Journal of Theoretical and Applied Information Technology
31st January 2022. Vol.100. No 2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MULTI-EXPERT SYSTEMS: FUNDAMENTAL CONCEPTS AND APPLICATION EXAMPLES

[1]ALEXANDER MUSAEV, [2]DMITRY GRIGORIEV

[1] Saint-Petersburg State Institute of Technology (Technical University), St. Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences; Russia;
[2] Saint-Petersburg State University; Center for Econometrics and Business Analytics; Russia,
E-mail: [1] amusaev@technolog.edu.ru, [2] d.a.grigoriev@spbu.ru

ABSTRACT

In this paper, we propose the concept for creating a multi-expert system (MES) as a distributed decision support system. We identify the fundamental differences between MES and multi-agent systems, and present options for MES structure and formalized models for their description. Furthermore, we consider examples of MES use in management problems of multidimensional non-stationary processes characteristic of unstable immersion environments.

Keywords: *Multidimensional Non-Stationary Processes, Multi-Expert Control, Distributed Decision, Multi-Expert Asset Management, Knowledge Extraction.*

1. INTRODUCTION

One of the important and rapidly developing trends in modern management theory and *artificial intelligence* (AI) methods is the creation of distributed *decision support systems* (DSS). The resulting management decision in such systems is made by matching and integrating local conclusions generated by so-called experts - independent or related subsystems of data analysis.

The most typical example of a distributed DSS are *multi-agent systems* (MAS) [1], [2], [3], [4], [5], [6]. An MAS is a system of interacting intelligent agents, conceptually constrained by the requirements of autonomy, limited representation and decentralization. As a rule, individual software agents are not associated with AI and make only local decisions constructed by a specified data analysis algorithm. However, the network system that they form makes it possible to obtain effective compromise solutions through iterative agreement and compromise.

An interesting feature of MAS is the potential ability to implement self-organization mechanisms typical for swarm intelligence [7], [8], [9], [10], [11]. Another important feature of MAS is the ability to exchange information between agents, usually implemented via a weighted query matrix. By iteratively exchanging data, agents form compromise decisions that are acceptable to all or most stakeholders with conflicting interests. In particular, agents can be programmed based on the belief-desire-intent model (BDI) for this purpose [12], [13]. This approach enables solving many different applied problems of coordination, cooperation, joint learning, etc.

Further development of distributed DSSs is associated with the need to abandon the aforementioned restrictions inherent to the MAS concept. In particular, for many forecasting and management problems, there is no need to restrict the agent's access to all available information about the control object and its immersion environment. Rejection of decentralization is of even greater importance. For many applied problems, the most practical solution will be hierarchical systems that make management decisions, in which expert supervisors, in the process of developing terminal decisions, integrate local proposals generated by experts of a lower level.

Various methods have been proposed to combine different strategies into a single solution. The analytical hierarchical process (AHP) and VIKOR [14] are based on calculating the weights of each strategy in the overall solution. The risk and profitability of the strategy can be criteria for the task of calculating the weight. Voting [15] is another method in which the majority of decisions are indicated as a general decision. Some ensemble methods make a combination of predictions using linear regression. At the same time, these approaches do not imply a connection between their software agents and the ability of an expert supervisor not to rely entirely on their decisions, like a human manager. Financial markets belong to the area of stochastic chaos [16], where the future effectiveness of a strategy cannot be predicted from its history. Therefore, the hierarchical system of making a trading decision will demonstrate stable behavior. Due to the indicated discrepancies with the MAS paradigm, this paper proposes an alternative variant of a distributed DSS: a *multi-expert system* (MES) in foreign exchange trading, free from the mentioned limitations. The role of an intelligent agent is played by *a software expert* (SE), which forms its own solution to the task at hand. Unlike an agent, it has access to all the available information. The main difference from MAS is that the final version of the solution is formed in the management layer by a supervisor expert, which means that the condition of equality of all agents is not satisfied.

First, we propose a methodology of constructing such MES. We will, therefore, conceptualize the essential features of the proposed distributed DSS using verbal and formalized descriptions. Then effectiveness criteria of MES trading decisions on the financial market is provided. Finally, the improvement of the indicators of trading decisions when using MES, even when using simple trading strategies, is demonstrated.

2. MES: STRUCTURE AND FUNDAMENTALS

2.1 Description

We present a verbal description of a multi-expert system in the form of a set of interconnected theses that define, at the conceptual level, its functionality, structure and construction specifics.

1. An MES is a distributed system for extracting knowledge from heterogeneous primary information flows.
2. In technical terms, an MES is a universal organizational and technical complex of automated decision support, typical, in particular, for the tasks of strategic and operational management of complex dynamic processes.
3. The MES structure is formed on the principles of distributed transformation of information, taking into account the modern DSS construction principles, such as information stores and databases, network technologies, expert systems, etc.
4. The theoretical platform of the project is based on the paradigms of *data mining*, artificial and hybrid intelligence, cognitive computing, text mining and other types of poorly structured information, etc.
5. The MES architecture, in general, is three-level. An example can be seen in Figure 1.

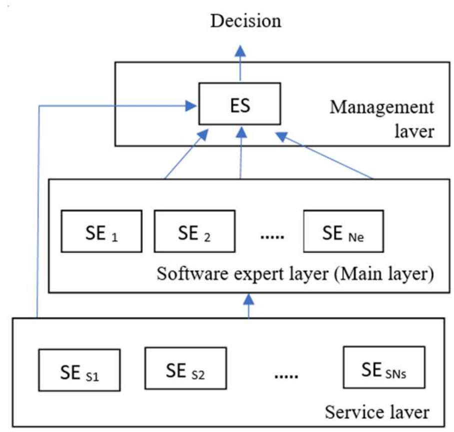


Figure 1: A version of a three-level MES structure with one expert supervisor

6. The main layer is represented by the working software experts, each of whom has full access to all available information relevant to the task at hand. Within this layer, there is a complete decentralization of the data analysis process, and experts are autonomous. At the same time, if the means of network communication are available, it is possible to build an MES that allows mutual exchange of information between experts on the basis of communication protocols. The main type of a working expert is a *software expert* (SE), but it is possible to employ a human in its place, or utilize other means of data analysis.
7. In general, an MES is based on a hierarchical structure in which the terminal outputs are constructed by the top level of data analysis. In the simplest case, this level is represented by an expert-supervisor, who is charged with coordinating the working experts and developing the final solution to the task at hand.
8. The bottom or service layer is designed for data preprocessing and analysis used to produce auxiliary information useful for the experts of the above layers.

