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Integration of Gaussian Processes and Particle Swarm Optimization for Very-Short Term Wind Speed Forecasting in Smart Power

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ABSTRACT

This article describes how the integration of renewable energy in the power grid is a critical issue in order to realize a smart grid infrastructure. To that end, intelligent methods that monitor and currently predict the values of critical variables of renewable energy are essential. With respect to wind power, such variable is the wind speed given that it is of great interest to efficient schedule operation of a wind farm. In this article, a new methodology for predicting wind speed is presented for very short-term prediction horizons. The methodology integrates multiple Gaussian process regressors (GPR) via the adoption of an optimization problem whose solution is given by the particle swarm optimization algorithm. The optimized framework is utilized for the average hourly wind speed prediction for a prediction horizon of six hours ahead. Results demonstrate the ability of the methodology in accurately forecasting the wind speed. Furthermore, obtained forecasts are compared with those taken from single Gaussian process regressors as well from the integration of the same multiple GPR using a genetic algorithm.

KEYWORDS

Gaussian Process Regression, Particle Swarm Optimization, Smart Power, Wind Speed Forecasting

1. INTRODUCTION

Integration of renewable energy in the power grid is one of the cornerstones in building the smart power system of the future (Farhangi, 2010). Renewable energy is not only a sustainable source of energy, but most importantly, it may contribute in greener and less polluted cities of the future (Brenna et al., 2012). Therefore, utilization of

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renewable energy has profound benefits that may not go overlooked. With respect to energy sources, solar and wind are the most prominent and promising energy sources (Dincer, 2000).

Wind power is produced by the operation of wind mills. The driving force behind the wind power production is the wind intensity as it is expressed in terms of speed. In order to fully exploit the wind speed and produce adequate amount of power, the wind mills are grouped together in an area of close geographic vicinity. The group of wind mills as a whole consists of a "wind farm" that may be seen as the equivalent of a power plant, which uses conventional fuel (Papathanassiou and Boulaxis, 2006).

As opposed to conventional power plants the wind farm does not constantly produce the same amount of power. The reason behind that is the nature of the driving force; wind speed is a stochastic variable and cannot be controlled by human means (Aksoy et al., 2005). As a result, scheduling wind power production is a very challenging task and difficult to fully exploit. For instance, during consumption peak hours, when there is a great need for excess power, wind farms might not produce any power because of the lack of wind. In contrast, wind power may be available during times in which the load demand is very low, e.g., after midnight. In addition, the lack of efficient solution for large scale electricity power, results in wasting the generated from wind power.

Smart power systems come to fill the gap in efficient utilization of wind power. They are the result of the integration of power systems with information technologies (Alamaniotis et al., 2010). The overall idea is that use of information in power systems may compensate for the lack of physical storage (Alamaniotis and Tsoukalas, 2013). One of the crucial tools in implementing smart power systems is anticipation (Alamaniotis and Agarwal, 2014; Tsoukalas and Gao, 2008). Anticipation promotes planning and subsequent scheduling of production and consumption activities; in other words, it allows the intelligent management of the power system.

With respect to wind power production, anticipation may be adopted for wind speed forecasting. Speed forecasting allows wind farm operators to schedule the operation of the wind mills and estimate the amount of produced energy at specific time of the day. In addition, it assists 1) the system operator to schedule the operation of the plant units, and 2) the market operator to determine the cost of power ($/Kwh). Overall, wind speed forecasting is a great tool for the efficient and economically operation of power system (Wang et al., 2004).

In this paper, a new methodology for wind power forecasting is being presented. The methodology aims in predicting the wind speed in very short-term prediction horizon. It should be noted that there is a high variety of methods that exist in the literature that use tools from artificial intelligence and statistics (Cadenas and River, 2010; Du et al., 2008; Li and Shi, 2010;Lei at al., 2014; Soman et al., 2010). However, most of those methods deal with the problem of short term forecasting, e.g., a day ahead forecasting, while they require a huge amount of data. Our methodology, aspires in solving the problem of predicting the wind speed for a very short ahead of time horizon, while using a minimal amount of previous recorded data. Furthermore, it aims in capturing the dynamics of the wind in very short term ahead of time, and subsequently predicting any abrupt changes in wind speed.

