Michael Smurfit Graduate School of Business

University College Dublin

Real-time, personalised analytics for predicting and managing energy consumption

Ruben Carvalho and Orna Duggan

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Supervisor: Professor Pádraig Cunningham

Head of School: Professor Ciarán Ó hÓgartaigh

Orna dedicates this to her parents Bridie and John

Ruben dedicates this to Shane and TT

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Abstract

There are impending changes in the electricity market that will open up practical requirements for models that can handle dynamic and unpredictable electricity consumption profiles in real-time. Throughout the years, UCD has recorded electricity consumption data across the campus in floors and buildings. This continuous stream of data points provides a valuable resource that allows us to question whether traditional modelling methods – that focus on a subset of data to model and predict future energy needs – can be improved to meet these impending market requirements.

With this objective in mind and using Linear Regression, this research explores the potential for models that are capable of re-training with new data on a regular basis over an indefinite period. The study compares the performance of three models, a regular "static" model, a "self-update" model, in which the model is regularly retrained with new data as it becomes available and an "ageing" model, in which new data is added, as old, potentially less-relevant data is dropped or "aged out" at the same time.

We find that static, self-update and ageing models behave differently when training windows of different sizes are used. For the UCD buildings included in this study, we propose an optimum design, in which the model switches from "self-update" to "ageing" when a certain threshold size of training window is reached. We find that feature (attribute) selection should not be included when the self-update model is used, but may be applied in the ageing model. The research concludes by noting that changes to the electricity market that will be implemented from 2017 will have a profound impact on the typical electricity consumption profile for many customers. Our findings indicate that the qualities and characteristics of self-update and ageing models may be very suitable for application in the prediction of these new, less predictable consumption patterns.

Chapter 1

Introduction

> *"It is our priority to remove all barriers to the internal energy market so that energy can flow freely everywhere in the EU. The single European energy market must become a reality for all businesses and consumers by 2014."*
>
> — Günther Oettinger, EC Commissioner for Energy, March 2011

1.1 The Rationale for this Research

Ireland is currently preparing to join the single European Energy Market, also known as the "Target Model". This means that from 2017, the way in which electricity is generated, bought, sold and consumed will change, leading to a more dynamic, unpredictable environment. This new marketplace will bring both challenges, and opportunities. Customers (such as University College Dublin (UCD)) who are generally passive participants in today's electricity market, will have the opportunity to proactively participate in a demand-side market in which electricity may be sold back to the grid in real-time at a premium price.

Incentivised by the availability of lower electricity prices and enabled by the Smart Grid and by Smart Building Energy Management Systems (BEMS), customers will be able to plan consumption to coincide with periods of low cost electricity, typically when wind production is at its highest. There will be a disruption in electricity consumption patterns, particularly in peak demand times. The market will become far less predictable, while the requirements to accurately predict short term electricity needs will become greater.

A scan of the literature shows that much work has been done to predict building energy consumption. These models are successful, and high levels of accuracy have been achieved (Gibbons, 2012) (Azadeh and Sohrabkhani, 2006). However, by and large, these models are static, that is, they are frozen immediately after training and testing and do not evolve any further. There is evidence (Potočnik *et al.*, 2014), (Lifna, 2014) that the current field of (static) predictive models are not sufficiently adequate for the demands of a dynamic, Smart Grid environment.

1.2 Research approach

To address the challenge described above, our research considers the potential for models that can successfully predict electricity consumption in real-time, by updating with new data on a regular basis over an indefinite period.

With this in mind, this study explored the comparative performance of three different types of predictive models:

1. A regular "Static" model.
2. A "Self-Update" model, in which the model is regularly retrained with new data as it becomes available.
3. An "Ageing" model, in which the model adds new data, and also drops old, potentially less-relevant data at the same time.

Our research used electricity consumption data from UCD buildings to explore the impact of different design choices for the model (e.g. training window size, "update" window size, "drop" window size, and attribute selection. The purpose of this testing was to build and compare personalised models, capable of predicting electricity requirements. UCD data provided a suitable, readily available proxy for typical demand profiles in energy consumption.

Initial tests were carried out to identify the most appropriate algorithm for application in this research project. Based on its overall performance and fast execution times in these tests, Linear Regression (LR) was chosen in preference to Neural Networks (NN) and Support Vector Machines (SVM) models and was used in this research. However, we note that there is a future research opportunity in the evaluation and optimisation of a preferred algorithm.

1.3 Research Contribution

The contribution of this research was the formulation of clear answers to the following questions:

1. What is the impact of adding the ability for existing static models to self-update with newly observed data (i.e. creation of a Self-Update model)?
2. Does removing (ageing out) some of the data previously used to generate a model produce an improvement in the overall model performance (i.e. creation of an Ageing Model)?
3. Depending on the building being analysed, does using a subset of features produce better results than using a complete set of attributes (i.e. Attribute Selection)?
4. Is it possible to quantify an optimal threshold between static and self-updating models?
5. Having optimised, the model, is there a practical or commercial application for such a model?

Our work found that Static, Self-Update and Ageing Models behave differently when training windows of different sizes are used. Therefore, for the UCD buildings included in this study, we propose that the optimum design is a combination, in which the model switches from "Self-Update" to "Ageing" when a certain threshold size of training window is reached.

We also found that feature (attribute) selection should not be included when the Self-Update Model is used, but may be applied in the Ageing Model.

We conclude our research by noting that changes to the electricity market that will be implemented from 2017 will have a profound impact on the typical electricity consumption profile for many customers. Our findings indicate that the qualities and characteristics of Self-Update and Ageing Models may be very suitable for application in the prediction of these new, less predictable consumption patterns.

Chapter 2

Literature Review

2.1 General

A review of the literature highlights the scope and volume of research that has been carried out to develop and optimise predictive models for application in energy management (Azadeh and Sohrabkhani, 2006), (Kalogirou, 2000), (Korolija *et al.*, 2013). In their 2009 review, Aggarwal *et al.* (Aggarwal *et al.*, 2009) indicated that the forecasting of energy load is so good that models frequently achieve Mean Average Percentage Error (MAPE) values of less than 3%. However, Potočnik *et al.* (Potočnik *et al.*, 2014) note that complexity of choice that occurs in the development of an optimum energy prediction model. They said "*it is not possible, from the existing literature, to obtain clear answers to the following questions: which input variables and extracted features are the most relevant for the construction of forecasting models? What are the required embedding dimensions of the inputs? Which model is the most suitable for use as a forecasting tool in real-world short-term natural gas forecasting applications? Should the model be linear or non-linear? Do adaptive models outperform non-adaptive models?*".

The questions asked by Potočnik are applicable to electricity prediction and are very close to the questions considered in this research. Therefore, the following literature review is organised around the following headings:

- Choice of a preferred model
- Static versus Self-Update and Ageing Model design
- Model attributes and window selection

Finally, because of the commercial focus of this dissertation, we also review research into the applications of predictive models in energy management.

2.2 Selection of preferred model

A review of the literature shows the application of a broad variety of models used for energy load forecasting. Yang *et al.* (Yang *et al.*, 2005) observed the variety of models that have been used in the literature for prediction (time-series models, Fourier series models, regression models, Artificial Neural Network (ANN) models and fuzzy logic models), noting that each has its advantages and disadvantages and that performance can vary depending on circumstances.

In 2001, a review of the application of ANN in renewable energy systems (Kalogirou, 2001), highlighted the range of situations including the forecasting of annual and monthly building energy consumption, using 11 different parameters. Potočnik (Potočnik *et al.*, 2014) observed that regression analysis has typically been the most popular modelling technique in predicting energy consumption, although ANN is also commonly used.

Two recent review papers provide a useful overview of research in the prediction of energy consumption. Ahmad *et al.* (Ahmad *et al.*, 2014) reviewed the application of ANN, SVM and Hybrid models in forecasting electricity consumption. The authors outlined the advantages of ANN such as its effectiveness in modelling non-linear patterns, its flexibility, and its broad applicability. However, the authors did note that large NNs may require very high processing times. The authors suggest that SVM can offer a high level of accuracy, but that its complexity and associated time requirements can make it impractical. They highlighted that hybrid models can outperform other singular models, referring to a two-stage adaptive model (Fan and Chen, 2006) that uses Self Organized Map (SOM) and SVM for next day hourly forecasting of energy consumption. Zhao and Magoulès (Zhao and Magoulès, 2012) undertook a meta-analysis of predictive models for building energy consumption. The authors reviewed four primary methods – Engineering, Statistical Methods, ANN and SVM. Their comprehensive review included specific methods such as Auto-Regressive Integrated Moving Average (ARIMA), Conditional Demand Analysis, Principal Component Analysis (PCA), Back Propagation NN, General Regression NN. Evaluating each methodology according to complexity, accuracy, ease of use, running speed and inputs, the author concluded that:

- Both ANN and SVM methods offer high or fairly high accuracy.
- Statistical methods as easy to use although are less accurate and often somewhat slower than ANNs.

- SVMs are disadvantaged by high complexity and low running speeds.
- ANNs are also complex, however the authors report that they combine efficient running speeds with reasonable accuracy.

Singhal and Swarup (Singhal and Swarup, 2011) forecast future electricity market price using ANNs. Taking 8 months of electricity price data, 6 months of data was used to train the model. Training was then carried out for individual days of a test month, representing three different scenarios – normal price trends, day when a small spike in price occurred and day when a large spike in price occurred. The authors included 13 input attributes representing time, demand and historical price in a 3-layer NN. The model was most effective in measuring normal price trends, but was less effective in predicting price spikes. The model was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Both measures gave different results and the authors recommended that both be used to provide an accurate evaluation of the model.

Prevost *et al.* (Prevost *et al.*, 2011) carried out research to predict the energy load in a cloud data centre using NNs and Auto Regressive Prediction Filters. The authors noted that their ultimate objective is to support energy balancing by predicting and then dynamically responding to the power consumption requirements of the data centre using appropriate controls. Test windows ranging from 1 second to 20 seconds were used with acceptable levels of forecast accuracy decreasing with increasing window size. In all window sizes, the linear model out-performed the NN for all forecast intervals. The linear model also demonstrated an inverse relationship between forecast accuracy and distance into the future the load is being forecasted.

Tso and Yau (Tso and Yau, 2007) compared the performance of Regression Analysis, NNs and Decision Tree models in the prediction of electricity consumption in domestic homes. They found comparable results for each of the three models. Attributes applied to the model included household size, characteristics and appliances owned. It was evaluated using Square Root Average Squared Error (RASE). The research was separated into two phases: summer and winter. This allowed the models to select different attributes to reflect the seasonality of energy consumption. With summer data, the decision tree performed marginally better than Regression and NN models. With winter data, the NN provided the best performance. The authors explain this difference in performance by the fewer number of significant attributes influencing energy consumption during the summer months. During this period, they note that "*the decision tree model, with its simpler structure, is more accurate than other models*".

Short-term modelling of energy consumption has been the research topic of previous MScBA dissertations in recent years. Kearney (Kearney, 2014) used PCA followed by MultiLayer Perceptron (MLP) NN to forecast day ahead electricity prices in the Irish system. PCA was recommended to address the "curse of dimensionality" impact that many experienced in many NNs. Kearney discusses the characteristics of a well-conditioned NN – including the standardisation of input and output variables, selection of algorithm and optimisation of weights values and the number of hidden nodes. MAPE and RMSE were used to evaluate the outputs from each Neural Network. Gibbons (Gibbons, 2012) carried out day ahead forecasting of energy consumption in three UCD buildings. His study used the same source data as used in this research, although using different buildings. ARIMA, Multiple Linear Regression and Neural Networks models were trained for three groups of data (Weekday, Saturday, Sunday & Holidays). Gibbons used Maximum Absolute Average Error (MaxAE) and MAPE. The three models gave MAPE values of between 6% and 11% with the strongest results achieved with NN. The MaxAE identified outlying errors, often associated with once off events, e.g., the day of the UCD ball when campus closes for a half day.

2.3 Static versus Self-Update and Ageing Model model design

In recent years, research has begun to focus on studying the effect of "Self Updating" models (otherwise known as "Adaptive" or "Accumulative"). Self-Updating models "learn" as they proceed, by adding to the training window and revising the model at each update. Models may continue to accumulate data or may incorporate an ageing process, in which old data is dropped from the model as appropriate as new data is added (Ruano *et al.*, 2006). Ruano *et al.* compared static and adaptive neural network models for the prediction and control of air conditioned system in a Portuguese school. Input variables included inside and outside air temperature, relative humidity and solar radiation and a Multi Objective Genetic Algorithm (MOGA) was used to optimuse the number and lag times of each input variable based on complexity, validity and performance. The model was trained using 10 days of data with subsequent 3-4 days used to test the model. The static model performed well when trained on March data and applied in April. It showed a significant dis-improvement when the same model was applied in August. They found that their static model worked well for the period close in time to the test days, but poorly for periods later in the year. An adaptive model with a first in – first out sliding window policy was also developed and tested. Window sizes of 1 day, 3 days and 8 days were tested and the authors used data from April to August. The authors found that the 8-day window gave an RMSE that was one order of magnitude lower than the same model using a one-day window. The authors postulated that the adaptive model would not learn as effectively when smaller sliding windows were used. Using an 8 – day window, to test predictions over a five month period from April to August, 2004, the authors reported an improvement in RMSE from 0.208 with the static model to 0.013 with the adaptive model.

Yamin *et al.* (Yamin *et al.*, 2004) studied short term price forecasting in a US electricity market. The research consisted of three steps: a simulation of the electricity market to determine prices, use of the simulation data to train an ANN followed by forecasting of price. Three different models were compared with increasing numbers of inputs (previous day Market Clearing Price (MCP), previous day and forecast load, previous day and forecast reserve). Adaptive and non-adaptive (static) ANNs were also compared. The non-adaptive model used fixed training weights in the ANN. The adaptive ANN was updated on a regular basis according to test results. MAPE values in the range from 8.63% to 52.71% were achieved, with the adaptive model outperforming the non-adaptive model each time. The authors recommended an adaptive model, using 4 weeks training data, inclusion of pre-processing step (to eliminate price spikes) and exclusion of reserve data as the optimum approach based on their results.

Potočnik *et al.* (Potočnik *et al.*, 2014) compared static and adaptive approaches for modelling natural gas consumption in domestic and industrial environments. They also compared the effectiveness of linear and non-linear models in predicting natural gas consumption. Linear models (stepwise regression, auto-regressive) and non-linear neural network and support vector regression models were tested for their ability to carry out one-day ahead forecasting. The author's goal was to demonstrate that "*a successful forecasting solution can be obtained by a balanced combination of feature extraction, feature selection, and the construction of a simple linear model with an adaptation mechanism*". Input attributes included cumulative daily gas consumption, average daily temperature, cumulative daily solar radiation, minimum daily temperature, maximum daily solar radiation and weekly gas consumption index (used to distinguish between weekend and week days). Data from two separate intervals was used. Season 1, from 5th November 2011 to 26th April 2012, was used for training the model. Season 2, from 9th November 2012 until 31st March 2013 was used for testing the model. Static models were frozen on completion of the training, while the adaptive models were updated after each forecast. The performance of each model was measured using Mean Absolute Range Normalised Error and adjusted Correlation Coefficient (R^2) value.

