An Approach of Electric Power Demand Forecasting using Data-Mining Method: a case study of application of Data-Mining technique to improvement of decision-making

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Abstract: In this paper, for the aim to build the management plan of stable electric power supply and accommodation, the monthly electric demand prediction approach with dynamic and adaptive mechanism connected to the business environment is proposed.

The proposed prediction adopts the Kalman-Filter as the basic prediction scheme and possess two characteristics stated below. One is the state-space built with the principal component time-series integrated by time-series PCA (Principal Component Method) from multi business indices related the targeted time-series. The other is the self-organized auto-updating of the state-space by structured neural network.

The proposed scheme shows considerably accurate prediction than any other models with single variable time-series and the obvious effect appears to the high accuracy by adopting time-series PCA as a Data-Mining technique. From these effects, the proposed prediction scheme might be considered to give an improvement to the stable electric power supply and accommodation. And this prediction scheme can be applied to various management areas, so it might be considered to be an effective method for decision-making support.

Keywords: Electric power supply; Knowledge extraction; Data-Mining technique; Kalman-Filter processing; Self-organized state-space; Principal component time-series; Batch-Sequential method

1. Introduction

1.1 Electric demand forecasting for improvement of decision-making

Needless to say, forecasting is an important element for decision-making support. The common theme through decision-making is “selection and decision” and the forecasting is indispensable for the optimal realization of this theme. This is explained obviously by the fact that the forecasting is positioned as a core method of DSS (Decision Support System) which has been developed until now. In this paper, as the case study of the improvement to reasonable and effective decision-making, an approach to the electric power demand forecasting adapted to business variation is proposed and its effect is verified.

In modern days, high activity of industry as IT leading and high dependence to electric power in daily life, require still more increase and higher stability of electric power. It is needless to say that high accurate prediction of electric power demand has a decisive role for these requirements.

In investigating of electric power demand, following 3-type demand patterns must be considered corresponding to time span of demand. [10]

・ long range demand under the influence of population, big plant, building, etc,

・ monthly demand required by industrial and economic activities, etc,

・ short range demand required by urgent need.

For the first pattern, in order to cope with building a new electric power station, the long-range prediction based on yearly demand, is needed. For the last point, for the urgent demand or change of supply route caused by disaster, the short-range prediction with hour range variation of demand is required. [12] On the other hand, the stable supply of electric power, which is connected with business trend and daily life activities, requires highly accurate supply plan at the power station and accommodates with each other. For these requirements, the highly accurate monthly prediction, which is reflected by trend and seasonable variance, is indispensable.

We propose an adaptive and dynamic prediction approach, which is reflected by business trend and seasonable variance, and show its effectiveness. By the reason for the basic character of this approach, which has a dynamic adaptability to the business environment, this approach is considered as a reasonable and effective decision-making method to the stable supply of electric power.

1.2. Requirements to monthly demand forecasting of electric power

As above stated, the requirements to monthly prediction of electric power demand are listed as follows.

・ prediction scheme adapted to the past demand time-series,

・ prediction mechanism reflected to the movement of business environment.

The first requirement states that this prediction has to be a dynamic and adaptive prediction scheme, which picks up the peculiar variation of the past time-series. Obviously, this scheme is not based on the static scheme as 'curve fitting' or 'regression formula' but based on the movement of time-series moment by moment and high prediction accuracy is required. About this scheme, a series of approaches based on the structured neural network, which learned by the past variation of demand time-series are investigated. [2,8] In this paper, the Kalman-Filter is adopted as the framework of the prediction. The Kalman-Filter is the real-time estimate/prediction scheme with multi input/output. It processes the state-space, which constructs the system, and the measurement-space, which observes the time-series and transforms to the state-space, separately. The outline of the Kalman-Filter is described in **Appendix 1**.

The second requirement states that this prediction requires the scheme, which reflected to the movements of business environment. For this reason, the movement of business environment, which influences electric power demand, should be adopted to this prediction mechanism. Namely, this prediction has the basis that electric power demand is under the movement of business environment, builds the framework which extracts the integrated factors from the electric power and the related business indices. The integrated factors time-series are sequentially extracted from the electric power time-series and the related business indices time-series by PCA (Principal Component Analysis) method, and are built as the explanatory variables of the state-space. The outline of PCA is described in **Appendix 2**.

The concept of "Data-Mining" states "discover of new knowledge from accumulated data" mainly. Namely, this is the concept, which does not verify the previously set hypothesis, but discover any new facts or rules from accumulated data. [4,5,6] So, the various types of neural network are used frequently as the empirical modeling approach based on the accumulated data. [13,17]

We use the time-series PCA as the integrating method. The component time-series are integrated from the original time-series by PCA and independent with each other.

Under above definition of "Data-Mining", the proposed prediction scheme can be based on "Data-Mining" basically. Namely, the business environments are integrated and extracted from the some accumulated business indices. And the targeted electric power demand time-series is predicted with these business environments. The demand prediction approach investigated here, realizes the second of above stated requirements from the aspect of "Data-Mining".

