Time Series Analysis of Domestic Electricity Load Profiles

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10th January 2012

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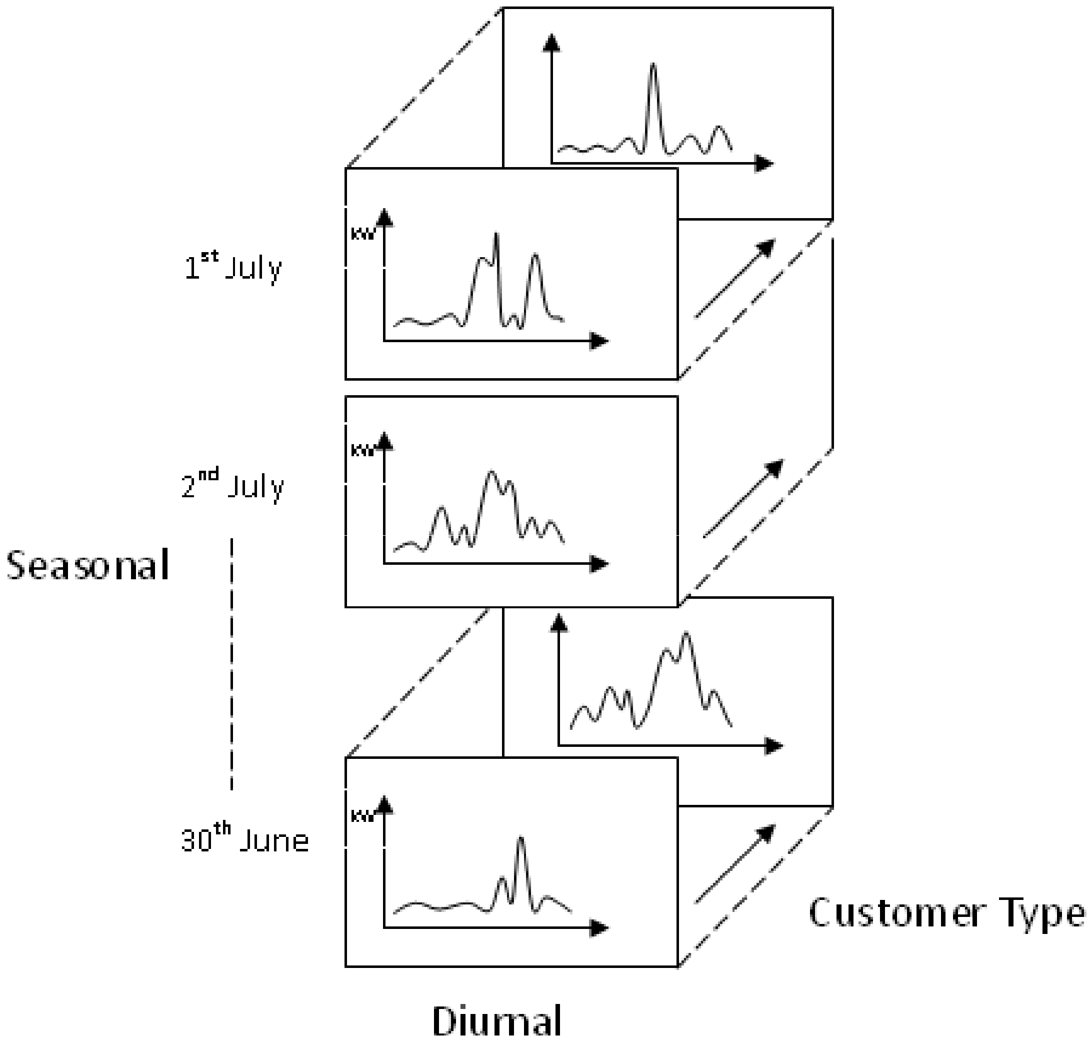
Objective

Design of high time resolution models for domestic electricity demand in Ireland

- Stochastic profiles at thirty minute intervals
- Capable of modelling individual dwelling types
- Other socio-economic variables (dwelling size, no. of occupants, occupancy, appliance holdings)
- Used alongside renewable energy technology models

Characterising Domestic Electricity Load Profiles

- Diurnal (over a 24hr period)
- Seasonal (days of the week to months/seasons)
- Customer type (number of occupants, dwelling size etc..)



