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Expert-Statistical Processing of Data and the Method of Analogs in Solution of Applied Problems in Control Theory

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Abstract: The paper provides an outline of the expert-statistical approach to developing control and identification systems. An expert-statistical method of data processing designed for forecasting short time series is discussed in detail. New adaptive algorithms for inventory control are described. The usage of these algorithms in applied expert-statistical systems to support decision making process is discussed.

1. INTRODUCTION

In the mid 1990s in the Institute of Control Sciences RAS (ICS) a tool for integration of heterogeneous information within the same control system referred to as expert-statistical methods (ESM) for data processing was proposed (Mandel', 1996, 1997). Main applications of the new tool have been made to social-economic systems and organization control systems. In 2006 the ESM applications also included problems of control and identification of technological processes and engineering objects (Mandel', 2006).

A brief introduction of the expert-statistical approach to data processing and expert-statistical control systems is given. The ESM of analogs first described in (Belyakov *et al*, 2002a) and its potential applications to the solution of identification and control problems are discussed.

New adaptive inventory control algorithms are suggested as a basic model within the applied expert-statistical inventory control system.

2. EXPERT-STATISTICAL APPROACH TO DATA PROCESSING

2.1. Background

Block-diagram of the expert-statistical system (ESS) is given in Fig. 1

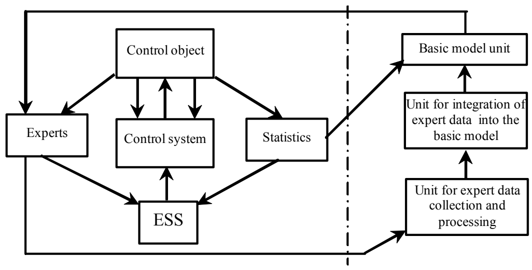

Fig. 1. Block-diagram of the ESS.

The ESS consists of three main units: basic model unit, unit of collecting and processing of expert information, and unit for integration of expert data into the basic model. For various and many examples of application of ESS to the solution of problems of organization control, inventory control and marketing see (Mandel', 1996, 1997, 2006). Of a particular interest is the unit for integration of expert data into the basic model. It is the structure and the algorithmic content of this unit that predetermine a possibility of the successful solution of the respective control problem. In the subsection below we will briefly discuss the structure of this unit.

2.2. Unit for integration of the expert data into the basic model

The unit of integration of expert data into the basic model contains a set of procedures (techniques of interviewing, questionnaire surveys, etc.) for extracting expert knowledge and generating thereby a sort of expert system (ES). In most cases, however, in contrast to the conventional systems using knowledge, the ES in the ESS are as a rule much more straightforward. The point is that ESS are developed for the control objects with regard to which one can be quite certain that a priori and a posteriori information available to the designers and users on the ways of their functioning and characteristics is sufficient for developing a "nearly" complete model of the system described. The criterion of objective data being "almost sufficient" (it can well be illusory) is the smallness of the residual dispersion for a preliminary "sketchy" model of the system which is formed at the stage of the preliminary survey using a priori data.

Regrettably, numerous attempts failed to obtain accurate estimates of the residual dispersion or similar characteristics which would strictly verify us being in the domain where expert-statistical approach is applicable. Obviously with small values of the residual dispersion one can most likely choose between conventional methods of statistical identification and ESM. Moreover, with the growing residual dispersion one has to decide on the borderline between the expert-statistical approach and the purely expert methods which would eventually end up in ES.

The conditionality of any "strict" conclusions stems from the fact that even with small values of residual dispersion (obtained in the learning sample!) there are no guarantees that a decision maker (DM) would carry out the recommendations based on the identified model. This failure to obey may mask both a mistake of DM, or lack of confidence, or his belief in the sample being not statistically representative (does not contain information on all "modes" of functioning of the object described).

A bright illustration of the above is the situation with computerization of complex processes in such fields as chemistry, petrochemistry, petroleum processing and many others (see, for instance, (Dozortcev *et al*, 2003; Kasavin, 1972). In this case classical successful attempts of automation and the preceding identification stages boil down to application of two basic approaches.

