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# Price Forecasting of Electricity Markets Based on Local Gaussian Process

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***Abstract* – In a competitive electricity market, short-term electricity price forecasting are very important for market participants.Electricity price is a very complex signal as a result of its non-linearity, non-stationary and time-variant behavior. This studypresents a new approach to short-term electricity price forecasting. The proposed method is derived by integrating the kernelprincipal component analysis (KPCA) method with the local Gaussian Process (GP), which can be derived bycombining the GP with the local regression method. Local prediction makes use of similar historical data patterns in the reconstructed space to train the regressionalgorithm. In the proposed method, KPCA is used to extract features of the inputs and obtain kernel principal components forconstructing the phase space of the time series of the inputs. Then local GP is employed to solve the price forecastingproblem. The proposed method is evaluated using real-world dataset. The results show that the proposed method can improvethe price forecasting accuracy and provides a much better prediction performance in comparison with other recentlypublished approaches.**

***Keywords* – Gaussian Process, Kernel Principal Component Analysis, Local Gaussian Process, Price Forecasting.**

## I. Introduction

Accurate forecasting of the electricity price has become a veryvaluable tool. This is because of the upheaval of deregulationin electricity market. Accurate and efficient electricityprice forecasting becomes more and more important forelectricity markets. Electricity prices forecasting is usedfor various purposes, such as speculation, derivativepricing, risk management and real option valuation. Withthe accurate short-term price forecasting, the powersuppliers can build their bidding strategies to maximize their payoff and achieve the maximum benefit and on theother hand, consumers can minimize its utilization cost.

Short-term price forecasting in a competitive electricitymarket is still a challenging task because of the specialelectric price characteristics [1], [2], such as high-frequency,non-stationary behavior, multiple seasonality, calendareffect, high volatility, high percentage of unusual prices,hard non-linear behavior etc. Therefore price forecastingmethods are vital for all market participants for theirsurvival under competitive environment [3].

In the literature, several techniques for short-termelectricity prices forecasting have been reported, namelytraditional and artificial intelligence (AI)-based techniques.The traditional techniques include autoregressive integratedmoving average (ARIMA) [4], [5], wavelet-ARIMA [6] andmixed model [7] approaches. Although, these techniquesare well established to have good performance, they cannotalways represent the non-linear characteristics of thecomplex price signal. Moreover, they require a lot ofinformation, and the computational cost is very high.

On the other hand, AI-based techniques have been usedby many researchers for the price forecasting in electricitymarkets. These methods can deal with the non-linearrelation between the influencing factors and the pricesignal, therefore the forecasting precision is raised. Thesetechniques include neural network (NN) [8], [9], radial basis function NN [10], fuzzy neural network (FNN) [11],[12], weighted nearest neighbors (WNN) [13], adaptivewavelet neural network (AWNN) [14], hybrid intelligentsystem (HIS) [15], cascaded neuro-evolutionary algorithm(CNEA) [16], hybrid neural-evolutionary model [17], thecombination of neural networks with wavelet transform(NNWT) [18] and the hybrid approach (WPA) whichcombines wavelet transform, particle swarm optimization and adaptive-network-based fuzzy inference system [3].These approaches can be much more efficientcomputationally, if the correct inputs are considered.

Another method used for function regression isthe Gaussian process (GP) that is based on Bayesianmodeling [19]. The important advantage of GP overother non-Bayesian models is its explicit probabilisticformulation, which gives the ability to infer modelparameters such as those that control the kernel shape andthe noise level. In contrast to classical methods, by usingthe GP, we obtain not only a point prediction but apredictive distribution. This advantage can be used toobtain the prediction intervals that describe a degree ofbelief of the predictions [20]. The application of the GP toprediction problem in [21] has shown a high accuracyachieved especially at noisy environments.

All the above techniques are known as global predictors inwhich a predictor is trained using all data available but give aprediction using a current data window. The global predictorssuffer from some drawbacks which are discussed in theprevious work [22], [23].

