Reference Signal Generator for Active Power Filters Using MGP-FIR filter Designed by Evolutionary Programming

Tomáš Komrska and Seppo J. Ovaska

Abstract—**This paper describes a high-performance reference signal generator for active power filters extracting the fundamental signal component from distorted current signals. In order to achieve high-quality output as well as computationally effective algorithm, the generator employs an adaptive and predictive MGP-FIR (Multiplicative General Parameter) bandpass filter designed by evolutionary programming. Detailed procedures of MGP-FIR filtering and evolutionary optimization are first discussed; theoretical conclusions are verified by illustrative simulation results.**

Index Terms—**Active power filter, current injection method, current reference generator, adaptive filtering, predictive filtering, evolutionary programming.**

I. INTRODUCTION

DUE to increasing use of power converters, which are nonlinear loads, the voltages and currents of AC networks are often not sinusoidal; but considerable harmonics, sub-harmonics, and inter-harmonics are distorting the 50/60-Hz fundamental frequency. Recently, active power filters are used increasingly for reducing the harmful distortion. The active power filter injects harmonic currents of opposite amplitude to the corrupted load current [1]. Thus, the unwanted harmonics are attenuated and the result is a highly sinusoidal line current. This kind of active power filter needs an accurate reference current signal that does not contain any delay (phase lag).

We could solve this current generator problem by using a bandpass filter, but conventional fixed bandpass filters always cause some delay when the primary frequency component is varying around its nominal value (50/60 Hz +/– 2%). Moreover, the sampling and analog-to-digital converter circuits, signal processing computations, and output circuitry do cause inherent propagation delay that has to be compensated. Therefore, it would be advantageous to use an *adaptive predictive filter*.

T. Komrska is with the Department of Electromechanics and Power Electronics, Faculty of Electrical Engineering, University of West Bohemia in Pilsen, Univerzitní 26, 306 14 Plzeň, Czech Republic (phone: +420 377 634 450, e-mail: komis@kev.zcu.cz).

S. J. Ovaska is with the Faculty of Electronics, Communications, and Automation, Helsinki University of Technology, FI-02150 Espoo, Finland (e-mail: seppo.ovaska@tkk.fi).

Väliviita and Ovaska [2] proposed such a system containing an LMS-FIR (Least Mean-Square Finite Impulse Response) filter, which is two-step-ahead predictive and the adaptation is realized by using the classical Widrow-Hoff LMS algorithm. The proper function of their system was verified by simulations. Later on, however, it was found out that this particular system was working properly only shortly (< 20 s) after starting the algorithm, but no more in the longer run. Therefore, an improved system was created by Han *et al*. [3]. They fixed the serious coefficient-drifting problem, and verified the proper function successfully by both extensive simulations and a single-phase implementation of the complete active power filter. Their improved system is shown in Fig. 1.
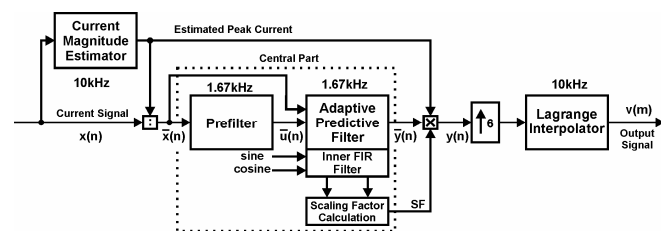

Fig. 1. LMS-based current reference generator improved by Han *et al*.

First, the input signal $x(n)$ is normalized using current magnitude estimator to make the peak amplitude approximately one. The simple peak detector is realized by choosing the maximum value of the input samples during one-half period of the fundamental sinusoid.

The central part consists of a prefilter, an adaptive predictive filter, and a fundamental component compensation block. The LMS-based adaptive predictive bandpass filter is operating according to following equations:

$$\bar{y}(n) = H^T(n)\overline{U}(n) \tag{1}$$

$$H(n+1) = \delta \cdot H(n) + 2\mu\bar{e}(n)\overline{U}(n-1) \tag{2}$$

$$\bar{e}(n) = \bar{x}(n) - H^T(n)\overline{U}(n-1) \tag{3}$$

where $\bar{x}$ is the normalized input signal and $\bar{y}$ the filter's output signal, $H(n) = [h(0), ..., h(N-1)]^T$ and $\overline{U}(n-1) = [\bar{u}(n-1), ..., \bar{u}(n-N)]^T$ are the filter coefficient vector and the data vector in the FIR window, respectively, N is the

length of the FIR filter ($N = 22$), μ is the adaptation gain factor, δ is the leakage factor and $\bar{e}$ is the output error. Such an algorithm has a considerable number of degrees of freedom, and it can also adapt to other signal components besides the fundamental one. Therefore, the overall structure contains a prefilter, which attenuates the harmonics and ensures that the LMS-FIR filter adapts to the fundamental signal component only; but it increases system complexity.