The former relies on obtaining a set of complex nonlinear static models using the piecewise approximation technique (Kasavin, 1972). This approach can be used for an easy modeling of the multimode objects not at all reflecting their dynamics.

The latter approach (which, among other things, is also used for developing simulators (Dozortcev *et al*, 2003)) uses the description of the process via a set of local physical-chemical model with the subsequent their integration into a global model respecting the geometry and physical-mechanical properties of transportation tools connecting local processes. At first, this approach compared to the former one seems to be more adequate to the real process, however, it does not handle the multimodality feature equally well. To make it more adequate the simulation experiments are done for the process involved with the subsequent presentation of the simulation results to the process engineers. Having studied the simulation results the process engineers provide their comments telling how in their expert opinion the process should have behaved in the respective situations. Their recommendations are presented as a sort of the ES which substitutes the created set of physical-chemical and physical-mechanical models in the critical situations identified by expert process engineers. As an alternative (or addition) to the above approaches one can use the expert-statistical approach.

3.2. An example of application

Consider the above arguments applied to the latest version of the expert-statistical inventory control system ADAPIN ("ADAPtive INventories"), the first version of the ESS ADAPIN was described in Borzenko *et al.*, 1990. ESS ADAPIN is designed to study the pattern of change in the demand for commodities, estimate the stock-out probability, and forecast requests for replenishing the stock. Order sizes generated by the ADAPIN system make it possible to meet the service requirements specified by the user.

An obvious mechanism for inventory control in the context of stochastic behavior and intrinsic uncertainty of the demand statistics is offered by adaptive control schemes. To solve the inventory planning (scheduling) problem, which means, generate scheduled requests for the whole period of planning (a year, a quarter, a month) at the level of a major warehouse one may use the following adaptive algorithm (Lototsky *et al*, 1987):

$$\hat{\mathbf{x}}_{n+1} = \mathbf{x}_n - \mathbf{G}_n(\mathbf{p}_n - \mathbf{r}_0), \tag{1}$$

where $\hat{\mathbf{x}}_{n+1}$ is a planned value of the carryover stock at the beginning of the next planning period, $\mathbf{x}_n$ is a real value of the initial stock vector in the previous planning period, $\mathbf{p}_n$ is a vector (commodity type-wise) of the stockout probability in the previous period, $\mathbf{r}_0$ is a vector of service levels, while $\mathbf{G}_n$ is a matrix of coefficients at the n-th step which meets conditions:

$$\sum_n \|\mathbf{G}_n\| = \infty, \ \sum_n \|\mathbf{G}_n\|^2 < \infty. \tag{2}$$

For inventory control the ESS ADAPIN uses so-called "myopic", parametric two-level (S, s)-inventory control strategies. In this case adaptive algorithms for recalculation of the strategy parameters can be written as (Lototsky *et al*, 1991):

$$\begin{aligned} S_{t+1} &= S_t[1 - \gamma_t(\text{sgn}(x_t - z_t) - r)], \\ s_{t+1} &= s_t - \gamma'_T(rs_t - s_t \text{sgn}(x_t - z_t) - Q_t(z_t - x_t) + B], \end{aligned} \tag{3}$$

where

$$\text{sgn}(y) = \begin{cases} 1 \text{ if } y \geq 0, \\ 0 \text{ if } y = 0, \\ \text{-1 if } y < 0; \end{cases} \quad Q_t(y) = \begin{cases} 0 \text{ if } y > S_t, y < s_t, \\ y \text{ if } s_t \leq y \leq S_t, \end{cases}$$

x_t is the stock at the t-th step, z_t is demand at the t-th step, r is the service level, B is the parameter which is a function of supply and storage costs, while coefficients $\{\gamma_t\}$ and $\{\gamma'_t\}$ meet the conditions

$$\sum_g \gamma_n = \sum_g \gamma'_n = \infty, \ \sum_n \gamma_n^2 < \infty, \sum_n (\gamma'_n)^2 < \infty.. \tag{4}$$

