An Abductive Inference Model for Control Chart Selection

by Nazatul Aini Abd Majid, Mohammed Khatim Hasan, Hazura Mohamed and Abd Malik Md Yusof

Abstract: This paper introduces an abductive inference model and a new algorithm based on the abductive inference for handling control chart selection. Usually, the inputs for the control chart selection systems nowadays consist of answers for a series of questions related to the observation data characteristics whereas the output is the explanation about the data. Using abductive logic, a reverse system model can be generated. This system model takes the observation data as inputs and produces a diagnosis by generating sets of data characteristics that explain the observation data.

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I. INTRODUCTION

In a production line, quality control engineers or quality supervisors are responsible for managing the control chart selection to monitor the process to ensure that the manufacturing process is in a controlled state. A control chart detects any assignable cause in the process so that scrap and rework can be avoided. Through the ensuing years, many different formulations for the control chart has become known, such as moving average and range charts, proportion (P) charts, number of defectives (c) charts, cumulative sum (CUSUM) charts and EWMA charts (Dagli & Smith 1994). Thus, the selection of control chart to suit a particular process and set of data has become a difficult task. Selecting a wrong control chart can result in many false alarms, leading to expensive and fruitless searches for assignable causes. Over the past years, considerable effort has been committed towards developing computer tools that can assist in the control chart selection (Dagli & Smith 1994; Masud 1993; Shewhart 1992).

The need to develop control chart selection system is increasingly becoming more important as manufacturers receive increased demand for high quality new product from their client. A good quality product is an outcome of a good quality manufacturing process (Guh 1999). Most attempts to develop intelligent selection tools have relied on the use of Expert System (Dagli & Smith 1994; Masud 1993; Shewhart 1992). Expert system based approaches have been the most successful so far. Nevertheless, the system required knowledge domain given by the user by answering a series of questions.

This paper presents a new approach for handling control chart selection by abducing the knowledge domain from the observation data. The algorithms and the model of abductive inference for control chart selection are described. The proposed approach has been tested using real and sample data and some results are presented.

II. CONTROL CHART SELECTION USING ABDUCTIVE INFERENCE.

An informal definition of abduction is generally taken as inferring the best or most plausible explanation from a given set of facts (Peng & Reggia 1990). This concept may be made clearer by referring to the following example.

observation (conclusion)	These balls are red
+ general rule	All the balls in the box are red
specific case	**These balls are from the box**

Let us see how abduction can be applied for the control chart selection using preceding example.

observation (conclusion)	This data has subgroup size < 10, big shift size and no autocorrelation
+ general rule	All data that have subgroup size < 10, big shift size and no autocorrelation is suitable for X bar R control chart
specific case	**This data is suitable for X bar R control chart**

For the control chart selection, seven general rules have been generated as follow.

Table 1. General Rules for Control Chart Selection

No	General rules
1)	All the data that have subgroup size < 10, big shift size and no autocorrelation are suitable for X bar R control chart. Alternative control chart: Median control chart
2)	All the data that have subgroup size ≥ 10, big shift size and no autocorrelation are suitable for X bar S control chart
3)	All the data that have subgroup size > 1, small shift size and no autocorrelation are suitable for EWMA chart. Alternative chart: CUSUM chart
4)	All the data that have subgroup size = 1, small shift size and no autocorrelation are suitable for EWMA chart. Alternative chart: a) Moving Averange control chart b) CUSUM chart
5)	All the data that have subgroup size = 1, big shift size and no autocorrelation are suitable for individual control chart
6)	All the data that have subgroup size = 1 and positive autocorrelation are suitable for EWMA chart (EWMA predict and EWMA Prediction Error)
7)	All the data that have subgroup size = 1 and negative autocorrelation are suitable for ARIMA Model

It is possible to model a system that applies abductive inference on the resulting system to carry out a diagnosis (Davis 1984). In order to illustrate how abductive inference may be used to select the suitable control chart, a model has been developed as shown in Figure 1.

