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PREDICTIVE AGENTS FOR CONTROL OF INTELLIGENT MANUFACTURING ENTERPRISES

A. LINKEVICH, F. PANTELEENKO
(Polotsk State University)

A general mathematical framework is put forward to model modern intelligent manufacturing enterprises that constitute distributed complex systems. The problem of control of such an object is reduced, to a considerable extent, to the task of forecasting future states of elements of the system, which amounts to the standard issue of prediction of time series. To cope with the latter problem, it is suggested to use frames in Hilbert space.

1. Introduction

A number of economical, social, biological, and other dynamical systems constitute ensembles of interacting agents that exhibit a reach variety of collective phenomena including deterministic chaos, fractals, self-organization, etc. Agents can have different beliefs, expectations, desires, intentions, strategies, and objectives. (The term *agent* is also used in another sense in computer science – see Section 2).

An important particular class is distributed dynamical systems that have little centralized control and communication between their agents, but still should behave in a prescribed manner (a variety of systems of such a kind are considered, e.g., in [1] and references available at

http://www.ge.infn.it/econophysics and

http://www.unifr.ch/econophysics).

The seminal paper [2] has introduced a simple model of adaptive economic agents and posed the so-called El Farol bar problem. In a generalized form the question is when elements (agents) of a distributed system do not operate "at cross purposes" and can achieve a prescribed global goal avoiding frustration. Treatment of actions in terms of the minority game [3] provides a fruitful approach to model market mechanisms and investigate self-organization and other collective phenomena in social and biological systems. Other theoretical tools are also successfully applied such as methods of quantum field theory [4] and gauge fields geometry [5], a self-similarity analysis [6] and so on.

The main aim of our work is to advance a framework to model similarly modern *manufacturing enterprises* (MEs) and to broaden thereby the area of application of methods of mathematical physics in addition to social and biological systems considered, e.g., in papers [1 – 8]. In a sense, our treatment of a ME is close in spirit to the minority game. So, in our model, like in markets, agents simultaneously and adaptively compete for limited resources of the ME, have heterogeneous strategies, expectations, knowledge, objectives, etc. Our second objective is to outline basic points of software applications developed together with our collaborators for real industrial employment.

The key idea of our approach is to provide each node (element, constituent) of a ME with an intelligent agent that should fulfil control of operation of the node. Such a controlling agent has to process available information to forecast the state of the ME, which appears efficient to elaborate decisions for the node.

A modern ME should meet a stif competition, produce rapid responses to market changes, incorporate new technologies and other handy innovations (see [9; 10] and references therein). To cope with cost, quality and timeliness of products, MEs have to ensure integration and distributed organization of heterogeneous constituents, open and dynamic structure, integration of humans with software and hardware, interoperability, agility, scalability, fault tolerance, etc. To accomplish these and other objectives, *autonomous agents and multi-agent systems* (MASs) can be useful (for an introduction see, e.g., [10]). So, in distributed intelligent MEs, they can be used to encapsulate legacy software applications and integrate MEs' activities with those of their suppliers, customers and partners into an open, distributed intelligent system via networking, represent manufacturing resources, products, operations, etc. to facilitate planning, scheduling and execution control, provide administration services and information management, facilitate communication, cooperation and coordination between agents, incorporate a whole scheduler or planner into manufacturing planning and scheduling systems.

An interesting particular concept of intelligent MEs is the *holonic manufacturing system* suggested in 1994 by the HMS consortium [11]. That is a ME whose elements (materials, machines, products, etc.) have autonomous and cooperative properties. In contrast to a centralized setup, activity of any element is determined by cooperation with other constituents. Intelligent software and hardware agents are used to represent such components of the ME.

Our paper is organized as follows. In the next section we sketch a standpoint on autonomous agents and multi-agent systems and overview two developed tools to handle uncertain informtion in the course of inter-agent communication. Section 3 contains a concise presentation of a software platform designed so as to support operation of controlling agents of a ME. In Section 4 we put forward a mathematical framework to model modern MEs composed of interacting constituents. Main properties of frames defined in Hilbert spaces are summarized in Section 5, while in Section 6 frames are used as a means to perform least squares approximation of experimental data and prediction of time series. The paper relies significantly on our previous works [10; 12 – 17] and some papers of our colleagues (see, e.g., [18]).

