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Energy consumption analysis of residential swimming pools for peak load shaving

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HIGHLIGHTS

- Energy consumption of homes with and without swimming pools is analyzed.
- A modified weighted difference change-point model is proposed.
- Circulating pumps of residential swimming pools contributes 8.79% peak load.
- Considering minimizing the peak load, the peak load can be reduced by 4.64%.
- Considering minimizing the cost, the peak load can be reduced by 3.15%.

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ABSTRACT

Peak load shaving is a very important issue, however, most of peak load shaving methods either require extra investments or reduce the comfort of the consumers. This paper analyzes the impact of circulating pumps of residential swimming pools on the peak load, and shows that shifting the active time of circulating pumps of residential swimming pools could shave the peak load without requiring extra investments or reducing the comfort of the consumers. First, based on an extensive dataset containing hourly energy consumption readings of 1005 residents during March 2011 and October 2012 in South Ontario, this paper analyzes the features of the energy consumptions of residents with and without swimming pools. Second, this paper proposes a novel non-intrusive appliance load monitoring method to estimate the energy consumption of circulating pumps of residential swimming pools. The advantages of the proposed method are that, compared with other non-intrusive appliance load monitoring methods, it does not require high sampling rate data or prior information of the appliance, therefore the cost of implementation is reduced and users' privacy is protected. Finally, this paper shows that, the average hourly energy consumption of CPRSP is 0.7429 kW h. During the peak hour, circulating pumps of residential swimming pools contributes 20.11% energy consumption of residents with swimming pools, as well as 8.79% peak load of all neighborhoods. When considering minimizing the peak load, by postponing circulating pumps of residential swimming pools for 8 h rather than turn them off, the peak load can be shaved by 4.64%. When considering minimizing the cost of circulating pumps of residential swimming pools, the peak load can be shaved by 3.15% by postponing circulating pumps of residential swimming pools for 6 h, meanwhile the peak hour is postponed from 18:00 to 19:00.

1. Introduction

For an electric power system, as storage of electricity is much more difficult than other energy resources such as oil and gas, the volume of electricity produced in the supply side is mainly in accordance to the need in the demand side [1]. The load on an electric power system is time-variant, and to avoid issues such as brownouts, electricity producers have to provide power in response to immediate demand on the demand side. The maximum possible load is referred as peak load, which usually happens in the late afternoon in summer when many people go back home and begin using appliances for cooling, cooking and lighting, etc. [2]. Peak load is less common in cold weather, as people can use more types of resources such as gas and oil for heating. A high peak load does not only increases the infrastructure cost and the

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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 non-swimming season, between Nov. 15, 2011 and Feb. 29, 2012, during which all swimming pools are expected to be closed
Ω	the swimming season, between Jul. 1, 2011 and Aug. 30, 2011, as well as between Jul. 1, 2012 and Aug. 30, 2012, during which all swimming pools are expected to be opened
A	the aggregated energy consumption
B	base load
N	the temperature-independent energy consumption
T	the temperature-dependent energy consumption
E	the CPRSP energy consumption
ΔA	$\Delta A = A^p - A^n$ where A^p and A^n are aggregated energy consumption of homes with and without swimming pools
L	the low level period of ΔA
U	the ascending period of ΔA
H	the high level period of ΔA
D	the descending period of ΔA

Superscripts

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

Subscripts

Φ	data during the non-swimming season
Ω	data during the swimming season
L	data during the low level period of ΔA
U	data during the ascending period of ΔA
H	data during the high level period of ΔA
D	data during the descending period of ΔA

power generation cost, but also increases carbon emission and the maintenance cost of transmission lines and equipment, therefore peak load shaving is an very important issue [3].

Peak load shaving can be achieved both on the supply side and the demand side. On the supply side, to shave the peak load, methods such as direct load control [4,5], emergency demand response [6,7], critical peak pricing [8], and real time pricing [8,9] are usually used. While on the demand side, to shave peak load, methods such as renewable energy [10,11] and electric energy storage [12,13] have been widely studied. A major difficulty of peak load shaving is that, consumers may be unwilling to participate in some of these programs. For example, direct load control allows the power supplier directly control the status of appliances, and customers will receive various payments as rewards. Direct load control is an effective method for peak load shaving, however, for example, in the Texas reliability entity region in the United States, only 0.11% customers enrolled in direct load control [14]. The main reason may be that, from consumers psychology perspective, direct load control may disrupt their lifestyle and comfort. Meanwhile, for peak load shaving on the demand side, extra investment is an obstacle for renewable energy and electric energy storage.

This paper analyzes the impact of residential swimming pools on the energy consumption of homes based on hourly meter readings, as well as how much the peak load can be shaved by shifting load of circulating pumps of residential swimming pools (CPRSP), rather than turn them off. The reasons of this study are that, first, residential swimming pools have been widely installed in developed countries. In the USA, the number of residential swimming pools is over five million, and over the last 10 years, the number is growing by 4% every year [15]. In the greater Sydney region in Australia, 23% homes have residential pool pumps [16]. Second, in many developed countries, residential swimming pools are the second largest electrical load of residents, right after air conditioners (ACs). In the USA, every year nearly 14 billion kW h electricity is used to maintain swimming pools, and homes with swimming pools consume an average of 50% more electricity than homes without swimming pools [15] during the summer season. Third, as CPRSP are used for pool water circulation and purification, compared with direct load control or electric energy storage, controlling the activity periods of CPRSP would not reduce user comfort. Furthermore, it does not require any extra investment. Therefore, shaving peak load by controlling the activity periods of CPRSP is practical.

Based on an extensive dataset has been setup containing hourly energy consumption readings of 1005 residents during March 2011 and October 2012 in South Ontario, Canada, this paper analyzes the energy consumption of CPRSP and its impact on the peak load. The contributions of this paper can be summarised as follows:

First, features of the energy consumption of homes with and without swimming pools are analyzed, and it is found that:

1. Although hourly energy consumptions of some homes with swimming pools are less than that of homes without the swimming pools, the average daily energy consumptions of homes with swimming pools are greater than that of homes without the swimming pool. The peak ratio of them is 1.699 in August and the valley ratio is 1.180 in January.
2. Although the average daily energy consumption profiles of homes with and without the swimming pools jitter all the time, especially when the outdoor temperature is in a high level, the difference profile between them is much more smooth and presents a obvious periodicity.
3. For the average daily energy consumption profiles of homes with and without the swimming pools, as well as their difference, their correlations with the outdoor temperature vary with the outdoor temperature, however such correlations are significant only during the summer season (June, July and August).
4. During all season, the average daily energy consumption profiles of homes without the swimming pool has a stronger correlation with the outdoor temperature than that of homes with swimming pools.
5. there is no obvious difference between the energy-related living habits of home with and without swimming pools, e.g., the time of getting up and the time of the main energy-related family activities.
6. the main energy-related family activities during the summer are 2 h earlier than that during other seasons. However, the getting up time during all season is consistent, i.e. between hour 5 and hour 6.

Second, this paper proposes a non-intrusive energy consumption estimation method WDCP* for CPRSP. The advantages of the proposed method are that it does not require high sampling rate data or prior information of the appliance, therefore the cost of implementation is reduced and users' privacy is protected. Applying the proposed method on the dataset, this paper shows that:

1. The average hourly energy consumption of CPRSP is 0.7429 kW h, and the minimum and the maximum hourly energy consumptions are 0.4970 kW h at 9:00 and 0.9974 kW h at 17:00, respectively.

2. During the peak hour, CPRSP contributes 20.11% energy consumption of residents with swimming pools, as well as 8.79% peak load of all neighborhoods.
3. When considering minimizing the peak load, by postponing CPRSP for 8 h rather than turn them off, the peak load can be shaved by 4.64%. When considering minimizing the cost of CPRSP, the peak load can be shaved by 3.15% by postponing CPRSP for 6 h, meanwhile the peak hour is postponed from 18:00 to 19:00.

The remainder of this paper is organized as follows. Related works and materials are presented in Section 2 and Section 3. In Section 4, features of the energy consumption of homes with and without swimming pools are analyzed. In Section, a non-intrusive energy consumption estimation method WDCP* for CPRSP is proposed, and results and discussion are given in Section 6. Finally, Section 7 gives the conclusion.

2. Related works

From a global perspective, the total household energy consumption is very huge, which accounts for about 30% of the global energy consumption [17,18]. At present many homes in developed countries have residential swimming pools. According to [15], the number of residential swimming pools in the USA is over five million, and the number is growing by 4% every year over the last 10 years. Meanwhile, Fan et al. show that 23% homes have residential pool pumps in the greater Sydney region in Australia [16]. A typical residential pool pump still has a 1.5 horse CPRSP, most of which are running daily during the swimming season, to prevent stagnation of water and resulting water quality deterioration, as well as the hassles of household mechanical tinkering. As a result, in many developed countries, residential swimming pools are the second largest electrical load of residents, right after air conditioners. According to a study carried out by a for-profit company Opower, the energy consumption of swimming pools is a reliable indicators to reflect the residents' features, such as energy-related behaviours and family lifestyle [16]. Residents with swimming pools usually have larger houses, higher income levels, and larger family size. Meanwhile, the features of behaviours of residents with swimming pools are also different with that of residents without the swimming pools. All of these factors result in a higher overall energy consumption, and homes with pools used more energy than homes without pools regardless of size, vintage, or season. In the Western USA, the annual energy consumption of homes with swimming pools is 30% than that without the swimming pool. Such number increases to 50% during the summer season. Another study shows that San Antonio homes with swimming pools consume over 40% more energy than that without the swimming pool [19]. In the greater Sydney region in Australia, the annual average daily energy consumption of homes with swimming pools is 93% higher than that without the swimming pool [16]. In additional, Wang et al. show that hotel swimming pools also significantly increase the energy consumption per night [20]. As a result, every year nearly 14 billion kW h electricity is used to maintain swimming pools in the USA.

Currently there are some works analyzing the energy consumption of CPRSP [15,21,22]. In [15,21], each circulating pump is equipped with a specific meter, and the energy consumption of the circulating pump is directly obtained from the meter. In these studies, extra investment is needed for these meters, making these methods difficult to be used in other scenarios. Recent years, lots of efforts have been paid close attention to non-intrusive appliance load monitoring (NIALM), which disaggregates the energy consumption of appliances from the aggregated energy consumption readings from a single meter. Compared with intrusive appliance load monitoring (IALM) used in [15,21], NIALM does not require any extra investment, making it more and more popular. Currently there are many NIALM methods [23–29]. Most of NIALM methods disaggregate the energy consumption of different appliances mainly based on events detection, such as steady-state events [27–30] and transient-state events [23,26,31] related to current or voltage. Meanwhile, supervised [23] methods and unsupervised [27,28] methods are used to identify the energy consumption of appliances. However, these NIALM methods are not suitable for the CPRSP energy consumption in this work. First, as most of NIALM methods are event-based, these methods require that all events (e.g. appliances turning on/off) are detectable. In other words, during one sampling period, the running state of an appliance should not change more than once. Actually, when using transient-state features, NIALM methods usually require very high sampling rates (e.g. greater than 1MHZ) [23,26,31], and when using steady-state features, NIALM methods usually require sampling rates greater than 1HZ [27–30]. Perez et al. [30] has found that the accuracy of the NIALM methods decrease dramatically following with the increase of the sampling period. However, in this work, hourly aggregated energy consumption data is used, and the sampling rate is too low to capture the state changes of appliances, therefore NIALM methods [27–30] can not be used for this paper. There are a few NIALM methods using very low sampling rate data. For example, in [25], a NIALM method based on discriminative sparse coding using hourly data is proposed. However, such method require detail prior information of appliances such as the types of appliances and corresponding power. However, in this work, such information is invaluable. Meanwhile, for a practical NIALM issue, it is difficult to obtain such prior information. Finally, from the aspect of the features of CPRSP, the power of CRPSP is generally in the range of 0.35 kW h and 1.45 kW h [32], which is similar with other residential appliances. As a result, the operations of turning on/off of CPRSP are difficult to be identified by the changes of the energy consumption profiles. Meanwhile some CPRSP may run uninterrupted, meaning that there is no *event* for these CPRSP. Therefore, CPRSP energy consumption can not be estimated by these NIALM methods. In [22], a weighted difference change-point model (WDCP) is proposed to estimate the CPRSP energy consumption. The main idea of WDCP is that, in a certain region, for residents with and without swimming pools, the ratio of their temperature-independent energy consumption is approximately equal to the ratio of their temperature-dependent energy consumptions during the swimming season. However, such assumption is from the observation on a specific dataset, which limits its availability.

