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Prediction of Manufacturing System Using Improved Infomax Method Based on Poor Information

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***Abstract*— The improved infomax method consists of the bootstrap methodology, the grey system theory, and the information entropy theory. The bootstrap methodology is adopted to imitate the generated information vector of large size by bootstrap resampling from the current information vector of small size, the grey system theory is used to introduce the generated information vector into the grey prediction model for forecasting the future information vector of large size, and the information entropy theory is employed to predict a probability distribution of the future information via the maximum entropy criterion. Information prediction of a manufacturing system is put into practice under the condition of poor information. Case studies of the diameter and roundness of a tapered rolling bearing raceway present that the method is able to make reliably information prediction of a manufacturing system only with the current information of small size and without any prior information of probability distributions.**

***Index Terms*—Manufacturing system, Information-poor system, Regulation, Information prediction, Improved infomax method.**

I. INTRODUCTION

In mass production, a manufacturing system must be preset for forecast and guarantee of quality of products to be processed [1-4].The statistical approach is generally used in the process of regulation of the system. Because regulation and output information forecast of the system are conducted synchronously, the output information must be of a normal distribution along with the known standard deviation and coverage factor in advance. For an abnormal distribution or a new manufacturing system, information about the probability distribution, standard deviation, and coverage factor is commonly unknown or incomplete, showing that the statistical approach only relied on a normal distribution is invalid [4-6].

The infomax theory finds its position of strength in extraction of some information of the probability distribution of an information source [7-10]. In the field of information process, infomax means maximizing information in virtue of the maximum entropy criterion. But, the maximum entropy criterion entirely depends on rich information for evaluation of the probability distribution of an information source. Therefore, the infomax theory does nothing if poor information.

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Poor information means incomplete information, such as, in system analysis, a known probability distribution only with a small sample, an unknown probability distribution only with several data, and trends without any prior information, and so forth [5-6].The information-poor theory is a new theory that is able to settle the problem of information-poor systems by fusing many ideas of mathematics and mechanics, such as, statistics, fuzzy sets, rough sets, grey system theory, information entropy theory, chaos theory, norm theory, and bootstrap methodology [11-18].

During regulation of a manufacturing system without any prior information about probability distributions, only the current information vector of small size can be obtained by test cutting. Regulation aims at, based on the current information vector, predicting whether the future information vector of large size output by the system is in the interval specified in advance. It can be seen that the current information is characterized by poor information.

With the help of the information-poor theory, this paper proposed an improved infomax method for regulation and information prediction of a manufacturing system with poor information.

The improved infomax method consists of the bootstrap methodology, the grey system theory, and the information entropy theory. The bootstrap methodology is adopted to imitate the generated information vector of large size by bootstrap resampling from the current information vector of small size, the grey system theory is used to introduce the generated information vector into the grey prediction model for forecasting the future information vector of large size, and the information entropy theory is employed to predict a probability distribution of the future information via the maximum entropy criterion. Thus, regulation and information prediction of a manufacturing system may be put into practice under the condition of poor information.

Experimental investigation on regulation and information prediction of the diameter and roundness of the tapered rolling bearing raceway is conducted to test the effectiveness of the method proposed.

II. IMPROVED INFOMAX METHOD

A. Collection of Current Information

Assume information output by a manufacturing system is specified within the interval $[I_L, I_U]$, where I_L stands for the lower limit and I_U stands for the upper limit. In the process of regulation, current information output by the manufacturing system is collected by a measurement system and the result is expressed as a vector $\mathbf{X}$, as follows:

$$\mathbf{X}=(x(1),x(2),...,x(n),...,x(N));n=1,2,...,N \quad (1)$$

where **X** is the current information vector of small size, and $x(n)$ is the nth element in **X**, and N is the number of the elements in **X**.

In (1), the number N of the elements in **X** is a small integer, and in generally, its values take in the range of [4, 10] for low manufacture costs.

Based on the current information vector of small size, a generated information vector of large size can be imitated by the bootstrap.

