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SWARM INTELLIGENCE APPROACH FOR SIMULATION MODELING OF DISTRIBUTED POWER SYSTEMS

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***Abstract**—The approach for multiagent systems' simulation models' adaptation is proposed. It uses the methods of swarm intelligence and fuzzy logics to describe the collective behavior of decentralized system agents. The practical use of this approach is demonstrated by the simulation model of a distributed power system, as well as the use of swarm intelligence for some other systems.*

Index Terms—Simulation modeling; swarm intelligence; fuzzy logic; power systems UDC.

I. INTRODUCTION

The approach is proposed that is able to support the adaptation of some simulation models to real-world indicators and enhance their stability through the introduction of swarm intelligence. This approach involves the use of methods of fuzzy logic and swarm intelligence to describe the collective behavior of agents of a decentralized system. Event-oriented programming is actively used to simulate agent behavior, and fuzzy logic is used to describe agent responses to events.

II. SIMULATION MODELING OF FUZZY SYSTEMS

Simulation modeling is used in all spheres of human activity, beginning with models of technical, technological and organizational systems, and ending with the problems of human development [1]. The review [2] shows that simulation modeling is one of the most common methods used in practice.

The main task of fuzzy modeling is to find a finite set of local input-output relationships that describe the system or process in the form of fuzzy IF-THEN rules. The training of fuzzy systems involves two main steps: the definition of the structure and the evaluation of the parameters. At the first stage, the characteristics of a fuzzy system are determined, such as the number of fuzzy rules, the number of linguistic terms, into which input and output variables are divided. This stage can be performed using the subjective data distribution, diffusion algorithm or fuzzy cluster analysis [3].

III. FIRST TYPE OF FUZZY SETS

A fuzzy set of the first type (FS1) is a set in which the membership function of an element of a set can take any values in the interval [0, 1], and not just the values 0 or 1, as described in [4]. This indicates that the element enters the fuzzy set with some certainty.

In general, FS1 can be defined as follows:

$$\tilde{A} = (B, f),$$
$$f \to B : X; \quad f \in [0,1], \quad X = \varnothing.$$

where B is a basis; X is a universal set; f is a mapping of a basis on a universal set.

IV. SECOND TYPE OF FUZZY SETS

Fuzzy sets of the second type (FS2) are a generalization of fuzzy sets of the first type and are used to handle more uncertainty.

They make it possible to describe all the uncertainty in the membership function of the fuzzy sets theory. If, however, the uncertainty is sufficiently low, then FS2 can be reduced to FS1.

Proceeding from the above definition of FS1, we can derive a formula for determining a fuzzy set by an n-order

$$\tilde{A}_n = \left\{ f(x) \middle| \forall x \in B, \quad f(x) = \tilde{A}_{n-1} \right\}.$$

When describing objects and phenomena using fuzzy sets, the concept of fuzzy and linguistic variables is used.

A fuzzy variable is characterized by a triple $< \alpha, X, A >$, where α is variable name; X is universal set (domain of definition for α); A is fuzzy subset of X, describing restrictions on the values of a fuzzy variable α.

A linguistic variable is a set <β, T, X, G, M>, where β is name of the linguistic variable; T is a set of its values (a term-set) that represent the names of fuzzy variables whose domain of definition is the set X.

The set T is called the base term-set of the linguistic variable; G is a syntactic procedure that allows to operate with elements of the term set T, in particular, to generate new terms (values).

The set $T \cup G(T)$, where $G(T)$ is the set of generated terms, which is called the extended term set of the linguistic variable; M is a semantic procedure that allows you to convert a new value of the linguistic variable formed by procedure G into a fuzzy variable, that is, to form a reciprocal fuzzy set.

To avoid a large number of characters:

- the symbol β is used both for the name of the variable itself and for all its values;
- to denote a fuzzy set and its name, one symbol is used. For example, the term "young" is the value of the linguistic variable β = "age", and, at the same time, the fuzzy set Y ("young").

A fuzzy output is formed when the following steps are completed:

- fuzzification converts the clear values measured at the output of the control object into fuzzy quantities that are described by linguistic variables in the knowledge base;
- formation of knowledge base – description of linguistic variables and fuzzy sets;
- formation of decision block – fuzzy conditional (if – then) rules embedded in the knowledge base are used to convert fuzzy input data into necessary control actions that are also fuzzy;
- defuzzification – converting fuzzy data from the output of the decision block to a clear value that is used to control the object.

