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MODELS OF DECISION-MAKING SUPPORT ON LOCAL ENERGY CONVERSION SYSTEMS

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We consider decision support models on local energy conversion systems in vagueness conditions. The problem of fuzzy multicriterial analysis of local energy conversion systems is considered as fuzzy non-linear programming problem of with a few incompatible criteria. We offer the sequence of decision-making steps in the fuzzy multicriterial analysis of the informal choice convolution scheme for transition from vectorial criterion to a scalar combination. We consider multi-agent model due to their ability to solve large-scale problems that are difficult to implement in single-agent approximation.

Keywords: fuzzy sets, energy conversion, decision support

Introduction

The modern scientific and technological decisions on creation of energetic complexes are characterized characterized by the transition from traditional energy development as a highly centralized system with a predominance of large generation sources to a variety of types and forms of energy development, including small distributed power engineering. Traditionally mathematical simulation of energy conversion systems is used for the solution of project tasks: load calculation, definition of transformers, transmission line route selection etc. [1]. Development of information technologies, in particular business intelligence tools, allows us to spread scope of mathematical simulation to other stages of life cycle of a power supply system [2].

The power supply system is a complex set of technical equipment. Therefore the stage of synthesis of the initial option of its structure requires decision-making in the conditions of uncertainty. The modern theory of making decision in the complicated systems allows us to describe uncertainty models by means of fuzzy set theory (FST).

Some uncertainty models aren't connected to the randomness concept, and reflect incompleteness of our knowledge of studied object and its interaction with surrounding environment. For example, the emergence of new working bodies for which the thermodynamic properties are unknown, complicates problem of estimating the energy efficiency of perspective local energy conversion systems, as obtaining information requires the long and expensive researches of thermophysical properties. Application of model of vagueness allows us to offer an effective way to the decision of this problem and to pass a traditional stage of determination of thermodynamic properties of not studied substances.

Comparison over of the uncertainty theories is presented in [3]. Fuzzy models are the system models, which are constructed, used and analysed with principles of FST and fuzzy logic. Fuzzy models provide an essential tool for research of both individual components and the whole system at various stages of its analysis in the case of qualitative elements domination over the quantitative.

Popular mathematical modeling packages (MATLAB, fuzzyTECH etc.), allow user to concentrate on application questions of fuzzy inference systems and to be released from developing those systems. However, the use of such subject-oriented software requires analysts to involve in design that restricts FST application.

Data Mining is intended to improve power supply system structure using results of laboratory measurements, monitoring power system parameters, computer simulations. Effective means of solving complex Data Mining problems difficult to formalize are artificial neural networks (ANNs). Models using ANNs are universal and bind in unified manner target agent functions (thermodynamic, economic, eecological, social, etc.) with management variables. The disadvantage of neural network paradigm is the large volume of training sample.

Proceeding from explained, development of the software tools intended for mathematical simulation of energy conversion systems, remains the actual task

Objective and task

The *aim* is to create an information system to support decision-making (DSS) on local systems of electrical power supply of customers as a part of low or middle power energetic complexes.

To achieve this goal in the paper we solve such *problems*:

- formalization of the problem of fuzzy and multi-criteria selection of energy system;
- creation data warehouse for project and experimental data;
- construction of training samples for ANNs;
- providing of high-rate of convergence and reliability in the concordance of vagueness models of data and knowledge due to application of multiagent calculating models.

Formalization of the problem

Formulation of any problem of multi-choice contains three objects - a set of possible solutions, vector criterion and the preference relation of the decision maker.

Applying the Edgeworth-Pareto principle allows exclude obviously unacceptable solutions from the set of all possible. Informed choice of a Pareto-optimal solution is possible only if there is information, often in the form of coefficients of the relative importance of the criteria that are usually appointed by experts. Informed choice of a Pareto-optimal solution is possible only if there is information, often in the form of coefficients of the relative importance of the criteria that are usually appointed by experts.

The principle of hierarchy analysis [4], based on pairwise comparisons of objects of choice on different criteria with use of tenball scale and the subsequent ranking of a set of objects for all criteria and goals can be used to determine the relative importance of criteria. Mutual relations between criteria are taken into account by the constructing of hierarchy of criteria and application of pair comparisons for the exposure of importance of criteria and subcriteria. The method is simple and gives a good accordance to intuitional presentations.

The basic method of measuring of experts preferences, used in the method of hierarchy analysis, is pair comparisons. Each expert shall compare in pairs all objects by each criterion and give an assessment of preference on a tenball scale. The choice of this scale due to the following reasons: the higher the number of grades of the scale, the more accurate the expert assessment. It is extremely difficult to carry out simultaneous comparing more than nine objects. Therefore there are enough nine gradations for their distinguishing.

