The Impact on Energy Consumption of Daylight Saving Clock Changes

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Abstract

The focus of this work is an investigation of the effect of prevailing time regime on energy consumption. In particular we perform analysis demonstrating potential energy savings which could be obtained were Great Britain to maintain Daylight Savings Time (DST) over winter, instead of reverting to Greenwich Mean Time (GMT). We review the literature on the effect of DST on energy consumption and show that this indicates a justification for considering the issue. Our headline result is in agreement with many related studies in that advancing the clock by an hour in winter would lead to energy savings of at least 0.3% of daily demand in Great Britain. In deriving this result we have adopted methodologies currently used in load prediction, in particular Support Vector Regression, to estimate energy demand on a half-hourly basis.

Corresponding cost savings are found to be higher (due to the nonlinear increase of costs) and we find them to be on the order of 0.6% over the months considered. In terms of environmental impact we find the saving to be approximately equivalent to 450,000 tonnes of CO_2. In deriving these results we adopt a conservative approach such that we consider them *lower bounds* on any true savings.

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1. Introduction

This work analyses British electricity demand from 2001 to 2008 and discusses the change in electricity demand that could result from an extension of Daylight Saving Time (DST) over the months currently on Greenwich Mean Time (GMT)[1]. DST is a measure adopted by many countries worldwide to improve use of available daylight during the summer; a direct result of this is a change in energy consumption. However, it appears that there has only been a limited focus on quantifying the impact on energy usage in Great Britain (GB) that would result from advancing official clock time from GMT to DST.

The material in this paper is based on British electricity consumption, with data being provided on a half-hour basis by National Grid (NG), together with temperature and illumination information. An initial examination of the data suggests for instance when the change in clock time from British Summer Time (BST) to GMT occurs in October, afternoon peaks in consumption are higher than they would be on BST. An obvious assumption to make is that this would results from it getting darker an hour earlier. However a number of key questions remain, for example,

1. Is this genuinely supported by all data?
2. Is this an effect that would be observed anyway, given that days are getting shorter and colder?
3. If it is a genuine effect, is it offset by changes at other times *e.g.* in the morning?

1.1. Background

DST was introduced in the United Kingdom (UK) during World War I in 1916. During World War II, DST was further advanced by an hour, with clock time on GMT+1 during the winter months and GMT+2 during the summer.

[1]For ease of exposition we use the term DST (instead of summer time in winter) to refer to the clock time regime on one hour ahead of GMT in winter, the object of our investigation.

This was known as British Double Summer Time (BDST). Official clock time reverted to the GMT/DST arrangement in 1947.

The late 1960s / early 1970s saw two relevant trials which aimed in part to quantify the impact of clock change on energy consumption, focussing in particular on year-round DST. The first of these was over the period from March, 1968 until October 1971 in which the UK used BST year-round in an attempt to reduce energy consumption. A review of this time (Her Majesty's Stationary Office, 1970) found that under BST there was an increase of around 2.5% in energy consumption, in the morning and a decrease of around 3.0% in the evening. However the result was not considered large enough to justify continuing the trial in the prevailing political climate of the time, when media interest was predominantly on increased traffic accidents in the morning (without consideration of reduced accidents in the evenings) associated with advancing clock time. Since then the only significant DST-related event in the UK has been the putting back of the date of onset of DST by two weeks in 1981 to align with clock change dates in European Union (EU) countries on Central European Time (CET), while the UK remained one hour behind CET year-round. This was formalised by EU Directives in 2001.

Another period of extended DST was adopted in the United States of America (USA) following Middle-East oil-embargoes. This lasted from January 6, 1974 until April 27, 1975. A study of this (Ebersole *et al.*, 1974) found indications of a reduction in electricity consumption of the order of 0.7% during spring, an increase in autumn, and a decrease of around 1.0% in winter. However this study also found an increase in gasoline consumption during these times. Furthermore, a subsequent review of these figures cast doubt on the reductions claimed (Filliben, 1976). More definitive trial data is now available as daylight saving time has been extended in the USA. A recent report on this suggests a possible saving in the range discussed, of 0.5% has been achieved (Belzer *et al.*, 2008).

While no such action has been taken in the UK, the 2007 Energy White Paper (DTI, 2007) identified three key energy-related issues: climate change, security of supply and fuel poverty. If a reduction in electricity demand were to accompany a change in clock time policy, this would be relevant to all three issues. In more detail,

1. *Climate Change*: the power generation sector currently accounts for roughly a third of all CO_2 emissions in the UK (BERR, 2008). Any reductions in electricity consumption will contribute to carbon abatement, but the greatest savings can be made during hours of peak demand. Peak demand generally occurs after the end of the workday, at 5:30pm and also after sunset. When these two coincide the resulting peak is significantly higher. To deal with these transitory peaks in demand, methods of power generation that have shorter powering-up times are employed such as pumped storage, Open Cycle Gas Turbines (OCGT) and oil generators. These provide quick and easy power, but the latter two have much higher marginal costs and also higher marginal carbon emissions due to their low efficiencies and high fuel prices.

2. *Security of Supply*: The UK is currently facing a threat to the security of its electricity supply due to anticipated reductions in electricity generation from large combustion and nuclear plants. Nuclear power currently provides 18% of the UK's electricity demand, but 10 of the 13 reactors (accounting for 69% of total nuclear generation) are due to close within the next 6 years (DTI, 2007). Within 15 years, all but one of them are expected to have shut down, leaving only 10% of current nuclear capacity. The introduction of the Large Combustion Plant Directive (LCPD) in 2001 has exacerbated this situation, having reduced electricity capacity since 2007 and requiring further reductions in 2015 (EON, 2009). Any means of reducing electricity demand will aid in reducing any shortfalls in generation capacity.

