Temporal Resolution Load Model for Regional Residential Electricity Consumption

Angreine Kewo [1*], Pinrolinvic Manembu [2], Xiufeng Liu [1], Per Sieverts Nielsen [1]

[1] DTU Management Engineering, [2] Sam Ratulangi University

ABSTRACT

High resolution electricity load profiles are often used for analysis-based decision makings, energy modeling, or other modeling tasks such as regional electricity consumption (EC). However, due to privacy issues or the essential lack of such data, it is difficult to obtain high-resolution load profiles. This paper presents a temporal resolution model to synthesise regional residential electricity load profiles. This model first uses a bottom-up approach to generate fine-grained load profiles with the inputs including the weather temperature, national holidays, and demography data. Then, the synthesized load profiles are adjusted in order to reconcile the aggregate consumption at the regional or city level. The model employs the weighting proportion of age group and employment rate as the fundamental characteristics that represents the regional profile. The temporal resolution load method is applied to model Amsterdam as a case city. The result indicates that the model can well-captured the characteristics of residential electricity consumption on a daily and seasonal basis, and the relationship between electricity consumption and temperature. The presented method is capable of handling large amounts of data and provides a better estimation of the residential electricity consumption at the regional level by focusing on the main characteristics of the region.

Keywords*: temporal resolution, residential, load, energy, electricity consumption.*

INTRODUCTION

The residential energy sector plays a crucial role in achieving a more energy efficiency goal and emissions reduction. The emissions generated by the local consumption are difficult to displace to other countries or regions. Therefore, in relation to the residential energy-saving potential, it is essential to understand the residential energy consumption at the local level, specifically electricity load. In fact, studies on regional residential electricity load are rarely performed. A novel computational method is required to handle a large amount of population data set and measure the precision of residential electricity consumption per unit with respect to time, namely temporal resolution. In this work, a temporal resolution load profile method is developed for improving the real time value estimation of residential electricity consumption at the city level based on the population characteristics. It is employed an hourly temporal resolution data to analyse the residential electricity consumption based on seasonal day type, typical seasonal days and it is relationship with climate factor at the city or regional level.

RESEARCH QUESTION

In providing the regional residential hourly load, finding the representative load pattern is challenging. The load pattern should represent the main regional characteristics. Therefore, the relevant method is required to fit the nature of data in collection and to provide temporal resolution load pattern based on seasonal day, representative days and the relationship with climate factors.