This paper is organized as follows. In the next section, a brief description of Gaussian process regression (GPR) (Rasmussen, 2006) and particle swarm optimization (PSO) (Alamaniotis et al., 2012) is given. Section 3 describes the proposed forecasting methodology, while section 4 gives the results taken on a set of real world data. Lastly, section 5 concludes the paper and highlights the main points.

2. BACKGROUND

2.1. Gaussian Process Regression

The Gaussian (or normal) distribution is probability distribution function that is defined by two parameters, namely, the mean and the variance. Likewise, the Gaussian process (GP) is a process fully defined by two functions, namely, the mean and the covariance function:

$$GP \sim N\left(m(x), C(x^T, x)\right) \tag{1}$$

where $m(x)$ denotes the mean function, and $C(x^T,x)$ the covariance function (Rasmussen, 2006).

In the milieu of machine learning, a Gaussian process is entailed in the subgroup of kernel machines, given that it can defined with the aid of a kernel function (Bishop, 2006). A kernel function is any valid analytical function that may be expressed in the dual form (Bishop, 2006):

$$k\left(x_1, x_2\right) = f\left(x_1\right)^T \cdot f\left(x_2\right) \tag{2}$$

with f(x) being the "basis function."

In the context of kernel machines, the covariance function in (1), i.e., $C(x',x)$ is set equal to a kernel function, i.e., $C(x',x) = k(x',x)$, while the mean function is set equal to zero, i.e., m(x)=0. The latter is a convenient choice toward deriving the regression framework of learning Gaussian processes, known as Gaussian process regression (GPR) (Rasmussen, 2006).

Derivation of GPR framework assumes a predeterimed population of pairs (i.e., training datapoints), that contain a known output **t** for a known input **x**. Furthermore, it adopts as a starting point the simple linear regression model:

$$y = b_0 + \sum_{i=1}^{N} b_i x_i \tag{3}$$

with b's being the regression coefficients and N the number of training datapoints. Thus, by utilizing the N training datapoints the GPR framework aims at predicting the target value t_{N+1} of an unknown input x_{N+1}. To that end, it is assumed that the joint distribution between the N available datapoints, denoted as $\mathbf{x}_N$, and the unknown x_{N+1} is also Gaussian. Based on that assumption, it has been shown (Rasmussen, 2006; Mackay,1998) that the GPR framework provides a predictive distribution whose mean and covariance functions are given by the following formulas respectively (Mackay, 1998):

$$m(x_{N+1}) = \mathbf{k}^T \mathbf{C}_N^{-1} \mathbf{t}_N \tag{4}$$

$$\sigma^2 \left(x_{N+1}\right) = k - \mathbf{k}^T \mathbf{C}_N^{-1} \mathbf{t}_N \tag{5}$$

where $\mathbf{C}_N$ denotes the NxN matrix of covariances among the N training datapoints, $\mathbf{k}$ denotes the vector of covariances between the new $N+1$ and each of the N points, and lastly k is a scalar value.

Overall, we may conclude that selection of the appropriate kernel allows the modeler to control the output predictive distribution. Therefore, kernel selection plays an important role depending on the application.

2.2. Particle Swarm Optimization

Evolutionary computing is a branch of artificial intelligence algorithms inspired by natural processes. One prominent evolutionary algorithm is the particle swarm optimization that emulates the behavior of birds in a flock (Shi, 2001). PSO has been applied to a high variety of complex problems where solution to an optimization formulation is required.

PSO utilizes the synchronization of movements of a set of particles (i.e., potential solutions) in the parameter space. Its goal is to search for an optimal solution of the optimization problem at hand. To that end, every particle changes positions in the space by: 1) moving toward the best neighbor, and 2) moving back to the position of the most recent best solution. Particle movement is expressed by the following formula:

$$\mathbf{x}_k \left(t+1\right) = \mathbf{x}_k \left(t\right) + \mathbf{v}_k \left(t+1\right) \tag{6}$$

where $\mathbf{v}_k(t)$ is a factor that expresses the velocity of particle k at time t, and $\mathbf{x}_k(t)$, $\mathbf{x}_k(t+1)$ are the particle positions at times t and $t+1$ respectively. The velocity factor of (1) expresses the speed of the particle moving into the search space and is computed by:

$$\mathbf{v}_k \left(t+1\right) = \mathbf{v}_k^{in} \left(t\right) + \mathbf{v}_k^{cogn} + \mathbf{v}_k^{soc} \tag{7}$$

with $\mathbf{v}^{in}$ being the inertia factor (i.e., system memory), $\mathbf{v}^{cogn}$ the cognitive factor (particle's own experience), and $\mathbf{v}^{soc}$ the social factor (neighbor particle experience).