2.2 Formalizing MES Definitions

Consider the formalized description of MES as a structured set of experts who form knowledge in the form of a joint solution of the given problem. In this case, the term *expert* refers to a transformer of input data into *knowledge*, i.e. into formalized and structured information with minimal redundancy, used in the process of solving a particular problem.

An expert can be formalized as operator

$$Exp: \{Y_{\langle 1:k-1,M\rangle},\ Y_{k,M}\} \Rightarrow D_{k,} \quad k = 1,\dots,N \quad (1)$$

where N is the volume of observations stored in the database, M is the size of the state vector, $Y_{\langle 1:k-1,M\rangle}$ is a set of retrospective data stored in the database that reflects the results of monitoring changes and interconnections of the state vector parameters of the *control object* (CO) and the immersion environment $Y_{k,M}$ is a vector of current observations generated by the monitoring system, D_k is the decision generated by the expert at the k-th time count. In some cases, due to the obsolescence of information, not the entire array of retrospective data, but only L recent observations $Y_{\langle (k-L):(k-1),M\rangle}$ are used to make a decision.

Note that the knowledge formed by the experts can be not only a management decision, but also have some intermediate form, such as an assessment of the forecast of the state of the CO for a given time interval τ.

Expression (1) is a simplified form of decision making. In practice, the generated conclusion is almost always constrained by a set of conditions for its admissibility.

$$D_k \in D_{adm} = \{D(i), i = 1, \dots, N_D\}_{adm}, \quad k = 1,\dots,N \quad (2)$$

where D_{adm} is the set of admissible decisions, reflecting the constraints such as resources, risks, technical capabilities, etc., and N_D is the total number of admissible decisions for the countable set D_{adm} . Continuous constraints use a set of continuous intervals of admissible values

$$D_k \in D_{adm} = [d_{\min}, d_{\max}]_{adm}, k = 1,\dots,N. \quad (3)$$

The input data can be both well-structured, such as numerical arrays obtained in the process of monitoring the state of the currency or stock market, and poorly structured, such as text messages containing analytical reviews with forecasts of the dynamics of financial instruments quotations.

The structure of the output data is determined by the specifics of the problem to be solved. In particular, the generated knowledge can be a draft of a management decision, a prognostic scenario, a diagnostic report, etc.

In the case when the task of MES is to produce consistent management decisions, it uses the knowledge generated by a group of M_e working experts D_{kj}, $j = 1,\dots,M_e$ which it transfers to the hierarchically superior layer to the expert-supervisor. Working experts can be software modules implementing transformation (1) based on a given or developing data analysis algorithm, people, i.e. specialists in a given subject area, or management robots with data analysis functions. This paper focuses on software experts that generate a draft management decision fully automatically.

As already noted, we will distinguish one-, two- and three-level options for constructing an MES. In the first case, a decision is made by circulating decision projects created by individual experts in a network structure

$$S_{Exp} = \langle Exp(j), \quad C_{i,j}\rangle, i,j = 1,\dots,M_e \quad (4)$$

where $C_{i,j} \quad i,j = 1,\dots,M_e$ is the expert connection matrix. In MAS, the S_{Exp} structure consists of the main and the only expert layer. For a single-level peer-to-peer network, this layer consists of equal experts and, if they conform to conditions of autonomy, limited representation and decentralization, such a network conceptually coincides with a multi-agent system. As already mentioned, in the presence of a self-development mechanism, such a system can exhibit properties characteristic of a swarm intelligence [7], [8], [9], [10], [11].

This paper focuses on *a two-level MES* in which there is a main layer of experts and an overlying control layer consisting of one expert-supervisor responsible for generating output decisions. The expert supervisor is a software module that implements the functional operator

$$ExpS: \{Y_{\langle 1:k-1,M\rangle}, Y_{k,M}, D_{kj}\} \Rightarrow D_k, \quad k = 1,\dots,N,\ j = 1,\dots,M_e, \quad (5)$$

subject to constraints (2-3). Essentially, an expert supervisor takes over the coordination and processing of local decisions.

The three-level system (Fig. 1), as mentioned above, supposes an underlying layer of service experts which generate useful knowledge for the benefit of experts in the overlying layers. Examples of service layer expert functionality are analysis of dynamic characteristics of observation series, descriptive statistical analysis of data, and testing of statistical hypotheses concerning the probability characteristics of sample data.

The service layer SEs focused on knowledge extraction from text messages can preprocess texts (stemming, tokenization, lemmatization, etc.) or create service knowledge reflecting general trends in the immersion environment (e.g., market sentiment).

In the example below, software experts $SE_j, \quad j = 1,\ldots,N_e$ are used as workers who make independent decisions and pass them to the top layer, which consists of one expert-supervisor *ES*, responsible for making the terminal decision.

Obviously, the presented scheme, if necessary, can be generalized to variants of MES with interconnected main layer experts, with several supervisors and, if necessary, with a larger number of layers.

2.3 Features of MES as a DSS in Management Tasks

To specify and illustrate the provisions of MES construction, consider its implementation as a variant of a distributed DSS, which makes decisions in the interests of the management system. In this case, the MES is a hierarchical distributed DSS that transforms the set of input data arrays into useful knowledge necessary to solve the tasks assigned to it. The most characteristic example of such knowledge is the management decisions used in various kinds of control systems.