2. Autonomous Agents and Multi-Agent Systems

Agent-based computing is a promising paradigm of producing complex application software. Despite a great activity there is still much debate and little consensus concerning what agents are, though there appears some convergence of points of view. We adopt the following outlook on agents (for more detail see [10]). An agent can exercise control over its actions and operate independently of humans or others. An agent is provided with certain objectives and carries out flexible, content-dependent activity to achieve its objectives.

An agent may be characterized by mental attitudes. An agent acquires information about itself, other agents and its environment that constitutes its beliefs. The agent can experience different desires that compel to pursue different objectives, elaborate intentions, make and implement decisions.

An agent can interact with other agents (and humans) through communication by means of exchange of messages expressed in a knowledge language. The content of communication is meaningful statements about properties of agents and their environment, knowledge of agents, and their mental (propositional) attitudes in respect to the information.

A multi-agent system is designed so as to obtain an ensemble of interconnected agents that can operate beyond the capabilities of any individual. Complexity of tasks assigned to achieve together with the autonomy (self-control) of agents prevent forecasting and planning interrelations and foster the agents to make and implement flexible, content-dependent decisions on their interactions. Cooperation and competition among interacting agents enable self-organization of such a system. To endow controlling agents of a ME with ability to communicate with one another and with humans in accord with requirements of the international association FIPA (for more detail see, e.g., [10] and references therein), the model of FIPA compliant agents has been generalized in spirit of the fuzzy logic, and an interpreter of basic Prolog with an extended functionality has been offered [19; 10]. This program facilitate handling uncertain information by agents and should increase effectiveness of performance of the ME because information to be processed may naturally occur incomplete and imperfect due to a number of reasons.

Yet another means to cope with uncertain information and facilitate interaction of humans with agents, is the so-called "Regularized" English-Like Language (RELL) suggested in [10] for semantic treatment of information. To implement this way of communication, a first version of an interpreter has been developed [20] which allows translation (through a dialog) from the natural English to the RELL and vice versa.

3. Software Platforms to Support Operation of Agents

To provide an effective setup, a software platform has been suggested on the basis of economic principles modelled in such papers as [1 – 8]. This should enable, due to cooperation and competition between agents, self-organization of the system and thereby improvement of its performance [10]. The user of such a system is offered to suggest tasks from a certain problem domain and assign some points (money) to each of the tasks, while agents have mechanisms to generate the desire to gain points. A Task Manager Agent (TMA) of the system acts on behalf of the user and offer and allocate jobs between the agents on the basis of negotiations with them, and evaluate the results produced by the agents.

If an agent encounters difficulties in achieving a task it can ask other agents to help to tackle the job. This cooperation of agents becomes feasible through communication and negotiations, while competition between agents is caused by their attempts to gain points out of a limited total amount. This perfectly suits to models of a ME in which agents have to compete for limited resources of the system.

If the TMA regards that some task has successfully been achieved by an agent then the agent gets a certain amount of points. Each agent should pay for any resource and any service. An agent can obtain free of charge only information about resources and services provided on the platform. Certain points is automatically debited to support common services of the platform. If an agent has spent all its points, it can be eliminated from the game. In this way the Darwinist selection of most efficient agents is implemented similar to models of markets (see [1 – 8] for more detail).

In order to ensure proper operation of a complex ME, it is essential to carry out relevant measurements and adjustments. Such a system can include a number of elements so that parallel multi-channel signal processing is required. Moreover, extraordinary situations cannot be prevented when there are no regular routine ways to wrestle with emerging problems. Therefore development of systems for parallel signal processing and on-line decision-making is of great importance. Here we sketch a MAS intended to achieve such tasks [14].

Generally, data to be processed can fall into the following categories. *Calm data* pertain to cases when everything appears going well and no control influence is necessary, whereas *provoking data* signify appearance of tokens of abnormal states so that certain control actions are required. In particular, *extraordinary data* indicate a state of emergency when special actions are essential. *Monitoring data* should be processed so as to watch provoking signals. *Recording data* must be memorized. Provoking data may entail either a *routine* reaction or *intelligent* activity of the controller.

A meta-agent Manager (Master) governs interaction between all the other (working) agents (Slaves) and provides facilities for human control of the performance of the MAS.

Communication between agents is implemented through a common file that seems like an "ocean of information" simultaneously accessible to any agent.

4. A Model of an Intelligent Manufacturing Enterprise

Let us represent a manufacturing enterprise (ME) as a directed graph consisting of N uniformized generalized nodes that operate in discrete time $t=0,1,\ldots$. It is convenient to enumerate all relevant utilitities (products, services, workers, materials, information, energy, and other resources) that can, in principle, appear as an input or an output of a node and collect them in a set $U=\{u_\mu,\mu\in M\}$ where (multi) index μ may take on values from a set M.