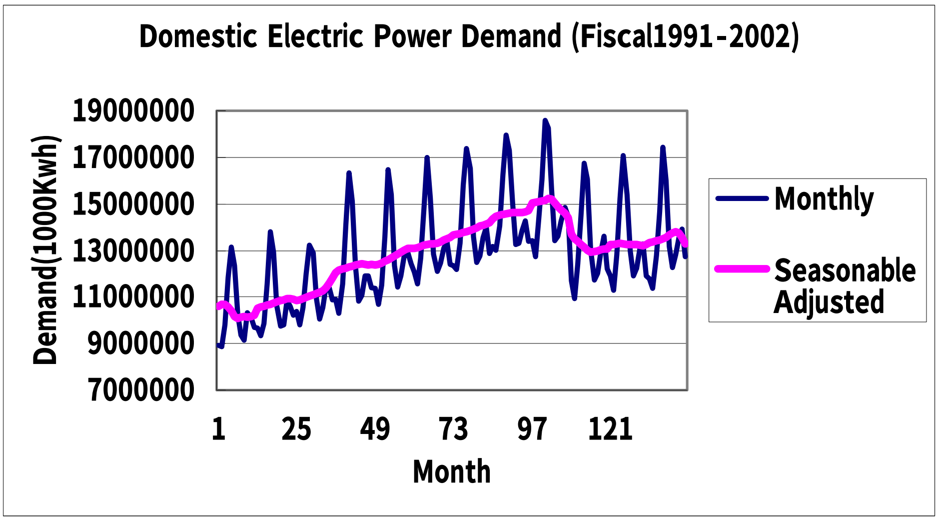
Considering the first requirement, this proposed prediction scheme is higher adaptive to quick varying time-series than slow varying. But according to the dynamic prediction framework, the prediction of this scheme is limited comparatively to short prediction. From the second requirement, this scheme has the reasonable reflections not only with the targeted time-series, but also with the related environments. This states that the selection of the indices time-series related with the targeted time-series is the key matter of the prediction.

2. Adaptive electric power demand prediction

2.1. Electric power demand time-series and business indices time-series

As the targeted electric power demand in this study, domestic industry electric power demand (monthly time-series) is adopted. This time-series is shown as Figure.1. The sample size is 144, and the period is twelve years from April.1991 to March.2003. For the reason that the evaluation of prediction is defined as the accuracy of the prediction error, the prediction period is set in rapidly changed period(two years from April.1999 to March.2000).

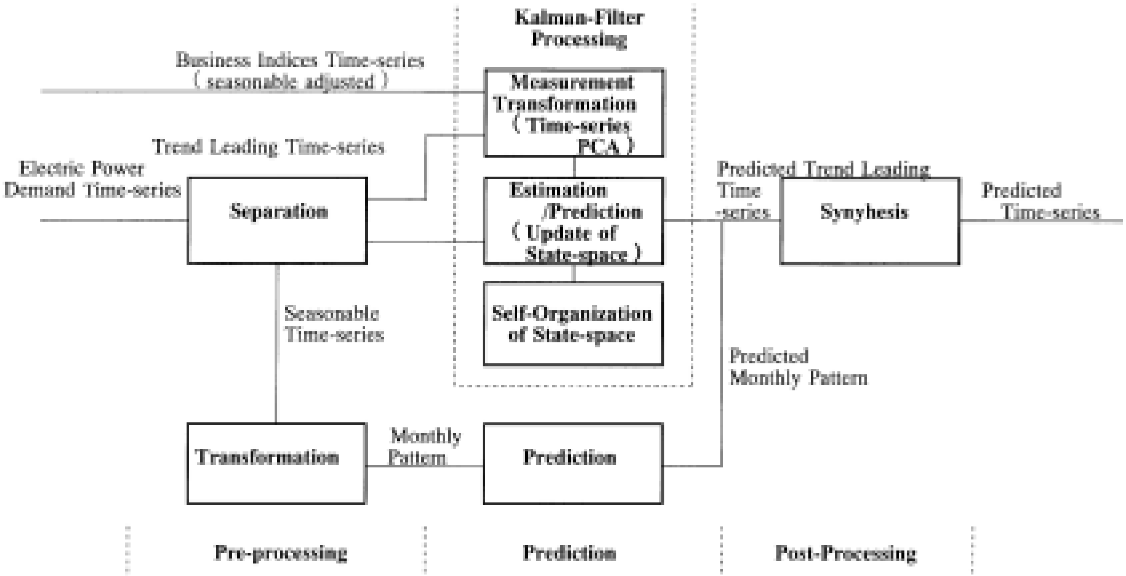
[Fig1. Monthly time-series of Domestic Industry Electric Power Demand (Fiscal 1991-2003), source Toyo-Keizai-Shinpo Corp, “Keizai-Tokei Nenkan”, 2003.]



(1) Total picture

The total picture of the processing scheme is shown as Figure.2.

