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Signal processing of stochastic forecast: seasonal electric power consumption in the scope of efficiency connected to renewable energy

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Abstract: The electric power system's seasonality would mitigate the problem of the energy volatility crisis. Seasonal identification is important in energy usage analysis to make a better an organization's energy performance. Identification of the seasonal component in a time series data is essential since it defines a fluctuation within an interval of time. This seasonal component can be identified as a periodic phenomenon. Signal processing models can be used in analyzing periodic data in the representation of sinusoidal function. Seasonal variations are an important factor influencing the behavior of an electric power and energy load. This paper introduces the application of deterministic functions in the Ornstein–Uhlenbeck process as a sinusoidal signal processing model in identifying seasonal components represented in periodic terms. We conducted extensive experiments to validate the model on three datasets in electric power and energy systems namely electricity load, household electric power consumption, and power consumption of the three source stations. Further, it can be obtained that the periodic continuous-time-inhomogeneous signal of Ornstein–Uhlenbeck model can be used to identify the seasonal term of the very short to medium horizon forecast of the electric power and energy system. Seasonal changes in energy consumption can be used in energy management in the scope of energy efficiency connected to renewable energy plans.

1. Introduction

Lowering energy consumption and operating costs begins with a thorough understanding of an organization's energy data. Organizing energy with energy management is a framework combining management and technology to develop a proactive and integrated plan with the intention to better an organization's energy performance. Organizing energy by energy management is a key aspect of an organization's overall environmental management system. Whereas, energy efficient as a part concept of energy management. Recent research investigates the energy management and energy efficiency, i.e., [1]

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study the challenge of the optimal design and energy management of a grid connected renewable energy plant composed of a solar thermal collector, photovoltaic system, ground source heat pump, battery, one short-term thermal energy storage and one seasonal thermal energy storage.

In energy usage analysis, it is important to look out for seasonal changes in consumption. The identification of patterns of time series data may include trend, seasonality, cyclicality, and random variability. The difficult one on the matter of how to identify seasonality is defined as a structure's pattern of changes over time. It is very important to identify seasonality variation that exists in the time series data to determine the most appropriate forecasting model. The existence of the seasonality may obscure trend and cyclical patterns [2].

Time factors include weekly periodicity and seasonal variations influence the behavior of an electric power and energy system loads [3]. Seasonality variation in time-series data refers to a pattern that occurs at a regular interval [4], while a periodicity is a pattern in a time series that occurs at regular time intervals [5]. Seasonality identification is essential because this component is the most important characteristic of time series. While seasonal variation is well understood, it enables more accurate inferences of the forecast model.

Many studies have been conducted to identify seasonal variation, which can be applied to various fields of life. Identification of seasonal variation in the diagnosis of acute myeloid leukaemia was provided by [6], [7] identify the seasonal of identification of PM10 in an industrialized city. [8] identify the spatial and seasonal variations of volatile organic compounds (VOCs) using passive air samplers in the metropolitan city of Seoul, South Korea. Whereas, [9] explores the seasonal rainfall variation in Indonesia under normal conditions, excluding the influence of El-Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) events. Seasonality of reactive power procurement would mitigate the problem of price volatility [10]. [11] quantify the seasonal variation of the resulting net electricity demand. [12] estimates the seasonal path of energy systems using the diffusion process model.

A simple way to correct for a seasonal component is to use differencing in which the seasonal component is modeled directly, then subtract it from the observations. The seasonal component in a given time series is likely a sine wave over a generally fixed period and amplitude. This can be approximated easily using a curve-fitting method. Seasonality identification using auto-correlation analysis [2], direct seasonal adjustment [13, 14], or ARMA [15].

Pramesti ([16]) proposed a time-inhomogeneous Ornstein–Uhlenbeck model with a sinusoidal signal processing as the deterministic function and provided the theoretical background of the model., i.e., the consistency and the asymptotic normality of the estimates. Recall the finding of [16], that is, the conditional mean of the process can be expressed as

$$\mathbb{E}_\theta[Y_t|y_0] = \frac{y_0}{e^{\lambda t}} + \mu_t(\theta),$$

where

$$\mu_t(\theta) = \sum_{k=1}^{K} \left(\frac{\omega_k}{\omega_k^2 + \lambda^2} \right) f_t(A,B,\omega),$$

