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Employing Grey System Model for Prediction of Electric Arc Furnace Reactive Power to Improve Compensator Performance

Abstract. *Electric arc furnaces (EAFs) are regarded as one of the major sources of voltage fluctuation in power systems which can contribute to a phenomenon known as flicker. One of the most convenient ways to mitigate flicker is employing static VAr compensators (SVCs). By employing prediction models to forecast EAF reactive power SVC performance can be improved very noticeably. In this paper a Grey system model is proposed to predict the reactive power and the efficiency of this method is investigated.*

Streszczenie. *Łukowe piece elektryczne są jednym w istotnych odbiorników system energetycznego powodujących wahania sieci, znane jako efekt flicker. Te wahania można zmniejszać stosując kompensator mocy biernej. W artykule zaprezentowano model Grey'a umożliwiający prognozowanie mocy biernej.(**Zastosowanie modelu Grey'a do prognozowania mocy biernej w systemie z piecami łukowymi**)*

Keywords. Electric arc furnace, Reactive power compensation, Grey system theory, Prediction
Słowa kluczowe: piece łukowe, kompensacja mocy biernej, flicker.

Introduction

Electric arc furnaces (EAFs) play a very significant role in various parts of industry especially in the steel production process due to their remarkable performance, accuracy and flexibility. The time-varying nature of EAFs introduces a phenomenon known as flicker which is mainly considered as voltage fluctuations in low frequency range, around 0.5 to 25 Hz.

One of the best options to mitigate the effects of flicker is to use VAr compensators including Static VAr Compensators (SVCs). It should be noted that reactive power measurement and thyristor ignition delays can limit SVC's ability to compensate flicker. Although faster and more solid means of compensation including static synchronous compensators (STATCOMs) can be employed to improve the compensation process performance, these solutions are generally expensive. Hence it seems logical to develop approaches to compensate this delay and contributes to the enhancement of SVC performance. These approaches are mainly based on prediction of EAF reactive power consumption for a half-cycle ahead [1]. In [2] the reactive power signal is considered as a time series and the prediction is made with considering it as an Auto Regressive Moving Average (ARMA) process. Time series are defined as a collection of data points mainly sampled equally in time intervals. The process by which the future values are forecasted based on information obtained from past and present time is regarded as time series prediction. Mainly there are two techniques for time series prediction, statistical and artificial intelligence based approaches. ARMA can be regarded as statistical models while neural network models are mainly perceived as artificial intelligence based approaches. Both of these techniques have some disadvantages; in non-linear problems, statistical models are not as accurate as neural network based approaches. They also may be too complex in order to predict future values of time series. Neural network models, on the other hand, can provide accurate results but the major criticism about them is that they demand a great deal of training data.

Grey system theory was first introduced by Deng (1982) and since then is frequently used in various fields of science including finance, agriculture, economics, engineering, etc [3-7]. Some studies conducted into Grey system theory are as follows: In [8] Grey system modeling is used to predict the yearly peak load of a power system. In [9] several different Grey system theory-based models are applied on the United States dollar to Euro parity. In some researches hybrid methods are used in order to enhance the prediction. For instance, in one study, a hybrid method is proposed to reduce the error of a dynamically tuned gyroscope using wavelet and linear regression techniques integrated into grey system model [10]. In an economic application fuzzification techniques are used in combination with Grey system theory to forecast the stock prices [11].

In several papers, various prediction approaches are applied in order to forecast reactive power of an EAF. For example, stochastic approaches like adaptive filter methods Normalized Least Mean Square (NLMS) and Recursive Least Square (RLS) [12] and online genetic algorithm [13] are used to online calculation of ARMA coefficients to predict the reactive power of an EAF and therefore improve the compensation process by SVC. However, in comparison with statistical models, Grey system is much faster and requires less computation cost, and also compared with neural network model it requires less data to predict. These advantages made grey system an excellent choice for predicting arc furnace reactive power.

In this work, we use Grey system theory to predict the reactive power consumption of Mobarakeh Steel Company (MSC) and show the superiority of this approach in comparison with adaptive filter and online genetic algorithm. The organization of this paper is as follows: the concept of Grey system theory is given the next section. Data records employed in the prediction are introduced in section 3. Indices to evaluate the performance of prediction method are introduced in section 4. Adaptive filter methods (NLMS and RLS) and online Genetic algorithm method are defined in Section 5. Prediction results are shown in section 6 and conclusions are given in section 7.

Grey system Theory

The following are the fundamental concepts used in Grey system theory [14-15].

A) Accumulated Generating Operation (AGO)

Grey system theory is mainly based on AGO by which the raw data will be preprocessed in a way that the output data becomes smoother and will have exponential characteristics which makes it possible to use first-order differential equation to characterize the system behavior.

