AN INTRODUCTION TO LOCAL OPERATIONAL USE OF NWP PRODUCTS

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ABSTRACT

Owing to the fact that the background situation about local operational use of NWP products at the stations under provincial ones in China is different from that of developed countries, a suitable approach is suggested to improve the interpretation techniques of NWP products, which includes predictor analysis and selection, combination of different NWP products, synthetic statistical method(SSM), auto-adjustment of MOS equations to numerical model and developing a suitable software of objective weather forceast system on microcompute etc. This approach proves to be effective after more than three years' practice.

I. INTRODUCTION

The interpretation techniques of numerical weather prediction (NWP) products had reached a high level by the late seventies. The local interpretation techniques have also succeeded in forecasting precipitation type and surface wind in the developed countries since Local AFOS MOS Program (LAMP) was suggested by Ghlan (1980). But either PPM (perfect prognosis method) or MOS or LAMP is run only at regional and national meteorological centers (RMCs or NMCs) preparing NWP or meteorological stations where plenty of NWP products can be received through high-speed telecommunication lines. For stations under prorincial ones in China without the above-mentioned conditions they have to try to use the analyses and prediction products from the National Meteorological Center (BMC)[1)] and JMA in facsimile charts and from ECMWF in grid-point values. Thus, the background of local interpretation of NWP products in the stations under provincial ones in China is different from that of developed countries in the following aspects: (1) poor capacity and less accuracy of products of numerical model from facsimile charts; (2) lack of potential predictors chosen from less items of the products available; (3) decreasing in the forecast accuracy of MOS equation caused by the frequent changes of NWP model in NMCs and RMCs; (4) lack of objective forecast guidance.

In view of the above-mentioned facts, we cannot imitate indiscriminately the interpretation techniques and methods developed in foreign countries. Attention must be paid to developing a feasible and effective approach for the local operational use of NWP products in China. The approach is suggested as follows.

II. ANALYSIS AND SELECTION OF PREDICTORS

Due to the disadvantageous conditions aforesaid, predictor analysis and selection are

1) BMC did not transmit its NWP products in grid point values until September 1985.

the important steps, for the whole process of the local operational use of NWP products. The methods can be used here as follows.

1. *Using Multivariable Analysis Methods to Extract Meteorological Field Information and Remedy Degenerated Predictors*

Factor analysis method, a branch of multivariable analysis, is introduced to extract the information of a meteorological field to remove the random noise brought about by the poor accuracy of the products on facsimile charts. It is proved that the longer the valid period is, the more superiority the method has. Contained in it are the Four methods.

(1) *Empirical orthogonal function (EOF) method*

EOF is used here to collect the main components which are orthonormalized. And each of them consists of a part of the whole field information. The variance of the field can be explained by a few main components which are used as predictors to make forecast equations. Because of the orthogonality, the main components can be drawn one by one, and it is not necessarily to recalculate the regression coefficients of those components which have been drawn in the equations. On the average, the T-score of them is about 4.5 greater than that by the equations made of some single predictors (with % omitted, similarly hereinafter), especially about 9.8 greater for 168 and 192 h forecasts.[2)]

(2) *Canonical correlation analysis method*

This mehod is used to study the correlationship between two variable groups. Let one group be a predictand and the other be a forecast field, such as 500 hPa geopotential height, 850 hPa temperature, 700 hPa vorticity etc. Thus a few canonical variables with greater canonical correlation coefficients represent the main correlation between the predictand and the forecast field. Furthermore, the distribution of weights in the expression of canonical variable apparently implies the synoptic significance. After analysing some forecast fields for the same predictand with this method, we can obtain several canonical variables which have passed the confidence test. They are used to derive forecast equations. It is found that in the nine forecast equations established by this method their T-scores are 9. 1 higher than the operational ones.

(3) *Corresponding analysis method*

Utilizing the antithetic property of sample space and variable space the corresponding analysis method is able to consider the predictors and the sample points of the predictand on a same factor loading plane. In the light of their distribution, the predictors, which are close to some category sample set of the predictand, are selected to derive the forecast equations. Compared with the equation constructed by step-wise screening method, the corresponding analysis increases accuracy by 3.7 on the average, especially by 9.9 for 144 h and 168 h forecasts.