3. *Fuel Poverty*: this is defined as occurring when a household has to spend over 10% of its income on fuel use in order to provide an adequate level of warmth (Boardman, 1991). Since 2004 rising energy prices had led

to increased levels of fuel poverty in the UK (DTI, 2007). Clock time informed by patterns of peak demand should reduce individual expenditure on fuel. An associated decrease in electricity generation costs would provide savings that can be passed onto the consumer.

2. Previous Work

A broad review of the overall field is given by Aries and Newsham (2008), with a focus on lighting energy use. The motivation for this is that lighting is the key area affected by such a change. Indeed it was the primary motivation for the original, and oft-cited comment on the need for DST by Benjamin Franklin (Franklin, 1784), and remains so today. Furthermore, with increasing awareness of energy consumption there is renewed interest in the impact of DST on electricity demand levels.

As detailed by Aries and Newsham (2008), results obtained by the Energy Information Administration (EIA) have shown that residential electricity consumption is around 36% of the overall total in the USA, of which around 9% is used for lighting[2] (Seiferlein and Boyer, 2005). Given these figures, and that an optimistic target for reducing lighting requirements through time-change is 20%, then it would seem that we are looking for an impact on overall energy consumption of around $0.5 - 1.0\%$.

Varying approaches to the problem have been taken by researchers. Some have concluded that there may in fact be increased energy consumption due to shifting to DST. Key such contributions are listed in Table 1. Meanwhile several studies have found no evidence of a significant change one way or the other, these are listed in Table 2. However the majority of work has drawn the conclusion that there are gains to be made in reducing energy consumption through judicious use of DST — see Table 3. A review of these studies shows that the majority of research supports the idea that there is the potential for

[2]These figures are likely to be similar for the UK.

Reference	Comment
Kotchen and Grant (2008)	An empirical study of the state of Indiana which found an expected increase in residential electricity demand of 1-4%.
Shimoda *et al.* (2008)	A simulation model which predicts an overall 0.13% increase in residential electricity consumption in Osaka.
Kellogg and Wolff (2007)	An empirical study of the state of Victoria in Australia during the Sydney Olympics, when the change to DST was shifted, finds an overall increase in electricity consumption.
Pout (2006)	A simulation approach to predict an increase of 1% in energy consumption in the UK under year-round DST and 2% under BDST.
Rock (1997)	Find that DST increases electricity usage by 0.24% in the USA.

Table 1: An overview of literature finding an increase in energy consumption due to the shifting of DST.

Reference	Comment
Kandel and Sheridan (2007)	Consider Energy usage in California and analysis based on a change in the timing of the daylight saving time shift. This analysis made use of Ordinary Least Squares (OLS) and found no statistically significant change in energy consumption.
Indiana Fiscal Policy Institute (2001)	Conducted an Indiana-based empirical study which could not find conclusive changes.
Fischer (2000)	Based on German consumption, this found an overall neutral impact of DST on lighting energy.
Littlefair (1990)	A light switch simulation when considering the UK under BDST and while he found a 5% increase in commercial lighting, he also found a 5% decrease in domestic lighting. These results may have been different had the study considered year-round BST.
Filliben (1976)	In reviewing the study conducted by Ebersole *et al.* (1974) on the impact of year-round DST in the USA due to the oil crisis, concluded that the results were inconclusive.

Table 2: An overview of literature finding no significant change in energy consumption due to the shifting of DST.

Reference	Comment
Belzer *et al.* (2008)	An empirical study in the USA based on recent changes to DST policy, which found possible electricity savings 0.5%.
Fong *et al.* (2007)	A simulation of buildings in Japan which concluded that the resulting reduction in electricity consumption would vary from area to area, but be greater under double DST than under DST.
Kandel and Metz (2001)	A simulation of demand in California which found that year-round DST could reduce winter peak consumption by up to 3.4% and daily consumption by 0.5%. Meanwhile they found double DST would mean summer peak reduction by 0.6% and daily savings of 0.2%.
Reincke and van den Broek (1999)	Simulation methods used to study the impact of DST on EU countries and found possible savings of between 0 and 0.5% depending on country.
Ramos and Diaz (1999)	An empirical analysis of Mexico which found possible electricity savings of 0.83%.
Ramos *et al.* (1998)	A theoretical study of Mexico which anticipated savings in electricity consumption between 0.65% and 1.10%.
Hillman (1993) (and its precursor, Hillman (1988))	conducted an empirical study of the impact of year-round DST in the UK, finding a 0.8% decrease in demand for domestic lighting. Hillman (1988) was a key reference for the energy-related findings of Home Office (1989). In particular these works identified the reduction of peak evening demand (see Section 3) as a desirable outcome.
Hillman and Parker (1988)	Looked empirically at UK electricity demand under year-round DST, finding an overall reduction on the order of 0.5%.
Bouillon (1983)	Conducted building simulations to anticipate a 1.8% overall reduction in electricity demand.
Ebersole *et al.* (1974)	Studied the impact of year-round DST in the USA due to the oil crisis and found a reduction in demand of 0.7% during spring, an increase in autumn, and a decrease of around 1.0% in winter. However this study also found an increase in gasoline consumption during these times.
Her Majesty's Stationary Office (1970)	Looked at the initial results from the period from March, 1968 until October 1971 in which the UK used BST year-round and found an approximate 0.5% reduction in electricity consumption.