Results of an expert assessment of objects register in the form of the matrixes of pairwise comparisons. The principal eigenvector of the matrix is interpreted as a vector of priorities of the objects being compared.

R. Bellman and L. Zadeh offered a scheme [5], realizing the process of making decision in the conditions of vagueness, when aims and limitations of multicriterion task are set by fuzzy sets. According to the principle of the Bellman-Zadeh diagram decision-making is meant as a choice of the object which is at the same time fitting both the indistinct purposes, and indistinct restrictions.

A model to support decision making based on fuzzy sets tools [2] is used in our DSS. Model takes into account the uncertainty of purpose, as a consequence of the incompleteness of our knowledge about the reaction of the environment on the functioning of local energy conversion systems. It is assumed that the target functions - exergetic efficiency and net income, along with environmental restrictions in the conditions of uncertainty of different nature can be represented by fuzzy sets. The global criterion of balance K is a vectorial criterion.

The problem of thermoeconomic optimization is considered as a problem of indistinct non-linear programming with n incompatible criteria (for example, economic and thermodynamic), m – management variables and k non-linear restrictions:

$$Optimize K[K_1(X), K_2(X), \ldots, K_n(X)], \; i = 1,2,\ldots,n$$

under conditions

$$C_i \equiv G_{Li} \le G_i(X) \le G_{Ui}, \; i = 1,2,\ldots,k,$$

$$X_{Li} \le Xx_i \le X_{Ui}, \; i = 1,2,\ldots,m,$$

where $K_i(X)$ represent the fuzzy local criteria of effectiveness; $X(X_1, X_2, \ldots, X_m)$ – vector of required management variables; G_{Li}, G_{Ui} - lower and upper limits of restrictions of $G_i(X)$, respectively; X_{Li} и X_{Ui} - lower and upper bounds for the required management variables.

Multicriteria approach is based on a combination of the formal and informal procedures of decision-making for finding of an alternative solution. The formal mathematical means for permission of a multicriteria problem are absent and additional exogenetic information is necessary. According to [3-5] the next sequence of decision-making steps in the fuzzy thermoeconomic analysis of the energytransforming systems is used.

- Determination of area of an optimality according to Pareto (or compromise areas) - XP, in which the coordinated solution of the conflict between criteria with opposite interests is reached;
- Submission criteria and constraints in the form of fuzzy sets to display of unstructured situations (so-called procedure of "fuzzying" of criteria);
- Informal choice of the diagram of a convolution for transition from vectorial criterion $K[K_1(X), K_2(X), \ldots, K_n(X)]$ to a scalar combination $K_1(X), K_2(X), \ldots, K_n(X)$;
- Estimation of final vector $X_{opt} \in X_P$, minimizing the fuzzy sources of uncertainty.

In the field of Pareto there is no single optimum decision, rather it is a set of alternative solutions. These decisions are optimum in a wider sense - there are no solutions of more significant if all aims are simultaneously attained. The optimality according to Pareto is considered as the tool for receiving alternatives, from which the designer can choose the final decision. Determination of area of Pareto is carried out by means of algorithm of normal boundaries [6].

The following step consists in determination of a final set of parameters of Pareto set, by means of additional external information and transformation of vectorial criterion in the scalar. This step represents a certain complexity in aspect of its formalization. In accordance with the recommendations of [7] obtained from the analysis of ways to convert the vector criterion in scalar we used the scheme [3]. A final decision was determined as a result of intersection of all fuzzy criteria and restrictions displayed by their functions of accessory $\mu(X)$:

$$\mu_K(X) = \mu_{Kth}(X) \cap \mu_{Kec}(X) \cap \mu_{Gi}(X),\ i = 1,2,\ldots,k,\ X \in X_P .$$

Membership functions of objectives and constraints can be chosen in different ways depending on a problem context. One possible fuzzy convolution schemes is shown below:

- As an initial approximation choose a vector *X*. The maximum (minimum) values for each criterion of K_i are set as result of the solution of the scalar task of maximizing (minimization) for each of criteria. Results are designated as "ideal" points $\{X_j^0,\ j = 1,\ldots,m\}$.
- Matrix [T] where diagonal elements – "ideal" points, it is defined as follows:

$$[T] = \begin{bmatrix} K_{th}(X_1^0) & K_{th}(X_2^0) \\ K_{ec}(X_1^0) & K_{ec}(X_2^0) \end{bmatrix}$$