Owing to the complexity and non-linearity of the historicalelectricity price data, the time-series reconstruction techniquecan be applied to the electricity price forecasting. Phasespace reconstruction is an important step in local predictionmethods. The traditional time-series reconstructiontechniques usually use the coordinate delay (CD) method tocalculate the embedding dimension and the time delayconstant of the time series [24]. The traditional time-seriesreconstruction techniques have a serious problem. Theproblem is that there may be correlation between differentfeatures in reconstructed phase space. Consequently, thequality of phase space reconstruction and modeling will beaffected [25]. In order to overcome the drawbacks oftraditional methods, the kernel principal component analysis(KPCA), which is one type of non-linear principalcomponent analysis (PCA), is used to reconstruct the phasespace of time series [26], [27].

In this paper, a local predictor approach based on provenpowerful regression algorithm which is GP combined withspace reconstruction of time series is introduced. In theproposed method, the phase space is reconstructed based onKPCA method, so that the problem of the traditionaltechniques can be avoided [26]. The proposed local GP approach has been evaluated using a real-world datasetwhere the historical price data from Spanish are the maininputs for training. This real-world dataset is commonlyused as the test case in several price forecasting papers [3],[4], [6]–[8], [11], [13]–[16], [18]. The Spanish market has a hardnon-linear behavior and time variant functionalrelationship [6] making it a real-world case study withsufficient complexity.

The contributions of this paper are to propose a novelmethod for day-ahead price forecasting of electricitymarkets and to improve forecasting accuracy in comparisonwith the results obtained with other recently publishedapproaches.

The paper is organized as follows. Section II reviews the GP method. Section III describes the local GP algorithm. Experimental results and comparisons with other approaches are presented in Section IV. Finally, Section V concludes the work.

## II. Gaussian Process

The GP model will be briefly reviewed in this section, moredetailed can be found in [20, 28].

GP [30] hasprovided a promising non-parametric Bayesian approachparticularly suited to regression problems. The Bayesiananalysis of forecasting models is difficult because a simpleprior distribution over parameters implies a complex priordistribution over functions [20]. GP is flexible enough torepresent a wide variety of interesting model structures, many of which would have a large number of parameters ifthey were formulated in more classical fashion.

The aim of Bayesian prediction is to compute the distribution $P(y_{N+1}/x_{N+1}, U_N)$ of output $y_{N+1}$ given a test input $x_{N+1}$ and a set of $N$ training points $U_N = \{x_i, y_i\}$.Using Bayes' rule, the prediction of the GP is in thefollowing form:

$$P(y_{N+1}/x_{N+1},U_N)=\frac{1}{H}\exp\left(-\frac{(y_{N+1}-\hat{y}_{N+1})^2}{2S^2_{\hat{y}_{N+1}}}\right) \qquad (1)$$

where $H$ is a normalized constant and $\hat{y}_{N+1}=\eta^T C_N^{-1} y_N$, $S^2_{\hat{y}_{N+1}}=\gamma-\eta^T C_N^{-1}\eta$, $C_N^{-1}$ is the inverse of thecovariance matrix of the training data, $\eta$ denotes the $N \times 1$covariance between the training data and $y_{N+1}$ and $\gamma$denotes the variance of $y_{N+1}$. Contrary to the classicalmethods, a prediction distribution can be obtained, not justa step prediction, which can be used to obtain theconfidence intervals of the prediction [19].The covariance function is chosen such that the correlationbetween the different training examples is expressed. Thesquared exponential function is used in this paper asfollows [20]

$$C(x^{(i)},x^{(j)})=v_0\exp\left(-\frac{1}{2}\sum_{l=1}^{m}a_l(x_l^{(i)}-x_l^{(j)})^2\right)+b \qquad (2)$$

where$m$ is the dimension of the input variables, $b$, $a_l$ and $y_0$are the hyper parameters of the covariance function, which aredetermined using the maximum likelihood method.