The leakage factor δ is necessary for stable filter operation; otherwise, the weight-drift problem of the coefficient vector $H(n)$ appears. Unfortunately, the multiplication by leakage factor causes attenuation of the input. The fundamental component compensation block estimates its value and repairs the output $\bar{y}$ using a scaling factor (see Fig. 1).

The output of the predictor is sampled at a rate of 1.67 kHz. For some applications, however, such a 600-μs time resolution of the output may not be sufficient. Therefore, a second-order Lagrange interpolator with an up-sampling rate of six is included in the scheme, which enables us to increase the output sampling frequency to 10 kHz. On the other hand, the interpolator introduces a one-sample delay into the output signal. Consequently, the LMS-FIR filter has to be one-step-ahead predictive ($\bar{U}(n-1)$ in (2)) to be able to compensate for this delay.

The improved system discussed above meets the harmonics requirements, and its output signal is a high-quality sinusoid, which is suitable for using as the current reference signal. Nevertheless, the improved adaptive filtering method has a high computational complexity with **125** multiplications and **98** additions within a single sampling period (600 μs). Thus, when implementing such a system, a high-performance digital signal processor is needed for practical sampling rates. This clearly limits the usability of that method in applications where the algorithms are implemented in low-cost microcontrollers or FPGA (Field Programmable Gate Array) circuits.

Fortunately, there is a possibility to replace the rather complicated filtering system of Han *et al.* [3] with a reduced-rank adaptive filter having a considerably lower computational complexity. Therefore, we used the advanced MGP-FIR (Multiplicative General Parameter Finite Impulse Response) algorithm that needs only **5** multiplications and **42** additions [4] (in case of $N = 40$) for comparable harmonics reduction ability. Moreover, the prefilter and the fundamental component compensation part are not needed any more. Our modified block diagram is illustrated in Fig. 2.
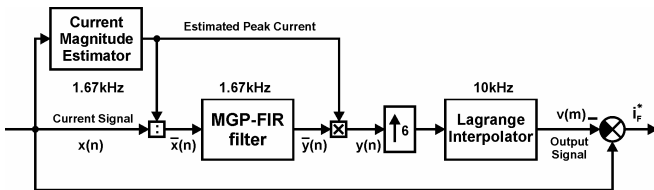

Fig. 2. Modified current reference generator containing MGP-FIR.

II. MULTIPLICATIVE GENERAL-PARAMETER FILTERING

This rather unknown adaptive filtering algorithm was introduced by Vainio and Ovaska in [5]. It is a structurally simple and highly efficient scheme with low computational burden; it provides effective attenuation of harmonic disturbances without phase shifting the fundamental line frequency component, it offers robust adaptation around the nominal frequency, and it needs only $N + 2$ additions (N is the filter length) and 5 multiplications. The MGP-FIR filter is illustrated in Fig. 3.
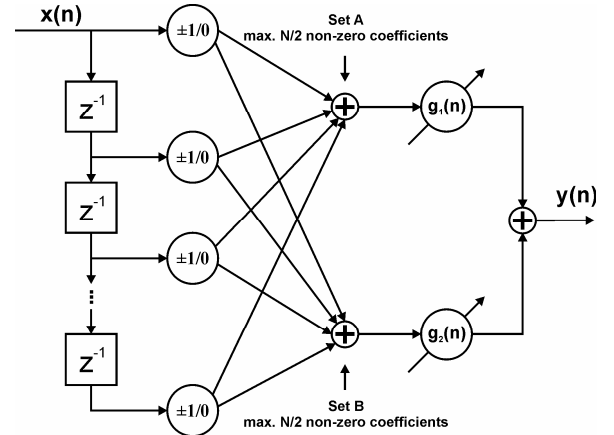

Fig. 3. MGP-FIR filter with two adaptive coefficients.

In our MGP-FIR implementation, the filter output is computed as

$$y(n) = g_1(n)\sum_{k=0}^{N-1} h_A(k)x(n-k) + g_2(n)\sum_{k=0}^{N-1} h_B(k)x(n-k) \quad (4)$$

where $g_1(n)$ and $g_2(n)$ are the multiplicative general parameters, $h_A(k)$ and $h_B(k)$, $k \in \{1, 2, ..., N-1\}$, are the fixed subfilter coefficients. In a p-step-ahead prediction configuration, the multiplicative general parameters are updated according to the following equations:

$$g_1(n+1) = g_1(n) + \mu[x(n) - y(n-p)]\overbrace{\sum_{k=0}^{N-1} h_A(k)x(n-k)}^{\text{Subfilter #1}} \quad (5)$$

$$g_2(n+1) = g_2(n) + \mu[x(n) - y(n-p)]\overbrace{\sum_{k=0}^{N-1} h_B(k)x(n-k)}^{\text{Subfilter #2}} \quad (6)$$

where μ (< 1) is the adaptation gain factor. Thus, μ considerably affects the g_1- and g_2-parameters convergence during input transients as well as the residual oscillations, typical for reduced-rank adaptive filters, in steady state.