where $f_t(A,B,\omega)$ is an inhomogeneous function of sinusoidal signal processing. Whereas, the mean of (say) autoregressive-moving-average (ARMA) is

$$\mathbb{E}[y_t] = \frac{c}{1+\sum_{l=1}^{p} \alpha_l}$$

(see [3] for reference). Considering the properties of mean-reversion, where the movement of the variable follows its average, and the average contains a sinusoidal signal processing component, then, this component can be taken into account to capture the periodicity pattern of the variable. Moreover, in the results of [16], the theoretical background of the estimates is satisfied in $nh \to \infty$, and $nh^2 \to 0$. This means, that under a high-frequency scheme in the periodic sinusoidal signal of Ornstein–Uhlenbeck, that is, in very large datasets, the model can be considered to overcome the nonlinear components of the paths.

Therefore, this paper continues the result of [16], namely to apply the proposed model in identifying seasonal components of the time series that are represented in periodicity term. We feel sure that the model of sinusoidal signal processing of Ornstein–Uhlenbeck [16] would be interesting for future issues in terms of identifying seasonal variations. We chose the electric power and energy systems dataset. Based on the theoretical background of the model provided by [16], we believe the model can be considered in identifying the seasonal component in the electric power and energy systems time series dataset.

From the background above, we can state the important contributions of the research objectives of the study, namely:

1. Seasonality is a crucial aspect of time-series analysis. Seasonal term identification provides a better understanding of data variables and helps forecast better. The periodic continuous-time-inhomogeneous signal of Ornstein–Uhlenbeck model can be used to identify this term properly, that is, the nature of the mean-reversion and high-frequency schemes in the Ornstein–Uhlenbeck process, the author believes the proposed model is more realistic to apply to electric power and energy systems.
2. Understanding the use of the continuous-time-inhomogeneous signal of Ornstein–Uhlenbeck forecast in identifying seasonal terms in periodic representation in the electric power and energy system
3. The implementation of sinusoidal signal processing in the drift of Ornstein–Uhlenbeck model is very necessary for capturing periodic and harmonic system patterns. Studies on the frequency components of the periodic continuous-time-inhomogeneous sinusoidal signal of Ornstein–Uhlenbeck process have never been carried out. The results of the [16] research are the first findings of the theoretical background of the frequency components of the periodic continuous-time-inhomogeneous sinusoidal signal of Ornstein–Uhlenbeck process. The application of this model is very important to introduce the use of the Ornstein–Uhlenbeck model in identifying seasonal terms in time series data in both short and medium-term forecasting horizon time.

2. Methods and Materials

The mean-reversion model can describe a wide range of behaviors, particularly in electric power and energy systems. The Ornstein–Uhlenbeck process is a well-known stochastic process that represents the characteristic of the process to drift towards the mean. Mean reversion is the term for this phenomenon. The trend, seasonal dynamics, and possible irregular effects of time series phenomena are represented by a function of time in the drift in a time-inhomogeneous Ornstein–Uhlenbeck model, see [17] and [18] for results about the periodic functional tendency. Periodic continuous time as a deterministic function in the drift of the Ornstein–Uhlenbeck model can be considered to capture the periodicity term in the energy's paths.

Periodic phenomena[19] can be analyzed using a sinusoidal processing model. A repeating pattern within any fixed period is known as seasonal variation ([4]), while a periodicity is a pattern in a time series that occurs at regular time intervals ([5]). Hence, the seasonal variation can be used in analyzing seasonal phenomena with periodic signals.

Identifying seasonal effects is a critically important aspect of accurately predicting the development of systems. Based on this background, we provide the application of [16] in identifying a seasonality component. We believed that the periodic continuous-time sinusoidal signal processing of a time-inhomogeneous Ornstein–Uhlenbeck model

$$dY_t = \left(-\lambda Y_t + \sum_{k=1}^{K}[A_k \cos(\omega_k t) + B_k \sin(\omega_k t)]\right)dt + \sigma dw_t, \quad t \geq 0, \quad Y_0 = y_0 \tag{2.1}$$

(see [16] for reference) can be used in identifying the seasonal variation in very short to medium-term electric power and energy system forecasting problems.

