Gearbox Health Monitoring by Evolutionary Optimization

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***Abstract*—Diagnosis of mechanical faults in rotating structures is a challenging and complex task, especially in the presence of multiple interacting components like gearboxes in machines, and huge background noise. In this paper, a novel gearbox fault diagnosis algorithm based on particle swarm optimization and band pass filtering is presented. Vibration signal acquired from gearbox is adaptively filtered through a band pass filter optimized by particle swarm optimization for extraction of faulty pulses buried in huge background noise. The effectiveness, feasibility and robustness of the proposed method are demonstrated on experimental data. The proposed method has successfully achieved reasonable speed up factor required for real-time applications and at the same time, the quality of the results is preserved.**

***Index Terms*—vibration measurement, structural health diagnostic, signal processing, band pass filters, particle swarm optimization.**

I. Introduction

Gearbox is an inseparable part of a mechanical drive train in a rotating machine. Gearbox transfers speed and torque from one shaft to another. An early diagnosis of gearbox faults in rotating machines is an important task to avoid serious breakdown and to prevent loss of production. Vibration based analysis technique is one of the most commonly used techniques to monitor gearboxes. It is non-destructive, reliable and permits continuous monitoring of machines [1]. When a fault arises in a gearbox, the amplitude of the vibration signal emanating from the gearbox is increased. The vibration signal exhibits an increase in the amplitude in a specific region of its spectrum. With suitable vibration analysis, it is possible to detect faults in gearboxes and make appropriate structural health related decisions.

In the past, a variety of vibration based analysis techniques were used for diagnosis and early detection of faults in gearboxes [2]-[4]. In [5] a gearbox based electromechanical system is analyzed using torsional vibration analysis. A packet wavelet analysis (WA) method is proposed in [6], where authors use WA to extract faulty information from vibration signals emanating from a helicopter's gearbox. In [7] a reciprocating compressor coupled with alternating current (AC) induction motor is analyzed through torsional vibration analysis.

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Vibration based methods for fault detection can be classified into two groups. The grouping is based on the nature of the incoming signals, categorized as stationary and non-stationary. Statistical properties of the non-stationary signals change over time and hence, the features extraction methods should account for time resolution. On the contrary, stationary signals do not change their statistical properties over time. Therefore, the features extraction methods for these signals differ in nature. Methods like short time Fourier transform (STFT) and WA falls into the domain of non-stationary signals. Whereas, analysis of stationary signals include spectrum, cepstrum and other statistical and model based methods.

This paper uses the vibration analysis method combined with nature inspired optimization framework to detect faults in gearboxes of machines. Biologically inspired optimization methods have been successfully applied in different fields of scientific computing and became a formal area of study in computer science as soft computing. The extraordinary complexity of the natural world provides us with remarkably robust and well-designed optimization frameworks [8]. Many different organisms in nature have a natural tendency to form swarms, for instance, birds and fish. Swarming behavior is so prevalent in nature. The global optimization problem is flourished by these nature-inspired techniques, such as ant colony optimization, genetic algorithms (GAs), simulated annealing, genetic programming (GP) and others [9], [10].

Particle swarm optimization (PSO) is yet, another type of nature-inspired technique that works on population based stochastic optimization principle. PSO was first proposed by Kennedy and Eberhart in 1995 [11]. As compared to other evolutionary population based algorithms like GA, PSO has an advantage of being simple in implementation, faster convergence and fewer parameters [12], [13]. Researchers have proposed different variants of PSO with random inertia weights, periodic and adaptive mutation strategies, genetic mutation operators and neural networks in order to increase the convergence performance and to avoid local minima [14], [15].

Many researchers have investigated the implementation of PSO for fault diagnosis of machines. In [16], PSO in conjunction with exact WA and support vector machine (SVM) classifier is used for fault detection in the gearbox. In [17], PSO is used to calculate an optimal placement of vibration sensor for fault detection in gearbox. Another

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interesting research on fault diagnosis in gearbox based on PSO optimization is presented in [18], where PSO is used to train back propagation neural networks (NN). The method increases the convergence speed of the NN and avoids getting stuck in local extremum. Although, the computational complexity of PSO is not suitable for real time applications, the process can be modified to speed up the convergence.

