Hybridization Method of Intelligent Models

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***Abstract*—The development trends of intelligent models are generalized. The approach to systematization and classification of hybrid models is described. Examples of classification of known hybrid intelligent models related to each considered approach to their hybridization are given. The proposed method of hybridization of intelligent models is considered.**

***Keywords*—hybridization of intelligent models, fuzzy model, neural network model, evolutionary modelling**

I. Introduction

At present the researches in the field of creation of intelligent models are actively conducted. The main tendencies of their development are the following:

- these intelligent models are actively used for the solution of poorly structured and unstructured problems;
- these intelligent models based on representation and processing of heterogeneous data and knowledge;
- principles of hybridization and adaptability are used more and more widely;
- problems can be solved in conditions of various types of uncertainty (stochastic, statistical, not stochastic, linguistic).

At present intensive researches are carried out in the field of the following intelligent modelling [1]: fuzzy models based on theories of fuzzy computing, fuzzy sets and relations, fuzzy measure, fuzzy logic and inference; neural networks models based on artificial neural network theory; methods and technologies of evolutional modelling and genetic algorithms.

For each intelligent model is possible to define the development trends.

The development trends of fuzzy models are the following:

- development of fuzzy mathematics (of fuzzy computing, fuzzy sets and relations, fuzzy measure, fuzzy logic etc.);
- designing of fuzziness into traditional mathematical models;
- designing of fuzzy models which correspond to features of tasks;
- hybridization of fuzzy models of various types;
- use of fuzzy models, methods and technologies for problem solving in various subject areas.

The development trends of neural networks models are the following:

- designing of neuron-like elements of artificial neural networks;
- designing of neural networks which correspond to the features of tasks;
- designing of algorithms of artificial neural networks training;
- combination of neural networks models of various types;
- use of neural networks models, methods and technologies for solving problems in various subject areas.

The development trends of evolutionary modelling methods and technologies are the following:

- designing of genetic operators, criteria and search strategy;
- designing of genetic algorithms providing the greater accuracy and rapid convergence;
- developing of approaches to adaptation of genetic algorithms for problem solving in various subject areas.

At present the intensive researches are conducted in the field of creation of hybrid intelligent models, methods and technologies. Hybridization of these intelligent models allows them to complement each other.

Hybridization compensates the restrictions of each of these models and it also provides tolerance to uncertainty and partial validity of the data used to achieve flexibility of decisions [2].

However, up to now, there is no unified approach to hybrid models systematization. The purpose of this paper is the following: to systematize of existing hybrid models; to develop a mechanism for hybridization of intelligent models.

II. HYBRIDIZATION METHOD OF INTELLIGENT MODELS

Hybridization can be realized in different ways: either between models related to different intelligent technologies, or within the same intellectual technology [3]. In both cases hybridization of intelligent models is possible on the basis of one of following approaches:

- hybridization “with functional replacement” – one of the model is picked out as a dominating model, and its separate components are replaced with components of other model;
- hybridization “with interaction” – several models are used relatively independently, and thus they solve various particular tasks in achieving the final goal, exchanging data.

Let’s briefly consider these approaches of hybridization, firstly, by the example of various intelligent technologies and, secondly, within the limits of a separate technology. Let’s demonstrate realization of the hybridization approach “with functional replacement” on the example of fuzzy models’ and neural networks. We will consider fuzzy rule-based models as the dominant, and we will design each separate component of these models on the basis of neural networks. Possible ways of such hybridization allow to distinguish a separate class of fuzzy rule-based neural models (the first sign mentioned – fuzzy – is dominant) [3-5].

In case the neural networks are used as dominating models, then realization of separate components of these models can be executed on the basis of fuzzy models’ components. Possible ways of such hybridization allow distinguish a separate class of neural fuzzy models (the first mentioned sign – neural – is dominating) [6].

Hybridization “with functional replacement” in the context of separate technology is most peculiar to neural networks technology (i.e. hybridization neural networks models only).

Let’s demonstrate realization of the hybridization approach “with interaction” by the example of fuzzy models and neural networks technologies (to be more precise, fuzzy rule-based models and neural networks as above). According to this method the following models can be offered:

- fuzzy rule-based models with use of neural networks for space partition of input variables and formation multidimensional membership functions of antecedents for them;
- joint using of fuzzy rule-based models and neural networks for computing and “interchange” by parameter values [7].

The approach of hybridization of intelligent models “with interaction” is the most important at performance of complex problems. Complex problems are the problems that require the use of various models for performance of separate stages or particular tasks to achieve general purpose.

Let’s consider the hybridization method “with interaction” within the limits of one technology by the example of fuzzy models at realization of complex problems [3]. This method consists of the following stages.

Stage 1. Decomposition of a complex problem into set of particular tasks.

$$Problem = \{Task_1, Task_2, \ldots, Task_n\}.$$

Here *Problem* – complex problem; $Task_i$ – particular task, $i = 1, \ldots, n$.