It should be noted that time series data can have random characteristics, if this randomness is omitted; it will become easier to derive any special characteristics of that data. The main goal of AGO is to transform an irregular and random series of data into a smooth series with less random characteristics. For example, consider the following sequence:

$X^{(0)}=(2,4,7,5,9,1)$

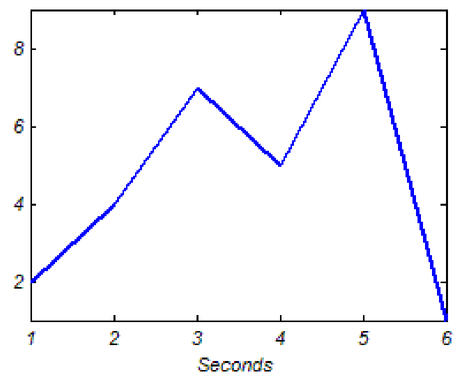

Fig. 1. The original set of data.

Obviously, $X^{(0)}$ has a great deal of randomness. Let $X^{(1)}$ be the first-order AGO of $X^{(0)}$. AGO is defined as:

(1) $X^{(1)}(k) = \sum_{i=0}^{n} X^{(0)}(i) \ , k = 1, 2, \dots, n.$

So $X^{(1)}$ would be:

$X^{(1)}=(2,6,13,18,27,28)$

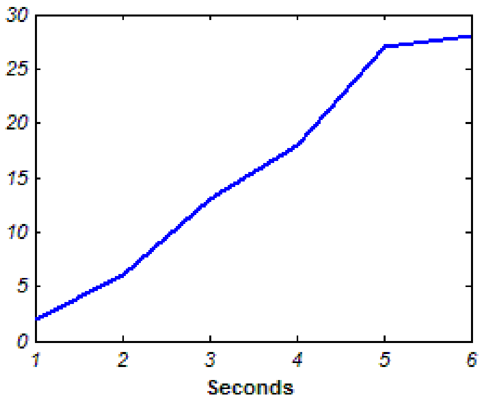

Fig. 2. The processed data by AGO.

By comparing Fig.1 with Fig.2 one can observe that $X^{(1)}$ is much smoother than $X^{(0)}$ and has turned into a mono-increasing series of data.

B) Grey forecasting model

Basically, in the grey system theory *GM (n,m)* denotes for grey model. In this case, *n* stands for the order of the difference equation and *m* shows the number of variables. In most cases *GM (1,1)* is used due to the fact that it is fast and require a small amount of computation effort and at the same time it has acceptable accuracy.

An important consideration when using *GM (1,1)* is that only non-negative data can be used, in this way $X^{(1)}$ will become mono-increasing. In order to use grey system model for prediction the time series data should first be subjected to AGO. Assume the initial sequence of data as:

(2) $X^{(0)}=[\ X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)]$

Applying AGO we have:

(3) $X^{(1)}=[\ X^{(1)}(1),X^{(1)}(2), \dots, X^{(1)}(n)]$

Now using $X^{(1)}$ we generate the mean sequence $Z^{(1)}$ which is defined as:

(4) $Z^{(1)}(k)=0.5X^{(1)}(k)+0.5X^{(1)}(k\text{-}1) \quad , \qquad k=2,3,\dots,n.$

The grey model of *GM (1,1)* can be defined as:

(5) $X^{(0)}(k)+aZ^{(1)}(k)=b$

By the means of least square method one can solve this equation for *(a,b)*:

(6) $\binom{a}{b} = (B^TB)^{-1}B^TY$

Where *B* and *Y* can be calculated as:

(7) $$B = \begin{pmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \dots & \dots \\ -Z^{(1)}(n) & 1 \end{pmatrix}$$

(8) $$Y = \begin{pmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ \dots \\ X^{(0)}(n) \end{pmatrix}$$

After determining *a* and *b*, future values of $X^{(1)}$ (showed as: $\hat{X}^{(1)}(i)$) can be obtained using equation (5):

(9) $\hat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}$

Now by using an inverse AGO (IAGO) the future values of $X^{(0)}$ can be calculated as:

(10) $\hat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-ak}(1 - e^{a})$

For long input sequences with large amount of data another approach is conventional, in this method when a new entry is inserted the last data goes out and the number of samples which are used in the prediction process will remain constant. This method is called Rolling model and it requires less computation effort and is faster.

Data records

In order to obtain an accurate model to predict system reactive power, a large amount of information about the nature of EAFs is required. In this paper actual voltage and current data of MSC are collected and used to calculate the reactive power. A single line diagram of the EAFs system is shown in Fig 1. This plant includes a step-down transformer to reduce the voltage level from 400 kV to 63 kV for EAFs transformers and 33 kV for two SVCs that are aimed to mitigate the flicker problem. In practice each SVC includes a 108 MVAr TCR and 97.2 MVAr capacitor banks to filter the harmonics.