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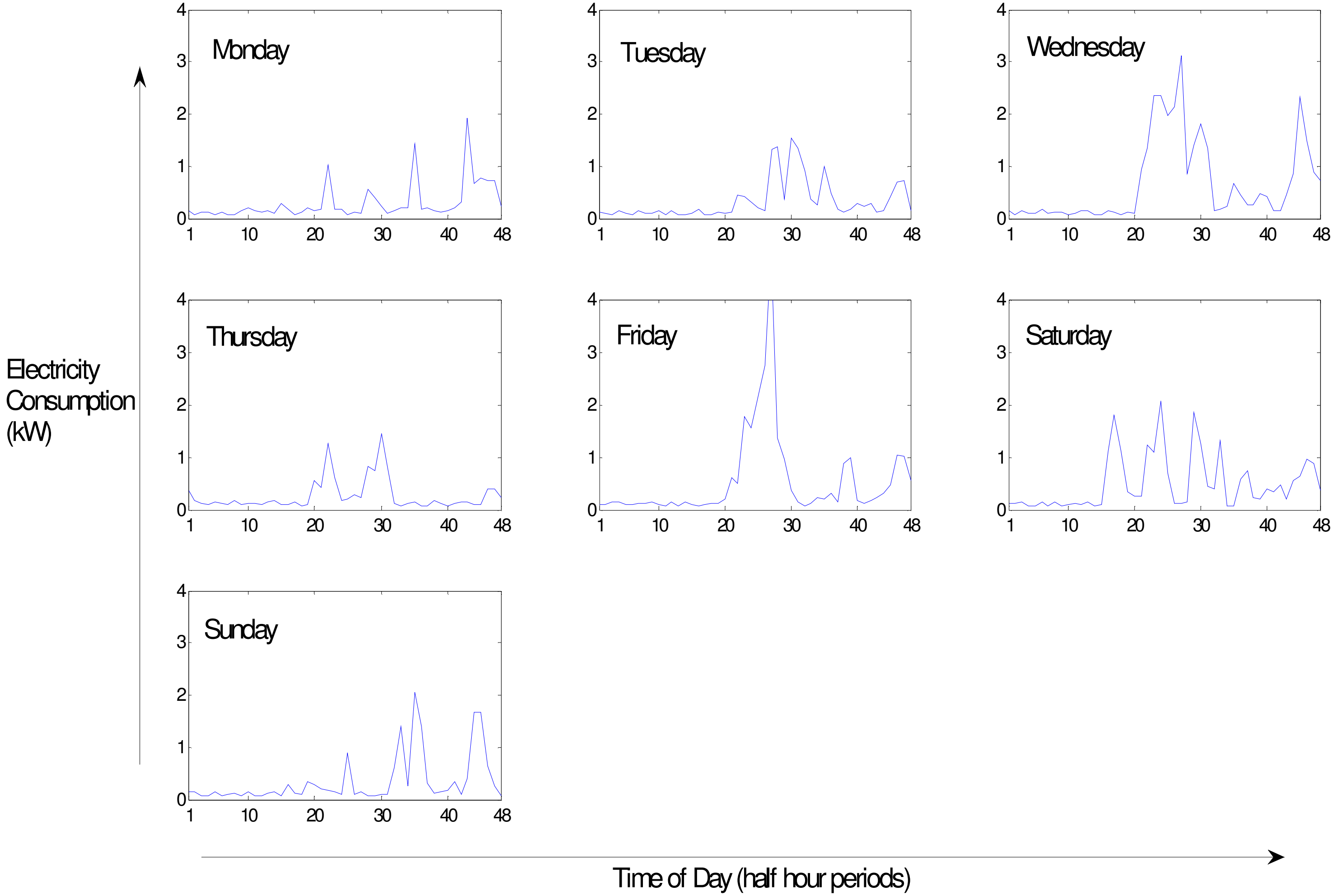
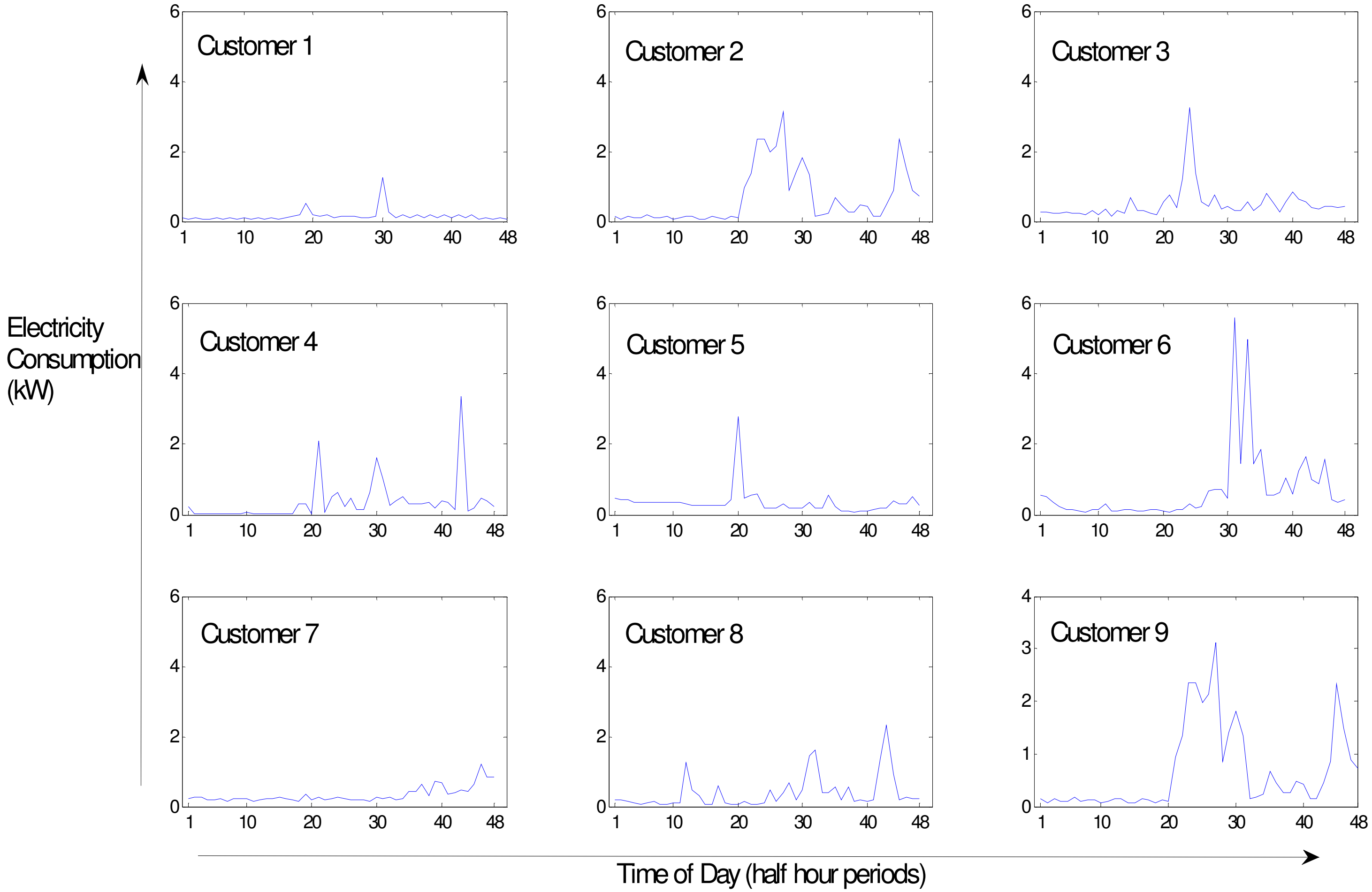

Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Electricity Consumption (kW)
Time of Day (half hour periods)



