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FORECASTING TELECOMMUNICATION TRAFFIC USING THE ENHANCED STEPWISE PROJECTION MULTIPLE REGRESSION METHOD

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Abstract. In this paper, one new technological forecasting method, called the Enhanced Stepwise Projection Multiple Regression (ESPMR), is proposed for dealing with the traffic loads that are measurement data but not real values. It combines the adjusting and detecting concepts of SPA (the Sequential Projection Algorithm) with the estimating method of linear regression model, and considers the periodical factor into forecasts if the data series has the periodical traces. Two empirical studies on the forecasting for the International Telecommunication Traffic Loads of Taiwan and the Metropolitan Telecommunication Traffic Loads of Taipei illustrate good and stable results by executing the ESPMR system.

Keywords: The ESPMR, The base value, Measurement data, Periodical length, Flag

1. INTRODUCTION

Forecasting is one of the most pervasive elements of managerial decision-making. In telecommunication industry, traffic forecasts play an important role in network planning and management, and facilities planning. Predictions that are too low will cause network and facility deficiency. While predictions that are too high will result in a premature expansion of networks and facilities that increase cost to the company.

In the past decades, *both econometric and time series methods concerning the traffic forecasting had made a great progress*: A.J. David and C.D. Pack [3] proposed the Sequential Projection Algorithm (SPA) concept in the 1979's International Teletraffic Congress (ITC) first.

The traffic forecasting study was greatly improved by SPA. In 1982, C.D. Pack and B.A. Whitaker [6], and J.P. Moreland [5] were devoted to advanced studies on SPA method.

They employed the *Kalman Filtering technique* to build the smoother SPA procedure by estimating state variables recursively. In 1985, R. Warfield and M. Rossiter [7] established a similar forecasting method by statistical analysis to quantify error in forecasting process. Tests using sample data indicate that the proposed estimator of equivalent measurement duration is acceptable in terms of bias and variance. In 1992, H.J. Chang and F.J. Lin [2] added the adjustment concept to the regression model, and applied it to the International Traffic Forecasting study. The empirical study illustrated that using the adjusted values to replace the measurement data has much better results on fitting model and forecasting.

In this paper, we would propose one technological forecasting method for dealing with the traffic loads, called the Enhanced Stepwise Projection Multiple Regression (ESPMR) method.

Because of the Telecommunication Electronic loss, there will be some measurement error between measurement traffic data (measurement data) and the real one, even it may be very small, *it is not possible for us to get the real one directly*. Hence, we want to get a reliable *base value to replace measurement data for reducing* measurement error in ESPMR Method. According to descriptions, this method will combine the adjusting and detecting concepts of *SPA with the estimating method of linear regression model, and considers the periodical factor into forecasts if the data series has the periodical traces. That is, the measurement data will be replaced by base values which are derived from the proposed algorithm for fitting regression model in each stage, and the forecasts will appear the advantages of periodical trends.*

2. THE CONCEPT OF ESPMR

The ESPMR is one of adaptive traffic forecasting methods. This method combined the adjusting and detecting concepts of SPA with the estimating method of linear regression model, and also considers the periodical factor into forecasts if the data series has the periodical traces. It mainly consists of three characteristics. They are (1) modifying the most newly measurement data in the forecasting procedure to fit a more reliable model, (2) adding the features of regression explanatory variables and parameters estimating to forecasting procedure, and (3) using the periodical factors to update the forecasts. The flowchart of ESPMR is shown in Figure 1, and the executing operation of ESPMR is illustrated with Figure 2.

From Figure 1 and Figure 2, the procedures of ESPMR method can be decsribed as the following:

1. Collect all of data (including *response and explanatory variables*).

2. Select an initial *tentative fitting model* by analyzing these data, and determine the periodical length and flags if data series has periodical traces. At the same time, determine the minimum historical record number to fit the regression model (the given number must be greater than no. of explanatory variables plus 1) in each stage.

3. Generate the initial values of the fitting model. In ESPMR method, just the same as SPA, it needs initial values to start the work at first stage. In general, the initial values are obtained by special methods. One practical method used in this paper will be described in section 5.

4. Estimate parameters of the fitting model by the base values. The base values of first stage are the initial values.

5. Go to step 9, if all the data have been processed. Otherwise, process step 4 to step 8 repeatedly.

6. Project the next period forecast and its confidence interval by this model under a given statistical significance when the next measurement data is not over yet.

7. Detect the outlier by the critical value of the confidence interval. If the next period measurement data lies outside the confidence interval, it will risk at type I error, *then replace it with a critical value for calculating the base value*.
   If two continuous outliers have the opposite directions (i.e. sign not repeated), then the preceding rule is satisfied (see as Figure 3). And if two continuous outliers have the same directions (i.e. sign repeated), then there are two conditional cases discussed: (I) If the second continuous value is just the periodical flag, then the preceding rule of opposite directions is also satisfied in this case. At this time, we will keep the characteristic of first continuous value to the third continuous value (*if there are three continuous outliers*). (ii) *If the second continuous value is not the periodical flag, then the projection trend is significant, we will give up the above replacing rule and the base value's generating algorithm. We replace it with the measurement data as the computing base value directly* (see as Figure 4).
8. Get the base value by the algorithm that will be proposed in section 3. The next period measurement data (*response variable* data), *forecasting value and its confidence interval, and the explanatory variable informations are needed in this step.*
9. Calculate the periodical factor, described in section 4, if the data series has periodical traces, and process future forecasting.