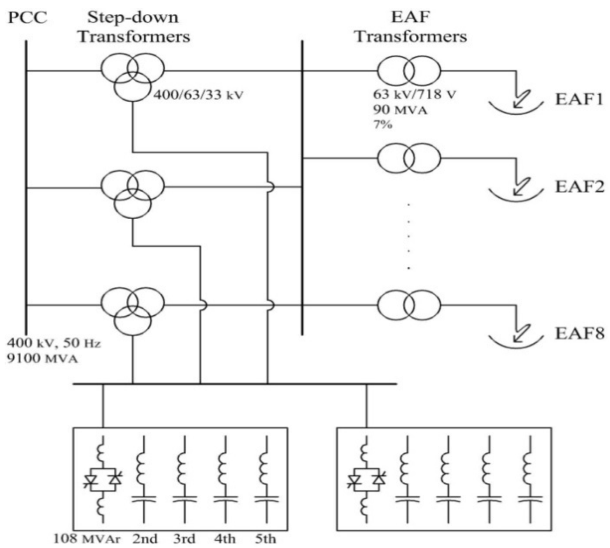

Fig. 3. Single line diagram of EAFs installed in MSC [16]

Voltage and currents values are measured at the primary side of arc furnace transformer and each data set is sampled with 128 μs sampling time (or the sample frequency is 7812.5 Hz). Data sets include records that cover 100 s of the EAF operation. For efficient operation of SVC, it should be provided with a signal that precisely indicates the fundamental reactive power of the furnace. One suitable option is the fundamental reactive power of the arc furnace calculated at each period with one cycle integration period and updated in each half cycle [16]. Therefore 100 s data records will produce time series of reactive power with 10000 (=100/0.01).

Prediction performance evaluation

Because the main concern of this paper is the performance of compensators, like SVC, facing flicker produced EAFs, some indices will be defined in order to assess the performance of SVC using different methods of prediction [12, 16]. These indices use PSD of prediction error signal *e* which is the difference between the forecasted value and the real value of EAF reactive power and is defined as [17]:

(11) $PSD(f) = \frac{1}{nf_s}\left|\sum_{t=1}^{n} e(t)e^{-i2\pi ft}\right|^2$

where *N,* PSD *f* and *fs*, denote the data record length, the value of PSD at frequency *f* and the sampling frequency (that is equal to 100Hz for reactive power time series) respectively. The first index is flicker mitigation factor (FMF) which basically considers weighted prediction error corresponding to each data record *j* and is defined as [16]:

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

where $PSD^q_j\ (f)$ denotes the PSD associated with the *j* th source reactive power data record in the absence of SVC and $PSD^{qs}_j\ (f)$ denotes the PSD associated with the *j* th source reactive power data record in the presence of SVC and *c*(*f*)s are the weighting flicker factors proposed by IEC [18].

In the control systems, prediction of the future can be perceived as a high pass band filter which may magnify the high frequency components [16]. Therefore, High frequency mitigation factor (HMF) which considers frequencies ranging from 16 to 25 Hz is used to evaluate the performance of the proposed prediction method and compare it with conventional approaches. HMF is defined as [16]:

(13) $HMF_j = \frac{\sum_{f=16}^{25} PSD_j^{qs}(f)}{\sum_{f=16}^{25} PSD_j^{q}(f)}$

Standard deviation (STD) is also used to compare the results of the Grey system method with other methods of prediction.

Adaptive filters

In this paper, the reactive power of EAFs are predicted using ARMA based models in order to be compared with the results obtained from Grey system. It is proved that ARMA model coefficients should be updated as long as they are used for prediction intention [12]. In this section three different methods are used to calculate the coefficients of ARMA models.

A) NLMS

NLMS is an adaptive filter by which the coefficients of model is calculated and is illustrated by the following equations [19-20]:

(14) $\hat{q}(t) = W^T(t)x(t)$

(15) $e(t) = q(t) - \hat{q}(t)$

(16) $W(t+1) = W(t) + \frac{\mu}{x^T(t)x(t)+\psi} e(t)x(t)$

In the above equations $\hat{q}$ stands for the predicted value, *q* is the real future value, *x* denotes vector of time series value in the previous time, *e (t)* is the error signal and *w (t)* signifies the coefficient vector. μ is a parameter that plays a very significant role in the algorithm's performance, if its value is chosen too large it may make the algorithm unstable, on the other hand, small values of μ can reduce the convergence speed of the algorithm.