Table 3: An overview of literature finding an increase in energy consumption due to the shifting of DST.

energy savings. However there is unlikely to be a single solution to the issue of daylight saving. The following considerations apply.

- *Regional and Seasonal Considerations* — latitude and climate vary from region to region, affecting sunlight, temperature and existing mean times. Reincke and van den Broek (1999) emphasise that the change in electricity demand due to DST varies from country to country. For example, Kandel and Metz (2001) show that Californian demand peaks at mid-day in the summer due to heavy use of air-conditioning. In contrast, in the UK annual peak demands occur at just after 5pm during the winter (for more details on this see Section 3). Another example is the Portuguese case, presented as evidence against a trial period on DST in winter in the UK (Hansard, 2006). However, Portugal already enjoys an hour more light in the evenings on GMT than does the UK, through being located further south. Thus it does not require a clock change for Portugal to achieve the benefits that advancing the clock by an hour in winter would offer the UK.

- *Timeframe* — the global economy has changed significantly in the past 40 years, and studies from the 1970's, although revealing about electricity demand during that time, cannot accurately reflect the impact of DST on current electricity demand.

- *Demand Measure* — some studies have not clearly distinguished or measured the difference between the impact of DST on peak demand versus its effect on overall demand.

For these reasons, together with the fact that there appears limited recent literature on the effect in GB we have used regression techniques to revisit how DST affects electricity consumption in GB. In doing this we have adapted state-of-the-art methods for performing electricity load prediction to the problem at hand. In particular we adopt a nonlinear regression approach. The need to take a nonlinear approach has been highlighted by Henley and Peirson (1997) who discuss the nonlinear nature of the problem at length.

As a first step it is important to identify the key contributors to energy consumption. As highlighted by many of the above references temperature is clearly important, indeed Hor *et al.* (2005); Pitt (2000); Douglas *et al.* (1998); Hackney (2002) make clear that they consider it the most important variable. This is not only due to effects such as increased use of heating / air conditioning, but also due to losses in transmission cables at different temperatures. As results in Hor *et al.* (2005) show, attempts to quantify this as a linear relationship typically perform poorly and consequently they resort to piecewise linear approaches. They also incorporate wind speed, humidity (as discussed in this context by Rüdenauer and Gensch (2004)), illumination and rainfall information together with socioeconomic factors such as population growth and Gross Domestic Product (GDP) in an attempt to construct a similar regression concerned with monthly electricity demand. Al-Alawi and Islam (1996) (see also Al-Alawi and Islam (1997)) list a similar collection of important variables, further including snowfall.

In addition to piecewise linear methods, subsets of these input variables have historically also been used in Neural Network (NN) approaches (Azzam-ul-Asar and McDonald, 1994; Ringwood *et al.*, 2001; Park *et al.*, 1991; Islam *et al.*, 1995; Kermanshahi *et al.*, 1993; Lee *et al.*, 1993), expert systems (Rahman and Bhatnagar, 1988; Mangeas, 1995), fuzzy logic approaches (Al-Abuky *et al.*, 1995; Park and Park, 1989) as well as traditional linear methods (Gunel, 1987; Watson *et al.*, 1987, for example). Genetic and evolutionary algorithms have also been applied to the problem (Heine and Neumann, 1994; Maifeld and Sheble, 1994).

The literature on the problem of load forecasting is too vast to be covered in depth here. Surveys such as that by Metaxiotis *et al.* (2003) provide an overview (see also Feinberg and Genethliou (2005); Rui and El-Keib (1995)). While some researchers are persisting with methods such as fuzzy regression (Song *et al.*, 2005), most recent work has tended more towards kernel-based regression methods (Rivieccio, 2001; Mahandes, 2002; Chen *et al.*, 2004; Espinoza *et al.*, 2005; Pai *et al.*, 2005; Wang and Wang, 2008, among others).

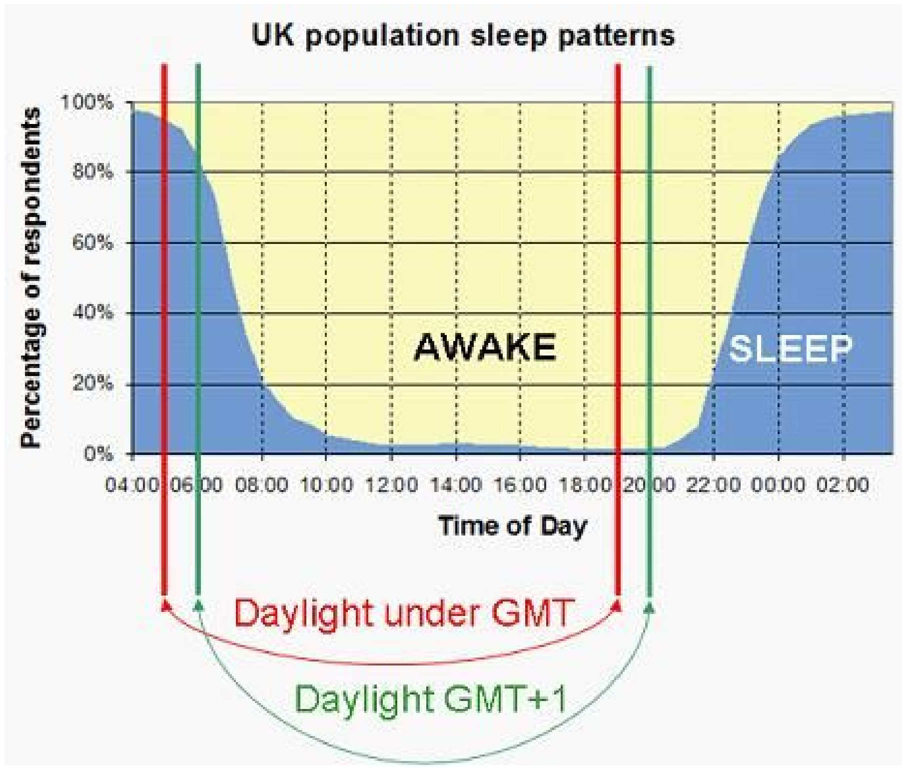
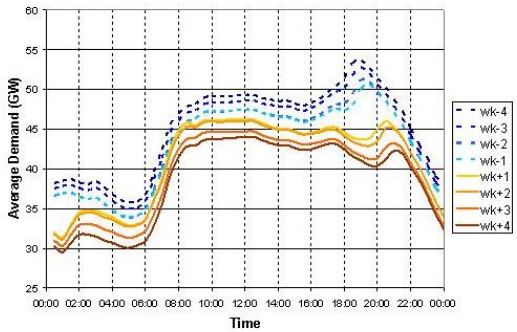