Let K be a number of steps in the planning period. The ESS ADAPIN uses two models to evaluate components of $\mathbf{p}_n$:

$$\hat{p}_n^{(1)} = 1 - \frac{1}{K} \sum_{k=1}^{K} \frac{(\bar{z} - z_k)^+}{\bar{z}}, \tag{5}$$

where $x^+ = \max(0, x)$, $\bar{z} = K^{-1} \sum_{k=1}^{K} z_k$, and

$$\hat{p}_n^{(2)} = 1 - \frac{1}{K}\sum_{k=1}^{K}\frac{(\bar{z}-x_k)^+}{\bar{z}}\text{sign}(\bar{z}-z_k), \qquad (6)$$

where $\text{sign}(y) = \begin{cases} 1 & \forall y > 0, \\ 0 & \forall y \le 0. \end{cases}$

In the decision making process an expert is provided with the results of statistical processing, whereas decisions made by the expert are treated as feedback in the expert-statistical systems for inventory control. In ESS ADAPIN the user may choose between estimates $\hat{p}_{\rm n}^{(1)}$ and $\hat{p}_{\rm n}^{(2)}$, he also may update the order size for replenishing the stock.

That is to say, if $\hat{x}_{t+1}$ is the stock size recommended by the expert-statistical system for the next step, while the expert-user specifies the order size assuming that the stock should equal

$$\bar{x}_{t+1} = \hat{x}_{t+1} + \Delta x, \qquad (7)$$

then, using data on the expert adjustment Δx, the model parameters, specifically, the coefficients $\{g_t\}$ are updated.

The main adaptive algorithm is a one-dimensional analog of algorithm (1), where the coefficients γ_t are described as

$$\gamma_t = \frac{\mu_t x_t}{\nu_t + t}, \qquad (8)$$

where μ_t and ν_t are parameters which may be a function of time. Now if the expert-made adjustment Δx at the t-th step meets (7), then it follows from (1), (7) and (8) that

$$\Delta x_t = \frac{\mu_t x_t}{\nu_t + t}(p_t - r_o) - \hat{x}_{t+1} + x_t, \qquad (9)$$

which is to be treated as an equation in variables μ_t and ν_t.

It is exactly the equation that is solved in the ADAPIN system when recalculating the parameters μ_t and ν_t, and when the following constraints hold: $\mu^{(0)} \le \mu_t \le \mu^{(1)}$, $\nu^{(0)} \le \nu_t \le \nu^{(1)}$, where $\mu^{(0)}, \mu^{(1)}, \nu^{(0)}, \nu^{(1)} \ge 0$, and $\mu^{(0)} \ne 0$, chosen to meet the convergence requirements (4).

3. METHOD OF ANALOGS IN PREDICTION OF SHORT TIME SERIES

3.1. Background

In a sufficiently general case, the time series can be represented by the sum of three components:

1) systematic component, trend;

2) relatively smooth oscillations about the trend which occur with a greater or lesser regularity (in particular, the seasonal effect);

3) random (called also sometimes "nonsystematic" or "irregular") oscillations.

Traditionally, the statistical methods of time series prediction mostly come to decomposing the observation sequence, predicting each its component, and merging the individual predictions (Box *et al*, 1970). Obviously, statistically reliable prediction of time series is possible (being trust) only if the *prediction base period*, that is, the number of the known values of the time series, is sufficient to draw reliable conclusions about the time profile of each component.

Statistical analysis suggests that in order to take care fully into account all components the prediction base period should contain several hundreds of units. For periods of several tens of units, satisfactory predictions can be constructed only for the time series representable as the sum of the trend, seasonal, and random components. What is more, such models must have a very limited number of parameters. Series made up by the sum of the trend and the random component sometimes may be predicted for even a smaller base period. Finally, for a prediction base period smaller than some calculated value $N_{\min}$, a more or less satisfactory prediction on the basis of observations is impossible at all, and additional data are required. The value of $N_{\min}$ is defined by the desired prediction accuracy, its maximum horizon, trend nature (model), and the random component of the time series. For the given requirements on prediction, we refer to the time series as *short* if its base (observation) period is smaller than $N_{\min}$.