III. OPTIMIZATION OF MGP-FIRs

When designing the MGP-FIR filter described above for a specific application, optimal subfilter coefficients must be found. Here, these fixed $h_A(k)$ and $h_B(k)$ coefficients may only have values of +1, 0, and −1, and the two subfilters are sharing a single delay line. Besides, each filter tap belongs

either to the Subfilter #1 or to the Subfilter #2. Consequently, when optimizing the computationally efficient MGP-FIR filter for certain application specifications, we have to solve a discrete optimization problem that is highly nonlinear. Therefore, it is necessary to use some advanced search method to address the MGP-FIR optimization problem.

A. Evolutionary Programming

Ovaska presents in [4] (pp. 211–213) an efficient MGP-FIR optimization procedure using evolutionary programming, which is a nature-inspired search method belonging to so-called soft computing. The evolutionary programming algorithm (EPA) is related to better-known genetic algorithms that are used routinely in various engineering applications [6]. However, in case of EPA, N_p parents generate always N_p offspring; both the parents and offspring are included in the selection and can thus be part of the next generation. Evolutionary programming is used increasingly for solving demanding optimization problems also in the field of electric power systems.

Fig. 4 shows the straightforward evolutionary programming algorithm used in our work.
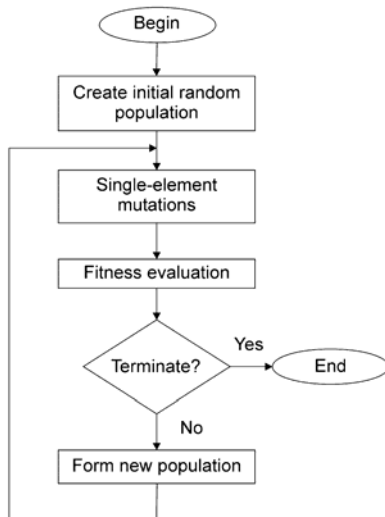

Fig. 4. Evolutionary programming algorithm for solving the optimization problem of multiplierless sub-filters.

First, an initial random population is created. Each candidate is a pair of N-length vectors: one vector for Subfilter #1 and the other for Subfilter #2. The vector elements correspond to subfilter coefficients, and they may have values $\{-1, 0, +1\}$. When some element of Subfilter #1 has a value ± 1, then the corresponding element in Subfilter #2 is equal to 0, and vice versa. The total number of non-zero coefficients in all candidate solutions must always be equal to N.

Next, a random perturbation step follows. Single-element mutations are performed for randomly selected coefficients, either $-1 \rightarrow 0/+1$, $0 \rightarrow \pm 1$, or $+1 \rightarrow -1/0$, for each solution pair in the population. After a randomly selected coefficient of Subfilter #1 is mutated, the corresponding coefficient

of Subfilter #2 may also be mutated according to the rules described above to keep the number of non-zero coefficients equal to N. Thus, the size of the enhanced (initial and mutated) population is $N_P + N_P = 2N_P$. The performance of each candidate solution is evaluated with a fitness score by so-called fitness function, which will be discussed later.

Now, the population can be sorted in the order of decreasing fitness score, which is the next stage of the algorithm. Only the fittest N_p solutions are selected from the sorted population to the new population and the N_p poorest ones are discarded. Thus, the selection process has built-in elitism and the best fitness of the population never decreases.

This entire procedure is repeated until terminal conditions are reached. If we perform sufficient number of iterations (typically < 500), the candidate solution with the fittest score in the final generation will be either the global optimum or, at least, a competitive local optimum.

B. Fitness Function

The fitness function specifies our explicit requirements on the candidate solution. Characteristics of each individual in the population are analyzed and its fitness for the specific task is evaluated by the fitness score.

In our case, each candidate solution is simulated with a representative test signal until the particular MGP-FIR filter is converging; its performance is measured by a fitness function that consists of three simultaneous objectives: convergence speed, harmonics attenuation, and white noise gain ("wide-band attenuation"). Therefore, this EPA stage has a rather high computational burden. The fitness score is in our case computed as

$$F = \frac{1}{ITAE(\alpha \cdot A_{\max} + (1-\alpha)NG_{\max})} \tag{7}$$

where $ITAE$ is the integral of time absolute error, $A_{\max}$ is the maximum amplitude of 3rd, 5th, 7th, 9th, 11th, and 13th harmonics, $NG_{\max}$ is the maximum of noise gains computed as

$$NG(n) = \sum_{k=0}^{N-1}[g_1(n)h_A(k)]^2 + \sum_{k=0}^{N-1}[g_2(n)h_B(k)]^2 . \tag{8}$$

The α-parameter in (7) enables us to emphasize the influence of either odd harmonics or NG value that considerably changes the filter characteristic. The important α-parameter search will be discussed later.

In order to optimize the filter also for the nominal frequency variation, our test signal is composed of three individual sequences of 300 samples [4]: 49, 50, and 51 Hz (corrupted by 3rd–13th order odd harmonics), because the fundamental signal component is assumed to vary 2% around its nominal value. We constructed the three artificial current signals as

$$x(n) = \sin(\omega_F n) + \sum_{m \in \{3,5,7,9,11,13\}} 0.15 \cdot \sin(m\omega_F n) \cdot \tag{9}$$

where ω_F corresponds to the three fundamental frequencies 49/50/51 Hz. In addition, the individual fitness function

components (*ITAE*, A_{max} and NG_{max}) are computed for each frequency and their worst values are used for fitness evaluation. A comprehensive discussion on the optimization of MGP-FIR coefficients is available in [4].