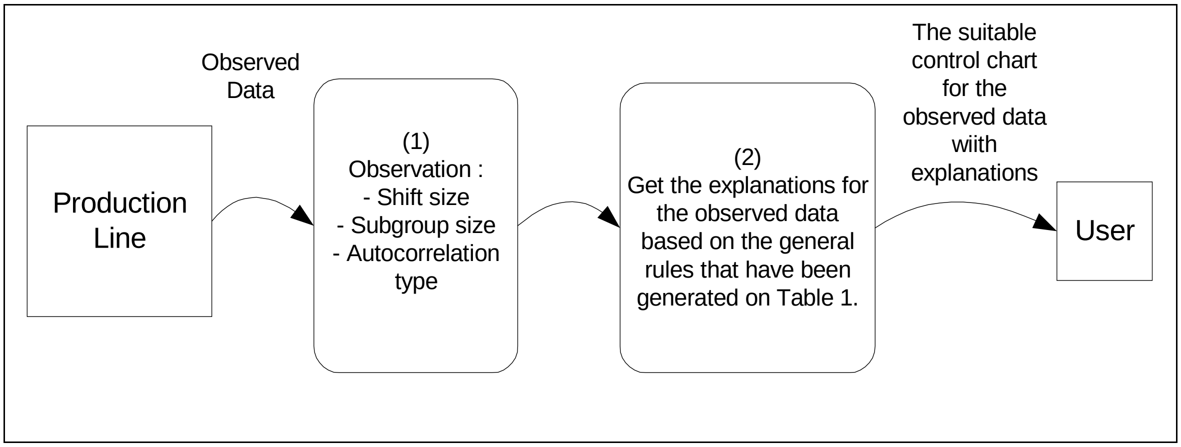


Figure 1. A Model of Abductive Inference for Control Chart Selection

III. ALGORITHM AND IMPLEMENTATION

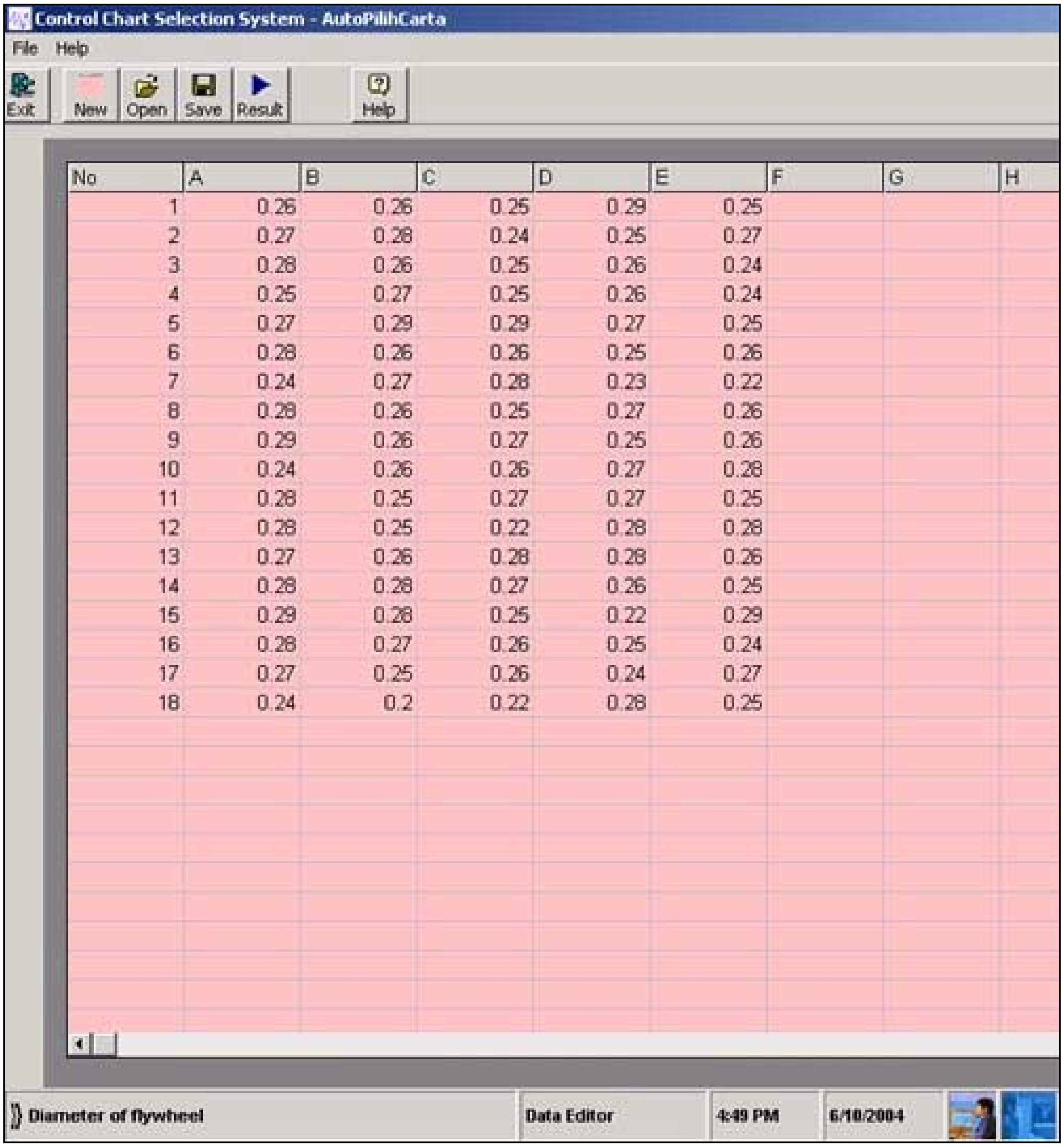
The model described in Figure 1 can be programmed in a computer. To implement the proposed technique we applied the abductive inference algorithm that will be discussed briefly in this section.