Each node gets some utilities from other nodes, transforms them (or, in particular, keeps intact), and gives some available utilities to other nodes. Thus we suppose that a generalized node i at each time step t $(t=0,1,\ldots)$ has $m+1$ inputs $x^t_{i0\mu_0},x^t_{i1\mu_1},\ldots,x^t_{im\mu_m}$, and $n+1$ outputs $y^t_{i0\nu_0},y^t_{i1\nu_1},\ldots,y^t_{in\nu_n}$, where $x^t_{ij\mu}\in U$ is the utility of kind μ obtained at time t by node i from node j, while $y^t_{ik\nu}\in U$ is the utility of kind ν transfered at time t by node i to node k. Notice that input $x^t_{i0\mu}$ serves to denote utilities produced by node i by itself, and output $y^t_{i0\nu}$ correspond to utilities qualified as ultimate outputs of the ME as a whole.

Let us suppose further that control of operation of a node is performed by an intelligent, in a sense, agent endowed with abilities to gather, collect, and process relevant information so as to elaborate decisions for the node. Then it can appear advantageous if such an agent is able to predict values of so-called switching variables for future time moments given values of these quantities in the past. These variables are defined so as to indicate decisions made by node i.

Namely, the value $s^t_{ij\mu}=+1$ corresponds to the decision made by node i at time moment t to give (starting with the next time moment $t+1$) utility μ to node j, while $s^t_{ij\mu}=-1$ means the decision to try to get utility μ from node j (though this intention, can appear not successful).

We introduce also the probability $P_{ij\mu}(T)$ that the decision to transfer utility μ from node i to node j will be accomplished within time interval T.

It is obvious that not all of the switching variables are relevant for operation of a given node. It is reasonable therefore to determine, for any node i, vector $\sigma_i=\left(\sigma_{\alpha_1\beta_1\rho_1},\sigma_{\alpha_2\beta_2\rho_2},\ldots,\sigma_{\alpha_{L_i}\beta_{L_i}\rho_{L_i}}\right)$ whose components constitute an ordered subset of all quantities $s_{ij\mu}$ arranged according to attainability and importance for the agent (node) i to make and exploit forecasting. Then the task to be achieved by agent i reduces to the following: given values $\sigma^{t'}_i$ for $t'=t,t-1,\ldots,t-T_p$, find values $\sigma^{t''}_i$ for $t''=t+1,\ldots,t+T_f$.

It seems promising to treat any σ_i as an integer number, or even as an approximation of a rational number. In the latter case, a natural way to improve (if necessary) predictions is to enhance the accuracy of the approximation of these rational numbers by taking into account the states of more nodes.

Thus the problem of control of operation of nodes is reduced, in part, to the standard task of forecasting time series, and controling agents should be provided with ability to make such predictions. It turns out that frames in Hilbert spaces appear a promising tool to accomplish forecasting relevant events.

5. Frames in Hilbert Spaces

As is known, a set of vectors $\{|h_a>\in H,\ a\in A\}$ can constitute a basis in a vector space H if these vectors are linearly independent. This property allows to obtain the formula of the inverse transform of vectors. It is remarkable however that the above-mentioned condition can be weakened so that so-called *frames* may be used instead of *bases* for transforms of vectors, i.e. *frame* is a generalization of *basis*.

We accept the following definition [21; 15 – 17]. A *frame* in a Hilbert space H is a set of vectors $\{|h_a>\in H,\ a\in A\}$ such that there exists a set of vectors $\{|h^a>\in H,\ a\in A\}$ constituting a *recirocal (dual) frame* with respect to the first one in the sense that jointly these sets provide resolution of unty in the form

$$I=\int_A d\mu(a)|h^a><h_a|=\int_A d\mu(a)|h_a><h^a|. \quad (1)$$

Here $\mu(a)$ is a Borel measure supported on a set A. These representations provide the inverse transforms for the expansion of vectors. So, if we expand a vector $|u>\in H$ over the reciprocal frame $\{|h^a>,\ a\in A\}$ so that $|u>=\int_A d\mu(a)\,u_a\,|h^a>$ hen the components $u_a=<h_a|u>$ are expressed through the vectors of the original frame $\{|h^a>,\ a\in A\}$. And vice verse, if we take the representation $|u>=\int_A d\mu(a)\,u^a\,|h^a>$ then the coefficients are $u^a=<h^a|u>$.

