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Electricity demand forecasting for decentralised energy management

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ABSTRACT

The world is experiencing a fourth industrial revolution. Rapid development of technologies is advancing smart infrastructure opportunities. Experts observe decarbonisation, digitalisation and decentralisation as the main drivers for change. In electrical power systems a downturn of centralised conventional fossil fuel fired power plants and increased proportion of distributed power generation adds to the already troublesome outlook for operators of low-inertia energy systems. In the absence of reliable real-time demand forecasting measures, effective decentralised demand-side energy planning is often problematic. In this work we formulate a simple yet highly effective lumped model for forecasting the rate at which electricity is consumed. The methodology presented focuses on the potential adoption by a regional electricity network operator with inadequate real-time energy data who requires knowledge of the wider aggregated future rate of energy consumption. Thus, contributing to a reduction in the demand of state-owned generation power plants. The forecasting session is constructed initially through analysis of a chronological sequence of discrete observations. Historical demand data shows behaviour that allows the use of dimensionality reduction techniques. Combined with piecewise interpolation an electricity demand forecasting methodology is formulated. Solutions of short-term forecasting problems provide credible predictions for energy demand. Calculations for medium-term forecasts that extend beyond 6-months are also very promising. The forecasting method provides a way to advance a novel decentralised informatics, optimisation and control framework for small island power systems or distributed grid-edge systems as part of an evolving demand response service.

1. Introduction

An energy transition is needed to address environmental challenges of greenhouse gas-induced warming and increased carbon emissions, which are largely driven by a rapid growth in global population [1]. Smart city technologies can help reshape cities to become more efficient and their energy infrastructures more sustainable [2]. Recent trends toward decarbonisation, digitalisation and decentralisation are seeking to build out centralised state owned power assets, focusing instead on investments in energy storage, demand response and improved energy efficiency [3]. In the energy field, these principles are often expressed in smart infrastructure initiatives that are focused on increasing capacity of low carbon technologies while improving the efficiency and resilience of energy production [4]. Constructing energy systems into more sustainable forms means electricity demand forecasting is necessary. As a broad guideline, research has shown that energy consumption in buildings accounts for approximately 40% of the world's energy resources and emits circa one-third of greenhouse gases [5,6]. Considering the long lifespans and complex challenges associated with regeneration of old building stock [7], more accessible energy retrofit initiatives to achieve energy saving targets are needed. Tangible measures that improve energy efficiency include lifestyle changes, e.g., use of smart meters [8], and distribution system planning as well as improving load and resource forecasting methods and approaches [9].

Numerous technical barriers make forecasting of electricity demand challenging, especially in areas that support a combination of different distributed renewable energy generators that lack the flexibility and capacity offered by centralised energy systems. Analysis of temporal data and development of forecasting models are often presented as multivariate time series problems [10–13]. However, multivariate time series considers simultaneous time-dependent variables where each variable depends not only on its past values but also has some dependency on other variables. Thus, multivariate prediction may prove difficult to extract enough meaningful information that is useful for predicting future states. In contrast, a univariate time series with a single time-dependent variable may offer an improved alternative when prediction time horizons are small [14].

In this paper we propose a data-driven methodology for modelling electricity demand forecasting. Using this approach, researchers have been able to show evaluation of energy prediction models based on collected energy consumption data outperform more informed models

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Nomenclature

n	number of observations
t	time
y_t	value of y at time t
y_i	original value of y at time i
l	lower input range (min-max feature scaling)
u	maximum of input range
x_{min}	minimum value of x in range
x_{max}	maximum value of x in range
k	number of equal sized segments
PAA	piecewise aggregated approximation
$\bar{x}_i$	mean value of each segment
$\bar{X}_i$	k-dimensional vector of $\bar{x}_i$
$S_i(x)$	piecewise function
$a_i, \ldots, d_i$	cubic polynomial coefficients
lo	start data point of PAA segment
hi	end data point of PAA segment
R^2	coefficient of determination
d_t	demand forecast predicted value
O_t	observed (actual) values at time stamp t
c	weekly seasonality period index
$MTWTF$	days of week
SS	days of weekend

that rely on laws of physics and often complex building configurations [15,16]. This work has uniqueness by using techniques that are in part long established in data mining processes that aim to extract useable patterns in huge data sets [17]. Research in this paper is specific to GB National Grid demand data [18]. Accurate predictions using demand data from other sources is straightforward. However, obtaining reliable econometric forecasts in electricity demand using data collected from developing states experiencing rapid growth, is more challenging [19]. Demand data collected from countries in conditions of stable economic growth, when combined with piecewise interpolation, the forecasting model is developed on the premise that a forecasting session is dependent on a lookup table derived uniquely from a univariate quantitative time series. The implication of this novel semi-autonomous simplified lumped model has the potential to offer decentralised electricity network operators' knowledge of wider aggregated rate of future energy consumption. Thus, enabling decentralised energy management systems to proactively shift load demand on small island electricity grids or distributed grid-edge systems as part of an evolving demand response service or on receipt of base-point dispatch instructions (Fig. 1).

The rest of the paper is structured as follows. Section 2 introduces the proposed methodology for electricity demand forecasting. Section 3 extends the background to this article by placing the proposed methodology as an essential component of a much broader and evolving demand response service. Results and discussions are provided in Section 4. Finally, in Section 5, the main conclusions are presented with recommendations for future work.