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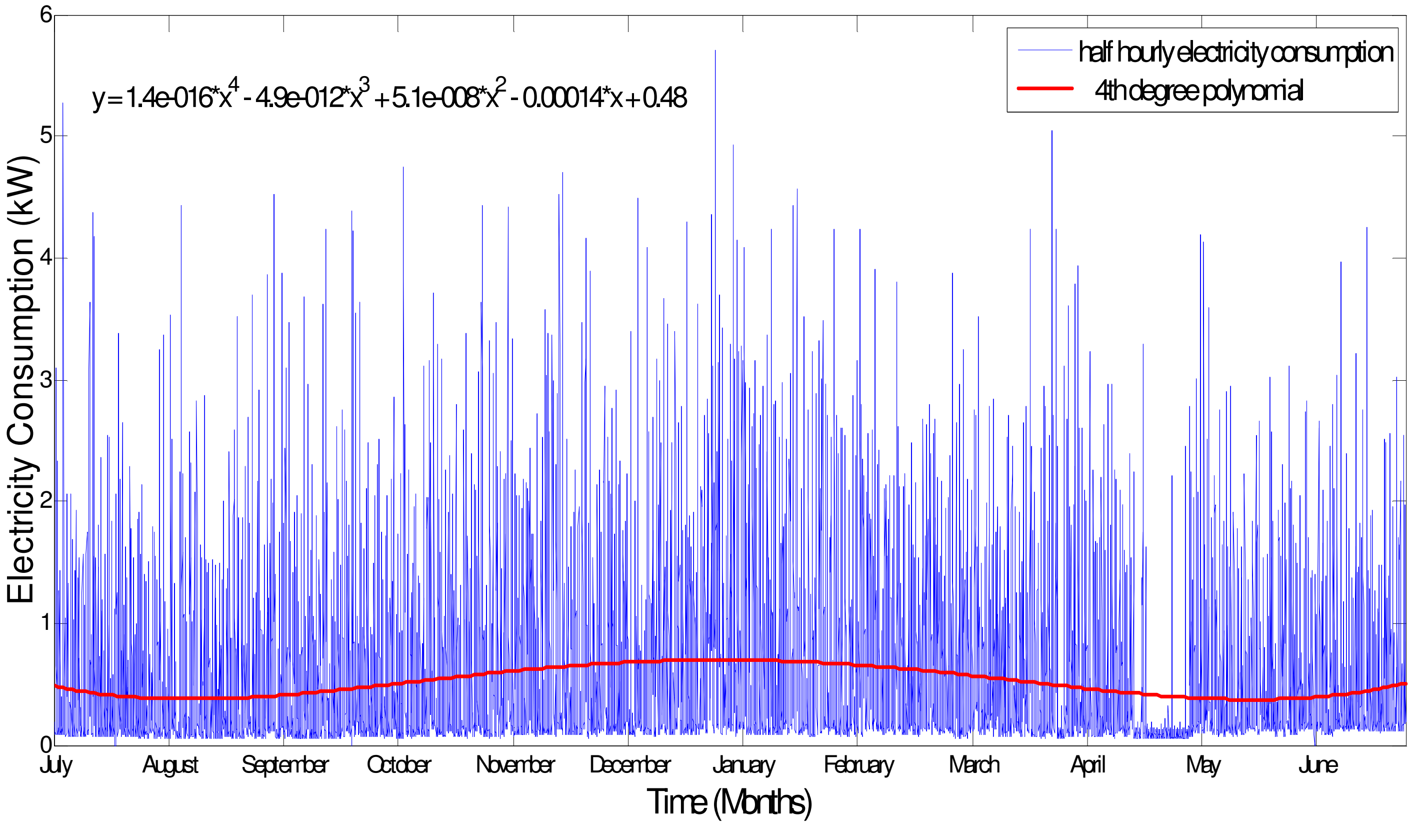

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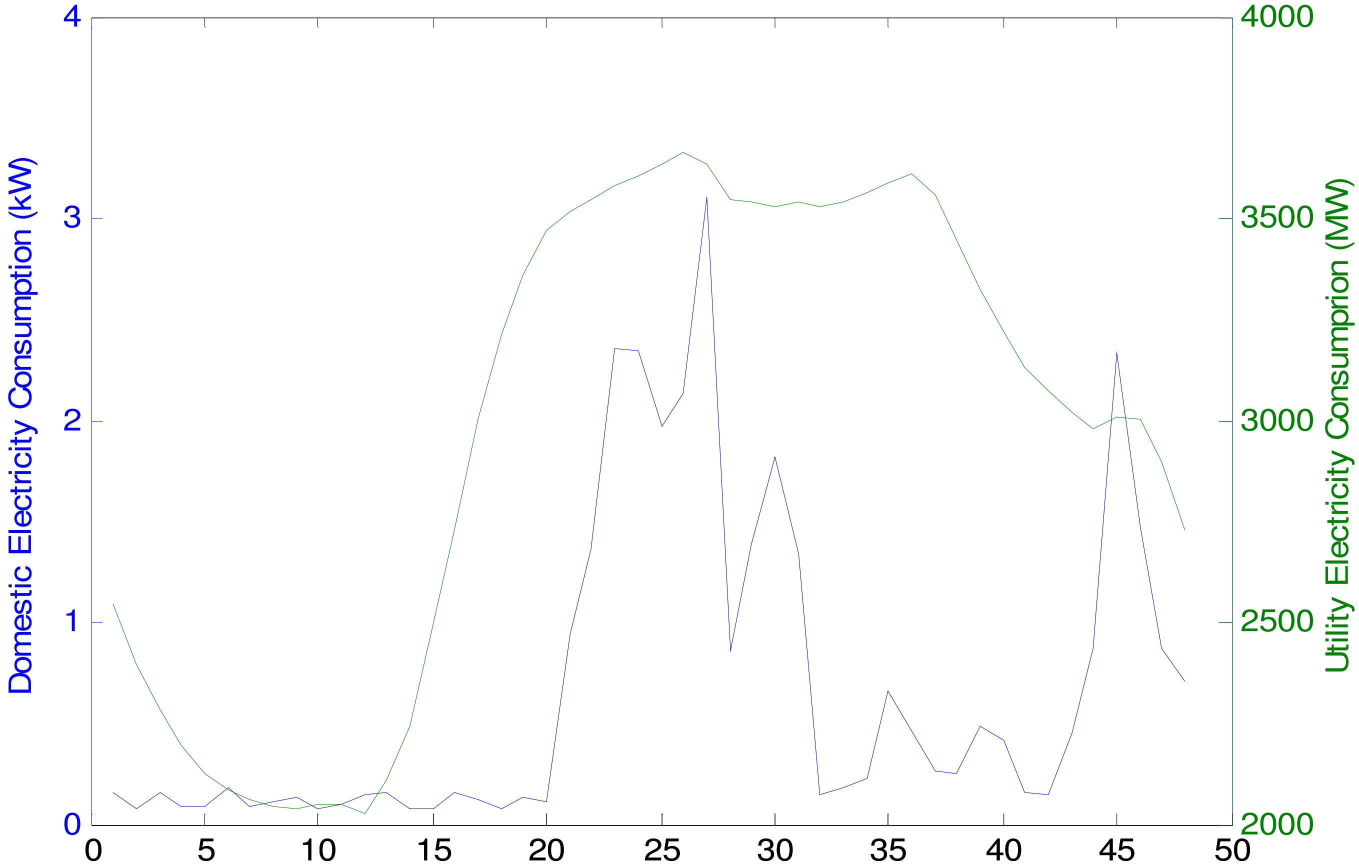
Current Time Series Methodologies

- Fourier Transforms
- Neural Networks
- Gaussian Processes
- Autoregressive
- Fuzzy Logic
- Wavelets
- Multiple Regression/Probabilistic

Utility v's Domestic Load Profile



Methodology

- Apply a time series process that can accurately characterise domestic electricity consumption patterns
- The simpler the better (i.e. least number of descriptors)
- Model must contain temporal and magnitude components to determine the impact of dwelling and occupant characteristics on the load profile shape

