Improving Long-Term Electricity Price Predictions: A Comparison of Pure GPR and Hybrid LP-GPR Models

Giulia Taromboli
Energy Department
Politecnico di Milano
Milan, Italy
giulia.taromboli@polimi.it

Guillaume Koechlin
MOX, Department of Mathematics
Politecnico di Milano
Milan, Italy
guillaume.koechlin@polimi.it

Filippo Bovera
Energy Department
Politecnico di Milano
Milan, Italy
filippo.bovera@polimi.it

Piercesare Secchi
MOX, Department of Mathematics
Politecnico di Milano
Milan, Italy
piercesare.secchi@polimi.it

***Abstract*—The capital-intensive nature of renewable energy sources calls for robust assessments of expected revenues to mitigate investment risks and, in turn, lower their cost-of-capital. Consequently, long-term electricity price prediction has become an important support for decision-making in the electricity sector. This paper presents a comparative study of two electricity price dynamics models for long-term applications. The first approach relies on Fourier decomposition and Gaussian Process Regression (GPR), using only yearly regressors values as inputs. The second model combines linear-polynomial (LP) and GPR components to separately capture supra-weekly and sub-weekly dynamics, assessing whether annual regressors variations influence supra-weekly dynamics. Both models adopt Italian day-ahead electricity prices for training (2011–2023) and testing (2024). The results shows that the hybrid LP-GPR model seems to achieve better accuracies than the pure GPR model, thereby demonstrating the need for a trade-off between high-time granularity input data and model simplicity.**

***Index Terms*—, Fourier decomposition, Gaussian Process regression, linear-polynomial regression, long-term electricity price forecasting, renewable energy**

I. INTRODUCTION

In recent years, the growth of electricity generated by non-programmable renewable energy sources (NP-RES) has played a key role in modifying the market dynamics linked to the electricity price. While previously demand-related patterns were dominant [1], with higher prices during the day and lower prices during the night, nowadays the electricity price is also influenced by NP-RES generation. The variability and unpredictability of NP-RES, combined with their zero marginal costs of production, determine a very high price volatility and an increased uncertainty about future market trends. Since spot markets (e.g., day-ahead market – DAM) run on the merit order logic, a first tangible impact of a large NP-RES diffusion consists in the displacement of traditional units, characterised by higher marginal costs [2]. Being excluded from the market during those hours with high NP-RES production, traditional units raise their offered price when NP-RES generation is low, resulting in the well-known duck curve and *dunkelflaute* dynamic, frequently observed in recent years [3]. The major uncertainty in spot electricity prices and the expected increase in NP-RES penetration linked to decarbonization targets, pushed a lot of research effort to concentrate on electricity price forecasting (EPF) and market dynamics analysis, especially in the short-term [4] [5].

While short-term dynamics are relevant due to the prominent role of spot markets liquidity, the capex-intensive nature of NP-RES is calling for robust forecasts also in the long-term. Indeed, NP-RES assets already reached the so-called market-parity, but their costs structure, concentrated on capital expenditures, still poses a lot of challenges to investors, who are uncertain about future revenues. The possibility to make well-informed decisions about future market prices could lower investments risks, thus decreasing the cost of capital for decarbonization investments. Despite this, long-term electricity price forecasting (LT-EPF) has received little attention within the scientific debate. This work aims to address this gap.

In the literature, two main approaches are commonly adopted for long-term electricity price prediction: (i) econometric models and (ii) statistical models. In econometric models, electricity prices are predicted by replicating the market dynamics, thus by reconstructing the hourly demand and supply curves. For instance, Coester et al. [6] use this approach to assess the impact of RES capacity expansion in the electricity market. Moreover, Ziel et al. [4] extend their X-Model [7], initially designed for short-term forecasting, by incorporating features for long-term applications up to three years, still relying on econometric principles. Although these approaches are able to capture market dynamics, they require high-time granularity data as input to produce forecasts with the same resolution. However, such data are unlikely to be available in long-term applications, where only low-time resolution scenario data may be accessible. On the other hand, statistical models, widely used in short-term forecasting, have also been applied for long-term electricity price prediction. For instance, the study of Yousefi et al. [8] proposes a S-ARIMA model for predictions up to three years. However, this approach still relies on high-resolution input data. To tackle the issue of