The short time series are representable as the sum of trend and random component. For the short time series, detailed study of the properties of the random component makes no sense because for small base periods the statistical conclusions prove to be insufficiently reliable. However, the random component can not be completely discarded because its value shows the mismatch between the actual values of the time series over the prediction base period and those calculated from the model. The mismatch can be used to specify the prediction based on the experts opinions.

In this case, the decision makers have at their disposal a very limited (firstly often hollow) measurement statistics and can resort to the help of expert or expert team. If the observation sample is limited and its information is too scant for reliable estimation and prediction, then it is advisable to unite all the objective (statistics, measurements) and subjective (expert) information available to the DMs or, stated differently, to make use of the expert-statistical approach (Mandel', 1996, 1997).

3.2. Analog method in the problems of prediction

The analog method proceeds from the assumption that in some knowledge domains the experts try to predict the time series on the basis of their concepts of objects or processes whose prehistory they know well. It is also assumed that the number of these objects or processes is sufficiently great and the attribute space of the objects making up the core of experts professional experience yields to neat or – as it is often the case – fuzzy classification (Bauman *et al*, 1982, 1999; Bauman, 1988). In formal terms, this means that it is possible to construct algorithms (recurrent, in particular) to determine the extremum of the given metric functional

$$D = \sum_i p^{A_i} \chi\left(M^{A_i} / p^{A_i}\right), \quad (10)$$

where χ is a convex function, A_i are the point classes, p^{A_i} are the a priori probabilities of the classes A_i, and M^{A_i} are the first unnormalized moments of the classes A_i. At that, membership in a class, if neat, is established by a characteristic function assuming 1 on the object belonging to the fixed class or 0, otherwise, or by the membership function $h_i(x) : 0 \le h_i(x) \le 1$ with $\sum_{\text{i}} (h_i(x))^2 = 1$, if fuzzy.

This means in fact that the expert experience can be structured in a sense. Generally speaking, however, there is no obvious need for such classification in the object attribute space because the experts are free to manage their experience and the scheme of automatic classification is just a formal model of the space at hand. Nevertheless, as will be seen below, the methods of automatic classification can prove to be very useful for prediction.

Structuring and analysis of their own experience enable the experts to generate for each of the newly presented time series (called below the prediction object, PO) a list of previously observed objects that from their point of view are analogs of the PO. The PO presented to the expert is a segment of a time series of length *N*: *y*(*t*), *t* = 0, 1, 2,… , *N*, (in a special case of no data sample, *N* can be zero). In response to the presented data sample (and/or revealed PO), the expert lists analog objects represented in the prediction system data base by "complete" time series, that is, series of lengths considerably exceeding *N*.

Let *Z* be the set of the numbers of the analog objects indicated by the expert. The expert has the right – not the obligation – to define two more numerical characteristics for each object: the similarity coefficient $l_k,\ k \in Z$, (by default assumed to be unity) and the scale coefficient $s_k,\ k \in Z$, (by default assumed to be unity).

3.3. Procedure of Prediction by the Analog Method

Interaction of the expert and the expert-statistical prediction system (ESPS) provides the set *Z* of analogs of the PO under consideration. For this set, the ESPS database contains information about "complete", that is, represented by much longer time series, realizations of operation of the analog objects. This information is represented by the collection $\{x_k(n),\ k \in Z,\ n = 0,1,2,...,N_1\}$ where $N_1 >> N$. Additionally, the sets of values of the similarity, $\{l_k,\ k \in Z\}$, and scale, $\{s_k,\ k \in Z\}$, coefficients are given.

To predict the values of the PO time series at the instant *n*, *n* > *N*, the following formula can be used now:

$$\hat{y}(n) = L^{-1} \sum_{k \in Z} \alpha_k l_k s_k x(n), \quad (11)$$

where $L = \sum_{k \in Z} l_k$. For $N > 0$, the values of the coefficients $\alpha_k,\ k \in Z$, in (11) are established from:

$$\min_{\{\alpha_k,\ k \in Z\}} L^{-2} \sum_{n=1}^{N} \left(\sum_{k \in Z} \alpha_k l_k s_k x(n) \right)^2 . \quad (12)$$

If *N* = 0, that is, if there is no data sample on PO at all, then all $\alpha_k,\ k \in Z$, are assumed to be equal to 1.

