Multi-Time Series and -Time Scale Modeling for Wind Speed and Wind Power Forecasting

Part II: Medium-Term and Long-Term Applications

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Abstract—**This paper represents the second part of an entire study which focuses on multi-time series and -time scale modeling in wind speed and wind power forecasting. In the first part of the entire study [1], firstly, moving average (MA), weighted moving average (WMA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models are introduced in-depth. Afterwards, the mentioned models are analyzed for very short-term and short-term forecasting scales, comprehensively. In this second part of the entire study, we address the medium-term and long-term prediction performance of MA, WMA, ARMA and ARIMA models in wind speed and wind power forecasting. Particularly, 3-h and 6-h time series forecasting models are constructed in order to carry out 9-h and 24-h ahead forecasting, respectively. Many valuable assessments are made for the employed statistical models in terms of medium-term and long-terms forecasting scales. Finally, many valuable achievements are discussed considering a detailed comparison chart of the entire study.**

Keywords—Time series methods; forecating; medium-term; long-term; wind speed; wind power

I. INTRODUCTION

In recent decades, the wind power generation has become a major energy source due to the fossil fuel depletion, the political incentives for low carbon generation and environmental concerns about global warming [2, 3]. The main indicator of this case is based on the increase in size and capacity of wind turbines. The rotor diameter and the power generation of wind turbines have reached to 145 m - 10 MW in 2015 from 15 m - 50 kW in 1980 [4, 5]. Despite these rapid developments in wind turbine industry, wind power penetration still poses some operational challenges in maintaining the reliability of power systems due to the wind fluctuations [6]. Inherently, power system operators needs accurate wind speed and wind power forecasts in order to include wind power generation into economic scheduling, to solve reserve allocation problems and to optimize the operational costs [7, 8].

As discussed in Part I [1], many research efforts have been done in the focus of different prediction methods and different time horizons for wind speed and wind power forecasting. In case of reflecting the research activities in the literature, different prediction methods based on physical, statistical and soft computing modeling are overviewed in [9, 10, 11, 12]. In addition, different time horizons based on very short-term, short-term, medium term and long-term scales are utilized in [13, 14, 15, 16]. These works have discussed specific aspects of wind speed and wind power forecasting. However, MA, WMA, ARMA and ARIMA models considered in our entire study (that means both Part I and Part II) have not been handled with the mentioned four time scales for an extensive performance analysis in wind speed and wind power forecasting, yet.

To aid our discussion, the main goal of this Part II is to conclude the analysis started in Part I by means of conducting a detailed analysis on the prediction accuracy of the proposed statistical models in medium-term and long-term wind speed and wind power forecasting. As a result of filling a gap in the field of wind speed and wind power forecasting, the robustness and the weakness assessments of MA, WMA, ARMA and ARIMA models are realized for very-short term, short-term, medium-term and long-term forecasting periods. In addition, the properties belong to wind speed and wind power dataset [17] and the theoretical instructions belong to MA, WMA, ARMA and ARIMA models [18, 19, 20] have been given in Part I. In here, mean absolute percentage error (MAPE) is preferred again for a proper comparison of forecasting results [21].

II. MEDIUM-TERM FORECASTING RESULTS

Every three consecutive data points in the 1-h time series dataset are aggregated into a mean 3-hourly value and thus, the final dataset used for medium-term forecasting includes 320 data points for each parameter. The wind speed and wind power values averaged at 3-h intervals are picturized in Figures 1 and 2, respectively. In these figures, the maximum values are measured as 17.03 m/s for wind speed and 1996.61 kW for wind power.

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Figures 3 and 4 show 9-h ahead wind speed forecasting results and errors, respectively. ARIMA(2,1,2) model accomplishes lower forecasting errors than MA, WMA and ARMA(1,1) models. MAPEs of them are realized as 13.86%, 39.35%, 37.20% and 29.98%, respectively. MA model represents the weakest forecasting performance. Besides, Figures 5 and 6 demonstrate 9-h ahead wind power forecasting results and errors, respectively. Distinctly, ARMA(2,2) model succeeds better forecasting accuracy than MA, WMA and ARIMA(1,2,2) models. MAPEs of them are acquired as 72.41%, 117.31%, 81.35% and 109.84%, respectively. Similarly, MA model ensures more unstable estimation period, again. In the stage of checking the optimal models in 9-h ahead forecasting against the persistence model, the improvement percentages of ARIMA(2,1,2) and ARMA(2,2) models are calculated as 53.65% and 4.35%, respectively. Consequently, it is clear that ARIMA(2,1,2) and ARMA(2,2) models play critical roles in 9-h ahead wind speed and wind power forecasting, respectively.