Models/Model Attributes	Advantages	Disadvantages
Fourier Series	Some physical significance can be attached to the coefficients of the series - e.g. cos or sin dtermines more or less night time electricity consumption[1].	By definition are poor at approximating sharp spikes as functions (sines and cosines stretch out to infinity) [33]
Neural Networks	Ability to handle non-linear relationships between i/p and o/p. Combining neural networks (to model seasonality) with fourier series can lead to a simpler strucuture being chosen with the same performance [3]	Black box approach. Unclear relationship between i/o and o/p i.e very difficult to determine cause and effect especially with an unknown dataset and hence there is a possability to give unexpected results [21]
Gaussian Processes	Simplicity in modelling as a system can be completely described by two moments (mean and variance) [10]. Two more advantages in [12]. Models can be determined using a relatively small number of points (unlike neural networks) [11].	Has difficulty modelling high peaks and troughs of a domestic load profile. Computational load associated with the need to invert the covariance matrix [12]. As number of model parameters increases linearly, CPU time increases exponentially [10].
Autoregressive	Small number of parameters compared to other models (for ARIMA) [1]	parameter values varied unpredictably with small changes in profile shape [1]
Fuzzy Logic	Can use a large amount of input variables to model output. Fuzzy model attractive in a sense that the relationship between i/p and o/p is clariffied, unlike the black-box method (i.e. NN) [21].	Complicated model structure. Not suitable for large-scale complicated systems [21].
Wavelets	Can handle non-stationary discrete signals [24]. Are well suited to approximating data with shap discontinuities such as domestic load profiles [33]. Has advantage over the Fourier transform in that it allows each frequency conponent to be considered with an appropiate temporal resolution [24].	High frequency conponents are often treated as noise in this model type [23]
Multiple Regression		Large number of parameters required to model daily load p

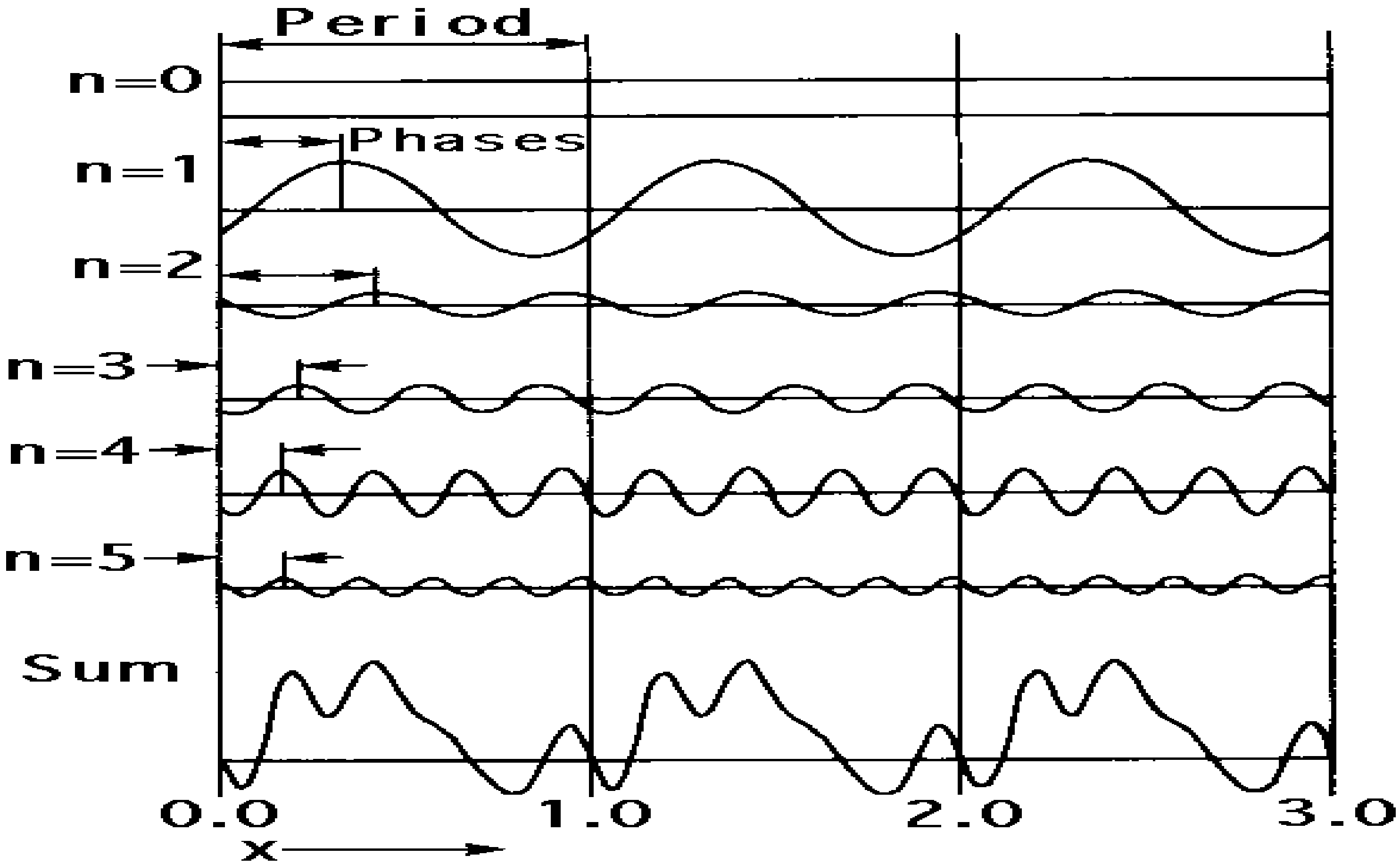
Time Series Models (Fourier Transforms)

$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n cos(nx) + \sum_{n=1}^{\infty} b_n sin(nx)$$

$$a_0 \frac{1}{\pi}\int_0^{2\pi} f(t)dt\,; \quad a_n = \frac{1}{\pi}\int_0^{2\pi} f(t)cos(nt)dt; \quad b_n = \frac{1}{\pi}\int_0^{2\pi} f(t)sin(nt)dt \quad where\ n = 1,2,3$$

The individual coefficients a_n and b_n, where (n=1,2,3…) correspond with the magnitude of each sinusoid at a particular frequency which when summed together represent the original time series signal.

Time Series Models (Fourier Transforms)



Time Series Models (Gaussian Processes)

$$f(z|\gamma) = \sum_{i=1}^{M_c} w_i f\left(z \middle| \mu_i, \sum i\ \right)$$

where M_c is the number of mixture components and w_i is the weight of the *i*th mixture component, subject to $w_i > 0$ and . The mean and variance of each density function is represented by μ_i and respectively.