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2) In this paper, all results except for those specified, are the average T-score of the operational precipitation occurrence prediction (POP) (1—7 days) in 1984—1986 in Suzhou Meteorological Observatory, Jiangsu Province.

(4) *Ridge regression method*

Because of the collinear property among predictors, sometimes predictors with good synoptic significance cannot all be drawn into same forecast equation by linear regression method, such as step-wise screening regression method. For example, with regards to two predictors representing the upper-air eddy and corresponding surface cyclone respectively, usually only one of them is possibly drawn into the equation. Though the other can be picked up by decreasing the test of confidence, this will make the estimated regression coefficient unstable. By adding a small value K to the diagonal elements of the predictor covariance matrix, ridge regression method can prevent the matrix from degenerating. Thus, the ridge regression coefficient can be written as follows:

$$\hat{\beta}(K)=(X^TX+KI)^{-1}X^TY,$$

where X is the sample matrix of predictors, Y is sample vector of the predictand. Obviously the curve of $\hat{\beta}(K)$ called ridge trace can be obtained when K varies. The ridge trace of predictors in the 120 h forecast equation of POP in June and July is shown in Fig. 1. Owing to the collinear property between x_3 and x_5, $\hat{\beta}(0)$ of x_5 is very small and can be eliminated when x_3 is drawn into the equation. It is evident all the ridge traces become stable at $K=0.1$ and $\hat{\beta}$ (0.1) of x_5 increases apparently. Thus, the ridge regression equation includes x_2, x_3, x_5 x_7 and its T-score is 5.4 higher than that derived by linear regression method.

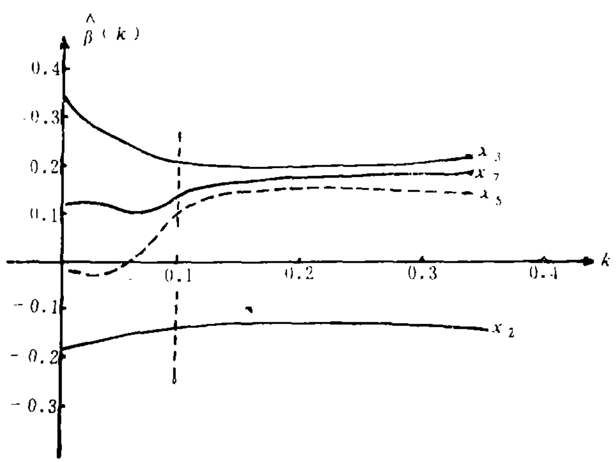

Fig. 1. The ridge traces of predictors in the 120 h forecast equation of POP in June and July.

2. *Physical Method*

Physical method, which refers to the use of NWP products based on the analysis of physical cause of weather process formation, will strengthen the physical basis of the interpretation work. For example, the synoptic and dynamic analysis methods of large-scale disturbance resolution in wavenumber are applied to the local operational use of medium-range products and satisfactory results are found as follows.

(1) According to the prevailing wavenumber from spectrum analysis, the dependent samples are classified to prepare forecast equations. The T-score of these equations is 62.3

on the average while 53.0 for the equations derived from the whole samples.

(2) The study of the dynamic analysis of the large-scale disturbance in wave-domain has shown that the transfer of angular momentum and its divergence, energy variation and the nonlinear wave interaction are close related with the medium-range variation of general circulation. By taking some harmonic waves, which make greater contribution to the occurrence and development of the medium-range weather process, the aforecited physical quantities are calculated from ECMWF grid point products to compose the forecast equations. The T-score of 96 h and 120 h forecasts of POP in June and July is 69.8 and 62.9 on the average, respectively. The results are better than 60.3 and 58.7 of the corresponding operational forecast.

(3) Based on physical relationship, more predictors for MOS are derived from the limited NWP products available to improve the accuracy of MOS equation. For instance, although only 500 hPa height and sea surface pressure of ECMWF grid point products are availabe, 1000 hPa height, thickness of 500/1000 hPa, geostrophic wind and vorticity are calculated as potential predictors.

III. COMPARISON AND COMBINATION OF THE PRODUCTS FROM DIFFERENT NUMERICAL MODELS

For local stations under provincial ones in China, three kinds of NWP products are available as described in the introduction of this paper. Using perfect prognosis method (PPM) to the above mentioned three kinds of numerical model outputs, their forecasting abilities on the operational local weather forecast are evaluated objectively. This enables forecasters to apply PPM equations with the best numerical model output for various seasons. As shown in Tables 1 and 2, for instance, whether in spring or in summer the ECMWF products are the best.