III. LONG-TERM FORECASTING RESULTS

Every 2 consecutive data points in the 3-h time series dataset are aggregated into a mean 6-hourly value and thence, the final dataset used for long-term forecasting contains 160 data points for each parameter. The wind speed and wind power values averaged at 6-h intervals are drawn in Figures 7 and 8, respectively. In these figures, the highest values are observed as 15.02 m/s for wind speed and 1968.94 kW for wind power.

Figures 9 and 10 illustrate 24-h ahead wind speed forecasting results and errors, respectively. ARMA(1,2) model turns out more robust forecasting performance than MA, WMA and ARIMA(1,2,1) models. MAPEs of them are carried out as 38.38%, 46.62%, 55.61% and 74.21%, respectively. ARIMA(1,2,1) model causes the highest forecasting errors. Furthermore, Figures 11 and 12 depict 24-h ahead wind power forecasting results and errors, respectively. At this time, ARMA(1,1) model executes more reliable forecasting accuracy than MA, WMA and ARIMA(1,1,2) models. MAPEs of them are observed as 409.69‰, 570.43‰, 577.50‰ and 623.72‰, respectively. ARIMA(1,1,2) model has the most unsteady estimation process. In the stage of checking the optimal models in 24-h forecasting against the persistence model, the improvement percentages of ARMA(1,2) and ARMA(1,1) models are calculated as 45.91% and 13.59%, respectively. Particularly, ARMA(1,2) model has a remarkable effect in 24-h ahead wind speed forecasting. However, it is not applicable for ARMA(1,1) model due to the its high error rate.