3. Materials

In Ontario Canada, residential swimming pools are generally installed outdoor, and the swimming season is usually between May and October when the outdoor temperature is high enough. During the use of the swimming pools, the pool water inevitably contains pollutants, making it turbid and stink. Such water may cause diseases at eyes, ears, skin and digestive organs, as a result, generally a swimming pool is equipped with a water circulation and purification system. Note that in Canada, gas rather than electricity is used to heat swimming pools. For a residential swimming pool, if the pool water is polluted seriously, the swimming pool water circulation and purification system is vulnerable to damage. Therefore, to prevent stagnation of water and resulting water quality deterioration, as well as the hassles of household mechanical tinkering, most CPRSPs would run for a long period every day, e.g., 10 h or even uninterrupted during the swimming season.

In this paper, hourly energy consumption readings of 1005 residents in a specific neighborhood in Ontario Canada have been collected, where 346 residents have swimming pools and the rest 659 residents do not have swimming pools. The period is from March 1st 2011–October 31th 2012, and the total number of samples is 14713200. Corresponding outdoor temperature data is obtained from Weather Canada (weather.gc.ca), and linear interpolation is carried out if outdoor temperature data is lost.

4. Energy consumption analysis for homes with and without swimming pools

In this section, energy consumptions of homes with and without swimming pools are analyzed in different time levels, e.g., the raw hourly level, the daily level, and the monthly level.

Fig. 1 gives raw hourly energy consumption profiles of 4 homes with swimming pools, and as comparisons, Fig. 2 gives raw hourly energy consumption profiles of 4 homes without the swimming pool. Meanwhile, corresponding outdoor temperatures are given in each figure. From Figs. 1 and 2 it can be seen that, first, outdoor temperatures have an obvious cyclical changes, the peak is at around hour 3500 and the valley is at around hour 7500. Second, distributions of energy consumption profiles of homes are complex and different from each other. Meanwhile, most of hourly energy consumptions are greater than 0, and hourly energy consumptions of homes with swimming pools are not always greater than that of homes without the swimming pool. Third, there is a certain correlation between the energy consumption profiles and outdoor temperatures. When outdoor temperatures are in a high level, e.g., temperatures between hour 2000 and hour 5000, as well as hours after 11000, hourly energy consumptions of all homes are also in a relative high level. However, in the rest of the time, the correlation between energy consumption profiles and outdoor temperature is not obvious.

Due to the daily periodicity of residents' activities, the daily energy consumption may be more regular than that of hourly energy consumption. To verify it, Figs. 3 and 4 give daily energy consumption profiles of homes in Figs. 1 and 2, respectively. Note that in Figs. 3 and 4, temperatures are daily averaged. Compared with hourly energy consumption profiles in Figs. 1 and 2, it can be seen that, daily energy consumption profiles present more obvious regularity, e.g., daily energy consumption profiles of all homes change obviously with the outdoor temperatures during day 100 and day 200, as well as days after 450. However, similar with Figs. 1 and 2, in the rest of the time, the correlation between daily energy consumption profiles and outdoor temperatures is not obvious.

Furthermore, average daily energy consumption profiles of homes with and without the swimming pools, as well as their difference, are given in Fig. 5. Meanwhile, to present the relationship between energy consumption and time more clearly, Fig. 6 gives average daily energy consumption profiles of homes with and without the swimming pools in each month, as well as the difference and the ratio between them. Furthermore, the peaks and the valley of the four profiles are given in Table 1.

As shown in Figs. 5 and 6, and Table 1, first, the average daily energy consumption profiles of homes with and without the swimming pools, as well as their difference and ratios are periodic and correlated with the outdoor temperature. The peaks of average daily energy consumption profiles of homes with and without the swimming pools, as well as their difference occur in July, and the peak of the ratio occurs in August. Meanwhile, the valleys of average daily energy consumption profiles of homes with and without the swimming pools, as well as their difference occur in April, while the valley of the ratio occurs in January.

From Figs. 5 and 6, and Table 1 it can be seen that, first, although hourly energy consumptions of some homes with swimming pools are less than that of homes without the swimming pools, the average daily energy consumptions of homes with swimming pools are greater than that of homes without the swimming pool, and the peak ratio is 1.699 in August and 1.180 in January. Second, although the average daily energy consumption profiles of homes with and without the swimming pools jitter all the time, especially when the outdoor temperature is in a high level, the difference profile between them is much more smooth and presents a obvious periodicity. It may come from the fact that, for a certain home with the swimming pool, the usage pattern (e.g., daily start time, stop time and the operating power) of CPRSP is usually fixed. However, it can not be considered that the difference profile entirely comes from the energy consumption of CPRSP. As discussed in [15], compared with homes without the swimming pool, the homes with swimming pools usually have larger houses, more family members, higher income levels. All of these factors would promote a higher energy consumption in homes with swimming pools. As a result, the differences are greater than 0 during the winter when the swimming pools are closed.

To analyze the relationship between energy consumption and outdoor temperature quantitatively, Fig. 7 gives average hourly energy consumptions of homes with and without swimming pools, as well as their differences and outdoor temperatures in each month. Meanwhile, the peak hours and the valley hours are given in Figs. 8 and 9.

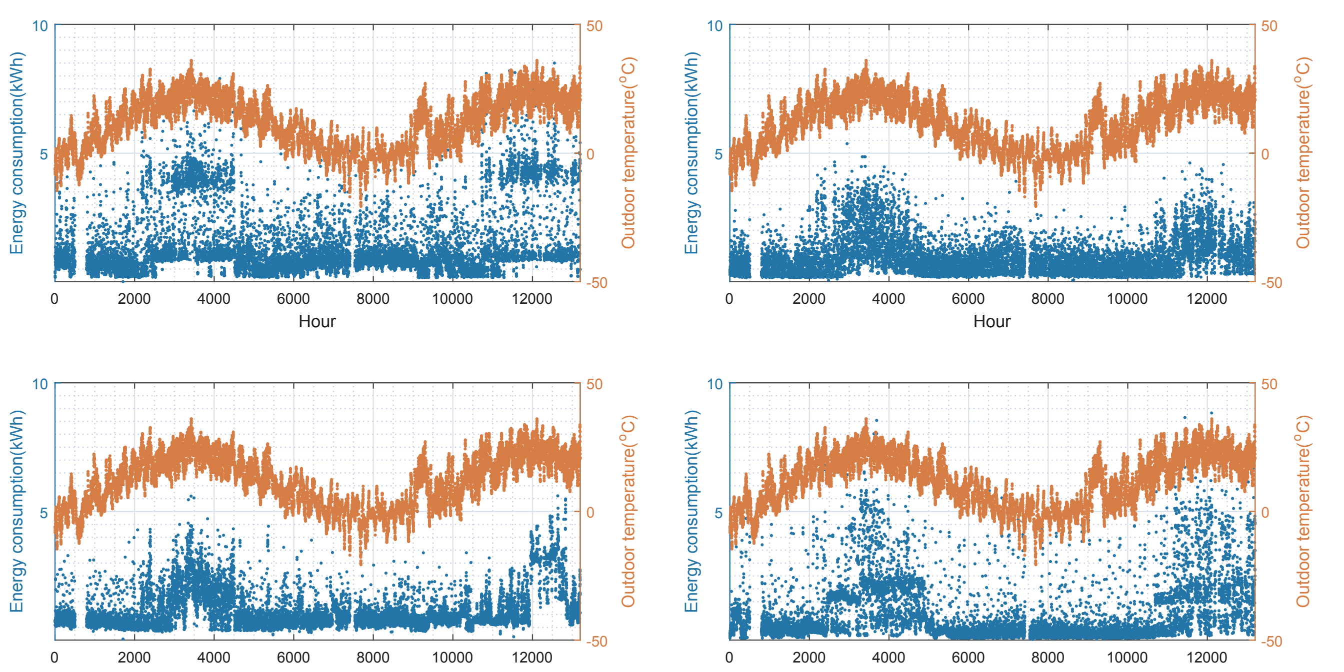


Fig. 1. Examples of raw hourly energy consumption profiles of 4 homes with swimming pools.

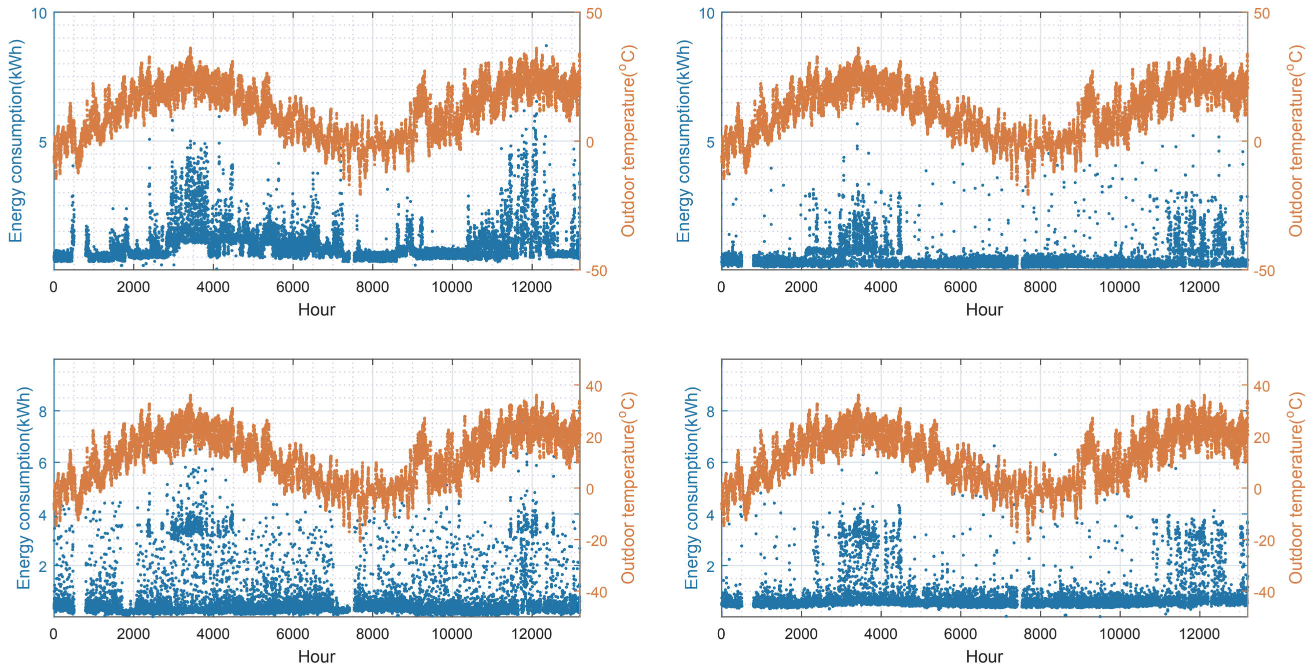


Fig. 2. Examples of raw hourly energy consumption profiles of 4 homes without the swimming pool.