As described above, the features of the ESPMR are summarized as the following:

- The reliable base values obtained by their measurement data and forecasting values are being substituted for the measurement data during *the repetitious fitting model*.

- A reasonable algorithm approach to generate the base value is used. At each stage, information from all past measurement data is combined with the current measurement data and then *projected forward to form a forecast.*

- We will get a *smoother and reliable forecasting result by applying the newly periods and the adjusted data to fit the regression model in each stage.*

- In case the historical data series is an obvious ascending or descending trend, the projection *effects will be finely expected.*

- It considers the periodical factor into forecasting values when processing the future forecasting.

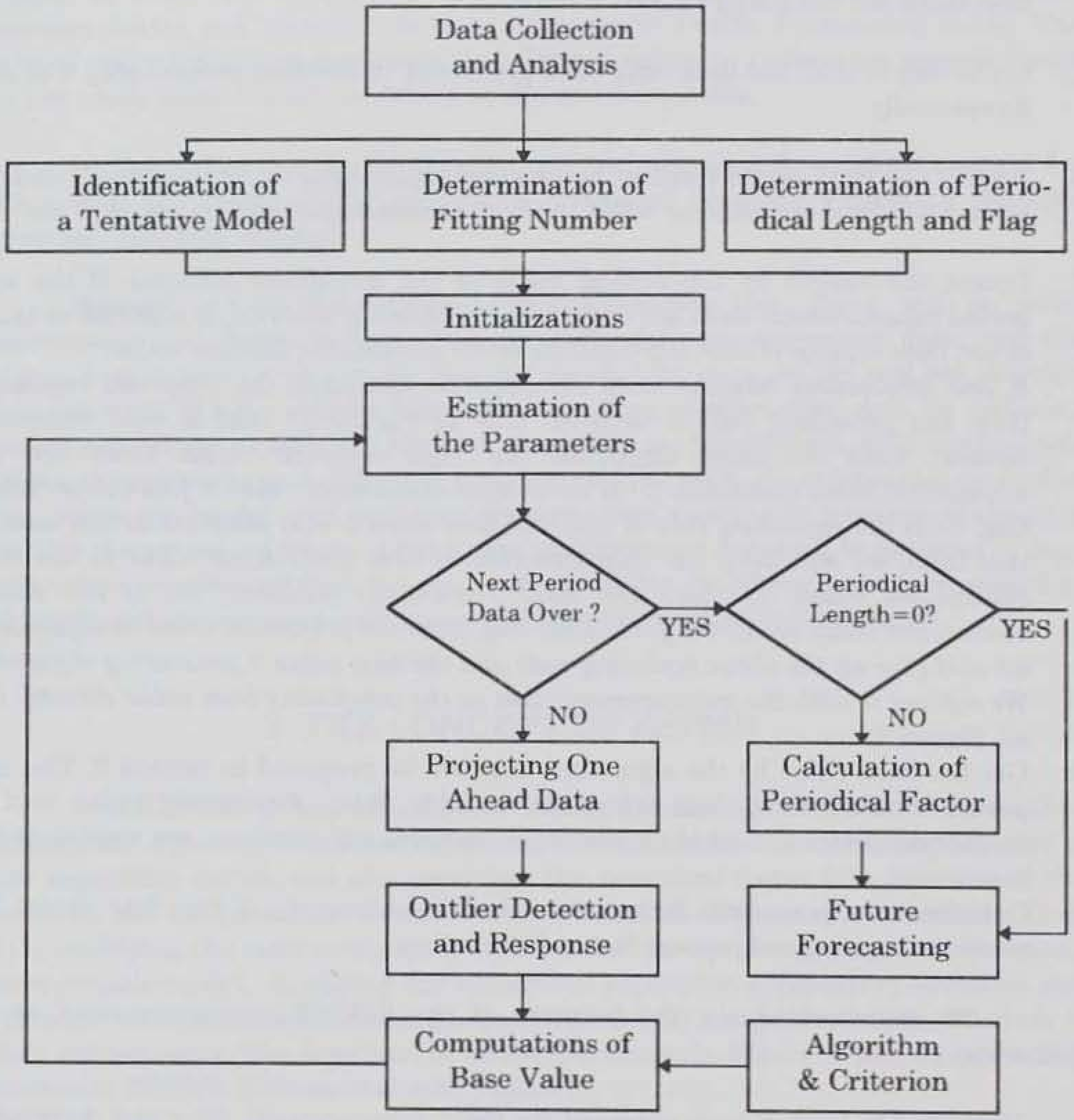
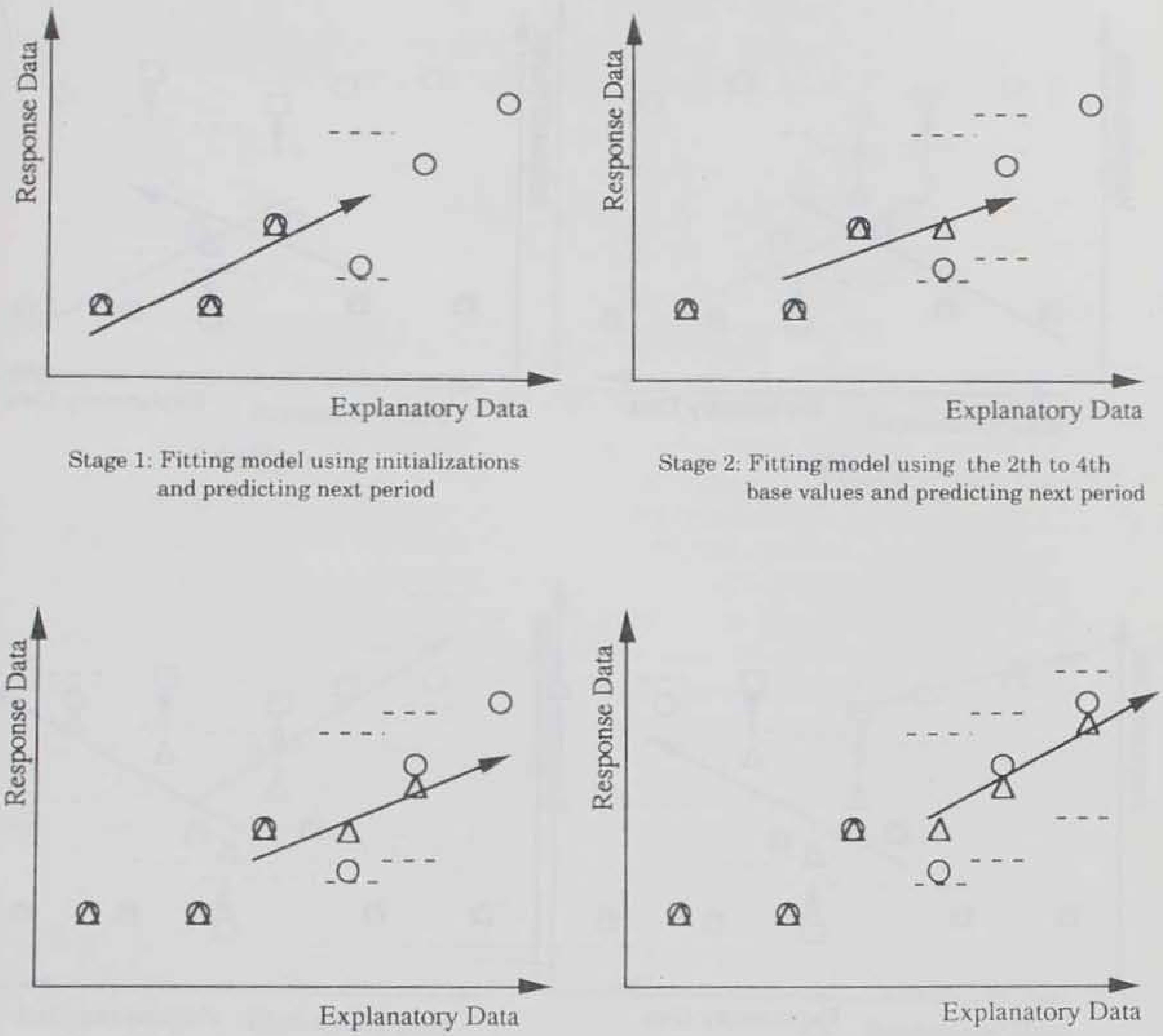