This study gave different results depending on whether the gas consumption data was for the domestic (home) or industrial (local gas distributor). Experiments with data from both domestic and industrial settings showed that the non-linear NN and Support Vector Regression (SVR) models did not give any benefit over the simpler stepwise regression and auto-regression models. For the domestic setting, the adaptive model gave no additional benefit over the static model. The authors suggest that the reason for this is that the relatively uniform or stationary domestic system does not benefit from updating the model. They suggested that using industrial distribution data which is more dynamic and lends itself to better prediction dynamic showed better performance using the adaptive model.

Yang *et al.* (Yang *et al.*, 2005) built models to predict building energy consumption using static, adaptive (where data is added but not taken away) and sliding window (in which the training window is kept constant as the oldest data is removed and the latest is added) models. The authors noted the potential advantages and disadvantages of each approach:

Static Model:

- Better with larger training sets but large windows required to achieve good predictions.

Accumulative Model:

- Capable of identifying both local (for example, daily) and the global (seasonal) trends of energy variation.
- However, volume of data may become too large to be manageable. The authors also note the possibility that recent changes to the accumulative training data set have a smaller impact on the model training because their quantity is less compared to the older data.

Sliding Windows Model:

- They note that the small and constant size of the training data makes it possible to train and run faster models.
- However, with only shorter term data available, the authors note the risk of losing information about annual or seasonal changes in energy usage. (This may be mitigated by a carefully planned update strategy)
- The authors note the difficulty of determining the optimum window size ahead of time. If the window is too large, it defeats the purpose of limiting the amount of training data. If the window size is too small, it may not be possible to understand and predict energy demand.

Using synthetic data (free of noise), the authors designed and tested 9 static, accumulative and sliding window models. Models used time-lagged data – either Temperature, Energy demand or both. Using a combination of PCA and time lagged temperature data, the authors developed a static model with RMSE of 11.4Kw.

In developing an accumulative model, the authors trained a set of data for June for use as a baseline model. On a day by day basis, the hourly predictions were made and as each day was predicted, it was added to the model. Two models were run. The first with time lagged temperature data and the second with time lagged electrical chiller demand data. The RMSE for both were 28.3kW and 28.9 kW respectively.

The authors used the same architecture in developing its sliding window model. On a trial and error basis, the authors tested four different sliding window sizes, giving very different results and illustrating the need for very fine tuning in order to maximise the balance between accuracy and computational complexity. Starting with a baseline training window of 20 days, the authors tested sliding windows of 10, 20, 30 and 40 days, yielding RMSE errors ranging from 45.5 kW for window size of 10 days to 3.00 kW using a window size of 30 days.

Paudel *et al.* (Paudel *et al.*, 2013) described a "pseudo dynamic" model for predicting the short term energy consumption in a commercial building. The dynamic component of the model was focussed on the operational level of the plant, which switches between different levels, depending on day (working or not) and time of working day. The static attributes applied in the Neural Network were occupancy profile, outside temperature, sunlight and work on/off day. The authors recommend normalisation of the data to support faster convergence of the ANN. The pseudo dynamic model was found to perform better than static with an increase in the R^2 from 0.61 to 0.85 in the learning model.

An approach for personalised classification modelling was described by Kasabov (Kasabov *et al.*, 2014; Kasabov, 2007). They described personalised modelling as being concerned with modelling for individual input vectors, thereby predicting unknown outcomes for an individual. They identify medicine, medicine, ecology, business, finance and crime prevention as key applications for personalised modelling and note that K-Nearest Neighbour is the simplest methodology for building such models.

2.4 Model attributes and window selection

Cancelo *et al.* (Cancelo *et al.*, 2008) forecasted the energy load in the Spanish Market Operator from one day to one week. They observed that model behaviour varies depending on the day of the week and the time of the year. A linear model was developed comprising four components to reflect normal load, weather sensitivity, special dates (bank holidays) and a random component. For horizons up to 3 days, they used hourly forecasts, moving to daily composite forecasts beyond this, up to 10 days ahead. The authors noted the complexity of relationship between energy consumption and seasonality. For example, they note the impact of August holidays (During August 2005, industrial production fell by 30% due to summer shutdown). They note that the model performs better at different time periods. For example, during a day of normal activity, the MAPE was 1.14% at 7 am and increased to 1.64% at 6 pm.

In order to forecast energy load and price for the Australian Energy Market between 1 hour and 6 hours ahead, Mandal *et al.* (Mandal *et al.*, 2006) identified demand as having the most influence on energy price, finding that it also accounted for temperature variance. The authors used Euclidean norms to identify similar days to the forecast day. They used three windows of data to select the days with the most similar demand to the forecast date. These windows were:

- -45 days from the forecast date,
- $\pm$ 45days from the same date the previous year and
- $\pm$ 45days from the same date two years previously

The average data of three similar days from these data windows was included in an ANN. From a design perspective, this reflected the most useful attribute (demand) while also allowing a simple ANN to be built. Other training data included actual hourly price (Pt), actual hourly load (Lt) and a time factor (h) to represent the hour ahead. The research produced MAPE values of 9.75% when predicting 1 hour ahead, rising to 20.03% for six hour ahead predictions. The authors observed that the deterioration in error was a result of a cumulative effect from previous hour's readings.

Cho *et al.* (Cho *et al.*, 2004) compared the effect of training window on the accuracy of a static model for predicting annual energy consumption in a single model building. The authors tested daily, weekly and monthly training periods using a linear regression model on data from a single season using outside temperature and historical consumption as input attributes. The authors reported increased accuracy with increased training period. Errors in excess of 100% were reported for the model developed with a training window of 1 day. With 1 week of data, errors of between 3% and 30% were recorded. With 3 months of data, the model yielded errors of between 0.6% and 1.6%. The authors also identified a "comfort" threshold of 20% error and calculated the probability of the error exceeding 20%. This probability also decreased with increasing training window. The study showed different results, depending on whether the training data was selected from January, February or March. In all studies, models that used February and March data was better than models developed using January data. However, the authors did not comment the monthly variation that was observed.

Two papers (Ifrim *et al.*, 2012) and (Grimes *et al.*, 2014) predicted the price in the Irish electricity market and applied it to explore the impact of cost-aware scheduling in a hypothetical market in which real-time prices would be available to the domestic market. Using linear regression, linear SVM and various kernel SVM – two models were developed: Feature selection was also used, building up from simple models using historical System Marginal Price (SMP) as the only input attribute, then adding information about shadow price, system load, wind generation and calendar data in subsequent models. Two approaches to model evaluation were applied – the first approach predicted and compared price with average system price. The second model compared the learned difference between the actual SMP and average SMP for the same period.

A test period of 88 days (3 months) in 2011 was used to generate forecast price data. This was then input to a Mixed Integer Linear Programming (MILP) to optimise schedule based on lowest price. The authors found that building cost-aware schedules using forecasts of actual electricity market price, is feasible, and leads to significant cost savings. Both models out-performed the current Single Energy Market Operator (SEMO) model, with the second model performing slightly better at 28% improvement in Mean Squared Error (MSE).

2.5 Applications of predictive models in the Energy Market

In an overview of applications for the smart grid, Lifna (Lifna, 2014) identified distributive control, demand prediction, generation prediction and demand response as being four key areas in which technological advances must be continued before the full potential of the Smart Grid can be realised. Several reviews have been carried out to overview applications of Artificial Intelligence and/or predictive analytics in energy management. Dounis (Dounis, 2010) highlighted the importance of Energy Load prediction as an integral part of an intelligent BEMS, noting their capacity to give better answers than statistical methods. The authors reviewed applications of NN, SVM, Time Series, Fuzzy Logic and Genetic Algorithms (GA) for energy load prediction.

Grimes *et al.* (Grimes *et al.*, 2014) noted that much of current research into modelling of energy consumption focusses on data centres, which are recognised as consuming as much electricity as a medium-sized town. Carrying out research in the Irish context, Grimes et al analysed the impact of cost forecasting in a hypothetical situation in which customers would pay real-time prices for electricity. The authors made the case for real-time predictive capacity, noting that Ireland has a high price volatility (peak prices as high as 15 times the average were recorded in 2010) but that the market does not currently reflect this volatility (tariff prices are fixed and calculated well in advance).

The authors note that unaccounted volatility is absorbed by the suppliers and make the point that real-time pricing can offer a huge potential benefit for large electricity consumers that can exploit the price volatility for their operations.

Foley *et al.* (Foley *et al.*, 2010) carried out a strategic review of electricity system models from a European and international perspective. Their paper includes a review of how systems have changed over recent years (from monopoly to de-regulation). The authors examine the current advances in systems modelling, considering it in timeframes ranging from seconds and milliseconds (e.g. demand variation) to months (seasonal generation planning) and years (demand growth).

Chen *et al.* (Chen *et al.*, 2013) explored the relationship between human behaviour and energy consumption. They observed that although households and buildings account for more than 40% of energy consumption, little detail is available regarding the underlying patterns of human behaviour that drive that consumption. Using Waikato Environment for Knowledge Analysis (WEKA) Learning Toolset, the authors applied 2 months of sensor data from several domestic appliances to train a model that predicted the activities associated with the energy consumption at a given point in time. The model achieved between 70% and 90% accuracy with best results achieved using SVM and NN.

2.6 Conclusions

This brief literature review illustrates that there are multiple dimensions and approaches in the design and optimisation of predictive models for energy load and/or energy price. The research does not point to an agreed optimum model, attributes, training or test window size. There are many popular methods and approaches with good results achieved. Table C.1 in Appendix C provides a summary of the approaches to models reviewed in this literature review. This provided the starting point in developing the methodology and models presented in this dissertation.

Chapter 3

Commercial rationale

Energy is just one of many sectors that are adapting to or taking advantage of the availability of data on a real-time, rapid-fire basis and the development of predictive models that can handle this data. Business models that have been based on static information face the opportunity (or threat) of disruption from the availability of a constantly updated flow of information. Such disruption is imminent for the Irish and international energy markets. Before 2020, a combination of policy and technological advances will drive fundamental change to the way Ireland's electricity market works (CER and Regulator, 2011).

To understand the implications and potential applications of for real-time, personalised electricity prediction, a series of interviews were carried out as part of this research, along with desk research. The objective of these interviews was to:

1. Understand the data being used in this research in the context of UCD's overall energy consumption and energy management practices.
2. Describe how the energy market will change over the coming years through advances in policy and technology.
3. Identify implications and applications for real-time, personalised prediction in the context of these changes.
4. Draw conclusions to inform the design of real-time, self-updating models for the prediction of energy consumption.

Our findings are summarised in this chapter. A summary of interviewees is provided in Table B.1 in Appendix B.

3.1 UCD electricity consumption at a glance

UCD's annual energy costs are in the region of €7.5 million. In consumption terms, this equates to approximately 35 GWh (35,000,000 kWh) of electricity consumed per annum (equivalent to 18,000 houses). Some general statistics about this consumption are provided below:

- 90% of consumption took place on Belfield Campus.
- Electricity accounted for 60% of cost; Gas for 35% and Wood pellets for 5% of cost.
- Electricity is used for a range of purposes, approximately broken down as follows:
  - Lighting 35%
  - Heating, Ventilating and Air Conditioning (HVAC) 30%
  - Computers 10%
  - Space Heating 5%
  - Water Heating 5%
  - Appliances / Others 15%

For several years, UCD has collected electricity consumption data for most of its buildings at 15 minute intervals. Depending on the building, each 15 minute energy reading is in the order of 1-50 kWh, less than 1 millionth of the total annual consumption for the university. This provides an unprecedented level of granularity, volume and speed of data. The availability of this constantly updated supply of data, along with rapid development of the Smart Grid (Siemens, 2012) (CER and Regulator, 2011), provide the commercial starting point for this research.

3.2 The current Single Energy Market

Electricity cannot be easily stored. Because of this, the generation of, and customer demand for, electricity must be balanced on an ongoing basis. This is the function of the Single Energy Market (SEM). The SEMO ensures a balanced market for producing, buying and selling electricity that meets the following requirements:

- Balance the generation of energy with demand on a real time basis

- Capacity to meet demand spikes
- Conserves energy
- Minimises cost.

SEMO operates a mandatory, centralised market. No trading of electricity takes place outside of this centralised market. The market has four main stakeholder groups as illustrated in Figure 3.1.

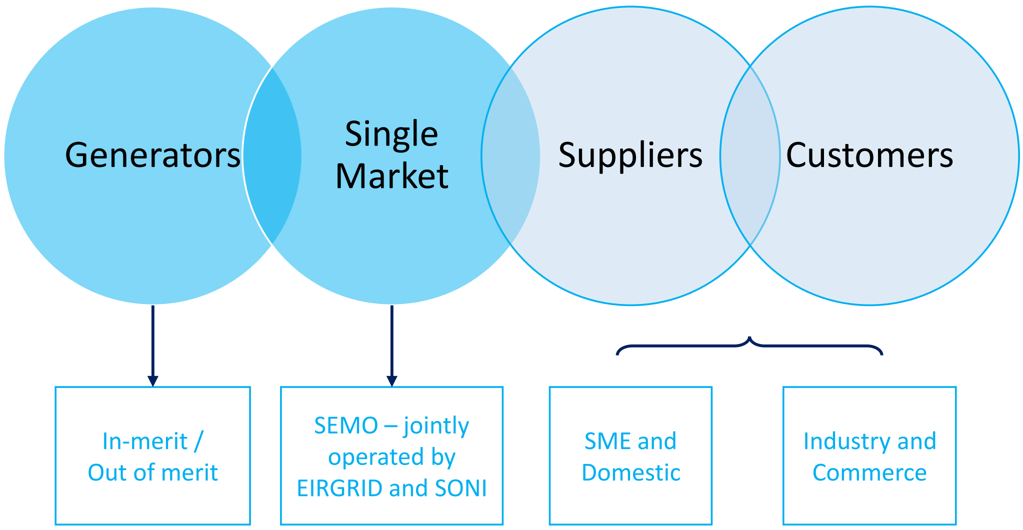

Figure 3.1: High level illustration of the main participants in Ireland's single energy market

A high level summary of the current Single Electricity Market is outlined here. Detailed information about the single electricity market along with market statistics are available from the Commission for Energy Regulation Factsheet on the Single Electricity Market (CER, 2011).

- Electricity trading on any day "D" begins at 10 am on day "D-1" when SEMO invites market generators to submit their expected "short-run" costs for the next day[1].
- Based on the bids received, SEMO identifies the least cost generators to supply the next day system demands.

[1]Short run costs do not include the basic fixed costs of generating electricity or any related costs which are covered by a separate capacity payment. This allows the market to select green sources of electricity, which have the lowest short run costs.