2. Electricity demand time series forecasting methodology

The proposed data-driven methodology is divided into three distinct parts (Fig. 2). Analysis of a chronological sequence of discrete observations is first performed and the composition of the univariate one-dimensional time series is determined. In the second step, a dimensionality reduction technique is applied before piecewise interpolation is used in the third step to smooth subsequent consecutive polynomial segments. A resultant lookup table provides the necessary metadata for the forecasting algorithm to model the demand characterisation. The objective is to maintain an accurate 4-h electricity demand prediction

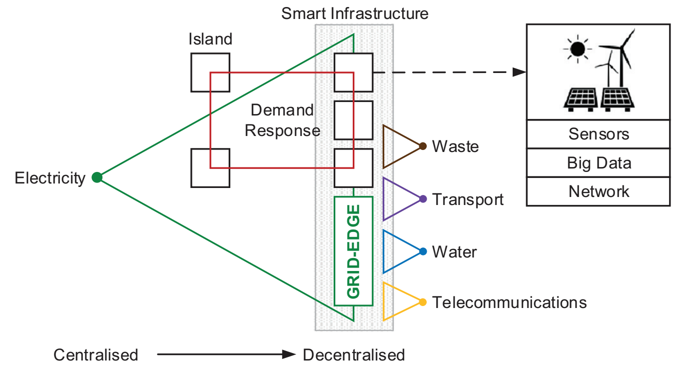

Fig. 1. Electricity demand in smart infrastructure.

horizon. However, results show this can be changed to much longer periods while maintaining competitive results.

2.1. Composition of time series

The Electricity System Operator (ESO) in Great Britain publishes historic national demand data [18]. The data represents the generation requirement, utilising National Grid operational generation metering recorded at 30-min intervals. In this paper analysis is based on national demand data from 1 April 2005 to 31 March 2019, comprising 245,424 data items. The performance of the proposed forecasting method is validated against more recent demand data. The first task is to extract meaningful characteristics. Computing the autocorrelation of the time series identifies the periodicity of the signal. Fig. 3 shows the time period between each peak is consistent with a typical weekly pattern consisting 5 similar weekday oscillations followed by 2 weekend day oscillations, also of similar form.

Regression is used to remove fluctuations in the time series and to identify potential seasonal and cyclic behaviour. The approach used to remove the trend from the time series first calculates the least squares regression line before subtracting the deviations from the least squares fit line from the time series. Given the equation for a straight line is $y = bx + a$ where b is the slope of the line and a is the y-intercept, the best fit line for points $(x_1, y_1), \ldots, (x_n, y_n)$ is given by $y - \bar{y} = b(x - \bar{x})$ where

$$b = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{n} (x_i - \bar{x})^2 \quad (1)$$

and $a = \bar{y} - b\bar{x}$. In the absence of outliers, Eq. (2) is used to apply the min-max feature scaling which normalises the time series. Where the lower input range $l = 0$ and maximum of input range $u = 100$.

$$x' = l + \left[(x - x_{min})(u - l)\right] / (x_{max} - x_{min}) \quad (2)$$

A 9 × 48 × 14 multi-dimensional array characterises 14 distinct weeks, where each week identified commences on the Monday immediately following the lowest recorded demand data in each year (2005 to 2019). Measurements recorded at 30-min intervals for each day are assigned to columns 1 to 48; the mean value of rows 1–5 (weekdays) and rows 6 and 7 (weekend days) are assigned to rows 8 and 9, respectively. A mean value of the collective row 8 and row 9 are then computed to enumerate a generalised demand profile shape for any weekday and weekend day, respectively.

A simple moving average of order n process given at Eq. (3) smooths the original demand data y_i; where n represents a set number of observations for one month and year, respectively.

$$y_t = \frac{1}{n} \sum_{i=t-n+1}^{t} y_i \quad (3)$$

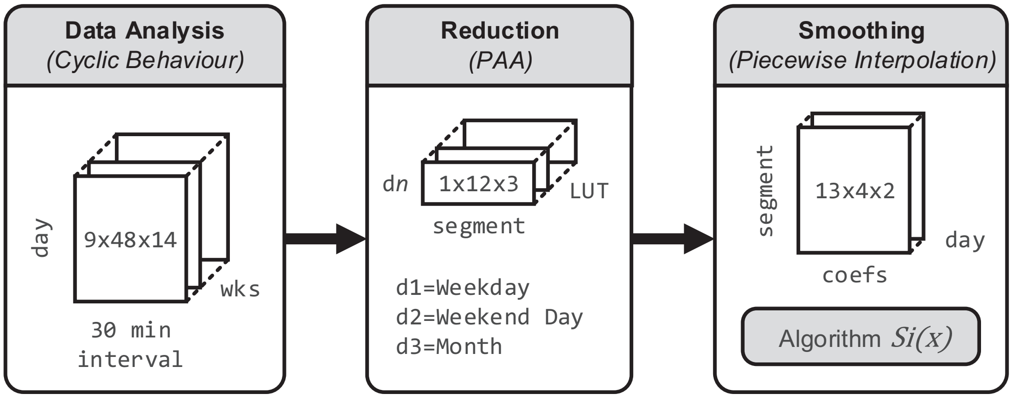

Fig. 2. A visual representation of the methodology.