In this study ARMA (2, 1) is chosen for modeling EAF reactive power, in this case the prediction equation using NLMS would be

(17) $\hat{q}(t+1) = k_1 q(t) + k_2 q(t-1) + k_3 e(t)$

(18) $e(t) = q(t) - \hat{q}(t)$

B) RLS

Another adaptation algorithm which is frequently employed in various adaptive filters is RLS. In comparison to NLMS it converges faster but requires more calculation, it can be illustrated using the following equations:

(19) $k(t) = \frac{\lambda^{-1}P(t-1)x(t)}{1+\lambda^{-1}x^H(t)P(t-1)x(t)}$

(20) $\hat{q}(t) = W^H(t-1)x(t)$

(21) $e(t) = q(t) - \hat{q}(t)$

(22) $W(t) = W(t-1) + k(t)e(t)$

(23) $P(t) = \lambda^{-1}P(t-1) - \lambda^{-1}k(t)x^H(t)P(t-1)$

Where *P*, *λ* and *k* denote, the inverse of signal correlation matrix, a constant near to one and the gain vector respectively [12].

C) Online Genetic

In online application of genetic algorithm and in each sample, error function (fitting function) is calculated based on the last *L* errors. In other words, in online genetic algorithm, the fitting function is calculated by the newest values of time series in each generation [13].

(24) $f_t(i) = \sum_{m=t-L}^{t} e_i^2(m)$

ft (i) , $e_i(m)$ and *L* are fitting function at time *t* for chromosome *i*, the prediction error at time *m* for chromosome *i* and effective number of samples used in fitting function respectively. Parameters of online genetic algorithm like execution frequency of algorithm, number of samples used in the fitting function, chromosome number and generation number should to find properly. Regarding the ability of genetic algorithm in online calculation of average value of the time series, the prediction relationship including the term related to average value is considered as:

(25) $\hat{q}(t+1) = k_1 q(t) + k_2 q(t-1) + k_3 e(t) + k4$

(26) $e(t) = q(t) - \hat{q}(t)$

The parameters in online genetic algorithm are selected as:

- The execution frequency of the algorithm: once for each sample;
- Number of samples used in calculation of fitting function (*L*): 100;
- Chromosome number: 30;
- Generation number in each algorithm execution: 1.

Simulation results

In this section, two prediction approaches are employed to forecast the reactive power consumption of electric arc furnaces in MSC. In the first approach the system is modeled by *ARMA (2, 1)* while the model coefficients are calculated online by NLMS, RLS and Genetic algorithm. In the other method the reactive power is predicted by *GM(1,1)* rolling model.

Firstly effect of reactive power prediction on the enhancement of SVC performance is investigated. Fig. 4 shows the reactive power consumption of one of EAFs regarding to a data record. The SVC is provided by two different reference signals, in the first scenario the reactive power consumption of the present sample is considered as the reference signal without any prediction. Although, in this way the SVC tracks the reactive power demand of the plant, the reactive power at the source side is relatively large and a huge proportion of EAF reactive power will remain uncompensated. On the other hand if the reactive power of next sample is predicted by the *GM (1, 1)* and is given to SVC, error signal (the reactive power at the source side) will diminish significantly, which illustrates the advantage of prediction in compensation of reactive power. Fig 5 shows the resulted reactive power at source side when not using prediction and for using Grey system for prediction according to a portion of one recorded data.

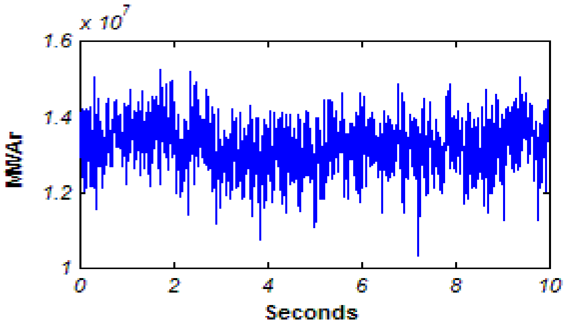

Fig 4. Reactive power consumption of EAF.

In the second scenario, the results of predicting by Grey system is compared to those obtained from *ARMA (2, 1)* when using NLMS, RLS and online Genetic algorithm for updating coefficients. In this study a *GM(1, 1)* rolling model with entry data interval equal to 5 is employed. Table 1 presents the standard deviation of reactive power at the source side for different compensation approaches for 15 sets of 100 s reactive power time series. Table 2 shows FMF for Different approaches and Table 3 gives HMF of these methods. In tables, FMF, HMF and STD are calculated as two forms for error signal. In the first form, to neglect the initial error in the model coefficients calculation, the first 500 samples of the error signal (corresponding to the first 5 s) are not taken into account to calculate the indices. In the second form, to calculate the indices, the first 5000 components of the error signal (corresponding to first 50 s) are ignored. The indices obtained in the first form (NSD1, FMF1, and HMF1) reflect the transient performance of the algorithm. The steady state performance of the algorithm is indicated by the indices obtained in the second form (NSD2, FMF2, and HMF2).