- This bidding process gives the Short Run Marginal Price (SRMP) also known as the Shadow Price. Additional requirements in supply during day "D" is met by generators at short notice who are paid an "uplift price".
- The combined SRMP and Uplift Price gives the System Marginal Price (SMP) for the system. The SMP is calculated after trading on "D+1" and finalised on "D+4" after balancing had been completed.
- The final SMP is the price paid by suppliers and received by generators.
- Typically, the highest SMP corresponds to the period of peak consumer demand between 5 pm and 7 pm every evening. The market as it currently operates ensures a reliable supply of electricity at the lowest cost. However, for suppliers and consumers, their role is passive:
  - Prices paid by suppliers are determined after the trading day (ex-post) on day "D+4".
  - Consumers pay a fixed price that is set in advance of trading.
  - Market balancing is socialised across all suppliers, thereby eliminating all incentives or penalties relating to electricity consumption practices.

As a result, although suppliers and consumers have certainty of their electricity costs, but limited control over the prices they pay or incentive to reduce overall consumption.

3.3 Changes to the Single Electricity Market – the Target Model

Coordinated by the Commission for Energy Regulation (CER) in the Republic of Ireland and the Northern Ireland Authority for Energy Regulation, Ireland is currently preparing to join the single European Electricity Market, also known as the "Target Model". The European Union (EU) Target Model is one of the pillars of the EU's internal market (CER and Regulator, 2012). Its objective is to ensure that, through the harmonisation of market rules and removal of cross-border barriers, electricity and gas will be freely traded across Europe. Ireland received a dispensation to the timeline for joining the EU Target Model and is currently preparing to join in 2017.

Adoption of the EU Target Model will bring fundamental changes to the structure and operation of Ireland's electricity market. These changes and the key differences in market structure are:

- Removal of barriers to create a single internal EU market.
- Transition from centralised a bilateral market.
- Creation of a dynamic market place with trading windows ranging from long-term to real time. These include:
  - Forwards Market (future trading over months and years),
  - Day Ahead Market,
  - Intra-day (continuously traded up to 1 hour before real-time) and
  - Balancing (real-time) Market.
- Transition to Ex-Ante (forecast) pricing based on day-ahead and intra-day trading. On introduction of the Target Model, patterns and characteristics that are current features of the Electricity Market will be disturbed. Periods of peak demand will change and electricity prices will become more variable and less predictable:
- Different prices may apply in any given hour as a result of the flexibility provided by a dynamic market.
- Prices will also vary with time, driven by variations in production such as fluctuations in Wind Power and enabled by the flexibility of a dynamic market.
- Wind power will become an increasingly attractive, although unpredictable source of electricity generation as systems adapt to take advantage of its unpredictable, ad-hoc nature.
- Peak demand will not necessarily happen between 5 pm and 7 pm every evening (as in the current market). Instead, incentivised by greater flexibility, cost savings and enabled by Smart Building Electricity Management Systems, customers will plan consumption to coincide with periods of lowest cost electricity.. Thus, consumption will begin to track electricity market prices rather than the market tracking consumption rates.

The Target Model will introduce a Demand Side Market. Customers, (who may include large consumer organisations such as UCD) will have the opportunity to participate in by selling electricity back to the grid at appropriate times for a higher price than its purchase price.

3.4 Technological Developments

Forecasting energy consumption is just one research area of several that are contributing to the development of the Smart Grid. Already, Smart Metering is common-place and ultimately, all participants in the Grid, from generators and distributors to customers will be fully connected. Lifna (Lifna, 2014) identified four key technological challenges that remain to be addressed in respect of the Smart Grid. These are:

- Distribution control,
- Demand prediction,
- Generation prediction and
- Demand response.

By 2020, new technologies will be available that will drive fundamental change to the consumption and management of electricity. UCD is a participant, along with the energy company Glen Dimplex, in the RealValue Consortium. This is a €12 million project, funded through Horizon 2020. The objective of this project is to develop intelligent, programmable, local small scale energy storage for space and water heating. These will essentially be the next generation of electrical storage heaters and UCD will be one of the first organisations in Europe to use these heaters. This means that interest in secure, inexpensive and controllable sources of electricity will increase over the coming years.

Other developments that will fundamentally change the patterns and predictability of electricity consumption are:

- Enhanced control through improvements in electricity storage. Advances in Photovoltaic panels for solar energy are providing capacity for on-site storage and managed electricity consumption. Battery storage has also improved dramatically.
- Better buildings built to Passive House Standards in which a combination of insulation, heat recovery, on site renewables and solar gain will also influence electricity demand.

For UCD, the technological and market advances described here will dramatically change its electricity consumption profile. To proactively manage this consumption in a more variable and unpredictable environment, the availability of real time predictive capacity will be an essential requirement.

3.5 Summary

As a result of policy and technological developments, fundamental changes are expected to take place in the electricity market over the coming years:

- Electricity consumption patterns will become more dynamic and less predictable. Peak demand will be unlikely to take place every evening at 5 pm-7 pm. Instead, it will follow periods of lower production costs (e.g. when wind production is high).
- Under the "Target Model", organisations who are in the position to predict and control their short-term electricity requirements will be in a position to participate in and generate income from the demand-side market.
- Electricity pricing will become more dynamic. Prices that are currently determined after electricity has been traded will be set in advance of trading, thereby necessitating good predictive models. In addition, different prices may be charged for electricity during the same hour. The balancing market will operate in real-time, in which organisations may sell electricity to or buy it back from the grid at a premium.
- Organisations that are able to predict requirements well and adapt their consumption to respond to periods of lower cost electricity will be able to minimise their electricity costs. Conversely, organisations that need to buy electricity at short notice will be able to do so, but will pay a premium for it.
- The relative importance of electricity as the primary source of energy will increase if a trend towards storage heaters for space and water heating is realised. Therefore, the capacity to understand and control patterns of consumption will become more important.

The increase in dynamism and associated loss of predictability that will accompany the above changes, provide the practical driver for this research. The market will become far less predictable, while the need to predict future consumption will become greater. Static models that serve current requirements, may not be fit for purpose as energy consumption patterns become more complex (Potočnik *et al.*, 2014). We suggest that a dynamic model with the ability to update itself as new data becomes available may be better able to serve the these future requirements. This is the key area of application for real-time predictive analytics and a key enabler for a consumer organisation such as UCD to become a proactive participant in the Smart Grid.

Chapter 4

Methodology

4.1 Research objectives – the problem

In 2001, Laney described Big Data as a three dimensional framework using the "*3Vs*" – Volume, Variety and Velocity (Laney, 2001). Each dimension can be summarised as follows:

- *Volume* refers to the amount of data that is collected,
- *Variety* refers to the number of attributes and features that are captured and
- *Velocity* refers to the speed at which this data is being made available.

Although this research addressed issues related to all three "*Vs*", the main focus was on *Velocity*, in an attempt to understand in which circumstances does updating a traditional static model with fresh data improve its ability to predict future energy requirements.

Throughout the years, UCD has proceeded with the collection of the energy demands across the campus in floors and buildings. This continuous stream of data points allows us to question whether traditional modelling methods – that focus on a subset of data to model and predict future energy needs – can be improved. There are impending changes in the electricity market that will directly result in more dynamic and unpredictable electricity consumption profiles for organisations such as UCD. As outlined in Chapter 1, the traditional models that have been sufficient for prediction purposes up to now may no longer be adequate. With a continuous stream of data available to us, we have the opportunity to build self-updating models that are able to predict electricity consumption in a dynamic, unpredictable environment.

A typical approach in machine learning, independent of the subject being studied, is to select a subset of the available data, build a model using a new or existing algorithm and use it to make predictions. However, in reality, new data is continuously being made available, making it possible to explore other alternatives that take advantage of this highly dynamic context.

Table 4.1 contains a small sample of the energy demands (in kWh) of the Computer Science building.

Consumption date	**Consumption reading (kWh)**
2013-01-15 15:30	13.73
2013-01-15 15:45	13.59
2013-01-15 16:00	13.82
2013-01-15 16:15	13.44
2013-01-15 16:30	13.74
2013-01-15 16:45	13.20
2013-01-15 17:00	12.95
2013-01-15 17:15	12.32

Table 4.1: Energy consumption for the Computer Science building

This dynamic context, where fresh observations might be used to improve static models, can be further expanded. The behaviour of a model that self-updates with fresh new data can be measured against models that are completely static, or those that additionally age out (or simply drop) data that was previously used. Additionally, we also proposed to study the effects of attribute or feature selection, where models that use all available data attributes are compared against models that do not use all the features.

As previously referenced in section 1.3, we set out to answer the following questions:

1. What is the impact of adding the ability for existing static models to self-update with newly observed data?
2. Does removing (ageing out) some of the data previously used to generate a model produce an improvement in the overall model performance?
3. Depending on the building being analysed, does using a subset of features produce better results than using a complete set of attributes?

4. Is it possible to quantify an optimal threshold between static and self-updating models?

5. Having optimised, the model, is there a practical or commercial application for such a model?

4.2 Building Selection

Given the volume of buildings with available energy data for the research, some filtering was required. Initially, buildings with the most number of data points available were selected. This resulted in datasets with readings that ranged from early 2007 until February 2013. However, early readings were not consistent and had many missing entries. To avoid introducing bias while handling these entries, the buildings with the least amount of missing values were selected next.

In addition to the total number of missing values, the number of consecutive missing entries was also accounted for. Table A.1 in Appendix A provides more insight into the variation in the available data and the ratio of missing values.

The final step during the building selection phase was to manually analyse the patterns of the time-series data. Building usage varies, depending on its function. Some buildings maintain a constant usage of energy throughout the year and others have oscillations, due to the occupancy being seasonal. Datasets with more variation in the energy readings throughout the year were given preference. This was to reduce the predictability from the data during the learning phase.

As we can observe in Figure 4.1, the energy demand for the Computer Science building varies throughout the year. As expected the winter months have higher energy consumptions summer and off-college months, although there are also variations within these seasons.

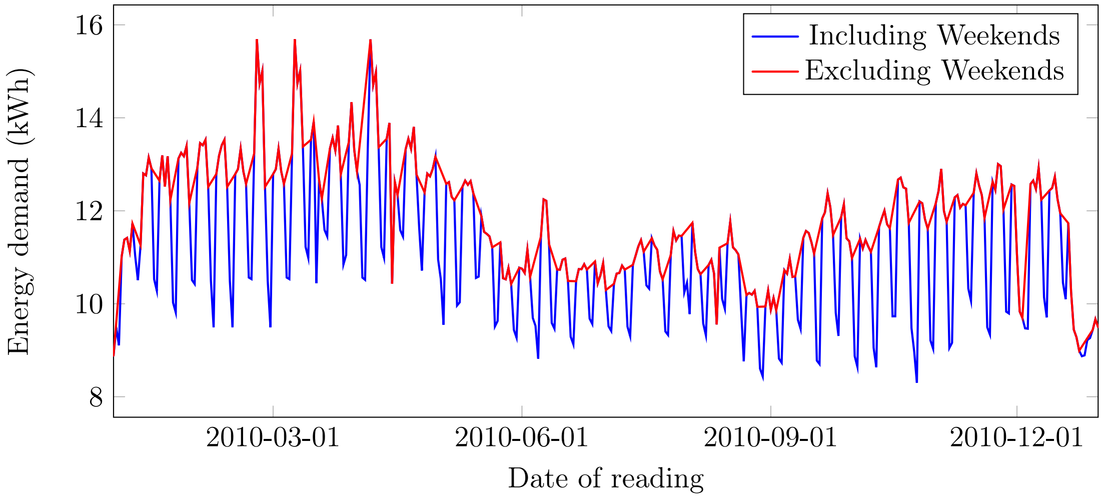

Figure 4.1: Computer Science building energy consumption – daily average

Alternatively, in Figure 4.2 we observe that the pattern of consumption in the Daedalus Data Centre is less variable throughout the year, making it less ideal for the research.

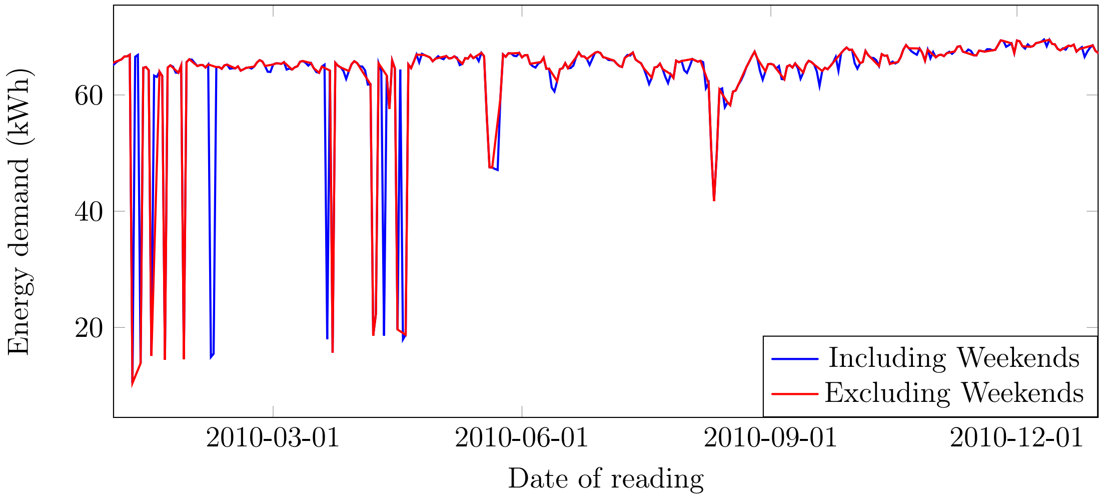

Figure 4.2: Daedalus Data Centre energy consumption – daily average

The final list of buildings selected for this research can be found in Table 4.2. All datasets cover the most recent energy consumption values available and were collected from January 1st 2010 until February 3rd 2013. As illustrated, the selected buildings are used for different purposes. They include residential buildings like Glenomena Block 10 to the Computer Science building which is used for both research and lectures. The ratio column contains the percentage of missing values in the overall number of instances.

Building Name	Instances	Missing	Consecutive	Ratio
Ardmore House	108480	110	56	0.10%
Belfield	108480	26	8	0.02%
Computer Science	108480	154	106	0.14%
CRID Ground Floor	108480	44	12	0.04%
Daedulus Total	108480	18	6	0.02%
Glenomena Block 10	108480	17	8	0.02%
Nova Total	108480	28	9	0.03%

Table 4.2: Selected buildings for the research

4.3 Research Engine implementation details

The research engine for this work was built as a set of independent components, each responsible for addressing a separate implementation requirement. The chosen programming language was Java and the modelling tool used was Waikato Environment for Knowledge Analysis (WEKA) (Hall *et al.*, 2009) as it is completely built in Java and provides a diverse set of data mining tools and creation and evaluation of machine learning models. For further details on how to configure the development environment, please refer to Appendix D.