Table 1. Average T-score of POP of June and July

Models	48h	72h	96h	120h
JMA	72.9	62.3	60.0	50.0
ECMWF	76.5	74.3	78.9	57.7
Model B	72.7	63.6		

Table 2. Average T-score of POP from March to May

Models	72h	96h	120h	144h	168h
JMA	59.9	33.0	57.0	50.1	67.2
ECMWF	61.3	61.7	61.1		

Because of the limitation of products, the information provided by them must be utilized as far as possible. The three kinds of numerical model outputs include different products and the different products provide distinct forecasting information. Thus the predictors selected from different numerical models on different levels are combined to derive forecast equations so as to supplement the shortage of information from just one numerical model. For example, combining the 48 h prediction of 500 hPa geopotential height produced by model B with the 48 h prediction of rainfall and the 72 h prediction of surface pressure for 72 hours provided by JMA model, the 72 h forecast equation of the probability of precipitation occurrence is derived. Comparisons are made between this equation and those derived from the products produced by single model from March to May as shown in Table3. It is found that the T-score of the former, as compared with the latter is raised by 4.3 to 5.8.

Table 3. Average T-score of POP of the Three Equations Derived by the Products from B, JMA and B+JMA Models

Year	B	JMA	B+JMA
1983	61.0	60.6	64.4
1984	57.1	62.3	65.8
1985	61.3	60.9	66.5
Average	59.8	61.3	65.6

IV. SYNTHETIC STATISTICAL METHOD (SSM) USED IN THE INTERPRETATION OF NWP PRODUCTS

In local operational use of NWP products, PPM has been compared with MOS by using the same predictors and statistical methods. With the constant improvement of numerical models during the past three years of 1982 to 1984, PPM proved as effective as MOS shown in Table 4. As for the principles of statistical method, PPM utilizes the long historical data to specify local weather from their concurrent (or nearly concurrent) weighted combinations of meteorological parameters. Consequently, the derived equations are stable as compared with MOS. However the bias and inaccuracy of numerical model products will inevitably produce corresponding errors in the statistical forecast. On the other hand, even though the archiving output data from numerical model is not long enough, the bias and inaccuracy of the numerical model, as well as the local climatology, are automatically built into MOS forecast system. Therefore, the combination of PPM and MOS is implemented by two ways to make up deficiencies mutaully. Firstly the PPM forecast result is offered as the sole predictor to MOS procedure. It will not only correct the bias of the predictors, but also remedy the insufficiency of MOS information. So it is called the corrected MOS (CMOS). Secondly, the predictor value from current NWP output is corrected by autoregression method (AR) or the group method of data handling (GMDH) before it is substituted to the PPM equation (Zhu, 1986). Then it is called the corrected PP (CPP). What is more, besides some data observed after the initial time of NWP, according to forecaster's experience some time-lag predictors for valid period more than 24 h, which are effective in practice, are also introduced into the CMOS and CPP equations.

It is evident that the first five methods in Table 5 are special cases of SSM. In order to illustrate it more clearly, the SSM system is shown in Fig. 2. Table 6 shows the average T-score of six methods of PPM, MOS, CMOS, CPP, SSM (1) and SSM (2). It is indicated that the SSM system, which often gets better T-score than other methods, is appropriate for preparing forecasts within 7 days.

Table 4. Average T-score of MOS and PPM

Methods	24h	48h	72h	96h	120h	144h	168h	average
MOS	69.0	73.3	61.8	62.1	59.2	60.7	48.7	62.1
PPM	73.4	63.8	62.2	65.1	61.8	53.3	57.5	62.4