These tables clearly demonstrates that using Grey system for prediction of reactive power will have more advantages as long as flicker is concerned. The last row of each table presents average value of 15 series. It is observed that standard deviation and FMF of compensation without prediction is approximately 10 times larger than predicting with Grey system and HMF is about 4 times larger.

A comparison between compensation of 15 data records of reactive power time series using different prediction approaches has been drawn by employing the indices introduced earlier. In Fig. 6 standard deviation for varies methods of compensation are showed. Figures 7 and 8 present FMF and HMF of these methods. It is observed that Grey system prediction method reduces standard deviation and HMF very significantly, while it diminishes FMF moderately.

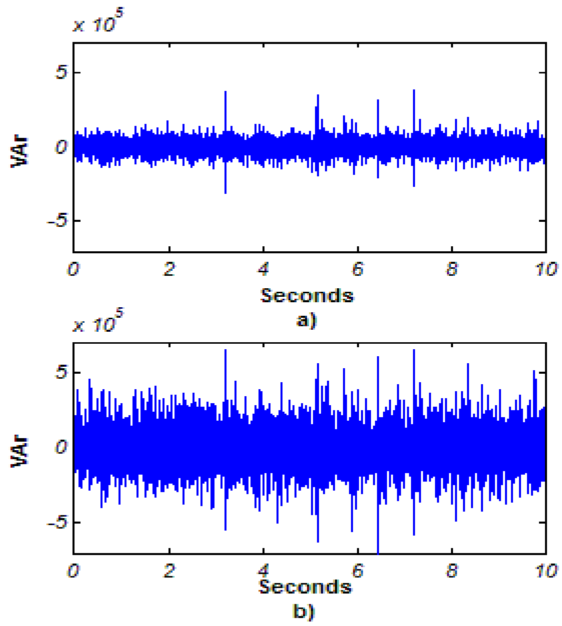

Fig 5. Compensation error produced by a) *GM*(1,1) and b)by using no prediction.

Table 1. Standard deviation of reactive power delivered by source for different prediction approaches.

	std1					std2				
	No Pred.	**GM(1,1)**	**RLS**	**NLMS**	**Gen Alg.**	**No Pred.**	**GM(1,1)**	**RLS**	**NLMS**	**Gen Alg.**
1	0.1999	0.0691	0.1993	0.1758	0.1559	0.2066	0.0729	0.2050	0.1771	0.1630
2	0.2073	0.0765	0.2159	0.1922	0.1625	0.2245	0.0847	0.2328	0.2047	0.1755
3	0.1648	0.0522	0.1568	0.1481	0.1262	0.1722	0.0547	0.1608	0.1433	0.1310
4	0.2012	0.0654	0.1672	0.1548	0.1394	0.2098	0.0631	0.1496	0.1391	0.1317
5	0.1885	0.0630	0.1625	0.1490	0.1337	0.1914	0.0592	0.1419	0.1330	0.1239
6	0.1572	0.0533	0.1313	0.1224	0.1091	0.1687	0.0533	0.1220	0.1140	0.1079
7	0.2242	0.0834	0.1598	0.1537	0.1375	0.2003	0.0763	0.1489	0.1364	0.1269
8	0.1523	0.0530	0.1000	0.1100	0.0895	0.1685	0.0544	0.1139	0.1121	0.1024
9	0.1468	0.0521	0.1031	0.1074	0.0909	0.1722	0.0591	0.1194	0.1128	0.1055
10	0.1399	0.0512	0.0876	0.1142	0.0792	0.1793	0.0557	0.1048	0.1030	0.0959
11	0.1682	0.0499	0.0839	0.1094	0.0780	0.1683	0.0493	0.0819	0.0835	0.0763
12	0.2021	0.0635	0.1220	0.1035	0.1076	0.1883	0.0571	0.1013	0.1018	0.0943
13	0.2225	0.0763	0.1660	0.1610	0.1414	0.2323	0.0716	0.1558	0.1508	0.1414
14	0.2007	0.0577	0.0996	0.1243	0.0940	0.2080	0.0591	0.1020	0.1032	0.0963
15	0.1800	0.0498	0.1012	0.1035	0.0926	0.1681	0.0447	0.0856	0.0866	0.0804
Avg.	0.1837	0.0611	0.1353	0.1353	0.1158	0.1906	0.0610	0.1350	0.1268	0.1168

Table 2. FMF of reactive power delivered by source for different prediction approaches.