Results

Compared models using the following parameters and functions:

- R^2 and Descriptive Statistics
- Total Electricity Consumption
- Maximum Demand
- Load Factor
- Time of Use (maximum electricity demand)
- Temporal and magnitude components (autocorrelation and spectral components)

Results

Model	Mean	Median	Standard Deviation	Maximum	Minimum
Fourier Transforms	0.8743	0.8761	0.0418	0.9878	0.6774
Gaussian Processes	0.9447	0.9473	0.021	0.9931	0.7843

Results (Total Electricity Consumption)

Model	Mean	Median	Standard Deviation	Maximum	Minimum	Scale Parameter (η)	Shape Parameter (β)
Targeted Time Series	4,146kWh	4,008kWh	1,870kWh	9,651kWh	414kWh	4,687	2.38
Fourier Transforms	4,146kWh (0%)	4,008kWh (0%)	1,870kWh (0%)	9,651kWh (0%)	414kWh (0%)	4,687 (0%)	2.38 (0%)
Gaussian Processes	4,047kWh (-2.39%)	3,903kWh (-2.62%)	1,835kWh (-1.87%)	9,462kWh (-1.96%)	413kWh (-0.24%)	4,576 (-2.37%)	2.37 (-0.42%)

Results (Maximum Demand)

Model	Mean	Median	Standard Deviation	Maximum	Minimum	Scale Parameter (η)	Shape Parameter (β)
Targeted Time Series	2.34kW	2.29kW	0.92kW	6.18kW	0.14kW	2.6293	2.7425
Fourier Transforms	1.68kW (-28.21%)	1.66kW (-27.51%)	0.68kW (-35.29%)	3.89kW (-58.87%)	0.09kW (-55.56%)	1.8904 (-28.10%)	2.6885 (-1.97%)
Gaussian Processes	2.23kW (-4.70%)	2.20kW (-3.93%)	0.88kW (-4.35%)	5.99kW (-3.07%)	0.13kW (-7.14%)	2.5082 (-4.61%)	2.7394 (-0.11%)

Results (Load Factor)

Model	Mean	Median	Standard Deviation	Maximum	Minimum	Scale Parameter (η)	Shape Parameter (β)
Targeted Time Series	23.23%	22.35%	5.76%	48.69%	11.29%	-1.4935	0.1299
Fourier Transforms	31.79% (36.85%)	30.76% (37.63%)	6.59% (4.41%)	66.72% (37.03%)	18.05% (59.88%)	-1.1703 (-21.64%)	0.109 (-19.17%)
Gaussian Processes	24.74% (6.5%)	23.74% (6.22%)	6.54% (13.54%)	51.76% (6.31%)	11.89% (5.31%)	-1.434 (-3.98%)	0.138 (6.24%)

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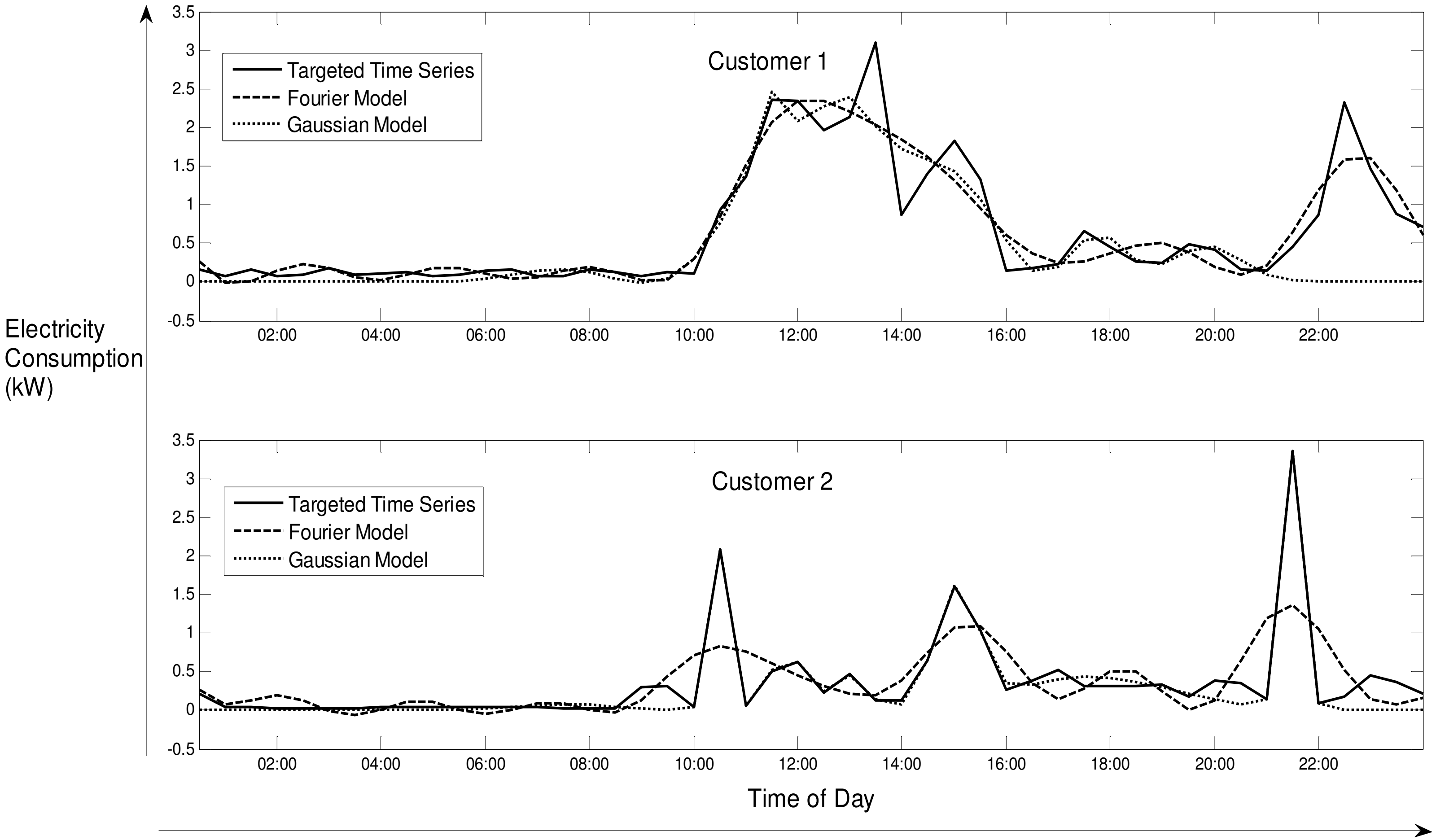
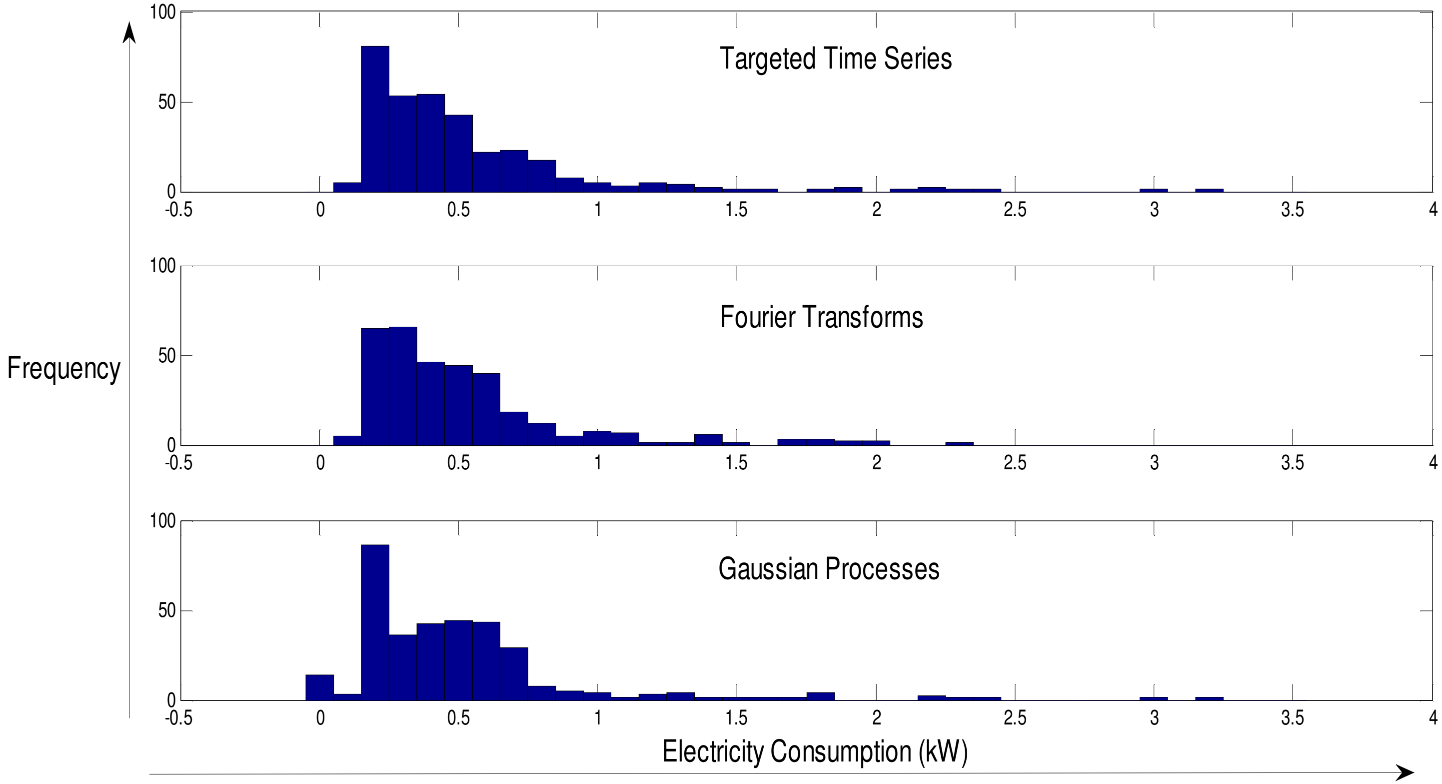
Results (Time of Use)