In general, Equations (6) and (7) are iteratively updated until a global optimal solution is identified. To that end, a stopping criterion is adopted to designate the end of iterations, and subsequently to identify a solution. The stopping criterion must target in 1) preventing PSO from identifying a suboptimal solution, and 2) maintaining low computational complexity. Several stopping criteria that have been applied in PSO development are discussed in (Engelbrecht, 2007).

PSO requires the initialization of a set of particles, i.e., the swarm, and their placement in random positions in the search space. However, particle placement, and subsequent movement is constrained by the boundaries of the search space; particles ending outside the search space are not able to contribute to the solution finding. Each particle in the swarm moves independently (6) and (7) and all of them converge after a number of iterations to the best position (best solution). Overall, the main idea behind PSO is the use of multiple particles and their subsequent synchronization of movements in the space.

3. VERY-SHORT TERM WIND SPEED FORECASTING

3.1. Problem Statement

Integration of renewable sources in electricity power system is a key point for developing the future smart power grid. In particular, the integration of wind driven energy systems and the efficient management of the generated energy pose significant challenges. The dynamic nature of the wind expressed as varying wind speed, is the main source of those challenges.

Smart power systems aspire to manage the generated from wind energy by utilizing the available data and information flow. In smart power, anticipation plays the most significant role in efficient management of the power grid. Therefore, speed forecasting is at the center of attention in wind energy systems given that it may provide 1) the amount of generated energy and 2) the time intervals of wind energy availability. Hence, wind speed forecasting may contribute to integration of wind power to the power grid in an efficient way.

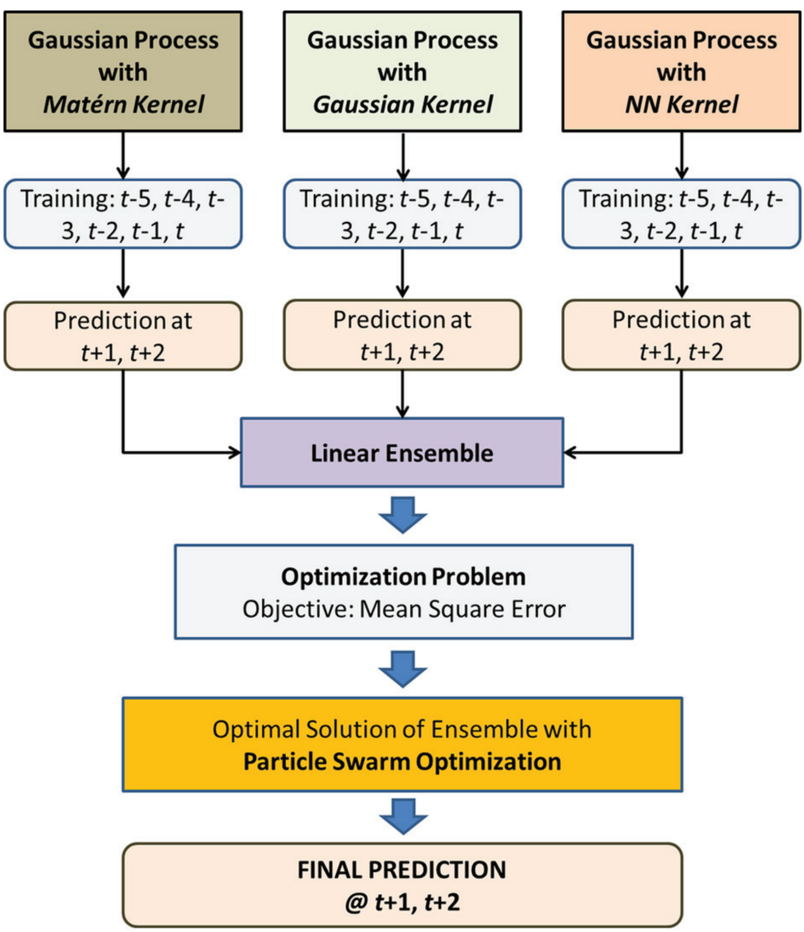
The variability of wind speed with respect to time, allows forecasting to be performed in various ahead-of-time intervals. The length of the interval, i.e., forecasting horizon, varies from minutes to years ahead, with each forecasting horizon serving a different purpose. The focus of the current manuscript is the very-short-term forecasting of wind speed, and more specifically, predicting the hourly wind speed values for two hours ahead of the current time.