B. Simulation of Generated Information

According to the bootstrap, B simulation vectors of size N, viz., the bootstrap resampling samples, can be gained by an equiprobable sampling with replacement form the current information vector **X**. They can be considered as a generated information vector of large size, as follows:

$$\boldsymbol{\Theta} = (\boldsymbol{\Theta}_1, \boldsymbol{\Theta}_2, \ldots, \boldsymbol{\Theta}_b, \ldots, \boldsymbol{\Theta}_B); b = 1,2,\ldots,B \tag{2}$$

where B is the number of the simulation vectors, $\boldsymbol{\Theta}$ is the generated simulation information vector, and $\boldsymbol{\Theta}_b$ is the bth simulation vector that is expressed as

$$\boldsymbol{\Theta}_b = (\theta_b(1), \theta_b(2), \ldots, \theta_b(n), \ldots, \theta_b(N)) \tag{3}$$

where is the nth element within $\boldsymbol{\Theta}_b$.

In (2), the number B of the simulation vectors is a large integer, and in generally, its values take in the range of [1000,1000000] for accurate prediction of future information of manufacturing system with poor information using improved infomax method.

Based on the generated information vector of large size, a future information vector of large size can be forecasted by the grey prediction model.

C. Prediction of Future Information

According to the grey system theory, the first-order accumulated generating operator (1-AGO) $\boldsymbol{\Phi}_b$ of the generated simulation vector $\boldsymbol{\Theta}_b$ is given by

$$\boldsymbol{\Phi}_b = (\varphi_b(1), \varphi_b(2), \ldots, \varphi_b(n), \ldots, \varphi_b(N)) \tag{4}$$

with

$$\varphi_b(n) = \sum_{j=1}^{n} \theta_b(j) \tag{5}$$

The grey prediction model is defined as

$$\frac{\mathrm{d}\varphi_b(n)}{\mathrm{d}n} + c_{b1}\varphi_b(n) = c_{b2} \tag{6}$$

where n is regarded as a continuous variable, and c_{b1} and c_{b2} are coefficients to be estimated.

Let the mean vector be

$$\mathbf{Z}_b = (z_b(2), z_b(3), \ldots, z_b(n), \ldots, z_b(N)); n = 2,3,\ldots,N \tag{7}$$

with

$$z_b(n) = (0.5\varphi_b(n) + 0.5\varphi_b(n-1)) \tag{8}$$

The least-squares solution to (6) with the initial condition $\varphi_b(1)=\theta_b(1)$ is

$$\eta_b(N+1) = \left(\theta_b(1) - \frac{c_{b2}}{c_{b1}}\right)\exp(-c_{b1}N) + \frac{c_{b2}}{c_{b1}} \tag{9}$$

where $\eta_b(N+1)$ is information of trend prediction for the generated simulation vector $\boldsymbol{\Theta}_b$, and the coefficients c_{b1} and c_{b2} are given by

$$(c_{b1}, c_{b2})^{\mathrm{T}} = (\mathbf{D}^{\mathrm{T}}\mathbf{D})^{-1}\mathbf{D}^{\mathrm{T}}\boldsymbol{\Theta}_b^{\mathrm{T}}; n = 2,3,\ldots,N \tag{10}$$

with

$$\mathbf{D} = (-\mathbf{Z}_b \mathbf{I})^{\mathrm{T}} \tag{11}$$

where **I** is the unit vector of size $N-1$.

According to the inverse AGO, the bth element of future information predicted is given by

$$x_b = \eta_b(N+1) - \eta_b(N) \tag{12}$$

It follows that the future information vector $\boldsymbol{\Lambda}$ predicted by the grey prediction model is obtained as

$$\boldsymbol{\Lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_b, \ldots, \lambda_B) \tag{13}$$

Based on (13), the probability distribution of future information to be output by the manufacturing system can be forecasted by the maximum entropy criterion.

D. Prediction of Probability Distribution of Future Information

According to the infomax theory, the probability distribution of future information to be output by the manufacturing system should satisfy the maximum entropy criterion.

From the maximum entropy criterion, information entropy H is defined as

$$H = -\int_{\Omega} f(x)\ln f(x)\mathrm{d}x \tag{14}$$

where x stands for a random variable of describing future information, Ω stands for the feasible region of x, and $f(x)$ stands for the predicted probability-distribution of x.

