Day-ahead Price Forecasting of Electricity Markets by a New Hybrid Forecast Method

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Abstract

Energy price forecast is the key information for generating companies to prepare their bids in the electricity markets. However, this forecasting problem is complex due to nonlinear, non-stationary, and time variant behavior of electricity price time series. Accordingly, in this paper a new strategy is proposed for electricity price forecast. The forecast strategy includes Wavelet Transform (WT), Auto-Regressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFN).Also, an intelligent algorithm is applied to optimize the RBFN structure, which adapts it to the specified training set, reduce computational complexity and avoids over fitting. In the proposed forecast strategy, the WT provides a set of better-behaved constitutive series, ARIMA generates a linear forecast and RBFN is developed as a tool for nonlinear pattern recognition to correct the forecast error. The proposed strategy is applied for price forecasting of electricity market of mainland Spain and its results are compared with the results of several other price forecast methods. These comparisons confirm the validity of the developed approach .

Keywords**—**Wavelet Transformer, Electricity Price Forecast, ARIMA, RBFN

I. Introduction

The price forecasting problem has become more important problem in restructured power system. This problem is complex and nonlinear. The volatility and nonlinearity of this system directly affect the accuracy of price forecasting, a deficiency which influences market bidding strategies and leads to an unstable market. According to the combination of increasing consumption and obstruction of different types, and the extension of existing electrical transmission networks and these power systems are operated closer and closer to their constrains. By contrast, the electricity market lacks storage for practical purposes, which is an intrinsic source of volatility. Regarding to this fact that accurate price forecasting is critical for producers, consumers and retailers, different techniques have been presented in this field. In fact, they must set up bids for the spot market in the short term and define contract policies in the medium term. In addition, they must define their expansion plans in the long term. For these reasons, all the decisions that each market player must take are strongly affected by price forecasts [1-6].

For the mentioned problem, several strategies have been published by researchers in recent years [7-13]. Auto Regressive (AR) [14], Auto Regressive Moving Average (ARMA) [15], and the Auto Regressive Integrated Moving Average (ARIMA) [16] are some of the previous efforts. Considering the moments of a time series as variant where the error term does not have zero mean and constant variance as with an ARIMA process, the Generalized Auto Regressive Conditional Heteroskedastic (GARCH) [17] was proposed. A wavelet Transform signal processing technique presented in[18]. And Dynamic Regression (DR) and Transfer Function (TF) models presented in [19]. Although these approaches are very accurate, most of them are linear and thus cannot capture nonlinear patterns. Moreover, their computational cost is very high and requires a lot of information.

Accordingly, some new strategies have been proposed for this problem which is based on Artificial Neural Networks (ANN). Multi-Layer Perception (MLP) neural network [20-21], Decoupled Extended Kalman Filter (DEKF) are used as a second-order learning algorithm to adjust the weights of the neural network [22], and Fourier and Hartley Transforms [23] is a signal processing techniques. Recurrent and cascade Neural Networks (RNN) [24-25] which have feedback loops, are said to provide satisfactory results for electricity price forecasting, where it is a non-stationary time series prediction. This classification is summarized in Fig. 1.

Regarding to some problems in the mentioned strategies, this paper proposes a hybrid model to solve the mentioned problem. Accordingly, a hybrid wavelet-ARIMA and Radial Basis Function Neural (RBFN) model are used based on a meta-heuristic algorithm which is named Modified Invasive Weed Optimization (MIWO) [26]. This method is inspired from weed colonization and motivated by a common phenomenon in agriculture that is colonization of invasive weeds. Actually, the weeds have shown with