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limited input data availability while preserving market dynamics in long-term applications, the work by Gabrielli et al. [9] proposes a novel methodology based on Fourier decomposition and Fourier coefficients prediction through Gaussian Process Regression models. The main idea is to see the electricity price as a Fourier series, with certain frequencies that capture specific market dynamics. As a result, only annual regressors values are required as input since the model needs to predict just a single value for each considered frequency in each predicted year. This method is hence effective in dealing with the data availability problem when predicting electricity prices in the long-term, therefore it is selected as benchmark for this study. However, using only yearly regressors values, the approach may fail in effectively capturing some intra-annual price dynamics, which may be correlated with both commodities costs (e.g. natural gas and emission allowances prices) and weather condition (e.g. water or sun availability).

For these reasons, this paper proposes a hybrid Linear Polynomial-Gaussian Process Regression (LP-GPR) model. Rather than accurately predicting electricity price over long time horizons, the proposed model aims to capture the structural electricity prices dynamics while limiting the granularity of the input data. Indeed, the hybrid LP-GPR model consists of two main components: (i) a time-domain linear-polynomial regression model to represent the annual electricity price trend with a quarterly granularity, and (ii) a frequency-domain Gaussian Process Regression model to capture electricity price dynamics from a weekly up to an hourly basis. The LP-GPR model is compared to a pure GPR model, developed following the methodology proposed in [9].

The rest of the paper is organized as follows. Section II describes the methodology adopted for the development of the models. Section III presents the results of their application to the Italian DAM prices. Finally, Section IV summarises the most relevant results of the study.

II. METHODOLOGY

This section introduces the adopted methodology framework. In particular, two models are presented. A first pure GPR model, based on the work of [9], and a second hybrid LP-GPR model, proposed by the authors. Note that both models aim to capture only the main electricity price behaviour, while leaving out the modelling of extreme price values, which falls outside the scope of this work.

A. Pure GPR Model

In the following, the pure GPR model is developed starting from the methodology proposed in [9]. The main idea behind this approach is that the DAM price can be seen as a yearly periodic function, consisting of a base evolution f_t and a residual R_t, as shown in eq. (1). As a periodic function, it can be described as a Fourier series, so as the sum of trigonometric functions, each associated with its own amplitude and frequency. In the Fourier frequency domain, it is possible to identify relevant and residual frequencies, which are responsible for capturing the main price behaviour f_t and the extreme price values R_t, respectively.

$$p_t = f_t + R_t \quad \forall t \in n_{hours} \tag{1}$$

The pure GPR model tries to predict the main price behaviour f_t by estimating the Fourier coefficients of selected relevant frequencies. As anticipated, the residual component R_t is not included in this analysis. The approach follows four main steps, outlined below.

1) Relevant Fourier coefficients determination The Fourier transform is applied to the yearly series of hourly DAM prices, independently for each year. Therefore, the original hourly signal is translated in a yearly multivariate time series, where each year is represented by its set of Fourier coefficients. However, only the Fourier coefficients of selected relevant frequencies are considered. These frequencies capture specific market dynamics, as illustrated in TABLE I, and are associated with the highest coefficient magnitudes, as shown in Figure 1.

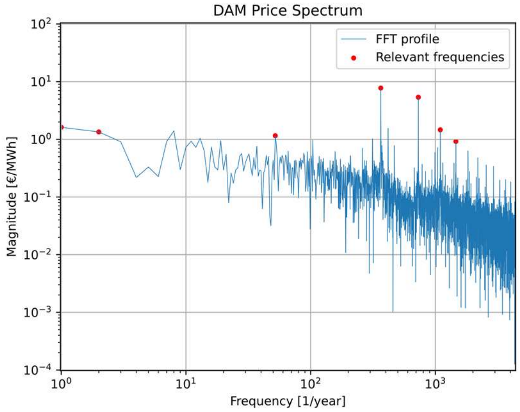

Figure 1. Frequency spectrum of day-ahead electricity market price.

TABLE I. SELECTED RELEVANT FREQUENCIES.

