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Extremely Short Time Modeling of Wind Power Variations

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Abstract- One of the main challenges in the operation of wind farms is the time varying nature of output power. So far, many studies have been done for modeling the variations of wind farm power. However the extremely short time modeling of active and reactive powers variations, which is not considered in previous studies, is essential for modeling and analyzing the power quality issues caused by wind farms. The variations of active/reactive powers in the wind turbine and wind farms with sampling time equal to 0.01 s are studied and modeled in the present paper. For this purpose, a massive amount of actual records of voltage and current waveform data are collected from the Manjil wind farm in the north of Iran. Analyses of results show that the rate of change of active/reactive powers of the wind turbine and wind farm is high in time periods equal to 0.01 s. A stochastic model based on the auto-regressive moving-average (ARMA) process is proposed to model the fast variations of active/reactive powers of the wind turbine and wind farm. The presented model as a basic and simple model can be utilized in many applications such as SVC control system to compensate the reactive power and flicker suppression of wind plants.

Keywords wind power modeling; wind power variations; time series; ARMA processes.

1. Introduction

In recent years, due to the increasing of energy demand, shortage of conventional fossil fuels and environmental pollution problem, the renewable energy sources has rapidly increased around the world [1]. Wind energy is one of the most attractive renewable energy sources which is seriously considered [2]. One of the major issues in wind generation is fluctuations in the power production of the wind turbines. In recent years increasing penetration of wind power in the power system has caused more focus on the fluctuations of wind turbine output power [3]. The short time fluctuations of wind power are mainly due to the influences of turbulence intensity, tower shadow, blade pitching error, yaw misalignment, wind shear, tower oscillation and the fluctuations of wind speed [4]. So far, several wind farm models have been presented for studies such as transient responses [5], security and economic operation [6], sub-synchronous resonance [7], operational outage [8]. However, modeling of wind power variations for short periods is essential for the power system operation and planning.

According to Figure 1, in general, stochastic modeling of the wind power generation can be divided in two approaches. Approaches based on the wind speed measurements [9-15] and approaches based on the wind power measurements [16]. In the first category, wind speed measurements and an accurate wind farm model are needed. Whereas, in the second category, the wind power measurements are directly used to build a wind power model [16]. In [9-14], first wind speed model is obtained from recorded wind speed time series (WSTS) and then wind power model is attained through transforming the modeled WSTS to wind power time series (WPTS) by applying a suitable wind farm model.

The presented wind speed model in [9-11] is the Markov chain model. While, in [12] the wavelet-based model and in [13, 14] autoregressive moving average (ARMA) model are proposed for modeling the wind speed. In [15], first the wind power data are attained from converting WSTS measurements to WPTS and then based on these WPTS, a transition matrix based on discrete Markov model is proposed for modeling the wind power. In [16], using the wind power measurements, a stochastic wind power model based on an autoregressive integrated moving average (ARIMA) is proposed.

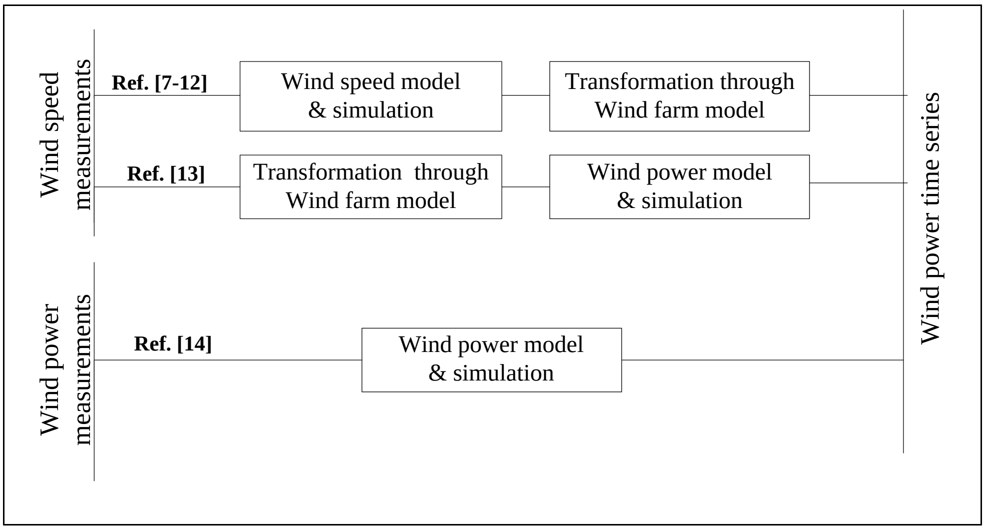


Fig. 1. Approaches of modeling wind power

Table 1. Time-scale classification of wind speed/power variations modeling

Time horizon	Range	Applications	References
Extremely short-term	Less than 0.02 s	- Power quality issues	Present paper
Very short-term	Few seconds to 30 minutes ahead	- Electricity market clearing - Regulations actions	[18-24]
Short-term	30 minutes to 6 hours ahead	- Economic Load Dispatch Planning - Load Increment/Decrement Decisions	[25-31]
Medium-term	6 hours to 1 day ahead	- Generator Online/Offline Decisions - Operational Security in Day-Ahead Electricity Market	[32-42]
Long-term	1 day to 1 week or more ahead	- Unit Commitment Decisions - Reserve Requirement Decisions - Maintenance Scheduling to Obtain Optimal Operating Cost	[43-47]

Table 1 classifies the wind speed/power modeling and forecasting methods based on time scales. Based on the forecasting horizon used in the previous studies, they can be classified to four categories [17]; very short-term [18-24], short-term [25-31], medium-term [32-42] and long-term forecasting [43-47].

Despite there are many studies about modeling and forecasting the wind speed and wind power variations, however none of the presented studies deal with the extremely short time scale. Extremely short time modeling of active and reactive powers variations is essential for modeling and analyzing of power quality issues caused by wind farms. Flicker is the most important power quality issue which is caused by extremely fast variations of wind farm active and reactive powers. Flicker phenomenon relates to variations of system voltage magnitude in frequency range between 0.5 Hz to 25 Hz. Hence, analysis of flicker requires sampling frequency of active and reactive powers not less than 2*25=50 Hz. In other words the minimum sampling time of wind farm powers is 0.02 s. Therefore the required sampling time for flicker analysis is far less than the considered time periods in previous modeling studies for wind powers variations.

In this study with a large number of actual records, fast variations of wind farm powers in extremely short time periods were observed. Figure 2 shows the active and reactive power relevant to a record where fast variations exist in extremely short time periods. The same variations can be seen in other records. Therefore, the models proposed so far cannot present an appropriate model for wind power variations. The present study focuses on modeling the fast variations of wind farm powers in extremely short time periods which are not considered in the previous studies. As it is presented in Table 1, this paper opens a new time-scale category of wind power variations modeling. The variations of wind farm active and reactive powers at every 0.01 s are modeled which can be used in analyzing power quality issues caused by wind farms.

For this purpose, many actual records of instantaneous voltage and current waveform were collected at different weather conditions during the winter and the summer seasons from the Manjil wind farm in north of Iran. Every record length is equal to 10 s with sampling time equal to 128 µs. Active and reactive powers corresponding to the recorded instantaneous voltage and current were calculated.