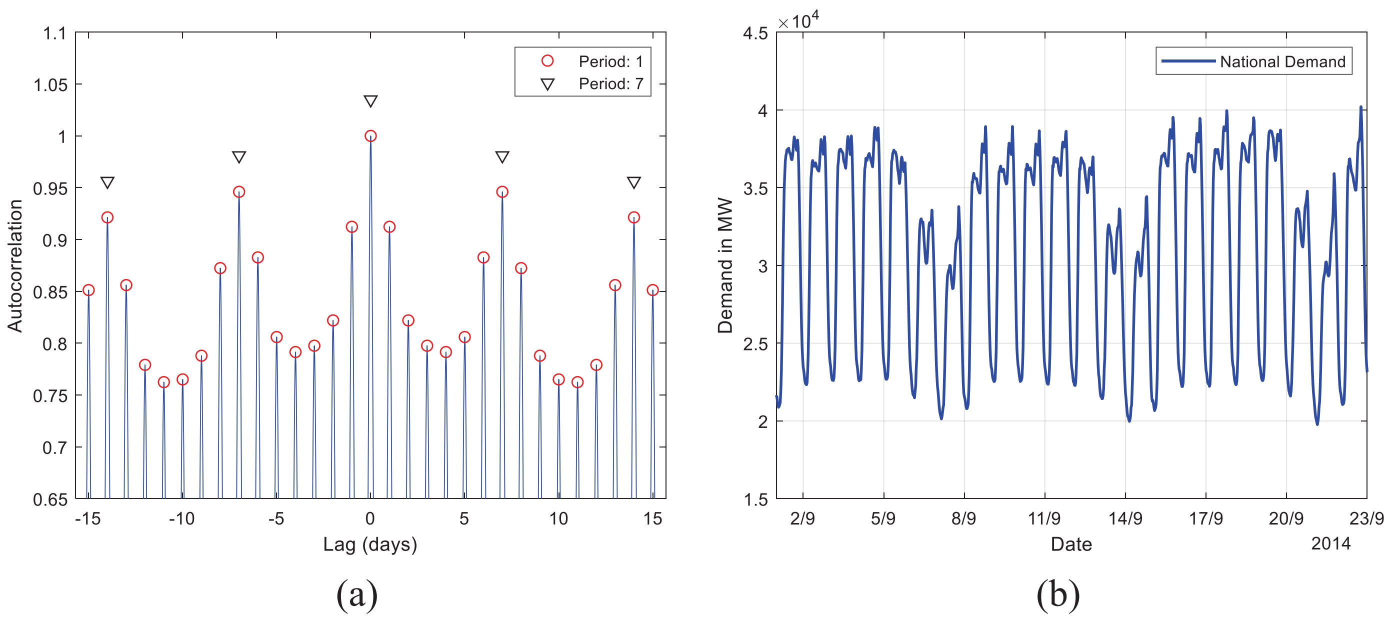

Fig. 3. (a) Autocorrelation shows weekly pattern, (b) UK National Demand profile.

Analysis reveals in addition to daily/weekly characteristics the time series also displays seasonality and negative secular trend with constant variability. The general idea is to define a model from historical time series that enumerates the cyclic behaviour and negative secular trend that can be used as part of the forecasting algorithm. For seasonality, the basic route is to calculate the mean of each moving average 12-month period before applying a dimensionality reduction technique. Furthermore, in this strategy the negative secular trend is expressed in mathematical terms by using Eq. (1). Here, the coefficients for a polynomial that is a best fit (least squares method) of the given set of data are calculated.

The composition of the time series observed is characterised by 3 seasonal patterns: weekday, weekend day and month. Given the volume of historical data available, a yearly trend is also identified. In the following sections we first present a method to reduce time series feature dimensionality and then formulate the forecast prediction algorithm.

2.2. Dimensionality reduction

Time series analysis is a statistical technique often used to analyse the pattern of discrete observations over time to forecast future events. When the number of observations is large, time series analysis becomes time consuming. Dimensionality reduction techniques can be used to help improve the classification of big data for time series analysis, thus improving the efficiency of the forecasting process. Piecewise aggregate approximation (PAA) proposed by Keogh et al. [20] is a well-known technique that reduces the dimensionality of a time series and for data representation. We choose to approximate the data with a piecewise coefficient such that the period between each change point is 2-h. In this method, the normalised demand time series window of size n is first divided into k segments of equal length. The average value of the data of the segments is then used as the representative value of each segment. Therefore, the demand time series PAA representation will be a k-dimensional vector $\bar{X}_i = \bar{x}_1, \ \ldots \ , \bar{x}_n$ of the mean values of each segment. The dimensionality reduction calculation is computed by Eq. (4).

$$\bar{x}_i = \frac{k}{n} \sum_{j=\frac{n}{k}(i-1)+1}^{\frac{n}{k}i} x_j \tag{4}$$

Simply stated, in order to reduce the time series dimensionality of length n to k, the data is first divided into k equally sized segments then the mean value of the data in each segment is calculated. The subsequent vector of these values represents the reduced dimensionality of the original dataset.

Table 1
Piecewise coefficient lookup table.

Weekday	Weekend day	Month
[15.34, 10.47, 24.00, 77.11, 95.94, 98.02, 93.98, 94.64, 96.79, 84.46, 73.32, 36.16]	[11.87, 3.80, 3.29, 29.24, 55.42, 60.76, 53.30, 51.31, 59.67, 58.02, 55.84, 28.58]	[40.11, 32.81, 30.23, 29.39, 29.00 34.97, 44.18, 57.63, 61.01, 65.00, 63.33, 53.23]

The equation provides the mean of the elements in the equi-sized frames which makes up the vector of the reduced dimensional time series. The method is applied to the *day* and *month* features. A numerical investigation comparing different piecewise coefficients confirms reduced dimensionality while preserving enough information about the original data.

After the time series is transformed into segments using PAA technique the data is discretised, grouping the continuous input into a finite number of discrete bins. The translation means the data dimensionality can be reduced further and converted into a symbol string using symbolic aggregate approximation (SAX), i.e., each region is assigned a symbol according to the determined change points. In the context of data mining, SAX is comparable to other techniques including discrete Fourier transform and discrete wavelet transform while requiring less storage [21]. This strategy is particularly useful for low-complexity solutions, as they are less data-intensive than more complex econometric methods and models needed for forecasting [22]. In this work, the SAX symbol string (symbolic conversion) is a 4-bit binary representation of the discrete bin the continuous input was assigned after discretization.

In contrast to using techniques based on pattern sequence similarity, the proposed methodology extracts singularities of bin data to create a series of lookup tables (LUT). Given the length of each piecewise segment, the process of creating lookup tables for weekday, weekend day and month PAA or SAX representations is straightforward. In this paper, we present a LUT based on piecewise coefficient only. The main advantage of using the PAA approach in this context is that it requires less computational effort when compared to symbol mapping techniques in order to achieve a visualisation of the time series. Furthermore, segment centre points are placed at fixed regular intervals which results in a cubic interpolation were many of the demand data characteristics are retained during the transformation. In other words, the higher the reduction ratio is, the worse the performance of calculated approximation. This combination of findings has important implications for developing an energy optimisation algorithm described in Section 3.