Frequency	**Dynamic**
0	Mean value
1	Year
2	Half-year
52	Week

(a) Supra-weekly dynamics.

Frequency	**Dynamic**
365	Day
730	Half-day
1095	8 hours
1460	6 hours

(b) Sub-weekly dynamics.

2) GPR models training An independent single-output GPR model is trained for each real or imaginary component of the relevant Fourier coefficients; therefore, two models are trained for each relevant frequency, one for the real component a_f and one for the imaginary component b_f. Each model takes as input the series of historical coefficient values as target variable and the series of historical yearly values for selected price drivers as regressors. For each model, the selected regressors are those minimising the error metrics on the test dataset. Moreover, a kernel function must be chosen for each GPR model. The importance of this choice lies in the fact that, in a Bayesian statistical interpretation, this function makes assumptions about the *prior distribution* over functions, also modelling the covariance between the target variables y_i and y_j, in period i and j respectively, as a function of the corresponding regressors x_i and x_j [10]. In the context of this analysis, the periods i and j represent the years. The kernel function for each GPR model is chosen from a list of available kernels, shown in TABLE II, as the one maximising the log-marginal likelihood on the training dataset [10]. Note that the hyperparameters of the covariance function are optimised during the training of the associated GPR model.

TABLE II. KERNEL FUNCTIONS CONSIDERED FOR ANALYSIS.

Name	**Expression**
Constant	$k(x_i, x_j) = c$
Linear	$k(x_i, x_j) = x_i^T x_j$
Quadratic	$k(x_i, x_j) = (x_i^T x_j)^2$
Cubic	$k(x_i, x_j) = (x_i^T x_j)^3$
Exponential	$k(x_i, x_j) = \sigma^2 \exp\left(-\frac{\lVert x_i - x_j \rVert}{2l^2}\right)$
Squared exponential	$k(x_i, x_j) = \sigma^2 \exp\left(-\frac{\lVert x_i - x_j \rVert^2}{2l^2}\right)$
Matern	$k(x_i, x_j) = \sigma^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu}\lVert x_i - x_j \rVert}{l}\right)^\nu K_\nu \left(\frac{\sqrt{2\nu}\lVert x_i - x_j \rVert}{l}\right)$

3) Relevant Fourier coefficients prediction The trained GPR models are used to predict the target variables. In this work, the prediction is limited to the test years to validate the models. Therefore, each GPR model takes as input the historical test-years yearly values of selected regressors and predicts the corresponding coefficient component.

4) Filtered price computation The predicted Fourier coefficients are back-transformed in the time domain. The resulting hourly price represents a filtered price containing only the relevant frequencies. Therefore, it captures only the base evolution of the DAM price in the corresponding year.

B. Hybrid LP-GPR Model

The hybrid LP-GPR model proposed by the authors is hereby presented. The proposed model works similarly to the pure GPR model, except that sub-weekly and supra-weekly dynamics are treated separately. The reason behind this modification relies on the fact that the pure GPR model takes as input only yearly values of price drivers, thereby overlooking their intra-annual patterns. However, variations throughout the year in certain regressors, especially gas price and load demand, may influence supra-weekly dynamics. These effects may not be captured if the model relies only on drivers with a year-by-year variation. As a consequence, the hybrid LP-GPR model combines two approaches to separately handle supra-weekly and sub-weekly dynamics. Particularly, the sub-weekly dynamics are predicted using the methodology already explained in Section II.A but, in this case, the analysis focuses only on relevant coefficients with frequency higher than 52. Meanwhile, the supra-weekly dynamics are captured as an annual trend and predicted through a time-domain linear-polynomial (LP) regression model.

Therefore, the hybrid LP-GPR model consists of two sub-models working in parallel: a time-domain LP regression model for supra-weekly dynamics, and a frequency-domain GPR model for sub-weekly dynamics. In the end, both predicted prices are combined: the predicted trend is added to the sub-weekly filtered price, resulting in the combined hourly price which integrates both sub-weekly and supra-weekly dynamics.

In the following, the LP sub-model is described. It follows three main steps.

1) Historical trend determination The electricity price trend is calculated as the weighted average price per quarter, with weights based on the number of days in each month of the quarter.