Figure 1: An illustration of how the UK population's waking times align with daylight. *Clearly shifting between GMT and DST alters this alignment.* Data Source: UK Office of National Statistics.

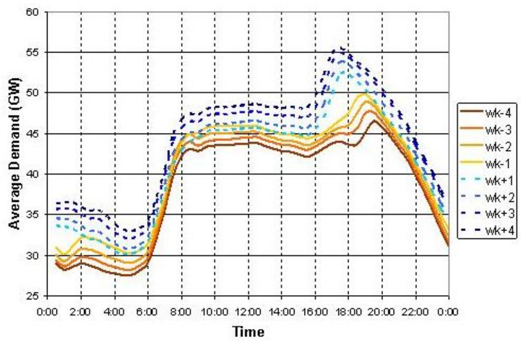
Part of the work to be presented here focuses purely on anticipating the peak energy consumption, a regression problem in itself. This has independently been tackled in the literature (California ISO, 2007; Suzara, 2008), with the approach being to use second or third order polynomials taking temperature as an input.

3. Description of the Problem

Intuitively, minimizing energy usage for heating and lighting can be better achieved by aligning people's waking hours with the hours of daylight, see for instance, Figure 1. This illustrates the issue; on the day highlighted it would seem that BST (=GMT+1) is better aligned with people's sleep patterns in GB than is GMT.



(a) March / April clock-change weeks



(b) October / November clock-change weeks.

Figure 2: Average energy demand in the UK over the weeks around the clock-change time — Average taken over the years 2001-2008, using National Grid data *cf.* Section 4. *Here it appears that although there is an unavoidable baseline shift in energy consumption over time, there is also a change in average profile form when going from BST to GMT. This seems to exacerbate energy consumption differences over time.*

While this issue might initially appear to be fairly simple to reconcile, particular nonlinear effects mean that a slight change can significantly affect the overall energy consumption. These can be further understood through Figures 2 and 3. Figure 2 shows that the overall profile follows a fairly predictable pattern. At first, as might be expected — very low demand occurs in the early morning hours. This then ramps up, as people wake and begin their activities, and reaches somewhat of a plateau during the mid-part of the day. As dark falls and people begin to head home we observe a clear peak. It can be seen from these Figures that on GMT (dotted lines), the evening peaks are higher than they would be under the BST regime. Some initial results (Hill *et al.*, 2009;

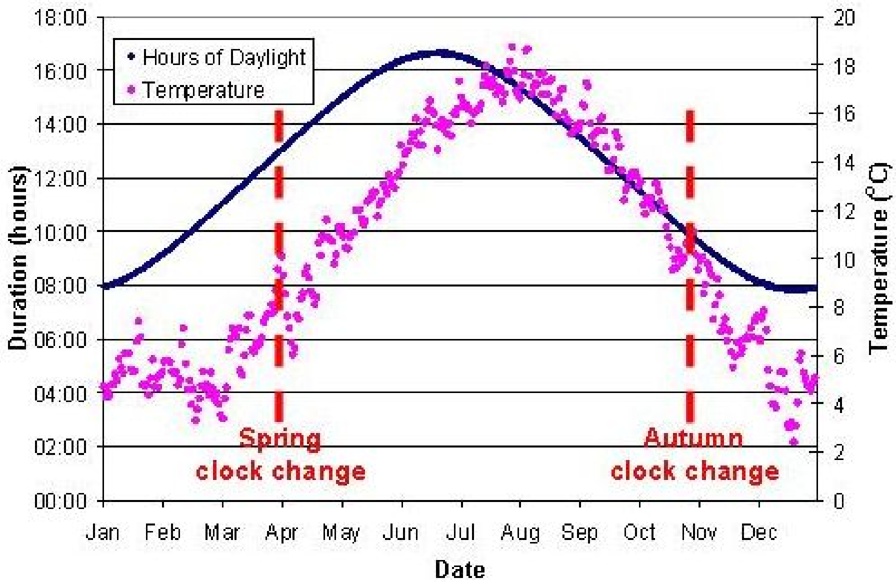


Figure 3: Changes in daylight and temperature over a year in the UK — Average taken over the years 2001-2008, using National Grid data *cf.* Section 4.