IV. SIMULATION RESULTS

A. MGP-FIR Filter Optimization

The number of candidates N_p is the only task-specific parameter in the EPA. According to experience presented in [4], it is practical to choose $Np \geq N$, when designing an *N*-length filter. In our case, filters of $N = 30$, 40, and 50 have been designed by EPA, consequently, we have used $N_p = 45$ in case of $N = 30/40$ and, $N_p = 55$ in case of $N = 50$.

Next, in the optimization procedure, the appropriate μ-parameter must be chosen for particular MGP-FIR filter used in the fitness evaluation stage; the μ amplifies the prediction error and affects also the gradient of g_1 and g_2 (see (5) and (6)). Generally, the longer filter we are designing, the smaller μ we should use during the optimization. When designing the filters of $N = 30$, 40, and 50, we set the $\mu = 0.0008$, 0.0005, and 0.0003, respectively.

In order to achieve a high-quality solution, it is necessary to perform a sufficient number of EPA iterations, so that the fitness score of the best candidate in the generation is converged. Therefore, 800 generations have been computed to design a high-performance multiplierless filter, as shown in Fig. 5.
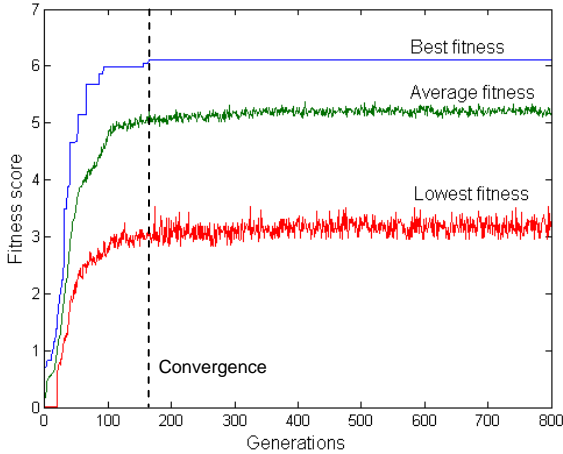

Fig. 5. EPA maximizing the fitness score; $N = 40$, $\alpha = 0.3$.

B. α-Parameter Search

The α-parameter has a significant impact on the characteristics of the designed filter. As we can see in the fitness function (7), the α-parameter gives emphasis either on the wide-band noise suppression or on the odd harmonics attenuation. Thus, the α-value can be chosen in accordance with task-specific requirements, and it enables us to achieve high flexibility during the system design. However, when designing the reference signal generator for active power filters, it is necessary to find a trade-off between the noise

suppression and the odd harmonics attenuation. Figs. 6 and 7 show the differences in instantaneous magnitude responses for $\alpha = 0.3$ (more emphasis given on *NG*) and $\alpha = 0.8$ (more emphasis given on the odd harmonics attenuation).
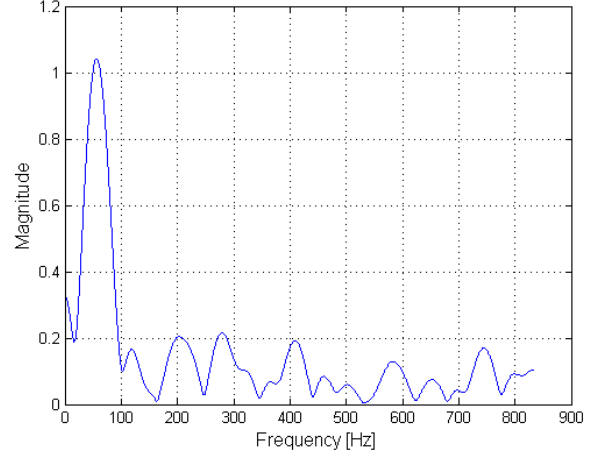

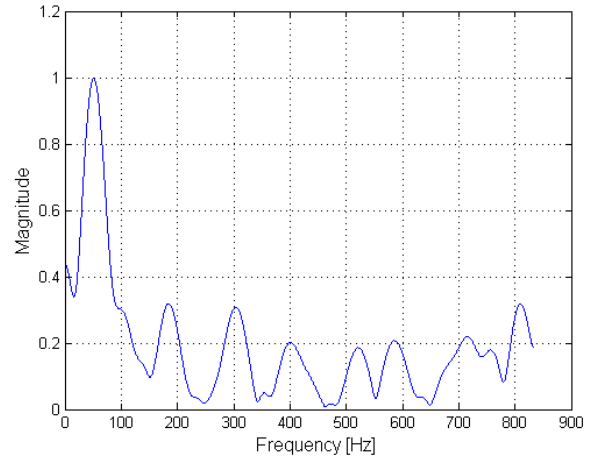Fig. 6. MGP-FIR filter magnitude response designed with $\alpha = 0.3$.