## III. Local Gaussian Process

### A. Time-series reconstruction based on KPCA

In recent years, to process non-linear time series, KPCA isused to overcome the CD method problem [27]. In KPCA, the computations are performed in a feature space that isnon-linearly related to the input space. This feature space isthat defined by an inner product kernel in accordance withthe Mercer's theorem [29]. However, unlike other forms ofnon-linear PCA, the implementation of KPCA relies onlinear algebra by mapping the original inputs into a highdimensionalfeature space via a kernel map,which makesdata structure more linear. In this paper, the commonly usedGaussian kernel is employed. The detail introduction of thebasic KPCA can be viewed in [25], [26], [29].

### B. Local GP

Local prediction is concerned with predicting the future basedonly on a set of $K$ nearest neighbors in the reconstructedembedded space without considering the historical instanceswhich are distant and less relevant. Predictions of this kindare to establish a curve for the most recent data, and thenmake predictions based on the established curve. Localprediction constructs the true function by subdivision of thefunction domain into many subsets (neighborhoods).Therefore the dynamics of time series can be captured stepby step locally in the phase space and the drawbacks ofglobal methods can be overcome.

Two important aspects should be concerned in the localpredictor algorithm. The first one is how to choose suitableneighbor points. In this work, the Euclidean distance isused to choose the nearest patterns. The second is how longinto the predicted series we can trust, in other words whatis the number of the nearest neighbors. In general, thenumber of the nearest neighbors ($K$) must be larger thanthe dimension of the time series. However, if the number istoo large, some far away points may be taken into accountand this could reduce accuracy.

There are some methods used in literatures to find theparameter ($K$) such as cross validation [30] and bootstrap[31]. This parameter should be high- for low-density datasets,whereas it should be low for high density ones. So, in thispaper, $K$ is calculating by using a systematic methodproposed by us in [23] as follows

$$K = \text{round}\left(\frac{\alpha}{N \times k_{\max} \times D_{\max}} \sum_{i=1}^{N} \sum_{k=1}^{k_{\max}} D_k(x_i)\right) \quad (3)$$

where, $N$ is the number of training points, $k_{max}$ is the maximum number of nearest neighbors, $D_k(x_i)$ is the distance between each training point x and its nearest neighbors while $D_{max}$ is the maximum distance, $\frac{1}{N \times k_{\max} \times D_{\max}} \sum_{i=1}^{N} \sum_{k=1}^{k_{\max}} D_k(x_i)$ is the average distance around the points which is inversely proportional to the local densities and $\alpha$ is a constant. The two constants $k_{max}$ and $\alpha$ are very low sensitivity parameters. $k_{max}$ can be chosen as a percentage of the number of training points ($N$) for efficiency while α can be chosen as a percentage.

In general, the proposed local GP algorithm consists of four stages.The first stage reconstructs the time series using the embeddingdimension and the time delay constant. The second stage findsthe $K$ closest vectors, or nearest neighbors, of observedvariables in the data set for each query vector. The third stageconstructs the model using only the $K$ nearest neighbors, andthe fourth stage evaluates the model using the query vector asthe input to estimate the process output. These stages canbe described in details as follows:

- Stage 1: Load the multivariate time series dataset D $=\{x_i(t), t = 1, ..., N$ and $i = 1, ..., n\}$, and set parameter$K$ (the number of the nearest neighbors), and the parametersfor GP algorithm.Then, reconstruct the multivariate time series dataset $\hat{D}$.
- Stage 2: Choose the Euclidian distance as the distance metric in the phase space,

$$d(X, Z) = \sqrt{\sum_{j=1}^{d} [x(t_1 - (j-1)m) - Z(t_2 - (j-1)m]}$$

between$Z$ (the query point) and each $X$ in $\hat{D}$ (corresponding to two reconstructions of $x(t_1)$ and $x(t_2)$) and finding the $K$ nearest neighbors $\{X_z^1, X_z^2, ..., X_z^K\}$

- Stage 3: Regarding each neighbor $\{X_z^l\}_{l=1}^K$ as a point in the domain and $\{x(Z_l + T)\}_{l=1}^K$ as the target value where $T$ is the prediction step, and training the SVR algorithm to obtain support vectors and correspondingweight coefficients.
- Stage 4: Calculate the prediction value $x(t + T)$ of the query vector $Z$ based on the GP algorithm. Then, the stages 2 to 4 can be repeated until the futurevalues of different query vectors are all acquired.