3.4. Analog method: fields of application and practical recommendations

It is recommended to use the expert-statistical prediction procedures based on the analog method if:

– there is no statistical information about the PO or prediction can be based only on the subjective information;

– the expert for some reasons is unwilling or finds it difficult to reveal the interval or point estimates of the future values of time series;

– there is expert information about the PO that allows one to classify (identify) it with one or another similarity class;

– there exists a representative set of statistical information about a substantial number of objects from the given knowledge domain.

3.5. Analog method: reliability estimate

Estimation of reliability (trust) of the analog method (Mandel', 2000) requires many experiments because the degree of trust of the predictions generated on the basis of very short, sometimes lacking, samples depends in fact on the expert's competence and on the performance of the decision support ESPS. The results of some experiments with such the EXPAM system that was developed at Trapeznikov Institute of Control Sciences are described in (Belyakov *et al*, 2002a). As was noted in this paper, large-scale experiments with such systems are very difficult because they distract high-paid skilled experts for a long time. Therefore, the following two variants of actions to estimate reliability and effectiveness of the decision support ESPS are possible:

1) careful logging and analysis of the results of introducing into practice and running such systems;

2) design of simulation systems for the decision support ESPS's where computers simulate behavior of experts interacting with the ESPS.

One of such simulation systems, EXPRIM, was designed at Trapeznikov Institute of Control Sciences. In this system, a sixteen-parameter model of expert behavior was realized. It simulates various levels of professionalism and psychological types of experts dealing with prediction of demand for new products on the basis of the EXPAM decision support ESPS. The reader is referred to (Belyakov *et al*, 2002a, b). for a detailed description of the experiments with the EXPRIM and EXPAM systems. For the case of hollow (!) data sample, we just present one revealing graph (see Fig. 2) of the prediction accuracy vs. expert professionalism varying from the lowermost (abscissa is 1) to the uppermost ("wizard" expert, abscissa is 5).

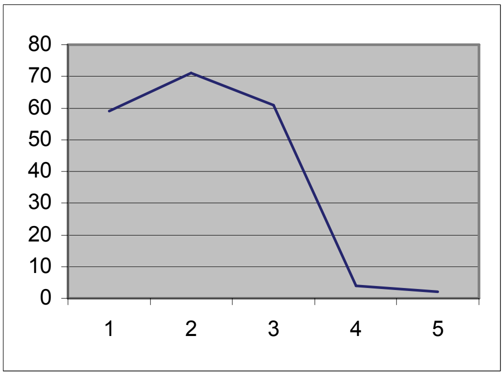

Fig. 2. The rms prediction error deviation for the first point vs. expert professionalism.

The accuracy of prediction proved to be sufficiently high already at the first point (!) of the future series (we recall that the sample is empty at all for the first point). We draw attention to the fact that in the simulation experiment even the experts who actually have the zero level of professionalism (professionalism parameter 1) and choose analogs "higgledy-piggledy" corrected choice of analogs by means of the EXPAM system so that at the first step their prediction accuracy was quite passable 60 %.

4. ADAPTIVE ALGORITHMS FOR INVENTORY CONTOL AND THEIR APPLICATIONS

4.1. Background

Several groups of adaptive algorithms have already been developed for the solution of various problems in the inventory control theory, see, for instance (Lototsky *et al*, 1987, 1991; Belyakov *et al*, 2005). Initially these have been algorithms intended for systems to control supplies by the criterion of meeting the specified level of services provided to consumers of type quite close to algorithm (1):

$$\hat{x}_{n+1} = x_n - \gamma_n[\hat{\pi}_n - \rho], \quad (13)$$

where $\hat{x}_{n+1}$ is an estimate of the recommended stock at the (n+1)-th step, x_n is a real stock at the n-th step, ρ – is the specified service level, $\hat{\pi}_n$ is the estimate of the probability of no shortage at the n-th step, while $\{\gamma_n\}_{n=1}^{\infty}$ is a sequence of non-negative coefficients meeting the known conditions (4).