One of the main contributions of this paper is a combination of two different techniques to speed up the optimization process. We use Brent's method to reduce the solution search space and give an advantageous start to PSO in order for PSO to converge faster. Another method we use is an inclusion of a squared penalty in the objective function that makes unfit or bad swarms worse and avoids them to be followed by others.

The rest of the paper is organized as follows. In Section II, we discuss the basics of the proposed methodology. We first describe the transient nature of the faulty signals emanating from rotating machines. We then present a PSO optimization paradigm along with Chebyshev band pass filtering. Section III discusses the nature of the fault we are trying to detect in this study. The feasibility of the proposed methodology is demonstrated in Section IV through simulations on experimental vibration signals emanating from gearboxes present in mechanical drive trains of rotating machines. Finally, we conclude our study in Section V.

II. The Methodology

Transients are short duration pulses present in vibration signals emanating from faulty or cracked mechanical structures [19]. The duration of these transients, in the time domain, usually lasts 1-10 msec. In the frequency domain, transients are spanned over a wide bandwidth. The amplitude and slope of these transient pulses represent the severity of the faults.

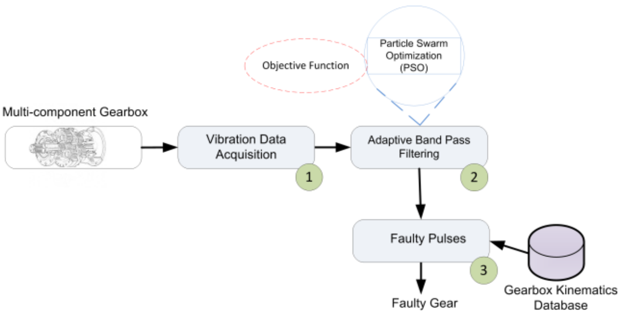


Figure 1. Flowchart of the proposed method - PSO adaptive filtering.

The proposed method is shown in Fig. 1. After data acquisition and conditioning, the method uses Chebyshev band pass filtering along with PSO. The PSO optimizes the parameters of the band pass filters to maximize an objective function based on kurtosis.

In the PSO optimization process, we use Brent's method to optimize one of the main parameters of the Chebyshev band pass filter and then initialize the PSO along with suitable ranges of all the parameters. This step gives an advantageous start to the PSO and at the same time reduces the search space for the PSO. Consequently, the PSO converges in less time.

As indicated above, kurtosis is used as an optimization cost function or an objective function to be maximized. The objective function also makes use of penalty functions in order to speed up the convergence performance. The PSO optimization paradigm combined with the Chebyshev band pass filtering provides enough information and reasonable detection of transients for features extraction and fault classification in a reasonable amount of time.

A. Band Pass Filtering

A band pass filter is designed and the PSO tunes its parameters. Fig. 2 shows different design parameters for a typical band pass filter. We design a Chebyshev band pass filter because of its speed as it is carried out by recursion rather than convolution. The Chebyshev band pass filter applies a mathematical strategy to achieve a faster roll off by allowing ripples in the frequency response. Here, we will design only type1 Chebyshev filter by allowing ripples only in the pass band. We control four parameters, centre frequency F_c, quality factor Q, filter order N and pass band ripples R_p.

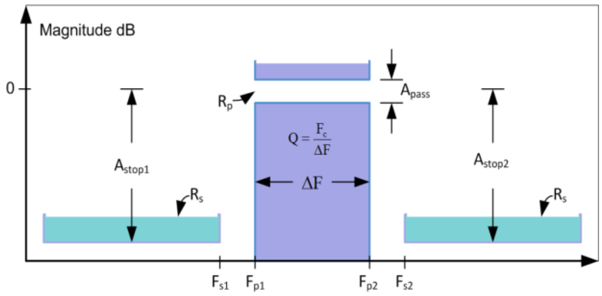


Figure 2. The band pass filter.