A. Algorithm

The diagnosis proceeds in two steps. In the first step, the user input the observation data. Then, in the second step, information that can be abductively inferred from the observation data is determined. Once this step is completed, the suitable control chart for the observation data should be known.

B. Implementation

A program was developed to implement the proposed method and to perform the diagnosis. The program includes a data editor as depicted in Figure 2 and a diagnosis module. The coding was done in Visual Basic. This language was chosen because it offers powerful user interface development features. The language also allows for stand-alone run time modules that are compatible with the Windows (TM) operating system.



No	A	B	C	D	E	F	G	H
1	0.26	0.26	0.25	0.29	0.25			
2	0.27	0.28	0.24	0.25	0.27			
3	0.28	0.26	0.25	0.26	0.24			
4	0.25	0.27	0.25	0.26	0.24			
5	0.27	0.29	0.29	0.27	0.25			
6	0.28	0.26	0.26	0.25	0.26			
7	0.24	0.27	0.28	0.23	0.22			
8	0.28	0.26	0.25	0.27	0.26			
9	0.29	0.26	0.27	0.25	0.26			
10	0.24	0.26	0.26	0.27	0.28			
11	0.28	0.25	0.27	0.27	0.25			
12	0.28	0.25	0.22	0.28	0.28			
13	0.27	0.26	0.28	0.28	0.26			
14	0.28	0.28	0.27	0.26	0.25			
15	0.29	0.28	0.25	0.22	0.29			
16	0.28	0.27	0.26	0.25	0.24			
17	0.27	0.25	0.26	0.24	0.27			
18	0.24	0.2	0.22	0.28	0.25			

Figure 2. Data Editor

IV. TEST RESULTS

The algorithm discussed in the previous section was tested using observation data taken from the industry. One of the data is the diameter of flywheel as depicted in Figure 2. The data was taken from an automotive production line in Malaysia. The corresponding result generated was:

Data type: variables
Subgroup size: 5
Shift Size: not Small

Autocorrelation: not exist

Solution:
X bar R control chart

The solution is illustrated in Figure 3. In this case the program correctly identified the suitable control chart for the observation data.