In accordance with models (1), (5), the input information for the MES as a whole and for each software expert of the main layer is:

- arrays of retrospective data $Y_{\langle k-L:k-1,M\rangle}$and operational data $Y_{k,M}$reflecting the current state of the CO and its immersion environment;
- a list of constraints (2-3) that determine the suitability of the constructed decisions;
- information from other working SEs in the presence of a network communication environment (4).

Local decisions of the main layer experts serve as primary input information for the expert-supervisor $D_{kj,} \quad j = 1,\ldots,N_E, \quad k = 1,\ldots,N$. The structured data of the lower layer of service experts is additional input for the SEs and the expert-supervisor.

The output information of the MES is the knowledge necessary to solve the problem which has been contained in a latent form in the input data. In management tasks, the most natural form of such knowledge is draft management decisions $D_{k,} \quad k = 1,\ldots,N$.

In this paper, we focus on the task of proactive management, based on the results of predicting the state of the CO $\tilde{Y}_{[k+1,k+\tau]}$ for the prediction interval $[k+1,\ k+\tau]$. In this article, as an example, we consider a variant of MES construction, in which experts form independent decisions. In this case, the supervisor acts as a system for collection and weighted processing of local decisions, which ultimately makes it possible to make a terminal management decision.

It is necessary to pay attention to the specifics of a MES with a network structured SE layer (4). In this case, the experts are interconnected and have the ability to consistently adjust their local decisions in the process of mutual exchange of information. In this case, the role of the supervisor is reduced to the coordination of the SE network and a consistent analysis of the formed solution.

The increased efficiency of the MES as a distributed DSS is provided due to its structural redundancy, which increases the stability of the input data analysis procedures.

It is quite obvious that in the presence of one expert, evenly superior in decision quality to the results formed by all other experts, the use of MES has no practical meaning. Thus, the creation of MES is always focused on solving problems in complex non-stationary environments, when different technologies of making decisions alternately prove to be more preferable, and traditional adaptation schemes do not have enough time to identify emerging changes and effectively close the feedback loop.

Hence, there is a requirement to analyze the efficiency of the MES in the context of the stability of the control system functioning, i.e., preserving

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

acceptable effectiveness in a wide range of non-stationary changes in the input data. The term "acceptable" in this case means striving to achieve the highest level of functional efficiency, subject to strict compliance with the suitability criterion.

It is advisable to carry out the basic implementation of SEs in the form of a unified software-algorithmic module. The differences between the experts lie in the mathematical apparatus used and the parameters of the data processing program. Further development of SEs will involve the specification of the features of current situations that allow their parametric or structural adaptation, i.e., the presence of local-stationary sections of observation sequences in the input data.

The main function of an expert-supervisor, as already noted, is balanced processing of decisions formed by SEs and the development of a terminal management decision. This raises the problem of continuous or periodic assessment of the weight characteristics of working experts. Traditionally, this problem is solved by "running" the SEs on a training polygon, which makes it possible to compare the decisions they form with the optimal ones. For unstable immersion environments, in which estimates of the dynamic characteristics of the observed process rapidly become obsolete, a sliding observation sample $Y_{\langle (k-L_0):(k-1),M \rangle}$ directly adjacent to the current time point is used as such a data polygon.

The volume of the data polygon L_0 is selected based on the contradictory requirements of its minimization, needed to evaluate the effectiveness of an individual SE according to the most recent data, and its maximization, needed to assess the quality of the expert's functioning in a wide range of changes in the properties of the observation series. This problem may not have a general minimax solution, or it may not meet the specifics of the problem being solved. In this regard, this issue is solved individually for each specific task, taking into account its features. The same considerations are valid when choosing the volume of historical observations L $Y_{\langle (k-L):(k-1),M \rangle}$ used by SEs in the development of local decisions.

The presence of a layer of service experts significantly complicates the communication environment of the MES, since the knowledge they generate is rather heterogeneous. This requires building a library of data exchange protocols, which include a set of parameters formed by different service experts.

When using the scheme of interacting experts in the main layer of the MES, it is also necessary to create a communication environment with information exchange protocols. These issues have already been developed in the construction of the communication environment between MAS agents. In a multi-expert system, it is necessary to create an additional communication system with the top control layer, and with the layer of service experts if there is one. It should be noted that in this case, the supervisor also coordinates the circulation of coordinating information between the experts.

The proposed structure of MES is universal. Its implementation requires to be adapted to the specifics and formalized description of a particular applied task. As an example, consider the implementation of MES for the problem of managing financial assets at electronic capital markets.

3. EFFECTIVENESS

3.1 Suitability Criteria

Terminal assessment of MES effectiveness, as well as any information system, is carried out based on the effectiveness of the metasystem, in whose interests it is created and operates. Criteria and methods for evaluating the effectiveness of information systems are given, for example, in [17]. Following the proposed methodology, we will distinguish between necessary criteria of suitability of management decisions and sufficient conditions of their superiority and optimality.

The criterion of decision suitability $D_{k,}$ $k = 1,\dots,N$ refers to satisfying relations (2-3), i.e. its numerical characteristics conform to the available set of a priori constraints.

The optimality criterion requires that the numerical indicator $\Upsilon(D)$, reflecting the quality of a decisions, be the best, i.e. correspond to some extreme value on the set of acceptable decisions

$$D_k^* = opt: \Upsilon(D_k^*) = \underset{i}{extr}\big(\Upsilon(D)\big), \quad \forall D \in D_{adm}, \quad k = 1,\dots,N, \quad i = 1,\dots,N_{D_0} \tag{6}$$

where $D_{i,k} \in D_o = \{D_0(i), \quad i = 1,\dots,N_{D_0}\}$ is the set of admissible decisions.