Fig. 7. MGP-FIR filter magnitude response designed with $\alpha = 0.9$.

Extensive simulations have been performed in order to find an appropriate α-value for the fitness function, which would enable the evolutionary programming algorithm to design a high-performance reference generator. We have designed and tested MGP-FIR filters for all $N = 30, 40$, and 50 with $\alpha \in \{0.1, 0.2, ..., 0.9\}$.

TABLE I
HARMONIC COMPONENTS OF TEST INPUT SIGNAL.

Harmonic order	Amplitude [%]
Fundamental	100
5th	22.6
7th	10.5
11th	7.3
13th	4.7
THD	26.4

In order to compare our results with those of Han *et al.* [3],

we applied a similar test signal described above in Table I (however, we used a 50-Hz fundamental).

Besides the appropriate filter magnitude response, the total harmonic distortion (THD), and the spectrum of the output signal are also the main criteria when searching for the optimal α-value. In Fig. 8, we can see the THD and the amplitudes of odd harmonics in the output signal versus the α-parameter used in the filter design.
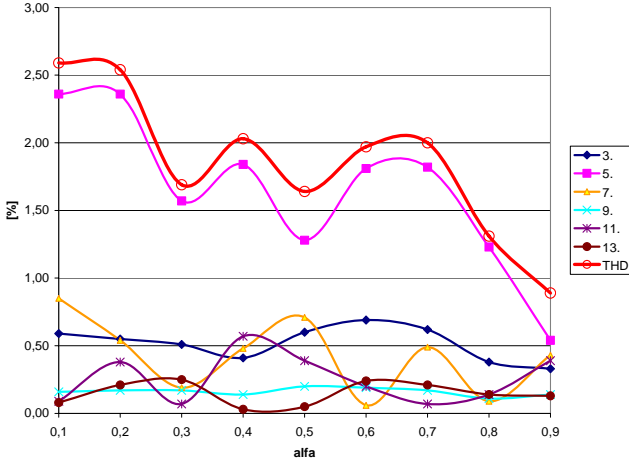

Fig. 8. THD and amplitudes of odd harmonics in the output signal versus the α-parameter. The MGP-FIR filter of length $N = 40$, designed with $\mu = 0.0005$, and evaluated with $\mu = 0.0003$.

The main distorting component in the test signal is the 5th harmonic (22.6%) which is also the main component in the output spectrum. Consequently, the 5th harmonic has the main impact on the THD value, as we can see in Fig. 8. In cases of $\alpha = 0.1$ and $\alpha = 0.2$, the *NG* suppression is weighted by 90% and 80%, respectively, whereas odd harmonics suppression is weighted by only 10% and 20%, respectively, during the filter optimization. Such filters have narrow passband and a reasonable *NG* suppression throughout the entire stopband. However, these filters are not so good at odd harmonics attenuation; therefore, the THD and 5th harmonic are considerably high.

The lowest THD and 5th harmonic amplitude we can find in Fig. 8 for $\alpha = 0.9$. Nevertheless, considering the magnitude response shown in Fig. 7, such a filter cannot be seen as a general-purpose solution. The main emphasis, in this case, is given on the odd harmonics attenuation but, consequently, the *NG* suppression throughout the entire stopband is relatively poor; considerably high peaks at "don't care" frequencies can be found in the magnitude response.

For reasons discussed above, and with accordance to other simulation results, a conclusion can be drawn that the most appropriate general-purpose solution is achieved with $\alpha = 0.3$ or 0.7. Nevertheless, in general, it is always practical to design multiple MGP-FIR filters by using various α-values and choose an appropriate task-specific solution by considering the magnitude response as well as the spectrum and the THD of the output signal.

C. μ-Parameter Discussion

The μ-parameter or adaptation gain factor (see (2) and (3)) significantly affects the dynamic behavior as well as the THD of the output. For real application, a suitable compromise between dynamic behavior and the output signal quality has to be found. As we can see in (2) and (3), μ multiplies the prediction error and affects directly to the updated g_1 and g_2 parameters, which are starting from zero and converging during the initial transient phase.

However, because of adaptive characteristic of the filter, g_1 and g_2 are not constant even in steady state, but they are oscillating slightly. Consequently, fresh harmonics, which are not present in the input signal, may appear in the output spectrum due to the inherent modulation effect (typically the 3rd harmonic; see Fig. 8) or the attenuation of some harmonics is not consistent with the instantaneous magnitude response.

The dynamic behavior or the output signal quality can be improved by tuning of the μ-parameter. It is possible to reduce the modulation-related THD with a smaller μ value. On the other hand, the convergence is becoming faster but more oscillatory with increasing μ.

Table II presents THD for various α- and μ-values for filter lengths $N = 30$, 40, and 50; Table III makes it possible to consider the impact of μ-parameter on the dynamic behavior (50-Hz input signal).

TABLE II
TOTAL HARMONIC DISTORTION VERSUS α - AND μ -PARAMETER.