Figure 1. The executing procedure for ESPMR method



Stage 1: Fitting model using initializations and predicting next period

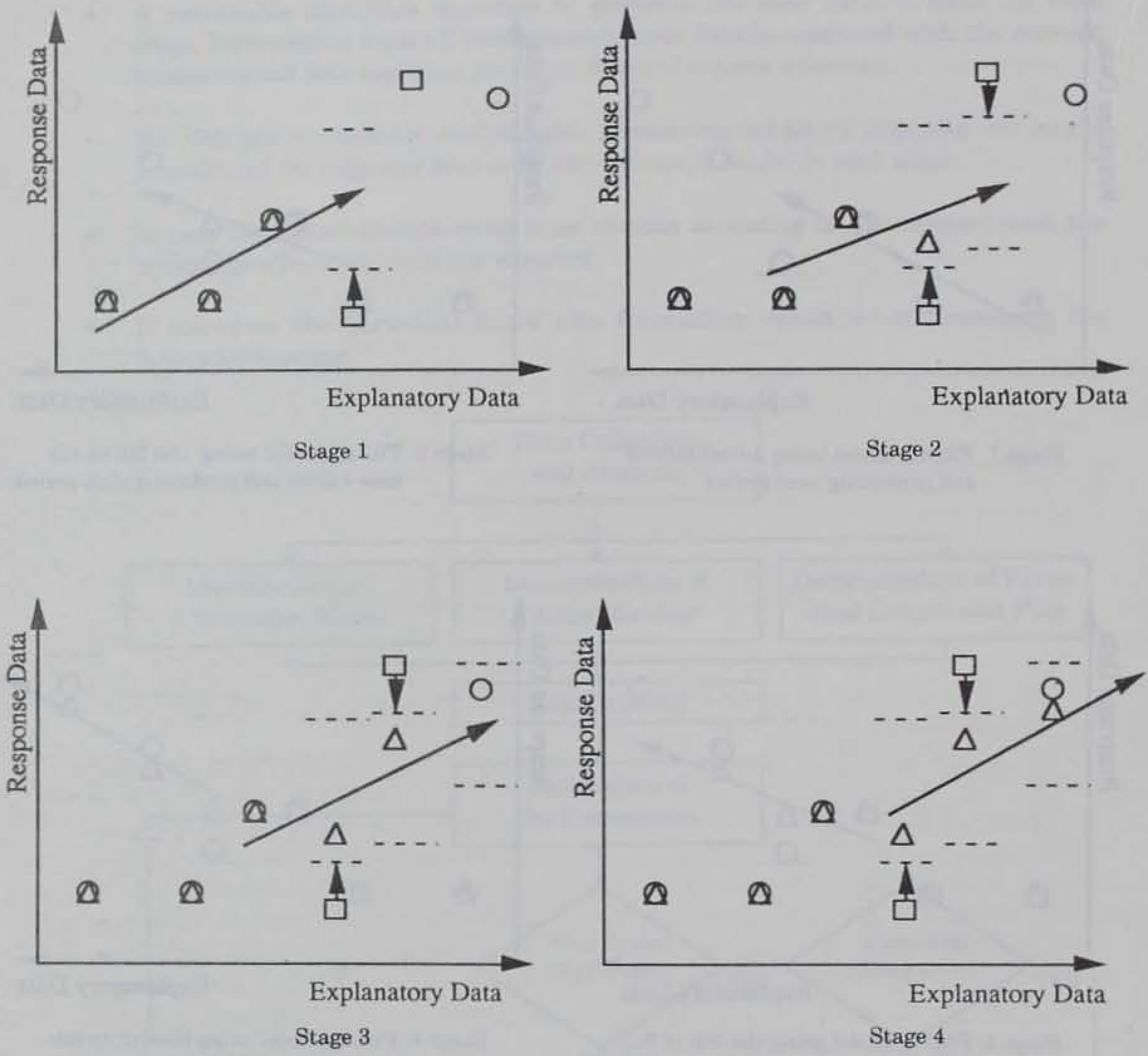
Stage 2: Fitting model using the 2th to 4th base values and predicting next period

Stage 3: Fitting model using the 3th to 5th base values and predicting next period

Stage 4: Fitting model using the 4th to 6th base values and forecasting future

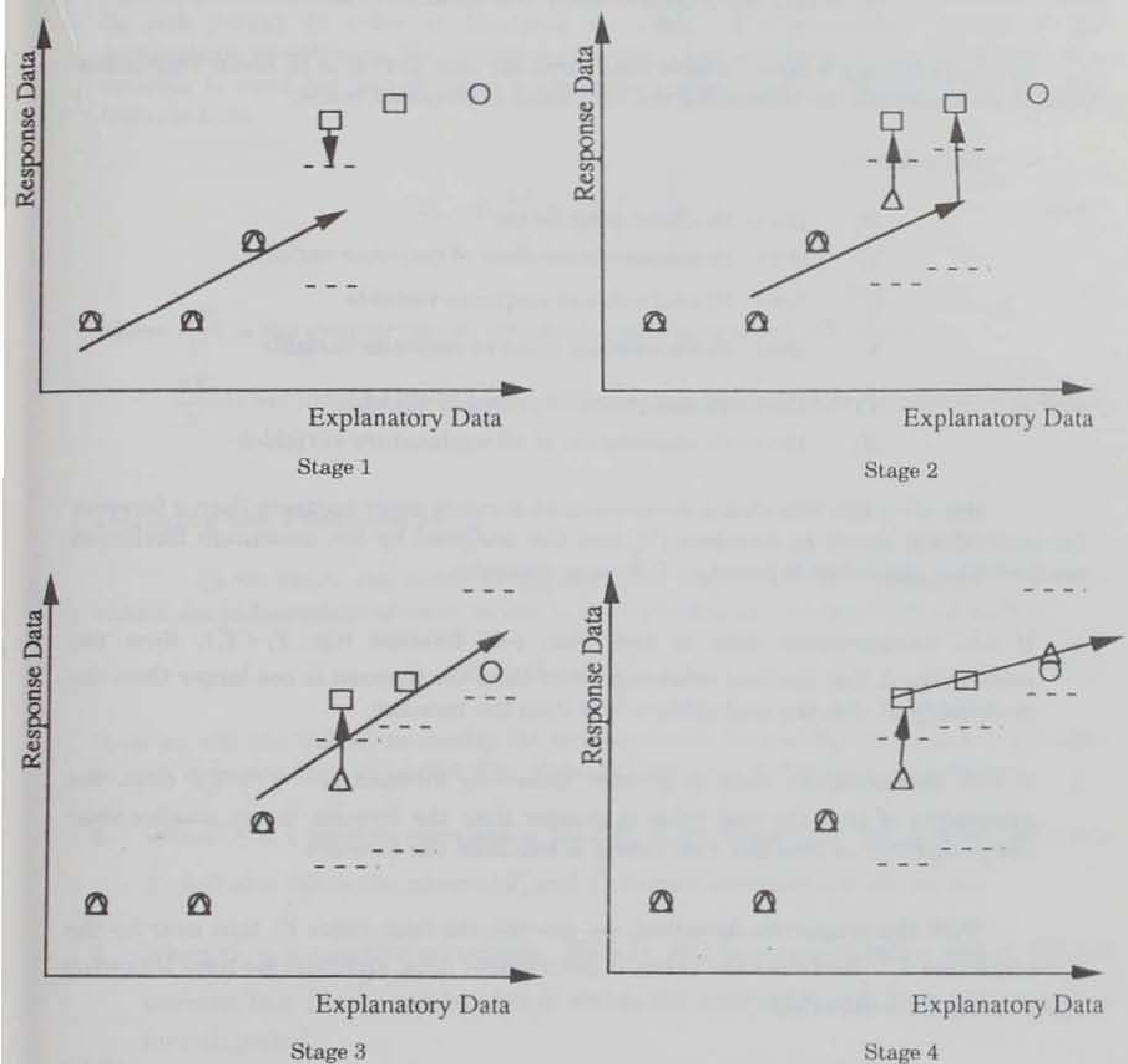
NOTES: 1. Suppose the number for fitting model in each stage is 3.
2. Define the symbols
O is the measurement data (observed data)
Δ is the base value derived from the algorithm in section 3
□ is the outlier
→ is the prediction value
..... is the confidence boundry (outlier threhold)