Let

$$H \to \max \tag{15}$$

along with the following constraints:

$$\int_{\Omega} f(x)\mathrm{d}x = 1 \tag{16}$$

$$\int_{\Omega} x^i f(x)\mathrm{d}x = m_i; i = 0,1,\ldots,M \tag{17}$$

where i is the order of the origin moment, m_i is the ith order origin-moment of x, and M is the highest order.

In (17), the ith order origin-moment is given by

$$m_i = \frac{1}{B}\sum_{b=1}^{B} x_b^i \tag{18}$$

Using Lagrangian multiplier method, the predicted probability-distribution can be obtained as

$$f(x) = \exp\left(\lambda_0 + \sum_{i=1}^{M}\lambda_i x^i\right) \tag{19}$$

Put (19) into (16), and it can be obtained that

$$\int_{\Omega} \exp\left(\lambda_0 + \sum_{i=1}^{M}\lambda_i x^i\right)\mathrm{d}x = 1 \tag{20}$$

Solve (20), and the results can be obtained, as follow:

$$e^{-\lambda_0} = \int_{\Omega} \exp\left(\sum_{i=1}^{M}\lambda_i x^i\right)\mathrm{d}x \tag{21}$$

$$\lambda_0 = -\ln\left(\int_{\Omega} \exp\left(\sum_{i=1}^{M}\lambda_i x^i\right)\mathrm{d}x\right) \tag{22}$$

where λ_i is the ith Lagrangian multiplier.

Equation (21) can be calculated in the form of partial differential equation for λ_i, and the result can be obtained as:

$$\frac{\partial \lambda_0}{\partial \lambda_i} = -\int_{\Omega} x^i \exp\left(\lambda_0 + \sum_{i=1}^{M} \lambda_i x^i\right) \mathrm{d}x = -m_i \tag{23}$$

Similarly, equation (22) can be calculated in the form of partial differential equation for λ_i, and the result can be obtained as

$$\frac{\partial \lambda_0}{\partial \lambda_i} = -\frac{\int_{\Omega} x^i \exp\left(\sum_{i=1}^{M} \lambda_i x^i\right) \mathrm{d}x}{\int_{\Omega} \exp\left(\sum_{i=1}^{M} \lambda_i x^i\right) \mathrm{d}x} \tag{24}$$

And then, equation (25) can be obtained according to (23) and (24), as follow:

$$m_i \int_{\Omega} \exp\left(\sum_{i=1}^{M} \lambda_i x^i\right) \mathrm{d}x - \int_{\Omega} x^i \exp\left(\sum_{i=1}^{M} \lambda_i x^i\right) \mathrm{d}x = 0 \tag{25}$$

Finally, on the basis of (14)-(18), the values of the ith order origin-moment m_i of x can be obtained, after that, M equation sets can be established to solve the values of λ_1, $\lambda_2 \ldots \lambda_M$ according to (25), and then the value of λ_0 can be calculated in line with (22).

Based on the probability distribution $f(x)$ of future information shown in (19), the parameter of future information can hence be predicted by statistics.

E. Prediction of Parameter of Future Information

In this paper, the parameter of future information includes the predicted true value and the predicted interval.

According to the statistics, the predicted true value is defined as

$$X_0 = \int_{\Omega} x f(x) \mathrm{d}x \tag{26}$$

Let the significance level be $\alpha \in [0, 1]$, then the confidence level P can be given by

$$P = (1-\alpha) \times 100\% \tag{27}$$

At the given confidence level P, the predicted interval $[X_L, X_U]$ is defined as

$$[X_L, X_U] = [X_{\alpha/2}, X_{1-\alpha/2}] \tag{28}$$

where X_L is the lower bound, X_U the upper bound, $X_{\alpha/2}$ is the value of the variable x corresponding to a probability $\alpha/2$, and $X_{1-\alpha/2}$ is the value of the variable x corresponding to a probability $1-\alpha/2$.

F. Reliability Analysis

Under the confidence level P, the relationship between the predicted interval and the specified interval is as follows:

$$x \in [X_L, X_U] \subseteq [I_L, I_U] \tag{29}$$

After regulation is done, actual information output by the system should also satisfy (29); and if not, reliability analysis must be made.

Assume the actual information vector is obtained as

$$\mathbf{X}_A = (x_A(1), x_A(2), \ldots, x_A(s), \ldots, x_A(S)); s = 1, 2, \ldots, S \tag{30}$$

where $\mathbf{X}_A$ is the actual information vector, $x_A(s)$ is the sth element, and S is the number of the elements within $\mathbf{X}_A$.