	FMF1					FMF2				
	No Pred.	GM(1,1)	RLS	NLMS	Gen. Alg.	No Pred.	GM(1,1)	RLS	NLMS	Gen. Alg.
1	0.0846	0.0079	0.0133	0.0213	0.0267	0.0832	0.0083	0.0142	0.0165	0.0275
2	0.0814	0.0084	0.0159	0.0223	0.0274	0.0941	0.0102	0.0191	0.0199	0.0320
3	0.0524	0.0043	0.0084	0.0143	0.0158	0.0565	0.0047	0.0090	0.0099	0.0160
4	0.0919	0.0081	0.0139	0.0195	0.0207	0.0844	0.0066	0.0106	0.0123	0.0145
5	0.0879	0.0080	0.0137	0.0178	0.0211	0.0778	0.0064	0.0106	0.0106	0.0142
6	0.0765	0.0079	0.0112	0.0177	0.0171	0.0673	0.0051	0.0085	0.0095	0.0118
7	0.1209	0.0149	0.0173	0.0226	0.0206	0.1232	0.0162	0.0190	0.0174	0.0226
8	0.0773	0.0092	0.0096	0.0162	0.0121	0.0688	0.0069	0.0091	0.0101	0.0119
9	0.0914	0.0106	0.0130	0.0182	0.0164	0.0870	0.0095	0.0121	0.0121	0.0156
10	0.0762	0.0102	0.0091	0.0205	0.0109	0.0722	0.0069	0.0077	0.0089	0.0095
11	0.0638	0.0059	0.0062	0.0142	0.0066	0.0627	0.0057	0.0060	0.0063	0.0062
12	0.0909	0.0081	0.0096	0.0143	0.0112	0.0831	0.0072	0.0080	0.0085	0.0093
13	0.1287	0.0123	0.0151	0.0280	0.0232	0.1256	0.0101	0.0122	0.0144	0.0169
14	0.0875	0.0070	0.0081	0.0154	0.0085	0.0863	0.0068	0.0078	0.0086	0.0082
15	0.0658	0.0047	0.0065	0.0097	0.0079	0.0582	0.0041	0.0054	0.0064	0.0060
Avg.	0.0851	0.0085	0.0114	0.0181	0.0164	0.0820	0.0076	0.0106	0.0114	0.0148

Table 3. HMF of reactive power delivered by source for different prediction approaches.

	HMF1					HMF2				
	No Pred.	GM(1,1)	RLS	NLMS	Gen. Alg.	No Pred.	GM(1,1)	RLS	NLMS	Gen. Alg.
1	1.3357	0.3172	0.8821	0.5242	0.5851	1.2989	0.3105	0.8534	0.5275	0.5643
2	1.3881	0.3281	0.9211	0.5743	0.5943	1.3814	0.3272	0.8710	0.5665	0.5698
3	1.3611	0.3092	0.9077	0.5619	0.5842	1.2453	0.2815	0.7419	0.4856	0.4755
4	1.3479	0.3093	0.9019	0.5197	0.5900	1.3215	0.2958	0.8216	0.5135	0.5448
5	1.3269	0.2994	0.8366	0.5366	0.5804	1.3259	0.2960	0.8556	0.5581	0.5486
6	1.3396	0.3266	0.9053	0.5362	0.6147	1.3036	0.3033	0.9034	0.5787	0.6342
7	1.3105	0.3194	0.7558	0.4541	0.4642	1.3002	0.3116	0.7663	0.4984	0.4626
8	1.2769	0.3127	0.7840	0.4594	0.5499	1.2728	0.3050	0.7872	0.4898	0.5742
9	1.2833	0.3037	0.8011	0.4788	0.5270	1.2903	0.2989	0.8090	0.4888	0.5466
10	1.2910	0.3316	0.8071	0.5692	0.5662	1.2839	0.3026	0.8014	0.5056	0.6091
11	1.2696	0.2873	0.6839	0.4122	0.5015	1.2372	0.3134	0.7547	0.4550	0.5598
12	1.3204	0.3176	0.7754	0.4451	0.5048	1.3034	0.3153	0.7566	0.4702	0.5206
13	1.3099	0.3044	0.7699	0.5066	0.5250	1.2942	0.2932	0.7668	0.4781	0.5735
14	1.2626	0.2932	0.6957	0.4036	0.5006	1.2605	0.2918	0.7138	0.4311	0.5116
15	1.2726	0.2993	0.7718	0.4570	0.5137	1.2674	0.3000	0.7657	0.4855	0.5241
Avg.	1.3131	0.3106	0.8133	0.4959	0.5468	1.2924	0.3031	0.7979	0.5022	0.5480