THD [%]									
N = 30	α								
μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0008	6.77	5.69	6.13	5.61	3.23	4.79	4.53	3.46	3.04
0.0006	6.22	5.29	5.61	5.06	2.98	4.37	4.18	3.11	2.88
0.0004	5.72	4.91	5.13	4.55	2.76	3.99	3.88	2.81	2.75
N = 40	α								
μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0005	3.81	3.48	2.64	2.88	2.68	3.15	2.85	2.32	1.53
0.0004	3.17	2.99	2.14	2.42	2.13	2.54	2.41	1.80	1.19
0.0003	2.59	2.54	1.69	2.03	1.64	1.97	2.00	1.31	0.89
N = 50	α								
μ	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0003	4.99	2.78	2.31	2.73	3.10	2.16	2.24	2.04	2.32
0.0002	3.62	1.71	1.48	1.87	2.07	1.49	1.61	1.22	1.56
0.0001	2.42	0.84	0.87	1.14	1.16	0.91	1.12	0.60	0.87

TABLE III
AVERAGE STARTUP TIME FOR VARIOUS α -VALUES.

Average Startup Time [ms]					
μ	N = 30	μ	N = 40	μ	N = 50
0.0008	36	0.0005	34	0.0003	33
0.0006	42	0.0004	40	0.0002	41
0.0004	57	0.0003	46	0.0001	64

D. Optimal Solution

As discussed above, various MGP-FIR filters have been designed and multiple simulations have been performed to find an optimal solution for the proposed current reference generator. When selecting the appropriate coefficient vector, we operated with following optimal solution criteria:

- Startup transient approximately 2–3 cycles of the fundamental signal component (e.g., 40–60 ms).
- Total harmonic distortion of the output less than 2.6% (with test signal described in Table I).
- Reasonable *NG* suppression throughout the entire stopband.
- Considerable attenuation of odd harmonics.
- Computational burden as low as possible.

We could achieve the lowest computational burden with the filter length of 30. On the other hand, such a solution cannot meet our requirements with the THD of approximately 4%, while considering also the dynamic behavior.

In accordance with the criteria of reasonable *NG* suppression and considerable odd harmonics attenuation, the solution $N = 40$ designed by $\alpha = 0.3$ has the appropriate characteristics (see the magnitude response in Fig. 6). Moreover, the startup transient takes 45 ms even if we use μ of 0.0003, which enables us to achieve a high-quality output signal with THD = 1.69% (see in Table II).

However, the filtering system performance increases when extending the filter length. The most appropriate magnitude response can be found for the candidate of $N = 50$ designed by $\alpha = 0.8$. In this case, it is possible to reduce the THD to 1.22% ($\mu = 0.0002$) and 0.60% ($\mu = 0.0001$), respectively. Nevertheless, such a solution has a reduced dynamic response; the startup transient with 53 ms ($\mu = 0.0002$) cannot compete with the proposed 40-length solution discussed above. In addition, once the increased computational burden is taken into account, the 50-length filter is not profitable for our application, whereas the 40-length candidate fulfills the determined criteria and can be chosen as a competitive trade-off solution.

E. Performance Verification

As discussed above, the 40-length solution designed by the fitness function with $\alpha = 0.3$ and operating with $\mu = 0.0003$ ($\mu = 0.0005$ was used during the design) has been chosen for the signal reference generator. The proposed filter shows satisfactory characteristic; its instantaneous magnitude response is depicted in Fig. 6.

The 50-Hz testing signal described by Table I was used for performance verification. Total harmonic distortion of such an input is 26.4 %. The $\mu = 0.0003$ reduced from the $\mu = 0.0005$, which was used for the design, does not deteriorate the dynamic behavior significantly and the oscillations of g_1- and g_2-parameters are low; therefore we have achieved a high-quality output signal with THD = 1.69%. Its spectrum (excluding the fundamental component) is depicted in Fig. 9. Fig. 10 shows the dynamic behavior during the startup. In Figs. 11 and 12, we can see the system operation after a frequency step change (notice the red circle). When changing the input frequency, the THD increases to 2.63% and 2.44% for 49 and 50 Hz, respectively.

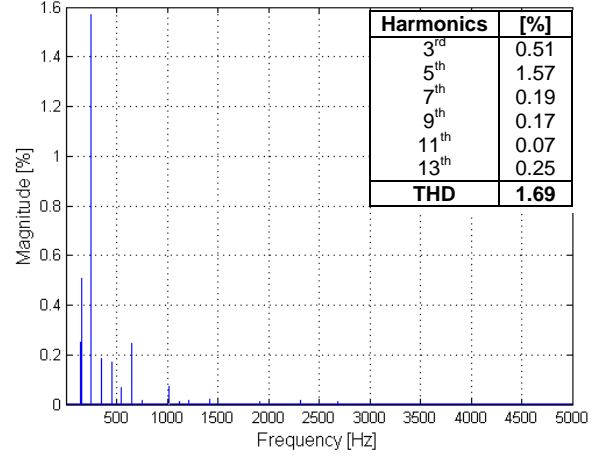| Harmonics	[%]
3rd	0.51
5th	1.57
7th	0.19
9th	0.17
11th	0.07
13th	0.25
THD	**1.69**

