Hybrid Model for Large Scale Forecasting of Power Consumption

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Abstract. After the electricity liberalization in Europe, the electricity market moved to a more competitive supply market with higher efficiency in power production. As a result of this competitiveness, accurate models for forecasting long-term power consumption become essential for electric utilities as they help operating and planning of the utility's facilities including Transmission and Distribution (T&D) equipments. In this paper, we develop a multi-step statistical analysis approach to interpret the correlation between power consumption of residential as well as industrial buildings and its main potential driving factors using the dataset of the Irish Commission for Energy Regulation (CER). In addition we design a hybrid model for forecasting long-term daily power consumption on the scale of portfolio of buildings using the models of conditional inference trees and linear regression. Based on an extensive evaluation study, our model outperforms two robust machine learning algorithms, namely random forests (RF) and conditional inference tree (ctree) algorithms in terms of time efficiency and prediction accuracy for individual buildings as well as for a portfolio of buildings. The proposed model reveals that dividing buildings in homogeneous groups, based on their characteristics and inhabitants demographics, can increase the prediction accuracy and improve the time efficiency.

Keywords: Smart grid; Multiple linear regression; Time series models; Random forests; Conditional inference trees.

1 Introduction

Load forecasting can be defined as the process of estimating the power consumption needs of a specific geographical area in a certain point in time. It plays an essential role in planning the facilities of electric utilities including Transmission and Distribution (T&D) equipments in the demand side management, and in the energy purchases by utilities as well. The accuracy and reliability of forecasting models have a significant impact on electric utilities. On one hand, insufficient power supply due to the underestimation of electricity demand may cause the system to operate in a critical region where a total collapse of the system is possible. On the other hand, the excess power supply due to the overestimation of power consumption leads to high costs for operating too many power supply units and as a result a drop in the investment due to extra energy purchases.

Previously, power utilities could predict the future consumption using statistical metrics regarding economic growth such as the industrial growth index and population statistics such as the growth index of residential buildings. Nowadays, multiple power utilities can operate in the same area in which the customers have different power suppliers to subscribe to and not only one supplier. This makes it difficult for the power utilities to rely on the previously mentioned statistics such as the economic and population growth indexes to predict future consumption.

To assist the future investments of power utilities, we need to provide an estimation of the mean power consumption of current and new constructions based on the historical consumption data and the different factors that affect that consumption. A real-time measurements of residential power consumption can be provided by the installation of smart meters in residential buildings. However, Germany for example will not follow the European Commission program for 80% deployment of smart meters by 2020. Instead, it will adopt a phased approach that will address its specific requirements around energy efficiency and renewable energy integration. This fact triggers the need to design new models which are capable of leveraging the smart metering technology and cope up with the difficulties of integrating smart meters in nowadays networks.

In this work, we propose a new approach to overcome these issues by installing smart meters in a representative subset of the population in a region. This subset should cover the variety of domestic and small and medium enterprises(SME) buildings. Then, by modelling the consumption pattern of the participants in this trial, we can generalize the solution to predict the population's future power consumption. To estimate the long-term power consumption of a population, we integrate the effect of time-independent factors such as building characteristics and demographic features of inhabitants and time-dependent factors such as weather conditions, workdays and holidays.

The paper is organized as follows: Section 2 gives an overview of related work in the domain of power consumption forecasting. In Sect. 3, we introduce our concept for the long-term forecasting of power consumption. Sections 4, 5 focus on the long-term prediction model design while Sect. 6 presents the comparative analysis and evaluation of the proposed model against RF and ctree. Finally, Sect. 7 summarizes the paper and discusses future work.

2 Related Work

The problem of modelling and forecasting electrical consumption has been intensively studied in the past decades. Long-term and medium-term forecasting of power consumption are used by the utilities mainly for future planning and maintenance purposes. A wide variety of models have been proposed for the purpose of power consumption forecasting. They can be classified into five categories, namely averaging models [11],[13][12], regression models [2], [5], [10], [7],

[6], time series models [20], [16], artificial intelligence models [23], [15], [14], [19], and hybrid models [18], [21].