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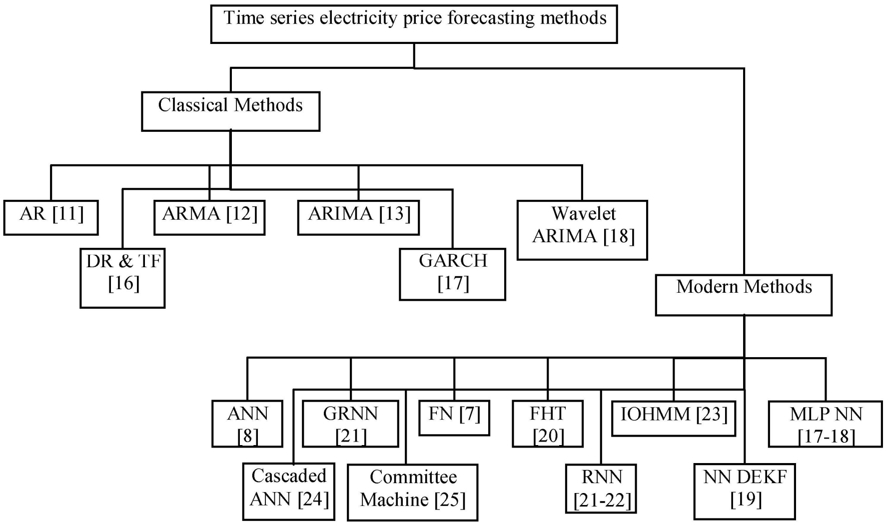

Fig. 1. Common time series approaches for electricity price forecasting

adaptive nature and very robust which turns them to undesirable plants in agriculture. Advantages of the proposed price forecasting method are:

- The original price signal is decomposed by WT.
- The linear patterns in the time series are recognized by ARIMA.
- Outputs of ARIMA model are recomposed via inverse wavelet transform.
- RBFN network is used to correct the errors of the wavelet- ARIMA predictor to pick up potential nonlinear patterns hidden in the residual term.
- MIWO optimizes the center and width of radial basis function, as well as the size of RBFN network.

The remaining parts of the paper are organized as follows. In the second section, the proposed price forecast strategy is described. Section three presents the obtained numerical results. Section four concludes the paper.

II. THE HYBRID PRICE FORECAST MODEL

A. Wavelet Transformer

Finding an appropriate model for input data is one of the most interesting research fields. Where, it is worth to develop forecasting methods featured with more accuracy while less input data is used. As mentioned in introduction section, different models have been proposed for this issue. In this paper, we have combined the wavelet-ARIMA model with the RBFN network, where the error of the wavelet-ARIMA model is predicted by RBFN network prior to forecasting process.

The basic concept in wavelet analysis begins with the selection of a proper wavelet (mother wavelet) and then performing an analysis on its translated and dilated versions. A wavelet can be defined as a function $\psi_{(x)}$ with a zero mean;

$$\int_{-\infty}^{+\infty} \psi_{(x)} dt = 0 \tag{1}$$

A signal can be decomposed into many series of wavelets with different scales *a* and translation *b*:

$$\psi_{(a,b)(x)} = \frac{1}{\sqrt{a}} \psi_{\left(\frac{x-b}{a}\right)} \tag{2}$$

So, the continuous wavelet transform $W_{(a,b)}$ of signal $f_{(x)}$ with respect to a wavelet $\psi_{(x)}$ is given by [18]:

$$W_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f_{(x)} \psi_{\left(\frac{x-b}{a}\right)} dx \tag{3}$$

where scale parameter *a* controls the spread of the wavelet and translation factor *b* determines its central position. $\psi_{(x)}$ is also called mother wavelet. A $W_{(a,b)}$ coefficient, represents how well the original signal $f_{(x)}$ and the scaled/translated mother wavelet match each other.

The original signal $f_{(x)}$ can be reconstructed by inverse wavelet transform:

$$f(x) = \int_{0}^{\infty} \int_{-\infty}^{+\infty} \frac{1}{a^2} Wf_{(b,a)} \psi_{b,a(x)} dbda \tag{4}$$

Thus, the set of all wavelet coefficients $W_{(a,b)}$, associated to a particular signal, is the wavelet representation of the signal with respect to the mother wavelet. Since the CWT is achieved by continuously scaling and translating the mother wavelet, substantial redundant information is generated. Therefore, instead of doing that, the mother wavelet can be scaled and translated using certain scales and positions usually based on powers of two [27]. This scheme is more efficient and just as accurate as the CWT [28]. It is known as the Discrete Wavelet Transform (DWT):

$$W_{(m,n)} = 2^{-(m/2)} \sum_{t=0}^{T-1} f_{(t)} \psi_{\left(\frac{t-n.2^m}{2^m}\right)} \tag{5}$$

Where T is the length of the signal $f_{(t)}$. The scaling and translation parameters are functions of the integer variables m and n (a=2^m, and b=$n.2^m$); t is the discrete time index.