Assume there are w elements within the actual interval $[I_L, I_U]$ of the actual information vector $\mathbf{X}_A$ but outside the predicted interval $[X_L, X_U]$, then the reliability R of manufacturing system is defined as

$$R = \left(1 - \frac{w}{S}\right) \times 100\% \tag{31}$$

The value of the reliability R of future information about manufacturing system can be used for evaluation the result of prediction using the improved infomax method. The larger the value of the reliability R of manufacturing system is, the more efficient the improved infomax method is; and vice versa. If the reliability $R \geq P$, the result is reliable; or else, the result is unreliable.

III. CASE STUDIES

Two rolling bearing ring grinding machines are involved in case studies for grinding the inner ring of the tapered rolling bearing corded with 30204. One is the internal grinding machine and the other is the raceway grinding machine. The two are used to grind the inner ring bore diameter and the inner ring raceway, respectively, and the experimental investigation on regulation and information prediction to test reliability of the improved infomax method.

A. Simulation Experiment for Information Prediction of Bore Diameter

The probability distribution of the bore diameter after grinding is considered as a normal distribution in the simulation experiment.

Elements of simulation information about grinding errors of the bore diameter are simulated by means of the simulation model based on the normal distribution with the mathematical expectation of 0 A and the standard deviation of 0.1 A. The number of elements is 1024, and the 2014 simulation information elements are constituted an information sequence $\mathbf{X}_{2014}$, as shown in Fig. 1.

The former 5 elements of $\mathbf{X}_{2014}$ are selected as the elements of the current information vector $\mathbf{X}$ (N=5), corresponding to sequence numbers from 1 to 5 of the simulation information sequence $\mathbf{X}_{2014}$, and the later 1019 elements of $\mathbf{X}_{2014}$ are selected as the elements of the actual information vector $\mathbf{X}_A$ (S=1024−5=1019), corresponding to the sequence numbers from 6 to 1024 of the simulation information sequence $\mathbf{X}_{2014}$.

The actual interval $[I_L, I_U]$ of the actual information vector $\mathbf{X}_A$ is obtained by the statistics, as follow:

$[I_L, I_U]$=[−0.19769, 0.18686].

According to the bootstrap, let B=10000. The generated information vector $\mathbf{\Theta}$ of size $N \times B$=50000 is simulated according to the bootstrap resampling from the current information vector $\mathbf{X}$ of size N=5. Based on the generated information vector $\mathbf{\Theta}$, the future information vector $\mathbf{\Lambda}$ of size B=10000 is predicted according to the grey prediction model, and the result is shown in Fig. 2.

With the help of the information entropy theory, let the highest order M be 5. According to (14)-(18), the values of the ith order origin-moment m_i of x are obtained, and the results are

$\{m_1, m_2, m_3, m_4, m_5\}$={−0.29809, 0.99164, −0.55897, 2.28190, −1.55168}.

And then, M (M=5) equation sets are established according to (25), the values of λ_1, $\lambda_2 \ldots$, λ_5 are solved according to the 5 equation sets established, and the results are

$\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5\}$={−0.50472, −0.22257, 0.10711, −0.06341, −0.00789}, and the value of λ_0 is calculated according to (22), and the result is

$$\lambda_0=1.08453.$$

Based on the future information vector $\mathbf{\Lambda}$, the probability distribution $f(x)$ of future information about manufacturing system is predicted in the light of the maximum entropy criterion and the result is shown in Fig. 3.