As shown in Fig. 7, the average hourly energy consumptions of homes with swimming pools are greater than that of homes without the swimming pool in each month. Meanwhile, compared with the average hourly energy consumptions of homes with swimming pools are greater than that of homes without the swimming pool, the difference profiles are much more smooth. From Figs. 8 and 9 it can be seen that, peak hours and valley hours of energy consumptions of homes with and without swimming pools are close with each other, which means that there is no obvious difference between the living habits of home with and without swimming pools, e.g., the time of getting up and the time of the main energy-related family activities. Furthermore, during the summer (June, July and August), the peak hours of energy consumptions are between hour 18 and hour 19, while during other season, the peak hours of energy consumptions is between hour 20 and hour 22. It means that the main energy-related family activities during the summer are 2 h earlier than that during other seasons. However, according to Fig. 9, the getting up time during all season is consistent, i.e. between hour 5 and hour 6.

Fig. 10 gives the correlations between hourly energy consumption profiles (with and without swimming pools, as well as their difference) and the outdoor temperature in each month, and peaks and valleys of correlations are given in Table 2. From Fig. 10 and Table 2 it can be seen that, first, all three correlations change with the outdoor temperature, i.e., when the outside temperature is high, the three

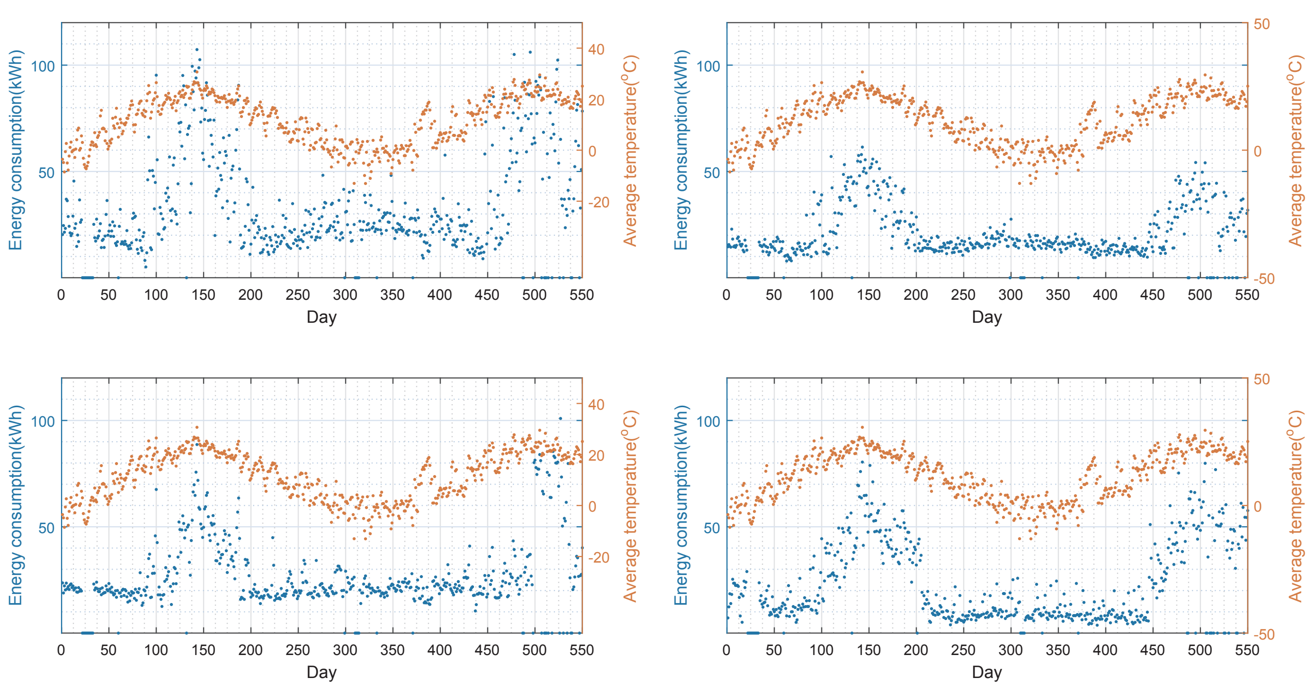


Fig. 3. Daily energy consumption profiles of homes in Fig. 1.

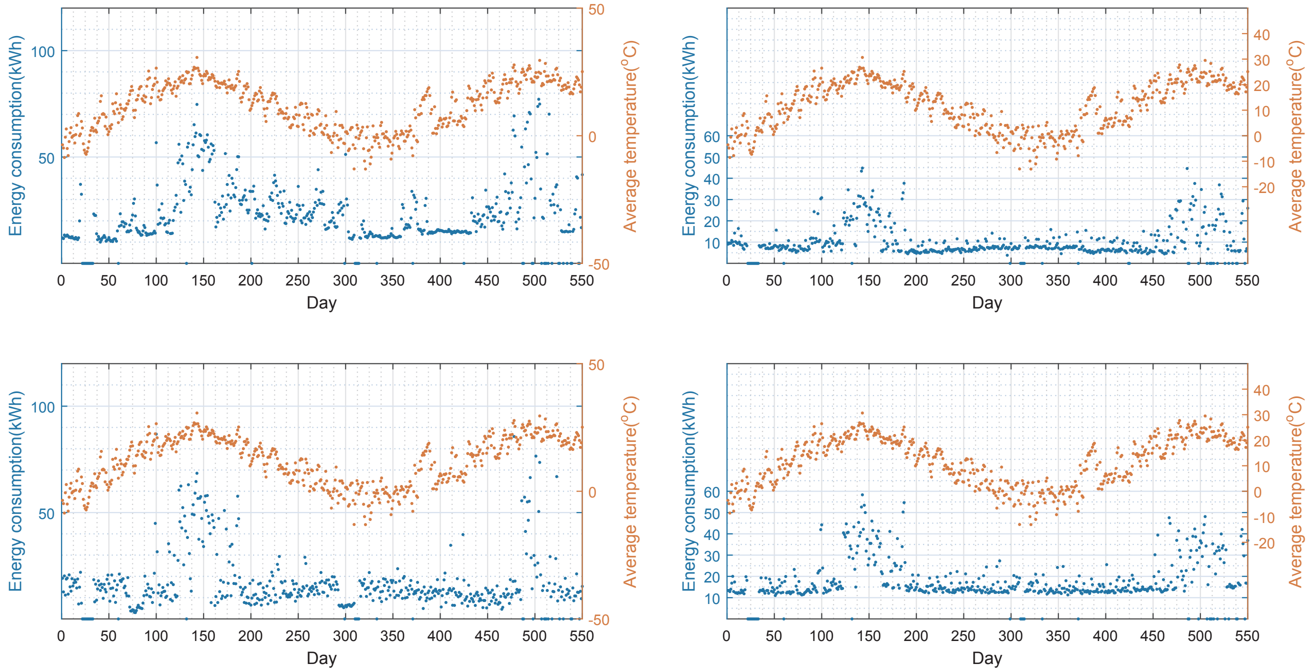


Fig. 4. Daily energy consumption profiles of homes in Fig. 2.

correlations are large, and vice versa. Second, in all months, compared with homes with swimming pools, the energy consumption of homes without the swimming pool has a stronger correlation with the outdoor temperature. A important reason of this phenomenon is that, as an significant component of the energy consumption of homes with swimming pool, the energy consumption of CPRSP is independent to the outdoor temperature.

5. The WDCP* model for CPRSP energy consumption estimation

5.1. The change-point model

Change-point models are widely used steady-state data-driven models to obtain the relationship between the energy consumption of buildings and the outdoor dry-bulb temperature. According to ASHRAE (the American Society of Heating, Refrigerating, and Air-Conditioning Engineers) [33], a change-point model is to fit a piecewise linear regression with unknown change points on the Energy consumptions vs.

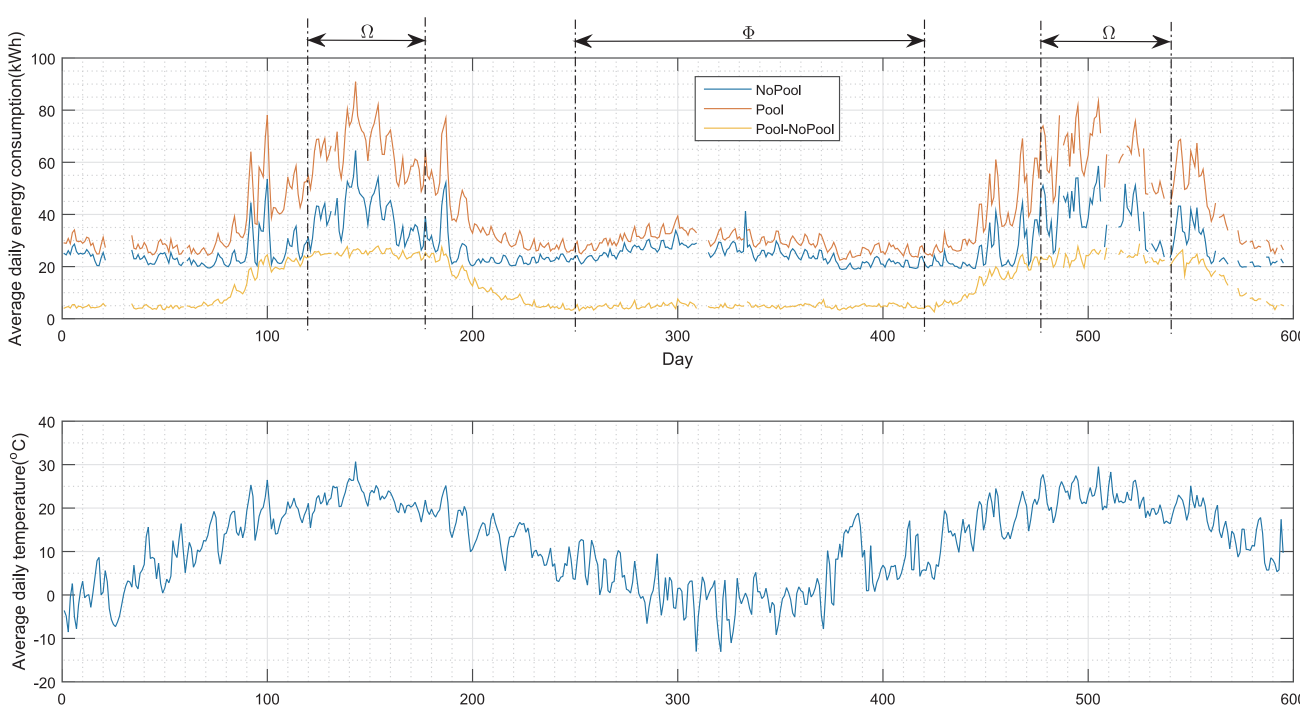


Fig. 5. Average daily energy consumption profiles.