Averaging models are characterized by their simplicity as they make their prediction based on averaging the power consumption of similar points of time horizon such as day, month, and year. They only require the historical consumption information. S. Aman et al. presented in [1] an empirical comparison between several prediction methodologies for short-term forecasting of power consumption. In their first scenario, they have evaluated the Time of the Week (ToW) averaging model using the 15-min interval load demand in a week calculated as the average over all weeks. This simple model can be used to predict the power consumption in a granularity of 15-min as the kWh value for that interval.

More complex than averaging models, regression tree (RT) models build a decision tree to represent the non-linear relationship between the predictors and the response variable. S. Aman et al. proposed a prediction model based on regression trees to forecast the short-term power consumption of campus micro-grids using indirect indicators [2]. In this work, the authors classify power consumption indicators into direct and indirect. Direct indicators include the historical weather information and the power consumption data from smart meters. Indirect indicators include seasonal patterns such as day of the week, semester and holidays, and academic calendar as well as static knowledge of the building characteristics such as surface area. They provide prediction models at the building and campus levels for daily and 15-min intervals by training a CART regression tree based on the direct and indirect indicators. Also Time series (TS) models try to predict future power consumption based on previous historical observations. The commonly used approaches include Moving Average (MA), Auto-Regressive Integrated Moving Average ($ARIMA$) and the Pattern Sequence-based Forecasting (PSF) [17].

Artificial intelligence techniques such as neural networks, support vector machines, and pattern matching techniques show promising capabilities in forecasting and modelling power consumption. An overview of different AI techniques is provided in [14]. Among all AI-based methods, the technique of artificial neural networks (ANNs) has received substantial attention in forecasting power consumption due to its flexibility in learning load series and modelling the non-linearity between power consumption and the exogenous variables influencing it as well as providing fairly acceptable results. S. Wan et al. developed an artificial neural network model for modelling the electricity load of campus buildings in [22]. The input data of the network includes building consumption history and the time-depended climate variables such as dew point, rainfall rate, pressure, wind speed, humidity and temperature.

The majority of previous research works for power consumption forecasting focus on homogeneous buildings such as residential or industrial buildings regardless of their differences i.e. demographic data, and building characteristics. Moreover, they consider the prediction of future demand growth of current networks without taking into consideration new or planned constructions. Another limitation of the current research conducted in this field is that it did not take in consideration the difficulties of integrating smart meters in today's networks as well as the geographical structure of the network where each area is monitored independently. In this work, we try to tackle these issues by investigating the possibilities of estimating the long-term daily power consumption for a population out of a representative sample.

3 Concept and Dataset

In this work, we follow a multi-step statistical analysis methodology as shown in Fig. 1 in which we use time-dependent predictors such as temperature, business days, and holidays combined with time-independent predictors such as demographic data, and building characteristics to estimate the power consumption of existing and future planned buildings on different scales. In the first step, we build the Building-Performance regression model that correlates the power consumption with time-independent factors by following a stepwise approach for the selection of predictors. This model provides good insights into the average monthly power consumption of individual buildings. Furthermore, it assists the process of excluding the data which belongs to buildings with consumption patterns not representative of the population, in order to reduce the errors in next modelling steps.

In the second step, we investigate the possibility of building a hybrid model which uses conditional inference trees [8] to divide buildings into homogeneous groups using the time-independent factors and then create a multi-linear regression model for each group to estimate the daily power consumption using time-dependent predictors, demographic data, building characteristics and number of available appliances. Later, this model is adapted for the prediction of future power consumption of new buildings by removing the predictors related to available appliances and part of demographic data. The model will be capable of predicting the daily long-term power consumption for the whole population.

The used dataset in this work is provided by the Commission of Energy Regulation (CER) in Ireland. CER has started a project to collect measurements about power consumption of individual buildings using smart metering technologies. The trials took place over a period of eighteen months during 2009 and 2010. Raw data representing the 30-minute power consumption readings in kWh of individual buildings was collected. More than 5000 smart meters were installed in Irish homes and businesses in eight urban areas and three villages [4]. Pre-trial and post-trial surveys were conducted for both residential and business participants. Residential participants, which are considered for the evaluation, provided information about the following aspects in the survey:

- Demographic features of residents such as number of people living in the house, age groups, household income and employment status.
- Physical characteristics of the house such as floor size, house type, number of bedrooms, heating type and insulation.