Actually, the Mallat strategy is used to implement DWT using filters [18] which has two stages as; decomposition and reconstruction. Depending on the selected resolution levels, the time-series signals are decomposed into a number of wavelet coefficients where, in this manuscript ARIMA technique has been hybrid in this section. If the resolution level is defined as n, after decomposing the signal, there will be one approximation coefficient series with n number of detail coefficient series. For each wavelet coefficient signal, one ARIMA is required to perform the corresponding prediction.

At first, the input is decomposed by the wavelet transform to obtain the available historical price series in a set of four constitutive series. This wavelet offers an appropriate tradeoff between wave-length and smoothness. The wavelet transform applied to price series $P_h(h=1,\ldots T)$ result in 4 series denoted by a_h, b_h, c_h, and d_h; $h=1,\ldots T$. This series are denominated and is denominated the Approximation series. Thus, applying the wavelet transform to the original prices series results in;

$$W(P_h; h=1,...,T) = \{a_h, b_h, c_h, d_h; h=1,...,T\} \tag{6}$$

Then, the ARIMA model of each constitutive series is applied to forecast its 24 future values for day d.. Then the inverse wavelet transform is used to estimate the hourly prices for day d using the estimates for day d of the constitutive series. The inverse wavelet transform is used in turn to reconstruct the estimate series for prices, i.e.,

$$\begin{aligned} &W^{-1}(\{a_h^{est}, b_h^{est}, c_h^{est}, d_h^{est}; h=T+1,...,T+24\}) = p_h^{W,est} \\ &h=T+1,...,T+24 \end{aligned} \tag{7}$$

B. ARIMA Model

The standard statistical methodology to construct an ARIMA model includes the following [29].

- A class of models is formulated assuming certain hypotheses.
- A model is identified for the series considered.
- The parameters of the model are estimated.
- If the hypotheses of the model are validated, the procedure continues in next step; otherwise, the procedure continues in second step to refine the model.
- The model is used to forecast.

In this procedure, ARIMA model is;

$$\phi(B) p_h = c + \theta(B) \varepsilon_h \tag{8}$$

Where p_h is the price at hour h and ε_h is the error term. Polynomials $\varphi(B)$ and $\theta(B)$ are functions of the back-shift operator B (observe that $B^s{}_{ph}=p_{h-s}$). That is, $\varphi(B)p_h=p_h-\varphi_1 p_{h-1}-\ \varphi_2 p_{h-2}-\ldots\varphi_{nF} p_{h-nF}$, and $\varphi_k(k=1,\ldots,nF)$ are polynomial coefficients, and $\theta(B)\varepsilon_h=\ \varepsilon_h-\theta_1\varepsilon_{h-1}-\theta_2\varepsilon_{h-2}-\ldots-\theta_{nT}\varepsilon_{h-nT}$ and $\theta_k(k=1,\ldots,n_T)$ are polynomial coefficients.

Then, the initial selection is based on the observation of the autocorrelation and partial autocorrelation plots [30]. Further refinement of the selection is based on physical knowledge and on engineering judgment. Once the parameters of the polynomials different from 0 have been identified (through plot observation, physical knowledge and engineering judgment), these parameters should be estimated. The estimation procedure is made by historical data. Then, a diagnosis check is used to validate model assumptions. If the estimated model is appropriate, then, the residuals should behave in a manner consistent with the model.

C. RBFN Technique

RBFN technique is needed to avoid the cost of trial and error to determine the feasible RBFN structure to fit the specified training set and improve the generalization ability. Numerical studies have been conducted for evaluation of the proposed method. The experiments show that despite using of fewer data, the results are generally more accurate in comparison with other methods [31].