Table 5. Function Expressions of SSM

Acronym	Developed Equations	Applied Equations
CS	$\hat{Y}_t = f_1(X_0)$	$\hat{Y}_t = f_1(X_0)$
PPM	$\hat{Y}_t = f_2(X_t)$	$\hat{Y}_t = f_2(\hat{X}_t)$
MOS	$\hat{Y}_t = f_3(\hat{X}_t)$	$\hat{Y}_t = f_3(\hat{X}_t)$
CMOS	$\hat{Y}_t = f_4[f_2(\hat{X}_t), \hat{X}_t]$	$\hat{Y}_t = f_4[f_2(\hat{X}_t), \hat{X}_t]$
CPP	$\hat{Y}_t = f_2(X_t), \tilde{X}_t = f_5(\hat{X}_t)$	$\hat{Y}_t = f_2[f_5(\hat{X}_t)]$
SSM(1)	$\hat{Y}_t = f_6[X_0, f_2(\hat{X}_t), \hat{X}_t]$	$\hat{Y}_t = f_6[X_0, f_2(\hat{X}_t), \hat{X}_t]$
SSM(2)	$\hat{Y}_t = f_7(X_0, X_t), \tilde{X}_t = f_5(\hat{X}_t)$	$\hat{Y}_t = f_7[X_0, f_5(\hat{X}_t)]$

*$\hat{Y}_t$ stands for the estimators predicted, X_0 time-lag predictors, X_t simultaneously observed predictors, $\hat{X}_t$ predictors of NWP products, $\tilde{X}_t$ the corrected $\hat{X}_t$.

Table 6. Average T-scores of MOS, PPM, CMOS, CPP, SSM(1) and SSM(2)

Valid Period	MOS	PPM	CMOS	CPP	SSM(1)	SSM(2)
24	69.0	73.4	67.2	78.4	75.5	80.4
48	73.3	63.8	76.1	78.3	71.4	78.2
72	61.8	62.2	65.9	66.7	63.9	67.3
96	62.8	61.5	64.0	65.3	65.2	67.1
120	60.4	60.7	62.8	63.3	62.5	65.0
144	61.9	62.5	63.4	62.9	63.4	66.8
168	50.3	59.3	58.4	60.0	59.0	57.2

V. AUTOMATIC ADJUSTMENT OF MOS EQUATIONS TO THE NUMERICAL MODEL

Because of the differences of error characteristics, use of the new model may decrease the MOS skill without redevelopment. For stations under provincial ones in China, it is impossible to re-derive the MOS equations from archiving outputs of new numerical model in time, so the impact due to the model changes cannot be ignored. Our attention must be paid to the research of the automatic adjustment of MOS equations to the numerical model.

Three statistical methods with the ability of automatic adjustment are used: (1) Logit regression model with recursive algorithm (LRR) (Brelsford,1968), (2) increasing memory model of linear regression (IMMR), and (3) limited memory model of linear regression (LMMR).

For comparison, regression estimation of event probability (REEP) procedure is also introduced in the experiment. Equations of probability forecasts for three ranked categories

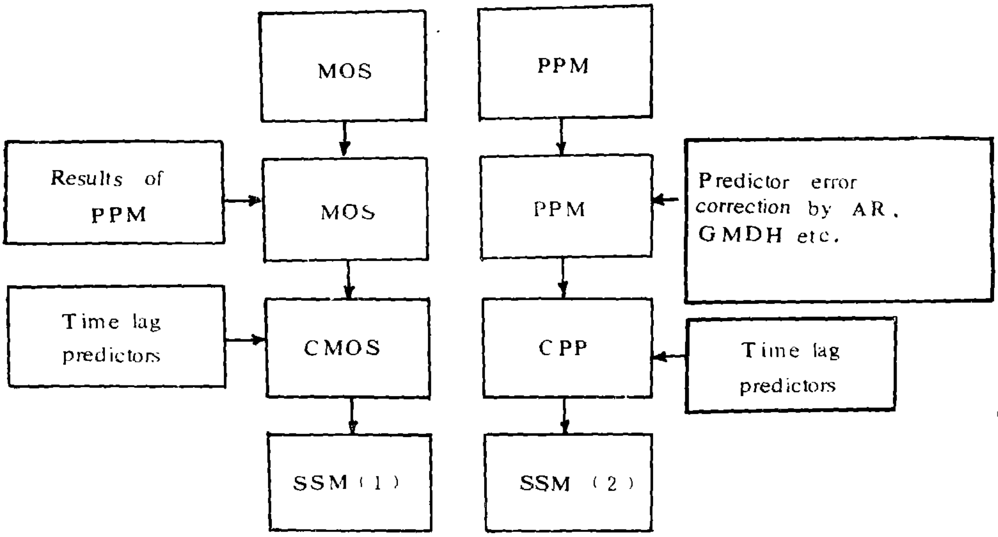

Fig. 2. SSM system.