As an example, let’s consider the decomposition of a complex problem – *situational analysis* – on following particular tasks:

- $Task_1$ – identification of a situation;
- $Task_2$ – estimation of alternative decisions;
- $Task_3$ – prognosis of the resulting situation.

Stage 2. Specifying the requirements to fuzzy models for each of particular tasks.

The *following classification of requirements to intelligent models for particular tasks is offered:*

- R_1 – *subject of knowledge: {*$R_{1,1}$ *– about object of management;* $R_{1,2}$ *– about a management method;* $R_{1,3}$ *– about interrelation of events;* $R_{1,4}$ *– about the decision-maker “relation” to object of management;* $R_{1,5}$ *– about the decision-maker “relation” to a management method};*
- R_2 – *type of time analysis: {*$R_{2,1}$ *– statics;* $R_{2,2}$ *– short-term dynamics;* $R_{2,3}$ *– long-term/complete dynamics};*
- R_3 – *uncertainty type: {*$R_{3,1}$ *– the stochastic;* $R_{3,2}$ *– not stochastic;* $R_{3,3}$ *– stochastic and not stochastic};*
- R_4 – *method of knowledge acquisition: {*$R_{4,1}$ *– primary;* $R_{4,2}$ *– secondary}.*

For each particular task $Task_i (i=1, \ldots, n)$ one or several possible groups of these requirements can be determined:

$$Task_i, i = 1, \ldots, n : \{G_{i,1}, G_{i,2}, \ldots, G_{i,mi}\}$$

Here m_i – number of possible groups of requirements for a task $Task_i$.

The example of requirements to fuzzy models for particular tasks ($Task_1$, $Task_2$ and $Task_3$) is presented in Table 1.

Stage 3. Classification of intelligent models and concretization of their possibilities to meet the requirements for particular tasks.

The following classification of fuzzy models depending on their purpose is offered:

- universal fuzzy models (rule-based, relational, functional);
- task-oriented fuzzy models:
  - functional and relational estimation models;
  - models of events (linguistic lotteries, event trees, failure trees, Bayesian networks, game models);
  - state models and management models (“state-action” models, situational networks with the direct/inverse method of model design, cognitive maps, Markovian and semi-Markovian

Table I
REQUIREMENTS TO FUZZY MODELS FOR PARTICULAR TASKS

Particular tasks	Group of requirements	Requirements			
		R_1	R_2	R_3	R_4
$Task_1$	$G_{1,1}$	$R_{1,2}$	$R_{2,1}$	$R_{3,3}$	$R_{4,1}$
	$G_{1,2}$	$R_{1,2}$	$R_{2,2}$	$R_{3,3}$	$R_{4,1}$
$Task_2$	$G_{2,1}$	$R_{1,4}$	$R_{2,1}$ OR $R_{2,2}$ OR $R_{2,3}$	$R_{3,2}$	$R_{4,1}$
	$G_{2,2}$	$R_{1,2}$	$R_{2,2}$	$R_{3,3}$	$R_{4,1}$
	$G_{2,3}$	$R_{1,2}$	$R_{2,3}$	$R_{3,3}$	$R_{4,2}$
$Task_3$	$G_{3,1}$	$R_{1,1}$	$R_{2,2}$ OR $R_{2,3}$	$R_{3,3}$	$R_{4,1}$
	$G_{3,2}$	$R_{1,2}$	$R_{2,2}$ OR $R_{2,3}$	$R_{3,3}$	$R_{4,1}$

models, Petri nets, automatons, decision trees) [3].

Stage 4. Specification of set of the intelligent models that meets requirements for particular tasks.

"The covering tree" of complex problem is formed by a set of corresponding fuzzy models on the basis of Stages 2 and 3. The example of "the covering tree" for a considered problem is presented in Fig. 1.

Stage 5. Selection of a subset of the intelligent models providing minimal "covering" of a complex problem.

Minimal "covering" of a complex problem is such a subset of fuzzy models where even removal of one of the models leads to impossibility of the problem solution.

The following subset of fuzzy models for a considered example is selected:

- fuzzy situational network with the direct method of model design (basic model);
- fuzzy model "state-action" (supplementary model);
- linguistic lotteries (supplementary model).

III. EXAMPLE OF THE COMPOSITIONAL FUZZY MODEL FOR THE EFFICIENCY ESTIMATION OF ENERGY- AND RESOURCE SAVING

Figure 2 shows the structure of the compositional fuzzy model for the efficiency estimation of energy- and resource saving, based on the proposed method [8].

The compositional fuzzy model consists of the sets of the following models:

- fuzzy cognitive models for estimating the effects of actions on the subsystems' indicators (power supply, heat and water supply);
- fuzzy rule-based models for efficiency estimating of energy- and resource saving of subsystems: power supply, heat and water supply;
- generalized fuzzy rule-based model for efficiency estimating of energy- and resource saving of system as a whole.

