20	21	22	23	24
r	1.0752	1.0921	1.1367	1.1576	1.1790	1.2100
k_0 (10^{-6})	−0.3636	0.5799	−0.3517	−0.9815	0.3793	−0.2516
$A(^\circ)$	1.043	0.974	0.6039	1.104	0.3028	0.4419

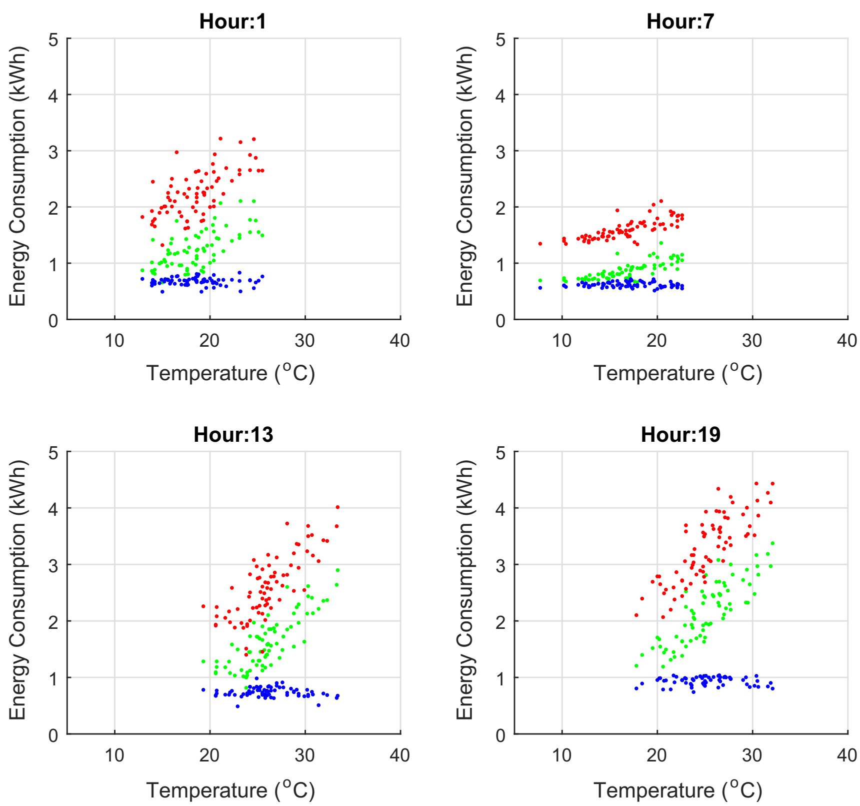


Fig. 9. Results of the proposed WDCP model at Hour 1, 7, 13 and 19, where red points and green points indicate the energy consumption of homes with and without swimming pools during the pool season, and blues points are results of $\Re^p_\Omega - r \times \Re^n_\Omega$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

energy consumption of CPRSP, homes with swimming pools, and homes without swimming pool. From Fig. 10 can be seen that, during the peak hour, energy consumptions of CPRSP and homes with swimming pools are 0.9538 and 4.6840, respectively. Therefore, CPRSP contributes $0.9538/4.6840 * 100\% = 20.36\%$ energy consumption of homes with swimming pools during the peak hour. By comparing the two profiles, it can be seen that the overall trends of the two profiles are similar, but the trend of the profile of CPRSP is smoother. For example, peak hours of CPRSP and homes with swimming pools are 19:00 and 17:00, respectively, which are close to each other. Note that energy consumptions of CPRSP at 17:00, 18:00 and 19:00 are nearly constant.

Furthermore, even excluding the CPRSP energy consumption, the energy consumption of homes with swimming pools is larger than that of homes without the swimming pool. The reason is that homes with residential swimming pools are usually richer and bigger than homes without swimming pools, as discussed by Fisher [16].