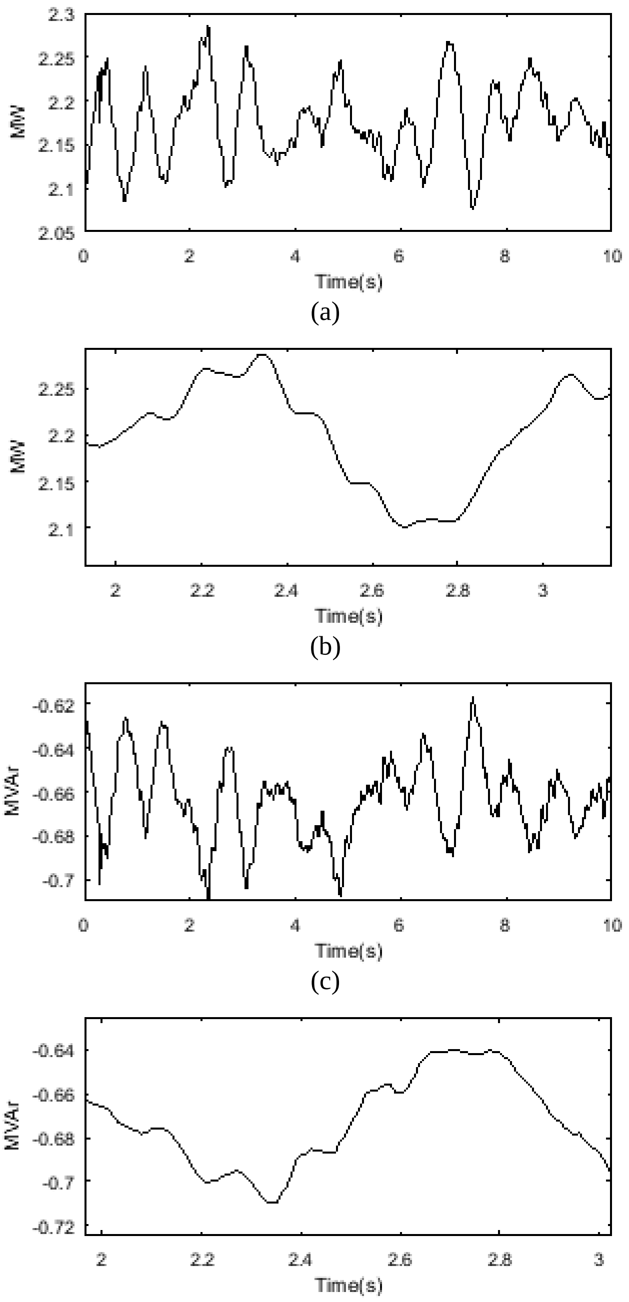


Fig. 2. Generated active and reactive powers for a recorded data from a substation in Manjil wind farm, (a) active power for 10 s (b) active power for 1 s (c) reactive power for 10 s (d) reactive power for 1 s

The calculation method is the full cycle integration method with a moving window which is updated every half cycle (10 ms). As the result the active and reactive powers can be considered time series with sampling time equal to 10 ms and with total length equal to 10 s (1000 samples). Auto correlation function (ACF) is utilized to discover the correlation between adjacent power samples and also to discover if the process is stationary or not. Also autoregressive moving average (ARMA) model is utilized for modeling of these fast variations of wind farm powers. Four model adequacy tests are utilized to select the most appropriate ARMA order. The attained ARMA models can be used for various applications such as simulation of wind farms for applications which needs their variation nature for extremely short time periods. An application that is presented here is forecasting the wind farm reactive power to control and improve the SVC performance to mitigate the flicker [48-52].

2. Description of the Recorded Data

In this research, in order to obtain an accurate model for wind farms reactive power variations, a large amount of the actual instantaneous voltage and current waveform data are collected from the Manjil wind farm, in north of Iran (coordinates: 36°44′18.1″ N 49°23′51.5″ E). The data are gathered in different weather conditions during the winter and summer. This plant, in total, includes 108 wind turbines with wound rotor induction generator rated at 660 KW and 66 wind turbines with squirrel cage induction generator rated at 330, 500 and 550 kW. These measurements have been done in two cases:

Case 1: The wind turbine equipped with squirrel cage induction generator, rated at 550 KW. The data records are measured at the stator terminals of wind turbine.

Case 2: The substation including 12 squirrel cage induction generator wind turbine, rated at 330, 500 and 550 KW. The single line diagram of this substation is given in Fig.3 and data records are measured at the PCC point presented in this figure.

The data records include three-phase instantaneous voltages and currents. An accurate power analyzer which is capable of recording the instantaneous voltage and current waveforms is utilized for this purpose. Each data record is 10 s real-time wind farm operations with sampling time equal to 128 µs. The data records used in this study are 50 three-phase data records (150 single phase records) in case 1 and 109 three-phase data records (327 single phase records) in case 2.

3. Calculation of Active and Reactive Powers

The full cycle integration method that is updated in each half cycle is used for active and reactive power calculation. The sampling time of voltage and current is 128 µs, as a result there are 156 samples per cycle and 39 samples in every 1/4 cycle. The discrete active and reactive power calculated by full cycle samples that is updated every half cycle is as follow [48]:

$$p(n) = \frac{1}{156} \sum_{s=78(n-1)+1}^{78(n+1)} v(s) i(s) \tag{1}$$

$$q(n) = \frac{1}{156} \sum_{s=78(n-1)+1}^{78(n+1)} v(s-39) i(s) \tag{2}$$

where s is the sample number of voltage and current and n denotes the related half-cycle number.

