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Multivariate Process Monitoring and Diagnosis: A Case Study

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Abstract. In manufacturing industries, monitoring and diagnosis of multivariate process out-of-control condition become more challenging. Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process. In order to achieve these requirements, the application of an appropriate statistical process control framework is necessary for rapidly and accurately identifying the signs and source out-of-contol condition with minimum false alarm. In this research, a framework namely, an Integrated Multivariate Exponentially Weighted Moving Average with Artificial Neural Network was investigated in monitoring-diagnosis of multivariate process mean shifts in manufacturing audio video device component. Based on two-stages monitoring-diagnosis technique, the proposed framework has resulted in efficient performance.

Introduction

In manufacturing industries, process variation has become a major source of poor quality. When manufacturing process involves two or more correlated variables, an appropriate scheme is necessary to monitor these variables jointly. In addressing this issue, the traditional multivariate statistical process control (MSPC) frameworks such as T^2 [1], multivariate cumulative sum (MCUSUM)[2] and multivariate exponentially weighted moving average (MEWMA)[3] are known effective in detecting the process mean shifts. Nevertheless, they are lack of capability in identifying the source variables that responsible to the process mean shifts. In other word, it is unable to provide diagnosis information for a quality practitioner towards finding the root cause errors and solution for corrective action. In order to overcome this problem, an enhanced framework that integrates the traditional MEWMA with Artificial Neural Network (ANN) based model was investigated. This proposed framework aims for detecting process mean shift rapidly with minimum false alarm and accurately classifying the source variables of mean shifts. Details discussion is organized as follows. Section 2 briefly presents the framework of an integrated MEWMA-ANN. Section 3 then discusses on monitoring-diagnosis performances based on industrial case study. Section 4 finally outlines some conclusions.

An Enhanced Framework

An integrated MEWMA-ANN framework was designed based on two stages monitoring and diagnosis technique as shown in Figure 1. Process monitoring refers to the identification of process status either it is running within a statistically in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process in mean shifts. In the first stage monitoring, the MEWMA control chart is utilized for triggering mean shifts in multivariate process based on 'one point out-of-control' procedure. Once the shift is detected, the Synergistic-ANN model is then utilized for conducting second stage monitoring and diagnosis by recognizing data stream pattern contained point(s) out-of-control.

Modeling of data patterns of multivariate process mean shifts, and design and training-testing of the synergistic-ANN recognizer can be referred in reference [4]. It should be noted that the following initial setting needs to be performed before it can be put into application:

- Load the trained the raw data-ANN recognizer into the system.
- Set the values of means (μ_{01}, μ_{02}) and standard deviations (σ_{01}, σ_{02}) of multivariate in-control process (for variables X_1 and X_2). These parameters can be obtained based on historical samples.
- Perform in-process quality control inspection until 24 observations to begin the system.