2) LP model training A linear-polynomial model, as shown in eq. (2), is trained using the quarterly historical electricity price values as target variable and the quarterly historical gas price x_G and load demand x_D values as regressors.

$$p_t(x_G, x_D) = \beta_0 + \beta_1^G \cdot x_{G,t} + \beta_1^D \cdot x_{D,t} + \beta_2^D \cdot x_{D,t}^2 \qquad (2)$$
$$\forall t \in N_{samples}$$

Particularly, we aim to model two distinct relationships between the target variable and the regressors: a linear relationship with the gas price, and a quadratic relationship with the load demand. Indeed, the electricity price increases as the gas price rises. On the other hand, the load demand only affects the electricity price at high demand levels, due to its inelastic nature. Therefore, beyond a certain threshold, higher demands lead to higher prices as well.

3) Trend prediction The trained model is used to predict the target variable. In this work, the prediction is limited to the test years to validate the model. Therefore, the LP model takes as input the test-years quarterly historical gas price and load demand values and predicts the electricity price trend with quarterly granularity as well. Finally, these four predicted values (each representing a different season day) are used to construct an hourly trend profile through cubic interpolation.

C. Model Validation and Comparison

In this section, the framework adopted for the model validation and comparison is presented. For both models, the validation is conducted in the time-domain by analysing the error between the hourly price predicted through the methodology in the test years and the hourly filtered or combined price, according to the model, obtained starting from the actual data in the same years.

- *Pure GPR model* In this model, the error is computed by comparing the predicted filtered price, obtained by back-transforming the predicted relevant Fourier coefficients, with the actual filtered price, derived from the actual relevant Fourier coefficients.
- *Hybrid LP-GPR model* For this model, the error analysis is performed separately for each sub-model. Therefore, the performances of the two sub-models are assessed independently. Regarding the LP sub-model, the error is determined by comparing the predicted trend and the actual trend. Meanwhile, for the GPR sub-model, the error is computed by comparing the predicted sub-weekly filtered price, obtained through the predicted Fourier coefficients, with the actual sub-weekly filtered price, derived from the actual relevant

Fourier coefficients. Note that, in this case, just relevant frequencies higher than 52 are considered.

Finally, the models are compared in the model comparison phase. In particular, the predicted main price behaviours (the filtered price for the pure GPR model, and the combined price for the hybrid LP-GPR model) are compared against the actual DAM price in the test years. Note that the latter includes all price components, therefore both the main and residual behaviours. However, this comparison is made to evaluate the models performances on the same reference.

Both model validation and comparison are based on the error metrics summarised in TABLE III. The Mean Absolute Error (MAE) determines the prediction deviation from the actual values in absolute terms, while the Mean Absolute Percentage Error (MAPE) provides this evaluation in percentage terms. Finally, the R^2 metric assesses whether the prediction captures the overall pattern of actual values.

TABLE III. ERROR METRICS CONSIDERED FOR MODEL VALIDATION AND COMPARISON.

Error metric	**Error metric expression**
MAE	$\frac{1}{n_{hours}}\sum_{t=1}^{n_{hours}}\left\|p_{t,act}-p_{t,pred}\right\|$
MAPE	$\frac{100}{n_{hours}}\sum_{t=1}^{n_{hours}}\left\|\frac{p_{t,act}-p_{t,pred}}{p_{t,act}}\right\|$
R^2	$1-\frac{\sum_{t=1}^{n_{hours}}\left(p_{t,act}-p_{t,pred}\right)^2}{\sum_{t=1}^{n_{hours}}\left(p_{t,act}-p_{mean}\right)^2}$

III. RESULTS

This section illustrates the obtained results when both proposed models are adopted. Indeed, both models are trained and tested using Italian DAM prices spanning from 2011 to 2024 [11] as target variable. The models are trained on data from 2011 to 2023, while the testing horizon is limited to 2024 only to assess whether the proposed models can capture key price dynamics. The available regressors for the GPR models refer to Italy as well and comprise: yearly mean gas price [12], annual total load demand [13] [14], annual total PV production [13] [15] and annual total thermoelectric production [13] [15]. Quarterly values of gas price and load demand, needed for the LP sub-model of the hybrid LP-GPR model, are computed starting from daily values for the Italian system [16] [17].