B. The Brent's Method

The Brent's method was proposed by Richard Brent in 1973 [20]. The Brent's method uses a hybrid approach of speedy, open methods and reliable bracketing methods to speed up the convergence for one dimensional search problems. We use a combination of golden section bracketing method and quadratic interpolation to search for an optimum point over the objective function for at least one major parameter that influences more in convergence, F_c for band pass filter in our case. In golden section search, four carefully spaced points are iteratively considered as shown in Fig. 3.

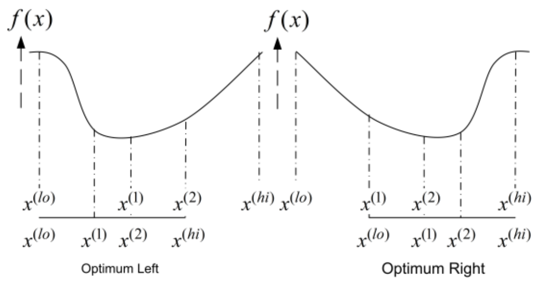


Figure 3. The golden section search.

Leftmost $x^{(lo)}$ is always a lower bound on the optimal x^*, and $x^{(hi)}$ is an upper bound. The function optimum lies between the interval $\left[x^{(lo)}, x^{(hi)}\right]$. Points $x^{(1)}$ and $x^{(2)}$ are the intermediate points. Each iteration determines whether the objective is better at $x^{(1)}$ or $x^{(2)}$, if $x^{(1)}$ proves better, the move direction for the next iteration is left and $x^{(2)}$ becomes $x^{(hi)}$ and if $x^{(2)}$ proves better, the more direction for the next iteration is right and $x^{(1)}$ becomes $x^{(lo)}$. The choice of interior points define the efficiency of the search, whether it is $\left[x^{(1)}, x^{(hi)}\right]$ or $\left[x^{(lo)}, x^{(2)}\right]$ interval, golden section search proceeds by keeping both these intervals equal in length. The two middle points of the golden section search are spaced according to

$$\begin{aligned} x^{(1)} &= x^{(hi)} - \alpha(x^{(hi)} - x^{(lo)}) \\ x^{(2)} &= x^{(lo)} + \alpha(x^{(hi)} - x^{(lo)}) \end{aligned} \tag{1}$$

where $\alpha = 0.618$ is the golden ratio and $\alpha = (-1+\sqrt{5})/2$. Although, the golden section search algorithm is reliable, but it is slow and the narrowing of the interval containing optimum requires considerable computation. We combine quadratic fit search with golden section search for rapid convergence taking full advantage of three point pattern fit. We fit a quadratic function through three points and have a unique minimum or maximum, whichever, we are seeking for the given objective function $f(x)$. The unique optimum of quadratic function agreeing with $f(x)$ at three point pattern $(x^{(lo)}, x^{(1)}, x^{(2)})$ occurs at

$$x^{(q)} = x^{(1)} - \frac{1}{2}\frac{\left(x^{(1)}-x^{(lo)}\right)^2\left[f\left(x^{(1)}\right)-f\left(x^{(2)}\right)\right]-\left(x^{(1)}-x^{(2)}\right)^2\left[f\left(x^{(1)}\right)-f\left(x^{(lo)}\right)\right]}{\left(x^{(1)}-x^{(lo)}\right)\left[f\left(x^{(1)}\right)-f\left(x^{(2)}\right)\right]-\left(x^{(1)}-x^{(2)}\right)\left[f\left(x^{(1)}\right)-f\left(x^{(lo)}\right)\right]} \tag{2}$$

The algorithm starts with golden section search and calculates four points $(x^{(lo)}, x^{(1)}, x^{(2)}, x^{(hi)})$. It then determines the search direction (right or left) and fits a quadratic function with either $(x^{(lo)}, x^{(1)}, x^{(2)})$ or $(x^{(1)}, x^{(2)}, x^{(hi)})$. It calculates the quadratic fit $x^{(q)}$ from (2) and again applies golden section search to discard one point and so on. The combination of parabolic interpolation and golden section bracketing methods can speed up the optimal search process by 35-40% as compared to golden section bracketing only [20].

C. Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique. PSO was first proposed by Kennedy and Eberhart in 1995 [21]. PSO mimics the social behavior of birds and fish schooling. Similar to other population based stochastic optimization techniques, like GA, PSO starts with a population of random solutions and eventually converges to find an optimal solution. The population in PSO consists of particles that fly in n-dimensional solution search space and follow the position of the best particle. Each particle in the solution search space is described by its position vector $\mathbf{x}_i$ and velocity vector $\mathbf{v}_i$. The velocity and position update equations of the PSO are

$$\begin{aligned} \mathbf{v}_{k+1}^i &= w\mathbf{v}_k^i + c_1 r_1 \frac{\left(\mathbf{p}^i - \mathbf{x}_k^i\right)}{\Delta t} + c_2 r_2 \frac{\left(\mathbf{p}_k^g - \mathbf{x}_k^i\right)}{\Delta t} \\ \mathbf{x}_{k+1}^i &= \mathbf{x}_k^i + \mathbf{v}_{k+1}^i.\Delta t \end{aligned} \tag{3}$$

where $\mathbf{p}^i$ is the best position of each particle, $\mathbf{p}_k^g$ is the global best position of a particle in the swarm. The constants c_1 and c_2 are self-confidence factor and swarm confidence factor respectively. The value of c_1 and c_2 is normally taken in the range $[0 \quad 1]$. The parameters r_1 and r_2 are randomly generated and uniformly distributed in the range $[0 \quad 1]$. This avoids any entrapment in a local optimum and provides good coverage of the solution search space. The time step is Δt and can be taken as 1. In (3), w is inertia weighting and is usually a linear descending function as

$$w = w_{\max} - \left(w_{\max} - w_{\min}\right)\frac{T}{T_{\max}}. \tag{4}$$

where T and $T_{\max}$ are current and maximum iteration respectively. Each particle's best position is evaluated through a fitness function as described in next sub-section.

D. Objective Function

The objective function or fitness function used for the PSO optimization is maximization of kurtosis. Kurtosis is the degree of peakedness of a distribution, defined as a normalized form of the fourth central moment μ_4 of a distribution. Kurtosis is defined as

$$\begin{aligned} &\max Kurt = \frac{\frac{1}{N}\sum_{i=0}^{N-1}\left(X_t(i) - \mu\right)^4}{\sigma^4} \\ &s.t. \\ &\beta_{\min} \le \beta \le \beta_{\max} \\ &a_{\min} \le a \le a_{\max} \end{aligned} \tag{5}$$

Here, $\beta_{\min} \le \beta \le \beta_{\max}$ and $a_{\min} \le a \le a_{\max}$ are the constraints on the shape parameter β and the scale parameter a for the wavelet filter. Similar constraints can be defined for the band pass filter. We use penalty method and drop constraints of non-linear objective function by substituting new terms in the objective function penalizing infeasibility in the form

$$\max \textit{ or } \min F(x) = f(x) \pm \mu \sum_i p_i(x) \quad (6)$$

Here, "+" for minimization problems and "–" for maximization, μ is a positive penalty multiplier and p_i are functions satisfying

$$p_i(x) \begin{cases} = 0 & \text{if } x \text{ satisfies constraint } i \\ > 0 & \text{otherwise} \end{cases} \quad (7)$$

The new unconstrained objective function becomes

$$\max Kurt = \frac{\frac{1}{n}\sum_{i=0}^{n-1}\left(X_t(i)-\mu\right)^4}{\sigma^4} - \ldots$$
$$\mu\left[\max^2\left\{0, \beta_{\min}-\beta\right\} + \max^2\left\{0, \beta-\beta_{\max}\right\} + \ldots \right. \quad (8)$$
$$\left. \max^2\left\{0, a_{\min}-a\right\} + \max^2\left\{0, a-a_{\max}\right\}\right]$$