The periodic sinusoidal signal processing, say

$$q_t(\beta) = \sum_{k=1}^{K} [A_k \cos(\omega_k t) + B_k \sin(\omega_k t)], \quad \omega_k \equiv 2\pi k \delta, \quad \beta = (A, B, \omega).$$

have been used in analyzing periodic data or phenomena [19]. The involvement of the signal processing in the drift of the Ornstein–Uhlenbeck model is used to capture the seasonal term in the periodic representation of the time series data. Since the characteristic of the electric power and energy systems follow to mean-reversion system, whereas, the Ornstein–Uhlenbeck process is one of the popular model that has these properties then definitely, the advantages of Ornstein–Uhlenbeck forecast in identifying the seasonality of signals is provided an appropriate time series forecast model in the electric power and energy systems.

We apply the proposed model [16] by describing the electric power and energy systems. We choose three electric power and energy system dataset, namely electricity load from Tokyo Electric Power Company (TEPCO), France household electric power consumption, and power consumption of Tetouan city in Morocco. We also compare the performance of $\hat{\theta}_n$ of the least-squares estimators (LSE) of [16] with its least absolute deviation-estimators (LADE), $\check{\theta}_n$; just for computationally comparisons. With the same methodology step in the LSE, we change the objective function of the LSE with the LADE, that is,

$$\check{\theta}_n \in \underset{\theta}{\operatorname{argmin}} \sum_{j=1}^{n} \left| Y_{t_j} - \left(Y_{t_{j-1}} - \lambda h Y_{t_{j-1}} + h h_{j-1}(\beta) \right) \right|.$$

In this study, we implement a train-test split to evaluate the model that consists of splitting the dataset into training and testing sets; namely, we select an arbitrary split point: all records up to the split points are taken as the training dataset, and all the records from the split point to the end of observations is taken as the test set. One set was then used to train the model, and the testing dataset was used to evaluate the model (see, e.g., in [20] and [21]). All calculations in the empirical results have been performed in the R program.

3. Seasonal electric power and energy systems

We apply the proposed model [16] by describing the electric power and energy systems. We choose three electric power and energy system dataset, namely electricity load from Tokyo Electric Power Company (TEPCO), France household electric power consumption, and power consumption of Tetouan city in Morocco. We also compare the performance of $\hat{\theta}_n$ of the least-squares estimators (LSE) of [16] with its least absolute deviation-estimators (LADE), $\check{\theta}_n$; just for computationally comparisons. With the same methodology step in the LSE, we change the objective function of the LSE with the LADE, that is,

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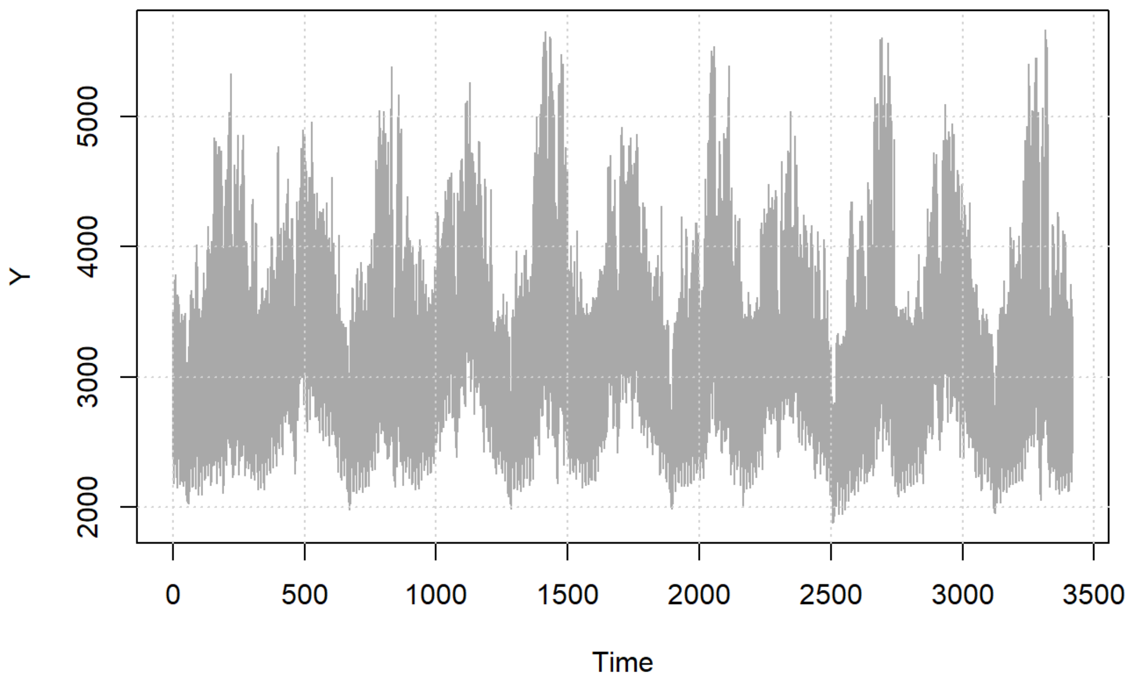


Figure 1. Hourly System Electricity Time Series (2016-2022).