- The maximum and minimum boundaries of criteria are defined:

$$K_i^{\min} = \min_j K_j(X_j^0) = K_i(X_i^0),\ i = 1 \ldots n;$$
$$K_i^{\max} = \max_j K_j(X_j^0),\ \ i = 1 \ldots n.$$

- Membership functions for all fuzzy goals presented in the form:

$$\mu_{Ki}(X) = \begin{cases} 0, & if\ \ K_i(X) > K_i^{\max} \\ \dfrac{K_i^{\max} - K_i}{K_i^{\max} - K_i^{\min}} & if\ \ K_i^{\min} < K_i \le K_i^{\max}, \\ 1, & if\ \ K_i(X) \le K_i^{\min} \end{cases}$$

- Fuzzy constraints have the following structure:

$$C_j(X) \le C_j^{\max} + d_j,\quad j = 1, 2,\ldots q$$

where d_j – real parameter which designates distance from admissible offset for boundary $C_j^{\max}$ of *j-th* restriction. The corresponding membership function is defined as follows:

$$\mu_{Cj}(X) = \begin{cases} 0, & if\ \ C_j(X) > C_j^{\max} \\ 1 - \dfrac{C_j(X) - C_i^{\max}}{d_j} & if\ \ C_j^{\max} < C_j(X) \le C_j^{\max} + d_j, \\ 1, & if\ \ C_j(X) \le C_j^{\max} \end{cases}$$

- The final decision is defined as the intersection of all indistinct criteria and constraints represented by their membership functions. This problem reduces to the standard nonlinear programming problem: find such values of *X* and *λ*, where, on maximizing *λ*, conditions will be satisfied:

$$\lambda \le \mu_{Ki}(X), \quad i = 1, 2, \ldots, n;$$
$$\lambda \le \mu_{Cj}(X), \quad j = 1, 2, \ldots, q$$

The decision of multicriterion problem exposes the value of operator of optimality *Optimize* and depends on experience of accepting decision person and his understanding of problem.

Data warehouse designing

Mining can not rely only on the data of their own corporation development. These data will be insufficiently. Tools, allowing us to integrate and store heterogeneous data from various sources are necessary.

As a model of design and experimental data warehouse it is common to use a multi-dimensional space with discrete number of values for each dimension. In the model we selected as measures are taken Time, capital costs, insurance costs, labor costs, ecology indicators are taken as dimensions in the model we selected. Target functions - exergetic efficiency and net profit are used as measures or facts. Time is a hierarchical dimension, measures and dimensions are stored in the data mart using the scheme snowflake.

The developed integration tools allow you to import data from available sources in a network.

Construction of training samples for ANNs

Using multi-layer neural networks as predictive models is caused by ability of ANNs to simulate arbitrary nonlinear continuous functions from training on a set of previously known data.

Neural network models appear to be most promising for modeling energy conversion systems, since they allow you to construct training sets for ANNs based on known models, that already have proved the adequacy, and, then, using the appropriate algorithms, to create neural networks, displaying efficiency criteria of local energy conversion systems, for the further acceptance of compromise decisions.

Procedure of identification of local energy conversion systems on the basis of neuronetwork model structures is multi-stage and includes the following main stages:

- construct the set of data that is used to train the data model;
- the choice of the model structure;
- model training;
- decision making on the adequacy of the model.

Standard training algorithm that implements classical scheme back error propagation is the gradient descent method. Program implementations of algorithms were borrowed by us from a neuronetwork packet of MATLAB [8]. The choice of a method of training isn't the universal and each new task requires its own rules for its decision.

The assessment of efficiency of cycles of energytransforming systems is carried out by methods of engineering thermodynamics. If thermodynamic properties of working environments are known, the calculation of the transformation coefficients (COP - Coefficient Of Performance) in direct and inverse cycles is carried out according to standard expressions. Energy efficiency of direct and inverse cycles is a functional of the parameters of equations of state working environments, for example, the critical parameters and a normal boiling point (input values). To define local energy conversion systems transformation coefficients for the new or low-studied working environment of calculation of thermodynamic properties, it is necessary to construct training set for known working bodies, for that the coefficient of transformation or other technological indexes (output values) is known. After completing the construction of an artificial neural network, we will be able to predict the COP or other value for the new working body only by its input parameters.