The fuzzy cognitive models are affected by events from groups of measures $A_{s_j} = \{a_{k_j}^{(s_j)}\}, k_j = 1, \dots, K_j$, corresponding to subsystems $\forall s_j \in S$. As a result, the values of the output variables $p_1(s_j)$ and $p_2(s_j)$ of these models, which (together with indicators $p_3(s_j)$ and $p_4(s_j)$, do not depend on the impact of the events) are fed to the inputs of fuzzy rule-based models for efficiency estimating $e(s_j), j = 1, \dots, J$ of energy- and resource saving of subsystems. Then, these estimates are aggregated into a generalized indicator $E(S)$ of energy and resource efficiency of the entire system S using generalized fuzzy rule-based model.

IV. CONCLUSIONS

The development trends of intelligent models are generalized. The approach to systematization and classification of hybrid models is offered. Examples of classification of known hybrid intelligent models related to each considered approach to their hybridization are given.

The proposed method of hybridization of intelligent models is considered. This method consists of the following stages:

(i) decomposition of a complex problem into set of particular tasks;
(ii) specifying the requirements to models for each of particular tasks;
(iii) classification of intelligent models and concretization of their possibilities to meet the requirements for particular tasks;
(iv) specification of set of the intelligent models that meets requirements for particular tasks;
(v) selection of a subset of the intelligent models providing minimal "covering" of a complex problem.

ACKNOWLEDGMENT

Research is supported by the grant of the Russian Foundation for Basic Research, project no. 18-07-00928_a.

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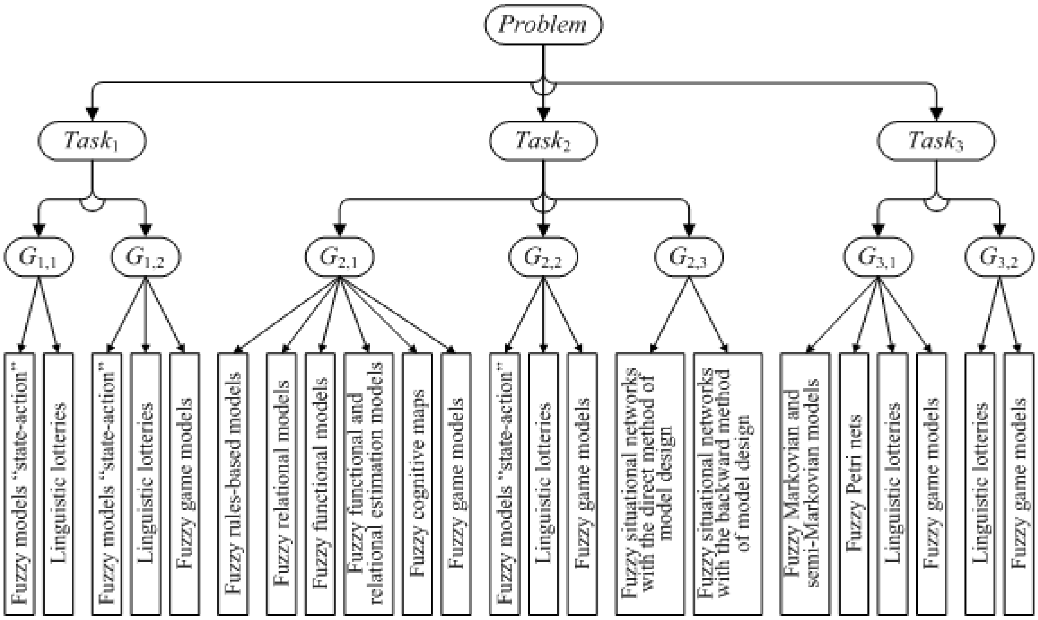

Figure 1. "The covering tree" of complex problem – situational analysis – by a set of fuzzy models

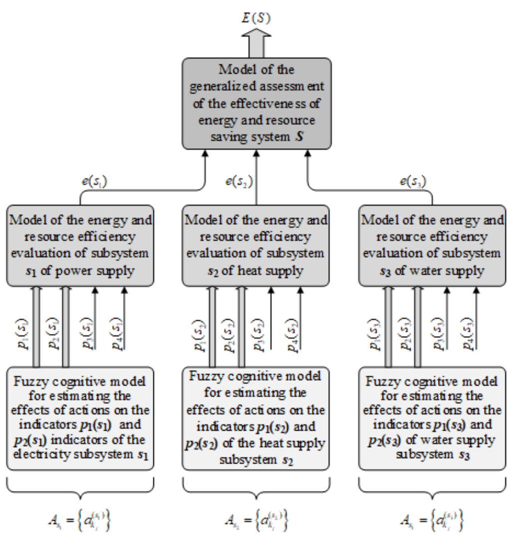

Figure 2. Structure of the compositional fuzzy model

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Метод гибридизации интеллектуальных моделей

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Обобщены тенденции развития интеллектуальных моделей. Описан подход к систематизации и классификации гибридных моделей. Приведены примеры классификации известных гибридных интеллектуальных моделей, в соответствии с рассмотренным подходом к их гибридизации. Рассмотрен предложенный метод гибридизации интеллектуальных моделей.

Received 21.12.19