3.2. Methodology

The main idea behind the proposed methodology is the development of a synergistic framework of multiple kernel machines, with particle swarm optimization being the essential relay for integrating the kernel machines. The type of kernel machines adopted in this work is the kernel modeled Gaussian processes, which have been proved to be efficient in forecasting applications (Alamaniotis et al., 2012 August). The block diagram of the proposed wind forecasting methodology is depicted in Figure 1.

Initially, we adopt a set of three Gaussian processes, each equipped with a different kernel function. In particular, the three kernels utilized in the current work are namely, the Matérn, Gaussian and Neural Network (NN) kernel. The analytical formulas of those kernels may be found in (Rasmussen, 2006). It should be noted that each kernel models various data properties. Regarding the kernels used in the current work, the Matérn kernel models non-smooth processes, the Gaussian kernel stationary and smooth processes, and the neural network (NN) kernel non-stationary processes. The aforementioned kernels are comprised of one or more parameters that are evaluated in the training phase. In the next step, the three kernel machines are trained using the 6 most recent wind speed measurements. Given that in the current manuscript we consider hourly data then the training dataset is comprised of the hourly speed in the past 6 hours.

Figure 1. Block diagram of the wind forecasting methodology



Once training is completed the individual kernel machines are utilized for prediction making of the hourly wind speed in the next two hours. The individual predictions are recorded and forwarded to the next step where a linear ensemble is formed. The linear ensemble takes the form given below:

$$P_E(t) = \alpha_M \cdot P_M(t) + \alpha_G \cdot P_G(t) + \alpha_N \cdot P_N(t) \tag{8}$$

where $P_E(t)$ is the ensemble value at time t, and $P_M(t)$, $P_G(t)$, $P_N(t)$ the predicted values taken with Matérn, Gaussian, and NN kernels respectively. Similarly, the α_M, α_G, α_N are the linear coefficients that weigh the respective predictions. Therefore, the linear ensemble consists of the weighted prediction of the three individual predictions.

In the linear ensemble of (9) the unknown parameters are the three linear coefficients. To evaluate the linear coefficients, we formulate a single objective optimization problem. The objective function is the mean square error (MSE):

$$MSE = \frac{1}{6}\sum_{t=-5}^{0}\left(P_E(t) - R(t)\right)^2 \tag{9}$$

where $P_E(t)$ denotes the ensemble prediction, and R(t) the observed wind speed value for time t. It should be noted that in our work the MSE is computed between predicted and observed values of the most 6 recent measurements.

Additionally, there is the constraint that the linear ensemble coefficients must be semi-positive because they represent the contribution of each individual predictor to the overall ensemble. Therefore, the optimization problem takes the form given below:

$$\begin{aligned} &\underset{\alpha_M,\alpha_G,\alpha_N}{\text{minimize}} \quad \frac{1}{6}\sum_{t=-5}^{0}\left(P_E(t) - R(t)\right)^2 \\ &\text{w.r.t} \quad P_E(t) \geq 0 \\ &\text{where } P_E(t) = \alpha_M \cdot P_M(t) + \alpha_G \cdot P_G(t) + \alpha_N \cdot P_N(t) \end{aligned} \tag{10}$$

where we observe that the formulation demands the minimization of the objective function, i.e., MSE, with respect to the three linear coefficients.

Solution of (10) is sought using the particle swarm optimization algorithm. The solution of the problem is utilized to forecast the wind speed for one and two hours ahead of time, i.e., t+1 and t+2. It should be noted that the forecasting takes place every two hours. Therefore, the forecasting process takes the form of a sliding window of two-hour length.

Overall the presented methodology aims at capturing the wind dynamics through the use of multiple kernels, and a weight assigning process driven by PSO.