Given each PAA segment is equivalent to a 2-h epoch, the time series original 245,424 data items is now reconstructed from just 12 elements for each *day* and *month* feature (Table 1). This opens the possibility to perform forecasting up to 1 calendar month based on weekday and weekend day LUT. Extending the time horizon further up to 12-months requires the month LUT. When a seasonal adjustment is included, forecasting beyond 12-months is achievable. The mathematical representation of seasonal adjustment is derived using a straight-line approximation of the 12-month moving average, i.e., $y = bx + a$ where $b = 0.000442$ and the y-intercept a is set to the initial calculated weekday value.

2.3. Piecewise interpolation

When reducing the dimensionality of large data using piecewise aggregated approximation a compromise must be reached between how much the dimensionality of the original data can be reduced and the capacity to maintain competitive results. A cubic interpolation is used to obtain a somewhat smoother interpretation of the graph first created using the piecewise coefficient lookup table. Calculating a cubic polynomial that interpolates points of interest helps restore the shape of the original demand forecast profile. The centre point of each PAA segment defines a set of evenly spaced nodes. The piecewise function $S(x)$ interpolates all local data points and hence confines the ill-effects of any erroneous data points, Eq. (5).

Table 2
Piecewise cubic polynomial coefficient lookup table.

Weekday				Weekend day			
a_i	b_i	c_i	d_i	a_i	b_i	c_i	d_i
21.000	0	0.512	−0.256	21.000	0	0.750	−0.375
21.000	−1.024	−1.024	0.155	21.000	−1.501	−1.501	0.200
10.470	−1.755	0.841	0.111	3.802	−3.895	0.902	0.010
24.002	10.294	2.171	−0.256	3.296	3.801	1.022	−0.088
77.116	10.563	−2.104	0.160	29.242	7.771	−0.029	−0.069
95.942	1.409	−0.185	−0.009	55.425	4.212	−0.861	0.035
98.022	−0.518	−0.297	0.044	60.764	−0.976	−0.436	0.053
93.986	−0.802	0.226	0.004	53.302	−1.901	0.205	0.037
94.648	1.196	0.273	−0.109	51.312	1.490	0.643	−0.123
96.800	−1.872	−1.041	0.184	59.670	0.717	−0.836	0.138
84.466	−1.344	1.173	−0.383	58.022	0.675	0.826	−0.283
73.323	−10.360	−3.427	0.687	55.848	−6.283	−2.565	0.490
21.000	−4.8140	4.814	−1.203	21.000	−3.309	3.309	−0.827

$$S_i(x) = a_i + b_i\left(x - i_{lo}\right) + c_i\left(x - i_{lo}\right)^2 + d_i\left(x - i_{lo}\right)^3 \tag{5}$$

Where $i \in [0, 1, \ldots, n]; x \in [lo, hi]$; where lo and hi define the start and end data points of each PAA segment, respectively. The cubic polynomial coefficients are represented by the parameters a_i, b_i, c_i and d_i (Table 2). Tuning the first and end polynomial interpolants helps prevent extreme endpoint behaviour and improves concatenation of weekday and weekend day demand profiles. A 13 × 4 × 2 multi-dimensional array defines a new polynomial coefficient structures for weekday and weekend day (Table 2).

2.4. Baseline and performance evaluation indices

Assessing the accuracy of the demand forecast is an important consideration. In reviewing the literature, Makridakis and Hibon [23] found that simple forecast methods "do as well, or in many cases better than statistically sophisticated ones like ARIMA and ARARMA models". For information that contrasts the ARIMA model to the long range and short range forecast provided by an ARARMA model, see Parzen [24]. Comparison of the findings with those from other studies confirms that the simplest benchmark in forecasting literature is calculated using the random walk. The forecast from a random walk model is equal to the last recorded observation, thus the random walk model underpins naïve forecasts. That is, $\hat{y}_{t+h|t} = y_t$, where $\hat{y}_{t+h|t}$ represents the estimate of y_{t+h} based on the data $y_1, \ldots, y_t$. Visual inspection of the demand time series shows the data contains daily, weekly and monthly seasonal patterns (Fig. 3) and, if the dataset extends over years, a 12-month negative secular trend with constant variability. Naïve2 forecasting model is well suited to seasonally adjusted data, therefore the first benchmark of the proposed methodology will be assessed using this method. In this analysis we limit h to 7-days (336 samples) which incorporates the distinct variation between weekday and weekend day seasonality. Thus, the forecast can be written as

$$\hat{y}_{t+h|t}(t) = \begin{cases} y_{t+h}(t) \\ y_{t(h-7)}(t) \end{cases} \quad \text{where } h \text{ includes days of } 1-\text{week (MTWTFSS)} \tag{6}$$

The second method used to compare the proposed methodology is based upon the simple notation for forecasts with a seasonal pattern

$\hat{y}_{t+h|t} = (u_{t-1} + v_{t-1})s_{t-c}$, where c represents the weekly seasonality period index ($c = 336$), $\hat{y}_{t+h|t}$ is the h-step ahead forecast and,

$$\text{Level } u_t = \alpha\left(y_t/s_{t-c}\right) + (1+\alpha)\left(u_{t-1} + v_{t-1}\right)$$
$$\text{Trend } v_t = \beta\left(u_t - u_{t-1}\right) + (1+\beta)v_{t-1} \tag{7}$$
$$\text{Seasonality } s_t = \gamma\left(y_t/u_t\right) + (1-\gamma)s_{t-c}$$

where α, β and γ are the smoothing parameters. The Holt-Winters additive method, Eq. (7), is one of several exponential smoothing methods that has the capacity to deal with seasonality and can be easily applied. However, for the Naïve2 and Holt-Winters forecasting models to remain effective they are required to be re-trained as new observations become available. The lack of recent demand information for these models is a serious weakness and impacts the models continued performance.