Chong *et al.*, 2011) also suggest that this peak is higher under GMT than DST. Quantifying this effect is a key aspect of this work. It is also important to investigate what happens in the morning — would a reduction in the evening peak be accompanied by a higher morning peak? This would be obviously counter-productive; accordingly, although the literature cited does not anticipate such an outcome we aim to quantify morning consumption changes.

Essentially we reduce the problem reduces to focus on a particular time of day, for instance 5pm under GMT. We observe energy consumption in the recent period, and ask what this would have been if clock time had been on 6pm as under BST? Prevailing light and temperature conditions would be the same (*cf.* Figure 3), only clock time would have changed. How can we infer the energy demand if the clock were advanced?

The approach we adopt is to make use of nonlinear regression, in particular nonlinear regression based on Radial Basis Functions (RBFs). Qualitatively the underlying idea here is to take data on energy consumption at particular times of day, with given light and temperature levels. Under another combination of time, light and temperature the framework will output a weighted average of previously observed energy consumption levels as a prediction of corresponding consumption with this new sample. The weighting involved in this is dependant on the similarity of previously observed data with this new data point. For instance, if we consider a day on which, at 5pm it is 15 degrees, and sunny, and infer the expected electricity consumption from a change in clock time, the regression will average the consumption previously observed, weighting that at similar times and with similar weather more strongly than that at different times or on dark, cold days.

The particular framework which we use for this is Support Vector Regression (SVR). Initially developed during the 1990s, it now has a solid literature quantifying aspects of its performance — see Schölkopf and Smola (2002) for an introduction and key references. While there are many variants, we use here the standard form of the methodolgy. This is not without precedent, Chen *et al.* (2004) successfully used the same approach to make predictions of electricity loads in a competition.

Support Vector Regression aims to find a nonlinear mapping from some input vector $x \in \mathcal{X}$ to a real-valued output, $y \in \mathbb{R}$. For our purposes x is a vector containing data such as time of day, temperature, *etc.* In doing this the function $f : \mathcal{X} \to \mathbb{R}$ is found[3]. Several software packages are available which implement the algorithm outlined. We use the LIBSVM package by Chang and Lin (2001) together with `MATLAB`. This was also the package used in the winning entry of the EUNITE electricity load prediction competition (Chen *et al.*, 2004).

4. Implementation Details

The data we analysed is British electricity demand data, supplied by National Grid. This is half-hourly data beginning on January 3, 2001 until April

[3]For further details see Hill *et al.* (2009).

30, 2008. Although it includes all days, we have removed non-working days as these have a significantly different profile of energy usage and our initial aim is to prototype our methodology in the most straightforward and commonplace setting possible.

In setting up the problem we first determine the form of the input vector, x. In this we include time, temperature, and illumination information, as also supplied by National Grid. As was discussed in Section 2 these are a subset of what have been identified as key features in the load forecasting problem *cf.* work by Douglas *et al.* (1998); Pitt (2000); Hackney (2002); Hor *et al.* (2005).

We focus our regression on demand during the periods of the day most liable to be affected by the shift in clock time. These are 4:00am until 11:30am and 2:30pm until 10:30pm, *cf.* Figure 2. In doing this we make the assumption that energy usage at other times, *e.g.* at 1pm, is unaffected by a one hour clock change. We also restrict our analysis to the 'shoulder months', in particular from February 15, until May 15 and from September 15 until December 15. Estimates were not attempted for January, since no comparable historical data is available from nearby times of year to indicate what power consumption to anticipate given a clock change.

A further component of x which we include is the energy usage at 3am when considering the early time interval and that at 1pm when considering the later time interval. This is to give some information about prevailing consumption in that day at unaffected times. We normalize the output upon which we are regressing by the average energy consumption over the previous year. Specifically, a given day's electricity consumption profile is expressed as a percentage of the average consumption over the year immediately preceding it. This is in order to correct for the fact that overall electricity consumption has been steadily increasing over the period under consideration[4].

Thus we are taking time, temperature, illumination and prevailing energy usage as inputs in an effort to infer a function such that were we to have new

[4] This increase is clear from the National Grid data.

such inputs we could determine what we expect the corresponding electricity demand to be. In the context of the problem we are considering, this should allow us to say what the energy consumption on a given day would be, were DST to be in place instead of GMT.

Quantitatively we express the time as a percentage of progression through the day, *i.e.* a number between 0 and 1. Temperature data is whitened and illumination data is normalized to also range between 0 and 1.

5. Results

We present here two sets of results. First, in Section 5.1 we discuss the big picture of electricity usage across the entire day. Second, we present results from an analysis of the afternoon peak energy consumption, in Section 5.3. The practical impact of this analysis is covered in Sections 5.4 and 5.5 which discuss cost implications and environmental considerations respectively.

5.1. Looking at the Entire Day

After initial preprocessing of the data we ran a SVR optimization on 26,829 samples. As the aim is to find the effect of changing from GMT to DST then for all relevant GMT samples we shift the given time forward by an hour and use f to find what we expect the energy demand to be. Note that in doing this we are restricted to ensuring that the new time lies within the range we originally input to the algorithm.