4. RESULTS

In the current work, the presented forecasting methodology is tested on real world wind speed datasets. The speed data are coming from the National Renewable Energy Laboratory (NREL) Observed Atmospheric and Solar Information System (OASIS) (Andreas and Wilcox, NREP report). The testing dataset include average hourly wind speeds for the dates January 1, 2017 - January 16, 2017 and are measured in m/s. Furthermore, the training of the Gaussian process models is performed by the *Pollak-Ribiere* optimization algorithm (Alamaniotis et al., 2012).

Results obtained with each of the individual Gaussian process regressors as well with the presented GP-PSO methodology are presented in Table 1. In addition, results taken with a genetic algorithm are also given; the genetic algorithm (GA) is applied for solution finding of the optimization problem in (11). Results in Table 1 are provided with respect to MSE obtained for the whole day for each of the tested predictors. Furthermore, for visualization purposes Figure 2-5 present the forecasted speed signal against the real wind speed values.

We observe in Table 1 that the proposed GP-PSO method is a robust method that provides the lowest error in a high number of cases. It does not always provide the lowest MSE because the presented methodology weighs the individual GP regressors to make the final prediction. We observe that the GP equipped with the NN kernel gives very high error in the majority of the cases, and that adds some bias in the ensemble.

Table 1. Wind speed forecasting results

Day Year 2017	Mean Square Error (MSE)				
	GPR Matérn	GPR Gaussian	GPR NN	Ensemble GP-GA	Ensemble GP-PSO
Jan 1	4.3760	3.2278	19.5567	5.5826	5.5141
Jan 2	0.9309	0.9930	4.8403	2.7597	2.3507
Jan 3	3.4792	3.4183	7.3549	3.0299	3.0283
Jan4	2.3489	2.5974	8.1688	2.6938	2.5270
Jan 5	2.9935	2.6757	10.1454	2.4794	2.3222
Jan 6	4.4923	4.4388	6.9932	4.1001	4.0532
Jan 7	3.0224	2.5706	12.0454	3.3698	3.1949
Jan 8	3.4567	3.5819	7.1300	2.1973	2.1695
Jan 9	6.7584	6.3367	9.0655	8.2583	8.2583
Jan 10	4.9825	5.2828	9.5152	2.1465	1.6106
Jan 11	7.2305	7.3023	7.6721	5.5978	5.5523
Jan 12	1.5299	1.5808	2.2429	1.9449	1.8578
Jan 13	3.1357	3.4640	4.1996	3.6720	3.6720
Jan 14	3.8547	3.9875	6.1555	5.1869	5.1841
Jan 15	3.2337	2.8951	3.3283	3.4411	3.4386
Jan 16	5.8400	5.8776	6.5554	6.4865	6.4401