Model	Mean	Median	Standard Deviation
Targeted Time Series	30.7	31.16	3.52
Fourier Transforms	31.44 (2.41%)	31.84 (2.18%)	3.62 (2.84%)
Gaussian Processes	29.63 (-3.49%)	29.91 (-4.01%)	3.3 (-6.25%)

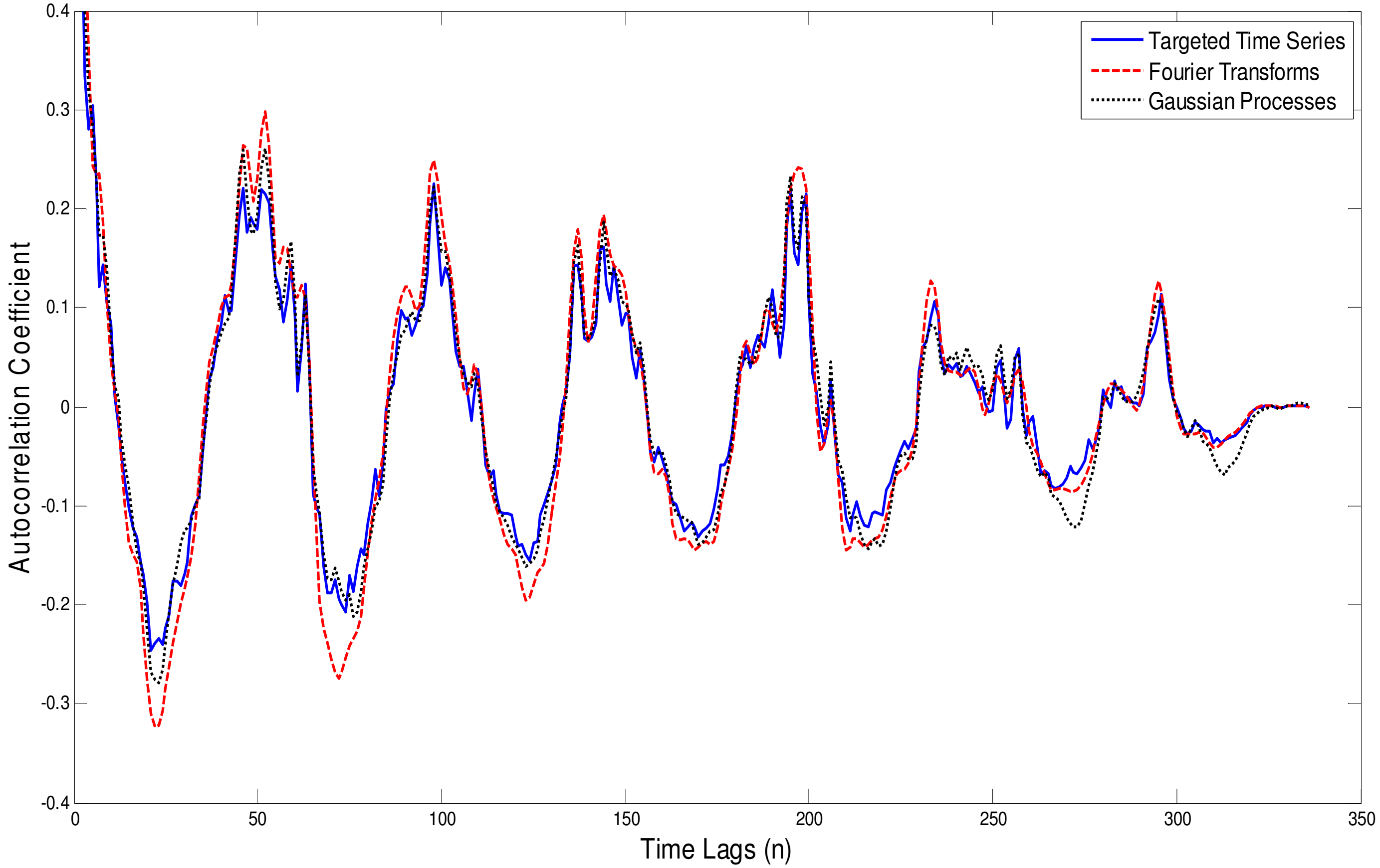
Results (Time Series Plot)