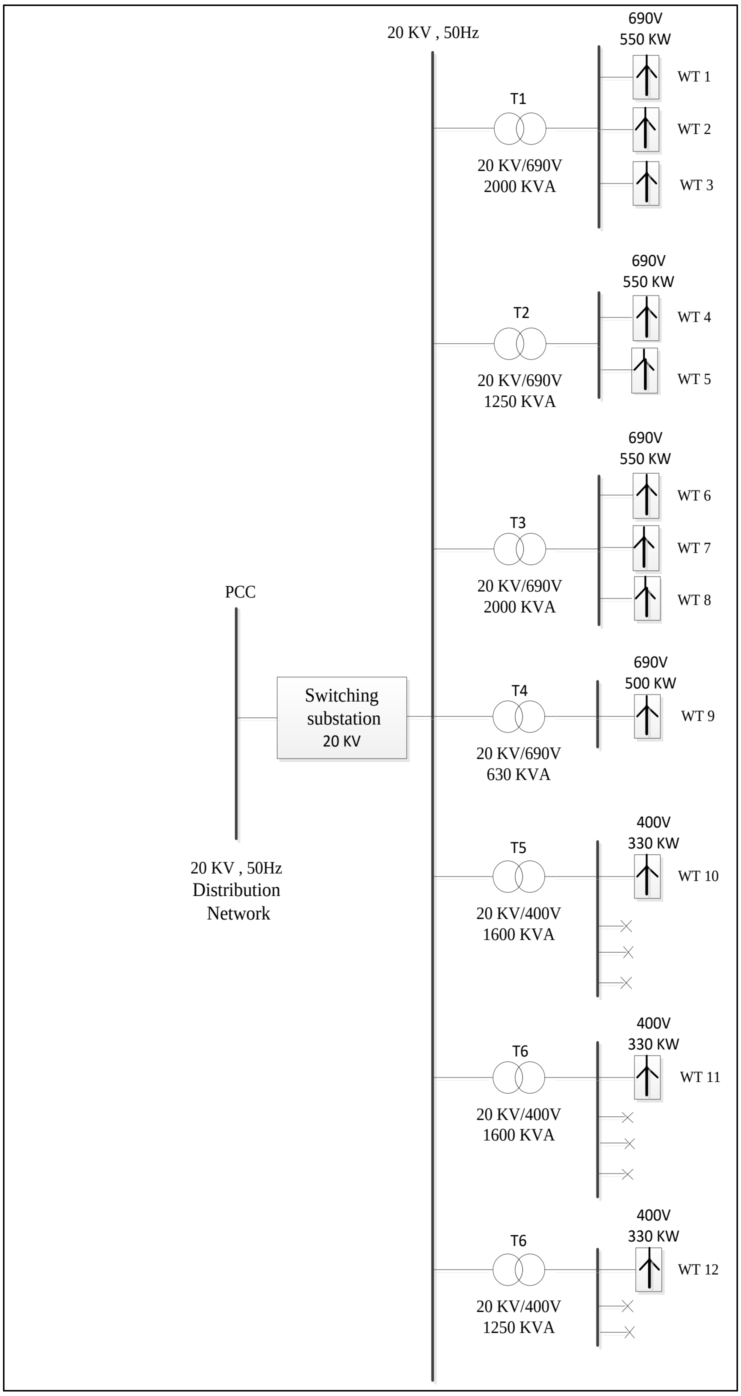


Fig. 3. Structure of the studied substation in Manjil wind farm

4. Modeling the Variations of Wind Farm's Active and Reactive Powers

In this section, using the auto correlation function (ACF), correlation between the samples in time series of wind farm's active and reactive powers is investigated. Then in the second step ARMA models are utilized for modeling these time series.

4.1. ACF

ACF shows the correlation between the consecutive samples of time series. Here, first 30 components of the ACF for all recorded data (all active and reactive powers signals in case 1 and 2) are calculated and then its average considering all records is calculated by (3) [48]:

$$r_k^{mean} = \frac{1}{N}\sum_{j=1}^{N} r_k^j \qquad k = 1,2,\ldots,30 \tag{3}$$

where r_k^j denote *kth* ACF component for the *jth* record and N is total number of data records in any case. In this study, to investigate the effect of window length on the estimation accuracy, data records with lengths 10 s and 1 s are considered. For this purpose, all 10 s data records in cases 1 and 2 are divided to 1 s time series. Therefore, we have 1500 and 3270 data records with length 1 s for case 1 and 2 respectively.

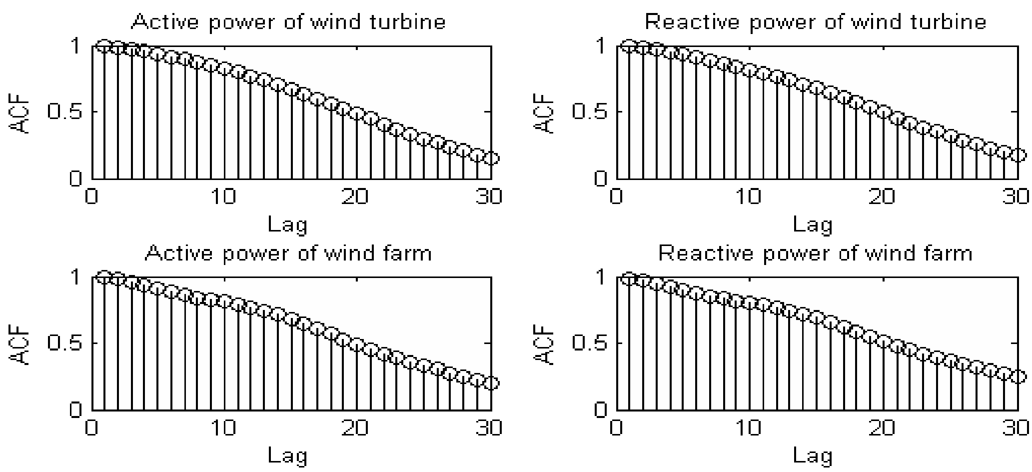
Figure 4 shows the mean ACF (MACF) for the 10 s and 1 s data records. As can be seen, in all cases, r_k^{mean} of signals dies down quickly by increasing of k . However the decaying rate of MACF for 1 s time series is bigger than 10 s time series. This fact shows that the time series are more stationary for shorter time periods. In the other hand, Figure 4 shows that ACF values are considerably large. This means that there is dependability between the consecutive samples in the active and reactive powers time series of wind farm and wind turbine and therefore these power signals are predictable for the next half cycles.

4.2. Investigating ARMA Models

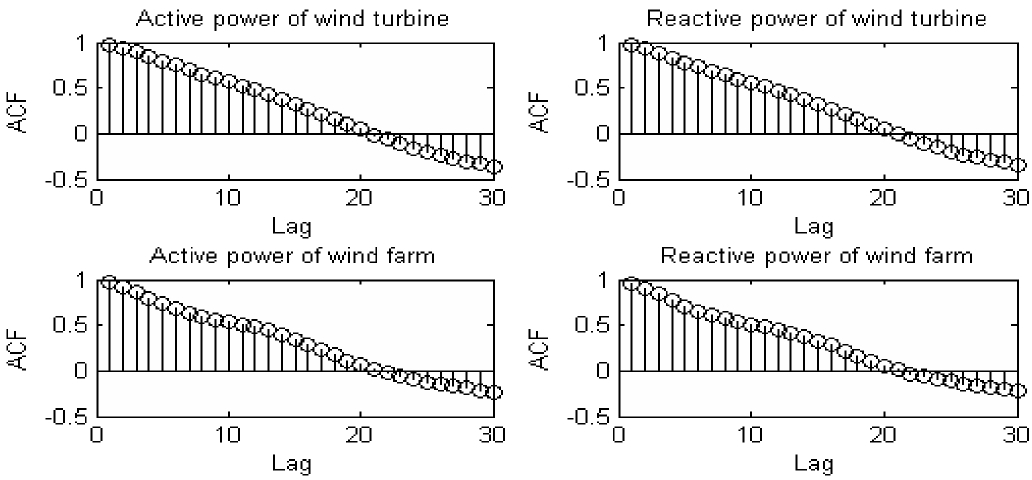
Autoregressive moving average (ARMA) models are based on the idea that the present value of the time series can be explained as a function of past values. ARMA models can be used for modeling and predicting the random phenomena such as wind generation. So far several studies have been done for modeling the wind power and wind speed, based on the ARMA model, considering different time prediction horizons [16, 53-55]. However, in this paper, the fast fluctuation of wind power has been considered and ARMA model is employed for modeling the very fast variations of wind farm's active and reactive powers. An ARMA process of order (p, q) which is denoted as ARMA(p,q) is given as follows [56]:

$$z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + ... + \varphi_q z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - ... - \theta_q a_{t-q} \quad (4)$$

The process value at sample t is denoted by z_t. a_t is a Gaussian noise with zero mean and specified variance at sample t and a_{t-q} is the value of a at sample t-q. Model orders p and q belongs to autoregressive (AR) and moving average parts of the ARMA model. Coefficients $\varphi 1$, …, φ_p, θ_1, …, θ_q are the model parameters. In case of q=0 the model is called Auto regressive (AR) and if p=0 the model is called moving average (MA).