In illustrating these results we have taken all data for a given month and for each day we have expressed the outcome as a percentage of the total energy demand *observed* in that day. We have then averaged the results for all days in the month, over all years. It is clearly important to take into account the net effects of changes morning and evening. The inferred profiles of energy consumption are given in Figure 4. These highlight that while anticipated energy consumption is lower in the afternoon, it is higher in the morning for all months. Further illustration of these differences can be found in Figure 5. Again, here

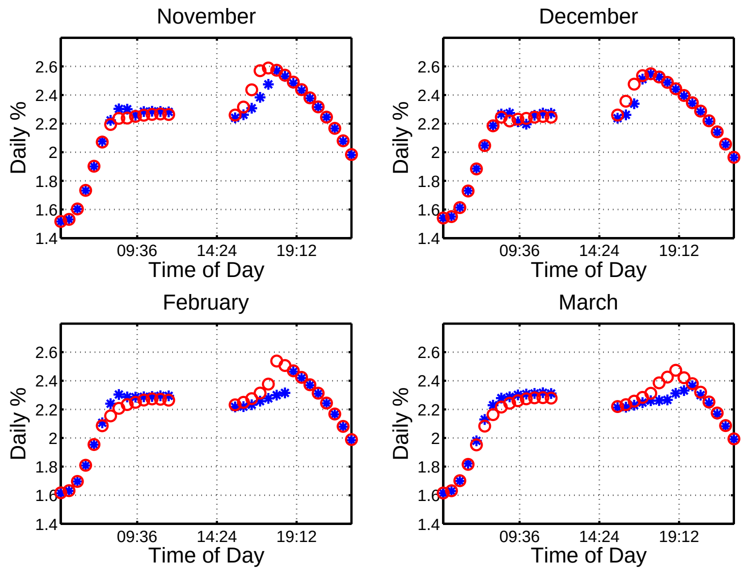


Figure 4: A comparison of inferred energy consumption profiles under GMT and as anticipated under BST. *GMT data is illustrated in red, BST in blue.*

average found energy consumption changes are plotted as a percentage of daily observed demand.

From these it can be seen that there is a pronounced projected increase in energy consumption in the morning, but that this is less than the pronounced projected decrease in the evening. The net changes range up to 0.32% of overall daily consumption in magnitude. The overall combined change in consumption is -0.32% in November, -0.22% in December, -0.32% in February, and -0.32% in March. In terms of actual power involved this translates to approximate savings of 6.6GWh, 4.8GWh, 6.7GWh, and 6.2GWh on average over an entire day in those months respectively.

A couple of points merit mention. The first is that in finding these differences we have taken a conservative approach to determining the average power

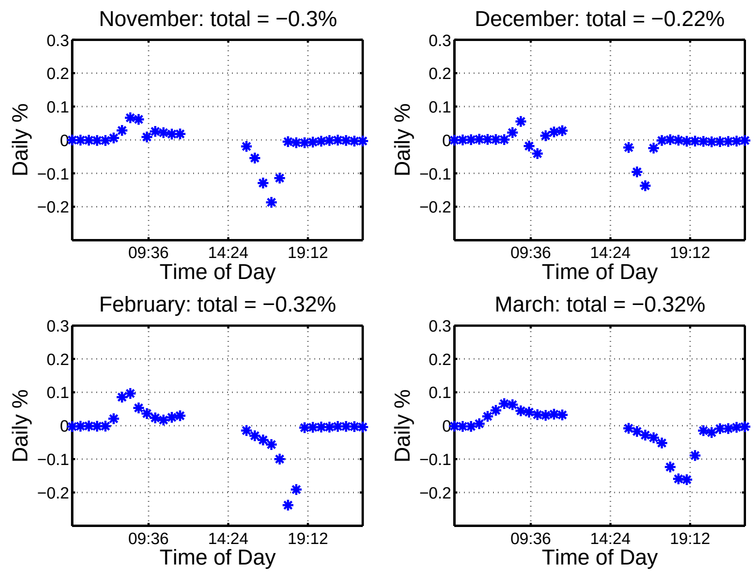


Figure 5: Average change in found energy consumption as a percentage of observed daily consumption.

changes. Where judgements have had to be made[5], we have erred to minimise the magnitude of any such change. As such we view these predicted changes as *lower bounds* on the true differences. The second point is that we have avoided making any mention of January, as this was found to be too far from the shoulder months from which known DST data could be used. Either side of the winter solstice, there are fewer hours of daylight but an advance in clock time can make more natural light available during evening peak demand; we would expect that clock time on DST in January would have at least the impact found for December.

5.2. Weekends

The analysis presented in Section 5.1 has focussed on weekdays. Attempts to model demand effects of clock time at weekends came up against variability

[5]For instance in the choice of algorithm parameters.

that make results less statistically consistent than for working days. While the results have universally indicated an energy saving on DST, identifying a specific number has proved difficult owing to a lack of data. It can be inferred from activity patterns, however that savings in energy consumption from early morning light on GMT would be lower than on working days. More workplaces are closed at weekends, people generally rise later at weekends but are active later in the day, leading to inferred savings at weekends from later sunset on DST.

5.3. Peak Investigation

One key result from the analysis in Section 5.1 is that, as anticipated, the afternoon peak energy consumption is reduced. Avoiding this sharp peak is desirable as it can necessitate the use of electricity generation which is less efficient or more polluting in terms of greenhouse gas emissions. In this section we investigate this issue further. As mentioned in Section 2, two relevant references for this work are those by California ISO (2007); Suzara (2008), who focus on second and third order polynomial fitting. We have compared these methods with SVR and found that the SVR implementation outperforms (Hill *et al.*, 2009; Chong *et al.*, 2011) in terms of the coefficient of determination (R^2) (see Table 4), and the time series autocorrelation of regression residuals. Bearing this in mind we then use SVR to estimate changes in peak energy demand in more detail than was done in Section 5.1.