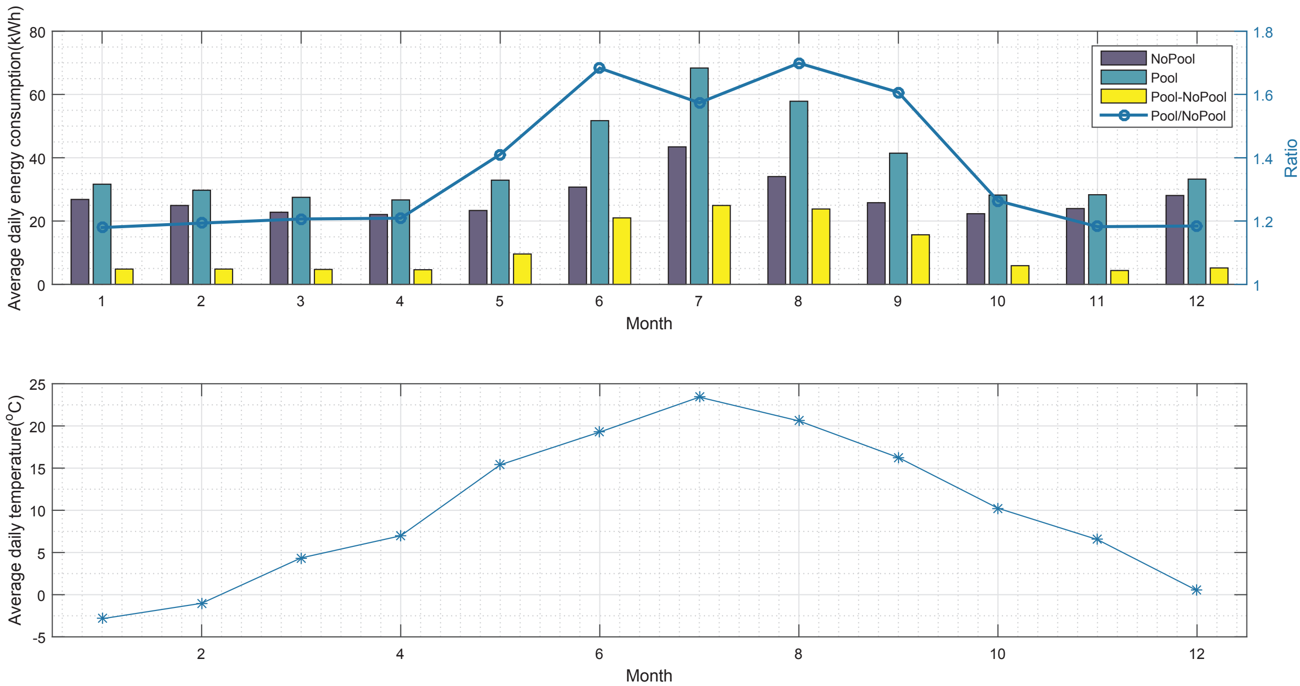


Fig. 6. Average daily energy consumption in each month.

Table 1
Peaks and valleys of different profiles.

	Peak time	Peak value	Valley time	Valley value
Pool	July	68.364 kW h	April	26.675 kW h
Nopool	July	43.441 kW h	April	22.066 kW h
Pool-nopool	July	24.923 kW h	April	4.365 kW h
Pool/nopool	August	1.699	January	1.180

outdoor Temperatures (EvOT). It is from the statistical point of view that, within a certain temperature range, the energy consumption for heating or cooling of buildings usually increases or decreases linearly with the outdoor temperature. Meanwhile, for some EvOTs, within a certain temperature range, the energy consumption does not depend on the outdoor temperature, and the gradients of corresponding linear regressions would be close to 0. Fig. 11 gives six EvOTs and the corresponding change-point models. In Fig. 11, blue stars are samples, piecewise lines are continues linear regressions on corresponding EvOTs, where the yellow (*gradient* < 0), the black (*gradient* = 0) and the red (*gradient* > 0) lines indicate the heating periods, the temperature-independent periods, and the cooling periods, respectively. Green circles are the locations of the change points. Taking Model 5 as an example, from left to right, before the first change point, it is a heating period, and the energy consumption decreases linearly with the outdoor temperature. Between the two change points, it is a temperature-independent period. Finally, after the second change point, it is a cooling period, and the energy consumption increases linearly with the outdoor temperature. From Fig. 11 it can be seen that using change-point models, it is easy to estimate the energy consumption based on the outdoor temperature.

5.2. The WDCP* model

Suppose A_Φ^n and A_Ω^n are average aggregated hourly energy consumptions of residents *without* the swimming pool during the non-swimming season and the swimming season, while A_Φ^p and A_Ω^p are average aggregated hourly energy consumptions of residents *with* swimming pools during the non-swimming season and the swimming season, respectively, then A_Φ^n,A_Φ^p,A_Ω^n and A_Ω^p can be modeled as,

$$A_\Phi^n = T_\Phi^n + N_\Phi^n = T_\Phi^n + B_\Phi^n \tag{1}$$

$$A_\Phi^p = T_\Phi^p + N_\Phi^p = T_\Phi^p + B_\Phi^p \tag{2}$$

$$A_\Omega^n = T_\Omega^n + N_\Omega^n = T_\Omega^n + B_\Omega^n \tag{3}$$

$$A_\Omega^p = T_\Omega^p + N_\Omega^p = T_\Omega^p + B_\Omega^p + E \tag{4}$$

where A is the average aggregated energy consumption, T is the average temperature-dependent energy consumption, e.g., the energy consumption of ACs, N is the average temperature-independent energy consumption, B is the average basic energy consumption for daily life of residents, e.g., the energy consumption of refrigerators, TV sets and microwave ovens, which can be considered temperature-independent. E is the average energy consumption of CPRSP, which is temperature-independent. The superscripts p and n indicate residents have swimming pools or not, and the subscripts Φ and Ω indicate data from the non-swimming season or the swimming season. For example, T_Φ^n is the average temperature-dependent energy consumption of residents without the swimming pool during the non-swimming season. For the energy consumption of residents with swimming pools during the swimming season, the temperature-independent energy consumption consists of the basic energy consumption and the CPRSP energy consumption, $N_\Omega^p = B_\Omega^p + E$, while for other cases, the temperature-independent energy consumption is equal to the basic energy consumption, $N_\Phi^n = B_\Phi^n$,$N_\Phi^p = B_\Phi^p$, and $N_\Omega^n = B_\Omega^n$.

In Ontario Canada, generally residents use gas for heating, and use electricity for cooling by air conditioners. Therefore, it can be considered that $T_\Phi^n = 0$ and $T_\Phi^p = 0$. Meanwhile, as B_Φ^n,B_Φ^p,B_Ω^n and B_Ω^p are temperature-independent, then $B_\Phi^n = B_\Omega^n$ and $B_\Phi^p = B_\Omega^p$, therefore Eq. (1)–(4) can be rewritten as,

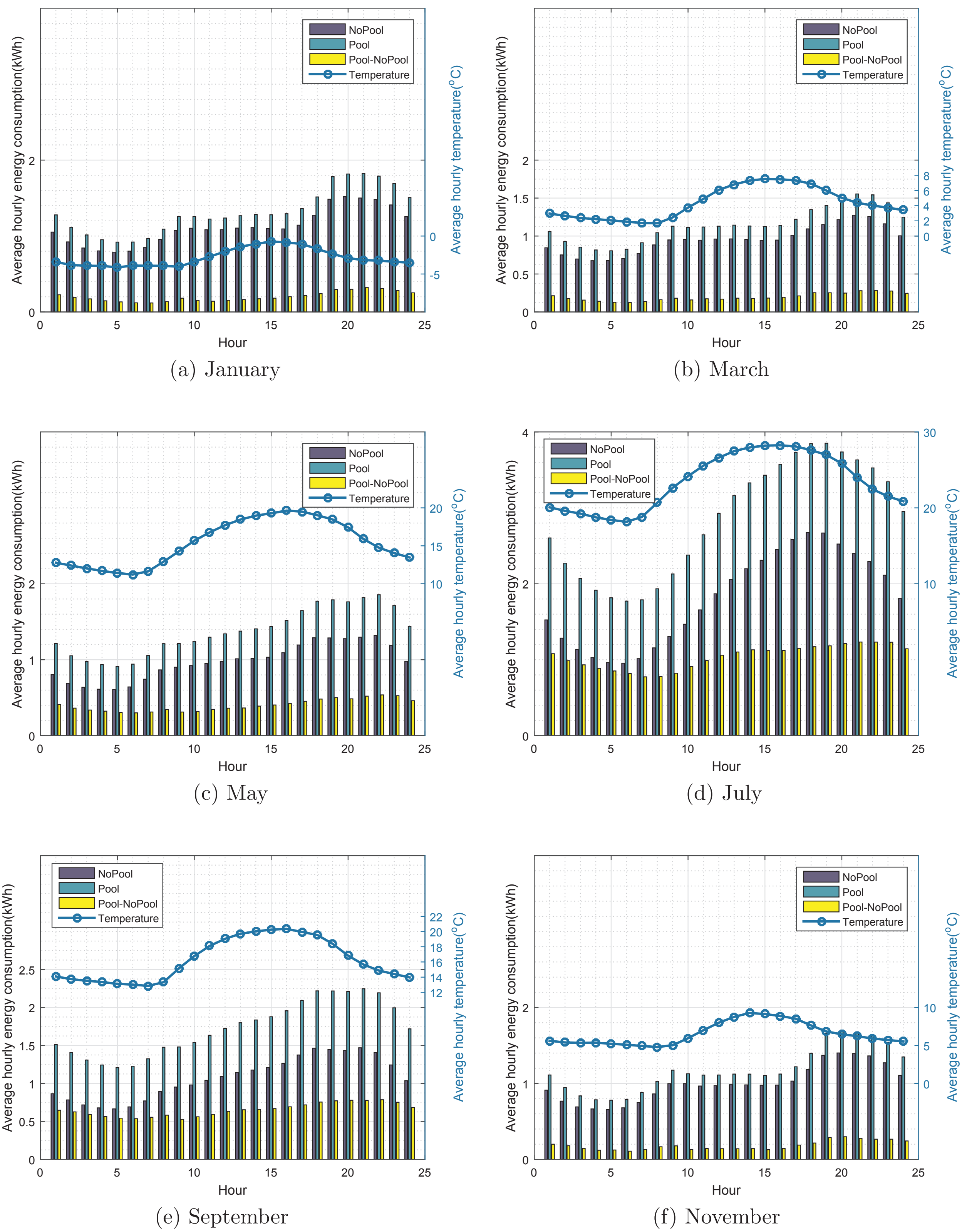
$$A_\Phi^n = B^n \tag{5}$$

$$A_\Phi^p = B^p \tag{6}$$

$$A_\Omega^n = T_\Omega^n + B^n \tag{7}$$

$$A_\Omega^p = T_\Omega^p + B^p + E \tag{8}$$

where $B^p = B_\Phi^p = B_\Omega^p$, and $B^n = B_\Phi^n = B_\Omega^n$.