[Figure.2 Total picture]



This scheme is composed of the pre-processing, the Kalman-Filter processing which is leading part, and the post-processing. In the pre-processing, the seasonable variation is separated from the original time-series. The irregular variation is removed from the separated trend leading time-series by smoothing (moving average method, etc), and the smoothed trend leading time-series is successively input to the measurement mechanism of the Kalman-Filter. The separated seasonal variable time-series is transformed to the seasonable monthly pattern. After it is input into the learned neural network, the prediction seasonal monthly pattern is generated.

In the measurement mechanism of the Kalman-Filter, the trend leading time-series and the business indices time-series (seasonable adjusted) are processed by principal component analysis and integrated into the some principal component time-series, then build the state space of the Kalman-Filter. In the state space, the electric power time-series and the principal time-series are input into the learned neural network. The prediction of each variable is gained as the output from the self-organized state space.

The post-processing is the synthesis of the prediction value from the generated prediction trend leading value and the prediction seasonable pattern. By this post-processing, the prediction value of the electric power demand which contained the seasonable variation can be gained. [15]

(2) Prediction of the trend leading time-series

The four business indices relating with domestic industry electric power demand are listed as follows. Their sample size and period are same and all seasonable adjusted.

x_1 : Gross Domestic Production (GDP)

x_2 : Index of Industrial Production (Mining and Manufacturing) (MMI)

x_3 : Building Construction Starts

x_4 : Stock Average

The targeted domestic industry electric power demand is defined as the fifth variable.

x_5 : Domestic Industry Electric Power Demand

The electric power demand is influenced extremely by the business environment represented as the indices of industry and daily life. We selected the representative 4 indices as the business environment. Namely, GDP shows domestic total production in quarter of year and represents business trend. Other 3 indices are the indices which reflect business trend at each time.

The second requirement stated in chapter **1.2** is represented as “the prediction processing, which reflected to the movements of business environment”. The basic data, which represented as the movement of business environment, are accumulated time-series of the business indices. Therefore, for this aim to the prediction processing, we investigate the processing framework using “Data-Mining” processing. For the realization of this point, following two methods are proposed.

The first is the method which reflects the movement of business environment to prediction mechanism. For solving this problem, the state-space of the Kalman-Filter needs not to be built by the observed variables directly, but by the principal components extracted from these observed variables. Namely, by the principal components time-series, the fewer and non-correlative components are represented than original observed variables. As a result, the variances of original variables are represented the variances of the integrated fewer principal components. This states that the independent variances are extracted from the total variances. The principal component analysis of the time-series is processed in the measurement transformation mechanism at each observation cycle, the state space is integrated and re-constructed from original time-series at each observation cycle.

The second is the update method of the state space at each update cycle. Generally, in the field of economics/management analysis, the time update of the system almost cannot be represented as logical model, but estimated by regression model, etc. As a result, the estimated parameters are constant and the model is not dynamical. Previously, we tried to introduce the self-organizing method using the neural network for solving this problem. This method aimed to detect the structural changes of the system by the learned neural network composed of the space-state variables. And as a result, it is regarded that the space state is updated. The prediction values are gained by inputting the latest time-series values to the renewed state space. By this method, in the case of the implicit relation of update mechanism in the economics/management field, the update also can be processed and the time update of space state can be represented. [9,14,16]

(3) Prediction of seasonable variation

As shown in Fig.2, the seasonable variation time-series is separated from the original time-series. The separating method is adopted CENSUS X.11. The extracted seasonable time-series is divided into every month and is reconstructed as seasonable monthly pattern. The prediction method to the monthly pattern is used structured type neural network. The training date sets are constructed as follows.

The 12 monthly patterns of the last/present year are signified as the input/output of the neural network. The pair data are set into the neural network and the net is learned. After learning, the monthly pattern of the present year is input into the learned network and the output is gained as the prediction monthly pattern.

2.2. Prediction process of trend leading time-series

(1) Extraction of the business environment by time-series PCA

Time-series Principal Component Analysis (PCA) generates the principal components time-series from the original time-series, and the principal components time-series is independent of each other.

As shown in Figure.3, this procedure is processed with the constant time period T_1 (batch) toward to time proceeding by moving one sample (Batch-Sequential Method). [11]

Here, $\{x_{ki}\}$ is the i-th business indices time-series at the time (k) and $\{y_k\}$ is the targeted time-series at the same time respectively. And $\{p_{kj}\}$ is generated the j-th principal component time-series at the same time. The indexes and the processing period are defined as follows.