V. Management of Distributed Power Systems

As a system, by the example of which it is possible to develop and apply the approach under consideration, a distributed power system control system was chosen. Against the backdrop of the growing and changing demand for electrical energy, the problem of its optimal distribution among consumers is exacerbated. Along with traditional energy fossils, renewable sources are increasingly being used. Technologies of their application are becoming more profitable and convenient. However, most of these sources do not allow producing the required amount of energy constantly. Their effectiveness depends on the season, time of day, current weather and natural conditions. In order to balance the supply and demand of energy produced using renewable and non-renewable resources in real time, intelligent management systems are needed.

The methods of swarm intelligence allow to optimize the distribution of energy: to link the objects of energy networks using different energy production centers (solar panels, wind farms, heat and power plants, etc.), on the one hand, and consumption centers (buildings, enterprises, electric cars, etc.) - on the other. New intelligent solutions can calculate the best ways and channels of energy transfer between its suppliers and consumers, to predict supply and demand, taking into account the accumulated statistical data.

In the distributed energy system management, this approach will improve the following indicators:

- increase the security and stability of the power grid infrastructure (if the system agent fails, the rest continue to operate and adjust to the situation);
- reduce energy carriers cost;
- distribute and use energy more efficiently, reduce greenhouse gas emissions.

VI. Simulation of a Distributed Power System

When simulating the swarm intelligence in a distributed power system, agents are divided into several types:

- electric power manufacturer;
- consumer;
- substation.

The producer (power station) produces electricity and has such properties as current and maximum power, the function of generating electricity. The consumer consumes electricity and has such properties as current and maximum consumption, overload indicator, power consumption function. The substation helps to balance and adjust the transmission of electricity.

The described agents of the system are connected to the network via power lines, which have such properties as throughput and transmission loss factor. An example of such a system is shown in Fig. 1. The squares are two solar power stations. They are connected to substations (yellow circles), which in turn are connected with consumers (red circles). Side of the power plants and consumers are depicted their power indicators (generated and consumed, respectively). Near to each power station and consumer its power indicator is shown (generated power and consumed power, respectively).

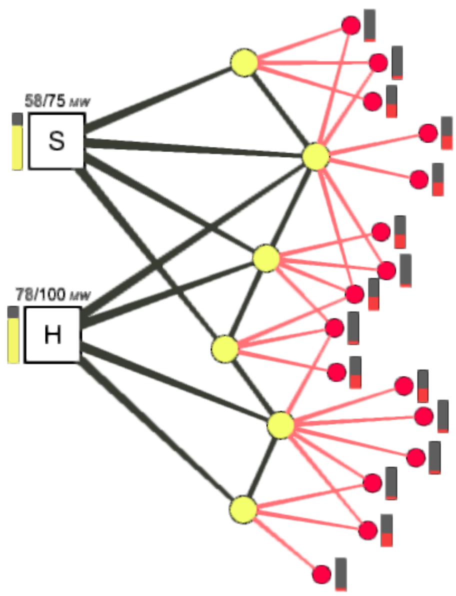

Fig. 1. Simulation model of the distributed power system

In the system time, the functions of generating and consuming for each agent of the system are updated every day, with small random deviations from the set standards (an example is shown in Fig. 2).