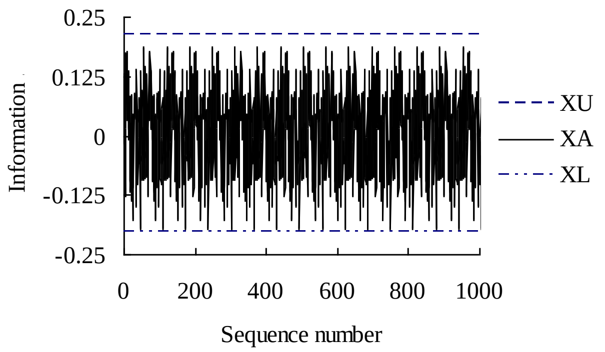

Fig. 1. Simulation information sequence $\mathbf{X}_{2014}$ of bore diameter

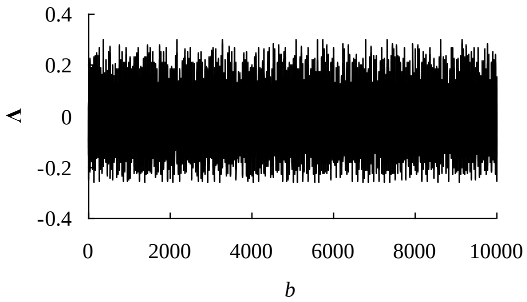

Fig. 2. Future information of bore diameter

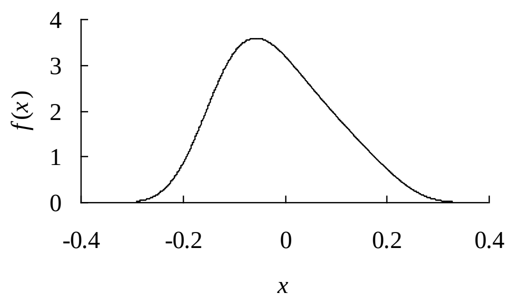

Fig. 3. Probability distribution of future information of bore diameter

Using the improved infomax method proposed in this paper, let the significance level α=0.05, and then the confidence level P=95%. Based on the probability distribution $f(x)$ of future information about manufacturing system, the predicted true value X_0 and the predicted interval $[X_L, X_U]$ are obtained, respectively, and the results are

$$X_0=-0.015,$$
$$[X_L, X_U]=[-0.202, 0.211].$$

Obviously, as shown in Fig. 1, there are not elements within the actual interval $[I_L, I_U]$ of the actual information vector $\mathbf{X}_A$ but outside the predicted interval $[X_L, X_U]$ and hence, it is obtained that the value of the reliability R of manufacturing system is

$$R=(1-0/1019)\times 100\%=100\%>P.$$

B. Practical Experiment on Information Prediction of Raceway Roundness

By grinding and measurement after regulation of the machine, information of the raceway roundness, in μm, is collected and the result is as follows:

1.08 0.90 1.06 1.28 0.88 1.87
1.16 1.06 0.97 1.01 0.70 1.15
0.72 1.08 0.67 1.10 0.98 1.15
1.14 1.64 0.73 0.87 1.91 1.95
1.19 0.78 1.51 1.39 1.39

and the above information collected of the raceway roundness is constituted a information sequence $\mathbf{X}_{29}$, as shown in Fig. 4.

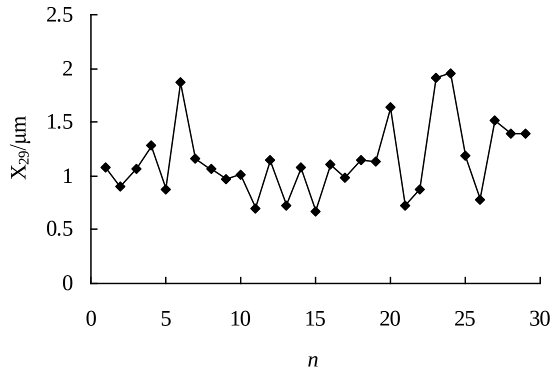

Fig. 4. The collected information sequence $\mathbf{X}_{29}$ of the raceway roundness

The former 6 values of $\mathbf{X}_{29}$ are selected as the elements of the current information vector $\mathbf{X}$ (N=6), corresponding to sequence numbers from 1 to 6 of the collected information sequence $\mathbf{X}_{29}$, and the later 23 values of $\mathbf{X}_{29}$ are selected as the elements of the actual information vector $\mathbf{X}_A$ (S=29−6=23), corresponding to the sequence numbers from 7 to 29 of the collected information sequence $\mathbf{X}_{29}$.