A less strict criterion of superiority supposes decisions that, at each time step of management $k = 1,\dots,N$, were superior in terms of quality to some reference decision $D_{0k} \in D_{adm}$ obtained, for example, at the previous step of management

$$D_k^0: \quad \Upsilon(D_k^0) \geq \Upsilon(D_{0k}). \quad (7)$$

In most practical tasks, the criterion of suitability should be strictly fuilfilled for each implementation. At the same time, for sufficient performance, criteria should be satisfied by averaged performance only. In this case the optimality criterion (6) will have the form

$$D_{1:k}^* = opt: \; \overline{\Upsilon}(D^*) = \underset{i}{extr}\left(\overline{\Upsilon}(D_{adm})\right), \quad i = 1,\dots,N_{D_0}, \quad (8)$$

and the superiority criterion (7), respectively, can be represented as

$$D^0: \quad \overline{\Upsilon}(D^0) \geq \overline{\Upsilon}(D) \quad (9)$$

Further generalization of this approach supposes using the distribution function of the decision quality indicator [14], [15] but its practical use requires a large number of repeated implementations to estimate the empirical distribution density with the required accuracy.

Linear sequential evaluation of decision effectiveness involves the admissibility of the superposition principle: the indicator of the terminal efficiency of the system is the sum of the quality indicators in the intermediate steps of management. For essentially nonlinear systems, the effectiveness is evaluated at the last control step $k = N$. In this case, in accordance with the general principles of system analysis, intermediate steps may not meet the requirements of optimality. Then the current management at the k-th step is selected based on the prognostic scenario for the time interval $\tau = N - k$.

3.2 Forecasting and Managing Financial Instruments at Electronic Capital Markets

A financial asset management decision made by a trader or a trading robot can be represented as a vector

$$D_j = (k,\ d,\ V,\ Y^*)_j, j = 1,\ 2, \dots \quad (10)$$

where k_j is the start of the operation (opening a position), d_j is the predicted direction of the quotation dynamics, V_j is the volume of financial investments in the operation, Y_j^* the threshold level of quotations, the achievement of which determines the completion of the operation (closing a position). As a result of the management decision, the capital changes by δK_j.

The task of an SE that uses technical analysis techniques is to consistently make decisions D_j, $j = 1,\ 2, \dots$ based on retrospective and current market monitoring data $\left(Y_{\langle (k-L):(k-1)\rangle},\ Y_k\right)$, $k = L+1,\ \dots, N$. In a more general case, an SE uses a combination of technical and fundamental analysis, the relevant additional information I_a for which most often exists in the form of text files with news feeds, analytical reviews, etc.

The most common and natural measure of effectiveness of the j-th control decision D_j is the capital gain $\Upsilon(D_k) = \delta K(D_k)$ resulting from its execution. A natural criterion for the suitability of a sequence of generated control decisions (10) is positive capital gain, i.e.

$$D_j \in D_{adm} \Leftrightarrow \delta K(D_j) \geq \delta K_{\min}, j = 1,2, \dots \quad (11)$$

where $\delta K(D_k)$ is the change in capital that occurred as a result of executing the management decision D_k ,and $\delta K_{\min} > 0$, $k = 1,\dots,N$ are the expenses due to the execution. Note that asset management does not occur at every step of observation, so the indices k and j do not coincide.

For the considered class of management problems in conditions of chaotic dynamics, it is impossible to establish a priori whether the made decision D_j corresponds to the suitability criterion (11). It is permissible only to compare the parameters of the generated decision with natural restrictions, for example, the deposit size. It seems promising to implement the decision suitability criterion based on a priori risk assessment, which consists of analyzing the effectiveness of the decision-making algorithm on a test data polygon.

Optimality criterion (6) of the generated decision D_j at the j-th step of asset management requires maximizing the expected profit, i.e. as a result of executing the generated management decisions.

$$D_j^* = opt: \quad \Upsilon(D_j^*) = \delta K(D_{ij}) = \underset{i}{max}, \quad \forall D_{ij} \in D_{adm}, \; j = 1,\dots,N_j, \quad i = 1,\dots,N_D$$

where $D_{i,j} \in D_o = \{D_0(i),\ \ i = 1,\dots,N_D\}$ is the set of admissible decisions.

In practice, the above expression is not constructive, because it does not take into account the stochastic nature of asset quotes. In this regard, effectiveness evaluation based on Bayesian estimates is more correct [19], [20]:

$$D_j^*: \ \Upsilon(D_j^*) = P_{ij}\delta K(D_{ij}) = \max_i, \quad \forall D_{ij} \in D_{adm}, \ \ j = 1,\dots,N_j, \ i = 1,\dots,N_D \quad (12)$$

where P_{ij}, $j = 1,\dots,N_j$, $i = 1,\dots,N_D$ is the probability that at the j-th management step the decision D_j will produce the largest capital gain $\delta K(D_{ij})$ among the set of admissible alternatives $i = 1,\dots,N_D$. It should be immediately clarified that in the process of real management, probability P_{ij} is replaced by its frequency estimate $\hat{P}_{ij}$, formed by testing the decision algorithm on data polygon $Y_{(k-L_0):(k-1)}$.

For the above example, due to the obvious additivity of the effectiveness indicator, the optimality criterion (8) of the whole management cycle can be presented as

$$D^* = opt: \ \ \Upsilon(D^*) = \sum_{k=1}^{N} \hat{P}_k \, \delta K(D_k) = \max_j.$$

The worst management result is due to the limited initial capital K_0, condition $\sum_{j=1}^{Nj} \delta K_j \le K_0$ means ruin of the trader.

4. EXPERIMENTS

4.1 Specifics of Modeling Financial Asset Quote Observation Series

We have a series of direct observations of the quotes of a financial instrument Y_k, $k = 1,\dots, N$. The conventional additive observation model for this class of random processes is [18], [19], [20]:

$$Y_k = X_k + v_k, \quad k = 1,\dots, N \quad (13)$$

where X_k, $k = 1,\dots, N$ is the systemic component formed by the smoothing filter and used in the decision-making process, v_k, $k = 1,\dots, N$ is the random component of observations, usually modeled, although not always correctly, by a stationary Gaussian process.

For the observation series generated by the process of market pricing, the systemic component is an oscillating non-periodic process with many local trends, described by the model of deterministic chaos [21], [22], [23], [24]. The random component in the quotation model usually does not meet the stationarity condition, is heteroscedastic and has a rapidly decaying autocorrelation function [24], [25]. As a result, the general quotation model (13) should be classified as stochastic chaos.