In this article, 4 indices are used to evaluate the performance of an individual forecasting progress. These include root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and the coefficient of determination or R Squared (R^2). A calculation that estimates the variance and differences using RMSE is defined as,

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(d_t - O_t\right)^2} \tag{8}$$

Where n denotes the number of observations, d_t are demand forecast predicted values and O_t are observed (actual) values at time stamp t.

Mean absolute percentage error is a measure that is widely used when comparing forecasting methods. The forecast error at time t is $e_t = O_t - d_t$. Hence, the percentage error $e_t = (O_t - d_t)/O_t$ so that the mean absolute error for period t is,

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{O_t - d_t}{O_t}\right| \times 100 \tag{9}$$

Mean absolute error is a scale-independent parameter that is used to demonstrate the efficiency of the forecasting outcome.

$$MAE = \frac{\sum_{t=1}^{n}\left|d_t - O_t\right|}{n} \tag{10}$$

The coefficient of determination R^2 is derived using a ratio of explained variation ($SS_{regression}$) i.e., how well the regression model represents the actual demand data, to the total variation (SS_{total}), i.e., the variation in the observed data,

$$R^2 = \frac{SS_{regression}}{SS_{total}} \tag{11}$$

The approach undertaken to analyse the prediction performances is described. Several benchmark tests are performed using a series of nominated test dates. For each specified test date, a new Holt-Winters estimation model is created using the previous 4-weeks of in-sample demand data. The forecast horizon window is set to include one within-week seasonal pattern, i.e., $h = 336$ ahead samples with smoothing parameters $\alpha = 0.82$, $\beta = 0$ and $\gamma = 0$. The construct of the proposed forecast model brings a distinct advantage, for each forecast session the practitioner can specify a start date and forecast horizon window. Therefore, the first set of tests compares the Holt-Winters benchmark model to forecasts generated using the same specified dates. In addition, a single Naïve2 benchmark model created using in-sample demand data (27 June to 3 July 2005) is compared to forecasts generated using the same nominated test dates. The Naïve2 model functions on the same principle as the proposed forecast model, i.e., it is not immediately dependent on the availability of new observed data.

3. Motivation

A proposed decentralised, informatics, optimisation and control framework, designed to optimise and schedule energy consumption in blocks of buildings requires access to a simplified lumped model for

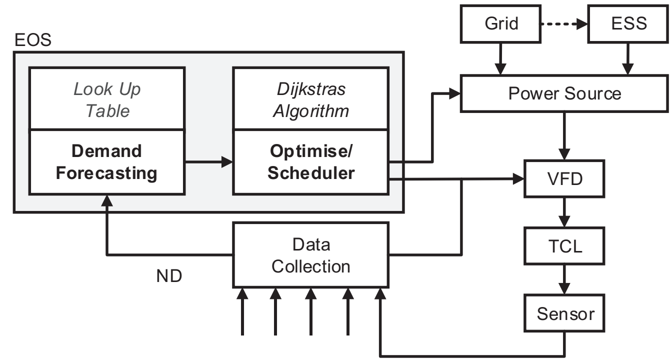

Fig. 4. Information flow block diagram.

electricity demand forecasting [25]. The research promotes using real-time grid frequency measurement for proactive and rapid restoration of frequency equilibrium during network stress events. In addition, an electricity demand forecasting session aims to serve as a secondary control, exploiting building thermal inertia, during evolving demand response services. However, modelling non-linear electricity consumption with a 4-h horizon window that can be easily generalised to forecast demand in decentralised locations is still underdeveloped. The purpose of this paper is to formulate a new methodology which will help address this gap.

A control framework proposes to influence zonal temperature setpoint through an multi-objective cost function that is based on a weight-based routing algorithm [26,27]. It's application in optimisation continues to attract much attention [28,29]. Traditionally the Dijkstra's algorithm is used to calculate the shortest path(s) in a weighted directed acyclic graph (DAG). Since the objective here is to optimise the transition between non-negative features in real-time over a finite period the construct of the Dijkstra's algorithm is of interest. In this context the total weight of each edge between any two consecutive nodes is calculated as a function of thermal comfort, cost (tariff) and rate at which electricity is consumed (demand). The proposed methodology estimates the rate at which electricity is consumed over a 4-h horizon window. Describing the demand profile using spine interpolation, it is possible to forecast demand at a higher rate than currently made available. A generalised block diagram that shows the contribution of demand forecasting is shown at Fig. 4.

4. Results and discussion

The above methodology has been applied to the UK electricity demand data (2005 to 2019). Fig. 5 shows the following data over a 24-h period: (1) enumerated mean demand data after dimensionality reduction technique (PAA) has been applied, (2) the 4-bit binary representation of the bin number that was assigned after symbolic discretization (SAX), and (3) a plot of generalised demand data for weekday (MTWTF) and weekend days (SS).

It can be noticed that the effect of SAX encoding reduces the weekday and weekend day LUT further from 12 elements to 7. Although discretization and SAX encoding offers the potential to reduce PAA dimensionality further, in the context of an energy optimisation system, a demand forecast based on PAA and piecewise interpolation has the potential to offer greater benefit. The results of constructing the cubic interpolants on the clamped discretised PAA subintervals are shown in Fig. 6(a). The plot compares the following 4 demand profiles: (1) actual demand data (Actual) measured over a 24-h period on Monday 4 July 2005, (2) calculated cumulative mean value (Cmean) of 14 selected weekday demand profiles over a 15 year period (2005 to 2019), (3) calculated local mean value (Lmean) of 4 weekday demand profiles week commencing 4 July 2005, and (4) calculated demand data (Model) using