(a) January (b) March (c) May (d) July (e) September (f) November

Fig. 7. Average hourly energy consumption profiles in each month.

From Eq. (8) it can be seen that, the energy consumption of CRPSP E can be obtained by,

$$E = A_{\Omega}^{p} - T_{\Omega}^{p} - B^{p} = N_{\Omega}^{p} - B^{p} = N_{\Omega}^{p} - A_{\Phi}^{p} \quad (9)$$

In Eq. (9), A_{Φ}^{p} is known, therefore, to obtain E, it only needs to obtain the temperature-independent energy consumption during the swimming season N_{Ω}^{p}.

At present degree days methods [33,34] and change-point models [35,36] are popular methods for the temperature-independent and temperature-dependent energy consumption disaggregation. As degree days methods highly depend on the user defined reference point temperature (RTP), and in this paper the change-point model is used to

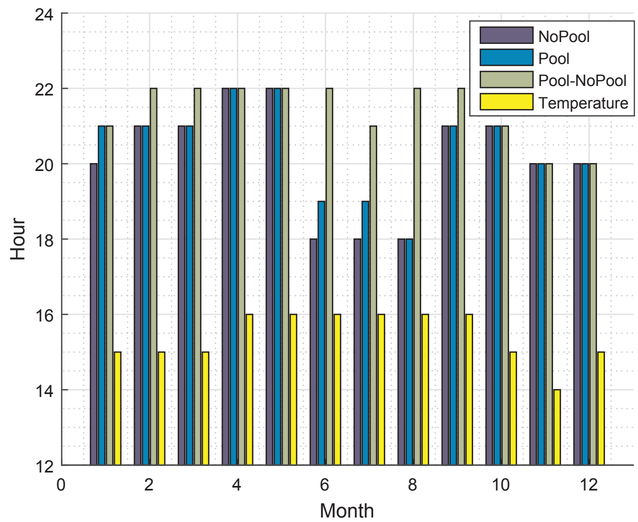


Fig. 8. Peak hours of different profiles in each month.

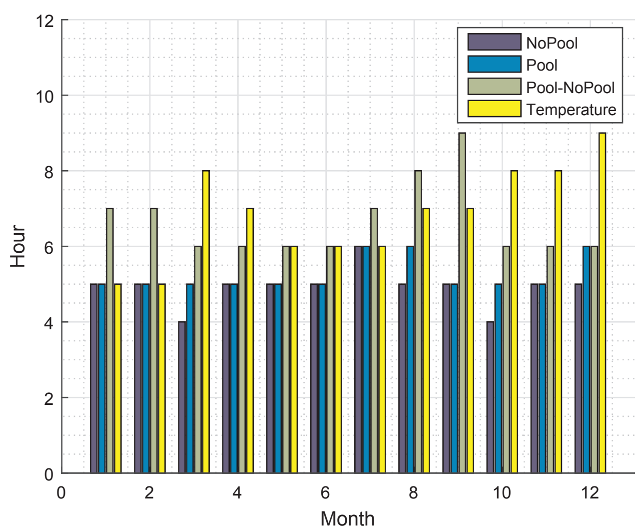


Fig. 9. Valley hours of different profiles in each month.

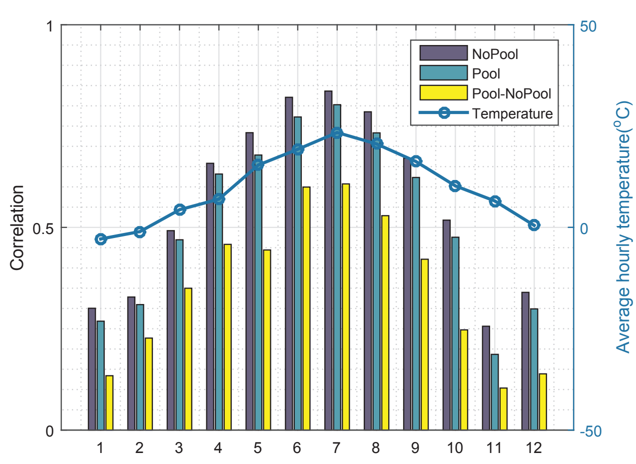


Fig. 10. Correlations between hourly energy consumption and outdoor temperature.

Table 2
Peaks and valleys of correlations.

	Peak time	Peak value	Valley time	Valley value
Pool	July	0.8028	November	0.1868
Nopool	July	0.8364	November	0.2562
Pool-nopool	July	0.6073	November	0.1037

disaggregate the temperature-independent and temperature-dependent energy consumption.

Change-point models estimate the temperature-independent load by carrying out piece-wise linear regression on EvOT. Fig. 12 gives EvOTs of residents with and without swimming pools, where red points, green points and blue points are samples from the non-swimming season Φ, the swimming season Ω and the rest period, respectively. From Fig. 12 it can be seen that no matter EvOT of residents with swimming pools, or EvOT of residents without the swimming pool, there is no obvious temperature-independent period that the gradient of linear regression on which is close to 0. It means that no reliable N_Ω^n or N_Ω^p can be obtained using the change-point model based on such EvOTs, as discussed in [35], therefore the change-point model can not used to estimate the CPRSP energy consumption E.

Rewriting Eq. (7),

$$0 = A_\Omega^n - T_\Omega^n - B^n \tag{10}$$

From Eqs. (8) and (10),

$$\begin{aligned} E &= A_\Omega^p - B^p - T_\Omega^p - \lambda \times (A_\Omega^n - T_\Omega^n - B^n) = (A_\Omega^p - \lambda \times A_\Omega^n) - (B^p - \lambda \times B^n) \\ &\quad - (T_\Omega^p - \lambda \times T_\Omega^n) = (A_\Omega^p - \lambda \times A_\Omega^n) - (A_\Phi^p - \lambda \times A_\Phi^n) - (T_\Omega^p - \lambda \times T_\Omega^n) \end{aligned} \tag{11}$$

where λ is a unknown weight.

In Eq. (11), λ,T_Ω^n and T_Ω^p are unknown. However, rewriting Eq. (11),

$$(A_\Omega^p - \lambda \times A_\Omega^n) = \underbrace{(T_\Omega^p - \lambda \times T_\Omega^n)}_{temperature-dependent} + \underbrace{(A_\Phi^p - \lambda \times A_\Phi^n) + E}_{temperature-independent} \tag{12}$$

From Eq. (12) it can be seen that, if a λ can be obtained making $(A_\Omega^p - \lambda \times A_\Omega^n)$ temperature-independent, i.e., $T_\Omega^p - \lambda \times T_\Omega^n = 0$, then the energy consumption of CPRSP E can be obtained by,

$$E = (A_\Omega^p - \lambda \times A_\Omega^n) - (A_\Phi^p - \lambda \times A_\Phi^n) \tag{13}$$

And λ can be obtained by,

$$\min_{\lambda} \ |k| \tag{14}$$

where k is the gradient of the linear regression on $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature. Note that Eq. (14) can not be solved by general optimization methods such as least squares, as $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. out temperature changes with λ. In this paper, the interior-point algorithm [37] is used for λ optimization.

6. Results and discussions

6.1. The relationship between λ and $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature

The key issue of obtaining E using Eq. (13) is optimizing λ, and Fig. 13 gives the relationship between λ and $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature, where Fig. 13a gives the relationship between λ and $|k|$,k is the gradient of the linear regression. Fig. 13b, c and d give some $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature under three typical λs. From Fig. 13a it can be seen that k changes linearly with λ. In Fig. 13b and c, $\lambda = 0$ and $\lambda = 1$, respectively, therefore actually Fig. 13b and c give A_Ω^p vs. outdoor temperature, as well as the difference between A_Ω^p and A_Ω^n vs. outdoor temperature.

From Fig. 13b and c it can be seen that there is no obvious temperature-independent period that the gradient of linear regression on it is close to 0. However, in Fig. 13d, when $\lambda = 1.167$ (the optimized result), the gradient of linear regression on it is equal to 0, therefore

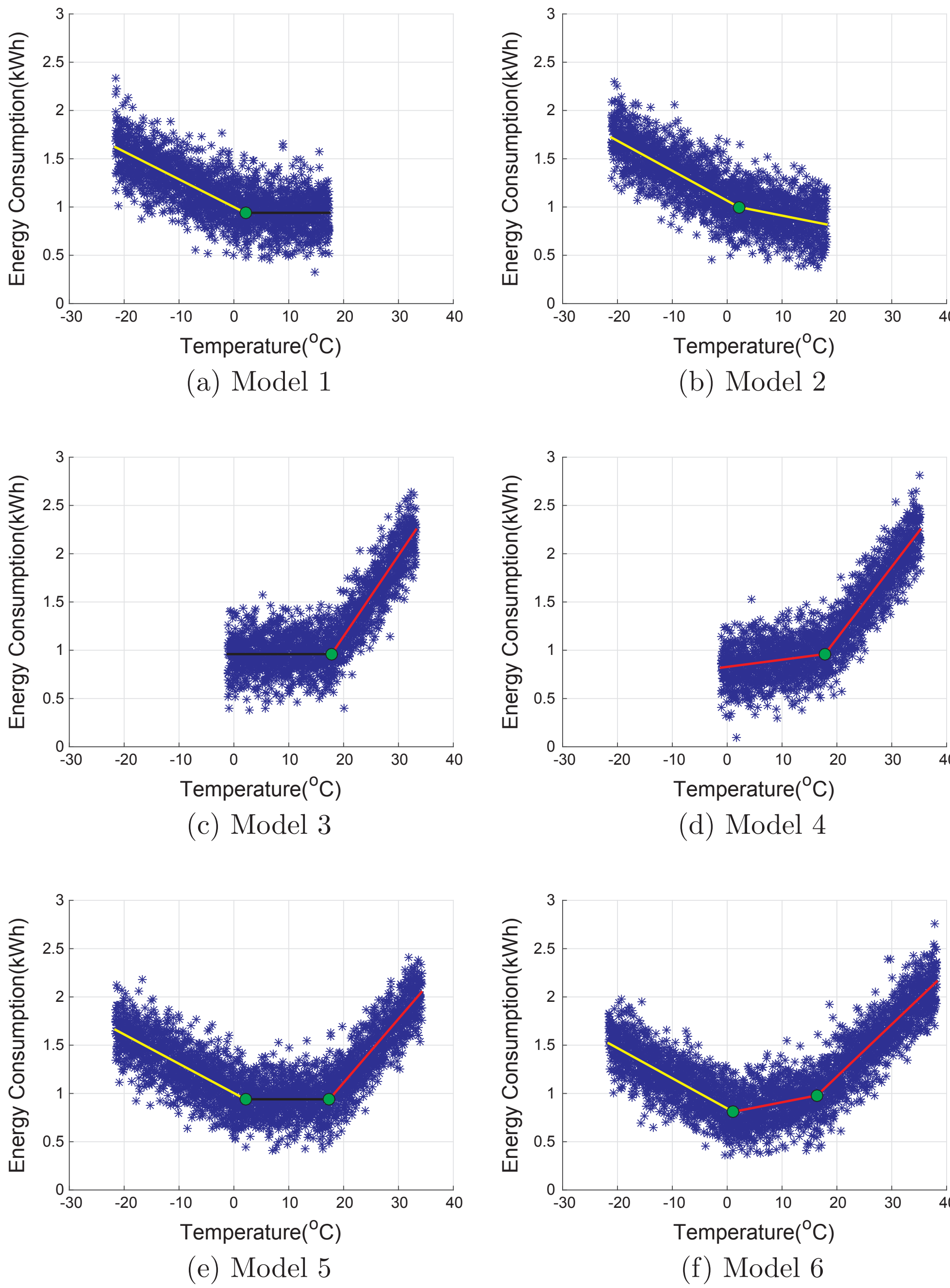


Fig. 11. EvOTs and the corresponding change-point models, blue stars are samples, piecewise lines are continues linear regressions on corresponding EvTs, where the yellow (*gradient* < 0), the black (*gradient* = 0) and the red (*gradient* > 0) lines indicate the heating, the base load and the cooling periods, respectively. Green circles are the locations of the change points. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