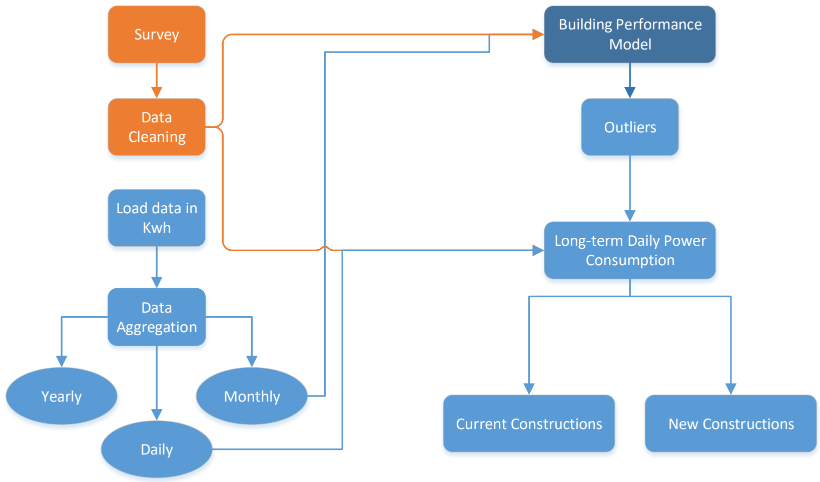

Fig. 1. Workflow for long-term daily power consumption forecasting model.

- Type and number of available electrical appliances in the house.
- Behavioral features of residents such as their usage patterns of electrical appliances as well as their awareness degree of the power each appliance consumes.

4 Building-Performance Multiple Regression Model

The building-performance multiple regression model can serve as a reference model for the power usage of the general population by interpreting the effect of different predictors on the average power consumption. The set of predictor variables consists of demographic data, building characteristics, heating sources as well as the number of available appliances. The multiple linear regression model can be expressed in the form:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip} + e_i \tag{1}$$

where y_i is the response variable representing the total power consumption of building i during the trial. $x_1, .., x_p$ refer to the predictor variables where p is the number of predictors. e_i is the estimation error for building i and $\beta_1, .., \beta_p$ are the regression coefficients.

The Multicollinearity due to a potential inter-correlation between different predictors may negatively affect the interpretation of partial regression coefficients and make it difficult to recognize relative importance levels. To avoid any negative effect of multicollinearity, a backward stepwise regression approach is used to select the best model, where iteratively in each iteration a subset of predictors that match best model performance is selected.

This model should represent the performance of the population buildings. Therefore buildings with abnormal power consumption are considered as outliers and their related power measurements are excluded from the dataset and then the model is fitted again. Based on the assumption of normal distribution of the total power consumption, a data point is considered as an outlier if its absolute value of the standardized residual is larger than 2 [10]. By defining the predicted power consumption as $\hat{y}_i$, the standardized residual can take the form:

$$\hat{z}_i = \frac{y_i - \hat{y}_i}{\hat{\sigma}} \tag{2}$$

where $\hat{\sigma}$ is the standard error.

5 Hybrid Model for Long-term Forecasting of Power Consumption

The idea behind developing a hybrid model is to get the benefits of several rigorous modelling techniques in order to achieve a high prediction accuracy. On one hand, modelling the effect of time-independent variables contributes to the prediction of mean power consumption. On the other hand, modelling the effect of time-dependent variables contributes to the modelling of the random error generated by seasonal patterns and temperature changes.

We utilize conditional inference trees (ctree) to group the heterogeneous set of buildings into several homogeneous groups based on time-independent variables, namely building characteristics, demographic data, heating source, and the number of different available appliances. Ctree is a non-parametric class of regression trees embedding tree-structured regression models into a well defined theory of conditional inference procedures [9]. Ctree recursively performs univariate splits of a dataset based on two stages. The first stage is the recursive binary partitioning which proceeds as follows:

1. Using significance test of the global null hypothesis of independence between the predictors and the response variable, the algorithm selects the predictor with the highest association with the response variable based on the p-value corresponding to significance test.
2. Select two subsets of the selected variable to split the observations into two disjoint groups. The splitting point is selected based on another statistical test.
3. Recursively repeat steps 1 and 2.