As an example, if the constraints $\beta_{\min} \le \beta \le \beta_{\max}$ and $a_{\min} \le a \le a_{\max}$ get satisfied, the μ part in (8) becomes zero, and if the constraints are not satisfied, a squared penalty is subtracted from the objective function that restricts the objective function to be maximized. This step also makes unfit swarms in the population worse so that they should fly in a different direction or towards more fit swarms. The inclusion of penalty functions in the objective function makes the population converge soon.

III. Nature of Faults

The types of faults we target in this study are gears tooth breakage due to bending fatigue and gears scuffing. The tooth of breakage generally originates from a crack in the root section of the gear tooth. Consequently, the whole tooth or a part of the tooth breaks away. Excessive tooth loads, cyclic stressing and ageing are the most common causes of the tooth breakage. When gears are loaded in this manner and subjected to enough repeated stress cycles, the gears teeth fail. Gear scuffing is characterized by material transfer between sliding tooth surfaces. Generally this condition occurs when inadequate lubrication film thickness permits metal-to-metal contact between gear teeth. Cracks, breakage and scuffing on gears teeth can be monitored through their gear mesh frequency. Gear mesh frequency or tooth mesh frequency is the frequency at which gears teeth meet together in the gearbox. Gear mesh frequency always exhibits a strong vibration component. An accurate evaluation of meshing stiffness between two gears can give an indication of fault present at the meshing frequency early in time.

IV. Simulations and Discussions

The vibration data used in this research are taken from National Renewable Energy Laboratory (NREL) in the USA, through a consortium called the Gearbox Reliability Collaborative (GRC) [22]. The data emanate from a planetary gearbox inside a windmill. The gearbox under test is one of two units taken from the field and redesigned, rebuilt and instrumented with over 125 sensors. The gearbox first finished its run-in in the NREL dynamometer test facility (DTF) and later was sent to a wind plant close to NREL for field test, where two oil losses occurred. The test turbine in the field is a stall-controlled, three-bladed, upwind turbine with a rated power of 750kW. The turbine generator operates at 1200 RPM and 1800 RPM nominal on two different sets of windings depending on the power. The planetary gearbox has an overall ratio of 1:81.491. It is composed of one low speed (LS) planetary stage and two parallel stages as shown in Fig. 4. This study uses data from a test case with main shaft speed of 14.72 RPM and high speed shaft (HSS) speed of 1200 RPM. The data are collected for the duration of 10 minutes at the sampling frequency of $F_s = 40\text{KHz}$.

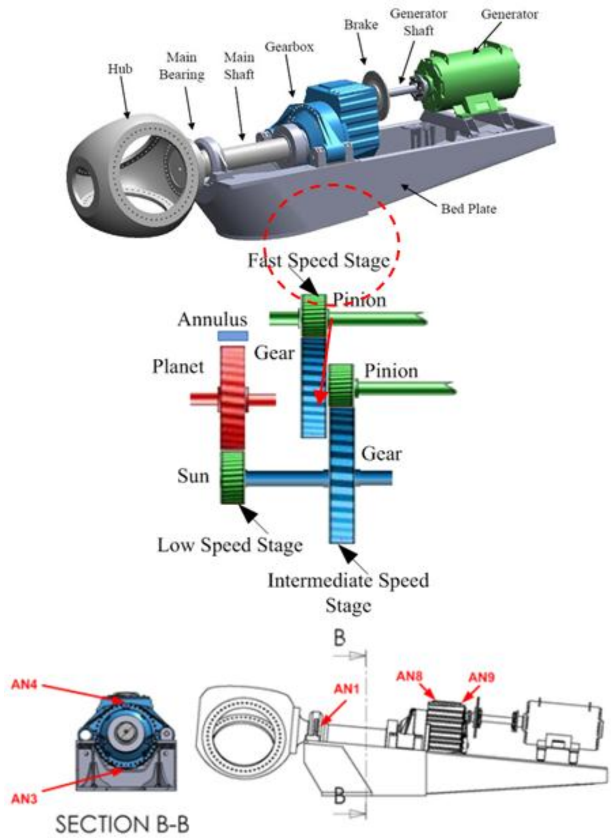
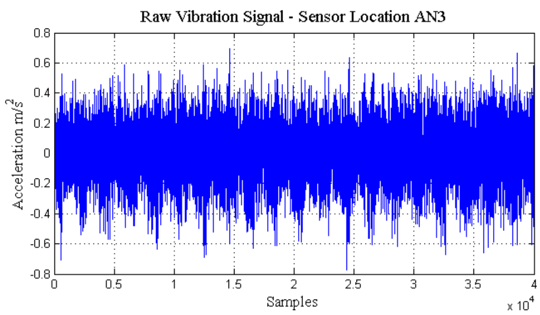