(a)



(b)

Fig. 4. Average ACF for the (a) 10 s data records and (b) 1 s data records

In this section based on the 10 s and 1 s recorded data, the best ARMA model order is attained. For this, first a number of ARMA model with different orders was selected as candidate ARMA model and then ARMA model order (p and q) was specified by using the model adequacy checking tests. The candidate ARMA models are defined at the different groups as follows:

Set 1: $\{AR(p),\ p=6,\ldots,12\}$

Set 2: $\{ARMA(p,1),\ p=5,\ldots,11\}$

Set 3: $\{ARMA(p,2),\ p=5,\ldots,11\}$

Set 4: $\{MA(q),\ q=6,\ldots,12\}$

Set 5: $\{ARMA(1,q),\ q=5,\ldots,11\}$

Set 6: $\{ARMA(2,q),\ q=5,\ldots,11\}$

Set 7: $\{Set\,1, Set\,2, Set\,3\}$

Set 8: $\{Set\,4, Set\,5, Set\,6\}$

Set 9: $\{Set\,7, Set\,8\}$

Based on actual recorded data, four adequacy checking tests are used to obtain the best ARMA model for wind power in cases 1 and 2. These tests are:

Test 1: Akaike's information criteria (AIC) [57].

Test 2: Schwarz criteria (SC) [57].

Test 3: the likelihood ratio test [57].

Test 4: t values [58].

In tests 1 and 2 for each data record, one model which minimizes (5) for AIC test and (6) for test SC is chosen.

$$AIC(m) = \ln \sigma_a^2 + 2m/n \tag{5}$$

$$SC(m) = \ln \sigma_a^2 + 2m/n \tag{6}$$

where σ_a^2 is the noise variance, m is the number of parameters estimated in the ARMA model that is equal to p+q and n is the time series length that is equal to 1000 and 100 for 10 s and 1 s data record respectively.

For test 3 a quantity is defined as [57]:

$$\lambda_{LR}(i) = n(\ln|\sigma_a^2(M-i)| - \ln|\sigma_a^2(M-i+1)|) \qquad i=1,\ldots,M-1 \tag{7}$$

In this test, first a maximum value is considered for model order (M) and i is assumed equal to one (i=1). The value of equation (7) is calculated. If condition (8) is satisfied, the suitable model order will be as M-1+i, otherwise the value of i is increased by one and the previous step is repeated.

$$\lambda_{LR}(i) > \chi^2_{0.95} \tag{8}$$

In test 4, the model with the maximum order in the set is selected and the last coefficient is checked. If the value of the last coefficient is close enough to zero, this means that the order of the model is higher than the required one. Therefore the model order is decreased by one and the above procedure is repeated.

Coefficients are close to zero when the following inequality is established for them [58].

$$t = \frac{value}{\text{standard division } of\ value} < w \tag{9}$$

where usually 'w' is selected between 1.5 and 3. To compare the various models, model validity (MV) is used that is defined as [48]:

$$MV = \frac{N_{AM}}{N_{DR}} \times 100 \tag{10}$$

where N_{AM} and N_{DR} respectively denote the number of data records that are adequately described by the model and the total number of data records. The procedure summery for calculating model validity and selecting the appropriate ARMA model order is shown in Fig. 5.

Tables 2 and 3 present the models validity resulted by applying tests 1- 4 for time series with 10 s length. Choosing the most proper ARMA model depends on the utilized model adequacy test and also the candidate model set. So, different tests and candidate sets may result in different selected ARMA models. This procedure of choosing the most adequate ARMA model becomes more complicated in case of large number of recorded time series. In the present paper to overcome this complexity, MV index is utilized. Also to have a comprehensive analysis, four tests have been used. Choosing the most proper ARMA model from large value of results is challengeable which depends on the person knowledge. Hence, different persons may choose different models and the answer is not unique. However, in the last section of this paper the sensitivity of the selected models on a specific application is analyzed. Based on the MV values in Tables 2 and 3, the proper ARMA models are selected.

Tables 4 and 5 present summary of ARMA orders proposed by tests 1- 4 for time series with 10 s and 1 s length, respectively. Tables 6 and 7 present the mean and standard deviation values of the ARMA coefficients for the selected models. The values in these tables can be used for simulation purposes of wind farms and turbines to study their effects on the power quality and also finding solutions to resolve these effects.

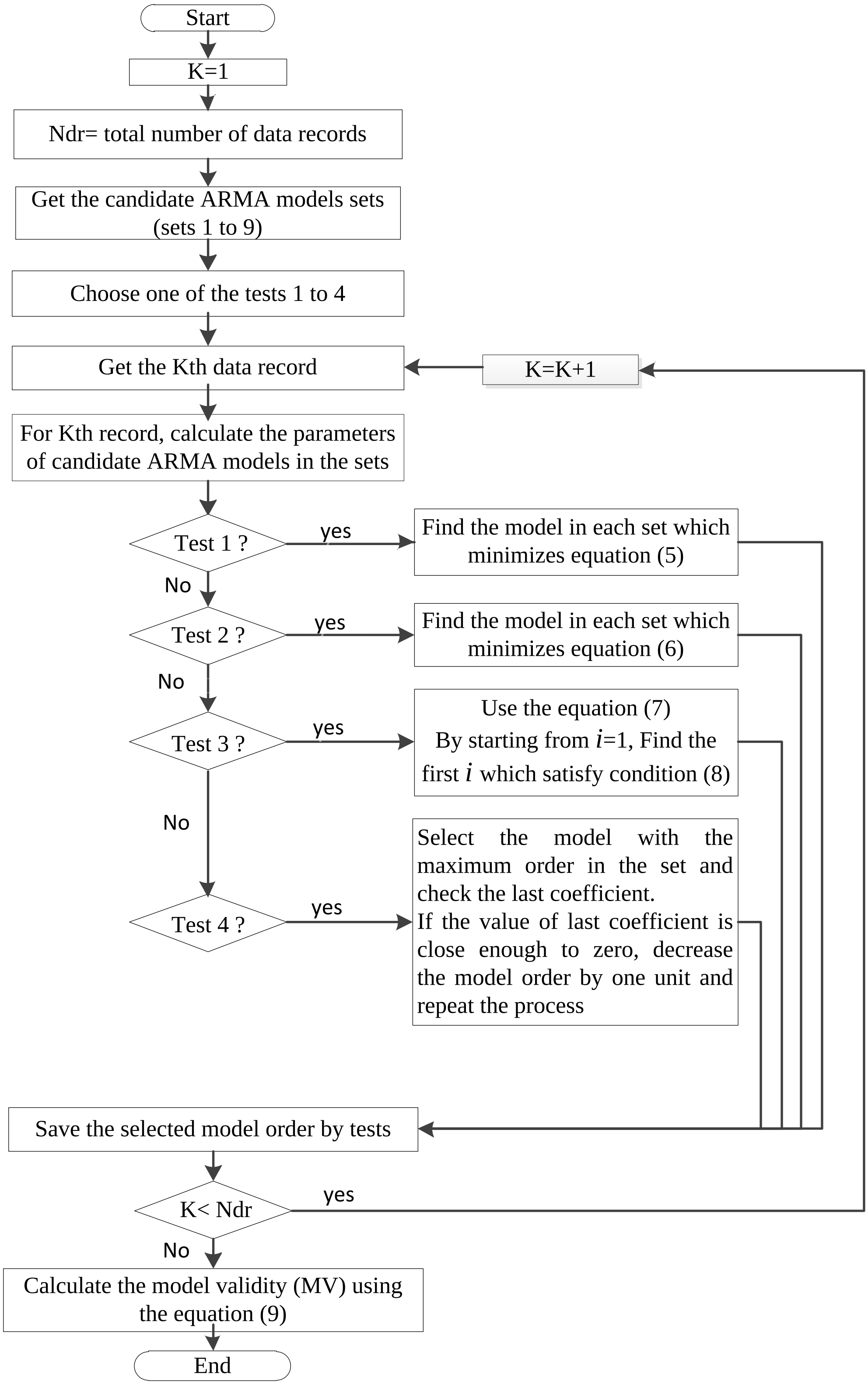


Fig.5. The procedure summery for calculating model validity

Table 2. Models validity for active and reactive power in case1 based on the 10 s data records