Next synthesized were adaptive algorithms to solve the problem of so cold "myopic" inventory control (for one step planning period) (see algorithm (3)).

4.2. New adaptive algorithms

When inventory control is done in a multi-step process using the criterion of the minimal total average cost an optimal strategy of choosing the order size belongs as a rule (Hadley *et al*, 1969) to the class of (R, r)-strategies. It is assumed that the distribution function $F(x)$ of the demand ξ for one step is a priori unknown and during the functioning of the supply system a sequence of demand values is registered $\xi_1, \xi_2, \ldots, \xi_n$.

For a stationary functioning mode of the inventory system the approximate recurrent algorithms have been obtained as (see Mandel' *et al*, 2008):

$$\begin{aligned}\hat{R}_{n+1} = \hat{R}_n - \gamma'_n[&(c+h)\hat{\bar{z}}_n/(\hat{R}_n - \hat{r}_n) \\ &+ (\hat{R}_n - \hat{r}_n)^{-2}\{(A + \hat{R}_n(c+h+2d) + \hat{r}_n(c-d))\hat{\bar{z}}_n - \\ &- \overline{cz^2}_n/2 + (h+d)\eta_2(\hat{R}_n, \hat{r}_n; \xi_n) - d(\hat{R}_n^2 - \hat{r}_n^2)/2\}],\end{aligned} \quad (14)$$

$$\begin{aligned}\hat{r}_{n+1} = \hat{r}_n + \gamma''_n[&(\hat{R}_n - \hat{r}_n)^{-1}(A + \hat{R}_n(c+h) - cr + (c-h)\bar{z}_n) \\ &+ (\hat{R}_n - \hat{r}_n)^{-2}\{(A + \hat{R}_n(c+h+2d) + \hat{r}_n(c-d))\bar{z}_n \\ &- \overline{cz^2}_n/2 + (h+d)\eta(\hat{R}_n, \hat{r}_n; \xi_n) - d(\hat{R}_n^2 - \hat{r}_n^2)/2\}],\end{aligned} \quad (15)$$

where A is a constant cost of placing an order, c is the price of unit inventory, h is the unit cost of inventory holding, d is the unit shortage cost, γ'_n and γ''_n are coefficients meeting the conditions of (5), $\eta(R, r; \xi)$ is the function of the type

$$\eta(R, r; \xi) = \begin{cases} (R^2 - r^2)/2 - \xi(R - r) & \text{if } \xi \le r, \\ (R^2 - \xi^2)/2 - \xi(R - r) & \text{if } r < \xi \le R, \\ 0, & \text{if } R \le \xi. \end{cases} \quad (16)$$

while recurrent estimates of the average demand value $\bar{z}_n$ and of the second moment $\overline{z^2}_n$ are obtained from the formulas:

$$\bar{z}_n = (n-1)\bar{z}_{n-1} / n + \xi_n / n, \quad (17)$$

$$\overline{z^2}_n = (n-1)\overline{z^2}_{n-1} / \mathrm{n} + \xi_n^2 / n. \quad (18)$$

4.3. Adaptive expert-statistical systems

When implementing algorithms (14)–(18) within the expert-statistical inventory control system the experts can correct estimates of parameters $\hat{R}_n$ and $\hat{r}_n$, as well as the impact on the coefficients of adaptive algorithms (14) and (15) by specifying the parameters λ_i and μ_i, $i = 1, 2$, in the formula which resembles (8):

$$\gamma_n^{'} = \lambda_1 / (\mu_1 + n) \text{ and } \gamma_n^{''} = \lambda_2 / (\mu_2 + n) \ . \quad (19)$$

5. CONCLUSIONS

The expert-statistical method implies that experts contribute to the solution of the forecasting problem based on the identification by the experts of the analogs of the process forecasted among the processes that they have observed earlier. It is assumed that for the earlier observed processes there exists rather representative statistical information which can be utilized along with rather limited statistical material directly with regard to the process forecasted.

One of the main mathematical tools of ESS basic models creating are adaptive or robust models. New adaptive inventory control algorithms under criteria of the minimal total average cost at planning period are the example of such basic model.

6. AKNOWLEGMENT

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