## IV. Numerical Results

### A. Forecasting accuracy evaluation

As in [3], [4], [6]–[8], [11], [13]–[16], [18], the mean absolute percentageerror (MAPE) and weekly error variance are considered toevaluate the accuracy in forecasting electricity prices.

The MAPE criterion is defined as follows

$$MAPE = \frac{100}{N} \sum_{h=1}^{N} \frac{|\hat{P}_h - P_h|}{\overline{P}} \quad (4)$$

$$\overline{P} = \frac{1}{N} \sum_{h=1}^{N} P_h \quad (5)$$

where $\hat{P}_h$ and $P_h$ are the forecasted and actual electricityprices at hour $h$, respectively, $\overline{P}$ is the average price of theforecasting period and $N$ is the number of forecasted hours. $\overline{P}$ is used in (4) to avoid the diverse effect of price close tozero [32].

A measure of the uncertainty of a model is the variability ofwhat is still unexplained after fitting the model, which can bemeasured through the estimation of the variance of the error.The smaller this variance, the more precise is the prediction ofprices [6]. Consistent with definition (4), weekly errorvariance can be estimated as:

$$\sigma_{e,week}^2 = \frac{1}{168} \sum_{h=1}^{168} \left(\frac{|\hat{P}_h - P_h|}{\overline{P}} - (e_{week})\right)^2 \quad (6)$$

$$e_{week} = \frac{1}{168} \sum_{h=1}^{168} \frac{|\hat{P}_h - P_h|}{\overline{P}} \quad (7)$$

### B. Parameters

To implement a good model, there are some importantparameters to choose. There are two important parameters inthe KPCA algorithm, which used to reconstruct the phasespace. These parameters are the number of principalcomponents ($n_c$) and $\sigma^2$ in the Gaussian kernel function. Thevalues of these parameters which computed using the crossvalidation method are $\sigma^2$=1.03 and $n_c$= 12. In the local prediction model, choosing the neighbourhoodsize ($K$) is very important step. So, this parameter iscalculated as described in Section III, where $k_{max}$ and $\alpha$ arealways fixed for all test cases at 50% of N and 90, respectively.

### C. Results

To evaluate the performance of the proposed local GP method, it has been applied for one day-ahead priceforecasting in the electricity market of mainland Spain. Priceforecasting is computed using historical hourly price data ofyear 2002 for the Spanish market, available at [33]. TheSpanish market is a duopoly with a dominant player,therefore the price changes are related to the strategicbehavior of the dominant player, which are hard to predict [3].

For the sake of clear comparison with other publishedmethods, no exogenous variables areconsidered. Also, forthe sake of a fair comparison, the same test weeks as in[3], [4], [6]–[8], [11], [13]–[16], [18] are selected, which correspond towinter, spring, summer and fall seasons of year 2002.Different sets of lagged prices have been proposed as inputfeatures for price forecasting in the Spanish market. Table 1shows the historical hourly price data as well as the numberof training and testing samples used to construct the local GP model which would be employed to forecast the pricedata of each test week.

To show the effectiveness of our proposed method, numerical simulations comparing with 11 other approaches(ARIMA, mixed-model, NN, wavelet-ARIMA, WNN,FNN, HIS, AWNN, NNWT, CNEA, and WPA)are conducted.

As in [3], [4], [6]–[8], [11], [13]–[16], [18], the error of each dayduring each test week is calculated. Then, the average errorof each method for each test week is calculated. Table 2shows a comparison between the local GP approach and11 other approaches (ARIMA, mixed-model, NN,wavelet-ARIMA, WNN, FNN, HIS, AWNN, NNWT,CNEA and WPA), regarding the MAPE criterion.The table also summarizes in the last column the overallmean performance for each method.