Fig. 9. Spectrum of the interpolated output signal; $N = 40$, $\alpha = 0.3$, and $\mu = 0.0003$ with 50-Hz test signal of Table I.
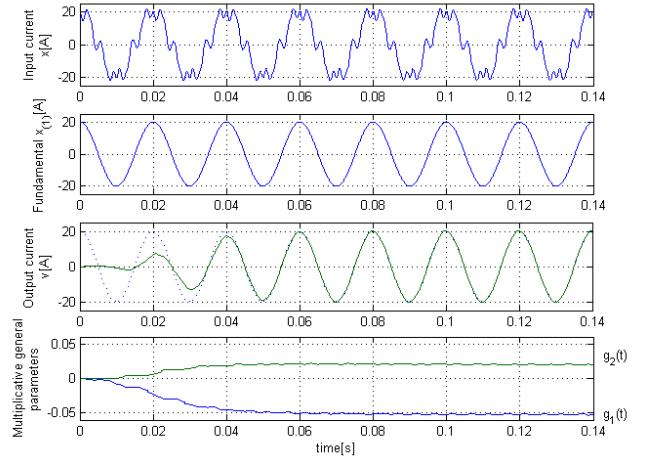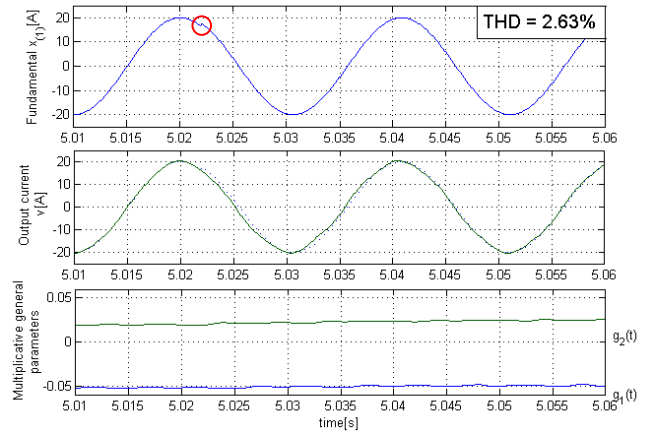

Fig. 10. Startup transient.

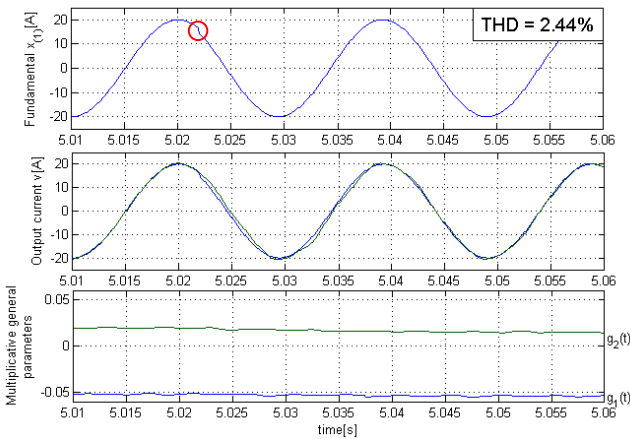Fig. 11. Step change of input frequency from 50 to 49 Hz.

Fig. 12. Step change of input frequency from 50 to 51 Hz.

F. Original versus New Structure

The original structure presented by Han *at al.* [3] employs two-step-ahead predictive (prefilter and interpolator compensation) LMS-FIR filter with the fifth order Butterworth IIR prefilter and the fundamental component compensation, which are necessary for proper system operation. Their proposed adaptive predictive filter operates perfectly as a bandpass filter with an accurate compensation capability of a phase shift. Simulation results of LMS-based system indicate that the level of output for the harmonics is extremely low as shown in Table IV. Nevertheless, such an algorithm has a high complexity with altogether 125 multiplications and 98 additions.

TABLE IV
HARMONIC COMPONENTS OF TEST OUTPUT SIGNAL OF HAN *ET AL.* [3].

Harmonic order	Amplitude [%]
Fundamental	100
5th	0.53
7th	0.245
11th	0.1
13th	0.075
THD	0.60

Our proposed reference signal generator is based on the efficient multiplicative-general parameter filtering method. This system is one-step-ahead predictive (interpolator compensation) and does not need any prefilter nor compensation algorithm for its proper operation. The computational burden is, therefore, considerably reduced compared to original system; only 5 multiplications and 42 additions are needed. Thus, the algorithm is highly suitable also for low-cost microcontrollers as well as FPGA circuits.

The distortion level of the output signal is presented by Table V. Apparently, our results are comparable to the original system performance of [3]. We have not achieved THD of 0.60%, but 1.69% is still extremely low value when taking into account that our generator does not contain any

prefilter. Moreover, the difference of 1.09% is negligible when implementing the system in a microcomputer and power electronics environment, where various additional phenomena deteriorate the output signal quality.