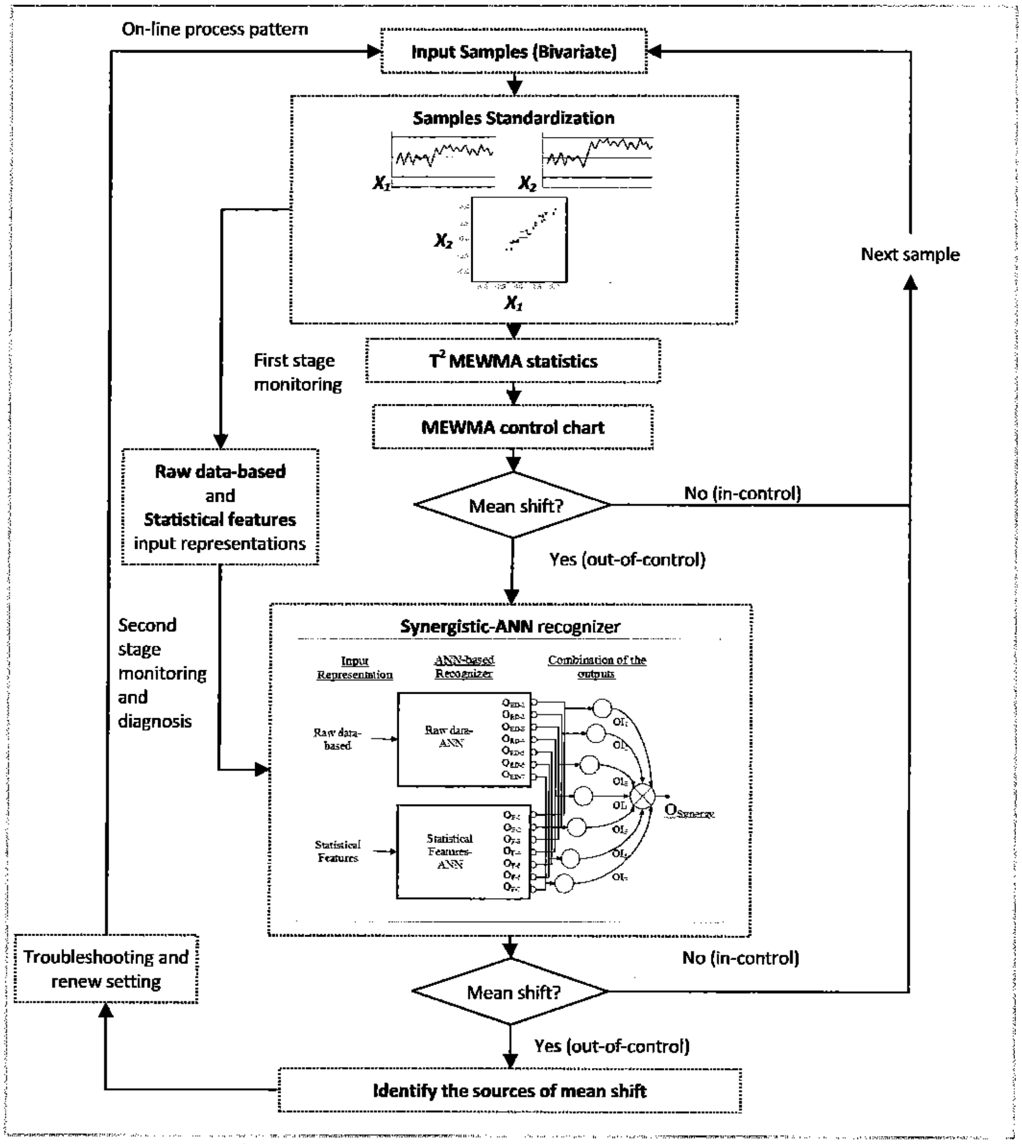


Figure 1: An Integrated MEWMA-ANN framework

Industrial Case Study

Broadly, the need for multivariate quality control (MQC) could be found in manufacturing industries involved in the production of mating, rotational or moving parts. In this research, investigation was focused on the manufacturing of audio video device (AVD) component, namely, roller head in Zhang Hui Industries (Malaysia) Sdn. Bhd. In an AVD, the roller head functions to guide and control the movement path of a film tape. Inner diameters of roller head (ID1 and ID2) as shown in Figure 2 are two dependent quality characteristics (multivariate) that need MQC. In practice, such functional features are still widely monitored independently using Shewhart control charts. It is unsure why MSPC was not implemented. Based on the author's point of view, it could be due to lack of motivation, knowledge and skills to adapt new technology.

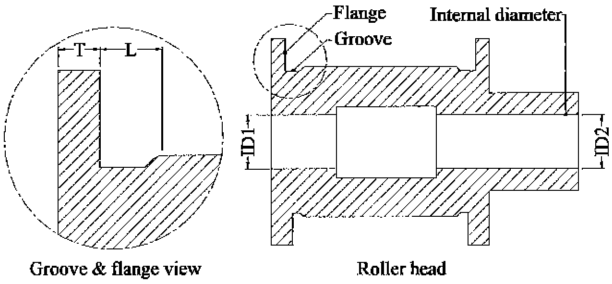


Figure 2: Functional features of roller head

The process plan for the manufacture of roller head can be illustrated in Figure 3. Initially, an aluminium extrusion round bar was turned to rough size (rough cut machining). Then, it was turned to size (finish cut machining) to form functional features such as inner diameters, and groove and flange, among others. The machining of inner diameters was then extended into honing process to achieve tight tolerance for bearing assembly. Hard coated surface was also necessary. As such, the finished work piece was electroplated by using nickel alloy before assembly.

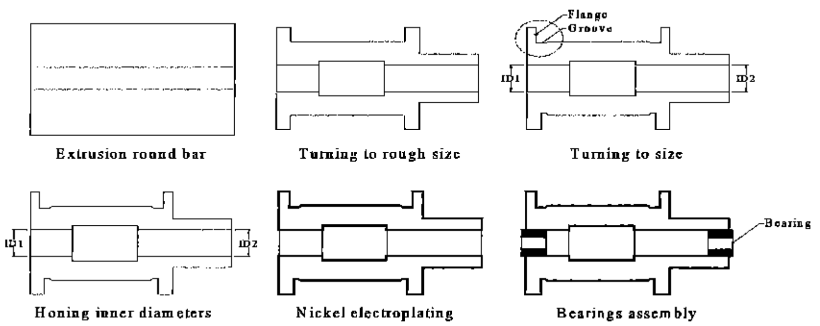


Figure 3: Process plan for the manufacture of roller head

Multivariate process variation can be found in turning to size operation due to "tool bluntness" as illustrated in Figure 4. These disturbances will cause unnatural changes in the process data streams as shown in Table 1. The work piece is automatically loaded into pneumatic chuck using a robotic system. Bluntness in the cutting tool will cause gradual decrement in both inner diameters (ID1, ID2) with positive cross correlation ($\rho > 0$).