Set	order	Test 1		Test 2		Test 3		Test 4		Set	Test 1		Test 2		Set	Test 1		Test 2	
		P	Q	P	Q	P	Q	P	Q		P	Q	P	Q		P	Q	P	Q
	(6,0)	0	0	0	1	0	0	0	0		0	0	0	1		0	0	0	1
	(7,0)	0	0	0	4	0	0	0	1		0	0	0	3		0	0	0	3
	(8,0)	3	0	16	8	4	1	7	1		2	0	8	7		2	0	7	5
Set 1	(9,0)	2	2	9	5	2	2	3	5		1	0	3	0		1	0	3	0
	(10,0)	8	5	15	18	8	5	8	13		5	1	15	14		5	1	15	7
	(11,0)	8	15	9	16	9	20	13	21		2	3	0	5		2	1	0	2
	(12,0)	79	79	51	48	77	72	69	59		34	52	28	39		34	37	27	33
	(5,1)	0	3	0	8	0	0	0	5		0	0	0	0		0	0	0	0
	(6,1)	1	1	2	3	0	0	1	1		0	0	0	0		0	0	0	0
	(7,1)	0	4	0	3	0	0	1	1		0	0	0	0		0	0	0	0
Set 2	(8,1)	13	13	21	33	9	13	22	32	**Set 7**	0	0	0	0		0	0	0	0
	(9,1)	17	7	25	8	17	7	14	8		1	1	2	1		1	0	2	1
	(10,1)	33	28	28	20	31	39	17	25		3	0	3	0		3	0	3	0
	(11,1)	35	45	24	25	43	41	46	29		1	10	0	8		1	6	0	5
	(5,2)	0	1	0	6	0	1	0	4		0	0	0	0		0	0	0	0
	(6,2)	0	1	0	4	0	0	1	0		0	1	0	1		0	0	0	0
	(7,2)	1	2	3	3	1	1	3	1		0	0	1	0		0	0	1	0
Set 3	(8,2)	14	7	25	19	11	8	12	27		3	3	7	2		3	0	7	2
	(9,2)	13	14	15	19	9	12	9	27		7	5	6	9		7	1	6	5
	(10,2)	33	27	31	24	37	35	25	17		15	7	11	5		15	3	11	4
	(11,2)	39	47	27	25	42	43	50	24		25	19	17	7	**Set 9**	25	14	17	7
	(0,6)	1	0	1	0	0	0	0	0		0	0	0	0		0	0	0	0
	(0,7)	1	0	1	0	0	0	0	0		0	0	0	0		0	0	0	0
	(0,8)	1	0	1	1	0	0	0	0		0	0	0	0		0	0	0	0
Set 4	(0,9)	2	1	2	3	1	0	1	0		0	0	0	0		0	0	0	0
	(0,10)	7	6	7	7	3	1	1	0		0	0	0	0		0	0	0	0
	(0,11)	9	11	9	10	11	11	2	0		0	1	0	1		0	0	0	0
	(0,12)	81	83	80	80	85	89	96	99		0	0	0	0		0	0	0	0
	(1,5)	2	18	3	26	0	7	0	14		0	0	1	1		0	0	0	0
	(1,6)	3	13	9	37	1	7	3	35		1	0	3	1		0	0	0	0
	(1,7)	4	5	3	10	0	5	0	3		0	0	1	1		0	0	0	0
Set 5	(1,8)	9	5	17	9	3	15	10	13	**Set 8**	2	1	9	0		0	0	1	0
	(1,9)	9	17	13	9	7	19	7	9		3	0	7	0		0	0	0	0
	(1,10)	6	13	10	2	9	15	21	4		1	0	7	0		0	0	0	0
	(1,11)	67	28	44	7	79	32	59	21		44	0	30	0		1	0	1	0
	(2,5)	4	1	6	3	0	0	1	1		1	1	3	3		0	0	0	0
	(2,6)	2	0	9	2	1	0	1	0		0	0	1	1		0	0	0	1
	(2,7)	2	0	6	1	0	0	2	1		1	0	3	0		0	0	0	0
Set 6	(2,8)	4	3	7	3	3	0	1	1		3	3	3	3		0	0	0	0
	(2,9)	9	5	15	7	11	2	5	2		3	5	3	6		0	0	0	0
	(2,10)	19	22	11	42	20	33	9	43		3	21	2	41		0	5	0	11
	(2,11)	61	69	47	43	65	65	81	52		37	69	27	43		0	30	0	14

Table 3. Models validity for active and reactive power in case 2 based on the 10 s data records

Set	**order**	**Test 1**		**Test 2**		**Test 3**		**Test 4**		**Set**	**Test 1**		**Test 2**		**Set**	**Test 1**		**Test 2**	
		P	**Q**	**P**	**Q**	**P**	**Q**	**P**	**Q**		**P**	**Q**	**P**	**Q**		**P**	**Q**	**P**	**Q**
	(6,0)	0	3	0	15	0	3	0	4		0	3	0	14		0	3	0	14
	(7,0)	0	3	1	8	0	2	0	3		0	3	1	8		0	3	1	8
	(8,0)	0	1	0	2	0	0	0	0		0	1	0	2		0	1	0	2
Set 1	(9,0)	1	2	3	1	0	2	1	1		0	2	2	1		0	2	2	1
	(10,0)	1	2	1	1	1	2	2	2		1	2	1	0		1	2	1	0
	(11,0)	50	55	74	64	64	65	73	71		16	18	26	22		16	17	26	22
	(12,0)	49	34	20	10	35	26	23	17		15	19	9	6		15	18	9	6
	(5,1)	0	4	0	11	0	1	0	12		0	0	0	1		0	0	0	0
	(6,1)	0	3	3	18	0	0	1	4		0	0	0	0		0	0	0	0
	(7,1)	1	2	3	2	1	1	2	0		0	0	0	0		0	0	0	0
Set 2	(8,1)	5	27	9	36	4	18	7	12	**Set 7**	0	0	0	0		0	0	0	0
	(9,1)	8	8	20	6	10	5	23	4		0	0	2	0		0	0	2	0
	(10,1)	16	13	14	6	17	23	11	3		1	0	1	0		1	0	1	0
	(11,1)	70	42	51	20	69	51	56	64		2	0	0	0		2	0	0	0
	(5,2)	1	3	2	9	0	0	1	8		0	1	0	3		0	1	0	2
	(6,2)	2	5	4	11	0	0	0	2		0	1	0	3		0	1	0	2
	(7,2)	2	3	6	5	0	1	11	3		0	1	5	1		0	1	5	1
Set 3	(8,2)	6	6	6	6	2	2	6	0		2	0	2	0		2	0	2	0
	(9,2)	35	6	61	15	46	8	63	33		21	2	37	9		21	2	37	9
	(10,2)	24	7	13	8	26	13	9	7		17	2	8	3		17	2	8	3
	(11,2)	32	70	7	47	26	77	10	45		24	45	5	26		24	43	5	24
	(0,6)	0	0	0	0	0	0	0	0		0	0	0	0	**Set 9**	0	0	0	0
	(0,7)	0	0	0	0	0	0	0	0		0	0	0	0		0	0	0	0
	(0,8)	0	1	0	1	0	0	0	0		0	0	0	0		0	0	0	0
Set 4	(0,9)	2	1	2	2	0	0	0	0		0	0	0	0		0	0	0	0
	(0,10)	4	4	5	5	0	1	0	0		0	0	0	0		0	0	0	0
	(0,11)	11	16	11	16	11	16	0	0		0	0	0	0		0	0	0	0
	(0,12)	83	79	83	76	89	83	100	99		0	0	0	0		0	0	0	0
	(1,5)	5	13	11	25	1	3	0	17		0	0	2	2		0	0	0	0
	(1,6)	6	3	13	15	1	1	6	13		0	0	3	0		0	0	0	0
	(1,7)	2	3	2	8	0	1	0	0		0	0	0	0		0	0	0	0
Set 5	(1,8)	4	1	10	2	1	1	5	3	**Set 8**	1	0	4	0		0	0	0	0
	(1,9)	3	11	4	14	4	16	1	10		0	0	2	0		0	0	0	0
	(1,10)	2	11	2	6	3	15	4	2		0	0	1	0		0	0	0	0
	(1,11)	78	58	59	31	90	62	83	54		27	0	25	0		0	0	0	0
	(2,5)	1	12	3	24	0	0	1	11		1	12	1	22		0	1	0	4
	(2,6)	7	14	11	18	0	2	0	2		7	14	9	18		0	1	0	2
	(2,7)	4	18	9	24	1	5	2	2		3	18	6	24		0	1	0	1
Set 6	(2,8)	6	7	6	5	2	5	1	5		5	7	6	5		0	0	0	0
	(2,9)	13	16	18	8	11	20	13	2		9	16	6	8		0	1	0	1
	(2,10)	12	17	9	14	13	35	11	60		7	17	6	14		0	0	0	0
	(2,11)	57	15	44	8	73	33	73	16		39	14	30	7		1	0	0	0