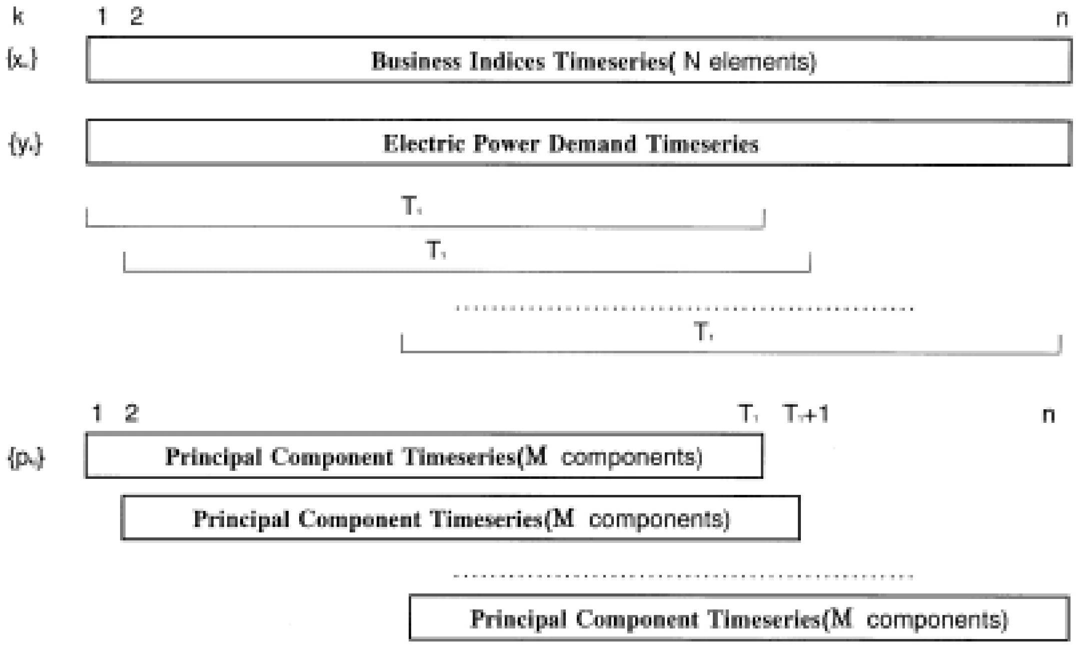
index of the principal components : $j = 1,2,....,M$

index of the original variables : $i = 1,2,....,N$

processing period : T_1

Considering that $\{x_{ki}\}$ is the business indices, the integrated component $\{p_{kj}\}$ can be the common movement of business movements. Therefore, the time-series of the principal components are assumed to be represented the movement of the business environment

[Figure.3 Generation of principal component time-series by Batch-Sequential Method]



(2) Self-organizing of state-space

In case of building the Kalman-Filter, main role is the determination of the state transition matrix. Generally, the dynamics of the system is presented with the group of the differential equations in physical system and the transition matrix is formulated. Otherwise, in the case of the targeted electric power demand time-series, its dynamical movement almost cannot be presented deductively and gained by the estimation of regression analysis from the past time-series. In this case, the transition matrix is composed of regression constants and is not presented with time variation. Therefore, the Kalman-Filter cannot be applied to non-stationary system by the reason for its theoretical framework.

To solve this problem, the self-organization of the state space is introduced as a cope to the dynamics of it. Namely, this method is based on that each element of the state transition matrix is sequentially determined by the self-organization process with the state variables and their correlations, at each cycle taking in the observed data. Previously, we proposed the revised GMDH (Group Method of Data Handling) which had linear correlation between the state variables, as the self-organizing method. [14] Here, the neural network is introduced, for the reason of taking in non-linear correlation.

The targeted variable time-series and the principal component time-series taken in the batch period (Batch-Sequential Method) T_1 are noted as follows.

Principal component time-series $\{ p_{ij} : i = 1,2,....,T_1 : j = 1,2,...,M \}$

Targeted variable time-series $\{ y_i : i = 1,2,....,T_1 \}$

Here, M is the number of principal components time-series, T_1 is the sample number of time-series in the batch period.

These time-series lumped together are noted as follow.

$$\{ x_{ij} : i = 1,2,....,T_1 : j = 1,2,...,m \} \qquad (m = M + 1)$$

The neural network type self-organizing state space is structural type . The applied neural network is trained using the data sets of neighboring time as training data at constant interval. At each cycle of the Kalman-Filter processing, the state transition matrix is renewed by the above stated process. By this training process, the learned transition matrix is generated and the prediction value is obtained by inputting the values of the latest state variables into the renewed state space. Namely, k is the updating time, in order to generate the state transition matrix $\Phi_{k+1,k}$, the training input/output time-series are set as follows.