These results show that the local GP approachoutperforms other approaches used in the comparison. TheMAPE for the Spanish market based on local GP has anaverage value of 4.40%. Table 3 shows the MAPEimprovements of the local GP over other approaches.

Table 1: Hourly price data for forecasting model constructions and testing

| Seasons | Historical hourly price data | Test week | Number of samples: Training data | Number of samples: Testing data |
|---|---|---|---|---|
| Winter | 1 January–17 February | 18–24 February | 1152 | 168 |
| Spring | 2 April –19 May | 20–26 May | 1152 | 168 |
| Summer | 2 July –18 August | 19–25 August | 1152 | 168 |
| Fall | 1 October–17 November | 18–24 November | 1152 | 168 |

Table 2: Comparative MAPE Results

| Prediction method | MAPE Winter | Spring | Summer | Fall | Average |
|---|---|---|---|---|---|
| ARIMA [4] | 6.32 | 6.36 | 13.39 | 13.78 | 9.96 |
| mixed model [7] | 6.15 | 4.46 | 14.90 | 11.68 | 9.30 |
| NN [8] | 5.23 | 5.36 | 11.40 | 13.65 | 8.91 |
| Wavelet ARIMA[6] | 4.78 | 5.69 | 10.70 | 11.27 | 8.11 |
| WNN [13] | 5.15 | 4.34 | 10.89 | 11.83 | 8.05 |
| FNN [11] | 4.62 | 5.30 | 9.84 | 10.32 | 7.52 |
| HIS [15] | 6.06 | 7.07 | 7.47 | 7.30 | 6.97 |
| AWNN [14] | 3.43 | 4.67 | 9.64 | 9.29 | 6.75 |
| NNWT [18] | 3.61 | 4.22 | 9.50 | 9.28 | 6.65 |
| CNEA [16] | 4.88 | 4.65 | 5.79 | 5.96 | 5.32 |
| WPA [3] | 3.37 | 3.91 | 6.50 | 6.51 | 5.07 |
| Local GP | 2.75 | 3.44 | 5.61 | 5.80 | 4.40 |

Table 3: Improvement of the local GP over other approaches

| | Average MAPE | Improvement,% |
|---|---|---|
| Local GP | 4.40 | --- |
| ARIMA [4] | 9.96 | 55.82 % |
| mixed model [7] | 9.30 | 52.69 % |
| NN [8] | 8.91 | 50.62 % |
| Wavelet ARIMA [6] | 8.11 | 45.75 % |
| WNN [13] | 8.05 | 45.34 % |
| FNN [11] | 7.52 | 41.49 % |
| HIS [15] | 6.97 | 36.87 % |
| AWNN [14] | 6.75 | 34.81 % |
| NNWT [18] | 6.65 | 33.83 % |
| CNEA [16] | 5.32 | 17.29 % |
| WPA [3] | 5.07 | 13.21 % |

In addition, Table 4 shows a comparison between the local GP approach and other approaches (ARIMA, NN, wavelet-ARIMA, FNN, AWNN, NNWT, HIS, CNEA and WPA), regarding the weekly error variance.The table also summarizes in the last column the overallmean performance for each method. For the WNN andmixed-model, the error variance has not been presented inthe respective references.

These results show that the local GP approach yieldsimproved forecast results and significantly outperformother approaches used in the comparison. The average errorvariance is smaller for the local GP approach, indicating lessuncertainty in the predictions. Table 5 shows the errorvariance improvements of the local GP over otherapproaches used in the comparison.

The above results indicates that the proposed local GP approach is less sensitivity to the electricity marketvolatility than the other price forecast techniques used inthe comparison. For instance, the Spanish electricity marketis more unstable in respect to price behavior in summerand fall seasons than winter and spring seasons because ofthe strategic behavior of the dominant player in the marketas discussed in [6], [11].