The actual interval $[I_L, I_U]$ of the actual information vector $\mathbf{X}_A$ is obtained by the statistics that is

$$[I_L, I_U]=[0.67, 1.95].$$

According to the bootstrap, let B=10000. The generated information vector $\mathbf{\Theta}$ of size $N\times B$=60000 is simulated by the bootstrap resampling from the current information vector $\mathbf{X}$ of size N=6. Based on the generated information vector $\mathbf{\Theta}$, the future information vector $\mathbf{\Lambda}$ of size B=10000 is predicted by the grey prediction model and the result is shown in Fig. 5.

With the help of the information entropy theory, let the highest order M be 5, the values of the ith order origin-moment m_i of x are obtained using (14)-(18), and the results are

$$\{m_1, m_2, m_3, m_4, m_5\}=\{-0.66228, 1.13472, -1.20998, 2.52210, -3.12965\}.$$

Then, M (M=5) equation sets are established according to (25), and the values of $\lambda_1, \lambda_2\ldots, \lambda_5$ are obtained by the 5 equation sets established, and the results are

$$\{\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5\}=\{-1.25214, -0.03375, 0.28821, -0.10344, -0.02185\},$$

and the value of λ_0 is calculated according to (22), and the result is

$$\lambda_0=-0.49900.$$

Based on the future information vector $\mathbf{\Lambda}$, the probability distribution $f(x)$ of future information about manufacturing system is predicted in the light of the maximum entropy criterion and the result is shown in Fig. 6.

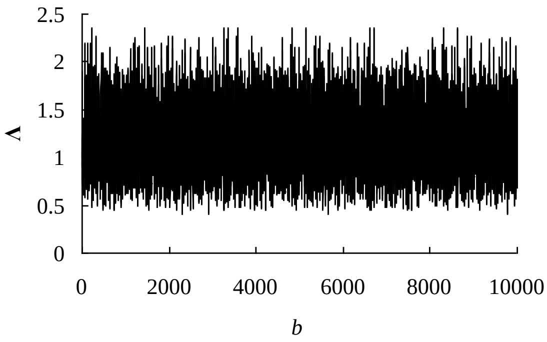

Fig. 5. Future information of raceway roundness

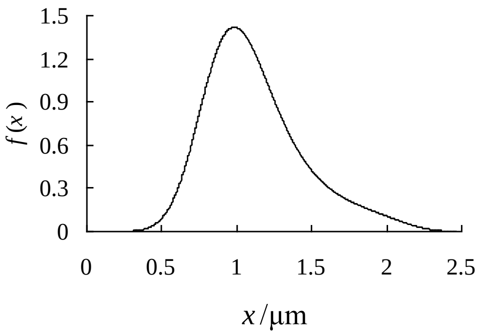

Fig. 6. Probability distribution of future information of raceway roundness

According to the improved infomax method proposed in this paper, let the significance level α=0.01, and then the confidence level P=99%. Based on the probability distribution $f(x)$ of future information about manufacturing system, the predicted true value X_0 and the predicted interval $[X_L, X_U]$ are obtained, respectively, and the results are

$$X_0=1.12,$$

$$[X_L, X_U]=[0.49, 2.15].$$

It can be seen that there are not elements within the actual interval $[I_L, I_U]$ of the actual information vector $\mathbf{X}_A$ but outside the predicted interval $[X_L, X_U]$ and hence, it is obtained that the value of the reliability R of manufacturing system is

$$R=(1-0/23)\times 100\%=100\%>P.$$

Case studies above present that the improved infomax method is able to make reliably regulation and information prediction of a manufacturing system only with the current information vector of small size and without any prior information of probability distributions.

As a result, the proposed method in this paper can be considered as one of complements for the existing infomax theory in use.

Mechanism of the improved infomax method is production of the future information vector of large size by means of the bootstrap and the grey prediction model based on the current information vector of small size and is prediction of the probability distribution with the help of the maximum entropy criterion relied on the future information vector of large size.

IV. Conclusions

The improved infomax method is able to make reliably regulation and information prediction of a manufacturing system only with the current information vector of small size and without any prior information of probability distributions.

Mechanism of the improved infomax method is production of the future information vector of large size by means of the bootstrap and the grey prediction model based on the current information vector of small size and is prediction of the probability distribution with the help of the maximum entropy criterion relied on the future information vector of large size.

The proposed method can be considered as one of complements for the existing infomax theory in use.

Conflict of Interest

The authors clearly acknowledge that this paper has no any potential conflict of interest.