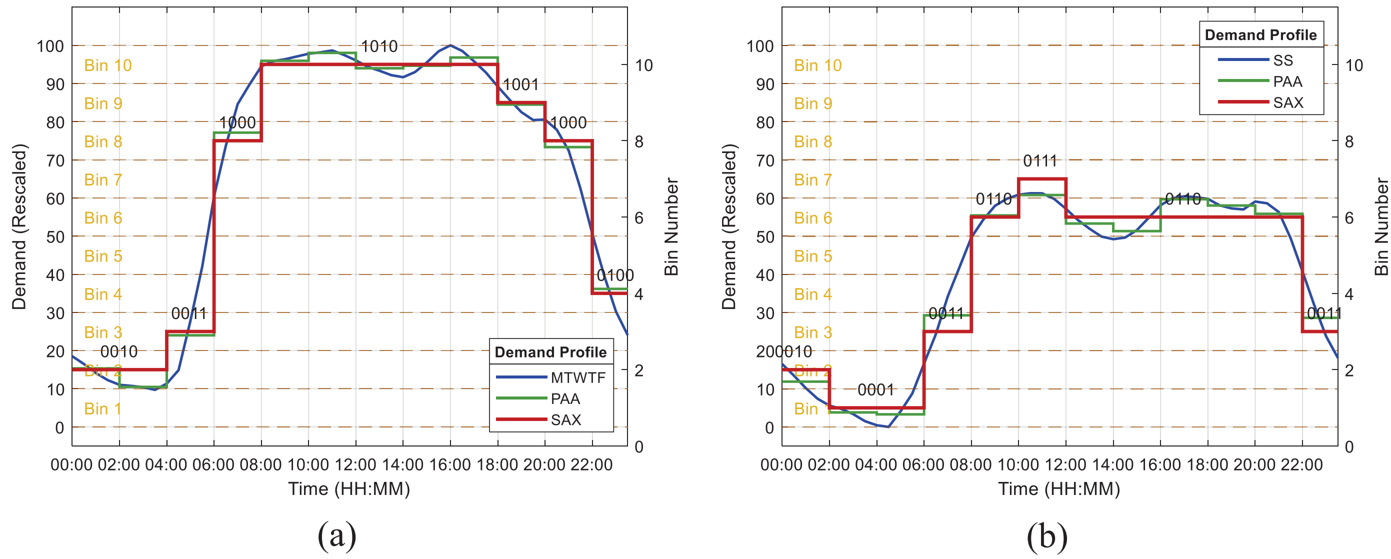

Fig. 5. 24-h period PAA (2-h) & SAX representations (a) weekday, (b) weekend day.

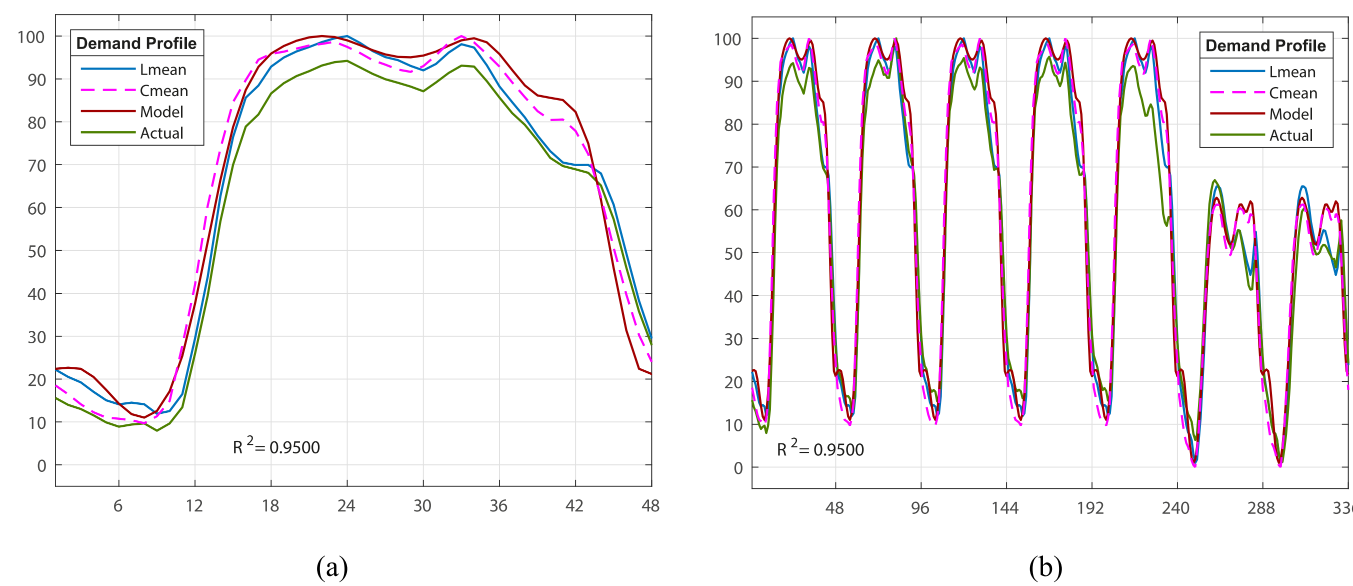

Fig. 6. Demand Profile representations 4-Jul-05 (a) 24-h period (b) 7-day period.

the methodology described in this article. Fig. 6(b) shows an extended 7-day period which includes concatenated weekday and weekend day demand profiles. A measure how close the *actual* and *model* demand data over this 7-day period is calculated $R^2 = 0.95$, $RMSE = 0.476$, and $MAE = 7.2262$.

A summary of experimental results comparing forecast data against measured demand data and out-of-sample demand data are detailed in Table 3.

The performance of the demand forecast data shown achieves an average R^2 value greater than 0.92. The demand forecast and actual plot provides a good way to assess the goodness-of-fit of a regression at a glance. There is evidence the measure of performance is degrading slightly as time progresses; Fig. 7(a) shows the demand profiles for week commencing 18 August 2014, and Fig. 7(b) week commencing 5 August 2019. Nevertheless, these visual representations demonstrate weekday and weekend day recorded demand profiles (Actual) remain consistent with the model forecast data (Model). A generalised shape of the varying rates at which electricity is consumed during each 24-h period is maintained.

Table 3
Performance of proposed model.