To reflect the impact of the use of CPRSP on the peak load, Fig. 11 gives the profile of the total hourly energy consumption of CPRSP (labeled as CPRSP), the profile of the rest energy

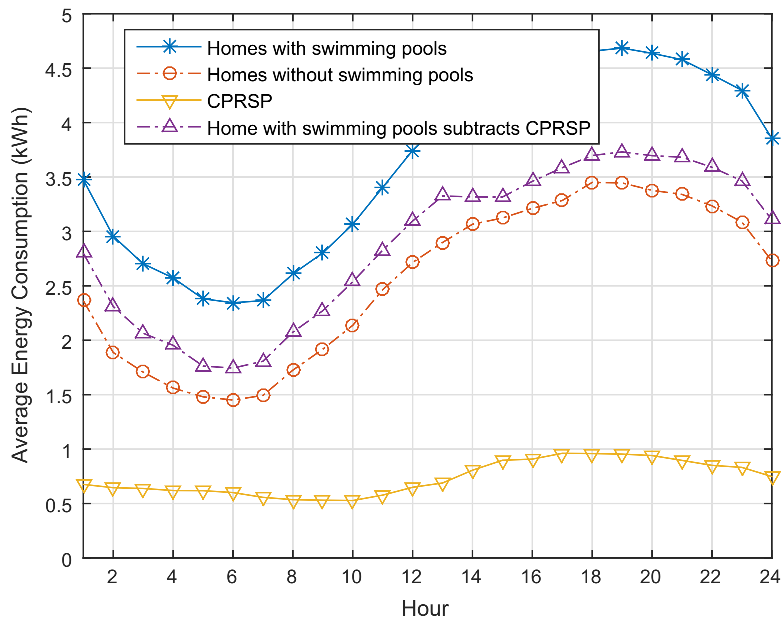


Fig. 10. The impact of CPRSP on homes with and without swimming pools.

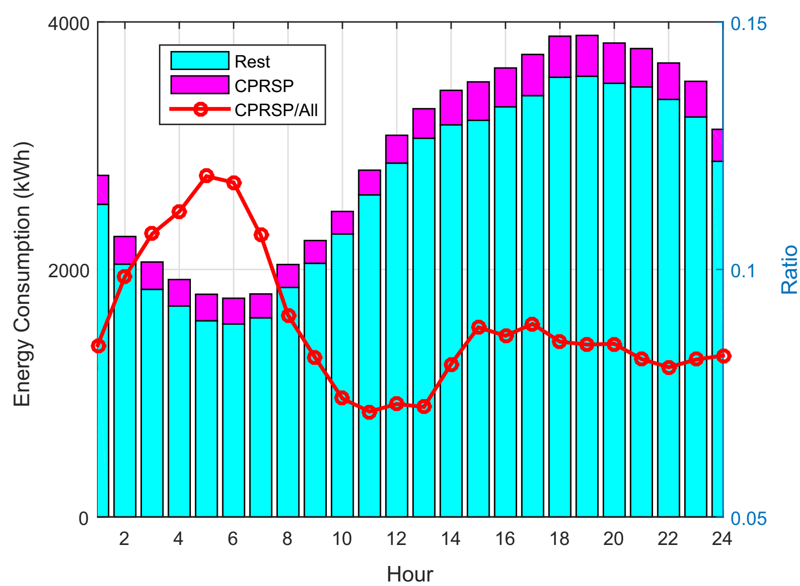


Fig. 11. The impact of the use of CPRSP on power system.

consumption (labeled as Rest), as well as the ratio of the energy consumption of CPRSP and the total energy consumption at each hour (labeled as CPRSP/All). As shown in Fig. 11, during the peak hour (19:00), the total energy consumption of all homes is 3891.24 kW h, and the total energy consumption of CPRSP is 330.01 kW h. Therefore, during the peak hour, $330.01/3891.24 * 100\% = 8.48\%$ energy is consumed by CPRSP. Therefore, if all CPRSP all stopped during peak hour, the peak load will be reduced by 8.48%.

4.2. Comparisons with other methods

Currently there is no other NIALM algorithm for the CPRSP energy consumption estimation. However, as discussed in Section 3, an alternative method is that first obtaining base load of Φ and Ω, and then calculating the difference between them. In this section, two temperature-based energy disaggregation methods, namely Birt et al. [33] and Shin and Do [32], are employed as comparisons. Birt is a multiple-phase change-point model method. Compared with the basic change-point model which regresses on the whole dataset, Birt carries out three separate three-phase piecewise regressions on 10th percentile data, median data, and 90th percentile data, receptively, and base load is defined based on the change point with the lowest energy consumption on 10th percentile data. In this paper the Birt method is used on Φ and Ω separately to obtain the base load of each period. To test the robustness of this method, regressions are carried out based on 5th,10th,15th, and 20th percentile data, and results are labeled as Birt5, Birt10, Birt15 and Birt20, respectively. Shin is a cooling degree-day method, and RTP is determined by a two-phase change-point model, in which one phase is forced to be temperature-independent to obtain the base load. Using the Shin method, the base loads during Φ and Ω can be obtained, then the CPRSP energy consumption can be estimated from the difference of them. Fig. 12 and Table 2 give estimated profiles of CPRSP energy consumptions using different methods.