Figure 4. (a) GRC Drive train configuration (b) Planetary gearbox (c) Sensor locations. (courtesy of national renewable energy laboratory)



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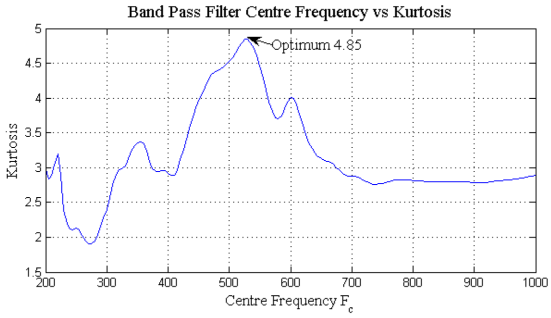

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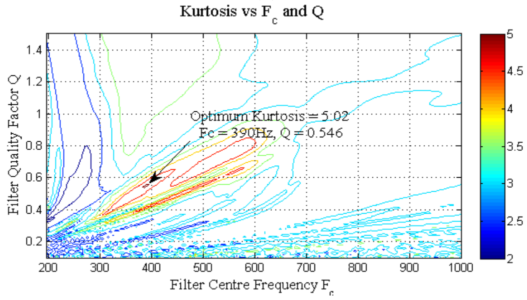

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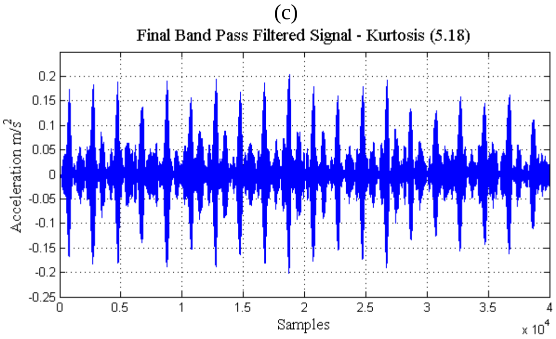

(d)

Figure. 5. The Chebyshev band pass filter optimized by the PSO.