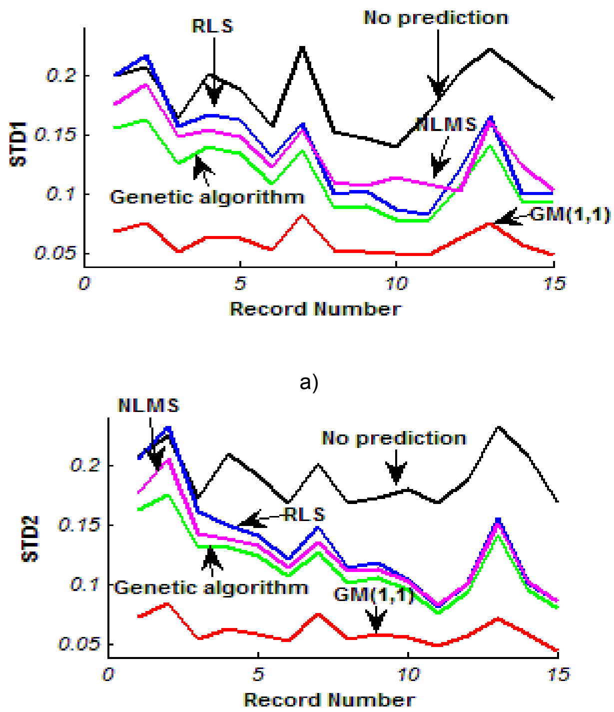

Fig 6. a) Standard deviation when the first 500 samples are ignored b) Standard deviation when the first 5000 samples are ignored.

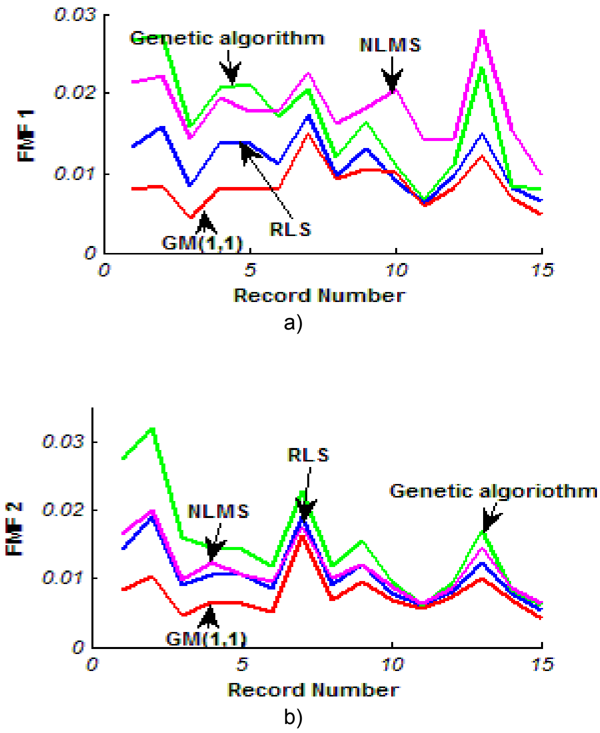

Fig 7. a) FMF when the first 500 samples are ignored b) FMF when the first 5000 samples are ignored.

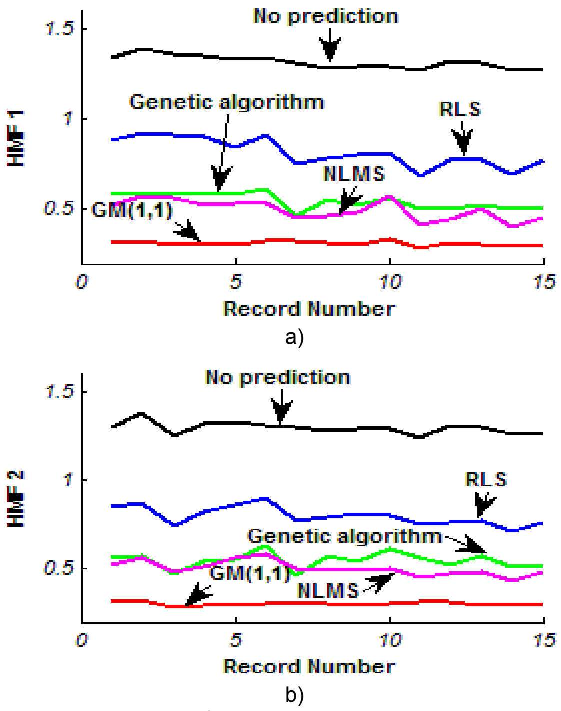

Fig 8. a) HMF when the first 500 samples are ignored b) HMF when the first 5000 samples are ignored.