Table 4: Weekly forecasting error variance

| Prediction method | Weekly error variance Winter | Spring | Summer | Fall | Average |
|---|---|---|---|---|---|
| ARIMA [4] | 0.0034 | 0.0020 | 0.0158 | 0.0157 | 0.0092 |
| NN [8] | 0.0017 | 0.0018 | 0.0109 | 0.0136 | 0.0070 |
| Wavelet ARIMA[6] | 0.0019 | 0.0025 | 0.0108 | 0.0103 | 0.0064 |
| FNN [11] | 0.0018 | 0.0019 | 0.0092 | 0.0088 | 0.0054 |
| AWNN [14] | 0.0012 | 0.0031 | 0.0074 | 0.0075 | 0.0048 |
| NNWT [18] | 0.0009 | 0.0017 | 0.0074 | 0.0049 | 0.0037 |
| HIS [15] | 0.0034 | 0.0049 | 0.0029 | 0.0031 | 0.0036 |
| CNEA [16] | 0.0036 | 0.0027 | 0.0043 | 0.0039 | 0.0036 |
| WPA [3] | 0.0008 | 0.0013 | 0.0056 | 0.0033 | 0.0027 |
| Local GP | 0.0007 | 0.0012 | 0.0034 | 0.0032 | 0.0022 |

Table 5: Improvement of the local GP over other approaches

| | Average error variance | Improvement,% |
|---|---|---|
| Local GP | 0.0022 | --- |
| ARIMA [4] | 0.0092 | 76.09 % |
| NN [8] | 0.0070 | 68.57 % |
| wavelet ARIMA [6] | 0.0064 | 65.63 % |
| FNN [11] | 0.0054 | 59.26 % |
| AWNN [14] | 0.0048 | 54.17 % |
| NNWT [18] | 0.0037 | 40.54 % |
| HIS [15] | 0.0036 | 38.89 % |
| CNEA [16] | 0.0036 | 38.89 % |
| WPA [3] | 0.0027 | 18.52 % |

So, the prediction error in theseseasons is higher than the prediction error in winter andspring seasons for all electricity price forecasting methods.However, the weekly MAPE and weekly error variance ofthe proposed local GP method has less seasonal variationthan the other approaches. It shows the better predictionability of local GP model for the non-stationary andhigh-frequency characterized price series.

The four plots of Figs. 1-4 provide daily errors for theconsidered four testing weeks, using the local GP. Theseresults indicate that the proposed local GP method has a very good performance.