Date	*RMSE*	R^2
04-Jul-05	0.476	0.950
10-Jul-06	0.445	0.948
09-Jul-07	0.380	0.962
21-Jul-08	0.416	0.958
03-Aug-09	0.335	0.974
19-Jul-10	0.477	0.959
08-Aug-11	0.392	0.967
02-Jul-12	0.368	0.966
24-Jun-13	0.405	0.957
18-Aug-14	0.363	0.960
13-Jul-15	0.682	0.891
08-Aug-16	0.775	0.839
12-Jun-17	0.856	0.803
30-Jul-18	0.944	0.822
05-Aug-19	0.692	0.877
Average:	0.534	0.922

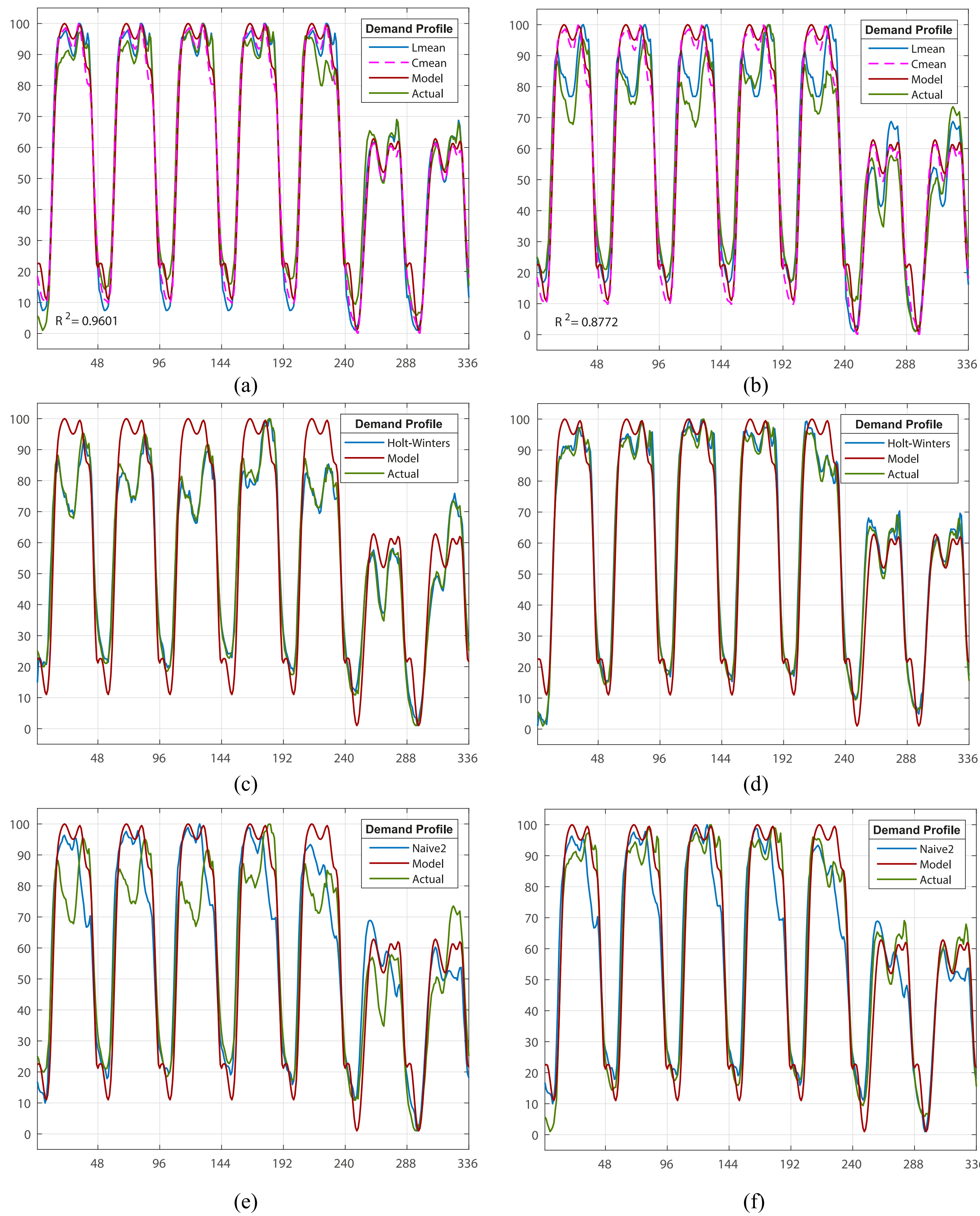

Fig. 7. Demand Profile representations h = 336 ahead (a) Model 18-Aug-14, (b) Model 5-Aug-19, (c) Holt-Winters 18-Aug-14, (d) Holt-Winters 5-Aug-19, (e) Naïve2 18-Aug-14, (f) Naïve2 5-Aug-19.

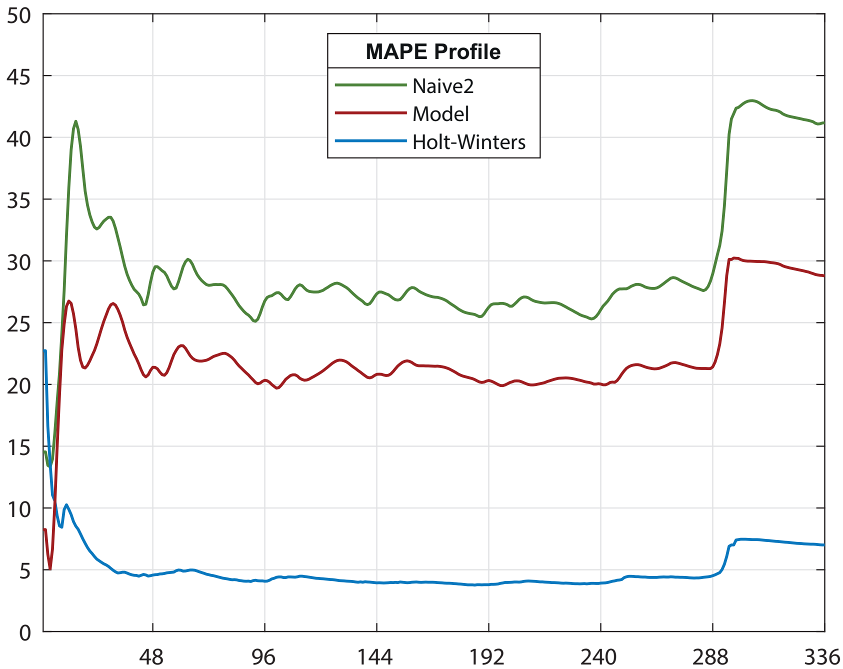

Fig. 8. Comparison of MAPE results for $h = 336$ ahead commencing 5-Aug-19.