Table 4. Summary table of ARMA orders proposed by tests 1- 4 for active and reactive powers in case1 and case 2 based on the 10 s data records

	Case 1		Case 2	
	Active power	Reactive power	Active power	Reactive power
Test 1	AR(12) ARMA(10,2) ARMA(11,2)	AR(12) ARMA(11,2) ARMA(2,11)	ARMA(9,11) ARMA(11,2)	AR(11) AR(12) ARMA(11,2)
Test 2	AR(12) ARMA(10,2) ARMA(11,2)	AR(12) ARMA(2,11)	AR(11) ARMA(11,2)	AR(6) AR(11) ARMA(11,2)
Test 3	MA(12) ARMA(11,2) ARMA(1,11)	AR(12) MA(12) ARMA(2,11)	AR(11) ARMA(9,2) MA(12) ARMA(1,11)	AR(11) ARMA(11,2) MA(12)
Test 4	AR(12) ARMA(2,11) MA(12)	AR(12) MA(12) ARMA(2,11)	AR(11) ARMA(9,2) MA(12) ARMA(2,11)	AR(11) ARMA(11,1) ARMA(11,2) MA(12)

Table 5. Summary table of ARMA orders proposed by tests 1- 4 for active and reactive powers in case1 and case 2 based on the 1 s data records

	Case 1		Case 2	
	Active power	Reactive power	Active power	Reactive power
Test 1	ARMA(11,2) ARMA(2,10) ARMA(2,11)	ARMA(2,10) ARMA(2,11)	ARMA(7,2) ARMA(9,2) ARMA(10,2)	ARMA(9,2) ARMA(11,2)
Test 2	AR(6), AR(8) AR(12)	AR(6), AR(8) AR(9)	AR(6), AR(9) ARMA(7,2)	AR(6) ARMA(6,1)
Test 3	AR(12) ARMA(2,10) ARMA(2,11)	ARMA(2,10) ARMA(2,11)	AR(11) ARMA(11,2) ARMA(2,11)	AR(11) ARMA(9,2)
Test 4	AR(8), AR(12) ARMA(2,11)	AR(6), AR(8) ARMA(2,10)	AR(9) ARMA(7,2) ARMA(9,2)	AR(11), AR(6) ARMA(9,2)

Table 6. Means and standard deviations of models coefficients obtained for active and reactive powers based on the 10 sec data records

	Case 1				Case 2			
	Active power		Reactive power		Active power		Reactive power	
Model order	*AR(12)*		*AR(12)*		*ARMA(9,2)*		*ARMA(11,2)*	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
φ_1	-2.4202	0.2252	-1.7581	0.1902	-1.7121	0.2522	-1.5398	0.4086
φ_2	2.1071	0.4448	1.1260	0.2982	0.0793	0.5632	0.0474	0.9118
φ_3	-1.2032	0.4717	-0.8610	0.3392	1.0087	0.5373	0.6418	0.8434
φ_4	1.1144	0.5176	0.8253	0.3055	-0.3420	0.3386	-0.1736	0.4819
φ_5	-0.8877	0.4758	-0.5527	0.3210	0.2606	0.2317	0.2261	0.3655
φ_6	0.6703	0.4847	0.5070	0.3055	-0.3479	0.1835	-0.1964	0.2694
φ_7	-0.8593	0.5294	-0.4525	0.2777	0.0769	0.1571	0.0652	0.1932
φ_8	0.6069	0.4933	0.2425	0.2833	-0.2403	0.1360	-0.1643	0.1716
φ_9	-0.1946	0.4400	-0.1868	0.2634	0.2169	0.0796	0.0848	0.1266
φ_{10}	0.2051	0.3825	0.1101	0.2098			-0.1019	0.1011
φ_{11}	-0.2257	0.2550	-0.0564	0.1675			0.1108	0.0600
φ_{12}	0.0868	0.0855	0.0567	0.0728				
θ_1					0.4204	0.3114	0.1642	0.4209
θ_2					-0.4726	0.2465	-0.5861	0.3638

Table 7. Means and standard deviations of models coefficients obtained for active and reactive powers based on the 1 sec data records

	Case 1				Case 2			
	Active power		Reactive power		Active power		Reactive power	
Model order	*AR(12)*		*AR(6)*		*ARMA(7,2)*		*ARMA(9,2)*	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
φ_1	-2.5271	0.2380	-1.8483	0.2217	-2.1196	0.5936	-1.6147	0.6419
φ_2	2.3079	0.5435	1.1143	0.3624	1.1051	1.4386	0.4462	1.2087
φ_3	-1.2634	0.7204	-0.5628	0.3813	0.2181	1.5536	0.1649	1.1051
φ_4	1.0867	0.7897	0.5246	0.3146	-0.1176	0.9501	0.0309	0.6531
φ_5	-0.9366	0.7564	-0.2407	0.2828	0.1782	0.6543	0.1616	0.5353
φ_6	0.7498	0.7641	0.0129	0.1362	-0.5139	0.5658	-0.2091	0.5018
φ_7	-0.9873	0.8192			0.2496	0.2723	0.1536	0.4341
φ_8	0.7599	0.7882					-0.3006	0.3484
φ_9	-0.2432	0.7240					0.1671	0.1895
φ_{10}	0.2233	0.6319						
φ_{11}	-0.2819	0.4305						
φ_{12}	0.1117	0.1442						
θ_1					-0.0145	0.6720	0.0785	0.6962
θ_2					-0.3063	0.6431	-0.3182	0.6354

5. Application of the Proposed Modeling Method

Variations of the wind farm output power is the main drawbacks of the wind farms. It can causes the voltage fluctuations and as result flicker [59]. One of the widely applied solutions for flicker mitigation is to employ static VAr compensator (SVC) for reactive power compensation [60]. However, due to half-cycle delay in SVC response, relevant to reactive power measurement and thyristor ignition, the ability of SVC in reactive power compensation is limited and cannot fully compensate the flicker [61].