3.1. Electricity load from TEPCO

A short-term dataset was obtained from TEPCO Holdings's files [22], and consisted of twenty-four-time series, one for each hour during a day, of hourly power demand system electricity consumption, with three decimal points. The twenty-four electricity consumption time series, for the seven years, starting April 1, 2016, and ending June 9, 2022, as a first casual look at the hourly system electricity (Y represents the electricity load, in kW) time series in Figure 1, which exhibits a clear seasonal component and periodicity pattern. Figure 1 also shows a trend of mean reversion, that is, when the load is high, its demand tends to increase, putting downforce on the load. Conversely, when the load is low, the electricity demand tends to decrease, providing an uplift to the load.

Table 1-4 summarizes the overall results of performance of estimates corresponding to different n and h for 2017, 2018, and 2019 loads; with their RMSE. We took the past electricity demand data in the period January 17, 2017, to July 11, 2017; January 27 to December 8, 2018; February 11 to June 16, 2019. From Table 1 and Table 4, it seems that the models are overfitting. A model is overfitting if there exists a less complex model with a lower test the Root Mean Squares Error (RMSE) [23]. Overfitting indicates that the model fits the data very well, but due to the complexity of the pattern of the seasonality for any particular time series, we should care to predict the new data of the same system. Table 2 for $n = 7500$ reports the results that the models are relatively underfitting. A model is underfitting if there exists a more complex model with lower test RMSE [23]. Further, the models seem underfitting.

It can be seen from Table 2; for electricity load in 2018, $n = 7500; h = 0.1, 0.07$, and Table 3, that the performance of the LSE is better than the LADE.

The path of the load and the approach model of the sinusoidal signal processing of Ornstein–Uhlenbeck model can be visualized as in Figure 2.

Table 1. The performance of $\hat{\theta}_n$, for electricity load in 2017, and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	$h=0.03$		$n=4000$		
	$n=4100$	$n=4200$	$h=0.03$	$h=0.09$	$h=0.3$
$\hat{\lambda}$	0.005	0.005	0.005	0.002	0.0005
$\hat{A}_1$	1.513	1.524	1.529	1.374	1.523
$\hat{B}_1$	1.782	1.787	1.780	1.810	1.674
$\hat{A}_2$	1.528	1.492	1.499	1.528	1.442
$\hat{B}_2$	1.754	1.753	1.756	1.801	1.619
$\hat{\delta}$	1.530	1.546	1.526	1.523	1.829
RMSE	528.936	541.560	527.781	527.764	527.790
	(1058.368)	(1168.052)	(838.256)	(838.063)	(838.160)

Table 2. The performance of $\hat{\theta}_n$ for electricity load in 2018, and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	$h=0.07$		$n=7500$		
	$n=7450$	$n=7550$	$h=0.7$	$h=0.1$	$h=0.07$
$\hat{\lambda}$	0.0007	0.0007	0.00007	0.0005	0.0007
$\hat{A}_1$	1.517	1.516	1.431	1.481	1.538
$\hat{B}_1$	1.798	1.791	1.916	1.873	1.799
$\hat{A}_2$	1.497	1.506	1.498	1.439	1.497
$\hat{B}_2$	1.765	1.762	1.734	1.794	1.754
$\hat{\delta}$	1.517	1.531	1.500	1.506	1.522
RMSE	779.218	775.608	778.058	777.130	777.139
	(451.756)	(480.421)	(463.496)	(462.103)	(462.057)

3.2. France household electric power consumption

The time series is composed of a one-minute sampling rate of electric power consumption in a house located in Sceaux, Paris, France, between December 16, 2006, and ending December 13, 2008. The data set available at the [24] is made available under the "Creative Commons Attribution 4.0 International (CC BY 4.0)" license. We considered four data of the energy consumed, namely:

- GAP represents the active energy consumed (in Wh) in the household by electrical equipment not measured in SM1 and SM2;
- GRP represents the reactive energy consumed (in Wh) in the household by electrical equipment not measured in SM1 and SM2;
- SM1 represents energy sub-metering no 1 (in Wh of active energy) corresponds to the kitchen, containing mainly a dishwasher, an oven, and a microwave;
- SM2 represents energy sub-metering no 2 (in Wh of active energy) corresponds to the laundry room, containing a washing machine, a tumble-drier, a refrigerator, and a light.