of precipitation amounts are derived from the archiving outputs of JMA's NH-8L and 12L-HSM models (JMA changed her operational model on March lst, 1983) respectively and are operationally used for three years. Table 7 shows that three methods get the better results and their automatic adjustment ability is proven. Among them LRR and IMMR prove to be much more effective. Furthermore, such a conclusion can be reached that no matter which period is the valid time and which method is used, the T-score of the equations derived from the output of the same model is better than the other. This gives us a proof that the numerical model changes must result in lowering the accuracy of MOS equations.

Table 7. Average T-score of Probability Forecast of Three Ranked Categories of Precipitation Amounts

Methods	36h		96h		120h		144h	
	NH-8L	12L-HSM	NH-8L	12L-HSM	NH-8L	12L-HSM	NH-8L	12L-HSM
LRR	73.2	75.4	68.5	71.3	63.4	65.8	61.3	64.1
IMMR	71.3	72.6	66.3	70.8	62.9	64.8	59.1	59.9
LMMR	67.6	69.6	61.7	63.6	53.2	60.4	51.8	52.9
REEP	64.6	66.8	58.7	59.2	50.3	53.8	48.2	52.3

Since what we are interested in is the accuracy of probability forecasts of ranked categories, the ranked probability score (Epstain, 1969)

$$RPS_f=\frac{3}{2}-\frac{1}{2(k-1)}\sum_{i=1}^{k}\left[\left(\sum_{n=1}^{i}P_n\right)^2+\left(\sum_{n=i+1}^{k}P_n\right)^2\right]-\frac{1}{k-1}\sum_{i=1}^{k}|i-j|\cdot P_i$$

used here as the basic measure of accuracy and the skill score

$$SS=\frac{\overline{RPS_f}-\overline{RPS_c}}{\overline{RPS_c}}\times 100\,\%$$

are expressed in Table 8. Here $P_1, P_2, \ldots, P_k$($k=3$ in this paper), is the probability of k possible categories of precipitation amounts, j is the category of precipitation amounts which actually occurs. And $\overline{RPS_f}$ is the average RPS for forecast, while $\overline{RPS_c}$ the average RPS for climatology on the basis of historical precipitation data of 20 years. Table 8 indicates the same results as shown in Table 7.

Table 8. $\overline{RPS_f}$ and SS of Four Methods

Methods	$\overline{RPS_f}$ and SS	36h		96h		120h		144h	
		NH-8L	12L-HSM	NH-8L	12L-HSM	NH-8L	12L-HSM	NH-8L	12L-HSM
LRR	$\overline{RPS_f}$	0.8821	0.9160	0.8424	0.8775	0.8648	0.8648	0.7578	0.8420
	SS	25	26	23	24	22	22	17	19
IMMR	$\overline{RPS_f}$	0.8142	0.8482	0.7722	0.8073	0.7896	0.6768	0.7999	0.8420
	SS	23	24	21	22	20	17	18	19
LMMR	$\overline{RPS_f}$	0.5767	0.6445	0.5616	0.6318	0.6392	0.5640	0.6315	0.7157
	SS	16	18	15	17	16	14	14	16
REEP	$\overline{RPS_f}$	0.5089	0.5767	0.5616	0.6669	0.5640	0.6016	0.5052	0.6736
	SS	14	16	15	18	14	15	11	15

The verification of four methods for several valid periods indicates that LRR and IMMR have better ability of automatic adjustment. In order to find out which has quicker response, the changes of the category differences between forecast and observation is investigated with the increase of recurrence times. It is found from Figs. 3 and 4 that two lines of LRR reach in coincidence after more than 20 times recurrence calculation, while about 30 times for IMMR.

Thus both the investigation of the accuracy and the response speed of automatic adjustment show that LRR is one of the best methods, especially when the numerical model is changed frequently.