Given the conclusion that SVR can be used to obtain better results than those in the literature based on polynomial regression, we have also made an investigation into the reduction of peak energy consumption over time which would follow from employing DST in winter. The resulting plot is shown in Figure 6. From this it can be seen that there is a pronounced projected decrease in peak energy consumption. The changes range up to 4% of the daily peak values, with far greater peak savings being made in February / March than in November / December. Looking back at Figure 5 we can see that this is offset slightly by a greater projected increase in morning consumption in February /

	Training set			
Method	R^2	Bias	Std. Dev.	MSE
Linear least squares	0.912 ± 0.005	0.000	0.028	0.769×10^{-3}
Polynomial least squares	0.927 ± 0.005	0	0.025	0.638×10^{-3}
Gaussian kernel ν-SVR	0.950 ± 0.004	-0.004	0.021	0.4498×10^{-3}
	Test set			
Method	R^2	Bias	Std. Dev.	MSE
Linear least squares	0.910 ± 0.014	0.000	0.028	0.784×10^{-3}
Polynomial least squares	0.925 ± 0.014	0.000	0.026	0.655×10^{-3}
Gaussian kernel ν-SVR	0.942 ± 0.013	-0.004	0.023	0.521×10^{-3}

Table 4: Bootstrapped estimates of the coefficient of determination (R^2), bias, standard deviation, Mean Squared Error of the regression estimates, based on 250 resampled sets, and a training / test set approach.

March. This leads to the net savings being similar. However, February and March appear to be the time when clock time on DST could do most to help to reduce evening peaks in the daily consumption profile which we have seen to be a particularly costly and polluting feature of current demand.

5.4. Impact on Costs

Costs are a key consideration when looking at effects such as these. It is known to be the case that the spot price can move significantly during peaks in electricity demand. This is a highly non-linear relationship, since a unit of power can cost significantly more during a period of high demand than it would during a period of low demand. In order to investigate what the impact of lessening the peak (*cf.* Section 5.3) might be in terms of cost we have used half-hourly price data[6] and combined this with our projected changes in demand[7]. This was done for 2002-2007 (years limited due to price data restrictions) to find approximate potential cost savings. In particular the analytical steps involved were,

1. Use the previously found results for a change in electricity consumption on a half-hourly basis.

[6] SBP and SSP data from Elexon Best View Prices 2009.

[7] This analysis could be more extensive in that it be extended to include prices in the derivative markets (*i.e.* the forward contracts that are used for a large part of the market) however we have limited it to the spot price for a first overview of the cost implications.

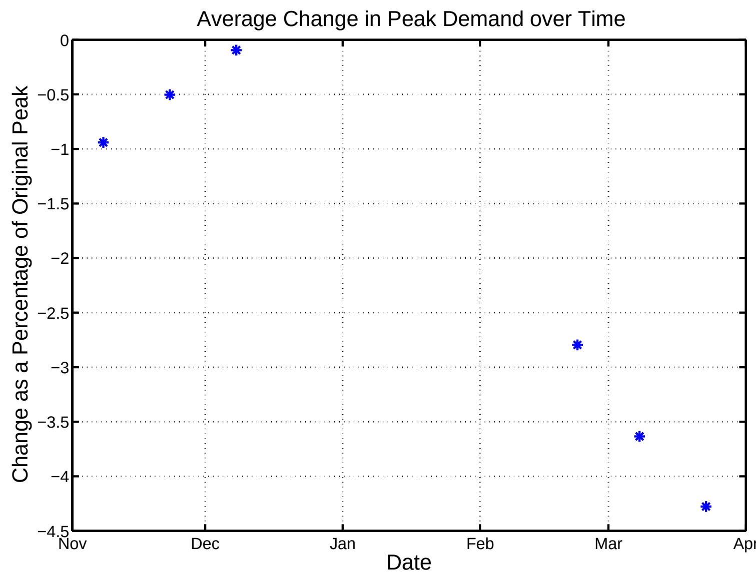


Figure 6: Average change in found energy peaks.

2. Align these with the price data for the same period of time.
3. Find the percentage change in the amount that would have been paid assuming a locally linear model.
4. Average these percentage changes across months and years *i.e.* average the results of all days in November 2002-2007.

Resulting percentage cost changes are shown in Figure 7. When combining these results to month-by-month cost savings expressed as a percentage of daily costs we have savings of 0.8% in November, 0.3% in December, 0.7% in February, and 0.6% in March. Note that these are higher than the raw energy savings for the reasons discussed.

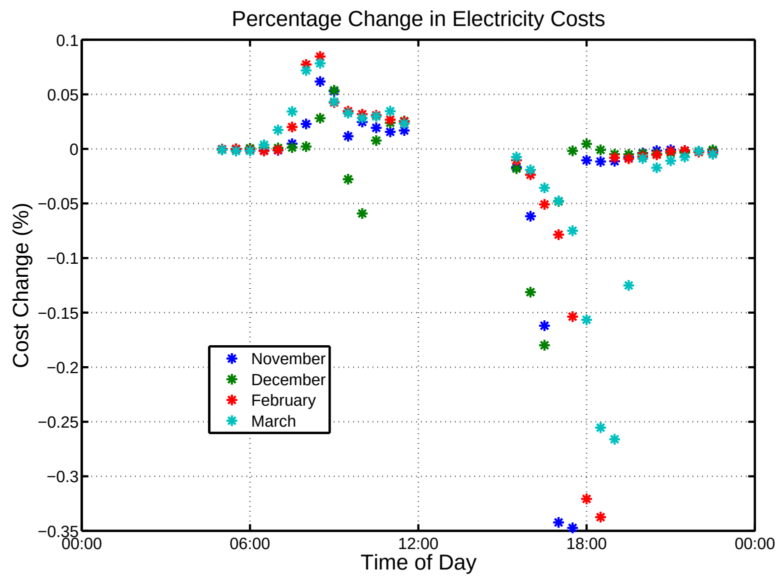


Figure 7: Average change in found energy peaks.