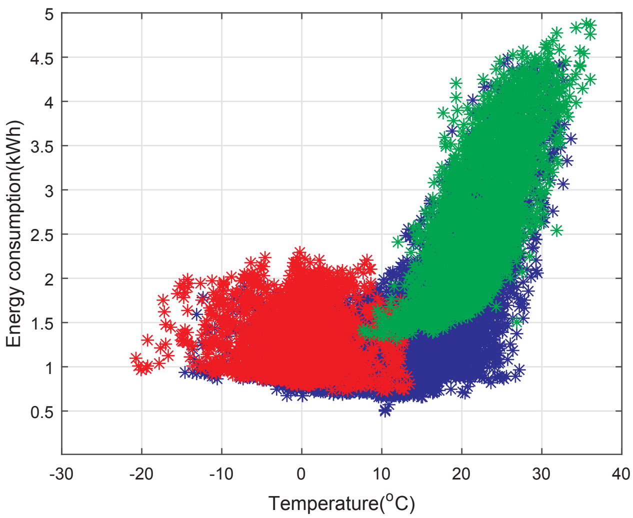
$\lambda = 1.167$ can be used to obtain E based on the dataset of all hours using Eq. (13).

6.2. CPRSP energy consumption estimation

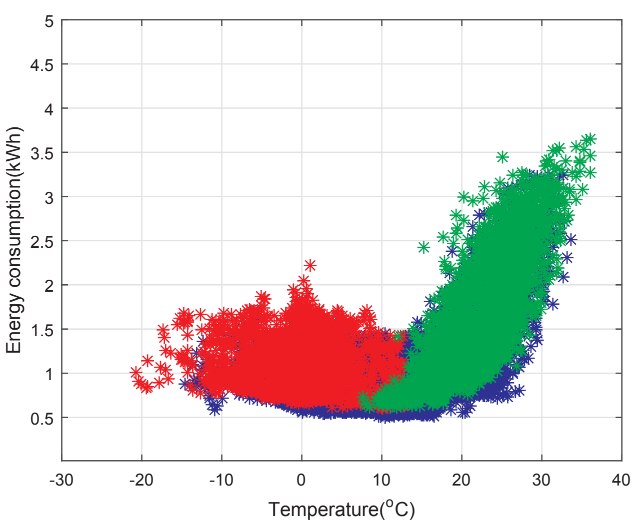
In this section CPRSP energy consumption in each hour is estimated using Eq. (13), and optimized λs for all hours are shown in Fig. 14, from which it can be seen that for different hours, optimized λs vary. However, for adjacent hours, corresponding optimized λs are close to each other.

Fig. 15 gives $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature under optimized λ for different hours. Owing to limited space, only $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature for hour 4, hour 8, hour 12, hour 16, hour 20 and hour 24 are given. According to the discussion in Section 5.2, if a λ can be obtained making $(A_\Omega^p - \lambda \times A_\Omega^n)$ temperature-independent, i.e., $T_\Omega^p - \lambda \times T_\Omega^n = 0$, then the energy consumption of CPRSP E can be obtained by Eq. (13). From Fig. 15 it can be seen that, the distributions of all $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature under optimized λ are close to be horizontal, meaning that they are temperature-independent, according to the theory of the change-point model [33], therefore the energy consumption of CPRSP can be obtained.

Fig. 16 gives CPRSP energy consumption estimation, where the proposed method is labeled as WDCP*. Three temperature-based energy disaggregation methods, namely Birt [35], Shin [34], and WDCP [22] are employed as comparisons. Birt is a multiple-phase change-point model method, which 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



(a) residents with swimming pools



(b) residents without the swimming pool

Fig. 12. EvOTs of residents with and without swimming pools, where red points, green points and blue points are samples from the non-swimming season Φ, the swimming season Ω and the rest period, respectively. As there is no obvious temperature-independent period in Fig. 12a and Fig. 12b, the temperature-independent energy consumption can not be obtained using the change-point model on these EvOTs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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, and 15th percentile data, and results are labeled as Birt5, Birt10, and Birt15, 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. The main idea of WDCP [22] is that, in a certain region, for residents with and without swimming pools, the ratio of their temperature-independent energy consumption is approximately equal to the ratio of their temperature-dependent energy consumptions during the swimming season,

$$\frac{B_\Omega^p}{B_\Omega^n} = \frac{T_\Omega^p}{T_\Omega^n} = r \tag{15}$$

where r is the ratio. It is from the observation except the use of swimming pools, there is no significant difference between residents with and with swimming pools. Then E can be obtained:

$$E = (A_\Omega^p - r \times A_\Omega^n) - (T_\Omega^p - r \times T_\Omega^n) \tag{16}$$

As the energy consumption of CPRSP is temperature-independent, if a r can be found which satisfies,

$$T_\Omega^p - r \times T_\Omega^n = 0 \tag{17}$$

then the energy consumption of CPRSP can be obtained by,

$$E = A_\Omega^p - r \times A_\Omega^n \tag{18}$$

Therefore, based on the WDCP model, the energy consumption of CPRSP is temperature-independent can be obtained without estimating the temperature-independent energy consumption during the swimming season and the non-swimming season.

As shown in Fig. 16 and Table 3, using different methods, although the estimated peak hours and valley hours of CRPSP are similar, the estimated peak power and valley power are different. Furthermore, results of Birt methods using different thresholds are significantly different, which means that such method highly depends on the user defined parameters, therefore results are unreliable. Meanwhile, it can be seen that the results of WDCP and WDCP* are close to each other. However, the WDCP method depends on the assumption of Eq. (15). Although in [22] such assumption has been proved on the specific dataset, it may fail on other datasets. Compared with the WDCP model, the proposed WDCP* method does not depend on such assumption, therefore results of WDCP* are more reliable than that of WDCP.

6.3. The impact of CPRSP on the load profile of the peak day

Energy consumption profiles of all homes can be obtained from the dataset directly. It can be found that peak load occurs at 18:00, Jul. 21, 2011, as a result, the peak day is Jul. 21, 2011, and the peak hour $H_{max} = 18$.

Fig. 17 gives the impact of CPRSP on the energy consumption profile on the peak day, where Fig. 17a gives the impact of CPRSP on residents with swimming pools, while Fig. 17b gives the impact of CPRSP on all residents. From Fig. 17a it can be seen that for the ratio of the energy consumption between CPRSP and residents with swimming pools changes with hours, and the maximum ratio and the minimum ratio are at hour 5 and hour 11, respectively. Meanwhile, at the peak hour $H_{max} = 18$, the ratio is 20.11%. From Fig. 17b it can be seen that for the ratio of the energy consumption between CPRSP and all residents changes with hours, and the maximum ratio and the minimum ratio are at hour 5 and hour 11, respectively, which are the same to that of residents with swimming pools. Meanwhile, at the peak hour $H_{max} = 18$, the ratio is 8.79%.

From Fig. 17 it can be seen that the energy consumption of CPRSP takes a relative large part of the overall energy consumption of residents with swimming pools. And if all of these CPRSP are stopped, then peak load would be shaved by 8.79%. However, according to Table 3, the minimum energy consumption of CPRSP is 0.4970 kW h, it may be resulted from those CPRSP running uninterrupted, therefore stopping these CPRSP may reduce users' comfort.

6.4. Peak load shaving by load shifting of CPRSP

Because shifting the running period of CPRSP earlier or later would not reduce users's comfort, this section quantifies how much the peak load can be shaved by shifting load of CPRSP, rather than turn them off. First, this paper quantifies how much peak load can be shaved by minimizing the power cost of CPRSP. Second, this paper quantifies the

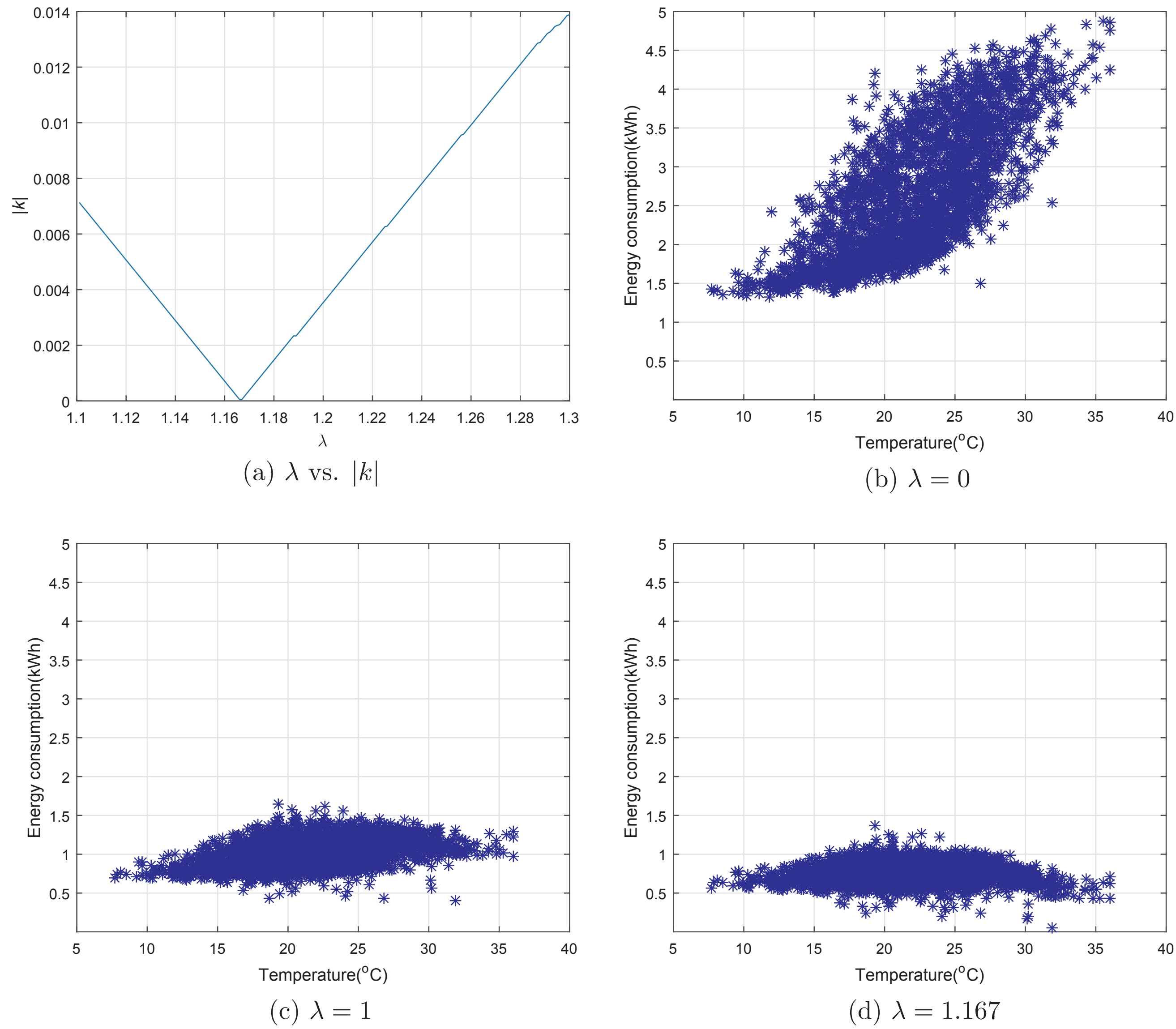


Fig. 13. The relationship between λ and $(A_{\Omega}^{p} - \lambda \times A_{\Omega}^{n})$ vs. outdoor temperature, where k is the gradient of the linear regression.