Figure 2. An Illustration for the Operation of ESPMR Method



NOTES: 1. Suppose the number for fitting model in each stage is 3.
2. Define the symbols
○ is the measurement data (observed data)
Δ is the base value derived from the algorithm in section 3
□ is the outlier
⟶ is the prediction value
..... is the confidence boundry (outlier threhold)

Figure 3. Rensponse of outliers (Sign not repeated)



NOTES: 1. Suppose the number for fitting model in each stage is 3.

2. Define the symbols

O is the measurement data (observed data)

Δ is the base value derived from the algorithm in section 3

□ is the outlier

→ is the prediction value

..... is the confidence boundry (outlier threhold)

Figure 4. Response of outliers (Sign repeated)

3. THE ALGORITHM FOR BASE VALUE

In order to get more reliable base value for each period to fit linear regression model, an algorithm for calculating the *base value* is proposed below.

Let's denote

H_i : the i – th adjustment factor

Y_i : the i – th measurement data of response variable

Y_i^R : the i – th real value of response variable

$\hat{Y}_i$: the i – th forecasting value of response variable

$\overset{\Delta}{Y}_i$: the i – th base value of response variable

X_i : the i – th observation of all explanatory variables

Based on the idea that a measurement is much more accurate than a forecast for quantifying errors in forecasts [7], and the analyzed by the maximum likelihood method. This algorithm is based on following concepts.

1. If i-th measurement data is less than i-th forecast (i.e. $Y_i < \hat{Y}_i$), then the probability of that the real value is greater than the forecast is not larger than the probability of that the real value is less than the forecast.

2. If i-th measurement data is greater than i-th forecast (i.e. $Y_i > \hat{Y}_i$), then the probability of that the real value is greater than the forecast is not smaller than the probability of that the real values is less than the forecast.

With the properties described, we can use the base value $\overset{\Delta}{Y}_i$ that near by the Y_i to estimate Y_i^R. And the base value, measurement data, and forecast have following relationship for i-th period:

$$\overset{\Delta}{Y}_i = \hat{Y}_i + H_i\,(Y_i - \hat{Y}_i) = H_i\,Y_i + (1 - H_i)\hat{Y}_i \tag{3.1.}$$

The i-th base value $\overset{\Delta}{Y}_i$ of response variable is the sum of the product for i-th measurement data and corresponding weight (adjustment factor H_i) and the product for i-th forecast and corresponding weight (1- H_i). In the above formula, if we want to get the base value $\overset{\Delta}{Y}_i$, the mainly problem is how to obtain the adjustment factor H_i first. In the following context, we will provide an iteration method to calculate the adjustment factor and the base value under the given critical criterion.

Defining the Relationship Between Response and Explanatory Variables

Let Gi be the function that is composed of the response variable and explanatory variables. And we assume Gi is the functional relationship between the qrowth rate of measurement data and the average growth rate of explanatory variable value for i-th period. In order to interpret the effect of a percentage change of the explanatory variable on the response variable. The notation of the elasticity of a variable is used for this purpose in economics and business. Hence, we define the formula to be

$$G_i = f\left(\frac{\Delta Y_i}{Y_i}, \frac{\Delta X_i}{X_i}\right) = \frac{\frac{\Delta Y_i}{Y_i}}{\frac{\Delta X_i}{X_i}} \tag{3.2.}$$

where $\frac{\Delta Y_i}{Y_i}$ is the growth rate of the measurement data for i-th period

$\frac{\Delta X_i}{X_i}$ is the average growth rate of the explanatory variable values for i-th period

Defining the Function of H_i

As we know, the values of the elasticity may be positive or negative. And the values are independent of units in which the variables are measured. Now we let

$$H_i = G_i / (1 + G_i) \tag{3.3.}$$

then we will use this H_i to modify the measurement data to become a new base value in each iteration for i-th period. The H_i and G_i have the following relationship.

1. When G_i is a positive correlation, then H_i is always within the interval (0,1), and $\overset{\Delta}{Y_i}$ will also fall in the interval Y_i and $\hat{Y}_i$ in each iteration for i-th period.