5.5. Environmental Impact

To put the size of potential energy savings in context — the results obtained are approximately equivalent to that consumed by 210,000 households[8] or 74% of the domestic electricity consumption of Glasgow in 2008[9]. Based on an average emission of 505 tonnes of carbon dioxide (BERR, 2008), such a saving in electricity consumption would lead to an annual saving of approximately 450,000 tonnes of CO_2.

5.6. Results in Context of Future Policy Considerations

The quantitative results presented in this section are broadly in agreement with those in the majority of studies summarized in Section 2. Given that re-

[8]Based on average domestic electricity consumption of 4198kWh per household in GB during 2008 (DECC, 2010).

[9]Based on total domestic electricity sales of 1,201.4 GWh in Glasgow City in 2008 (DECC, 2010).

search studies have approached the problem with a variety of analytical methodologies and with different data sets, there is evidence of a real long-term phenomenon which has not been mitigated by technological progress and shifts in economic activity over forty years.

Our investigation has been on the expected impact of advancing the clock by an hour in winter. The question arises as to whether equivalent savings would be found by advancing the clock an hour in summer, on a Single Double Summer Time regime (GMT+1 hours in winter, GMT+2 hours in summer). We set out to use a robust methodology grounded in known evidence. This involved training the prediction equation on known data on demand under GMT+1. There are no similar data available for GMT+2 in summer since this clock time regime has not been adopted since World War 2 when it was aimed at conserving fuel. However if we compare data on the sleep/waking patterns of the population with daylight hours under the present clock time regime, we see a misalignment which could be reduced by advancing the clock in summer (Chong *et al.*, 2011). This would result in lighter evenings at a time when demand is high during the season when early morning light occurs at a time of low demand. A trial period on GMT+2 in summer would provide the precise evidence on savings.

Looking to the future is always a speculative activity, however the following considerations may be important,

1. A continuation of the current misalignment between daylight hours and energy consumption, would be expected if the current DST regime is maintained. Advancing the clock could lead to reductions in overall pollution levels due to electricity generation, as well as to the overall cost of power. As the power savings from a change in clock time have been identified in other research as being in the 0.5-1.0% range, this would be the expected saving, at least in the near future (approx. 20 years). However it is not possible to anticipate long-term developments which may significantly alter the alignment issue.
2. One of the possible long-term developments mentioned in the previous

paragraph is that consumption is likely to undergo a serious step-change if electric cars become mainstream, and power is sourced from the grid. This could add a new dimension to the overall consumption profile but uncertainties prevent realistic modeling at this point.

3. Another possible long-term development relates to the growth of renewables — if particular renewable technologies begin to supply a significant percentage of electricity demand then it may be advantageous to align consumption peaks with their generation peaks.

6. Conclusion

A review of the literature on the effect of DST on energy consumption has indicated that there is a strong case for considering the issue and the likely savings to be made. This is not surprising as dates for DST reflect historical precedent rather than considered attempts to minimise energy consumption. For example DST ends two months before the winter solstice but does not resume until three months after the winter solstice, for historical reasons and not because of practical considerations.

The impact on energy consumption of altering the timing of DST varies from country to country for many reasons. However countries with shorter, colder days in winter have the most to gain from careful consideration of the issue given the way consumption peaks early in the evening when an extra hour of light can have a major impact.

We undertook a further study of the effect altering clock time on the daily peak in energy demand. A sharp peak in demand requires recourse to the use of electricity generation which is less efficient and more polluting in terms of greenhouse gas emissions. In comparison with existing methods for this analysis (*esp.* polynomial fitting) we found that SVR significantly outperformed in terms of regression residuals. We also concluded that peak savings could range from 0.5% in December to slightly more than 4.0% in March.

We found corresponding cost savings to be higher (due to the nonlinear increase of costs at peak times) in the order of 0.8% in November, 0.3% in

December, 0.7% in February, and 0.6% in March. Meanwhile, in terms of environmental impact we find the saving to be approximately equivalent to 450,000 tonnes of carbon dioxide.

In deriving these results we adopted a conservative approach such that we consider them *lower bounds* on any true savings. We also avoided making any study of January. We made use of a robust method which calls for known data to train the prediction equation, but data on time/temperature/light levels prevalent in mid-winter were too far from known data in DST months to make possible accurate predictions using this approach. As the daylight profile in January, the other side of the winter solstice, resembles December, it would not be surprising to find January showing a reduction in demand on DST similar to that found for December, outside the holiday period.

Our headline result is that having BST year-round would lead to energy savings on the order of at least 0.3% in the months in which the UK currently has GMT. In deriving this result we have adopted methodologies currently used in load prediction, in particular SVR, to estimate energy demand on a half-hourly basis. This resulted in predicted daily savings of 0.32% in November, 0.22% in December, 0.32% in February, and 0.32% in March. In terms of actual power involved this translates to approximate savings of 6.6GWh, 4.8GWh, 6.7GWh, and 6.2GWh on average over an entire day in those months respectively. Note that these figures are very similar to those obtained independently and cited in our review of the literature, *cf.* Belzer *et al.* (2008); Kandel and Metz (2001); Ramos and Diaz (1999); Hillman and Parker (1988), for example.

7. References

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