As shown in Fig. 12 and Table 2, the estimated peak time and valley time of CRPSP are similar among different methods. However, there are significantly differences among the estimated peak powers and valley powers using these methods. As the ground true of the CPRSP energy consumption is not available, the effectiveness of the proposed WDCP model cannot be verified directly. However, these methods can be compared from four aspects.

First, results of Birt5, Birt10, Birt15 and Birt20 are significantly different, indicating that the Birt method highly depends on user defined parameters, therefore corresponding results are unreliable. Meanwhile, in the Shin method, one phase is forced to be temperature-independent to obtain base load. However, as shown in Fig. 8, Φ and Ω have no stable temperature-independent periods, making such method also unreliable. In contrast, the WDCP method has no such issue as it does depend on the base load estimation and user defined parameters.

Second, as the estimated CPRSP energy consumption is the average of all homes with swimming pools, and the activity period of CPRSP is typically 8–12 h a day, regardless of the weather or residents activities [16], therefore the profile of the CPRSP should change smoothly with time in a day round. However, compared with the result of WDCP, results of other methods are with much stronger volatility.

Third, the power of CPRSP is usually between 0.35 kW h and 1.45 kW h [41]. Suppose the average power of CPRSP is $(0.35 + 1.45)/2 = 0.9$ kW h, and all CPRSP open and run simultaneously during the power time of CPRSP, then the peak power of CPRSP should be close to 0.9 kW h. As shown in Fig. 8 and Table 2, the peak power estimated by WDCP is 0.9612 kW h, while results of other methods are larger than 1.2 kW h, and results of Birt15 and Birt20 are even larger than 1.4 kW h, therefore results of WDCP are more reasonable.

Fourth, in [15], Danny gives the impact of major appliances such as space heating, space cooling, and pool pump on the total average annual electrical loads for 204 residences in Central Florida. The main goal of that work is to obtain load profiles for major appliances, and to identify ways in which the residential peak load might be reduced. It is shown that during the peak hour 17:00 in July, a typical pool pump consumed 0.94 kW h in average. Based on WDCP, the peak time is 17:00 and the peak power is 0.9612, both are very close to results given in [15]. However, in [15], end-uses have been recorded directly through specific meters for each use, thus figures are accurate and not based on estimations. Therefore validity of the proposed WDCP model can be proved.

5. Discussion

5.1. Features of the energy consumption estimation of CPRSP

Compared with typical NIALM isses, three factors make the energy consumption estimation of CPRSP unique: hourly sampling data, no prior information, as well as specific EvOT of Φ and Ω. First, Although most of steady-state signatures based NIALM methods do not emphasize the importance of the sampling frequency, an implicit assumption is that the sampling rate needs to be high enough to capture most of state changes of major appliances [19,20,24,30], or the prior information of use patterns of appliances must be available [18]. NIALM needs to captures state changes (events) of major appliances, and they would fail if an appliance's state has changed multiply times during two successive samples [19,30]. However, in this work only hourly data is available, and the sampling rate is too low to capture events of major appliances, [18] proposes discriminative disaggregation sparse coding based on hourly data, however, the prior dictionary of use patterns of appliances is required. Second, prior information such as operational states or training dataset of CPRSP are not available, e.g., CPRSP work under different operational models with different powers, and some energy effective CPRSP may run permanently, and such types of appliances cannot be detected by generic NIALM methods. Third, the power of CPRSP is usually between 0.35 kW h and 1.45 kW h [41], which is not significantly higher than other residential appliances. Therefore, the state of CPRSP cannot be identified by the absolute value of the aggregated load.