An example of quotation dynamics for the three most common pairs of currency instruments, illustrating the above features of observation series, is shown in Figure 2.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

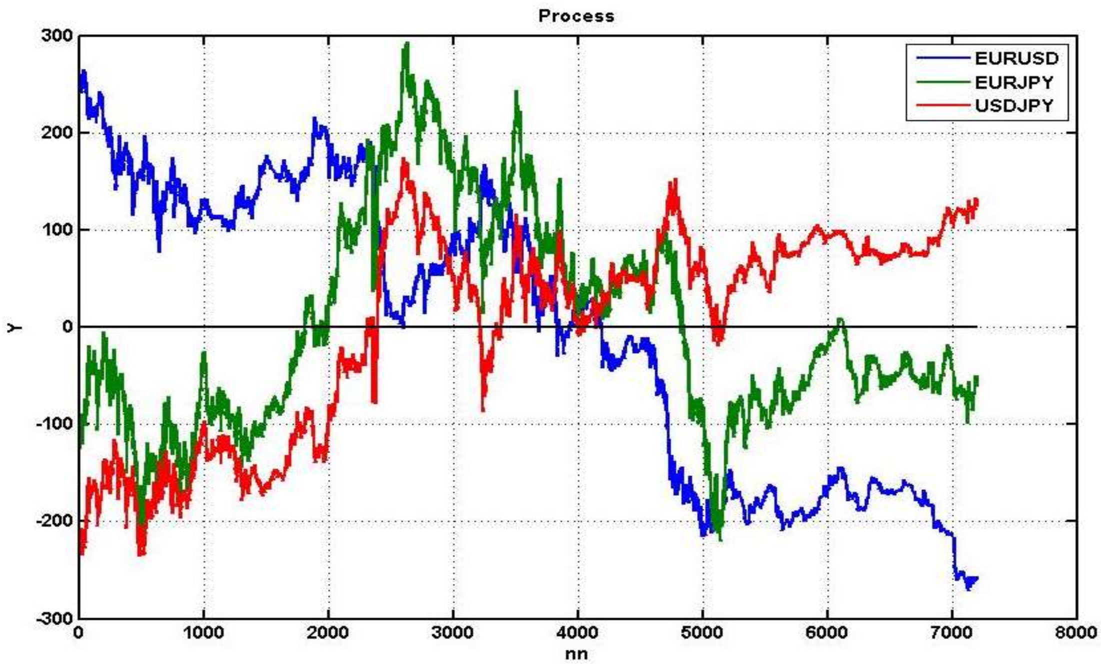


Figure 2. Example quotation dynamics of the three most common currency instruments

Under these conditions, conventional computational schemes used to identify the observed process and predict it in the interests of proactive management are ineffective. The traditional approach to improving the effectiveness of management by adapting forecasting algorithms also does not increase the stability of the solution due to the fact that the time of adjustment of the tracking loop is too long to track chaotic variations in the dynamics of the observed process. Hence, the expediency of using a distributed MES, which solve the forecasting problem using a group of SEs, each of which is based on different algorithms for predicting decisions.

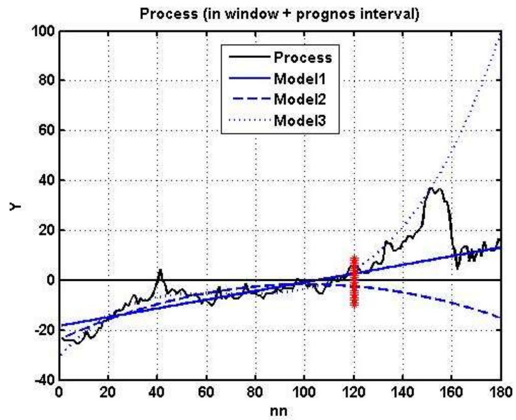
As already noted, simultaneous processing of decisions formed by various SEs does not produce the most accurate forecast. If there were an SE that was uniformly superior to the other decisions-making algorithms, the accuracy would only decrease if their results were processed together. However, in a situation where the effectiveness of each SE varies depending on the input data, the combined processing of the results makes it possible to improve the average management efficiency, or, in other terms, to increase the stability of the DSS.

4.2 Example: A Multi-Expert System Based on Statistical Polynomial Prediction Algorithms

To illustrate the task of constructing a MES, let us consider a simplified two-level system in which the main layer of software experts consists of simple polynomial extrapolation algorithms. The difference between SEs is in the degree of the approximating polynomial m and the size L of the sliding window $Y_{k-L,k}$, in which the parametric identification of the polynomial model $P_k(a) = a_i\, t^i,\ \ t = 1,\ \dots,\ L$ is performed.

As an example, we consider a problem in which the observed process is the result of monitoring changes in the normalized values of quotations of the EURUSD currency pair for two hours (120 minute counts). Based on the results of observations, we construct polynomial models of low orders $m = 1,2,3$ by fitting parameters $\hat{a}_i,\ \ i = 1,\ \dots,\ m$ using the least squares method. Next, an extrapolation forecast is made for an interval of 1 hour (60 minute counts).

Examples of modeling and extrapolation forecasting of the dynamics of quotations of the specified currency pair are shown in Figure 3.



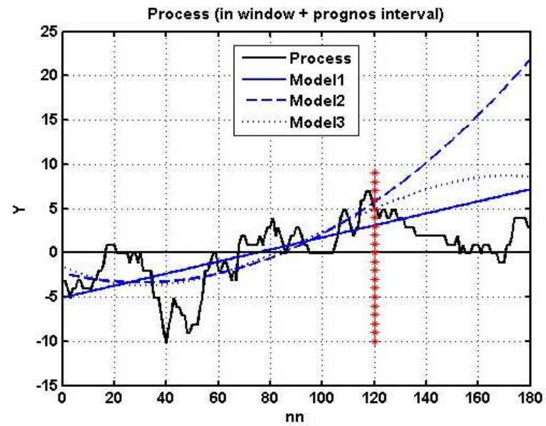


Figure 3. Examples of SE implementation based on extrapolation predictors of orders 1-3 for two different observation windows.