We analyze the empirical performance of $\hat{\theta}_n$ of the GAP and GRP; SM1 and SM2 with a train-test split of 90%. The performance of $\hat{\theta}_n$ and the RMSE is reported in Tables 5 and 6. From Table 5, the test RMSE of GAP is greater than the train RMSE. Whereas, for GRP, the test RMSE decreases as the train RMSE. The results indicate the model of GAP is overfitting, while the model of GRP is relatively underfitting.

Table 3. The performance of the $\check{\theta}_n$ for electricity load in 2018, and considered n and h; just for comparisons. The RMSE of the train is given with the RMSE of the test in parenthesis

$\check{\theta}_n$	$n=7500$	
	$h=0.1$	$h=0.07$
$\hat{\lambda}$	0.001	0.0007
$\hat{A}_1$	1.375	1.516
$\hat{B}_1$	1.842	1.791
$\hat{A}_2$	1.559	1.506
$\hat{B}_2$	1.840	1.762
$\hat{\delta}$	1.433	1.531
RMSE	781.582	781.570
	(534.095)	(533.819)

Table 4. The performance of $\hat{\theta}_n$ for $n = 3000$ of electricity load in 2019, and considered h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

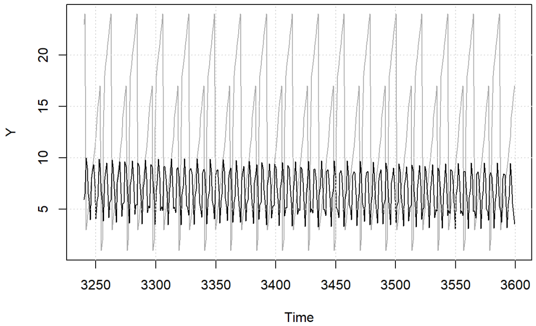
	$n=3000$		
$\hat{\theta}_n$	$h=0.05$	$h=0.065$	$h=0.071$
$\hat{\lambda}$	0.005	0.004	0.004
$\hat{A}_1$	0.693	0.681	0.699
$\hat{B}_1$	0.960	0.974	0.977
$\hat{A}_2$	0.608	0.605	0.596
$\hat{B}_2$	0.846	0.836	0.838
$\hat{\delta}$	0.575	0.568	0.567
RMSE	610.483 (921.875)	610.486 (921.974)	610.479(921.990)

As can be seen in Table 6, we can find out the fact that the test RMSE is less than the train RMSE. The model of SM1 and SM2 tends to be underfitting. The seasonality of the one-minute sampling rate of electric power consumption in the kitchen (period from December 16, to December 18, 2006) and laundry room (period from December 16, to December 20, 2006), can be approximated by the model (2.1) with the same periodic sinusoidal signal that its estimator listed in Table 6. This evidence indicates that the consumption of electric power in both rooms has the same pattern of periodicity in the given periods. Further, we also deduce that the performance of the LSE in Table 6 is better than the LADE in Table 7.

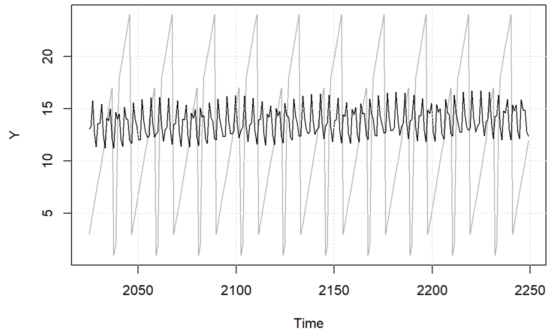
3.3. Power consumption of Tetouan city

According to reference [25], the data set that is available at [26] comprises the power consumption data (in kWh) in Tetouan city, collected every ten minutes from the supervisory control and data acquisition system of Amendis company which is distributed the energy to the three different source stations located in northern Morocco, namely Quads, Smir and Boussafou. We considered three data of their power consumption. To conclude this Section, the performance of the LSE of the power consumption of Quads, Smir, and Boussafou was analyzed with a train-test split of 90%.