In this section, a method is presented based on the proposed modeling of short time wind power variations to compensate the time delay in SVC response and improve its performance. In the proposed method, the wind farm reactive power are predicted for half cycle ahead and used as the input control signal of the SVC rather than the calculated reactive power at the present instant. For this purpose, a prediction block is added to the traditional control system that uses ARMA models in order to predict and provide the value of reactive power for the next half cycle. By this way, the time delays of the SVC are considerably compensated.

There are two control loops in the control system. The first loop that includes the prediction block is named fast control loop (its delay is about 10 ms). This control loop measures the wind farm reactive power and indicates the required reactive power that should be supplied by the SVC. The duty of the fast control loop is to compensate the fast variation of wind farm reactive power by using the SVC. It should be noted that the traditional control system does not include the prediction block in this loop. The second loop is dynamically slower than the first loop (the time constant is about 200 ms) and measures the reactive power supplied by the main grid.

To evaluate the efficiency of the proposed prediction method in the reduction of flicker, first three scenarios are defined and then two indices are employed to evaluate and compare the proposed method with traditional methods regarding SVC performance improvement and flicker suppression. Scenarios are as

Scenario 1: In the first scenario there is no SVC in the system. A fixed capacitor is used to compensate the mean of wind farm reactive power variations.

Scenario 2: In the second scenario SVC is used for the compensation with the traditional control.

Scenario 3: In the third scenario SVC is used with the proposed prediction method in the control system.

The defined indices are based on reactive power variations at the range of frequencies between 1 to 25 Hz (flicker frequencies). Equation 10 obviously shows the direct relation between voltage and reactive power deviations of the source [62].

$$\frac{\Delta V}{V} \cong \frac{\Delta Q_L}{S_{sc}} \qquad (11)$$

So, the reactive power deviation is a suitable indicator for voltage deviations and rate of flicker. Power Spectral Density (PSD) of reactive power variations can be used to evaluate the performance of various methods in flicker mitigation. PSD of signal is defined as follows [63]:

$$PSD_j(f) = \frac{1}{n.f_s} \left| \sum_{t=1}^{n} u_j^{norm}(t) e^{-i2\pi f t} \right|^2 \qquad (12)$$

Here, n denotes data record length, PSD(f) represent PSD of signal *e* at frequency f and fs=100 Hz, which represents sampling frequency of reactive power (because it is updated every 0.01 s).

The first index is Variation Mitigation Factor (VMF) and defined as [48]:

$$VMF(f) = \frac{1}{n} \sum_{j=1}^{n} \frac{PSD_j^{qs}(f)}{PSD_j^{q}(f)} \qquad 1 \le f \le 25 \qquad (13)$$

Where $PSD_j^{qs}(f)$ and $PSD_j^{q}(f)$ present PSDs of the source reactive power variation corresponding to jth recorded data at frequency f when compensation is performed by SVC and with no compensation, respectively. VMF index shows the ability of compensator to mitigate the reactive power variations with frequencies in range of flicker frequencies (1 to 25 Hz). The smaller values of this index represent better compensation performance, as for ideal reactive power compensation, VMF value is equal to zero for all frequencies. Figure 6 shows VMF results for conventional and proposed control algorithms, based on the 10 s, when AR(12) and ARMA(11,2) are used to model the reactive power in cases 1 and 2, respectively. Figure 7 is as same as Fig. 6 except it is corresponding to 1 s data and ARMA(2,10) and ARMA(9,2) are used for the prediction of reactive power for a half cycle ahead. It can be seen that, in all cases, the VMF values have been less severely with the proposed method.

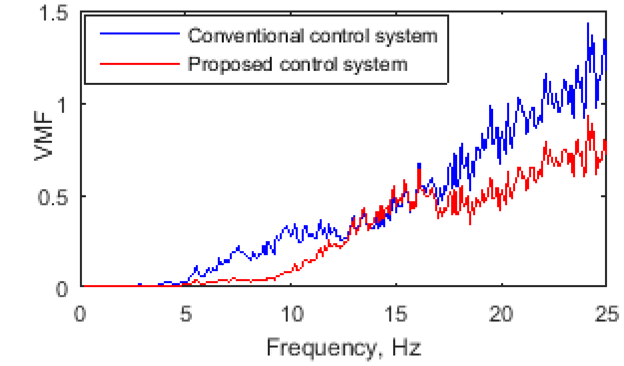
The second index is Flicker Mitigation Factor (FMF) and defined for the frequency range of 1 to 25 Hz. The smaller FMF values indicate better performance of compensator to reduce the reactive power variations at PCC. FMF for recorded data with number j (FMFj) can be expressed as [48]:

$$FMF_j = \frac{\sum_{f=1}^{25} c(f).PSD_j^{qs}(f)}{\sum_{f=1}^{25} c(f).PSD_j^{q}(f)} \qquad (14)$$

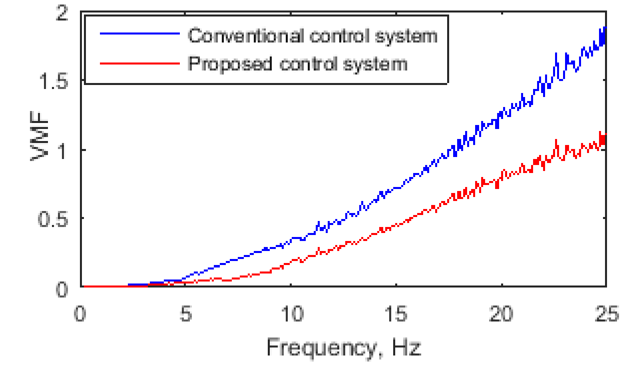
The different flicker frequencies have a different influence on flicker. Therefore, a weighting factor c(f) is defined for each frequency according to IEC 868 standard [64], which its maximum is for f=8.8 Hz. The mean and maximum values of FMF related to the conventional method and proposed method are shown in Table 8. The values of FMF related to the proposed method have reduced in both of two cases. These results obviously show the suitable performance of the proposed method. The lower values of the two defined indices indicate better performance of the SVC with proposed control method to mitigate the flicker in wind farms.

5.1. Sensitivity Analysis of ARMA Orders

The effect of ARMA model order on the defined indices (VMF and FMF) is analyzed in this section. For this purpose a wide number of ARMA model orders are utilized to predict the wind farm reactive power for 10 ms ahead. Based on all records, by using equations 13 and 14 the indices VMF and FMF are calculated. Table 9 presents the VMF and FMF resulted from the applying of various ARMA orders for prediction the reactive power. Results show that the flicker indices reduce slightly by increasing the model orders. It can be concluded that the sensitivity of flicker indices to ARMA model orders is low.