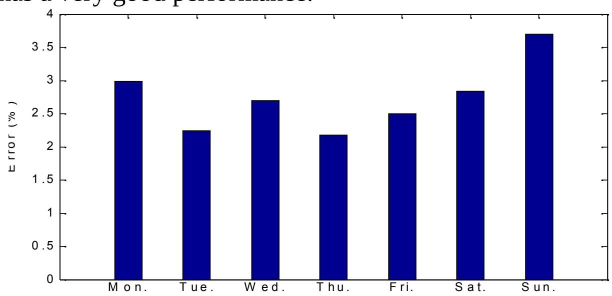


Fig.1. Daily errors corresponding to local GP approach for the winter week

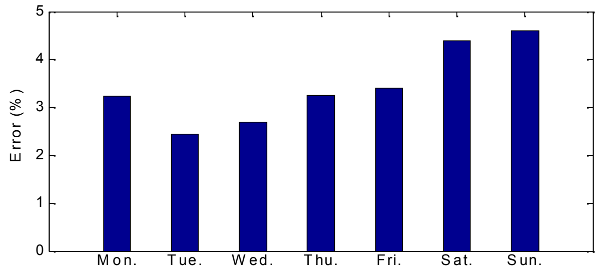


Fig.2. Daily errors corresponding to local GP approach for the spring week

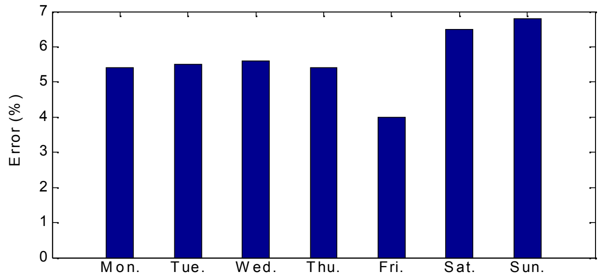


Fig.3. Daily errors corresponding to local GP approach for the summer week

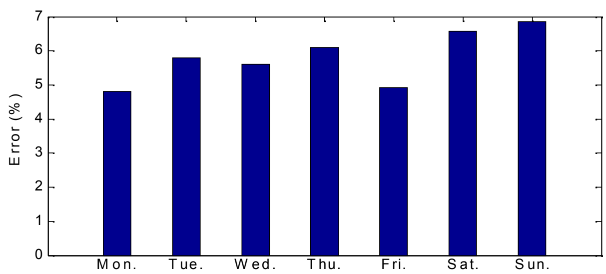


Fig.4. Daily errors corresponding to local GP approach for the fall week

Table 6: Results of all 52 weeks of year 2002

| | MAPE | Error variance |
|---|---|---|
| CNEA [16] | 5.38 | 0.00360 |
| Local GP | 4.45 | 0.00223 |

Table 7: Comparative MAPE results of one week ahead forecasting

| Prediction method | MAPE | | | | Average |
|---|---|---|---|---|---|
| | Winter | Spring | Summer | Fall | |
| CNEA [16] | 9.15 | 8.38 | 9.12 | 10.32 | 9.24 |
| Local GP | 4.71 | 5.79 | 9.67 | 9.97 | 7.54 |

To further study the superiority of local GP method, it isalso executed for all 52 weeks of year 2002 for the Spanishelectricity market and compared with CNEA [16] method. The results are shown in Table 6.

These results show that the proposed local GP methodimproves the weekly MAPE for the 52 weeks of year 2002over the CNEA [16] method by 17.29%. In addition, the results show that theobtained weekly MAPE for 52 weeks and the obtainedweekly error variances for 52 weeks for the proposedmethod are close to the results of Tables 2 and 4, respectively. The average of weekly MAPE for 52 weeks is4.45%against 4.40% in Table 2 (average of the four testweeks), whereas the average of weekly error variances forboth 52 weeks and the four weeks are almost the same.These results show the robustness of the proposed local GP method and its performance in a long run for acomplete year.

In addition, the proposed local GP method is examinedfor one week ahead (168 h ahead) price forecasting. Theresults are shown in Table 7.

These results show that the improvement in the averageMAPE of the proposed approach with respect to the CNEA[16] method for one week ahead forecasting are18.40%. As expected, the week aheadMAPE values of the proposed method are larger than itsday-ahead values.

## V. Conclusion

In this paper, a new approach for electricity price forecasting has been proposed. In order to overcome the drawback of thetraditional time-series reconstruction techniques, the KPCAmethod is used in the proposed method to reconstruct thephase space of time series. The proposed method can bederived by combining the GP with the local regressionmethod and employing the KPCA method for datapreprocessing. Therefore the drawbacks of global methodscan be overcome.

As Bayesian model, GP assumes that the parameters ofthe regression model are determined according to aprobability distribution, whereas other non-Bayesian modelsare basically a point prediction method. Therefore the local GP method can achieve better performance than othernon-Bayesian models in non-stationary and high-frequencysignals such as electricity prices.

The application of the local GP method to electricity priceforecasting is both novel and effective. A real-world datasetfrom Spanish has been used to evaluate the

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performance ofthe proposed method which has been compared with 11 other approaches (ARIMA, mixed-model, NN, wavelet-ARIMA, WNN, FNN, HIS, AWNN, NNWT, CNEA and WPA). The numerical results show the superiority of the proposed method over all other approaches. So that the local GP method can be recommended to the utility engineers because the obtained accuracy is very good for the practical application which makes it particularly attractive for real-world applications.

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