Conclusions

In this paper Grey system theory was employed to predict the reactive power consumption of EAF at the SVC bus. *GM (1, 1)* rolling model with entry data interval equal to 5 was used for prediction. The results were compared with those obtained from ARMA models in which the model coefficients were updated using two common adaptation algorithms (NLMS and RLS) and a Genetic online algorithm. Three comparison indices were introduced to measure the effectiveness of these approaches. These indices mostly concern about the effects of flicker and evaluate the performance of these approaches in relatively low frequency. The results confirm the superiority of Grey system model as it reduces HMF and standard deviation very drastically. Although Grey system prediction model is capable of reducing FMF, and has a better performance in comparison with other means of prediction, it does not mitigate this index as much as it reduces HMF.

REFERENCES

[1] H. Samet and M. Parniani, "Predictive Method for Improving SVC Speed in Electric Arc Furnace Compensation," *IEEE Trans. on Power Delivery, vol. 22, no. 1, Pages 732_734,* January 2007

[2] H. Samet and M.E.H Golshan, "Employing Stochastic Models for Prediction of Arc Furnace Reactive Power to Improve Compensator Performance," *IET Generation, Transmission & Distribution, vol. 2, issue 4, Pages 505_515,* July 2008

[3] S. Liu and J. Forrest, "The Current Developing Status on Grey System Theory," *The Journal of Grey System2 (*2007*)*

[4] D. Proske and P.H.A.J.M Van Gelder, "Prediction of Complex Systems Using Grey Models," *ECI Conference on Geohazards*, 2006

[5] E. Kayacan, Y. Ozin and O. Kaynak, "Grey System Modeling Approach for Sliding-Mode Control of Antilock Braking System," *IEEE Trans. on Industrial Electronics, vol. 56, no. 8 pp.3244_3252,* August 2009

[6] S. Hui, F. Yang, Z. Li, Q. Li and J. Dong, "Application of Grey System Theory to Forecast the Growth of Larch," *International Journal of Information and Systems Sciences, vol. 5, no. 3-4, Pages 522_527*, 2009

[7] Y. Huang and T. Yu, "The Hybrid Grey-Based Models for Temperature Prediction," *IEEE Trans. on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 27, no. 2, Pages 284_292,* April 1997

[8] H. Yang, T. Liang, K. Shih and C.Huang, "Power System Yearly Peak Load Forecasting: A Grey System Modeling Approach," *International Conference on Energy Management and Power Delivery, vol. 1, Pages 261_266,* November 1995

[9] E. Kayacan, B. Ulutas and O. Kaynak, "Grey System Theory-Based in Time Series Prediction," *Expert Systems with Applications, vol. 37, issue 2, Pages 1784_1789,* March 2010

[10] C. Fan, Z, Jin and W. Tian, "A Hybrid Grey-Based Model for Drift Signal of DTG," *IEEE International Conference on Neural Networks and Signal Processing, vol. 2, Pages 1702_1705,* December 2003

[11] Y. F. Wang, "Predicting of Stock Price Using Fuzzy Grey Prediction Systems," *Expert Systems with Applications, vol. 22, issue 1, Pages 33_38,* January 2002

[12] M. E. Hamedani Golshan and H. Samet, "Updating Stochastic Model Coefficients for Prediction of Arc Furnace Reactive Power," *Electric Power Systems Research, vol. 79, issue 7, Pages 1114_1120,* July 2009

[13] M. E. Hamedani and H. Samet, "Updating Stochastic Models of Arc Furnace Reactive Power by Genetic Algorithm," *14th International Conference on Harmonics and Quality of Power, Pages 1_9,* September 2010

[14] D. Julong, "Introduction to Grey System Theory," *The Journal of Grey System 1 (*1989*), Pages 1_24*

[15] N. Shimizu, O. Ueno and C. Komata, "Introduction of Time Series Data Analysis Using Grey System Theory," *2nd International Conference on Knowledge-Based Intelligent Electronic Systems, Pages 67_72,* April 1998

[16] H. Samet, M. R. Farhadi and M.R.B. Mofrad, "Employing Artificial Neural Networks for Prediction of Electrical Arc Furnace reactive Power to Improve Compensator Performance," *IEEE International Energy Conference and Exhibition (ENERGYCON), Pages 249_253,* September 2012

[17] P. Stoica and R. L. Moses, "Introduction to Spectral Analysis," *Prentice Hall,* 1997

[18] IEC Standard 868, Flicker Meter-Functional and Design Specifications, 1996

[19] G. C. Sih, "Method and Apparatus for Frequency Selective Adaptive Filtering," *US Patent 5,644,596* (1997)

[20] B. Farhang Boroujeny, "Adaptive Filters: Theory and Applications," *John Wiley*, 1988

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