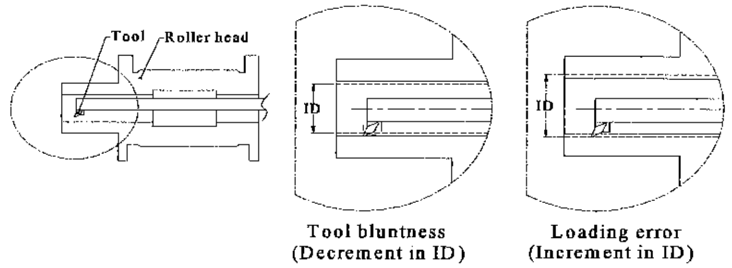
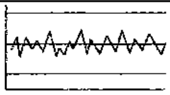
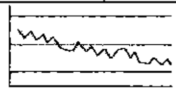
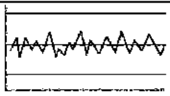
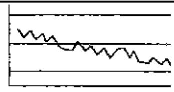


Figure 4: Process variation occurred in turning-to-size operation

Table 1: Sources of variation in machining inner diameters

	Process noise, N(0, 0)	Tool bluntness, DS(1, 1)
X_1 (ID1)	 Normal	 Downward Trend
X_2 (ID2)	 Normal	 Downward Trend

The mean (μ) and standard deviation (σ) of multivariate in-control process were determined based on the first 24 samples (observations $1^{st} \sim 24^{th}$). Tool bluntness begins between observation samples $41^{st} \sim 50^{th}$. The monitoring-diagnosis performance results are summarized in Table 2, whereby the determinations of process condition (monitoring) and source variables of mean shifts (diagnosis) are based on outputs of the framework as shown in Table 3. In the first 40 samples, the integrated MEWMA-ANN framework was able to correctly identify the mutlivariate process data streams as in normal patterns (N). This means that this enhanced framework was effective to identify multivariate in-control process without triggering any false alarm. Bluntness of the cutting tool begins at sample 41^{st}. In relation to out-of-control detection capability, this framework can be observed as sensitive to detect multivariate process mean shifts rapidly recognizing the multivariate process data streams as in down-shift patterns (DS(1,1)) starting from sample 44^{th} (at window range $21^{st} \sim 44^{th}$). In diagnosis aspect, this enhanced framework can be observed as effective to clasify the source variables of mean shifts without mistake.

Conclusions

This paper investigated the performance of an integrated MEWMA-ANN framework in monitoring and diagnosis of multivariate process. Based on two-stages monitoring and diagnosis approach, the proposed framework is capable to rapidly identify the multivariate in-control process condition without triggering any false alarm. In addition, it is also effective in accurately clasifying the source variables of mean shifts without mistake. Since this research is focused on mean shifts causable patterns, further research will be extended to other causable patterns such as trends and cyclic.