The next sub-sections outline the different components that were purposely built for this research. These included data-preprocessing, attribute or feature generation and other design consideration.

4.3.1 Data Pre-Processing

The original datasets provided for this research required some adaptation in order to be able to be processed by the modelling tool. These were initially provided in Comma Separated Values (CSV) format but were converted to Attribute-Relation File Format (ARFF) format (WEKA, 2015). Although WEKA supports files in both formats, ARFF provides a mechanism to identify the type of each attribute (numeric, date, ...), simplifying the validation process.

As explained earlier, the initial datasets contained the time-series data with the energy consumptions for the buildings. These were then transformed into ARFF format with the attributes *reading_ date* in date format, and *reading_ value* in numeric format. These attributes were then used to generate other calendar attributes, as described in section 4.3.2.

Missing values in all datasets were replaced with the mean of all energy readings. Interpolation could have also been used, however this could lead to overfitting so we decided against it. Also, some datasets were missing more than a full day of consecutive data, making it difficult to set interpolation parameters and ranges.

4.3.2 Attribute generation

At the core of this research is the ability to generate new attributes from the initial time-series data. To this effect, a new component was built that supports dynamic generation of calendar attributes, given a time-series with the date/time and the value of the energy reading.

IsWeekend	**InSemester**	**7 weeks**	...	**4 weeks**	**1 week**	**t**
0	1	11.8	...	10.3	8.9	11.2
1	1	11.2	...	10.9	9.3	9.6
1	1	12.4	...	11.3	9.7	10.1
0	1	10.8	...	11.0	10.2	11.9

Table 4.3: Attribute generation

In total, 19 attributes were identified for inclusion in the last phase of the study, see section 4.4.4. These were historical, calendar and temperature-related and are all summarised in Table 4.4.

Weekend/Week (Binary)	Outside air temperature	Readings at previous 1, 2, 5 days
In Semester/Not (Binary)	Readings at previous 1, 2, 3, 6, 12, 18 Hours	Readings at previous 1, 2, 4, 5, 6, 7 weeks
Christmas/Not (Binary)		

Table 4.4: Attributes available

Up to phase 3 of the research, the default approach was to include all attributes each time a model was tested. In phase 3, WEKA's "feature" selection capability was switched on. The objective of Attribute selection was to explore the following questions:

- Could the models use fewer attributes but still maintain its accuracy? (This could have important practical implications for the model)
- Are some attributes more relevant to the predictive models? If yes, what are those attributes?
- Are some attributes irrelevant to all buildings? If yes, what are those attributes?
- What opportunities (if any) are there for personalisation of models through attribute selection?

The performance of the model with or without attribute selection was then tested and the preferred attributes for each building were also identified.

4.3.3 Model Evaluation

A design decision was made to use Relative Absolute Error (RAE) as the default measure for evaluating the performance of each model.

Relative Absolute Error is defined as:

$$RAE = \frac{\sum_{i=1}^{n} \left|\hat{\theta}_i - \theta_i\right|}{\sum_{i=1}^{n} \left|\bar{\theta}_i - \theta_i\right|}$$

Where:

θ_i : the observed energy consumption value
$\hat{\theta}_i$: the predicted energy consumption value using a static or self-update model
$\bar{\theta}_i$: the mean value of the observed energy consumption

Throughout much of the research, the focus was not on the RAE value for each model. Rather, it was on the difference in RAE between 2 models. We therefore discuss the comparative performance rather than the actual performance.

4.3.4 Acceptance criteria

Our design considerations also identified what would count as success or acceptance criteria.

At its simplest level, the direct improvement in the model performance as a result of introducing self-update capability, ageing capability or attribute selection was the clearest acceptance criteria.

However, other less direct acceptance criteria were identified. These included:

- Improvement in execution speed for the model
- Simplification of the model without (significant) loss of performance.
- Specific improvement in model performance, particularly at periods when consumption patterns may be less predictable
- Increase in robustness, such as including a decrease in model sensitivity and its ability to be applied across a number of different situations.

These acceptance criteria are considered again in Chapter 5, where we present and analyse the results of this work.

4.4 Design Considerations

We approached the design and testing of the models in four phases as summarised here.

- Phase 0: Evaluation of algorithms – Linear Regression (LR), Neural Networks (NN) and Support Vector Machines (SVM) were evaluated to identify a suitable algorithm for application in the research.
- Phase 1: Validation of the models and initial exploration of the effects of model parameters on model performance.
- Phase 2: Introduction of a wider range of training parameters and development and testing of self-update capability.
- Phase 3: Introduction of an "Ageing" model and introduction and testing of attribute selection.

4.4.1 Phase 0: Selection of preferred algorithm

This initial phase was carried out at the outset of the research to explore the effect of using different algorithms to drive the model. Static Models were trained on a sample of data from the Computer Science Building using three different algorithms. The relative performance of each algorithm was compared under the following two headings:

- Performance of the model generated using that algorithm
- Model execution time

Table 4.5 shows the average prediction error for LR, NN and SVM respectively, using training windows of 4, 12, 26, 32, 52 and 64 weeks and commencing the training in January.

	LR	NN	SVM
Average error	45.86	88.27	42.30
Execution time	36s	7m 31s	7h 17m 34s

Table 4.5: Average prediction error and total execution time

As the table shows, models that were developed using LR and SVM performed almost twice as well as the model that was developed using NN.

SVM was also better than LR, albeit by a much smaller margin of approximately 3%. However, as the runtime data shows, SVM was far slower than either LR or NN and was unlikely to be able to perform the scale and volume of testing that was required for the project.

A special note should be made on the poor NN performance as the literature shows that these algorithms are notorious for being sensitive to parameter selection (learning rate, momentum, number of units in the hidden layer and others). As Bashiri and Geranmayeh explain, "almost a trial and error method is used, but it needs more computational time and is not a precise method" (Bashiri and Geranmayeh, 2011).

Based on these results, the decision was taken to use Linear Regression for this research on the basis that it would perform significantly better than NN and perform much faster than SVM.

4.4.2 Phase 1: Quality Assurance and early stage testing

The objectives of Phase 1:

- Quality assurance and validation of the model by training and testing with a relatively small cross-section of data and a sample number of buildings.
- Initial exploration of suitable attributes and baseline windows for predicting energy consumption
- Exploration of the potential for generating a self-updating model using an initial selection of update windows.

To meet these objectives, Phase 1 tests were designed as follows:

Parameters	**Test choice**
Buildings	Computer Science (Mixed academic) Daedalus Total (Computer services) Glenomena 9 (Residential)
Model	Linear Regression
Attributes	Consumption at 15, 30, 45 minutes Consumption at 1, 2, 3, 5, 12, 18 hours Consumption at 1, 2, 3, 4, 5, 6, 7 days
Baseline (Training) Window	500 data points ($<$ 1 week)
Update Window	500 data points ($<$ 1 week)
Test Window	500 data points ($<$ 1 week)
Starting month	January
Error method	Relative Absolute Error

Table 4.6: Phase 1 design parameters

Validation was carried out by comparing the model (as developed using Java) with a manual execution of the same run on a selection of buildings.

On a series of spot checks across all test instances, the results of runs using manual and Java model were identical. This provided confirmation that the code was correct for all buildings.

A self-updating version of the model was also tested against manual execution on Weka UI and was found to deliver the same results.

This allowed us to conclude that the model was fit for purpose and could be used for subsequent, more comprehensive testing of the data.

4.4.3 Phase 2: Testing of a wider range of parameters and introduction of self-update capability

Taking the learnings and recommendations from Phase 1, Phase 2 of the research was designed to take account of the following:

- Wider baseline (training) windows
- Inclusion a wider range of attributes, including more historical attributes
- Inclusion of data a wider range of UCD buildings
- Further exploration of self-updating models, using different update window sizes
- Exploration of the impact of training the model at different months.

Phase 2 tests were designed as follows:

Parameters	Test choice
Buildings	Belfield House (Admin / Research) Computer Science (Mixed academic) CRID Ground Floor (Research) Glenomena 9 (Residential) Glenomena 10 (Residential)
Model	Linear Regression
Attributes	Weekend (Binary) In Semester (Binary) Christmas (Binary) Outside air temperature (Value) Consumption at 1, 2, 3, 6, 12, 18 hours Consumption at 1, 2, 5 days Consumption at 1, 2, 4, 5, 6, 7 weeks
Baseline (Training) Window	4 weeks (2688 data points) 8 weeks (5376 data points) 16 weeks (10752 data points) 32 weeks (21504 data points) 64 weeks (43004 data points)
Update Window	1 and/or 2 weeks to give a common foundation across all of the tests Range of update windows up to and including the size of the baseline window (e.g. for the 64 week baseline, update windows of 2, 16, 32 and 64 weeks were tested)
Test Window	1 week 2 weeks
Starting month	For all baseline, update and test windows, the performance of static and self-updating windows were tested starting at a different month
Error method	Relative Absolute Error

Table 4.7: Phase 2 design parameters

4.4.4 Phase 3: Introduction of "Ageing" model and Attribute Selection

The objectives of phase 3 of the research were:

- confirm the observations made in Phase 2,
- adapt the model to introduce an "ageing out" capability in which old data is discarded by the model as new data is added,

- explore the impact of attribute (feature) selection on performance and
- generate a comprehensive set of results to inform recommendations from the study.

Phase 3 tests were designed as follows:

Parameters	**Test choice**
Buildings	Ardmore House (Administration) Belfield House (Admin / Research) Computer Science (Mixed academic) CRID Ground Floor (Research) Dedalus (Computer Services) Glenomena 10 (Residential) Nova (Admin / Research)
Model	Linear Regression
Attributes	Weekend (Binary) In Semester (Binary) Christmas (Binary) Outside air temperature (Value) Consumption at 1, 2, 3, 6, 12, 18 hours Consumption at 1, 2, 5 days Consumption at 1, 2, 4, 5, 6, 7 weeks
Baseline (Training) Window	4 weeks (2688 data points) 12 weeks (8064 data points) 16 weeks (10752 data points) 26 weeks (34944 data points) 32 weeks (21504 data points) 52 weeks (34944 data points) 64 weeks (43004 data points)
Update Window	1 day 1, 2, 4, 8, 16, 32, 52 and 64 weeks
Test Window	Same as update window
Ageing (drop) window	Same as update window 1 day 1, 2, 4, 8, 16, 32, 52 and 64 weeks
Starting month	January, February, March, April, May, June, July, August, September, October, November and December
Error method	Relative Absolute Error

Table 4.8: Phase 3 design parameters

4.4.5 Design of the Ageing Model

The concept of "ageing out" data was introduced in the 3rd and final phase of the research. The Ageing Model was designed to maintain the baseline at a constant size, by dropping old data every time the model was updated with new data. A simple Ageing Model was used, employing a "sliding window" approach in which the oldest data is discarded from the model as the newest data is added. The performance of the Ageing Model was then compared against Static and Self Update Models across all training window sizes, update and "drop" window sizes and starting months.

Note. In designing the Ageing Model, it was observed that if the size of the Update Window exceeds the size of the Training Window, the Self-Update and Ageing Models will skip over data. From a practical and also a testing perspective, this was undesirable, therefore a flag was built into the models to ensure that the Update Window could not be larger in size than the Training Window in any test situation.

Figure 4.3 provides a visualisation of the final execution process at this point. For each of the seven buildings selected, see section 4.2, the research engine was able to generate models using different sizes of baseline, update, ageing and test windows. Results collected included evaluations of the three models being studied – static, self-update and self-update with ageing – with and without feature selection.

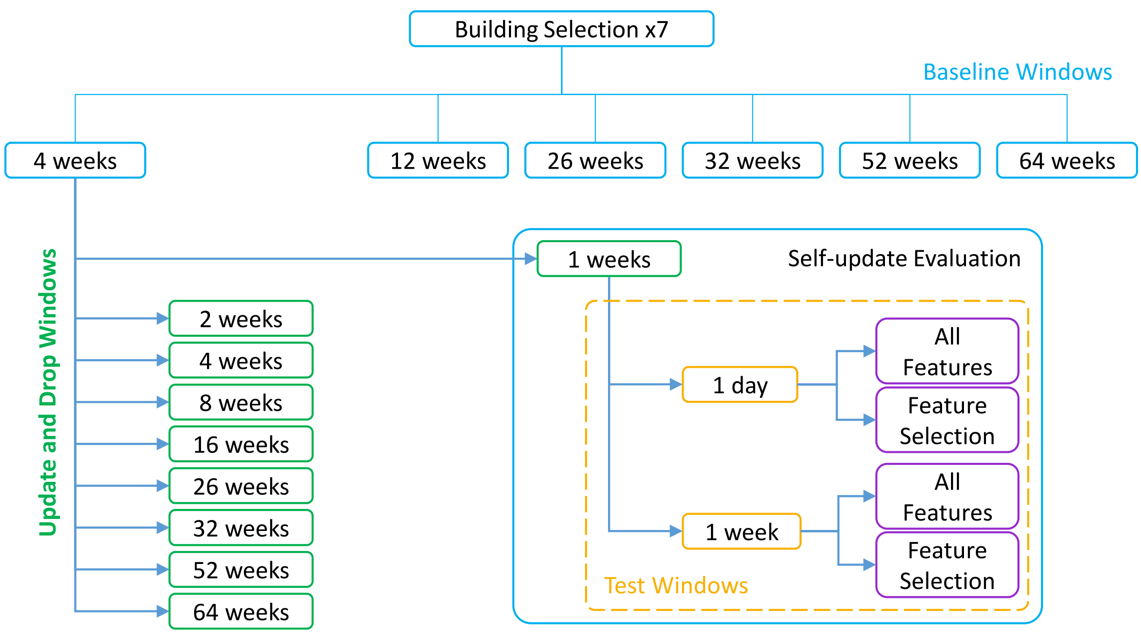

Figure 4.3: Different window sizes for Baseline, Update, Drop and Test windows

Chapter 5

Results

In this chapter, the performance of the three types of models – Static, Self-Update and Ageing – is compared:

- We look at how various choices in the design of the models impacted their comparative performance. In particular, these choices include window size and starting month.
- We also evaluate the impact of attribute selection on the comparative performance of the models.

This chapter is closed out with an overall summary of our results and analysis. Please see Chapter 6 for a discussion of these results and conclusions from this research.

Note: Linear Regression analysis was applied to test all of the models. This was a design choice made as a result of early-stage testing of different algorithms. Linear Regression was selected as the preferred algorithm as it had a significantly lower error than NN and much faster execution time than SVM. This is discussed in some detail in section 4.4.1.

5.1 Overall Comparison of Models

The purpose of this research study was to identify if the introduction of self-update and ageing capability could have a positive effect on the model's performance. Having, said that, we felt that it was important to also consider the individual performances of the three models, particularly to understand how the models handled variation and unpredictability in the electricity consumption profiles in the buildings studied.