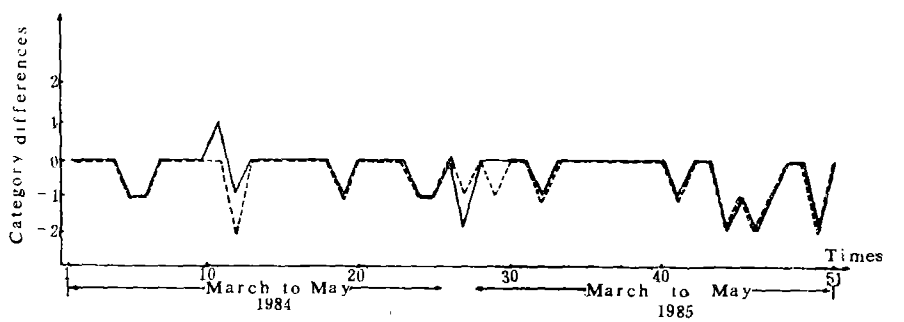

Fig. 3. The changes of the category differences between the observation and 96 h forecasting equations based on the archiving data of 12L-HSM (solid line) and NH-8L (dashed line) for LRR.

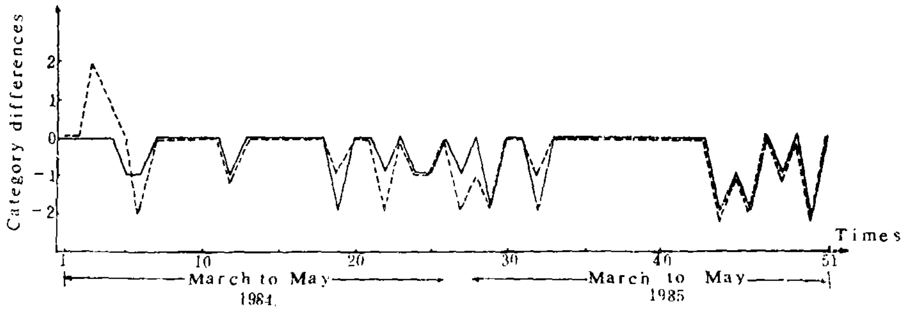

Fig. 4. As in Fig. 3, except for IMMR.