2. When G_i is a negative correlation, then H_i will be a real number, and it will not warrant that the $\overset{\Delta}{Y_i}$ will be always within the interval Y_i and $\hat{Y}_i$ in each iteration for i-th period.

Calculating the Adjustment Factor and Base value

Now, we consider that if the measurement data of i-th period lies within the forecasting confidence interval, then

Step 1: Add one unit $\frac{\Delta Y_i}{Y_i}$ value to the numerator of G_i given in (3.2.) to increase the influence of response variable.

Step 2: According to this new G_i value to update H_i from (3.3.).

Step 3: Calculate the new base value from (3.1.) for the i-th period.

Step 4: The given critical criterion for getting new $\overset{\Delta}{Y_i}$ (the i-th period base value) is described as below:

$$\text{if } SS_i \le \frac{\sum_{j=1}^{k} SS_{i-j}}{k} \qquad k < i$$

then the base value is satisfied, we accept $\overset{\Delta}{Y}_i$ to estimate Y_i^R else recur to Step 1.

where H_i is the i-th period adjustment factor, $SS_i = \left(\overset{\Delta}{Y}_i - Y_i\right)^2$ is square error of the i-th period base value and measurement data, and $\frac{\sum_{j=1}^{k} SS_{i-j}}{k}$ is the mean square error of previous k periods' base values and measurement data (where $k<i$ and k is the given number to fit regression model in each stage).

Because the measurement data is usually closer to the real one, even the measurement one is not the real value, the iteration for finding the base value will be stop when the square error of the base value and measurement data is less than mean square error of previous k periods' base values and mesurement data.

4. CALCULATION FOR PERIODICAL FACTOR

If the data series has the periodicity, it would be better to modify forecasting values by using the periodical factor directly. For the ESMPR, one method of calculating periodical factor is described as follows:

Let's denote following indexes

m: the fixed length which one flag lies at least for each periodicity
s : the s-th number within each periodicity
r : No. of periodicity for flag s

Then we can calculate the periodical factor P_s for flag s from following formula:

$$P_s = \frac{\frac{Y_s}{\hat{Y}_s} + \frac{Y_{s+1m}}{\hat{Y}_{s+1m}} + \frac{Y_{s+2m}}{\hat{Y}_{s+2m}} + \dots + \frac{Y_{s+(r-1)m}}{\hat{Y}_{s+(r-1)m}}}{r} = \frac{\sum_{i=0}^{r-1} \frac{Y_{s+im}}{\hat{Y}_{s+im}}}{r} \qquad s \le m \qquad (4.1.)$$

where Y_{s+im} is the $(s+im)$-th measurement data of response variable.
$\hat{Y}_{s+im}$ is the $(s+im)$-th forecasting value of response variable.

From (4.1.), we can find that the periodical factor for flag s is the average rate between measurement data and its forecasting value for all past flag s.

Now, we use this factor P_s to modify forecasting value for flag s in each future periodicity from formula (4.2.) for improving the forecasting performance.

$$\hat{\hat{Y}}_{s+m(r+j)} = P_s \hat{Y}_{s+m(r+j)} \qquad j = 0, 1, 2, \ldots \tag{4.2.}$$

where $\hat{Y}_{s+m(r+j)}$ is the $(s+m(r+j))$-th forecasting value (flag $(s+m(r+j))$) of response variable

$\hat{\hat{Y}}_{s+m(r+j)}$ is the modifying value of $\hat{Y}_{s+m(r+j)}$ by factor P_s.

5. EMPIRICAL EXAMPLE

Because the continuous and repetitious calculations are necessary, an executing ESPMR system programmed in C language has been developed for the empirical operation. The user prepared input file including the measurement data, initial values, and all explanatory variables. As executing program, the user inputs the name of data file, the number for fitting model in each step, the number of explanatory variables, and the periodical length and flags (if data series has the periodicity) from the interactive screen of ESPMR system sequentially. Finally, the system will forecast future period forecasts according to all of input information and contents of data file. The formats of input and output file are shown in Appendix.

Two forecasting cases of Taiwan for the International Outgoing Traffic Loads (the data series have the periodical traces) and the Metropolitan Outgoing Traffic Loads of Taipei (the data series have not periodical traces) are used to test the feasibility of ESPMR method.

Case 1: *The Forecasting for Ten International Trunk Groups of Taiwan*

The measuring traffic loads of ten international trunk groups of Taiwan were collected from 1988 to 1990 by four quarters (11 quarterly data total for each trunk group). They are extracted from the summary reports of ITA (the International Telecommunications Administration of Taiwan). We analyzed the quarterly outgoing traffic loads. Each quarterly busy hour traffic load is equal to the average of 3-month carried traffic loads. The collected explanatory variable is the number of subscribers which comes from the Statistical Abstract of Telecommunications published by DGT (the Directorate General of Telecommunications).

In this study, we use the quarterly data series 1988-1989 to execute ESPMR system, and select the number to fit the model in each stage is 5. While, about the initial values (which are needed at the first stage of fitting model), we use one practice method to generate in this paper. That is, for getting current period's initial value, we ignore the current period measurement data and use the rest period data to fit one regression model. Then, we use this model to project the forecasting value of this current period backwardly and use this value as the initial value. Because of using five period data to fit the model in each stage, the first five quarterly data of each trunk group are given to fit individual regression model and to get initial value.

