Prediction Models: An Overview

Introduction

Being able to forecast energy flows and temperature parameters inside a building in an accurate way is key to the implementation of action plans suggested by the OPTIMUS DSS.

A prediction model is used to forecast data, based on input variables which can influence future behaviour of output data. Four prediction models have been developed in the framework of OPTIMUS, in order to support the implementation of the OPTIMUS DSS:

1. Renewable energy production.
2. Energy consumption.
3. Indoor temperature.
4. Energy prices.

Prediction Model 1: Renewable Energy Production

Two main options can be considered when dealing with models to predict hourly energy production from photovoltaics:

1. Estimation of an integrated model for all 24 hours/day, followed by disaggregation to an hourly basis.

2. Creation of a separate individual model for each hour of the day.

The first method was initially considered, as it is less complicated and has low computational costs. However, it did not provide the detailed information needed for specific hours (e.g. sunrise and sunset) in the day which is important to know for PV energy production. As a result, the second method was selected for further development, as forecasts at an hourly level, using Multiple Linear Regression (MLR) modelling, provided the level of accuracy needed.

Prediction Model 2: Energy Consumption

In order to model the total energy use of a building, energy consumption data were subdivided into categories based on hours and on days (i.e. working / non-working) Such categorisation:

1. Minimises the probability of large errors due to the misspecification of the time and the schedules of the building to occur, and;

2. Leads to more simplified models with fewer regressors.

Thus, the effect of the rest of the influential variables, such as outdoor temperature and humidity, becomes clearer and can in turn be estimated more effectively. In this case, 48 different MLR models were calculated, each one predicting a specific hour of the day for two types of days (working and no-working). The forecasts for each hour and day were then chronologically sorted to produce a one week forecast (168 hours). In cases where zero or negative forecasts are produced (mainly due to occasional low quality data) the determined base load of the building is used to fill the missing forecasts. In addition to weekends and holidays, strikes may also be considered as non-working days and taken into account if information is available well in advance.

Prediction Model 3: Indoor Air Temperature

The grey box approach was applied to predict the indoor air temperature trend during the heating period. The heating period was subdivided into cut-off period, boost period and normal heating period. For both cut-off and boost periods the regressors (time constant (τ) and ratio between the total amount of the heat gain and the total heat transfer (Φ/H)) were found.

The methodology was applied for the entire heating season: for each weekend/holiday the time constant and Φ/H value were calculated; for each cut-off period and boost period different Φ/H values were calculated.

An average value of the time constant was found for the whole heating period. A correlation was found between Φ/H values and the average outdoor air temperature both for cut-off and boost periods. This correlation may be used to identify a Φ/H value for the week after considering the forecast outdoor air temperature.

Prediction model 4: Energy prices

The energy prices prediction model implementation is divided into two complementary activities:

1. The electricity bill prediction model implemented will forecast the energy cost for the next billing period, based on historical data for consumption and the energy prices trend. The electricity bill is calculated taking as reference a known formula, according to the monthly average of the energy spot market prices.

2. The energy spot market prices forecasting model will take as reference the market spots of the day ahead regulators. Two approaches are implemented to deliver a forecast about the day ahead prices, namely MLR modules that take as input a series of values gathered from spot markets, as well as a formula that models the shape of the daily energy prices chart.

The OPTIMUS project

OPTIMUS aims to design a Decision Support System (DSS) to help towns and cities reduce CO_2 emissions by optimising energy use in public buildings.

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