We can see that the quality of the model itself, evaluated by the degree of closeness to the real process (using the quadratic similarity metric) noticeably improves with increasing the degree of the approximating polynomial, as one would expect. However, this conclusion does not apply at all to the quality of the forecast. Moreover, an increase in the degree of the approximating model can lead to extremely large forecasting errors.

Note that the conclusion about the unsuitability of the simplest polynomial forecasting for asset management in electronic markets is quite obvious. In the context of this article, the question is posed differently - is it possible to improve the forecasting results by processing the results obtained in different ways (different SEs) at a higher level of data analysis (supervisor level).

According to the task, the supervisor receives prediction results at each observation step from three SEs of the underlying layer, each of which implements polynomial extrapolation with a given model order. At the same time, the choice of the best approximating model on the sliding observation interval adjacent to the current count does not guarantee the best quality of the forecast due to the chaotic nature of the process described above.

As mentioned earlier, the implementation of an expert-supervisor can be based on Bayesian analysis of prior risks [19], [20] and using them as weight characteristics when processing decisions obtained by various SEs. A priori risks of each SE are calculated as estimates of the average values of forecast errors $\delta\tilde{Y}^{i}_{k,\tau}$ generated on the sliding data polygon $Y_{k-nS,k} = [Y_{k-nS},\ldots, Y_k]$, $k = 1,\ldots, N$ volume in nS counts. The supervisor generates a step-by-step forecast for the time interval τ as a linear combination of predictied decisions generated by the SE of the underlying MES layer:

$$\tilde{Y}_{k+\tau} = \frac{\sum_{i=1}^{m} w_{k,i}\tilde{Y}^{i}_{k+\tau}}{\sum_{i=1}^{m} w_{k,i}}, k = 1,\ldots, N-\tau \qquad (14)$$

In this case, the weights are estimated as the values inverse to the estimated values of Bayesian risks $w_{k,i} = (R^{\tau}_{k,i})^{-1}$.

As an example, we consider the problem of step-by-step estimation of the standard errors of the forecast for an SE that uses linear quadratic statistical extrapolation and an expert supervisor with Bayesian data processing (14) for 100 different forecasted areas of $\tau = 50$ minute counts in size.

A sliding sample of 120 counts was used as an interval for training the SE (constructing an approximating model), and a sliding sample of size nS=300 counts was used for assessing Bayesian risks. The resulting estimates of the standard deviations are presented for the three considered forecasting options in Figure 4.

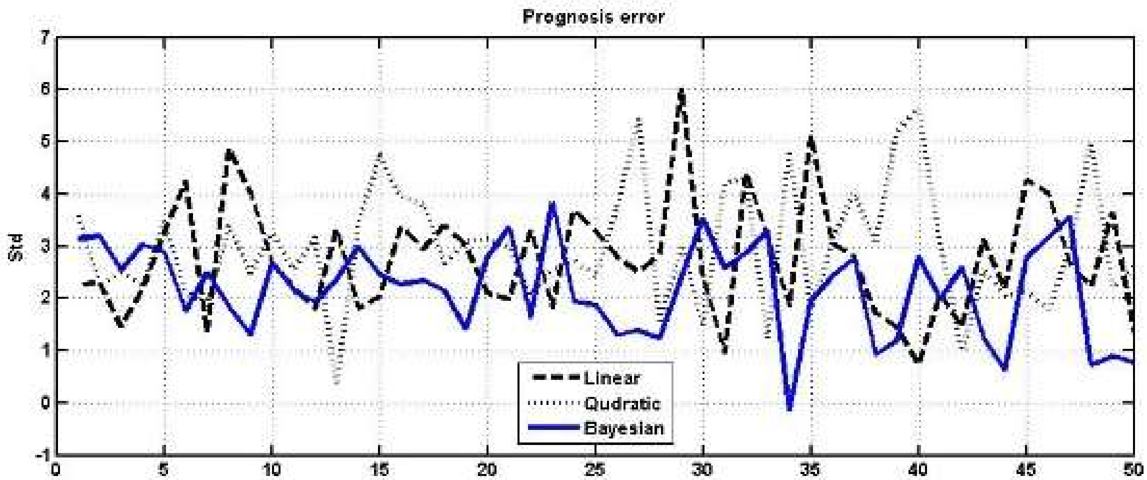


Figure 4. Linear, quadratic and Bayesian prediction errors for non-stationary observation series

As can be seen from the presented figures, it is not possible to achieve uniformly superior forecast accuracy for chaotic observation series, as expected. At the same time, the use of MES with a Bayesian supervisor allows to improve the quality of the prediction compared to the considered polynomial computational schemes by 8-10% on average.

Note that this example does not claim to be used as a DSS in asset management tasks. The proposed scheme is used only as a simplified example to illustrate the technique of MES application. To build an effective management system in a multidimensional chaotic immersive environment, a system of heterogeneous software experts with information support from the service layer and a self-developing supervisor computational scheme is required. We are planning to cover these issues in our subsequent publications.

4.3 Example: A Multi-Expert System Based on Heterogeneous Information Sources

Consider an MES with three heterogeneous working software experts SE-1-3, generating recommendations or draft decisions on managing a financial asset, and an expert supervisor of an ES that makes the final decision. Let SE-1 implement a trading management strategy based on the detection of a trend and investing in an asset that has an explicit trend. In contrast, let SE-2 be based on the strategy in which the exit of the trajectory of the asset quotation beyond a set threshold is regarded as a random fluctuation that dynamics of market pricing will inevitably reverse. This approach generates a recommendation to open a position in the opposite direction to the detected local trend and to close it when the quotation reaches the level of the so-called "fair price".

The third expert, SE-3, belongs to the service layer and is a text analyzer that extracts information about the "mood" of the market from analytical reviews. Essentially, the task is to transform the content of available analytical reviews prepared by fundamental market analysts into a fuzzy solution such as “quotes are rising,” “falling” or “on average, not changing” (the so-called sideways trend). The supervisor receives recommendations on asset management from SE-1 and SE-2 in the form of commands for opening and closing positions, as well as service information from SE-3, and forms final versions of management decisions based on the data obtained.