Figure 5.1 compares the performances of the three models side by side for Ardmore House. The following observations were made in relation to this direct comparison:

- Under some design conditions, the models behave very similarly to each other. This was particularly the case during regular periods of electricity consumption (e.g. Monday-Friday during a regular working week).
- Each of the three models showed an increase in error during weekends and, particularly during special holiday periods such as Christmas, St Patrick's Day etc. This differentiation between weekdays, weekends and holidays was illustrated in Figure 4.3 and also shown in previous research (Gibbons, 2012).
- Although none of the models shown here performed well in absolute terms[1], the results indicated that Self-Update and Ageing Models may be more effective at handling "unpredictable" periods such as Christmas than the Static Model is. This pattern is illustrated here and was observed for all the buildings included in the study.

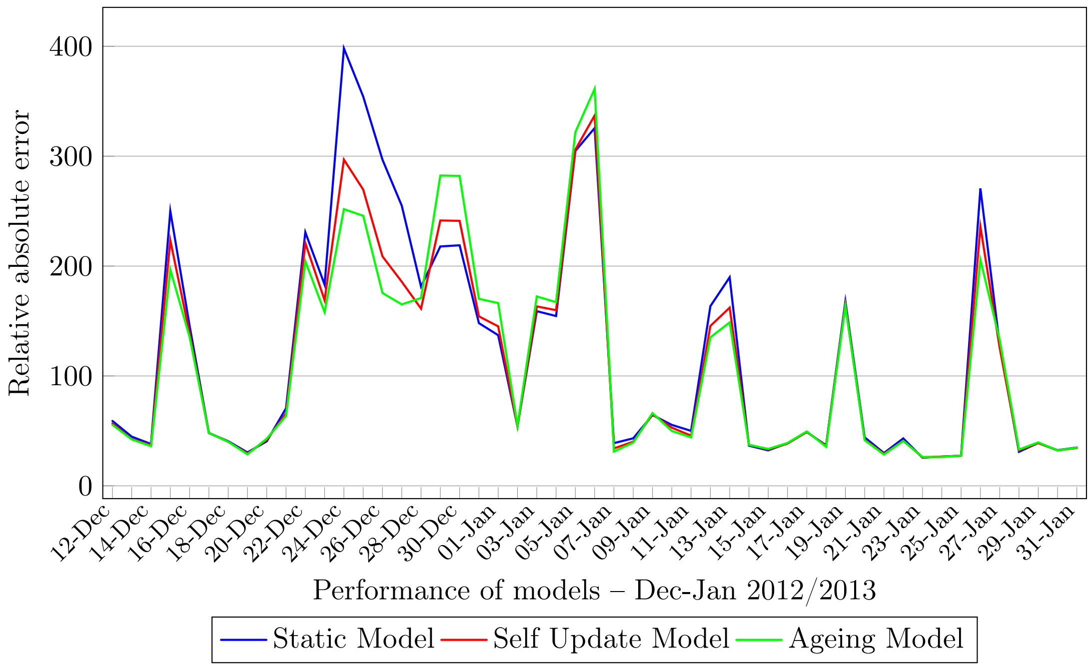

Figure 5.1: Direct comparison of the performance of Static, Self-Update and Ageing Models for the period Christmas, 2012 (Ardmore House; Training Window=64 weeks, Update and Drop Windows=2 weeks

[1]The optimisation of these models was not our objective

5.2 Effect of Design Choices on the Comparative Performance of Models

For each test carried out on the models, a number of design considerations were available and were found to affect the comparative performance of the models. In this section, we consider the effect of the following design choices:

1. The size of the Training Window
2. The size of the Update and "Drop" Windows
3. The choice of starting Month

5.2.1 Effect of the Training Window Size

In all buildings, it was observed that when the training window was small, the Self-Update Model outperformed the Static Model by a considerable margin (as high as 30%). As the size of the training window increased, the improvement in performance achieved by the Self-Update Model declined until the performance of the two models converged. Figure 5.2 illustrates how the performance of Static and Self-Update models converged as the size of the training window increased.

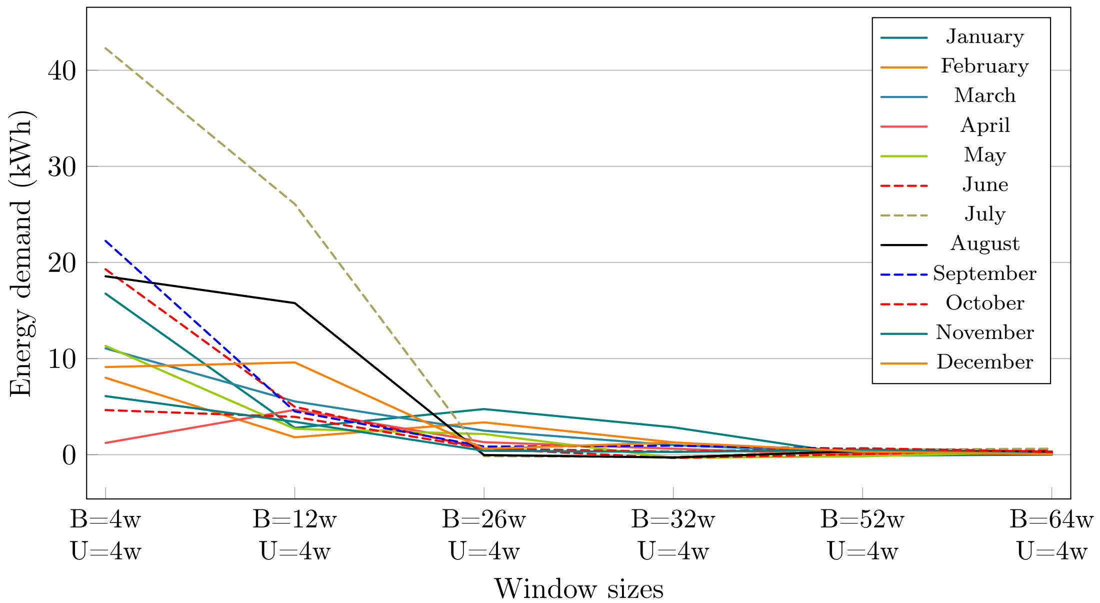

Figure 5.2: Difference in error of Self-Update Model compared to Static Model for different Training Windows and an Update Window of 4 weeks (CRID Ground Floor, Training Window=4-64 weeks, Update Window=4 weeks, all attributes included)

The same pattern was observed for all buildings, however the size of the training window at which the models converged varied. Table 5.1 illustrates this.

Building	**Baseline window (at which the advantage of self-updating model over static falls below 1%)**
Ardmore	64 Weeks +
Belfield	64 weeks
Computer Science	12-26 weeks
CRID	32-52 weeks
Daedalus	52 weeks
Nova	64 weeks
Glenomena 10	64 weeks

Table 5.1: The Training Window at which the comparative advantage of the Self Update Model over Static Model falls below 1%

The performance of the Ageing Model was compared against Static and Self Update Models for different training window sizes. The results are illustrated in Figures 5.3 and 5.4 below. They highlight that with smaller training windows, the Ageing Model significantly under-performed when compared against both the Static and Self Update Models. With larger training windows, the performance of the models converged. By 52 or 64 weeks, the Ageing Model performed at least as well and, in some instances, marginally better (in the region of 1%-5%) than the other two models.

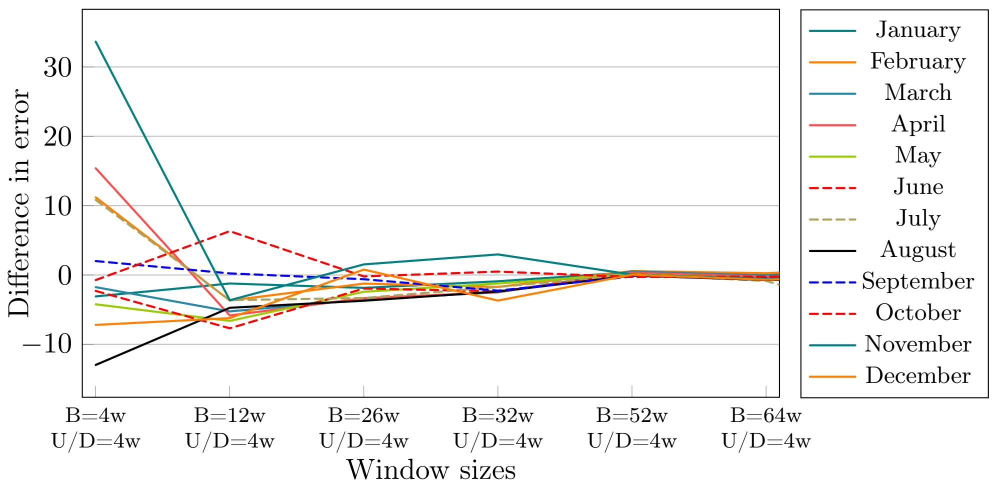

Figure 5.3: Difference in error between Ageing and Static Models for different Training and Update/Drop Windows of 4 weeks (Ardmore House, Ageing versus Static, Training Windows=4-64 weeks, Update/Drop Windows=4 weeks, all attributes included)

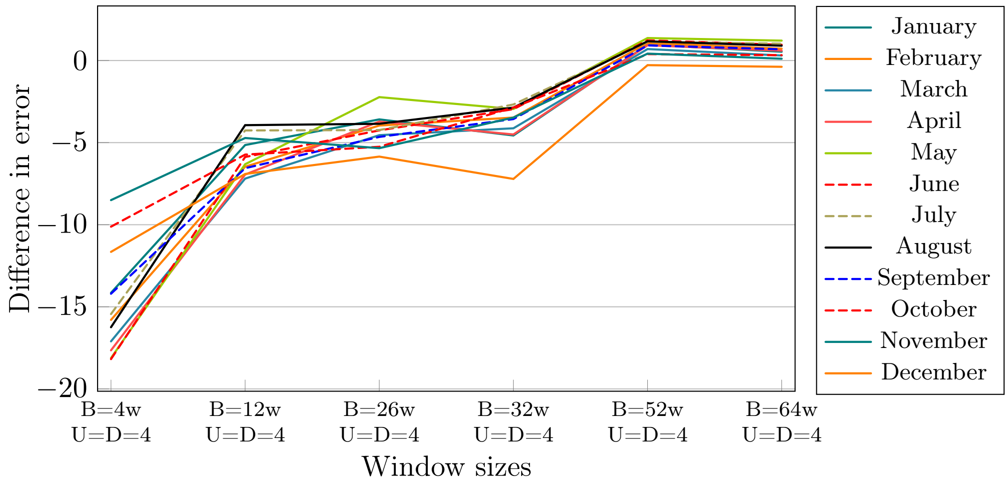

Figure 5.4: Difference in error between Ageing and Self-Update Models for different Training Windows and Update/Drop Windows of 4 weeks (Ardmore House, Ageing versus Self-Update, Training Windows=4-64 weeks, Update and Drop Windows=4 weeks, all attributes included)

To understand the effect of the training window size, we examined its direct effect on each model. We found that the effect was largely concentrated in the Static Model. There was a slight effect for the Ageing Model and almost no effect for the Self-Update Model. Effectively, the performance of the Static Model improves each time the training window is increased. This continues until, eventually the Static Model performs as well as the Self-Update and Ageing Models. This is illustrated in Figure 5.5 below. In this example, we observed that the performance of the three models converged with each other at a training window of 52 weeks.

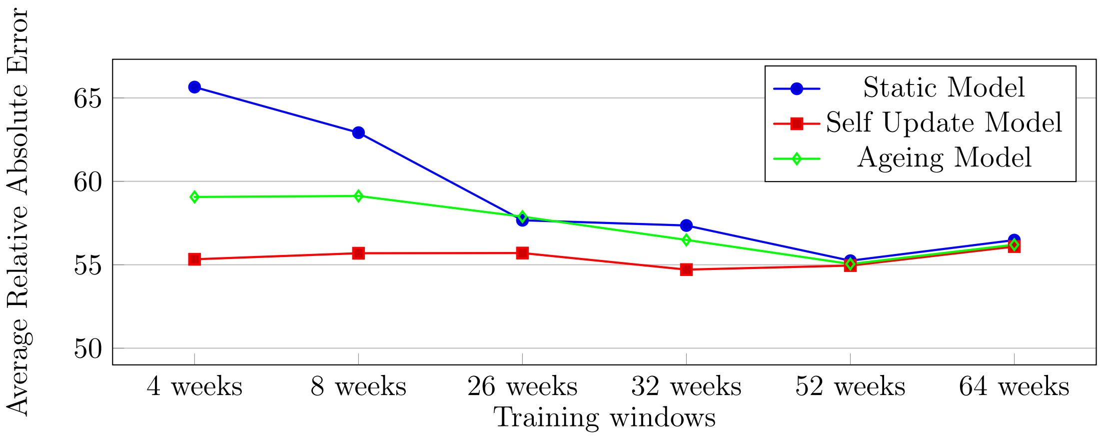

Figure 5.5: Direct Comparison of the Average Errors (Relative Absolute Error) of Static, Self-Update and Ageing Models (Glenomena 10, Training Windows=4-64 weeks, Update Window=1 week, Test Window=1 day)

5.2.2 Effect of the Update and Drop Window Size

A study of the effect of different update window sizes showed that the size of the update window (and, as a result of our design decision, the size of the drop window), had very little effect on the performance of any of the models. This is illustrated in Figure 5.6 below. As this example shows, we observed some mild variation in model performance at large update windows sizes, but this was not significant.

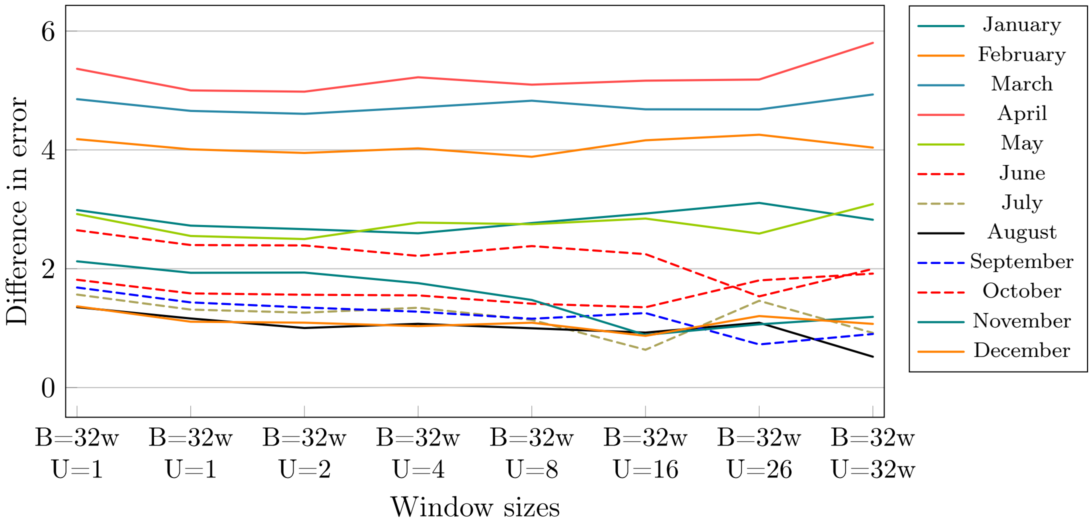

Figure 5.6: Difference in error of Self-Update Model and Static Model for different Update Windows and a Training Window of 32 weeks (Belfield Campus, Training Window=32 weeks, Update Window=1 day-32 weeks, all attributes included)

The effect of update window on the comparative performance of Ageing Models was also tested and is illustrated in Figure 5.6. We observed that the average errors achieved by the Ageing Model at different update window sizes were sometimes exactly the same or were very, very close in value. This is illustrated Table 5.2 below.