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References

[1] A. G. Charitopoulos, E. E. Efstathiou, C. I. Papadopoulos, P. G. Nikolakopoulos and L. Kaiktsis, "Effects of manufacturing errors on tribological characteristics of 3-D textured micro-thrust bearings", CIRP Journal of Manufacturing Science and Technology, vol. 6, no. 2, 2013, pp. 128-142.

[2] E. Ceretti and T. Ozel, "Manufacturing technologies and systems for medical devices", International Journal of Mechatronics and Manufacturing Systems, vol. 6, no. 3, 2013, pp. 213-214.

[3] A. P. Estrada-Vargas, E. López-Mellado and J.J. Lesage, "Input-output identification of controlled discrete manufacturing systems", International Journal of Systems Science, vol. 45, no. 3, 2013, pp. 456-471.

[4] R. E. Hodgett, E. B. Martin, G. Montague and M. Talford, "Handling uncertain decisions in whole process design", Production Planning & Control, vol. 25, no. 12, 2014, pp. 1028-1038.

[5] X.T. Xia, "Reliability analysis of zero-failure data with poor information", Quality and Reliability Engineering International, vol. 28, no. 8, 2012, pp. 981-990.

[6] X.T. Xia, X.Y. Cheng, Y.Z. Zhang and Z.Y. Wang, "Grey bootstrap method of evaluation of uncertainty in dynamic measurement", Measurement, vol. 41, no.6, 2008, pp. 687-696.

[7] B. Moreno and A. J. Lõpez, "Combining economic forecasts by using a maximum entropy econometric approach", Journal of Forecasting, vol. 32, no. 2, 2013, pp. 124-136.

[8] D.J. Miller, H. Soleimani, "On an Objective Basis for the Maximum Entropy Principle", Entropy, vol.17, no. 1, 2015, pp. 401-406.

[9] J.Y. Lee, S.Y. Lee, S. Park, "Maximum entropy test for GARCH models", Statistical Methodology, vol. 22, January 2015, pp. 8-16.

[10] P. Ferreira and A. Dionísio, "An application of general maximum entropy to utility", International Journal of Applied Decision Sciences, vol. 6, no. 3, 2013, pp. 228-244.

[11] C. Park, "Determination of the joint confidence region of the optimal operating conditions in robust design by the bootstrap technique", International Journal of Production Research, vol. 51, no. 15, 2013, pp. 4695-4703.

[12] G.D. Li, S. Masuda and M. Nagai, "Predictor design using an improved grey model in control systems", International Journal of Computer Integrated Manufacturing, vol. 28, no. 3, 2015, pp.297-306.

[13] S. Panda, D. Mishra, B. B. Biswal and P. Nanda, "Optimization of Multiple Response Characteristics of EDM Process Using Taguchi-Based Grey Relational Analysis and Modified PSO", Journal of Advanced Manufacturing Systems, vol. 14, no. 3, 2015, pp. 123.

[14] D. Brown, R. Sadiq and K. Hewage, "An overview of air emission intensities and environmental performance of grey cement manufacturing in Canada", Clean Technologies and Environmental Policy, vol. 16, no. 6, January 2014, pp. 1119-1131.

[15] D. Yazid, G. Reza, "Energy Substitutability in Canadian Manufacturing Econometric Estimation with Bootstrap Confidence Intervals", Energy Journal, vol. 31, no. 1, 2010, pp. 121-148.

[16] Q. Wang, Z.Y. Wang, Z.P. Mourelatos and J. H. Fu, "Estimation of measurement results with poor information using the dynamic bootstrap grey method", Measurement, vol. 57, November 2014, pp. 138-147.

[17] R.B. Azhiri, R. Teimouri, M. G. Baboly, "Application of Taguchi, ANFIS and grey relational analysis for studying, modeling and optimization of wire EDM process while using gaseous media", The International Journal of Advanced Manufacturing Technology, vol. 71, no. 1-4, 2014, pp. 279-295.

[18] B. Morenoa, M.T. García-Álvarezb, C. Ramosa, E. Fernández-Vázqueza, "A General Maximum Entropy Econometric approach to model industrial electricity prices in Spain: A challenge for the competitiveness", Applied Energy, vol. 135, December 2014, pp. 815-824.

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