A. *Pure GPR Model*

This section illustrates the results obtained on the test dataset when the pure GPR model is applied. TABLE IV shows the optimal kernel function obtained by maximising the log-marginal likelihood on the train dataset for each GPR model.

TABLE IV OPTIMAL KERNEL FUNCTION FOR EACH TRAINED GPR MODEL.

Coefficient	**Kernel function**	**Regressors**
a0	Linear	Gas price, load demand
a1	Linear	Gas price Load demand
a2	Exponential	
a52	Linear	PV production Thermoelectric production
a365	Constant	
a730	Linear	
a1095	Squared exponential	
a1460	Exponential	
b1	Exponential	
b2	Matern with $\nu = 1.5$	
b52	Linear	
b365	Linear	
b730	Linear	
b1095	Exponential	
b1460	Constant	

Figure 2 represents the actual and predicted filtered price in 2024 when the pure GPR model is applied. Moreover, Figure 3 shows the same variables but over two weeks. As expected, the pure GPR model lacks in capturing the supra-weekly price patterns, while it is effective in modelling the sub-weekly dynamics.

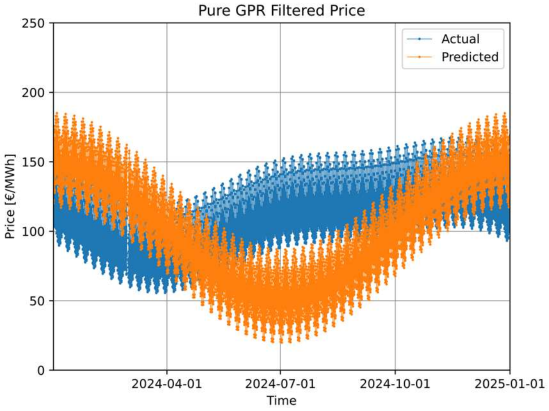

Figure 2. Actual and predicted filtered prices over 2024 computed through the pure GPR model.

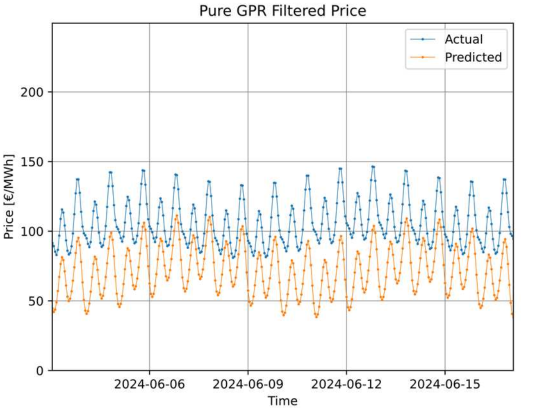

Figure 3. Actual and predicted filtered prices over two weeks in 2024 computed through the pure GPR model.

B. *Hybrid LP-GPR Model*

This section illustrates the results obtained on the test dataset when the hybrid LP-GPR model is applied. Figure 4 shows the actual and predicted combined price in 2024 when the hybrid LP-GPR model is applied. As noted, the sub-weekly dynamics are still effectively captured. Moreover, the supra-weekly dynamics are now also efficiently represented. In this sense, the hybrid LP-GPR model represents a trade-off between two key factors: the need for high-time granularity data that better accounts for regressors variations throughout the year; and the need to maintain the model as simple as possible to ensure feasibility in long-term applications.

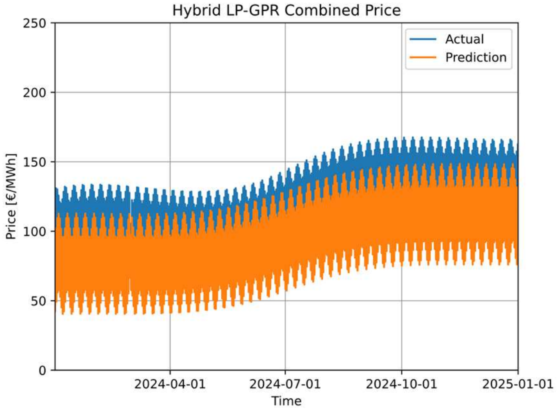

Figure 4. Actual and predicted combined prices over 2024 computed through the hybrid LP-GPR model.