A. Chebyshev Band Pass Filter Optimized by the PSO

In this section, we discuss the application of the Chebyshev band pass filter optimized by the PSO. Fig. 5(a) shows one of the vibration signals recorded. A band pass filter is initialized, and the PSO optimizes the filter parameters to maximize the objective function. At first, we use the Brent's method to search for the filter's centre frequency F_c that maximizes the objective function. The other filter parameters like quality factor Q, filter order N and pass band ripples R_p are kept constant at values $Q = 0.707$, $N = 4$ and $R_p = 1$. Fig. 5(b) gives an idea where the kurtosis maximization occurs at 4.85 for $F_c = 527$ Hz, found by the Brent's method. We then initialize the PSO search for the filter parameter ranges, $200 < F_c < 100$ Hz, $0.5 > Q < 2$, $2 > N < 8$ and $1 < R_p < 6$. The PSO parameters used in this search are shown in Table I. We see that the PSO maximizes the kurtosis to 5.18 with $F_c = 420.40$ Hz, $Q = 0.54$, $N = 3$ and $R_p = 2.99$. Fig. 5(c) plots kurtosis against F_c and Q. In Fig. 5(c), it is evident that the kurtosis maximization occurs in the range of $300 < F_c < 400$ Hz and $0.4 > Q < 0.6$. Fig. 5(d) plots the final filtered vibration signal with kurtosis value equal to 5.18 and faulty pulses are clearly visible. As shown in Table I that the PSO uses five swarm particles, Fig. 6 plots the slowest particle's (particle 4) best position versus iterations. It is shown in Fig. 6 that particle 4 reaches the optimum point in 80 iterations and thus making the whole population converge after 80 iterations.

TABLE I PSO PARAMETERS

Parameter	Value
No. of iterations	100
No. of swarm particles	5
Inertia weight w	0.9 to 0.4
Self confidence factor c_1	1.4961
Swarm confidence factor c_1	1.4961
Parameters r_1 and r_2	rnd$[0-1]$
Threshold for success	0.0001

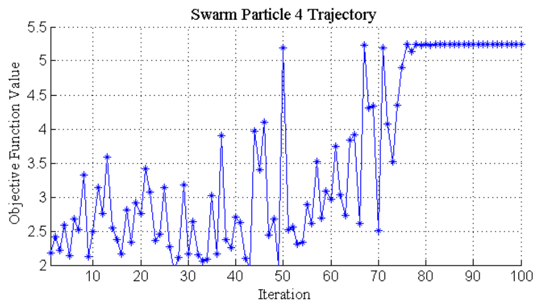

Figure 6. Swarm particle 4 local best positions.

Figure 7. Severe scuffing on the high speed pinion. (courtesy of national renewable energy laboratory)

The band pass filter has four parameters to be optimized by the PSO, F_c, Q, R_p and N. It takes 16.64 seconds for PSO to converge on Intel Core i5 with 4GB of RAM. The band passed signal reaches the kurtosis value of 5.18. Since, a noisy signal emanating from a healthy machine follows Gaussian distribution and kurtosis of Gaussian distributed signal is 3.0, the value of 5.18 does not indicate severe faults on the gears. It could be scuffing on the gears' surfaces but not the breakage. A visual inspection of the gearbox proves the hypothesis of scuffing as shown in Fig. 7.

V. CONCLUSION

In this paper, a PSO optimized adaptive filtering method is proposed for gearbox fault detection in rotating structures of electromechanical machines. The method demonstrates reasonable computational complexity and improves response time, which proves its applicability for real time fault detection. The method is verified on experimental data. Many authors have proposed modifications in the PSO to increase the convergence speed or to avoid local minima and stagnation. In our proposed method, we increased the convergence speed of the PSO by two techniques, reducing the solution search space and adding penalty methods in the objective function. The proposed method will be used to extract any possible fault emanating from different mechanical structures inside the electric machines at different time stamps and in different frequency regions.

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REFERENCES

[1] C. Ciandrini, "Fault detection and prognosis methods for a monitoring system of rotating electrical machines," in *Proc. IEEE Int. Conf. Ind. Electron*, 2010, pp. 2085–2090.

[2] S. S. H. Zaidi, S. Aviyente, M.Salman, K. K. Shin, and E. G. Strangas, "Prognosis of gear failures in DC starter motors using hidden markov models," *IEEE Trans. Ind. Electron.*, vol. 58, no. 5, pp. 1695–1706, May. 2011.

[3] W. Q. Lim, D. H. Zhang, J. H. Zhou, P. H. Belgi, and H. L. Chan, "Vibration-based fault diagnostic platform for rotary machines," in *Proc. IEEE IECON*, Nov. 2010, pp. 1404–1409.