In the second stage, it fits a constant model in each leaf node of the generated tree. It is important to mention the differences between Ctree and other popular regression tree algorithms such as CART and C4.5. Both CART and C4.5 examine all the possible splits and select the covariate that maximizes the cell purity. Both methods suffer from overfitting and bias towards partitioning based on covariates with multiple splits. The overfitting can be overcome by tree pruning. However, there is no statistical significance analysis that can prove whether there is a significant improvement due to the split or not. On the contrary, Ctree algorithm is statistically more valid, it recursive applies a split based on the theory of permutation tests in which partitioning is stopped when there is no significant association between the predictors and the response variable.

After dividing the buildings into several homogeneous groups, a multiple linear regression model is applied on each homogeneous group to model the daily power consumption of that group using time-dependent predictors, namely temperature, holidays, business days, and weekends. Moreover, a subset of time-independent variables including floor size, number of bedrooms, people description, built year and home description is used for the purpose of predicting the base power consumption of different buildings in the same group as shown in Fig. 2. The advantage of using ctree is that the split process tends to apply split on a subset only if a significant improvement can be achieved rather than grouping buildings based on heuristics such as the information gain as is the case in CART algorithm.

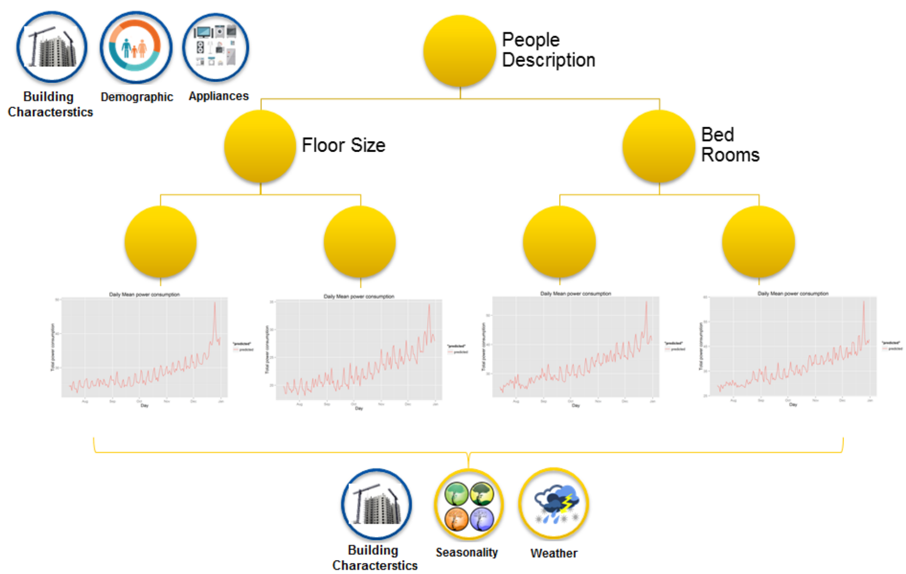

Fig. 2. The hybrid model design . Ctree model is used based on time-independent predictors for grouping the buildings into several homogeneous groups. Afterwards, an individual linear regression model is fitted for each group based on building characteristics and time-dependent factors.

6 Evaluation

In this section we evaluated the predictive performance of our proposed hybrid model. As a first step, we cleaned the dataset from outliers which are buildings with abnormal power consumption when compared to the majority of buildings with same characteristics. For detecting outliers, we utilized the Building-Performance model explained in Sec. 4. Table 1 shows the main factors contributing to the power consumption of residential buildings. This set mainly included the description of people i.e. retired and all over 15 years old, the building characteristics, the number of different appliances, the cooker type, and the water heating source. Thereafter, buildings with abnormal power consumption were excluded from the evaluation. As mentioned before, the iterations of the stepwise regression approach stop when no more improvement of the model accuracy can be achieved and the main features will be fixed then.