Figure 2. Hourly wind speed forecasts against true speed for January 3, 2017

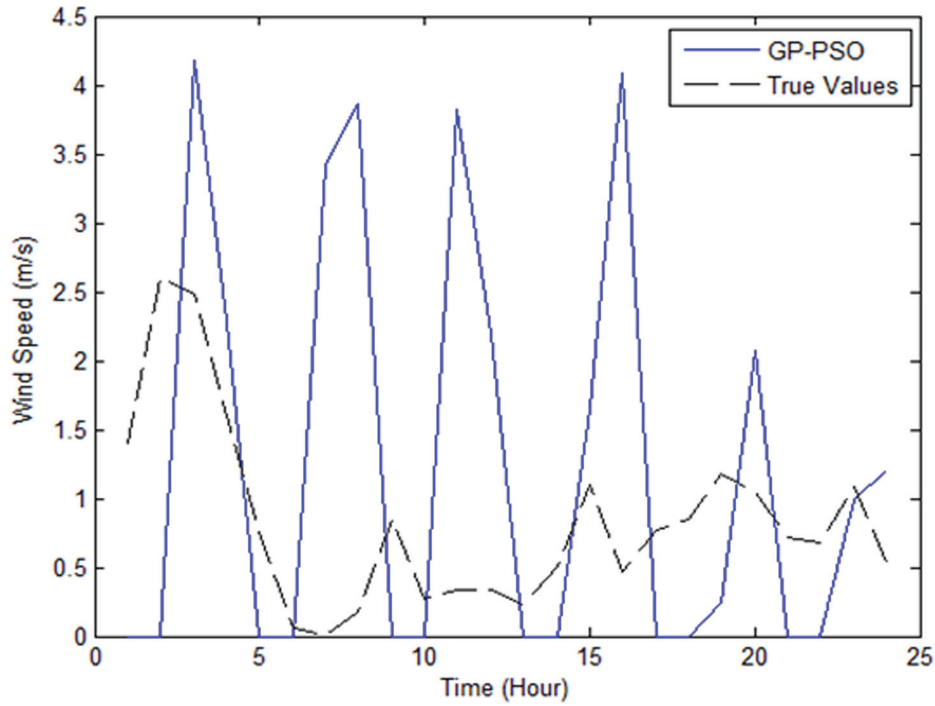


Figure 3. Hourly wind speed forecasts against true speed for January 7, 2017

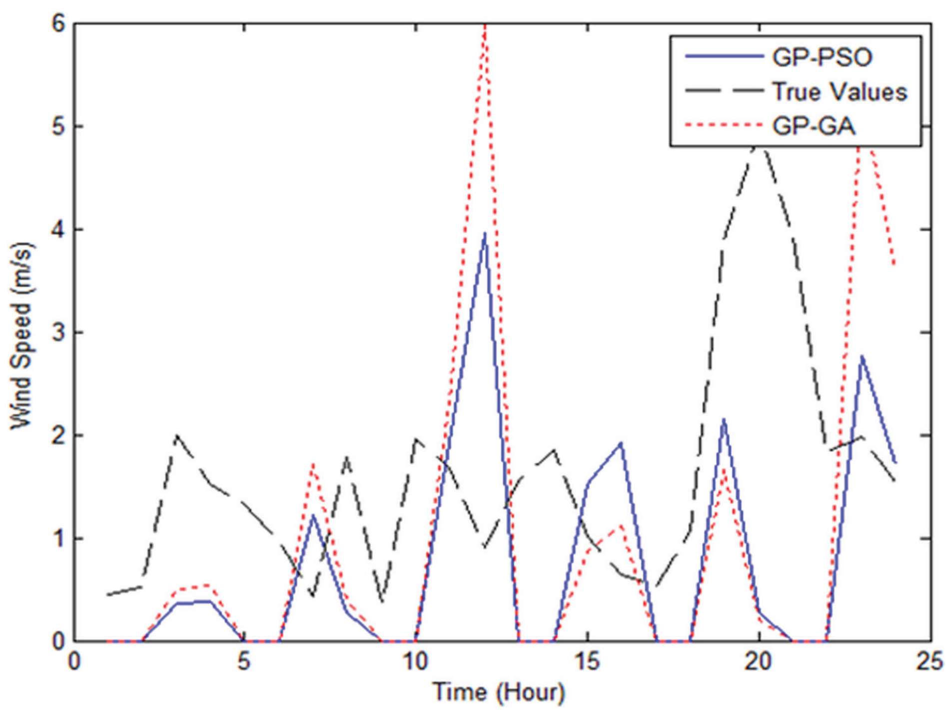


Figure 4. Hourly wind speed forecasts against true speed for January 8, 2017

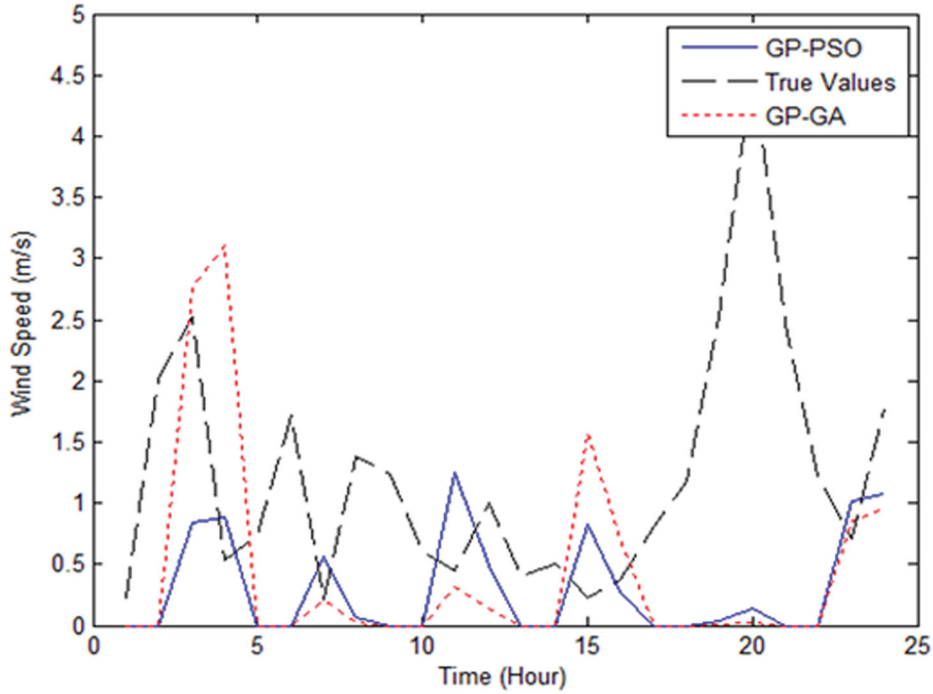
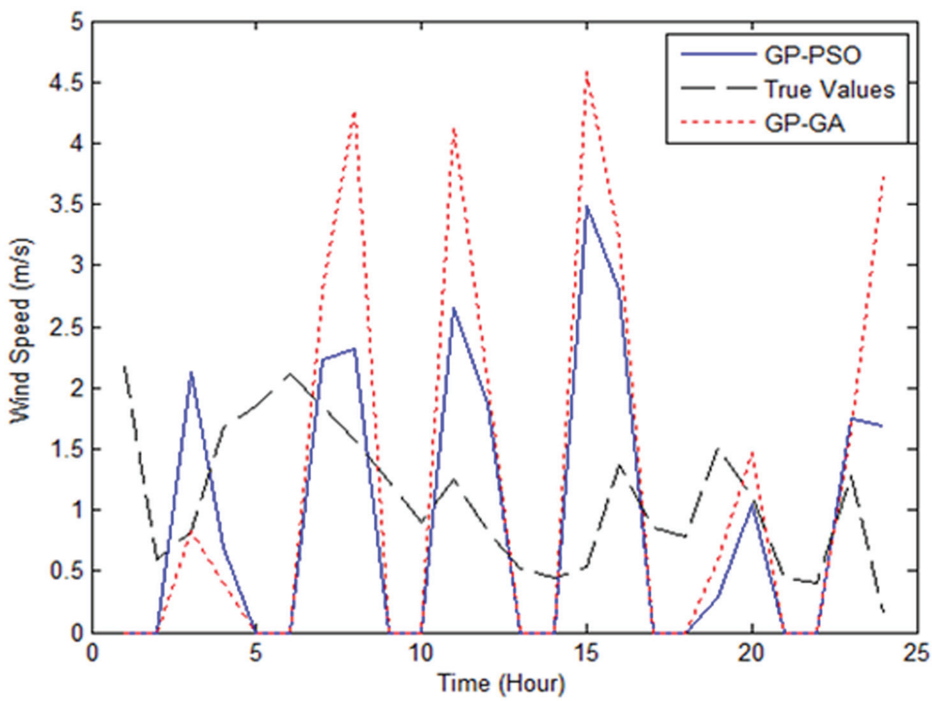


Figure 5. Hourly wind speed forecasts against true speed for January 10, 2017



However, it should be noted that the GP-PSO provides low error in all tested cases, which designates the robustness of the method. In addition, the use of PSO provides lower error in all cases compared to optimization with the genetic algorithm.

With regard to the rest forecasters, i.e., the individual GPR, there is no a single model that performs better than the rest in all cases. Though the Gaussian kernel provides the lowest error in many cases, it does not consistently perform better than the rest. This observation supports the statement that we do not know a priori which kernel will be the best performer in our forecasting. Given that the PSO ensemble is a robust method and consistently provides low error, then the GP-PSO method is preferable that individual GPR forecasters.

5. CONCLUSION

A new methodology for wind speed forecasting that is applicable in developing smart power systems is discussed in the current manuscript. The presented methodology that integrates a set of three kernel modeled Gaussian processes with Particle swarm optimization is tested on a set of real wind speed data. Results exhibit the robustness of the methodology in predicting the hourly wind speed, while proving that the use of PSO improves performance as compared to Genetic algorithms.

Future work will move to two directions: 1) testing of a higher number of kernels beyond the three ones presented in this work, and 2) extensive testing in larger dataset. Furthermore, comparison with other optimization methods will be also planned.

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