The supervisor uses the recommendations of the first expert if, according to the service expert, news leading to the emergence of a local trend is expected. In the opposite case, the supervisor makes decisions based on the recommendations of the second expert.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

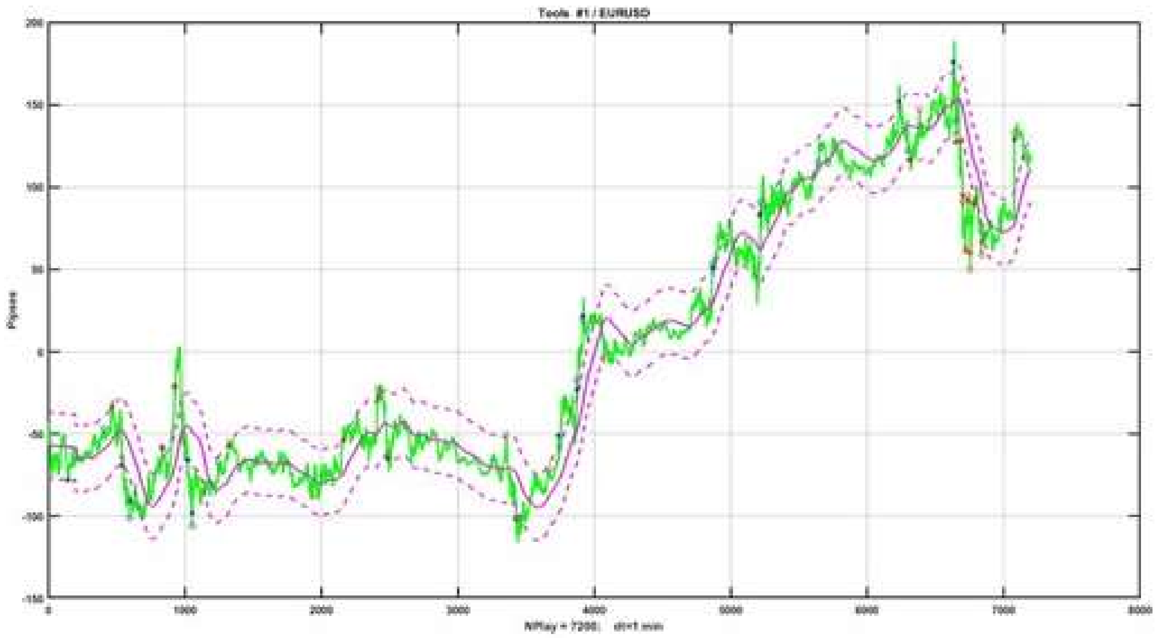


Figure 5. Example of asset management based on a multi-expert system

For comparison, we used trading simulations on the same 5-day price change interval. We used the real quotes of the EURUSD currency pair. We compared three management options: using the recommendations of the first SE, second SE and, in the third case, the MES described above.

An example of MES-based management is shown in Figure 5. The green line represents the trajectory of changes in quotations; the solid crimson line is formed by the exponential filter with velocity correction. Correction is necessary because an exponential filter with a large gain provides insufficient smoothing, and reducing the value of this coefficient leads to a lag of the smoothed curve. Velocity correction provides a satisfactory level of smoothing and a significant reduction of lag.

The dotted lines define a "corridor" within which quote fluctuations can be considered to contain no clear trend. The standard value of such fluctuations relative to the exponential average lies in the range of points $s(\delta\tilde{Y}_k) = 15 - 25$. In this example, we set the corridor width to 40 p. The position was closed at $dL = 20$ p. from the opening level in both directions. Asterisks indicate the moments of opening a position, gain is denoted by diamonds and stop-loss executions are marked with circles.

A comparison of the trading results for these three options is shown in Table 1. It can be seen that the independent use of SE 1 or SE 2 leads to a loss. Using MES, it is possible to construct a management strategy from the streams of two losing recommendations, which in general produces gain. Applying sequential evolutionary optimization, for example, as described in [26], [27], can increase the gain by another 5-8%.

TABLE 1. COMPARISON OF TRADING RESULTS OF SE AND MES

Decisions	Result (pipses)	Probability of gain	Average gain	Average loss
SE-1	-84	0.47	35.5	- 34.7
SE-2	-36	0.50	34.7	- 35.5
MES	14	0.53	34.1	- 32.3

It should be pointed out, that the given example cannot serve as proof of the guaranteed advantage of the MES. In chaos, nothing is guaranteed at all. In this example, correct recommendations given by expert analysts in the form of text reviews were used as service information, which in turn were correctly extracted by the SE using text analysis. In general, the correctness of the results of fundamental analysis is not guaranteed.

On the other hand, the most primitive versions of trading robots were used as SE 1-2 for clarity. The use of more complex variants of SEs, for example, those based on multi-regression analysis of markets with sequential correction of statistical estimates of financial instrument values based on evolutionary modeling or artificial neural networks, will significantly increase MES effectiveness.

In addition, a significant potential for improving MES is contained in modern technologies for joint processing of expert recommendations based on the theory of conflicts and compromises [28], [29]. These questions, as well as the development of the theoretical foundations of MES, are the subject of our further research.

5 CONCLUSIONS

This article makes the first attempt to justify a distributed knowledge generation system based on hierarchical information interaction between a group of heterogeneous experts, which can be either implementations of data analysis algorithms or humans.

This article is preliminary and requires extensive additional work both in terms of the concept of MES as a distributed information system for generating knowledge, and in terms of the general mathematical formalization of a distributed DSS.

The given examples, despite their simplified form, show significant potential of distributed information structures, which would help in solving many problems of big data and joint analysis of heterogeneous and poorly structured data (Data Fusion). In particular, it is expected that it will be possible to obtain positive results in such unsolved problems so far, such as predicting the state of unstable media, managing multidimensional chaotic processes, etc.