	Update/Drop Window Size							
	1 week	4 weeks	8 weeks	16 weeks	26 weeks	32 weeks	52 weeks	64 weeks
Average Relative Absolute Error for ageing model (2012) Baseline=64 weeks	72.6539	72.8976	72.9172	73.1526	73.5825	73.7653	72.1608	74.5583

Table 5.2: Average error for the Ageing Model, using different update/ageing windows (Ardmore House, Training Window=64 weeks, Update Window=1-64 weeks, all Attributes included in the model)

We explain this by considering that the "sliding window" design of the model meant that an update/drop window of 2, 4, 8, 16, 32 and 64 weeks will update the model at different pace or frequency. However, it will also deliver training windows that are either identical or very close to each other as the model moves forward. This is illustrated in Figure 5.7 below which shows how two Ageing Models with different update window sizes correspond with each other.

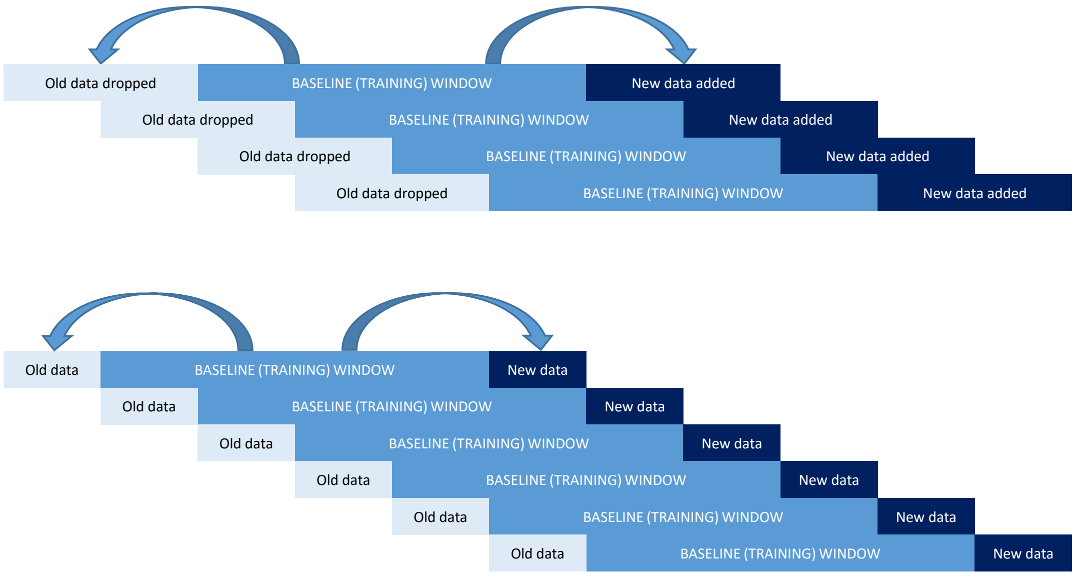

Figure 5.7: Illustration of the "sliding window" approach of the Ageing Model and how different update window sizes can give exactly the same training windows

5.2.3 Effect of the Starting Month on Model Performance

In all of the tests carried out, the comparative performance between models varied, depending on which month the model commenced training. This monthly effect can be seen in Figure 5.8 just below.

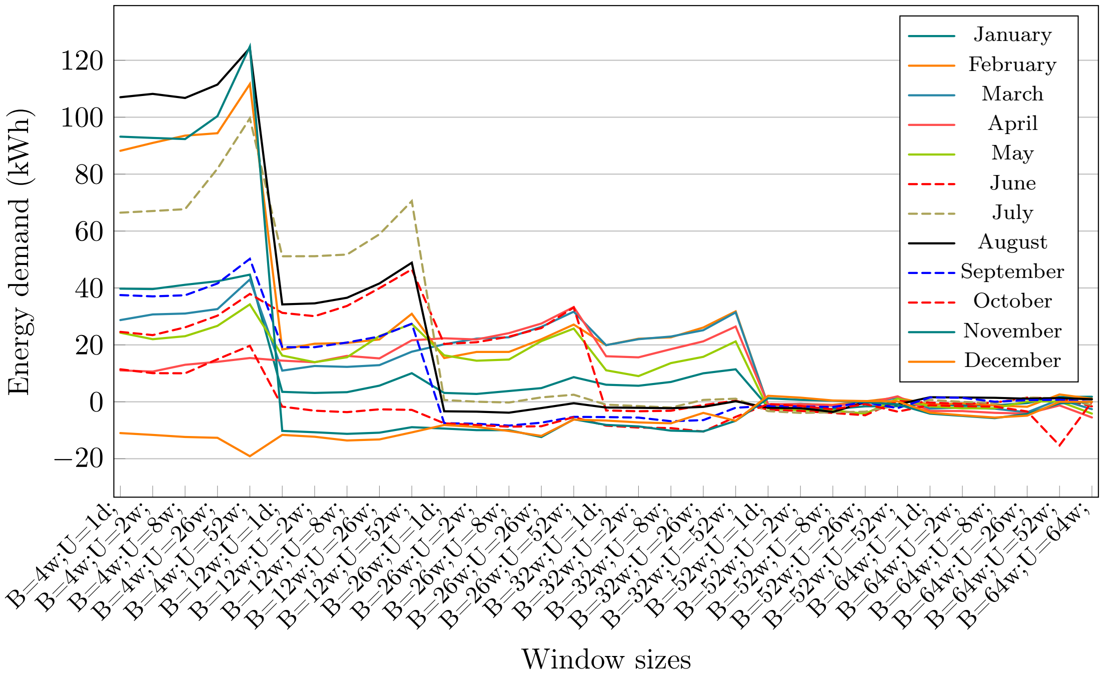

Figure 5.8: Difference in error of between Static and Self-Updating Models for the Daedalus Building, across different training and update windows

To explore this effect, the errors of static, self-updating and ageing models were directly compared with each other. This showed that the effect of the choice of starting month was concentrated in the Static Model and was especially pronounced when the training window was small. The choice of starting month had little or no direct effect on the relative performance of Self-Update and Ageing Models.

These observations are illustrated in Table 5.3 and Figure 5.9 below. These show that the average error for both Self-Update and Ageing was largely unaffected by changes to the starting window.

	Month (in 2010) in which training of model was commenced											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Average 2011 Prediction Error (Static Model)	26.45	25.46	28.31	26.13	22.94	21.81	23.75	25.08	30.06	27.47	37.96	21.55
Average 2012 Prediction Error (Static Model)	20.95	26.03	25.54	23.32	19.66	20.48	20.48	22.01	26.82	22.08	34.75	21.24
Average 2011 Prediction Error (Self-Updating Model)	22.01	21.36	21.31	20.88	21.75	21.33	20.70	21.92	21.01	22.36	21.67	20.41
Average 2012 Prediction Error (Self Updating Model)	18.53	18.74	18.74	18.63	18.85	18.51	18.71	18.88	19.03	18.58	18.78	18.89
Average 2011 and 2012 Prediction Error (Static Model)	23.70	25.74	26.92	24.72	21.30	21.14	22.12	23.54	28.44	24.78	36.36	21.40
Average 2011 and 2012 Prediction Error (Self-Updating Model)	20.27	20.05	20.02	19.76	20.30	19.92	19.70	20.40	20.02	20.47	20.23	19.65

Table 5.3: Average prediction error for Static and Self-Updating Models (for Computer Science Baseline window=4 weeks, Update window=1 week, Test Window=1 week)

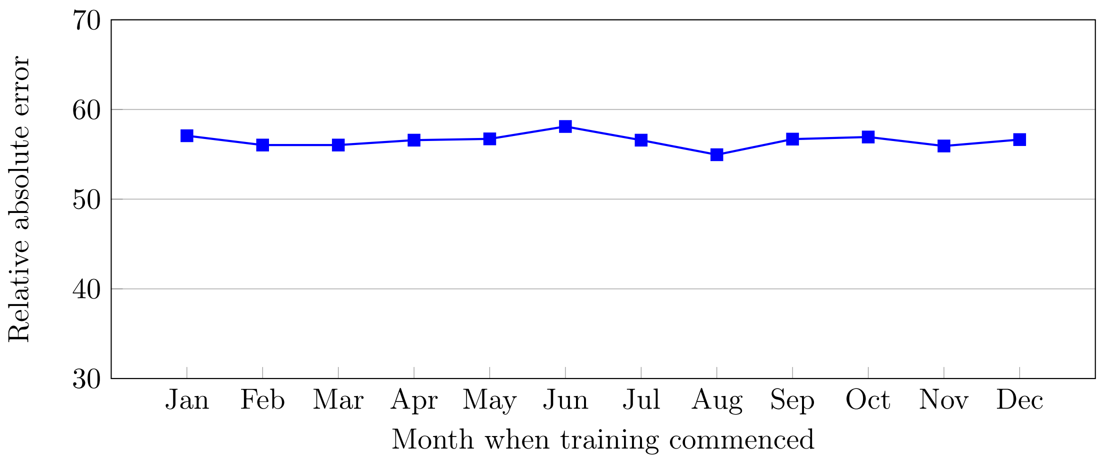

Figure 5.9: Average daily prediction error for Ageing Model (Belfield, Training Window=4 weeks, Update window=1 week, all attributes included)

5.3 Effect of Attribute Selection on the performance of the Models

By default, in this research, all 19 attributes were included each time the model was run. In this part of the study, WEKA's "Feature Selection" capability was switched on so that only the attributes that most contributed to the model's performance were selected for inclusion. When feature selection capability was switched on, the following was observed:

- For any given building, the selected features remained exactly the same, for all models (Static, Self-Updating, Ageing) and for all training and update/drop windows.
- The buildings themselves varied, with different attributes selected, depending on the building in question. The attributes selected for each building are summarised in Table 5.4.

Building	**Selected Attributes**
Ardmore House	IsWeekend; InSemester; 1h; 2h; 1d; 1w
Belfield House	IsWeekend; InSemester; IsChristmas; OutsideAirTemperature; 1h; 2h; 1d; 1w; 2w
Computer Science	IsWeekend; InSemester; IsChristmas; 1h; 2h; 3h; 18h; 1d; 1w; 2w; 7w
CRID	IsWeekend; IsChristmas; 1h; 2h; 3h; 18h; 1d; 1w; 2w; 4w; 6w
Daedalus	IsWeekend; InSemester; IsChristmas; 1h; 2h; 1d; 1w; 7w
Nova	IsWeekend; InSemester; IsChristmas; 1h; 2h; 1d; 1w; 2w; 4w; 7w
Glenomena 10	IsChristmas; 1h; 2h; 1d; 2d; 5d; 1w

Table 5.4: Summary of attributes selected by WEKA in for each Building

As illustrated by Table 5.4, some attributes (1 day, 1 week, Christmas) were of importance to all buildings. Some of the available (historical) attributes were not selected by any model.

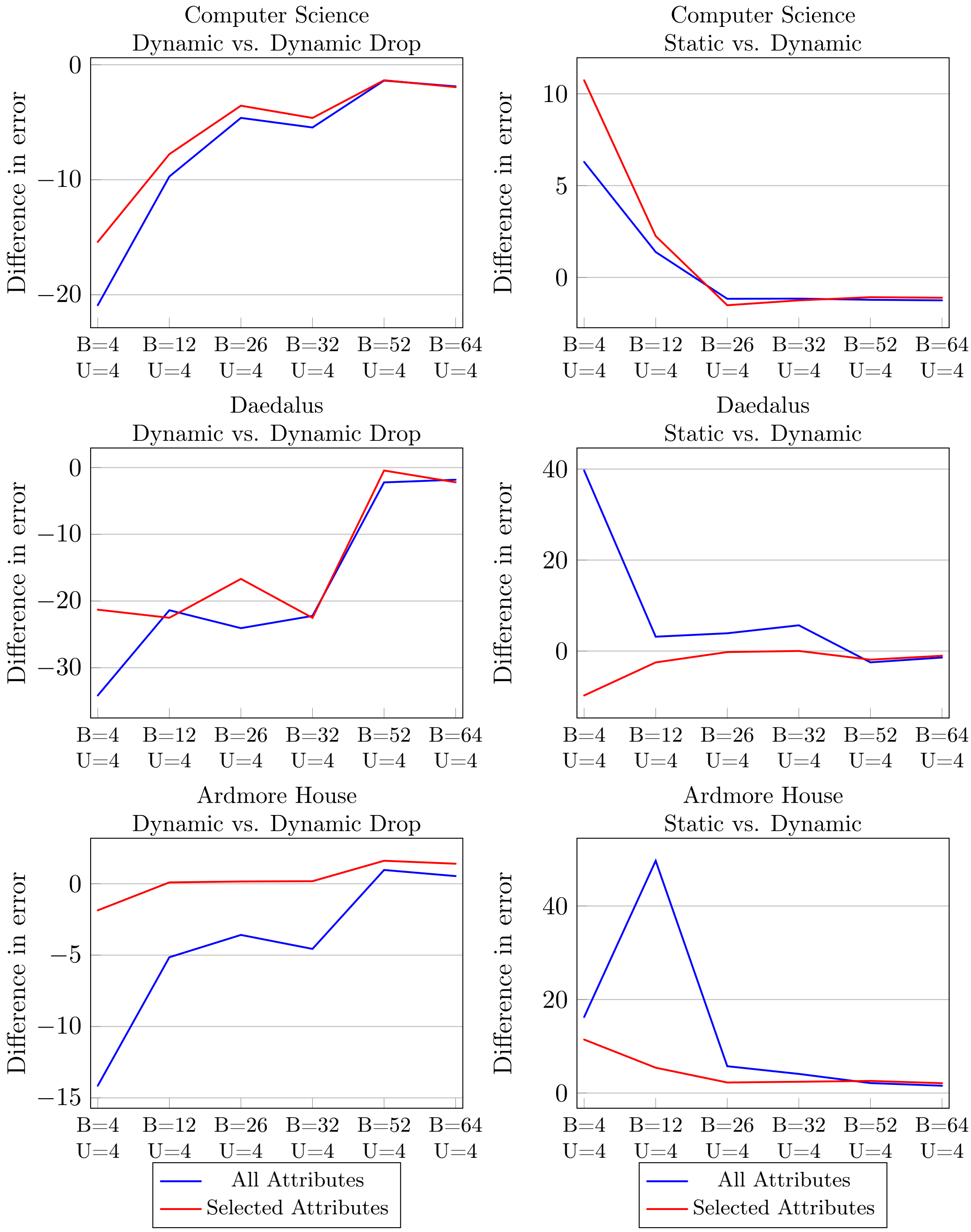

Figure 5.10: Difference in performance between models, depending on whether or not attribute selection was carried out (Computer Science, Daedalus and Ardmore House Buildings, Training Commenced in January, Training windows=4-64 weeks, Update/Drop window=4 weeks)

As shown in Figure 5.10, the selection of attributes had a somewhat erratic effect on the comparative performance of each model, depending on the building it was applied to.