Radial Basis Function Neural Network (RBFNN) consists of three layers as input layer, output layer and only one hidden layer. The model of RBFNN is as follows:

$$f(I) = \varphi\left(\frac{\|I - c_i\|}{r_i^2}\right)^2 \tag{9}$$

$f\,(I)$ is the output of i^{th} neuron of hidden layer and I is an input training vector; ψ (•) is radial basis function used in non-linear mapping c_i is center for i^{th} hidden layer neuron and r_i is radius for i^{th} hidden layer neuron.

$$\|I - c_i\| = \sqrt{(I_1 - c_{i1})^2 + (I_2 - c_{i2})^2 + ... + (I_q - c_{iNi})^2} \quad (10)$$

Where, $\|I - c_i\|$ is Euclidean distance and it can be calculated by the above equation, where q is number of inputs in one training pattern. The widths (σ) of the basis function are decided by the singular values of $G_{tr}.G_{tr}^{+}$ and Y_{tr} are pseudo inverse of G_{tr} and output training patterns matrix respectively.

$$G_{tr} = \left(\|I_q - c_i\|^2\right) = \exp\left(-\frac{N_h}{d_{\max}}\|I_q - c_i\|^2\right) \quad (11)$$
$$W = G_{tr}^{+} \times Y_{tr}$$

The data flow starting from input layer, traverse through a hidden layer and arrives at the output layer. Input as well as output layers of RBFNN have linear activation functions, however the hidden layer neurons has a radial basis function (Gaussian) activation function [32].

$$Y = W^T \times G_{tst}^T \quad (12)$$

where

$$G_{tst} = \left(\|I_{tst} - c_i\|^2\right) = \exp\left(-\frac{\|I_{tst} - c_i\|^2}{2\sigma^2}\right) \quad (13)$$

Input layer weight matrix has value 1 for all its elements, because input is direct and linearly mapped to hidden layer.

D. *MIWO Algorithm*

This time series is used to estimate the error of wavelet-ARIMA method. Thus, a part of the time series of forecast error is used to train the RBFN using Invasive Weed Optimization (IWO). The IWO is inspired from weed colonization and motivated by a common phenomenon in agriculture that is colonization of invasive weeds. Actually, the weeds are very robust which turns them to undesirable plants in agriculture. Since its advent IWO has found several successful engineering applications like tuning of Robot Controller [26], Optimal Positioning of Piezoelectric actuators [33], development of recommender system [34], antenna configuration optimization [35], and etc.

IWO is a meta-heuristic algorithm which mimics the colonizing behavior of weeds. In this algorithm, the process starts with initializing a population. It means that the population of initial solutions is randomly generated over the problem space. Then the population members produce seeds depending on their relative fitness in the population. In other words, the numbers of seeds for each member are beginning with the value of S_{min} for the worst member and increases linearly to S_{max} for the best member [35]. This technique can be summarized as:

1) Initialization

In this step, a finite number of weeds are initialized at the same element position of the conventional array which has a uniform spacing of "$\gamma/2$" between neighboring elements.

2) Reproduction

The individuals, after growing, are allowed to reproduce new seeds linearly depending on their own, the highest, and the lowest fitness of the colony (all of plants). The maximum (S_{max}) and minimum (S_{min}) number of seeds are predefined parameters of the algorithm and adjusted according to structure of problem. The schematic seed production in a colony of weeds is presented in Fig. 2. In this figure, the best fitness function is the lower one [35].

3) Spatial Distribution

The generated seeds are being randomly distributed over the d-dimensional search space by normally distributed random numbers with mean equal to zero; but varying variance. This step certifies that the produced seeds will be generated around the parent weed, and leading to a local search around each plant. However, the standard deviation (SD) of the random function decreases over the iterations, which is defined as:

$$SD_{ITER} = \left(\frac{iter_{\max} - iter}{iter_{\max}}\right)^{pow} \left(SD_{\max} - SD_{\min}\right) + SD_{\min} \quad (14)$$

SD_{max} and SD_{min} are the maximum and minimum standard deviation, respectively. And *pow* is the real number. This step ensures that the probability of dropping a seed in a distant area decreases nonlinearly with iterations, which result in grouping fitter plants and elimination of inappropriate plants.