[4] P. Vieira, M. A. S. Bobi, C. R. Gomes, H. S. Gomes, and M. P. Do Nascimento, "Vibration monitoring of electric generators without sensor dedicated ," in *Proc. IEEE ICIT*, March 2010, pp. 451–456.

[5] S. H. Kia, H. Henao, and G. A. Capolino, "Torsional vibration effects on induction machine current and torque signatures in gearbox-based electromechanical system," *IEEE Trans. Ind. Electron.*, vol. 56, no. 11, pp. 4698–4699, Nov. 2009.

[6] G. G. Yen and K. C. Lin, "Wavelet packet feature extraction for vibration monitoring," *IEEE Trans. Ind. Electron*, vol. 47, no. 3, pp. 650–667, June 2000.

[7] J. H. Holdrege, W. Subler, and W. E. Frasier, "AC induction motor torsional vibration consideration—a case study," *IEEE Trans. Ind. Appl.*, vol. IA-19, no. 1, pp. 68–73, Jan/Feb. 1983.

[8] M. Wahde, *Biologically Inspired Optimization Methods – An Introduction*, 1st ed. WIT Press, Aug. 2008.

[9] Melanie Mitchell, *An Introduction to Genetic Algorithms*, 1st ed. MIT Press, Feb. 1998.

[10] H. Iba, T. K. Paul, and Y. Hasegawa, *Applied Genetic Programming and Machine Learning*, 1st ed. CRC Press, Aug. 2009.

[11] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE International Conference on Neural Networks*, Dec. 1995, pp. 1942–1948.

[12] B. Samanta and C. Nataraj, "Use of particle swarm optimization for machinery fault detection," *Engineering Applications of Artificial Intelligence*, vol. 22, no. 2, pp. 308–316, March 2009.

[13] F. J. Lin, L. T. Teng, J. W. Lin, and S. Y. Chen, "Recurrent functional-link-based fuzzy-neural-network-controlled induction-generator system using improved particle swarm optimization," *IEEE Trans. Ind. Electron*,. vol. 56, no. 5, pp. 1557–1577, May 2009.

[14] Y. V. Pehlivanoglu, "A new particle swarm optimization method enhanced with a periodic mutation strategy and neural networks," *IEEE Trans. Evol. Comput.*,, no. 99, 2012.

[15] Y. Del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J. C. Hernandez, and R. G. Harley, "Particle swarm optimization: Basic concepts, variants and applications in power systems," *IEEE Trans. Evol. Comput.*, vol. 12, no. 12, pp. 171-195, April 2008.

[16] A. H. Zamanian and A. Ohadi, "Gearbox fault detection through PSO exact wavelet analysis and SVM classifier," in *Proc. 18th Annu. International Conference on Mech. Eng.*, May 2010, pp. 11–13.

[17] H. X. Pan, X. Y. Wei, and X. Xu, "Research of optimal placement of gearbox sensor based on particle swarm optimization," in *Proc. 8th IEEE INDIN*, July 2010, pp. 108–113.

[18] H. Xia Pan, Q. F. Ma, and X. Y. Wei, "Research on fault diagnosis of gearbox based on particle swarm optimization algorithm," in *Proc. IEEE ICM*, July 2006, pp. 32–37

[19] Z. K. Zhu, R. Q. Yan, L. H. Luo, Z. H. Feng, and F. R. Kong, "Detection of signal transients based on wavelet and statistics for machine fault diagnosis," *Mech. Syst. Signal Process.*, vol. 23, no. 4, pp. 1076–1097, May 2009.

[20] S. C. Chapra, *Applied Numerical Methods with Matlab for Engineers and Scientists*, 3ed. McGraw-Hill, Jan 2011.

[21] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proc. IEEE International Conference on Neural Networks*, vol. 4, pp. 1942–1948. Dec. 1995

[22] H. Link, W. LaCava, J. van Dam, B. McNiff, S. Sheng, *et al*., "Gearbox reliability collaborative project report: Findings from phase 1 and phase 2 testing," NREL/TP-5000-51885, 2011.

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