We took the power consumption of Quads in the period January 14, to February 4, 2017; Smir in the period February 11, to March 11, 2017, and Boussafou in the period January 7, to February 4, 2017. Table 8 summarizes the results of the performance of $\hat{\theta}_n$ and the RMSE. The test RMSE of Quads increases as the train RMSE; the test RMSE of Smir decreases as the train RMSE; the test RMSE of Boussafou increases as the



(a) $n = 4000$.



(b) $n = 2500$.

Figure 2. $(Y_{t_j})_{j=0}^{n}$ (dark grey) versus the model (black) of the electricity load from February 28 to August 13, 2017, and January 27, to May 11, 2018, respectively; with $K = 3$; $h = 0.9$. Time in hourly.

Table 5. The performance of $\hat{\theta}_n$ with $n = 900$ of GAP and GRP, and considered h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	GAP		GRP	
	$h = 0.7$	$h = 0.8$	$h = 0.7$	$h = 0.8$
$\hat{\lambda}$	0.002	0.002	0.053	0.067
$\hat{A}_1$	0.485	0.487	0.510	0.539
$\hat{B}_1$	0.528	0.495	1.036	0.979
$\hat{A}_2$	0.731	0.713	1.027	1.052
$\hat{B}_2$	0.360	0.464	0.812	3.527
$\hat{\delta}$	0.848	0.761	0.694	0.643
RMSE	500.603	500.629	41.609	40.554
	(506.358)	(506.705)	(27.995)	(25.345)

train RMSE decreases. The model of Quads and Boussafou tend to be underfitting. For Quads and Boussafou; $h = 0.003$, we can see from Table 10 that the performance of the estimates of both is better than the LADE.

4. Conclusions and Future Works

From Subsection 3.1-3.3 we can summarize the following.

1. The salient feature of electricity consumption is seasonality. The hourly electricity load of TEPCO (Subsection 3.1) shows that the seasonality of the past electricity demand in the period January 27 to December 8, 2018, can be approximated by a periodic sinusoidal signal processing model in the drift of the model (2.1). Further, the proposed model (2.1) can be used for medium-term forecasting using hour-by-hour Japan electricity load data.
2. The results of electric power in Subsection 3.2 indicate that the seasonality of the one-minute sampling rate of the reactive energy consumed for December 16 to December 17, 2006, can be approximated by a periodic sinusoidal signal. Whereas, the seasonality of the one-minute sampling rate of electric power consumption in the kitchen and laundry room in the periods December 16 to December 20, 2006, can be approximated by the model (2.1) with the same periodicity. Seasonality identification to manage building electrification also has mentioned in [27], that is, the study proposed renewable energy and seasonal energy storage by identifying the building electrification seasonality of the electricity demand.

Table 6. The performance of $\hat{\theta}_n$ for SM1 and SM2, and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	SM1, $n=2100$		SM2, $h=0.73$		
	$h=0.73$	$h=0.83$	$n=2100$	$n=5100$	$n=6100$
$\hat{\lambda}$	0.399	0.265	−0.001	0.404	0.398
$\hat{A}_1$	0.100	0.314	0.185	0.164	0.097
$\hat{B}_1$	0.500	0.193	0.021	0.489	0.499
$\hat{A}_2$	0.699	0.744	0.570	0.719	0.712
$\hat{B}_2$	0.100	0.278	0.508	0.117	0.136
$\hat{\delta}$	1.100	1.014	1.000	0.975	0.974
RMSE	6.738	6.742	9.546	12.220	12.021
	(2.021)	(2.051)	(5.216)	(6.653)	(4.062)

Table 7. The performance of $\check{\theta}_n$ for SM1 and SM2, and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\check{\theta}_n$	SM1, $n=2100$		SM2, $h=0.73$		
	$h=0.73$	$h=0.83$	$n=2100$	$n=5100$	$n=6100$
$\hat{\lambda}$	−0.0003	−0.0003	0.0001	$5.3e-05$	$4.6e-05$
$\hat{A}_1$	0.158	0.250	0.314	0.176	0.175
$\hat{B}_1$	0.587	0.643	0.536	0.617	0.621
$\hat{A}_2$	0.811	0.754	0.515	0.736	0.740
$\hat{B}_2$	0.303	0.344	0.370	0.340	0.346
$\hat{\delta}$	0.977	0.834	0.974	0.944	0.932
RMSE	6.083	6.077	9.837	11.206	10.993
	(0.681)	(0.899)	(5.216)	(5.538)	(3.015)

The numerical studies confirm that the seasonality of a time-inhomogeneous Ornstein–Uhlenbeck process led to a good result for very short-term forecasting using minute-by-minute data.