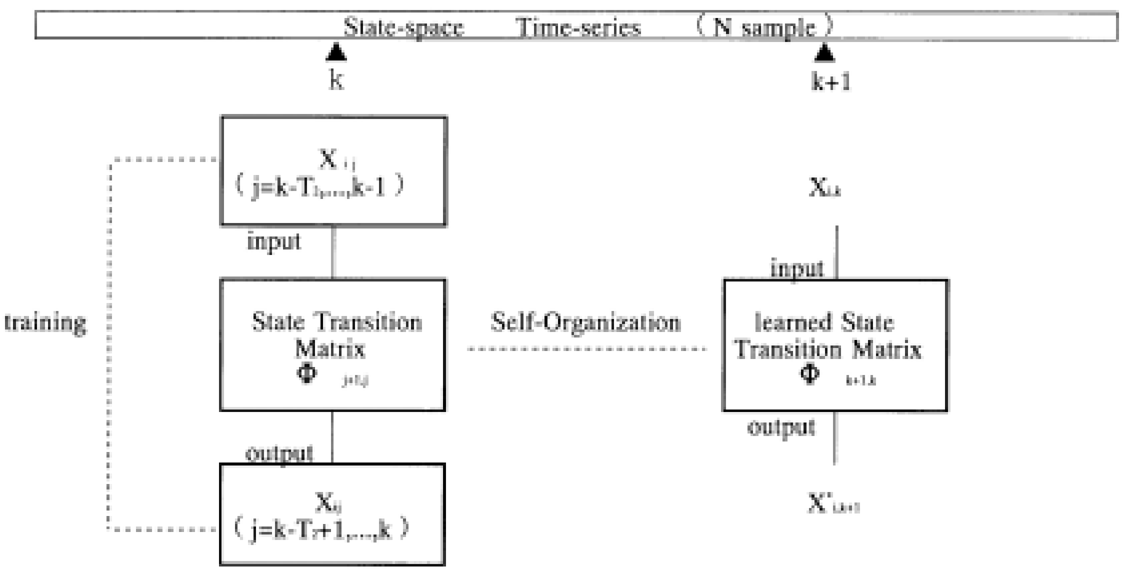
・training input $\{ x_j : j = k - T_2,....,k-1 \}$ (T_2 is learning period)

・training output $\{ x_j : j = k - T_2 + 1,....,k \}$ (T_2 is learning period)

The learning period is a part of the batch period, therefore $T_2 < T_1$ is obvious.

These procedure is showed as Figire.4.

[Fig4. Time variation of state space transition]



By taking in { x_k } to the learned neural network, { $x_{k+1}{}^*$ } are gained as the prediction value.

2.3. Seasonable prediction and synthesis of prediction values

As shown in Fig.2, the seasonable variation time-series $\{S_i : i = 1,2,....,n\}$ is separated from the trend leading time-series by CENSUS X.11. The seasonal variation time-series is divided into every month and the monthly seasonable pattern R_{il} is generated from it.

$$\{R_{il} : i = 1,2,....,12 : l = 1,2,...., L\}$$

Here, i, l is the index of month, year respectively, and L is last year. n is the size of sample and $L = n/12$.

The generation method of the prediction seasonal pattern is structural neural network. The neural network is learned by the training data set and the training data sets are composed as pair of input/output data. The l yearly seasonal pattern is input of the training data and $(l+1)$ yearly pattern is output. After learning, L yearly pattern is taken in the neural network, then $(L+1)$ yearly prediction pattern is gained.

Next, the trend leading prediction time-series which gained in chapter 2.2 and the prediction seasonal pattern which is above stated, are synthesized into the prediction time-series. The synthesizing method is the inverse process of the separation process which stated in Figure.2.

3. Evaluation to the proposed scheme

3.1. Evaluation to the trend leading prediction

The targeted prediction time-series is Domestic Electric Power Demand Time-series shown in Fig.1. The period of it is from Aplil.1991 to March.2003 and has 144 sample size. We define the accuracy of the prediction error as the evaluation standard and select the prediction period with the most rapid variation. Therefore, the prediction period is from Aplil.1999 to March.2001. The previous 8 years (96 samples) time-series is set as the initialization period for the calculation of the state space and the state noise. The batch period (T_1) which generates the principal component time-series is 8 years (96 samples), it is moved by 1 sample toward time proceeding at each cycle updated in the prediction period.

In the initial period, the state space of the Kalman-Filter is derived by the regression calculation in its period. In the successive prediction period (2 years), the principal component time-series is generated by the measurement mechanism of the Kalman-Filter at each of the observation. The state space composed by the generated principal time-series is sequentially updated by self-organization of the neural network, its convergence error is set as the state noise. The learning period (T_2) of the neural network is previous half year as the reason for avoidance of over learning.

(1) Principal component time-series (Data-Mining processing)

In the initialization period, after principal component analysis to above stated five time-series, upper three eigenvalue and accumulated proportion are obtained as follows.

		eigenvalue	accumulated proportion
first PC	(p_1)	0.0396	0.722
second PC	(p_2)	0.0080	0.867
third PC	(p_3)	0.0047	0.953

We use three principal components which make up 95 percent of the accumulated proportion. The factor loading of each $\{p_1, p_2, p_3\}$ from $\{x_1, x_2, x_3, x_4, x_5\}$ is as follows. The meaning of $\{p_1, p_2, p_3\}$ are considered as below stated.

	x_1	x_2	x_3	x_4	x_5
p_1	0.050	-0.001	-0.051	-0.063	0.175
p_2	0.006	0.024	0.045	0.064	0.035
p_3	0.065	-0.001	0.011	-0.005	-0.017

- p_1 : makes up 72 percent of total variation, and is effected by $\{x_5\}$ especially, considered as the representative of electric power demand itself.
- p_2 : makes up 14 percent of total variation, and effected by $\{x_3, x_4\}$, considered as the representative of business movement.
- p_3 : makes up 9 percent of total variation, and effected by $\{x_1\}$, uncertain factor.