For the Computer Science Building, the selection of attributes had a small, positive effect on the comparative performance of the Self-Updating Model when compared to the Static at small training windows. It also had a very small, positive effect on the performance of the Ageing Model when compared to the Self-Update Model. However, when the training windows were large, the performance of all training models converged and attribute selection had no observable effect.

For both the Daedalus and Ardmore House Buildings, the effect of attribute selection was positive at small training for the Ageing Model when compared to the Self-Update Window. However, a negative effect was observed on the performance of the Self-Update Model when compared to the Static Model.

To understand more about the effect of attribute selection on the comparative performance between Self-Update and Ageing Models, we looked directly at the errors for both types of model. Figures 5.11 and 5.12 show the performance of the two models for Ardmore House, depending on whether or not attributes were selected.

It is apparent that for both models, attribute selection may help the performance of the Ageing Model when training windows are of a small size. At small training windows, the Ageing Model changes very quickly. Attribute selection may help by reducing the amount of "variability" that the model has to take into account, although this proposition would require deeper consideration of the effect of Attribute Selection, before it could be confirmed. However, at higher training window sizes, the effect of attribute selection plateaued (in the case of the Ageing Model) or became negative (in the case of the Self-Update Model).

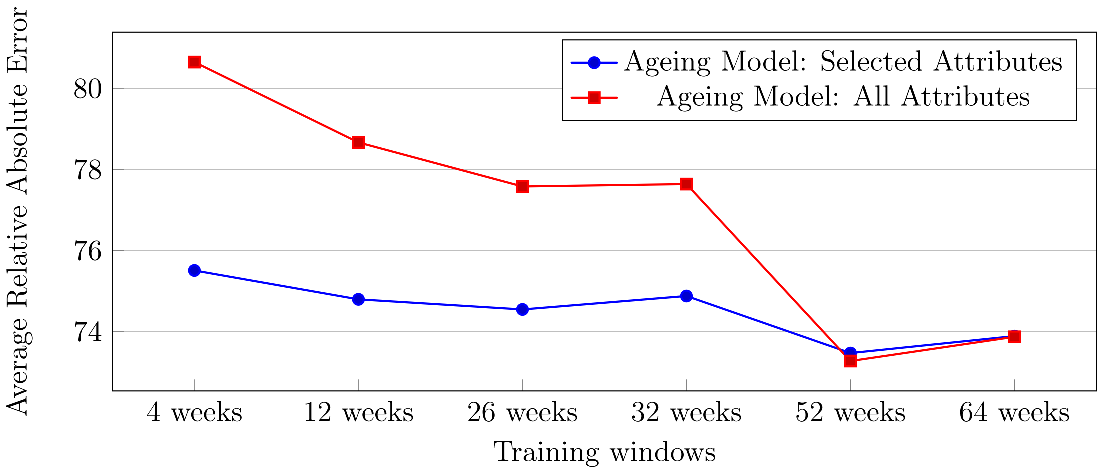

Figure 5.11: Prediction errors for the Ageing Model depending on whether attributes were selected or all attributes were used (Ardmore House, Training Window=4-64 weeks, Update Window=Drop Window=1 week, Test Window=1 day)

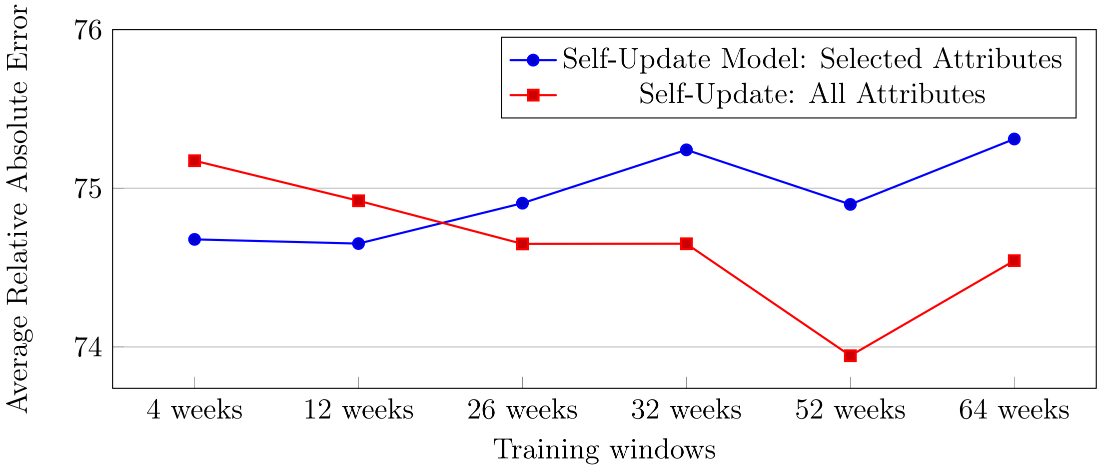

Figure 5.12: Prediction errors for the Self Update Model depending on whether attributes were selected or all attributes were used (Ardmore House, Training Window=4-64 weeks, Update Window=Drop Window=1 week, Test Window=1 day)

Therefore, based on these results, there is some evidence that the selection of attributes may not be of benefit when larger training windows are used. Having said that, it is important to note that the model error may not be the only consideration when evaluating the impact of attribute selection. As noted in Chapter 4, other considerations are:

- The availability of a good range of attributes (It may be necessary to ask if the model could still perform well if a wide selection of attributes were not available?)
- The effect of attribute selection on runtimes (particularly for NN and SVM, reducing the number of attributes can help to manage slow runtimes caused by the curse of dimensionality).
- Because Linear Regression was used to test the model, the selection of attributes is built in as a result of the co-efficient for each variable in the regression model.

We conclude by observing that where an increase in error occurred as a result of the selection of attributes, the effect was not large (in the region of 1-2%). On this basis, there are likely to be occasions when attribute selection is desirable for the overall performance of the model and this will require further research.

5.4 Summary of findings

For the test cases under observation, the models were found to perform differently, depending on the selected parameters. These findings were presented in some detail in this chapter. The key findings are summarised in these bullets:

- When larger training windows (of 52 weeks upwards) are available, Static, Self-Update and Ageing Models all perform comparably with each other.
- However, when training windows are smaller (32 weeks or less), there may be significant advantage from utilising self-updating capability but not "ageing out" capability.
- At large training windows, the performance of the Ageing Models may be marginally better than either the Static or Self-Update Models.
- Overall, the Self-Update Model is more robust to changes in design parameters than the other models. Its performance was largely unaffected by changes in training window size, update window size or starting month.
- The Ageing Model behaves very erratically at smaller training window sizes, but eventually "settles down" as the training window becomes more established and proportionately larger than the update and drop windows.
- There is some evidence that Self-Update and Ageing Models may be able to perform better than Static Models during periods of increased unpredictability (such as Christmas and Holidays)
- There was a high level of commonality between buildings in preference of attributes.
- However, overall, attribute (Feature) selection showed a positive effect for the Ageing Models when smaller training windows were used. It had a negative effect for the Static and Self-Update Models. The size of the effect varied, depending on the building that the model was tested on.

Chapter 6

Discussion and conclusions

As outlined in Chapter 1, our proposed research contribution is to explore possible answers to the following questions:

1. Can a real-time, personalised, predictive model be developed that will give better performance than existing models?
   (a) Does the introduction of self-update capability improve the performance of such a model?
   (b) Does the introduction of "ageing out" capability improve the performance of such a model?
   (c) Does the introduction of attribute (feature) selection improve the performance of such a model?
2. Having optimised the model, is there a practical or commercial application for such a model?

To address these research questions, we built and compared three different models, with linear Regression as the preferred algorithm for application in all models:

1. A regular "Static" model.
2. A "Self-Update" model, in which the model is regularly retrained with new data as it becomes available.
3. An "Ageing" model, in which the model adds new data, and also drops old, potentially less-relevant data at the same time.

Each of the three models was characterised by a number of design choices, such as the size of training window, update window and drop window, inclusion of "attribute" selection or not. These choices influence the actual performance of each model as well as their performance relative to each other. Having identified the effects of various design parameters in Chapter 5, we now address the questions identified in our research contribution. Finally, we close out this chapter by make recommendations in relation to the optimisation and application of personalised, models for real time prediction of energy consumption.

6.1 Did the introduction of self-update capability improve performance?

Based on this research, the answer to this question is a conditional 'Yes'. The introduction of self-update capability improves the model but only if the training window is not sufficiently big enough (i.e. 32 weeks or less).

As the size of the training window increases, the relative improvement provided by the Self-Update Model declines until it compares more or less equally to the Static Model. Analysis of the results showed that the impact of training window size is concentrated on the Static Model. The performance of the Static Model improves with increasing training window size until it eventually matches the Self-Update Model. Once this happens, there is no further advantage to be gained continuing with the self-update capability.

Two other characteristics of the Self-Update Model that are important when considering its overall performance:

- The Self-Update Model can perform better than the Static Model when predicting consumption during irregular periods, such as Christmas and other holidays. This was observed even at high training windows when the overall performance of the Self-Update Model was not significantly better than the Static Model. This is a key characteristic of Self-Update Models that may have important application for future requirements.
- The Self-Update Model also demonstrated a reduced sensitivity to design choices when compared to the Static Model. Its performance did not vary when different training or update windows were used. This relative robustness may be a valuable characteristic that would allow the model to be easily applied to a range of practical situations.

The Self-Updating Model has one significant down-side. It grows rapidly and may quickly become unfeasible to use. This is particularly unhelpful if there is no apparent advantage from the continuous addition of data to the model.

6.2 Did the introduction of "ageing out" capability improve performance?

Based on this research, the answer to this question is a conditional 'No'.

At small training window sizes, the Ageing Model performs very poorly and quite erratically. It is much less effective than either the Static or Self-Update Models. However, and importantly, the model improves rapidly as the size of training window is increased. For all of the buildings studied, the Ageing Model converges with or shows small improvements on the Self Update Model when the size of the training window reaches 52 weeks or more.

The Ageing Model showed other characteristics that are important when considering its overall performance:

– The Model showed greater capability than either Self Update of Static Models to predict consumption during irregular periods, such as Christmas and other holidays. This was observed even at high training windows when the overall performance of the three models were comparable.

– The Ageing Model also avoided the continuous growth in size that was a characteristic of the Self-Update model. Because it drops data on a regular basis, it avoids the risk of growing unfeasibly large and also avoids the cost and inconvenience of holding irrelevant data.

6.3 Did the introduction of attribute (feature) selection improve performance?

This research provided little evidence to suggest that attribute selection improved the performance of the predictive models.

Attribute selection does improve the performance of the Ageing Model at small training windows. Its inclusion has been shown to mitigate the poor performance of the model, but this is not enough to make it a viable alternative to either the Static or Self-Update

Model. As the performance of the Ageing Model improves with larger training windows, the effect of attribute selection declines. The exact effect varies with each building, showing the potential for personalisation in relation to attribute selection.

Without undertaking further research into the causes and effects of attribute selection, it is not possible to say categorically why attribute selection improves the Ageing Model in some, but not all, circumstances. We suggest that the positive effect of attribute selection may be due to a "steadying" effect on the Ageing Model. At small training window sizes, the model has a very large amount of variability. The selection of attributes may help to simplify the model, thereby improving its performance when the "turnover" of data is relatively high.

It is important to note that attribute selection may have implications and potential benefits aside from its direct effect on model performance. From a practical perspective:

– A wide range of attributes may not always be available to the predictive model. Thus, a model that is robust enough to perform with or without attribute selection will always have better real-world applicability.

– Attribute selection may help to reduce execution times for NN and SVM algorithms and help improve their suitability for use in self-updating models. This is less relevant for Linear Regression Models as the coefficients applied to each attribute in the regression equation already reflect their relative importance.

We conclude this section by noting that there is further work to be carried out to identify and fully understand the most appropriate selection of attributes for a predictive model and to understand the impact of attribute selection and potential for personalisation on future models.

6.4 Practical application – Proposed Strategy

In Chapter 3, we discussed the commercial rationale for this research, noting that the coming years will see considerable disruption in the electricity market. The main characteristics of this market will be an increased dynamism and unpredictability in electricity consumption patterns. A real-time balancing market will be introduced and electricity pricing will be based on forecast rather than historical data.

These changes will drive a requirement for predictive models that perform well in real-time, dynamic and unpredictable circumstances. Existing (largely static) predictive models, may not be adequate for the requirements of this new market. However, the availability of a continuous stream electricity consumption data provides an opportunity for models that can take advantage of the availability of new data by evolving on an indefinite basis. Our proposal is based on the following findings from this research:

1. If training windows are not sufficiently large, Self-Update Models will perform significantly better than traditional Static Models. As the training window increases, this advantage diminishes.
2. Ageing Out data is not helpful to the models if the training window is small. However, the Ageing Model improves and "catches up" with the other models as the size of the training window increases.
3. Ageing and Self-Update Models have the potential to perform better than Static models during unpredictable periods of consumption (such as peak periods, Christmas and even weekends).
4. Other factors such as the inherent robustness of the Self-Update Model and the capacity of the Ageing Models to discard old, irrelevant data may be very useful from a practical perspective.
5. Attribute selection is not advised for Static or Self-Update Models but may be applied for the Ageing Model.

Considering the practical requirements of the future market combined with our research findings, we propose a strategy that draws on the performance of the different models. This model would optimise the size of the training window using the Self-Update Model. Once the optimum training window is reached, the model would then switch to the Ageing Model, thereby maintaining the training window size, while continuing to add new data as it becomes available. This proposed design is illustrated in Figure 6.1.