Another important issue is that, when using change-point models [33,34], the base load is assumed as a constant during different seasons, because it is temperature-independent. However, such

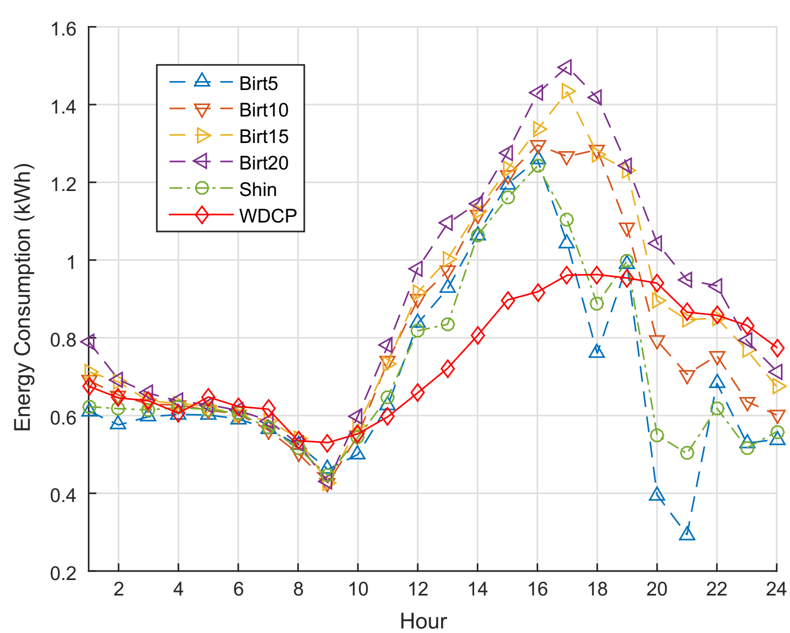


Fig. 12. CPRSP energy consumption estimation using different methods.

Table 2
Results of different methods.

	Birt5	Birt10	Birt15	Birt20	Shin	WDCP
Peak power	1.2590	1.2960	1.4330	1.4975	1.2423	0.9627
Peak hour	16:00	16:00	17:00	17:00	16:00	17:00
Valley power	0.2933	0.4267	0.4259	0.4294	0.4453	0.5304
Valley hour	9:00	9:00	9:00	9:00	9:00	9:00
Average power	0.6988	0.8010	0.8475	0.8942	0.7196	0.7425

assumption is not reliable, as base load may be different during different seasons. These differences may not have a great impact on the qualitative analysis, but can reduce the accuracy of quantitative analysis. However, the WDCP model avoids this issue by only using data during Ω, meanwhile avoids estimating base load directly.

5.2. The generalness of the WDCP model

Although the proposed WDCP model is designed based on features of CPRSP, it can be used for other appliances. For example, the energy consumption of ACs has been widely studied [42,43]. However, these methods are either based on complex models with many predefined parameters [42] or questionnaires [43]. Using the proposed WDCP model, if in a region, first, not all residential homes have AC; second, energy consumption profiles of homes can be obtained; third, homes with AC can be identified by the external sections of AC; then the energy consumption of AC can be calculated by the WDCP method with a slight modification:

$$\frac{B_a}{B_n} \approx \frac{T'_a - T_a}{T_n} \tag{15}$$

where B_a and B_n are base loads of homes with and without ACs, T'_a is temperature-dependent energy consumptions of homes with ACs, T_a is the energy consumption of ACs, T_n is the temperature-dependent energy consumption of homes without AC. In Eq. (15), B_a, B_n, T'_a and T_n can be obtained by the basic change-point model. If Eq. (15) satisfies A.1, then the energy consumption of ACs T_a can be obtained using the WDCP model.

6. Conclusion and future work

This paper analyzes the energy consumption of CPRSP and the impact of CPRSP on the power system during March 2011 and October 2012 in South Ontario, Canada. First this paper shows that temperature-based energy disaggregation methods and NIALM methods are not suitable for this work. Second, this paper shows that during the pool season, for homes with and without swimming pools, the ratio between their base loads is approximately equal to the ratio between their temperature-dependent energy consumptions. Third, a novel WDCP model has been proposed. Based on the WDCP model, the average hourly energy consumption of a poop pump is 0.7425 kW, which contributes 20.36% energy consumption of homes with swimming pools, as well as 8.48% peak load of all neighborhoods. Therefore, the peak load could be reduced by 8.48% if all CPRSP all stopped during peak hour.

In this paper, the energy consumption of CPRSP is estimated based on hourly aggregated measurements without additional prior information of CPRSP. In theory, higher sampling rate of measurements and more prior information of appliances will improve the accuracy and the generalness of the model. However, at present there is few studies that consider the relationship among the data sampling frequency, appliances' prior information, the model accuracy, and the model generalness in a unified framework. In future this work would try to establish more linkages among these factors.

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