(2) State-space and construction of the Kalman-Filter

The building of the state-space and the Kalman-Filter are as follows.

- state variables

first PC – third PC : $\{p_1, \ p_2, \ p_3\}$

domestic electric power demand : $\{x_5\}$

Above listed are basic time-series and the next four combinations are applied to the modeling.

Model A : $\{p_1, \ x_5\}$ Model B : $\{p_1, \ p_2, \ x_5\}$

Model C : $\{p_1, \ p_2, \ p_3, \ x_5\}$ Model D : $\{x_1, x_2, x_3, x_4, x_5\}$

The model D does not adopt principal components but original 5 variables. In this model, the measurement matrix is unit matrix.

・state transition matrix

Each element is regression coefficient derived in the initial period (Fiscal 1991-1998). Considering independence with the principal component each other, the relation formula of each component between k and $(k-1)$ is represented in **Appendix 3**.

In the prediction period (Fiscal 1999-2000), the previous half year time-series are taken in the neural network as the training series, the output is gained by the input of the latest data. The number of elements in the input/output layers is the same number of the state-variables of each model (A,B,C,D). And the intermediate layer is one, its number of elements is the half of the number of the state variables. The convergence error in learning is about 10^{-2}.

・measurement matrix

The measurement matrix generates from the observed time-series to the state variable time-series by the principal component analysis using batch-sequential method, each element is the coefficient calculated by principal component analysis.

・state noise

In the initialization period, the RMS (Root Mean Square Error) value of the regression formula of each state variable is set as the state noise, corresponding each model. The RMS value about $\{x_5\}$ at each model is as follows.

Model A: 0.0080 Model B: 0.0145

Model C: 0.0075 Model D: 0.0074

In prediction period, the state noise is convergence RMS value derived by learning of the neural network. This is calculated and updated at each prediction cycle.

・measurement noise

The measurement noise is RMS value between each variable time-series and its smoothed time-series (Moving Average Processing, averaging width is 3 samples, moving width is 1 sample). The RMS value of $\{x_5\}$ is as follows. This value is used commonly through all models and periods.

x_5 : 0.0040

(3) Evaluation to prediction accuracy

The error (RMS value) of the trend leading prediction applied by each model (A, B, C, D) is listed as Table1. In order to verify the efficiency of this scheme, two cases of the predictions in the most rapid varying period (Fiscal 1999-2000) and in the most slow varying period (Fiscal 1997-1998) are tested. These are listed in Table1. Adding these comparisons, the estimation error applied by AR (Autoregressive Model) is listed simultaneously. (The detail is shown in **Appendix 4.**) The reason why AR model is adopted as the comparison with the proposed scheme is that AR model is the dynamic model with single time-series. In another description, the effectiveness by adopting multi-variable method in the proposed scheme is also expected.

From the result of the trend leading, it is discovered that model B has the minimum prediction error. In comparison with the estimation error derived by each model, the error except model B are small uniformly, the auto regulation with the noise valance involved in the Kalman-Filter is active. This fact shows that model B has the large estimation error than any other and model B has better tracing power to the targeted time-series. AR model built by single time-series has the estimation error with equal order to model B, but the prediction error is extremely large. It is verified that this prediction scheme with the Kalman-Filter and self-organized neural network has considerably high efficiency to the prediction. Also, from the result showed in Figure.2, the seasonable pattern by learning with neural network is efficient obviously.

[Table.1. Comparison prediction/estimation error derived by trend leading]

＜Fiscal 1999－2000, most rapidly varying period＞

Model Name	Model A	Model B	Model C	Model D	ＡＲ（２）
Prediction error	0.0311	0.0257	0.1276	0.0720	------
Estimation error	0.0001	0.0020	0.0001	0.0001	0.0241

AR(2): second order AR model with least AIC

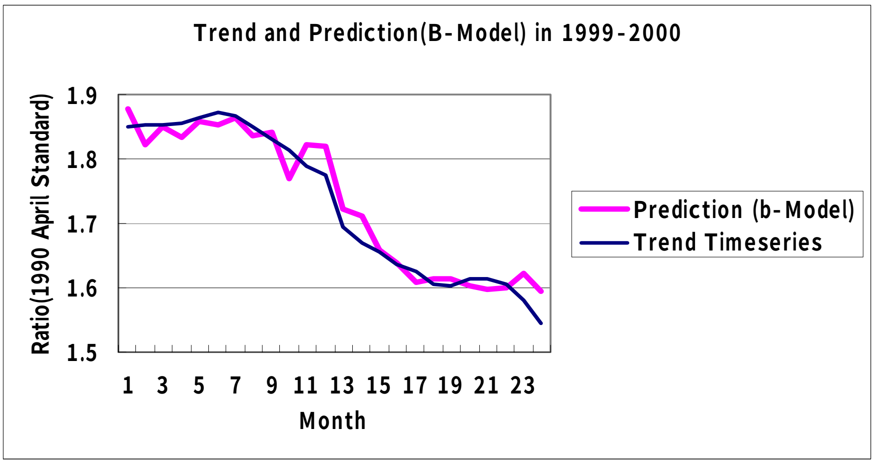
＜Fiscal 1997－1998, most slowly varying period＞