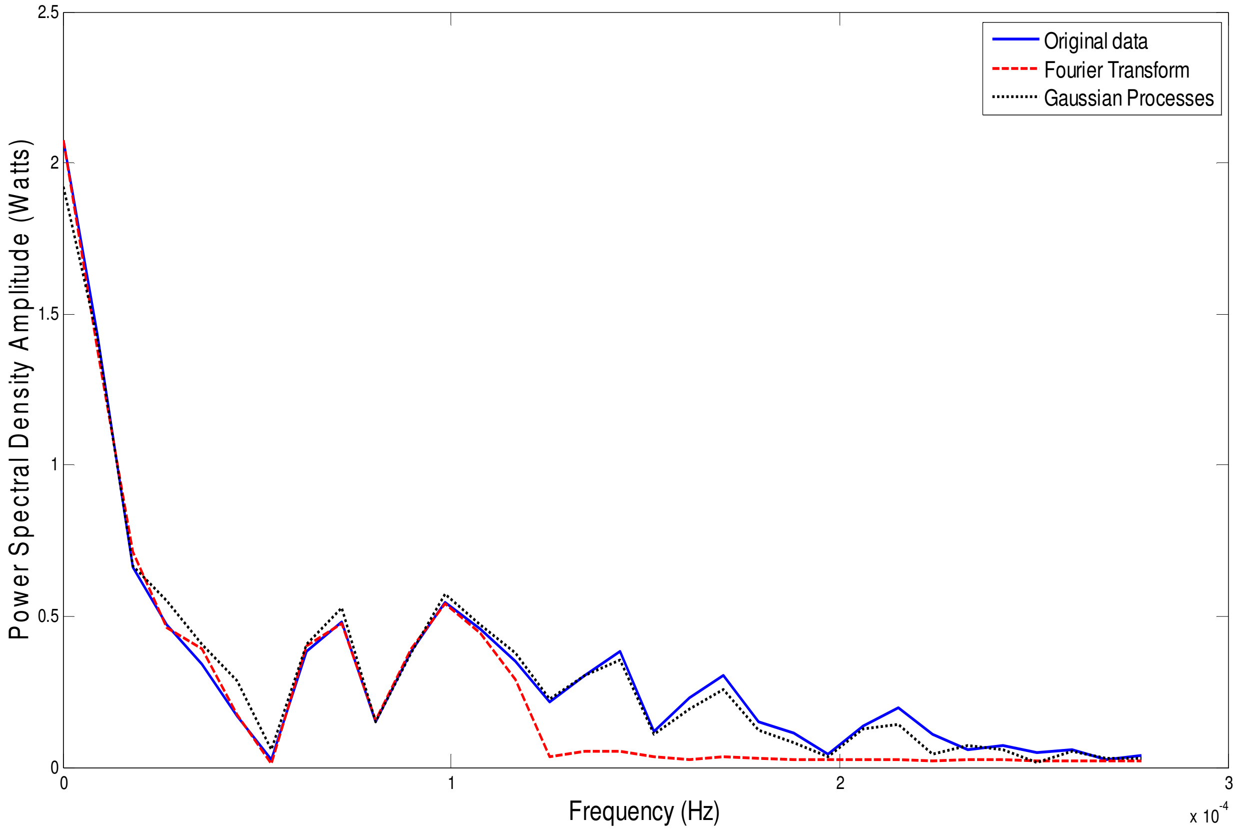
Results (Frequency Histogram)



Results (Autocorrelation)



Results (Spectral Periodgram)