C. *Discussion of Results*

The results of the model validation and comparison are presented below. TABLE V shows the resulting error for each error metric and each proposed model, including a breakdown of the LP and the GPR sub-models for the hybrid LP-GPR model. As can be observed, the pure GPR model is associated with an extremely low R^2 value due to its difficulties in effectively capturing supra-weekly dynamics. Additionally, both the MAE and MAPE metrics show suboptimal performances. In contrast, the GPR sub-model of the hybrid LP-GPR model shows very good performances across the R^2 metric. In this model, the significantly large MAPE is linked to the fact that the sub-weekly filtered price has a zero mean. Therefore, although the MAE is not particularly large, it still leads to high MAPE values. On the other hand, the LP sub-model delivers good results in terms of MAE and MAPE, while its R^2 value remains relatively low. However, this can be mainly attributed to the limited number of predicted points (just four per year in this work) due to the need of ensuring model applicability in long-term predictions.

TABLE V RESULTS OF MODEL VALIDATION ANALYSIS.

Model		**MAE [€/MWh]**	**MAPE [%]**	**R^2 [-]**
Pure GPR		31.63	32.19	- 1.54
Hybrid LP-GPR	GPR sub-model	7.85	262.41	0.67
	LP sub-model	16.84	15.70	- 0.24

Finally, TABLE VI shows the results of the model comparison against the actual DAM prices in 2024. Both proposed models show large errors across all error metrics. However, this is expected since the comparison involves on one hand the base component of DAM prices (modelled by the pure GPR and the hybrid LP-GPR models), while on the other hand the full DAM prices profile, including also the residual component. Nevertheless, it can be noted that the hybrid LP-GPR model outperforms the pure GPR model due to its ability to capture supra-weekly dynamics.

TABLE VI RESULTS OF MODEL COMPARISON ANALYSIS.

Model	**MAE [€/MWh]**	**MAPE [%]**	**R^2 [-]**
Pure GPR	34.45	57.76	- 0.90
Hybrid LP-GPR	21.87	35.13	0.15

IV. CONCLUSIONS

In this paper, two models are developed and compared for modelling electricity price dynamics using limited time-granularity input data to ensure model feasibility in long-term applications. The first pure GPR model aims to predict the main price behaviour by leveraging selected relevant frequencies in the Fourier domain, using only yearly exogenous variables as input data. Meanwhile, the second hybrid LP-GPR model, proposed by the authors, combines linear-polynomial and GPR models to separately handle supra-weekly and sub-weekly dynamics. This approach is based on the hypothesis that supra-weekly dynamics are driven by exogenous variables variations rather than seasonal regimes. Both models are trained on Italian DAM prices from 2011 to 2023 and tested on 2024 data. The testing is conducted in two ways: first, each model is independently validated against the actual main price behaviour, computed according to its respective methodology; then, a model comparison is performed against the actual DAM prices, which includes both main and residual components. The validation phase shows that the hybrid LP-GPR model achieves better error metrics than the pure GPR model due to its ability to capture supra-weekly dynamics. However, the comparison phase shows large errors across all considered error metrics since the comparison involves simplified prices, including only the main price behaviour, against a full price, including both main and residual components. However, the hybrid LP-GPR model still outperforms the pure GPR model, once again demonstrating its enhanced ability to model supra-weekly dynamics.

Future research could develop in two parallel directions. First, efforts could focus on improving accuracy against full prices by incorporating price residuals into the models. Moreover, the model could be applied for scenarios analysis to assess the potential day-ahead electricity prices under different gas price and load demand scenarios —for instance, in cases of higher or lower electrification of consumption.

To conclude, regressors variations throughout the year play a determinant role in modelling the supra-weekly electricity price dynamics. Therefore, a trade-off should be found between the need for high-time granularity input data and the limited availability of such data when applying these models for predictions very far in the future. The hybrid LP-GPR model proposed by the authors appears to be effective in addressing this challenge.

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