Model Name	Model A	Model B	Model C	Model D	ＡＲ（３）
Prediction error	0.0262	0.0242	0.1076	0.0849	------
Estimation error	0.0001	0.0026	0.0001	0.0001	0.0034

AR(3): third order AR model with least AIC

The prediction time-series of the trend leading derived by model B is showed in Figure.5.

[Figure.5. Prediction value derived model B(Fiscal 1999-2000)]



The following are shown from the results of table.1 and figure.5.

・The prediction scheme using the Kalman-Filter and the learned state space by self-organizing mechanism brings about 2.4 percent (the standard is the demand of 1991 fiscal) error accuracy, and it possess considerably accurate prediction than AR model. And this scheme insures this accuracy to the rapid varying of the original time-series.

・The state space which built with the principal component time-series, exhibits higher effect than with the original variables. The number of the principal components is need to be increased until accumulated proportion reaches the determined standard, but need not to be increased so many over the standard.

3.2. Evaluation to synthesized prediction

The error of the synthesized prediction is listed as Table.2, as well as the case of the trend leading prediction. The synthesizing process is the multiplication the predicted trend leading time-series with the predicted monthly pattern. Namely, this is the inverse process which separates the trend leading time-series from the original time-series.

[Table.2. Comparison prediction / estimation error derived by synthesized series]

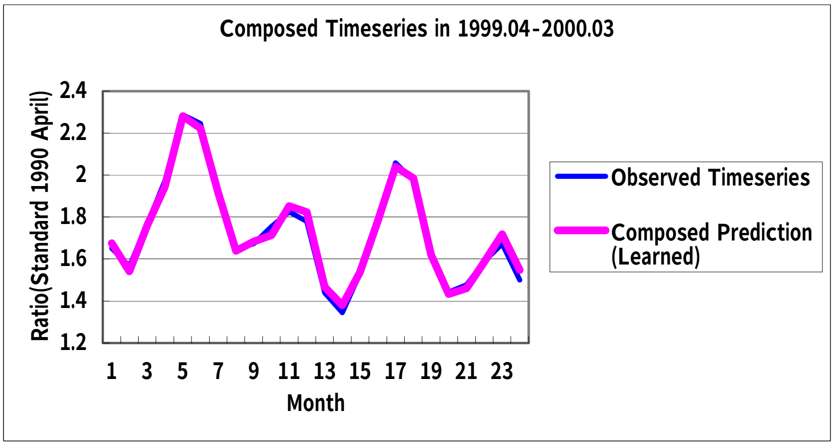
＜Fiscal 1999－2000＞

Model Name	Model A	Model B	Model C	Model D
Prediction Error （learned pattern）	0.0784	0.0629	0.1625	0.0838
Estimation Error(average Pattern)	0.0833	0.0790	0.1687	0.0946

The “learned pattern” is gained by taking in seasonable monthly pattern to the learned neural network. The number of the elements in the input/output layers is twelve. The intermediate layer is one, and the number of its elements is the quarter of the number in the input/output layer's elements. The "average pattern" is gained by averaging them over the same period which is the learning.

In Figure.6 as shown below, the prediction time-series of the synthesized time-series with the trend leading derived by model B and the learned pattern is shown.

[Figure.6. The synthesized prediction time-series (Fiscal 1999-2000) using learned pattern]



The following are proved from the results of Table.2 and Figure.6.

- The learning of the seasonable monthly pattern contributes to total accuracy of the prediction time-series. The error accuracy of the synthesized prediction time-series possesses about 5-6% (the standard is the demand of 1991 fiscal) and is also considered to show considerable accuracy.
- In comparison with the trend leading time-series, the prediction accuracy of synthesized time-series is lower considerably. This problem can be caused by the less accurate prediction of the seasonable variation pattern than the trend leading.

4. Conclusion and discussion

Until now, we tried to investigate the scheme of the demand prediction, which had the time-varying state space by the learning of neural network and proved that this approach gave better accuracy than auto-regressive method, etc. Here, we tried to build the state space by the principal components in place of the original variables and also tried to change from the state-space built by the multi-variables with correlation each other, to the state space built by fewer independent multi-variables. It is proved that the common variance extracted by the principal component analysis is effective considerably. Considering the extracted principal components are represented as the independent business movements, the state space is composed by fewer variables than the original variables. Summing up these points, this scheme is represented as follows.