Table 2: Monitoring-diangosis performance results

i	Original samples		Standardized samples		Window range	Monitoring-diagnosis decision
	X_{i_1} (ID1)	X_{i_2} (ID2)	Z_{i_1} (ID1)	Z_{i_1} (ID2)		MEWMA-ANN
1	7.9420	7.9428	0.3393	1.0790		
2	7.9412	7.9420	−1.1414	−0.5917		
3	7.9412	7.9416	−1.1414	−1.4271		
4	7.9420	7.9428	0.3393	1.0790		
5	7.9412	7.9420	−1.1414	−0.5917		
6	7.9412	7.9416	−1.1414	−1.4271		
7	7.9420	7.9428	0.3393	1.0790		
8	7.9424	7.9420	1.0797	−0.5917		
9	7.9416	7.9420	−0.4010	−0.5917		
10	7.9412	7.9416	−1.1414	−1.4271		
11	7.9416	7.9424	−0.4010	0.2437		
12	7.9428	7.9432	1.8201	1.9144		
13	7.9420	7.9424	0.3393	0.2437		
14	7.9416	7.9424	−0.4010	0.2437		
15	7.9424	7.9428	1.0797	1.0790		
16	7.9412	7.942	−1.1414	−0.5917		
17	7.9412	7.9416	−1.1414	−1.4271		
18	7.9420	7.9424	0.3393	0.2437		
19	7.9428	7.9428	1.8201	1.0790		
20	7.9420	7.9424	0.3393	0.2437		
21	7.9412	7.9416	−1.1414	−1.4271		
22	7.9424	7.9428	1.0797	1.0790		
23	7.9424	7.9424	1.0797	0.2437		
24	7.9420	7.9424	0.3393	0.2437	1 ~ 24	N
25	7.9412	7.9416	−1.1414	−1.4271	2 ~ 25	N
26	7.9424	7.9420	1.0797	−0.5917	3 ~ 26	N
27	7.9424	7.9428	1.0797	1.0790	4 ~ 27	N
28	7.9412	7.9420	−1.1414	−0.5917	5 ~ 28	N
29	7.9420	7.9428	0.3393	1.0790	6 ~ 29	N
30	7.9420	7.9424	0.3393	0.2437	7 ~ 30	N
31	7.9412	7.9420	−1.1414	−0.5917	8 ~ 31	N
32	7.9420	7.9428	0.3393	1.0790	9 ~ 32	N
33	7.9428	7.9424	1.8201	0.2437	10 ~ 33	N
34	7.9416	7.9424	−0.4010	0.2437	11 ~ 34	N
35	7.9424	7.9432	1.0797	1.9144	12 ~ 35	N
36	7.9428	7.9424	1.8201	0.2437	13 ~ 36	N
37	7.9416	7.9420	−0.4010	−0.5917	14 ~ 37	N
38	7.9420	7.9424	0.3393	0.2437	15 ~ 38	N
39	7.9424	7.9420	1.0797	−0.5917	16 ~ 39	N
40	7.9416	7.9420	−0.4010	−0.5917	17 ~ 40	N
41	7.9408	7.9412	−1.8818	−2.2625	18 ~ 41	N
42	7.9408	7.9408	−1.8818	−3.0978	19 ~ 42	N
43	7.9404	7.9408	−2.6222	−3.0978	20 ~ 43	N
44	7.9404	7.9408	−2.6222	−3.0978	21 ~ 44	DS (1 1)
45	7.9404	7.9404	−2.6222	−3.9332	22 ~ 45	DS (1 1)
46	7.9400	7.9404	−3.3626	−3.9332	23 ~ 46	DS (1 1)
47	7.9400	7.9400	−3.3626	−4.7686	24 ~ 47	DS (1 1)
48	7.9396	7.9400	−4.1029	−4.7686	25 ~ 48	DS (1 1)
49	7.9396	7.9396	−4.1029	−5.6040	26 ~ 49	DS (1 1)
50	7.9396	7.9396	−4.1029	−5.6040	27 ~ 50	DS (1 1)

$(\mu_1, \mu_2) = (7.9417, 7.9422)$; $(\sigma_1, \sigma_2) = (4.6687 \times 10^{-4}, 4.2495 \times 10^{-4})$

Note: Observation samples highlighted in grey ($41^{st} \sim 50^{th}$) represent out-of-control process

Table 3: Output of the framework in relation to the monitoring-diagnosis decision

	RW	1-24	2-25	3-26	4-27	5-28	6-29	7-30	8-31	9-32
	ρ	0.8280	0.8449	0.8007	0.7962	0.8062	0.7962	0.7792	0.7927	0.8336
MEWMA-ANN	Decision based on MEWMA control chart	N	N	N	N	N	N	N	N	N
	RW	10-33	11-34	12-35	13-36	14-37	15-38	16-39	17-40	18-41
	ρ	0.7944	0.7671	0.7721	0.7083	0.7144	0.7245	0.6695	0.6683	0.7088
MEWMA-ANN	Decision based on MEWMA control chart	N	N	N	N	N	N	N	N	N
	RW	19-42	20-43	21-44	22-45	23-46	24-47	25-48	26-49	27-50
	ρ	0.7591	0.8002	0.8325	0.8530	0.8731	0.8911	0.9069	0.9199	0.9372
MEWMA-ANN	N	**1.5200**	**1.1136**	0.7150	0.3311	0.1207	0.0603	0.0307	0.0251	0.0156
	US(10)	0.2578	0.1864	0.1696	0.1573	0.2009	0.2195	0.2576	0.2872	0.3176
	US(01)	0.1618	0.1330	0.1175	0.1344	0.1543	0.1851	0.2120	0.2664	0.3710
	US(11)	0.1186	0.1163	0.1329	0.1918	0.1753	0.1515	0.1708	0.1700	0.1626
	DS(10)	0.1363	0.1007	0.1063	0.0890	0.0823	0.0788	0.0842	0.0791	0.0576
	DS(01)	0.4044	0.5004	0.4905	0.6189	0.3953	0.3682	0.3018	0.2669	0.3030
	DS(11)	0.2582	0.6196	**0.9434**	**1.1542**	**1.5168**	**1.5218**	**1.5927**	**1.5403**	**1.5065**

Note: **Bolt value** represents the maximum output of ANN that determines pattern category

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