3. In the given periods, the seasonality of power consumption of Quads and Boussafou (Subsection 3.3) has similarities. This evidence is supported by the seasonality of ten minutes of power consumption can be approximated by (2.1) with the same periodic sinusoidal signal processing model. Furthermore, [25] confirms the similarities because of the hot weather and vacation time. The results also confirm that the seasonality of a time-inhomogeneous Ornstein–Uhlenbeck process can be used for short-term forecasting with ten-minute-by-ten-minute data.

Overfitting indicates that model (2.1) fits the data very well, but due to the complexity of the pattern of the seasonality for any particular time series, we should care to predict the new data of the same system (see Table 1 and 4 of electricity load in 2017, 2019, respectively; Table 5 of GAP of France energy consumption). From the numerical experiments, we can deduce the following.

- In the computational comparisons, the performance of the LSE is better than the LADE;
- The proposed model (2.1) can capture the seasonal variation in very short-term to medium-term horizon forecasts. The performance of the estimates is very satisfactory for very short-term problems. We presume this happens because of the sensitivity of the periodic sinusoidal signal processing model in

Table 8. The performance of $\hat{\theta}_n$ and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	Quads, $n=3000$		Smir, $n=4000$		Boussafou, $n=4000$	
	$h=0.002$	$h=0.003$	$h=0.002$	$h=0.003$	$h=0.002$	$h=0.003$
$\hat{\lambda}$	0.070	0.047	0.013	0.009	0.055	0.036
$\hat{A}_1$	0.191	0.192	0.186	0.184	0.147	0.184
$\hat{B}_1$	0.156	0.160	0.177	0.156	0.162	0.154
$\hat{A}_2$	0.681	0.708	0.721	0.692	0.702	0.698
$\hat{B}_2$	0.412	0.432	0.454	0.441	0.457	0.423
$\hat{\delta}$	0.145	0.095	0.102	0.152	0.110	0.166
RMSE	8817.515	8817.581	4492.407	4492.372	5144.363	5144.285
	(7755.679)	(7756.834)	(4505.368)	(4505.327)	(4443.826)	(4443.972)

Table 9. The performance of $\hat{\theta}_n$, and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\hat{\theta}_n$	Quads, $n=3000$		Boussafou, $n=4000$	
	$h=0.002$	$h=0.003$	$h=0.002$	$h=0.003$
$\hat{\lambda}$	0.069	0.046	0.098	0.043
$\hat{A}_1$	−0.049	−0.146	−1258.468	0.201
$\hat{B}_1$	0.123	0.335	1207.519	0.115
$\hat{A}_2$	0.727	0.461	1001.718	0.686
$\hat{B}_2$	0.503	0.361	−715.493	0.331
$\hat{\delta}$	0.014	0.226	0.0945	0.156
RMSE	8817.870	8817.986	4923.835	5194.563
	(7670.738)	(7670.666)	(5373.743)	(5041.249)

approaching the process, therefore, we should take care in applying the model to the new systems in each term horizon forecast.

A class of models that can capture a time variation is the periodic model, while the features of seasonality that appear as a periodic pattern are common at least with daily and weekly series (see [3], [28], and [19]). The behavior of an electric power system load depends on time which is include the term of periodicity and seasonal variations. In this study, practical experiments confirms that the proposed model (2.1) with the periodic continuous-time sinusoidal signal can be used to capture the seasonal variation in very short to medium-term problems. We feel sure that the proposed model (2.1) is appropriate for long-term forecasting (e.g., in-stock exchange problems). In this view, in addition to the model of [29] for medium and short-term forecasting, the model [16] as the periodic sinusoidal signal processing of a time-inhomogeneous Ornstein–Uhlenbeck model can be used to identify a seasonal variation that appears in a periodicity pattern in all-time horizon forecasts, excluding the long short-term problems in the electric power and energy systems load.