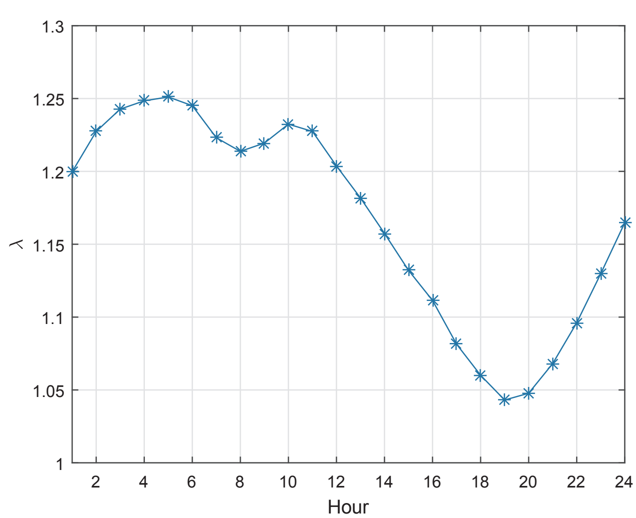


Fig. 14. Optimized λs for different hours.

maximum shaving of the peak load by postponing the running period of CRPSP. Table 4 gives electricity rates and prices during summer in Ontario Canada [38], and Fig. 18 gives the relationship between the postponed hour and the average daily cost of CPRSP as well as the ratio of peak load shaving. From Fig. 18 it can be seen that the average daily cost of CPRSP and the ratio of peak load shaving vary with the postponed hour. Note that the postponed hour for the minimum average daily cost of CPRSP is 6, while the postponed hour for the maximum ratio of peak load shaving is 8. Fig. 19 gives the impact of the use of CPRSP on the peak day, from which it can be seen that when considering minimizing the peak load, by postponing CPRSP for 8 h rather than turn them off, the peak load can be shaved by 4.64%. When considering minimizing the cost of CPRSP, peak load can be shaved by 3.15% by postponing CPRSP for 6 h, meanwhile the peak hour is postponed from 18:00 to 19:00.

6.5. The feasibility of the proposed method

A high peak load does not only increases the infrastructure cost and the power generation cost, but also increases carbon emission and the maintenance cost of transmission lines and equipment, therefore peak load shaving is a very important issue. Peak load shaving can be

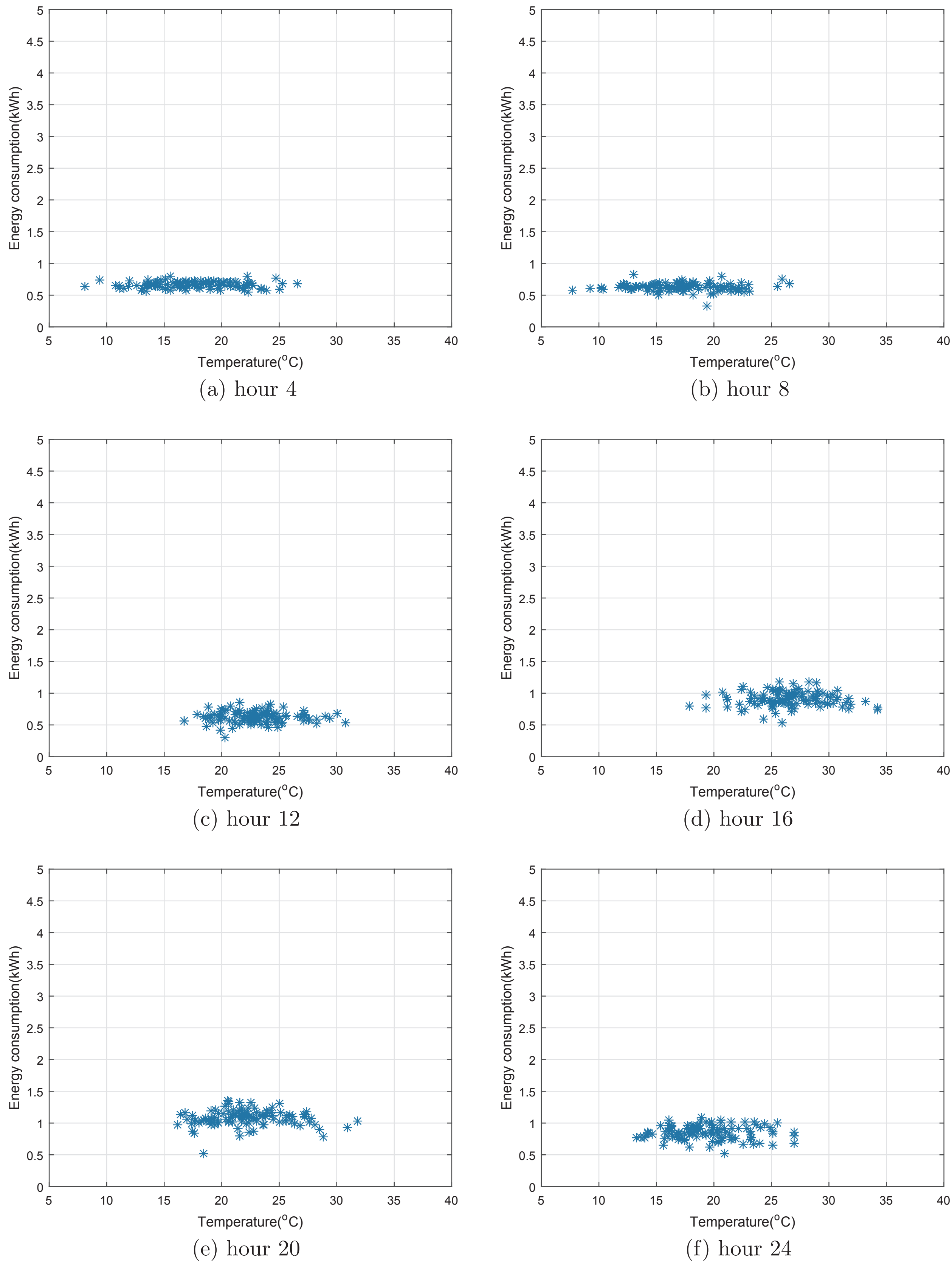


Fig. 15. ($A_{\Omega}^{p}-\lambda \times A_{\Omega}^{n}$) vs. outdoor temperature under optimized λs for different hours.

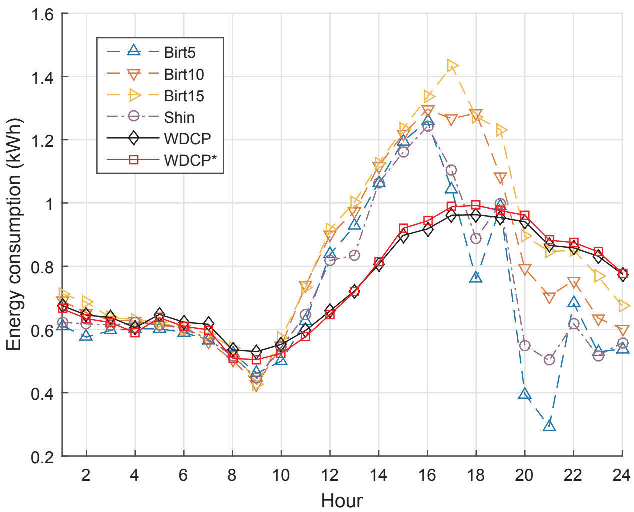


Fig. 16. CPRSP energy consumption estimation using different methods.

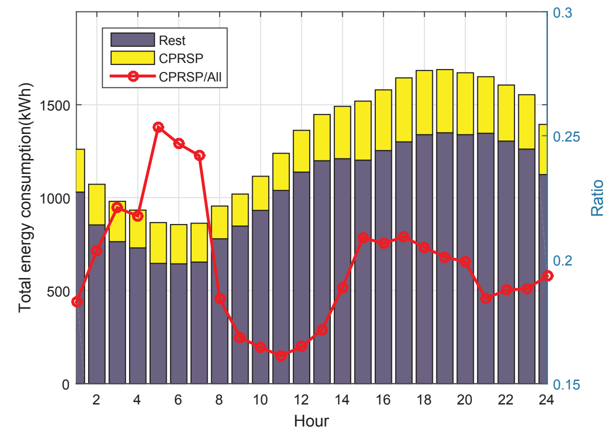
Table 3
Results of different methods.

	Birt5	Birt10	Birt15	Shin	WDCP	WDCP*
Peak power	1.2585	1.2956	1.4332	1.2428	0.9623	0.9974
Peak hour	16:00	16:00	17:00	16:00	17:00	17:00
Valley power	0.2941	0.4259	0.4251	0.4459	0.5312	0.4970
Valley hour	9:00	9:00	9:00	9:00	9:00	9:00
Average power	0.6982	0.8019	0.8469	0.7193	0.7423	0.7427

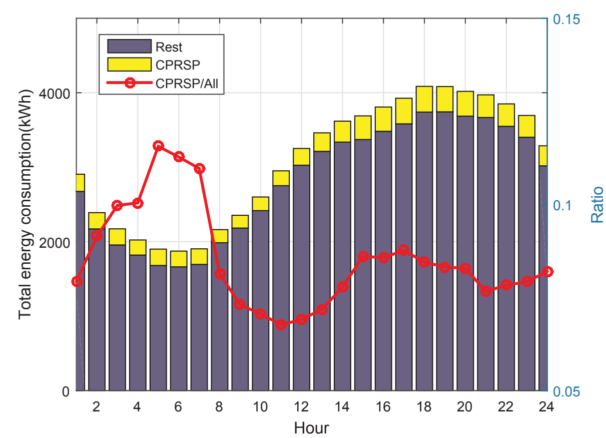
achieved both on the supply side and the demand side. On the supply side, to shave the peak load, methods such as direct load control, emergency demand response, critical peak pricing, and real time pricing are usually used. While on the demand side, to shave peak load, methods such as renewable energy and electric energy storage have been widely studied. However, most of peak load shaving methods either require extra investments or reduce the comfort of the consumers. For example, direct load control allows the power supplier directly control the status of appliances, and customers will receive various payments as rewards. Direct load control is an effective method for peak load shaving, however, for example, in the Texas reliability entity region in the United States, only 0.11% customers enrolled in direct load control. The main reason may be that, from consumers psychology perspective, direct load control may disrupt their lifestyle and comfort. Meanwhile, for peak load shaving on the demand side, extra investment is an obstacle for renewable energy and electric energy storage. However, in the proposed method, as CPRSP are used for pool water circulation and purification, compared with direct load control or electric energy storage, controlling the activity periods of CPRSP would not reduce user comfort. Meanwhile, it does not require any extra investment including devices and sensors. Furthermore, according to Fig. 18, based on the proposed method, the average daily cost of CPRSP will be reduced from CAD 1.918 to CAD 1.762, and the users' operation is only to postpone CPRSP for 6 h by timers. Such operation doesn't require any extra investment, meanwhile it would not reduce any comfort of users. Therefore, shaving peak load by controlling the activity periods of CPRSP would be a feasible method.