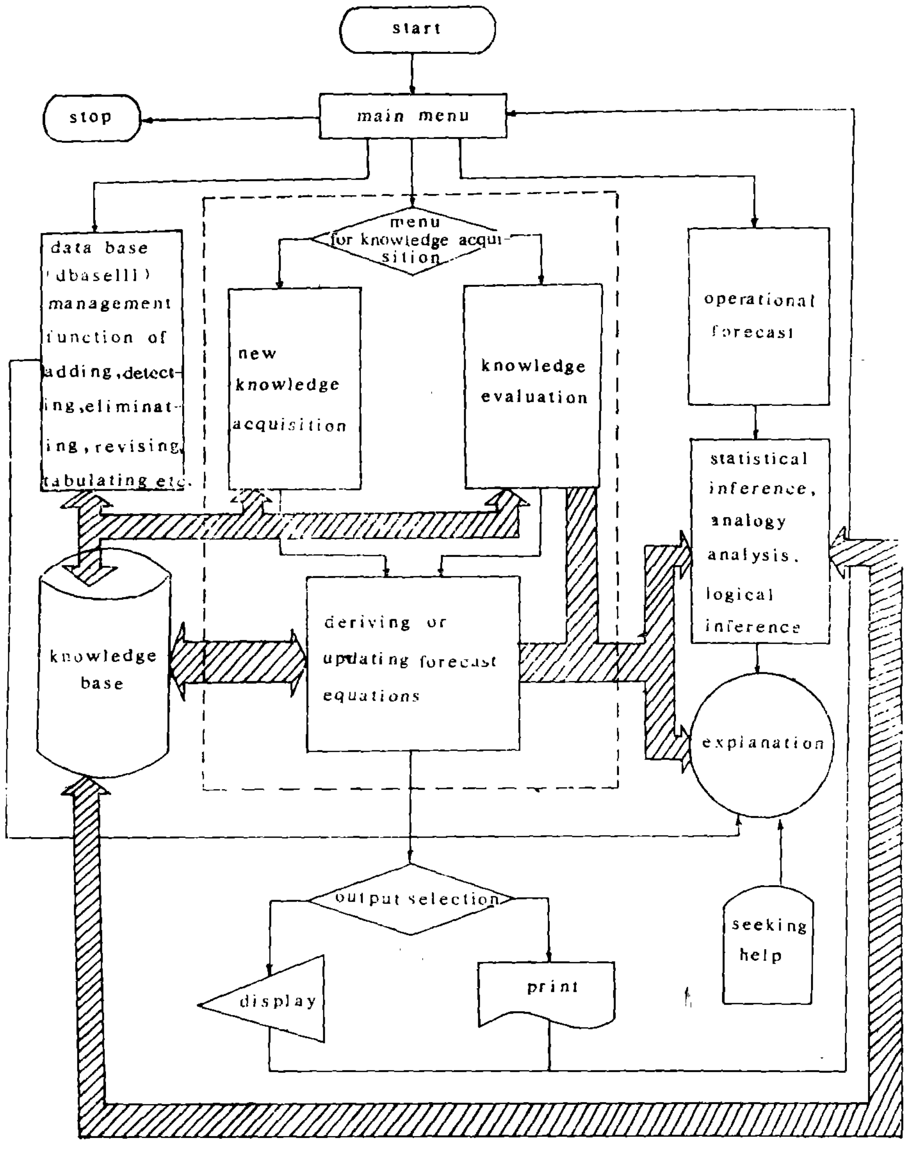

Fig. 5. The objective weather forecast system.

VI. DEVELOPING OBJECTIVE WEATHER FORECAST SYSTEM ON MICROCOMPUTER

In order to make the approach aforecited in operational use, it is necessary to design a suitable application software package on microcomputer, which is not expensive and can be afforded by the stations. Based on the technique of data base dbase-III, we introduce the principle of artificial intelligence, such as inference engine, the function of explanation and knowledge acquisition, etc., to complete the objective weather forecast system (OWFS) (Re, 1986). As shown in Fig. 5, OWFS is composed of three function blocks, each of which includes several subfunction blocks. They are shown as follows.

1. *The Function Block of Base Management*

Using dbase-III management function, under a batch order by means of multistage submenu tree, the function of adding, eliminating, detecting, revising and tabulating are carried out for the bases of NWP products, observed data, forecast equations and processed predictors. And the exchange and share of data between dbase-III and programme of advanced algorithmic language are also realized.

2. *The Function Block of Knowledge Acquisition*

This block can objectively evaluate the knowledge already stored in the system and update it. For instance, instead of the degenerated forecast equations, new equations with satisfactory accuracy are led into the system.

3. *The Function Block of Forecast Application*

The block can automatically select the essential data for preparing forecast from knowledge base. Then several forecast results are inferred by the function of inference sub-block to determine the equations which have better accuracy in recent period and to get the final forecast with explanation. According to predictor selection and forecast methods, the block also works with the operations of detecting, revising, adding, tabulating etc. Finally, the forecast conclusion and its explanation are given in two ways, displaying on the screen and hard copy.

VII. CONCLUSION

OWFS has been operationally run on microcomputer IBM PC-XT to prepare POP, the probability of categories of precipitation amounts and maximum, minimum and daily mean temperature for three years. Table 9 shows the average T-score of POP for forecast time shorter than 2,3,4,5,6 and 7 days from 1984 to 1986 and its increments relative to historical average accuracy of traditional methods, which is 60.9 for forecast time shorter than 2 days and 50.4 for 3 days. Because there is no historical average T-score for more than 3-day forecast, the increments of 4 to 7 days are relative to the historical average 50.4.

Though the period of operational use is not long enough to get rid of some fortuity attached more or less, all above-mentioned results have passed the test by a confidence of 0.05. Therefore this approach can guarantee higher T-score than traditional methods and improve the accuracy of daily operational weather forecasts, especially forecasts from 3 to 6 days. This effectiveness promises a broad prospect for local operational use of NWP

Table 9. Average T-score of POP Forecast by OWFS and Its Increments Relative to Historical Average T-score

Items	Forecast Time in Days					
	≤2	3	4	5	6	7
T-score	62.1	57.0	57.8	56.9	53.9	50.8
Increment	1.2	6.6	7.4	6.5	3.5	0.4

products.

Since many developing countries have similar background in the field of NWP product interpretation. Hopefully, the approach and the results introduced in the paper will be feasible and effective in improving the work in these countries. It is also wished that this paper will be of use for other countries in improving their operational use of NWP products and weather forecasting service.

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