The ESPMR system forecasts the quarterly traffic loads for ten international trunk groups of Taiwan in 1990 (4 periods for quarterly data of each trunk group). For convenient comparison, the measurement data and forecasting results of two methods (one is ESPMR method, and the other one is traditional regression method) are shown in Table 1, the forecasting errors and MAPE are shown in Table 2.

Case 2: *The Forecasting for Seven Exchange Areas of Taipei*

The measuring traffic loads of seven exchange areas of Taipei were collected from 1985 to 1992. They are extracted from the yearly traffic summary reports of NTTA (the North Taiwan Telecommunication Administration). The collected explanatory variable is the no. of subscribes which comes from the marketing department of NTTA.

In this study, we use the data series 1985-1990 to establish simple regression model, and select the number to fit the model in each stage is 4. And then, we also employee the same method that is mentioned in Case 1 to generate initial values repeatedly. Because of using four period data to fit the model in each stage, the first four year data (1985-1988) of each exchange area are given to fit individual regression model and to get initial value.

The ESPMR system forecasts the outgoing traffic loads for seven exchange areas of Taipei from 1991 to 1993. As the Case 1, for convenient comparison, the measurement data and forecasting results of two methods (one is ESPMR method, and the other one is traditional regression method) are also shown in Table 3, the forecasting errors and MAPE are shown in Table 4.

From the results of tables, we could see clearly that the average MAPE value of ESPMR Method is much lower than the traditional regression (especially Case 2) and the ESPMR Method which has more numbers of forecasts is more accurate than the traditional method (from the absolute error point). That is, the forecasts of ESPMR method are more stable than traditional regression method for most international trunk groups and exchange areas. It appears that the ESPMR method is more smooth and reliable as well as some good forecasting methods.

Table 1. The Quarterly Traffic Load Forecasts (Measurement Data) of Ten International Trunk Groups by ESPMR and Traditional methods

unit: Erl

Trunk Group Name	Quarter	1990			
		1	2	3	4
France	measurement	3057.24	3374.09	3290.46	3928.63
	ESPMR	3014.70	3220.20	2969.80	3521.51
	regression	3163.08	3406.90	3602.60	3764.40
Finland	measurement	251.98	278.08	238.08	326.12
	ESPMR	272.84	295.00	243.97	327.49
	regression	267.63	288.95	306.06	320.21
Sweden	measurement	1026.70	1100.90	950.73	1151.48
	ESPMR	1013.05	1187.50	981.27	1179.79
	regression	1040.56	1113.73	1172.47	1221.02
Spain	measurement	790.01	933.74	807.77	1022.05
	ESPMR	785.94	970.36	735.72	921.62
	regression	817.06	881.06	932.42	974.89
Italy	measurement	1950.97	2297.58	1887.04	2343.48
	ESPMR	1930.01	2355.23	1678.96	2205.26
	regression	1974.58	2100.27	2201.15	2284.55
Ireland	measurement	145.42	165.51	158.95	167.03
	ESPMR	138.44	164.22	160.82	169.06
	regression	141.28	154.54	165.18	173.98
Austria	measurement	863.68	979.65	986.84	1059.23
	ESPMR	878.92	944.77	898.50	1041.31
	regression	908.28	983.46	1043.80	1093.23
Mexico	measurement	237.28	285.29	318.87	341.78
	ESPMR	266.15	292.80	314.19	331.88
	regression	275.81	306.29	330.76	350.99
U.S.A.	measurement	80765.45	86370.16	91813.20	95005.79
	ESPMR	79323.34	85705.73	87744.27	90844.08
	regression	78912.10	83544.07	87261.80	90335.40
Canada	measurement	6557.78	7154.52	7584.79	8286.47
	ESPMR	6331.89	6964.94	7335.94	7705.55
	regression	6284.70	6832.08	7269.63	7632.20

Table 2. The International Ttraffic Load Forecasting Errors and MAPEs for Ten Trunk Groups by ESPMR and Regression Method

unit: Erl

Country Name	Quarter for 1990				MAPE
	1	2	3	4	
France	42.54	153.89	320.66	407.12	0.06498
	-105.84	-32.81	-312.14	164.23	0.04510
Finland	-20.86	-16.92	-5.89	-1.37	0.04024
	-15.65	-10.87	-67.99	5.91	0.09806
Sweden	13.65	-86.60	-30.54	-28.31	0.03666
	-13.86	-12.84	-221.74	-69.54	0.07898
Spain	4.07	-36.62	72.05	100.43	0.05765
	-27.05	52.68	-124.65	47.16	0.07234
Italy	20.65	-57.65	208.09	138.23	0.05104
	-23.62	197.31	-314.11	58.93	0.07217
Ireland	6.98	1.29	-1.87	-2.03	0.01639
	4.14	10.97	-6.23	-6.95	0.04040
Austria	-15.24	34.88	88.34	17.92	0.03932
	-44.60	-3.81	-56.97	-34.46	0.03571
Mexico	-28.87	-7.51	4.68	9.90	0.04535
	-38.53	-21.00	-11.89	-9.21	0.07365
U.S.A.	1442.11	664.43	4068.94	4161.71	0.02841
	1853.35	2826.09	4551.41	4670.39	0.03860
Canada	225.90	189.58	248.85	580.93	0.04085
	273.08	323.43	315.16	654.27	0.05181
Average					0.04209
					0.06068

Notes: (1) the first forecasting error (just as 42.54 of first quarter in France) is generated by ESPMR method.