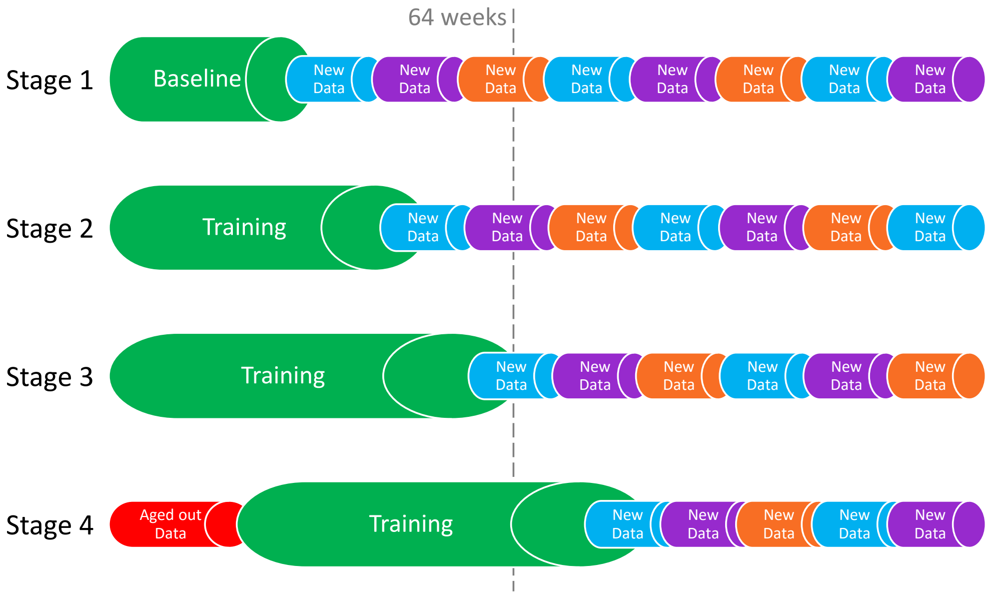

Figure 6.1: Illustration of the proposed future design of the real-time predictive model for electricity consumption in UCD buildings

The suggested parameters are described in detail in Table 6.1:

Design consideration	**Recommendation**
Prediction tool used	Linear Regression However, possibility for optimisation of algorithm choice as a personalisation feature
Model design	Self-Update Model until until target training window of 64 weeks is reached Freeze training window at 64 weeks (this may also be subject to personalisation) The model switches to Self-Updating to Ageing Model
Update window	At the discretion of the decision maker (however, smaller windows of approximately 4 weeks would be preferable initially)
Drop window	Same as update window (further research may be carried out to explore other options)
Test size	1 day
Starting month	At the discretion of the decision maker
Error measure	Relative Absolute Error
Attribute selection	Attribute selection should be applied when Ageing Model is introduced (further research required) Consider additional attributes and possibility of personalisation

Table 6.1: Summary of the recommended model design

As illustrated above, the opportunities for personalisation of the model lies in the following four areas:

- Training window: The model may include a performance threshold that is set to identify when the optimum training window has been reached and the Self-Update Model should switch over to the Ageing Model.
- Sliding Window: On transitioning to the Ageing Model, the size of update and drop windows would be optimised for each building, so that the model is updated at a frequency that balances performance with the cost of retraining the model.
- Preferred Algorithm: The strategy may also include an initial step that would allow a preferred algorithm to be selected at the outset for a particular building.
- Attribute selection: If attribute selection is built into the model, it would require personalisation since the research shows that different buildings have different preferred attributes.

It should be noted that this proposal does not ignore the essential requirement for high-performing model. The optimisation of the algorithm and reduction of the Relative Absolute Error is a key next step towards preparing a model that would be of practical value.

6.5 Conclusion

In conclusion, changes to the electricity market that will be implemented from 2017 will have a profound impact on the typical electricity consumption profile for many customers. Our findings indicate that the qualities and characteristics of Self-Update and Ageing Models may be very suitable for application in the prediction of these new, less predictable consumption patterns. Such models may play a key role in opening up new opportunities for all participants in the electricity market to exercise control over their electricity consumption patterns and costs, thereby benefiting from an economic and conservation perspective.

Chapter 7

Future research

In this work, we have proposed a strategy for a model to predict electricity consumption in real time for UCD buildings. This opens up opportunity for further research, to ensure a comprehensive body of work, address some outstanding questions and optimise the model in a real life context. Here we outline these areas where further research is required.

1. Optimisation of algorithm choice and performance

   A design choice made early in this research project was that LR would be used as the preferred Algorithm and this was used throughout the project. This choice was made for reasons of performance as well as efficiency, but no further work was carried out to optimise the individual models. We note that the performance of NN and SVM algorithms can be optimised through careful design such as selection of attributes. This work to optimise the individual performance of algorithms, maximise the performance of the model is an area where future research is required. There is also the opportunity to explore the possibility and benefits of adding algorithm selection as a personalisation feature in the model.

2. Expansion and further research into the effects of attribute selection

   Attribute selection was explored in this research, however the choice of attributes was not comprehensive and our findings were not fully conclusive regarding the potential benefit of attribute selection in the future practical application of the model.

   We suggest that further research is required to include a wider range of attributes, for example additional historical attributes (either closer in time or further back in time), along with a wider range of weather-related attributes.

We also suggest that the effects of attribute selection should be explored in the context of NN and SVM models, with a view to optimising the performance of these algorithms.

3. Explore variety and relative size of update/drop windows

   In this research, we opted for a very simple sliding window design. In this, the update and drop windows were maintained at the same size and data was always added and dropped at the same time. There may be value in exploring different relationships between the update and drop windows, for example the impact of varying the timing at which new data is added and old data is dropped.

4. Explore implementation and optimisation of predictive models for practical application with real, live data

   In this research, we have devised a proposed strategy for designing an optimum predictive model based on current profile of UCD electricity consumption. Future changes in the electricity market that will be characterised by electricity consumption profiles that is far more uncertain than current data suggests. We therefore suggest that further research will be valuable to explore the application and optimisation of this strategy using real data and in the context of the 2017 market changes.

Appendix A

Research data

Table A.1 shows the information related to the data available to this research, including the total number of instances in each dataset, the total number of missing values, the maximum number of consecutive missing values and the ratio of missing values against all data instances. The rows highlighted represent the seven buildings selected.

Building Name	**Instances**	**Missing**	**Consecutive**	**Ratio**
Glenomena Block 10	**108480**	**17**	**8**	**0.02%**
Glenomena Block 9	108480	17	8	0.02%
Daedulus Total	**108480**	**18**	**6**	**0.02%**
Belfield	**108480**	**26**	**8**	**0.02%**
Nova Total	**108480**	**28**	**9**	**0.03%**
Sports Centre	108480	28	10	0.03%
BL3 Lab	108480	31	9	0.03%
Daedulus Chiller	108480	32	13	0.03%
Sports Centre Sandwich Bar	106217	32	12	0.03%
CRID Total	108480	34	14	0.03%
Nova Phase 3	108480	43	21	0.04%
CRID Ground Floor	**108480**	**44**	**12**	**0.04%**
NVRL	108480	50	20	0.05%
Nova Phase 2	108480	60	20	0.06%
Belfield House Total	104004	64	31	0.06%
Belfield House 1st Floor	104004	64	31	0.06%
Conway Institute	108480	73	36	0.07%
Belfield House Ground Floor	104004	72	31	0.07%

Table A.1 – *Continued on next page*

Table A.1 – *Continued from previous page*

Building Name	Instances	Missing	Consecutive	Ratio
Ardmore House	**108480**	**110**	**56**	**0.10%**
O'Reilly Hall	108480	118	18	0.11%
Computer Centre Server Room	108480	126	107	0.12%
Computer Centre	108480	154	114	0.14%
Computer Science	**108480**	**154**	**106**	**0.14%**
Tierney Building	108480	189	42	0.17%
Daedulus Data Centre	108480	202	100	0.19%
CSCB	108480	263	210	0.24%
MBRS	108480	322	25	0.30%
Clinton Institute for American Studies	108480	413	374	0.38%
UCD Chaplaincy	108480	565	374	0.52%
Insomnia	108480	683	103	0.63%
AIB Bank	108480	822	582	0.76%
Newman Building	108480	825	582	0.76%
Student Centre	108480	970	508	0.89%
Walking Duct	108480	971	582	0.90%
Restaurant	108480	1073	582	0.99%
Quinn School	108480	1898	1474	1.75%
Infusion	108480	3595	1401	3.31%
Post Office	108450	3883	1210	3.58%
Food Science	108480	5534	3946	5.10%
Agriculture	108480	5907	4608	5.45%

Table A.1: Building data

Appendix B

Interviews carried out

Table B.1 displays the list of all individuals that were interviewed as part of this research.

Interviewee	Organisation	Role
Kieran Brassil	UCD Buildings & Services	Energy Programme Coordinator
Richard Kelly	DCU Estates	Estates Manager
Alan Duggan	Bord Gáis Energy	Energy Efficiency Manager
Dr Antonio Ruzzelli	Wattics	CEO
Paul Acton	SAS Analytics	SAS Institute
Patrick Liddy	Enernoc	Director, Regulatory Affairs and Operations
Eoin McLoughlin	MCL Analytics	Director

Table B.1: Summary of interviews carried out

Appendix C

Literature Review Comparison

Table C.1 displays a summary of tools and models identified throughout the literature review. It provides an overview of the design features the authors used to address the problems at hand.

Author(s)	Problem addressed	Model	Input variables (incluiding FS)	Forecast interval	Training window	Update window	Test window	Static/ Dynamic	Error measured
Singhal et al	Future Market Clearing Price	3 layer ANN	Day, Time, Change in demand (t-1), Price	Hourly	6 months	N/A	48 hours Spikes	Static	MAE RMSE
Ahmad et al	Review building energy prediction	SVM, ANN Hybrid	Varied	Varied	Varied	N/A	Varied	Static	Varied
Cancelo et al	Forecast electricity load	ARIMA	Temperature, Holidays, Basic load	Hourly Daily	7 days	4-10 days	Next day Next week	Dynamic	MAPE
Mandal et al	Market price and Load	ANN	Previous price, load, temperature, similar days	1-6 hours	Previous 45 days	N/A	1-6 hours	Static	MAPE, Max and Min
Paudel et al	Building heating	ANN	Occupancy, solar, holiday, power	Hourly for 24 hours	19 days	N/A	4 days	Pseudo Dynamic	RMSE, R^2
Prevost et al	Data centre energy load	ANN	Requests to server	1 - 20sec	1,000 data points	N/A	65 data points	Static	RMSE
Ruano et al	Air conditioning demand	ANN	Temperature, solar, humidity	1 day	10 days	1-8 days	3 days	Static	RMSE
Tso et al	Domestic homes consumption	Regression ANN, Decision Tree	House design, Appliances owned	Season (Summer/Winter)	1,000 data points	N/A	Weekly	Static	RASE
Yamin et al	Electricity market price	ANN	Time, historical price, reserve	Daily	1-8 weeks	7 days	7 days	Static vs Dynamic	MAPE
Potočnik et al	Natural gas consumption	ARIMA ANN SVM	gas consumed, temperature, solar, day identifier	Daily	Season Nov ’11 – Apr 12	Daily	Season Nov ’12 – Apr ’13	Dynamic	MAPE
Kearney	System electricity prices	PCA NN	Commodity prices, Historical Demand Day before SMP	Monthly	536 data points (70% data)	N/A	280 data points (15% data)	Static	MAPE RMSE

Table C.1 – *Continued on next page*

Table C.1 – *Continued from previous page*

Author(s)	**Problem addressed**	**Model**	**Input variables (incluiding FS)**	**Forecast interval**	**Training window**	**Update window**	**Test window**	**Static/ Dynamic**	**Error measured**
Gibbons	Energy load in UCD	ARIMA Regression ANN	Weather, Occupancy 1 day, 1 week lag	Daily	6 months	N/A	5 months	Static	MAPE
Yang et al	Air conditioning	ANN	Air, water Temperature Time lags to 3 hours	Daily by hour	21 days	Daily	10, 20, 30, 40 days	Static Dynamic Ageing	RMSE
Cho et al	Gas consumption	Regression	Daily Temperature Gas consumption	Annual	Days/months	N/A	Not provided	Static	MAE
Aggarwal et al	Energy price	Various	Market Uncertainty Behavioural Temporal	Various	Various	Various	Various	Various	Various

Table C.1: Summary table of literature

Appendix D

Research Engine source code

In order to compile and execute the source code for the research engine, the following tools will be required:

– **Java:** all code was developed using *Java 1.8.0 Update 51 (64 bits)* as it uses more recent features, including Streams and functional programming (Oracle, 2015)

– **Maven 3.3.3:** dependency management tool for Java libraries (Apache, 2015).

– **WEKA:** "collection of machine learning algorithms for data mining tasks. It also contains tools for data pre-processing, classification, regression, clustering, association rules and visualization" (Hall *et al.*, 2009). The version used was the latest available in the Subversion trunk as of July 31st 2015. The source code is included with this submission.

– **Eclipse IDE:** although not required to execute the code, the Eclipse IDE (Foundation, 2015) – version 4.5 (MARS) – was used for development.

In order to load the research engine environment into an existing Eclipse workspace, simply unzip the attached source code file (*Research Engine Source Code.zip*) and perform the following steps in Eclipse:

File → Import → Maven → Existing Maven Projects

And select the location where the source is located. This should create four separate projects in Eclipse named: *data-processing*, *dissertation-core*, *dissertation-executor* and *weka-dev*.

All main method executions have been defined in the *dissertation-executor* project.

Acronyms

ANN Artificial Neural Network. 5, 6, 8, 10, 11, 62, 63

ARFF Attribute-Relation File Format. 25, 26

ARIMA Auto-Regressive Integrated Moving Average. 5, 7, 62, 63

BEMS Smart Building Energy Management Systems. 1, 12

CER Commission for Energy Regulation. 17

CSV Comma Separated Values. 25

EU European Union. 17, 18

GA Genetic Algorithms. 12

HVAC Heating, Ventilating and Air Conditioning. 15

LR Linear Regression. 2, 28, 29, 56

MAE Mean Absolute Error. 6, 62, 63

MAPE Mean Average Percentage Error. 4, 7, 8, 11, 62, 63

MaxAE Maximum Absolute Average Error. 7

MCP Market Clearing Price. 8

MILP Mixed Integer Linear Programming. 12

MLP MultiLayer Perceptron. 7

MOGA Multi Objective Genetic Algorithm. 7

MSE Mean Squared Error. 12

NN Neural Networks. 2, 5–8, 12, 13, 28, 29, 35, 47, 52, 56, 57, 62

PCA Principal Component Analysis. 5–7, 10, 62

R^2 Correlation Coefficient. 8, 10, 62

RAE Relative Absolute Error. 27

RASE Square Root Average Squared Error. 6, 62

RMSE Root Mean Square Error. 6–8, 10, 62, 63

SEM Single Energy Market. 15

SEMO Single Energy Market Operator. 12, 15, 16

SMP System Marginal Price. 12, 17, 62

SOM Self Organized Map. 5

SRMP Short Run Marginal Price. 17

SVM Support Vector Machines. 2, 5, 6, 12, 13, 28, 29, 35, 47, 52, 56, 57, 62

SVR Support Vector Regression. 8

UCD University College Dublin. 1–3, 7, 14, 15, 18–21, 56, 57, 63

WEKA Waikato Environment for Knowledge Analysis. 13, 25, 64

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