TABLE V
HARMONIC COMPONENTS OF TEST OUTPUT SIGNAL OF OUR SYSTEM.

Harmonic order	Amplitude [%]
Fundamental	100
3rd	0.51
5th	1.57
7th	0.19
9th	0.17
11th	0.07
13th	0.25
THD	1.69

V. CONCLUSION

This contribution deals with a current reference generator for active power filters. Its task is to extract the fundamental signal component from distorted input for control algorithms of power converters without any delay.

We successfully removed the original computationally complex adaptive predictive filter from the reference generator presented by Välivita and Ovaska in [2] and replaced it by the computationally efficient and robust MGP-FIR filter. We performed tailoring and optimization of the new adaptive predictive filter using a nature-inspired evolutionary programming algorithm proposed in [4].

The new reference generator has a narrow passband and considerable attenuation on odd harmonics as well as good dynamic behavior. According to our simulations results, the filtering system extracts the fundamental signal component of the distorted input signal with THD of 26.4% without any delay, and the output THD is only 1.69%.

The dynamic behavior or the output signal quality could be improved by tuning of the μ-parameter. It is possible to reduce THD with a smaller μ value.

In comparison with the LMS-FIR (least mean-square) filter of Han *et al.* [3] with 125 multiplications and 98 additions within a sampling period of 600 μs, our efficient MGP-FIR algorithm needs only 5 (–96%) multiplications and 42 (–57%) additions for comparable harmonics reduction ability. Thus, it is more suitable for low-cost microcontrollers and FPGA circuits.

REFERENCES

[1] A. H. Samra and A. Teshome, "Current injection method to eliminate harmonics," *IEEE Industry Applications Magazine*, vol. 1, no. 2, 1995, pp. 28–33.
[2] S. Väliviita and S. J. Ovaska, "Delayless method to generate current reference for active filters," *IEEE Transactions on Industrial Electronics*, vol. 45, no. 4, pp. 559–567, 1998.
[3] B.-M. Han, B.-Y. Bae and S. J. Ovaska, "Reference signal generator for active power filters using improved adaptive predictive filter," *IEEE Transactions on Industrial Electronics*, vol. 52, no. 2, 2005, pp. 576–584.

[4] S. J. Ovaska, "Predictive filtering methods for power systems applications," in *Computationally Intelligent Hybrid Systems: The Fusion of Soft Computing and Hard Computing.* S. J. Ovaska, Ed. Hoboken, NJ: John Wiley & Sons, 2004, pp. 203–240.

[5] O. Vainio and S. J. Ovaska, "Adaptive lowpass filters for zero-crossing detectors," *Proceedings of the 28th Annual International Conference of the IEEE Industrial Electronics Society*, Seville, Spain, Nov. 2002, pp. 1483–1486.

[6] R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, Wiley, New York, 1998.

Tomáš Komrska received an M.Sc. degree in electrical engineering from the University of West Bohemia, Pilsen, Czech Republic, in 2006. He is currently a full-time Ph.D. student in the Department of Electromechanics and Power Electronics, Faculty of Electrical Engineering, University of West Bohemia. His research interests are in control of power electronics and electric drives using DSP and FPGA circuits and digital signal processing.

Seppo J. Ovaska received an M.Sc. degree in electrical engineering from Tampere University of Technology, Finland, an Lic.Sc. degree in computer science and engineering from Helsinki University of Technology, Finland, and a D.Sc. degree in electrical engineering from Tampere University of Technology in 1980, 1987, and 1989, respectively.

He is currently a Professor in the Faculty of Electronics, Communications, and Automation, Helsinki University of Technology. Before joining Helsinki University of Technology in 1996, he was a Professor in the Department of Information Technology, Lappeenranta University of Technology, Finland (1992–1996). From 1980 to 1992, he held engineering, research, and R&D management positions with Kone Elevators and Nokia Research Center, both in Finland and in Kentucky. In the summer of 1999, he was a Visiting Scientist at Muroran Institute of Technology, Japan; in the summers of 2000 and 2001, at Virginia Polytechnic Institute and State University; in the summers of 2002–2004, at Utah State University; and in the summer of 2005, at the University of Passau, Germany. He served the academic year of 2006–2007 as a Professor of Electrical and Computer Engineering at Utah State University. His research interests are in computational intelligence, evolutionary computation, artificial life, and industrial electronics. During his career, he has authored or coauthored more than 230 papers in peer-reviewed journals, international conferences, and edited books. He edited "Computationally Intelligent Hybrid Systems: The Fusion of Soft Computing and Hard Computing" (Wiley-Interscience, 2004), and holds nine patents in the area of systems and control.

Dr. Ovaska was the Founding General Chair of the IEEE Nordic Workshop on Power and Industrial Electronics in 1998. He is a recipient of the Most Active Technical Committee Award (2006) and two Outstanding Contribution Awards (2000 and 2002) of the IEEE Systems, Man, and Cybernetics Society.