After the removal of outliers, we got 892 residential buildings out of 930 used in the Building-Performance model, while the remaining 38 were excluded through the backward stepwise regression approach. Then, we divided the dataset into a training set of 753 residential buildings and another 139 buildings for out of sample accuracy evaluation of the model. This step was done statistically, by classifying the buildings using ctree and selecting 80% of each group for training and the rest for testing. Dividing the buildings into homogeneous insured that the testing sample covers the existing variety in power consumption based on the buildings and the residents characteristics.

After getting a representative sample by excluding buildings with abnormal consumption, we classified the buildings using ctree model into homogeneous groups based on the listed time-independent predictors in Sec.5. Therefore, ctree model should be configured to produce groups in which buildings are as homogeneous as possible. Ctree uses the argument *mincriterion* as the value 1 - *P-value* corresponding to a significance test of dependency between a singe predictor and the response variable. This value must be exceeded in order to implement a split. In this work we set *mincriterion* to 0.90. The argument *minbucket* defines the minimum sum of weights in a terminal node which, in the default configuration, is equal to the number of data points that belong to a terminal node. These weights of individual buildings can be changed to give different importance levels to different data-points. For our evaluation purposes, we kept the default weights and set *minbucket* to 75, so we have no less than 75 data points for building the multiple linear regression model. After that a separate multi-regression model was designed for each group using time-dependent predictors, and a subset of time-independent predictors Sec. 5.

Figure 3 shows the prediction performance of our hybrid model with ctree's *mincriterion* = 0.90 and *minbucket* = 75. This figure shows the actual aggregated daily power consumption of all buildings compared to the prediction results. The predicted daily total consumption was calculated by predicting the daily power consumption of each individual building for six months in advance using our hybrid model. Thereafter, prediction results of all buildings were ag-

Table 1. The Building-Performance final model coefficients. Std. Error is the standard deviation of the sampling distribution of the estimates of the coefficients under the standard regression assumption. t-statistic is used to test whether the corresponding regression coefficient is different from 0 and $\Pr(>|t|)$ is the p-value of the corresponding t-statistics. Intercept is the mean of the response variable when all predictors values equal 0.

Coefficient	**Estimate**	**Std. Error**	**t-value**	**Pr**$(>|t|)$
(Intercept)	-2.995e+03	3.775e+02	-7.934	8.48e-15
People description	6.079e+02	8.455e+01	7.189	1.69e-12
Floor size	2.836e-01	7.365e-02	3.851	0.000128
Bedrooms	4.378e+02	7.111e+01	6.157	1.25e-09
Water central heating system	-2.323e+02	1.479e+02	-1.571	0.116663
Water electric(immersion)	3.509e+02	9.609e+01	3.652	0.000280
Water heating (Gas)	-5.435e+02	1.423e+02	-3.819	0.000146
Water heating (Oil)	-2.729e+02	1.200e+02	-2.274	0.023293
Water heating (Other)	-1.628e+03	8.723e+02	-1.866	0.062394
Cook	-2.634e+02	7.533e+01	-3.497	0.000501
Tumble dryer	4.529e+02	1.174e+02	3.857	0.000125
Dishwasher	4.296e+02	1.281e+02	3.355	0.000837
Electric heater plug in	1.622e+02	6.928e+01	2.341	0.019511
Stand alone freezer	3.134e+02	8.788e+01	3.566	0.000388
TV greater 21	1.972e+02	5.469e+01	3.605	0.000334
Desktop computers	5.562e+02	8.141e+01	6.832	1.83e-11
Laptop computers	3.146e+02	5.755e+01	5.467	6.39e-08
Games consoles	2.612e+02	6.441e+01	4.056	5.56e-05

gregated and compared to the sum of actual daily power consumption of all buildings in the dataset.

In order to generalize the proposed model to be capable of predicting the power consumption of new constructions, we removed the factors related to inhabitants such as the number of different appliances as well as how they cook and the demographic data related to the number of people in different age groups.

We compared the performance of our hybrid model against two robust machine learning algorithms, namely conditional inference tree and random forests [3] with the same used datasets for training and testing. For the random forests model, we set the number of bootstrapped trees to grow to ntree = 500. This number should not be too small to insure that each record in the dataset is predicted at least few times. While ctree was used with same configurations as in our model $mincriterion = 0.90$ and $minbucket = 75$.