6.6. Discussions on the settings and assumptions

In this paper, although there is no explicit parameter to be set, the WDCP* model depends on the definitions of the non-swimming season Φ and the swimming season Ω, as well as the assumption that the energy consumption of CPRSP is independent to the outdoor temperature. This section will discuss these two issues in detail.



(a) the impact of CPRSP on residents with swimming pools



(b) the impact of CPRSP on all residents

Fig. 17. The impact of CPRSP on the energy consumption profile on the peak day.

Table 4
Electricity rates during summer in Ontario.

Categories	Time ranges	Electricity rates (CAD/kW h)
Off-peak	7PM-7AM	0.077
Mid-peak	8AM-11AM, 6PM-7PM	0.113
On-peak	12AM-5PM	0.157

According to Eq. (13), the energy consumption of CPRSP E is estimated using A_Ω^p,A_Φ^p,A_Ω^n and A_Φ^n, therefore the definitions of the non-swimming season Φ and the swimming season Ω are very important. In this paper, Φ and Ω are defined based on the analysis on ΔA shown in Fig. 5,

$$\Delta A = A^p - A^n = (T^p + B^p + E) - (T^n + B^n) = (T^p - T^n) + (B^p - B^n) + E = \Delta T + \Delta B + E \quad (19)$$

In Fig. 5, A^p,A^n and ΔA are labeled as Pool, NoPool, and Pool-NoPool.

From Fig. 5 it can be seen that, according to the trend, the distribution of ΔA can be divided into four periods: the low level period L (approximately from day 1 to day 60, and from day 250 to day 420), the high level period H (approximately from day 120 to day 180, and from day 480 to day 540), the ascending period U (the transition period from L to U), and the descending period D (the transition period from H to L). Note that L is mainly in winter, the outdoor temperature is low, and swimming pools are generally not used. Meanwhile H is mainly in

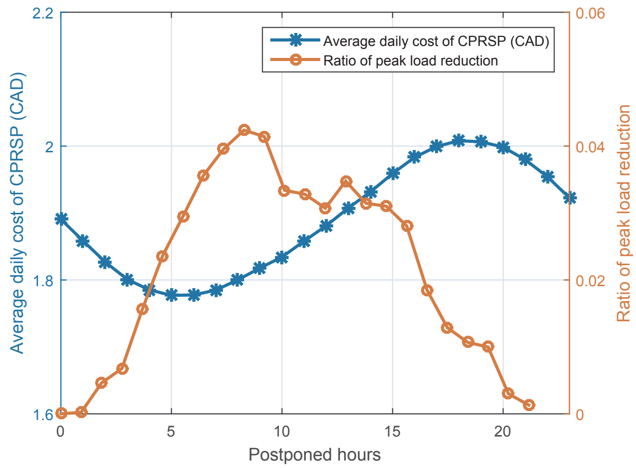


Fig. 18. The impact of the use of CPRSP on power system.

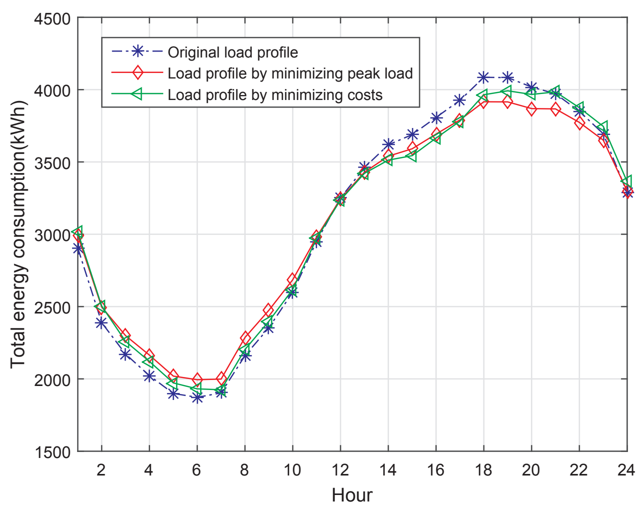


Fig. 19. The impact of the use of CPRSP on the peak day.

summer, the outdoor temperature is high, and many swimming pools are in use during this period. Therefore,

$$\Delta A_L = \Delta T_L + \Delta B_L \tag{20}$$

$$\Delta A_H = \Delta T_H + \Delta B_H + E \tag{21}$$

As shown in Fig. 5, during the high level period, both of A_H^p and A_H^n have high correlations with the outdoor temperature and vary greatly with the change of the outdoor temperature. While during the low level period, both of A_L^p and A_L^n have low correlations with the outdoor temperature, which is in accordance with the analysis in Fig. 10. It is from the fact that, the temperature-dependent energy consumption is mainly used for cooling and heating. For the residents analyzed in this paper, during summer, cooling is achieved mainly using air conditioners whose energy consumption depend on the outdoor temperature. While during winter, heating is achieved mainly using other energy sources such as gas rather than electrical energy.

Compared with A^p and A^n, the distribution of ΔA is much smoother, which indicates that the impact of the outdoor temperature on ΔA is much smaller. It can be explained that, the main difference between A^p and A^n is the use of swimming pools, and the energy consumption of CPRSP is temperature-independent. As a result, the impacts of the outdoor temperature on A^p and A^n are largely consistent, and ΔA mainly depends on ΔB and E in Eq. (19). Note that ΔB is temperature-independent and can be considered almost invariable during the low level period and the high level period, therefore the difference between ΔA_H and ΔA_L mainly depends on the energy consumption of CPRSP E. It is worth noting that during the low level period, ΔA_L is close to a constant, therefore ΔT_L is close to zero. However, during the high level period, ΔA_H varies with the change of the outdoor temperature in a small range. It is from the fact that, the temperature-dependent components of A_H^p and A_H^n are slightly different due to the factors such as the differences of the size of houses and living habits of the residents, therefore ΔT_H cannot be ignored. As a result, E cannot be directly obtained by $\Delta A_H - \Delta A_L$.

From the above analysis, the change of ΔA during all seasons in Fig. 5 can be explained that, first, when the outdoor temperature is low (the low level period), most of CRPSP are inactive. With the increase of outdoor temperature (the ascending period), more and more CPRSP are active. Note that E is calculated by the total energy consumption of all *active* CPRSP divided by the number of all CPRSP, therefore E as well as ΔA rise gradually with the increase of active CPRSP. During the high level period, the number of active CPRSP is stable in a certain range. After that, with the decrease of the outdoor temperature (the descending period), more and more CRPSP are inactive. Finally, most of CPRSP are inactive, i.e., $E \approx 0$, and then ΔA enters into a new the low level period. Therefore, the high level period with a stable number of active CPRSP can be used as a swimming season to analyze the energy consumption of CPRSP. To make it no ambiguity, some data at the edge of H are ignored, and the swimming season is defined from Jul. 1, 2011 to Aug. 30, 2011 and Jul. 1, 2012 to Aug. 30, 2012.

Furthermore, a longer swimming season can include more data of A^p and A^n, which can make the results more robust. However, if the swimming season consists of data from periods L,U or D, some inactive CPRSP would be included in the estimation of E. As a result, the estimation of E would be lower. For example, the estimation of E is 0.7429 kW h when Jul. 1, 2011 to Aug. 30, 2011 and Jul. 1, 2012 to Aug. 30, 2012 are selected as the swimming season as did in this paper. However, it is reduced to 0.5837 when May 15, 2011–Sep. 15, 2011 and May 15, 2012–Sep. 15, 2012 are selected as the swimming season.

Another issue is the relationship between the CPRSP energy consumption and the outdoor temperature. This paper considers that the CPRSP energy consumption is independent to the outdoor temperature. Although the CRPSP energy consumption cannot be measured directly as there is no specific smart meter installed on them, the relationship between the CPRSP energy consumption and the outdoor temperature can be derived from three aspects.

The first aspect is the work pattern of CPRSP. For a residential swimming pool, when the outdoor temperature is cold, e.g., in winter, the swimming pool would be drained and covered with a lid. When the outdoor temperature is warm enough, the resident would decide to begin using the swimming pool, and the swimming season for this resident begins. As the dirty swimming pool water will damage the water circulation system, during the swimming season, CPRSP will be active all day long or control by the timer to carry out the swimming pool water circulation to keep the pool water clean. When as the outdoor temperature is too cold for swimming, the resident would terminate his swimming season in this year. Then the swimming pool would be drained and covered with a lid again, until the swimming season in the next year begins. Therefore the use of CPRSP is independent with the outdoor temperature, and the CPRSP energy consumption can be considered independent to the outdoor temperature.

The second aspect is based on the distribution of ΔA in Fig. 5. As discussed above, the temperature-dependent component of ΔA is small, which is mainly from ΔT. As a result, the correlation between the energy consumption of CPRSP and the outdoor temperature is very low. Therefore, the CPRSP energy consumption can be considered independent to the outdoor temperature.

The third aspect is the estimation results shown in Fig. 15, which gives $(A_\Omega^p - \lambda \times A_\Omega^n)$ vs. outdoor temperature under optimized λ for different hours. According to the discussion in Section 5.2, if the CPRSP energy consumption is independent to the outdoor temperature, then if a λ can be obtained making the distributions of $(A_{\Omega}^{p} - \lambda \times A_{\Omega}^{n})$ vs. outdoor temperature is close to be horizontal. It can be seen that results in Fig. 15 reflect such this phenomenon, therefore, the CPRSP energy consumption can be considered independent to the outdoor temperature.

7. Conclusion and the future work

As a high peak load does not only increases the infrastructure cost and the power generation cost, but also increases carbon emission and the maintenance cost of transmission lines and equipment, recent years peak load shaving has been attracted more and more attention. However, most of peak load shaving methods either require extra investments or reduce the comfort of the consumers. Based on an extensive dataset containing hourly energy consumption readings of 1005 residents during March 2011 and October 2012 in South Ontario, this paper analyzes the energy consumption of circulating pumps of residential swimming pools and its impact on the peak load. This paper first analyzes the features of the energy consumption of homes with and without swimming pools, then proposes a novel non-intrusive appliance load monitoring method to estimate the energy consumption of circulating pumps of residential swimming pools. Finally, this paper quantifies how much peak load can be shaved by shifting the active time of circulating pumps of residential swimming pools.

The target of the project described in this paper is to provide suggestions for power supply companies to establish appropriate power supply plans. From the point view of power supply companies, they mainly focus on the overall pattern of the load profile in a region, especially the characteristics of the peak load, as well as the factors that affect the peak load, rather than individual power consumption patterns. Therefore, in this paper, the average energy consumption values are used, and the regional users overall energy consumption pattern is analyzed. In next step, this project will be extended to analyze the individual-level and subgroup-level features of residential energy consumption. Furthermore, in the future, some new projects will be established and specific smart meters will be install on circulating pumps of residential swimming pools to directly verify the proposed method.

Acknowledgements

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