METHODOLOGY

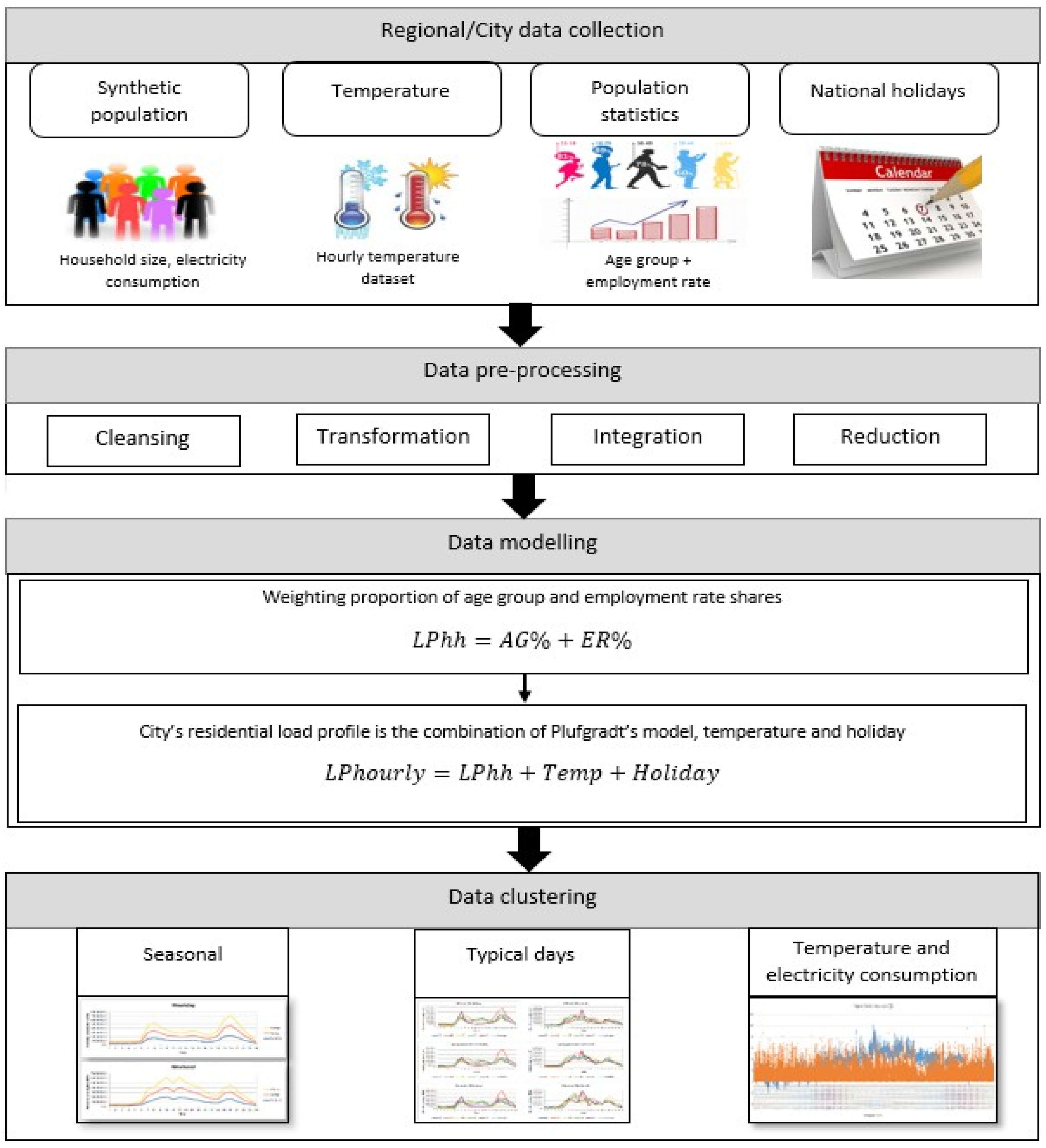

Figure 1. Regional temporal resolution framework (Kewo, 2018)

1. Data collection

The data availability and data sources may improve the quality of output. The right data collection method will allow only high quality data, improve reliability and efficiency resulting in high quality output. Therefore, it is important to scope and categorize what kind of quantitative data we need. Our data collection contains socio-economic data, climate data, electricity consumption data and since we want to have the spatial temporal information, a related geographical data is required.

2. Data selection and preprocessing

Defining a specific point of time is essential in order to perform data selection according to the defined period. The nature of our data in collection is panel dataset, which is a cross sectional data sample at specific point in time. In this case, we have defined to model the load profile of year 2015. The selection of period is important, so the data are balance since it is retrieved in the same period. A synthetic population dataset was developed using the combination of Iterative Proportional Fitting (IPF) and mixed integer programming.

Task	Problem/issue	Solution/Technique
Cleaning	Missing data	Ignore the record Determine and filling the missing value manually Use an expected value
	Noisy data	Binning methods, Clustering, Machine learning
	Inconsistent data	External reference, Knowledge engineering tools
Transformation	Different format, scale or unit	Normalisation, aggregation and generalisation
Integration	Different standards among data sources	Combine data into a consistent database
Reduction	Complex analysis or infeasible	Reduce un-necessary observations, variables or values

3. Data modelling

a. Weighting proportion methods

We couple the share of age groups and employment rate, and apply this weighting composition to the total population, as the main characteristics that represent the city profile . This weighting composition, the combination of age groups and employment rate, is a fundamental input for data modeling. The population age is categorised in three groups: 0 – 14 years old, 15 – 64 years old and above 64 years old. Furthermore, we have identified the information of employment rate in the city. The sum of employment share and unemployment share is represent the city's employment profile. In this case, the employment rate is measured based on the labour force population.

b. City load profile modeling

The household electricity load profile is modelled using the Pflugradt's model. Pflugrandt's has developed the model with a strong focus on the behavioural aspect. Therefore, our model combines the household load profiles which is the city's weighting composition with Pflugradt's model, hourly temperature and national holiday to obtain the hourly load resolution at the city level.

4. Data Clustering

the electricity consumption patterns are analysed at three levels: seasonal average pattern, typical day pattern and the relationship of temperature and electricity consumption pattern.