- The proposed scheme based on the framework of the multi variable and dynamic prediction supplies considerable accurate prediction and this prediction mechanism is considered to contribute to the decision-making support.
- The adoption of the principal components time-series can extract common and independent variables and the extracted principal components are gained from the accumulated data. Therefore, this approach has a Data-Mining like character.
- The prediction accuracy is considerably lower in the synthesized time-series than in the trend leading time-series. It can be needed that the seasonable monthly pattern must be predicted with high accuracy.

At last point, as well as the method which realizes to give high accuracy of the seasonable monthly pattern, the separating and synthesizing methods between the trend leading time-series and the seasonable pattern shall be the core theme of these approach. [16]

Appendix 1. Kalman-Filter

The Kalman-Filter is the rational, sequential and real-time estimation/prediction processing scheme based on linear system theory.

The basic formulas of the Kalman-Filter are presented by the state vector and the measurement vector. [1,3,14]

$$x_{k+1} = \Phi_{k+1,k} x_k + v_k \tag{1}$$

$$y_k = H_k x_k + w_k \tag{2}$$

Here,

x_k : state vector $\Phi_{k+1,k}$: state transition matrix

v_k : state noise vector

y_k : measurement vector H_k : measurement matrix

w_k : measurement noise vector

k represents each time. The state noise and measurement noise are independent each other. And they are assumed to be white noises which are non-correlative at each time. Generally in processing the Kalman-Filter, the direct solution of state equation and measurement equations is not used but the sequential algorithm which updates error covariance matrix of state noise at each observation cycle, is adopted.

Appendix 2. Principal Component Analysis

Principal Component Analysis integrates from multi variables with correlates each other to independent multi components. The application PCA to time-series data is described as follows.

At any time, the j-th component is presented as [7]

$$p_j = \Sigma_{l=1}^{N} f_{jl} x_l \qquad (3)$$

Here, $\{x_l\}$ is l-th time-series,

index of the principal components : $j = 1,2,....,M$

index of the original variables : $l = 1,2,...., N$

and

$$\Sigma_{l=1}^{N} f_{jl}^2 = 1 \qquad (4)$$

$$\Sigma_{l=1}^{N} f_{il} f_{jl} = 0 \quad (i \neq j) \qquad (5)$$

M is determined by the proportion of the accumulated eigenvalue, which occupies generally about 80-90 percent. The principal components are selected in the order of high to low eigenvalue. f_{jl} is a component corresponding to an eigenvalue, f_j is obtained as the linear combination of them. f_{jl} is determined at each time (with constant time period), as shown by formula (3), the time-series of the principal component $\{p_j\}$ can be generated over the entire period.

Generally, M is far small than N ,$\{ p_j : j = 1,2,...., M \}$ is considered to present the common variances of the original variables. Considering the independence of each component to the other components, the time-series of the principal component is assumed also to be independent.

Appendix 3. The relation formula of each components

The relation formulas of $p_{1,k}$, $p_{2,k}$, $p_{3,k}$ between k and $(k-1)$ are follows.

$$p_{1,k} = - 0.0095 + 1.0155\, p_{1,k-1} \qquad (6)$$

$$p_{2,k} = 0.1431 + 0.9208\, p_{2,k-1} \qquad (7)$$

$$p_{3,k} = 0.2926 + 0.6571\, p_{3,k-1} \qquad (8)$$

For each model, the relation formulas of $\{x_5\}$ between k and $(k-1)$ are as follows.

Model A: $x_{5,k} = 0.0159 + 0.0407\, p_{1,k-1} + 0.9607\, x_{5,k-1}$ (9)

Model B: $x_{5,k} = - 0.0159 + 0.2221\, p_{1,k-1} + 0.0616\, p_{2,k-1} + 0.7670\, x_{5,k-1}$ (10)

Model C: $x_{5,k} = 0.0051 - 0.4072\, p_{1,k-1} - 0.1929\, p_{2,k-1} + 0.1517\, p_{3,k-1}$

$$+ 1.4715\, x_{5,k-1} \qquad (11)$$

$$\text{Model D:}\quad x_{5,k} = 0.0245 + 0.0319\, x_{1,k-1} - 0.0782\, x_{2,k-1} + 0.0175\, x_{3,k-1}$$

$$- 0.0003\, x_{4,k-1} + 1.0024\, x_{5,k-1} \qquad (12)$$

Appendix 4. Comparison with AR model

This model is autoregressive model with a single time-series (domestic electric power demand time-series only). To apply AR model, the applied time-series must be made into stationary time-series, this process fits the curve to original time-series, subtracts it from original time-series in 10 years (fiscal 1991-2000) and the residual time-series is generated. The residual time-series is stationary and can be applied by autoregressive approach. The optimal AIC (Akaike's Information Criteria) order is 2 in 1991-2000 and 3 in 1991-1998.

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