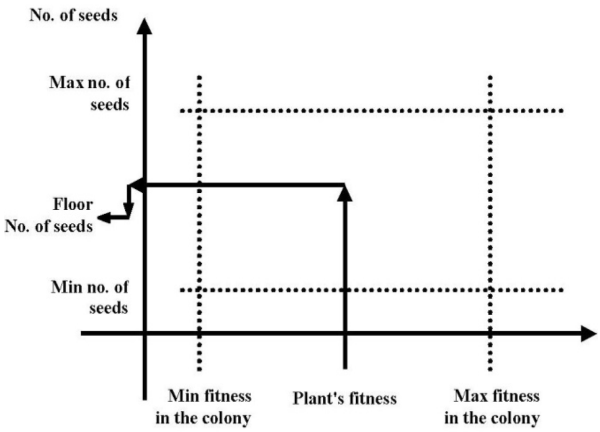

Fig. 2. Schematic seed production in a colony of weeds

4) Competitive Exclusion

When the maximum number of population in a colony is reached (P_{max}), each weed can produce seeds and spread them. Then, new seeds with their parents are ranked together with respect to their fitness. This technique is known as competitive exclusion and is also a selection procedure of IWO. Next, weeds with lower fitness are omitted to reach the maximum allowable population size in a colony. This mechanism using the "survival of the fittest" idea [35] gives a opportunity to plants with lower fitness to reproduce, and if their offspring have good fitness, they can survive in their offspring's existence.

5) Termination Condition

The total process continues until the maximum number of iterations has been reached, and we hope that the plant with the best fitness is the closest one to the optimal solution.

6) Modifications

For modified IWD, we add the $|cos(iter)|$ which is a variation in SD to explore solutions more quickly and prevents the new solutions to be spread out of the search space when the SD is relatively large which is described as:

$$SD_{ITER} = \left(\frac{iter_{\max} - iter}{iter_{\max}}\right)^{pow} \left|\cos\left(iter\right)\right| \left(SD_{\max} - SD_{\min}\right) + SD_{\min} \quad (15)$$

In classical IWO, the seeds are generated from a plant with a certain standard deviation that is decreased as number of iteration increases. Thus, the plants slowly undergo a behavioral transformation from an explorative nature to an exploitative one.

Actually the routine of decreasing SD is modified, such that if the weeds are near a suspected optimal solution then it can exploit quickly rather than wait for the standard deviation to decrease to a reasonable value, which might happen near the end of the run. In this strategy the SD varies within an envelope, so much less values of SD chooses much before the end of the run. Figure 3, shows the total schematic of proposed forecast model.

III. NUMERICAL RESULTS

For this step the second case of Spanish electricity market based on four weeks corresponding to four seasons of year 2002 is presented. This situation results in price changes related to the strategic behavior of the dominant player, which are hard to predict [5-6]. For this case study, some price forecasting strategies have been proposed in literature as the ARIMA time series [29] and etc. Also, it can be considered that during peak hours the Spanish market shows even higher dispersion, which causes more uncertainty in periods of high demand, producing less accurate forecasts. So, it can be claimed that this case study is a real world case study with considerable complexity. The forecasting performance for this market and hourly prices is presented in Fig. 4 and 5, respectively.

In this paper, Mean Absolute Percentage Error (MAPE) is considered as types of accuracy measures [5-6]:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N} \frac{\left|P_i^{true} - P_i^{forecast}\right|}{\overline{P}_i^{true,N}} * 100\% \quad (16)$$

Where N=24 for daily forecasts, N=168 for the weekly forecasts, and $\overline{P}_i^{true,N}$ is the average true price for the N^{th} hour.

In this case, four season results presented in Tables 1 and 2 where, fourth week of February, May, August, and November are selected for winter, spring, summer, and fall seasons, respectively [36].Also, Table 8 presents the variances of the prediction errors