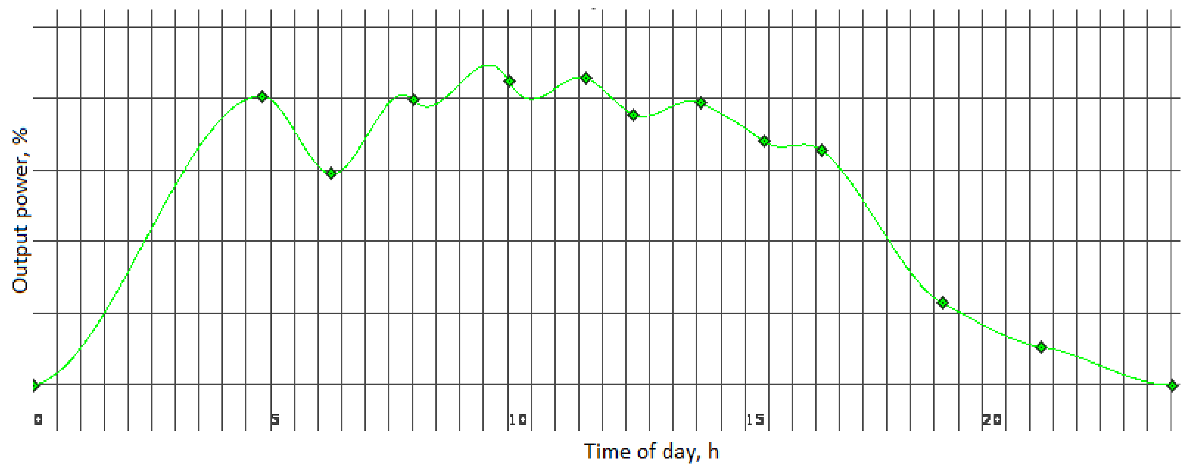

Fig. 2. The graph of the function of electricity generation per day at a solar power plant

The goal of the producer agents is to ensure a stable supply of electricity: no more, no less than the amount demanded by consumers. The agent can predict supply and demand, considering the statistical data accumulated in himself and other agents, and also react to events and the consequences of the influence of his environment, using fuzzy logic in its behavior.

VII. Conclution

Using the example of a simulation model of a distributed power system, an approach was demonstrated that provides the ability to simulate swarm intelligence systems with fuzzy logic in agent behavior.

Such systems are highly resistant to failures, adaptive to real world indicators and flexible in adjustment. The user of the system can customize the behavior of agents by specifying the necessary membership functions and quantitative characteristics in reactions to events that are programmed by the system developer.

In addition to distributed power systems, examples of systems in which there is a need for their modeling are the swarm control systems of unmanned vehicles. The car connected to the system of swarm intelligence can autonomously move in the flow of machines, "anticipating" obstacles and turns, and also exchanging data with other vehicles. Information about the local traffic situation and the desired maneuvers of other traffic participants, coming from sensors and cameras of their own and from neighboring cars, allows choosing optimal maneuvers, minimizing collision risks. By this principle, it is possible to establish a decentralized transport system with self-organizing unmanned vehicles.

Another example of the use of this approach can be the simulation of systems of service robots-rescuers. Natural disasters (earthquakes, floods) and large technogenic accidents bring great destruction and take many human lives. It is necessary to react to such situations as quickly as possible. The faster the victims are found, the more lives you can save. Robots-rescuers can penetrate into the most complex obstructions, places of accidents and fires, while overcoming hard difficulties (high temperatures, water cut, lack of visibility, etc.). Equipped with swarm intelligence, cameras and sensors, robots can act together, covering the entire territory of the disaster. Each of them operates according to algorithms, taking into account the behavior of other robots of the decentralized system and the data coming from them. It is enough for the rescuer-operator of such a system to submit separate commands to determine the detection area and regulate the behavior of agents of the system.

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Ю. І. Рудяков, В. М. Томашевський. Імітаційне моделювання ройового інтелекту в мультиагентній системі

Запропоновано підхід, який може бути використаний для адаптації імітаційних моделей мультиагентних систем за рахунок використання методів ройового інтелекту і нечіткої логіки для опису колективної поведінки агентів децентралізованої системи. Практичне застосування цього підходу продемонстровано на прикладі імітаційної моделі розподіленої енергосистеми, а також на прикладі використання ройового інтелекту для деяких інших систем.

Ключові слова: імітаційне моделювання; ройовий інтелект; нечітка логіка; енергосистеми.

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Напрямок наукової діяльності: імітаційне моделювання, моделювання систем передачі та обробки даних, систем управління медичними підрозділами, виробничих і організаційних систем.
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Ю. И. Рудяков, В. Н. Томашевский. Имитационное моделирование роевого интеллекта в мультиагентной системе

Предложен подход, который может быть использован для адаптации имитационных моделей мультиагентных систем за счет использования методов роевого интеллекта и нечеткой логики для описания коллективного поведения агентов децентрализованной системы. Практическое применение этого подхода продемонстрированно на примере имитационной модели распределенной энергосистемы, а также на примере использования роевого интеллекта для некоторых других систем.

Ключевые слова: имитационное моделирование; роевой интеллект; нечеткая логика; энергосистемы.

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