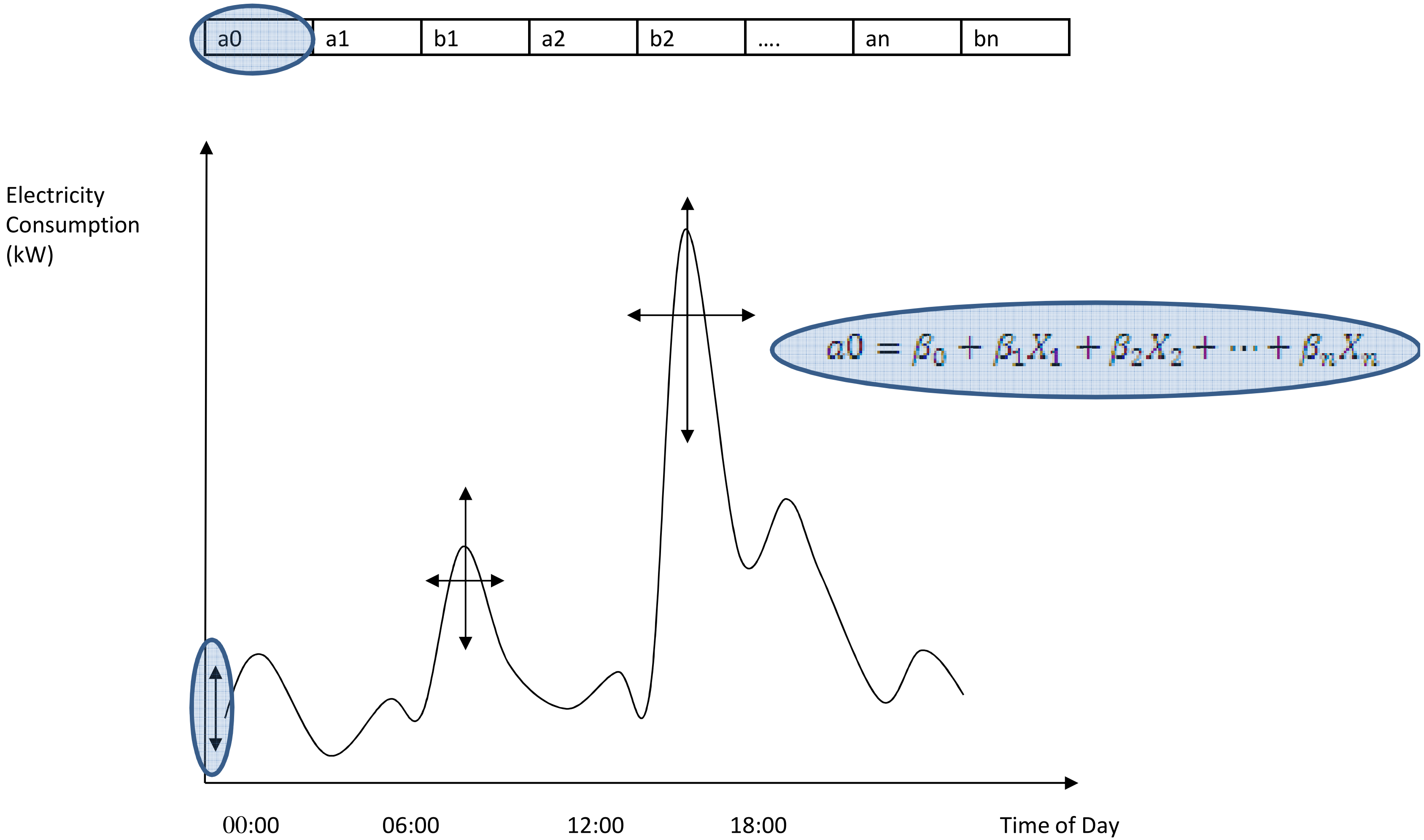


Results Summary

- Fourier Transforms better at modelling customer type 1 i.e. smoother load profiles
- Gaussian Processes better at modelling customer type 2 i.e. fast changing load profiles

Methodology (cont)

- Both Fourier Transforms and Gaussian Processes represent temporal and magnitude components in their model descriptors
- Determine seasonality component and de-trend model parameters
- Apply regression to each model descriptor with dwelling and occupant characteristics for each day of the year and determine influence per customer type
- Validate the results



a0
a1
b1
a2
b2
....
an
bn
Electricity
Consumption
(kW)
$a0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$
00:00
06:00
12:00
18:00
Time of Day

Conclusions

- Time series approaches narrowed down to two most appropriate - Fourier Transforms and Gaussian Processes
- Fourier Transforms better at modelling smoother domestic load profiles where as Gaussian Processes superior at representing fast changing changing profiles
- Methodology presented to model change in profile shape by dwelling and occupant characteristics.

Thank You
&
Any Questions

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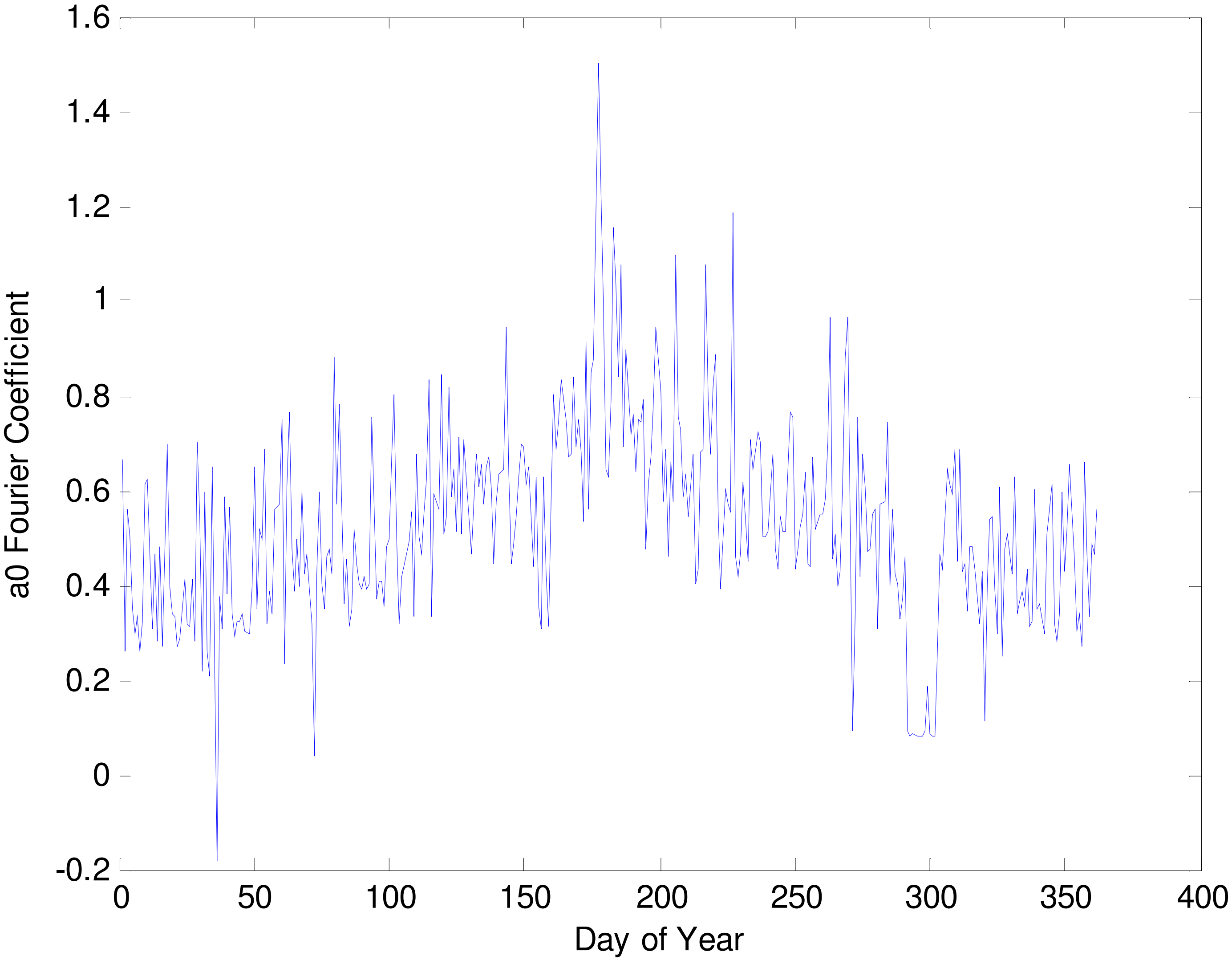

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