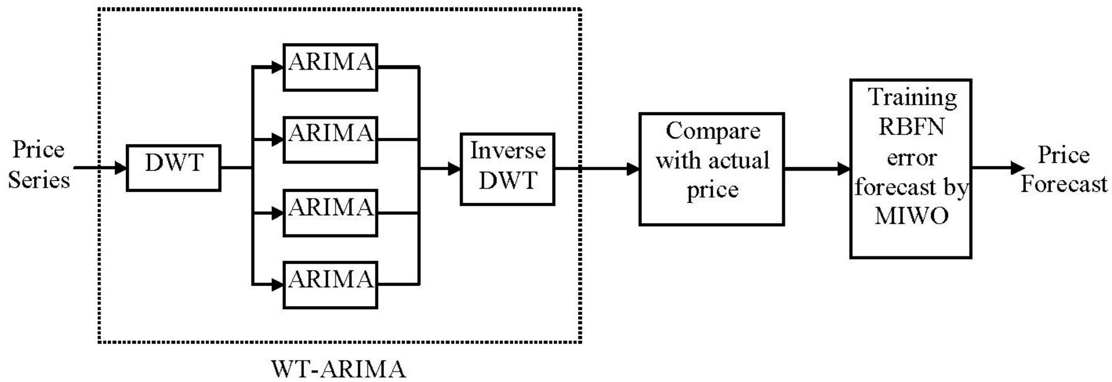

Fig. 3. Total schematic of the proposed wavelet-ARIMA-RBFN-MIWO model

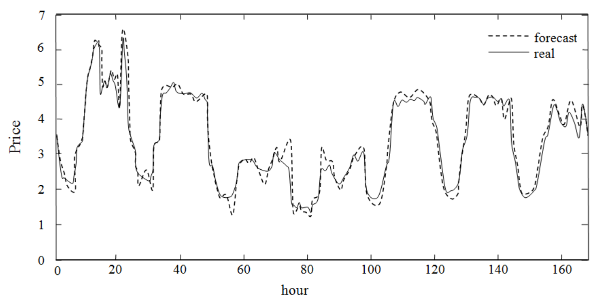

Fig. 4. 24 h ahead forecasts for the summer test week of Spanish market

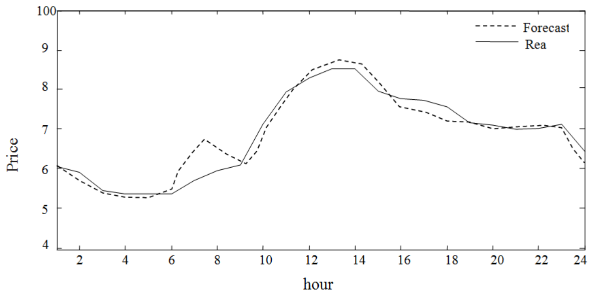

Fig. 5. Hourly prices (solid) and price forecasts (dashed) the Spanish electricity market

for the six methods as well as the proposed strategy. According to these numerical results, it can be claimed that the proposed method has good forecasting in such market in comparison with other methods. In table 1, the proposed method could provide good results in all of seasons. But, the results of AWNN is better that the proposed method in winter and in the remaining results the mentioned model of this paper is superior. In table.2, the AWNN is better in winter and the HIS is better in summer. But, in remaining results the proposed model could provide better results.

IV. CONCLUSION

In this paper the Wavelet Transform (WT), Auto-Regressive Integrated Moving Average (ARIMA) and Radial Basis Function Neural Networks (RBFN) are proposed as a hybrid forecast method for day-ahead price of electricity market based on MIWO. In this model, the MIWO is applied to optimize the network structure which makes the RBFN be adapted to the specified training set, reducing computation complexity and avoiding over fitting. The proposed technique is tested over Spanish electricity market through comparison with other new recent price forecast techniques. Obtained results demonstrate the validity of proposed model in this problem.

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TABLE I
Weekly MAPE values in terms of percentage (%) for 4 weeks of the Spanish electricity market

Test Week	ARIMA [36]	Wavelet-ARIMA [36]	FNN [36]	Mixed Model [36]	MLP [36]	HIS [36]	AWNN [36]	Proposed
Winter	6.32	4.78	4.62	6.15	5.23	6.06	3.43	4.84
Spring	6.36	5.69	5.30	4.46	5.36	7.07	4.67	4.47
Summer	13.39	10.70	9.84	14.90	11.40	7.47	9.64	7.03
Fall	13.78	11.27	10.32	11.68	13.65	7.30	9.29	6.12
Average	9.96	8.11	7.52	9.30	8.91	6.98	6.76	5.62

TABLE II
V_{week} for 4 weeks of Spanish electricity market in year 2002

Test Week	ARIMA [36]	Wavelet-ARIMA [36]	FNN [36]	HIS [36]	AWNN [36]	Proposed
Winter	0.0034	0.0019	0.0018	0.0034	0.0012	0.0015
Spring	0.0020	0.0025	0.0019	0.0049	0.0031	0.0027
Summer	0.0158	0.0108	0.0092	0.0029	0.0074	0.0053
Fall	0.0157	0.0103	0.0088	0.0031	0.0075	0.0031
Average	0.0092	0.0064	0.0054	0.0035	0.0048	0.0029

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