Table 2 demonstrates a relative comparison between our proposed hybrid model, ctree, random forests and the generalized version of our model in terms of model accuracy and time efficiency. For the accuracy evaluation, the Mean Absolute Percentage Error(MAPE) and the Mean Absolute Error (MAE) were used. MAPE is preferable for reporting since it presents the results as a percentage which makes it more interpretable, while MAE is less sensitive to very large

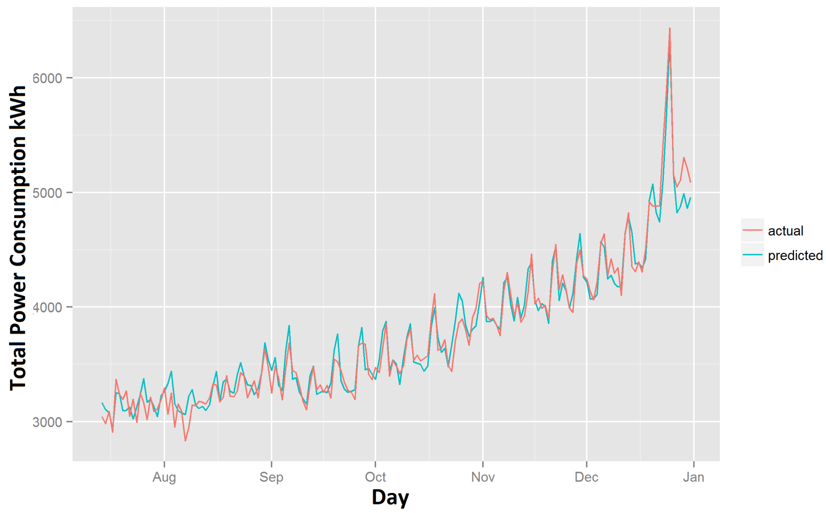

Fig. 3. Prediction accuracy of the proposed hybrid model with mincriterion=0.90 and minbucket=75.

errors in prediction compared to other measures.

$$MAE = \frac{1}{N}\sum_{h=1}^{N} |x_h - \hat{x_h}| \tag{3}$$

$$MAPE = \frac{100\%}{N}\sum_{h=1}^{N} \left|\frac{x_h - \hat{x_h}}{x_h}\right| \tag{4}$$

Where $\hat{x_h}$ is the predicted value, x_h is the actual value and N is the number of predicted samples.

Table 2. MAPE, MAE and execution time for individuals and portfolio of buildings.

	Individual buildings		**Portfolio of buildings**		**Time**
Model	MAPE	MAE	MAPE	MAE	
Ctree	58.65%	10.51	4.84%	176.44	5 minutes
Random Forest	52.34%	9.65	5.38%	215.63	10 days
Proposed Model	49.01%	8.82	2.43%	89.41	1 minute
Generalized Model	50.67%	9.00	3.43%	123.11	1 minute

The results in Table 2 show that the proposed approach outperformed ctree and random forests in terms of prediction accuracy and time efficiency. The hybrid model required around one minute for generating the model. Ctree needed 5 minutes which is still feasible and 10 days were required by the random forests for the modelling step which can be justified by the high number of trees used by the random forests in order to achieve high accuracy. Moreover, the lowest values of MAPE for individual buildings and portfolio of buildings were also achieved using the proposed hybrid model.

7 Discussion and Future Work

In this work, we designed a hybrid model for daily long-term power consumption forecasting on the scale of portfolio of buildings using conditional inference tree and linear regression models. The hybrid model outperformed two robust machine learning algorithms in terms of time efficiency and prediction accuracy. The proposed model showed that, clustering individual buildings into homogeneous groups, based on building's characteristics and their inhabitants demographics, can improve the prediction accuracy and increase time efficiency by reducing the search space. In future work, other modelling techniques will be used instead of the linear regression model to predict individual groups consumption in the hybrid model. Also we are interested in extending this work by designing an ensemble forecasting model by applying multiple modelling techniques on each group of the Ctree leaves. The ensemble model could be a fusion of the predicted values from different models in an equation with different weights for each model.

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