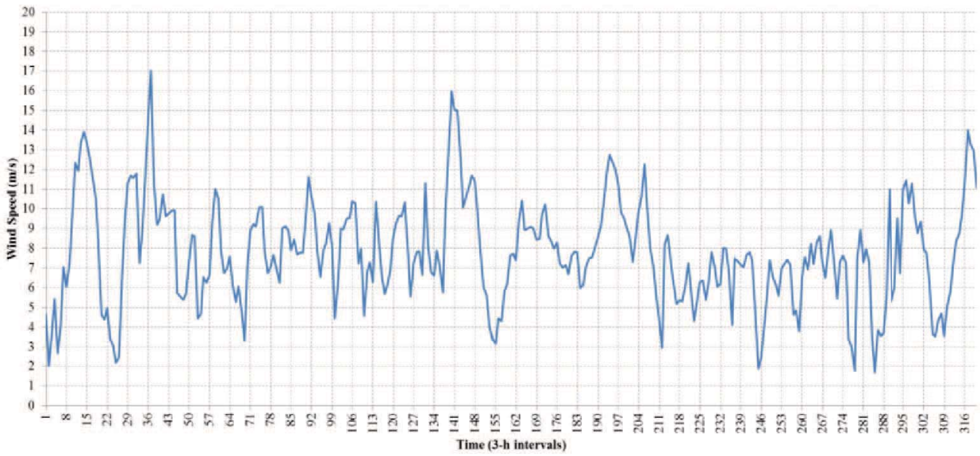

Fig. 1. Wind speed time series at 3-h intervals

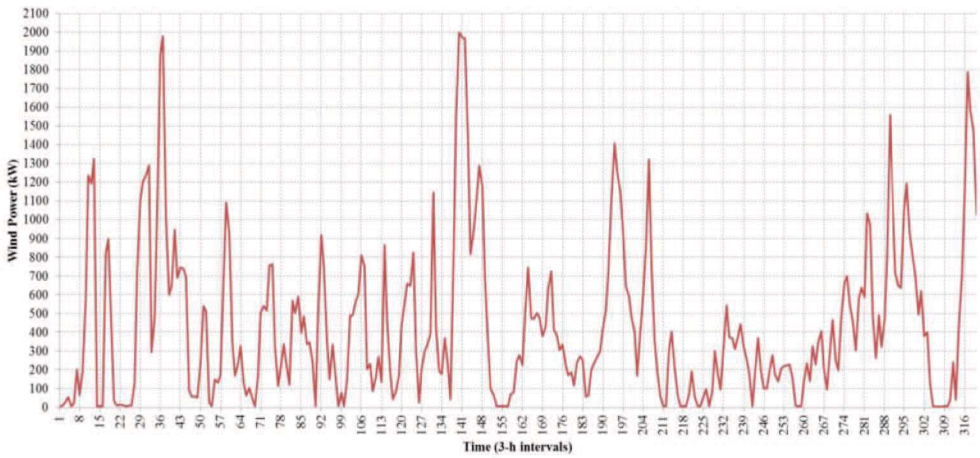

Fig. 2. Wind power time series at 3-h intervals

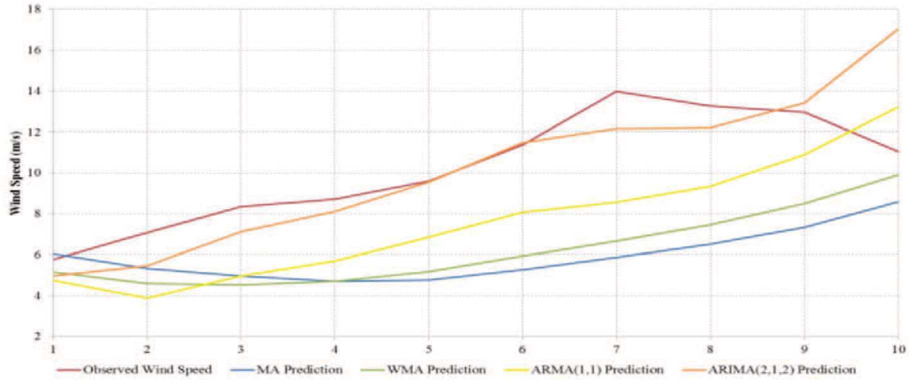

Fig. 3. 9-h ahead forecasting results for wind speed parameter

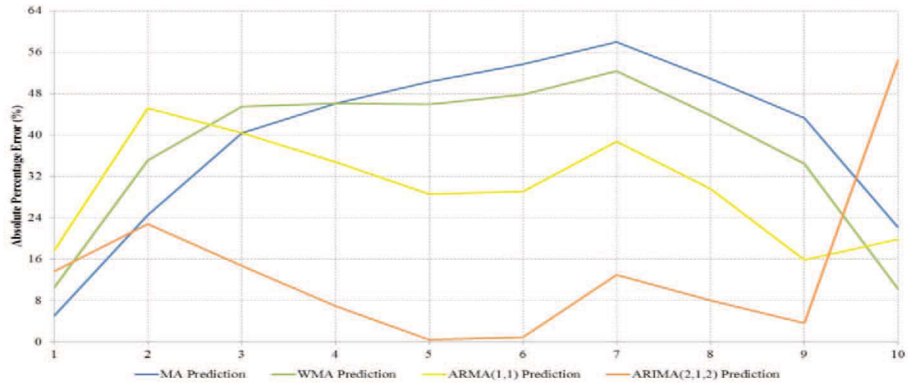

Fig. 4. 9-h ahead forecasting errors for wind speed parameter

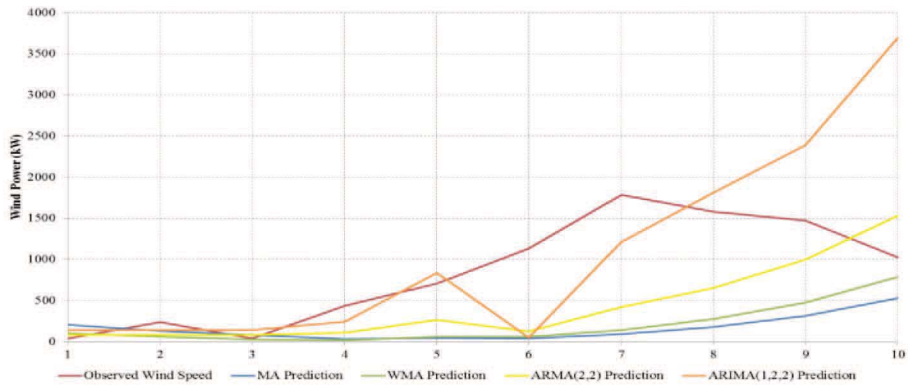

Fig. 5. 9-h ahead forecasting results for wind power parameter

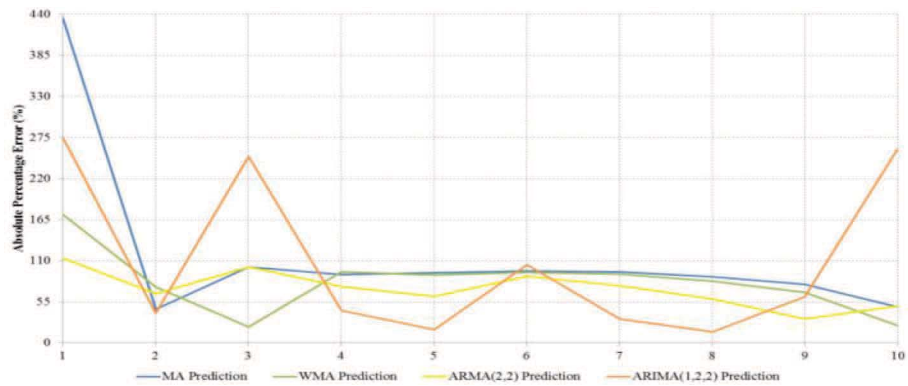

Fig. 6. 9-h ahead forecasting errors for wind power parameter

IV. CONCLUSION

In this second part of the entire study, medium-term and long-term applications for wind speed and wind power forecasting are presented with the main concern on MA, WMA, ARMA and ARIMA models. In consequence of the Part II, it is shown that ARIMA model in 9-h ahead wind speed forecasting and ARMA models in 9-h ahead wind power forecasting and 24-h ahead wind speed and wind power forecasting optimize the prediction accuracy, properly. However, MA models in 9-h ahead wind speed and wind power forecasting and ARIMA models in 24-h ahead wind speed and wind power forecasting reduce the prediction accuracy, seriously. Apart from these accomplishments, all models employed in medium-term and long-term wind speed and wind power forecasting outperform the persistence model in the benchmark test.

As a result of Part I and Part II, the following comparison chart enables researchers to make a number of detailed assessments about the prediction performance of MA, WMA, ARMA and ARIMA models in very short-term, short-term, medium-term and long-term wind speed and wind power forecasting. Some of them are as follows:

- The error rates increase in parallel with the time horizon in wind speed and wind power forecasting.
- The improvement percentages decrease in case of shortening the time horizon in wind speed forecasting. However, it shows nonlinear characteristics in wind power forecasting.
- MA and WMA models never optimize the prediction accuracy as best forecasting models in both wind speed and wind power forecasting.
- ARMA models mostly come into prominence by providing lower prediction errors in both wind speed and wind power forecasting.
- MA and ARIMA models usually create the worst prediction performance in both wind speed and wind power forecasting.
- The proposed time series forecasting models specially worsen the improvement percentage regarding the persistence model in 10-min ahead wind speed forecasting.
- Particularly, the obtained forecasting errors indicate that the proposed time series forecasting models are not suitable for long-term wind power applications.

In future studies, the proposed multi-time series and -time scale analyses should be applied for other renewable energy sources.