Table 4
Weekly MAE and MAPE (in%) on prediction of forecast horizon $h = 336$ ahead.

Date	***MAE***			***MAPE***		
	Model	Holt-Winters	Naïve2	Model	Holt-Winters	Naïve2
04-Jul-05	7.226	1.270	2.930	19.330	3.230	8.860
10-Jul-06	6.016	0.690	10.150	15.490	2.470	30.610
09-Jul-07	5.355	0.670	10.780	14.330	2.470	33.760
21-Jul-08	5.765	1.200	10.260	16.630	3.960	33.430
03-Aug-09	4.642	1.520	9.970	15.280	5.310	35.770
19-Jul-10	6.805	1.000	10.440	17.550	3.860	34.890
08-Aug-11	5.882	1.490	11.070	23.450	5.900	48.160
02-Jul-12	5.419	0.820	10.780	16.240	2.180	41.880
24-Jun-13	6.168	1.070	10.110	16.350	3.000	31.840
18-Aug-14	5.223	2.050	11.440	28.120	6.080	44.590
13-Jul-15	9.440	1.350	13.180	24.330	3.650	49.060
08-Aug-16	11.123	1.740	14.070	38.960	4.900	46.190
12-Jun-17	13.027	1.870	14.270	36.370	4.760	38.690
30-Jul-18	12.895	1.990	17.230	57.060	9.560	84.800
05-Aug-19	10.412	1.970	13.730	53.040	7.010	41.180
Average:	7.693	1.380	11.361	26.169	4.556	40.247

Table 4 reports the benchmark test results. Both MAE and MAPE values are presented when the forecast horizon $h = 336$ ahead. The figures show the out-of-sample Holt-Winters exponential smoothing forecasting accuracy is far more competitive than the proposed model, the MAE and MAPE average figures support this. This result is not unexpected and seems reasonable since the Holt-Winters model was re-baselined for each of the test dates. A visual comparison of Holt-Winters method and actual demand data for 18 August 2014 and 5 August 2019 are shown in Fig. 7(c) and (d); a plot showing the model forecast for the same periods is added for reference. Further test results were derived comparing the second benchmark standard Naïve2 and actual demand data. The results of the Naïve2 model for within-week seasonality indicate the proposed model performance has greater benefit than the Naïve2 method.

Fig. 7(e) and (f) shows the Naïve2 method forecast against the actual demand data for $h = 336$ ahead period commencing 18 August 2014 and 5 August 2019, respectively. For completeness, the proposed model forecast for the same period is shown. The corresponding MAPE figures confirm the relative performance of each of the models used. Predictably the Holt-Winters model outperforms the proposed model, which can be attributed to regular updates to the estimation data and relatively short forecast horizon window.

Fig. 8 compares the MAPE figures derived from each model based on a single week ahead forecast. The relative performance ranking of the Naïve2, proposed model and Holt-Winters method is confirmed and consistent with earlier results shown in Table 4. While the proposed model overall performance figures are not equally comparable to the Holt-Winters results, it is reassuring the proposed model outperforms the widely used benchmark Naïve2 method. Furthermore, given the Holt-Winters model reliance to update the estimation data for continuous and effective forecasting and the proposed model ability to output short to medium term forecasts independent of any such updates, the proposed model will operate more effectively as part of a wider energy management system described in Section 3. It must be remembered that the proposed method is conceptualised for operation without any direct on-line measurement of the demand to be predicted, whereas the other methods require such measurements.

5. Conclusion

Knowledge of future electrical demand is essential for operators of small-island power systems and electrical distribution networks operating in the grid-edge. Machine learning based models designed to forecasting future energy needs are often opaque and difficult to interpret in comparison to more classical approaches [30]. The main contribution of this paper is to show that a series of simple data transformations provide an effective representation of demand time series. More sophisticated data-intensive econometric methods and models needed for forecasting are available. Yet at the same time, the simple method proposed may offer greater benefit to operators of energy forecasting for decentralised energy management. A simplified lumped model that forecasts future recursive rates of aggregated energy consumption on a wider network has been derived using a $13 \times 4 \times 2$ multi-dimensional array. Using popular benchmark models, we have shown that despite the proposed model underperforming when compared with a Holt-Winters seasonal model, the results outperform the seasonal naïve model forecasts. Designed to function independent without the need to maintain an estimation dataset means the simplicity of this approach allows for rapid deployment of future modification to the polynomial coefficients, thus ensuring its longevity. This finding suggests that the behaviour of existing energy optimisation technologies may benefit from similar approaches. For example, support for energy planning of assets operating in the grid-edge including domestic households and in small island communities where the emergence of the prosumer continues to trend. In future work we intend to evaluate the effectiveness of the demand forecast contribution. More specifically activities include using knowledge of future electrical demand as part of a multi-objective optimisation problem implemented using a weight-based routing algorithm within the context of energy management in the built environment. Here, estimating the aggregated demand without any centralised server, will operate as part of an evolving demand response service that can curtail load demand proactively or on receipt of base-point dispatch instructions while minimising discomfort for end users.

Conflicts of interest

The authors declare that there is no conflicts of interest.

CRediT authorship contribution statement

Sean Williams: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Michael Short:** Conceptualization, Resources, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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