(2) the second forecasting error (just as -105.84 of first quarter in France) is generated by Regression method.

Table 3. The Outgoing Traffic Load Forecasts for Seven Exchange Areas of Taipei by ESPMR and Regression method

unit: Erl

Exchange Area	Year	1991	1992	1993
East Area	measurement	30866.5	34583.3	38155.6
	ESPMR	31505.7	35628.8	40110.4
	regression	32005.2	36300.5	40969.1
South Area	measurement	29703.2	33053.4	36142.3
	ESPMR	30050.4	33775.2	37823.9
	regression	30776.7	34758.0	39085.6
North Area	measurement	17935.3	19297.4	20711.2
	ESPMR	18343.8	20161.3	22136.8
	regression	18809.3	20789.1	22941.1
West Area	measurement	14273.2	16428.0	18610.9
	ESPMR	14015.1	15845.9	17835.9
	regression	13993.7	15825.5	17816.6
South Suburb	measurement	11422.6	12437.1	13366.2
	ESPMR	11609.5	12849.1	14196.5
	regression	11846.4	13168.1	14604.9
North Suburb	measurement	9971.4	11010.5	12202.1
	ESPMR	10138.7	11406.9	12785.3
	regression	10191.4	11479.6	12879.8
Keelung Area	measurement	4185.9	4511.7	4867.1
	ESPMR	4236.0	4606.1	5008.5
	regression	4254.7	4630.1	5038.3

Table 4. The Traffic Load Forecasting Errors and MAPEs for Seven Exchange Areas of Taipei by ESPMR and Regression Method

unit: Erl

Exchange Area	Year			MAPE
	1991	1992	1993	
East Area	-639.2	-1045.5	-1954.8	0.03404
	-1138.7	-1717.2	-2813.5	0.05341
South Area	-347.2	-721.8	-1681.6	0.02667
	-1073.5	-1704.6	-2943.3	0.05637
North Area	-408.5	-863.9	-1425.6	0.04542
	-874.0	-1491.7	-2229.9	0.07787
West Area	258.1	582.1	775.0	0.03172
	279.5	602.5	794.3	0.03295
South Suburb	-186.9	-412.0	-830.3	0.03717
	-423.8	-731.0	-1238.7	0.06281
North Suburb	-167.3	-396.4	-583.2	0.03350
	-220.0	-469.1	-677.7	0.04005
Keelung Area	-50.1	-94.4	-141.4	0.02050
	-68.8	-118.4	-171.2	0.02584
Avearge				0.03273
				0.04990

Notes: (1) the first forecasting error (just as -639.2 of 1991 in East Area) is generated by ESPMR method.

(2) the second forecasting error (just as -1138.7 of 1991 in East Area) is generated by Regression method.

6. CONCLUSIONS

In this paper, one new technological forecasting method, ESPMR, is proposed for dealing with the traffic loads which are measurement data but not real values. It combines the adjusting and detecting concepts of SPA with the estimating method of linear regression model, and considers the periodical factor into forecasts if the data series has the periodical traces. We integrate the concepts of stepwise adjusting base value, a computing algorithm, regression model fitting, and the periodical factor together to carry out a smoother forecasting result. Because the continuous and repetitious calculations are necessary, an executing ESPMR system programmed in C language has been developed for the empirical study. From empirical cases, we can find the forecasts of ESPMR method are more smooth and reliable as well as some good forecasting methods. It appears that the ESPMR is one good method.

In order to enhance the Stepwise Projection Method studies, we may suggest further study directions to develop newly calculating algorithms for base value as possible to improve forecasting effect.

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APPENDIX

(1) The form of input file:

No.	measurement	base value	explanatory variable
01	1457.85	1638.80	5000036
02	1881.54	1727.28	5120521
03	1736.90	2018.88	5240251
04	2292.56	2100.76	5332285
05	2403.08	2278.45	5431556
06	2713.04	0	5566834
07	2516.59	0	5692183
08	2936.10	0	5822663
09	0	0	5945244
10	0	0	6089398
11	0	0	6205100
12	0	0	6300755

(1) The form of output file:

No. of fitting model for each stage=5
Periodical Length=4 Flags=2,3
Total data=12 Historical data=8 Forecasts=4

No.	measurement	base value	forecast	low	upper
1	1457.85	1638.80	--	--	--
2	1881.54	1727.28	--	--	--
3	1736.90	2018.88	--	--	--
4	2292.56	2100.76	--	--	--
5	2403.08	2278.45	--	--	--
6	2713.04	2671.95	2478.74	2243.49	2714.00
7	2516.59	2430.60	2868.56	2554.15	3182.96
8	2936.10	2910.60	2748.00	1951.89	3544.10
9	--	--	3014.70	2190.13	3839.26
10	--	--	3220.20	2458.48	4590.69
11	--	--	2969.80	1997.99	3941.60
12	--	--	3521.51	3963.76	4745.93