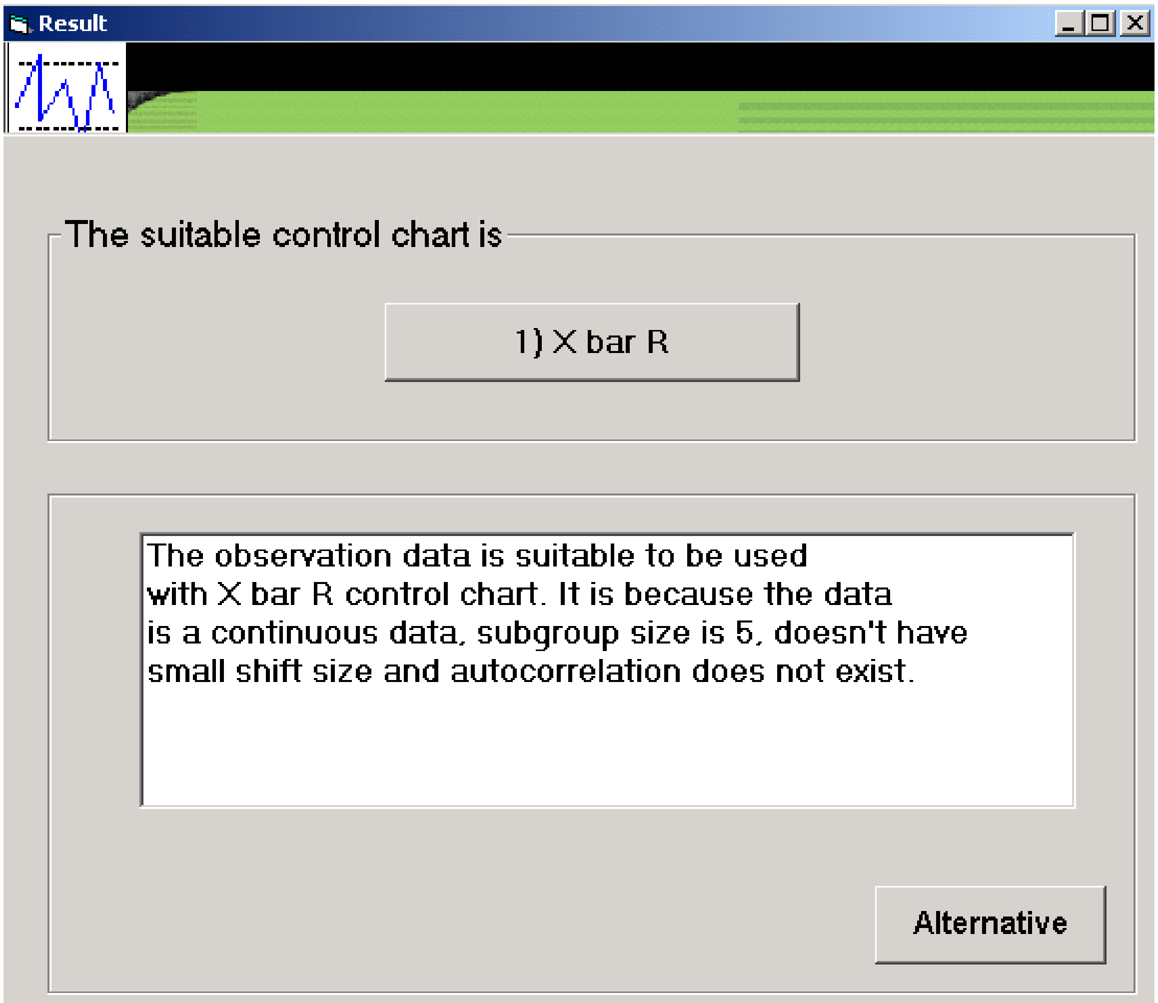


Figure 3. The Suitable Control Chart is X bar R Control Chart

To test a different characteristic of data, a sample of observation data as shown in Table 2 has been used as a test data.

Table 2. Test Data

No	A	B
1	0.091	0.096
2	0.108	0.105
3	0.117	0.079
4	0.105	0.12
5	0.114	0.083
6	0.11	0.108
7	0.087	0.097
8	0.109	0.099
9	0.105	0.094
10	0.1	0.117
11	0.089	0.091
12	0.076	0.091
13	0.119	0.101
14	0.093	0.111
15	0.115	0.101
16	0.125	0.107
17	0.101	0.107
18	0.093	0.093
19	0.108	0.104
20	0.109	0.112
21	0.092	0.105
22	0.092	0.098
23	0.096	0.075
24	0.082	0.081
25	0.106	0.083
26	0.088	0.104
27	0.085	0.076
28	0.069	0.098
29	0.094	0.099
30	0.073	0.092
31	0.097	0.095
32	0.077	0.087
33	0.084	0.093
34	0.108	0.088
35	0.091	0.098

The sample had been taken from a statistic book (Alwan 2000) and the result generated was:

Data type: variables
Subgroup size: 2
Shift Size: Small
Autocorrelation: not exist

Solution:
EWMA chart

The program was tested using 35 observation data and each data has different characteristic. It was observed that the diagnosis carried out by the program was always correct.

V. CONCLUSIONS

This paper presents a method for using abduction for a control chart selection system and illustrates its application in the production process. The proposed method was implemented and successfully tested using real and sample data. Therefore, the researcher hopes that this automated selection of control chart system can assist process engineers, quality control engineers, quality supervisors and production operators in the production departments to deal with the quality control practices in the industry.

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