Application of multiagent calculating models

To provide reasonable complexity of model training, in the paper, an approach that uses a class of computational models is considered - the so-called multi-agent models [9], for simulation of a set of the purposes of the local energy conversion system separate elements, which as a result of interaction create global properties of system, as a whole. The mathematical apparatus providing the solution of such tasks includes elements of game theory, complex systems theory, evolutionary programming and other sections of applied mathematics. The general structure of agent-based models based on the triple system "stimulus - response - consensus" and it is implemented in the form of interactive model. Interactive scheme carried out in stages. In the beginning a query follows from an arbitrary agent about possibility of achievement of its local aim. Other agents, depending on own purposes, create response of a network to this request. The dialogue established consensus between agents, providing stability of the system. Totality of such processes provides a transition from a microlevel (separate agents) to the macrolevel (system as whole). Thus, a simple behavior of isolated agents generates complicated behavior of the whole system.

Growing interest in the study of multi-agent systems is due such their intrinsic quality as ability to solve problems of big dimensionality, which are difficult for implementing in single agent approximation. High speed of convergence and reliability in coordination of different models of uncertainty of data and knowledge is thus provided. The most widely used agent-based models for concerted solutions under the coordination of the various points of view in dialog communicative processes [10]. Software of different architecture [11-13] are developed for information support the agent-based models in processes of coordination, communication and concordance. Software package RETSINA (Reusable Task Structure Based Intelligent Network Agents), proposed in [14], is among computing instruments of agent-based simulation of general purpose, constructed according to the scheme of the purpose of the agent as response to different incentives. The Multiagent Systems Engineering (MaSE) [15] is based on sequence of operations, starting from the initial specification of the system and to the adoption of solutions. At the analysis stage MaSE model uses the hierarchy of goals, while on design stage classes of agents both the appropriate class diagrams and communications are created. In [16] UML extension (AUML packet) is offered. Different aspects of simulation of the agents, including both class diagrams of agents, and charts of protocols are provided in AUML. Though these approaches, in principle, support cooperation of personal agents, collective interaction is insufficiently elaborated. Methodology Tropos [17] aims at making the analysis of exogenous requirements and constraints in the implementation of the decision-making sequence. Absence of support of protocols and simulation of dynamics of system is marked [18] as shortcomings of this approach. These disadvantages are avoided in the concept Prometheus [19], in which the software of engineering tasks and detail processes in the agent-based networks are supported. Here 3 phases are considered: 1) system specification; 2) agents network architecture design; 3) detailed and specified design of a network. DECAF (Distributed, Environment-Centered Agent Framework) system [20] is a tool for designing, development and implementation of agent-based objectives in a complex environment. Performed analysis of tools confirmed the possibility of real-world multi-agent systems development.

Conclusion

The developed system is tested on the problems of constructing the training samples from agent-based models for finite-time direct and reverse cycle power plants and training samples from agent-based models of the dynamics of energy efficiency of refrigeration systems.

It is expedient to apply in software implementations of DSS on local systems of electrical power supply of customers the perspective methods of simulation using fuzzy models, multi-dimensional data warehouse, neuronetwork model structures and multiagent calculating models.

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МОДЕЛІ ПІДТРИМКИ ПРИЙНЯТТЯ РІШЕНЬ ПО ЛОКАЛЬНИХ СИСТЕМАХ ПЕРЕТВОРЕННЯ ЕНЕРГІЇ

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Розглянуто моделі підтримки прийняття рішень в умовах невизначеності у локальних системах перетворення енергії. Задачу нечіткого багатокритеріального аналізу локальних систем перетворення енергії розглянуто як задачу нечіткого нелінійного програмування з кількома несумісними критеріями. Запропонована послідовність кроків ухвалення рішення в нечіткому багатокритерійному аналізі неформального вибору схеми згортки для переходу від векторного критерію до скалярної комбінації. Розглядаються мультиагентні моделі завдяки їх здатності вирішувати задачі великої розмірності, які важко реалізувати в одноагентному наближенні.

Ключові слова: нечіткі множини, перетворення енергії, підтримка прийняття рішень

МОДЕЛИ ПОДДЕРЖКИ ПРИНЯТИЯ РЕШЕНИЙ ПО ЛОКАЛЬНЫМ СИСТЕМАМ ПРЕОБРАЗОВАНИЯ ЭНЕРГИИ

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Рассмотрены модели поддержки принятия решений в условиях неопределенности в локальных системах преобразования энергии. Задача нечеткого многокритериального анализа локальных систем преобразования энергии рассмотрена как задача нечеткого нелинейного программирования с несколькими несовместимыми критериями. Предложена последовательность шагов принятия решения в нечетком многокритериальном анализе неформального выбора схемы свертки для перехода от векторного критерия к скалярной комбинации. Рассматриваются мультиагентные модели благодаря их способности решать задачи большой размерности, которые трудно реализовать в одноагентном приближении

Ключевые слова: нечеткие множества, преобразования энергии, поддержка принятия решений