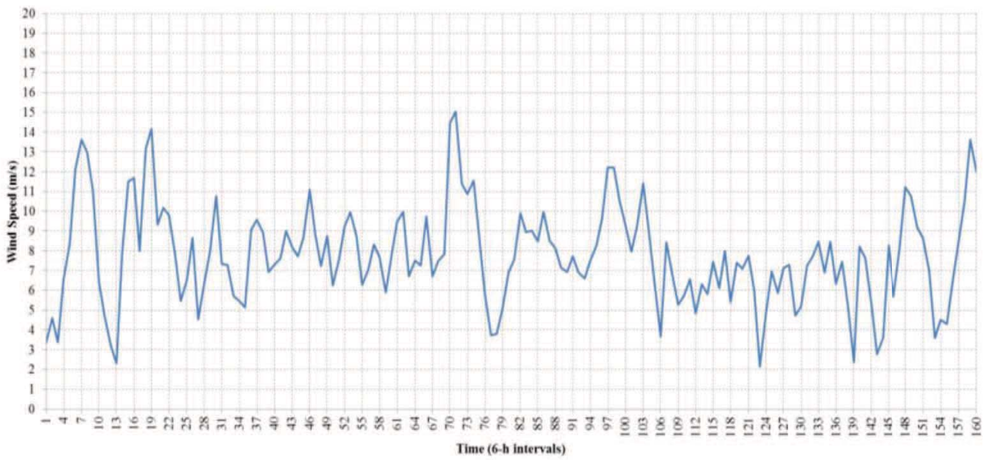

Fig. 7. Wind speed time series at 6-h intervals

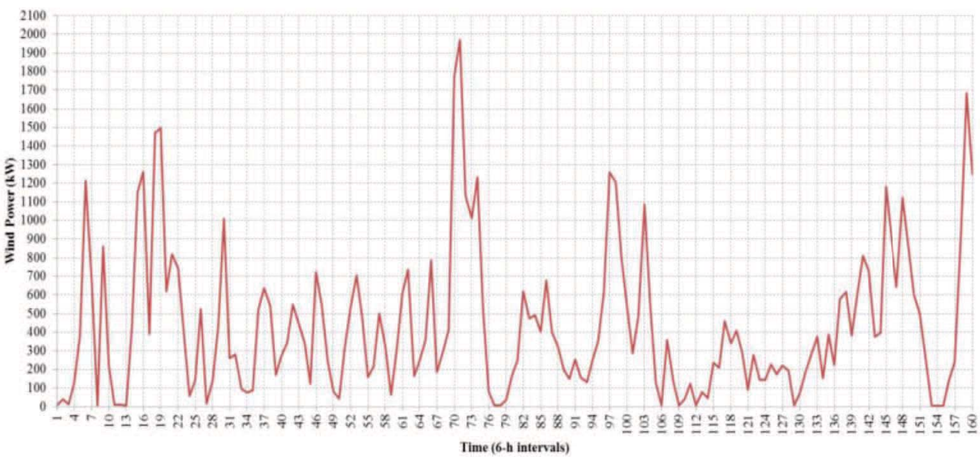

Fig. 8. Wind power time series at 6-h intervals

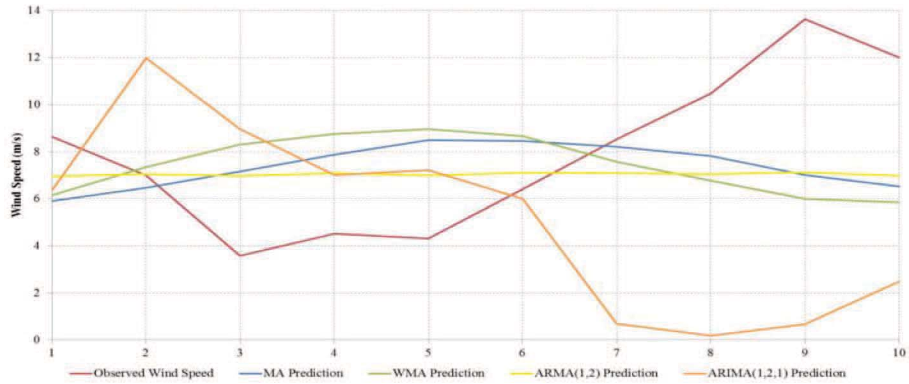

Fig. 9. 24-h ahead forecasting results for wind speed parameter

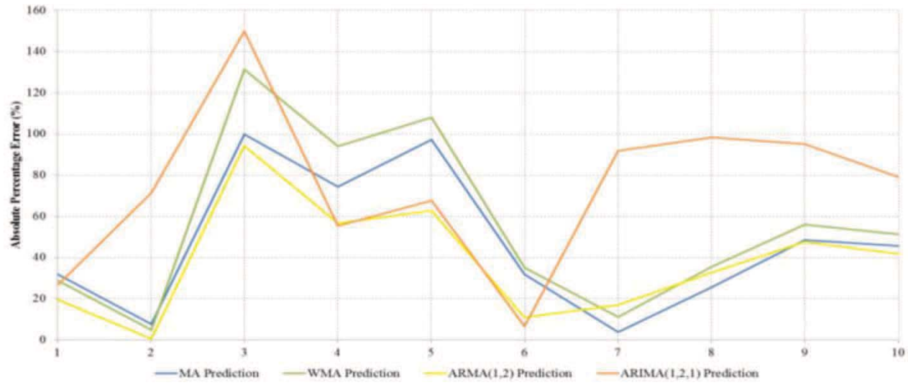

Fig. 10. 24-h ahead forecasting errors for wind speed parameter

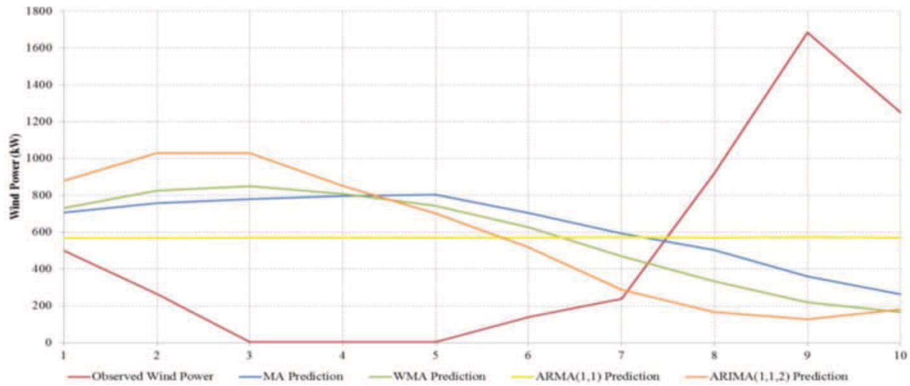

Fig. 11. 24-h ahead forecasting results for wind power parameter

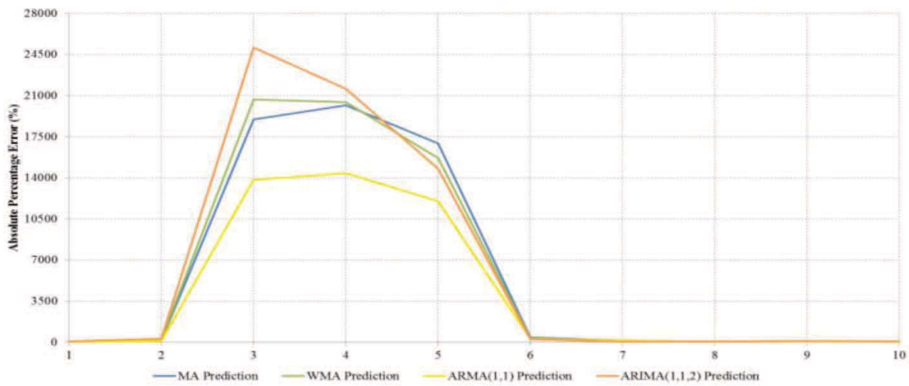

Fig. 12. 24-h ahead forecasting errors for wind power parameter

Table I. Comparison of wind speed and wind power forecasting results

	Time Horizon	Best Model	MAPE	Improvement Percent	Worst Model	MAPE (%)
Wind Speed Forecasting	10-min ahead	ARMA(2,2)	% 4.73	% -11.96	ARIMA(1,1,2)	% 6.99
	2-h ahead	ARMA(2,2)	% 13.81	% 10.04	ARIMA(1,1,1)	% 19.43
	9-h ahead	ARIMA (2,1,2)	% 13.86	% 53.65	MA	% 39.35
	24-h ahead	ARMA(1,2)	% 38.38	% 45.91	ARIMA(1,2,1)	% 74.21
Wind Power Forecasting	10-min ahead	ARIMA(1,1,2)	% 10.45	% 4.78	MA	% 16.42
	2-h ahead	ARMA(2,2)	% 20.33	% 32.36	ARIMA(2,1,2)	% 38.10
	9-h ahead	ARMA(2,2)	% 72.41	% 4.35	MA	% 177.31
	24-h ahead	ARMA(1,1)	‰ 409,69	% 13.59	ARIMA(1,1,2)	‰ 623.72

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