6 ACKNOWLEDGMENTS

The research of Alexander Musaev described in this paper is partially supported is partially supported by the Russian Foundation for Basic Research (grant 20-08-01046), state research FFZF-2022-0004. Dmitry Grigoriev research for this paper was funded by a Support from The Endowment Fund of St Petersburg University. The authors are grateful to participants at the Center for Econometrics and Business Analytics (ceba-lab.org, CEBA) seminar series for helpful comments and suggestions.

REFERENCES

[1] J. Ferber, *Multi-Agent Systems: An Introduction to Artificial Intelligence*, Boston, MA, United States: Addison-Wesley 1999. ISBN 0-201-36048-9.

[2] M. Wooldridge, *An Introduction to Multiagent Systems*, New York, United States: John Wiley & Sons Ltd, 2002.

[3] J. M. Vidal, "Multiagent Systems." 2006.

[4] G. Weiss, Ed., *Multiagent systems: a Modern Approach to Distributed Artificial Intelligence*, MIT press, 1999.

[5] P. G. Balaji and D. Srinivasan, "An introduction to multi-agent systems" in Innovations in multi-agent systems and applications-1, Berlin, Heidelberg: Springer, 2010, pp. 1–27.

[6] J. Florez-Lozano, F. Caraffini, C. Parra and M. Gongora, "Cooperative and distributed decision-making in a multi-agent perception system for improvised land mines detection", Information Fusion, 2020, 64, pp. 32-49.

[7] A. P. Engelbrecht, *Fundamentals of computational swarm intelligence*. Hoboken, NJ, United States: John Wiley & Sons, Inc, 2006.

[8] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, Nov. 1995, vol. 4, pp. 1942–1948.

[9] R. Sun, *Cognition and multi-agent interaction: From cognitive modeling to social simulation*. Cambridge University Press, 2006.

[10] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics*, vol. 26, no. 1, pp. 29–41, 1996.

[11] P. Miller, "The genius of swarms," *National Geographic*, vol. 212, no. 1, pp. 126–147, 2007.

[12] A.S. Rao and M.P Georgeff, "BDI-agents: From Theory to Practice," in *Proc. of the First International Conference on Multiagent Systems (ICMAS'95)*, San Francisco, 1995, pp. 312–319.

[13] M. Wooldridge, Reasoning about rational agents, Cambridge, MA, United States: *MIT Press*, 2003.

[14] K. Amin Ullah, Y. Ali, Analytical Hierarchy Process (AHP) and analytic network process methods and their applications: a twenty year review from 2000-2019: AHP & ANP techniques and

their applications: Twenty years review from 2000 to 2019, *International Journal of the Analytic Hierarchy Process*, 12.3, 2020.

[15] G. C. Calafiore, M. H. Morales, V. Tiozzo, S. Marquie, A classifiers voting model for exit prediction of privately held companies. In *2020 European Control Conference (ECC),* IEEE, pp. 615-620, 2020.

[16] A. Musaev, D. Grigoriev, Numerical Studies of Statistical Management Decisions in Conditions of Stochastic Chaos, *Mathematics*, 2022, 10(2):226, https://doi.org/10.3390/math10020226

[17] R.M. Yusupov, A.A. Musaev, D.A. Grigoriev, Evaluation of Statistical Forecast Method Efficiency in the Conditions of Dynamic Chaos. *In Proceedings of the 2021 IV International Conference on Control in Technical Systems (CTS)*, September 2021; pp.178–180. https://doi.org/10.1109/CTS53513.2021.9562780

[18] A. Musaev, D. Grigoriev, Analyzing, Modeling, and Utilizing Observation Series Correlation in Capital Markets. *Computation* 2021, 9, 88. https://doi.org/10.3390/computation9080088

[19] W. M. Bolstad and J. M. Curran, *Introduction to Bayesian statistics*. Hoboken, NJ, United States: John Wiley & Sons, 2016.

[20] M. Sekerke, *Bayesian risk management: A guide to model risk and sequential learning in financial markets*, Hoboken, NJ, United States: John Wiley & Sons, 2015.

[21] E. E. Peters*, Chaos and Order in the Capital Markets: A New View of Cycles, Prices, and Market Volatility*, 2nd ed. NY, USA: John Wiley & Sons, 1996.

[22] J. Gregory-Williams and B. M. Williams, *Trading Chaos: Maximize Profits with Proven Technical Techniques*, 2nd ed. Hoboken, NJ, USA: John Wiley & Sons, 2004.

[23] A. A. Musaev, "Modeling of trading assets quotations," *Inform. Autom. (SPIIRAS Proc.)*, vol. 17, 2011, pp. 5-32, doi: 10.15622/sp.17.1.

[24] A. Musaev, A. Makshanov, D. Grigoriev, Forecasting Multivariate Chaotic Processes with Precedent Analysis. *Computation*, 2021, 9, 110. https://doi.org/10.3390/computation9100110

[25] A. Musaev, D. Grigoriev, Analyzing, Modeling, and Utilizing Observation Series Correlation in Capital Markets. *Computation* 2021, 9, 88. https://doi.org/10.3390/computation9080088

[26] D. Simon, *Evolutionary optimization algorithms*, Hoboken, NJ, United States: John Wiley & Sons, 2013.

[27] A.A. Musaev and E.S Borovinskaya, "Evolutionary Optimization of Case-Based Forecasting Algorithms in Chaotic Environments", *Symmetry*, vol. 13, no. 2, pp. 301–317, 2021.

[28] N. I. Aralova, O. M. Klyuchko, V. I. Mashkin and I. V. Mashkina "Compromise Solution of Conflict Situations in the Problem of Optimal Control in Decision Making under the Complex Situational Conditions", *Electronics and control systems*, 2, 2019 ,77-83.

[29] H. S. Sii, T. Ruxton and J. Wang "Synthesis using fuzzy set theory and a Dempster—Shafer-based approach to compromise decision-making with multiple-attributes applied to risk control options selection", *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, *216* (1), 15-29., 2002.