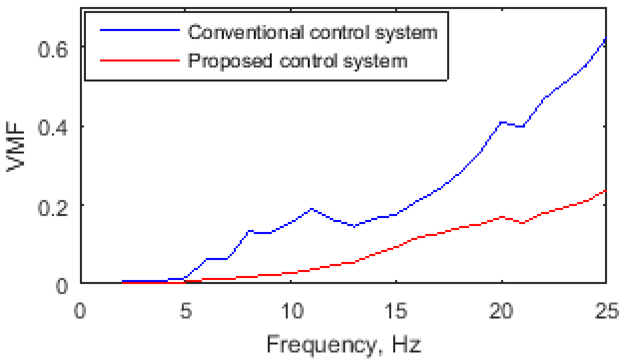


(a)

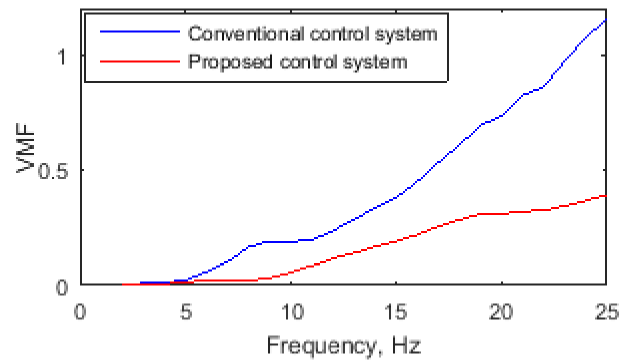


(b)

Fig. 6. VMF corresponding to the conventional and proposed control system for a) case 1 and b) case 2, based on the 10 s data records



(a)



(b)

Fig. 7. VMF corresponding to the conventional and proposed control system for a) case 1 and b) case 2, based on the 1 s data records

Table 8. The mean and maximum values of FMF corresponding to the conventional and proposed control system

		Conventional method		**Proposed method**	
		mean	**max**	**mean**	**max**
10 s data record	Case 1	0.0364	0.0923	0.0122	0.0525
	Case 2	0.0884	0.2460	0.0371	0.1514
1 s data record	Case 1	0.0348	0.2966	0.0065	0.1656
	Case 2	0.0548	0.4546	0.0138	0.3037

6. Conclusion

The nature of wind power in extremely short periods is modeled based on the large number of actual recorded voltage and current waveform data from Manjil wind farm in Iran. Using the recorded actual instantaneous voltage and current, the time series of active and reactive powers were attained. The observations reveal high variations of wind farm powers in extremely short time periods. By calculating the ACF for all recorded data, large dependability between the consecutive samples in the active and reactive powers time series of wind farm and wind turbine are observed. This fact reveals that the active and reactive powers of wind turbine and wind farms are predictable for the next half cycles. For modeling these fast variations of active/reactive powers, a stochastic model was presented based on ARMA models. To have a comprehensive analysis, four model adequacy tests were utilized to select the most proper ARMA orders. Unlike the most studies which the most adequate model is chosen based on one time series, the challenge here is choosing the best models based of a large number of time series. An index named model validity is used for this purpose. The models with higher MV values were chosen as the adequate models. As an application of the proposed model, it was employed in SVC control system for flicker mitigation. Using the proposed model, the required reactive power for half cycle ahead was predicted and considered as input signal of SVC control system. Comparing the performance of SVC in flicker reduction using the proposed and traditional control system demonstrates a considerable improvement of SVC performance.

Table 9. VMF and FMF resulted from the applying of various ARMA orders for prediction the reactive power

Set	Model order	Mean of VMF in the specified frequency intervals — Frequency intervals (Hz)					FMF	
		0.1-5	5-10	10-15	15-20	20-25	Mean	Max
Set 1	(6,0)	0.0113	0.0946	0.3631	0.7336	1.0038	0.0457	0.1673
	(7,0)	0.0114	0.0913	0.3534	0.7425	1.0051	0.0451	0.1678
	(8,0)	0.0115	0.0875	0.3919	0.6833	0.9128	0.0433	0.1600
	(9,0)	0.0115	0.0828	0.3832	0.7410	0.8330	0.0426	0.1618
	(10,0)	0.0114	0.0841	0.3800	0.7071	0.8583	0.0422	0.1565
	(11,0)	0.0123	0.0765	0.4285	0.6436	0.9185	0.0415	0.1573
	(12,0)	0.0126	0.0761	0.4311	0.6325	0.9220	0.0414	0.1513
Set 2	(5,1)	0.0109	0.0961	0.3340	0.6434	0.9179	0.0441	0.1615
	(6,1)	0.0109	0.0878	0.3189	0.6519	0.9573	0.0418	0.1565
	(7,1)	0.0107	0.0864	0.3338	0.6383	0.9084	0.0413	0.1524
	(8,1)	0.0112	0.0783	0.3409	0.6589	0.7853	0.0392	0.1511
	(9,1)	0.0119	0.0775	0.3554	0.6656	0.7869	0.0394	0.1495
	(10,1)	0.0128	0.0741	0.3704	0.6152	0.8100	0.0385	0.1495
	(11,1)	0.0156	0.0733	0.4082	0.5869	0.8437	0.0388	0.1500
Set 3	(5,2)	0.0119	0.0963	0.3279	0.6004	0.9087	0.0429	0.1614
	(6,2)	0.0128	0.0895	0.3244	0.6311	0.9011	0.0415	0.1551
	(7,2)	0.0132	0.0874	0.3115	0.6333	0.9391	0.0410	0.1545
	(8,2)	0.0149	0.0829	0.3244	0.6196	0.8560	0.0396	0.1546
	(9,2)	0.0148	0.0739	0.3337	0.6810	0.7464	0.0383	0.1534
	(10,2)	0.0181	0.0723	0.3499	0.6554	0.7372	0.0379	0.1515
	(11,2)	0.0173	0.0674	0.3970	0.5702	0.7937	0.0371	0.1514
Set 4	(0,6)	0.0120	0.0230	0.1272	1.0492	1.1615	0.0331	0.1129
	(0,7)	0.0101	0.0237	0.2309	1.0796	0.8097	0.0333	0.1222
	(0,8)	0.0078	0.0263	0.4488	0.6759	1.1698	0.0341	0.1288
	(0,9)	0.0071	0.0323	0.5261	0.5678	1.3825	0.0365	0.1370
	(0,10)	0.0058	0.0449	0.4911	0.6790	1.0481	0.0367	0.1402
	(0,11)	0.0054	0.0579	0.4645	0.7839	0.9055	0.0379	0.1420
	(0,12)	0.0047	0.0599	0.4198	0.7660	0.9948	0.0371	0.1401
Set 5	(1,5)	0.0115	0.0982	0.3491	0.7466	0.9671	0.0469	0.1580
	(1,6)	0.0104	0.1009	0.3848	0.6672	0.9700	0.0465	0.1577
	(1,7)	0.0109	0.0935	0.3927	0.6882	0.8358	0.0451	0.1554
	(1,8)	0.0110	0.0943	0.3804	0.7066	0.8460	0.0451	0.1541
	(1,9)	0.0107	0.0906	0.4140	0.6346	0.9340	0.0444	0.1552
	(1,10)	0.0128	0.0872	0.3999	0.6329	0.8937	0.0440	0.1530
	(1,11)	0.0135	0.0855	0.4069	0.6393	0.8674	0.0433	0.1532
Set 6	(2,5)	0.0123	0.0962	0.3221	0.6571	0.8919	0.0439	0.1502
	(2,6)	0.0163	0.0939	0.3012	0.6543	0.9207	0.0436	0.1483
	(2,7)	0.0136	0.0864	0.3308	0.6273	0.8253	0.0412	0.1508
	(2,8)	0.0229	0.0837	0.3293	0.6693	0.7642	0.0420	0.1464
	(2,9)	0.0236	0.0791	0.3423	0.6293	0.7464	0.0404	0.1463
	(2,10)	0.0298	0.0763	0.3850	0.5599	0.8572	0.0409	0.1529
	(2,11)	0.0333	0.0757	0.3994	0.5520	0.8917	0.0416	0.1524

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