RESULTS

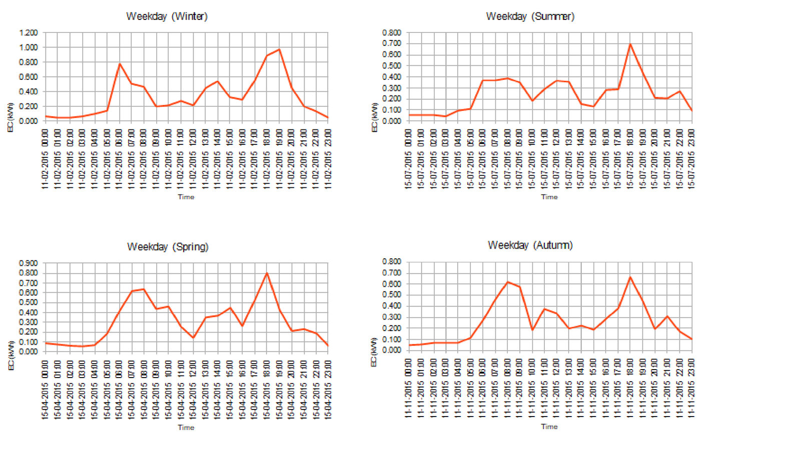

Figure 2 Seasonal representative day type - Weekday

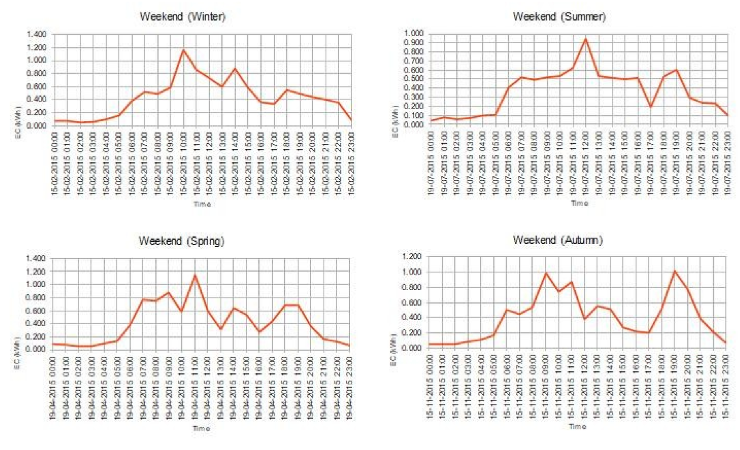

Figure 3 Seasonal representative day type - Weekend

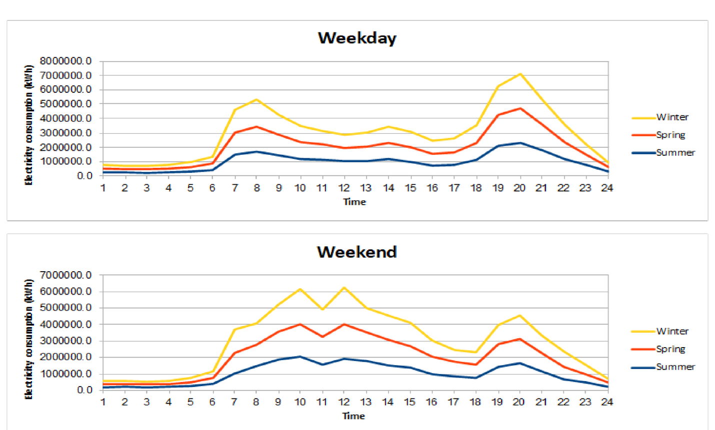

Figure 4 Average of seasonal day type at the city level

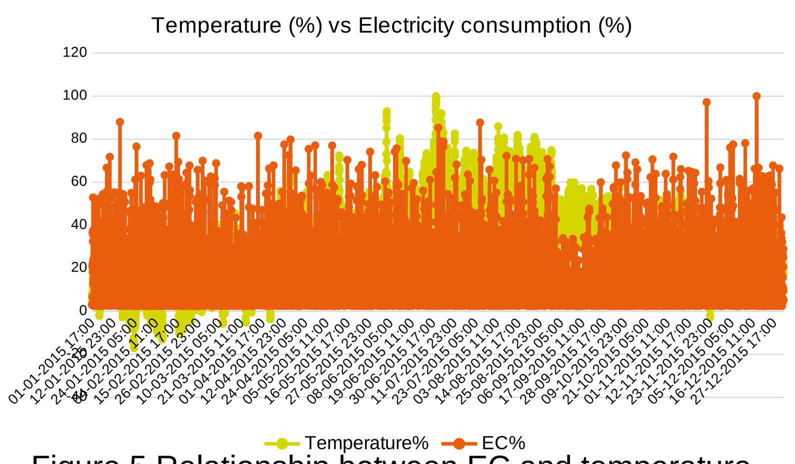

Figure 5 Relationship between EC and temperature

CONCLUSION and FUTURE WORKS

The presented approach provides a better estimation of the residential electricity consumption at the regional level by focusing on the age group and employment rate. The weighting proportion of age group and employment rate is the fundamental factor in defining the household profiles in the model. This novel approach is able to represent the regional main characteristics. Due to the nature of data collection where we employed a synthentic raw data, the pre-processing techniques could be minimized since the data are generated using a specific algorithm. Although in practice, such data collection availability might be challenging. The current advance of renewables energy and the future of electrical appliances make the meaning of seasonal representative day is not so obvious, since they may influence the people behaviour. Furthermore, this work may support the regional energy policy for better energy management. For future work, we would like to expand the work by performing a spatio-temporal resolution method, where we can analyse the electricity consumption load based on location. We would also like to apply this method to other cities.Furthermore, it is also interesting to develop platform of scenario policy and predict the residential emissions.

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DTU Management Engineering
Department of Management Engineering