Interestingly, an important point to note regarding the non-periodic sinusoidal signal capturing irregular (or non-linearity) components that are caused by irregular patterns (see [30–32] in the case of discrete-time chirp signal), is that we can consider non-periodic time-inhomogeneous Ornstein–Uhlenbeck model as paving the way to a massive solar energy supply and wind power generation in very short-term forecasting due to the existence of high non-linearity in the systems (e.g., [33], [34] for references).

Table 10. The performance of $\check{\theta}_n$ and considered n and h; just for comparison. The RMSE of the train is given with the RMSE of the test in parenthesis

$\check{\theta}_n$	$h = 0.003$	
	Quads	Boussafou
$\hat{\lambda}$	0.046	0.043
$\hat{A}_1$	−0.146	0.201
$\hat{B}_1$	0.335	0.115
$\hat{A}_2$	0.461	0.686
$\hat{B}_2$	0.361	0.331
$\hat{\delta}$	0.226	0.156
RMSE	8817.986	5194.563
	(7670.666)	(5041.249)

The sinusoidal processing model has been used in analyzing seasonal phenomena to the electric power and energy system load. We consider a periodic sinusoidal signal whose is modeled by the harmonic of the sinusoidal signal processing components. By the periodicity, we can find the stationary solution of the paths. The stationarity is easily relaxed since we employ that the sinusoidal signal is periodic. However, it is straightforward to generalize the model set, so it applies to the model where the continuous-time sinusoidal signal model is non-periodic.

We can set functions

$$X_t = \exp(f_t + Y_t),$$

with the deterministic function

$$f_t = \gamma_0 + \gamma_1 H_t + \gamma_2 P_t + \gamma_3 S_t,$$

and

- $H_t = 1$, if the % relative humidity (r.h) is between $30-60\%$, $H_t = 0$ otherwise;
- $P_t = 1$, if the temperature is between 15^0C-24^0C, $P_t = 0$ otherwise;
- $S_t = 1$, if the wind speed is between $2-10.5$ m/s, $S_t = 0$ otherwise.

Also,

$$dY_t = \left(-\lambda Y_t + \lambda h_t(\beta) + \frac{d}{dt} h_t(\beta)\right) dt + dw_t,$$

where Y_t is defined as the electric power and energy systems load,

To be triggered by the risk of a sudden change of jumps in mathematical descriptions, further, we can expand to the mean-reversion could be a starting point to introduce a time-inhomogeneous signal processing model in the Lévy-driven Ornstein–Uhlenbeck process

$$dY_t = \left(\alpha + \sum_{k=1}^{K} \beta_k f_k(t,\omega) - \lambda Y_t\right) dt + b(Y_t) dw_t + c(Y_{t-}) dJ_t,$$

where $\beta = (\beta_k)_{k=1}^K, \omega = (\omega_k)_{k=1}^K$, J is pure-jump Lévy process, $\lambda \in \mathbb{R}$ is a constant, $K \in \mathbb{N}$ is known (see [35] for reference).

A special case of interest is when the electric power and energy systems load is in the state-space form (e.g., [36], [37]), that is,

$$Y_t = y_0 + \int_0^t (-\lambda Y_s + h_s(\beta))ds + A_t \alpha_t + \sigma w_t, \tag{4.1}$$

with an unobserved process

$$\alpha_t = \Psi \alpha_{t-1} + \zeta_t, \tag{4.2}$$

where $\zeta_t \sim \mathcal{NID}(0, Q_t)$, and initial state distribution $\alpha_1 \sim \mathcal{N}(a_1, P_1)$, a_1, P_1 are fixed and known but can be generalized. Concerning seasonality, it is interesting to study further that (4.1) can capture the seasonality in the periodicity representation and non-periodic seasonal components in the state equation (4.2).

In other fields than electric power and energy system, we can apply the Gompertzian model

$$dY_t = (-\lambda \log Y_t + g_t(\alpha))Y_t dt + \sigma Y_t dw_t$$

approach to predicting virus, bacterial, and cancer cell growths (e.g., [38]). Exogenous factors that affect virus, bacterial, and cancer cell growths, e.g., moisture, pH level, oxygen level, and cell deformability; are included in a time-dependent function $g_t(\alpha) = \alpha_0 + \sum_{i=1}^{q} \alpha_i q_i(t)$.

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