It is the main point how to construct sets of vectors $|h_a>$ and $|h^a>$ so as to provide frames in Hilbert space H that are reciprocal (dual) to each other. Suppose that there exists an operator T such that $|h^a>=T|h_a>,\quad a\in A$.

Then the above problem amounts to finding this operator given a set of vectors $|h_a>$. Let us introduce the so-called metric operator $G=\int_A d\mu(a)\,|h_a>\,<h_a|$.

Then the required resolution of unity (1) is achieved if the operator T satisfies the equation $TG=I$. Therefore $T=G^{-1}$, and the problem is reduced to finding the inverse matrix G^{-1} if the lebel variable a can take on only discrete values.

6. Least Squares Approximation of Experimental Data and Forecasting Time Series Using Frames

Suppose that it is required to find such a function $y(x)$ that describes how an observable y depends on another observable x, i.e. this function should provide the best approximation of experimental data $(x_1,y_1),\ldots,(x_N,y_N)$ in the sense that the functional $E=\frac{1}{2}\sum_{i=1}^{N}\left(\frac{y_i-y(x_i)}{\sigma_i}\right)^2$ takes the minimum. Here σ_i is the standard (mean square) deviation of y_i. Then from the so-called normal equations one can find the coefficients of the expansion: $y^a=<h^a|\bar{y}>=\sum_{i=1}^{N}\bar{h}^a(x_i)\,y_i/\sigma_i^2$.

Suppose now that a scalar quantity $x(t)$ is measured at discrete times $t_0,t_1,\ldots,t_k=k\tau,\quad k=0,1,\ldots$, which gives a time series $x_0,x_1,\ldots$ to be processed. The common approach to forecasting time series is to use vectors in the embedding space (for an introduction see, e.g., [22]). Then the problem can be formulated as follows.

Let $y\in\mathbf{R}^d$ be a $d-$ dimensional vector composed of time delays of an observable x, i.e. $y_i\equiv y(t_i)\equiv y(i)=(x(i),x(i-1),\ldots,x(i-d+1))$ and $x_i\equiv x(t_i)\equiv x(i)$. It is required to find a map $F(\cdot)$ that describes time evalution of y: $y_{i+1}=F(y_i),\quad i=0,1,\ldots$.

Let us expand the function $F(y)$ over a frame $\{h_a(y),\ a\in A\}$ so as $F(y)=\int_A d\mu(a)F^a h^a(y)$. Using the resolution of unity one can find $y_{i+1}=\sum_{j=1}^{N_t}\Delta(y_i,y_j)y_{j+1}/\sigma_j^2$ where $\Delta(y,y')=\int_A d\mu(a)\;h_a(y)\,\bar{h}^a(y')$.

A similar form for the map $F(y)$ with a function $\Delta_M(y,y')$ of a patricular form is suggested by the kernel density estimation approach (see [22] and references therein). Our framework yields an expression for the probability density that looks similarly but we observe also how this representation arises and what the origin of the kernel $\Delta_M(y,y')$ is.

7. Conclusions

In this paper we put forward a general mathematical framework to model MEs that constitute complex distributed systems composed of interacting elements (nodes). To ensure a proper performance of such a system, it seems promising to provide each sufficiently autonomous element (node) of the system with a controlling intelligent agent. Then the effective control of the ME as a whole reduces, to a considerable degree, to predictions of states of nodes interconnected with a given element. The latter issue is nothing, but the standard problem of forecasting time series and different methods can be borrowed (see, e.g., [22]).

In particular, frames in Hilbert spaces can turn out to be an effective means for making such predictions. This conclusion is based on our preliminary computer simulations. We employed yet a simple model specified by the widely used logistic map $ax(1-x)$ to describe behavior of adaptive, predictive and competitive agents in an evolving chaotic environment along the lines of the paper [23]. A more detailed presentation of our numeric results as well as description of more realistic modeling MEs will be given elsewhere.

It is worth noting that effectiveness of operation of a ME as a whole depends heavily on the extent to which constituents (agents) of the ME compete with one another, because it is just presence of competition along with cooperation that makes self-organization of a system possible. Also, it seems extremely interesting to investigate how agents can be learnt (trained) to be efficient and what statistical properties a system of such agents can exhibit in its performance after the learning. One can expect that theoretical findings presented in [1; 3; 16; 17] can be useful to this end. Now this work is in progress.

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